A DATA-DRIVEN APPROACH TO MOTORCYCLE SAFETY: APPLYING MACHINE LEARNING AND DEEP LEARNING TO INJURY SEVERITY PREDICTION

SONITA SUM

A Thesis Submitted in Partial Fulfillment of the Requirements for the
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แนวทางการขับเคลื่อนข้อมูลความปลอดภัยของรถจักรยานยนต์: การประยุกต์ใช้การเรียนรู้ของเครื่องและการเรียนรู้เชิงลึก ในการพยากรณ์ความรุนแรงของการบาดเจ็บ

นางสาวสุนิตา สม

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาปรัชญาดุษฎีบัณฑิต

สาขาวิชาวิศวกรรมโยธา ขนส่ง และทรัพยากรธรณี

มหาวิทยาลัยเทคโนโลยีสุรนารี

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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy

Thesis Examining Committee

....

(Prof. Dr. Thaned Satiennam)
Chairperson

....

(Prof. Dr. Vatanavongs Ratanavaraha)
Member (Thesis Advisor)

....

(Assoc. Prof. Dr. Sajjakaj Jomnonkwao)
Member (Thesis Co-advisor)

....

(Prof. Dr. Wichuda Satiennam)
Member

....

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(Assoc. Prof. Dr. Yupaporn Ruksakulpiwat)
Acting Vice Rector for Academic Affairs and Quality Assurance

....

(Assoc. Prof. Dr. Pornsiri Jongkol)
Dean of Institute of Engineering

สุนิตา สม: แนวทางการขับเคลื่อนข้อมูลความปลอดภัยของรถจักรยานยนต์: การประยุกต์ใช้การเรียนรู้ของเครื่องและการเรียนรู้เชิงลึกในการพยากรณ์ความรุนแรงของการบาดเจ็บ (A DATA-DRIVEN APPROACH TO MOTORCYCLE SAFETY: APPLYING MACHINE LEARNING AND DEEP LEARNING TO INJURY SEVERITY PREDICTION)
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คำสำคัญ: ความรุนแรงของอุบัติเหตุรถจักรยานยนต์/ปัญญาประดิษฐ์/การเรียนรู้เชิงลึก/ปัญญาประดิษฐ์ที่อธิบายได้/Random Forest/โครงข่ายประสาทเทียมแบบคอนโวลูชัน/SHapley Additive exPlanations

อุบัติเหตุรถจักรยานยนต์เป็นปัญหาด้านสาธารณสุข และความปลอดภัยทางถนนที่ดำเนินมาอย่างต่อเนื่องในประเทศไทย ซึ่งผู้ขับขี่รถจักรยานยนต์เป็นกลุ่มที่มีสัดส่วนการเสียชีวิตจากอุบัติเหตุทางถนนมากที่สุด วิทยานิพนธ์ฉบับนี้มุ่งพัฒนาความเข้าใจทั้งในเชิงระเบียบวิธี และเชิงประจักษ์เกี่ยวกับความรุนแรงของการบาดเจ็บจากอุบัติเหตุรถจักรยานยนต์ ผ่านการศึกษา 4 ส่วนที่เชื่อมโยงกัน โดยบูรณาการเทคนิคอัลกอริทึมการเรียนรู้แบบมีผู้สอน การเรียนรู้เชิงลึก และปัญญาประดิษฐ์ที่สามารถอธิบายได้ งานวิจัยนี้ได้นำข้อมูลอุบัติเหตุระดับประเทศจากระบบบริหารจัดการข้อมูลอุบัติเหตุทางหลวงของประเทศไทย (HAIMS) มาใช้ในการวิเคราะห์ โดยมีเป้าหมายเพื่อยกระดับความแม่นยำในการพยากรณ์ ความสามารถในการตีความ และความเชื่อมโยงเชิงนโยบายของแบบจำลองความปลอดภัยของรถจักรยานยนต์ในบริบทของประเทศกำลังพัฒนา

การศึกษาที่ 1 ของวิทยานิพนธ์ฉบับนี้เป็นการเปรียบเทียบอัลกอริทึมการเรียนรู้แบบมีผู้สอน 4 รูปแบบ ได้แก่ Decision Tree, K-Nearest Neighbor, Naïve Bayes และ Random Forest(RF) กับแบบจำลองทางสถิติแบบดั้งเดิม โดยใช้ข้อมูลอุบัติเหตุในช่วงปี 2563–2565 ผลการวิเคราะห์พบว่าแบบจำลอง Random Forest ให้ประสิทธิภาพการทำนายที่ดีที่สุด (AUC = 0.726) และเมื่อใช้เทคนิค SHapley Additive exPlanations (SHAP) พบว่า สภาพเวลากลางคืน อุบัติเหตุที่เกี่ยวข้องกับรถบรรทุกขนาดใหญ่ เกาะกลางแบบกดร่อง และถนนสองช่องจราจร เป็นปัจจัยสำคัญที่ส่งผลต่อความรุนแรงของการบาดเจ็บ

การศึกษาเรื่องที่ 2 เป็นการประยุกต์ใช้กรอบการวิเคราะห์ Random Forest–SHAP เพื่อศึกษาความแตกต่างระหว่างพื้นที่เมือง–ชนบท และช่วงเวลา กลางวัน–กลางคืน ผลการศึกษาพบว่าความมืด รถบรรทุกขนาดใหญ่ และเกาะกลางแบบกดร่อง เป็นปัจจัยส่งเสริมหรือเพิ่มความรุนแรงของอุบัติเหตุ ในขณะที่เกาะกลางแบบมีกำแพงกั้น การชนเฉี่ยวด้านข้าง และสภาพแวดล้อมที่มีแสงสว่าง

เพียงพอจะสามารถช่วยลดความเสี่ยงของการเกิดอุบัติเหตุ

การศึกษาเรื่องที่ 3 เป็นการพัฒนาแบบจำลองโครงข่ายประสาทเทียมแบบคอนโวลูชัน สำหรับทางโค้ง ผลการศึกษาแสดงให้เห็นว่าโครงสร้างแบบสามชั้นให้ประสิทธิภาพดีที่สุด (accuracy = 0.634) เมื่อเทียบกับแบบจำลองโครงข่ายประสาทเทียมแบบคอนโวลูชันที่ลึกกว่า และแบบจำลองดั้งเดิม การวิเคราะห์ด้วย SHAP ชี้ว่าการมีรถบรรทุกขนาดใหญ่เข้ามาเกี่ยวข้อง การชนแบบประสานงา เกาะกลางแบบกดร่อง การขับขี่ด้วยความเร็วสูง และความมืด เป็นปัจจัยหลัก และจะทวีความอันตรายเพิ่มมากขึ้นเมื่อนำปัจจัยเหล่านี้มารวมกัน เช่น รถบรรทุกวิ่งในเวลากลางคืน เกิดการชนแบบประสานงาบนถนนที่มีเกาะกลาง

การศึกษาเรื่องที่ 4 เสนอแบบจำลองผสม (hybrid model) ที่สามารถอธิบายได้ ระหว่าง Random Forest และ แบบจำลองโครงข่ายประสาทเทียมแบบคอนโวลูชัน สำหรับการพยากรณ์ความรุนแรงของอุบัติเหตุรถจักรยานยนต์ในช่วงปี 2559–2566 แบบจำลองผสมนี้ (ร้อยละ 85 จาก CNN และ ร้อยละ 15 จาก RF) ให้ค่าความแม่นยำสูงสุด (accuracy = 58.9%) และค่าการตรวจพบ (recall = 69.9%) ซึ่งเหนือกว่าแบบจำลองเดี่ยวและ Binary Logistic Regression การตีความด้วย SHAP เน้นให้เห็นว่าแสงสว่างในเวลากลางคืน การจัดช่องจราจร ความโค้งของถนน ความเร็วในการขับขี่ และการดื่มแอลกอฮอล์ เป็นปัจจัยสำคัญที่กำหนดความรุนแรงของอุบัติเหตุ

จากการศึกษาทั้งหมดที่ได้กล่าวมาในข้างต้นนี้เป็นการยกระดับขอบเขตทางระเบียบวิธีของการสร้างแบบจำลองความรุนแรงของอุบัติเหตุ โดยเติมเต็มช่องว่างในงานวิจัยที่เกี่ยวข้องกับ “ความแม่นยำในการทำนาย” และ “ความสามารถในการอธิบายแบบจำลอง” ที่มีมาอย่างยาวนาน ผลการศึกษานี้สามารถใช้เป็นแนวทางในการพัฒนามาตรการความปลอดภัยของรถจักรยานยนต์ที่อ้างอิงตามหลักฐานข้อมูลเชิงประจักษ์ เช่น การปรับปรุงระบบไฟฟ้าส่องสว่างในเวลากลางคืน การจัดการความเร็วที่เหมาะสมตามลักษณะทางกายภาพของถนน การออกแบบเกาะกลางถนนให้มีประสิทธิภาพมากขึ้น และการฝึกอบรมผู้ขับขี่แบบมุ่งเป้าเฉพาะกลุ่ม ทั้งนี้วิทยานิพนธ์ฉบับนี้ได้พัฒนาโครงสร้างกรอบการวิเคราะห์ด้วยปัญญาประดิษฐ์ที่ครอบคลุม และสามารถอธิบายได้ สำหรับการวิเคราะห์ความรุนแรงของอุบัติเหตุรถจักรยานยนต์ ซึ่งมีส่วนสำคัญทั้งต่อการพัฒนาทางทฤษฎี และการกำหนดนโยบายเชิงปฏิบัติในงานวิจัยด้านความปลอดภัยทางการคมนาคม

สาขาวิชาวิศวกรรมขนส่ง

ปีการศึกษา 2568

ลายมือชื่อนักศึกษา ....

ลายมือชื่ออาจารย์ที่ปรึกษา ....

ลายมือชื่ออาจารย์ที่ปรึกษาร่วม ....

SONITA SUM: A DATA-DRIVEN APPROACH TO MOTORCYCLE SAFETY: APPLYING MACHINE LEARNING AND DEEP LEARNING TO INJURY SEVERITY PREDICTION. THESIS ADVISOR: VATANAVONGS RATANAVARAHA, Ph.D. 195 PP.

Keyword: Motorcycle crash severity/Machine learning/Deep learning/Explainable artificial intelligence/Random Forest/Convolutional Neural Network/SHapley Additive exPlanations

Motorcycle crashes constitute a persistent public health and transportation safety challenge in Thailand, where motorcyclists account for the majority of road traffic fatalities. This dissertation advances methodological and empirical understanding of motorcycle crash injury severity through four interrelated studies that integrate supervised learning, deep learning, and explainable artificial intelligence (AI) techniques. Drawing upon nationwide crash data from the Thailand Highway Accident Information Management System (HAIMS), the research collectively seeks to enhance predictive accuracy, interpretability, and policy relevance in motorcycle safety modeling within a developing-country context.

The first study of this dissertation compares four supervised learning algorithms—Decision Tree, K-Nearest Neighbor, Naïve Bayes, and Random Forest—against traditional statistical models using 2020–2022 crash data. The Random Forest model exhibited the best predictive performance (AUC = 0.726) and, through SHapley Additive exPlanations (SHAP), identified nighttime conditions, large-truck involvement, depressed medians, and two-lane roads as major contributors to severe injuries. The second study applies the Random Forest–SHAP framework to examine urban–rural and day–night variations, confirming that darkness, large trucks, and depressed medians increase severity, while barrier medians, side-swipe crashes, and well-lit environments reduce risk. The third study develops a Convolutional Neural Network (CNN) model for curved roadways, demonstrating superior performance of a three-layer architecture (accuracy = 0.634) over deeper CNNs and conventional models. SHAP analysis highlights large-truck involvement, head-on collisions, depressed medians, speeding,

and dark conditions as dominant factors, with hazardous combinations such as trucks operating in darkness and head-on collisions across all median types. Lastly, the fourth study introduces an explainable hybrid Random Forest–Convolutional Neural Network (RF-CNN) model for single-motorcycle crash severity prediction (2016–2023). The hybrid ensemble (85% CNN, 15% RF) achieved the highest accuracy (58.9%) and recall (69.9%), outperforming standalone models and Binary Logistic Regression, while SHAP interpretation emphasized nighttime lighting, lane configuration, curvature, speeding, and alcohol use as key determinants of severity.

Collectively, the four studies advance the methodological frontier of crash severity modeling by bridging the persistent gap between predictive performance and model interpretability. The empirical findings provide a robust foundation for developing evidence-based motorcycle safety interventions, including enhanced nighttime illumination, geometry-specific speed management, improved median design, and targeted rider training programs. Overall, this dissertation establishes a comprehensive, explainable machine learning framework for motorcycle crash severity analysis, contributing to both theoretical advancement and practical policymaking in transportation safety research.

School of Transportation Engineering | Student's Signature ....

Academic Year 2025 | Advisor's Signature ....

Co-advisor's Signature ....

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LIST OF ABBREVIATIONS

C^j	Summary score for model layout j
F	Full feature set (SHAP)
FN	False Negative
FP	False Positive
f(x)	Model output/prediction function
$H(X, O_j)$	Aggregated output of k decision trees (RF ensemble function)
P_{final}	Final prediction probability after combining RF and CNN outputs
$P(X \mid Y)$	Conditional probability of observing X given Y
P(Y)	Prior probability of class Y
$P(Y \mid X)$	Posterior probability of class Y given feature vector X
S	Initial training dataset consisting of N samples and M features
$S \subset F$	Subset of features
TN	True Negative
TP	True Positive
X	Feature vector
x_i	Value of feature i for a given instance
x_{ij}	Value of feature j for instance i
Y	Class variable
λ	Regularization parameter in CNN model
$\varnothing_i$	SHAP value of feature i
ω_{RF}	Weight assigned to the Random Forest component in RFCNN
ω_{CNN}	Weight assigned to the CNN component in RFCNN
AADT	Annual Average Daily Traffic
AUC	Area Under the Curve
AUROC	Area Under the Receiver Operating Characteristic Curve
CM	Confusion Matrix

LIST OF ABBREVIATIONS (Continued)

CNN	Convolutional Neural Network
DOH	Department of Highways
DL	Deep Learning
DT	Decision Tree
FPR	False Positive Rate
HAIMS	Highway Accident Information Management System
KNN	K-Nearest Neighbor
LR	Logistic Regression
MCC	Matthews Correlation Coefficient
ML	Machine learning
NB	Naïve Bayes
PAR	Prediction Accuracy Rate
PDO	Property Damage Only
RF–CNN	Hybrid Random Forest–Convolutional Neural Network
RF	Random Forest
ROC	Receiver Operating Characteristic Curve
RTI	Road Traffic Injuries
RTCs	Road Traffic Collisions
SHAP	SHapley Additive exPlanations
SMOTE	Synthetic Minority Oversampling Technique
WHO	World Health Organization
XAI	eXplainable Artificial Intelligence

CHAPTER I

INTRODUCTION

1.1 Background of the Study

Road traffic crashes continue to be a global public health challenge, causing approximately 1.19 million deaths and 20–50 million injuries each year (WHO, 2023). Vulnerable road users—motorcyclists, pedestrians, and cyclists—constitute more than half of global road traffic deaths, while low- and middle-income countries account for over 90% of all fatalities despite having only about 60% of the world's vehicles (Tavakkoli et al., 2022; Torfs & Meesmann, 2019; WHO, 2023). This ongoing crisis poses significant social and economic costs and continues to hinder progress toward the United Nations Decade of Action for Road Safety (2021–2030) and the Sustainable Development Goal (SDG) 3.6, which aim to halve global road deaths and injuries by 2030.

Motorcyclists are among the most vulnerable road users due to their physical exposure and limited protection compared with vehicle occupants (Lin & Kraus, 2009; Sivasankaran, Rangam, & Balasubramanian, 2021). In many developing countries with inadequate public transport systems, motorcycles have become a fast, cheap, and efficient means of mobility and are widely used for both personal and commercial travel (Bezabeh, Mohamed, Tripodi, & Schermers, 2022). However, this growing dependence on motorcycles has also turned them into a major public health concern, as motorcycle use in developing countries is increasingly associated with high rates of fatal and serious injuries (Tamakloe, Das, Aidoo, & Park, 2022). Thailand exemplifies this situation: motorcycles account for about 75 percent of registered vehicles and nearly three-quarters of all road fatalities (ThaiRSC, 2023). Despite ongoing safety efforts, Thailand's road fatality rate remains among the highest globally—approximately 32.7 deaths per 100,000 population (Kanitpong, Jensupakarn, Dabsomsri, & Issalakul, 2024).

Data from the Highway Accident Information Management System (HAIMS) of the Department of Highways indicate that motorcycle crashes frequently occur on both national and provincial highways. Many are associated with speeding, poor visibility, and inadequate lighting, particularly on curved or rural segments (Se, Champahom, Jomnonkwao, Chaimuang, & Ratanavaraha, 2021; Wisutwattanasak et al., 2024). The severity of motorcycle crashes is determined by an intricate interplay of roadway design, environmental factors, and rider behaviors such as alcohol use, distraction, and fatigue (Champahom et al., 2023).

Traditional crash severity models, such as binary logit and mixed logit frameworks, have long been applied to identify significant predictors of injury outcomes (Savolainen & Mannering, 2007). However, these approaches often rely on strict assumptions of linearity and homogeneity, which limit their ability to represent the complex and heterogeneous nature of crash data (Mannering, Shankar, & Bhat, 2016). With the increasing availability of large-scale datasets, the demand for advanced, data-driven analytical approaches that can reveal hidden patterns and nonlinear relationships has grown rapidly (Ali, Hussain, & Haque, 2024; Santos, Dias, & Amado, 2022).

1.2 Data-Driven Approaches in Crash Injury Severity Analysis

In recent years, data-driven analytical methods have become increasingly important in transportation safety research. These approaches can identify complex and nonlinear relationships among crash-related factors, addressing the limitations of traditional econometric models (Dong, Khattak, Ullah, Zhou, & Hussain, 2022). By leveraging large datasets, they enable a more comprehensive understanding of how roadway, environmental, and behavioral variables interact to influence crash severity.

Compared with conventional regression models, data-driven approaches offer greater flexibility and predictive capability, as they do not require predefined functional forms or distributional assumptions (Ali et al., 2024; Santos et al., 2022). They have therefore been increasingly adopted for crash analysis to enhance both prediction accuracy and policy relevance. Nonetheless, a critical challenge remains: these advanced models are often difficult to interpret, limiting their usefulness for decision-making in real-world safety management (Mannering et al., 2016).

Recognizing this limitation, researchers have begun developing interpretable data-driven frameworks that combine strong predictive performance with transparency (Dong et al., 2022; Kang & Khattak, 2022; Sadeghi, Aghabayk, & Quddus, 2024; Wisutwattanasak et al., 2024). These frameworks aim to identify the underlying mechanisms contributing to severe crashes while maintaining analytical clarity. Despite notable global progress, research in Thailand remains limited. Most existing studies rely on traditional methods or examine isolated contextual dimensions—such as spatial (urban–rural) or temporal (day–night) variation (Champahom et al., 2023; Se et al., 2023). However, relatively little attention has been given to roadway geometry in crash severity analysis, highlighting the need for more comprehensive frameworks.

1.3 Explainable Artificial Intelligence in Transportation Safety

While data-driven models offer strong predictive capabilities, their practical usefulness depends on how well their internal mechanisms can be understood. To address the challenge of model interpretability, Explainable Artificial Intelligence (XAI) has emerged as a promising development in transportation safety analysis. XAI provides a means of understanding and visualizing how complex analytical models generate their predictions, allowing researchers and policymakers to interpret the influence of individual variables on crash outcomes (Lundberg & Lee, 2017; Sadeghi et al., 2024). This approach enhances the transparency and trustworthiness of data-driven models, bridging the gap between advanced analytics and practical application in road safety policy.

In the context of crash injury severity analysis, XAI helps reveal how roadway design, environmental conditions, and behavioral factors interact to affect crash outcomes (Dong et al., 2022). Such interpretability allows transportation professionals to translate analytical findings into targeted, evidence-based safety measures. Recent studies have shown that combining explainability techniques with data-driven modeling can improve both predictive performance and practical understanding of risk factors (Dong et al., 2022; Sadeghi et al., 2024; Wisutwattanasak et al., 2024).

In Thailand, the application of explainable modeling techniques remains limited, although it is gradually increasing. Emerging local studies have begun applying interpretable frameworks to analyze motorcycle crash severity under diverse roadway and temporal conditions, reflecting a shift toward more transparent and data-informed safety research (Wisutwattanasak et al., 2024). Building upon these developments and addressing Thailand’s current research gaps, this dissertation applies explainable and data-driven analytical approaches to examine motorcycle crash injury severity using HAIMS data from 2016 to 2023.

Accordingly, this research develops an interpretable, data-driven framework to enhance understanding of motorcycle crash severity and support evidence-based policymaking in Thailand.

1.4 Purpose and Objectives of the Research

The purpose of this research is to develop and apply interpretable, data-driven analytical frameworks to predict motorcycle crash injury severity and to identify the most influential factors affecting injury outcomes under varying roadway and environmental conditions in Thailand.

To accomplish this purpose, the study pursues the following objectives:

1) To evaluate and compare data-driven predictive approaches for classifying motorcycle crash injury severity.

2) To examine spatial and temporal variations in motorcycle crash severity across urban–rural and day–night contexts.

3) To analyze the effects of roadway geometry—particularly curved segments—on motorcycle injury severity using advanced pattern- recognition techniques.

4) To investigate single-motorcycle crashes in order to uncover critical behavioral, environmental, and infrastructural factors associated with severe injury outcomes.

1.5 Scope of the Research

This research is conducted under the following defined scope:

1) Utilizing motorcycle crash data between 2016 and 2023 obtained from the Highway Accident Information Management System (HAIMS) under the Department of Highways, Thailand, which represent the most recent and complete datasets available for analysis.

2) Applying advanced data-driven analytical frameworks that integrate machine learning, deep learning, and explainable artificial intelligence techniques to achieve the defined research objectives.

3) Fully accounting for spatial, temporal, and geometric variations influencing motorcycle crash injury severity across different roadway, environmental, and behavioral contexts.

4) Examining motorcycle crash severity across multiple contexts, including spatial (urban–rural), temporal (day–night), geometric (curved roadways), and crash-type variations (including single-motorcycle crashes), to identify the key determinants of severe outcomes.

5) Providing evidence-based recommendations derived from interpretable analytical results to support data-driven motorcycle safety management and policy development in Thailand.

1.6 Research Questions

To address the stated objectives, the dissertation investigates the following research questions:

1) What are the primary factors influencing motorcycle crash injury severity on Thailand’s highways, and how can data-driven analytical approaches improve prediction accuracy?

2) How do spatial (urban–rural) and temporal (day–night) variations influence the patterns and determinants of motorcycle injury severity?

3) In what ways do roadway geometries, particularly curved road segments, contribute to differences in crash outcomes among motorcyclists?

4) What combinations of behavioral, environmental, and infrastructure-related factors lead to severe outcomes in single-motorcycle crashes?

5) How can interpretable, evidence-based analytical frameworks support data-driven safety interventions and policymaking for motorcycle crash reduction in Thailand?

1.7 Significance and Contributions of the Research

This dissertation contributes to theoretical understanding, methodological advancement, and practical improvements in motorcycle safety research.

1.7.1 Theoretical contributions

1) Provides empirical evidence of spatial, temporal, and geometric variations influencing motorcycle crash severity.

2) Enhances understanding of the interrelationships among roadway, environmental, and behavioral risk factors.

3) Strengthens the conceptual linkage between data-driven modeling and human–infrastructure interactions in transportation safety.

1.7.2 Methodological contributions

1) Applies interpretable data-driven frameworks to improve transparency in crash severity modeling.

2) Develops a deep learning framework with explainable analysis for geometry-specific crash prediction.

3) Introduces a hybrid modeling approach integrating machine learning and deep learning for balanced performance and interpretability.

1.7.3 Practical contributions

1) Generates actionable insights for policymakers regarding lighting enhancement, median design, curvature treatment, and speed management.

2) Supports Thailand's Decade of Action for Road Safety (2021–2030) and aligns with UN Sustainable Development Goal 3.6.

3) Provides a transferable analytical framework for developing countries facing similar motorcycle safety challenges.

1.8 Organization of the Dissertation

This dissertation is divided into 6 chapters as follows: Chapter I: Introduction, Chapter II: A Comparative Study of a Series of Supervised Learning Models for Motorcycle Crash Injury Severity Prediction, Chapter III: A Random Forest and SHAP-

Based Analysis of Motorcycle Crash Severity in Thailand: Urban-Rural and Day-Night Perspectives, Chapter IV: Predicting Motorcycle Crash Severity on Thailand's Curved Roadways: A Deep Learning Approach, Chapter V: An explainable RF-CNN model for injury severity prediction in single-motorcycle crashes, and Chapter VI: Conclusion and recommendations.

1.9 References

Ali, Y., Hussain, F., & Haque, M. M. (2024). Advances, challenges, and future research needs in machine learning-based crash prediction models: A systematic review. *Accident Analysis & Prevention, 194*, 107378. doi:https://doi.org/10.1016/j.aap.2023.107378

Bezabeh, G., Mohamed, N., Tripodi, A., & Schermers, G. (2022). Motorcycle Safety in Africa. *Abidjan, Côte d'Ivoire. African Development Bank*.

Champahom, T., Se, C., Aryuyo, F., Banyong, C., Jomnonkwao, S., & Ratanavaraha, V. (2023). Crash Severity Analysis of Young Adult Motorcyclists: A Comparison of Urban and Rural Local Roadways. *Applied Sciences, 13*(21), 11723. doi:https://doi.org/10.3390/app132111723

Dong, S., Khattak, A., Ullah, I., Zhou, J., & Hussain, A. (2022). Predicting and Analyzing Road Traffic Injury Severity Using Boosting-Based Ensemble Learning Models with SHAPley Additive exPlanations. *International Journal of Environmental Research and Public Health, 19*(5), 2925. doi:https://doi.org/10.3390/ijerph19052925

Kang, Y., & Khattak, A. J. (2022). Deep learning model for crash injury severity analysis using shapley additive explanation values. *Transportation Research Record, 2676*(12), 242-254. doi:https://doi.org/10.1177/03611981221095087

Kanitpong, K., Jensupakarn, A., Dabsomsri, P., & Issalakul, K. (2024). Characteristics of motorcycle crashes in Thailand and factors affecting crash severity: Evidence from in-depth crash investigation. *Transportation Engineering, 16*, 100227. doi:https://doi.org/10.1016/j.treng.2024.100227

Lin, M.-R., & Kraus, J. F. (2009). A review of risk factors and patterns of motorcycle injuries. *Accident Analysis & Prevention, 41*(4), 710-722. doi:https://doi.org/10.1016/j.aap.2009.03.010

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems, 30*. doi:https://github.com/slundberg/shap

Mannering, F. L., Shankar, V., & Bhat, C. R. (2016). Unobserved heterogeneity and the statistical analysis of highway accident data. *Analytic Methods in Accident Research, 11*, 1-16. doi:https://doi.org/10.1016/j.amar.2016.04.001

Sadeghi, M., Aghabayk, K., & Quddus, M. (2024). A hybrid Machine learning and statistical modeling approach for analyzing the crash severity of mobility scooter users considering temporal instability. *Accident Analysis & Prevention, 206*, 107696. doi:https://doi.org/10.1016/j.aap.2024.107696

Santos, K., Dias, J. P., & Amado, C. (2022). A literature review of machine learning algorithms for crash injury severity prediction. *Journal of Safety Research, 80*, 254-269. doi:https://doi.org/10.1016/j.jsr.2021.12.007

Savolainen, P., & Mannering, F. (2007). Probabilistic models of motorcyclists' injury severities in single-and multi-vehicle crashes. *Accident Analysis & Prevention, 39*(5), 955-963. doi:https://doi.org/10.1016/j.aap.2006.12.016

Se, C., Champahom, T., Jomnonkwao, S., Chaimuang, P., & Ratanavaraha, V. (2021). Empirical comparison of the effects of urban and rural crashes on motorcyclist injury severities: A correlated random parameters ordered probit approach with heterogeneity in means. *Accident Analysis & Prevention, 161*, 106352. doi:https://doi.org/10.1016/j.aap.2021.106352

Se, C., Champahom, T., Jomnonkwao, S., Wisutwattanasak, P., Laphrom, W., & Ratanavaraha, V. (2023). Temporal Instability and Transferability Analysis of Daytime and Nighttime Motorcyclist-Injury Severities Considering Unobserved Heterogeneity of Data. *Sustainability, 15*(5), 4486. doi:https://doi.org/10.3390/su15054486

Sivasankaran, S. K., Rangam, H., & Balasubramanian, V. (2021). Investigation of factors contributing to injury severity in single vehicle motorcycle crashes in India. *International Journal of Injury Control and Safety Promotion, 28*(2), 243-254. doi:https://doi.org/10.1080/17457300.2021.1908367

Tamakloe, R., Das, S., Aidoo, E. N., & Park, D. (2022). Factors affecting motorcycle crash casualty severity at signalized and non-signalized intersections in Ghana: Insights from a data mining and binary logit regression approach. *Accident Analysis & Prevention, 165*, 106517. doi:https://doi.org/10.1016/j.aap.2021.106517

Tavakkoli, M., Torkashvand-Khah, Z., Fink, G., Takian, A., Kuenzli, N., de Savigny, D., & Muñoz, D. C. (2022). Evidence from the decade of action for road safety: a systematic review of the effectiveness of interventions in low and middle-income countries. *Public Health Reviews, 43*, 1604499. doi:https://doi.org/10.3389/phrs.2022.1604499

ThaiRSC. (2023). Thailand Road Safety Annual Report 2023. Retrieved from https://www.thairsc.com/

Torfs, K., & Meesmann, U. (2019). How do vulnerable road users look at road safety? International comparison based on ESRA data from 25 countries. *Transportation Research Part F: Traffic Psychology and Behaviour, 63*, 144-152. doi:https://doi.org/10.1016/j.trf.2019.04.001

WHO. (2023). Road traffic injuries [Online]. Retrieved from https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries/

Wisutwattanasak, P., Se, C., Champahom, T., Kasemsri, R., Jomnonkwao, S., & Ratanavaraha, V. (2024). Factors affecting single and multivehicle motorcycle crashes: Insights from day and night analysis using XGBoost-SHAP algorithm. *Big Data and Cognitive Computing, 8*(10), 128. doi:https://doi.org/10.3390/bdcc8100128

CHAPTER II
A COMPARATIVE STUDY OF A SERIES OF SUPERVISED LEARNING MODELS FOR MOTORCYCLE CRASH INJURY SEVERITY PREDICTION

2.1 Abstract

Motorcycle crashes pose a major public health challenge in Thailand, where motorcyclists account for most traffic fatalities. This study aims to evaluate and compare the predictive performance of four supervised learning models—Decision Tree (DT), K-Nearest Neighbor (KNN), Naïve Bayes (NB), and Random Forest (RF)—for motorcycle crash injury severity using data from the Highway Accident Information Management System (2020–2022). After preprocessing, 36 explanatory variables covering roadway, environmental, accident causes, crash characteristics, and vehicle involvement were analyzed. To address class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) and cost-sensitive learning were applied, and models were validated using train–test splits with cross-validation. The Random Forest model achieved the best performance with an AUC of 0.726, balanced accuracy of 0.649, and Matthews Correlation Coefficient (MCC) of 0.308, outperforming the other algorithms. SHapley Additive exPlanations (SHAP) were used to interpret the RF model, identifying nighttime crashes, large truck involvement, and roadway features (e.g., depressed medians and two-lane roads) as key predictors of severe outcomes. These insights suggest countermeasures such as improving nighttime safety, dedicating truck lanes, and designing safer medians. The novelty of this study lies in integrating model comparison, imbalance-aware metrics, and SHAP interpretability to provide actionable, context-specific policy recommendations for motorcycle safety in Thailand.

2.2 Introduction

Motorcycle crashes remain a critical global road safety issue, with particularly severe implications in Southeast Asian countries where motorcycles are the dominant means of travel. In Thailand, motorcycles make up a large share of the vehicle fleet and are disproportionately involved in traffic-related injuries and fatalities. According to the World Health Organization (WHO, 2023), Thailand has one of the highest road traffic fatality rates in Southeast Asia, and around 75% of those affected are users of two- or three-wheel vehicles, predominantly motorcyclists. This pressing public health challenge underscores the need for effective, data-driven strategies to reduce the severity of motorcycle crashes.

The multifaceted nature of elements influencing motorcycle crash severity presents a significant challenge for traditional analytical methods. These factors encompass a wide range of variables, including rider characteristics, road conditions, environmental factors, and vehicle attributes. The intricate interplay among these variables necessitates sophisticated analytical approaches capable of capturing nonlinear relationships and complex interactions. Recently, the accelerated growth of data analytics and machine learning technologies has revolutionized the field of transportation safety analysis. These cutting-edge techniques offer powerful tools for processing large volumes of crash data, identifying patterns, and generating predictive models. Supervised learning models, in particular, have shown promise in analyzing crash data and predicting injury severity outcomes.

While conventional statistical methods, including multiple regression and logit approaches, have long been the cornerstone of crash analysis, they often fall short when dealing with the complex, nonlinear relationships inherent in motorcycle crash data. These traditional approaches rely on strict assumptions—such as data normality and independence of predictors—that often do not hold in real-world crash data, limiting their effectiveness in capturing complex injury risk patterns (Santos, Dias, & Amado, 2022). In contrast, machine learning techniques offer several advantages in this domain. They can handle large volumes of data with numerous variables, capture complex nonlinear relationships, and often provide superior predictive performance.

Machine learning models are also more adept at dealing with multicollinearity and interaction effects among predictor variables, which are common in crash data (Chan et al., 2022). Furthermore, some machine learning algorithms, including random forests and gradient boosting machines, offer built-in feature importance measures, providing an understanding of the varying impact of different elements on crash severity.

A range of supervised learning algorithms has been utilized in the study of crash data in different contexts. Decision Trees (DT), long valued in transportation safety research, have been widely used for their interpretability and ability to identify hierarchical relationships in crash risk factors (Mohamad, Jomnonkwao, & Ratanavaraha, 2022). K-Nearest Neighbors (KNN) has shown effectiveness in classifying crash severity based on similarity to historical data points (Sahu, Maram, Gampala, & Daniya, 2022). Naïve Bayes (NB) has demonstrated utility in handling categorical data and estimating crash probabilities given various factors (Yahaya, Jiang, Fu, Bashir, & Fan, 2019). Random Forests (RF) have gained popularity for their ability to capture complex interactions between variables and provide insights into factor importance while being less prone to overfitting (Scarano et al., 2023; Yan & Shen, 2022; Yang, Han, & Chen, 2023).

In recent years, comparative studies have been carried out in different countries to evaluate machine learning models for crash severity prediction. For instance, Wahab and Jiang (2019, 2020) conducted studies in Ghana comparing machine learning algorithms with statistical models, finding that Random Forest consistently outperformed traditional methods. (Champahom et al., 2022); Rezapour, Farid, Nazneen, and Ksaibati (2021); Rezapour, Molan, and Ksaibati (2020); Rezapour, Nazneen, and Ksaibati (2020) examined various algorithms in the United States, including logistic regression, decision trees, neural networks, and recurrent networks, highlighting both strengths and limitations. Mansoor, Jamal, Su, Sze, and Chen (2023) compared machine learning and statistical models in Pakistan and confirmed the strong performance of Random Forest, supported by SHAP analysis for interpretability. Kashifi (2023) applied XGBoost with SHAP in France to study two-wheeler crash severity, while Santos, Firme, Dias, and Amado (2024) compared multiple models in Portugal, identifying Random Forest and logistic regression as the most effective.

Despite these advances, comparative evaluations focusing specifically on motorcycle injury severity remain limited in low- and middle-income countries. Most prior studies have been conducted in developed countries, where traffic conditions, infrastructure, and enforcement differ substantially from Southeast Asian contexts. This leaves an important research gap for Thailand, where motorcycles dominate daily mobility and crash fatality rates are disproportionately high. Moreover, while machine learning models often achieve higher predictive accuracy, their “black-box” nature limits their interpretability and practical policy application (Ali, Hussain, & Haque, 2024).

To address these gaps, this study introduces a unified framework that compares four supervised learning models—Decision Tree (DT), K-Nearest Neighbor (KNN), Naïve Bayes (NB), and Random Forest (RF)—while incorporating class imbalance handling and SHapley Additive exPlanations (SHAP) for interpretability. Using recent Thai crash data (2020–2022), this study provides both robust model evaluation and transparent explanations of critical factors influencing motorcycle crash severity. This contribution not only advances methodological rigor but also delivers actionable insights tailored to the high-risk conditions of Thailand and other low- and middle-income countries.

The subsequent sections of this manuscript are organized as follows: Section 2.3 presents a concise overview of the literature review, while Section 2.4 describes the data utilized. Section 2.5 outlines the methodological framework, followed by the results and discussion of model outcomes in Section 2.6. Section 2.7 provides the conclusion together with policy-oriented recommendations, and Section 2.8 presents the limitations of this study and directions for future research.

2.3 Literature Reviews

In recent years, numerous studies have applied machine learning techniques to predict motorcycle crash severity. Table 2.1 summarizes key findings from 2019 to

2024, highlighting methodological evolution, geographic focus, and recurring model performance trends. As shown in Table 2.1, scholarly investigations predominantly draw on data from developed countries, underscoring the need for expanded exploration in developing contexts like Thailand, where motorcycle accidents impose significant economic and social burdens.

In Ghana, Wahab and Jiang (2019) conducted a comprehensive study by comparing machine learning algorithms (J48, Random Forest, Instance-Based learning) with statistical models (Multinomial logit model, Binary logit models, Binary probit model, Ordered logit model). Their results showed that machine learning algorithms were more effective than conventional methods in assessing crash impact, with the Random Forest (RF) algorithm demonstrating the best agreement with experimental data. They identified location, time, and collision type as critical determinants of crash severity. A follow-up study by Wahab and Jiang (2020) compared Multi-layer perceptron (MLP), Rule induction (PART), and Classification and Regression trees (Simple Cart) models. The Simple Cart model outperformed PART and MLP with 73.81% accuracy, identifying factors such as location, settlement type, time, collision type, and crash partner as significant predictors of crash severity.

In the United States, Rezapour and Ksaibati (2020) compared numerous machine learning algorithms, such as Naïve Bayes (NB), Support Vector Machines (SVM), Long short-term memory (LSTM), Decision Tree (DT), and Deep neural networks (DNN). Interestingly, they found that deeper models did not necessarily enhance performance, with a simple LSTM model outperforming more complex alternatives. In the same year, Rezapour, Molan, et al. (2020) compared Binary logistic regression and Classification tree (CT) for injury severity prediction in the United States. They found that Binary logistic regression performed slightly better than Classification tree, although both models identified similar predictors and showed comparable performance in crash prediction. Furthermore, Rezapour, Nazneen, et al. (2020) explored deep learning techniques, evaluating Deep belief networks (DBN), Multilayer neural networks (MLNN), Recurrent neural networks (RNN), and Single-layer neural networks. Their findings indicated that RNN outperformed other neural network models in crash severity prediction, highlighting the potential of deep learning techniques within this area.

In another study, Rezapour et al. (2021) carried out a side-by-side assessment of Random Forest (RF), Support Vector Machines (SVM), Multivariate Adaptive Regression Splines (MARS), and logistic regression for injury severity prediction. Using k-fold cross-validation to assess misclassification rates, they found that the Random Forest algorithm surpassed other methods. Key factors influencing crash severity included speed, traffic volume, and rider's age. Similarly, Mansoor et al. (2023) compared Multinomial logit models (MNL), Random Forest (RF), Naïve Bayes (NB), and Gradient-boosted trees in Pakistan. The Random Forest algorithm was more effective than others with 86.7% accuracy. They used the SHAP method to identify consistent determinants across both statistical methods and machine learning approaches, highlighting the statistical models' limitations due to unobserved factors.

In France, Kashifi (2023) applied the XGBoost model and SHAP (SHapley Additive exPlanations) analysis to study two-wheeler crash severity. The study identified road category, urbanization level, two-wheeler category, and rider age as significant factors. It also noted that crash severity was higher for older riders and male two-wheeler riders, with rural areas, older riders, and non-helmet use associated with increased crash severity. Most recently, Santos et al. (2024) conducted a study in Portugal comparing Decision Tree (DT), XGBoost, Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), Gradient Boosting (GB), and K-Nearest Neighbor (KNN). They found that RF and LR models performed best in predicting injury severity. Key risk factors identified included alcohol consumption, motorcycle age, road type, and gender. The study also noted that accidents occurring on weekends, involving older motorcycles, and on dry roads tended to increase severity.

This review reveals a consistent trend toward the superior performance of machine learning models—especially Random Forest—in motorcycle crash severity prediction. The increasing use of SHAP analysis further highlights the need for model interpretability to support actionable policy insights. Building on this foundation, the present study contributes to the literature by implementing a unified framework that integrates model comparison, class imbalance handling (via SMOTE and cost-sensitive learning), and SHAP-based interpretability. Using a nationally representative Thai dataset (2020–2022), the study applies four supervised models and evaluates performance using both conventional and imbalance-aware metrics (Balanced Accuracy and Matthews Correlation Coefficient), offering a rare combination of methodological rigor and real-world relevance in an underexplored, high-risk context.

Table 2.1 Overview of research on motorcycle crashes injury severity within the past five years

Authors (Year)	Country	Models used	Best Results
Santos et al. (2024)	Portugal	Decision Tree (DT), Logistic Regression (LR), Random Forests (RF), Gradient Boosting (GB), XGBoost, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM)	Random Forests (RF) and Logistic Regression (LR)
Kashifi (2023)	France	eXtreme Gradient Boosting (XGBoost) algorithm for crash severity. SHapley Additive exPlanations (SHAP) analysis for feature ranking and interaction exploration.	
Mansoor et al. (2023)	Pakistan	Multinomial logit model (MNL), Random Forest (RF), Naive Bayes, Gradient-boosted trees methods	Random Forest (RF)
Rezapour et al. (2021)	US	Random Forest (RF), Support Vector Machines (SVM), Multivariate Adaptive Regression Splines (MARS), and logistic regression (LR)	Random Forest (RF)
Rezapour, Nazneen, et al. (2020)	US	Deep belief networks (DBN), Recurrent neural networks (RNN), Multilayer neural networks (MLNN), and Single-layer neural networks	Recurrent neural networks (RNN)

Table 2.1 Overview of research on motorcycle crashes injury severity within the past five years (Continued)

Authors (Year)	Country	Models used	Best Results
Rezapour, Molan, et al. (2020)	US	Binary logistic regression and classification tree (CT)	Binary logistic regression
Rezapour and Ksaibati (2020)	US	Support Vector Machines (SVM), Decision Tree (DT), Naïve Bayes (NB), Long short-term memory (LSTM), and Deep neural networks (DNN)	Long short-term memory (LSTM)
Wahab and Jiang (2020)	Ghana	Multi-layer perceptron (MLP), Rule induction (PART) and Classification and Regression trees (Simple Cart)	Simple Cart model
Wahab and Jiang (2019)	Ghana	Machine learning algorithms: J48, Random Forest, Instance-Based learning. Statistical model: Multinomial logit model (MNLM). Binary logit models, Binary probit model, Ordered logit model.	Random Forest (RF)

2.4 Data Description

This research utilizes data obtained from the Thailand Highway Accident Information Management System (HAIMS), focusing solely on motorcycle crashes occurring within the timeframe of 2020 to 2022. Throughout this three-year interval, a cumulative total of 12,266 motorcycle crashes were documented. Following an extensive data cleansing process, 36 variables were identified and organized into five distinct categories of explanatory factors, which encompass *roadway characteristics* (the number of lanes (2, 4, 6, or ≥ 8), surface type (asphalt or other), median type (no median, flush and painted, raised, depressed, or barrier), and intersection type (four-leg, T, Y, U-turn, public area connection, private connection, or bridge section)), *environmental characteristics* (daytime, raining), *causative factors of the accident* (front-path interruption, illegal passing, violating the traffic signs, alcohol consumption, drowsiness), *characteristics of the accident* (head-on, rear-end, side swipe in parallel lane, off carriageway to the left/right, out of control on carriageway), and *vehicles involved in the accident* (car, van, pick-up truck 4 wheels, truck more than 6 wheels).

The dataset covers crashes on Thailand's national highway network, spanning both urban and rural regions. These roads feature mixed traffic conditions—including a high volume of motorcycles, limited lane separation, and seasonal rainfall—that are known to affect crash dynamics and severity. Thailand's notably high motorcycle ownership and crash fatality rates make it a critical setting for severity modeling in developing countries.

Table 2.2 summarizes the descriptive statistics of the dataset and the injury severity distribution: Severe/Fatal (44.13%) and Minor/PDO (55.87%).

Originally, HAIMS categorized crash severity into four levels: property damage only (PDO), minor injury, severe injury, and fatality. However, severe and fatal crashes constituted a small fraction of the data, introducing class imbalance. To enhance model stability and predictive reliability, these were grouped into two categories: (1) Minor/PDO and (2) Severe/Fatal. This binary grouping approach is consistent with prior machine learning research on crash severity (Agheli & Aghabayk, 2025; Sadeghi, Aghabayk, & Quddus, 2024; Sum et al., 2025) and enhances the interpretability of results while maintaining predictive robustness.

Ethical approval. This study received the ethical approval from the Human Research Ethics Office of Suranaree University of Technology, Thailand (Approval Code: COE No.1/2568).

Table 2.2 Overview of variable descriptive statistics

Variables	Frequency (%)	Mean	SD
Injury Severity			
Severe/Fatal	5,413 (44.13%)		

Table 2.2 Overview of variable descriptive statistics (Continued)

Variables	Frequency (%)	Mean	SD
Minor/PDO	6,853 (55.87%)		
Roadway Characteristics			
UNDER MAINTENANCE	421 (3.43%)	0.034	0.182
UNDER CONSTRUCTION	669 (5.45%)	0.055	0.227
LANE = 2	3,606 (29.40%)	0.294	0.456
LANE = 4	5,479 (44.67%)	0.447	0.497
LANE = 6	1,161 (9.47%)	0.095	0.293
LANE ≥ 8	1,780 (14.51%)	0.145	0.352
ASPHALT	10,135 (82.63%)	0.826	0.379
NO MEDIAN	3,886 (31.68%)	0.317	0.465
FLUSH AND PAINTED MEDIAN	1,208 (9.85%)	0.098	0.298
RAISED MEDIAN	3,611 (29.44%)	0.294	0.456
DEPRESSED MEDIAN	2,183 (17.80%)	0.178	0.383
BARRIER MEDIAN	1,378 (11.23%)	0.112	0.316
PLAIN ROAD	12,004 (97.86%)	0.979	0.145
FOUR-LEG_INT	564 (4.60%)	0.046	0.209
T_INT	714 (5.82%)	0.058	0.234
Y_INT	127 (1.04%)	0.010	0.101
U_TURN	785 (6.40%)	0.064	0.245
CONNECT_PUBLIC AREA	424 (3.46%)	0.035	0.183
CONNECT_PRIVATE	211 (1.72%)	0.017	0.130
BRIDGE SECTION	177 (1.44%)	0.014	0.119
Environmental Characteristics			
DAYTIME	7,409 (60.40%)	0.604	0.489
RAINING	574 (4.68%)	0.047	0.211
Accident Causes			
FRONT-PATH INTERRUPTION	2,801 (22.84%)	0.228	0.420
ILLEGAL PASSING	95 (0.77%)	0.008	0.088
VIOLATING THE TRAFFIC SIGNS	356 (2.90%)	0.029	0.168

Table 2.2 Overview of variable descriptive statistics (Continued)

Variables	Frequency (%)	Mean	SD
ALCOHOL CONSUMPTION	238 (1.94%)	0.019	0.138
DROWSINESS	107 (0.87%)	0.009	0.093
Accident Characteristics			
HEAD-ON	564 (4.60%)	0.046	0.209
REAR-END	3,515 (28.66%)	0.287	0.452
SIDE SWIPE IN PARALLEL LANE	2,107 (17.18%)	0.172	0.377
OFF CARRIAGEWAY TO THE LEFT/RIGHT	825 (6.73%)	0.067	0.250
OUT OF CONTROL ON CARRIAGEWAY	492 (4.01%)	0.040	0.196
Accident-involved Vehicles			
CAR	3,438 (28.03%)	0.280	0.449
VAN	165 (1.35%)	0.013	0.115
PICK-UP TRUCK 4 WHEELS	3,536 (28.83%)	0.288	0.453
TRUCK MORE THAN 6 WHEELS	1,298 (10.58%)	0.106	0.308

Note: SD = Standard Deviation

2.5 Methodology

2.5.1 Methodological framework

The overall methodological framework of this study is illustrated in Figure 2.1. The flowchart outlines the sequential stages of the research process, beginning with data collection from the Highway Accident Information Management System (HAIMS) for motorcycle crashes during 2020–2022. The next steps involve data preprocessing and feature categorization, followed by handling class imbalance using Synthetic Minority Oversampling Technique (SMOTE) for KNN and NB, and class weights for DT and RF. Model training was performed with an 80/20 stratified train–test split and 5-fold cross-validation, accompanied by hyperparameter optimization using GridSearchCV and RandomizedSearchCV. Four supervised learning models—Decision Tree (DT), K-Nearest Neighbor (KNN), Naïve Bayes (NB), and Random Forest (RF)—were developed and tuned.

