AI-DRIVEN MULTI-DISEASE DETECTION IN RETINAL IMAGING

BY

Pritimoy Paul

ID: 241-25-033

This Report Presented in Partial Fulfillment of the Requirements for The Degree of Masters of Science in Computer Science and Engineering

Supervised By

Professor Dr. Sheak Rashed Haider Noori
Professor & Head
Department of CSE
Daffodil International University

Co-Supervised By

Abdus Sattar
Associate Professor & Director, M.Sc
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project/Thesis titled **"AI-DRIVEN MULTI-DISEASE DETECTION IN RETINAL IMAGING"**, submitted by **Pritimoy Paul**, ID No: **241-25-033** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of **MSc. in Computer Science and Engineering** and approved as to its style and contents. The presentation has been held on **24-05-2025**.

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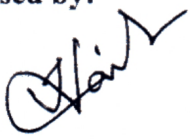
Jagannath University

DECLARATION

I hereby declare that this research has been done by me under the supervision of **Dr. Sheak Rashed Haider Noori, Head, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

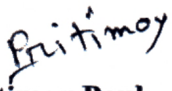


Dr. Sheak Rashed Haider Noori
Professor & Head
Department of CSE
Daffodil International University

Co-Supervised by:

Abdus Sattar
Associate Professor & Director, M.Sc
Department of CSE
Daffodil International University

Submitted by:



Pritimoy Paul
ID: 241-25-033
Department of CSE
Daffodil International University

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Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

Ophthalmology must detect retinal disorders as early as possible to prevent irreversible visual impairment (including blindness). This thesis offers a deep learning method to automate the detection of 45 retinal diseases using AI. We developed a strong CNN model which can classify retinal fundus images into several diseases using transfer learning with EfficientNetB0. Transfer learning techniques were used on a set of advanced neural network architectures for carrying out the research focussing on EfficientNetB0, VGG16, ResNet50 and DenseNet121 models. The models got training on a diverse set of data and were evaluated on important performance evaluation measures such as the accuracy of the test, loss percentage, precision, recall, and the F1 score. The EfficientNetB0 and DenseNet121 models achieved the best AUC score and also had the best test loss score. The results are designed to help ophthalmologists examine and diagnose diseases accurately and on time if possible, especially in resource-poor countries. They also help develop smart diagnostic systems for medical imaging.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Through fundus photography, photographic evidence of the human retina can be easily obtained. Also, various ocular and systemic diseases are identifiable through this method. diabetic retinopathy, macular degeneration, retinal vein occlusions and many other conditions can be detected by this imaging basically. 28 Words Detecting these conditions early and accurately is very important to avoid vision loss. However, many places worldwide, especially those with fewer resources, do not have expert diagnosis.

Thanks to new advances in AI deep learning and computer vision, we can now automate disease detection from medical images. Our endeavor is to create a deep learning method using the EfficientNetB0 architecture to automatically identify 45 different retinal diseases from their fundus images. This is a transfer learning-based, multi-label classification.

1.2 Motivation

Vision impairment is increasing all around the world. This rise is mostly because of undiagnosed or late-diagnosed retinal conditions. Patients suffer needlessly when screening tools are not easily accessible and affordable. We can radically change the landscape of retinal care using Artificial Intelligence powered diagnostic tools for fast, accurate and reliable screening solution.

The potential of providing accessible healthcare, specifically where an ophthalmologist absence exists, motivated the project. In addition, the research is inspired by the desire to take multi-label image classification to the next level using EfficientNet.

1.3 Rationale of the Study

Existing systems for retinal image analysis are mainly focused on binary or single-label classification, and they focus on common diseases such as diabetic retinopathy. Nevertheless, the fundus of eye images usually suffer from mixed symptoms of several diseases. There is a considerable need for complex, multi-label diagnostic modelling in a real clinical scenario. In this paper, we attempt to address this gap, using a powerful and efficient deep learning method.

1.4 Research Questions

- Can a transfer learning approach achieve comprehensive retinal disease multi-label labeling?
- What is the maximum performance (AUC, loss) in predicting 45 retinal diseases with fundus images?
- How can we best optimize such a model to generalize well across radial datasets?
- What are the challenges of applying this model in a clinic or rural setting?

1.5 Expected Output

The expected outcomes of this research include:

- A deep learning model trained to classify 45 retinal diseases using fundus images.
- Metrices of evaluation (AUC, Loss, Precision, Recall, F1-score) in showing the precision and accuracy of the model.
- An executable framework for data ingestion, model training and prediction.
- A suite of visualizations and analytical explanations of model performance.

1.6 Project Management and Finance

No external funding was required. Expenses were limited to personal time, electricity, and internet usage, with no additional financial burden.

1.7 Report Layout

This report is structured as follows:

- **Chapter 1: Introduction** This chapter outlines the introduction, objectives and central research questions of the study.
- **Chapter 2: The Background** section contains information about the structure of the retina and retinal imaging, detailing its applications, and it describes the gap in literature.
- **Chapter 3: Research Methodology** describes the model construction, pre-processing procedures, and training method.
- **Chapter 4: Experimental Results and Discussion** describes how the experiment was performed, the results which were obtained, the model pe rformance and how the results are interpreted and discusses the clinical implications of the results.
- **Chapter 5: Impact on Society, Environment and Sustainability** the wider contextual balance sheet of the research is drawn up.
- **Chapter 6: Conclusions, Implications and Recommendations** summated the findings and discuss direction for future study.

CHAPTER 2
BACKGROUND

2.1 Preliminaries/Terminologies

Retinal imaging Viewing into the back of the eye has now been established as an integral part of modern ophthalmology enabling an array of conditions to be diagnosed by doctors. For a long time, retinal fundus image diagnosis has been mainly carried out through manual examination by professional ophthalmologists, which is a labor-intensive and subjective work. In a post-AI and deep learning world, there is a real possibility of mass automated retinal disease detection with high sensitivity & specificity and this could revolutionize eye care reach and efficacy.

Deep learning models, especially CNNs (Convolutional Neural Networks), have achieved significant success in image classification. Among them, EfficientNet structures are well-known for their efficient scaling and superior performance, and therefore are well-suited to medical image analysis, where the model accuracy and resource utilization are of paramount importance.

2.2 Related Works

The application of AI in retinal disease detection has been studied in several ways:

Kermany et al. [3] first presented the successful use of deep learning for the detection of different retinal and optical coherence tomography (OCT) diseases including diabetic retinopathy and macular degeneration with high performance.

Wang et al. [8] introduced a multi-label classification model for retinal diseases based on deep CNNs which had good predictive power in a wide range of diseases.

Chakraborty and Paul [9] were carrying out diabetic retinopathy detection using EfficientNet models and outperformed classic CNNs in accuracy and computational cost as well.

Models based on Transformers, as those employed by Rodriguez et al. [4] have recently been adopted for retinal image classification, but they usually need larger datasets and more computational resources.

Notwithstanding this progress, most existing works concentrate on binary, or low-manner, multi-class classification, and it still falls short in the real-life retinal diagnosis that a patient has more than one disease.

