Inception Separable CNN for Retinal Disease Classification

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Outline of Presentation

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INTRODUCTION

- **Aims**
- **Objectives**

1 Introduction

- Aims

- Combine the Separable CNN with Inception model.
- Increase the accuracy of model for precise diagnosis of retinal disease.

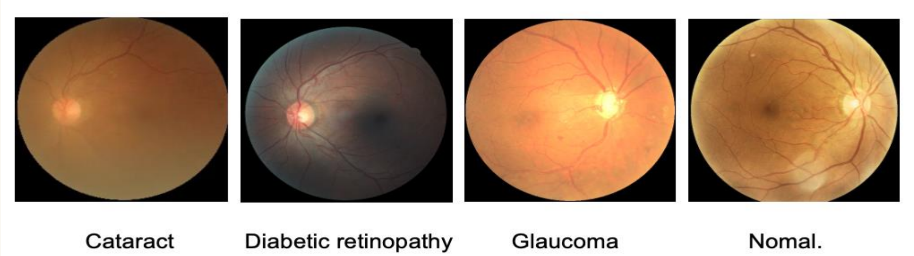

Figure 1 Samples of retinal disease OCT images

- Design a web application for the model.

1 Introduction

- Objectives

- Search and compare existing retinal disease classification models.
- Construct deep learning model based on separable CNN with Inception model.
- Optimize the model to improve accuracy.
- Compare the performance of different model with the proposed model using the same dataset.
- Present the graphic user interface (GUI) to the direct audience.

2

Background Review

- **Comparison of existing models proposed in different papers**

Existing models proposed in different papers

Researchers	Year	Techniques	Accuracy
Meenu et al. [1]	2022	Depthwise separable CNN	93.5%
Kermany et al. [2]	2018	Inception V3	96.6%
Alqudah et al. [3]	2019	Novel Automatic CNN structure	95.3%
Rajagopalan et al. [4]	2021	Deep CNN framework	95.7%
Mahendran et al. [5]	2020	Decision tree classifier	92%
Najeeb et al. [6]	2018	Single layer CNN structure.	95.66%
Bhadra and Kar [7]	2020	Deep multi-layered CNN	96.5%
Intaraprasit et al. [8]	2023	MobileNetV2	99.8%

Table 1 Literature Review of different approach about retinal disease classification

