Ecole Nationale Supérieure d'Ingénieurs de Tunis

الجمهورية التونسية
وزارة التعليم العالي والبحث العلمي
جامعة تونس
المدرسة الوطنية العليا للمهندسين بتونس

Master thesis

A Deep Learning System for Diabetic Retinopathy, Lesion Segmentation and Disease Grading

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OUTLINE

01 Overview

Highlighting the main points and key elements of RD

02 Research Aim

Defines the purpose and direction of the research project

03 Dataset

The quality and relevance of the data significantly impact the outcomes and conclusions drawn from the research study

04 Semantic segmentation

Understand, analyze, and segment the image

05 Grade classification

Understand, analyze, and Classify the images

06 Conclusion

Summarizes the main points and findings discussed in the body of the work

642 million !

In 2017, around 425 million DR patients were recorded globally, with an estimated increase of up to 642 million by **2040**.[1]

DR is a dangerous illness that leads to blindness among the working-age population. It is also the most dreaded complication of diabetes, as it increases the risk of other diseases like kidney disorders, heart disease [2], and mortality [3].

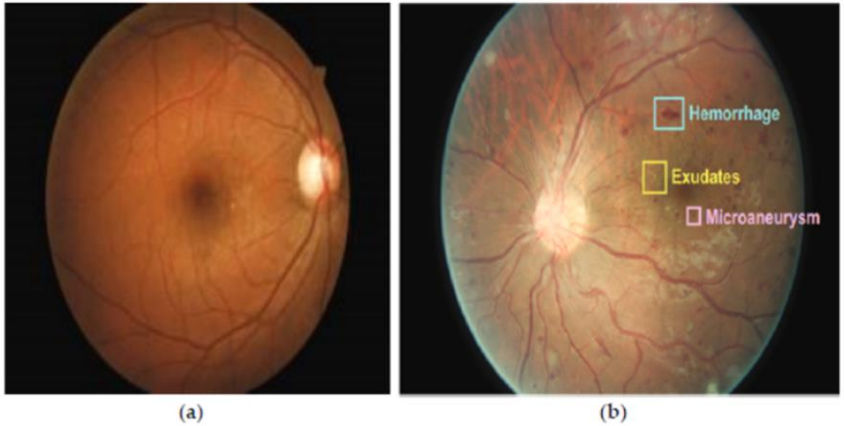
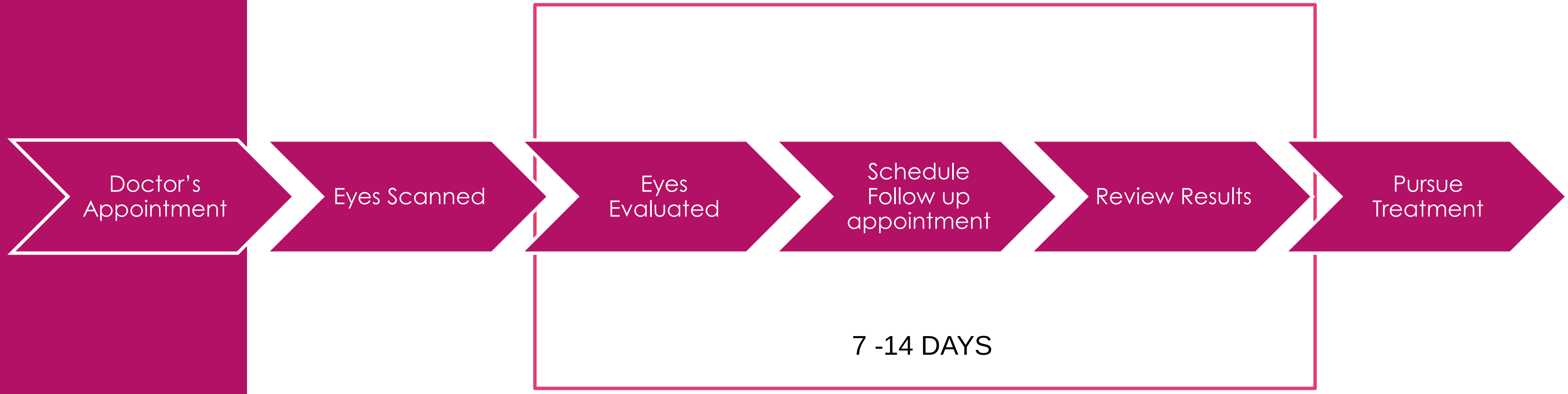


Figure 1.1: (a) the eye structure of a non-DR patient, (b) the eye structure of a patient with DR.

Current Diagnosis Process



2 weeks

Proposal Diagnosis Process

Overview

01 Diabetic retinopathy (DR) is a condition that occurs in human eyes due to diabetes mellitus.

02 Risk factors can increase the likelihood of developing DR :
Duration of diabetes, High blood pressure,
Pregnancy and High cholesterol levels.

03 **Motivation**: Early Detection of DR

04 Deep learning is a powerful subset of artificial intelligence used to analyze DR in computer-aided applications

Research Aim

Research Aim

“

We tackled two significant challenges in medical image analysis:

1. DeepLabV3+ based system for lesion segmentation, demanding in-depth knowledge of deep learning techniques.

2. Swin Transformer-based system for diabetic retinopathy grading, striving to achieve superior results compared to recent advancements in the field. These endeavors pushed our technical boundaries, highlighting our commitment to innovative solutions in the realm of medical imaging.

”

Dataset

Dataset

IDRiD (Indian Diabetic Retinopathy Image Dataset).

It includes standard DR lesions and carefully annotated normal retinal structures below a pixel level.

This comprehensive information makes IDRiD ideal for developing and evaluating image analysis algorithms for early detection of DR.

Dataset

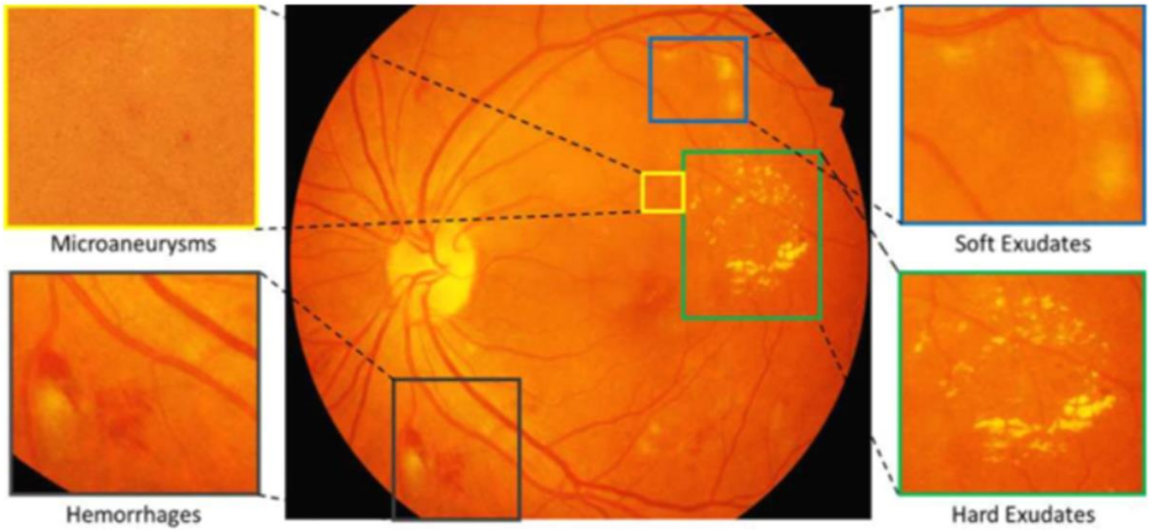


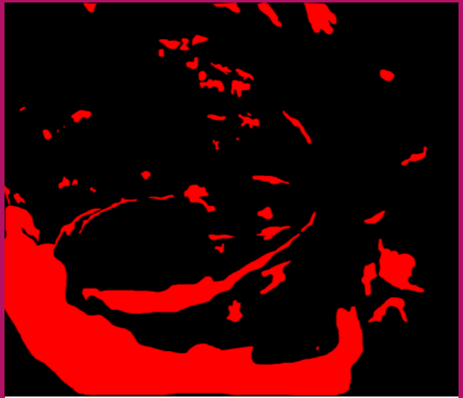
Figure 2.1: Color fundus photograph showing various retinal lesions associated with diabetic retinopathy, including microaneurysms, soft exudates, hemorrhages, and hard exudates [34].

