EYE DISEASE RECOGNITION USING DEEP LEARNING

BY

Pritam Datta

ID: 232-25-026

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

Supervised By

Abdus Sattar
Assistant Professor & Coordinator MSc
Department of CSE
Daffodil International University

Co-Supervised By

Dr. Arif Mahmud
Associate Professor & Program Director MIS
Department of CSE
Daffodil International University

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APPROVAL

This Thesis titled **"Eye Disease Recognition Using Deep Learning"**, submitted by **Pritam Datta**, ID No: **232-25-026** 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 M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **11-01-2025**.

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Jagannath University

DECLARATION

I hereby declare that I have done this research under the supervision of **Abdus Sattar, Assistant Professor & Coordinator MSc, Department of CSE,** Daffodil International University. I also declare that neither this thesis nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Abdus Sattar
Assistant Professor & Coordinator MSc
Department of CSE
Daffodil International University

Co-Supervised by:

Dr. Arif Mahmud
Associate Professor & Program Director MIS
Department of CSE
Daffodil International University

Submitted by:

Pritam Datta
ID: 232-25-026
Department of CSE
Daffodil International University

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ABSTRACT

The diseases of the eyes are among the leading threats to the health of individuals around the world and, in many cases, lead to the complete loss of vision if left untreated. Ocular diseases have been diagnosed in the early stages using recent developments in medical image analysis, particularly CNN's. This paper presents a brief literature survey on trends in deep learning for the diagnosis of ocular diseases with a special emphasis on the possibilities of CNN in the diagnosis of ocular diseases. It focuses on the development and critical assessment of DL models trained from different datasets to effectively detect different ocular diseases including DR, glaucoma, and cataracts. Because of intense architectural designs in training techniques and improvement methodologies, the models can perform high accuracy rates hence the role of deep learning in reshaping the ophthalmology field. Besides the strictly technical aspects of the work, the findings emphasize that clinic density increases health quality because it enables early disease diagnosis, thus eliminating vision loss. It also covers ethical issues and useful considerations on practice in healthcare facilities. the work gives an overview of the revolution in identifying ocular diseases by deep learning and a bright future in improving the eye healthcare system across the world.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Thinking practically, how we see the world is through the amazing creation of natural design: the human eye. It is however weak to several illnesses and diseases that if the right diagnosis and treatment are not taken, then complete blindness of the affected organ is eminent, and the general body health is compromised. Glaucoma, retinopathy, cataracts, and various other eye illnesses are among the world's most dangerous diseases. These diseases if diagnosed at an early stage and correctly can be managed adequately for the preservation of vision. The following is our research proposal on Eye Disease Detection because these illnesses have severe impacts on patients and society. This paper aims to focus on "Eye Disease Detection" since such illnesses have a powerful impact on peoples' and communities' lives. To give an example, cataracts are now the major source of blindness globally which is a routine event. Every year millions of people around the globe experience cataracts which makes their vision progressively worse.

It is not often that persons have any indication of this until its advancement gets in the way of day-to-day functioning. Similarly, glaucoma and diabetic retinopathy gradually create a decline that may be prevented or minimized if diagnosed early. Our drive is based on deep learning, a part of artificial intelligence, and its ability, not just in rapid identification. As it turns out deep learning algorithms are a more effective approach to diagnose ocular illness accurately and more efficiently because deep learning algorithms can extract the patterns and features automatically from the large data and it reduces the physical destruction of the ocular images too. Our goal is to revolutionize the diagnostic and identification processes for these disorders through deep learning which will create new possibilities in ocular health. The focus of this work is the application of transfer learning for the identification of eye diseases. The primary objective is the design of an intelligent system for the identification and categorization of ocular diseases from medical images.

Thus, when employing transfer learning, we propose that it is possible to utilize the information and feature representations between large image datasets whereby accurate and efficient illness detection can be achieved. The adjustment to the proposed method is concerned with the convolutional neural network that has been used in the detection of ocular disorders. Taking advantage of the pre-existing model, the system utilizes eye pictures as the input to obtain the relevant details. There is then the determination of the specific eye condition by passing these extracted variables to the classification model. It is possible to significantly enhance the effectiveness concerning early diagnosis of eye diseases and methods for identifying them. Diagnosis of eye diseases requires the use of pre-trained models & transfer learning, which this study compares & evaluates.

The results obtained in the experiment clearly show how effective transfer learning is in diagnosing and categorizing three distinct types of eye diseases. Due to the nature of this report, it's important to provide you with an overview of our approach to the entire study process. Details of our research methods, experimental results, impact on society, and conclusion to this eye illness detection backdrop are given in the subsequent chapters of this book. Each level contributes to a better understanding of how deep learning may extend the identification of eye ailments and their implications for the remainder of the medical sciences.

1.2 Motivation

The reason why transfer learning has been applied to diagnostics of the ocular pathologies is based on the fact that the methodology increases the speed and accuracy of the identification system and increases its applicability to other forms. The needed time and amount of computational power at the stage of model construction can be decreased if to apply the pre-trained models. The private models trained in advance have all the abilities to learn several features generalized meant for the objective of eye disease detection. Moreover, transfer learning addresses the lack of data problem which is natural while working with diseases like ocular or when concentrating on some phenotypes of ocular diseases. It has the potential to deal with real system deviations and the real system variation most frequently recorded in clinics through the application of the pre-learned strong and relatively invariable feature vectors by the pre-trained models. This is another advantage of transfer learning because it makes further development possible once it is underway.

It could spread could continue updating the new diseases and trends in eye health because existing data and other forms of knowledge assurances can be fed into the model. It guarantees that the method for the detection of eye diseases will be relevant and efficient in the future. With every consideration made, transfer learning is therefore a rigorous and ethical manner of boosting the diagnosis of eye diseases that in turn boosts general health and vision.

1.3 Rationale of the Study

Eyes diseases include many diseases that affect different types of eyes and have a major negative impact on people’s vision and overall health. These illnesses are dangerous for the world's health because if the treatment is not administered the patient will lose their eyesight irreversibly. Knowledge of the type and frequency of eye diseases, their cause, and definitive therapy contributes to preserving the visual health and overall well-being of the affected population. The motivation is apparent when in the search for eye disease detection, for illustration. Another evidential sign that man is a marvel of biological evolution – the eye, is the primary organ of sight. Sjogren’s syndrome is nevertheless capable of provoking several illnesses and conditions that may affect sight and cause blindness irreparably. For several strong reasons, this susceptibility makes dispensing extensive investigation into eye illnesses an inevitable necessity.

To begin with, ocular disorders can manifest themselves in so many different forms. These are such as cataracts, glaucoma, diabetic retinopathy, and macular degeneration of the elderly. These ailments may greatly reduce the individual’s ability for normal eyesight and perform most of life’s ordinary tasks. Scientists hope to learn about the special characteristics of these illnesses— their causes, evolution, and manifestations— by studying them. An understanding of these concepts is necessary for the formulation of successful plans for disease prevention, early diagnosis, and control. Furthermore, improving medical intervention and general treatment requires investigations into eye illnesses. Since failure to identify and treat these disorders may lead to loss of vision and poor quality of life for patients affected by these diseases, the early diagnosis of diabetics is crucial. Academician aims to develop new diagnostic tools and treatment approaches that can help to reduce the impact of the diseases of the eye, reduce financial losses, and increase the use and efficiency of resources in medicine.

1.4 Research Questions

1. What type of Eye conditions can be recognized and classified using deep learning models?
2. How do deep learning-deployed ocular disease detection methods affect traditional diagnostic techniques?

1.5 Expected Output

My major objective is to have this research paper prepared for publication in one of the most prestigious journals. The ultimate purpose is highly constructive with regards to giving out helpful contributions in the works of inventing disease management strategies; advancing the understanding of the disease processes, and establishing long-term strategies within the field of eye disease identification.