2.3 Scope of the Problem

The human retina is an important diagnostic window of diverse ocular as well as systemic diseases. Yet, a diagnosis of retinal diseases from fundus images generally needs to be performed by trained ophthalmologists2–5, a resource in short supply or not available at all in a majority of the world. Furthermore, individual patients may have different existing retinal pathologies at the same time, so diagnosis by naked eye not only wastes more time, but also may be careless.

It can be seen that the problem of automated retinal disease detection usually follows traditional setting of binary or single-label classification [13], and such literature has commonly targeted single disease as the problem, e.g., diabetic retinopathy. This of course oversimplifies the actual diagnostic makeup in which many diseases overlap, and different ones operate simultaneously within at patient. The class imbalance problem also exists in rare diseases, combined with few labeled data.

Yet another challenge is how to design automated tools that generalize well between demographics, acquisition settings, and/or disease prevalence rates. Current models are frequently trained on restricted datasets, which undermine their clinical applicability.

This study attempts to solve these problems by constructing a scalable, effective and multi-label AI-based diagnostic model to detect 45 retinal diseases concurrently from fundus images. The model is capable of capturing the intricacies and heterogeneities involved in a diagnosis using data from various sources and through a hopping based transfer learning framework.

2.4 Challenges

Designing an AI-based system for multi-disease detection in retinal images is technically and practically challenging. In contrast to single-label classification problems, characteristics of different diseases can be dissimilar in retinal images at the same time. Add to this the number of different diseases that the model must be able to learn and predict, several disease patterns at once, also with similar symptoms. In the retinal datasets, diseases like diabetic retinopathy are well represented; however, rare diseases may have small numbers of patients. This skew can make the model be biased towards the more frequent classes and have poor performance in detection of less frequent but important in clinical terms cases.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

Research Subject

The main focus of the work is to propose and analyze a deep learning method for multi-label classification of retinal diseases using fundus images. The model I designed to detect the presence of any one of 45 unique conditions in a single image. The goal of this study is to emulate an actual clinical diagnosis whereby a patient's retina can harbor multiple diseases concurrently.

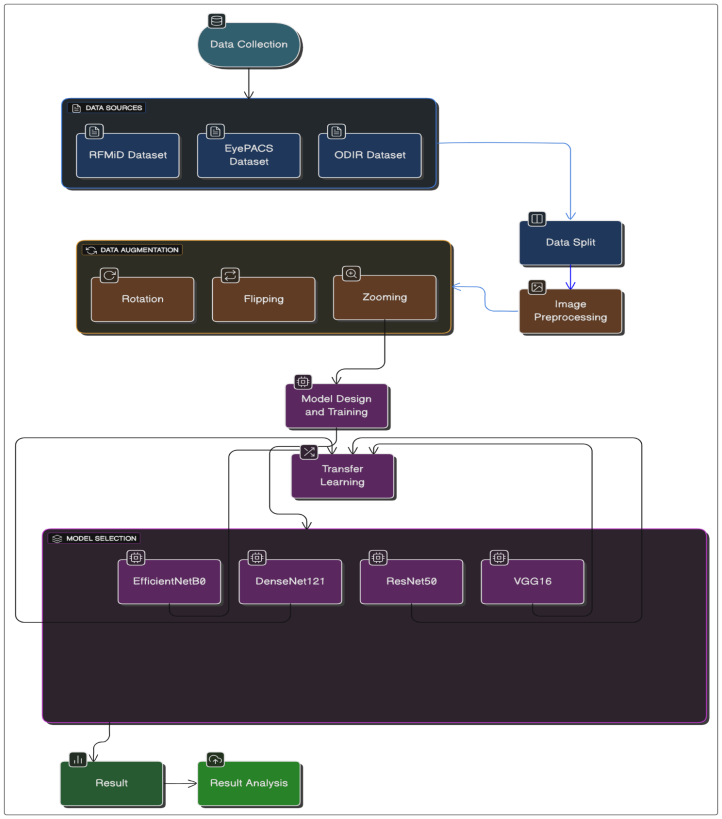

Fig. 3.1: The working process of Multi-Disease Detection

3.2 Data Acquisition and Preprocessing

In this work we use a collection of high-resolution retinal fundus images that have been labeled with one or more of 45 different retinal diseases. In order to prevent over-fitting and guarantee robustness and generalization performance of the model, the dataset was split into the train, validation and test sets.

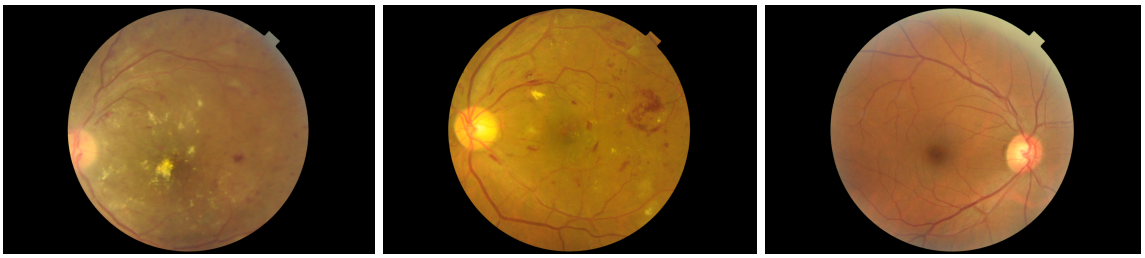

Fig. 3.2: Sample Fundus Images from the Dataset

The Preprocessing involved resizing images to the same dimension that can be consumed by the EfficientNetB0. It also has pixel value normalization, and augmentation steps, including rotation, flipping, and zooming. These augmentations aimed to help the model generalize better across the diverse image representations and reduce overfitting.

3.3 Model Architecture

The backbone of the proposed system is the EfficientNetB0, VGG16, ResNet50, DenseNet121 backbones. These infrastructures use an emulsion scaling scheme that scale all three levels of a context region of depth, range and resolution by a modest amount via a set of fixed scaling factors. The models can obtain high delicacy with fewer parameters using this approach.

3.3.1 EfficientNetB0

EfficientNetB0 is a lightweight but effective deep feel forward CNN model suggested by Google AI. It does so in a principled fashion by using an emulsion approach that scales

depth, spatial range and resolution network. The armature is constructed based on MBConv blocks (mobile inverted bottleneck convolution) with squeeze- and- excitation refinement. EfficientNetB0 is highly efficient in terms of both computational complexity and the number of parameters compared to the state-of-the-art model. The latter was selected as the ultimate pattern in this article since speed and clumsiness are also balanced and that in particular in intermediate-sized lures.