Dataset

HE image

HEMORRHAGES

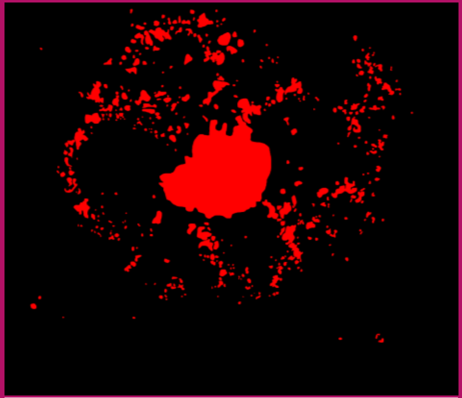
This is the original of HE image



HE mask

HEMORRHAGES

This is the mask of the original HE image



EX mask

HARD EXUDATES

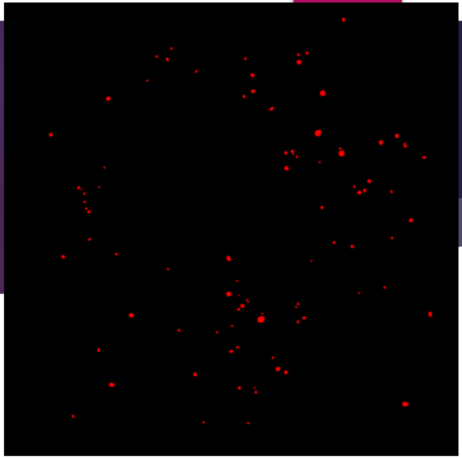
This is the mask of the original EX image

EX image

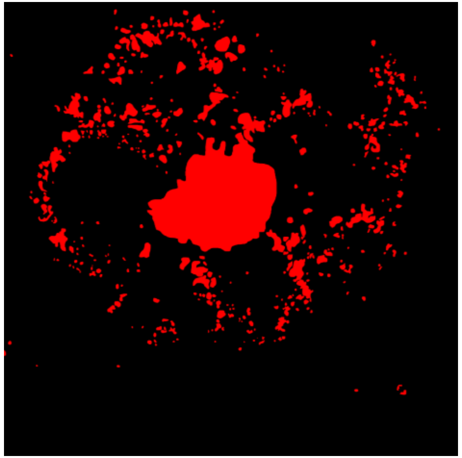
HARD EXUDATES

This is the original EX image

IMAGES + MASKS

The same image can contain 1 or more pathological classes at the same time.

Semantic segmentation

Semantic segmentation

01 Plays a pivotal role in medical imaging, revolutionizing the way healthcare professionals analyze and interpret images

02 Enhances accuracy, efficiency, and effectiveness across various aspects of healthcare

03 Its algorithms can assist in the early detection of diseases it can identify early signs of DR, enabling timely interventions to prevent vision loss

04 Finally , it assigns a label to every pixel in an image to identify the object or area it belongs to

Objective

- Develop specialized binary segmentation models for every class.
- Through the individual segmentation of each class, we intend to enhance the model’s capacity to identify delicate nuances and complexities associated with DR.
- This focused method enables us to tackle any imbalances within the dataset and refine parameters that are unique to each class, leading to improved accuracy and a more reliable segmentation process.

The step-by-step approach

- we will create a distinct binary segmentation model for each class (MA, HE, EX, SE).
- Parameter Tuning.
- Data Augmentation.
- Re-training and Evaluation.

Process for the final scenario

The process is repeated for each pathological classes

Data Preparation

Collect and organize data specific to the target class

Model Training

Fine-tune model parameters

Threshold Optimization

Determine the optimal threshold for binary classification using techniques like IoU, F1 score

Evaluation

Record these metrics in a table for analysis

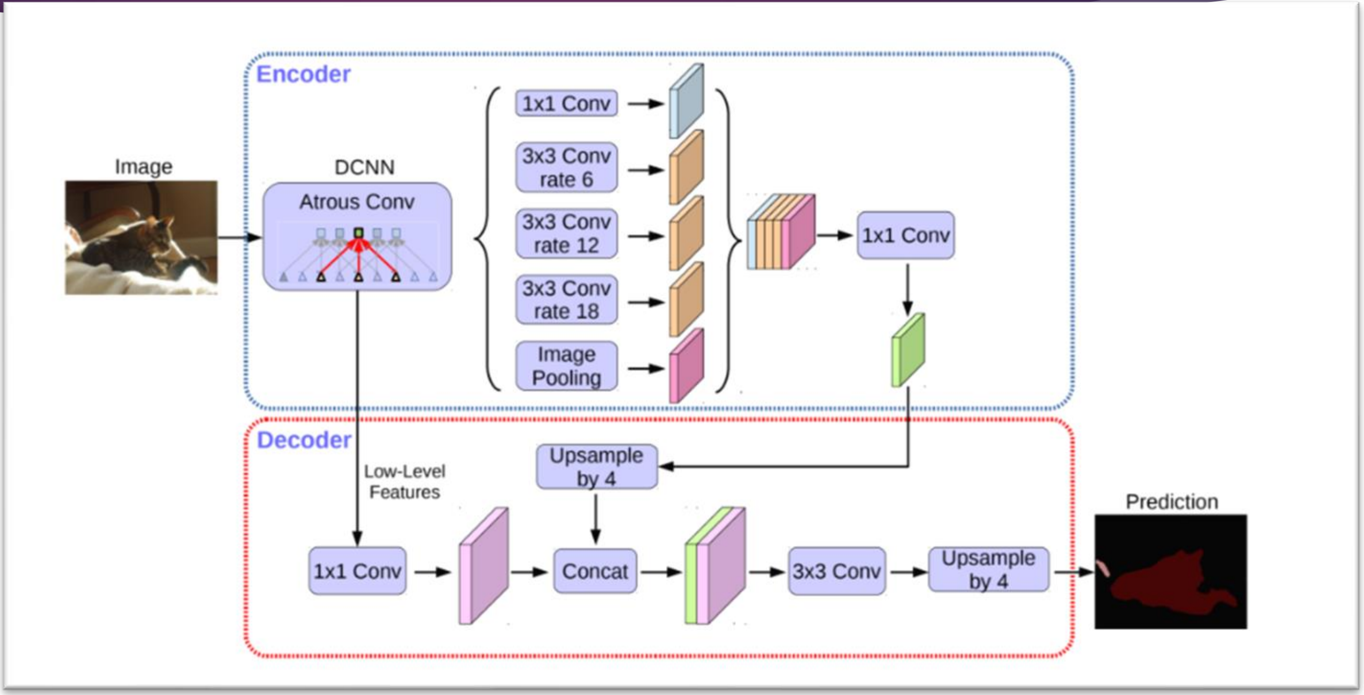
Data Augmentation

Augment the dataset with techniques like to increase diversity and robustness

Testing New Images

Present the segmented images for each class, including original, **CLAHE enhanced**, and contrast-adjusted images

DeepLabv3+ Overview



EXUDATES (EX)