The optimized models were then compared using both conventional and imbalance-sensitive metrics, including accuracy, balanced accuracy, precision, recall, F1-score, area under the curve (AUC), and Matthews Correlation Coefficient (MCC). Based on performance evaluation, the best-performing model was selected and further interpreted using SHapley Additive exPlanations (SHAP) to identify the most influential predictors. Finally, the findings were discussed, and policy recommendations were proposed to improve motorcycle crash safety outcomes.

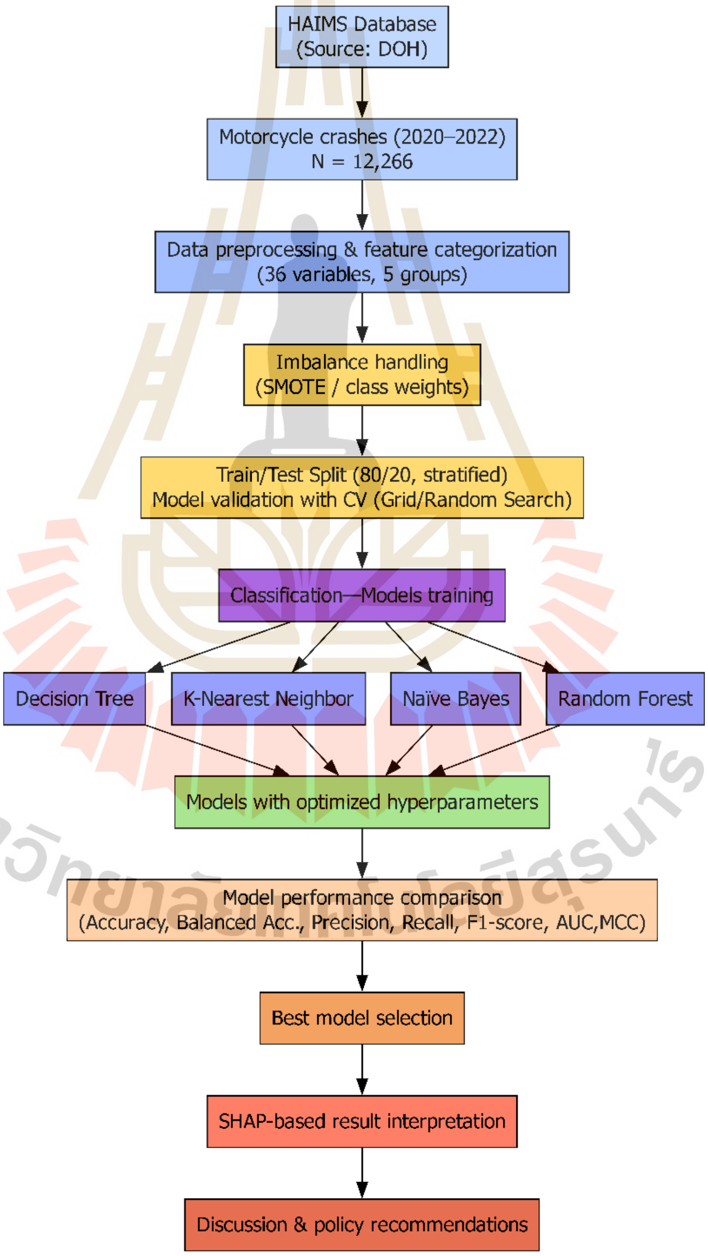

Figure 2.1 Methodological framework of the study

2.5.2 Model descriptions

2.5.2.1 Decision Tree (DT)

Decision Tree (DT) represents a widely utilized methodology within the domain of machine learning, predominantly employed for classification endeavors, commonly referred to as the classification tree methodology. The DT employs a flowchart-like framework for categorization. Internal nodes indicate tests on variables, connectors denote test results, and terminal nodes indicate class categories. The routes leading from root to terminal nodes illustrate categorization guidelines. DT, along with the related influence diagram, serves as a visual and analytical decision support mechanism for classification analysis. In crash severity modeling, each node signifies a severity predictor while each branch reflects a state of the variable. A tree leaf represents the anticipated injury severity based on the training dataset's information. Upon acquiring a new crash sample from the test dataset, predictions regarding crash severity can be derived by tracing the tree from root to leaf utilizing variable values. The crux of the decision tree lies in selecting optimal attributes, aiming for branch nodes to exhibit maximal category homogeneity, thus enhancing node purity.

2.5.2.2 K-Nearest Neighbor (KNN)

The KNN algorithm is alternatively known as the Nearest Neighbor Classification (NNC). In the context of a predictive modeling scenario, the KNN algorithm determines a data point by examining the k closest data points. It applies the nearest neighbor rule, assigning a new sample to a particular class based on the closeness of a group of existing labeled data instances. In essence, the instance's classification is determined by the predominant class among k nearest data points (Sambasivam, Amudhavel, & Sathya, 2020). The KNN methodology necessitates two critical decisions: the selection of the value of *k* and the selection of a proximity measure. The best k value is typically established by experimenting with various values for this parameter and identifying the one that yields the highest predictive accuracy. The Euclidean distance, which can be conceptualized as the physical distance between points in a two-dimensional space, serves as the distance metric utilized in the KNN algorithm.

2.5.2.3 Naïve Bayes (NB)

The Naïve Bayes algorithm represents a supervised machine learning technique often utilized as a linear model for different categorization tasks. It is rooted in Bayes' theorem and operates under the premise that the features within the dataset are independent given certain conditions. It is acknowledged that, on occasion, the assumption of independent features may be compromised; nevertheless, the Naïve Bayes algorithm demonstrates commendable performance even when operating under such unrealistic assumptions, particularly in scenarios involving limited sample sizes (Domingos & Pazzani, 1997). In the context of a classification task, let Y denote the variable subject to classification, while X signifies a collection of features represented as $x=(x_1,x_2,\ldots,x_n)$ Based on Bayes' theorem, the anticipated likelihood of the class variable $Y=y_i$ contingent upon, is articulated as follows (Equation (2.1)):

$$P(Y=y_i \mid X)=\frac{P\left(X=x=(x_1,x_2,\ldots,x_n) \mid Y=y_i\right)P(Y=y_i)}{P\left(X=x=(x_1,x_2,\ldots,x_n)\right)} \tag{2.1}$$

The Naïve Bayes algorithm is characterized by its rapid computation, ease of implementation, accuracy, and robustness, making it a widely used as a classification technique applied in a diverse array of use cases (Kazmierska & Malicki, 2008).

2.5.2.4 Random Forest (RF)

The RF algorithm, as introduced by Breiman (2001), constitutes a collective learning approach built on the foundation of the decision tree framework. It utilizes a resampling technique to generate k subsets from the original dataset and subsequently utilized to train k decision trees. The random forest is constructed by combining individual models. This RF method effectively reduces the problem of overfitting commonly associated with decision tree (DT) models. Each decision tree within the RF framework makes predictions using the test set, and the ultimate classification is decided by a consensus vote among the models.

To implement the RF algorithm, it is imperative to determine two critical parameters: the total count of trees (k) to be generated and the subset of features chosen at each split (m). The algorithm draws k bootstrap samples from the initial dataset, while the remaining portion, known as the out-of-sample data, is employed to evaluate the predictions' accuracy. Following the cultivation of k trees utilizing m randomly selected attributes, predictions for novel instances are established by combining the outcomes of these k trees. The initial data set is illustrated in the following manner (Chen et al., 2016):

$$S=\left[\left(x_i,y_j\right),i=1,\ 2,\ldots,N,j=1,\ 2,\ldots,M\right] \tag{2.2}$$

In which x signifies an instance and y corresponds to an attribute of S Every entry in the initial training data encompasses N samples and M features. The method for choosing resampled subsets and formulating the random forest technique using multiple trees is delineated below:

$$S_{Train}=\left[S_1,S_2,\ldots,S_k\right] \tag{2.3}$$

In this context, S_{Train} includes a portion of k bootstrap training sets. Consequently, k decision trees are built using these k sets. These k trees are subsequently aggregated to form an RF technique, as illustrated below:

$$H\left(X,O_j\right)=\sum_{i=1}^{k}h_i\left(x,O_j\right),\left(j=1,\ 2,\ \ldots,\ m\right) \tag{2.4}$$

In this context, X denotes the input feature array derived from the training set, $H\left(X,O_j\right)$ represents a meta- level decision tree model, and O_j is an independently and identically distributed sequence that governs the development trajectory of the tree.

2.5.3 Model training and validation

All models were trained using an 80/20 train-test split with a fixed random seed of 42 to ensure reproducibility, a common approach in traffic safety and crash severity prediction studies (Acı, Mutlu, Ozen, & Acı, 2025; Mohsin, Choudhury, & Muyeed, 2025; Sonnatthanon & Choocharukul, 2025). Stratified sampling preserved the class distribution across splits. For model evaluation and tuning, 5-fold cross-validation was applied using GridSearchCV or RandomizedSearchCV, with AUC as the primary scoring metric. To avoid potential bias, SMOTE was applied only to the training set, with the test set left unchanged. Hyperparameter tuning was conducted with stratified cross-validation, and results were evaluated using both conventional and imbalance-sensitive metrics (balanced accuracy, MCC, and AUC). Preliminary comparisons with and without SMOTE confirmed that the oversampling procedure improved class balance without introducing significant synthetic noise. To address class imbalance, SMOTE was applied for KNN and NB, while DT and RF used class_weight='balanced'. All final performance metrics were computed on the independent test set. For hyperparameter optimization, DT, KNN, and NB models were tuned using GridSearchCV, while RF used RandomizedSearchCV with 100 iterations. Key parameters such as max_depth, min_samples_split, and class_weight (DT), n_neighbors and distance metrics (KNN), var_smoothing (NB), and n_estimators, max_depth, and class_weight (RF) were systematically explored. This approach ensured that each model was fairly tuned under comparable validation settings before performance comparison. All models were evaluated on the same stratified test set using consistent performance metrics to support a transparent and equitable comparison.

2.5.4 Model performance evaluation metrics

The primary measures for judging categorization methods include accuracy, precision, recall, F1-Score and the Area Under the Curve (AUC). These metrics have been widely utilized in studies on traffic crash severity prediction (Dia et al., 2022; Dong, Khattak, Ullah, Zhou, & Hussain, 2022; Ijaz, Zahid, & Jamal, 2021). They are derived from the confusion matrix (CM) as presented in Table 2.3. Columns in the CM indicate predicted class instances, while rows indicate actual class instances, with correct predictions located on the diagonal. True positives (TP) and True negatives (TN) refer to instances that are accurately identified. A false positive (FP) is an instance incorrectly labeled as positive, whereas a false negative (FN) is an instance incorrectly labeled as negative. The performance metric calculation formulas are specified in Equations (2.5)–(2.8).

Accuracy is defined as the proportion of correctly classified crashes. However, due to the moderate class imbalance in crash severity data, relying solely on accuracy may provide a misleading assessment of model performance. To address this, additional metrics were examined. Balanced Accuracy captures the average recall for both classes, providing a more equitable measure under imbalance. Matthews Correlation Coefficient (MCC) evaluates the overall quality of binary classifications by considering all elements of the confusion matrix and is particularly robust for imbalanced data. Together, these metrics offer a more comprehensive and fair evaluation of model performance.

Accuracy represents the fraction of instances that are accurately recognized:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2.5}$$

Precision is the ratio of accurate positive predictions:

$$\text{Precision (P)} = \frac{TP}{TP + FP} \tag{2.6}$$

Recall quantifies the correctly classified positive instances:

$$\text{Recall (R)} = \frac{TP}{TP + FN} \tag{2.7}$$

The F1-Score, representing the harmonic mean of precision and recall, varies between 0 and 1, with 1 signifying optimal effectiveness and 0 signifying the least:

$$F1\_Score = \frac{2\times(R\times P)}{R+P} \tag{2.8}$$

The Area Under the Curve (AUC) for the Receiver Operating Characteristic (ROC) curve, frequently referred to as AUROC, represents an exceptionally valuable evaluative metric. The ROC curve, alternatively termed the sensitivity/specificity curve, constitutes a probabilistic graphical representation that facilitates the assessment of classification model efficacy. A classification model exhibiting an AUC value proximate to 1 is typically proficient in accurately predicting the binary outcomes of 0 as 0 and 1 as 1.

Table 2.3 Confusion Matrix (CM)

Total instances		Predicted class	
		Positive	**Negative**
Actual class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

2.5.5 SHapley Additive exPlanations (SHAP)

According to Lundberg and Lee (2017), the SHAP methodology employs Shapley values to clarify the outcomes generated by machine learning techniques. Drawing from joint game analysis, these scores quantify the specific impact of all attributes on the overall outcome (Štrumbelj & Kononenko, 2014). Initially, the SHapley Additive exPlanations methodology constructs a framework incorporating all input features. It then creates another version that omits the feature of interest, thereby allowing for an examination of how its exclusion influences the model's accuracy. The SHAP score associated with a feature is characterized as its incremental impact on the prediction. The subsequent equation is employed to compute the SHAP score for the feature (Tahfim & Yan, 2021):

$$\varnothing_i = \sum_{S\subseteq X\setminus\{i\}} \frac{|S|!\left(|X|-|S|-1\right)!}{|X|!}\left[f_{S\cup\{i\}}\left(x_{S\cup\{i\}}\right)-f_S\left(x_S\right)\right] \tag{2.9}$$

In this context, $\varnothing_i$ denotes the incremental impact of a feature, synonymous with its SHAP score; X signifies the entirety of features; S represents a smaller group of all features; and x_s indicates the scores corresponding to the features within S To evaluate the effect of the specific feature in question, a framework $f_{s \cup \{i\}}$ is developed that includes this feature, while another framework f_s is developed without it. The predictions yielded by the two models are subsequently juxtaposed with the current output, represented as $f_{s \cup \{i\}}\left(x_{s \cup \{i\}}\right) - f_s\left(x_S\right)$. Given that the specific feature in question is also contingent upon other features within the framework, the discrepancies are computed across all conceivable the smaller group of all features (Lundberg & Lee, 2017).

2.6 Model Results and Discussions

2.6.1 Model performance comparison

To gauge the efficacy of multiple machine learning techniques in anticipating the seriousness of traffic injury, this study implemented and evaluated four distinct models: Decision Tree (DT), K-Nearest Neighbor (KNN), Naïve Bayes (NB), and Random Forest (RF). The effectiveness of these algorithms was quantified by utilizing a wide range of metrics to ensure thorough evaluation.

Table 2.4 provides a comprehensive summary of the performance metrics for each model. The models demonstrated slight variations in accuracy, with Random Forest (RF) achieving the highest accuracy at 0.666, followed by Decision Tree (DT) at 0.656, Naïve Bayes (NB) at 0.629, and K-Nearest Neighbor (KNN) at 0.623. Precision, which evaluates the proportion of true positive predictions among all predicted positives, was also highest for RF (0.663), followed by DT (0.652), NB (0.627), and KNN (0.625). Similarly, Recall, reflecting the proportion of true positive instances correctly identified, aligned with the accuracy rankings: RF at 0.666, DT at 0.656, NB at 0.629, and KNN at 0.623. The F1-Score, a harmonic mean of precision and recall, ranged from RF at 0.660 to DT at 0.648, NB at 0.628, and KNN at 0.623.

Among the performance metrics, the Area Under the Curve (AUC) provided the clearest differentiation of the models' discriminative abilities. As illustrated in Figure 2.2 and Table 2.4, the AUC values emphasize each model's ability to distinguish between classes. RF achieved the highest AUC at 0.726, indicating superior discriminative performance. This was followed by DT at 0.700, KNN at 0.676, and NB at 0.673. Figure 2.2(a-d) display the individual ROC curves for each model, providing a detailed visual comparison of their performance across varying thresholds.

In addition to conventional metrics, Table 2.4 also reports Balanced Accuracy and Matthews Correlation Coefficient (MCC) to account for class imbalance. RF again achieved the highest values in both (Balanced Accuracy = 0.649, MCC = 0.308), reinforcing its superior generalization performance and robustness against class bias.

In summary, the Random Forest model consistently outperformed the other algorithms across all evaluation metrics, making it the most effective approach for predicting motorcycle crash severity in this study. This superior performance is likely due to its ensemble structure, which enhances stability, reduces overfitting, and captures complex nonlinear interactions among predictors—advantages especially relevant in heterogeneous crash data. These results align with previous studies that have demonstrated RF's consistent edge in traffic safety prediction tasks (Mansoor et al., 2023; Rezapour et al., 2021; Santos et al., 2024; Wahab & Jiang, 2019). In contrast, the lower performance of NB and KNN may stem from their respective assumptions about feature independence and local similarity, which can limit their accuracy in high-dimensional, correlated crash datasets. From a practical standpoint, RF's strong showing across conventional and imbalance-sensitive metrics (Balanced Accuracy, MCC) reinforces its suitability for real-world implementation, offering both predictive strength and reliability in imbalanced datasets common in traffic injury research.

Taken together, these comparisons confirm that ensemble methods such as Random Forest are particularly well suited for heterogeneous and imbalanced crash data. While simpler methods like KNN and NB may offer interpretability or computational efficiency, their limitations reduce their practical utility for policy applications where accuracy and robustness are essential.

Compared to previous studies, our results confirm the strong performance of Random Forest reported in other contexts such as Ghana, Pakistan, and Portugal, but also demonstrate its robustness in Thailand where motorcycle crashes dominate the road traffic landscape. This extension to a low- and middle-income country context adds new evidence that ensemble models remain effective even when data conditions and traffic patterns differ substantially from those in high-income countries.

Table 2.4 Overview of performance metrics for each model

Models	Accuracy	Balanced Accuracy	Precision	Recall	F1-Score	AUC	MCC
Decision Tree (DT)	0.656	0.636	0.652	0.656	0.648	0.700	0.285
K-Nearest Neighbor (KNN)	0.623	0.618	0.625	0.623	0.623	0.676	0.235
Naïve Bayes (NB)	0.629	0.620	0.627	0.629	0.628	0.673	0.241
Random Forest (RF)	0.666	0.649	0.663	0.666	0.660	0.726	0.308

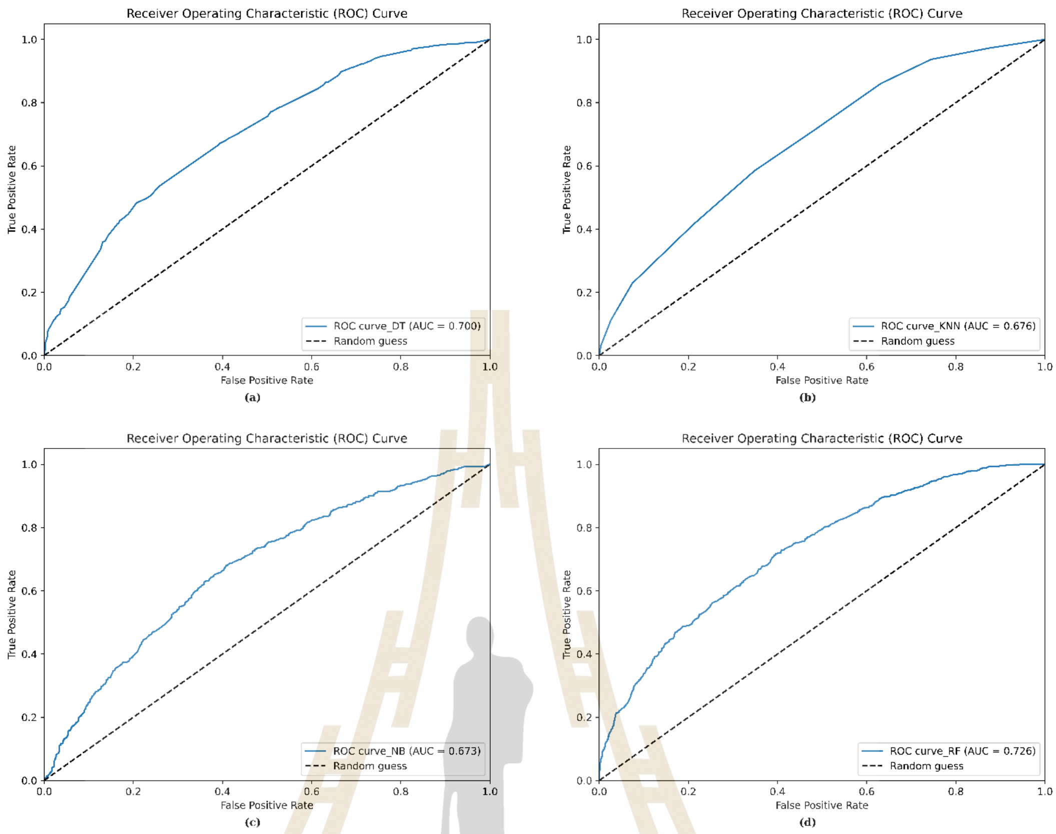

Figure 2.2 Comparison of Area Under the Curve (AUC): *(a) AUC_DT; (b) AUC_KNN; (c) AUC_NB; (d) AUC_RF*

2.6.2 Model interpretation

To interpret the predictions of the most effective model, SHapley Additive exPlanations (SHAP) were used to analyze the Random Forest output. This interpretability method allows us to unpack the 'black box' nature of machine learning model, revealing the nuanced interplay of various features in predicting crash outcomes.

The SHAP bee swarm plot in Figure 2.3 provides valuable insights into the variables affecting the assessment of the seriousness of injuries in motorcycle crashes as predicted by the Random Forest model, particularly for predicting whether crash results in severe or fatal injuries (class 1). The SHAP scores plotted on the X-axis illustrate the degree of impact every variable has on the model's outcome: positive SHAP scores increase the likelihood of a severe outcome, while negative values decrease it. The features are ranked by their importance on the Y-axis, with the most critical factors at the top.

Key predictors associated with increased injury severity include nighttime crashes, involvement of large trucks, the presence of depressed medians, two-lane roads, pick-up trucks, and head-on collisions. These conditions contribute to a higher predicted probability of severe or fatal injuries (class 1). In contrast, crashes occurring during the daytime, side-swipe and rear-end collisions, and those involving passenger cars are linked to a reduced likelihood of severe outcomes. These patterns are consistent with prior research and highlight practical roadway and vehicle-related conditions that elevate or mitigate injury severity.

The following discussion expands on these findings by explaining how each key feature influences the model's predictions, supported by prior research.

At the forefront of influential factors, the result shows that the time of day plays a pivotal role in injury severity prediction. Daytime crashes are associated with lower injury severity compared to nighttime incidents. This temporal effect aligns with previous research by Chang, Yasmin, Huang, Chan, and Haque (2021), who found that unlit darkness was linked to higher injury severity, which can be attributed to decreased visibility and longer reaction times during nighttime conditions (Marcoux, Yasmin, Eluru, & Rahman, 2018). The stark contrast between daytime and nighttime crash severities underscores the need for enhanced safety measures during darker hours, such as improved road lighting and increased awareness campaigns targeting night riders.

The involvement of large trucks (more than six wheels) emerges as the second most critical factor, showing a strong correlation with increased injury severity. This finding resonates with recent research by Kanitpong, Jensupakarn, Dabsomsri, and Issalakul (2024); Laphrom et al. (2024), who attributed this heightened risk to the substantial size and mass differentials between trucks and motorcycles. The vulnerability of motorcyclists in such collisions highlights the urgent need for strategies to mitigate these high-risk interactions, possibly through dedicated lane policies or advanced warning systems for both truck drivers and motorcyclists. This highlights the urgent need for truck lane management or separation strategies to reduce motorcycle–truck conflicts.

Furthermore, the analysis reveals that side swipes in parallel lanes lead to less serious injuries. This counterintuitive finding might be attributed to the glancing nature of these impacts, as suggested by Agyemang, Adanu, and Jones (2021) in their comprehensive study of factors influencing motorcycle collision severity. Additionally, the presence of cars in crash scenarios shows a mixed impact, with a slight tendency towards decreased severity, possibly due to the comparative protection offered by car structures in collisions with motorcycles. This trend was similarly observed in an investigation conducted by Se et al. (2023).

The results point out that road infrastructure elements demonstrate significant influence on crash severity outcomes. Depressed medians are connected to more severe injuries, potentially owing to the higher risk of more severe impacts or rollovers. This aligns with the findings by Se, Champahom, Jomnonkwao, Chaimuang, and Ratanavaraha (2021), who observed that flush and depressed median factors produce a favorable marginal impact on fatal injuries, consequently raising the chances of fatalities during a collision. Conversely, barrier medians slightly decrease injury severity, likely due to their protective function in preventing cross-median collisions, agreeing with the research from Champahom et al. (2022). A plausible explanation is that a barrier median limits the possibility of turning, guiding such actions to safer locations, which helps to decrease the risk of head-on accidents and dangerous overtaking scenarios.

Moreover, the number of lanes shows varied effects, with two-lane roads slightly increasing severity risk. This nuanced impact of road configuration on motorcycle safety supported by Se et al. (2023), which demonstrated that collisions on two-lane roadways exhibit a significantly elevated the likelihood of severe injuries and fatalities compared to collisions on four-lane roadways. This phenomenon might arise because two-lane roadways are often non-separated and situated in rural regions characterized by elevated speed limits; consequently, incidents on these roadways are susceptible to severe impacts, including head-on crashes and accidents related to excessive speed. This suggests that targeted investment in safer rural two-lane roadways could substantially reduce motorcycle crash severity.

With regard to road surface, crashes on asphalt road surface displayed a relatively neutral impact, with a slight tendency towards reduced severity compared to other surface types, corresponding to observations by Champahom et al. (2022), who uncovered that the severity of crashes is typically higher on concrete surfaces than those on asphalt pavements. One possible explanation may be the material properties of asphalt, providing better traction and smoother driving surfaces, are likely to contribute to safer driving conditions and reduced injury severity.

The analysis additionally highlights that the feature related to four-wheeled pick-up trucks shows high SHAP scores, indicating a higher likelihood of severe injuries in collisions involving such vehicles. Pick-up trucks often have higher centers of gravity, which can contribute to rollover crashes, leading to more severe injuries. Past research by Chang et al. (2016) reported that collisions involving substantial vehicles, including pick-up trucks and tractor-trailers, have been demonstrated to significantly elevate the probability of death by 77% in non-intersection accidents and by 102% in intersection, correspondingly.

With respect to the collision types, the model result demonstrates distinct impacts: rear-end collisions lead to less serious injuries than those associated with alternative categories, while head-on crash, when they occur, are strongly associated with increased severity. In head-on collisions, the substantial force generated by vehicles moving directly towards each other is likely to escalate the level of injury severity (Champahom et al., 2022; Chang et al., 2021; Prentkovskis, Sokolovskij, & Bartulis, 2010).

The findings further delineate that crashes involving a front-path interruption are linked to a higher probability of serious injuries. Positive SHAP values suggest that these interruptions, which may involve sudden obstacles or loss of control, significantly increase the likelihood of serious consequences. The finding is reasonable and supported by prior studies, owing to the significant deceleration triggered by sudden stopping (Huang, Chin, & Haque, 2008; Zhou & Chin, 2019).

The model also captures the heightened risk associated with out-of-control incidents on carriageways and the varied impacts of road construction zones. Areas under construction demonstrated a minimal impact on injury severity, suggesting that reduced speeds in these zones may offset potential hazards. In construction zones equipped with amber or warning signals, motorists exhibited a decreased chance of being involved in serious accidents (Ghasemzadeh & Ahmed, 2019).

Notably, crashes occurring on roads with four or more than eight lanes, roads with raised medians, and roads without medians show minimal SHAP influence, suggesting negligible contribution to injury severity. Additionally, crashes involving U-turns or occurring during rainy conditions show a small but positive association with severe injuries.

While many of these results are consistent with international studies, some differences also emerge. For instance, the prominence of rural two-lane roads and depressed medians as critical predictors appears more specific to Thailand's infrastructure context, where motorcycles frequently share non-divided highways with heavy vehicles. This contrasts with findings from high-income countries, where factors such as alcohol or speeding often dominate severity models. These differences highlight the importance of tailoring countermeasures to local traffic and roadway conditions rather than directly transferring strategies across regions.

By combining these interpretations with evidence from prior studies, the analysis not only validates existing knowledge but also identifies context-specific risks unique to Thailand, strengthening the case for tailored countermeasures.

These findings highlight not only statistical associations but also practical risk factors that can guide targeted safety measures. While Section 6 presents the overall policy recommendations, the discussion here emphasizes how specific predictors—such as nighttime conditions, large trucks, and rural roadway features—directly influence crash severity and therefore warrant particular attention from policymakers.

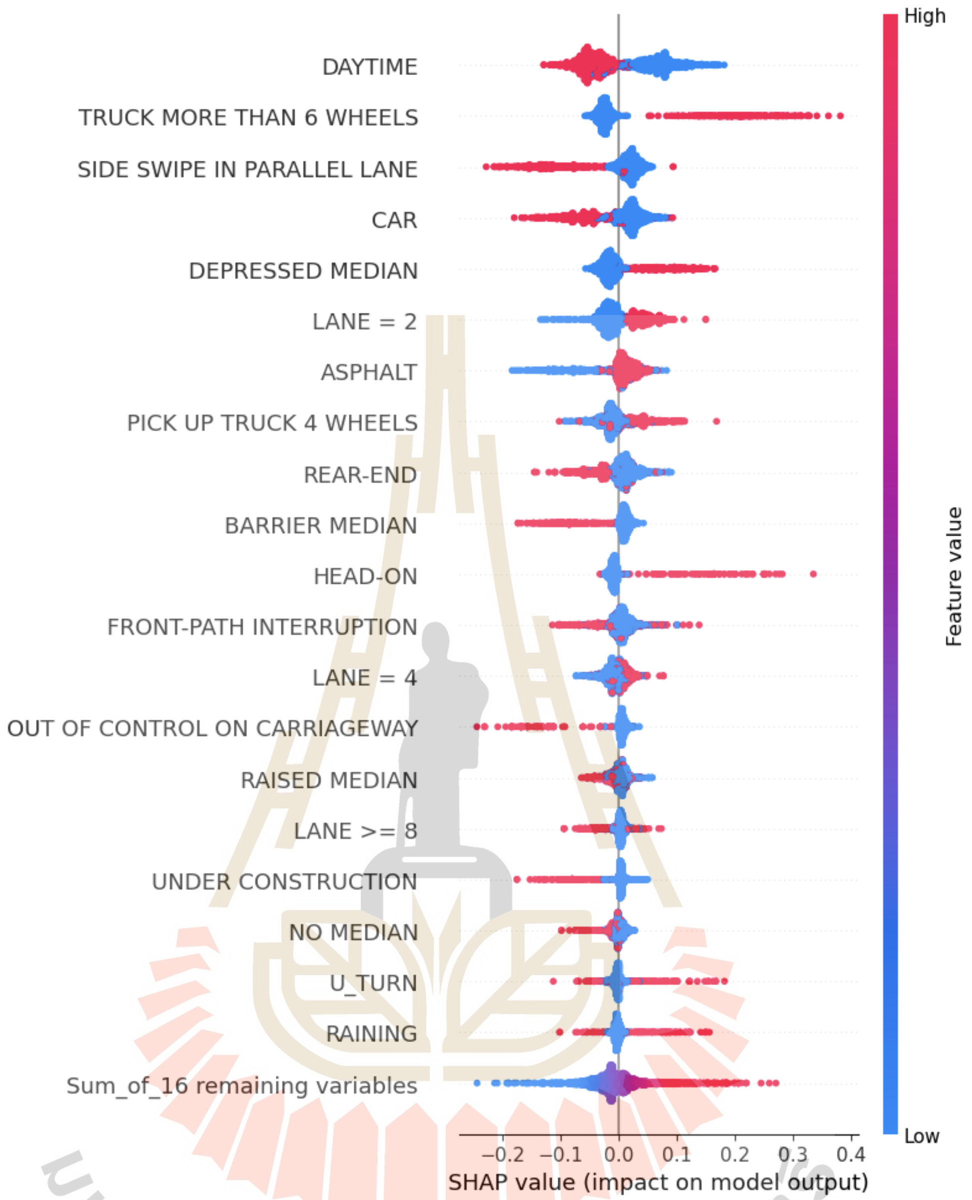

Figure 2.3 The impact of features on motorcycle crash injury severity

2.7 Conclusion and Recommendations

This study evaluated the predictive performance of four supervised learning algorithms—Decision Tree (DT), K-Nearest Neighbor (KNN), Naïve Bayes (NB), and Random Forest (RF)—to model motorcycle crash injury severity using nationally representative crash data from Thailand (2020–2022). Thirty-six explanatory variables were analyzed across roadway, environmental, vehicle, crash types, and causative factors. After preprocessing and addressing class imbalance, the models were trained, validated, and compared across multiple conventional and imbalance-sensitive metrics. The Random Forest model consistently outperformed the other approaches, achieving the highest accuracy, balanced accuracy, AUC, and MCC, confirming the advantage of ensemble-based methods for heterogeneous and imbalanced traffic data. The SHAP analysis provided transparency into model predictions by identifying critical determinants of severity, including nighttime crashes, large truck involvement, depressed medians, two-lane roads, and head-on collisions. These findings highlight both behavioral and infrastructure-related conditions that exacerbate motorcyclist vulnerability in Thailand.

The contribution of this study lies in demonstrating the utility of ensemble methods for crash severity analysis in a motorcycle-dominated, low- and middle-income country context, while also addressing the interpretability challenge through SHAP analysis. Based on the insights gained, several countermeasures are recommended. First, nighttime safety improvements are needed, including better road lighting, reflective pavement markings, and stricter enforcement during hours of darkness. Second, large truck management should be prioritized by introducing truck lane separation or time-based restrictions in areas with high motorcycle traffic. Third, roadway infrastructure enhancements are critical, particularly on two-lane rural highways, where interventions such as centerline barriers, median treatments, and shoulder widening could reduce the risk of head-on and high-impact crashes. Additionally, improving the design of depressed medians and strengthening traffic control in construction zones can help mitigate severe crash outcomes. While some measures such as truck lane separation may face practical challenges in Thailand's current infrastructure, other interventions—including lighting improvements, reflective markings, enforcement, and low-cost roadway treatments—are more immediately feasible and can still provide substantial safety benefits. Collectively, these measures can substantially reduce injury severity among motorcyclists. Beyond methodological contributions, this study demonstrates how machine learning combined with SHAP interpretability can support context-specific, evidence-based policymaking to reduce the burden of motorcycle crashes and improve overall road safety.

2.8 Limitations and Future Research

Undeniably, this research, like any other, is not without its limitations. Future investigations may extend the analysis by incorporating additional machine learning methodologies, including Neural Networks, Bayesian Networks, Deep Learning, and advanced ensemble or boosting approaches such as Gradient Boosting and XGBoost. These techniques may achieve higher predictive accuracy and help uncover additional latent patterns in crash dynamics, offering further insight into the trade-offs between predictive strength, interpretability, and practical applicability in traffic safety analysis.

Another limitation is that this study did not explicitly apply dimensionality reduction or feature selection methods. Although the moderate number of predictors (36 variables) and the use of tree-based models with embedded feature selection helped mitigate overfitting risk, future work could systematically evaluate feature selection or dimensionality reduction approaches such as PCA, LASSO, or recursive feature elimination to further validate and refine predictor sets.

This study was also limited by the absence of certain contextual factors, such as road lighting conditions, traffic density, and enforcement data, which may act as unobserved confounders. Although proxy variables such as time of day and roadway type capture some of these effects, future research should integrate richer datasets, including road inventory databases, traffic monitoring systems, and enforcement records, to more directly account for these influences and improve explanatory power.

Finally, this study focused on retrospective crash severity prediction using historical crash records, which limits direct application in real-time crash risk warning systems. Future research should explore integration with real-time data streams (e.g., traffic sensors, weather stations, and GPS devices) and develop methods to adapt SHAP interpretability to streaming contexts, enabling dynamic and actionable risk warnings.

2.9 References

Acı, Ç. İ., Mutlu, G., Ozen, M., & Acı, M. (2025). Enhanced Multi-Class Driver Injury Severity Prediction Using a Hybrid Deep Learning and Random Forest Approach. *Applied Sciences (2076-3417), 15*(3). doi:https://doi.org/10.3390/app15031586

Agheli, A., & Aghabayk, K. (2025). How does distraction affect cyclists' severe crashes? A hybrid CatBoost-SHAP and random parameters binary logit approach. *Accident Analysis & Prevention, 211*, 107896. doi:https://doi.org/10.1016/j.aap.2024.107896

Agyemang, W., Adanu, E. K., & Jones, S. (2021). Understanding the factors that are associated with motorcycle crash severity in rural and urban areas of Ghana. *Journal of advanced transportation, 2021*(1), 6336517. doi:https://doi.org/10.1155/2021/6336517

Ali, Y., Hussain, F., & Haque, M. M. (2024). Advances, challenges, and future research needs in machine learning-based crash prediction models: A systematic review. *Accident Analysis & Prevention, 194*, 107378. doi:https://doi.org/10.1016/j.aap.2023.107378

Breiman, L. (2001). Random forests. *Machine learning, 45*, 5-32.

Champahom, T., Wisutwattanasak, P., Chanpariyavatevong, K., Laddawan, N., Jomnonkwao, S., & Ratanavaraha, V. (2022). Factors affecting severity of motorcycle accidents on Thailand's arterial roads: multiple correspondence analysis and ordered logistics regression approaches. *IATSS research, 46*(1), 101-111. doi:https://doi.org/10.1016/j.iatssr.2021.10.006

Chan, J. Y.-L., Leow, S. M. H., Bea, K. T., Cheng, W. K., Phoong, S. W., Hong, Z.-W., & Chen, Y.-L. (2022). Mitigating the multicollinearity problem and its machine learning approach: a review. *Mathematics, 10*(8), 1283. doi:https://doi.org/10.3390/math10081283s

Chang, F., Li, M., Xu, P., Zhou, H., Haque, M. M., & Huang, H. (2016). Injury severity of motorcycle riders involved in traffic crashes in Hunan, China: a mixed ordered logit approach. *International journal of environmental research and public health, 13*(7), 714. doi:https://doi.org/10.3390/ijerph13070714

Chang, F., Yasmin, S., Huang, H., Chan, A. H., & Haque, M. M. (2021). Injury severity analysis of motorcycle crashes: A comparison of latent class clustering and latent segmentation based models with unobserved heterogeneity. *Analytic methods in accident research, 32*, 100188. doi:https://doi.org/10.1016/j.amar.2021.100188

Chen, J., Li, K., Tang, Z., Bilal, K., Yu, S., Weng, C., & Li, K. (2016). A parallel random forest algorithm for big data in a spark cloud computing environment. *IEEE Transactions on Parallel and Distributed Systems, 28*(4), 919-933. doi:https://doi.org/10.1109/TPDS.2016.2603511

Dia, Y., Faty, L., Sarr, M. D., Sall, O., Bousso, M., & Landu, T. T. (2022). *Study of supervised learning algorithms for the prediction of road accident severity in Senegal.* Paper presented at the 2022 7th International Conference on Computational Intelligence and Applications (ICCIA).

Domingos, P., & Pazzani, M. (1997). On the optimality of the simple Bayesian classifier under zero-one loss. *Machine learning, 29*, 103-130.

Dong, S., Khattak, A., Ullah, I., Zhou, J., & Hussain, A. (2022). Predicting and analyzing road traffic injury severity using boosting-based ensemble learning models with SHAPley Additive exPlanations. *International journal of environmental research and public health, 19*(5), 2925. doi:https://doi.org/10.3390/ijerph19052925

Ghasemzadeh, A., & Ahmed, M. M. (2019). Exploring factors contributing to injury severity at work zones considering adverse weather conditions. *IATSS research, 43*(3), 131-138. doi:https://doi.org/10.1016/j.iatssr.2018.11.002

Huang, H., Chin, H. C., & Haque, M. M. (2008). Severity of driver injury and vehicle damage in traffic crashes at intersections: a Bayesian hierarchical analysis. *Accident Analysis & Prevention, 40*(1), 45-54. doi:https://doi.org/10.1016/j.aap.2007.04.002

Ijaz, M., Zahid, M., & Jamal, A. (2021). A comparative study of machine learning classifiers for injury severity prediction of crashes involving three-wheeled motorized rickshaw. *Accident Analysis & Prevention, 154*, 106094. doi:https://doi.org/10.1016/j.aap.2021.106094

Kanitpong, K., Jensupakarn, A., Dabsomsri, P., & Issalakul, K. (2024). Characteristics of motorcycle crashes in Thailand and factors affecting crash severity: Evidence from in-depth crash investigation. *Transportation Engineering, 16*, 100227. doi:https://doi.org/10.1016/j.treng.2024.100227

Kashifi, M. T. (2023). Investigating two-wheelers risk factors for severe crashes using an interpretable machine learning approach and SHAP analysis. *IATSS research, 47*(3), 357-371. doi:https://doi.org/10.1016/j.iatssr.2023.07.005

Kazmierska, J., & Malicki, J. (2008). Application of the Naïve Bayesian Classifier to optimize treatment decisions. *Radiotherapy and Oncology, 86*(2), 211-216. doi:https://doi.org/10.1016/j.radonc.2007.10.019

Laphrom, W., Se, C., Champahom, T., Jomnonkwao, S., Wipulanusatd, W., Satiennam, T., & Ratanavaraha, V. (2024). XGBoost-SHAP and Unobserved Heterogeneity Modelling of Temporal Multivehicle Truck-Involved Crash Severity Patterns. *Civil Engineering Journal, 10*(6), 1890-1908. doi:http://dx.doi.org/10.28991/CEJ-2024-010-06-011

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems, 30*. doi:https://doi.org/10.48550/arXiv.1705.07874

Mansoor, U., Jamal, A., Su, J., Sze, N., & Chen, A. (2023). Investigating the risk factors of motorcycle crash injury severity in Pakistan: Insights and policy recommendations. *Transport policy, 139*, 21-38. doi:https://doi.org/10.1016/j.tranpol.2023.05.013

Marcoux, R., Yasmin, S., Eluru, N., & Rahman, M. (2018). Evaluating temporal variability of exogenous variable impacts over 25 years: An application of scaled generalized ordered logit model for driver injury severity. *Analytic methods in accident research, 20*, 15-29. doi:https://doi.org/10.1016/j.amar.2018.09.001

Mohamad, I., Jomnonkwao, S., & Ratanavaraha, V. (2022). Using a decision tree to compare rural versus highway motorcycle fatalities in Thailand. *Case studies on transport policy, 10*(4), 2165-2174. doi:https://doi.org/10.1016/j.cstp.2022.09.016

Mohsin, A. S., Choudhury, S. H., & Muyeed, M. A. (2025). Automatic priority analysis of emergency response systems using internet of things (IoT) and machine learning (ML). *Transportation Engineering, 19*, 100304. doi:https://doi.org/10.1016/j.treng.2025.100304

Prentkovskis, O., Sokolovskij, E., & Bartulis, V. (2010). Investigating traffic accidents: a collision of two motor vehicles. *Transport, 25*(2), 105-115. doi:https://doi.org/10.1016/j.cstp.2022.09.016

Rezapour, M., Farid, A., Nazneen, S., & Ksaibati, K. (2021). Using machine leaning techniques for evaluation of motorcycle injury severity. *IATSS research, 45*(3), 277-285. doi:https://doi.org/10.1016/j.iatssr.2020.07.004

Rezapour, M., & Ksaibati, K. (2020). Application of various machine learning architectures for crash prediction, considering different depths and processing layers. *Engineering Reports, 2*(8), e12215. doi:https://doi.org/10.1002/eng2.12215

Rezapour, M., Molan, A. M., & Ksaibati, K. (2020). Analyzing injury severity of motorcycle at-fault crashes using machine learning techniques, decision tree and logistic regression models. *International journal of transportation science and technology, 9*(2), 89-99. doi:https://doi.org/10.1016/j.ijtst.2019.10.002

Rezapour, M., Nazneen, S., & Ksaibati, K. (2020). Application of deep learning techniques in predicting motorcycle crash severity. *Engineering Reports, 2*(7), e12175. doi:https://doi.org/10.1002/eng2.12175

Sadeghi, M., Aghabayk, K., & Quddus, M. (2024). A hybrid Machine learning and statistical modeling approach for analyzing the crash severity of mobility scooter users considering temporal instability. *Accident Analysis & Prevention, 206*, 107696. doi:https://doi.org/10.1016/j.aap.2024.107696

Sahu, S., Maram, B., Gampala, V., & Daniya, T. (2022). Analysis of road accidents prediction and interpretation using KNN classification model. In *Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2022, Volume 2* (pp. 163-172): Springer.

Sambasivam, G., Amudhavel, J., & Sathya, G. (2020). A predictive performance analysis of vitamin D deficiency severity using machine learning methods. *IEEE Access, 8*, 109492-109507. doi:https://doi.org/10.1109/ACCESS.2020.3002191

Santos, K., Dias, J. P., & Amado, C. (2022). A literature review of machine learning algorithms for crash injury severity prediction. *Journal of safety research, 80*, 254-269. doi:https://doi.org/10.1016/j.jsr.2021.12.007

Santos, K., Firme, B., Dias, J. P., & Amado, C. (2024). Analysis of motorcycle accident injury severity and performance comparison of machine learning algorithms. *Transportation research record, 2678*(1), 736-748. doi:https://doi.org/10.1177/03611981231172507

Scarano, A., Riccardi, M. R., Mauriello, F., D'Agostino, C., Pasquino, N., & Montella, A. (2023). Injury severity prediction of cyclist crashes using random forests and random parameters logit models. *Accident Analysis & Prevention, 192*, 107275. doi:https://doi.org/10.1016/j.aap.2023.107275

Se, C., Champahom, T., Jomnonkwao, S., Chaimuang, P., & Ratanavaraha, V. (2021). Empirical comparison of the effects of urban and rural crashes on motorcyclist injury severities: A correlated random parameters ordered probit approach with heterogeneity in means. *Accident Analysis & Prevention, 161*, 106352. doi:https://doi.org/10.1016/j.aap.2023.107275

Se, C., Champahom, T., Jomnonkwao, S., Wisutwattanasak, P., Laphrom, W., & Ratanavaraha, V. (2023). Temporal instability and transferability analysis of daytime and nighttime motorcyclist-injury severities considering unobserved heterogeneity of data. *Sustainability, 15*(5), 4486. doi:https://doi.org/10.3390/su15054486

Sonnatthanon, N., & Choocharukul, K. (2025). Crash severity prediction using a virtual geometry-group-based deep learning approach with images-based feature representation. *Results in Engineering, 27*, 106155. doi:https://doi.org/10.1016/j.rineng.2025.106155

Štrumbelj, E., & Kononenko, I. (2014). Explaining prediction models and individual predictions with feature contributions. *Knowledge and information systems, 41*, 647-665. doi:https://doi.org/10.1007/s10115-013-0679-x

Sum, S., Se, C., Champahom, T., Jomnonkwao, S., Sinha, S., & Ratanavaraha, V. (2025). A Random Forest and SHAP-based analysis of motorcycle crash severity in Thailand: Urban-Rural and Day-Night perspectives. *Transportation Engineering*, 100369. doi:https://doi.org/10.1016/j.treng.2025.100369

Tahfim, S. A.-S., & Yan, C. (2021). Analysis of severe injuries in crashes involving large trucks using K-prototypes clustering-based GBDT model. *Safety, 7*(2), 32. doi:https://doi.org/10.3390/safety7020032

Wahab, L., & Jiang, H. (2019). A comparative study on machine learning based algorithms for prediction of motorcycle crash severity. *PLoS one, 14*(4), e0214966. doi:https://doi.org/10.1371/journal.pone.0214966

Wahab, L., & Jiang, H. (2020). Severity prediction of motorcycle crashes with machine learning methods. *International journal of crashworthiness, 25*(5), 485-492. doi:https://doi.org/10.1080/13588265.2019.1616885

WHO. (2023). Road traffic injuries [Online]. Retrieved from https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries/

Yahaya, M., Jiang, X., Fu, C., Bashir, K., & Fan, W. (2019). *Enhancing crash injury severity prediction on imbalanced crash data by sampling technique with variable selection.* Paper presented at the 2019 IEEE Intelligent Transportation Systems Conference (ITSC).

