ภาคผนวก

บทความวิจัยระดับนานาชาติที่ได้รับการตีพิมพ์

บทความวิจัยระดับนานาชาติที่ได้รับการตีพิมพ์

1. S. Thongsri, P. Phoynok, C. Luecha, T. Khayan, P. Kijphitayarit and S. Poochaya, **"Development of 5G Standalone QOS Tester Device for CAV Communication,"** 2024 12th International Electrical Engineering Congress (iEECON), Pattaya, Thailand, 2024, pp. 1-5, doi: 10.1109/iEECON60677.2024.10537859

2. S. Thongsri, K. Bunchen and S. Poochaya, **"Enhancing Thailand Road Safety through Personal Driving Style Classification using Machine Learning Model"**
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Development of 5G Standalone QOS Tester Device for CAV Communication

Sitthisak Thongsri , Palakorn Phoynok, Chanapa Luecha, Tatiya Khayan, Pannatorn Kijphitayarit and Settawit Poochaya

School of Telecommunication Engineering,
Suranaree University of Technology Muang, NakhonRatchasima, Thailand 30000
Email: settawit@sut.ac.th

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***Abstract*—Focus on Connected-Autonomous-Shared-Electric Vehicle (CASE), Connected and Autonomous Vehicle Technologies are a famous topic in the world. CAV requires high performance of communication links. 5G communication is a high-performance communication system in Thailand. The service area of 5G mobile communication in standalone mode increases every year. Quality of Service (QOS) in 5G for CAV is important. Commercial 5G QOS tester device is expensive. Then, the developing of 5G QOS Tester and QOS parameters in terms of radio and end parameters: SS-RSRP, SS-SINR, SS-RSRQ, RTT, Upload, Download, Jitter of 5G standalone for CAV are presented in this work. Our results confirm that 5G standalone is a high-performance communication link for CAV data transmission.**

***Keywords*—V2N, 5G, NR, SA, and ITS**

I. Introduction

Nowadays, information and communication technology are developing rapidly. As a result, automotive technology has made traveling more comfortable, safe, and environmentally friendly, resulting in autonomous and connected vehicle technology (CAV) including vehicles that connect to various things. Vehicles with the ability to drive autonomously, car sharing, and the use of electric vehicles (CASE), which is a smart vehicle technology. Modern technologies that help in driving include the Advance Driver Assistance System (ADAS). Autonomous driving technology and vehicle-to-everything (V2X) technology. Our work focuses on testing and developing devices that help vehicles connect to the network through vehicle communications networks or vehicle-to-networks communication (V2N) to measure signal quality and appropriate area before deploying modern smart vehicle technology. In the intricate receiving telemetry and transmitting telecommands and collecting enormous amounts of data transmission. The functionality of Connected and Autonomous Vehicles (CAV), and the integrity of the system infrastructure stand as a linchpin for ensuring seamless operations. At the heart of this infrastructure lies the critical need for a high-performance communication link, a fundamental requirement for the transmission of data from the vehicle up to the cloud with 5G NR V2X technology that provides mobility management for V2N communication [1].

Connected and autonomous vehicles operate within an ecosystem where real-time data exchange is not merely a convenience but a necessity. To enable functionalities such as remote monitoring, over-the-air updates, and data-driven decision-making, CAVs rely on a robust communication link that facilitates the bidirectional flow of information between the vehicle and the cloud. This paper shows that 5G can support advanced V2X services by using V2N communication to send data to the cloud [2]. To achieve the desired level of performance in the communication link, various QOS parameters come into play. Synchronization Signal Reference Signal Received Power (SS-RSRP), Secondary Synchronization Signal Signal-to-Noise and Interference Ratio (SS-SINR), Synchronization Signal Reference Signal Received Quality (SS-RSRQ), and End parameters such as Average Upload (UL) and Average Download (DL) throughput, Round-Trip Time (RTT), and Jitter collectively define the quality of the communication link [3]. Finally, results present a 5G QOS tester device measuring V2X communication link performance in terms of radio and end parameters that supported the CAV communication link.

Fig. 1. Proposed 5G QOS Tester for CAV

II. System Infrastructure and 5G NR Performance Metrics

5G NR Performance parameters

Figure 1 shows the proposed system infrastructure. The Device Under Test (DUT) was produced with RPi4 and RM502Q-AE radio HAT (hardware attracted on top). DUT was installed inside the experimental vehicle. 5G NR performance parameters are separated into two types: Radio parameters and End parameters.