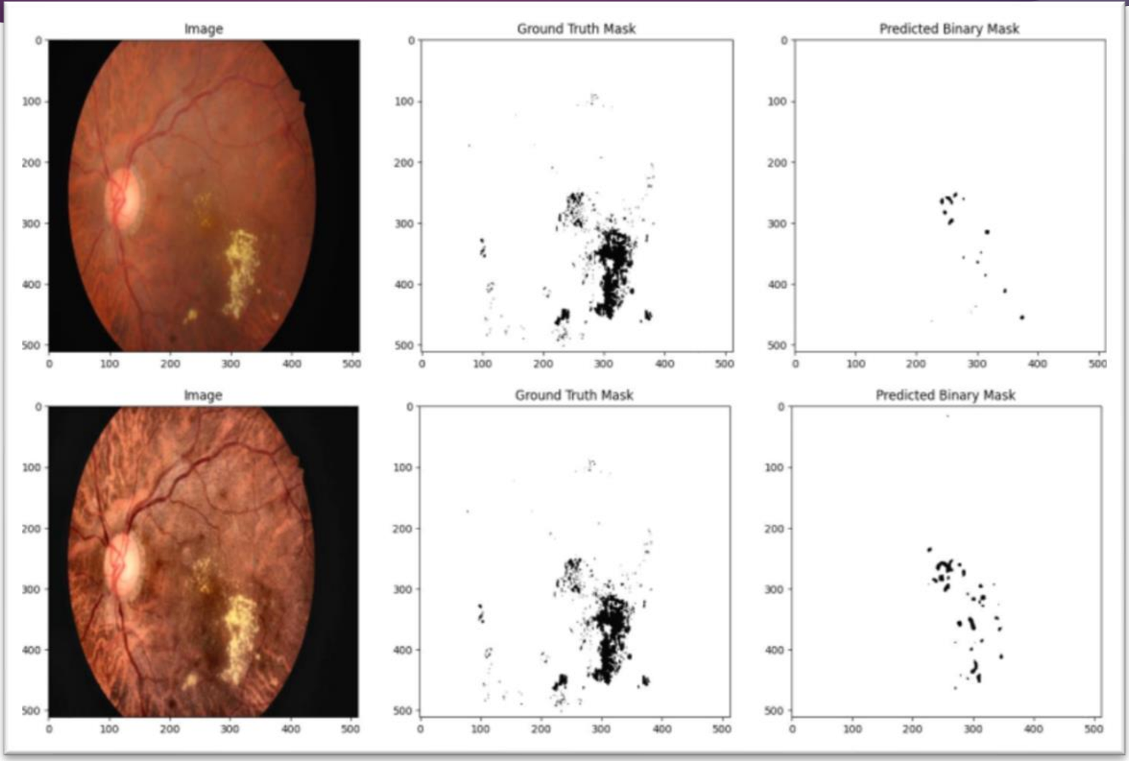


Image
Ground Truth Mask
Predicted Binary Mask
Image
Ground Truth Mask
Predicted Binary Mask

EXUDATES (EX)

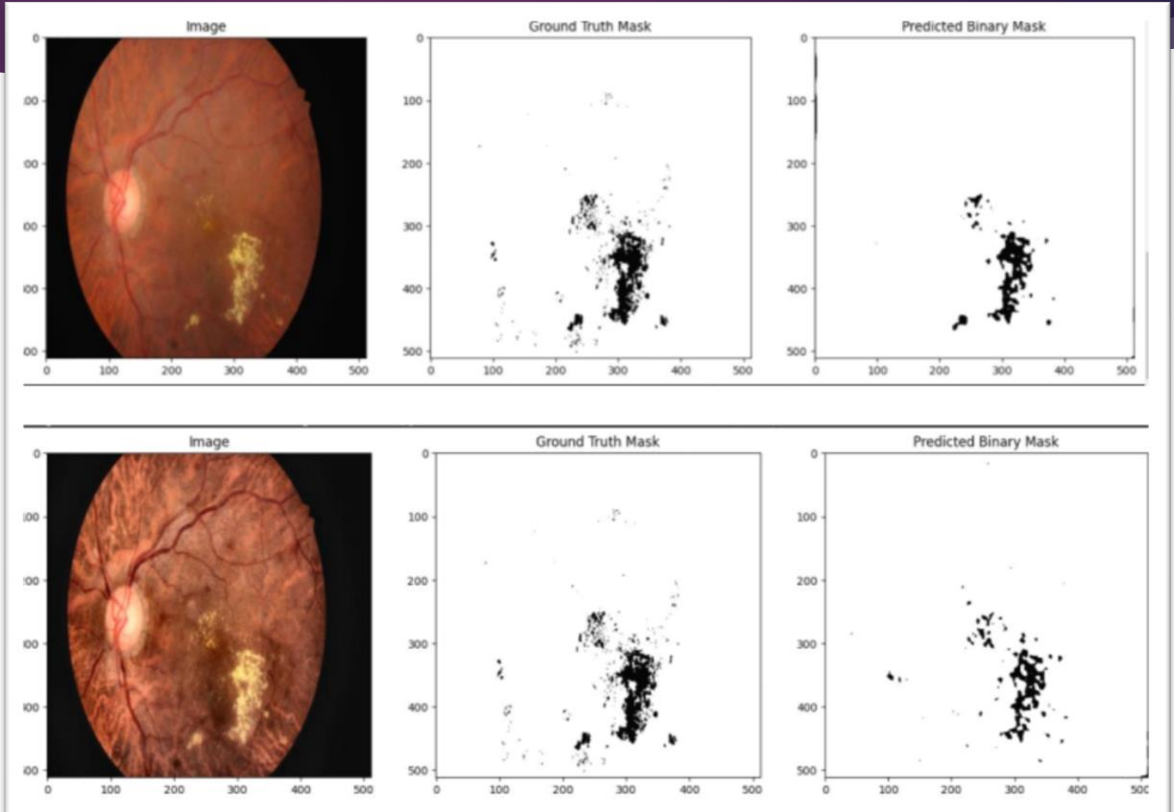


Image
Ground Truth Mask
Predicted Binary Mask
Image
Ground Truth Mask
Predicted Binary Mask

EXUDATES (EX)

	Original Data	Augmented Data
Average IoU	0.989573393916542	**0.993861649559938**
Average Dice Coefficient	0.9947491577171835	**0.9969186281786624**
Average Accuracy	0.9895896911621094	**0.9939063016106101**
Average Precision	0.9898170653820584	**0.9960621122489004**
Average F1 Score	0.9947491577171834	**0.9969186281786624**
Average Sensitivity	**0.9997506686761005**	0.9977780981188805
Average Specificity	0.12632448499761864	**0.48124558716655924**

Table 2.4: Comparison of Evaluation Metrics of EX.

HEMORRHAGES (HE)

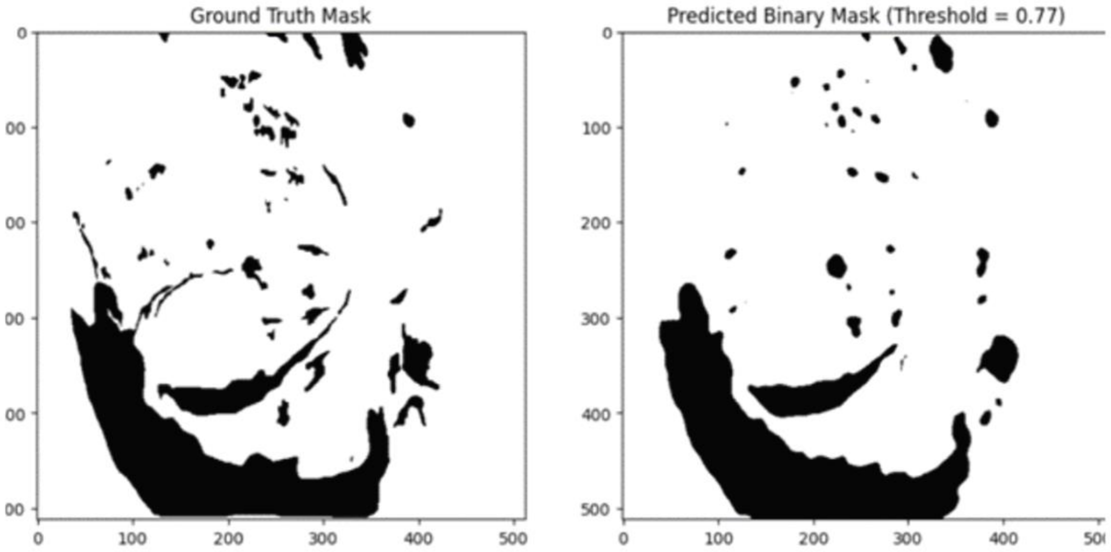
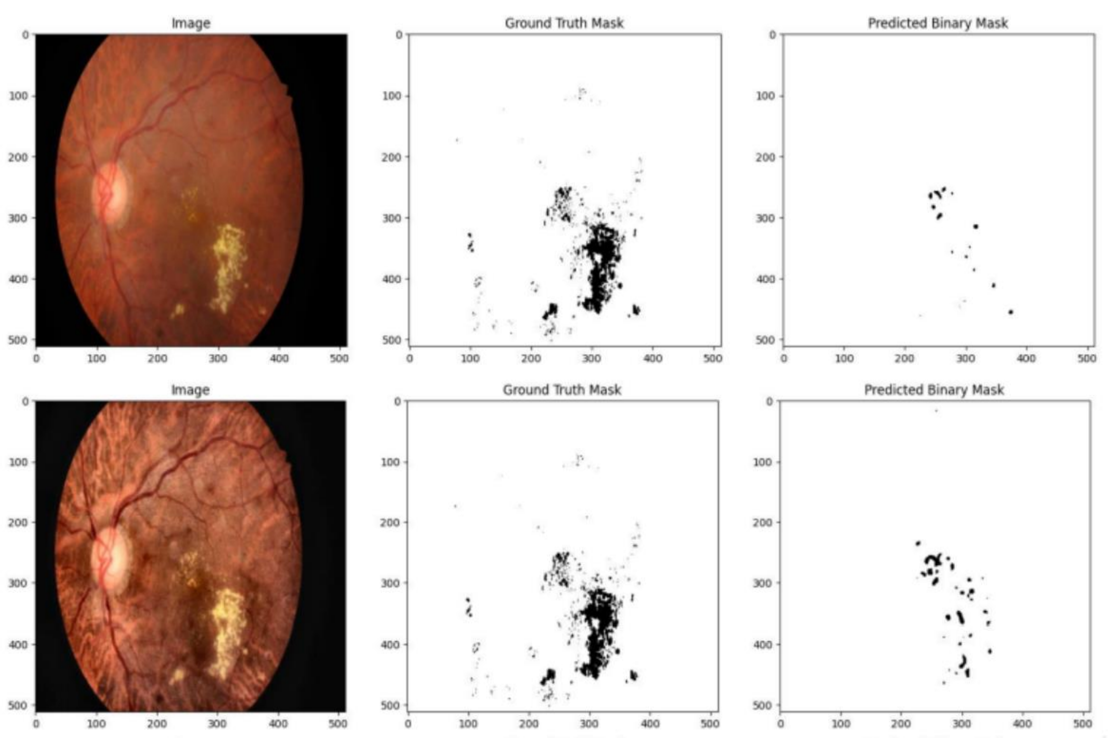


