CONTENTS

				Page	
ABST	ract II	N THAI .			
ABSTRACT IN ENGLISH					
ACKN	ACKNOWLEDGEMENTS				
CON	TENTS			VI	
LIST	OF TAB	LES		>	
LIST	OF FIGI	JRES .		XI	
CHA	PTER				
I	INTRO	ODUCTIO	N	1	
	1.1	Backgrou	und	1	
	1.2	Research	n Objective	4	
	1.3	Scope a	nd Limitations	4	
II	LITER	RATURE R	EVIEW	6	
	2.1	Diabetic	Retinopathy	6	
	2.2	Macula	and Optic Disc Detection	12	
		2.2.1	Conventional detection approaches	12	
		2.2.2	Novel detection approaches	15	
	2.3	Diabetic	Retinopathy Classification	17	
		2.3.1	Multi-classification	17	
	2.4	Evaluati	on Matrix	21	
		2.4.1	Confusion matrix	21	
		2.4.2	Accuracy, Precision, and Recall	22	
		2.4.3	F1 score	22	
		2.4.4	Receiver Operating Characteristic (ROC) curve	22	
		2.4.5	Area Under the Curve (AUC)	23	
		2.4.6	Quadratic Weighted Kappa (QWK) coefficient	24	
		2.4.7	Euclidean Distance (ED)	26	
		2.4.8	Intersection over Union (IoU)	26	
		249	Average Precision (AP) and Mean Average Precision (mAP)	26	

CONTENTS (Continued)

				Page
III	RESE	ARCH M	ETHODOLOGY	29
	3.1	Datase	t	29
	3.2	Image	Screening	31
		3.2.1	Optic disc and macula detection	31
		3.2.2	Screening algorithm by rulebased	34
		3.2.3	Screening algorithm by Machine learning (ML)	3!
	3.3	Evalua	tion of Image Screening	36
	3.4	DR Gra	ding	38
		3.4.1	Data preparation	38
		3.4.2	Data augmentation and balancing	38
		3.4.3	Architecture	38
			Swin Transformer	39
		3.4.4	Training setting and strategy	4(
	3.5	Evalua	tion of DR Grading	41
	3.6	Compu	utational Resources	41
IV	RESU	RESULTS AND DISCUSSION		
	4.1	Results	s of Image Screening	42
		4.1.1	Optical disc and macula detection	42
		4.1.2	Screening algorithm	45
	4.2	Ablatic	on Study of Image Screening	48
		4.2.1	Template size and sampling amount	48
		4.2.2	Matching functions	5(
		4.2.3	Region of interest (ROI)	52
		4.2.4	The generalization of the proposed method	53
	4.3	Results	s of DR Grading	54
	4.4	Ablatic	on Study of DR Grading	61
		4.4.1	Backbone model selection	61
		4.4.2	Data sampler	62
		4.4.3	Loss functions	64
		4.4.4	The impact of SMOTE	65
		4.4.5	The impact of fine-tuning	69

CONTENTS (Continued)

	Page
V CONCLUSION AND OUTLOOK	73
REFERENCES	78
APPENDIX	87
CURRICUI UM VITAF	89

LIST OF TABLES

Table		Page
3.1	The tabular data features for ML model.	35
4.1	The general performance of proposed method on IDRiD dataset.	43
4.2	The macula detection on Messidor dataset	43
4.3	The performace of proposed image screening	46
4.4	The performace of machine learning in image screening. Bold	
	represents the best score and underline represents the second	
	best score.	47
4.5	CCOEFF_NORMED achieves the highest AP ₅₀ score for both de-	
	tection task	52
4.6	The quantitative result of ROI technique.	52
4.7	The performace of machine learning in image screening. Bold	
	represents the best score and underline represents the second	
	best score.	54
4.8	The classification report of proposed model on the APTOS 2019	
	dataset	56
4.9	The classification report of proposed model on the APTOS 2019	
	dataset	59
4.10	The general performance of proposed model compared the hu-	
	man performance. Bold represents the best score	60
4.11	The general performance of each backbone model. Bold repre-	
	sents the best score and <u>underline</u> represents the second best	
	score	62
4.12	The influence of imbalance data sampler to DenseNet 161 and	
	Swin Transformer. Bold indicates the best score	63
4.13	The influence of loss functions on DenseNet 161 and Swin Trans-	
	former. Bold represents the best score	65
4.14	The classification report of Swin Transformer model with and with-	
	out SMOTE	66