1.6 Project Management and Finance

The research work does not receive funding from any individuals or organizations.

a) Project Management

The main goal of the current project is to set up an effective machine learning framework that employs transfer learning to diagnose ocular diseases correctly. To assess the disease-detection capabilities of the system, pre-existing models such as CNN, VGG19, ResNet, and Mobile Net are proposed. The project will be divided into distinct phases to which all the deadlines will be given. Such stages will entail data collection, development, data modeling, systemic development, testing, and implementation. The staff in this project will be data scientists, software engineers, machine learning engineers, and ophthalmology specialists. Potential problems in implementing this approach may be related to the absence or insufficiency of training data, errors in disease diagnosis, and difficulties in developing complex computational systems, where risk management will be critical.

To address these issues, strategies for risk management will be drawn for every considered risk. Of specific importance, there would be quality assurance measures to ensure the reliability of the system. To ensure that the system responds accurately and efficiently coupled with its ability to handle new types of disease patterns, the system will undergo extensive testing and validation. It will involve funding agencies, healthcare groups, and ophthalmologists. The process is also likely to actively seek feedback from any interested parties while at the same time publishing rather regular status updates.

b) Finance

The financial strategy needs to take into consideration all aspects of the project budget including system development, system testing and deployment, and data collection activities. The staffing compensation and computer resources needed to achieve these will start to add up quickly. Potential funding sources: government grants, health groups, and individuals who have an interest in the technology expansion of eye disease detection. The economic viability of the project will be analyzed with depth using a cost-benefit analysis. Such analysis will weigh system advantages, such as improved illness management and potentially better patient outcomes, against the costs associated with system development and maintenance. The computed ROI will use the impact of the system in improving disease detection rates and savings in healthcare expenditure. This project must undergo a thorough cost-benefit analysis if it is to be economically viable. Such an analysis would weigh the relative benefits of the system, such as improved management of diseases that could translate into better patient outcomes, against the costs of developing and maintaining the system. The ROI will be calculated based on the impacts of the system in enhancing disease detection rates and savings in health expenditure.

1.7 Report Layout

In this report, every chapter is analyzed in various ways, and in each chapter, several components are covered comprehensively. The following is the flow of this report:

Chapter 1, Introduction This section identifies the ability to diagnose eye diseases with a Fundoscopy image and why it is important. It also presented the introduction of my thesis, motivation for the study, rationale of the study, and what the result is projected to be.

In Chapter 2, Background I talk about the conditions surrounding our thesis. We have worked on four different models here. I discussed their principal ailment. Further, I talked about the related works and summary of the research.

In Chapter 3, Research Methodology I discussed the methodology of this thesis in detail in this chapter. I also discussed the search topic and instruments, the procedure of data gathering, statistical analysis, and implementation needs at this time.

In Chapter 4, Experimental Results and Discussion Here, I examined thoroughly the whole procedure and the results of the experiment in detail. I went into greater detail regarding my experimental results, my description of experiments, and the summary of my experiments.

In Chapter 5, Impact on Society, Environment, and Sustainability Here, I have explored social influence on our society in this chapter. The impact that society has on ethical issues and how to plan a future.

In Chapter 6, Summary, Conclusion, Recommendation & Implication for Future Research. This chapter presents the final ideas of the project. The chapter is responsible for showing the whole project report according to suggestions. I have also discussed the summary conclusion and implications for future research about the study.

CHAPTER 2
BACKGROUND

2.1 Preliminaries/Terminologies

In this research, I desired to employ transfer learning to design a viable and effective approach to diagnose disorders in ocular images. My objective is to at least enhance the detection of eye diseases through the help of deep learning models including CNN, Resnet, VGG19, and Mobile Net. My motivation lies in the challenges that exist in the identification of ocular diseases; firstly, ocular diseases do not have sufficient labeled data; secondly, it is important to detect ocular diseases with high accuracy and scalability. Indeed, this study mainly uses transfer learning approaches to detect eye illnesses. Our target is to create a fast and highly accurate diagnosis and treatment system for eye diseases with the use of such pre-models as CNN, Resnet, VGG19, and Mobile Net rerouting them to work in the specifics of the eye disorder identification.

2.2 Related works

"Deep Learning for Ocular Disease Recognition: An Inner-Class Balance" [1] is a text that looks at LeNet5, AlexNet, and other models as the core of deep learning when identifying eye diseases. It uses an eye disease Kaggle dataset. LeNet-5 claims to be correct at about 73% without any mention of the criterion, while AlexNet claims to be correct at around 87% and one can build a custom model that is at least 90-95% or better. The paper entitled [2] "Application of Deep CNN Networks in Eye Disease Detection" focuses on the utilization of CNNs in diagnosing eye disease and solely focuses on two classes: Glaucoma and Normal. Two types of models are employed: the CNN modifications and the one known as VGG-19. The data in this study were retrieved from Kaggle's sample public archive known as ODIR (Ocular Disease Intelligent Recognition). The illustrated present method is source and camera-independent for identifying ophthalmic diseases from the fundus image [2].

Utilizing the "Using Neural Network" the author proposed [3] a Convolutional Neural Network model for eye disease recognition the proposed CNN model has an F-score of

85 %; a Kappa score of 31 %; and an AVC value of 80.5 %. The data of this study was obtained from the ODIR- 5K dataset which includes color fundus photographs and diagnostic keywords of 5000 patients. An Automatic Ocular Disease Detection Scheme from Enhanced Fundus Images Based on Ensembling Deep CNN Networks is a method consisting of using several deep CNN models including ResNet50, InceptionResNetV2, and others [4].

EfficientNetB0 and EfficientNetB2 for the detection of ophthalmologic diseases [5]. This study is based on a large database of ocular diseases that contains the matched fundus photos of five thousand patients from various hospitals in China. For the upgraded images the ensemble method shows a higher accuracy of 86.08% confirming the effectiveness of the suggested approach in the diagnosis of ocular diseases. A method is discussed [6] in the paper "Ocular Diseases Detection using Recent Deep Learning Techniques" where the EfficientNet and DenseNet frameworks are employed. Using a specific value of the learning rate parameter, the highest-performing model was the EfficientNetB7 model with a maximum accuracy of 88.85%. The subject matters of this study were 5,000 fundus photos of patients collected by Shanggong Medical Technology Co., using the Ocular Disease Intelligent Recognition (ODIR) dataset [7].

Published article [8] Ltd titled "Novel Approach for Detection of Retinopathy" by Ltd. from many Chinese hospitals introduces a method to segment the blood vessels of retinal images by applying the canny edge detection approach and the CLAHE (Contrast-Limited Adaptive Histogram Equalization). The DRIVE database digital retinal images for vessel extraction were applied to the study's data. The proposed method outdoes various conventional edge detection techniques, particularly in capturing vascular patterns whose extraction is of great importance as seen in the paper [9] ; yet the paper lacks a quantitative measure of how accurate this suggested method is.

The paper entitled [10] "Glaucoma Detection from Fundus Camera Image" is mainly concerned with the detection of glaucoma from the images captured through a fundus camera. The work involves employing an image processing approach that is aimed at obtaining the CDR. The dataset used in this study includes 45 retinal fundus images from Arvind Eye Hospital in Pondicherry India. The research shows that the proposed method based on the fuzzy logic of detection achieves a detection ratio of about 93.5% of good results in diagnosis and classification [11] . The single-layer perceptron approach is incorporated into the cataract detection system and intended to categorize the eye conditions into normal, immature cataract, and mature cataracts. The research reports show that the detection system presented in this work has an accuracy level of 85 percent [12] . The paper uses a practical and feasible methodology of directly collecting data through the smartphone from cataract patients.

2.3 Scope of the Problem

The definition of the task at hand, in this case, the usage of machine learning in eye disease diagnosis through transfer learning of knowledge, would be: The main goal is to successfully and effectively detect all forms of different eye diseases. This would involve identifying and evaluating several conditions that are common causes of loss of vision in the eye. In detection, medical imaging of the eye for signs of any disease is to be analyzed. These images, through various machine learning techniques that must be developed and applied to them, have to extract relevant features. This is the key challenge: applying transfer learning meant for fine-tuning pre-trained models of VGG19, ResNet, Mobile net, and CNN in eye disease detection.