Figure 2.9: Predicted and Ground-truth images of HE.

HEMORRHAGES (HE)



HEMORRHAGES (HE)

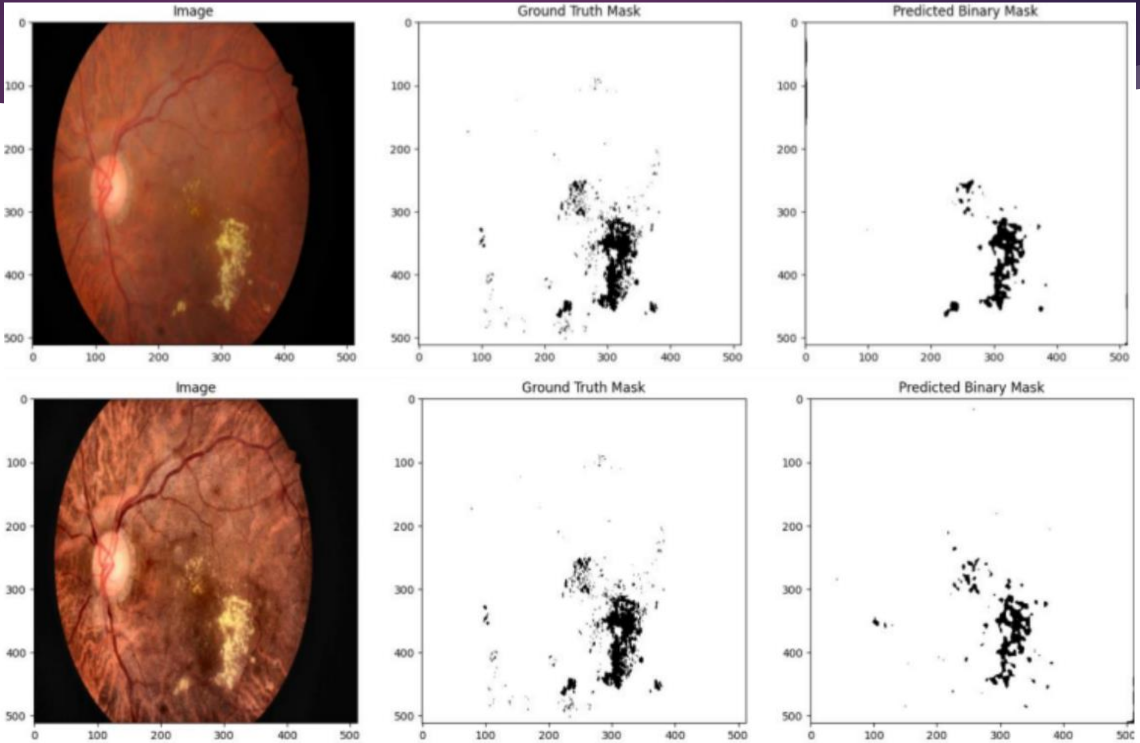


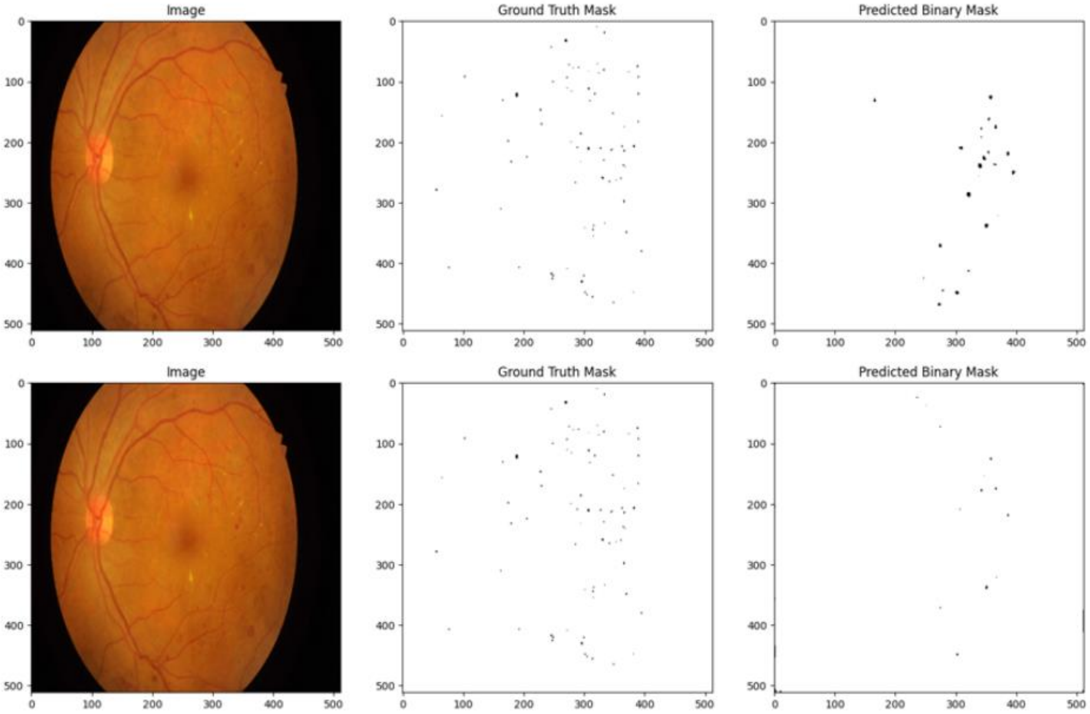
Figure 2.8: predicted images for each preprocessing.