Radio Parameters

SS-RSRP is the reference signal power value of the synchronization signal received in a wireless network or telecommunications system. The SS-RSRP value can be used to estimate the signal strength level in measuring and evaluating signal quality and connection in the mobile phone network system for connections and communications to work correctly and with maximum efficiency, the unit is dBm.

SS-SINR is the value used to measure signal quality in mobile or wireless telephone network systems is employed to identify the quality of signals and interference in the system. It indicates the ratio between the signal strength from the serving cell and the level of interference and noise in the network. This is done to evaluate the efficiency of connections and communication between mobile phones and service cells in the cellular network system or other wireless systems, ensuring optimal efficiency in connectivity and communication. The unit of measurement is in decibels (dB).

SS-RSRQ is the indicator of overall signal quality. Which is used to consider Handover to consider and change signal antennas. When the SS-RSRQ value is high, it indicates good channel quality. The unit is dB or Decibel, calculated as in Eq. (1), where N is the Physical Resource Blocks value.

$$SS-RSRQ = \frac{N \times SS-RSRP}{SS-SINR} \qquad (1)$$

End Parameters

Average Upload, or the average data transmission speed, is the rate at which data is uploaded on average over a specified period. It can be measured in bits per second (bps), bytes per second (Bps), kilobits per second (Kbps), or megabits per second (Mbps). The average upload speed is calculated by the internet system or device in use, and this value is provided to users. The average upload speed refers to the rate at which data is sent from the user's device to the server or the internet network. It is a crucial metric for assessing the performance of data upload.

Average Download, or the average data transfer speed, is the rate at which data is downloaded on average over a specified period. The download speed reflects the efficiency of receiving data from the network and is crucial for measuring and monitoring the speed of internet connections, especially in applications that require fast data transmission. The average download speed can be measured in units such as bits per second (bps), bytes per second (Bps), kilobits per second (Kbps), or megabits per second (Mbps).

RTT, or Round-Trip Time, is the duration measured from a ping operation, expressed in milliseconds (ms). Ping is a connectivity and responsiveness test for both the network and the destination host. It is a command on a computer that operates by sending an "echo request" of the Internet Control Message Protocol (ICMP) type to the target host and waiting for the corresponding "echo response" data. The measured duration is referred to as "RTT," and this RTT value indicates the status of the connection and the responsiveness of the target host. Assessing RTT values is a way to evaluate the network's and target host's connectivity and responsiveness.

Jitter is the variability in the time it takes for data to be transmitted from the source to the destination. This can affect the stability of real-time communication. Low jitter values contribute to smooth communication, while high jitter values indicate significant fluctuations in Round Trip Time (RTT), impacting the quality of real-time interactions and responsiveness.

Path Loss

Path Loss is the reduction in signal strength that occurs because of natural phenomena, occurring as the distance between the transmitting and receiving ends increases. It is categorized into three environmental types: urban, suburban, and rural. Simulation of all three environmental conditions is achieved by considering the distance between the transmitting and receiving devices, with the distance acting as a determinant of the environmental conditions [4].

There are three fundamental types of large-scale path loss models designed to forecast signal strength over distance for expansive areas. In the past, omnidirectional path loss models, also known as ABG models, were developed [5]. The alpha-beta-gamma (ABG) model is a significant multifrequency path loss model. Typically, multifrequency path loss models are necessary to standardize the path loss models, ensuring coverage across a wide spectrum of frequencies [6], as shown in Eq. (2).

$$PL^{ABG}(f,d)\,[dB] = 10\alpha\log_{10}\left(\frac{d}{d_0}\right) + \beta + 10\gamma\log_{10}\left(\frac{f}{f_0}\right) + X_{\sigma}^{ABG} \qquad (2)$$

In the given expression, α and β represent the path loss coefficients defining distance and frequency dependency, respectively. γ indicates the optimized offset for path loss, f denotes the operational frequency (in GHz), f_0 represents a fixed reference frequency, and $\square_{\sigma}^{\square\square\square}$ symbolizes the large-scale signal variabilities received concerning the distance in the direct path.

The Close-In (CI) free-space path loss model is a widely recognized path loss model [7]. Generally, this path loss model is utilized to illustrate the effects of the channel induced due to the surrounding environment. The Close-In (CI) free-space path loss model is shown in Eq. (3).

$$PL^{CI}(f,d)\,[dB] = FSPL(f,d) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_{\sigma}^{CI} \qquad (3)$$

In the provided context, n represents the Path Loss Exponent (PLE), X_{σ}^{CI} signifies a Gaussian random variable, σ symbolizes the standard deviation in decibels (dB), and d_0 indicates the physical reference distance (d_0 = 1m), *FSPL (f, d)* is the free space path loss (*FSPL (f, d) in dB*), which is dependent on carrier frequency (f in GHz), and the distance between transmitter and receiver antennas are represented in d (d in meter). The *FSPL (f, d)* can be calculated in Eq. (4).

$$FSPL(f,d) = 10\log_{10}\left(\frac{4\pi d_0}{\lambda}\right)^2 \qquad (4)$$

Where λ is wavelength of 5G NR n41 band.