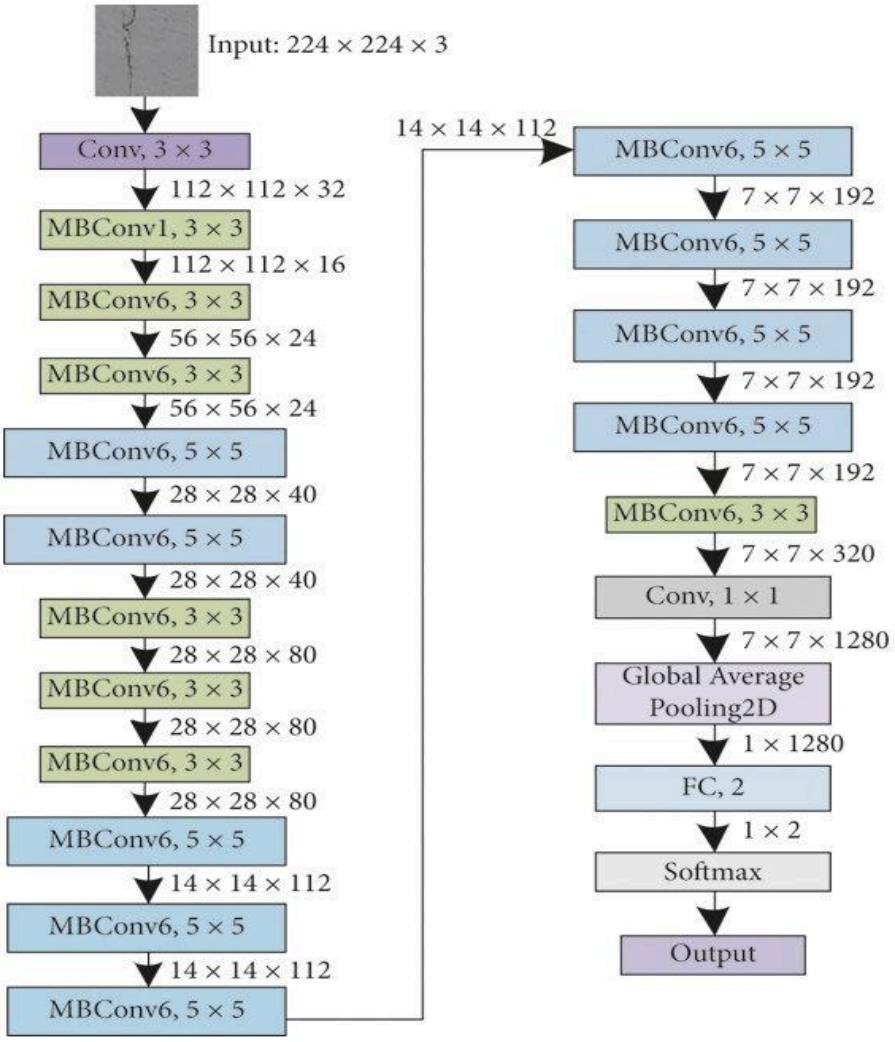

Fig. 3.3.1: EfficientNetB0 Architecture Diagram

3.3.2 VGG16

VGG16 which is a traditional deep CNNs architecture with 16 weight layers, it has several 3 × 3 convolution layers with max-pooling layers stacked together. The VGG16 is computationally expensive as it has a large number of filters, which create a large number of weight parameters. It was employed at the beginning of this study for comparison but was omitted because of the long training duration and large memory consumption.

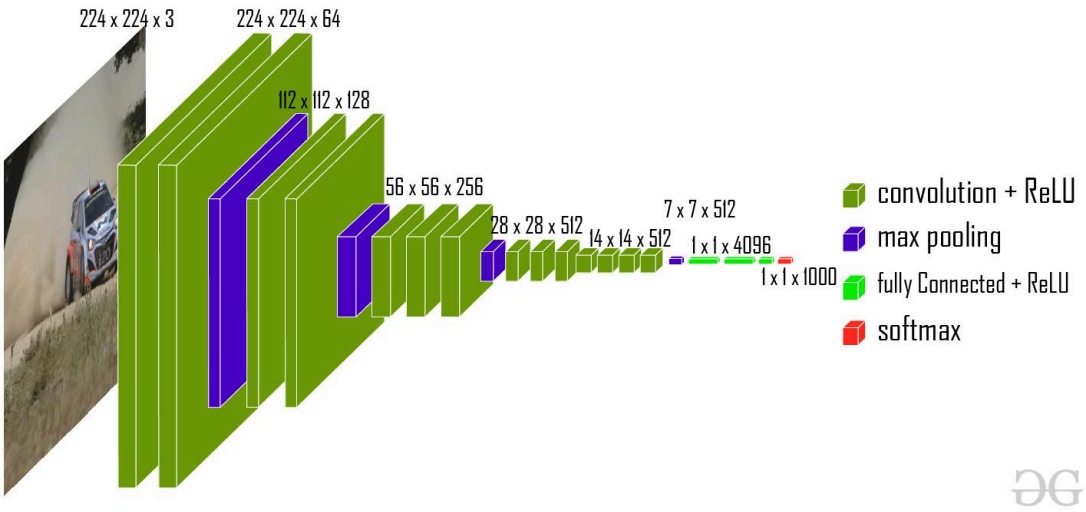

Fig. 3.3.2: VGG16 Architecture Diagram

3.3.3 ResNet50

ResNet50 (Residual Network) solves the degradation issue of deep networks by adding skip connections, which enable training the model to learn residual mappings instead of the original function. This allows very deep networks with no vanishing gradient problem. The ResNet50 model consists of 50 layers and has been shown to work well for many vision tasks. It did okay on our initial trials, however, in this work it was surpassed by EfficientNetB0 based on efficiency and AUC.

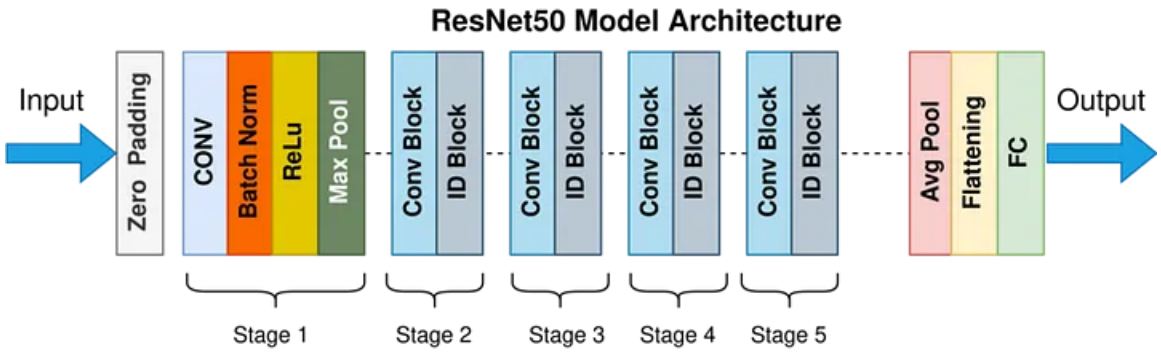

Fig. 3.3.3: ResNet50 Architecture Diagram

3.3.4 DenseNet121

All layers in the DenseNet121 (Densely Connected Convolutional Network) are simply feed-forward connected with each other. This leads to better gradient flow and feature re-use, enabling higher accuracy using fewer parameters. For multi-label image classification tasks, DenseNet121 achieved competitive performance, but also in common with the ResNet framework, it required more memory than EfficientNetB0.