HEMORRHAGES (HE)

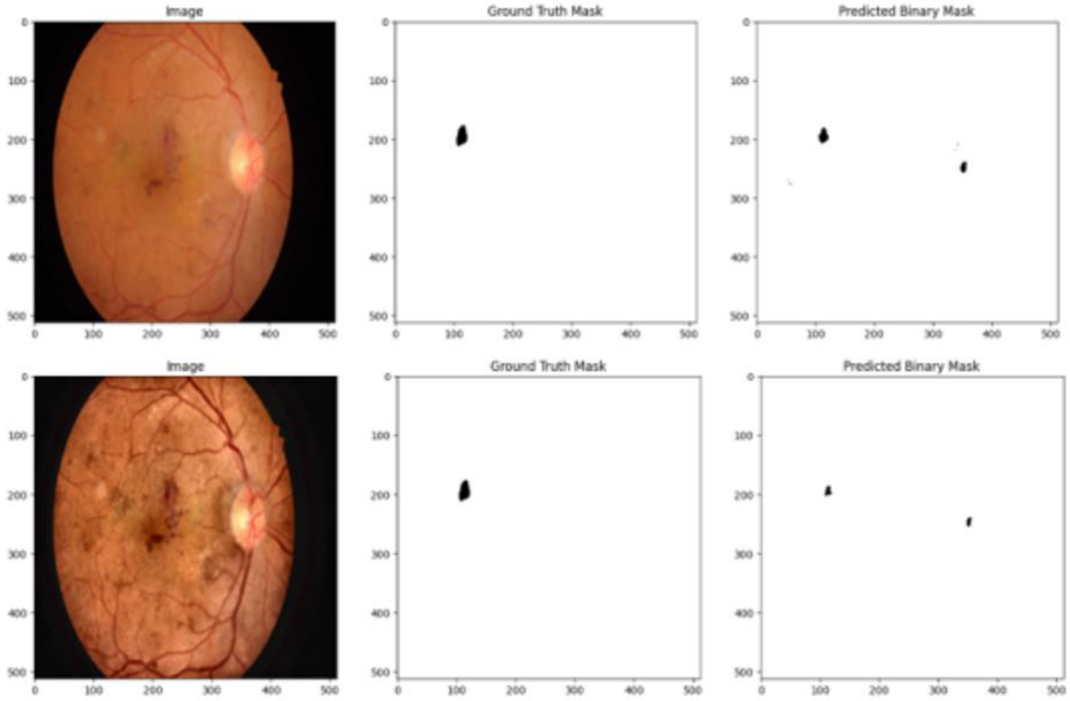
	Original Data	Augmented Data
Average IoU	0.9921892901502299	**0.9926495734642422**
Average Dice Coefficient	0.9960743473373306	**0.996302797500946**
Average Accuracy	0.9922149181365967	**0.9927182478063247**
Average Precision	0.9933964086209579	**0.9939732276465395**
Average F1 Score	0.9960743473373306	**0.996302797500946**
Average Sensitivity	**0.9987771511287098**	0.9986566653700363
Average Specificity	0.2567417639272256	**0.4097867826773220 5**

Table 2.7: Comparison of Evaluation Metrics of HE.

MICROANEURYSMS (MA)



SOFT EXUDATES (SE)



SOFT EXUDATES (SE)

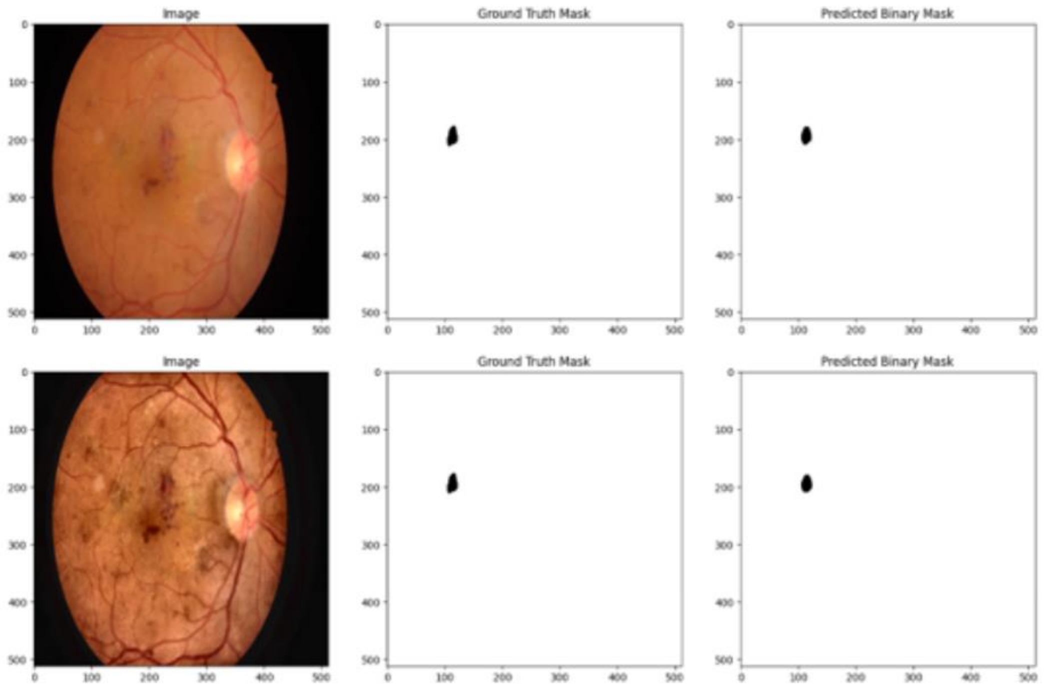


Figure 2.17: Predicted images for each preprocessing.

SOFT EXUDATES (SE)

	Original Data	Augmented Data
Metric	Value	Value
Average IoU	**0.9977395919739727**	0.9971015399135711
Average Dice Coefficient	**0.9988683739967876**	0.9985485502504086
Average Accuracy	**0.9977397918701172**	0.997109628677368
Average Precision	0.9978018852904015	**0.998846631074290**
Average F1 Score	**0.9988683739967876**	0.9985485502504087
Average Sensitivity	**0.9999373449167117**	0.9982508628440736
Average Specificity	0.02192429022082018	**0.707701543987550**

Table 2.13: Comparison of Evaluation Metrics of SE.

Comparison with Related Works

Table 2.14: Overview of reported techniques for DR lesion segmentation.

Ref #	Year	Methodology	Segmentation Techniques	Datasets	Results
[46]	2022	CNN U-Net, AlexNet, VG-GNet, Green Channel, Adam Optimizer	CNN U-Net	IDRiD	ACC = 98.68%
[42]	2022	Adaptive Active Contour, Otsu Thresholding, Morphological Operation, Median Filtering, Open-Close Watershed Transform, GLCM, ROI, LTP	Adaptive Active Contour, Watershed Transform, Otsu Thresholding	IDRiD	ACC = 60%
[6]	2021	EAD-Net, U-Net, CAM, PAM	EAD-Net, U-Net	IDRiD	ACC = 78%
[19]	2020	U-Net, ResNet34, Initialized to Convolution NN Resize (ICNR)	U-Net	IDRiD	ACC = 99.88%
[20]	2020	Deep CNN, DeepLabV3, Segnet, Conditional Random Field (CRF)	DeepLabV3, Segnet	IDRID	ACC = 88%

Comparison with Related Works

Table 2.14 – Continued from previous page

Ref #	Year	Methodology	Segmentation Techniques	Datasets	Results
[30]	2019	U-Net, HEDNet, HED-Net+cGAN, Conditional Generative Adversarial Network (cGAN), Patch-GAN, VGG16 Weighted Binary Cross-Entropy, Loss, CLAHE, Bilateral Filter	U-Net, HEDNet, HED-Net+cGAN	IDRiD	Precision = 84.05%
[21]	2019	Deep-CNN, Binary Cross Entropy, VGG16	Deep-CNN	IDRiD	Jaccard Index (IOU) = 85.72%
[49]	2018	Circular Hough Transform, Morphological Operations, Average Histogram, Contrast Enhancement, CCA	Circular Hough Transform	IDRiD	SF = 96.80%
Our work	**2023**	**Scenario 02: Data augmentation, CLAHE, Adjust the histogram**	**Deeplabv3+**	**IDRiD**	**ACC = 99%**

Diabetic Retinopathy Grading

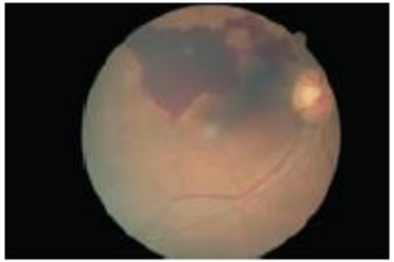
Stages of diabetic

(a) No DR

(b) Mild DR

(c) Moderate DR

(d) Severe DR



(e) Proliferative DR

DR Grade	Findings
No DR:	No visible sign of abnormalities
Mild DR	Presence of MAs only
Moderate DR	More than just MAs but less than severe NPDR
Severe DR	Any of the following: >20 intraretinal HEs Venous beading Intraretinal microvascular abnormalities no signs of PDR
Proliferative DR	Either or both of the following: Neovascularization Vitreous/pre-retinal HE