III. PROPOSED SYSTEM

Hardware and software development are explained in this section.

Hardware development

For hardware development, a Device Under Test (DUT) consisting of Raspberry Pi4 Model B has a Broadcom BCM2711, Quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.8GHz with memory 4GB, RM502Q-AE 5G HAT (hardware attracted on top) module is a device with various features. It supports connections with 4G and 5G networks and a 7-inch LCD Display for Raspberry Pi. A connection between a Raspberry Pi4 Model B and RM502Q-AE 5G HAT module is connected via a serial interface, and the connection between a Device Under Test (DUT) and a 7-inch LCD Display is connected via a USB port that is shown in Figure 1.

Software development

The software development of Device Under Test (DUT) is developed separately, but they will work together, with the software development being separated into 2 parts: software of radio parameters and software of end parameters, they are developed with Python, then the InfluxDB which is a database is retrieval parameters that is collected in comma separated values (CSV) file into Grafana dashboard, The software operation of both is shown in pseudocode algorithm as shown in Figures 2 and 3.

Algorithm 1 Radio Parameters Software

```
Start
While (True)
    Select the testing mode to measure radio parameters
    Request and get radio parameters from the base station
    Input are parameters SS-RSRP and SS-SINR
    If (SS-RSRP >= -95, SS-SINR >= 16)
        Show green color on the terminal display of each parameter
    Else if (-105 <= SS-RSRP < -95, 10 <= SS-SINR < 16)
        Show yellow color on the terminal display of each parameter
    Else
        Show red color on the terminal display of each parameter
    End if
    Store radio parameters in a CSV file
    Query radio parameters and parameters are related from a CSV file to the Grafana dashboard
    All parameters are displayed on the Grafana dashboard, on the terminal display
End
```

Fig. 2. Algorithm of radio parameters software operation

Algorithm 2 End Parameters Software

```
Start
While (True)
    Select the testing mode to measure end parameters
    Request and get end parameters from the base station
    Input are parameters RTT, Upload, Download
    If (RTT < 110, Upload > 1.25, Download > 5
        Show green color on the terminal display of each parameter
    Else if (110 <= RTT < 150 110, 0.5 <= Upload <= 1.25, 2.5 <= Download <= 4.9)
        Show yellow color on the terminal display of each parameter
    Else
        Show red color on the terminal display of each parameter
    End if
    Store radio parameters in a CSV file
    Query radio parameters and parameters are related from a CSV file to the Grafana dashboard
    All parameters are displayed on the Grafana dashboard, on the terminal display
End
```

Fig. 3. Algorithm of end parameters software operation

IV. RESULT

DUT was developed set of equipment and software for measuring 5G Quality Of Services (QOS), both radio parameters and end parameters, by measuring in the n41 band at the frequency range 2496 – 2690 MHz in the Advanced Smart City area inside the Suranaree University of Technology Science Park as shown in Figure 4, scale in meter. By testing a total of 20 points and divided into static and dynamic signal quality tests, the Next-Generation Node B is represented by green circles. In addition, our developed system and commercially available system measuring instruments were compared.

Fig. 4. Advanced Smart City area or Suranaree University of Technology Science Park area

Static Signal Quality Testing

In the case of Static signal quality testing, it will be used to test the signal for 1 minute. The test results can be seen in Figures 5, 6, and TABLE I.

From the results of the 5G static signal quality tests on Band n41 across all 20 test points and plotting the average values in Figure 7, it is evident that the SS-RSRQ signal in the Advanced Smart City area exhibits relatively stable signal quality. However, the SS-RSRP and SS-SINR signals show fluctuations corresponding to different conditions and end parameters, according to Table I, which illustrates the telecommunications service quality of the 5G SA Band n41 signal in the Advanced Smart City area, there is good quality of telecommunications services. The test results meet the telecommunications service quality standards as per the NBTC's measurement guidelines [8].