3

Methodologies

- **The proposed architecture of the project**

3 Methodologies

- Model Architecture

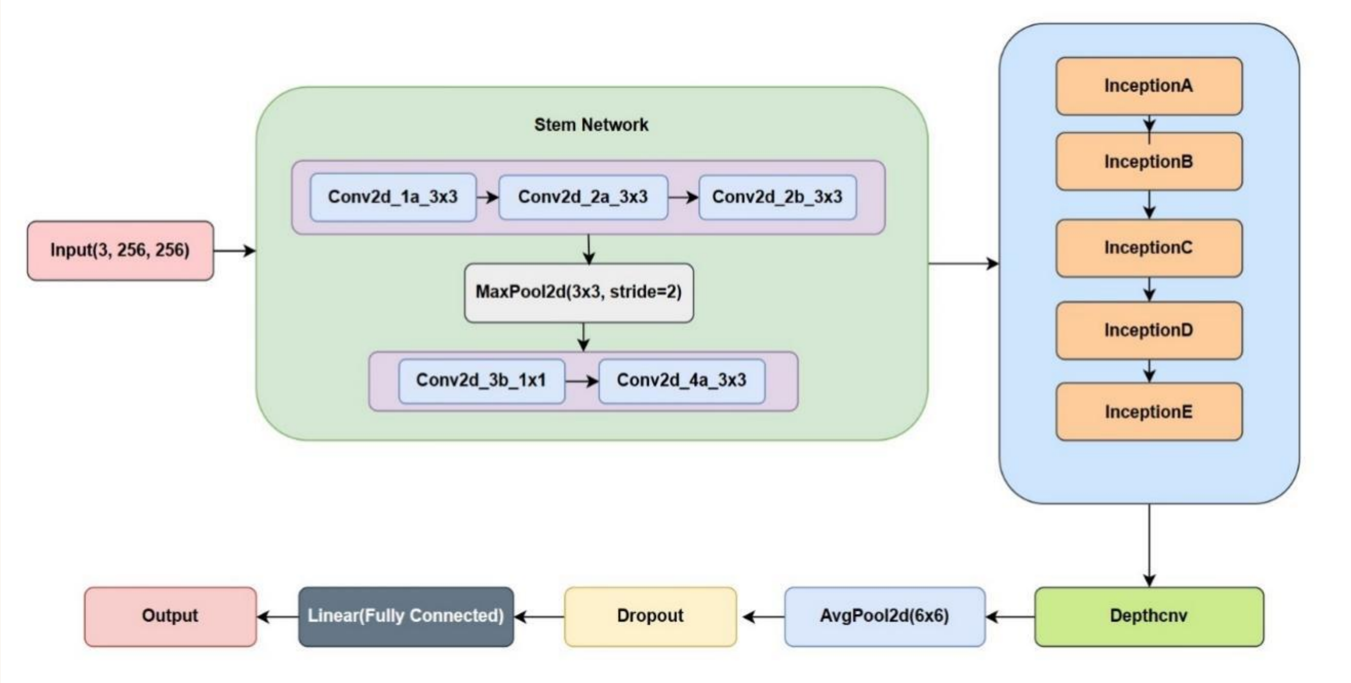

Figure 2 Model architecture

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Results

- Model Performance
- Model Explainability
- GUI Design

4 Results

- Model Performance

Hyper-parameter	value
Batch size	70
Learning rate	0.0001
Epoch	100

Table 2 Hyper-parameters setting

Evaluation metric	Result
Validation loss	0.057
Validation accuracy	91.9%
Precision (macro)	0.909
Recall (macro)	0.909
F1-Score	0.908

Table 3 Model performance

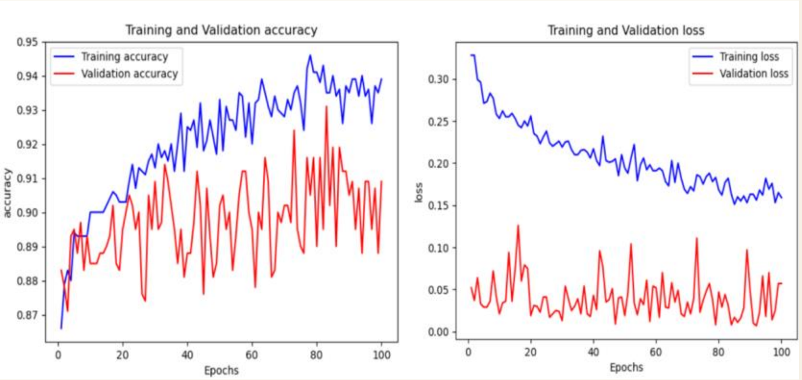

Figure 3 Model accuracy and loss curve

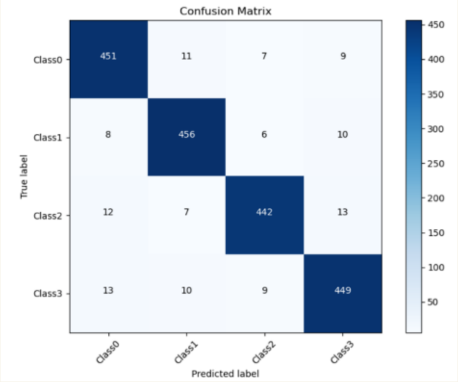

Figure 4 Confusion matrix

Validation loss = 0.057
Validation accuracy = 91.9%
Train loss = 0.159
Train accuracy = 94.6%