The project scope also entails the evaluation of various machine learning algorithms and a comparison of the different aspects related to their accuracy in disease detection. In this way, it would compare different machine learning algorithms and find out which algorithm best suits the task at hand. Another challenge pertains to developing a user-friendly interface that may be used for uploading eye images by users, including health experts and patients, for disease identification. It should give instant feedback to the user related to the detection of any eye disease, mentioning the type of disease. The incorporation of the disease detection system with the health management system will be fruitful in providing an end-to-end solution for managing eye diseases. It should be designed to handle a large number of users with images without affecting its performance. It should also be adaptable to emerging diseases and changing patterns of disease to ensure it is effective in detecting new, unforeseen patterns of eye disease.

2.4 Challenges

Ocular disease detection through machine learning coupled with transfer learning can have challenges just like in papaya fruit disease detection. Such challenges include amassing diverse and large datasets of ocular images representing both healthy and diseased cases. The performance will be impacted by the consistent quality, angle, and lighting conditions of the images. Images need to be properly labeled with ocular disease, which takes expertise in ocular pathology. Aside from those challenges, training deep learning models including CNN, VGG19, Mobile Net, and ResNet is computationally intensive and time-consuming, which may put resource demands on challenges. This becomes more valid in the case of limited data, as overfitting may result; the model performs well on the training but not on new, unseen data. The model must have a great generalization capability regarding ocular diseases not identified during the training phase. But then again, this might be achieved if the representative variations in certain disease patterns are not well-encompassed in the training set. Besides, real-time detection of disease, especially within a large. The volume of people or images taken might be cumbersome and would require efficient deployment of models with proper resource management. There is also the possibility of compatibility and integration issues while integrating the disease detection system into existing healthcare or medical management systems. Lastly, performances shown by the model could be sensitive to environmental changes brought about by, but not limited to, deviations in lighting or time of capture of images, affecting the accuracy and reliability of disease detection. Hence, addressing these challenges becomes important in ocular disease recognition using deep learning toward developing a reliable and effective system for diagnosis and management.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

In this study, I used some methods as one would in any research investigation; In this regard, I also drew knowledge points and newer methods of previous researchers who had worked in this area of the subject. As for the initial phases and the final part of my project, the descriptions will be offered in the corresponding sections of the present work. I collected data from the available GOOGLE and Internet sources only. Brightness adjustment and resizing along with data argumentation have been performed in data pre-processing. Data training and testing in the subsequent data extraction were also carried out. In progressing our work, I employed Deep Learning as an approach and also CNN, VGG19, MobileNet, and Resnet 15 to set the classification result.

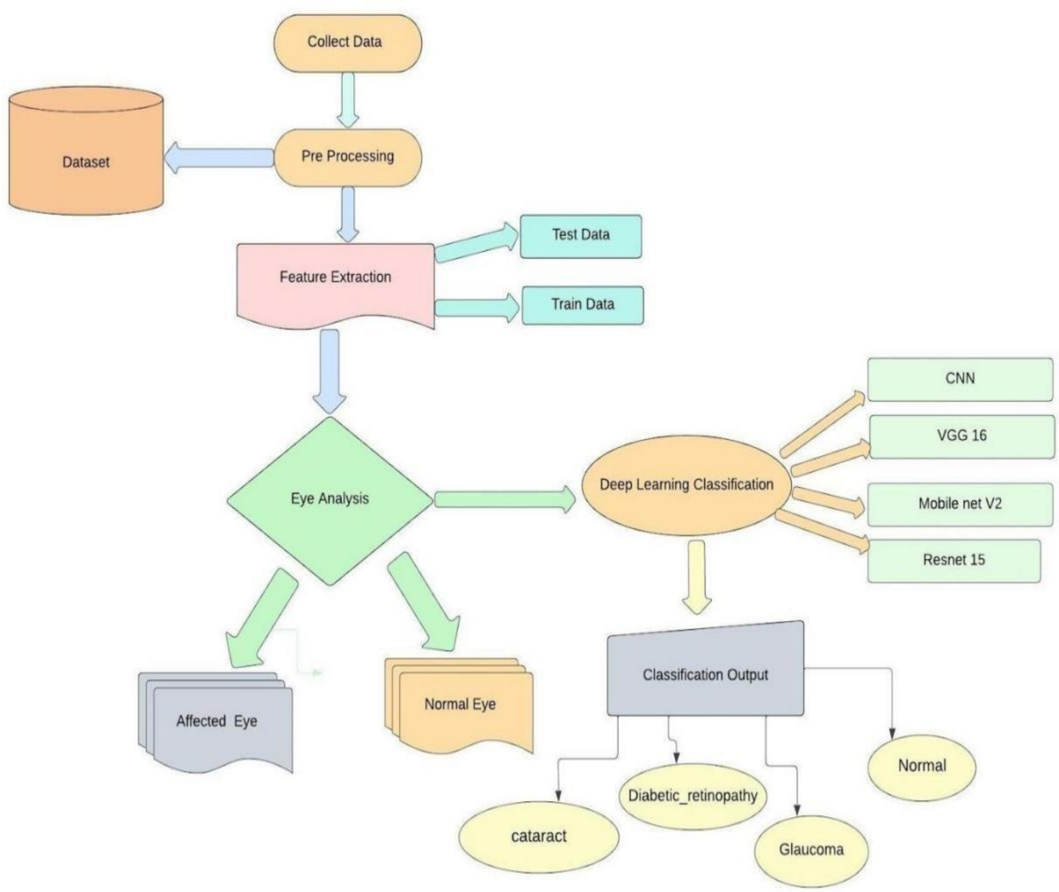

Figure 3.1: Working Procedure

3.2 Research Subject and Instrumentation

Eye Disease Recognition using Deep Learning is the title of our thesis proposal. Disease detection is a huge study area nowadays. I used some deep learning models in our study technique, as I used some mathematical functions in my proposed model. Since it needs a strong PC and GPU, working with a deep learning model will be very challenging for me. Following is the equipment and technology needed for the introduction of our product:

Hardware and Software:

- 8GB RAM and Intel Core i3 10th generation processor.
- 256 GB SSD
- GPU-enabled Google Colab

Development Tools:

- Window 10: The latest version of Windows.
- Python: 3.7.13
- TensorFlow: version 2.8.0 Backend
- NumPy
- Pandas

3.3 Data Collection Procedure

This research used the Eye Disease Intelligent Recognition (ODIR) dataset. Called Diabetic Retinopathy, it is considered one of the largest and most detailed datasets available in the Kaggle fully dedicated to the diagnosis of various types of eye diseases. Thus, having collected data from online resources, I grouped them into four classes.

3.4 Statistical Analysis

The photography I conducted was from an internet-based source where I procured 4217 pictures for my purpose. In this case, I've grouped them into two distinct categories. For training, I utilized 80% of the data while I used 20% of the data for testing. So, the two sets of groups that I have classified into four groups are as follows: Normal, senile cataract, diabetes retinopathy, and glaucoma.