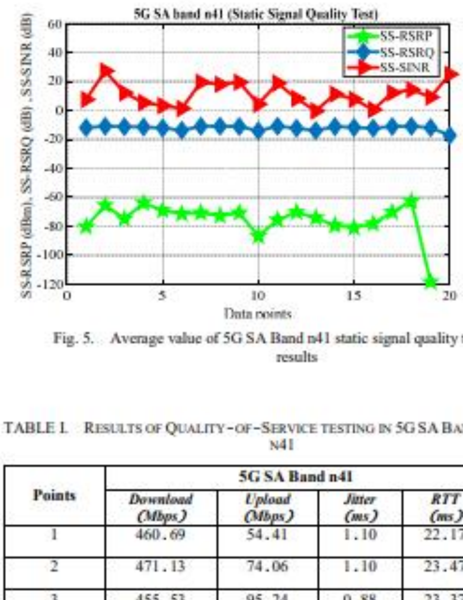

Fig. 5. Average value of 5G SA Band n41 static signal quality test results

TABLE I. RESULTS OF QUALITY-OF-SERVICE TESTING IN 5G SA BAND N41

Points	5G SA Band n41			
	Download (Mbps)	*Upload (Mbps)*	*Jitter (ms)*	*RTT (ms)*
1	460.69	54.41	1.10	22.17
2	471.13	74.06	1.10	23.47
3	455.53	95.24	0.88	23.37

Points	5G SA Band n41			
	Download (Mbps)	*Upload (Mbps)*	*Jitter (ms)*	*RTT (ms)*
4	332.51	48.18	0.52	23.30
5	239.50	55.73	0.45	22.10
6	147.04	32.29	1.48	21.13
7	278.73	63.61	2.29	21.00
8	285.86	65.63	0.15	23.30
9	322.60	71.28	2.29	19.10
10	480.86	91.58	1.40	20.47
11	488.76	87.21	0.75	22.63
12	419.34	92.73	0.15	23.13
13	275.74	68.82	0.81	19.60
14	271.95	60.42	1.31	20.90
15	273.33	61.97	2.31	20.33
16	214.26	56.33	0.73	21.64
17	356.22	49.64	0.62	19.97
18	442.05	81.59	0.82	20.47
19	354.73	64.57	3.56	21.13
20	459.78	71.54	1.53	21.97
Average	351.53	67.34	1.21	21.56

From static signal quality testing, end parameters were plotted on the Advanced Smart City map, then compared with the NBTC's telecommunications service quality standards by dividing the range of service standards region color, as shown in Figure 8.

Dynamic Signal Quality Testing

Dynamic signal quality test case, testing from the beginning to the end. The test results can be seen in Figures 7, 8, 9, and Table II.

Fig. 6. Overview of the Quality of Service of the 5G Band n41 signal

From the results of the 5G dynamic signal quality tests on Band n41, then plotting the values in Figure 7, They also plotted the points on the map showing that the overall signal quality of 5G SA Band n41 in the Advance Smart City area has good signal quality shown in Figure 8. and end parameters, which the result of the test of the quality of telecommunications services in the Advance Smart City area, which has the average test results in the test shown in Table II.

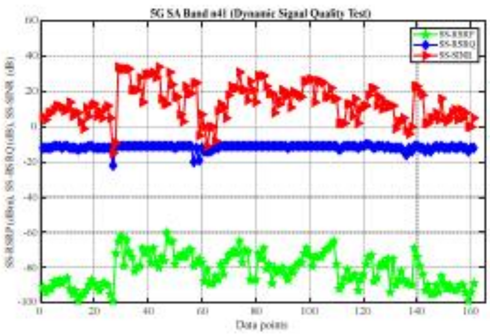

Fig. 7. The value of 5G SA Band n41 dynamic signal quality test results

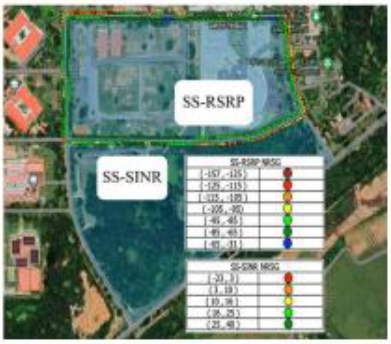

Fig. 8. Overview of 5G SA Band n41 radio parameters dynamic signal quality in the Advance Smart City area.

Results on average Quality-of-Service for dynamic signal quality testing, end parameters were plotted on the Advanced Smart City map, then compared with the NBTC's telecommunications service quality standards by dividing the range of service standards region color, as shown in Figure 9.

TABLE II. THE AVERAGE QUALITY-OF-SERVICE TESTING RESULTS FOR 5G SA BAND N41.