Yan, M., & Shen, Y. (2022). Traffic accident severity prediction based on random forest. *Sustainability, 14*(3), 1729. doi:https://doi.org/10.3390/su14031729

Yang, J., Han, S., & Chen, Y. (2023). Prediction of Traffic Accident Severity Based on Random Forest. *Journal of advanced transportation, 2023*. doi:https://doi.org/10.1155/2023/7641472

Zhou, M., & Chin, H. C. (2019). Factors affecting the injury severity of out-of-control single-vehicle crashes in Singapore. *Accident Analysis & Prevention, 124*, 104-112. doi:https://doi.org/10.1016/j.aap.2019.01.009

CHAPTER III

A RANDOM FOREST AND SHAP-BASED ANALYSIS OF MOTORCYCLE CRASH SEVERITY IN THAILAND: URBAN-RURAL AND DAY-NIGHT PERSPECTIVES

3.1 Abstract

Road traffic crashes pose significant public safety concern globally, causing severe injuries and fatalities. Motorcyclists face heightened crash risks and injury severity, particularly in developing countries like Thailand, where motorcycles serve as a primary mode of transportation. This study examines motorcycle crash severity across four distinct scenarios: urban daytime, urban nighttime, rural daytime, and rural nighttime. Analyzing 12,266 crashes from Thailand's Highway Accident Information Management System (HAIMS) spanning 2020–2022, Random Forest (RF) modeling combined with SHapley Additive exPlanations (SHAP) was applied to identify key severity determinants while enhancing model interpretability. The analysis revealed significant variations across scenarios based on roadway characteristics, environmental conditions, crash causes, and vehicle involvement. Crashes involving large trucks, head-on collisions, roads with depressed medians, and darkness were associated with increased severity. Conversely, those involving passenger cars, side-swipe collisions, roads with barrier medians, and well-lit locations exhibited lower severity. To assess its effectiveness, RF was benchmarked against Logistic Regression and Decision Tree models and consistently outperformed them across all crash scenarios. The models achieved classification accuracies of 66.5% (urban day), 64.7% (urban night), 63.8% (rural day), and 65.9% (rural night), while SHAP analysis illuminated the factors driving these predictions. These findings offer critical insights for policymakers and transportation planners, enabling the development of targeted interventions tailored to specific environmental and temporal conditions. By integrating machine learning

with explainable artificial intelligence, this study advances data-driven approaches for enhancing motorcycle safety and crash prevention measures.

3.2 Introduction

Road traffic crashes constitute a leading cause to severe injuries and fatalities affecting human lives globally. Each year, road traffic crashes claim nearly 1.19 million lives, while between 20 and 50 million people are injured, many of whom experience permanent disabilities (WHO, 2023). The majority of road traffic deaths involve vulnerable road users, such as motorcyclists, cyclists, and pedestrians, accounting for over fifty percent of the overall death. Furthermore, it is noteworthy that low- and middle-income countries experience over 90% of global road fatalities, even though these nations retain ownership of roughly 60% of the vehicles worldwide.

Thailand, in particular, faces significant road safety challenges. According to the latest worldwide report in 2018, Thailand ranks as the 9th country with the highest incidence of road traffic fatalities, recording 32.7 deaths per 100,000 population (WHO, 2023). Notably, around 75% of those affected are individuals who use two- and three-wheel vehicles, predominantly motorcyclists. Data from Thailand's Highway Accident Information Management System (HAIMS) (2020-2022), as illustrated in Figure 3.1, reveals 12,266 instances of motorcycle crashes, resulting in 6,853 cases of Property Damage Only (PDO)/Minor Injury and 5,413 cases of Severe/Fatal outcomes. Closer examination reveals significant variations in both the frequency of motorcycle collisions and the severity of injuries sustained between urban and rural locations, across both daytime and nighttime periods. For example, both incident frequency and fatality rates in rural areas exceed those in urban areas, with higher occurrence during daytime compared to nighttime.

As motorcycle crashes contribute to an increasingly larger share of total motorized vehicle fatalities (Li, Fang, Guo, Fu, & Qiu, 2021), there is a clear need for comprehensive investigation of factors influencing injury severity in motorcycle incidents. Recent studies highlight the importance of examining the interplay between environmental conditions, roadway characteristics, and crash-related variables in determining motorcycle injury severity. Numerous investigations have explored determinants impacting motorcycle crashes, with some focusing on comparative analysis of crash frequencies in various settings such as urban and rural environments (Champahom et al., 2020; Champahom et al., 2023; S. Islam & Brown, 2017; Se, Champahom, Jomnonkwao, Chaimuang, & Ratanavaraha, 2021). Additionally, Mohamad, Jomnonkwao, and Ratanavaraha (2022) employed decision tree analysis to contrast motorcycle fatalities between rural roadways and highways in Thailand. Regarding temporal factors, numerous studies have demonstrated the impact of diverse time periods on motorcycle injury severity outcomes (Alnawmasi & Mannering, 2023; Anarkooli & Hosseinlou, 2016; Se et al., 2023; K. Zhang & Hassan, 2019). However, few studies have simultaneously considered both urban-rural disparities and time-of-day differences, representing a critical research gap. Risk factors for motorcycle crashes likely vary across these dimensions, making it essential to analyze their interactions to develop more effective road safety interventions.

While conventional statistical methods like regression and logit models have traditionally dominated crash analysis, they struggle with the complex, nonlinear relationships in motorcycle crash data due to rigid assumptions about data distribution and variable independence (Santos, Dias, & Amado, 2022). Conversely, machine learning techniques offer several advantages in this domain. They can handle large volumes of data with numerous variables, capture complex nonlinear relationships, and often provide superior predictive performance. Machine learning models are also more adept at dealing with multicollinearity and interaction effects among predictor variables, which are common in crash data (Chan et al., 2022). Random Forest (RF) has emerged as particularly effective for crash severity analysis, constructing multiple decision trees that capture complex interactions without requiring explicit mathematical specifications. RF performs well with imbalanced datasets where severe injury cases are less frequent than minor ones and handles mixed data types efficiently while being less prone to overfitting (Scarano et al., 2023; Yan & Shen, 2022; Yang, Han, & Chen, 2023).

To enhance interpretability and address the "black box" nature of machine learning, this study employs SHapley Additive exPlanations (SHAP), a technique based on game theory principles that quantifies the contribution of each predictor to crash severity. SHAP provides locally accurate and globally interpretable feature importance scores, revealing both the direction and magnitude of each factor's impact across different crash contexts. By integrating RF with SHAP, this study ensures both high predictive accuracy and improved transparency in understanding key risk factors.

This study aims to fill the existing research gaps by investigating motorcycle injury severity in Thailand across four distinct crash scenarios: urban daytime, urban nighttime, rural daytime, and rural nighttime. By employing Random Forest modeling complemented by SHAP analysis, we provide a comprehensive data-driven approach to understanding the determinants of crash severity while ensuring model interpretability. The findings of this study have significant implications for policymakers, transportation planners, and road safety professionals, offering evidence-based recommendations to mitigate motorcycle crash severity tailored to different environmental and temporal contexts.

The rest of this paper is organized as follows: Section 3.3 provides a summary of the relevant literature on urban-rural disparities, time-of-day effects, and machine learning applications in crash severity analysis; Section 3.4 describes the empirical settings; Section 3.5 presents the methodological approach; Section 3.6 interprets the results; Section 3.7 discusses the model outcomes and implications; Section 3.8 provides conclusions and policy-related recommendations; and finally, Section 3.9 addresses limitations and future research directions.

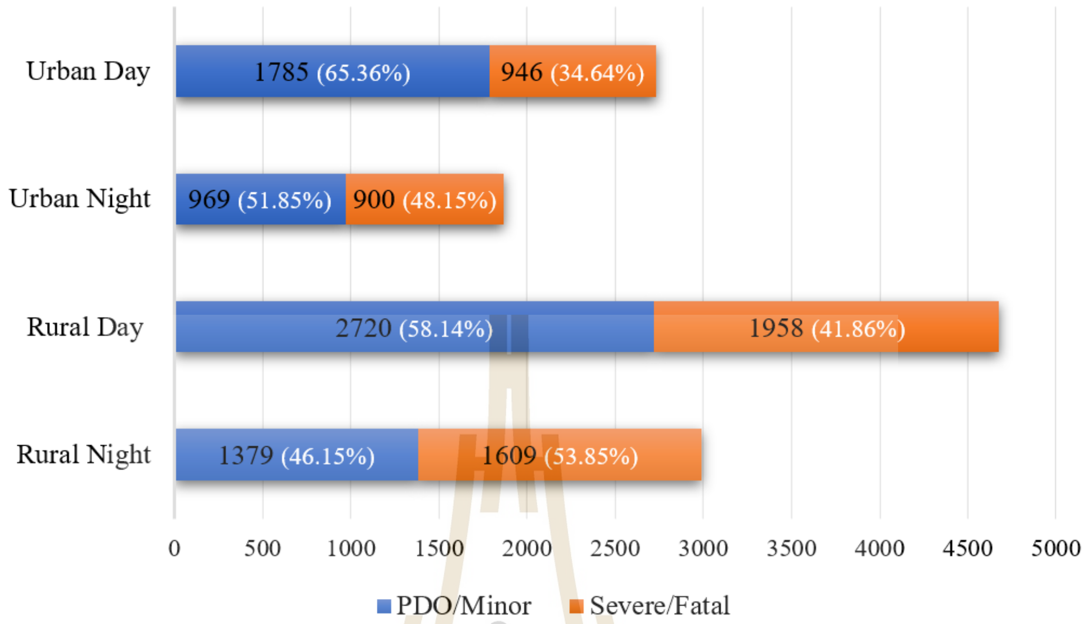

Figure 3.1 Motorcycle injury severity distribution during day and night occurred in urban and rural roadways

3.3 Literature Reviews

3.3.1 Urban-rural disparities

Urban and rural environments present distinctly different risk factors for motorcycle crashes due to variations in road conditions, traffic density, emergency response times, and infrastructure development. Previous studies have identified significant differences in motorcycle crash frequencies and the severity of crash injuries within urban and rural settings. Geedipally, Turner, and Patil (2011) utilized multinomial logit models for examining variations in determinants contributing to the severity of motorcycle crashes in urban versus rural environments. In research undertaken in Alabama, the US, the researchers employed random parameter logit models for investigating the variables that contribute to injury severity in motorcycle at-fault crashes within urban and rural regions (S. Islam & Brown, 2017). More recently, Se et al. (2021) explored a sophisticated statistical technique, the "correlated random parameters ordered probit model with heterogeneity in means" (CRPOPHM), for examining how determinants influencing the seriousness of motorcycle crash injuries vary between urban and rural environments. Agyemang, Adanu, and Jones (2021b) used mixed multinomial logit model to analyze and compare motorcycle collisions in Ghana's rural and urban areas. A recent study by Champahom et al. (2023) pinpointed factors increasing the risk of fatal crashes for young motorcyclists across different geographical contexts. Mohamad et al. (2022) used a decision tree model to compare motorcycle deaths in rural Thailand and on highways, demonstrating that most fatalities involved male riders on good roads in clear weather. Notably, their findings revealed that on rural roads (RRs), fatalities remained high even when riders were driving responsibly, particularly at night on roads lacking illumination, highlighting the unique safety challenges in rural environments.

3.3.2 Time-of-day disparities

Temporal factors, such as the time-of-day, exert a notable impact on the dynamics of motorcycle crashes. Daytime conditions typically offer better visibility and may be associated with higher traffic volumes due to commuting and commercial activities. In contrast, nighttime conditions introduce additional challenges, including reduced visibility, increased rider fatigue, and higher rates of alcohol impairment. Understanding how these time-of-day variations influence crash severity is vital for developing effective interventions and improving overall road safety. Research has consistently demonstrated that both the time of day a motorcycle crash occurs, and the corresponding lighting conditions significantly affect the severity of injuries sustained by motorcyclists. M. S. B. Shaheed, Zhang, Gkritza, and Hans (2011) investigated motorcycle visibility-related determinants affecting the seriousness of crash injuries in Iowa using a multinomial logit model (MNL) analysis, finding that crashes occurring at night were associated with more severe outcomes. Likewise, Robbins and Fotios (2020) employed an Odds Ratio (OR) approach to investigate how lighting conditions (daytime versus darkness) affect the likelihood of motorcycle crashes on road traffic collisions (RTCs), revealing significantly higher risk during darkness. A recent study by Se et al. (2023) analyzed four years of crash datasets to examine the contributors that heightened the probability of severe injuries or fatalities in traffic crashes that occurred during day versus night conditions, confirming that darkness amplifies the risk of severe outcomes even when controlling for other variables.

3.3.3 Analytical methodology of crash severity

The integration of machine learning algorithms into roadway safety research has grown substantially in recent years, offering powerful tools for identifying complex patterns in crash data that traditional statistical methods might miss. Various algorithmic approaches have been employed for traffic crash prevention and prediction, with Random Forest (RF) algorithms emerging as a particularly effective method for analyzing crash injury severity.

Random Forest algorithms have gained popularity across various fields in recent years, including crash injury severity analysis (AlMamlook, Kwayu, Alkasisbeh, & Frefer, 2019; M.-M. Chen & Chen, 2020; Elalouf, Birfir, & Rosenbloom, 2023; Koley, Mondal, & Ghosal, 2022; Rezapour, Farid, Nazneen, & Ksaibati, 2021; Scarano et al., 2023; Yan & Shen, 2022; Yang et al., 2023; J. Zhang, Li, Pu, & Xu, 2018; Z. Zhang et al., 2024), medicine (Doubleday, Zhou, Zhou, & Fu, 2022; Iwendi et al., 2020; Xu, Wang, Zheng, Cao, & Ye, 2021), statistics (Gregorutti, Michel, & Saint-Pierre, 2017; Schonlau & Zou, 2020), meteorology (Ding et al., 2023; Hariharan, 2021; Liu et al., 2023), and many other domains.

The superiority of RF for crash injury severity prediction has been demonstrated in multiple comparative studies. A comprehensive review by Santos et al. (2022) examined 56 studies from 2001 to 2021 and found that Random Forest consistently outperformed other methods such as Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbor (KNN) approaches in predicting road traffic crash injury severity. Most recently, Z. Zhang et al. (2024) constructed a Random Forest model utilizing real-time traffic data collected from connected vehicles to forecast freeway crash, demonstrating its superior performance compared to logistic regression, support vector machine, and extreme gradient boosting alternatives. Similarly, Koley et al. (2022) compared various techniques including Decision Tree, XGBoost, Random Forest, and Logistic Regression to predict vehicular crash severity. Their results showed that the Random Forest Classifier algorithm yielded the most favorable outcome, achieving an impressive accuracy rate of 95%. AlMamlook et al. (2019) further confirmed RF's potential for assessing the risk of serious outcomes in road collisions, with their findings indicating superior performance compared to Logistic Regression (LR), Naïve Bayesian Classifier (NB), and AdaBoost algorithms.

When directly comparing statistical methods to machine learning approaches, Random Forest consistently demonstrates superior predictive power. J. Zhang et al. (2018) evaluated the effectiveness of common statistical methods, namely the ordered probit (OP) model and multinomial logit model, alongside four widely used machine learning algorithms, including RF, KNN, DT, and SVM. Their key findings revealed that the RF method achieved the most accurate overall prediction, especially for severe crashes, while the OP model exhibited the weakest performance. Similarly, Rezapour et al. (2021) compared RF, SVM, Multivariate Adaptive Regression Splines, and Binary Logistic Regression methods for forecasting the seriousness of motorcycle accident injuries. Their findings confirmed that the RF model exhibited better performance, displaying the lowest rate of misclassification and a higher AUC (Area Under the Curve).

3.3.4 Research gap and study contribution

Despite Thailand's high rate of motorcycle-related fatalities, research on motorcycle crash severity within the country remains methodologically limited. Most existing studies have relied on descriptive statistics or traditional regression models, which often assume linear relationships and offer limited capacity to capture complex interactions among crash-related variables. In addition, these studies tend to examine isolated risk dimensions—such as roadway type, time of day, or lighting conditions—without jointly considering how spatial and temporal contexts influence crash severity.

Internationally, machine learning techniques have increasingly been used to improve crash severity prediction, with Random Forest (RF) emerging as one of the most widely applied models due to its robustness and ability to model non-linear relationships. While a few recent studies in Thailand have begun to explore machine learning approaches in traffic safety, their application remains limited, and

Random Forest in particular has not been extensively used to model motorcycle crash severity. Furthermore, few studies—either in Thailand or globally—have combined RF with interpretable methods such as SHapley Additive exPlanations (SHAP) to uncover how contextual factors affect crash outcomes.

This study addresses these gaps by applying Random Forest in conjunction with SHAP to analyze motorcycle crash severity across four distinct scenarios: urban daytime, urban nighttime, rural daytime, and rural nighttime. The integration of RF and SHAP enables both accurate prediction and transparent, scenario-specific interpretation of key severity determinants. In doing so, the study contributes to the emerging field of interpretable machine learning in road safety and provides data-driven insights to support targeted, context-sensitive policy interventions aimed at reducing motorcycle crash severity in Thailand.

3.4 Empirical Setting

Drawing upon a dataset from the Thailand Highway Accident Information Management System (HAIMS), this study analyzed 12,266 motorcycle crashes recorded between 2020 and 2022. After data cleaning, 44 explanatory variables were retained and grouped into five categories described below. These variables were selected through a manual, context-informed feature selection process, based on four key criteria: (1) empirical relevance from prior crash severity studies, (2) contextual importance to Thailand's roadway conditions, (3) acceptable data quality, excluding variables with excessive missing values, and (4) sufficient variability, omitting near-constant features. No automated feature selection technique was applied, as the Random Forest algorithm can internally assess feature importance and manage multicollinearity. Retaining all relevant features also supports interpretability using SHAP.

To enhance conceptual clarity and support the study's urban–rural and day–night analysis, the selected predictors were organized into five major categories:

1) *Roadway Characteristics* capture infrastructure-related features (e.g., lane configuration, curve type, median type, intersection type) that vary between urban and rural environments and influence crash outcomes.

2) *Environmental Characteristics* include lighting and surface conditions that affect visibility and hazard levels, particularly in day versus night comparisons.

3) *Crash Causes* represent driver behaviors and violations (e.g., speeding, alcohol, sign violation), which are often temporally sensitive and more prevalent in nighttime conditions.

4) *Crash Characteristics* reflect the dynamics and context of the crash (e.g., head-on, rear-end single-vehicle), all of which are closely associated with severity outcomes.

5) *Crash-involved Vehicles* identify the types of vehicles involved (e.g., large trucks, passenger cars), which influence crash energy and rider vulnerability due to differences in vehicle mass and design.

To investigate disparities in motorcycle crash severity across urban and rural roadways, during both daytime and nighttime, Table 3.1 presents descriptive statistics and crash severity distributions (i.e., PDO/Minor vs. Severe/Fatal) for each subgroup.

In this study, urban roadways refer to those located within municipal boundaries where major activity centers—such as shopping malls, businesses, and government offices—are concentrated, typically resulting in higher traffic density. Rural roadways refer to those outside municipal jurisdictions, generally serving areas with lower population density and traffic volume. Crashes were classified by time of day using a fixed-hour scheme: nighttime was defined as 18:01 to 06:00, and daytime as 06:01 to 18:00. This classification reflects the time-stamping system in the HAIMS dataset and is consistent with practices in Thai traffic safety research.

The original HAIMS dataset included four crash severity levels: property damage only (PDO), minor injury, serious injury, and fatality. However, the distribution across these categories was highly imbalanced, with relatively few observations for serious injuries and fatalities. For instance, in the urban daytime subset, only 34.6% of crashes were classified as severe or fatal. To ensure model stability and mitigate class imbalance, the severity levels were grouped into two categories: (1) PDO and Minor Injury, and (2) Severe Injury and Fatality. This binary grouping is consistent with prior machine learning studies on crash severity (Agheli & Aghabayk, 2025; Sadeghi, Aghabayk, & Quddus, 2024) and supports more reliable classification and interpretation.

PDO/Minor refers to crashes resulting in property damage only or minor injuries that involved medical treatment without hospital admission, such as bruises or superficial wounds. Severe/Fatal includes crashes that resulted in fatal injuries (loss of life) or severe injuries requiring hospitalization for at least 48 hours, including major trauma such as bone fractures, internal injuries, or loss of consciousness (Transport, 2024; Wisutwattanasak et al., 2024).

Table 3.1 Variables descriptions

Variables	Urban Roadways		Rural Roadways	
	Day	Night	Day	Night
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Injury Severity (Frequency and Percentage in the bracket)				
PDO/Minor	1,785	969	2,720	1,379
	(65.36%)	(51.85%)	(58.14%)	(46.15%)
Severe/Fatal	946	900	1,958	1,609
	(34.64%)	(48.15%)	(41.86%)	(53.85%)
Roadways Characteristics				
WORK ZONE	0.084	0.110	0.086	0.085
	(0.277)	(0.313)	(0.280)	(0.278)
LANE = 2	0.212	0.189	0.354	0.340
	(0.409)	(0.392)	(0.478)	(0.474)
LANE = 4	0.447	0.409	0.458	0.452
	(0.497)	(0.492)	(0.498)	(0.498)
LANE = 6	0.140	0.161	0.057	0.071
	(0.347)	(0.367)	(0.231)	(0.257)

Table 3.1 Variables descriptions (Continued)

Variables	Urban Roadways		Rural Roadways	
	Day	Night	Day	Night
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
LANE >= 8	0.183	0.221	0.107	0.122
	(0.387)	(0.415)	(0.310)	(0.328)
ASPHALT	0.738	0.713	0.891	0.876
	(0.440)	(0.452)	(0.312)	(0.329)
NO MEDIAN	0.235	0.213	0.379	0.359
	(0.424)	(0.410)	(0.485)	(0.480)
FLUSH AND PAINTED MEDIAN	0.105	0.094	0.103	0.089
	(0.306)	(0.291)	(0.303)	(0.285)
RAISED MEDIAN	0.382	0.380	0.232	0.259
	(0.486)	(0.486)	(0.422)	(0.438)
DEPRESSED MEDIAN	0.177	0.191	0.171	0.181
	(0.382)	(0.393)	(0.377)	(0.385)
BARRIER MEDIAN	0.101	0.121	0.116	0.112
	(0.301)	(0.327)	(0.320)	(0.315)
STRAIGHT	0.926	0.925	0.887	0.895
	(0.262)	(0.264)	(0.317)	(0.307)
CURVED	0.072	0.073	0.108	0.103
	(0.259)	(0.261)	(0.310)	(0.304)
ON SLOPE	0.009	0.005	0.013	0.008
	(0.095)	(0.069)	(0.114)	(0.091)
FOUR-LEG_INT	0.052	0.057	0.044	0.037
	(0.222)	(0.231)	(0.204)	(0.190)
T_INT	0.067	0.047	0.063	0.050
	(0.249)	(0.212)	(0.243)	(0.217)
Y_INT	0.012	0.011	0.010	0.008
	(0.111)	(0.103)	(0.102)	(0.089)
U_TURN	0.077	0.055	0.069	0.050
	(0.266)	(0.227)	(0.254)	(0.218)
CONNECT_PUBLIC AREA	0.050	0.026	0.038	0.021
	(0.218)	(0.158)	(0.190)	(0.144)

Table 3.1 Variables descriptions (Continued)

Variables	Urban Roadways		Rural Roadways	
	Day	Night	Day	Night
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
CONNECT_PRIVATE AREA	0.013 (0.114)	0.010 (0.100)	0.025 (0.155)	0.014 (0.116)
BRIDGE SECTION	0.019 (0.135)	0.023 (0.150)	0.008 (0.091)	0.015 (0.120)
Environmental Characteristics				
WET	0.037 (0.190)	0.059 (0.236)	0.051 (0.220)	0.079 (0.270)
RAINING	0.029 (0.167)	0.054 (0.225)	0.041 (0.198)	0.069 (0.253)
DARK_NO_ELEC	-	0.147 (0.354)	-	0.280 (0.449)
DARK_WITH_ELEC	-	0.853 (0.354)	-	0.720 (0.449)
Crash Causes				
SPEEDING	0.636 (0.481)	0.747 (0.435)	0.629 (0.483)	0.743 (0.437)
FRONT-PATH INTERRUPTION	0.292 (0.455)	0.151 (0.359)	0.280 (0.449)	0.137 (0.344)
ILLEGAL PASSING	0.007 (0.085)	0.006 (0.080)	0.010 (0.101)	0.005 (0.071)
UNSIGNAL	0.005 (0.074)	0.003 (0.057)	0.006 (0.078)	0.0003 (0.018)
VIOLATE THE TRAFFIC SIGNS	0.025 (0.156)	0.033 (0.179)	0.027 (0.161)	0.034 (0.181)
UNSKILLED DRIVING	0.004 (0.060)	0.002 (0.046)	0.004 (0.067)	0.004 (0.066)
DEFECTIVE CAR DEVICE	0.003 (0.054)	0.002 (0.040)	0.006 (0.074)	0.006 (0.080)
DRUNK	0.005 (0.069)	0.029 (0.168)	0.011 (0.104)	0.040 (0.196)

Table 3.1 Variables descriptions (Continued)

Variables	Urban Roadways		Rural Roadways	
	Day	Night	Day	Night
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
FATIQUE	0.008	0.010	0.010	0.006
	(0.089)	(0.100)	(0.102)	(0.075)
Crash Characteristics				
HEAD-ON	0.085	0.078	0.116	0.097
	(0.279)	(0.268)	(0.321)	(0.297)
REAR-END	0.421	0.356	0.392	0.324
	(0.494)	(0.479)	(0.488)	(0.468)
SIDE SWIPE	0.320	0.218	0.308	0.222
	(0.467)	(0.413)	(0.462)	(0.416)
SINGLE CRASH	0.114	0.261	0.132	0.263
	(0.317)	(0.439)	(0.339)	(0.440)
HIT PARKED VEHICLE	0.026	0.047	0.020	0.044
	(0.159)	(0.212)	(0.141)	(0.206)
Crash-involved Vehicles				
CAR	0.347	0.269	0.308	0.229
	(0.476)	(0.444)	(0.462)	(0.420)
VAN	0.015	0.011	0.016	0.011
	(0.120)	(0.105)	(0.124)	(0.103)
TRUCK 6 WHEELS	0.037	0.023	0.038	0.025
	(0.188)	(0.150)	(0.191)	(0.155)
TRUCK 10 WHEELS	0.052	0.060	0.041	0.058
	(0.222)	(0.237)	(0.199)	(0.234)
PEDESTRIANS	0.010	0.013	0.005	0.012
	(0.097)	(0.115)	(0.071)	(0.108)

Notes: SD = Standard Deviation

3.5 Methodological Approach

3.5.1 Random Forest (RF)

Random Forest stands as a frequently employed technique in ensemble learning, as proposed by Breiman (2001). It merges multiple decision trees possessing varied characteristics and predictive abilities, culminating in a notable enhancement of predictive accuracy. The RF model is composed of a collection of tree-based structures, each of which is trained using bagging to receive samples. Throughout the learning phase, the branches within every tree are divided using a random selection of features. Once the trees are trained and provided with input variables, every tree contributes to the prediction for the outcome variable, and the ultimate decision is determined by the majority of these votes. Random forest models, in contrast to simplistic decision trees, exhibit improved predictive accuracy, resilience against noise and outliers, and reduced risk of overfitting. Additionally, they offer the ability to assess the importance of input variables (or features) within the model (Ali, Hussain, & Haque, 2024; Breiman, 2001). RF finds extensive application in crash prediction modeling, encompassing predictions regarding crash incidents, frequency, and the severity of injuries. Implementing this method requires determining two key parameters: the number of trees to be generated and the quantity of variables chosen randomly as potential candidates at each split (Iranitalab & Khattak, 2017; J. Zhang et al., 2018).

RF was selected for its strong performance in modeling nonlinear relationships, robustness against multicollinearity, ability to handle imbalanced and heterogeneous crash data, and ease of integration with SHAP for interpretability. These strengths make RF particularly suitable for injury severity classification, especially when the aim is not only to predict but also to understand contributing factors in a transparent manner. Furthermore, previous comparative studies have consistently demonstrated the superior performance of RF in crash severity prediction tasks across various settings. As noted by Chakraborty, Gates, and Sinha (2023), RF is effective for crash injury severity modeling due to its strong classification performance, robustness to imbalanced and high-dimensional data, and partial interpretability through feature importance metrics.

3.5.2 Model performance measurement

This study assesses the predictive capability of RF using four crucial metrics: Accuracy, Precision, Recall, and F1-Score, with their mathematical representations given below (M.-M. Chen & Chen, 2020; Yan & Shen, 2022):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.1}$$

$$\text{Precision (P)} = \frac{TP}{TP + FP} \tag{3.2}$$

$$\text{Recall (R)} = \frac{TP}{TP + FN} \tag{3.3}$$

$$F1\_Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.4}$$

where True Positive (TP) and True Negative (TN) represent the quantities of accidents correctly identified, while False Positive (FP) and False Negative (FN) represent the quantities of accidents incorrectly identified (M.-M. Chen & Chen, 2020). A higher value for Accuracy, Precision, Recall and F1-Score signifies enhanced predictive capability of the model.

3.5.3 SHapley Additive exPlanations (SHAP)

Lundberg and Lee (2017) describe SHAP methodology as an approach that utilizes Shapley values to interpret outputs from machine learning models. These values, derived from game-theoretic collaboration, determine each feature’s effect on the overall prediction outcome (Štrumbelj & Kononenko, 2014). The SHAP framework operates by first establishing a model that contains all input features, then developing a comparative model that excludes the feature under examination, enabling assessment of how this omission affects model performance. A feature's

SHAP score represents its individual impact on the overall prediction. The formula below calculates the SHAP score for a specific feature (Tahfim & Yan, 2021):

$$\varnothing_i = \sum_{S \subseteq X \setminus \{i\}} \frac{|S|!\left(|X| - |S| - 1\right)!}{|X|!} \left[f_{S\cup\{i\}}\left(x_{S\cup\{i\}}\right) - f_S\left(x_S\right) \right] \tag{3.5}$$

Where $\varnothing_i$ represents the feature's incremental contribution (its SHAP score); X denotes the complete set of features; S is a subset of features; and x_S refers to the values associated with features in subset S. To analyze a particular feature's effect, a model $f_{S\cup\{i\}}$ is created that includes this feature, while an alternative model f_S excludes it. The predictions from both models are then compared against the current output, expressed as $f_{S\cup\{i\}}\left(x_{S\cup\{i\}}\right) - f_S\left(x_S\right)$. Since the feature's impact depends on interactions with other features in the model, differences are calculated across all possible feature subsets (Lundberg & Lee, 2017).

3.6 Results

3.6.1 Model performance metrics

The performance of the Random Forest model was rigorously assessed across different roadway environments and lighting conditions to examine its efficacy in classifying motorcycle crash severity. The model's performance was evaluated using key classification metrics, including accuracy, precision, recall, and the F1-score, to determine its predictive capability for two categories of crash severity: PDO/Minor and Severe/Fatal. Table 3.2 provides a comprehensive summary of the model's performance for both urban and rural roadways during daytime and nighttime conditions.

In urban roadways during daytime, the model reached an accuracy of 0.665. For PDO/Minor crashes, precision was 0.706, recall was 0.835, and F1-score was 0.765, indicating good capability in correctly identifying less severe crashes. For Severe/Fatal crashes, precision was 0.528, recall was 0.347, and F1-score was 0.419, suggesting moderate performance in identifying more severe crashes.

For urban roadways during nighttime, the model demonstrated an accuracy of 0.647. The precision, recall, and F1-score values were more balanced between severity classes compared to daytime, with PDO/Minor crashes having values of 0.650, 0.684, and 0.667 respectively, while Severe/Fatal crashes showed values of 0.643, 0.608, and 0.625 respectively.

In rural roadways during daytime, the model obtained an accuracy of 0.638. For PDO/Minor crashes, the precision was 0.703, recall was 0.653, and F1-score was 0.677. For Severe/Fatal crashes, precision was 0.561, recall was 0.617, and F1-score was 0.588, showing a more balanced prediction pattern between the two severity classes compared to urban daytime scenarios.

For rural roadways during nighttime, the model demonstrated an accuracy of 0.659. Interestingly, the model performed better at predicting Severe/Fatal crashes in this setting, with precision of 0.678, recall of 0.743, and F1-score of 0.709, compared to PDO/Minor crashes which had precision, recall, and F1-scores of 0.628, 0.551, and 0.587 respectively.

The Random Forest models demonstrated varying levels of predictive performance across different environmental and temporal contexts. Overall accuracy ranged from 0.638 to 0.665, with the most balanced classification performance observed in rural nighttime conditions. The model exhibited higher recall values for PDO/Minor crashes in most cases, suggesting a greater tendency to correctly classify these less severe crash instances. However, identifying Severe/Fatal crashes proved more challenging, particularly in urban daytime conditions, as indicated by the lower recall values.

Table 3.2 Comparison of model performance of Random Forest

Performance Metrics	Urban Roadways		Rural Roadways	
	Daytime	Nighttime	Daytime	Nighttime

	PDO/Minor	Severe/Fatal	PDO/Minor	Severe/Fatal	PDO/Minor	Severe/Fatal	PDO/Minor	Severe/Fatal
Accuracy	0.665		0.647		0.638		0.659	
Precision	0.706	0.528	0.650	0.643	0.703	0.561	0.628	0.678
Recall	0.835	0.347	0.684	0.608	0.653	0.617	0.551	0.743
F1-Score	0.765	0.419	0.667	0.625	0.677	0.588	0.587	0.709

To further validate the strength of the Random Forest classifier, two benchmark models—Logistic Regression (LR) and Decision Tree (DT)—were evaluated for comparison. Table 3.3 summarizes the classification accuracy, precision, recall, and F1-score across all four crash scenarios.

The results show that Random Forest consistently outperformed the benchmark models in all settings, supporting its selection as the primary model in this study. In addition to robust performance, Random Forest is well suited for integration with SHAP, which provides interpretable, scenario-specific insights into feature importance under varying environmental and temporal conditions.

Table 3.3 Comparison of classification performance between Random Forest and benchmark models across all crash scenarios

Scenario	Model	Accuracy	Precision	Recall	F1-Score
Urban Daytime	Random Forest	0.665	0.644	0.665	0.645
	Logistic Regression	0.656	0.623	0.656	0.611
	Decision Tree	0.631	0.599	0.631	0.603
Urban Nighttime	Random Forest	0.647	0.647	0.647	0.647
	Logistic Regression	0.564	0.668	0.564	0.469
	Decision Tree	0.545	0.558	0.545	0.495

Table 3.3 Comparison of classification performance between Random Forest and benchmark models across all crash scenarios (Continued)

Scenario	Model	Accuracy	Precision	Recall	F1-Score

Rural Daytime	Random Forest	0.638	0.644	0.638	0.640
	Logistic Regression	0.599	0.596	0.599	0.597
	Decision Tree	0.611	0.600	0.611	0.590
Rural Nighttime	Random Forest	0.659	0.656	0.659	0.656
	Logistic Regression	0.615	0.612	0.615	0.595
	Decision Tree	0.622	0.662	0.622	0.561

3.6.2 Model interpretation

To gain deeper insight into the factors influencing crash severity, an interpretability analysis was conducted using feature importance rankings and SHAP (SHapley Additive exPlanations) analysis, as shown in Figures 3.2 to 3.9. The importance of features, ranked according to their mean absolute SHAP values, is presented in Figures 3.2, 3.4, 3.6, and 3.8, with longer bars denoting higher significance. Meanwhile, Figures 3.3, 3.5, 3.7, and 3.9 reveal how each ranked feature influences the model's predictions, particularly regarding injury severity levels. In these plots, each point represents an individual crash instance, with horizontal position showing the SHAP value (impact on prediction) and color indicating the feature value (high values in red, low values in blue). The clustering patterns reveal crucial information about feature-prediction relationships:

1) *Positive correlation:* Red points (high values) on the right and blue points (low values) on the left indicate that higher feature values are linked to more severe crashes.

2) *Negative correlation:* Red points on the left and blue on the right suggest that higher values reduce crash severity.

3) *Mixed distributions*, with red and blue points scattered on both sides, suggest complex, context-dependent effects influenced by interactions with other factors.

4) The distribution width along the horizontal axis indicates the magnitude of a feature's potential impact, with wider spreads suggesting greater influence on severity predictions in certain contexts.

3.6.2.1 Urban daytime crashes

Figure 3.3 highlights several key factors contributing to severe urban daytime motorcycle crashes. Crashes on asphalt roadways, those involving large trucks, crashes on depressed medians, head-on collisions, U-turn-related crashes, six-lane roadway configurations, and crashes in work zone settings are particularly linked to increased severity.

On the other hand, certain crash characteristics are more frequently associated with property damage-only (PDO) or minor injuries. These include crashes involving passenger cars, side-swipe collisions, crashes on raised and barrier medians, rear-end collisions, and crashes occurring on straight roadways.

Some crash factors, however, demonstrate both positive and negative associations with severity. Speeding-related crashes, front-path interruptions, and crashes on four-lane roadways exhibit varying impacts, suggesting that their influence is dependent on other contributing elements. Similarly, crashes on eight-lane or wider roads, single-vehicle crashes, and incidents on flush and painted medians display distributions that extend across both sides of the zero line, emphasizing their context-sensitive role in crash severity.

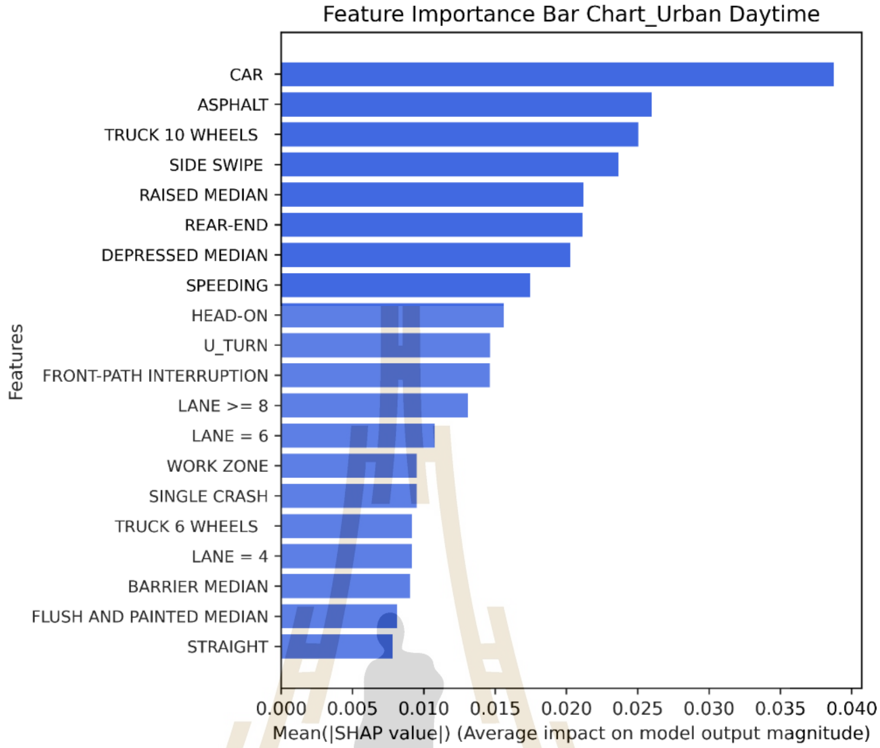

Figure 3.2 Feature importance ranking for motorcycle crashes in urban daytime

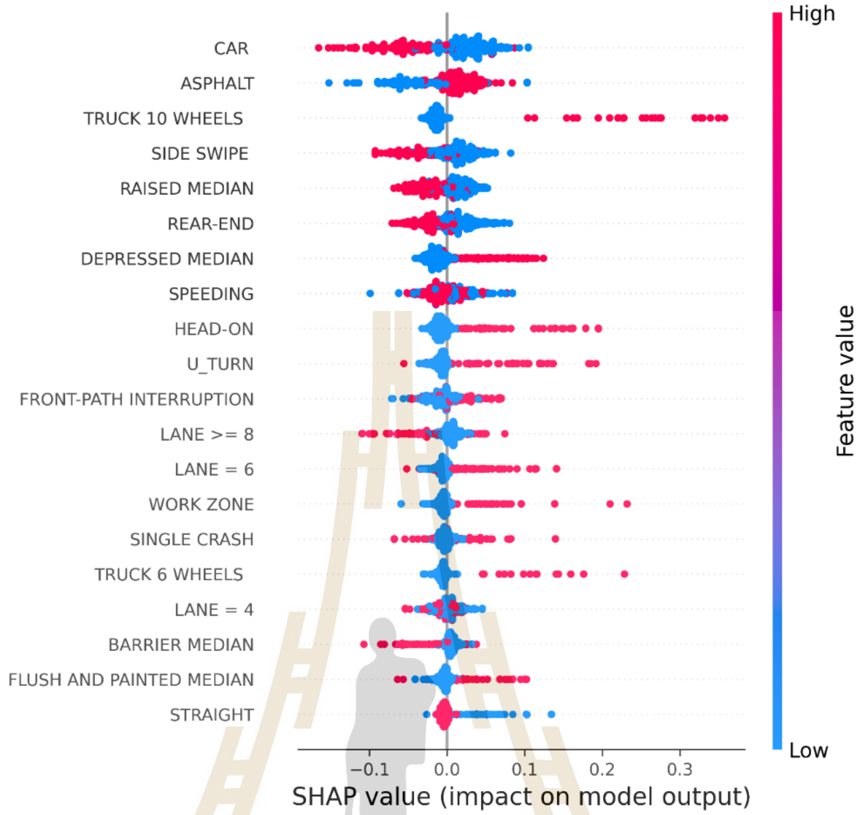

Figure 3.3 SHAP bee swarm plot of features impact for motorcycle crashes in urban daytime

3.6.2.2 Urban nighttime crashes

Figure 3.5 provides insight into the primary factors influencing severe crashes in urban nighttime conditions. Higher crash severity is frequently observed in cases involving asphalt roadways, depressed medians, large truck involvement, head-on collisions, parked vehicle crashes, and crashes occurring on double-lane roadways.

In contrast, crashes associated with lower injury severity or property damage tend to involve passenger cars, raised medians, side-swipe collisions, eight-lane or wider roadways, four-leg intersections, and dark areas with electric lighting.

Notably, crashes on four-lane roadways, rear-end collisions, and single-vehicle crashes exhibit both positive and negative correlations with crash severity, depending on interactions with other factors. Similarly, speeding-related crashes, incidents on six-lane roadways, front-path interruptions, crashes on roads without medians, and crashes in work zones display distributions spanning both sides of the zero line, reinforcing the context-dependent impact of these factors on crash severity.

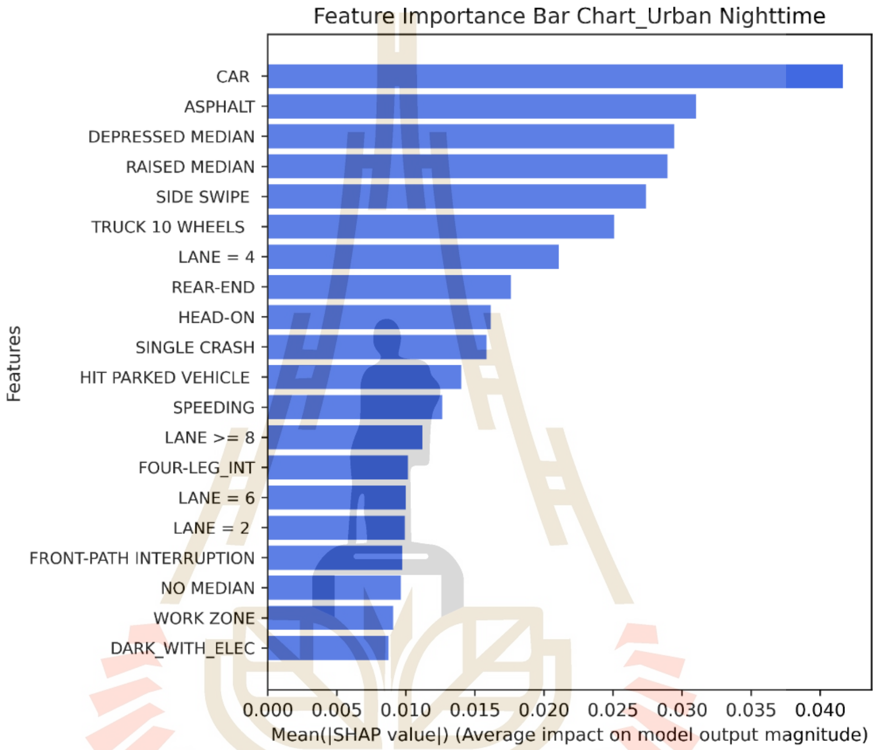

Figure 3.4 Feature importance ranking for motorcycle crashes in urban nighttime

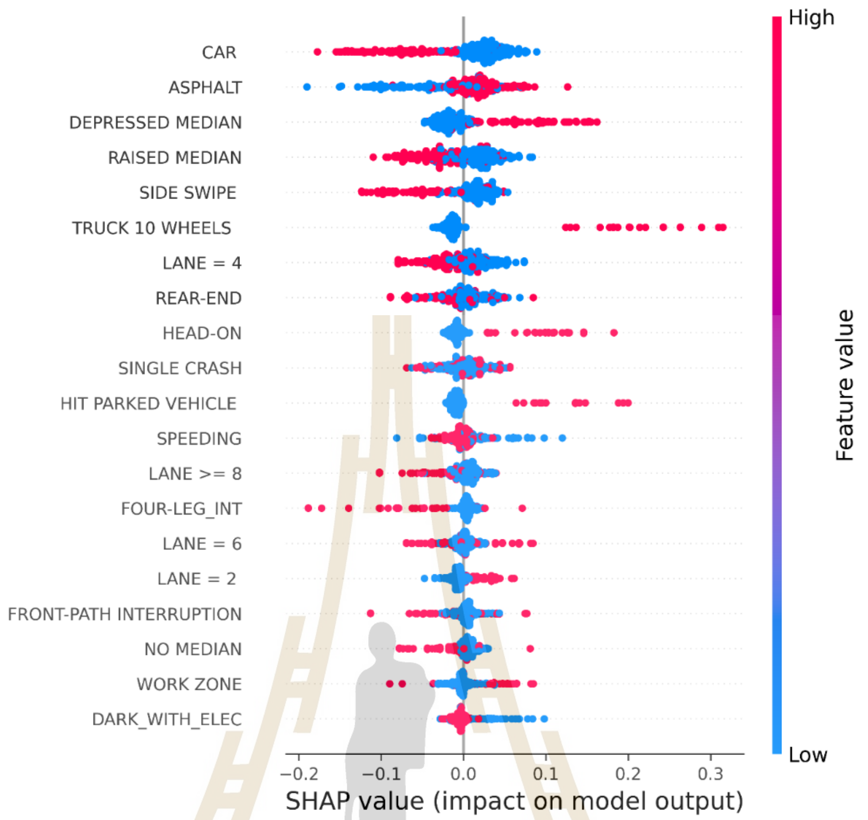

Figure 3.5 SHAP bee swarm plot of features impact for motorcycle crashes in urban nighttime

3.6.2.3 Rural daytime crashes

As shown in Figure 3.7, multiple factors contribute to severe crashes in rural daytime settings. Crashes involving depressed medians, head-on collisions, incidents on double- or four-lane roadways, those involving large trucks, U-turn-related crashes, and crashes occurring on curved roadways are linked to higher severity outcomes.

Conversely, PDO or minor injury crashes are more often observed in cases involving passenger cars, side-swipe collisions, crashes on barrier medians, work zone crashes, speeding-related crashes, crashes on roads without medians, crashes occurring on wider roadways (lane = 6; lane ≥ 8), and crashes occurring on straight roadways.