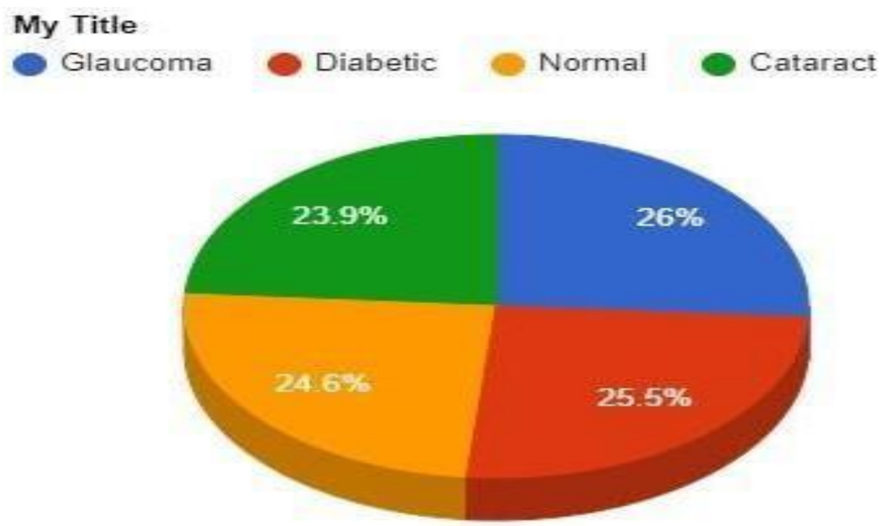

Figure 3.4.1: Categories Of Ocular Disease

These are the categories in the eye data: Glaucoma affects 26% of the eyes, Diabetic conditions affect 25.5%, normal ones are 24.6%, and 23.9% are suffering from Cataracts. Diseases of the eyes are one of the many examples in my dataset hence, in the graph below is the distribution of data based on these diseases and data leading to a healthy eye condition.

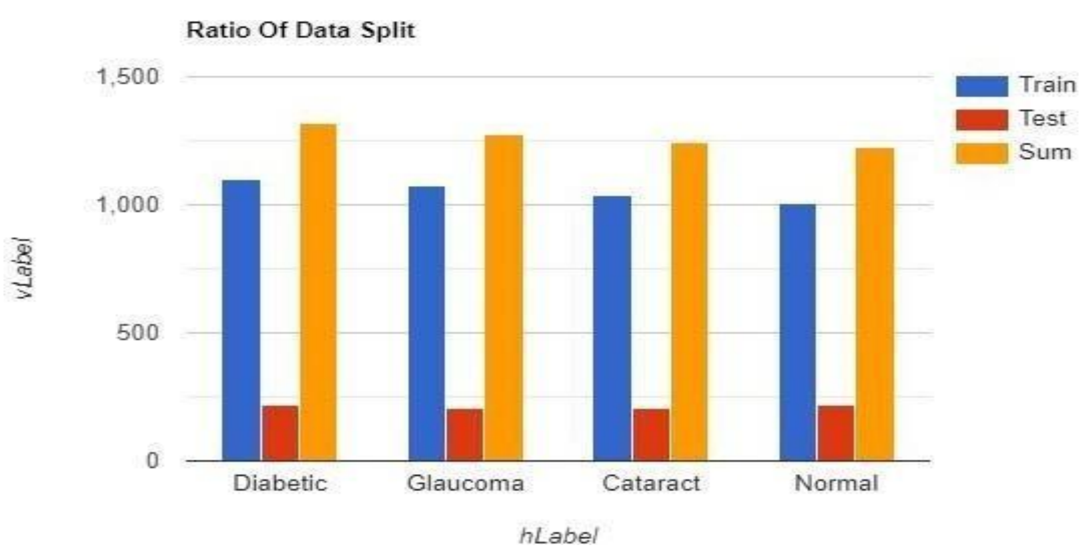

Figure 3.4.2: Ratio of Data Split

This figure represents the percentage of the total data collection, the data put into training and testing, and the overall count of data.

Table 3.4: Total of all different Eye images

Group of Eye Image	Total Data	Testing Dataset	Training Dataset
Cataract	1038	204	1038
Glaucoma	1007	204	1007
Diabetic retinopathy	1098	220	1098
Normal	1074	216	1074

3.5 Proposed Methodology

The ocular disease identification procedure includes the evaluation of each image in the input image dataset. The identification process assumes that the diseases are grouped scientifically – Normal, Cataract, Diabetic Retinopathy, or Glaucoma. The method that we propose in this context is based on deep learning techniques because deep learning includes a vast number of algorithms, models, and approaches. Specifically, I experimented with four main models: I found information about VGG16, Convolutional Neural Network, Resnet, and Mobile Net and all these are quite suitable for my proposed project.

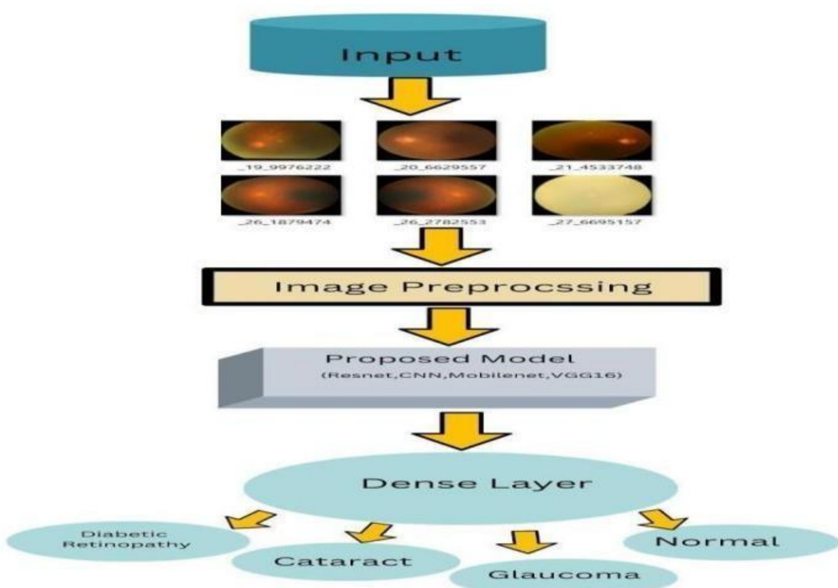

Figure. 3.5: Image Processing of Eye Disease Recognition

3.6 Deep Learning Models

This research developed a hybrid model named VGG16, CNN, Mobilenet V2, and Resnet for segmentation and then classified with a transfer learning model.

3.6.1 VGG16

VGG-16 is a deep CNN It has 16 layers, of which 13 layers of convolution and 3 of them are fully connected layers. VGG16 is a very simple yet very effective network used widely in image classification tasks. They employ 3x3 convolutional wavelets, ReLU tariffs, and max-pooling with pool sizes of 2x2. First developed for 1000 class image classification so it can be used in other inputs by just changing the number of output neurons in the last layer. Though complex numerically VGG-16 has been useful in today's society, especially in the field of deep learning and computer vision.

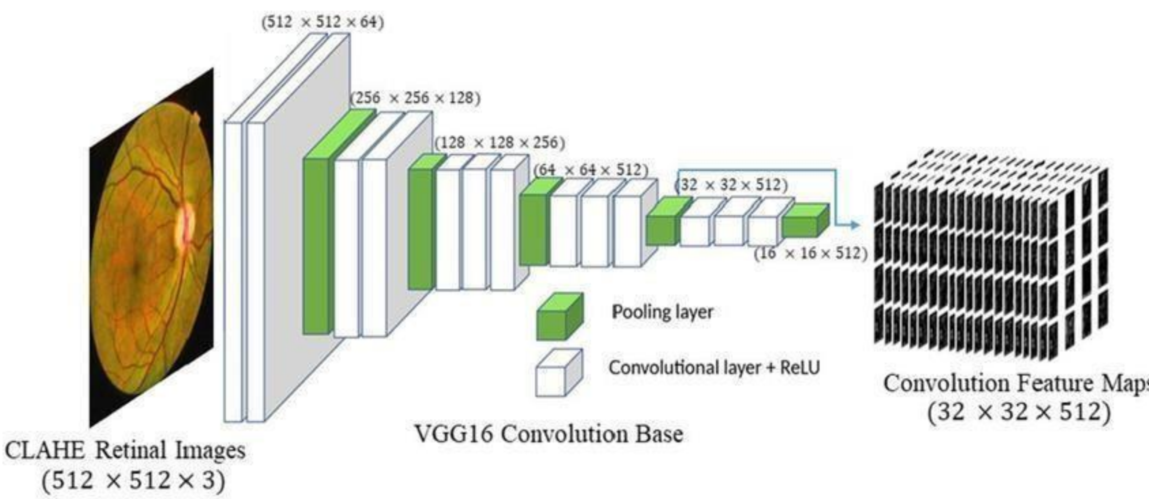

Figure 3.6.1: Architecture of VGG16

(i) As a first step in the VGG-16 model, an input image that in most cases is 224x224 pixels, three-channel RGB (Red, Green, Blue).