Time	5G SA Band n41			
	Download (Mbps)	*Upload (Mbps)*	*Jitter (ms)*	*RTT (ms)*
10/12/2023 8:41	223.26	31.77	0.51	19.9
10/12/2023 8:42	370.69	64.65	0.54	25
10/12/2023 8:43	412.83	28.19	0.5	24.9
10/12/2023 8:44	352.67	61.41	2.91	19.8
10/12/2023 8:45	209.71	36.02	3.08	23.4
Average	313.83	44.41	1.51	22.6

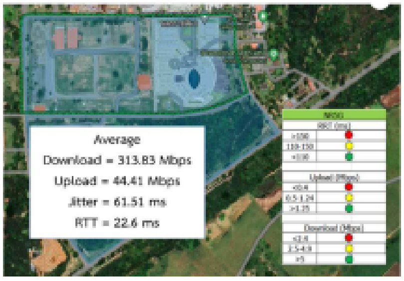

Fig. 9. Overview of the average Quality-of-Service testing results for 5G SA Band n41.

TABLE III. COMPARISON OF RADIO PARAMETERS BETWEEN OUR DUT AND TEST PHONE

5G SA Band n41		
Radio parameters	***Our DUT***	***Test phone***
SS-RSRP (dBm)	-68	-71
SS-RSRQ (dB)	-12	-12
SS-SINR (dB)	4	5

TABLE IV. COMPARISON OF END PARAMETERS BETWEEN OUR DUT AND TEST PHONE

5G SA Band n41		
Radio parameters	***Our DUT***	***Test phone***
Download (Mbps)	181.70	153
Upload (Mbps)	31.12	27.6
Jitter (ms)	2.99	3
RTT, Ping (ms)	19.94	26

Proposed System and Commercial Test Phone

Measuring the actual 5G signal quality by Device Under Test (DUT) found that the radio parameters obtained from the signal test and the actual signal quality test by phone were similar trend with same Physical Cell ID (PCI) accordign to table III. Speed test application was selected for measuring internet speed test. Results is presetned in in tabel IV the Device Under Test (DUT) used for testing is effective enough to be used in testing telecommunications service quality standards for 5G n41 band.

V. CONCLUSION

In conclusion, the system infrastructure of Connected and Autonomous Vehicles pivots on the robustness of the CAV communication link. Our results enhance the efficiency and reliability of data transmission and play a pivotal role in shaping the capabilities and limitations of autonomous vehicles.

In summary, the use of the 5G QOS Tester is crucial for evaluating the performance of 5G connections to provide efficient services for Connected and Autonomous Vehicles (CAV) in the context of Connected-Autonomous-Share-Electric Vehicles (CASE) systems. The testing has demonstrated the suitability of 5G Standalone (5G SA) New Radio (NR) in delivering high-performance and seamless services in this context. This work has conducted and presented test results to verify the suitability of 5G SA NR in the CAV service scenario for CASE, representing a crucial step in the experimentation and development of efficient and reliable autonomous vehicle systems.

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E-mail: icpei2024@gmail.com

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Enhancing Thailand Road Safety through Personal Driving Style Classification using Machine Learning Model

Sittisak Thongsri
School of Telecommunication Engineering
Suranaree University of Technology
Muang, NakhonRatchasima, Thailand
m6502560@g.sut.ac.th

Kriengkri Bunchen
School of Telecommunication Engineering
Suranaree University of Technology
Muang, NakhonRatchasima, Thailand
kriengkri.b@gmail.com

Settawit Poochaya
School of Telecommunication Engineering
Suranaree University of Technology
Muang, NakhonRatchasima, Thailand
settawit@sut.ac.th

***Abstract*—In Thailand, road safety remains a critical concern due to various factors, including diverse driving styles. To address this issue, this study proposes an approach utilizing machine learning models to classify personal driving styles, aiming to enhance road safety measures. By analyzing driving behavior data collected from Inertial Measurement Unit sensors (IMU), which is a telematics device. This study presents the simulation of a driver behavior dataset to determine the appropriate machine learning model. Then analyzes the dataset, selects features suitable for feature scaling, and trains models using machine learning algorithms, including Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), and Decision Tree (DT). Our results reveal that the Random Forest algorithm outperforms others, achieving an accuracy of 89%, precision of 78%, recall of 89%, and an f1-score of 82%. This highlights the effectiveness of the proposed approach in accurately driver behavior, which is classified as safety driving and unsafety driving, the study lays the foundation for the development of tailored road safety initiatives aimed at reducing accidents and promoting responsible driving practices in Thailand.**