4 Results

- Model Explainability

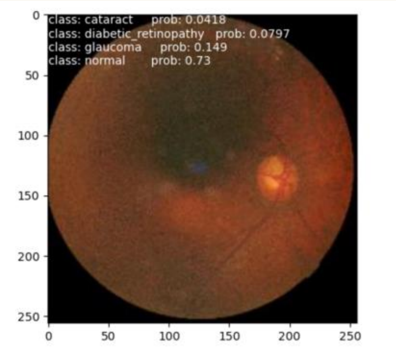

Figure 5 Model prediction

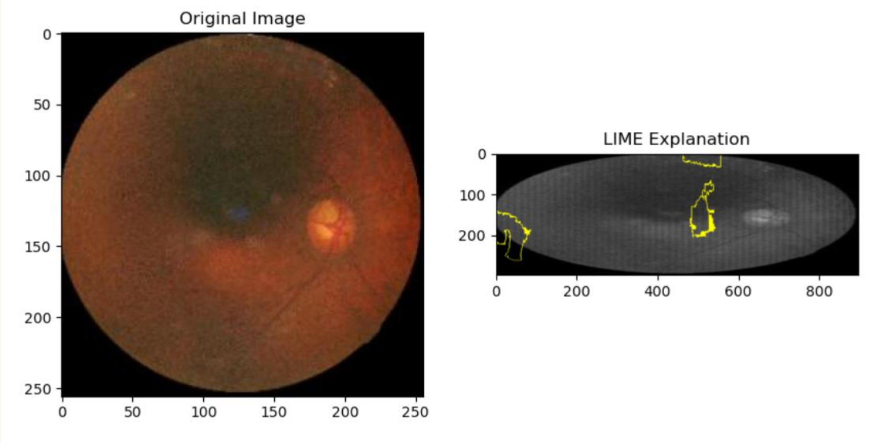

Figure 6 LIME explanation

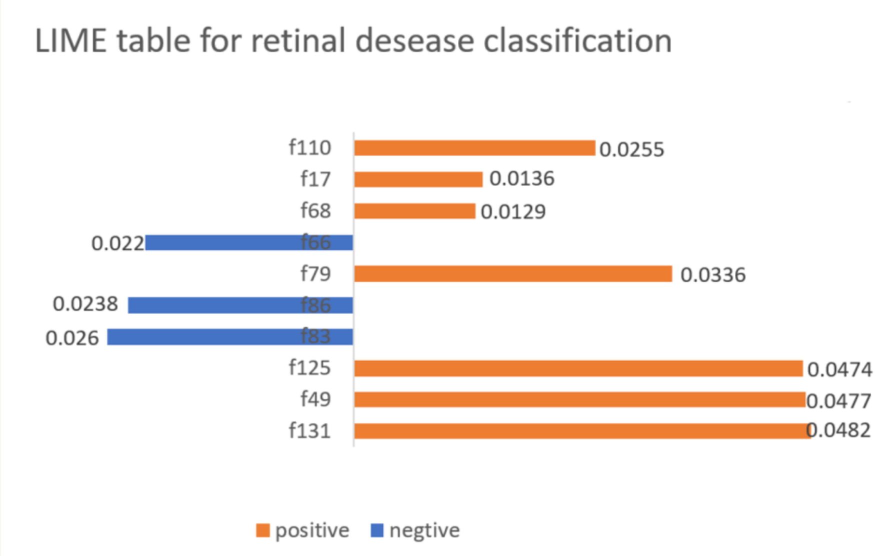

Figure 7 LIME explanation table

4 Results

- GUI Design

Figure 8 Home page of web app

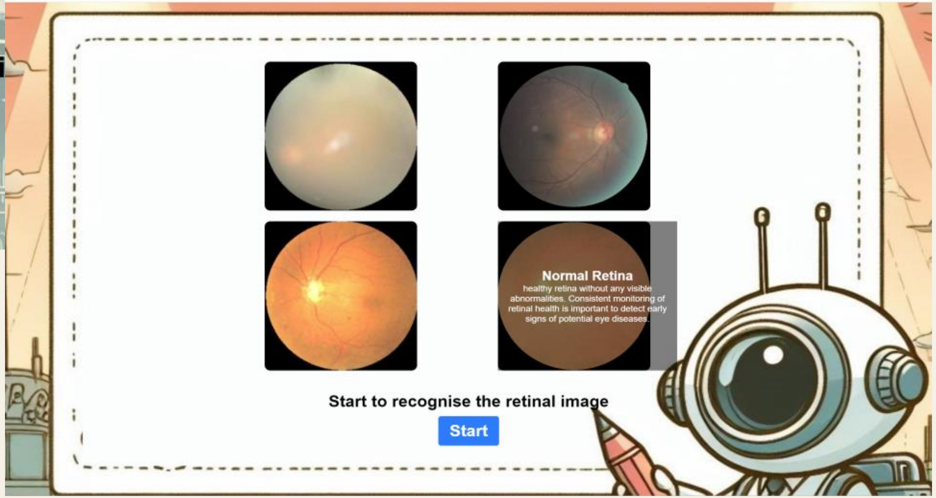

Figure 9 Learn more page of web app

4 Results

- GUI Design

Figure 10 Prediction page of web app

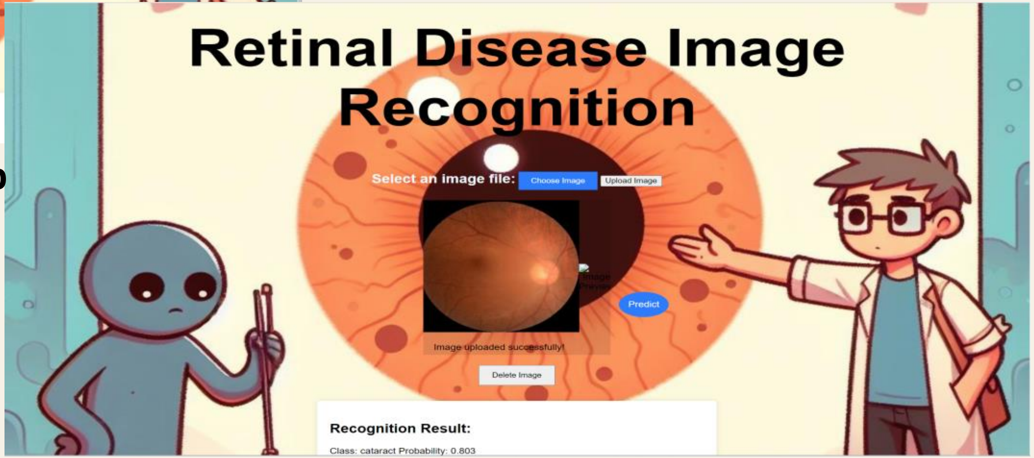

Figure 11 Demonstration of web app

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Limitations and Challenges

5 Limitations and Challenges

- Limited dataset: Insufficient image diversity.
- Enhancing model precision required.
- Inadequate data protection measures: Insufficient safeguarding of data.

6

Conclusion

6 Conclusion

- **Model architecture: Combined Inception and separable CNN.**
- **Automation of disease identification: Reduces manual reliance.**
- **Model evaluation: Training accuracy 94.6%, validation accuracy 91.9%, validation loss 0.057.**
- **Superiority over other models: High accuracy compared to ResNet, MobileNetV2.**

6 Conclusion

- Future Work

- Dataset improvement: Increase diversity, representativeness.
- Technique enhancement: Integrate new ML techniques.
- Parameter optimization: Further adjust for accuracy.
- Healthcare system integration: Combine real-time data.

Thanks for listening

Reference

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