LIST OF TABLES (Continued)

Table		Page
4.15	The classification report of DenseNet161 model with and without	
	SMOTE	67
4.16	The classification performance of KNN model with different pre-	
	trained models. Notably, we use macro score for comparison .	67
4.17	The classification report of Swin Transformer model with and with-	
	out SMOTE	68
4.18	The classification report of DenseNet161 model with and without	
	SMOTE	68
4.19	The classification performance of KNN model with different pre-	
	trained models. Notably, we use textbfmacro score for comparison	68
4.20	The classification performance of DenseNet161 and Swin s mod-	
	els before and after fine-tuning. Pretrained models are trained on	
	ImageNet-1K dataset. Fine-tuned models are pretrained model	
	and then, tuned on APTOS 2019 dataset. Notably, we use only	
	macro scores for comparison	69
4.21	The classification performance of KNN model with different image	
	types and pretrained models. Notably, we use only macro score	
	for comparison	70
4.22	The classification performance of DenseNet161 and Swin s mod-	
	els before and after fine-tuning. Pretrained models are trained on	
	ImageNet-1K dataset. Fine-tuned models are pretrained model	
	and then, tuned on APTOS 2019 dataset. Notably, we use only	
	macro scores for comparison	71
4.23	The classification performance of KNN model with different image	
	types and pretrained models. Notably, we use only macro score	
	for comparison	72

LIST OF FIGURES

Figure		Page
2.1	The retinal image comparison of normal and DR	9
2.2	Diabetic retinopathy (DR) lesions are categorized based on the	
	progression of lesion development; ranging from mild to severe	
	stages. a) Microaneurysms (MA); b) Retinal Hemorrhage (HM); c)	
	Hard Exudates (HE); d) Soft Exudates (SE); e) Intraretinal Microvas-	
	cular Anomalies (IRMA) and Venous Beading (VB); f) and g) Neo-	
	vascularization (NV); h) Fibrous Proliferation (FP); i) Preretinal and	
	Vitreous Hemorrhage (PRH, VH) Barbara Davis Center for Diabetes	
	School of Medicine, 2024	9
2.3	The figure illustrates the various severity levels of DR in the pa-	
	tient's retina: a) No DR; b) Mild NPDR; c) Moderate NPDR; d) Severe	
	NPDR; and e) PDR Karthik, 2019.	11
2.4	The confusion matrix	21
2.5	The ROC curve illustrate the trending of FPR and TPR as a function	
	of threshold.	23
2.6	ROC curve interpretation by curve reading	24
2.7	ROC curve interpretation by utilizing AUC	24
2.8	The figure illustrate the two PR curve including raw PR curve and	
	interpolated PR curve, which is obtained by utilizing the 11-point	
	interpolation approach	28
3.1	The class distribution of these datasets reveals that class 0 (no	
	diabetic retinopathy) is the majority class, indicating an imbalance	
	issue. The total number of images in the training sets of APTOS	
	2019 is 3,662	31
3.2	the cropped dark field images, a) images without cropping, b) im-	
	ages with cropping	32
3.3	The figure shows the result of ROI cropping from both eyes, a)	
	the left eye and b) the right eye. The macula and optic disc's	
	ground-truth locations are represented by the red and green dots.	33

LIST OF FIGURES (Continued)