***Keywords*—telematics, machine learning, driver behavior, data visualization, and IMU data**

I. INTRODUCTION

Road safety is a paramount concern in Thailand, where diverse driving styles intersect with complex traffic dynamics, presenting ongoing challenges for ensuring public safety and well-being. Despite concerted efforts and campaigns, road accidents continue to pose significant risks to motorists, pedestrians, and other road users. In response to this pressing issue, this study endeavors to pioneer an innovative approach utilizing machine learning methodologies to classify personal driving styles, with the overarching goal of advancing road safety measures nationwide. The increment of telematics devices, particularly Inertial Measurement Unit sensors (IMU), has revolutionized the landscape of data collection in the transportation sector. These devices offer granular insights into driver behavior, capturing various metrics such as acceleration, braking patterns, and vehicle trajectory. By harnessing data sourced from platforms like Kaggle and IMU sensors as in work [1], many papers proposed methodologies for driver behavior classification with machine learning algorithms, such as Logistic Regression Classifier, Gradient Boosting, and Random Forests, according to [2], in works on driver drowsiness detection for logistics and public transport applications to enhance road safety and comparative analysis of vehicle-based proposed support vector machine (SVM), detect driver drowsiness with IoT-based [3], [4]. In addition, driver behavior profiling indicate advantages driver behavior and driving style classification [5]. In the embedded world of driver behavior analysis, data are obtained by the in-vehicle sensors, such as Inertial Measurement Unit (IMU), Controller Area Network bus (CAN bus), and a GPS [6]. [7]. [8]. In IMU, CAN bus, and GPS features, the driving performance and driving characteristics were used for vehicle monitoring and diagnostic [9]. Driver behavior notify driver with posture based-inertial sensor, such as accelerometer and gyroscope, in terms of monitoring, and telematics using MEMS sensors, such as accelerometer, gyroscope, and magnetometer are features driver behavior monitoring [10]. This research seeks to analyze and categorize driving styles based on individual behaviors. Key to the success of this endeavor is the meticulous curation of feature sets that encapsulate the nuances of driving behavior. Through rigorous pre-processing and feature engineering techniques, the dataset is refined to facilitate the training of machine learning algorithms. These algorithms, ranging from classical methods like Support Vector Machine and Logistic Regression to more sophisticated ensemble techniques such as Random Forest and Gradient Boosting were deployed to discern patterns within the driving data.Moreover, the findings of this research extend beyond academic inquiry, offering practical applications in domains such as driver scoring and insurance. The classification of personal driving styles enables the establishment of driver scoring mechanisms, wherein individuals are assessed based on their adherence to safe driving practices. Such scoring systems can inform insurance premiums, with safer drivers being rewarded with lower rates, thereby incentivizing responsible behavior on the roads.In summary, this study represents a significant step forward in leveraging machine learning to enhance road safety in Thailand. By harnessing the power of data-driven insights, it offers a pathway toward mitigating the multifaceted challenges posed by diverse driving styles, ultimately fostering a safer and more sustainable transportation environment for all while simultaneously offering tangible benefits in driver scoring and insurance practices.

II. DATASET DESCRIPTION

This paper presents a detailed overview of a unique driver behavior dataset, specifically designed to facilitate research on driver behavior analysis. The dataset encompasses phone sensor data collected during various driving sessions, providing valuable insights into the dynamics of driver actions and vehicle movements. Through the integration of smartphone sensors, including accelerometers, gyroscopes, and GPS modules, the dataset offers a comprehensive perspective on driving behavior in real-world scenarios.

A. *Dataset Overview*

The "Phone Sensor Data While Driving a Car" dataset available on Kaggle contains data collected from smartphone sensors while the phone is in a moving vehicle. This dataset was designed to help analyze driving behavior and identify patterns or anomalies in driving styles, the "Phone Sensor Data While Driving a Car" dataset [2] consists of multiple sensor readings captured during driving sessions.

Key sensors include:

- Accelerometer: Captures linear acceleration in three dimensions (X, Y, Z).
- Gyroscope: Measures angular velocity around the X, Y, and Z axes.
- GPS: Provides geospatial data, including latitude, longitude, speed, heading, and distance.