Grading Challenge

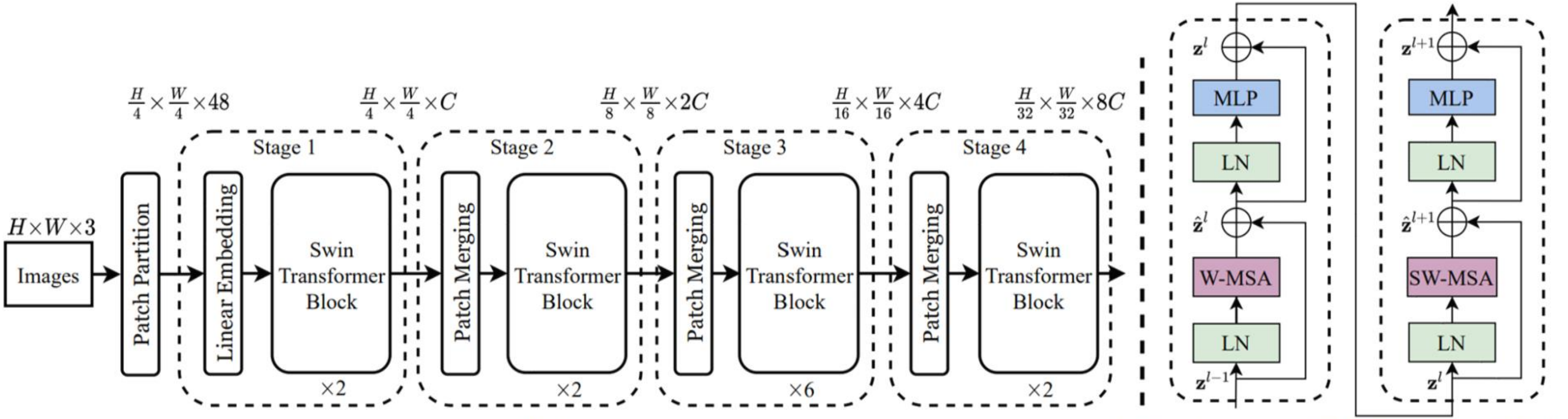
01 We will focus on fine-tuning the data preprocessing techniques to suit the input data for the model better.

02 We'll also use advanced data augmentation methods to increase the diversity and quantity of our training data.

03 At the same time, we'll be going through an extensive hyperpara meter tuning process to optimize the model's configuration even further.

04 By combining these efforts, we hope to significantly improve the model's performance and achieve our desired outcomes

Swin Transformer Overview



(a) Architecture

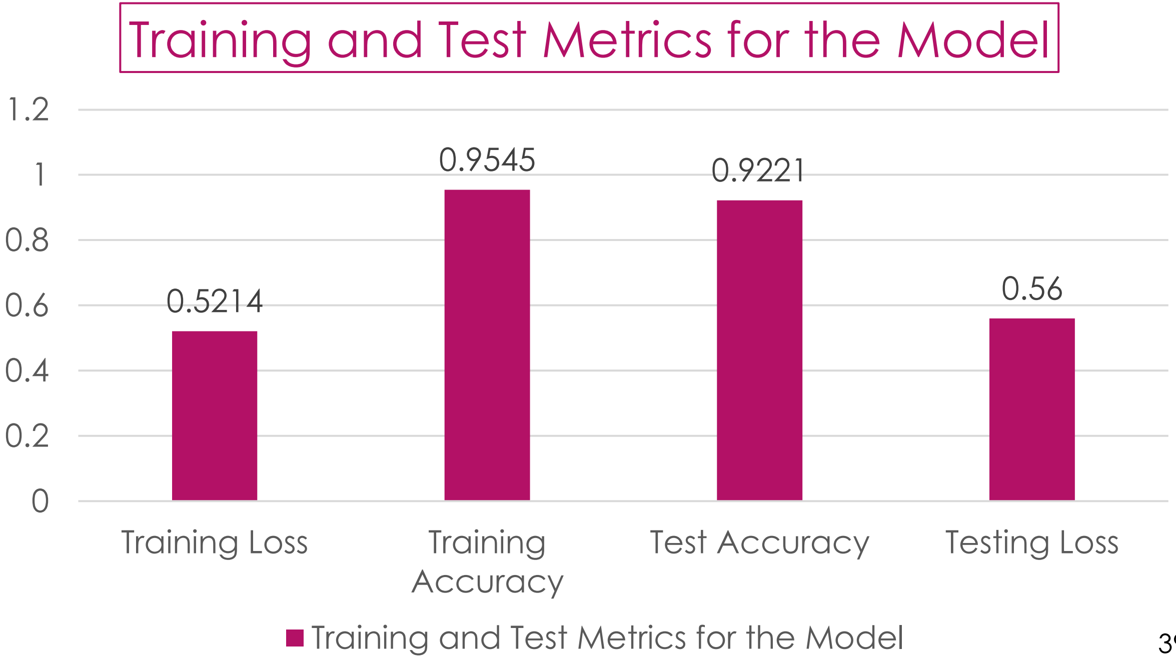
(b) Two Successive Swin Transformer Blocks

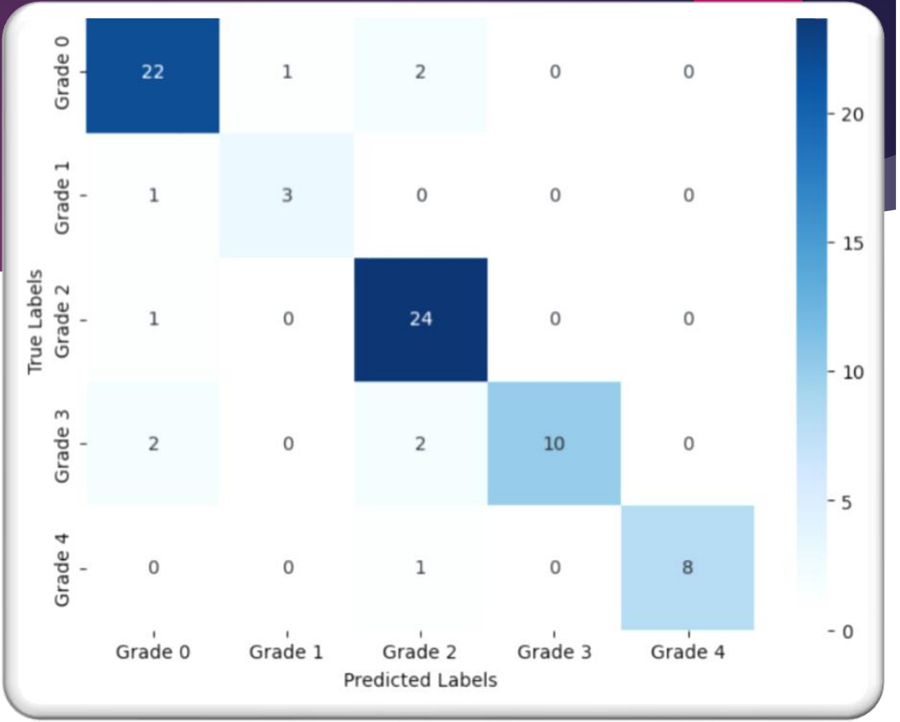
Evaluation

92.21% ACC

The provided model evaluati on metrics indicate a strong performance across both the training and test datasets

These results highlight the rob ustness and generalizability of the model, making it an asset for real-world applications