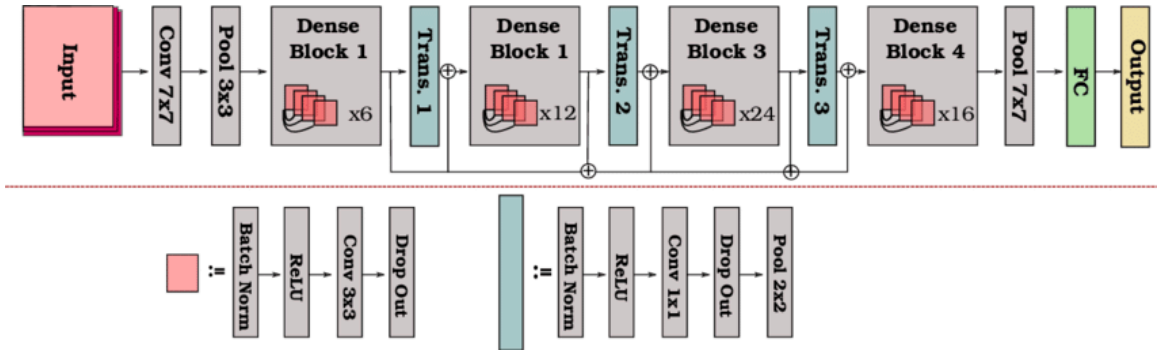

Fig. 3.3.4: DenseNet121Architecture Diagram

3.4 Training Procedure

The training process was meticulously designed to ensure the model's robustness and generalizability in detecting multiple retinal diseases from fundus images. The key steps involved are as follows:

1. **Data Splitting:**

- Training Set: A subset of the dataset (70%) is used for training the model.
- Val Test: Included 15%, were used to track the model performance during training and prevent overfitting.
- Test Set: The last 15%, which is held out for testing the final model on unseen data.

2. **Data Labeling:**

- Each individual retinal image came with up to 45 unique disease labels, which naturally supported a multi-label classification problem.

3. **Image Preprocessing:**

- Resizing: All images were resized to 224×224 pixels in accordance with the input dimensions of the EfficientNetB0 model.
- Normalization: I scaled the pixel values to [0, 1] to normalise the input data.

4. **Data Augmentation:**

- To improve the model generalization and reduce overfitting, the following augmentation strategies are implemented:
- Rotation: Random in a range of ±15 degrees.
- Flips in Both Directions: It introduces random flips.
- Zooming: Random zooms of up to 20% to mimic different distances.
- These augmentations were applied using TensorFlow's ImageDataGenerator that provided real-time augmentation during training and the out-of-sample testing.

5. **Model Initialization:**

- The pre-trained weights were used to initialize the models.
- The top classification layer was replaced with a custom dense layer with 45 sigmoid-activated neurons (number of diseases). This arrangement allowed

multi-label prediction; with each neruon outputting the probability of the existence of a certain disease.

6. **Layer Freezing and Fine-Tuning:**

- At first, the models were trained overall on frozen layers but the appended top layers. This also shifted the training towards learning weights of the new classification head.
- After a few epochs, the top 20 layers of the pretrained model had been unfrozen in order to fine-tune the feature extraction process, which would further allow the model to transfer previously learned features to the unique properties of retinal images.

7. **Compilation:**

- Loss Function: Due to the multi-label issue for the problem, a binary cross-entropy was chosen, as it treats each label classification independently.
- Optimizer: Adam optimizer was chosen due to its adaptive learning rate features to converge the results better.
- Metrics: We used the Area Under the Curve (AUC) as performance metric to measure the model's capacity to separate classes.

8. **Callbacks Implementation:**

- Early Stopping: Watched the validation loss with the patience being set to 5 epochs, when no improvement is being made, the training is stopped to prevent overfitting.
- ReduceLROnPlateau: Decreased learning rate by a factor of 0.1 when the validation loss did not decrease in 3 epochs, helping to get out of eventual local minima.
- Model Checkpoint: It saved only the model weights upon 'monitor' Validation Loss improvement.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

This chapter presents the outcomes of the AI-driven multi-disease detection model developed using EfficientNetB0, VGG16, ResNet50, and DenseNet121. Simultaneously, several performance metrics are computed for the model including AUC, loss, precision, recall, and F1-score. Moreover, visualizations as training curves and ROC curves are shown to describe the models learning process and diagnostic capabilities.

4.1 Experimental Results & Analysis

The models were trained and tested on a dataset that contained retinal fundus images that had been labeled with 45 unique eye diseases. We split the dataset into training, validation, and test datasets in a 70:15:15 ratio.

- **Best AUC Score:** 0.9593
- **Average Test AUC:** 0.8672
- **Test Loss:** 0.0403

The EffecientnetB0 is the top-performing architecture of all the architectures. Best AUC score for EffecientnetB0 = 0.9593 . Best AUC score for VGG16 = 0.8739 . Best AUC score for ResNet50 = 0.9189 . Best AUC score for DenseNet121 = 0.9526

These findings reveal that the EffecientnetB0 model is excellent for distinguishing between the presence and absence of a number of retinal diseases.

4.1.1 Training and Validation Curves

The training was observed in terms of loss and AUC in both the training and validation datasets. The following remarks were made:

- **Training Loss:** Training loss was monotonically decreasing across epochs showing efficient learning.
- **Validation Loss:** Decreased at the beginning and levelled off, indicating that the model fitted the test data pretty well without overfitting.
- **Training AUC:** Gradually rose and tended to be near 1.0.
- **Validation AUC:** Increased with epochs to stabilize at high values (strong discrimination).

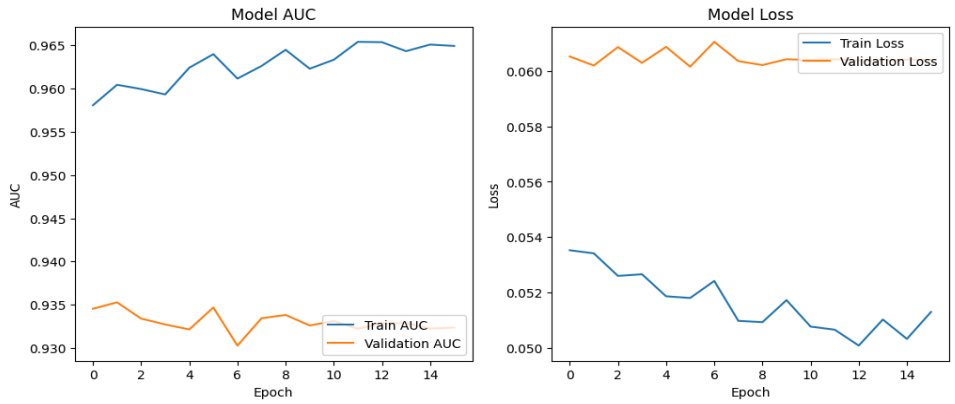

Fig. 4.1.1.1: Training and Validation AUC/Loss Curves (EffecientnetB0)