B. *Processing Steps*

Prior to driver behavior classification, the dataset undergoes rigorous preprocessing steps to ensure data quality and consistency. First, dataset visualization is performed to analyze the relationship of each individual feature. Then, appropriate features are selected and undergo feature scaling to resize them to be similar. The data is split into three parts using data splitting: the train set, validation set, and test set. Parts of the train and validation sets are integrated into

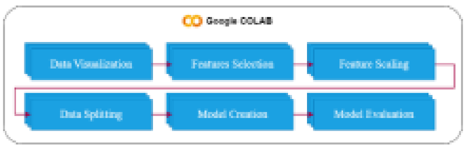

Figure 1. Processing Steps

the training process, while the test set is used for evaluating machine learning algorithms. Google Colab

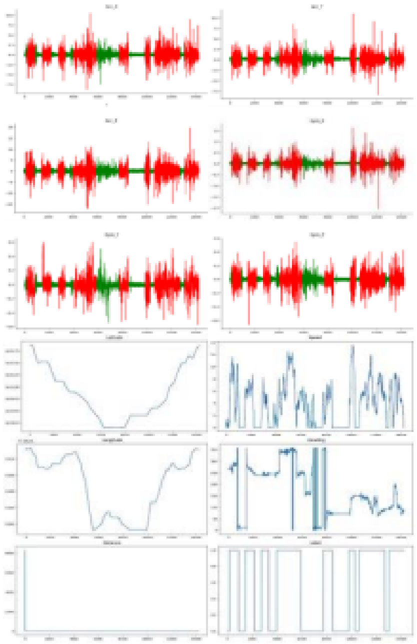

Figure 2. IMU-Smartphone sensors dataset visualization in time series plotting

Data Visualization

In this part, the dataset from Kaggle, which is IMU sensors or smartphone sensors dataset were visualized

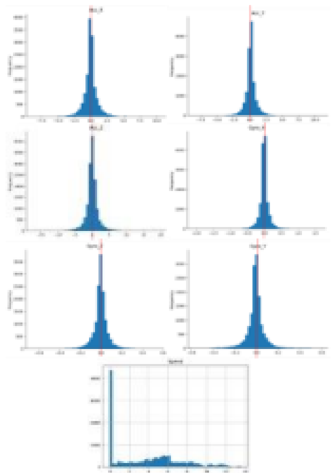

Figure 3. IMU-Smartphone sensors dataset visualization in histogram plotting

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will be used for all processes, and the processing steps are illustrated in Figure 1.

III. METHODOLOGY

In this section, processing steps will be described further regarding data preprocessing, machine learning algorithms, and performance evaluation. Since the dataset from Kaggle did not clearly indicate the distribution or relationships between features, data visualization techniques were employed to explore the shape of the dataset and examine the relationships between the features and to observe the distribution of the data. or this visualization, Twelve features were utilized: accelerometer X, accelerometer Y, accelerometer Z, gyroscope X, gyroscope Y, gyroscope Z, speed, heading, latitude, longitude, distance, and label, the visualization is presented in Figure 2, and Figure 3. According to Figure 2, features exhibiting correlations include accelerometer X, accelerometer Y, accelerometer Z, gyroscope X, gyroscope Y, gyroscope Z, speed, and label. Subsequently, the label was used as the target variable. The correlated features were plotted in the form of histograms to observe their distributions, as depicted in Figure 3. Analysis of Figure 3 indicates that accelerometer X, accelerometer Y, accelerometer Z, gyroscope X, gyroscope Y, and gyroscope Z follow a normal distribution pattern.

Feature Selection

In this part, based on data visualization, the appropriate dataset will be selected for the next step of processing. The features considered appropriate include accelerometer X, accelerometer Y, accelerometer Z, gyroscope X, gyroscope Y, and gyroscope Z.

Feature Scaling

In this part, that appropriated features will be scaled in same range of each feature, standardization or z-score normalization technique will be used to scaling features, due to features have normal distribution, standardization equation shown as equation (1).

$$z = \frac{x - mean}{SD} \qquad (1)$$

Where z is a sample of feature that scaled, x is a sample data that has not been scaled, mean is a average of features, according to the equation (2), SD is a standard deviation, according to equation (3).

$$mean = \frac{\sum_{i=0}^{n} x_i}{n} \qquad (2)$$

Where, x_i is sample data that index i, and n is the all-sample data number of feature.

$$SD = \sqrt{\frac{\sum_{i=0}^{n} (x_i - mean)^2}{n - 1}} \qquad (3)$$

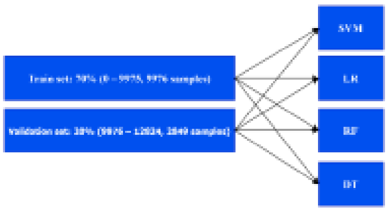


Figure 4. The training process of macine learning models

Data Splitting

In this part, the scaled features of the dataset will be split into three main parts: the train set (70%), validation set (20%), and test set (10%). The train and validation sets were used in the training process and for fine-tuning the machine learning algorithms, while parts of the test set were used for evaluating the models of machine learning.