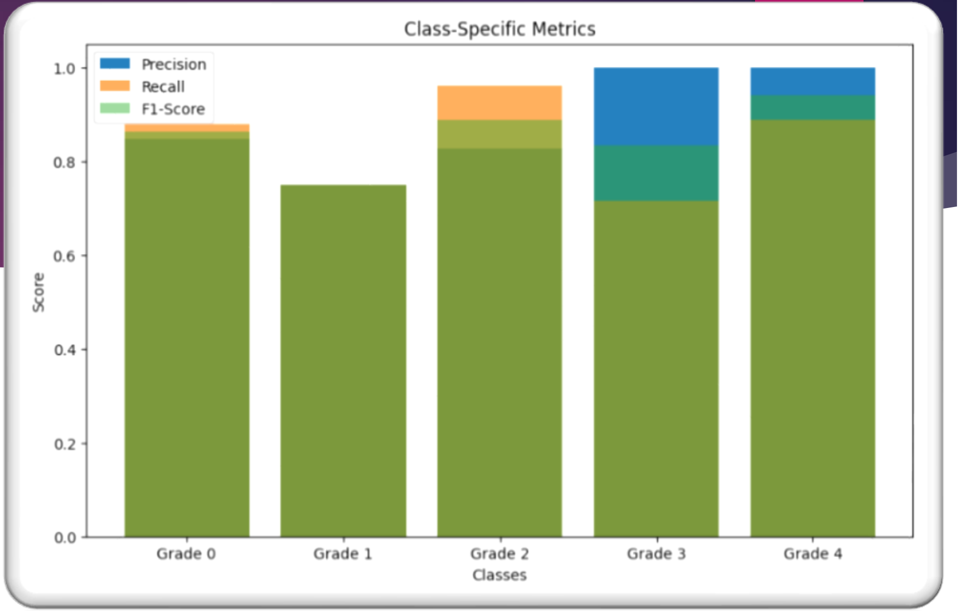


Confusion Matrix

Explanation

In this case, although there were a few misclassifications, the model's performance improved significantly compared to the previous evaluation

Evaluate Performance



Precision, recall, and F1-score for each class

These metrics offer valuable insights into the model's performance, particularly in a multi-class classification scenario where the importance of each class's accuracy can vary significantly

Comparison with Related Works

Table 3.5: Reported deep feature extraction methods and classifiers used in various studies.

Ref #	Year	Methodology	Deep Feature Extraction Method	Classifiers	Datasets	Results
[5]	2022	CNN, EyeNet, DenseNet E-DenseNet, Average Pooling (GAP)	E-DenseNet	Softmax	IDRiD	ACC = 93%
[33]	2021	Inception-V3, ResNet101, VGG-19, Naïve Bayes, KNN, SVM	Inception-V3, ResNet101, Vgg19	SVM	IDRiD	SP = 99.30%
[32]	2021	CNN, SqueezeNet, ResNet-50, Inception-V3, DFTSA-Net, CLAHE	DFTSA-Net	Softmax	IDRiD	SP = 95.50%
Our work	**2023**	**Scenario 02 : Fine-tuning data augmentation parameters**	**SwinTransformer**		**IDRiD**	**ACC = 92.21%**

A Remarkable Revelation !