Additionally, some crash factors demonstrate both increasing and decreasing effects on severity. Crashes on asphalt roadways, front-path interruptions, and rear-end collisions exhibit a wide range of SHAP values, illustrating the multifaceted nature of their impact on crash severity.

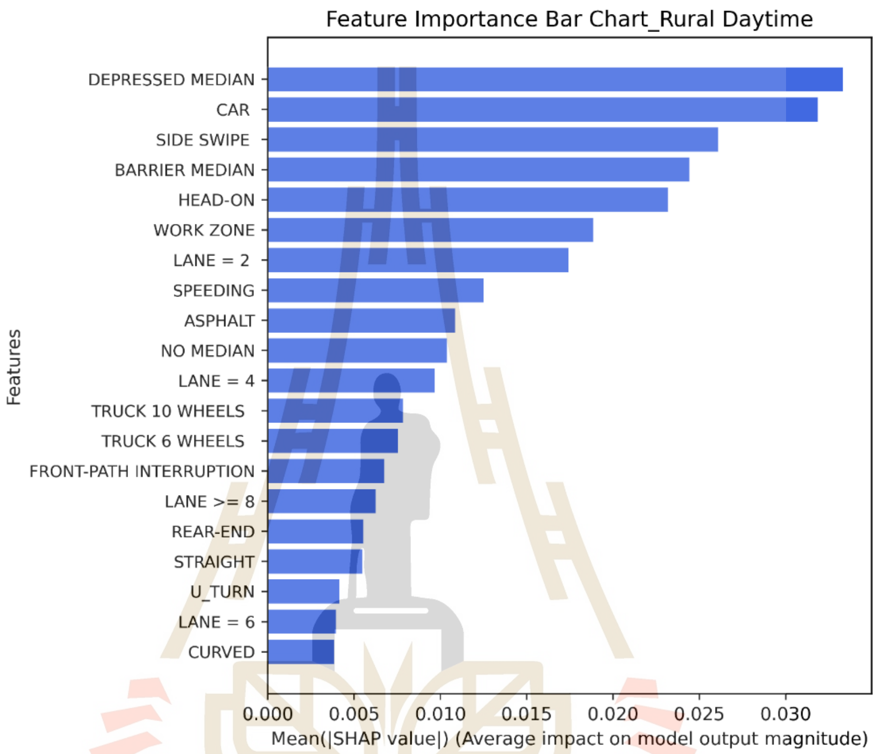

Figure 3.6 Feature importance ranking for motorcycle crashes in rural daytime

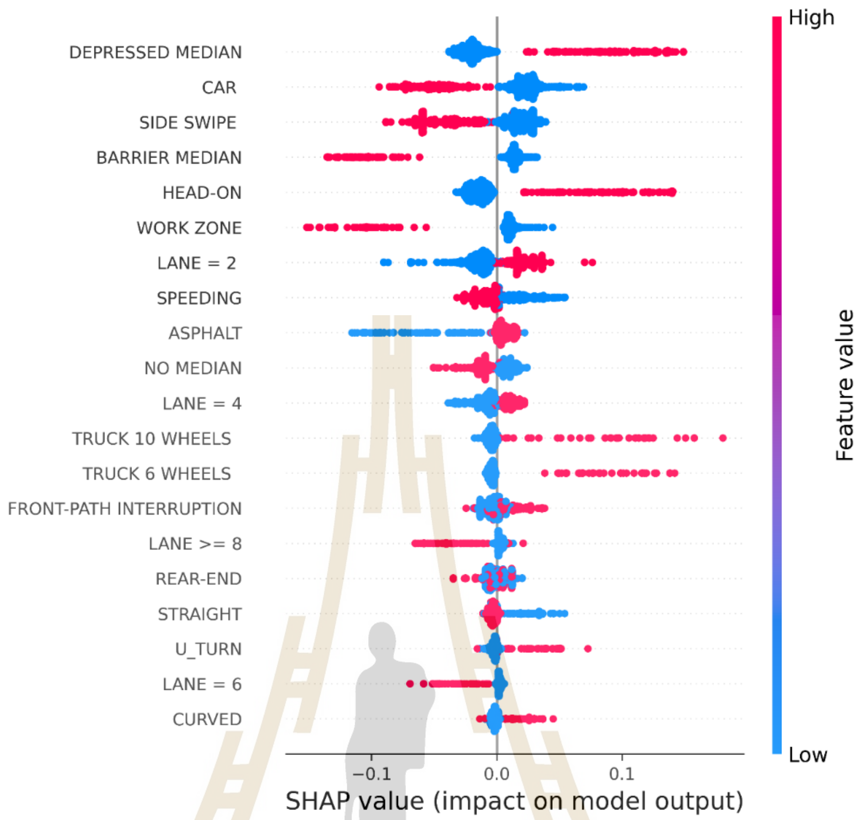

Figure 3.7 SHAP bee swarm plot of features impact for motorcycle crashes in rural daytime

3.6.2.4 Rural nighttime crashes

Figure 3.9 highlights the factors influencing rural nighttime crashes. Among those associated with higher severity are head-on collisions, crashes involving large trucks, crashes in dark areas without electric lighting, crashes on depressed medians, crashes on asphalt roadways, crashes on four-lane roadways, and violations of traffic signs.

By contrast, crashes with a greater likelihood of PDO or minor injuries tend to involve passenger cars, barrier medians, side-swipe collisions, dark areas with electric lighting, and crashes occurring on flush and painted medians.

Notably, speeding-related crashes, crashes on double-lane roadways, rear-end collisions, single-vehicle crashes, crashes on roads without medians, crashes involving raised medians, crashes occurring on straight roadways, and crashes in work zones exhibit mixed-distribution patterns. These patterns underscore the complex and multifaceted nature of the factors influencing motorcycle crash outcomes.

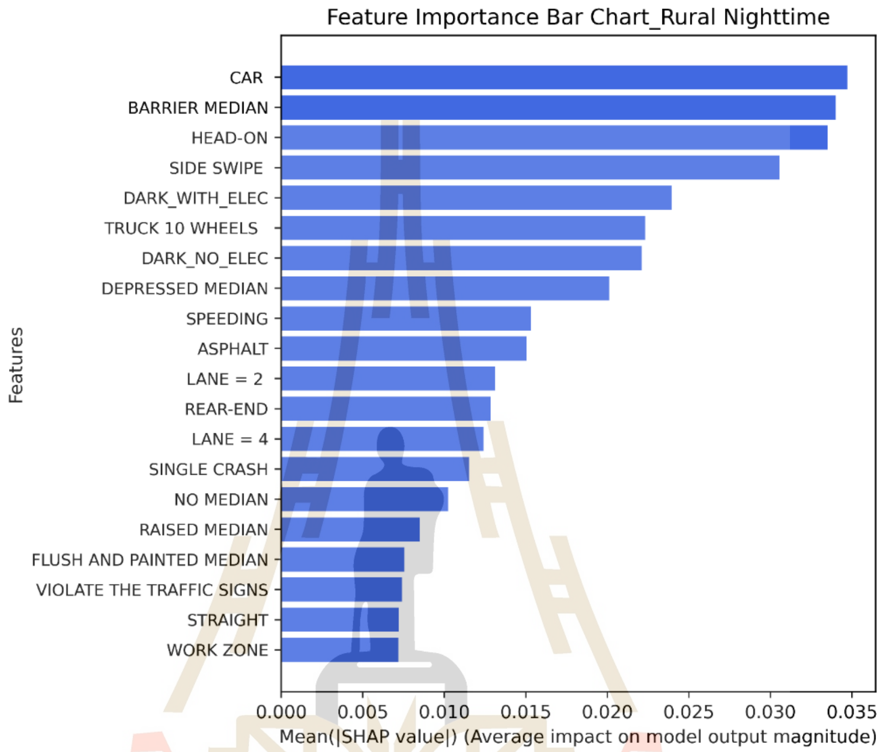

Figure 3.8 Feature importance ranking for motorcycle crashes in rural nighttime

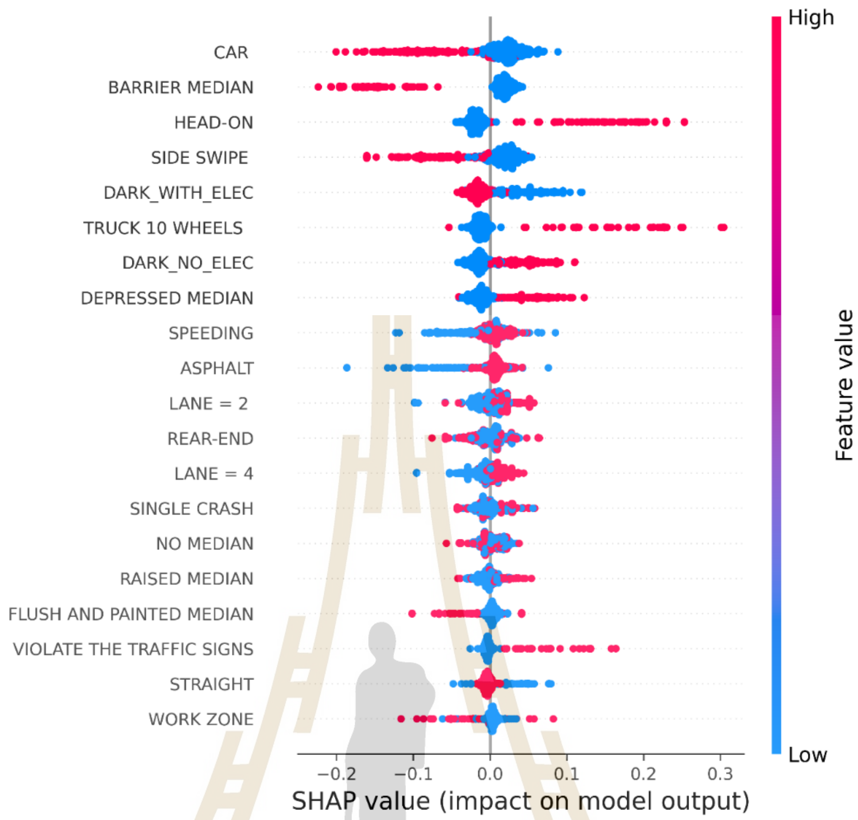

Figure 3.9 SHAP bee swarm plot of features impact for motorcycle crashes in rural nighttime

3.7 Discussion

3.7.1 Key predictors of crash severity across all settings

The SHAP analysis revealed several consistent factors influencing motorcycle crash severity regardless of environmental context, providing robust evidence for targeted safety interventions. The findings highlight both universal risk factors and context-dependent elements that shape crash outcomes.

Vehicle type emerged as the most consistent predictor across all settings. Crashes involving large trucks consistently demonstrated high positive SHAP values (as evident in Figures 3.3, 3.5, 3.7, and 3.9), resulting in significantly higher severity outcomes. This pattern underscores the inherent vulnerability of motorcyclists when colliding with substantially heavier vehicles, confirming findings from previous studies (Chang et al., 2016; Kanitpong, Jensupakarn, Dabsomsri, &

Issalakul, 2024; Laphrom et al., 2024; Savolainen & Mannering, 2007; M. S. Shaheed & Gkritza, 2014). The stark disparity between the protective structure of trucks and the exposed nature of motorcycles creates fundamentally hazardous conditions. Conversely, crashes between motorcycles and passenger cars consistently demonstrated negative SHAP values, associated with lower severity outcomes across all environments.

Collision configuration exhibited similarly consistent patterns in the SHAP analysis. Head-on collisions showed strong positive associations with increased severity in all environmental contexts, likely due to the combined velocity of opposing vehicles generating substantially higher impact forces. This finding aligns with Prentkovskis, Sokolovskij, and Bartulis (2010) and Chang, Yasmin, Huang, Chan, and Haque (2021), who emphasized the destructive nature of head-on collisions resulting from directly opposed momentum vectors. In contrast, side-swipe collisions consistently demonstrated negative SHAP values, linking them to lower injury severity, reflecting their glancing nature and reduced energy transfer to riders (Agyemang, Adanu, & Jones, 2021a).

Road characteristics significantly influenced crash severity across all settings. Depressed medians consistently showed positive SHAP values, associated with increased severity, possibly due to motorcyclists being ejected into lower-elevated areas, leading to secondary impacts. This observation supports findings by Champahom et al. (2020). Conversely, barrier medians demonstrated protective effects with negative SHAP values, reducing the likelihood of severe outcomes, consistent with Champahom et al. (2022), who found barrier medians moderately decrease injury severity.

Asphalt roadways were consistently linked to higher severity outcomes (positive SHAP values), particularly in urban settings. This may be attributed to urban asphalt surfaces developing reduced skid resistance due to traffic polishing and contaminant accumulation at stopping points, compromising tire grip during emergency maneuvers in complex traffic environments. Roadway width exhibited notable patterns across the SHAP analyses, with narrower roadways (double-lane in urban nighttime and rural daytime, four-lane in urban daytime and rural settings) generally associated with more severe crashes, aligning with previous research (Se et al., 2023; M. S. Shaheed & Gkritza, 2014; Vajari, Aghabayk, Sadeghian, & Shiwakoti, 2020). This trend likely reflects the limited space for evasive maneuvers in constrained environments.

Environmental conditions, particularly lighting, showed substantial impacts on crash severity in our SHAP analysis. In rural nighttime settings (Figure 3.9), dark areas without electric lighting demonstrated strongly positive SHAP values, correlating with higher severity outcomes. Conversely, the presence of electric lighting in both urban and rural nighttime environments showed negative SHAP values, linked to reduced crash severity, highlighting the crucial role of visibility in motorcycle safety. Adequate illumination likely enhances driver visibility and provides more time to react to potential hazards (Huang, Chin, & Haque, 2008; Savolainen & Mannering, 2007; M. S. Shaheed & Gkritza, 2014).

3.7.2 Variations in crash severity across urban-rural and day-night conditions

The SHAP analysis revealed important distinctions in how various factors influence motorcycle crash severity across different environmental contexts, suggesting the need for tailored safety approaches.

Maneuver-related crashes, particularly U-turn-related incidents, showed stronger positive SHAP associations with increased severity in urban and rural daytime settings (Figures 3.3 and 3.7) but appeared less influential in nighttime scenarios, aligning with previous research (P.-L. Chen & Pai, 2019; Moskal, Martin, Lenguerrand, & Laumon, 2007). This pattern suggests that visibility and driver expectancy play critical roles in these specific crash types. Daytime conditions potentially facilitate higher speeds during U-turn maneuvers, while limited nighttime visibility may prompt greater caution when executing such maneuvers.

In urban nighttime conditions (Figure 3.5), crashes involving parked vehicles were associated with higher severity (positive SHAP values), a pattern not observed in other settings. This may be attributed to several factors: reduced visibility of parked vehicles, inconsistent lighting creating shadow zones, and the sudden obstacle represented by parked vehicles in urban environments. Additionally, nighttime urban environments may involve riskier riding behaviors and more complex roadway environments, whereas better visibility in daytime conditions and lower traffic density in rural areas may mitigate such risks.

Roadway geometry influenced crash severity differently across environments in the SHAP analysis. Curved roadways emerged as a significant factor with positive SHAP values in rural daytime crashes (Figure 3.7) but showed less prominence in urban environments. This difference likely reflects the distinct geometric characteristics between urban and rural road networks, with rural areas featuring more challenging horizontal alignments and potentially higher operating speeds on curves. These conditions may pose additional hazards for motorcyclists due to increased difficulty in controlling their speed (Chang et al., 2021; M. Islam, 2021).

Compliance with traffic controls showed environment-specific impacts on crash severity. Traffic control violations were particularly problematic in rural nighttime settings (Figure 3.9), suggesting that reduced visibility, lower expectations of enforcement, or unfamiliarity with rural roads may contribute to this trend. Champahom et al. (2023) similarly found that traffic sign violations on rural roads increased variability in curved roadway crashes while reducing crash variability in the morning.

Road surface characteristics showed varying importance across settings in the SHAP plots. Asphalt surfacing had a stronger positive association with crash severity in urban environments (Figures 3.3 and 3.5) than in rural areas, suggesting potential interactions with urban-specific factors such as traffic density, stopping frequency, and intersection spacing.

Work zones also had contrasting effects based on the environment. In urban daytime settings (Figure 3.3), work zones were associated with increased crash severity (positive SHAP values), whereas in rural daytime environments (Figure 3.7), they correlated with reduced severity (negative SHAP values). This aligns with M. Islam (2022), who reported that construction zones decreased severe and fatal injury crashes only in rural daytime settings. Rural road construction companies are likely to implement extended warning zones with enhanced signage to alert motorcyclists to change road conditions. Additionally, this distinction reflects differences in work zone configurations, speed management strategies, and traffic conditions between urban and rural areas.

Contrary to expectations, speeding exhibited surprising context-dependent effects in the SHAP analysis. Speeding-related crashes sometimes showed negative SHAP values associated with lower severity in rural daytime settings (Figure 3.7). This counterintuitive finding may reflect that higher speeds in these areas often occur on straighter roads with fewer conflict points, which may mitigate crash severity despite increased velocity. Further investigation into using interaction effects in future models could clarify this relationship.

3.8 Conclusions and Policy-Related Recommendations

Drawing upon crash data involving motorcycle crashes in Thailand spanning from 2020 to 2022, this research employed machine learning techniques, specifically Random Forest (RF) models coupled with SHAP analysis, to analyze the determinants affecting motorcycle crash severity across different environmental contexts. The RF model was benchmarked against Logistic Regression and Decision Tree classifiers and demonstrated superior performance across all scenarios, further confirming its robustness for crash severity prediction. By separately analyzing urban and rural crashes during daytime and nighttime conditions, the research revealed both universal risk factors and context-dependent elements that shape crash outcomes.

The findings demonstrate that certain factors consistently influence motorcycle crash severity regardless of environmental context. Crashes involving large trucks, head-on collisions, and crashes on depressed medians were universally associated with increased severity outcomes. Conversely, crashes with passenger cars, side-swipe collisions, and the presence of barrier medians consistently correlated with reduced severity.

Importantly, the study uncovered significant variations in how risk factors manifest across different environmental settings. Factors such as U-turn maneuvers, curved roadways, work zones, and speeding exhibited distinct effects depending on the urban-rural and day-night context. These variations highlight the complexity of motorcycle crash dynamics and underscore the necessity for contextually tailored safety approaches rather than one-size-fits-all solutions.

The SHAP analysis provided valuable insights into not only which factors influence crash severity but also how these factors exert their influence. This deeper understanding enables more precise targeting of safety interventions according to specific environmental conditions, potentially leading to more effective reductions in severe and fatal motorcycle crashes. Coupled with SHAP, RF enabled interpretable and context-specific analysis of severity predictors, forming the analytical foundation for the targeted policy recommendations to enhance motorcycle safety:

Urban Daytime Setting: *(1) U-turn Management*: Implement dedicated U-turn lanes with appropriate signage and signals at high-traffic locations to reduce conflicts during these maneuvers. *(2) Work Zone Safety Enhancement*: Develop motorcycle-specific work zone protocols in urban areas, including reduced speed limits, increased buffer zones, and enhanced visibility of temporary traffic control devices. *(3) Lane Width Considerations*: Where feasible, consider widening narrow roadways (particularly six-lane configurations identified as high-risk) or implement motorcycle-friendly shoulder designs to provide escape paths during emergency situations. *(4) Large Vehicle Interaction Management*: Create time-based restrictions on large truck movements in high-density motorcycle traffic areas and implement educational campaigns targeting both truck drivers and motorcyclists for safe interactions. *(5) Median Design Improvements*: Retrofit depressed medians with safety features such as rumble strips or impact attenuators to mitigate the severity of crashes involving these structures.

Urban Nighttime Setting: *(1) Parked Vehicle Safety*: Enhance visibility of parked vehicles through improved street lighting, reflective markings, and strategic parking configurations that minimize sudden obstacles. *(2) Lighting Infrastructure Upgrades*: Prioritize lighting improvements in areas with high motorcycle traffic, focusing on consistent illumination that minimizes shadow zones and sudden changes in visibility. *(3) Double-Lane Road Safety*: Implement enhanced edge line markings and motorcycle-specific warning signs on urban double-lane roads that demonstrated high severity risk during nighttime. *(4) Intersection Approach Design*: Improve delineation and advance warning systems for intersections in nighttime conditions, particularly for four-leg intersections identified as potential risk factors. *(5) Large Vehicle Awareness Programs*: Develop nighttime-specific safety campaigns highlighting the particular risks of motorcycle-truck interactions in limited visibility conditions.

Rural Daytime Setting: *(1) Curved Roadway Treatments*: Implement enhanced curve warning systems, including dynamic speed feedback signs, chevron alignment signs, and high-friction surface treatments on curved segments of rural roads. *(2) U-Turn Restrictions*: Consider restricting U-turns at high-risk rural locations and providing designated U-turn facilities with appropriate acceleration and deceleration lanes where necessary. *(3) Lane Configuration Safety*: For double- and four-lane rural roadways identified as high-risk, implement centerline rumble strips, wider shoulders, and enhanced roadside clear zones to mitigate crash severity. *(4) Work Zone Best Practices*: Expand the implementation of effective rural work zone management techniques, including extended advance warning areas and motorcycle-specific messaging, which demonstrated protective effects in the analysis. *(5) Targeted Speed Management*: Develop context-sensitive speed management approaches that address the counterintuitive relationship between speeding and crash severity in rural areas, focusing on locations where other risk factors are present.

Rural Nighttime Setting: *(1) Lighting Improvements*: Prioritize strategic lighting installations at high-risk rural locations such as intersections, curves, and transition zones, given the strong association between dark conditions without lighting and severe crashes. *(2) Traffic Control Enhancement*: Improve visibility and conspicuity of traffic control devices through retroreflective materials, LED-enhanced signs, and consistent maintenance practices to address the increased risk associated with traffic sign violations. *(3) Lane Configuration Safety*: Implement enhanced delineation on four-lane rural roadways, including reflective pavement markings, post-mounted delineators, and roadside reflectors to improve nighttime visibility. *(4) Large Vehicle*

Safety Systems: Encourage adoption of motorcycle detection technologies for commercial vehicles operating in rural areas during nighttime hours. *(5) Public Awareness Campaigns*: Develop targeted educational campaigns addressing the specific risks of rural nighttime motorcycle riding, emphasizing reduced visibility, potential roadway hazards, and safe interaction with large vehicles.

The implementation of these tailored recommendations across the various environmental contexts could significantly enhance motorcycle safety by addressing the specific risk factors identified through SHAP analysis. This context-sensitive approach represents a shift from traditional one-size-fits-all safety strategies toward more targeted, effective interventions that recognize the complex interplay between environmental conditions and crash outcomes.

3.9 Limitations and Future Research Directions

This study has several limitations that should be acknowledged. First, reliance on reported crash data may underrepresent minor crashes and introduce reporting biases. Second, the study period (2020–2022) coincided with COVID-19 restrictions, potentially affecting traffic patterns and limiting generalizability. Future research should incorporate additional data sources, such as hospital records and telematics, to improve crash reporting accuracy. Extending the study period beyond COVID-19 would help assess whether the observed trends persist under normal traffic conditions.

In addition, this study focused on Random Forest due to its interpretability and robustness; however, other machine learning techniques such as neural networks, gradient boosting, or ensemble hybrid models may offer improved predictive power and warrant future investigation. Moreover, expanding the predictor set to include rider demographics, behavioral data, and real-time traffic or weather conditions could enhance model performance and insight.

Lastly, while the overall dataset includes 12,266 motorcycle crashes—sufficient for binary classification modeling (Pavlou et al., 2024)— the disaggregated subgroups (urban daytime: n = 2,731; urban nighttime: n = 1,869; rural daytime: n = 4,678; rural nighttime: n = 2,988) also meet accepted thresholds for training machine learning models. Although each subgroup contains a smaller proportion of severe/fatal cases, the sample sizes remain adequate for binary prediction tasks. However, this class imbalance may still affect classification sensitivity in certain scenarios. Future research could address this by aggregating additional years of data or integrating supplementary sources to improve the representation of less frequent outcomes and enhance model robustness.

3.10 References

Agheli, A., & Aghabayk, K. (2025). How does distraction affect cyclists' severe crashes? A hybrid CatBoost-SHAP and random parameters binary logit approach. *Accident Analysis & Prevention, 211*, 107896. doi:https://doi.org/10.1016/j.aap.2024.107896

Agyemang, W., Adanu, E. K., & Jones, S. (2021a). Understanding the factors that are associated with motorcycle crash severity in rural and urban areas of Ghana. *Journal of advanced transportation, 2021*(1), 6336517. doi:https://doi.org/10.1155/2021/6336517

Agyemang, W., Adanu, E. K., & Jones, S. (2021b). Understanding the factors that are associated with motorcycle crash severity in rural and urban areas of Ghana. *Journal of advanced transportation, 2021*, 1-11. doi:https://doi.org/10.1155/2021/6336517

Ali, Y., Hussain, F., & Haque, M. M. (2024). Advances, challenges, and future research needs in machine learning-based crash prediction models: A systematic review. *Accident Analysis & Prevention, 194*, 107378. doi:https://doi.org/10.1016/j.aap.2023.107378

AlMamlook, R. E., Kwayu, K. M., Alkasisbeh, M. R., & Frefer, A. A. (2019). *Comparison of machine learning algorithms for predicting traffic accident severity.* Paper presented at the 2019 IEEE Jordan international joint conference on electrical engineering and information technology (JEEIT).

Alnawmasi, N., & Mannering, F. (2023). An analysis of day and night bicyclist injury severities in vehicle/bicycle crashes: a comparison of unconstrained and partially constrained temporal modeling approaches. *Analytic methods in accident research, 40*, 100301. doi:https://doi.org/10.1016/j.amar.2023.100301

Anarkooli, A. J., & Hosseinlou, M. H. (2016). Analysis of the injury severity of crashes by considering different lighting conditions on two-lane rural roads. *Journal of safety research, 56*, 57-65. doi:https://doi.org/10.1016/j.jsr.2015.12.003

Breiman, L. (2001). Random forests. *Machine learning, 45*, 5-32.

Chakraborty, M., Gates, T. J., & Sinha, S. (2023). Causal analysis and classification of traffic crash injury severity using machine learning algorithms. *Data science for transportation, 5*(2), 12. doi:https://doi.org/10.1007/s42421-023-00076-9

Champahom, T., Jomnonkwao, S., Watthanaklang, D., Karoonsoontawong, A., Chatpattananan, V., & Ratanavaraha, V. (2020). Applying hierarchical logistic models to compare urban and rural roadway modeling of severity of rear-end vehicular crashes. *Accident Analysis & Prevention, 141*, 105537. doi:https://doi.org/10.1016/j.aap.2020.105537

Champahom, T., Se, C., Aryuyo, F., Banyong, C., Jomnonkwao, S., & Ratanavaraha, V. (2023). Crash Severity Analysis of Young Adult Motorcyclists: A Comparison of Urban and Rural Local Roadways. *Applied Sciences, 13*(21), 11723. doi:https://doi.org/10.3390/app132111723

Champahom, T., Wisutwattanasak, P., Chanpariyavatevong, K., Laddawan, N., Jomnonkwao, S., & Ratanavaraha, V. (2022). Factors affecting severity of motorcycle accidents on Thailand's arterial roads: multiple correspondence analysis and ordered logistics regression approaches. *IATSS research, 46*(1), 101-111. doi:https://doi.org/10.1016/j.iatssr.2021.10.006

Chan, J. Y.-L., Leow, S. M. H., Bea, K. T., Cheng, W. K., Phoong, S. W., Hong, Z.-W., & Chen, Y.-L. (2022). Mitigating the multicollinearity problem and its machine learning approach: a review. *Mathematics, 10*(8), 1283. doi:https://doi.org/10.3390/math10081283s

Chang, F., Li, M., Xu, P., Zhou, H., Haque, M. M., & Huang, H. (2016). Injury severity of motorcycle riders involved in traffic crashes in Hunan, China: a mixed ordered logit approach. *International journal of environmental research and public health, 13*(7), 714. doi:https://doi.org/10.3390/ijerph13070714

Chang, F., Yasmin, S., Huang, H., Chan, A. H., & Haque, M. M. (2021). Injury severity analysis of motorcycle crashes: A comparison of latent class clustering and latent segmentation based models with unobserved heterogeneity. *Analytic methods in accident research, 32*, 100188. doi:https://doi.org/10.1016/j.amar.2021.100188

Chen, M.-M., & Chen, M.-C. (2020). Modeling road accident severity with comparisons of logistic regression, decision tree and random forest. *Information, 11*(5), 270. doi:https://doi.org/10.3390/info11050270

Chen, P.-L., & Pai, C.-W. (2019). Evaluation of injuries sustained by motorcyclists in approach-turn crashes in Taiwan. *Accident Analysis & Prevention, 124*, 33-39. doi:https://doi.org/10.1016/j.aap.2018.12.015

Ding, J., Dai, Q., Fan, W., Lu, M., Zhang, Y., Han, S., & Feng, Y. (2023). Impacts of meteorology and precursor emission change on O3 variation in Tianjin, China from 2015 to 2021. *Journal of Environmental Sciences, 126*, 506-516. doi:https://doi.org/10.1016/j.jes.2022.03.010

Doubleday, K., Zhou, J., Zhou, H., & Fu, H. (2022). Risk controlled decision trees and random forests for precision medicine. *Statistics in medicine, 41*(4), 719-735. doi:https://doi.org/10.1002/sim.9253

Elalouf, A., Birfir, S., & Rosenbloom, T. (2023). Developing machine-learning-based models to diminish the severity of injuries sustained by pedestrians in road traffic incidents. *Heliyon, 9*(11). doi:https://doi.org/10.1016/j.heliyon.2023.e21371

Geedipally, S. R., Turner, P. A., & Patil, S. (2011). Analysis of motorcycle crashes in Texas with multinomial logit model. *Transportation research record, 2265*(1), 62-69. doi:https://doi.org/10.3141/2265-07

Gregorutti, B., Michel, B., & Saint-Pierre, P. (2017). Correlation and variable importance in random forests. *Statistics and Computing, 27*, 659-678. doi:https://10.1007/s11222-016-9646-1

Hariharan, R. (2021). Random forest regression analysis on combined role of meteorological indicators in disease dissemination in an Indian city: A case study of New Delhi. *Urban climate, 36*, 100780. doi:https://doi.org/10.1016/j.uclim.2021.100780

Huang, H., Chin, H. C., & Haque, M. M. (2008). Severity of driver injury and vehicle damage in traffic crashes at intersections: a Bayesian hierarchical analysis. *Accident Analysis & Prevention, 40*(1), 45-54. doi:https://doi.org/10.1016/j.aap.2007.04.002

Iranitalab, A., & Khattak, A. (2017). Comparison of four statistical and machine learning methods for crash severity prediction. *Accident Analysis & Prevention, 108*, 27-36. doi:https://doi.org/10.1016/j.aap.2017.08.008

Islam, M. (2021). The effect of motorcyclists' age on injury severities in single-motorcycle crashes with unobserved heterogeneity. *Journal of safety research, 77*, 125-138. doi:https://doi.org/10.1016/j.jsr.2021.02.010

Islam, M. (2022). An analysis of motorcyclists' injury severities in work-zone crashes with unobserved heterogeneity. *IATSS research, 46*(2), 281-289. doi:https://doi.org/10.1016/j.iatssr.2022.01.003

Islam, S., & Brown, J. (2017). A comparative injury severity analysis of motorcycle at-fault crashes on rural and urban roadways in Alabama. *Accident Analysis & Prevention, 108*, 163-171. doi:https://doi.org/10.1016/j.aap.2017.08.016

Iwendi, C., Bashir, A. K., Peshkar, A., Sujatha, R., Chatterjee, J. M., Pasupuleti, S., . . . Jo, O. (2020). COVID-19 patient health prediction using boosted random forest algorithm. *Frontiers in public health, 8*, 357. doi:https://doi.org/10.3389/fpubh.2020.00357

Kanitpong, K., Jensupakarn, A., Dabsomsri, P., & Issalakul, K. (2024). Characteristics of motorcycle crashes in Thailand and factors affecting crash severity: Evidence from in-depth crash investigation. *Transportation Engineering, 16*, 100227. doi:https://doi.org/10.1016/j.treng.2024.100227

Koley, S., Mondal, S., & Ghosal, P. (2022). *Smart Prediction of Severity in Vehicular Crashes: A Machine Learning Approach.* Paper presented at the 2022 5th International Conference on Computational Intelligence and Networks (CINE).

Laphrom, W., Se, C., Champahom, T., Jomnonkwao, S., Wipulanusatd, W., Satiennam, T., & Ratanavaraha, V. (2024). XGBoost-SHAP and unobserved heterogeneity modelling of temporal multivehicle truck-involved crash severity patterns.

Civil Engineering Journal, 10(6), 1890-1908. doi:http://dx.doi.org/10.28991/CEJ-2024-010-06-011

Li, J., Fang, S., Guo, J., Fu, T., & Qiu, M. (2021). A Motorcyclist-Injury Severity Analysis: A Comparison of Single-, Two-, and Multi-Vehicle Crashes Using Latent Class Ordered Probit Model. *Accid Anal Prev, 151*, 105953. doi:https://doi.org/10.1016/j.aap.2020.105953

Liu, R., Pang, L., Yang, Y., Gao, Y., Gao, B., Liu, F., & Wang, L. (2023). Air Quality—Meteorology Correlation Modeling Using Random Forest and Neural Network. *Sustainability, 15*(5), 4531. doi:https://doi.org/10.3390/su15054531

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems, 30*. doi:https://doi.org/10.48550/arXiv.1705.07874

Mohamad, I., Jomnonkwao, S., & Ratanavaraha, V. (2022). Using a decision tree to compare rural versus highway motorcycle fatalities in Thailand. *Case studies on transport policy, 10*(4), 2165-2174. doi:https://doi.org/10.1016/j.cstp.2022.09.016

Moskal, A., Martin, J.-L., Lenguerrand, E., & Laumon, B. (2007). *Injuries among motorised two-wheelers in relation to vehicle and crash characteristics in Rhone, France.* Paper presented at the Enhanced Safety Vehicle Conference, Lyon.

Pavlou, M., Ambler, G., Qu, C., Seaman, S. R., White, I. R., & Omar, R. Z. (2024). An evaluation of sample size requirements for developing risk prediction models with binary outcomes. *BMC Medical Research Methodology, 24*(1), 146. doi:https://doi.org/10.1186/s12874-024-02268-5

Prentkovskis, O., Sokolovskij, E., & Bartulis, V. (2010). Investigating traffic accidents: a collision of two motor vehicles. *Transport, 25*(2), 105-115. doi:https://doi.org/10.3846/transport.2010.14

Rezapour, M., Farid, A., Nazneen, S., & Ksaibati, K. (2021). Using machine leaning techniques for evaluation of motorcycle injury severity. *IATSS research, 45*(3), 277-285. doi:https://doi.org/10.1016/j.iatssr.2020.07.004

Robbins, C., & Fotios, S. (2020). Motorcycle safety after-dark: the factors associated with greater risk of road-traffic collisions. *Accident Analysis & Prevention, 146*, 105731. doi:https://doi.org/10.1016/j.aap.2020.105731

Sadeghi, M., Aghabayk, K., & Quddus, M. (2024). A hybrid Machine learning and statistical modeling approach for analyzing the crash severity of mobility scooter users considering temporal instability. *Accident Analysis & Prevention, 206*, 107696. doi:https://doi.org/10.1016/j.aap.2024.107696

Santos, K., Dias, J. P., & Amado, C. (2022). A literature review of machine learning algorithms for crash injury severity prediction. *Journal of safety research, 80*, 254-269. doi:https://doi.org/10.1016/j.jsr.2021.12.007

Savolainen, P., & Mannering, F. (2007). Probabilistic models of motorcyclists' injury severities in single-and multi-vehicle crashes. *Accident Analysis & Prevention, 39*(5), 955-963. doi:https://doi.org/10.1016/j.aap.2006.12.016

Scarano, A., Riccardi, M. R., Mauriello, F., D'Agostino, C., Pasquino, N., & Montella, A. (2023). Injury severity prediction of cyclist crashes using random forests and random parameters logit models. *Accident Analysis & Prevention, 192*, 107275. doi:https://doi.org/10.1016/j.aap.2023.107275

Schonlau, M., & Zou, R. Y. (2020). The random forest algorithm for statistical learning. *The Stata Journal, 20*(1), 3-29. doi:https://doi.org/10.1177/1536867X20909688

Se, C., Champahom, T., Jomnonkwao, S., Chaimuang, P., & Ratanavaraha, V. (2021). Empirical comparison of the effects of urban and rural crashes on motorcyclist injury severities: A correlated random parameters ordered probit approach with heterogeneity in means. *Accident Analysis & Prevention, 161*, 106352. doi:https://doi.org/10.1016/j.aap.2021.106352

Se, C., Champahom, T., Jomnonkwao, S., Wisutwattanasak, P., Laphrom, W., & Ratanavaraha, V. (2023). Temporal Instability and Transferability Analysis of Daytime and Nighttime Motorcyclist-Injury Severities Considering Unobserved Heterogeneity of Data. *Sustainability, 15*(5), 4486. doi:https://doi.org/10.3390/su15054486

Shaheed, M. S., & Gkritza, K. (2014). A latent class analysis of single-vehicle motorcycle crash severity outcomes. *Analytic methods in accident research, 2*, 30-38. doi:https://doi.org/10.1016/j.amar.2014.03.002

Shaheed, M. S. B., Zhang, W., Gkritza, K., & Hans, Z. (2011). *Differences in motorcycle conspicuity-related factors and motorcycle crash severities in daylight and dark conditions.* Paper presented at the 3rd International Conference on Road Safety and Simulation. Indianapolis.

Štrumbelj, E., & Kononenko, I. (2014). Explaining prediction models and individual predictions with feature contributions. *Knowledge and information systems, 41*, 647-665. doi:https://doi.org/10.1007/s10115-013-0679-x

Tahfim, S. A.-S., & Yan, C. (2021). Analysis of severe injuries in crashes involving large trucks using K-prototypes clustering-based GBDT model. *Safety, 7*(2), 32. doi:https://doi.org/10.3390/safety7020032

Transport, M. o. (2024). *Road Accident Report 2024*. Retrieved from https://www.mot.go.th/

Vajari, M. A., Aghabayk, K., Sadeghian, M., & Shiwakoti, N. (2020). A multinomial logit model of motorcycle crash severity at Australian intersections. *Journal of safety research, 73*, 17-24. doi:https://doi.org/10.1016/j.jsr.2020.02.008

WHO. (2023). Retrieved from Road traffic injuries [Online]. Available: https://www.who.int/news-room/ fact-sheets/detail/road-traffic-injuries [Accessed 13 December 2023]

Wisutwattanasak, P., Se, C., Champahom, T., Kasemsri, R., Jomnonkwao, S., & Ratanavaraha, V. (2024). Factors Affecting Single and Multivehicle Motorcycle Crashes: Insights from Day and Night Analysis Using XGBoost-SHAP Algorithm. *Big Data and Cognitive Computing, 8*(10), 128. doi:https://doi.org/10.3390/bdcc8100128

Xu, C., Wang, J., Zheng, T., Cao, Y., & Ye, F. (2021). Prediction of prognosis and survival of patients with gastric cancer by a weighted improved random forest model: an application of machine learning in medicine. *Archives of Medical Science: AMS, 18*(5), 1208. doi:https://doi.org/10.5114/aoms/135594

Yan, M., & Shen, Y. (2022). Traffic accident severity prediction based on random forest. *Sustainability, 14*(3), 1729. doi:https://doi.org/10.3390/su14031729

Yang, J., Han, S., & Chen, Y. (2023). Prediction of Traffic Accident Severity Based on Random Forest. *Journal of advanced transportation, 2023*. doi:https://doi.org/10.1155/2023/7641472

Zhang, J., Li, Z., Pu, Z., & Xu, C. (2018). Comparing prediction performance for crash injury severity among various machine learning and statistical methods. *IEEE Access, 6*, 60079-60087. doi:https://doi.org/10.1109/ACCESS.2018.2874979

Zhang, K., & Hassan, M. (2019). Crash severity analysis of nighttime and daytime highway work zone crashes. *PloS one, 14*(8), e0221128. doi:https://doi.org/10.1371/journal.pone.0221128

Zhang, Z., Nie, Q., Liu, J., Hainen, A., Islam, N., & Yang, C. (2024). Machine learning based real-time prediction of freeway crash risk using crowdsourced probe vehicle data. *Journal of Intelligent Transportation Systems, 28*(1), 84-102. doi:https://doi.org/10.1080/15472450.2022.2106564

CHAPTER IV

PREDICTING MOTORCYCLE CRASH SEVERITY ON THAILAND'S CURVED ROADWAYS: A DEEP LEARNING APPROACH

4.1 Abstract

Motorcycle crashes on curved roadways present unique safety challenges due to complex vehicle dynamics and increased risk exposure. In Thailand, where motorcycles dominate transport, crash data from 2016–2022 reveals a significantly higher fatal/severe injury rate on curved segments (56.77%) compared to straight segments (44.41%), despite curves comprising a smaller portion of the road network. This study develops Convolutional Neural Network (CNN) models to predict binary crash severity outcomes on curved roadways using 2,679 crash records from Thailand's Highway Accident Information Management System. The research systematically compared four CNN architectures with varying complexity (depths 3 to 10+) and found that simpler architectures (Layout I with depth 3) outperform deeper configurations (accuracy = 0.634, summary score = 53.61%). SHapley Additive exPlanations (SHAP) were applied to identify key risk factors and interaction effects. Results show that large trucks, head-on collisions, depressed medians, darkness conditions, speeding, two-lane roads and work zones are associated with higher predicted crash severity on curves, while urban settings, side-swipe crashes, and barrier medians are associated with lower predicted severity. SHAP interaction analysis identified combinations associated with elevated severity predictions, notably large trucks operating in darkness and head-on collisions regardless of median type. These findings support targeted interventions including differential speed management for large vehicles, enhanced illumination strategies, barrier median installations, and modified work zone protocols for curved segments. This research advances both methodological approaches for crash severity prediction and practical applications for motorcycle safety in countries with similar transportation contexts.

4.2 Introduction

Motorcycle crashes represent a significant public health concern worldwide, with particularly severe outcomes in Southeast Asian countries like Thailand where motorcycles constitute a predominant mode of transportation (WHO, 2023). The vulnerability of motorcyclists, combined with the challenging dynamics of navigating curved roadways, creates a unique risk profile that warrants specialized analytical approaches (Kvasnes, Pokorny, Jensen, & Pitera, 2021; Lemonakis, Eliou, & Karakasidis, 2021; Xin, Wang, Lee, & Lin, 2017). Despite substantial research on crash severity across various roadway geometries, the specific interaction between motorcycle operation and curved roadway segments remains inadequately explored, particularly in emerging economies with high motorcycle usage rates.

As illustrated in Figure 4.1, Thailand presents a compelling case study for such research. Analysis of motorcycle crash data from 2016 to 2022, sourced from the Thailand Highway Accident Information Management System (HAIMS), shows a substantially higher fatal/severe injury rate on curved roadways (56.77%) compared to straight segments (44.41%). This represents 1,521 fatal/severe injuries out of 2,679 curved roadway crashes versus 11,120 fatal/severe injuries among 25,039 crashes on straight segments—a nearly 28% higher fatal/severe injury rate on curves despite their smaller proportion of the overall road network. This disparity underscores the urgent need for specialized safety interventions focused specifically on curved roadway dynamics (Kronprasert, Boontan, & Kanha, 2021). Despite significant policy interventions, the country continues to face substantial challenges in reducing motorcycle-related injuries and fatalities. This persistent safety concern necessitates more sophisticated analytical approaches that can capture the complex, non-linear relationships between crash outcomes and contributing factors, particularly for the high-risk curved roadway environment.

Recent advances in computational methods, particularly deep learning techniques, offer promising new pathways for understanding and predicting crash severity. Convolutional Neural Networks (CNNs), while traditionally applied to image processing tasks, have demonstrated considerable potential for identifying complex patterns in structured data like traffic crash records. Their hierarchical feature extraction capabilities make them particularly well-suited for capturing the intricate interactions between roadway geometry, environmental conditions, human factors, and vehicle characteristics that collectively influence crash outcomes (Sunkpho, Se, Wipulanusat, & Ratanavaraha, 2025).

This research addresses critical gaps in the existing literature by developing CNN-based predictive models specifically tailored to motorcycle crashes on curved roadways in Thailand. Unlike previous studies that have predominantly focused on crash prediction (Lemonakis et al., 2021; Xin et al., 2017)/geometric design (Gabauer & Li, 2015; Kvasnes et al., 2021; Xin et al., 2019) or employed conventional statistical methods, this work employs advanced deep learning architectures to predict crash severity outcomes. Furthermore, the study integrates SHapley Additive exPlanations (SHAP) to enhance model interpretability, directly addressing one of the primary limitations of deep learning approaches – their "black box" nature.

By comparing predictive performance and underlying factors between curved and straight roadway segments, this research aims to identify the unique risk profiles associated with different roadway geometries and develop targeted safety interventions. The findings have particular relevance for Thailand and similar Southeast Asian contexts but offer broader methodological contributions to transportation safety analysis.

The primary objectives of this study are to: (1) develop and validate CNN models of varying complexity for predicting motorcycle crash severity on curved roadways; (2) identify the key factors contributing to severe crash outcomes through SHAP analysis; (3) compare factor importance between curved and straight roadway segments; and (4) propose geometry-specific safety interventions based on these findings. Through these objectives, the research seeks to challenge conventional assumptions about model complexity in transportation safety modeling while advancing both methodological approaches and practical applications for enhancing motorcycle safety on diverse roadway configurations.

The remainder of this manuscript is organized as follows: Section 4.3 provides a comprehensive review of relevant literature, highlighting methodological developments and knowledge gaps. Section 4.4 describes the data sources and preprocessing procedures. Section 4.5 details the CNN architecture and analytical framework. Section 4.6 presents the model results and interpretation through SHAP analysis, including policy implications derived from these findings. Finally, Section 4.7 summarizes key findings, and suggests directions for future research.

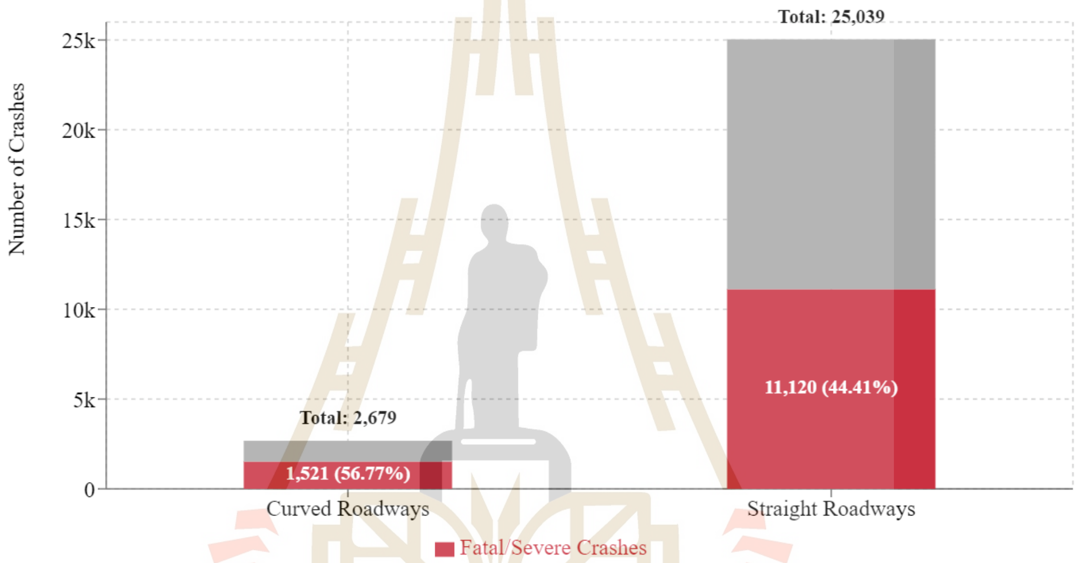

Figure 4.1 Thailand motorcycle crash severity by roadway type (2016-2022) (Data source: Thailand Highway Accident Information Management System 2016-2022)

4.3 Literature Reviews

This section synthesizes existing research on motorcycle crash severity on curved roadways through three complementary lenses: empirical findings across geographical contexts, methodological evolution, and critical research gaps.

4.3.1 Empirical studies on curved roadway crashes

Research on curved roadway crashes has identified critical factors influencing crash occurrence and severity across diverse contexts.