Figure		Page
3.4	The acceptance region of R1 and R2	35
3.5	The figure illustrates components of the image that are used to	
	calculate the Dy _{intercept} and Dr _{distance} features. (left) The Dy _{intercept}	
	is the deviation between OD-M line and reference line on the y-	
	axis at $x = 0$. (right) The $Dr_{distance}$ is the distance from the center	
	of the image to the center of the macula	36
3.6	The example of background images which generate by covering	
	the optic disc and macula by the mean value of fundus image	37
3.7	The distribution of the synthetic samples generated by SMOTE in	
	the prior and posterior stage.	39
3.8	The architecture and attention mechanism of the Swin Trans-	
	former. a) The window shifting mechanism allow the model to	
	capture global and nearest neihbour context. b) Swin Transformer	
	architecture and blocks	40
4.1	The agreement area of each R-criterion on Messidor dataset	43
4.2	The detection results of the proposed method on the IDRiD	
	dataset. The three images above (a–c) showcase good quality	
	predictions, whereas the images below (d-f) exhibit poor quality	
	predictions. Where, cross sign ($ imes$) is a predicted location, the dot	
	sign $(ullet)$ is a ground-truth location, the green color represents the	
	optic disc, and the red color represents the macula	44
4.3	The detection results of the proposed method on the Messidor	
	dataset. The three images above (a–c) showcase good quality	
	predictions, whereas the images below (d-f) exhibit poor quality	
	predictions. Where, cross sign ($ imes$) is a predicted location, the dot	
	sign (●) is a ground-truth location, and the red color represents	
	the macula	45
4.4	The confusion matrix of proposed image screening method	46
4.5	Example of image screening results: (a) True positive; (b-c) False	
	positive; (d) True negative; and (e-f) False negative	47

LIST OF FIGURES (Continued)

Figure		Page
4.6	The template parmeter of optic disc. Heatmap depictes the sen-	
	sitivity of template dimensions via the AP score. The line plot	
	shows the impact of sampling	48
4.7	The template parmeter of macula. Heatmap depictes the sen-	
	sitivity of template dimensions via the AP score. The line plot	
	shows the impact of sampling	49
4.8	The optimal template for optic disc and macula	50
4.9	The qualitative result of macula detection, a) without ROI, b) with	
	ROI. Where, cross sign ($ imes$) is a predicted location, the dot sign ($ullet$)	
	is a ground-truth location, the green color represents the optic	
	disc, and the red color represents the macula	53
4.10	The confusion matrix of proposed model	55
4.11	The figure illustrates the ROC curve and AUC for each class, indi-	
	cating that the proposed model outperforms in classifying class 1	
	across a variety of threshold values. However, the other classes	
	exhibit constraints related to the threshold value, impacting their	
	lower classification performance	57
4.12	The PR curve and AUC for each class, which is more informative	
	than the ROC curve in context of imbalance dataset	58
4.13	The confusion matrix of proposed model	59
4.14	The figure illustrates the ROC curve and AUC for each class, indi-	
	cating that the proposed model outperforms in classifying class 1	
	across a variety of threshold values. However, the other classes	
	exhibit constraints related to the threshold value, impacting their	
	lower classification performance	60
4.15	The PR curve and AUC for each class, which is more informative	
	than the ROC curve in context of imbalance dataset.	61

LIST OF FIGURES (Continued)

Figure		Page
4.16	The figure illustrates the data sampler strategies: a) the entire	
	training dataset; b) the training data in a batch with a sequen-	
	tial sampler strategy, which sequentially selects the data from	
	beginning to end; c) the training data in a batch with a random	
	sampler strategy, which randomly selects the data from the en-	
	tire dataset; and d) the training data in a batch with an imbalance	
	sampler strategy, which attempts to select the data from each	
	class. Each color represents data from a different class	63
4.17	The t-SNE visualization of the DenseNet 161 model's feature	
	space. The colors represent different classes; cyan is class 0; red	
	is class 1; green is class 2; orange is class 3; and yellow is class 4,	
	respectively. a) and b) illustrate the feature space of model with-	
	out tuning while c) and d) illustrate the feature space of model	
	with tuning. Moreover, a) and c) are the feature space of RGB	
	images while b) and d) are the feature space of grayscale images.	71
4.18	The t-SNE visualization of the Swin s model's feature space. The	
	colors represent different classes; cyan is class 0; red is class 1;	
	green is class 2; orange is class 3; and yellow is class 4, respec-	
	tively. a) and b) illustrate the feature space of model without	
	tuning while c) and d) illustrate the feature space of model with	
	tuning. Moreover, a) and c) are the feature space of RGB images	
	while b) and d) are the feature space of grayscale images	72
A.1	The Human Subject Protection (HSP) certificate from Suranaree	
	University of Technology.	88
Α 2	The Ethics of Al certificate from University of Helsinki	89