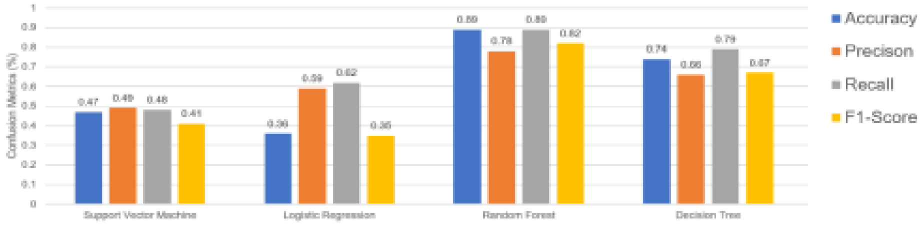
Model Creation

Dataset that split in train and validation sets will be taken in training process of machine learning algorithms, in this work, Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), and Decision Tree (DT), which are machine learning algorithms will be trained via Google COLAB, and then will be compared into the next section, this process shown as Figure 4. The train set, comprising 70% of the dataset (9975 samples), and the validation set, comprising 20% of the dataset (2849 samples), will be inputted into the training process with machine learning algorithms. Parameters for each algorithm will be tuned as follows:

- SVM parameters tuning: kernel is sigmoid function, C = 1000, gamma = auto, max iterations = -1, and random state = 109.
- LR parameters tuning: solver is limited-memory Royden-Fletcher-Goldfarb-Shanno (lbfgs), C = 0.5, random state = 1.
- RF parameters tuning: max depth = 1000, random state = 1, number of trees = 300.
- RF parameters tuning: criterion is Gini, max depth = 1000, random state = 1.

IV. RESULATS AND EVALUATIONS

Proposed model according to the model creation process will be evaluated with 4 main equations such as accuracy, precision, recall, and f1-score, as follow in equation (4), (5), (6), and (7), respectively.Where TPs is number of true positives, TNs is number of true negatives, FPs is number of false positives, FNs is number of false negatives. According to model evaluation results are shown in Figures 5. It is evident that the evaluation outcomes across various models exhibit a spectrum of performance, ranging from favorable to suboptimal. The detailed assessment is as follows:



Figures 5. The model evaluation results

$$accuracy = \frac{TPs + TNs}{TPs + TNs + FPs + FNs} \quad (4)$$

$$precision = \frac{TPs}{TPs + FPs} \quad (5)$$

$$recall = \frac{TPs}{TPs + FNs} \quad (6)$$

$$f1 - score = \frac{2 \times (precision \times recall)}{precision + recall} \quad (7)$$

- SVM evaluation results: accuracy is 0.47 or 47%, precision is 0.49 or 49%, recall is 0.48 or 48%, and f1-score is 0.41 or 41%.
- LR evaluation results: accuracy is 0.36 or 36%, precision is 0.59 or 59%, recall is 0.62 or 62%, and f1-score is 0.35 or 35%.
- RF evaluation results: accuracy is 0.89 or 89%, precision is 0.78 or 78%, recall is 0.89 or 89%, and f1-score is 0.82 or 82%.
- DT evaluation results: accuracy is 0.74 or 74%, precision is 0.66 or 66%, recall is 0.79 or 79%, and f1-score is 0.67 or 67%.

Based on the model evaluation results, Random Forest (RF) outperforms Support Vector Machine (SVM), Logistic Regression (LR), and Decision Tree (DT), achieving the highest accuracy at 89% and the highest f1-score at 82%. On the other hand, Logistic Regression (LR) exhibits the lowest performance, with an accuracy of 36% and an f1-score of 35%. However, it's important to note that these assessments may vary depending on specific criteria and use cases. Additionally, the choice of model should consider the nature of the data and the problem being addressed.

V. CONCLUSION

Conclusively, our study demonstrates the effectiveness of utilizing machine learning models to classify individual driving styles, aiming to enhance road safety measures in Thailand. With the Random Forest algorithm achieving an accuracy of 89%, precision of 78%, recall of 89%, and an f1-score of 82%, our proposed methodology provides a robust framework for accurately discerning safe and unsafe driving behaviors. This research contributes by introducing a novel approach leveraging machine learning techniques and analyzing data from IMU sensors. By offering insights into driving behavior classification, our study lays the groundwork for tailored road safety initiatives and promotes responsible driving practices nationwide.

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