In the United States, several influential studies have examined curved roadway crashes. These studies collectively demonstrate that crash risk on curves is influenced by multiple interrelated factors. Gabauer and Li (2015) identified curve radius, length, traffic volume, and adjacent curve location as key factors in Washington. Florida-based research by Xin et al. (2017); Xin et al. (2019) and Zhu, Lu, Zhang, Zhao, and Song (2019) highlighted the importance of curve characteristics, rider demographics, environmental conditions, and roadside features. Q. Ma, Yang, Wang, Xie, and Yang (2020) confirmed the significance of AADT, curve geometry, and speed limits nationally, while Wang, Li, and Shan (2021) emphasized pavement friction in Indiana. Al-Bdairi and Behnood (2021) found collision types and driver characteristics critical in Oregon, while Islam, Hosseini, and Jalayer (2022) identified speed limits, weather conditions, and vehicle factors in North Carolina. Research from outside the US provides valuable comparative perspectives that highlight both universal risk factors and region-specific challenges. Lemonakis et al. (2021) highlighted speed behavior on curved Greek roads, while Kvasnes et al. (2021) identified horizontal alignment features in Norway. Notably, Kronprasert et al. (2021) conducted the only identified Thai study, finding lane width, curve length, and curve types as primary factors affecting crash risk on rural roads. H. Wen, Ma, Chen, and Luo (2023) examined truck crashes on Chinese mountainous freeways, while Safari, Effati, and Arabani (2024) studied crash severity factors in Northern Iran. Recent studies from 2024 have expanded understanding of crash countermeasures (Ahmed, Mahmud, & Gayah, 2024), urban curve risks (Bejleri, Xu, Silva, & Srinivasan, 2024), driver-specific risk patterns (Hossain, Sun, Islam, Rahman, & Das, 2024), and the interaction of geometric and environmental factors (Safari et al., 2024).

Collectively, these studies demonstrate that crash outcomes on curved roadways result from complex interactions between roadway geometry, human factors, environmental conditions, and vehicle characteristics across diverse geographical contexts.

4.3.2 Methodological approaches in curved roadway crash analysis

The analytical methods used to assess curved roadway crashes have evolved from traditional statistical techniques toward more sophisticated machine learning approaches.

Early studies employed negative binomial regression (Gabauer & Li, 2015), mixed-effects logistic models (Xin et al., 2017), and case-control methodologies (Kvasnes et al., 2021; Xin et al., 2019). The field progressively advanced with zero-inflated negative binomial models (Q. Ma et al., 2020), Bayesian network analysis (Zhu et al., 2019), geographically weighted regression (Wang et al., 2021), and Safety Performance Functions (Kronprasert et al., 2021).

Recent research has increasingly utilized machine learning techniques to capture complex non-linear relationships in crash data. Manzoor et al. (2021) developed a hybrid Random Forest and Convolutional Neural Network model that demonstrated improved capability for pattern recognition in accident severity prediction. Safari et al. (2024) effectively combined spatial clustering with random forest and logistic regression to enhance predictive performance while maintaining interpretability.

Building on this methodological trajectory, CNNs represent a promising approach for analyzing the relationships affecting motorcycle crashes on curved roadways. Recently, Shaik, Islam, and Hossain (2021) found CNNs superior to traditional methods, while Rahim and Hassan (2021) converted numerical crash data to image representations for improved classification accuracy. Similarly, Yu, Li, Zhang, Liu, and Ma (2021) developed a Fusion CNN model that integrated sub-neural networks for categorical variables with multi-layer CNNs to analyze driver injury severity, uncovering hidden correlations and unobserved heterogeneity in the data. A comprehensive comparative analysis by Haghshenas, Guido, Vitale, and Astarita (2023) demonstrated CNNs (68.4% accuracy) outperformed ANNs (61.74%) in crash severity classification. Their sensitivity analysis further revealed that contextual factors had the highest impact on crash severity, reinforcing the importance of data-driven feature learning in CNN-based models. Meanwhile, Singh, Sharma, Rajput, and Kumar (2024) achieved 99.04% validation accuracy for real-time accident detection using CCTV footage. These studies collectively demonstrate CNNs' substantial advantages for crash severity prediction: automated feature learning, superior capture of non-linear relationships, improved generalization, and enhanced classification accuracy—providing a robust foundation for the current study's application of CNN-based modeling to Thailand's unique motorcycle safety challenges, where the complex nature of curved roadway crashes has remained largely unexplored through advanced computational approaches.

Despite CNNs' proven capabilities, their "black-box" nature remains a major challenge, necessitating interpretability techniques like SHAP. Ali, Hussain, and Haque (2024) recommended SHAP for interpreting machine learning-based crash prediction models, addressing limitations of other techniques in capturing feature interactions. SHAP has been widely applied in crash prediction research to explore feature importance and variable interactions (Akter, Susilawati, Zubair, & Chor, 2025; Ding et al., 2024; Hasan, Jalayer, Das, & Kabir, 2024; Kashifi, 2023; X. Ma, Huo, Lu, & Wong, 2025; X. Wen, Xie, Wu, & Jiang, 2021; Yang, Chen, & Yuan, 2021; Zahid et al., 2024).

The integration of CNNs with SHAP analysis represents a methodological advancement that balances predictive performance with interpretability—addressing a fundamental challenge in deep learning applications for transportation safety and enabling evidence-based policy interventions that specifically target high-risk factors on Thailand's curved roadways.

4.3.3 Research gaps and contributions

Despite extensive past research, significant gaps remain in the literature on motorcycle crash severity, particularly in relation to curved roadway environments. To situate these gaps within the broader methodological landscape, recent traffic safety studies have shown that analytical outcomes can vary considerably depending on the modeling framework employed. Cross-comparison studies of macro-level cyclist crashes highlight how different techniques yield distinct predictive performance (Guo, Osama, & Sayed, 2018). Research addressing underreporting in single-vehicle motorcycle crashes demonstrates that hybrid approaches using oversampling with random-parameters models improve severity estimation under data imbalance (Alnawmasi, Ziakopoulos, Theofilatos, & Ali, 2025). Similarly, studies examining bicyclists' red-light-running behavior underscore the need to model unobserved heterogeneity across facility types (Guo, Li, Wu, & Xu, 2018). These advances collectively emphasize the importance of flexible, data-driven approaches—supporting the methodological direction adopted in this study.

Against this broader methodological backdrop, three specific gaps emerge in curved-roadway motorcycle crash research. First, geographical imbalance exists with limited research from Southeast Asia—notably in Thailand, where only one study (Kronprasert et al., 2021) has examined crash factors on curved roadways, focusing exclusively on geometric design factors affecting crash frequency rather than crash severity. Second, while machine learning methods have been applied to traffic accident analysis in Thailand (Champahom et al., 2024; Laphrom et al., 2024; Mohamad, Jomnonkwao, & Ratanavaraha, 2022; Sunkpho et al., 2025), their use in predicting motorcycle crash severity specifically on curved roadways remains unexplored. Third, comparative analyses of factor importance between curved and straight roadways for motorcycle crashes are lacking, knowledge that is essential for developing targeted safety interventions.

This research addresses these gaps through four key contributions: (1) expanding geographical diversity in crash research by focusing on Thailand's unique context; (2) methodological innovation through the development of specialized CNN models specifically tailored for motorcycle crash severity prediction on curved roadways; (3) enhanced interpretability via SHAP analysis to demystify the "black-box" nature of deep learning predictions; and (4) comparing factor importance between curved and straight segments.

4.4 Data Description

This research utilized motorcycle crash data sourced from the Thailand Highway Accident Information Management System (HAIMS), specifically targeting the development and validation of a CNN model for injury severity prediction. The dataset encompasses a comprehensive seven-year period from 2016 to 2022, representing an extensive temporal analysis of motorcycle crash incidents.

Data preprocessing involved rigorous elimination of incomplete records and categorization into four interconnected domains: (1) geographical location attributes (urban setting); (2) roadway characteristics (work zone, number of lanes, surface type, surface type, median types, intersection type); (3) environmental characteristics (illumination conditions, weather conditions); and (4) crash characteristics (crash causation, crash typology, vehicle classifications). In this study, the term “large truck” refers specifically to heavy trucks with 6 wheels, 10 wheels, or more than 10 wheels, following the HAIMS vehicle classification. Smaller commercial vehicles such as pickups or vans are not included in this category.

The primary dataset focuses on 2,679 motorcycle crashes occurring on curved roadways, characterized by 37 independent variables. The injury severity distribution revealed 1,521 severe/fatal incidents (56.77%) and 1,158 minor/property damage only (PDO) incidents (43.23%). As a comparative benchmark, an additional 25,039 crash records from straight roadways were incorporated. Table 4.1 provides a detailed statistical overview of the variables, presenting a comprehensive analysis of motorcycle crashes occurring on curved roadways.

Ethical approval. This research proceeded with ethical authorization (Approval Code: COE No.1/2568) from the Human Research Ethics Office, Suranaree University of Technology, Thailand.

Table 4.1 Descriptive statistics of explanatory variables for motorcycle crashes on curved roadways

Variables (Description)	Count	%
Injury Severity		
Severe/Fatal	1,521	56.77%
Minor/PDO	1,158	43.23%
Location attributes		
URBAN (1 if crash occur in urban area; 0 otherwise)	522	19.48%
Roadway characteristics		
WORK ZONE (1 if crash in work zone area; 0 otherwise)	59	2.20%
LANE = 2 (1 if crash on 2-lanes road; 0 otherwise)	1,472	54.95%
LANE = 4 (1 if crash on 4-lanes road; 0 otherwise)	948	35.39%
LANE = 6 (1 if crash on 6-lanes road; 0 otherwise)	125	4.67%
LANE >=8 (1 if crash on 8-lanes road or wider lanes; 0 otherwise)	90	3.36%
ASPHALT (1 if crash on asphalt road surface; 0 otherwise)	2,456	91.68%
NO MEDIAN (1 if crash on road without median; 0 otherwise)	1,559	58.19%
FLUSH AND PAINTED MEDIAN (1 if crash on road with flush and painted median; 0 otherwise)	252	9.41%
RAISED MEDIAN (1 if crash on road with raised median; 0 otherwise)	428	15.98%
DEPRESSED MEDIAN (1 if crash on road with depressed median; 0 otherwise)	291	10.86%
BARRIER MEDIAN (1 if crash on road with barrier median; 0 otherwise)	143	5.34%

Table 4.1 Descriptive statistics of explanatory variables for motorcycle crashes on curved roadways (Continued)

Variables (Description)	Count	%
ON SLOPE (1 if crash on slope; 0 otherwise)	152	5.67%
T_INT (1 if crash at T-intersection; 0 otherwise)	133	4.96%
CONNECT_PUBLIC AREA (1 if crash on road connected to public area; 0 otherwise)	72	2.69%
Environmental characteristics		
DAYTIME (1 if crash during daytime; 0 otherwise)	1,655	61.78%
DARKNESS (1 if crash during nighttime without electrical light; 0 otherwise)	374	13.96%
DARK_WITH_ELEC (1 if crash during nighttime with electrical light; 0 otherwise)	650	24.26%
WET (1 if crash on wet road surface; 0 otherwise)	222	8.29%
RAINING (1 if crash during raining; 0 otherwise)	198	7.39%
Crash characteristics		
SPEEDING (1 if crash due to exceeding speed limit; 0 otherwise)	1,883	70.29%
FRONT-PATH INTERRUPTION (1 if crash due to obstruction in front; 0 otherwise)	402	15.01%
ILLEGAL PASSING (1 if crash due to passing illegally; 0 otherwise)	40	1.49%
VIOLATE THE TRAFFIC SIGNS (1 if crash due to violate the traffic signs; 0 otherwise)	48	1.79%
DRUNK (1 if alcohol use confirmed; 0 otherwise)	152	5.67%
SLEEPY (1 if rider is sleepy; 0 otherwise)	40	1.49%
HEAD-ON (1 if head-on crash occurs; 0 otherwise)	428	15.98%

Table 4.1 Descriptive statistics of explanatory variables for motorcycle crashes on curved roadways (Continued)

Variables (Description)	Count	%
REAR-END (1 if rear-end crash occurs; 0 otherwise)	520	19.41%
SIDE SWIPE (1 if side-swipe crash occurs; 0 otherwise)	393	14.67%
SINGLE CRASH (1 if single-vehicle crash occurs; 0 otherwise)	1,066	39.79%
HIT PARKED VEHICLE/OBSTRUCTION (1 if parked vehicle crash occurs; 0 otherwise)	76	2.84%
CAR (1 if car/cars involved; 0 otherwise)	446	16.65%
VAN (1 if van/vans involved; 0 otherwise)	46	1.72%
PICK UP CAR (1 if pick-up car/ pick-up cars involved; 0 otherwise)	375	14.00%
TRUCK 6 WHEELS (1 if truck/ trucks 6 wheels involved; 0 otherwise)	67	2.50%
TRUCK 10 WHEELS (1 if truck/ trucks 10 wheels involved; 0 otherwise)	69	2.58%
TRUCK MORE THAN 10 WHEELS (1 if truck/ trucks more than 10 wheels involved; 0 otherwise)	66	2.46%

4.5 Methodology

The methodology employs a comprehensive, multi-stage deep learning approach to predict motorcycle crash severity on curved roadways through advanced computational techniques.

4.5.1 Methodological workflow for motorcycle crash severity prediction

The research methodology follows a structured nine-stage workflow illustrated in Figure 4.2. After data collection and preprocessing, class imbalance was addressed using the Synthetic Minority Over-sampling Technique (SMOTE) to create synthetic examples of the minority class (Minor/PDO crashes). Four distinct CNN architectural variants were then developed and systematically evaluated: a baseline architecture (Layout I), a model incorporating dropout layers (Layout II), an architecture implementing L2-norm regularization (Layout III), and a combined approach (Layout IV). Model performance was assessed using multiple metrics, including accuracy, Prediction Accuracy Rate (PAR), False Positive Rate (FPR), and a comprehensive summary score. SHAP analysis was applied to provide interpretable insights into factors influencing crash severity, with findings translated into targeted safety recommendations.

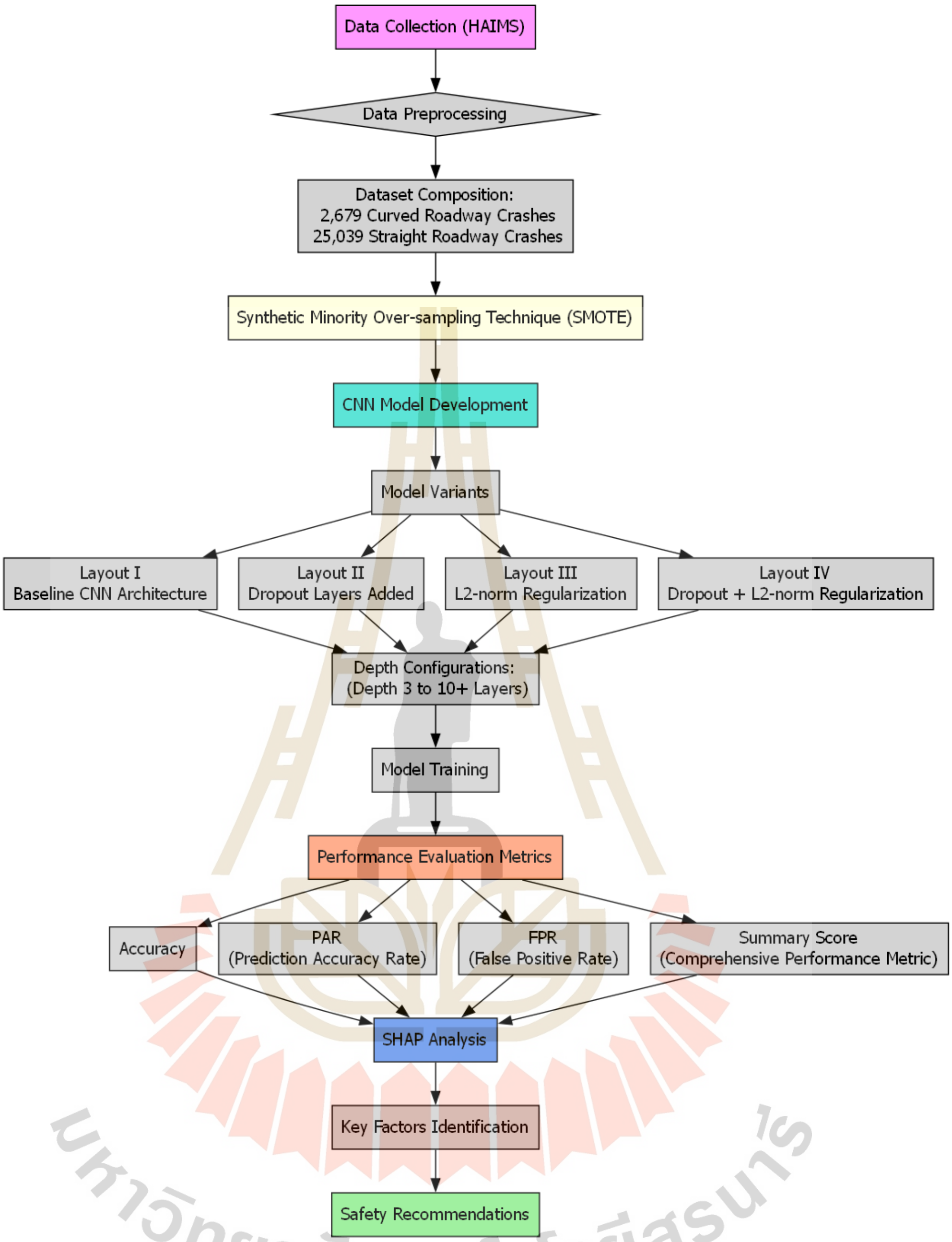

Figure 4.2 Methodological workflow for motorcycle crash severity prediction using CNN analysis

4.5.2 Convolutional Neural Network (CNN) model structure and design

The proposed framework leverages CNN's hierarchical feature extraction capabilities (Figure 4.3). The model processes input crash-related features through sequential layers of convolution and pooling operations that systematically extract meaningful patterns while reducing dimensionality.

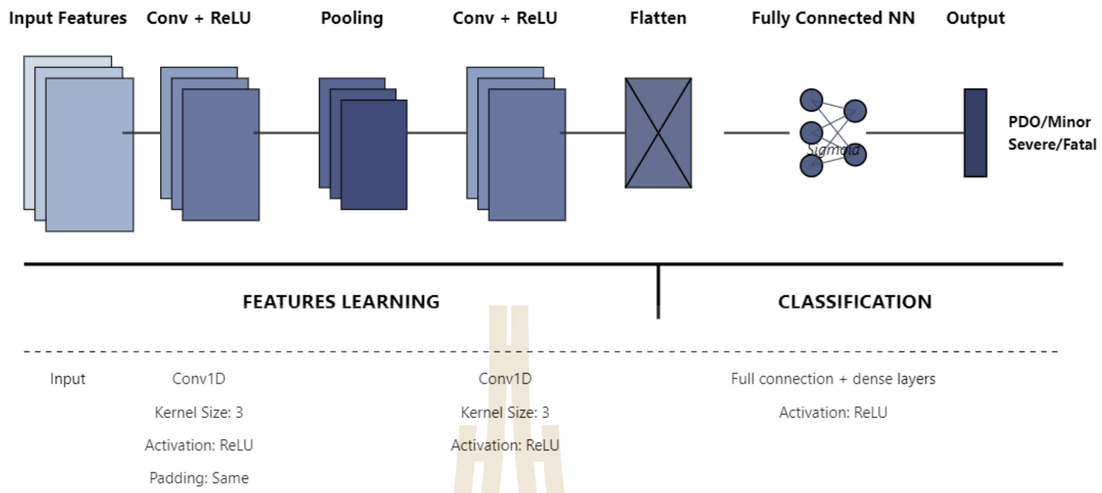

Figure 4.3 The structure of the CNN model

The model input features include multiple categories of variables coded as binary indicators (0 or 1): (1) geographical location attributes (urban setting); (2) roadway characteristics (work zone, number of lanes, surface type, median types, intersection type); (3) environmental characteristics (illumination conditions, weather conditions); and (4) crash characteristics (crash causation, crash typology, vehicle classifications).

All multi-categorical variables (e.g., number of lanes, median type, intersection type, surface type, illumination, crash type) were encoded using one-hot binary indicator encoding, where each category was converted into a separate 0/1 feature. This avoids imposing artificial ordering and enables the Conv1D filters to learn localized patterns across grouped inputs. After encoding, the final model input consisted of 37 binary features arranged as a one-dimensional vector with shape (37, 1), which served as the input to the convolutional layer.

The architecture begins with feature inputs transformed through specialized layers. Convolutional layers with Rectified Linear Unit (ReLU) activation functions identify local patterns through mathematical convolution operations. The ReLU activation function, defined as $f(x) = \max(0,x)$, introduces non-linearity by preserving positive values while zeroing negative inputs, facilitating efficient gradient propagation and enhancing pattern-learning capacity (Assi, 2020).

Following convolution, pooling operations reduce spatial dimensions while preserving essential information. The multi-dimensional feature maps are transformed into a one-dimensional vector through flattening, then processed by fully connected (dense) layers that integrate information, culminating in a final output layer with sigmoid activation that produces binary classification probabilities for crash severity outcomes.

A 1D Convolutional Neural Network was selected because it can capture localized interactions among the structured input features used in this study. The 37 crash-related variables form meaningful groups (e.g., roadway, environmental, and crash characteristics), and the convolutional filters in a 1D CNN are effective in learning these short-range dependencies while using fewer parameters than fully connected networks. This reduces overfitting risk for a moderate-sized dataset and has been shown in recent crash severity studies to improve the modeling of non-linear relationships.

4.5.2.1 Model Variants and Regularization Techniques

The investigation systematically evaluates four architectural variants with increasing complexity. The baseline architecture (Layout I) employs conventional convolutional and fully connected layers without additional regularization. Layout II incorporates dropout layers that randomly deactivate neurons during training. Layout III implements L2-norm regularization to constrain parameter magnitudes. Layout IV combines both dropout and L2-norm regularization techniques.

For each variant, architectures of varying depths (3 to 10+) are investigated as detailed in Table 4.2. These configurations progress from relatively simple structures (Conv1D ⇒ Flatten ⇒ Dense) to more complex arrangements incorporating additional convolutional, pooling, and dense layers.

Table 4.2 Depth structures for CNN architecture

Depth	Description	Structure
3	Standard CNN	Conv1D ⇒ Flatten ⇒ Dense
4	Adding Pooling	Conv1D ⇒ MaxPooling1D ⇒ Flatten ⇒ Dense
5	Adding Fully Connected Layers	Conv1D ⇒ MaxPooling1D ⇒ Flatten ⇒ Dense ⇒ Dense
6	Stacked Convolutions	Conv1D ⇒ MaxPooling1D ⇒ Conv1D ⇒ Flatten ⇒ Dense ⇒ Dense
10+	Deep Networks	Conv1D ⇒ Conv1D ⇒ MaxPooling1D ⇒ Conv1D ⇒ Conv1D ⇒ MaxPooling1D ⇒ Flatten ⇒ Dense ⇒ Dense ⇒ Dense

4.5.2.2 Objective Function

The model optimization process employs a custom objective function incorporating cross-entropy loss with regularization components, as detailed in (Yu et al., 2021):

$$\min -\sum_{i} y_i^* \log\left(y_i\right) + \lambda \|W\|_2^2 \tag{4.1}$$

Where y_i^* represents the actual crash severity classification, y_i denotes the model's predicted probability, W encompasses the network weight parameters, and λ controls the L2-norm regularization strength. This formulation establishes an equilibrium between classification accuracy and model complexity, promoting solutions that generalize effectively to previously unobserved data instances.

4.5.3 Model performance evaluation metrics

To assess the effectiveness of the CNN architectures, this study employs three complementary performance metrics: accuracy, prediction accuracy rate (PAR), and false positive rate (FPR) (Yu et al., 2021). These are calculated as:

$$\text{Accuracy} = \frac{\text{Number of correct classification}}{\text{Total number of cases}} \tag{4.2}$$

$$PAR_i = \frac{TP_i}{FN_i + TP_i} \tag{4.3}$$

$$FPR_i = \frac{FP_i}{FP_i + TN_i} \tag{4.4}$$

Models exhibiting heightened prediction accuracy rates (PAR) coupled with diminished false positive rates (FPR) demonstrate superior efficacy in the precise classification of injury severity categories. Consequently, a methodically constructed summary score (C) is derived for model layout j, quantified according to the following expression (Yu et al., 2021):

$$C^j = \sum_i PAR_i^j - FPR_i^j \tag{4.5}$$

where PAR_i^j and FPR_i^j represent the prediction accuracy rate and false positive rate coefficients, respectively, corresponding to the i^{th} motorcyclist injury severity classification within layout j.

Along with accuracy, PAR, and FPR, this study uses the composite C-score to compare CNN architectures. Originally introduced by Yu et al. (2021), the C-score balances correct detections and false positive penalties across severity classes, making it suitable for moderately imbalanced crash datasets. Unlike metrics such as the F1-score, which focus on precision–recall trade-offs for one class, the C-score provides a more holistic assessment of performance across both severity categories.

This makes it an appropriate and interpretable summary metric for evaluating the CNN models in this study.

4.5.4 Shapley-based interpretation of model

To navigate beyond the "black box" nature of CNN architectures, SHAP analysis was employed as suggested by Ali et al. (2024). The SHAP framework, introduced by Lundberg and Lee (2017), applies cooperative game theory principles to enhance interpretability of machine learning models. This approach quantifies feature importance by measuring how each input variable influences prediction outcomes (Štrumbelj & Kononenko, 2014). SHAP operates through a comparative mechanism: it evaluates prediction differences between a reference model containing all features and alternative models with specific features removed. This differential analysis reveals each feature's marginal contribution, quantified as its SHAP score (Tahfim & Yan, 2021), which is mathematically expressed as:

$$\varnothing_i = \sum_{S \subseteq X \setminus \{i\}} \frac{|S|!\left(|X|-|S|-1\right)!}{|X|!}\left[f_{S \cup \{i\}}\left(x_{S \cup \{i\}}\right) - f_S\left(x_S\right)\right] \tag{4.6}$$

Within this formulation, $\varnothing_i$ denotes the SHAP value, X represents the complete feature set, S signifies various feature combinations, and x_S corresponds to feature values within those combinations. The methodology evaluates the disparity between predictions generated by $f_{S \cup \{i\}}$ (model including the target feature) and f_S (model excluding it). Due to feature interaction effects, this evaluation process necessitates examining all potential feature subset permutations (Lundberg & Lee, 2017).

4.5.5 Model training and implementation details

In this study, the dataset was partitioned following a standard 80-20 ratio for training and testing. Python programming through Jupyter Lab provided the computational framework. SMOTE was implemented to balance the dataset before training. CNN architectural parameters were informed by empirical precedents (Yu et al., 2019; Yu et al., 2021), with systematic testing of six different filter quantity options (8, 16, 24, 32, 40, and 48) across each layout and depth configuration.

The Adam algorithm was utilized for model parameter estimation during the compilation phase, given its demonstrated effectiveness in training deep neural networks with sparse gradients (Kingma & Ba, 2014). A learning rate of 0.001 was applied following the commonly recommended default for the Adam (Kingma & Ba, 2014). Early stopping with a patience of 3 epochs was used to mitigate overfitting given the moderate dataset size (Prechelt, 2002). Random seeds were fixed at 42 across TensorFlow, NumPy, and SMOTE processes to ensure reproducibility (Pedregosa, 2011). No L2-regularization penalty (λ) was applied to the final selected architecture because the shallow CNN model did not exhibit validation overfitting, and L2 regularization is beneficial only when it reduces validation error (Goodfellow, Bengio, Courville, & Bengio, 2016).

4.6 Results and Discussion

4.6.1 Model performance comparison

The analytical results presented in Table 4.3 and 4.4 indicate that varying CNN depths yields differential predictive accuracy and injury severity classification outcomes for curved and straight roadway models, demonstrating that roadway geometry significantly influences the optimal architecture required for accurate crash severity prediction.

For curved roadway crashes (Table 4.3), Layout I with depth 3 exhibited superior performance, achieving the highest testing accuracy (0.634) and summary score (C = 53.61%). This configuration demonstrated balanced prediction capability with positive accuracy rates (PAR) of 61.69% for severe/fatal crashes and 65.12% for minor/PDO crashes. Deeper networks (10+ depth) consistently underperformed across all layouts, with testing accuracy declining to 0.529-0.586 and substantially lower C scores (10.36%-35.11%).

For straight roadway crashes (Table 4.4), Layout I with depth 5 achieved optimal performance with the highest testing accuracy (0.647) and summary score (C = 58.03%). This configuration exhibited strong capability in detecting severe/fatal crashes (PAR = 74.09%) while maintaining a reasonable false positive rate

(FPR = 54.92%). Similar to curved roadway crashes, deeper networks showed diminished performance, although the decline was less pronounced.

Across both roadway types, shallower CNN architectures outperformed deeper configurations. For curved roadways, the depth-3 layout achieved the highest accuracy, while for straight roadways the optimal performance was obtained with a depth-5 model. In contrast, networks with more than 10 layers consistently underperformed, reflecting overfitting due to limited crash data and the relatively low-dimensional, binary feature space. These results demonstrate that increasing architectural depth does not necessarily improve performance in moderate-sized crash datasets and highlight the importance of selecting model complexity proportional to data availability.

In summary, Layout I demonstrated the most robust performance across both roadway types, achieving the highest summary scores for both curved (C = 53.61%) and straight roadways (C = 58.03%). This suggests that Layout I's architecture effectively captures the underlying injury severity patterns regardless of roadway geometry. However, it required different optimal depths for each scenario (depth 3 for curved, depth 5 for straight roadways), indicating that straight roadway crashes may require more complex feature extraction to accurately predict severity outcomes. The result is supported by previous research (Yu et al., 2021), showing that increasing CNN layers with limited training data leads to premature training. Notably, dropout and regularization techniques successfully addressed overfitting as evidenced by reduced accuracy differentials between training and validation sets.

Table 4.3 Model fit comparison between different layouts and depths of CNN for curved roadway crashes

Layout	Depths	Accuracy		Performance by injury severity				Summary Score
		Training	Testing	Severe/Fatal		Minor/PDO		
				PAR	FPR	PAR	FPR	C
I	3	**0.600**	**0.634**	**61.69 %**	**34.88 %**	**65.12 %**	**38.31 %**	**53.61 %**
	4	0.587	0.622	52.92 %	28.24 %	71.76 %	47.08 %	49.37 %

Table 4.3 Model fit comparison between different layouts and depths of CNN for curved roadway crashes (Continued)

Layout	Depths	Accuracy		Performance by injury severity				Summary
		Training	Testing	Severe/Fatal		Minor/PDO		Score
				PAR	FPR	PAR	FPR	C
	5	0.585	0.621	61.69 %	37.54 %	62.46 %	38.31 %	48.29 %
	6	0.586	0.616	59.42 %	36.21 %	63.79 %	40.58 %	46.41 %
	10+	0.549	0.586	45.13 %	27.57 %	72.43 %	54.87 %	35.11 %
II	3	0.581	0.611	55.84 %	33.55 %	66.45 %	44.16 %	44.58 %
	4	0.582	0.606	53.25 %	31.89 %	68.11 %	46.75 %	42.71 %
	5	0.585	0.624	56.49 %	31.56 %	68.44 %	43.51 %	49.86 %
	6	0.570	0.606	66.56 %	45.51 %	54.49 %	33.44 %	42.09 %
	10+	0.550	0.565	67.53 %	54.82 %	45.18 %	32.47 %	25.43 %
III	3	0.591	0.624	58.12 %	33.22 %	66.78 %	41.88 %	49.79 %
	4	0.593	0.622	58.77 %	34.22 %	65.78 %	41.23 %	49.09 %
	5	0.584	0.622	69.16 %	44.85 %	55.15 %	30.84 %	48.61 %
	6	0.589	0.622	63.96 %	39.53 %	60.47 %	36.04 %	48.85 %
	10+	0.516	0.529	77.27 %	72.09 %	27.91 %	22.73 %	10.36 %
IV	3	0.579	0.622	59.74 %	35.22 %	64.78 %	40.26 %	49.05 %
	4	0.571	0.598	61.04 %	41.53 %	58.47 %	38.96 %	39.02 %
	5	0.587	0.632	63.96 %	37.54 %	62.46 %	36.04 %	52.84 %
	6	0.576	0.596	68.83 %	49.83 %	50.17 %	31.17 %	37.99 %
	10+	0.559	0.575	60.71 %	45.85 %	54.15 %	39.29 %	29.73 %

Table 4.4 Model fit comparison between different layouts and depths of CNN for straight roadway crashes

Layout	Depths	Accuracy		Performance by injury severity				Summary
		Training	Testing	Severe/Fatal		Minor/PDO		Score
				PAR	FPR	PAR	FPR	C
I	3	0.637	0.638	68.91 %	58.55 %	41.45 %	31.09 %	54.92 %
	4	0.646	0.645	70.67 %	58.18 %	41.82 %	29.33 %	57.71 %
	5	**0.661**	**0.647**	**74.09 %**	**54.92 %**	**45.08 %**	**25.91 %**	**58.03 %**
	6	0.637	0.639	79.56 %	47.64 %	52.36 %	20.44 %	54.39 %
	10+	0.613	0.622	83.82 %	39.73 %	60.27 %	16.18 %	47.10 %
II	3	0.637	0.640	71.06 %	56.61 %	43.39 %	28.94 %	55.34 %
	4	0.633	0.635	72.19 %	54.45 %	45.55 %	27.81 %	53.28 %
	5	0.638	0.641	80.79 %	46.76 %	53.24 %	19.21 %	55.10 %
	6	0.634	0.635	78.11 %	48.37 %	51.63 %	21.89 %	52.96 %
	10+	0.614	0.625	81.92 %	42.29 %	57.71 %	18.08 %	48.42 %
III	3	0.637	0.642	76.45 %	51.37 %	48.63 %	23.55 %	55.65 %
	4	0.637	0.641	75.61 %	52.07 %	47.93 %	24.39 %	55.35 %
	5	0.640	0.643	76.91 %	51.26 %	48.74 %	23.09 %	56.35 %
	6	0.641	0.645	78.85 %	49.54 %	50.46 %	21.15 %	56.79 %
	10+	0.617	0.623	80.72 %	43.24 %	56.76 %	19.28 %	47.93 %
IV	3	0.634	0.639	73.56 %	53.90 %	46.10 %	26.44 %	54.93 %
	4	0.631	0.633	76.21 %	49.87 %	50.13 %	23.79 %	52.16 %
	5	0.638	0.642	78.36 %	49.54 %	50.46 %	21.64 %	55.80 %
	6	0.633	0.634	74.41 %	51.89 %	48.11 %	25.59 %	52.59 %
	10+	0.616	0.627	82.52 %	42.15 %	57.85 %	17.48 %	49.32 %

Although formal classifier-level significance tests such as McNemar’s test are not directly applicable to comparing CNN architectures with different depths, the consistent decline in accuracy, PAR, FPR, and C-scores across deeper models provides strong empirical evidence that increased architectural complexity did not improve predictive performance. These trends, together with clear signs of overfitting, support the conclusion that the shallower CNN architecture generalizes more effectively for this dataset.

4.6.2 Model interpretation

To systematically identify and assess the critical determinants of crash severity across different roadway types, this research applied the SHapley Additive exPlanations (SHAP) method alongside feature importance analysis. This integrated analytical approach provides deeper insights than standard importance rankings by measuring both magnitude and direction of each factor's contribution to the prediction model. SHAP values represent associations rather than causal effects; therefore, all interpretations in this section refer to correlational patterns learned by the CNN model.

The interpretability analysis is illustrated in Figures 4.4 to 4.9, presenting feature importance rankings, directional impact through SHAP summary plots, and SHAP dependence plots illustrating feature interactions for both curved and straight roadways.

In this study, the HAIMS dataset defines “large trucks” as heavy vehicles with 6 wheels, 10 wheels, or more than 10 wheels. While this definition applies to both roadway types, their influence differs: on curved roads, both 6-wheel and 10-wheel trucks show strong positive SHAP values, whereas on straight roads the effect is driven mainly by 10-wheel trucks. This distinction supports consistent interpretation of truck-related predictors in the following analyses.

4.6.2.1 Curved roadway crash severity factors

The analysis of curved roadway segments (Figure 4.5) identifies several factors associated with crash severity. Among these, vehicle type emerged as a crucial determinant, with both six-wheel and ten-wheel trucks exhibiting strongly positive SHAP values (0.18 and 0.12 respectively). In Thailand's context, this finding is particularly significant given increased freight movement on rural highways with numerous curves, especially in the mountainous northern and eastern regions. The influence of large vehicles is notably stronger on curved segments compared to straight roadways, where truck-related crashes primarily relate to speed differentials. This finding aligns with previous research examining curve and slope effects on multi-vehicle truck crash severity on China's mountainous freeways (H. Wen et al., 2023). The study concluded that truck crashes on various combinations of slopes and curve radii significantly impact injury severity.

Similarly, head-on collisions showed significantly positive SHAP values, likely attributable to restricted sight distance and potential lane departure on curves (Safari et al., 2024). This reflects the predominantly two-lane rural highway network where narrow lanes and limited shoulders on curves create higher cross-centerline crash risks than on straight sections. Previous studies consistently identify head-on collisions as the most dangerous crash type with the highest fatality rates (Al-Bdairi & Behnood, 2021; Peng, Wang, & Wang, 2021; Saheli & Singleton, 2024).

Infrastructure elements also showed associations with crash severity, with depressed medians showing positive SHAP values, unlike in straight sections where they show mixed effects. A possible explanation for this trend is that depressed medians may be less effective as physical barriers or recovery areas, particularly in curved roadway segments where vehicle control is already challenged.

Moreover, environmental factors significantly affected crash likelihood. Dark locations (both with and without electric lighting) corresponded to positive SHAP values, corroborating prior studies (Abbasi, Piccioni, Sierpinski, & Farzin, 2022; Al-Bdairi & Behnood, 2021; Hossain et al., 2024; Xin et al., 2017; Zhu et al., 2019). The differential impact between curved and straight segments reflects Thailand's infrastructure development pattern, where roadway illumination is often insufficient along rural curved segments.

Speeding showed notable positive impact on crash severity, representing a particularly pronounced risk on curves due to centrifugal forces that compromise vehicle stability. The absence of curve-specific advisory speed signs often leaves drivers without adequate guidance for safely navigating curves. Existing studies suggest that roadway curves with higher speed limits present more challenging driving conditions and are associated with an increased probability of crashes (Al-Bdairi & Behnood, 2021; Lemonakis et al., 2021; Q. Ma et al., 2020; Safari et al., 2024; Xin et al., 2017). The primary cause of severe crashes at excessive speeds is decreased perception and reaction time (Al-Bdairi & Behnood, 2021; Safari et al., 2024).

Furthermore, lane configuration analysis revealed that two-lane roads (LANE = 2) with positive SHAP values, contrasting with straight roadways where wider roads exhibit higher severity associations. The increased risk on intermediate-width curves likely results from limited clear zones and recovery areas alongside curves in rural and peri-urban areas. This further supports the finding by Hossain et al. (2024), highlighting that roadway curves are responsible for a disproportionately large share of fatal and severe injury collisions, with the majority of these incidents taking place on rural two-lane (R2L) roadways.

Regarding operational contexts, work zones also demonstrated positive SHAP values, indicating higher predicted severity associations on curved roadways during construction activities. The likelihood of experiencing fatal injuries on curved road sections increases significantly, with a 69.0% higher probability during daylight hours and a 14.8% greater probability during nighttime conditions (Zhang & Hassan, 2019). Similarly, this aligns with research by Li and Bai (2009) showing that curved alignments in highway work zones contribute to 9% more fatal crashes than injury crashes.

Taken together, these results indicate that curved roadway segments are characterized by a distinct combination of severity-increasing factors—including large trucks, head-on crashes, depressed medians, darkness, speeding, two-lane configurations, and work zones—while protective factors such as urban settings, side-swipe crashes, barrier medians, and daylight conditions help mitigate crash severity. The contrast between these factor patterns and those observed on straight roadways reinforces the need for geometry-specific safety interventions rather than uniform countermeasures.

A deeper examination of feature interactions through SHAP dependence plots (Figure 4.6) reveals important nuances in how risk factors combine to relate to crash severity on curved roadways. In plots (a) and (b), there is a strong interaction between large truck types and darkness conditions, with trucks in darkness showing particularly elevated severity-associated SHAP values. This indicates that large trucks operating on curved segments during darkness present particularly elevated crash severity risks, consistent with the findings by Laphrom et al. (2024). Head-on collisions show interactions with median types (plots (c) and (d)), consistently producing positive SHAP values regardless of barrier or depressed median presence. These findings correspond with Effati, Darkhaneh, and Arabani (2025), demonstrating that diminished visibility conditions are associated with more intense head-on collisions by approximately 30% in normal weather. Darkness interactions with single vehicle crashes (plot (e)) and speeding (plot (f)) show darkness consistently contributing positively to crash severity, with the primary effect driven by darkness rather than strong interactions. This aligns with Dzinyela et al. (2025), who determined that motorcycle incidents on dark-not lighted roads and sections with curvature showed probabilities of 0.572 and 0.528 respectively for major injuries. Visual perception is crucial for motorcyclist protection, as Vlahogianni, Yannis, and Golias (2012) indicated that inadequate visibility correlates with elevated accident likelihood. Savolainen and Mannering (2007) confirmed that reduced sightlines from road curvature or insufficient lighting substantially heightens motorcycle-related injury severity. Overall, these interaction patterns indicate that the most influential severity-associated combinations on curved roadways involve large trucks operating under darkness and head-on collisions, regardless of median infrastructure. These patterns suggest that elevated severity predictions arise from combined associations rather than isolated factors.

Conversely, several factors exerted mitigating associations: side-swipe and rear-end collisions, roads without medians, single-vehicle crashes, urban areas, daytime conditions, front-path interruption, raised and barrier medians, and roads with eight or more lanes. Among these protective factors, barrier medians demonstrate a protective effect on curved segments in Thailand. Based on the SHAP dependence plots, the interaction between barrier medians and crash characteristics suggests they help mitigate severity in specific crash scenarios, though the overall pattern is complex. The protective effect of urban settings appears in the analysis, likely due to better infrastructure, lower operating speeds, and enhanced visibility in urban areas compared to rural environments where curved roadways present greater challenges.

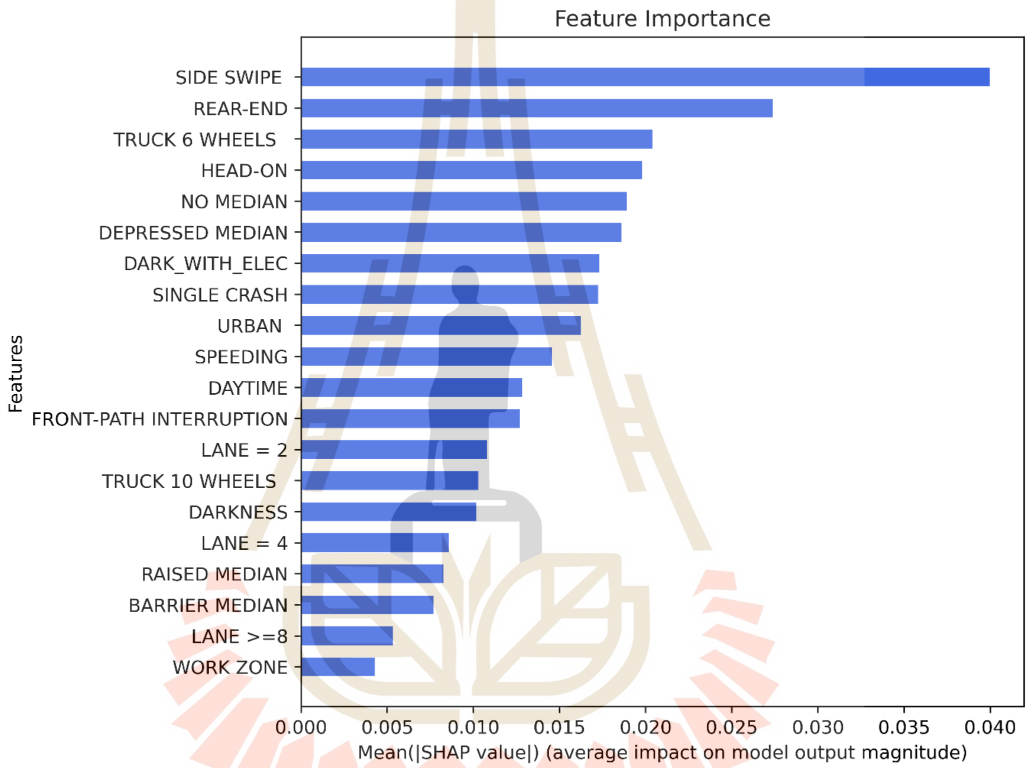

Figure 4.4 Feature importance for curved roadway crash model

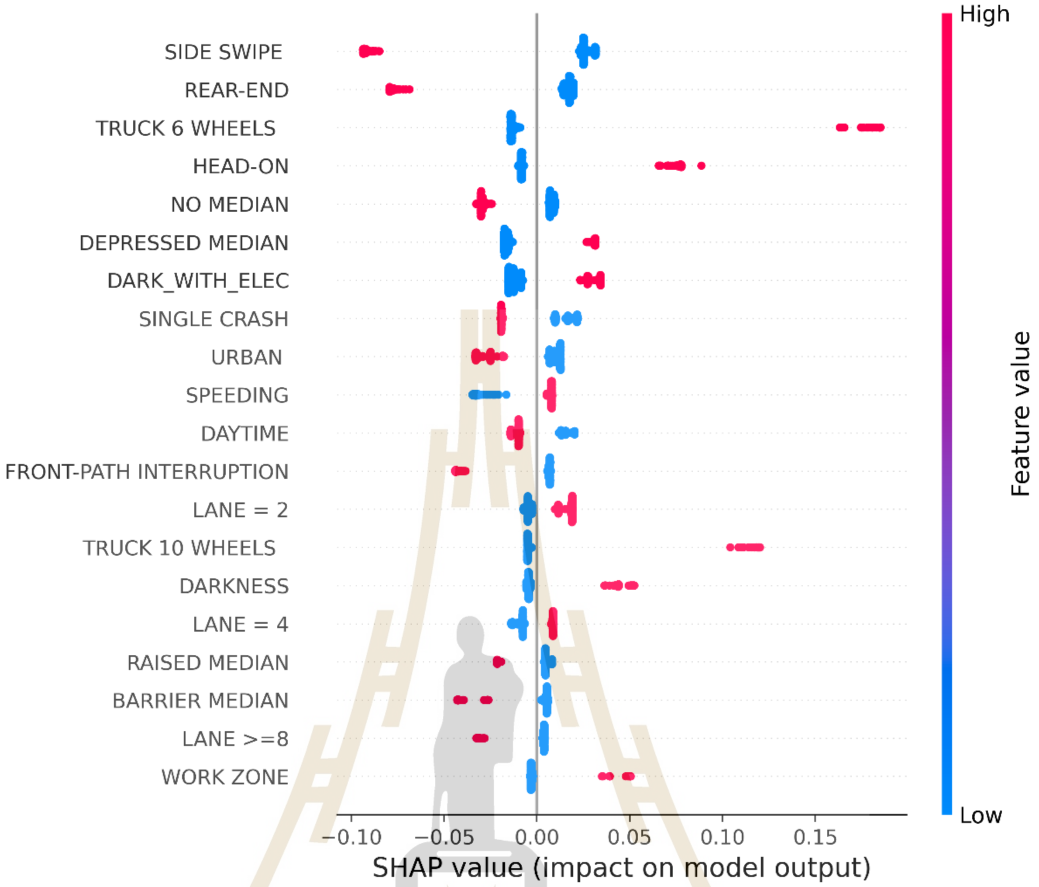

Figure 4.5 SHAP summary plot for feature impact on the model output for curved roadway crash model

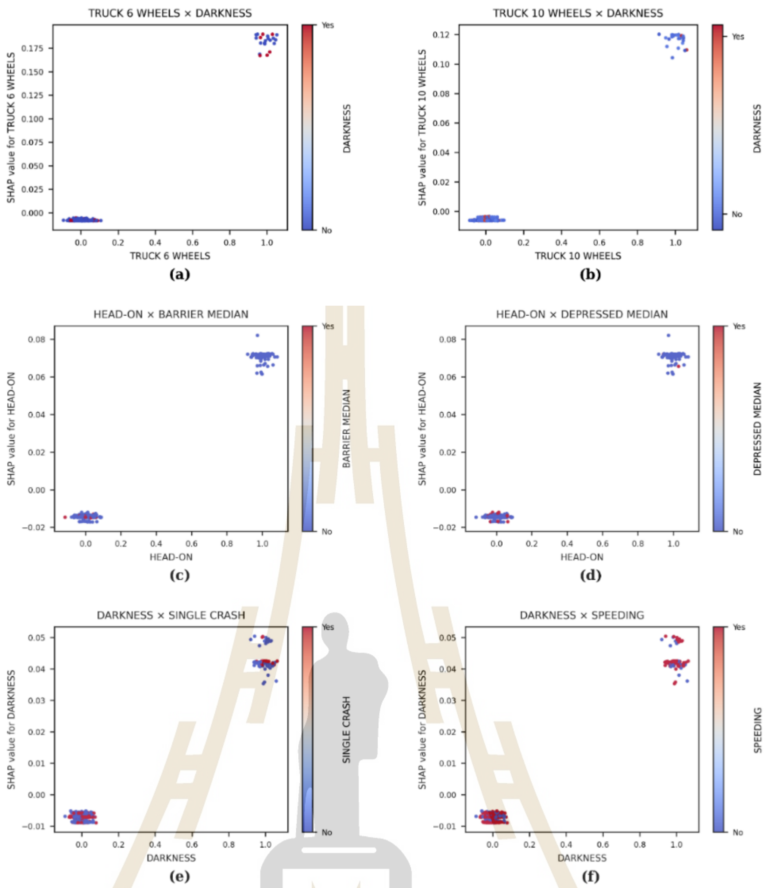

Figure 4.6 SHAP dependence plots illustrating feature interactions in motorcycle crash on curved roadways

4.6.2.2 Straight roadway crash severity factors

The analysis of straight roadway segments revealed distinct severity factors and interaction patterns distinct severity factors and interaction patterns (Figures 4.7 to 4.9). Key factors associated with higher predicted severity include large truck involvement, wider roadways (4+ lanes), front-path interruptions, traffic sign violations, asphalt surfaces, single-vehicle crashes, wet conditions, obstructions, U-turn related crashes, and poorly illuminated areas. Protective factors include passenger car involvement, daylight conditions, urban settings, barrier medians, and side-swipe collisions.