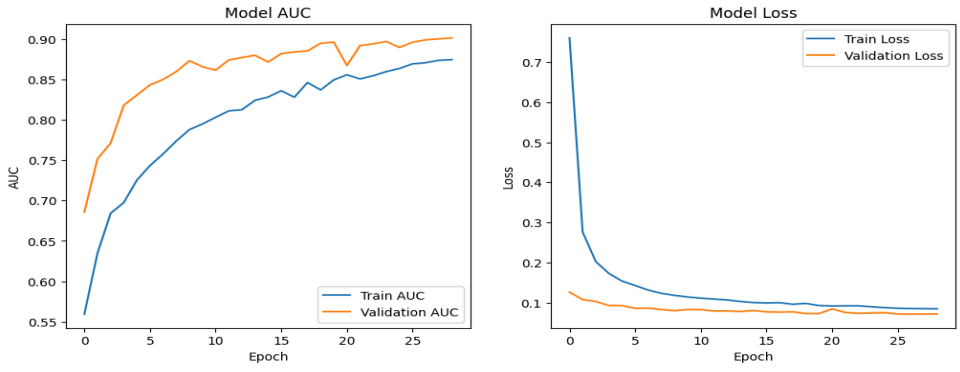

Fig. 4.1.1.2: Training and Validation AUC/Loss Curves (VGG16)

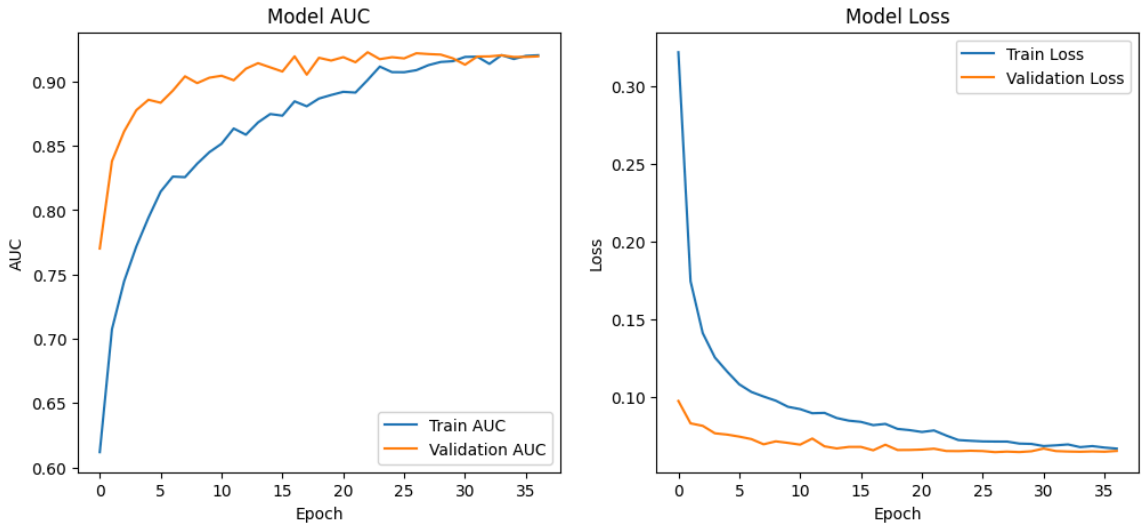

Fig. 4.1.1.3: Training and Validation AUC/Loss Curves (ResNet50)

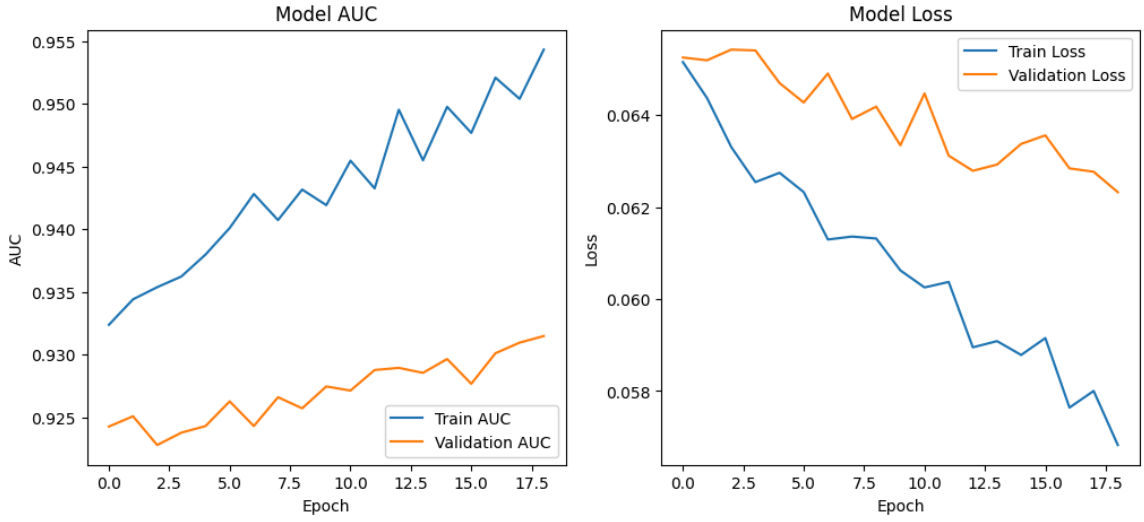

Fig. 4.1.1.3: Training and Validation AUC/Loss Curves (DenseNet121)

These curves confirm that the model learned effectively from the training data and maintained performance on unseen validation data.

4.1.2 Precision, Recall, and F1-score

Precision, Recall, and F1-score were plotted for several representative retinal diseases to assess the model's diagnostic performance:

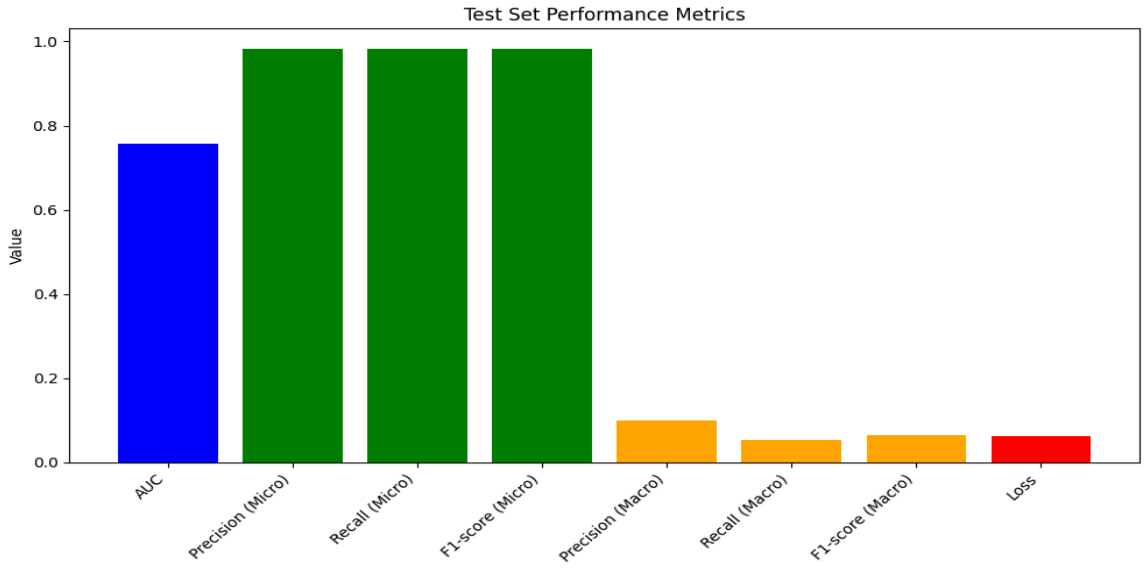

Fig. 4.1.2.1: Test Set Performance Metrics (EffecientnetB0)