(ii) VGG-16 has 13 layers of convolutional structure with 3 by 3 filters of ReLU activation.

(iii) VGG-16 consists of max-pooling layers. In most cases, max pooling is done with 2 x 2 pooling masks and with a pooling stride equal to 2.

(iv) VGG-16 has fully connected layers of 4096 neurons in the number of the layers 17,18 and 19.

3.6.2 Mobile Net V2

To deal with this issue MobileNetV2 uses depth-wise separable convolutions, which splits a conventional convolution into depth and point ones. While it uses REwLU6 non-linearities in bottleneck layers effectively it does not use them in otherwise narrow layers, to preserve the information. The layers relevant to this network are configured to work best where the initial layers specialize in elaborate characteristics and the later layers deal with more general characteristics. Since it does not occupy a lot of computational resources, MobileNetV2 outperforms in multiple tasks like image classification or object detection tasks, as well as easily transplanted between mobile systems and desktops.

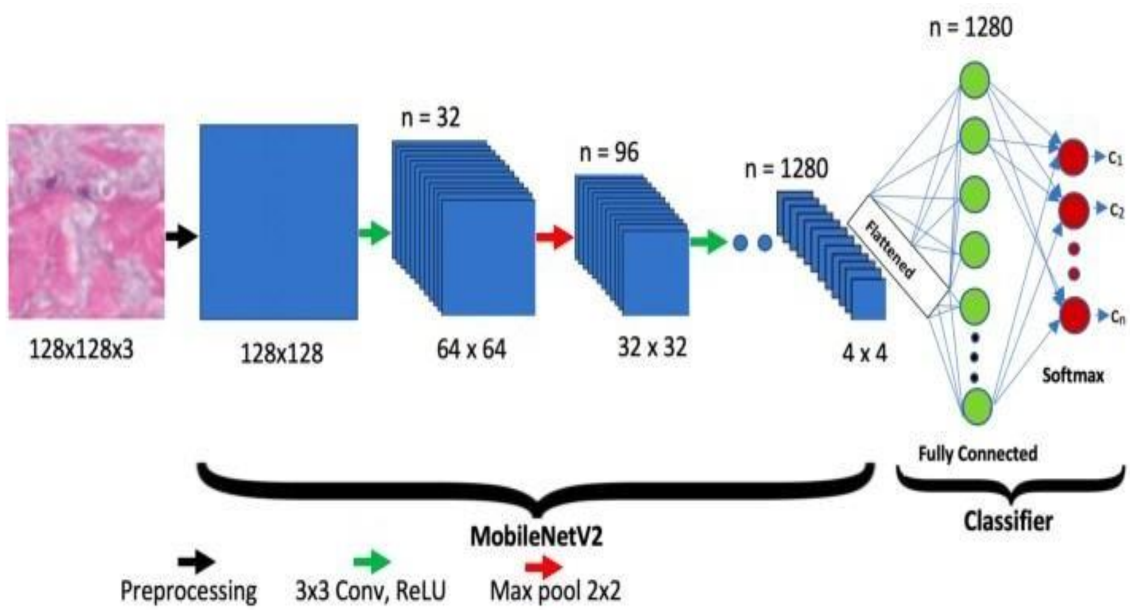

Figure 3.6.2: Architecture of Mobile Net V2

3.6.3 Convolutional Neural Network (CNN)

Contrary to fully connected neural networks CNN has its advantages in image recognition. A traditional CNN structure comprises four different types of layers: Concerning the architecture of CNN there are Convolutional layers, pooling layers, normalization layers and fully connected layers. As shown in the diagram, there is a general layout of CNNs used commonly in image classification.

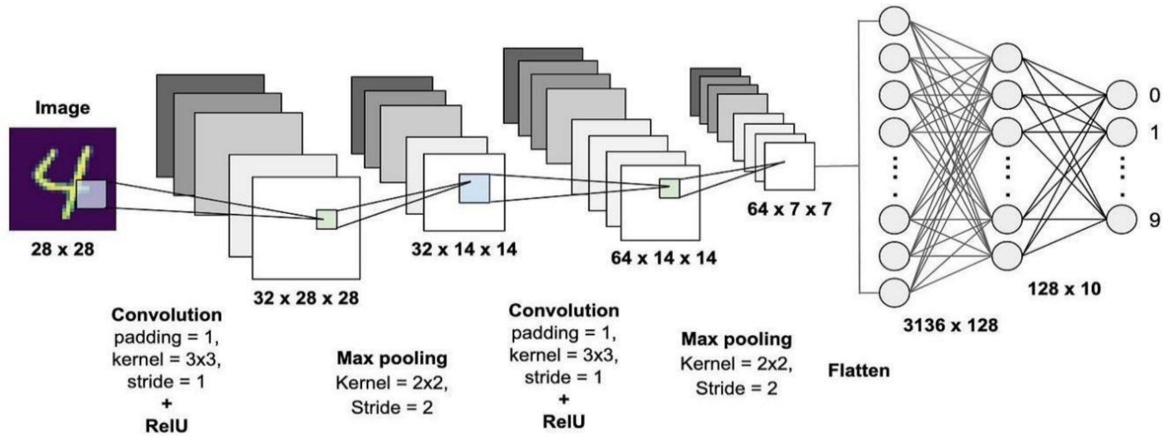

Figure 3.6.3: CNN for image recognition flowchart

3.6.4 Resnet

ResNet is a type of CNN that is used in image recognition. The first use case that was implemented by ResNet is on Deep Residual Learning for Image Processing. Since there are ResNet of various depths including fifty and one hundred and fifty two they would be called ResNet-50 and ResNet-152 respectively. The number after ResNet represents the number of layers or indeed the depth of the networks. For this work, we implemented ResNet-50, which is a deep convolutional neural network architecture with 50 layers.

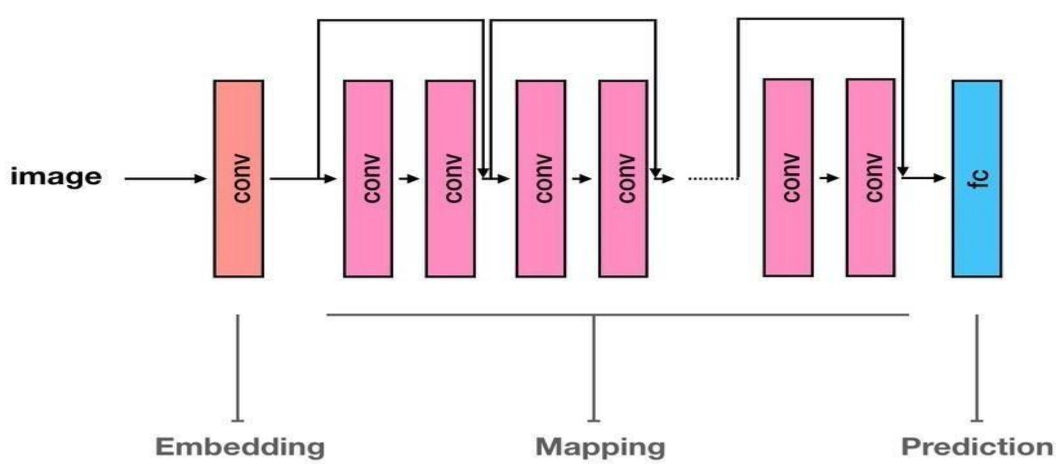

Figure 3.6.4: Architecture of ResNet

3.7 Implementation Requirements

The deep learning domain contains a lot of models for serving different purposes. My project proposal is built on four different models, all of which proved to be highly effective in detecting diseases from image data. My dataset predominantly consists of eye images, collected from online sources. The way these models work is that they automatically classify images, hence enabling them to recognize disease-related patterns with high accuracy. The eventual output of this painstaking image classification process is, in fact, the most correct when it comes to disease identification for my project.