The SHAP dependence plots (Figure 4.9) illustrate critical interaction patterns unique to straight roadways. Most notably, speeding 10-wheel trucks show substantially higher crash severity risk (plot (a)), contrasting with curved segments where truck-darkness interactions predominate. Four-lane roads consistently show positive SHAP values regardless of urban context (plot (b)), indicating the road configuration itself is associated with elevated predicted severity. Head-on collisions maintain high severity regardless of barrier presence (plot (c)), suggesting these crashes are particularly dangerous on straight segments due to higher operating speeds. A distinctive interaction for straight segments is between wet road conditions and speeding (plot (d)), where this combination creates particularly hazardous scenarios not as prominently observed on curved segments. Unlike curved roadways, darkness with electrical lighting shows mixed and context-dependent effects (plots (e-f)).

The comparative analysis between curved and straight roadway segments reveals both shared and unique determinants of crash severity, underscoring the necessity for geometry-specific safety interventions.

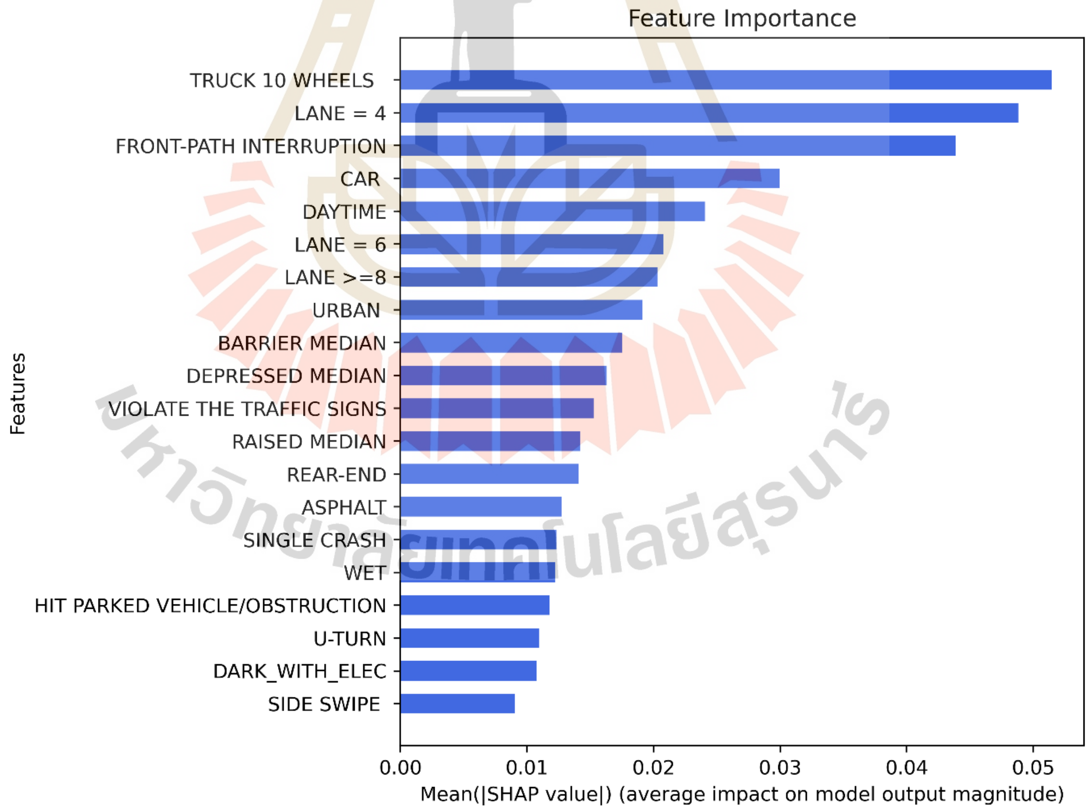

Figure 4.7 Feature importance for straight roadway crash model

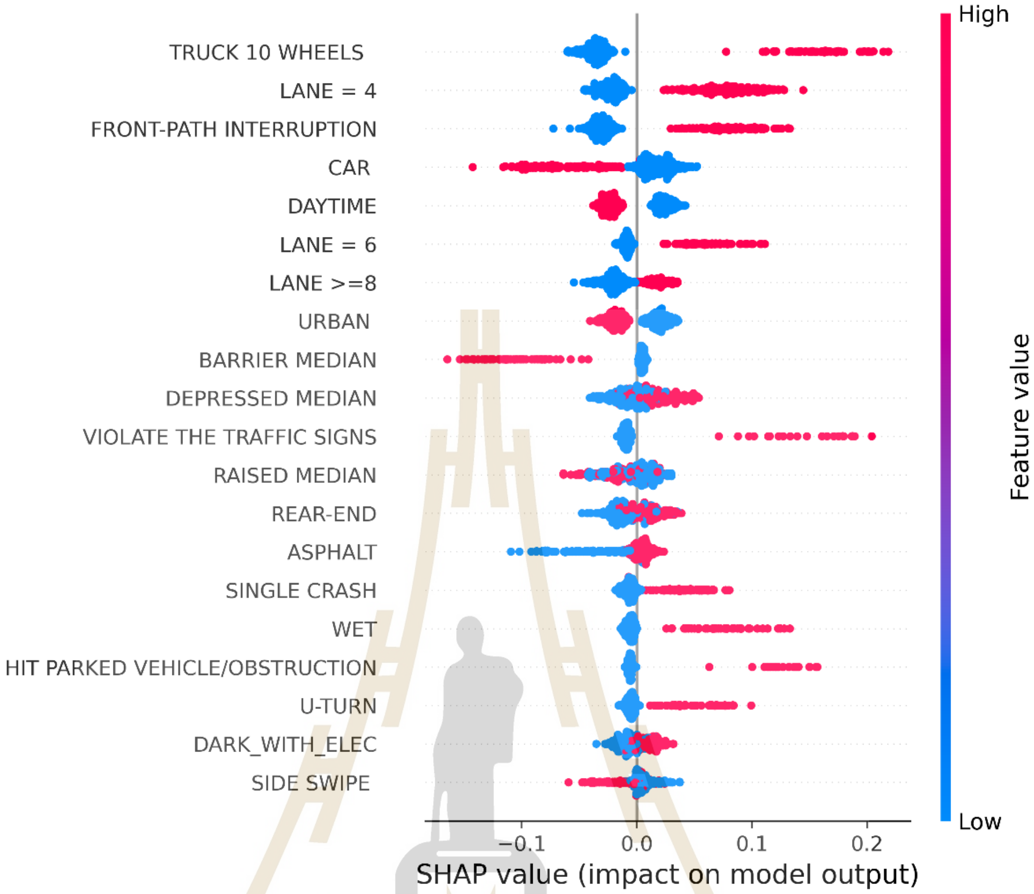

Figure 4.8 SHAP summary plot for feature impact on the model output for straight roadway crash model

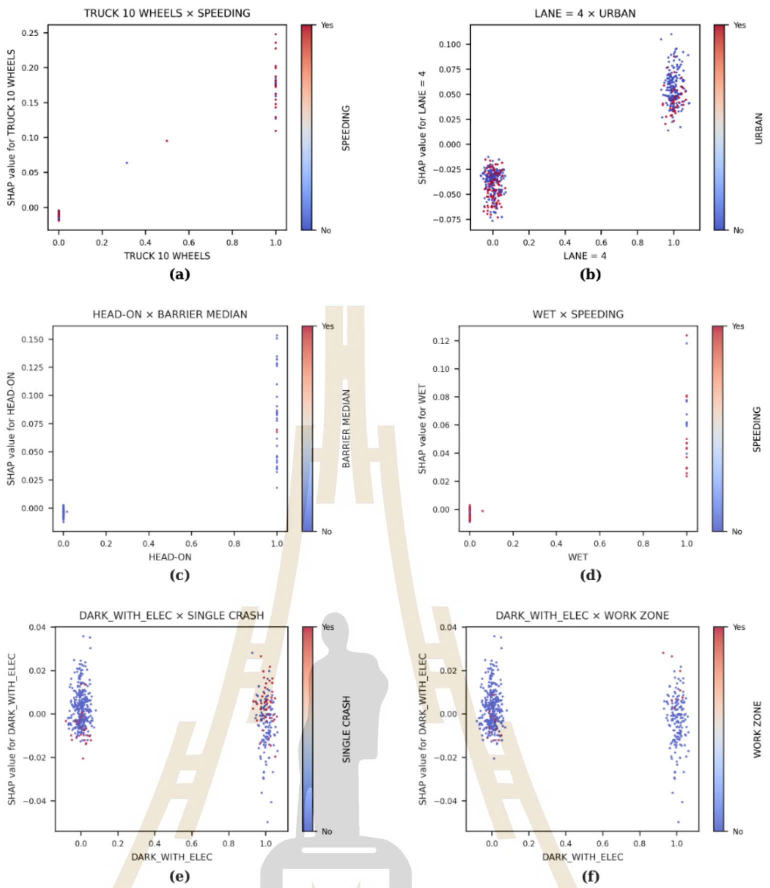

Figure 4.9 SHAP dependence plots illustrating feature interactions in motorcycle crash on straight roadways

4.6.3 Policy implications

Based on the geometry-specific findings from the CNN model and SHAP analysis, we propose evidence-driven safety interventions for curved roadways where the severity-associated patterns differ significantly from straight sections. ***(1) Infrastructure improvements:*** Prioritize barrier median installations with scientifically validated protective associations, replacing depressed medians that are associated with higher predicted severity. Implement semi-rigid W-beam guardrails and high-friction surface treatments on two-lane curved roads. ***(2) Specialized traffic management:*** Implement tailored speed management systems for large vehicles (truck-specific speed limits 15-20% lower than the general speed limit), addressing their severity-associated contributions. Enhance visibility through context-specific nighttime illumination strategies by installing ambient lighting on curves under 400m radius, establishing minimum illuminance standards, and deploying solar-powered LED units in rural areas. Strengthen work zone safety protocols by extending warning areas, adding motorcycle-specific signage, and strategically placing rumble strips. ***(3) Targeted education:*** Create comprehensive rider training programs/public awareness campaigns emphasizing curve-specific risk-associated patterns, focusing on condition linked with large vehicles, head-on collision risks, and speed management, with emphasis on rural areas with high curved roadway crash rates. ***(4) Enforcement measures:*** Speed enforcement on curved segments requires specialized approaches. Position automated speed cameras 50-100m after curve entry points, with intensified enforcement during evening and nighttime hours (6:00 PM to 6:00 AM) when the combination of speeding and darkness is associated with elevated severity predictions.

These targeted interventions address the unique patterns identified through our SHAP analysis and offer practical strategies for mitigating conditions associated with higher motorcycle crash severity on curved roadway segments.

4.7 Conclusion

Motorcycle crashes represent a critical public health challenge in Southeast Asia, with Thailand exemplifying the complex safety risks faced by vulnerable road users. The unique dynamics of curved roadways present distinct safety challenges due to the combined vulnerability of motorcyclists and the complex vehicle physics when navigating curves. This research addresses a crucial gap in understanding the multifaceted severity-associated factors specific to curved roadway motorcycle crashes, leveraging advanced computational techniques to unravel the intricate mechanisms associated with crash severity. By developing and comparing various Convolutional Neural Network (CNN) architectures and applying SHAP analysis for model interpretation, this research provides insights into the complex relationships between roadway characteristics, environmental conditions, and crash outcomes.

The research revealed distinct optimal CNN architectures for predicting crash severity based on roadway geometry, challenging the common assumption that deeper neural networks invariably yield better predictions. For curved roadways, a standard CNN architecture (Layout I) with minimal depth = 3 achieved superior performance (accuracy = 0.634, summary score C = 53.61%). Similarly, straight roadway crashes were most effectively modeled using the same standard architecture but with increased complexity (depth = 5), yielding slightly higher accuracy (0.647) and summary score (C = 58.03%).

The SHAP analysis revealed critical geometry-specific severity-associated factors for curved roadways, with large trucks, head-on collisions, depressed medians, darkness conditions, speeding, two-lane roads and work zones associated with higher predicted crash severity. SHAP interaction plots further demonstrated combinations of conditions—such as trucks operating during darkness and head-on collisions regardless of median infrastructure—that are associated with elevated severity predictions. The comparative analysis with straight roadways highlighted distinctive severity-associated patterns between the two geometries, reinforcing the importance of specialized safety interventions tailored to curved roadway dynamics.

The methodological insights contribute to both traffic safety research and machine learning applications in transportation engineering. Deep networks (10+ layers) consistently underperformed, suggesting that simpler architectures are more effective at capturing the underlying patterns in motorcycle crash data without overfitting. This finding challenges the prevalent "deeper is better" paradigm in deep learning applications and emphasizes the importance of appropriate model complexity for specific prediction tasks.

In conclusion, this study contributes to the growing body of research applying deep learning approaches to traffic safety by demonstrating the effectiveness of CNN models in predicting motorcycle crash severity and identifying geometry-specific severity-associated factors. The SHAP interaction analysis provides particularly valuable insights by identifying how multiple factors combine to correspond with heightened severity predictions, enabling more precise targeting of safety interventions to address these complex severity-related mechanisms. For instance, the interaction between large trucks and darkness conditions on curved roadways presents an especially elevated severity association that requires specialized countermeasures beyond those needed for either factor individually.

This study demonstrates the effectiveness of CNN architectures for predicting motorcycle crash severity on different roadway geometries. However, several limitations should be acknowledged. (1) Binary classification approach (severe/fatal vs. minor/PDO): The current approach uses a binary severity classification, which may oversimplify the injury severity spectrum. Future research should explore multi-class models capturing more nuanced injury gradations and investigate threshold-specific interventions tailored to different severity levels. (2) Data enrichment potential: Integrating advanced data sources—including precise curve geometry measurements, comprehensive motorcycle specifications, and detailed rider characteristics—could significantly enhance predictive precision and intervention specificity. Additionally, future studies should explore temporal variations in risk factors through time-series analysis to identify evolving safety challenges and adaptation needs. (3) Model generalizability limitations: The model's performance on future data may vary as transportation infrastructure, vehicle technologies, and rider behaviors evolve. Implementing periodic model retraining protocols and developing adaptive learning frameworks would enhance long-term prediction reliability. (4) Missing curve geometry variables: The HAIMS database lacks key geometric attributes such as curve radius, degree of curvature, superelevation, sight distance, and transition curves. These variables influence crash severity on curved segments, and their absence limits the model’s ability to fully capture geometry-related risks. Linking HAIMS data with roadway geometry inventories would address this limitation. (5) Model validation constraints: This study used an 80/20 train–test split and did not include k-fold cross-validation, confidence interval estimation, or comparisons with simpler baseline models such as logistic regression or random forests. External validation was also not feasible due to incompatible data structures across countries. These limitations restrict the contextualization and generalizability of the reported accuracy. Future work should incorporate cross-validation, baseline benchmarking, and external validation to improve robustness.

4.8 References

Abbasi, M., Piccioni, C., Sierpinski, G., & Farzin, I. (2022). Analysis of Crash Severity of Texas Two Lane Rural Roads Using Solar Altitude Angle Based Lighting Condition. *Sustainability, 14*(3), 1692. doi:https://doi.org/10.3390/su14031692

Ahmed, T., Mahmud, A., & Gayah, V. V. (2024). Crash modification factors of rumble strips on horizontal curves of two-lane rural roads: a propensity scores potential outcomes approach. *Accident Analysis & Prevention, 194*, 107371. doi:https://doi.org/10.1016/j.aap.2023.107371

Akter, R., Susilawati, S., Zubair, H., & Chor, W. T. (2025). Analyzing Feature Importance for Older Pedestrian Crash Severity: A Comparative Study of DNN Models, Emphasizing Road and Vehicle Types with SHAP Interpretation. *Multimodal Transportation*, 100203. doi:https://doi.org/10.1016/j.multra.2025.100203

Al-Bdairi, N. S. S., & Behnood, A. (2021). Assessment of temporal stability in risk factors of crashes at horizontal curves on rural two-lane undivided highways. *Journal of safety research, 76*, 205-217. doi:https://doi.org/10.1016/j.jsr.2020.12.003

Ali, Y., Hussain, F., & Haque, M. M. (2024). Advances, challenges, and future research needs in machine learning-based crash prediction models: A systematic review. *Accident Analysis & Prevention, 194*, 107378. doi:https://doi.org/10.1016/j.aap.2023.107378

Alnawmasi, N., Ziakopoulos, A., Theofilatos, A., & Ali, Y. (2025). Understanding the effects of underreporting on injury severity estimation of single-vehicle motorcycle crashes: A hybrid approach incorporating majority class oversampling and random parameters with heterogeneity-in-means. *Analytic methods in accident research, 45*, 100372. doi:https://doi.org/10.1016/j.amar.2025.100372

Assi, K. (2020). *Prediction of traffic crash severity using deep neural networks: a comparative study.* Paper presented at the 2020 International Conference on Innovation and Intelligence for Informatics, Computing and Technologies (3ICT).

Bejleri, I., Xu, X., Silva, K. R., & Srinivasan, S. (2024). Safety performance analysis of horizontal curves in urban areas. *Accident Analysis & Prevention, 195*, 107402. doi:https://doi.org/10.1016/j.aap.2023.107402

Champahom, T., Se, C., Watcharamaisakul, F., Jomnonkwao, S., Karoonsoontawong, A., & Ratanavaraha, V. (2024). Tree-based approaches to understanding factors influencing crash severity across roadway classes: A Thailand case study. *IATSS research, 48*(3), 464-476. doi:https://doi.org/10.1016/j.iatssr.2024.09.001

Ding, H., Wang, R., Chen, T., Sze, N., Chung, H., & Dong, N. (2024). A hybrid approach for modeling bicycle crash frequencies: integrating random forest based SHAP model with random parameter negative binomial regression model. *Accident Analysis & Prevention, 208*, 107778. doi:https://doi.org/10.1016/j.aap.2024.107778

Dzinyela, R., Dadashova, B., Westfall, G., Das, S., Silvestri-Dobrovolny, C., Adanu, E. K., & Lord, D. (2025). Analysis of motorcyclists crash severity using cluster correspondence and hierarchical binary logit models. *Multimodal Transportation, 4*(1), 100197. doi:https://doi.org/10.1016/j.multra.2025.100197

Effati, M., Darkhaneh, M. E., & Arabani, M. (2025). Factors Affecting the Injury Severity of Head-On Crashes on Undivided Rural Roads under Different Weather Conditions. *International journal of transportation science and technology*. doi:https://doi.org/10.1016/j.ijtst.2025.02.007

Gabauer, D. J., & Li, X. (2015). Influence of horizontally curved roadway section characteristics on motorcycle-to-barrier crash frequency. *Accident Analysis & Prevention, 77*, 105-112. doi:https://doi.org/10.1016/j.aap.2015.02.006

Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning* (Vol. 1): MIT press Cambridge.

Guo, Y., Li, Z., Wu, Y., & Xu, C. (2018). Exploring unobserved heterogeneity in bicyclists' red-light running behaviors at different crossing facilities. *Accident Analysis & Prevention, 115*, 118-127. doi:https://doi.org/10.1016/j.aap.2018.03.006

Guo, Y., Osama, A., & Sayed, T. (2018). A cross-comparison of different techniques for modeling macro-level cyclist crashes. *Accident Analysis & Prevention, 113*, 38-46. doi:https://doi.org/10.1016/j.aap.2018.01.015

Haghshenas, S. S., Guido, G., Vitale, A., & Astarita, V. (2023). Assessment of the level of road crash severity: Comparison of intelligence studies. *Expert systems with applications, 234*, 121118. doi:https://doi.org/10.1016/j.eswa.2023.121118

Hasan, A. S., Jalayer, M., Das, S., & Kabir, M. A. B. (2024). Application of machine learning models and SHAP to examine crashes involving young drivers in New Jersey. *International journal of transportation science and technology, 14*, 156-170. doi:https://doi.org/10.1016/j.ijtst.2023.04.005

Hossain, A., Sun, X., Islam, S., Rahman, A., & Das, S. (2024). Single-vehicle roadway departure crashes at rural two-lane highway curved segments: a diagnosis using pattern recognition. *International journal of transportation science and technology, 15*, 298-318. doi:https://doi.org/10.1016/j.ijtst.2023.10.005

Islam, M., Hosseini, P., & Jalayer, M. (2022). An analysis of single-vehicle truck crashes on rural curved segments accounting for unobserved heterogeneity. *Journal of safety research, 80*, 148-159. doi:https://doi.org/10.1016/j.jsr.2021.11.011

Kashifi, M. T. (2023). Investigating two-wheelers risk factors for severe crashes using an interpretable machine learning approach and SHAP analysis. *IATSS research, 47*(3), 357-371. doi:https://doi.org/10.1016/j.iatssr.2023.07.005

Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*. doi:https://doi.org/10.48550/arXiv.1412.6980

Kronprasert, N., Boontan, K., & Kanha, P. (2021). Crash prediction models for horizontal curve segments on two-lane rural roads in Thailand. *Sustainability, 13*(16), 9011. doi:https://doi.org/10.3390/su13169011

Kvasnes, S., Pokorny, P., Jensen, J. K., & Pitera, K. (2021). Safety effects of horizontal curve design and lane and shoulder width on single motorcycle accidents in Norway. *Journal of advanced transportation, 2021*(1), 6684334. doi:https://doi.org/10.1155/2021/6684334

Laphrom, W., Se, C., Champahom, T., Jomnonkwao, S., Wipulanusatd, W., Satiennam, T., & Ratanavaraha, V. (2024). XGBoost-SHAP and unobserved heterogeneity modelling of temporal multivehicle truck-involved crash severity patterns. *Civil Engineering Journal, 10*(6), 1890-1908. doi:http://dx.doi.org/10.28991/CEJ-2024-010-06-011

Lemonakis, P., Eliou, N., & Karakasidis, T. (2021). Investigation of speed and trajectory of motorcycle riders at curved road sections of two-lane rural roads under diverse lighting conditions. *Journal of safety research, 78*, 138-145. doi:https://doi.org/10.1016/j.jsr.2021.05.009

Li, Y., & Bai, Y. (2009). Highway work zone risk factors and their impact on crash severity. *Journal of Transportation engineering, 135*(10), 694-701. doi:https://doi.org/10.1061/(ASCE)TE.1943-5436.0000055

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems, 30*. doi:https://doi.org/10.48550/arXiv.1705.07874

Ma, Q., Yang, H., Wang, Z., Xie, K., & Yang, D. (2020). Modeling crash risk of horizontal curves using large-scale auto-extracted roadway geometry data. *Accident Analysis & Prevention, 144*, 105669. doi:https://doi.org/10.1016/j.aap.2020.105669

Ma, X., Huo, Z., Lu, J., & Wong, Y. D. (2025). Deep Forest with SHapley additive explanations on detailed risky driving behavior data for freeway crash risk prediction. *Engineering Applications of Artificial Intelligence, 141*, 109787. doi:https://doi.org/10.1016/j.engappai.2024.109787

Manzoor, M., Umer, M., Sadiq, S., Ishaq, A., Ullah, S., Madni, H. A., & Bisogni, C. (2021). RFCNN: Traffic accident severity prediction based on decision level fusion of machine and deep learning model. *IEEE Access, 9*, 128359-128371. doi:https://doi.org/10.1109/ACCESS.2021.3112546

Mohamad, I., Jomnonkwao, S., & Ratanavaraha, V. (2022). Using a decision tree to compare rural versus highway motorcycle fatalities in Thailand. *Case studies on transport policy, 10*(4), 2165-2174. doi:https://doi.org/10.1016/j.cstp.2022.09.016

Pedregosa, F. (2011). Scikit-learn: Machine learning in Python. In *Journal of machine learning research 12* (pp. 2825).

Peng, Z., Wang, Y., & Wang, L. (2021). A comparative analysis of factors influencing the injury severity of daytime and nighttime crashes on a mountainous expressway in China. *International journal of injury control and safety promotion, 28*(4), 503-512. doi:https://doi.org/10.1080/17457300.2021.1964089

Prechelt, L. (2002). Early stopping-but when? In *Neural Networks: Tricks of the trade* (pp. 55-69): Springer.

Rahim, M. A., & Hassan, H. M. (2021). A deep learning based traffic crash severity prediction framework. *Accident Analysis & Prevention, 154*, 106090. doi:https://doi.org/10.1016/j.aap.2021.106090

Safari, M., Effati, M., & Arabani, M. (2024). Spatial analysis of daytime and nighttime crash severity on horizontal curves of mountainous rural highways: A case study in Northern Iran. *Results in Engineering, 24*, 103344. doi:https://doi.org/10.1016/j.rineng.2024.103344

Saheli, M. V., & Singleton, P. A. (2024). Injury severity analysis of rural vehicle crashes involving familiar and unfamiliar drivers. *International journal of transportation science and technology, 13*, 1-13. doi:https://doi.org/10.1016/j.ijtst.2023.11.002

Savolainen, P., & Mannering, F. (2007). Probabilistic models of motorcyclists' injury severities in single-and multi-vehicle crashes. *Accident Analysis & Prevention, 39*(5), 955-963. doi:https://doi.org/10.1016/j.aap.2006.12.016

Shaik, M. E., Islam, M. M., & Hossain, Q. S. (2021). A review on neural network techniques for the prediction of road traffic accident severity. *Asian Transport Studies, 7*, 100040. doi:https://doi.org/10.1016/j.eastsj.2021.100040

Singh, R., Sharma, N., Rajput, K., & Kumar, M. (2024). *CNN-Based Model for Accurate Road Accident Severity Classification from CCTV Footage.* Paper presented at the 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC).

Štrumbelj, E., & Kononenko, I. (2014). Explaining prediction models and individual predictions with feature contributions. *Knowledge and information systems, 41*, 647-665. doi:https://doi.org/10.1007/s10115-013-0679-x

Sunkpho, J., Se, C., Wipulanusat, W., & Ratanavaraha, V. (2025). SHAP-based convolutional neural network modeling for intersection crash severity on Thailand's highways. *IATSS research, 49*(1), 27-41. doi:https://doi.org/10.1016/j.iatssr.2024.12.003

Tahfim, S. A.-S., & Yan, C. (2021). Analysis of severe injuries in crashes involving large trucks using K-prototypes clustering-based GBDT model. *Safety, 7*(2), 32. doi:https://doi.org/10.3390/safety7020032

Vlahogianni, E. I., Yannis, G., & Golias, J. C. (2012). Overview of critical risk factors in Power-Two-Wheeler safety. *Accident Analysis & Prevention, 49*, 12-22. doi:https://doi.org/10.1016/j.aap.2012.04.009

Wang, C., Li, S., & Shan, J. (2021). Non-Stationary modeling of microlevel road-curve crash frequency with geographically weighted regression. *ISPRS International Journal of Geo-Information, 10*(5), 286. doi:https://doi.org/10.3390/ijgi10050286s

Wen, H., Ma, Z., Chen, Z., & Luo, C. (2023). Analyzing the impact of curve and slope on multi-vehicle truck crash severity on mountainous freeways. *Accident Analysis & Prevention, 181*, 106951. doi:https://doi.org/10.1016/j.aap.2022.106951

Wen, X., Xie, Y., Wu, L., & Jiang, L. (2021). Quantifying and comparing the effects of key risk factors on various types of roadway segment crashes with LightGBM and SHAP. *Accident Analysis & Prevention, 159*, 106261. doi:https://doi.org/10.1016/j.aap.2021.106261

WHO. (2023). Road traffic injuries [Online]. Retrieved from https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries/

Xin, C., Wang, Z., Lee, C., & Lin, P.-S. (2017). Modeling safety effects of horizontal curve design on injury severity of single-motorcycle crashes with mixed-effects logistic model. *Transportation Research Record, 2637*(1), 38-46. doi:https://doi.org/10.3141/2637-05

Xin, C., Wang, Z., Lee, C., Lin, P.-S., Chen, T., Guo, R., & Lu, Q. (2019). Development of crash modification factors of horizontal curve design features for single-motorcycle crashes on rural two-lane highways: A matched case-control study. *Accident Analysis & Prevention, 123*, 51-59. doi:https://doi.org/10.1016/j.aap.2018.11.008

Yang, C., Chen, M., & Yuan, Q. (2021). The application of XGBoost and SHAP to examining the factors in freight truck-related crashes: An exploratory analysis. *Accident Analysis & Prevention, 158*, 106153. doi:https://doi.org/10.1016/j.aap.2021.106153

Yu, H., Chen, X., Li, Z., Zhang, G., Liu, P., Yang, J., & Yang, Y. (2019). Taxi-based mobility demand formulation and prediction using conditional generative adversarial network-driven learning approaches. *IEEE Transactions on Intelligent Transportation Systems, 20*(10), 3888-3899. doi:https://doi.org/10.1109/TITS.2019.2923964

Yu, H., Li, Z., Zhang, G., Liu, P., & Ma, T. (2021). Fusion convolutional neural network-based interpretation of unobserved heterogeneous factors in driver injury severity outcomes in single-vehicle crashes. *Analytic methods in accident research, 30*, 100157. doi:https://doi.org/10.1016/j.amar.2021.100157

Zahid, M., Habib, M. F., Ijaz, M., Ameer, I., Ullah, I., Ahmed, T., & He, Z. (2024). Factors affecting injury severity in motorcycle crashes: Different age groups analysis using Catboost and SHAP techniques. *Traffic injury prevention, 25*(3), 472-481. doi:https://doi.org/10.1080/15389588.2023.2297168

Zhang, K., & Hassan, M. (2019). Crash severity analysis of nighttime and daytime highway work zone crashes. *PloS one, 14*(8), e0221128. doi:https://doi.org/10.1371/journal.pone.0221128

Zhu, L., Lu, L., Zhang, W., Zhao, Y., & Song, M. (2019). Analysis of accident severity for curved roadways based on bayesian networks. *Sustainability, 11*(8), 2223. doi:https://doi.org/10.3390/su11082223

CHAPTER V

AN EXPLAINABLE RF-CNN MODEL FOR INJURY SEVERITY PREDICTION IN SINGLE-MOTORCYCLE CRASHES

5.1 Abstract

Single-motorcycle crashes represent a critical transportation safety challenge, particularly in developing countries with high motorcycle usage. This study proposes a novel hybrid Random Forest-Convolutional Neural Network (RF-CNN) model for predicting injury severity in single-motorcycle crashes, addressing the persistent trade-off between predictive accuracy and model interpretability.

Utilizing 5,975 single-motorcycle crashes from Thailand's Highway Accident Information Management System (2016-2023), this study implemented a weighted ensemble framework combining Random Forest interpretability with CNN pattern recognition capabilities. The methodology included Random Forest-based feature selection identifying 25 critical variables across four domains (temporal, roadway, environmental, and crash characteristics), class balancing using SMOTE, and a weighted fusion strategy (85% CNN, 15% RF). Model performance was evaluated against standalone Random Forest, CNN, and Binary Logistic regression baselines using accuracy, precision, recall, and F1-Score metrics.

The hybrid RF-CNN model achieved superior performance with 58.9% accuracy and a recall of 69.9%, outperforming all baseline models in severe-crash detection. SHAP explainability analysis revealed that nighttime conditions with electrical lighting emerged as the most influential severity factor, followed by lane configuration, curved roadway geometry, and behavioral factors including speeding and alcohol involvement. Complex interaction effects were identified, demonstrating the model's capability to capture non-linear risk relationships.

The findings provide actionable guidance for targeted interventions, including enhanced roadway lighting, curve-specific speed management, median upgrades, and improved work zone safety protocols. This research contributes to explainable AI

applications in transportation safety, demonstrating that hybrid modeling approaches can balance predictive performance with interpretability while supporting evidence-based motorcycle safety policy in developing countries.

5.2 Introduction

Single-motorcycle crashes are a pressing global public health concern, accounting for a disproportionate share of road fatalities and serious injuries worldwide (Ferko, Babić, & Pirdavani, 2025; Pervez, Lee, Huang, & Zhai, 2022). Unlike multi-vehicle collisions where crash dynamics are influenced by vehicle interactions, single-motorcycle crashes are primarily determined by the complex interplay between rider behavior, vehicle characteristics, roadway geometry, and environmental conditions (Shaheed & Gkritza, 2014). The vulnerability of motorcyclists, combined with their exposure to direct impact forces without protective vehicle structures, results in substantially higher injury severity rates compared to other road users (Lin & Kraus, 2009; Sivasankaran, Rangam, & Balasubramanian, 2021; Yannis, Golias, & Papadimitriou, 2005).

This crash type warrants focused analysis for two reasons. First, single-motorcycle crashes isolate risk factor relationships without the confounding effects of multi-vehicle interactions, allowing clearer identification of modifiable determinants. Second, prevention strategies differ from multi-vehicle crashes, relying more on roadway design improvements and rider behavior management rather than post-crash protection. Understanding these mechanisms is especially important in developing countries, where resources for large-scale infrastructure improvements are limited and interventions must be carefully prioritized. Focusing on a single crash type also minimizes the substantial behavioral and roadway heterogeneity introduced when multivehicle, pedestrian, or mixed crash configurations are analyzed together. Because these crash types follow different causal pathways and risk structures, combining them can obscure relationships that are specific to motorcycle dynamics. Narrowing the scope to single-motorcycle crashes therefore provides a more coherent analytical context for examining how roadway geometry, lighting, and rider behavior shape injury severity.

This challenge is particularly acute in developing countries experiencing rapid motorization, where traditional analytical approaches may prove insufficient. In Thailand, motorcycles constitute approximately 75% of registered vehicles, making motorcycle safety a paramount concern for transportation authorities (Champahom et al., 2022; WHO, 2023). The country's motorcycle fatality rate remains among the highest globally, with single-vehicle crashes representing a significant proportion of severe and fatal incidents. Thailand provides an ideal case study for advanced crash severity modeling due to its high motorcycle usage, diverse infrastructure conditions, and comprehensive crash data collection systems. These crashes often involve complex causation patterns that traditional statistical approaches struggle to capture comprehensively.

Conventional approaches to crash severity analysis have predominantly relied on statistical modeling techniques, including logistic regression (Bhuiyan et al., 2022; Lee, Guldmann, & von Rabenau, 2023; Yuxie Xiao et al., 2024), ordered probit models (Babaei & Kunt, 2024; Mphekgwana, 2022; Rezapour, Wulff, Mehrara Molan, & Ksaibati, 2021), multinomial logistic regression (Park & Park, 2022; Shiran, Imaninasab, & Khayamim, 2021), mixed logit models (Esmaili, Aghabayk, & Shiwakoti, 2022; S. M. Islam, Washington, Kim, & Haque, 2023; Yuan, Gan, Peng, & Xiang, 2022), and random parameter frameworks (Adanu, Powell, Jones, & Smith, 2023; Cai & Wei, 2023; Dzinyela, Dadashova, Adanu, & Lord, 2025). While these methods provide interpretable coefficient estimates and have established theoretical foundations, they face significant methodological constraints including assumptions of linearity, parameter stability, and restricted capacity to detect sophisticated non-linear interactions within predictor variables and crash outcomes (Mansoor, Jamal, Su, Sze, & Chen, 2023; Santos, Dias, & Amado, 2022). These limitations become particularly problematic when analyzing single-motorcycle crashes, where multiple risk factors interact in non-linear ways to influence injury severity.

In response to these limitations, the cutting-edge advancements in predictive algorithms and computational intelligence have evidenced superior performance in crash severity prediction tasks, offering enhanced pattern recognition capabilities and the expertise to model intricate non-linear correlations (Ali, Hussain, & Haque, 2024).

Random Forest algorithms have shown particular promise in transportation safety applications because of their resilience against outliers, expertise in processing mixed data types, and inherent feature importance ranking capabilities (Ferko et al., 2025; Scarano et al., 2023; Yang, Han, & Chen, 2023). Similarly, deep learning approaches, including Convolutional Neural Networks, have illustrated remarkable success in pattern learning applications, though their application to tabular crash data remains limited (Borisov et al., 2022).

However, a critical challenge persists in transportation safety research: the trade-off between predictive accuracy and model interpretability. Advanced machine learning models often achieve superior prediction performance but function as "black boxes," limiting their utility for evidence-based policy development and safety intervention design (Ali et al., 2024). Conversely, traditional statistical methods offer clear interpretability but may sacrifice predictive accuracy when dealing with complex, non-linear relationships characteristic of crash phenomena.

The emergence of explainable artificial intelligence (XAI) techniques, remarkably SHapley Additive exPlanations (SHAP), a method that quantifies individual feature contributions to model predictions, offers a promising solution to bridge this interpretability gap (Lundberg & Lee, 2017). SHAP analysis enables detailed examination of feature contributions and interactions in complex machine learning models, facilitating the translation of advanced predictive capabilities into actionable safety insights (Sum et al., 2025; Wisutwattanasak et al., 2024). However, the integration of explainable AI with hybrid modeling approaches for single-motorcycle crash analysis remains underexplored.

Furthermore, existing research has predominantly focused on individual modeling paradigms without systematic evaluation of hybrid approaches that combine complementary algorithmic strengths. Random Forest models excel in feature importance identification and handling of categorical variables, while Convolutional Neural Networks demonstrate superior pattern recognition capabilities in complex data structures (Acı, Mutlu, Ozen, & Acı, 2025; M. R. Islam, Wang, & Abdel-Aty, 2024). A weighted ensemble approach combining these complementary strengths could potentially achieve both enhanced predictive performance and maintained interpretability (Roudnitski, 2024).

The development of such hybrid approaches is particularly crucial for single-motorcycle crash analysis, where risk factor interactions are complex and safety interventions require precise understanding of causal mechanisms, highlighting the need for innovative approaches that can simultaneously achieve high predictive performance while maintaining transparency required for evidence-based policy development.

Addressing these methodological limitations is essential for advancing evidence-based motorcycle safety management. The integration of hybrid modeling with comprehensive explainability analysis represents a critical methodological advancement toward developing data-driven safety interventions that are both scientifically rigorous and practically implementable.

Therefore, this study aims to develop and validate a novel hybrid Random Forest-Convolutional Neural Network (RF-CNN) approach for single-motorcycle crash severity prediction, enhanced with comprehensive SHAP-based explainability analysis. The research objectives are threefold: (1) to develop a weighted ensemble framework combining Random Forest interpretability with CNN pattern recognition capabilities, (2) to evaluate the hybrid model's performance against individual component models and traditional statistical approaches, and (3) to implement comprehensive explainability analysis to identify critical risk factors and their interactions for evidence-based safety intervention development. The insights from this research will enrich the mounting evidence concerning explainable AI applications in transportation safety, demonstrating that hybrid modeling approaches can effectively balance competing demands of accuracy and interpretability. The results will provide actionable insights for motorcycle safety policy development and establish a methodological framework for advanced crash severity analysis in developing country contexts.

The remaining portions of this study are arranged in the following manner: Section 5.3 surveys prior research, Section 5.4 characterizes the database and empirical context, Section 5.5 describes the methodological framework, Section 5.6 reports outcomes and interpretation, Section 5.7 finalizes with implementation recommendations, and Section 5.8 highlights limitations and directions for subsequent research.

5.3 Literature Reviews

Existing literature examining injury severity in single-motorcycle crashes has been analyzed in this section. This review comprises two main components: the initial component investigates variables that influence single-motorcycle crash injury severity, while the subsequent component assesses frequently utilized modeling methodologies, encompassing statistical, machine learning, and deep learning techniques, to investigate single-motorcycle crash phenomena.

5.3.1 Contributing elements to single-motorcycle crashes

Multiple research investigations have established the critical role of diverse variables that determine the severity of single-motorcycle crashes. These factors encompass motorcyclist characteristics including age and gender, vital for determining vulnerability levels, in addition to alcohol use and protective equipment utilization, which considerably impact the probability of serious injuries. Environmental aspects including pavement conditions, visibility factors, meteorological conditions, and time-related variables all affect crash occurrence and outcomes. Furthermore, roadway design characteristics such as curve geometries, road classifications, motorcyclist behaviors including excessive speed and license compliance, and crash-specific elements such as impact patterns all determine level of injury. Research findings, presented in Table 5.1, identify the factors shaping single-motorcycle crash outcomes and demonstrate the complex, multifaceted nature of risk factor interactions that traditional statistical approaches struggle to capture comprehensively.

5.3.2 Single-motorcycle crashes injury analysis approaches

In analyzing critical risk variables in single-motorcycle crashes, investigators have broadly implemented diverse statistical modeling approaches. Traditional statistical methods include multinomial logistic regression (Ferko et al., 2025), random parameter logit frameworks with heterogeneity in means and variances (Alnawmasi, Ziakopoulos, Theofilatos, & Ali, 2025; Dzinyela et al., 2025; Pervez et al., 2022), ordered logistic models (Sivasankaran et al., 2021), binary and mixed logit models (M. Islam, 2021; Wang, 2022), and latent class multinomial logit approaches to address unobserved heterogeneity (Shaheed & Gkritza, 2014). Mixed-effects logistic models with random parameters have been employed to capture temporal and spatial variations (Xin, Wang, Lee, & Lin, 2017). Matched case-control designs with conditional logistic regression have been applied to examine geometric design effects on crash risk (Kvasnes, Pokorny, Jensen, & Pitera, 2021; Xin et al., 2019). Descriptive statistics combined with logistic regression have been used to analyze injury profiles using linked crash and hospital data (Sivasankaran, Rangam, & Balasubramanian, 2022). Statistical modeling approaches are acknowledged for their clear interpretation and understandability. These techniques are computationally efficient and capable of managing large datasets without requiring substantial computational resources or time investment. However, these methods possess limitations as they assume linear associations across explanatory factors and response variables, and the hypothesis that model parameters stay fixed among different data points might not be realistic in practical applications (Mansoor et al., 2023; Santos et al., 2022; Sum et al., 2025). Beyond linearity, binary logistic regression also assumes parameter homogeneity and cannot fully account for unobserved heterogeneity across roadway, behavioral, or environmental conditions. These constraints may oversimplify complex, non-linear crash mechanisms and lead to biased estimates. Further, BLR requires correct functional form specification, which is often unrealistic for heterogeneous crash data. These limitations motivate the use of machine learning and hybrid approaches capable of modeling non-linear interactions without strong parametric assumptions.

Machine learning (ML) approaches have recently become prominent as powerful alternatives to traditional statistical methods, addressing various limitations. Random Forest models have demonstrated effectiveness in single-motorcycle crash severity analysis, providing both prediction accuracy and feature importance identification (Ferko et al., 2025). Association rules mining using the Apriori algorithm has been applied to identify crash patterns and risk factor combinations in single-vehicle motorcycle crashes (Zulherman, Yang, & Yokota, 2022). Unlike statistical models that often depend on strict conditions, machine learning algorithms successfully detect intricate nonlinear linkages within dependent measures plus causal factors (Chan et al., 2022). A key strength concerning machine learning algorithms involves their capacity to process extensive data collections containing numerous features, enabling these methods to uncover concealed relationships that conventional analytical approaches might overlook. Additionally, machine learning algorithms exhibit high adaptability and can automatically process novel information, positioning them as effective for instantaneous analysis and responsive frameworks.

Advanced deep learning approaches have emerged as sophisticated alternatives for crash severity analysis. Deep Q-learning Network-based Imbalanced Classification (DQNIC) has been specifically developed to address class imbalance in crash severity data without requiring traditional resampling techniques (Zulherman, Yang, Shimizu, & Yokota, 2025). Light Gradient Boosting Machine (LightGBM) models combined with resampling methods including SMOTE, ENN, and SMOTEENN have achieved exceptional performance in fatality prediction, with accuracy rates reaching 96.6% and AUC values of 99.4% (Zulherman, Yang, Shimizu, & Yokota, 2024). XGBoost models with SHAP interpretation have been successfully applied to analyze factors affecting single versus multivehicle motorcycle crashes during different time periods (Wisutwattanasak et al., 2024). These approaches are skilled in identifying complex correlations plus data configurations from original inputs, qualifying them as especially suitable in contexts requiring multidimensional along with elaborate information sets. Additionally, integrating explainability methods such as SHAP (SHapley Additive exPlanations) with advanced models enhances model transparency, reliability, and interpretability (Wisutwattanasak et al., 2024; Zulherman et al., 2024, 2025), enabling investigators to comprehend the algorithm's reasoning mechanism along with the factors influencing its outputs.

Despite this progress, important research gaps remain. First, no study has yet developed a hybrid framework that combines Random Forest interpretability with CNN pattern recognition for single-motorcycle crash severity. Existing studies often sacrifice interpretability for accuracy, or vice versa, limiting their usefulness for policy-making. Second, there is no research validating whether key risk factors remain consistent across different modeling paradigms, which undermines confidence in findings and their policy relevance. Third, although explainable AI methods such as SHAP are increasingly used, comprehensive frameworks that systematically integrate prediction and interpretation for single-motorcycle crashes are still lacking.