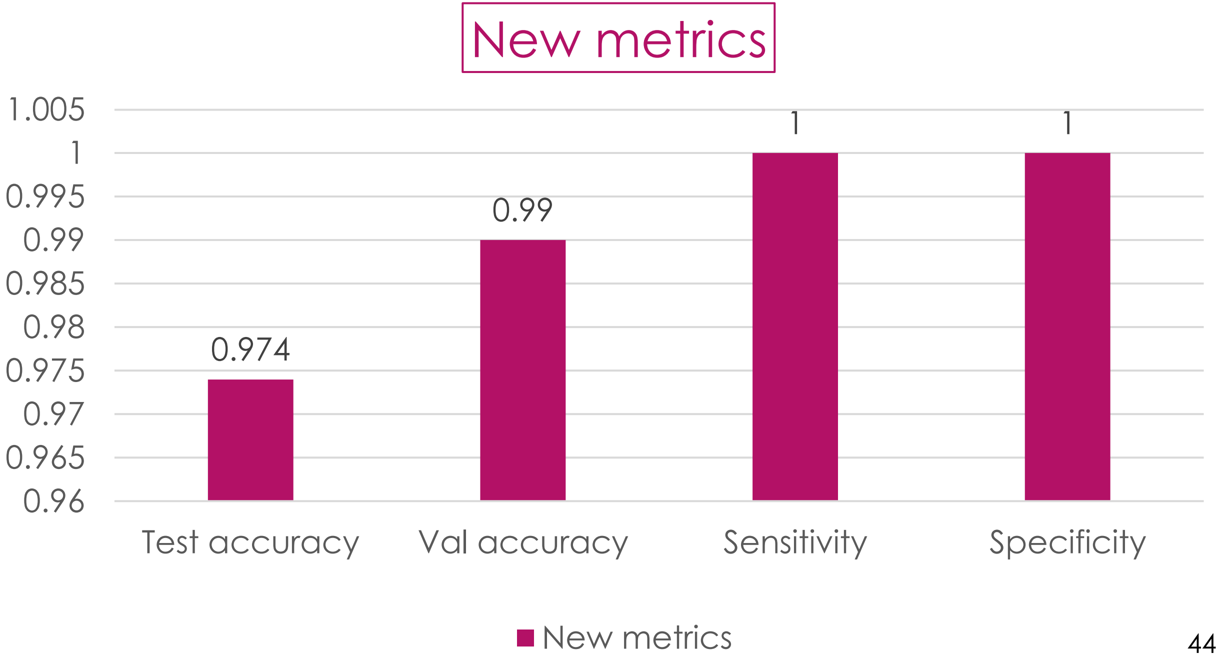
Evaluation

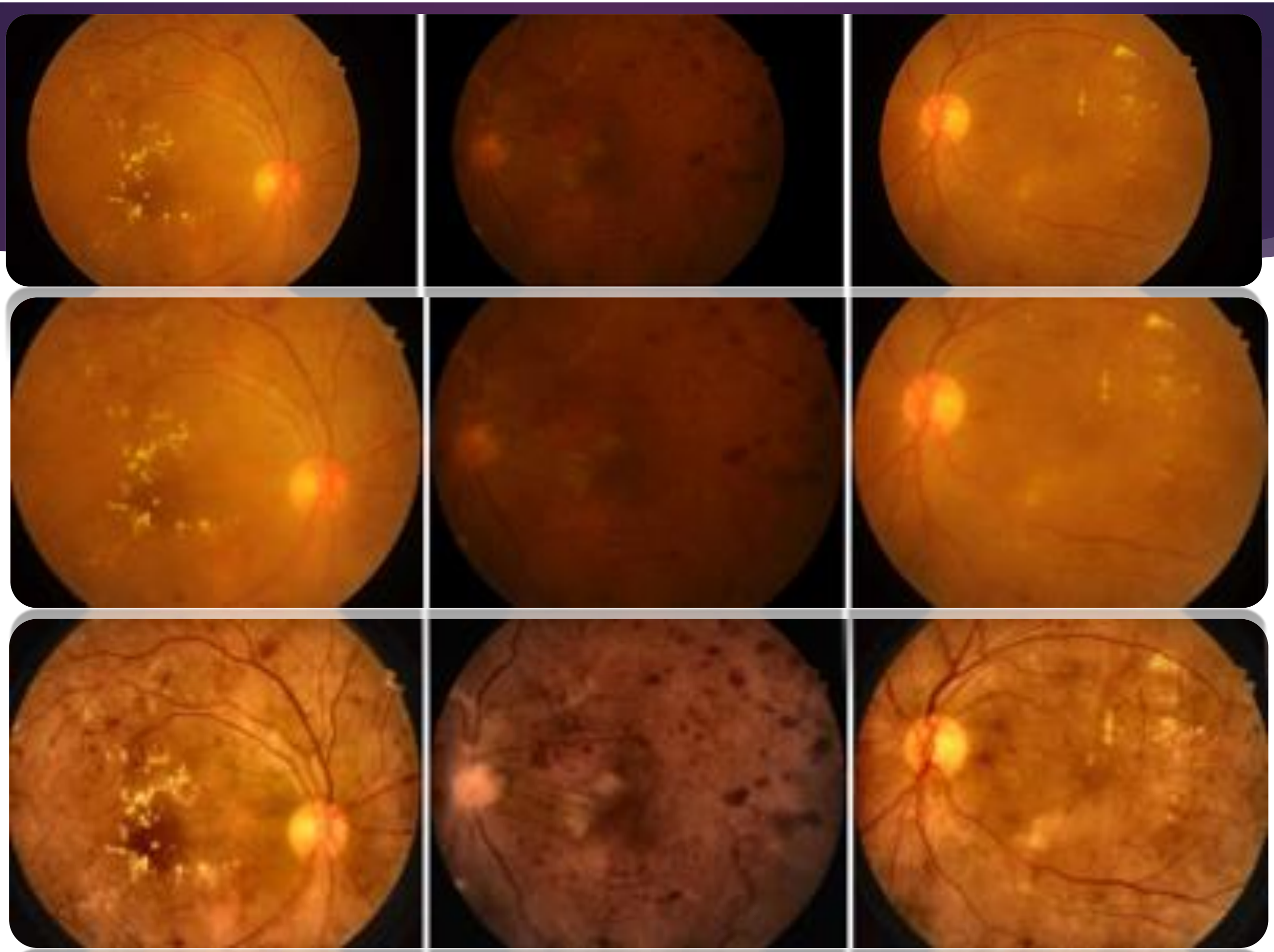
97.4% ACC

~~92.21%~~

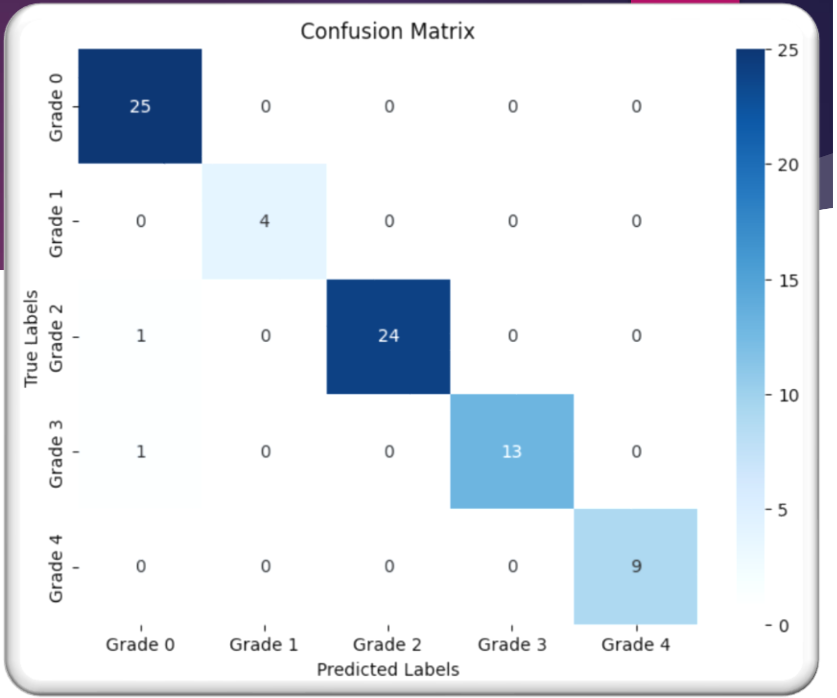
To further enhance our model's robustness, we introduced a novel cropping technique.

This strategic crop not only improved training efficiency but also mitigated the challenges posed by pixel similarities



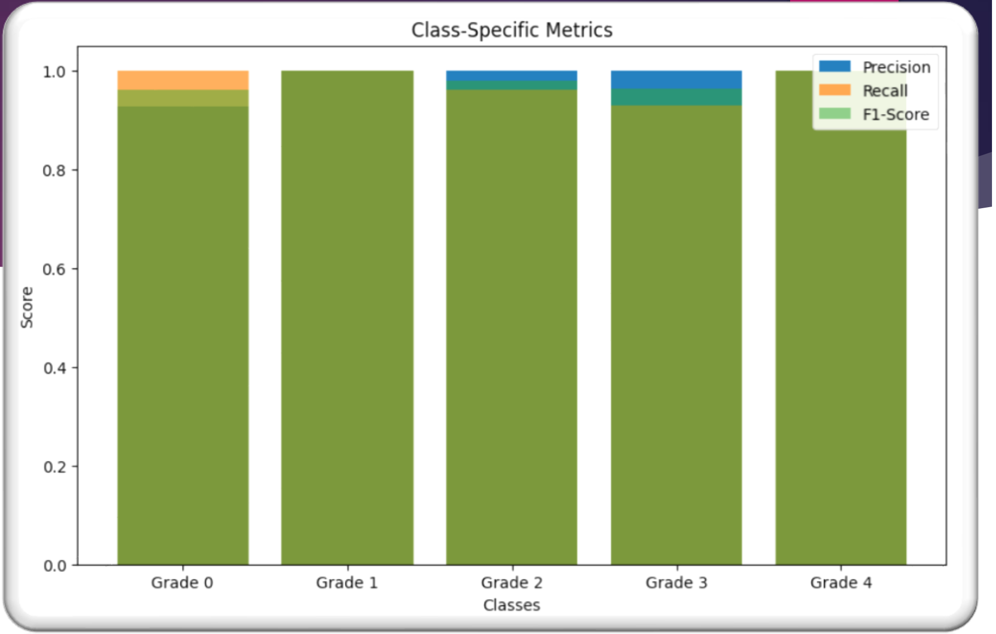


Confusion Matrix



Explanation

In this case, the model's performance improved significantly compared to the previous evaluation



Evaluate Performance

Precision, recall, and F1-score for each class

These metrics offer valuable insights into the model's performance, particularly in a multi-class classification scenario where the importance of each class's accuracy can vary significantly

Comparison with Related Works

Table 3.5 – Continued from previous page

Ref #	Year	Methodology	Deep Feature Extraction Method	Classifiers	Datasets	Results
New update	2023	Scenario 02 : Fine-tuning data augmentation parameters + Crop IMAGE (improving the image by removing unnecessary parts.	SwinTransformer		IDRiD	ACC = 97.45%, SP = 100%

Future work

- In our upcoming work, we're crafting a cutting-edge application designed to segment and classify DR images. Each distinct pathological class will be color-coded, simplifying interpretation for medical professionals.
- Our goal is to not only enhance accuracy in diagnoses but also streamline decision-making.
- The application will extend its utility by suggesting appropriate interventions, such as laser treatment for affected eyes.

Conclusion

01

Dataset

Dataset is ideal for developing and evaluating image analysis algorithms for early detection of diabetic retinopathy.

02

Segmentation

Our Scenario showcased the remarkable potential of class-specific binary segmentation, focusing on tailored preprocessing steps.

03

DR Grading

The backbone of our success lies in carefully handling the Swin Transformer and the preprocessing steps which proved instrumental in extracting complex patterns from our dataset.

50

Reference

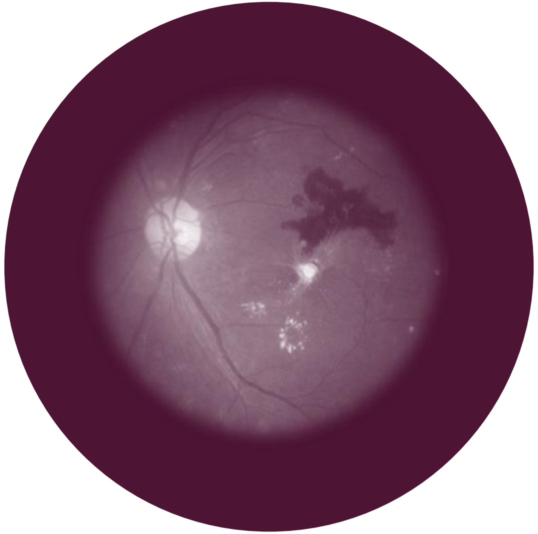
[1] International Diabetes Federation. “IDF diabetes atlas 8th edition”. In: International diabetes federation (2017), pp. 905–911

[2] Tien Y Wong et al. “Retinopathy and risk of congestive heart failure”. In: Jama 293.1 (2005), pp. 63–69

[3] Xiao-Hong Xu et al. “Diabetic retinopathy predicts cardiovascular mortality in diabe tes: a meta-analysis”. In: BMC Cardiovascular Disorders 20.1 (2020), pp. 1–8.

[4]

[5] Liu, Ze, et al. "Swin transformer: Hierarchical vision transformer using shifted windows. " Proceedings of the IEEE/CVF international conference on computer vision. 2021



Thank you !

Designed by Meher