CHAPTER 4

EXPERIMENTAL AND DISCUSSION

4.1 Introduction

Before proceeding to this section, let me have a quick discussion about the different algorithms used in the context of the detection of eye diseases for the project. Then, this chapter will present what was found and concluded using those algorithms. At this point, let me remind the readers that most of our work has been done on Deep Learning techniques. In the domain of the detection of eye diseases, we utilized four important algorithms for the classification of images: VGG16, CNN, Mobile Net V2, and Residual Neural Networks 15, commonly known as Resnet. Further sections detail the deep analysis of results thrown up by these models, with the evaluation of other relevant metrics. We used a very powerful optimizer, Adam and Admax, for optimizing our models and minimizing loss.

With such comprehensive training on the dataset, we expect both models to achieve a remarkable level of accuracy in disease detection. Among many optimizers available, Adam plays an important role in developing high performance during the training phase.

A well-equipped PC or laptop with good computation powers is required to effectively train such deep learning algorithms that run these models. This nature of the training process necessitates the use of a powerful Graphics Processing Unit to speed up computations. We initially began the training process for our proposed model of eye disease detection on a regular personal computer. However, we decided to move to Google Colab because of very long execution times and possible inaccuracies in the results at the training phase. Google Colab was found indispensable, and the ability to accomplish great feats therein helped the training of our models for this very important project in eye disease detection.

4.2 Descriptive Analysis

The confusion matrix has a really good explanation of what's the effectiveness of a deep learning classification system, which in essence depicts how many instances are assigned to each class. Accuracy is one metric that will quantify how correct the model is because it is a measure of the percentage of predictions made by the model out of all predictions:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \qquad \text{(i)}$$

Precision refers to that metric that looks into the ratio between the true positives and overall positive predictions of the model. It has been in wide use, principally for information retrieval.

$$\text{Precision} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Positives})} \times 100\% \qquad \text{(ii)}$$

Recall, in turn, gives the completeness of the model and is calculated as a ratio of the true positives to the sum of the true positives and false negatives:

$$\text{Recall} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Negatives})} \times 100\% \qquad \text{(iii)}$$

The F1-score balances both recall and precision, considering false positives and false negatives, accordingly, as given by the formula below:

$$\text{F1} - \text{Score} = \frac{(2 \times \text{Precision} \times \text{Recall})}{(2 \times \text{Precision} \times \text{Recall})} \times 100\% \qquad \text{(iv)}$$

The False Negative Rate, FNR, shows the share of negative class events that were wrongly predicted by the model:

$$\text{False Negative Rate} = \frac{\text{False Negatives}}{(\text{False Negatives} + \text{True Positives})} \times 100\% \qquad \text{(v)}$$

The Negative Predictive Value is the ratio of people who are correctly diagnosed as negative compared to the total number of all people whose tests are reported as negative:

$$\text{Negative Predictive Value} = \frac{\text{True Negatives}}{(\text{True Negatives} + \text{False Negative})} \times 100\% \qquad \text{(vi)}$$

Last but not least is the False Discovery Rate, worked out as the ratio of false positives to the sum of true positives and false positives:

$$\text{False Discovery Rate} = \frac{\text{False Positives}}{(\text{True Positives} + \text{False Positives})} \times 100\% \text{............(vii)}$$

Together, these metrics offer a complete perspective on the proposed deep-learning classification system for disease detection.

4.3 Comparative Analysis and Summary

Various machine learning algorithms were put into performance for the detection of eye diseases. This includes the Convolutional Neural Networks, VGG19, and ResNet.

The comparative models were ResNet v2 and Mobile Net V2. Of the various models compared, the ResNet model coupled with the Adam optimizer had the highest accuracy rate of 90.52% of all models. That means ResNet v2 is one of the best models for image recognition, and the detection of eye diseases is no exception.

Table 4.3: Comparative Analysis of Models

Model Name	**Optimizer**	**Test Accuracy**
CNN	Adam	86.61%
VGG 16	Adam	76.84%
Resnet 15 V2	Adam, Admax	90.52%
Mobile net V2	Adam, Admax	87.44%

Thus, the transfer learning of deep learning has been focused on in this study for recognizing eye diseases. The developed system will be useful with pre-trained models that have already.

This model was also pre-trained but had to be fine-tuned for the very purpose of eye disease detection. While this model was put under testing, it showed the highest rate regarding disease detection accuracy. It may be elaborated that deep learning, particularly transfer learning, has been proven to work efficiently in the detection of eye diseases. The CNN model gave an accuracy rate of 86.61%, below the Resnet model but still high with an accuracy rate of 90.52%. The performance of the Mobile net model is 87.44%, higher than CNN, but lower than Resnet; it means that the Mobile net also does well for the task, while not performing as well as Resnet15.

The study aims to propose an accurate and efficient approach to applying transfer learning in eye disease classification. By applying pre-trained deep learning models, which are fine-tuned by the specialty dataset related to ocular diseases, they aimed to enhance robustness and accuracy in ocular disease recognition. This is foresighted in saving the hassle associated with a lack of labeled data and ensuring that efficiency and scalability are realized in disease detection, biased on eye diseases. A total of 4217 images were gathered to make up the dataset for this study. The basis of this study is the transfer learning techniques applied in detecting eye diseases.

4.4 Experimental Result

The ultimate result is what matters most in any project. It is very well known that no machine on earth can give 100% accuracy. Though my study gave promising results, the models that I used sometimes showed imprecision. To get the best result, I have used three different models and two types of optimizers. I used VGG16, CNN, ResNet 15, and Mobile Net 15 V2 with Adam and Admax optimizers. These two optimizers generated four sets of different results. The Resnet model gave the best accuracy of 90.52%, showing that applying the Adam optimizer gave the best results. Then the Mobile net V2, which gave an accuracy of 87.44% came next in performance. However, the worst performance was given by VGG16 with an accuracy of 76.84%.

Table 4.4: Test result of different models and optimizer

Model Name	**Optimizer**	**Test Accuracy**
CNN	Adam	.8661
VGG 16	Adam	.7684
Resnet 15 V2	Adam,Admax	.9052
Mobilenet V2	Adam,Admax	.8742

4.4.1. CNN

In the table below, one can see that it was a CNN model using the Adam optimizer that achieved an accuracy of an impressive 86.61%. The table is sliced into eight columns, each having the training loss, training precision, training recall, training accuracy, and their corresponding metrics in testing-test loss, test precision, test recall, and test accuracy.

Table 4.4.1: Test and train result of CNN model with Adam Optimizer

Train Loss	Train Accuracy	Val Loss	Val Accuracy
.5131	.7856	.3739	.8720
.4889	.7958	.4466	.8436
.5042	.7942	.3292	.8886
.4851	.8077	.3924	.8637
.4659	.8176	.4698	.8377
.4620	.8210	.4385	.8341
.4645	.8157	.4792	.8235
.4660	.8148	.3908	.8483
.4513	.8165	.4541	.8460
.4484	.8259	.3943	.8661

4.4.2 VGG 16

We used one of the four models, the VGG16 model, and got a conclusion accuracy of 76.84%. The outcome of the last 10 epochs is demonstrated in a tabular format. The last four columns of the table represent the test set's loss, precision, recall, and accuracy.

Table 4.4.2: Test and train result of VGG 16 model with Adam Optimizer

Train Loss	Train Accuracy	Val Loss	Val Accuracy
.9183	59.51	.9145	58.96
.9019	61.26	.9008	60.38
.8855	62.15	.8791	61.92
.8688	63.66	.8608	64.06
8491	65.80	.8442	66.07
.8337	68.26	.8285	68.92
.8138	70.30	.8072	70.58
.7905	72.85	.7874	73.07
.7694	74.78	.7675	75.09
.7487	75.49	.7509	75.92

4.4.3 ResNet 15 V2

Among the four models tested with the Resnet 15 model, we achieved the best accuracy of 90.52%. For more precise data about performances, you can see the table with detailed breaks for the last seven training epochs.