Table 5.1 Overview of research on single-motorcycle crashes injury severity

Authors	Country	Methods	Key findings
Dzinyela et al. (2025)	USA	Partial temporally constrained random parameters logit model with heterogeneity in means	Older riders (≥65), high wind speed, low visibility, weekend crashes, and rural roadways increase severe injury risk. Urban crashes and those under daylight/clear conditions tend to lower severity. Several variables (e.g., age, wind, traffic volume) showed significant temporal variation.
Ferko et al. (2025)	Croatia	Multinomial Logistic Regression (MLR) and Random Forest (RF)	Rider age, alcohol consumption, inappropriate speed, crash type, and road type significantly affect severity. Older riders, county/local roads, curves, and roadside-object crashes increase severity. Sobriety and late hazard detection are linked to less severe injuries.
Alnawmasi et al. (2025)	Australia	Majority class oversampling combined with	Crashes during slowing/stopping reduce injury severity, while right-turn curves, newer motorcycles, scooters,

Table 5.1 Overview of research on single-motorcycle crashes injury severity (Continued)

Authors	Country	Methods	Key findings
		random parameter logit models with heterogeneity in means	ejection, overturns, and dry pavements increase it. Some effects vary by year.
Zulherman et al. (2025)	Japan	Deep Q-learning Network-based Imbalanced Classification (DQNIC) with SHAP	SHAP analysis showed that crash type, road width, terrain, road alignment, and collision point were key contributors. Curve segments, high-speed limits, fixed object collisions, rural roads, and elderly riders increased fatality likelihood.
Wisutwattanasak et al. (2024)	Thailand	XGBoost model with SHAP interpretation	Speeding, alcohol use, and falling asleep were major predictors of severity in nighttime single-vehicle crashes. Time-related factors (e.g. holidays, peak hours) and curved segments were influential in daytime crashes. Rear-end and head-on collisions were key in multivehicle crashes.
Pervez et al. (2022)	Pakistan	Random parameter binary logit model with heterogeneity in means and variances	Fatal injury risk increases in summer, weekends, and morning hours. Older riders, speeding, overtaking, U-turns, intersections, and fixed-object

Table 5.1 Overview of research on single-motorcycle crashes injury severity (Continued)

Authors	Country	Methods	Key findings
			crashes raise fatality likelihood. Crashes involving young riders, pillion passengers, or loss of control lower fatality risk. Female pillion clothing caught in wheels is a unique local risk factor.
Wang (2022)	Taiwan	Binary Logit and Mixed Logit Models accounting for heterogeneity	Midnight crashes, rural roads, traffic islands, dry pavements, high-speed roads, and fixed-object collisions (tree/pole) increase fatality risk in single motorcycle crashes. Helmet non-use, unlicensed status, age 55+, and BAC < 0.03% are critical risk factors.
Sivasankaran et al. (2022)	India	Descriptive statistics and logistic regression	Helmet non-use, underage riding, lack of valid license, tree collisions, rural roads, monsoon, and junction crashes increase fatality risk. Skidding crashes, multi-lane roads, and good weather are associated with lower fatality risk. Urban vs. rural patterns differ by crash type.
Sivasankaran et al. (2021)	India	Ordered logit model	Collision with trees, fixed objects, run-off-road events,

Table 5.1 Overview of research on single-motorcycle crashes injury severity (Continued)

Authors	Country	Methods	Key findings
			bad weather, urban roads, and lack of license increase fatal injury risk. Lower severity is associated with winter season, daylight, younger/working-age riders, U-turns, and overtaking.
Kvasnes et al. (2021)	Norway	Matched case-control design with conditional logistic regression	High accident risk is associated with sharp curves (R < 200 m), especially in segments with multiple adjacent curves that do not meet design standards. Wider lanes showed a trend of increased accident odds, while wider shoulders were linked to decreased odds. Horizontal alignment had greater influence than lane/shoulder widths.
M. Islam (2021)	USA	Mixed logit model with heterogeneity in means and variances	Injury severity patterns differ by age: older riders (>45) face higher fatal/severe injury risk, while younger riders (<25) are more prone to minor injuries. Key factors like helmet use, alcohol, and crash time have different effects across age groups.
Xin et al. (2019)	USA	Conditional logistic regression	Sharp non-reverse curves

Table 5.1 Overview of research on single-motorcycle crashes injury severity (Continued)

Authors	Country	Methods	Key findings
			(≤1500 ft radius) have the highest crash risk (OR=4.92), followed by sharp reverse and moderate reverse curves. Higher speed limits, vertical slopes, auxiliary lanes, and accessibility increase risk. Narrow widths, poor pavement, and reverse design may trigger rider compensation behaviors, reducing risk. Paved shoulders increase crash risk. Curve type interacts with radius in shaping risk.
Xin et al. (2017)	USA	Mixed-effects logistic model (random parameters)	Sharp curves increase severe injury probability by 7.7%; reverse curves by 5.82%. Rider behavior and environment (e.g., lighting, weekend, speed, alcohol, helmet use) significantly affect severity. Random parameters reveal unobserved heterogeneity (e.g., for moderate curves, older riders, and male riders). Poor pavement, full access control, and warning signage affect

Table 5.1 Overview of research on single-motorcycle crashes injury severity (Continued)

Authors	Country	Methods	Key findings
			severity in nuanced ways, often through safety compensation effects.
Shaheed and Gkritza (2014)	USA	Latent Class Multinomial Logit (LC-MNL) model	Speeding, rural roads, dry pavement, collisions with fixed objects, overturns, roadside crashes, no helmet use, and impaired riding increase fatal/major injury risk. Younger riders and crashes in summer were associated with lower severity. Two distinct crash classes were identified, highlighting the value of segmentation in modeling heterogeneity in severity outcomes.

5.4 Empirical Setting

5.4.1 Dataset overview

This study analyzed 5,975 single-motorcycle crashes from Thailand's Highway Accident Information Management System (HAIMS) spanning 2016-2023. HAIMS initially classified crash severity into four distinct levels: property damage only (PDO), minor injury, severe injury, and fatality. Due to the limited representation of severe and fatal crashes in the original four-level classification, which created significant class imbalance issues, these categories were consolidated into a binary framework. This consolidation also avoids the instability that arises when training multi-class models with sparsely populated severity levels and prevents unreliable SHAP attributions for extremely small classes, thereby improving both prediction reliability and interpretability. The binary categories used were: (1) Severe/Fatal (n=2,981, 49.89%) and (2) Minor/PDO (n=2,994, 50.11%). This classification strategy aligns with established practices in machine learning applications for crash severity analysis (Agheli & Aghabayk, 2025; Sadeghi, Aghabayk, & Quddus, 2024) and improves both model performance and result interpretation while preserving analytical rigor. The complete descriptive statistics of all variables are presented in Table 5.2.

5.4.2 Variable categories

The predictor variables were systematically organized into four distinct domains to facilitate comprehensive analysis and support the Random Forest feature selection process. This domain-based classification ensures balanced representation of different risk factor categories while maintaining theoretical coherence with established traffic safety research frameworks.

Temporal Characteristics captured crash timing patterns across years (2016-2023) and lighting conditions. Crashes were relatively evenly distributed across years, with 45.05% occurring during daytime and 54.95% during nighttime conditions (13.96% without electrical lighting, 40.99% with electrical lighting).

Roadway Characteristics included lane configuration, surface types, median treatments, and geometric features. Most crashes occurred on 4-lane (42.64%) and 2-lane roads (36.42%), with 87.05% on asphalt surfaces. Curved roadways accounted for 19.70% of crashes, while various median types showed different crash frequencies.

Environmental Characteristics encompassed weather and surface conditions. Wet road surfaces were present in 6.13% of crashes, with active rainfall during 5.32% of incidents, indicating most crashes occurred under normal weather conditions.

Crash Characteristics included behavioral and operational factors. Speeding was the dominant contributing factor (78.46%), followed by alcohol involvement (11.18%). Other factors included fatigue (2.73%), front-path interruption (3.16%), and unskilled driving (1.02%).

Ethical approval. This research proceeded with ethical authorization (Approval Code: COE No.1/2568) from the Human Research Ethics Office, Suranaree University of Technology, Thailand.

Table 5.2 Distributional characteristics of risk factors for single-motorcycle crashes (N = 5,975)

Variables (Description)	Frequency	Percentage (%)
Injury Severity		
Severe/Fatal	2,981	49.89%
Minor/PDO	2,994	50.11%
Temporal characteristics		
Y2016 (1 if crash occur in 2016; 0 otherwise)	689	11.53%
Y2017 (1 if crash occur in 2017; 0 otherwise)	721	12.07%
Y2018 (1 if crash occur in 2018; 0 otherwise)	823	13.77%
Y2019 (1 if crash occur in 2019; 0 otherwise)	850	14.23%
Y2020 (1 if crash occur in 2020; 0 otherwise)	791	13.24%
Y2021 (1 if crash occur in 2021; 0 otherwise)	737	12.33%
Y2022 (1 if crash occur in 2022; 0 otherwise)	674	11.28%
Y2023 (1 if crash occur in 2023; 0 otherwise)	690	11.55%
DAYTIME (1 if crash during daytime; 0 otherwise)	2,692	45.05%
DARKNESS (1 if crash during nighttime without electrical light; 0 otherwise)	834	13.96%
DARK_WITH_ELEC (1 if crash during nighttime with electrical light; 0 otherwise)	2,449	40.99%
Roadway characteristics		
WORK ZONE (1 if crash in work zone area; 0 otherwise)	275	4.60%
LANE = 2 (1 if crash on 2-lanes road; 0 otherwise)	2,176	36.42%
LANE = 4 (1 if crash on 4-lanes road; 0 otherwise)	2,548	42.64%

Table 5.2 Distributional characteristics of risk factors for single-motorcycle crashes (N = 5,975) (Continued)

Variables (Description)	Frequency	Percentage (%)
LANE = 6 (1 if crash on 6-lanes road; 0 otherwise)	482	8.07%
LANE >=8 (1 if crash on 8-lanes road or wider lanes; 0 otherwise)	670	11.21%
ASPHALT (1 if crash on asphalt road surface; 0 otherwise)	5,201	87.05%
MEDIAN OPENING (1 if crash on road without median; 0 otherwise)	2,177	36.44%
FLUSH AND PAINTED MEDIAN (1 if crash on road with flush and painted median; 0 otherwise)	461	7.72%
RAISED MEDIAN (1 if crash on road with raised median; 0 otherwise)	1,502	25.14%
DEPRESSED MEDIAN (1 if crash on road with depressed median; 0 otherwise)	1,066	17.84%
BARRIER MEDIAN (1 if crash on road with barrier median; 0 otherwise)	594	9.94%
CURVED ROADS (1 if crash on curved roadways; 0 otherwise)	1,177	19.70%
ON SLOPE (1 if crash on slope; 0 otherwise)	127	2.13%
FOUR-LEG_INT (1 if crash at four- legs intersection; 0 otherwise)	106	1.77%
T_INT (1 if crash at T-intersection; 0 otherwise)	167	2.79%
U-TURN (1 if crash at U-turn; 0 otherwise)	179	3.00%
Environmental characteristics		
WET (1 if crash on wet road surface; 0 otherwise)	366	6.13%
RAINING (1 if crash during raining; 0 otherwise)	318	5.32%
Crash characteristics		
SPEEDING (1 if crash caused by exceeding speed limit; 0 otherwise)	4,688	78.46%

Table 5.2 Distributional characteristics of risk factors for single-motorcycle crashes (N = 5,975) (Continued)

Variables (Description)	Frequency	Percentage (%)
FRONT-PATH INTERRUPTION (1 if crash caused by obstruction in front; 0 otherwise)	189	3.16%
UNSKILLED DRIVING (1 if crash caused by unskilled driving; 0 otherwise)	61	1.02%
DRUNK (1 if alcohol use confirmed; 0 otherwise)	668	11.18%
FATIGUE (1 if crash caused by being fatigue; 0 otherwise)	163	2.73%

Notes:

FRONT-PATH INTERRUPTION: police-reported contributing factor indicating that an unexpected obstacle (e.g., animal, debris, roadside object, or surface hazard) entered the motorcycle's travel path ahead, causing evasive action or loss of control.

UNSKILLED DRIVING: police-reported rider factor indicating insufficient riding skill or control (e.g., novice rider, poor curve-handling, improper braking, or maneuvering errors).

5.5 Methodology

5.5.1 Methodological framework overview

This study develops a novel hybrid Random Forest-Convolutional Neural Network (RF-CNN) approach for single-motorcycle crash severity prediction, combining the interpretability strengths of Random Forest with the pattern recognition capabilities of deep learning. The methodological framework encompasses four main phases: (1) data preprocessing and feature engineering, (2) hybrid model development, (3) performance evaluation, and (4) explainability analysis using SHAP (SHapley Additive exPlanations). Figure 5.1 illustrates the complete methodological workflow.

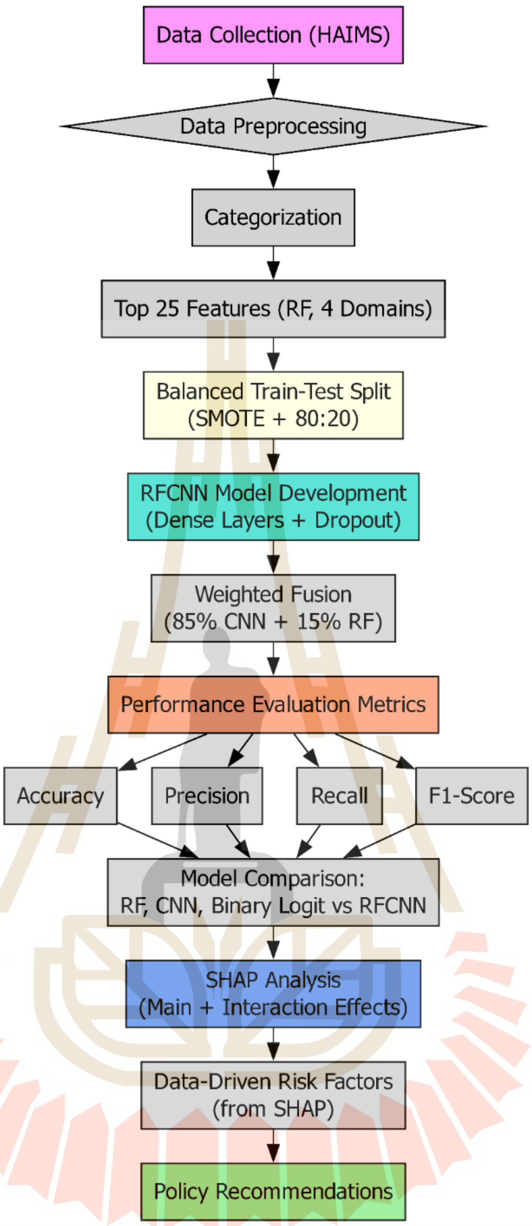

Figure 5.1 Methodological workflow for single-motorcycle crashes severity prediction using RFCNN analysis

5.5.2 Data preprocessing and feature engineering

5.5.2.1 Feature selection strategy

Random Forest was employed as a feature selection mechanism to identify the most predictive variables based on mean decrease in impurity scores. All 34 predictors were ranked using RF Gini importance scores, and alternative feature set sizes (Top 15, 20, 25, and 30) were evaluated within the RF-CNN framework. The top 25 most important features were selected, as this set consistently provided the best balance of accuracy, recall, and F1-score across the 10 random seeds while ensuring balanced representation across the four domains established in Section 5.4.2. RF was selected because it captures non-linear relationships among predominantly categorical crash variables and is relatively robust to multicollinearity. The full RF importance ranking is provided in Appendix A, and the correlation matrix for the selected predictors is presented in Appendix B.

5.5.2.2 Class imbalance treatment

Synthetic Minority Oversampling Technique (SMOTE) was applied prior to the train–test split to address the severe minority-class imbalance. SMOTE creates synthetic interpolated observations rather than duplicating existing cases, ensuring that no true test samples are introduced into the training set (Chawla, Bowyer, Hall, & Kegelmeyer, 2002). For deep and hybrid models, adequate minority-class representation is necessary for stable learning, as extreme imbalance can lead to biased or unstable model behavior (He & Garcia, 2009). Applying SMOTE before splitting ensures a sufficiently balanced feature space for both the Random Forest and CNN components. This approach is consistent with deep-learning crash severity studies in which key feature transformations occur before partitioning and model performance remains robust across data layouts (Yu, Li, Zhang, Liu, & Ma, 2021).

5.5.2.3 Data splitting and standardization

The balanced dataset was partitioned using stratified sampling with an 80:20 train-test split, following established practices in machine learning for crash severity analysis (Acı et al., 2025; Mohsin, Choudhury, & Muyeed, 2025; Sonnatthanon & Choocharukul, 2025).

To ensure robust performance estimates, analysis was conducted across 10 different random seeds (0-9). To quantify robustness across these runs, performance metrics were averaged across seeds and 95% confidence intervals were computed, with results reported in Appendix C. Feature standardization using StandardScaler was applied for the CNN component, while Random Forest utilized original feature scales due to its inherent robustness to scaling differences.

5.5.3 Hybrid Random Forest-Convolutional Neural Network (RF-CNN) model architecture

The proposed hybrid RF-CNN model combines Random Forest interpretability with CNN pattern recognition capabilities through weighted ensemble fusion for single-motorcycle crash severity prediction.

5.5.3.1 Random Forest component

The RF component employs 200 decision trees (n_estimators=200) with maximum depth of 20 levels (max_depth=20) following established RF practices (Breiman, 2001). To address class imbalance, the balanced_subsample class weighting strategy applies balanced weights to each bootstrap sample during tree construction, ensuring each tree receives balanced training data for improved minority class learning.

5.5.3.2 Convolutional Neural Network component

The CNN architecture consists of dense layers designed for tabular data classification: (1) Input Layer accepting 25 standardized features; (2) First Hidden Layer with 64 neurons and ReLU activation; (3) First Dropout Layer with 50% dropout rate; (4) Second Hidden Layer with 32 neurons and ReLU activation; (5) Second Dropout Layer with 50% dropout rate; and (6) Output Layer with 2 neurons and softmax activation for binary classification.

The Adam optimizer (learning rate=0.001) and categorical cross-entropy loss function are employed. Balanced class weights are computed and applied during training to handle class imbalance.

5.5.3.3 Training configuration and regularization

CNN training incorporates multiple regularization techniques: Early Stopping (patience=5 epochs), Learning Rate Reduction (50% reduction when validation loss plateaus for 3 epochs), batch size of 32 samples, maximum 10 epochs, and 20% validation split.

5.5.3.4 Weighted ensemble fusion strategy

The hybrid model integrates the outputs of the Random Forest and CNN through weighted soft voting (Kuncheva, 2014). In soft voting, each model produces a probability vector for the two crash-severity classes, and the final prediction is obtained by combining these probabilities using predefined weights. Formally:

$$P_{final} = \omega_{RF} \times P_{RF} + \omega_{CNN} \times P_{CNN} \tag{6.1}$$

Where P_{RF} and P_{CNN} denote the class-probability vectors generated by the RF and CNN components, respectively, and the weights satisfy $\omega_{RF} + \omega_{CNN} = 1$.

In this study, $\omega_{RF} = 0.15$ and $\omega_{CNN} = 0.85$.

The final class label is assigned according to:

$$\hat{y} = \mathrm{argmax}(P_{final})$$

This weighting scheme (85% CNN / 15% RF) was empirically determined by evaluating several alternative configurations (50/50, 60/40, 70/30, 75/25, 80/20, 85/15, and 90/10) across 10 random seeds using the same training pipeline and feature set. The 85% CNN / 15% RF configuration consistently achieved the strongest overall performance, including the highest recall, competitive F1-scores, and the most stable results across seeds. In this setting, the CNN component captured complex non-linear representations, while the RF component contributed structural robustness and reduced variance. Accordingly, this weighting was adopted for the final RF–CNN hybrid model.

For interpretability purposes, SHAP analysis was conducted using the Seed 8 model, which achieved the strongest recall and F1-score and displayed stable performance consistent with the seed-averaged trends.

5.5.3.5 Cross-validation strategy

The complete pipeline is executed across 10 different random seeds (0-9) with unique stratified train-test splits for each seed, providing robust performance estimates and confidence intervals for all evaluation metrics. This repeated hold-out strategy complements the single-seed results and supports the robustness analysis reported in Appendix C.

5.5.4 Model performance evaluation

5.5.4.1 Evaluation metrics

Model performance was assessed utilizing established binary classification criteria containing accuracy, precision, recall, and F1-Score. Such evaluation measures prove commonly employed in transportation safety research for crash severity analysis (M.-M. Chen & Chen, 2020; Dia et al., 2022; Dong, Khattak, Ullah, Zhou, & Hussain, 2022; Ijaz, Zahid, & Jamal, 2021; Sum et al., 2025; M. Yan & Shen, 2022). These metrics are particularly valuable for crash severity analysis as they provide comprehensive evaluation of model performance across both severity classes, which is crucial for safety applications.

Accuracy: Overall correct classification rate across all samples

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6.2}$$

Precision: Proportion of correctly identified severe/fatal crashes among all predicted severe/fatal cases

$$\text{Precision (P)} = \frac{TP}{TP + FP} \tag{6.3}$$

Recall (Sensitivity): Proportion of actual severe/fatal crashes correctly identified by the model

$$\text{Recall (R)} = \frac{TP}{TP + FN} \tag{6.4}$$

F1-Score: Harmonic mean of precision and recall, providing balanced performance assessment

$$\text{F1\_Score} = \frac{2 \times (R \times P)}{R + P} \tag{6.5}$$

In this context, True positives (TP) and True negatives (TN) correspond to properly classified observations. A false positive (FP) represents a case wrongly categorized as positive, and a false negative (FN) represents a case wrongly categorized as negative.

5.5.4.2 Benchmark comparison

The hybrid RF-CNN model was compared against individual component models (standalone Random Forest and CNN) and a Binary Logistic (BL) regression baseline to demonstrate the effectiveness of the ensemble approach. Binary logistic regression was selected as the traditional statistical benchmark due to its widespread use in crash severity analysis and its ability to provide interpretable coefficients for risk factor assessment (C.-F. Chen & Mu, 2022; Haworth & Debnath, 2013; Rezapour, Molan, & Ksaibati, 2020; Tamakloe, Das, Aidoo, & Park, 2022; Wong, Yang, & Szeto, 2021; X. Yan, Ma, Huang, Abdel-Aty, & Wu, 2011). This comparison allows for evaluation of whether the proposed hybrid approach provides meaningful improvements over established statistical methods. Performance comparison was conducted using identical feature sets and evaluation protocols to ensure fair comparison.

To maintain methodological coherence and ensure a fair comparison, more advanced ensemble and hybrid models (e.g., XGBoost, LightGBM, RF-LSTM, CNN-Transformer) were not included. Evaluating such architectures would require substantial hyperparameter tuning and architectural modifications that fall beyond the scope of this study. The benchmarking in this work focuses on widely used and theoretically distinct baselines (BL, RF, and CNN). Future research will expand evaluation to additional state-of-the-art models to further assess generalizability and robustness.

5.5.5 Model interpretability framework

5.5.5.1 SHAP analysis implementation

To overcome the interpretability challenges inherent in the hybrid RF-CNN model while maintaining its predictive capabilities, this study implements SHAP analysis, an explainability method recommended by Ali et al. (2024).

The SHAP methodology, developed by Lundberg and Lee (2017), leverages cooperative game theory foundations to improve machine learning model transparency. This technique determines feature significance by assessing the influence of individual input variables on crash severity predictions (Štrumbelj & Kononenko, 2014). SHAP functions using a differential evaluation approach: it compares predictions from a comprehensive model incorporating all 25 selected features against simplified models with targeted features excluded. This comparative analysis quantifies individual feature contributions to severe/fatal crash predictions through SHAP scores (Tahfim & Yan, 2021), mathematically represented as:

$$\varnothing_i = \sum_{S \subseteq X \setminus \{i\}} \frac{|S|!\left(|X| - |S| - 1\right)!}{|X|!}\left[f_{S\cup\{i\}}\left(x_{S\cup\{i\}}\right) - f_S\left(x_S\right)\right] \tag{6.6}$$

In this equation, $\varnothing_i$ represents the SHAP value, X denotes the entire feature space, S indicates different feature subsets, and x_S refers to the corresponding feature values in these subsets. The approach measures the difference between predictions from $f_{S\cup\{i\}}$ (incorporating the specific feature) and f_S (excluding the specific feature). Given the complex interactions among crash factors, this computational process requires evaluation across all possible feature combination permutations (Lundberg & Lee, 2017).

Unlike previous SHAP-based motorcycle crash studies that used SHAP with single-model architectures (e.g., XGBoost or DQNIC), the present study applies SHAP to a heterogeneous RF–CNN ensemble. This allows interpretation of hybrid decision processes that integrate tree-based rule learning with deep pattern extraction. In addition, the SHAP analysis includes interaction plots to reveal how roadway, lighting, and behavioral factors jointly influence severity—an aspect not examined in earlier SHAP applications. KernelExplainer was used to compute SHAP values for the hybrid model. Following best practices for explainability, SHAP computations were performed on the Seed 8 model, which achieved the strongest recall and F1-score, while seed-averaged performance statistics (mean ± 95% CI) are reported in Appendix C to demonstrate robustness across multiple initializations.

5.5.5.2 Feature importance and interaction analysis

Two complementary SHAP visualizations were generated:

Global feature importance: Summary plots (bee swarm plots) displaying feature importance rankings and impact directions across all test samples. Each point represents a single prediction, with color indicating feature value (red = high, blue = low) and x-axis position showing SHAP value magnitude and direction.

Feature interaction analysis: Dependence plots examining pairwise feature interactions for critical risk factors. These plots reveal how feature effects vary depending on values of other features, identifying synergistic or antagonistic relationships between risk factors.

5.6 Results and Discussion

5.6.1 Model performance evaluation

5.6.1.1 Baseline model comparison before feature selection

The initial model evaluation established performance baselines using the complete feature set from the HAIMS dataset, providing a foundation for subsequent feature selection impact assessment. Table 5.3 presents comparative performance metrics across different modeling approaches when utilizing all available variables without dimensionality reduction. The standalone CNN achieved the highest accuracy at 55.7%, followed by Random Forest at 54.6%, while the hybrid RF-CNN model obtained 53.9% accuracy. However, the RF-CNN model demonstrated a notably different performance profile, achieving substantially higher recall (73.8%) compared to both RF (53.7%) and CNN (53.7%), which resulted in the highest F1-Score of 0.616 among all models, surpassing both RF (0.541) and CNN (0.547) by considerable margins. This 12.9% improvement in F1-Score over CNN and 13.9% over RF indicates the hybrid model's superior capability in balancing precision and recall, particularly in identifying severe/fatal crashes despite lower overall accuracy. The high recall but lower precision (52.8%) suggests the model's tendency to prioritize sensitivity in detecting severe crashes when using the full feature set.

5.6.1.2 Enhanced performance through strategic feature selection

The implementation of Random Forest-based feature selection methodology, which systematically identified the top 25 most predictive variables across four analytical domains (temporal, roadway, environmental, and crash characteristics), yielded substantial performance improvements across all evaluated models. Table 5.4 demonstrates the enhanced metrics achieved through this dimensionality reduction approach. The hybrid RF-CNN model achieved the highest overall performance with 58.9% accuracy, representing a 9.3% relative improvement compared to its performance with all features. This improvement was accompanied by better balance between precision (57.3%) and recall (69.9%), yielding the highest F1-Score of 0.630 among all models.

Although the absolute accuracy gain over the strongest individual baseline (CNN: 56.3%) is modest at approximately 2.6% (≈ 3%), such incremental improvements are typical for heterogeneous crash datasets dominated by categorical variables. In safety–critical crash prediction tasks, the primary value of the hybrid model lies not in marginal accuracy gains but in its substantially higher recall and F1-score, which directly determine its effectiveness in detecting severe/fatal crashes.

More importantly, the RF–CNN model demonstrates a clear improvement in identifying high-severity outcomes, achieving a recall of 69.9%, compared with BL (58.7%), RF (54.5%), and CNN (56.5%). This gain substantially reduces false negatives—cases in which severe crashes are incorrectly classified as minor—which is critical for emergency response prioritization and infrastructure risk screening. While the corresponding precision (57.3%) indicates a higher number of false positives, such conservative over-classification is generally acceptable in transportation safety analytics, where the consequences of missing severe crashes are far greater than those of over-flagging lower-severity events. Consequently, recall and F1-score provide a more meaningful basis than accuracy for evaluating model performance in this context.

To further evaluate robustness, the RF–CNN model was trained across 10 random seeds. The mean F1-score (0.569; 95% CI: 0.541–0.597) and mean recall (0.586; 95% CI: 0.535–0.637) confirm that the selected Seed 8 model reflects performance within the upper but consistent range of expected outcomes. Detailed results appear in Appendix C.

The traditional Binary Logistic (BL) regression baseline achieved 58.3% accuracy with balanced precision (58.1%) and recall (58.7%), but its lower recall relative to the hybrid model indicates a higher likelihood of missing severe crashes. Similarly, although Random Forest and CNN showed minor accuracy improvements after feature selection (RF: 54.6%⟶54.9%; CNN: 55.7%⟶56.3%), neither matched the hybrid approach's performance. The consistently higher F1-score and recall of the RF–CNN framework highlight the value of combining tree-based structure with deep pattern recognition to support severe-crash detection in safety-critical domains.

5.6.1.3 Comparative analysis of model trade-offs

The results reveal distinct performance trade-offs between models. The RF-CNN hybrid approach prioritizes recall (69.9%) over precision (57.3%), making it particularly suitable for safety-critical applications where missing severe crashes (false negatives) carries higher consequences than false alarms. In contrast, the BL model maintains more balanced precision-recall trade-offs but at the cost of missing more severe crashes.

The feature selection process not only improved accuracy across all models but also enhanced the balance between precision and recall. For the RF-CNN model, precision increased from 52.8% to 57.3% (8.5% relative improvement) while maintaining high recall (69.9% vs. 73.8%), demonstrating that the selected features provide cleaner decision boundaries for classification.

Table 5.3 Comparison of models' performance using all features

Models	Accuracy	Precision	Recall	F1-Score
RF	0.546	0.546	0.537	0.541
CNN	0.557	0.558	0.537	0.547
RF-CNN	0.539	0.528	0.738	0.616

Table 5.4 Comparison of models' performance using significant features between RF-CNN and benchmark models

Models	Accuracy	Precision	Recall	F1-Score
RF	0.549	0.548	0.545	0.547
CNN	0.563	0.562	0.565	0.564
BL	0.583	0.581	0.587	0.584
RF-CNN	0.589	0.573	0.699	0.630

5.6.2 Model interpretation and explainability analysis

5.6.2.1 Global feature importance rankings

The SHAP analysis of the RF-CNN model trained on the top 25 features provides comprehensive insights into the hierarchical importance of factors determining single-motorcycle crash severity, ordered by their mean absolute SHAP values from top to bottom (Figure 5.2). The summary plot presents features ordered by their influence on model predictions for severe/fatal crash outcomes, where each point represents an individual crash observation. The horizontal position indicates the magnitude and direction of that feature's contribution to severity prediction, while the color gradient from blue (low feature values) to red (high feature values) reveals how different feature states affect crash outcomes.

At the top of the hierarchy, DARK_WITH_ELEC emerges as the most influential factor, showing predominantly positive SHAP values, indicating that nighttime crashes with electrical lighting increase severe/fatal crash probability. This evidence supports Wisutwattanasak et al. (2024) who found nighttime conditions as major predictors of severity in single-vehicle crashes, and Wang (2022) who found that midnight crashes increase fatality risk.

Following in importance, LANE = 4 displays mixed SHAP patterns with both positive and negative values, indicating that the effect of four-lane roads on crash severity depends on other contextual factors and interactions. Especially, four-lane roads increased crash severity in most contexts, likely due to higher traffic volumes and speeds, but showed reduced severity effects in specific urban nighttime scenarios, possibly reflecting lower traffic density and improved lighting conditions

(Shaheed & Gkritza, 2014; Sum et al., 2025; Vajari, Aghabayk, Sadeghian, & Shiwakoti, 2020).

Subsequently, DAYTIME shows predominantly negative SHAP values (red points on negative side), indicating that daytime conditions decrease severe/fatal crash probability, providing protective effects. This supports Sivasankaran et al. (2021) findings that daylight conditions are associated with lower severity outcomes.

Among the geometric factors, CURVED ROADS exhibits positive SHAP values when present, confirming that curved roadway geometry increases crash severity risk. This finding strongly supports Xin et al. (2017) who found that sharp curves increase severe injury probability by 7.7%, and Kvasnes et al. (2021) who identified sharp curves as high accident risk factors.

In terms of infrastructure characteristics, MEDIAN OPENING shows positive SHAP contributions, indicating that roads without median barriers increase severity risk compared to roads with median treatments.

Regarding construction areas, WORK ZONE exhibits negative SHAP values, indicating that temporary speed reductions, increased rider vigilance, and visual warnings in construction environments collectively lower the likelihood of severe or fatal outcomes—a pattern consistent with M. Islam (2022).

Concerning behavioral factors, SPEEDING shows positive SHAP values when present (red points on positive side), indicating that speeding increases crash severity risk, while its absence contributes negatively to severity predictions. Despite being present in 78.46% of crashes, its moderate ranking suggests other factors have stronger discriminating power for severity prediction.

Continuing down the hierarchy, temporal factors including various years (Y_2018, Y_2021, Y_2023) show different directional effects reflecting potential temporal variations in crash patterns. The relatively high SHAP contributions of the temporal indicators do not imply direct year-to-year causation but instead reflect broader contextual shifts occurring during those periods. These variables likely capture changes in traffic exposure, crash reporting completeness, enforcement intensity, and post-COVID mobility patterns. SHAP interaction patterns further show that year effects often amplify the influence of geometric and behavioral predictors such as CURVED

ROADS, SPEEDING, and WORK ZONE. Thus, the temporal variables are best interpreted as proxies for unobserved contextual conditions rather than independent determinants of crash severity.

Infrastructure elements such as DEPRESSED MEDIAN, RAISED MEDIAN, and BARRIER MEDIAN display varying protective or risk-enhancing effects. Behavioral factors like DRUNK show positive contributions when present, consistent with Pervez et al. (2022) and Ferko et al. (2025) findings on alcohol involvement. It should be noted, however, that alcohol involvement is often underreported in Thai crash databases due to limited roadside testing and inconsistent post-crash screening, meaning the 11.18% prevalence in the dataset likely understates the true magnitude of alcohol-related risks. Environmental factors including WET conditions and ON SLOPE demonstrate positive SHAP values, supporting Alnawmasi et al. (2025) findings on adverse conditions increasing severity risk.

To clarify the distinction between global and interaction SHAP effects, global SHAP summary plots capture the average influence of each predictor, while interaction plots show how feature effects change when combined with other variables. DARK_WITH_ELEC appears highly influential in the global analysis because roadway lighting in Thailand is typically installed on multilane arterials, divided highways, and curved segments—locations with inherently higher severity risk due to geometric complexity and higher travel speeds. SHAP interaction results further indicate that its effect intensifies when combined with CURVED ROADS, SPEEDING, and wider lane configurations. This pattern aligns with the speed-compensation phenomenon, where drivers travel faster under illuminated conditions. Thus, the elevated SHAP values reflect roadway context and behavioral adaptation rather than lighting itself causing higher injury severity.

5.6.2.2 Feature interaction analysis and dependency patterns

The SHAP dependence plots (Figure 5.3) reveal complex interaction patterns that demonstrate how feature effects vary depending on other variables, highlighting the hybrid RF-CNN approach's capability to capture non-linear relationships.

1) *Temporal-infrastructure interactions*

The DARK_WITH_ELEC × CURVED ROADS interaction (Figure 5.3a) shows amplified positive SHAP contributions when nighttime conditions coincide with curved roadways, indicating that electrical lighting cannot fully compensate for combined visibility and geometric risks. The DAYTIME × CURVED ROADS interaction (Figure 5.3c) demonstrates that daylight's protective effects are diminished on curved roads, suggesting geometric complexity can override visibility advantages.

2) Lane configuration and geometric interactions

The LANE = 4 × MEDIAN OPENING interaction (Figure 5.3d) reveals that four-lane roads exhibit different severity effects depending on median infrastructure, explaining the mixed global importance results. The CURVED ROADS × WORK ZONE interaction (Figure 5.3e) shows that geometric complexity combined with construction activities creates particularly hazardous scenarios with amplified positive SHAP contributions.

3) Behavioral-environmental interactions

The DARK_WITH_ELEC × SPEEDING interaction (Figure 5.3b) reveals that speed violations during nighttime conditions create disproportionate severity risks through exponential rather than additive effects. The SPEEDING × WORK ZONE interaction (Figure 5.3f) demonstrates multiplicative risk escalation when behavioral violations occur under constrained construction conditions.

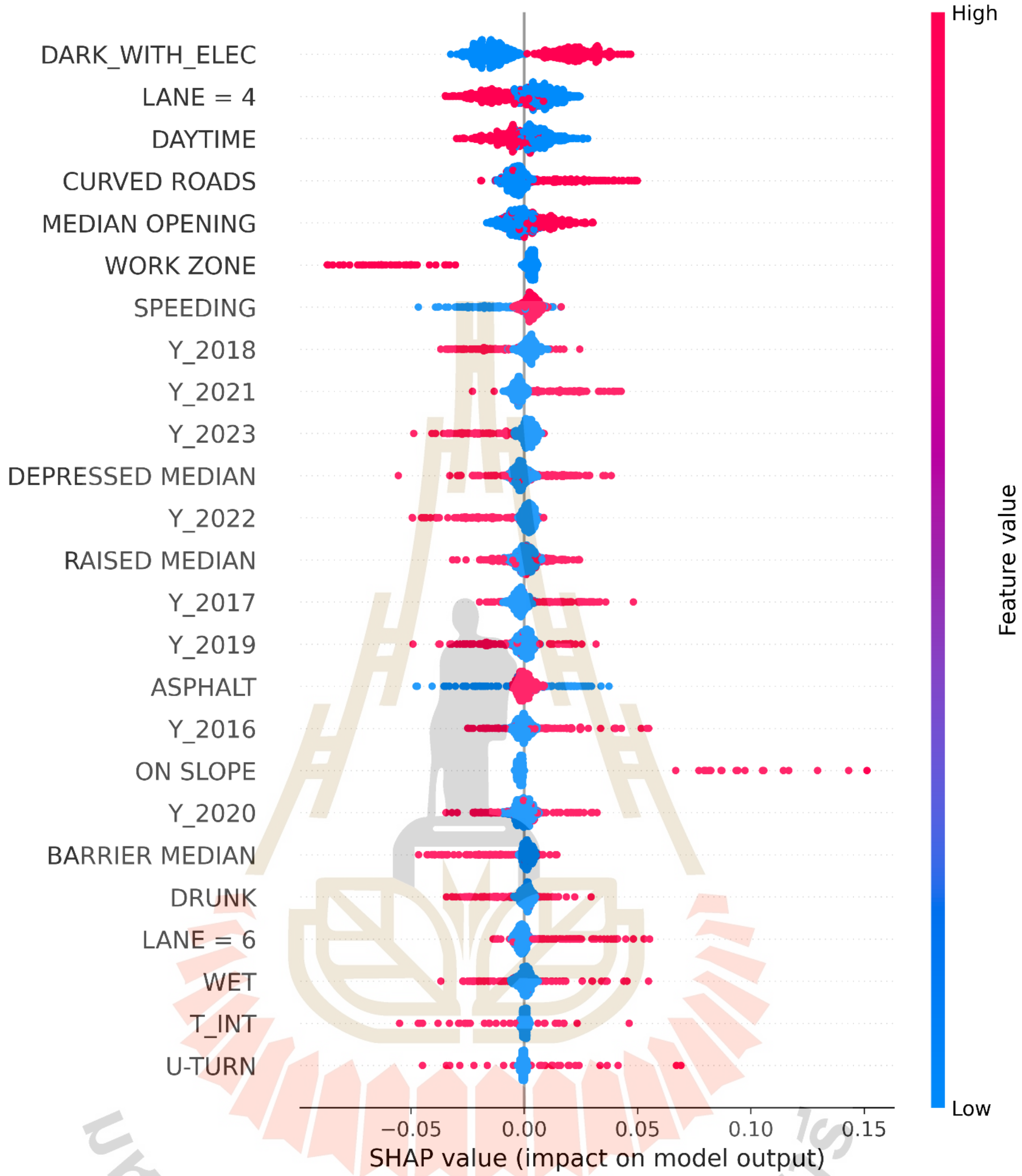

Figure 5.2 SHAP summary plot for feature impact on the model output for single-motorcycle crashes

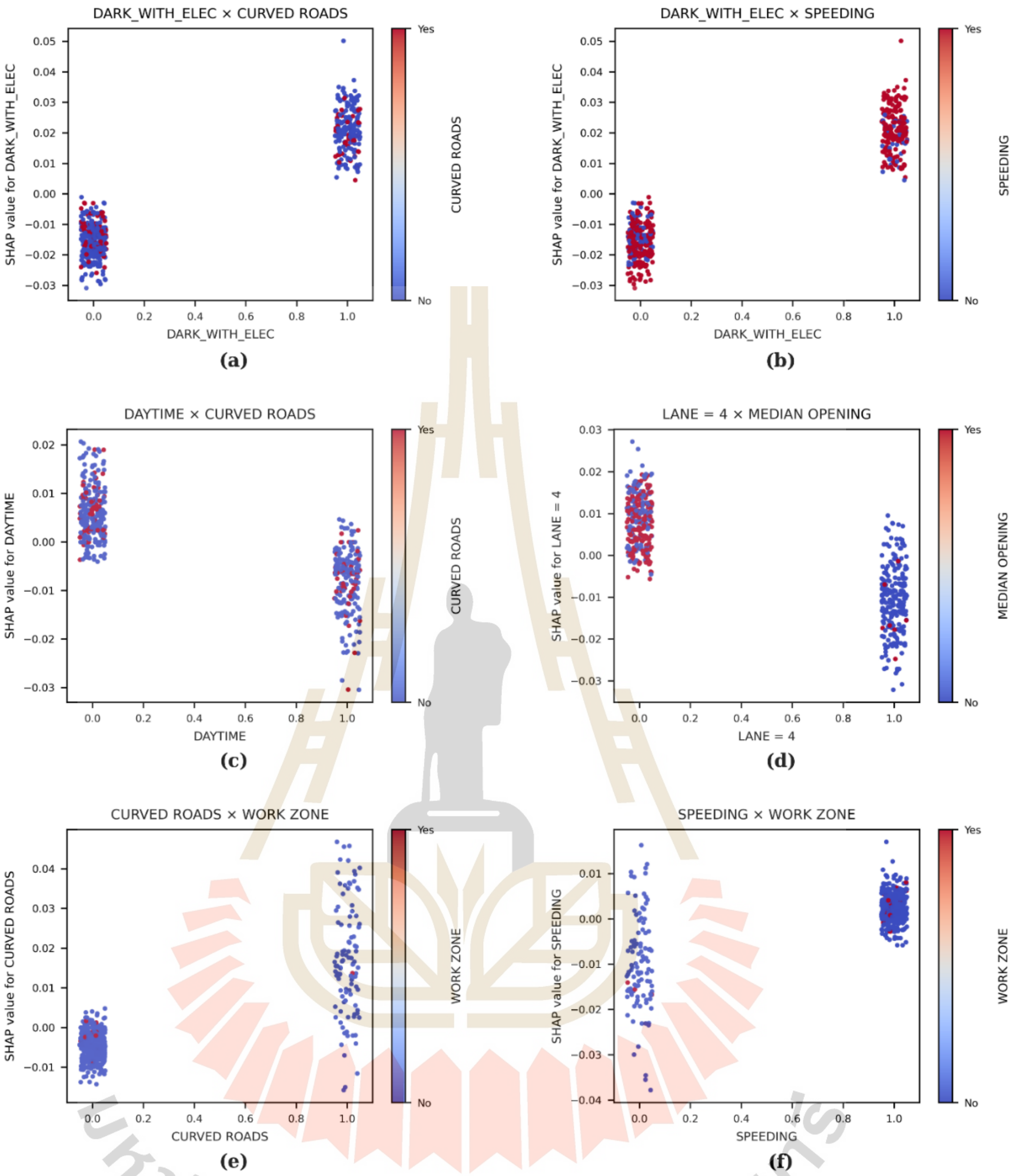

Figure 5.3 SHAP dependence plots illustrating feature interactions in single-motorcycle crashes

5.6.2.3 Policy implications and safety intervention priorities

The SHAP analysis identifies critical determinants of single-motorcycle crash severity in Thailand, providing an empirical basis for formulating targeted safety interventions. The results indicate several policy priorities. ***(1) Lighting and speed management:*** Improved lighting should be prioritized on high-risk curves, with phased deployment of LED systems consistent with international standards.

Weather-responsive activation may be piloted at selected sites, given cost constraints. Curve-specific speed limits reduced by 15–20 km/h below posted limits should be introduced through regulatory adjustments, with enforcement supported by Thailand's automated and mobile camera systems. Median upgrades to concrete barriers are recommended for high-crash corridors, while preserving essential community access. ***(2) Work zones:*** Nighttime work zones on curves require extended warning distances and temporary lighting. Specifications for contractors should mandate a 300-meter advance warning and encourage the use of dynamic message signs, consistent with Thailand's existing Variable Message Sign network. ***(3) Targeted enforcement:*** Nighttime enforcement should focus on speeding violations under DARK_WITH_ELEC and DARKNESS conditions identified as high-risk by SHAP. Mobile Highway Police units and automated cameras can support this strategy, with priority given to high-crash corridors. ***(4) Pavement treatments:*** High-friction surfaces should be installed on curves where crash frequencies exceed regional averages, particularly at sites with recurring nighttime crashes. ***(5) Rider training:*** Motorcycle-specific training on curve navigation should be integrated into Thailand's license renewal and rider education programs, with emphasis on young motorcyclists and ride-hailing drivers.

While detailed cost estimates are beyond the scope of the present dataset, SHAP effect magnitudes provide a principled basis for prioritizing feasible interventions. High-impact factors—such as roadway curvature, speeding, nighttime lighting conditions, and limited median protection—should be addressed first through low-cost, high-impact countermeasures (e.g., curve-specific LED lighting upgrades, targeted nighttime speed enforcement, and high-friction surfacing). Importantly, SHAP interaction results highlight compound risk contexts such as DARK_WITH_ELEC × CURVED ROADS, DARK_WITH_ELEC × SPEEDING, and LANE = 4 × MEDIAN OPENING, where combined effects significantly elevate injury severity. These interaction-informed insights enable transportation agencies to direct resources toward locations where multiple risk factors converge. More resource-intensive geometric improvements can subsequently be phased in as budgets allow, supported by project-level cost–benefit assessments conducted by local authorities.

5.7 Conclusion

This study developed a novel hybrid Random Forest-Convolutional Neural Network (RF-CNN) approach for predicting injury severity in single-motorcycle crashes using 5,975 crashes from Thailand's Highway Accident Information Management System (2016-2023). The research addresses critical gaps in transportation safety by combining Random Forest's interpretability with CNN's pattern recognition capabilities through weighted ensemble fusion.

The hybrid RF-CNN model achieved superior performance with 58.9% accuracy and notably high recall (69.9%), outperforming standalone Random Forest (54.9%), CNN (56.3%), and Binary Logistic regression (58.3%). Critically, the high recall performance addresses a key limitation in safety-critical applications where missing severe/fatal crashes carries higher consequences than false alarms. Random Forest-based feature selection of the top 25 variables across four domains significantly improved model performance, with the RF-CNN showing 9.3% accuracy increase compared to using all features.

The methodological framework demonstrates several innovations: The weighted ensemble fusion strategy (15% RF, 85% CNN) effectively combines CNN's superior predictive performance with RF's interpretability insights, while SMOTE implementation and balanced class weighting strategies address class imbalance challenges. Most importantly, this approach proves that advanced machine learning can provide both superior predictive accuracy and transparent decision-making processes essential for safety-critical applications, resolving the traditional accuracy-interpretability trade-off.

SHAP explainability analysis revealed nighttime conditions with electrical lighting as the most influential factor, followed by lane configuration effects, curved roadway geometry, and behavioral factors including speeding and alcohol involvement. The key finding is the identification of complex interaction effects, such as amplified risk when nighttime conditions coincide with curved roadways, demonstrating the hybrid model's capability to capture non-linear risk relationships that traditional statistical methods might miss.

The practical contributions include evidence-based guidance for targeted safety interventions: enhanced lighting systems on curved roadway segments, curve-specific speed limit reductions of 15-20 km/h with automated enforcement, median infrastructure upgrades on high-crash corridors, improved work zone safety protocols requiring 300-meter warning distances for nighttime construction, and integration of motorcycle-specific curve navigation training into license programs.

While the findings are promising, the study's scope is limited to single-motorcycle crashes in Thailand and relies on binary severity classification and historical tabular data. These factors may constrain generalizability to other crash types, geographic contexts, or real-time operational use. Future research should evaluate the RF–CNN framework across different regions, extend it to multi-class severity outcomes, and explore integration with real-time monitoring systems to support proactive safety management.

This research contributes to explainable AI applications in transportation safety, demonstrating that hybrid modeling approaches can balance competing demands of accuracy and interpretability. The findings are particularly valuable for developing countries experiencing rapid motorization where traditional statistical approaches may be insufficient for capturing complex risk relationships. The integration of advanced machine learning with comprehensive explainability analysis establishes a foundation for evidence-based motorcycle safety interventions and provides a replicable methodological framework for advanced crash severity analysis in developing country contexts.