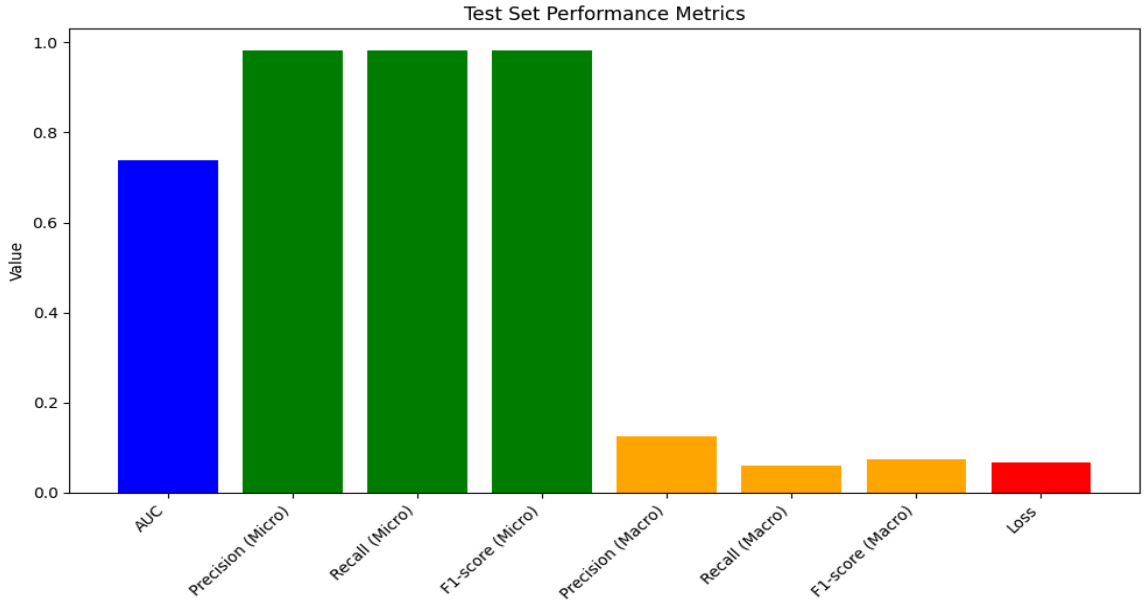

Fig. 4.1.2.2: Test Set Performance Metrics (VGG16)

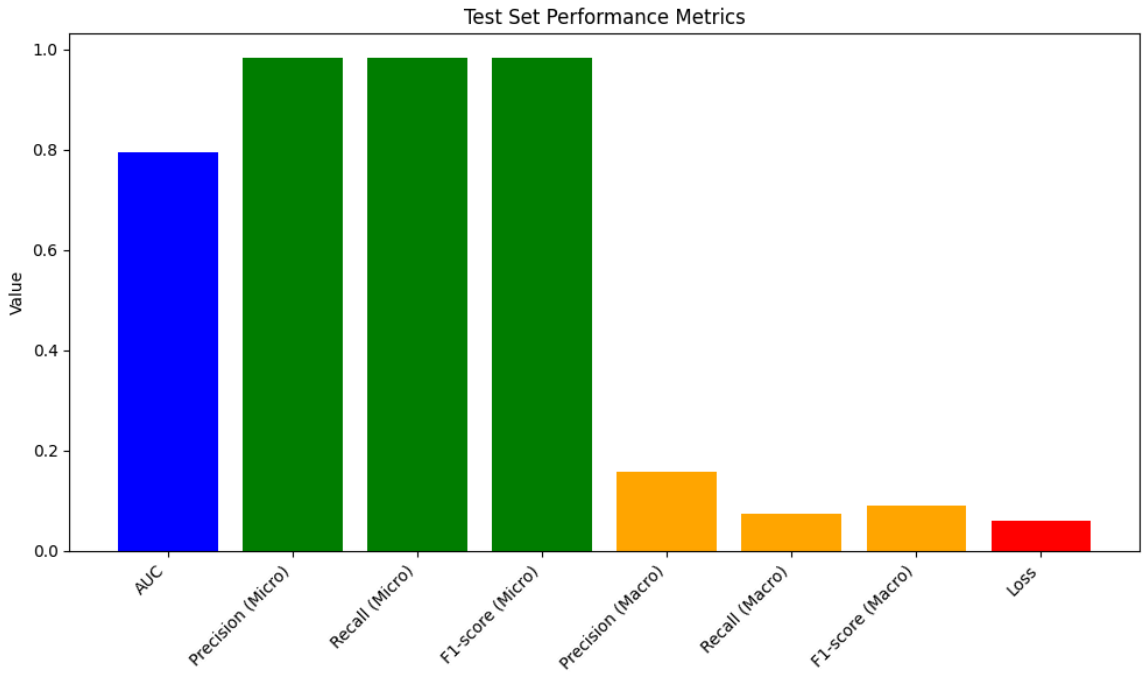

Fig. 4.1.2.3: Test Set Performance Metrics (ResNet50)