Table 4.4.3: Test and train result of ResNet 15 model with Adam Optimizer

Train Loss	Train Accuracy	Val Loss	Val Accuracy
.8149	.9778	.9299	.8910
.7184	.9778	.8502	.8886
.6437	.9828	.7784	.8934

.5803	.9810	.7400	.8815
.5311	.9831	.6948	.8768
.4908	.9792	.6503	.8815
.4574	.9801	.6246	.9052

4.4.4 Mobilenet V2

From the Mobile net algorithm, I obtained 87.44% accuracy. The following metrics allow a deeper look into the performance of the model on the training and validation dataset over the last 7 epochs in training:

Table 4.4.4: Test and train result of Mobile Net V2 model with Adam Optimizer

Train Loss	**Train Accuracy**	**Val Loss**	**Val Accuracy**
.8876	.9706	.9716	.8863
.7879	.9742	.8856	.8815
.7096	.9757	.8190	.8815
.6420	.9748	.7584	.8863
.5868	.9754	.7178	.9028
.5425	.9784	.6807	.8934
.5115	.9757	.6573	.8886

4.5 Discussion

My project implemented deep learning algorithms, and I have suggested four models of them. During the training, several loss functions were tested, but the final calculation of the loss function was left when all iterations were finished. In front of the beginning of the training, it was necessary to divide the data into train and test subsets.