5.8 Limitations and Future Research

Several limitations should be acknowledged. First, the study focuses exclusively on single-motorcycle crashes in Thailand, limiting generalizability to other crash types and geographic contexts. Future research should validate the RF-CNN approach across different configurations and international settings to address methodological gaps in machine learning-based crash prediction models (Ali et al., 2024). Second, while the hybrid model achieves superior recall performance, the precision-recall trade-off (57.3% vs. 69.9%) may result in false positive predictions, requiring exploration of dynamic threshold optimization approaches to address class imbalance challenges in crash severity prediction (Roudnitski, 2024). Third, the framework utilizes traditional tabular features without incorporating real-time traffic conditions, weather sensor data, or road surface monitoring systems that have shown promise in proactive traffic safety management (M. R. Islam et al., 2024). Integration of multi-source data including connected vehicle information and environmental sensor networks could enhance prediction accuracy and enable real-time risk assessment capabilities (Yuanyuan Xiao & Duan, 2025). Fourth, the binary classification approach (severe/fatal vs. minor/PDO) simplifies the original four-level severity classification. Future research should investigate multi-class extensions and real-time data integration to enhance prediction accuracy. Finally, although the hybrid RF-CNN model improves accuracy by about 3%, its main contribution lies in higher recall and F1-Score, which are more relevant for detecting severe/fatal crashes. Given the heterogeneous nature of crash data, modest accuracy gains are common. Future work should examine whether this performance pattern—particularly the high recall—is consistent when the RF-CNN framework is applied to different crash types or data environments.

5.9 References

Acı, Ç. İ., Mutlu, G., Ozen, M., & Acı, M. (2025). Enhanced Multi-Class Driver Injury Severity Prediction Using a Hybrid Deep Learning and Random Forest Approach. *Applied Sciences (2076-3417), 15*(3). doi:https://doi.org/10.3390/app15031586

Adanu, E. K., Powell, L., Jones, S., & Smith, R. (2023). Learning about injury severity from no-injury crashes: A random parameters with heterogeneity in means and variances approach. *Accident Analysis & Prevention, 181*, 106952. doi:https://doi.org/10.1016/j.aap.2022.106952

Agheli, A., & Aghabayk, K. (2025). How does distraction affect cyclists' severe crashes? A hybrid CatBoost-SHAP and random parameters binary logit approach. *Accident Analysis & Prevention, 211*, 107896. doi:https://doi.org/10.1016/j.aap.2024.107896

Ali, Y., Hussain, F., & Haque, M. M. (2024). Advances, challenges, and future research needs in machine learning-based crash prediction models: A systematic review. *Accident Analysis & Prevention, 194*, 107378. doi:https://doi.org/10.1016/j.aap.2023.107378

Alnawmasi, N., Ziakopoulos, A., Theofilatos, A., & Ali, Y. (2025). Understanding the effects of underreporting on injury severity estimation of single-vehicle motorcycle crashes: A hybrid approach incorporating majority class oversampling and random parameters with heterogeneity-in-means. *Analytic Methods in Accident Research, 45*, 100372. doi:https://doi.org/10.1016/j.amar.2025.100372

Babaei, Z., & Kunt, M. M. (2024). A correlated random parameters ordered probit approach to analyze the injury severity of bicycle-motor vehicle collisions at intersections. *Accident Analysis & Prevention, 196*, 107447. doi:https://doi.org/10.1016/j.aap.2023.107447

Bhuiyan, H., Ara, J., Hasib, K. M., Sourav, M. I. H., Karim, F. B., Sik-Lanyi, C., . . . Yasmin, S. (2022). Crash severity analysis and risk factors identification based on an alternate data source: a case study of developing country. *Scientific Reports, 12*(1), 21243. doi:https://doi.org/10.1038/s41598-022-25361-5

Borisov, V., Leemann, T., Seßler, K., Haug, J., Pawelczyk, M., & Kasneci, G. (2022). Deep neural networks and tabular data: A survey. *IEEE transactions on neural networks and learning systems, 35*(6), 7499-7519. doi:https://doi.org/10.1109/TNNLS.2022.3229161

Breiman, L. (2001). Random forests. *Machine learning, 45*, 5-32.

Cai, Z., & Wei, F. (2023). Modelling injury severity in single-vehicle crashes using full Bayesian random parameters multinomial approach. *Accident Analysis & Prevention, 183*, 106983. doi:https://doi.org/10.1016/j.aap.2023.106983

Champahom, T., Wisutwattanasak, P., Chanpariyavatevong, K., Laddawan, N., Jomnonkwao, S., & Ratanavaraha, V. (2022). Factors affecting severity of motorcycle accidents on Thailand's arterial roads: multiple correspondence analysis and ordered logistics regression approaches. *IATSS research, 46*(1), 101-111. doi:https://doi.org/10.1016/j.iatssr.2021.10.006

Chan, J. Y.-L., Leow, S. M. H., Bea, K. T., Cheng, W. K., Phoong, S. W., Hong, Z.-W., & Chen, Y.-L. (2022). Mitigating the multicollinearity problem and its machine learning approach: a review. *Mathematics, 10*(8), 1283. doi:https://doi.org/10.3390/math10081283s

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research, 16*, 321-357. doi:https://doi.org/10.1613/jair.953

Chen, C.-F., & Mu, P.-J. (2022). Multilevel analysis of injury severity of elderly motorcycle riders: The role of regional transport development. *Traffic injury prevention, 23*(2), 102-106. doi:https://doi.org/10.1080/15389588.2022.2027925

Chen, M.-M., & Chen, M.-C. (2020). Modeling road accident severity with comparisons of logistic regression, decision tree and random forest. *Information, 11*(5), 270. doi:https://doi.org/10.3390/info11050270

Dia, Y., Faty, L., Sarr, M. D., Sall, O., Bousso, M., & Landu, T. T. (2022). *Study of supervised learning algorithms for the prediction of road accident severity in Senegal.* Paper presented at the 2022 7th International Conference on Computational Intelligence and Applications (ICCIA).

Dong, S., Khattak, A., Ullah, I., Zhou, J., & Hussain, A. (2022). Predicting and analyzing road traffic injury severity using boosting-based ensemble learning models with SHAPley Additive exPlanations. *International journal of environmental research and public health, 19*(5), 2925. doi:https://doi.org/10.3390/ijerph19052925

Dzinyela, R., Dadashova, B., Adanu, E. K., & Lord, D. (2025). Assessing single motorcycle crash injury severity factor using a novel partial temporally constrained random parameters logit model. *Transportmetrica A: Transport Science*, 1-27. doi:https://doi.org/10.1080/23249935.2025.2478307

Esmaili, A., Aghabayk, K., & Shiwakoti, N. (2022). Latent class cluster analysis and mixed logit model to investigate pedestrian crash injury severity. *Sustainability, 15*(1), 185. doi:https://doi.org/10.3390/su15010185

Ferko, M., Babić, D., & Pirdavani, A. (2025). Riding the Edge–Unveiling the Key Factors behind Injury Severity in Single-Vehicle Motorcycle Crashes. *Promet-*

Traffic&Transportation, 37(4), 834-852. doi:https://doi.org/10.7307/ptt.v37i4.1091

Haworth, N., & Debnath, A. K. (2013). How similar are two-unit bicycle and motorcycle crashes? *Accident Analysis & Prevention, 58*, 15-25. doi:https://doi.org/10.1016/j.aap.2013.04.014

He, H., & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on knowledge and data engineering, 21*(9), 1263-1284. doi:https://doi.org/10.1109/TKDE.2008.239

Ijaz, M., Zahid, M., & Jamal, A. (2021). A comparative study of machine learning classifiers for injury severity prediction of crashes involving three-wheeled motorized rickshaw. *Accident Analysis & Prevention, 154*, 106094. doi:https://doi.org/10.1016/j.aap.2021.106094

Islam, M. (2021). The effect of motorcyclists' age on injury severities in single-motorcycle crashes with unobserved heterogeneity. *Journal of safety research, 77*, 125-138. doi:https://doi.org/10.1016/j.jsr.2021.02.010

Islam, M. (2022). An analysis of motorcyclists' injury severities in work-zone crashes with unobserved heterogeneity. *IATSS research, 46*(2), 281-289. doi:https://doi.org/10.1016/j.iatssr.2022.01.003

Islam, M. R., Wang, D., & Abdel-Aty, M. (2024). Calibrated confidence learning for large-scale real-time crash and severity prediction. *npj Sustainable Mobility and Transport, 1*(1), 1. doi:https://doi.org/10.1038/s44333-024-00001-9

Islam, S. M., Washington, S., Kim, J., & Haque, M. M. (2023). A hierarchical multinomial logit model to examine the effects of signal strategies on right-turn crash injury severity at signalised intersections. *Accident Analysis & Prevention, 188*, 107091. doi:https://doi.org/10.1016/j.aap.2023.107091

Kuncheva, L. I. (2014). *Combining pattern classifiers: methods and algorithms*: John Wiley & Sons.

Kvasnes, S., Pokorny, P., Jensen, J. K., & Pitera, K. (2021). Safety effects of horizontal curve design and lane and shoulder width on single motorcycle accidents in Norway. *Journal of advanced transportation, 2021*(1), 6684334. doi:https://doi.org/10.1155/2021/6684334

Lee, D., Guldmann, J.-M., & von Rabenau, B. (2023). Impact of driver's age and gender, built environment, and road conditions on crash severity: a logit modeling approach. *International journal of environmental research and public health, 20*(3), 2338. doi:https://doi.org/10.3390/ijerph20032338

Lin, M.-R., & Kraus, J. F. (2009). A review of risk factors and patterns of motorcycle injuries. *Accident Analysis & Prevention, 41*(4), 710-722. doi:https://doi.org/10.1016/j.aap.2009.03.010

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems, 30*. doi:https://doi.org/10.48550/arXiv.1705.07874

Mansoor, U., Jamal, A., Su, J., Sze, N., & Chen, A. (2023). Investigating the risk factors of motorcycle crash injury severity in Pakistan: Insights and policy recommendations. *Transport policy, 139*, 21-38. doi:https://doi.org/10.1016/j.tranpol.2023.05.013

Mohsin, A. S., Choudhury, S. H., & Muyeed, M. A. (2025). Automatic priority analysis of emergency response systems using internet of things (IoT) and machine learning (ML). *Transportation Engineering, 19*, 100304. doi:https://doi.org/10.1016/j.treng.2025.100304

Mphekgwana, P. M. (2022). Influence of environmental factors on injury severity using ordered Logit regression model in limpopo province, South Africa. *Journal of environmental and public health, 2022*(1), 5040435. doi:https://doi.org/10.1155/2022/5040435

Park, S., & Park, J. (2022). Multilevel mixed-effects models to identify contributing factors on freight vehicle crash severity. *Sustainability, 14*(19), 11804. doi:https://doi.org/10.3390/su141911804

Pervez, A., Lee, J., Huang, H., & Zhai, X. (2022). What factors would make single-vehicle motorcycle crashes fatal? Empirical evidence from Pakistan. *International journal of environmental research and public health, 19*(10), 5813. doi:https://doi.org/10.3390/ijerph19105813

Rezapour, M., Molan, A. M., & Ksaibati, K. (2020). Analyzing injury severity of motorcycle at-fault crashes using machine learning techniques, decision tree and logistic regression models. *International journal of transportation science and technology, 9*(2), 89-99. doi:https://doi.org/10.1016/j.ijtst.2019.10.002

Rezapour, M., Wulff, S. S., Mehrara Molan, A., & Ksaibati, K. (2021). Application of Bayesian ordinal logistic model for identification of factors to traffic barrier crashes: considering roadway classification. *Transportation letters, 13*(4), 308-314. doi:https://doi.org/10.1080/19427867.2020.1728041

Roudnitski, A. (2024). Evaluating road crash severity prediction with balanced ensemble models. *Findings*. doi:https://doi.org/10.32866/001c.116820

Sadeghi, M., Aghabayk, K., & Quddus, M. (2024). A hybrid Machine learning and statistical modeling approach for analyzing the crash severity of mobility scooter users considering temporal instability. *Accident Analysis & Prevention, 206*, 107696. doi:https://doi.org/10.1016/j.aap.2024.107696

Santos, K., Dias, J. P., & Amado, C. (2022). A literature review of machine learning algorithms for crash injury severity prediction. *Journal of safety research, 80*, 254-269. doi:https://doi.org/10.1016/j.jsr.2021.12.007

Scarano, A., Riccardi, M. R., Mauriello, F., D'Agostino, C., Pasquino, N., & Montella, A. (2023). Injury severity prediction of cyclist crashes using random forests and random parameters logit models. *Accident Analysis & Prevention, 192*, 107275. doi:https://doi.org/10.1016/j.aap.2023.107275

Shaheed, M. S., & Gkritza, K. (2014). A latent class analysis of single-vehicle motorcycle crash severity outcomes. *Analytic Methods in Accident Research, 2*, 30-38. doi:https://doi.org/10.1016/j.amar.2014.03.002

Shiran, G., Imaninasab, R., & Khayamim, R. (2021). Crash severity analysis of highways based on multinomial logistic regression model, decision tree techniques, and artificial neural network: A modeling comparison. *Sustainability, 13*(10), 5670. doi:https://doi.org/10.3390/su13105670

Sivasankaran, S. K., Rangam, H., & Balasubramanian, V. (2021). Investigation of factors contributing to injury severity in single vehicle motorcycle crashes in India. *International journal of injury control and safety promotion, 28*(2), 243-254. doi:https://doi.org/10.1080/17457300.2021.1908367

Sivasankaran, S. K., Rangam, H. K., & Balasubramanian, V. (2022). Original road safety research: Injury profiles and epidemiology of single vehicle motorcycle fatalities in Tamil Nadu, India, 2009-2017. *Journal of road safety, 33*(3), 40-54. doi:https://doi.org/10.33492/JRS-D-20-00125

Sonnatthanon, N., & Choocharukul, K. (2025). Crash severity prediction using a virtual geometry-group-based deep learning approach with images-based feature representation. *Results in Engineering, 27*, 106155. doi:https://doi.org/10.1016/j.rineng.2025.106155

Štrumbelj, E., & Kononenko, I. (2014). Explaining prediction models and individual predictions with feature contributions. *Knowledge and information systems, 41*, 647-665. doi:https://doi.org/10.1007/s10115-013-0679-x

Sum, S., Se, C., Champahom, T., Jomnonkwao, S., Sinha, S., & Ratanavaraha, V. (2025). A Random Forest and SHAP-based analysis of motorcycle crash severity in Thailand: Urban-Rural and Day-Night perspectives. *Transportation Engineering*, 100369. doi:https://doi.org/10.1016/j.treng.2025.100369

Tahfim, S. A.-S., & Yan, C. (2021). Analysis of severe injuries in crashes involving large trucks using K-prototypes clustering-based GBDT model. *Safety, 7*(2), 32. doi:https://doi.org/10.3390/safety7020032

Tamakloe, R., Das, S., Aidoo, E. N., & Park, D. (2022). Factors affecting motorcycle crash casualty severity at signalized and non-signalized intersections in Ghana: Insights from a data mining and binary logit regression approach. *Accident Analysis & Prevention, 165*, 106517. doi:https://doi.org/10.1016/j.aap.2021.106517

Vajari, M. A., Aghabayk, K., Sadeghian, M., & Shiwakoti, N. (2020). A multinomial logit model of motorcycle crash severity at Australian intersections. *Journal of safety research, 73*, 17-24. doi:https://doi.org/10.1016/j.jsr.2020.02.008

Wang, M.-H. (2022). Investigating the difference in factors contributing to the likelihood of motorcyclist fatalities in single motorcycle and multiple vehicle crashes. *International journal of environmental research and public health, 19*(14), 8411. doi:https://doi.org/10.3390/ijerph19148411

WHO. (2023). Retrieved from Road traffic injuries [Online]. Available: https://www.who.int/news-room/ fact-sheets/detail/road-traffic-injuries (Accessed 13 December 2023)

Wisutwattanasak, P., Se, C., Champahom, T., Kasemsri, R., Jomnonkwao, S., & Ratanavaraha, V. (2024). Factors affecting single and multivehicle motorcycle crashes: Insights from day and night analysis using XGBoost-SHAP algorithm. *Big Data and Cognitive Computing, 8*(10), 128. doi:https://doi.org/10.3390/bdcc8100128

Wong, R., Yang, L., & Szeto, W. (2021). Wearable fitness trackers and smartphone pedometer apps: Their effect on transport mode choice in a transit-oriented city. *Travel behaviour and society, 22*, 244-251. doi:https://doi.org/10.1016/j.tbs.2020.10.006

Xiao, Y., & Duan, Z. (2025). An explainable multi-task deep learning framework for crash severity prediction using multi-source data. *Scientific Reports, 15*(1), 21978. doi:https://doi.org/10.1038/s41598-025-09226-1

Xiao, Y., Lin, L., Zhou, H., Tan, Q., Wang, J., Yang, Y., & Xu, Z. (2024). Fatal crashes and rare events logistic regression: an exploratory empirical study. *Frontiers in public health, 11*, 1294338. doi:https://doi.org/10.3389/fpubh.2023.1294338

Xin, C., Wang, Z., Lee, C., & Lin, P.-S. (2017). Modeling safety effects of horizontal curve design on injury severity of single-motorcycle crashes with mixed-effects logistic model. *Transportation Research Record, 2637*(1), 38-46. doi:http://dx.doi.org/10.3141/2637-05

Xin, C., Wang, Z., Lee, C., Lin, P.-S., Chen, T., Guo, R., & Lu, Q. (2019). Development of crash modification factors of horizontal curve design features for single-motorcycle crashes on rural two-lane highways: A matched case-control study. *Accident Analysis & Prevention, 123*, 51-59. doi:https://doi.org/10.1016/j.aap.2018.11.008

Yan, M., & Shen, Y. (2022). Traffic accident severity prediction based on random forest. *Sustainability, 14*(3), 1729. doi:https://doi.org/10.3390/su14031729

Yan, X., Ma, M., Huang, H., Abdel-Aty, M., & Wu, C. (2011). Motor vehicle–bicycle crashes in Beijing: Irregular maneuvers, crash patterns, and injury severity.

Accident Analysis & Prevention, 43(5), 1751-1758. doi:https://doi.org/10.1016/j.aap.2011.04.006

Yang, J., Han, S., & Chen, Y. (2023). Prediction of traffic accident severity based on random forest. *Journal of advanced transportation, 2023*(1), 7641472. doi:https://doi.org/10.1155/2023/7641472

Yannis, G., Golias, J., & Papadimitriou, E. (2005). Driver age and vehicle engine size effects on fault and severity in young motorcyclists accidents. *Accident Analysis & Prevention, 37*(2), 327-333. doi:https://doi.org/10.1016/j.aap.2004.10.003

Yu, H., Li, Z., Zhang, G., Liu, P., & Ma, T. (2021). Fusion convolutional neural network-based interpretation of unobserved heterogeneous factors in driver injury severity outcomes in single-vehicle crashes. *Analytic Methods in Accident Research, 30*, 100157. doi:https://doi.org/10.1016/j.amar.2021.100157

Yuan, R., Gan, J., Peng, Z., & Xiang, Q. (2022). Injury severity analysis of two-vehicle crashes at unsignalized intersections using mixed logit models. *International journal of injury control and safety promotion, 29*(3), 348-359. doi:https://doi.org/10.1080/17457300.2022.2040540

Zulherman, D., Yang, J., Shimizu, K., & Yokota, Y. (2024). *Light Gradient Boosting Machine-Based Fatality Prediction of Single-Vehicle Motorcycle Crashes.* Paper presented at the 2024 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT).

Zulherman, D., Yang, J., Shimizu, K., & Yokota, Y. (2025). Deep Q-learning network-based imbalanced classification for fatality prediction of single-vehicle motorcycle crashes. *International Journal of Intelligent Transportation Systems Research, 23*(1), 175-191. doi:https://doi.org/10.1007/s13177-024-00440-1

Zulherman, D., Yang, J., & Yokota, Y. (2022). *Examining the factors affecting single-vehicle motorcycle crashes using association rules mining: Case study of japan.* Paper presented at the 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC).

CHAPTER VI
CONCLUSION

Motorcycle crashes continue to pose a significant public health challenge in Thailand, where motorcyclists account for a disproportionately high share of road fatalities. Understanding the determinants of motorcycle crash injury severity therefore requires analytical approaches capable of capturing nonlinear interactions and complex relationships among roadway, environmental, temporal, and behavioral factors. This dissertation, *A Data-Driven Approach to Motorcycle Safety: Applying Machine Learning and Deep Learning to Injury Severity Prediction*, advances both methodological development and empirical insight by integrating supervised learning, deep learning, and explainable artificial intelligence (XAI) across four interrelated studies. Drawing on comprehensive highway crash data from the Highway Accident Information Management System (HAIMS), the dissertation enhances predictive accuracy, strengthens interpretability, and supports evidence-based safety strategies in the Thai context.

The remaining sections of this chapter summarize the main contributions of the research. Section 6.1 provides an overview of the dissertation. Sections 6.2 to 6.5 present narrative summaries of each of the four core studies. Section 6.6 synthesizes the integrated contributions, followed by policy implications in Section 6.7. Finally, Section 6.8 outlines the study's limitations and identifies future research directions.

6.1 Overview of the Dissertation

The overarching aim of this dissertation is to enhance the analytical foundations of motorcycle crash injury severity research by applying interpretable, data-driven modeling approaches. While previous studies in Thailand have made important contributions, many relied on traditional econometric models that assume linearity and homogeneity, limiting the ability to capture nonlinear interactions and complex risk patterns. This dissertation addresses these gaps by exploring supervised machine learning models, interpretable Random Forest–SHAP frameworks, deep learning for geometric contexts, and a hybrid Random Forest–CNN ensemble for single-motorcycle crashes.

The research systematically analyzes motorcycle crash severity across multiple dimensions: spatial (urban–rural), temporal (day–night), geometric (curved roadways), and crash-type variation (single-motorcycle crashes), thereby integrating multiple modeling paradigms to examine how diverse risk factors interact under different roadway and environmental conditions. Rather than treating these dimensions in isolation, the dissertation adopts a unified perspective that links methodological development with substantive safety insights.

To provide an overall synthesis of the dissertation, Figure 6.1 presents a visual summary of the research objectives, the corresponding methodological approaches, the key findings from each study, and their combined policy and safety implications. This figure serves as a conceptual roadmap, illustrating how the four studies collectively contribute to an interpretable, data-driven framework for motorcycle crash injury severity analysis in Thailand.

This overview provides the context for the following sections, which summarize the major contributions of each study in detail.

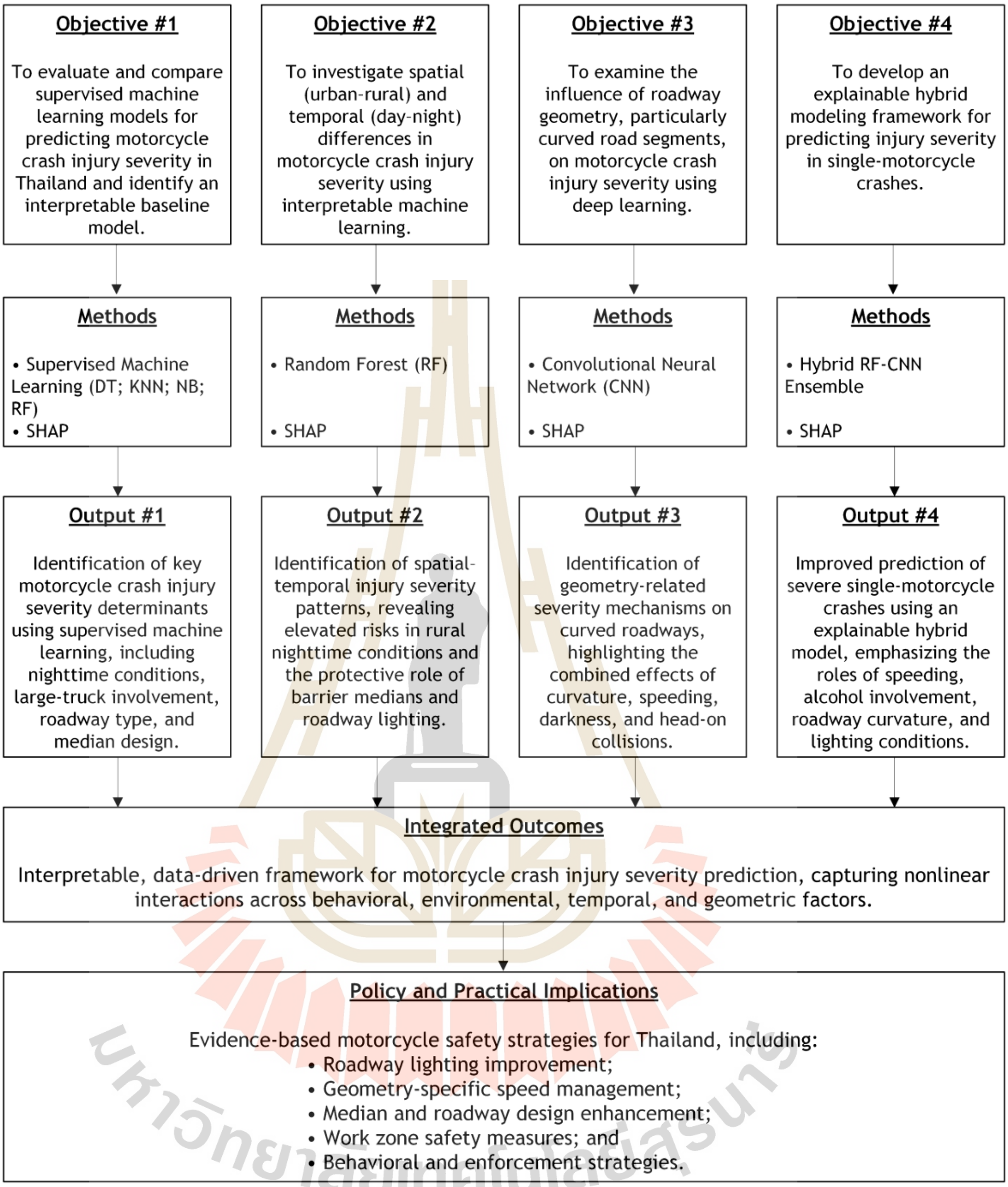

Figure 6.1 Overall summary of dissertation findings

6.2 Summary of the First Contribution

The first study establishes the analytical foundation of the dissertation by evaluating the predictive performance of four supervised machine learning algorithms—Decision Tree, K-Nearest Neighbor, Naïve Bayes, and Random Forest—in comparison with traditional statistical approaches. Using HAIMS motorcycle crash data from 2020–2022, the study aims to identify an efficient and interpretable predictive model capable of capturing the nonlinear and heterogeneous relationships inherent in crash data.

The results show that Random Forest offers the strongest predictive capability, achieving an AUC of 0.726, outperforming both traditional models and other machine learning algorithms. Unlike regression-based methods that impose restrictive assumptions regarding variable relationships, the Random Forest can identify complex interactions among roadway, environmental, temporal, and crash-specific factors, and, by incorporating SHapley Additive exPlanations (SHAP), the model provides clear and transparent insights into variable importance, enabling more meaningful interpretation of risk contributors.

SHAP analysis highlights nighttime conditions as a prominent contributor to severe injury outcomes, reflecting visibility-related challenges and behavioral risks associated with nighttime riding. Large-truck involvement also emerges as a major determinant, emphasizing the risks imposed by size and mass differentials between motorcycles and heavy vehicles. The presence of depressed medians and the predominance of two-lane highways further contribute to injury severity, suggesting the influence of roadway configuration on crash dynamics.

The study demonstrates the value of interpretable machine learning approaches as a foundation for advanced modeling, setting the stage for more context-specific analyses in later chapters.

6.3 Summary of the Second Contribution

Building on the strengths of the Random Forest–SHAP framework, the second study investigates motorcycle crash injury severity across spatial (urban vs. rural) and temporal (day vs. night) dimensions. This study addresses the need to understand how roadway environments and lighting conditions interact with crash mechanisms, recognizing that motorcycle risks differ substantially between urban and rural highways and across different times of day.

Using HAIMS data and the established Random Forest–SHAP methodology, the study identifies key risk factors that operate differently depending on location and time. Darkness consistently elevates injury severity, with rural nighttime crashes posing the greatest danger due to inadequate lighting, higher travel speeds, and longer emergency response times. Large-truck involvement again appears as a critical contributor to severe outcomes, reinforcing findings from the first study and suggesting that heavy vehicles create disproportionately high risks for motorcyclists across all contexts. Roadways featuring depressed medians show a heightened association with severe injuries, likely reflecting increased exposure to opposite-direction traffic and limited physical separation.

Conversely, barrier medians are found to reduce injury severity, particularly in rural areas where high-speed head-on or cross-median crashes are more frequent. Side-swipe collisions—typically associated with lateral conflicts—appear less severe than head-on or fixed-object collisions, especially in well-lit environments.

SHAP interaction visualizations reveal how combinations such as darkness and large-truck presence multiply injury severity risks, offering important insight for targeted interventions.

This study emphasizes the importance of jointly considering spatial and temporal conditions in motorcycle safety analysis, illustrating how interpretable machine learning can highlight context-specific risk dynamics.

6.4 Summary of the Third Contribution

The third study shifts focus toward understanding the influence of roadway geometry, particularly curved road segments, on motorcycle injury severity. Curved roadways introduce distinct challenges related to limited sight distance, lateral acceleration (centrifugal force), and lane position stability, all of which can increase the likelihood and severity of motorcycle crashes. However, traditional econometric methods often struggle to capture these complex geometric effects due to linearity constraints. To address this gap, the study develops a Convolutional Neural Network (CNN) specifically structured to detect multidimensional patterns associated with crashes on curved roadways.

Among several tested architectures, a three-layer CNN achieves the best performance with an accuracy of 0.634, outperforming deeper CNN structures and conventional statistical models. The model’s ability to learn nonlinear relationships makes it particularly suitable for understanding how geometric and behavioral factors interact on curved segments.

SHAP analysis reveals that large-truck involvement significantly elevates severity risk, particularly in scenarios where limited maneuvering space and complex sight distances reduce motorcyclists' ability to escape collision paths. Head-on collisions emerge as another dominant factor, reflecting the dangerous dynamics of lane deviations that often occur on curved roadways. Depressed medians continue to contribute to higher severity, whereas better-designed medians can help mitigate the risks associated with roadway curvature. Speeding and darkness compound the risks further, especially when combined with geometric constraints. For example, the model highlights how sharp curves, coupled with nighttime conditions and high traveling speeds, greatly increase the likelihood of fatal or severe crashes.

By integrating deep learning with XAI, this study provides a geometry-specific framework that captures risk factors traditional models struggle to represent, highlighting the need for curve-focused safety improvements.

6.5 Summary of the Fourth Contribution

The fourth study introduces a novel hybrid Random Forest–Convolutional Neural Network (RF–CNN) model for predicting single-motorcycle crash injury severity. Single-motorcycle crashes offer a unique analytical challenge because they isolate rider behavior and roadway conditions without the confounding influence of other vehicles. However, they also involve complex, nonlinear relationships that require advanced modeling strategies. The hybrid model addresses the ongoing trade-off between model accuracy and interpretability by leveraging the strengths of both Random Forest and CNN models.

Using HAIMS crash data from 2016–2023, the hybrid RF–CNN employs a weighted ensemble strategy—85% CNN and 15% Random Forest—to combine CNN's strong pattern recognition capabilities with the interpretability and feature importance insights offered by Random Forest. The hybrid model achieves an accuracy of 58.9% and a recall of 69.9%, outperforming standalone Random Forest, standalone CNN, and Binary Logistic Regression. The improved recall is particularly important in safety applications where the cost of misclassifying severe crashes is significant.

SHAP analysis provides a transparent view of the hybrid model's internal reasoning, highlighting nighttime conditions (with or without electrical lighting) as the most influential factor, followed by lane configuration, roadway curvature, speeding behaviors, and alcohol involvement. These findings align with earlier studies in this dissertation while offering deeper insights into how individual and contextual factors interact to shape single-motorcycle crash outcomes. For example, the analysis illustrates how speeding on curved, poorly lit roadways disproportionately increases the likelihood of severe injury.

This study demonstrates that hybrid ensemble strategies can balance predictive accuracy and interpretability in complex safety analyses and provides practical insights for managing single-motorcycle crash risks.

6.6 Integrated Contributions of the Dissertation

The four studies collectively contribute to theoretical, methodological, and practical advancements in motorcycle crash severity research.

6.6.1 Theoretical Contributions

1) Enhance understanding of spatial, temporal, geometric, and behavioral determinants of motorcycle injury severity.

2) Reveal nonlinear and heterogeneous relationships that are not readily captured by traditional models.

3) Strengthen the conceptual linkage between human behavior, infrastructure design, and crash outcomes.

6.6.2 Methodological Contributions

1) Demonstrate the value of interpretable machine learning models in transportation safety analysis.

2) Introduce deep learning approaches for capturing geometric influences on curved roadway crashes.

3) Develop an explainable hybrid RF–CNN model that balances predictive accuracy with transparency.

4) Consistently apply SHAP to enhance interpretability across all modeling frameworks.

6.6.3 Practical Contributions

1) Identify critical high-risk conditions, including nighttime riding, large-truck involvement, and curved roadway geometry.

2) Inform data-driven safety interventions, such as lighting upgrades, median improvements, and targeted enforcement.

3) Provide a transferable modeling framework applicable to developing-country contexts.

6.7 Policy and Practical Implications

The collective findings from the four studies provide a coherent set of evidence-based policy directions to improve motorcycle safety on Thailand's highway network. By integrating insights from supervised learning models, interpretable Random Forest–SHAP analyses across spatial and temporal contexts, deep learning assessments of curved segments, and the hybrid RF–CNN model for single-motorcycle crashes, several targeted interventions emerge as particularly critical for mitigating injury severity. The following recommendations are grounded in the empirical patterns consistently observed across the dissertation:

1) Lighting Improvements: Darkness consistently emerged as a major severity factor across the Random Forest–SHAP analyses and the hybrid RF–CNN model. Improving and maintaining roadway lighting—especially on rural highways and curved segments highlighted in the CNN study—can substantially reduce nighttime crash severity.

2) Geometry-Specific Speed Management: Both the curvature-focused CNN model and the hybrid model show that speeding on curves greatly increases injury severity. Implementing curve-specific speed limits and expanding automated speed enforcement can help moderate risks in these high-hazard locations.

3) Median and Roadway Design Enhancements: Depressed medians were repeatedly associated with higher severity across studies, while barrier medians showed protective effects. Upgrading depressed medians to barrier designs on high-speed corridors can prevent cross-median conflicts and reduce head-on crash severity.

4) Work Zone Safety Measures: The hybrid RF–CNN analysis indicates stronger risks under challenging environmental conditions. Enhancing nighttime work-zone management through clearer advance warnings, improved delineation, and temporary lighting can mitigate hazards for motorcyclists.

5) Behavioral and Enforcement Strategies: Speeding and alcohol involvement consistently ranked among the most influential severity factors. Targeted enforcement, data-driven deployment of checkpoints, and expanded motorcycle-specific training programs—particularly focusing on curve negotiation and hazard recognition—can help reduce behavior-related risks.

Collectively, these policy directions directly reflect the patterns identified across all four studies and provide a foundation for more proactive, evidence-based motorcycle safety management in Thailand.

6.8 Limitations and Directions for Future Research

While the dissertation provides robust methodological and empirical contributions, several limitations should be acknowledged. First, the HAIMS dataset lacks important crash-level details such as helmet characteristics, rider distraction, precise trajectory information, and detailed geometric measures (e.g., curve radius or superelevation). These missing variables restrict the capacity to model certain crash mechanisms comprehensively. Second, the binary classification used for injury severity simplifies the original four-level system, potentially masking meaningful distinctions between severe and fatal outcomes. Future studies could adopt multiclass or continuous severity scales to improve granularity. Third, although the models demonstrate strong predictive and interpretive capabilities within the Thai context, their generalizability to other regions or countries remains untested. Cross-regional validation would strengthen the robustness and applicability of the modeling frameworks. In addition, model robustness was not explicitly assessed across alternative samples, random seeds, or validation settings. Both the Logistic Regression–based benchmarks and the machine learning and deep learning models may exhibit sensitivity to data composition, class imbalance, or model initialization. Future research should incorporate systematic robustness testing to evaluate the stability of model performance and explanatory patterns. Finally, the modeling approaches used in this dissertation primarily rely on static crash data; incorporating real-time traffic, weather, or connected vehicle information could enable proactive risk prediction and contribute to dynamic safety management systems.

APPENDIX

APPENDIX A: FEATURE SELECTION DIAGNOSTIC

Table A.1 Random Forest feature importance ranking

Rank	Feature	Importance
1	ASPHALT	0.0640
2	CURVED ROADS	0.0615
3	SPEEDING	0.0426
4	LANE = 4	0.0400
5	Y_2018	0.0369
6	RAISED MEDIAN	0.0355
7	Y_2019	0.0334
8	DEPRESSED MEDIAN	0.0329
9	Y_2021	0.0328
10	Y_2017	0.0327
11	Y_2022	0.0319
12	Y_2016	0.0316
13	DAYTIME	0.0316
14	Y_2020	0.0311
15	WORK ZONE	0.0283
16	DRUNK	0.0281
17	Y_2023	0.0272
18	WET	0.0267
19	T_INT	0.0265
20	U-TURN	0.0264
21	LANE = 6	0.0261
22	BARRIER MEDIAN	0.0254

Table A.1 Random Forest feature importance ranking (Continued)

Rank	Feature	Importance
23	ON SLOPE	0.0250
24	DARK_WITH_ELEC	0.0246
25	MEDIAN OPENING	0.0244
26	LANE >=8	0.0243
27	LANE = 2	0.0223
28	FLUSH AND PAINTED MEDIAN	0.0220
29	RAINING	0.0216
30	DARKNESS	0.0191
31	FOUR-LEG_INT	0.0184
32	FATIGUE	0.0179
33	FRONT-PATH INTERRUPTION	0.0174
34	UNSKILLED DRIVING	0.0095

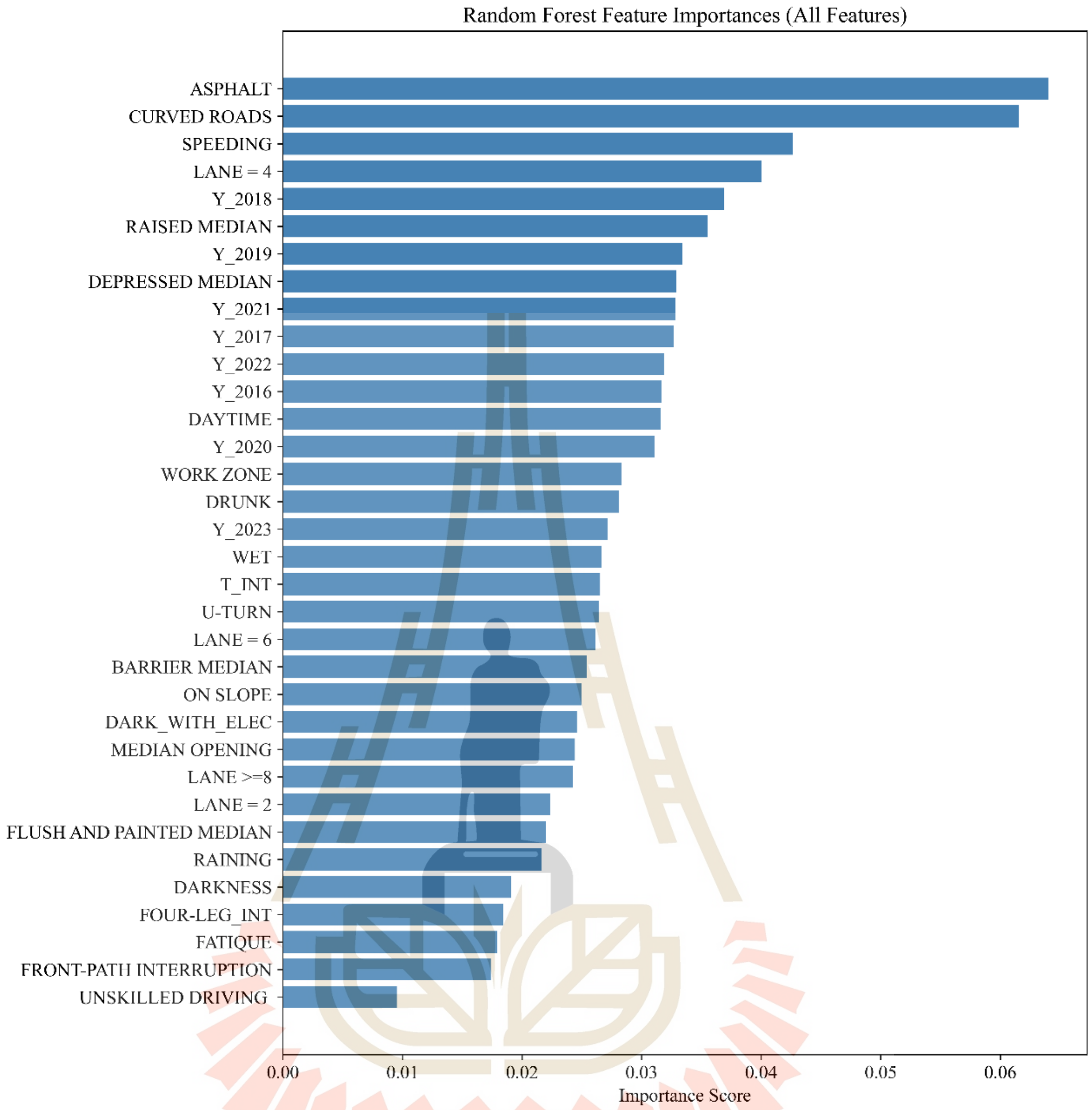

Figure A.1 Random Forest feature importance plot

APPENDIX B: CORRELATION MARIX FOR THE TOP 25 PREDICTORS

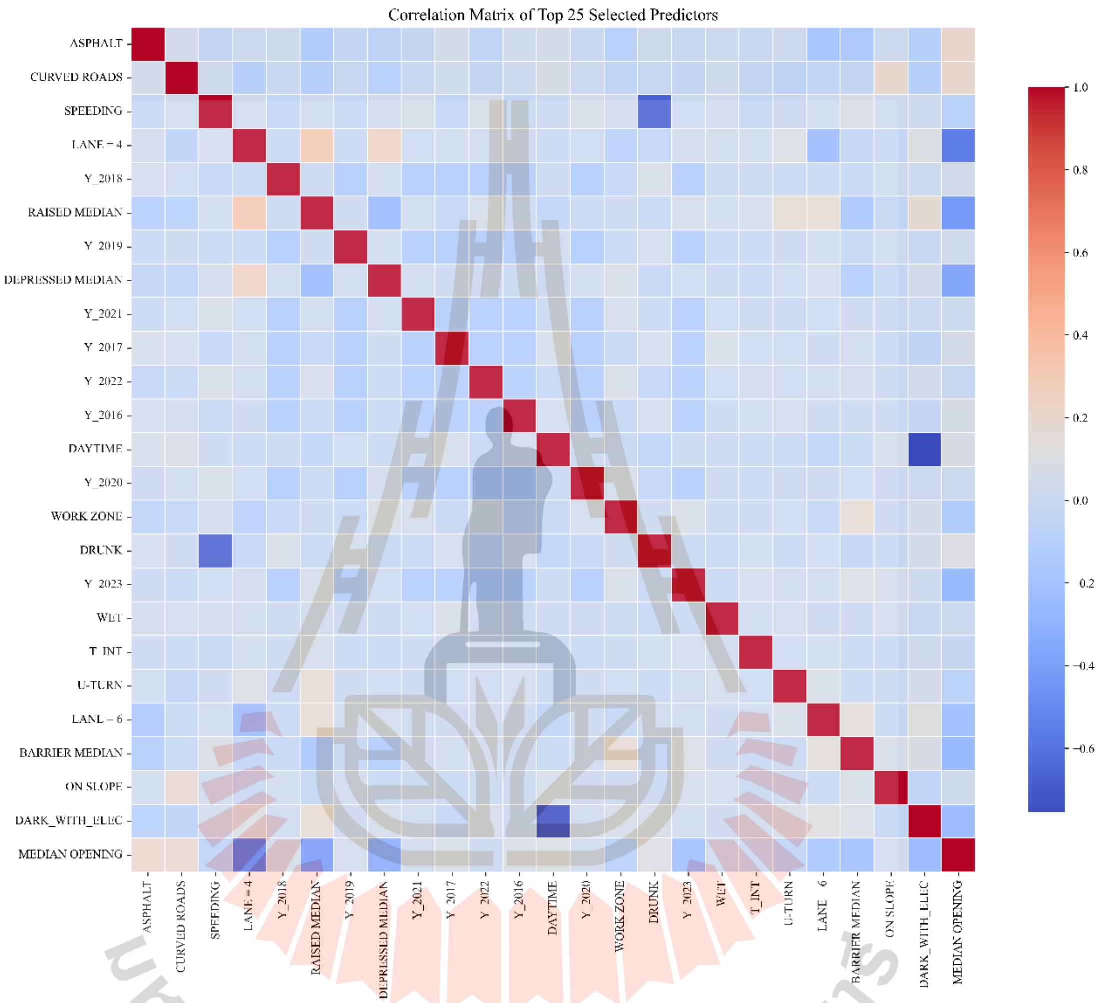

Figure B.1 Pearson correlation matrix of the top 25 selected predictors

APPENDIX C: PERFORMANCE ROBUSTNESS ACROSS 10 RANDOM SEEDS

Table C.1 Mean, Standard Deviation, and 95% Confidence Intervals (CI) RF–CNN model metrics across 10 seeds

Metric	Mean	Std. Dev	95% CI Lower	95% CI Upper
Accuracy	0.559	0.020	0.545	0.574
Precision	0.557	0.018	0.544	0.569
Recall	0.586	0.071	0.535	0.637
F1-score	0.569	0.039	0.541	0.597

LIST OF PUBLICATIONS

Sum, S., Se, C., Champahom, T., Jomnonkwao, S., Sinha, S., & Ratanavaraha, V. (2025). A Random Forest and SHAP-based analysis of motorcycle crash severity in Thailand: Urban-Rural and Day-Night perspectives. Transportation Engineering, 100369. doi:https://doi.org/10.1016/j.treng.2025.100369

Sum, S., Wisutwattanasak, P., Champahom, T., Jomnonkwao, S., & Ratanavaraha, V. (2025). A Comparative Study of a Series of Supervised Learning Models for Motorcycle Crash Injury Severity Prediction. Civil Engineering Journal. doi:https://doi.org/10.28991/cej-2025-011-10-014

Watcharamaisakul, F., Phojaem, T., **Sum, S.**, Champahom, T., Jomnonkwao, S., Wisutwattanasak, P., & Ratanavaraha, V. (2025). Perspectives of older people toward Thai high-speed rail promotion using the theory of planned behavior and the unified theory of acceptance and use of technology. Frontiers in Built Environment, 11, 1536080. doi:https://doi.org/10.3389/fbuil.2025.1536080

BIOGRAPHY

Dr. Sonita Sum was born on June 22nd, 1994, in Kandal Province, Cambodia. She completed her primary education at Bun Rany Hun Sen Primary School, secondary education at Preah Sihanouk Secondary School, and high school education at Hun Sen Khsach Kandal High School. She later earned a Bachelor's degree in Civil Engineering from the Institute of Technology of Cambodia (ITC), followed by a Master's degree in Transportation Engineering at Suranaree University of Technology (SUT).

Dr. Sonita Sum has conducted research and published scholarly work in the areas of transportation planning, transport policy, and transportation safety, with a particular focus on motorcycle crash injury severity, traffic safety analytics, roadway geometry effects, and the application of machine learning, deep learning, and Explainable Artificial Intelligence (XAI). Her work utilizes statistical and data-driven approaches to investigate critical safety issues such as motorcycle crashes, crashes on curved roadways, single-motorcycle collisions, and multi-factor injury severity mechanisms, including extensive analysis of crash characteristics across urban and rural environments and variations in crash outcomes during day- and night-time periods.

She has published research articles in several internationally recognized journals, including Transportation Engineering, Civil Engineering Journal, IATSS Research, and Case Studies on Transport Policy. Her publications contribute to advancing evidence-based safety analysis and methodological innovation in crash-injury severity research.

Her current research interests center on applying advanced analytical techniques—such as machine learning, deep learning, SHAP interpretability, and other XAI-based approaches—to deepen the understanding of crash mechanisms and support the development of effective transportation safety policies.