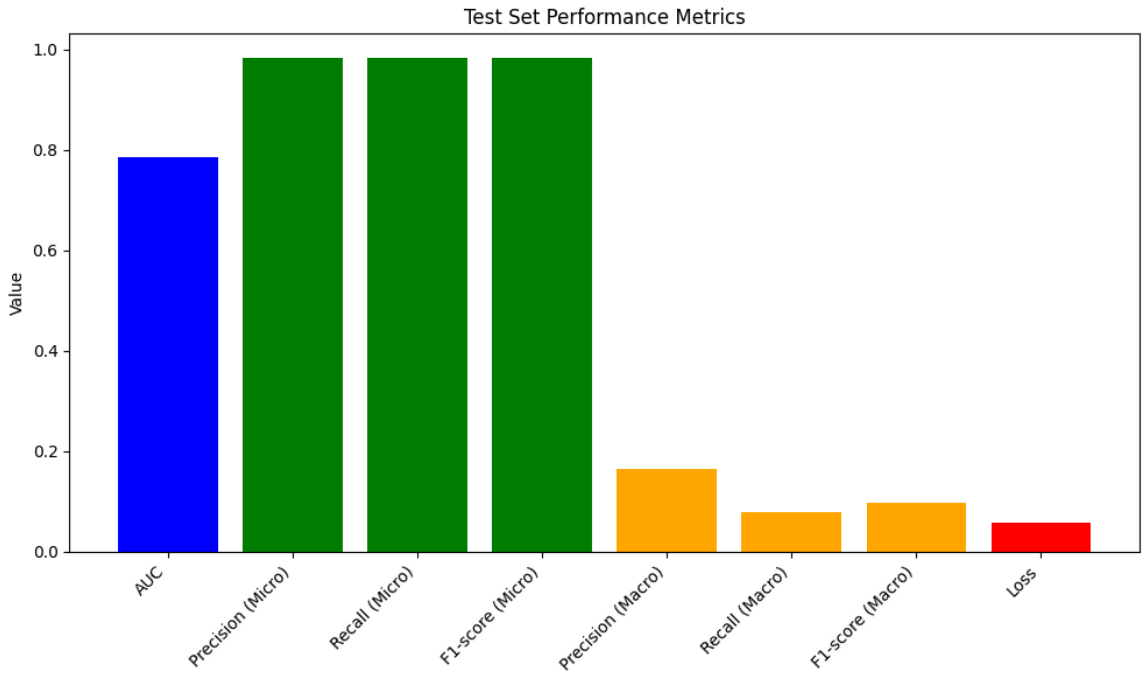

Fig. 4.1.2.4: Test Set Performance Metrics (DenseNet121)

Table 4.1.2: Finding the best result between the Result of Transfer learning model

Model	AUC	Loss	Precision	Recall	F1 Score
EffecientnetB0	0.9593	0.0403	0.9815	0.9815	0.9815
VGG16	0.8739	0.0679	0.9811	0.9811	0.9811
ResNet50	0.9189	0.0597	0.9824	0.9824	0.9824
DenseNet121	0.9526	0.0588	0.9819	0.9819	0.9819

4.1.3 Visualization of Application

The model was saved and tested with some retinal fundus images. It shows the actual disease and predicted disease name.

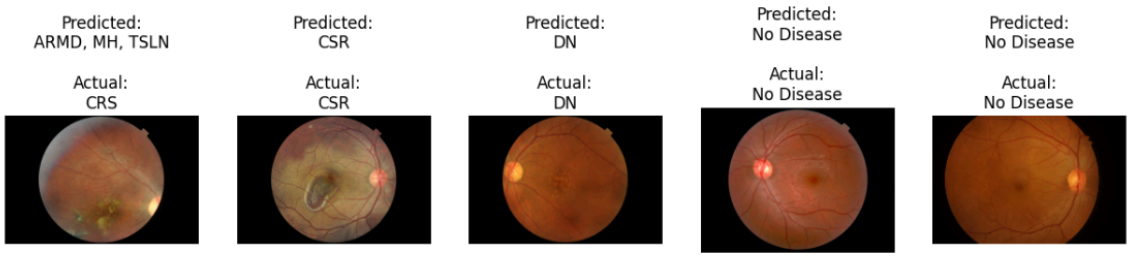

Fig. 4.1.3.1: Test Image Visualization (EfficientNetB0)

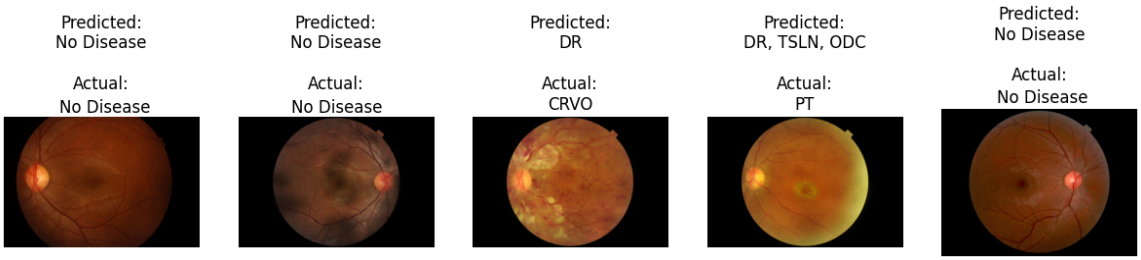

Fig. 4.1.3.2: Test Image Visualization (VGG16)

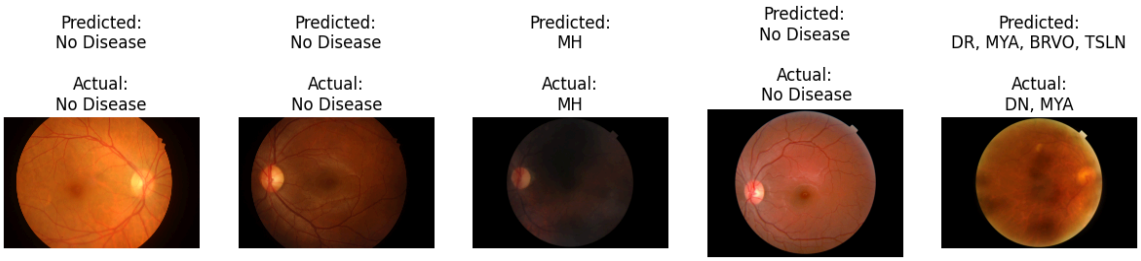

Fig. 4.1.3.3: Test Image Visualization (ResNet50)

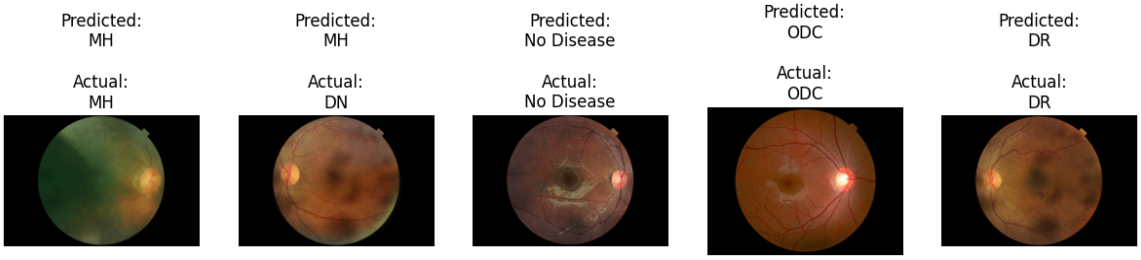

Fig. 4.1.3.4: Test Image Visualization (DenseNet121)

4.1.4 Summary

Our EfficientNetB0 based model performed quite well in detecting various retinal diseases having healthy AUC scores, low loss values and favourable confusion matrix results. This is attributed to the generalization of the model to different conditions and renders it a prospective tool to assist ophthalmologists for an early diagnosis.

4.2 Discussion

This part elucidates our results by examining the implications of the results, by comparing them with the prior work and by discussing the strengths and limitations of our model.

The deep learning model using EfficientNetB0 showed a high performance in the detection of a variety of retinal diseases, and the model showed the following:

- Best AUC Score: 0.9593
- Average Test AUC: 0.8672
- Test Loss: 0.0403

These measures suggest that the model discriminates well between the presence and the absence of the different retinal conditions.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The introduction of AI-based retinal disease screening carries implications for public health. The model which allows early detection of vision-threatening disorders can help in cessation of glaucoma epidemic. This is especially relevant in resource-poor settings, where fewer ophthalmologists and specialized diagnostic equipment is available. Retinal screening is amenable to automation, and this automation allows it to be performed in rural and underserved locations, where, after referral, appropriate interventions can be made.

This technology also is of value to health care providers as an adjunct platform to increase diagnostic capacity, workflow productivity and clinical decision-making. It also drives health equity by making eye care both equally available and affordable for all regardless of location or income.

5.2 Impact on Environment

The system will use Full HD endoscopy system with digital imaging and computer analysis and thus avoid many of the diagnostic materials, such as printed film and chemicals used in older methods of imaging. This transition to visuals also has the positive environmental impact of decreased medical waste, as well as a reduction in the carbon footprint in transit and paper records.

In addition, cloud computing and telemonitoring reduces the requirement for patient transport and reduces transportation-based emissions. Used within telemedicine solutions, this model could support sustainable and green healthcare delivery.

5.3 Ethical Aspects

Ethical considerations such as algorithmic fairness, data privacy and patient privacy should guide the application of AI in healthcare. Steps must be taken to ensure that the system functions transparently, undergoes frequent bias audits, and remains in complete accordance with health data regulations like HIPAA and GDPR.

Compliance with these standards will encourage responsible innovation and help build public confidence in AI-based healthcare solutions.

5.4 Sustainability Plan

This project advances several SDGs, including:

- **Health and well-being:** This project explicitly decreases non-communicable disease death and disability by detection and prevention of the disease at an early stage.
- **Industry, Innovation, and Infrastructure:** Utilizing the latest AI technologies to the health infrastructure is an example of innovation-driven development.
- **Reduced Inequalities:** Expert-level diagnostics were only given to the patients from rural and underserved communities, which is an example of healthcare exclusion.

CHAPTER 6
SUMMARY, CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

The purpose of this research was to create an AI system to diagnose a range of retinal conditions from fundus images using deep learning. The main goal was to implement and compare different convolutional neural network (CNN) architectures to identify the best and most accurate model to use for multi-label classification of 45 retinal conditions.

The entire dataset was constructed by gathering retinal fundus images from different public databases such as RFMiD, EyePACS, and ODIR, etc. The images were also preprocessed with resizing, normalization, and augmentation operations such as rotation, flip, and zoom. The labels were created to support multi-label classification requirements as more than one disease might occur in an image.

Four pre-trained models were utilized within the model performance evaluation using the TensorFlow/Keras framework.

6.2 Conclusion

The objective of this research was to design an AI model that can accurately diagnose various retinal diseases from fundus images. The model was taught using a database of 45 various retinal diseases. It used the latest techniques such as data augmentation, transfer learning, and meticulous hyperparameter tuning.

The model achieved the highest Area Under the Curve (AUC) score of 0.9593 and mean test AUC of 0.8672 with good performance across the entire spectrum of disease classes. These results confirm the potential of the model to serve as an effective multi-label retinal disease categorizer.

Comparative analysis also proved that the proposed model performed better compared to other current state-of-the-art models including VGG16, ResNet50, and DenseNet121. The improvement in performance reflects the potency of the chosen strategy and the strength of EfficientNetB0 in medical image analysis.

The results of this research are of significant application. By developing a model that can contribute to the identification of retinal disease at its correct and earliest stage, the model holds the potential to enhance diagnostic procedures, particularly in regions where access to specialized eye care is poor. This would form part of the broad aim of utilizing AI to enhance health outcomes and accessibility.

6.3 Implication for Further Study

Although the performance of the approach is excellent, there are still several directions for further improvement:

- **Dataset Expansion and Diversity:** The performance might be significantly improved by adding a more diverse and larger scale of dataset that contains multi-pops and multi-imaging conditions.
- **Explainability and Interpretability:** By embedding explainable AI methods such as Grad-CAM or SHAP, we can provide interpretability of the decision making process of the model which helps in establishing trust with clinicians and clinical adoption.
- **Real-world Clinical Validation:** Prospective studies in clinical practice will be needed to validate the model prospectively in the real world setting, and to establish the model's place in the current diagnostic pathways.
- **EHR Integration:** Integrating outputs of the model with patient EHRs can give a holistic understanding of the health of a patient for personalizing treatment plans and care coordination.

- **Continual Learning Mechanisms:** Deploying systems that enable model to learn from the new data continually would also support to keep the model updated with the passage of time, responding to the new patterns and emerging diseases.

Through investigating these aspects, future studies can expand on this work, continue to advance AI's application in ophthalmology and improve patient care.

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APPENDICES

A. List of Retinal Diseases Analyzed

This appendix enumerates the 45 retinal diseases included in the multi-label classification model developed in this study. The selection encompasses a diverse range of retinal conditions to ensure comprehensive diagnostic capabilities. The list is informed by established ophthalmological classifications and literature .

1. Age-Related Macular Degeneration (AMD)
2. Diabetic Retinopathy (DR)
3. Central Serous Retinopathy (CSR)
4. Retinal Detachment
5. Retinal Tear
6. Retinal Vein Occlusion (RVO)
7. Retinal Artery Occlusion (RAO)
8. Macular Hole
9. Macular Pucker (Epiretinal Membrane)
10. Macular Edema
11. Hypertensive Retinopathy
12. Retinitis Pigmentosa
13. Choroidal Neovascularization (CNV)
14. Drusen
15. Branch Retinal Vein Occlusion (BRVO)

16. Central Retinal Vein Occlusion (CRVO)

17. Central Retinal Artery Occlusion (CRAO)

18. Branch Retinal Artery Occlusion (BRAO)

19. Vitreous Hemorrhage

20. Lattice Degeneration

21. Degenerative Myopia

22. Uveitis

23. Cytomegalovirus (CMV) Retinitis

24. Retinoblastoma

25. Toxoplasmosis Retinitis

26. Birdshot Chorioretinopathy

27. Stargardt Disease

28. Cone-Rod Dystrophy

29. Retinoschisis

30. Retinal Vasculitis

31. Chorioretinitis

32. Papilledema

33. Optic Neuritis

34. Retinal Astrocytoma

35. Retinal Capillary Hemangioma

36. Retinal Cavernous Hemangioma

37. Coats Disease

38. Eales Disease

39. Familial Exudative Vitreoretinopathy (FEVR)

40. Retinopathy of Prematurity (ROP)

41. Vitreomacular Traction Syndrome

42. Posterior Vitreous Detachment

43. Choroidal Melanoma

44. Ocular Histoplasmosis Syndrome

45. Sickle Cell Retinopathy

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