4.5.1 Train and Validation Graph

4.5.1.1 VGG16

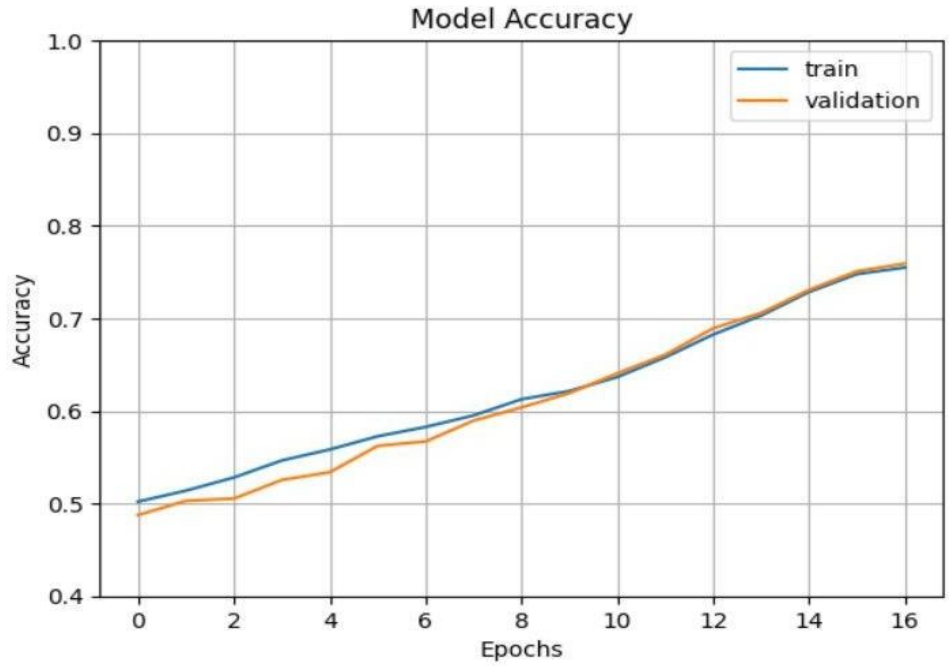

Figure 4.5.1.1: Train and Validation Graph of VGG16

4.5.1.2 Mobilenet V2

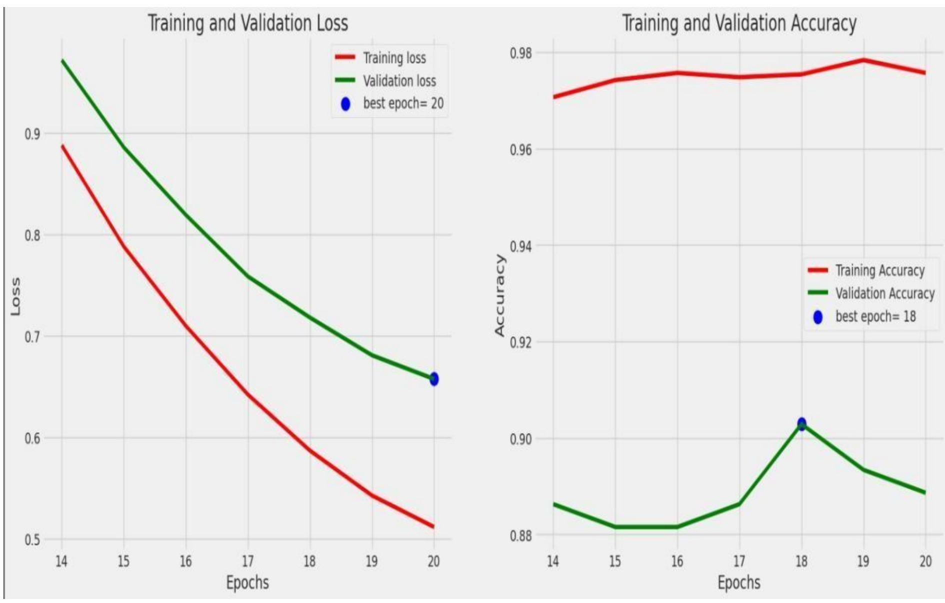

Figure 4.5.1.2: Train and Validation Graph of Mobilenet V2

4.5.1.3 Resnet 15

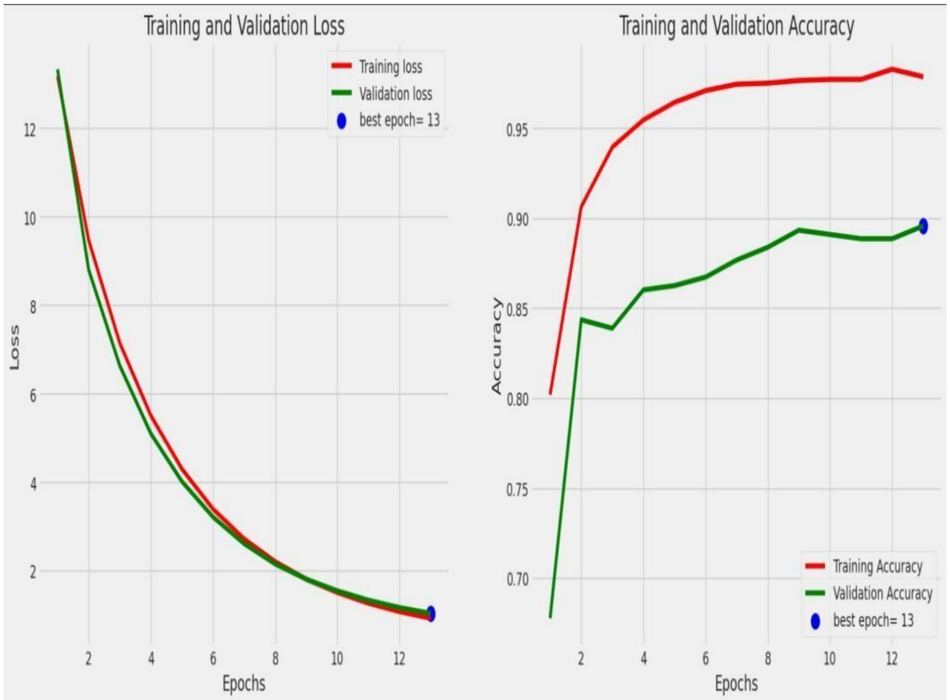

Figure 4.5.1.3: Train and Validation Graph of Resnet 15

4.5.1.4 CNN

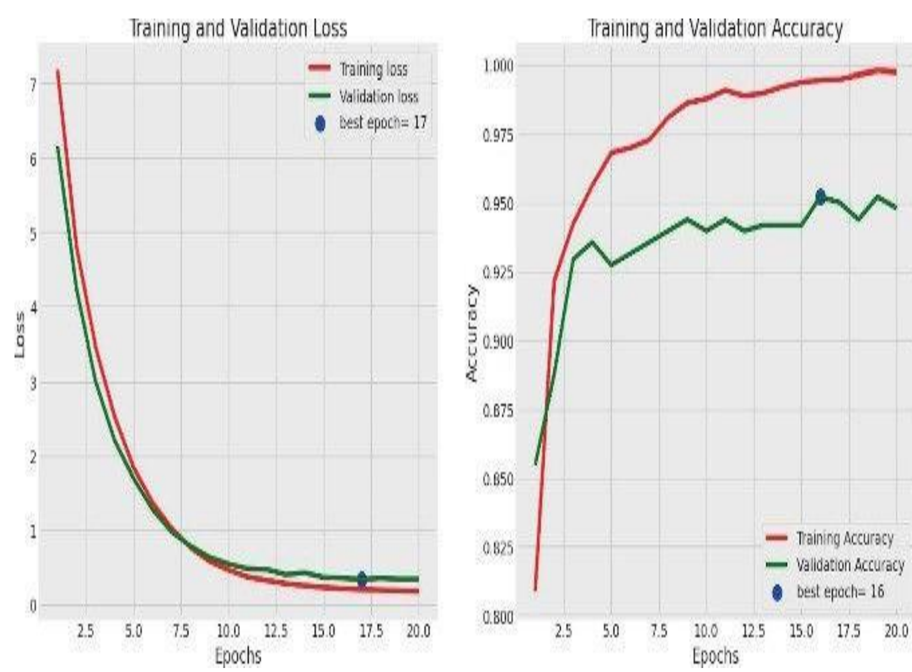

Figure 4.5.1.4: Train and Validation Graph of CNN

4.5.2 Confusion Matrix

4.5.2.1 VGG16

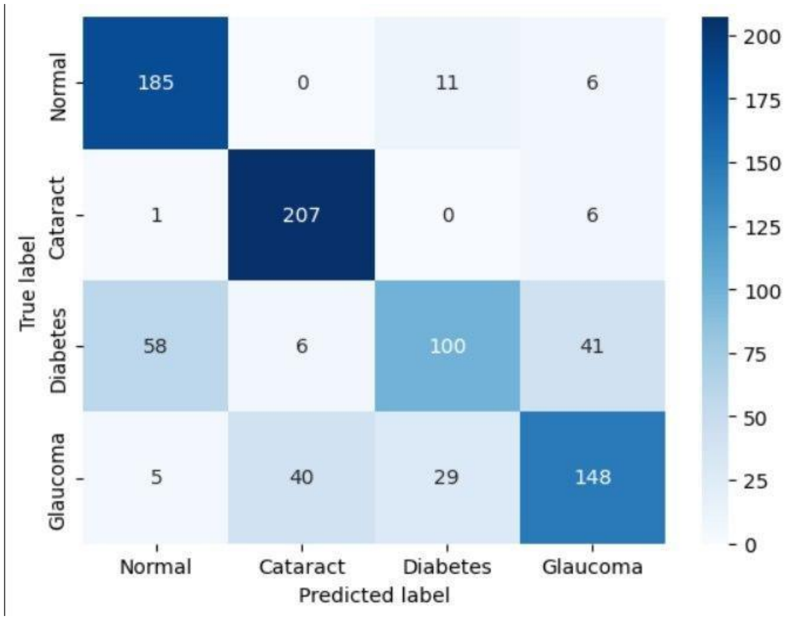

Figure 4.5.2.1: Confusion Matrix of VGG16

4.5.2.2 Mobilenet V2

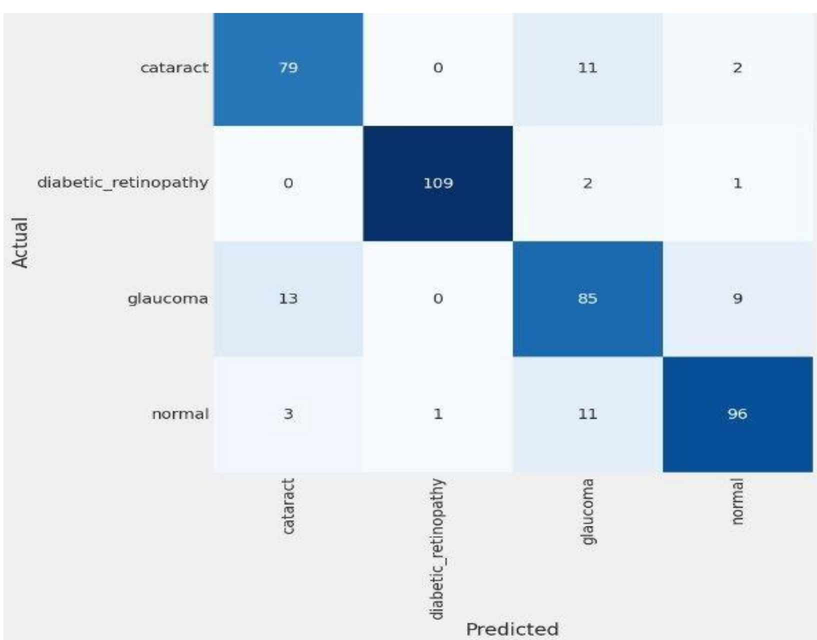

Figure 4.5.2.2: Confusion Matrix of Mobilenet V2

4.5.2.3 Resnet 15

Figure 4.5.2.3: Confusion Matrix of Resnet 15

4.5.2.4 CNN

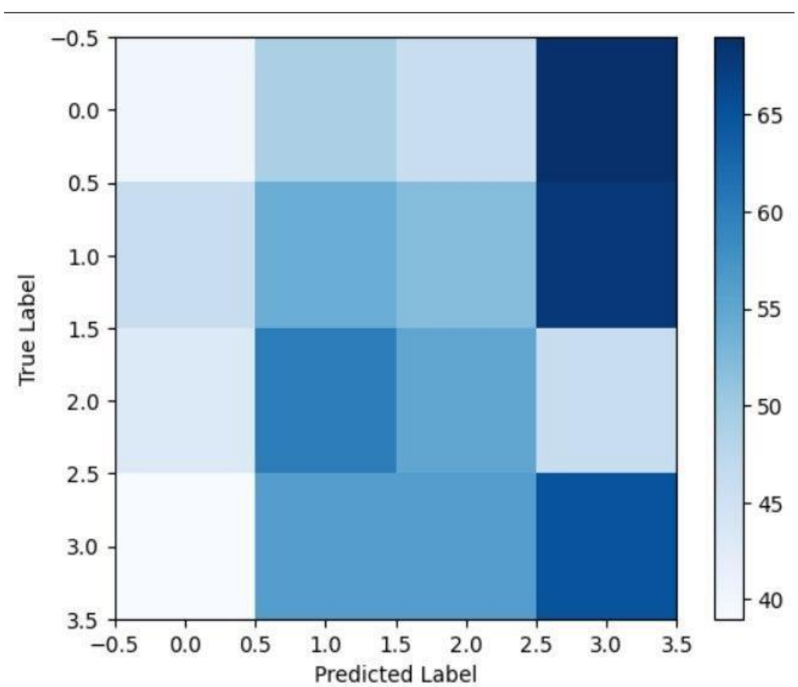

Figure 4.5.2.4: Confusion Matrix of CNN

4.5.3 Model Summary

This work uses a state-of-art deep learning approach and more specifically transfer learning to address the difficult problem of identifying ocular diseases using retinal images. Employing a dataset of fundoscopic images comprising diseased and normal eyes, this research incorporates pre-trained models that are trained on massive, relevant datasets to improve the performance of the analysis. This was achieved through transfer learning even though the precision of the models was not compromised by the change of this context. To process and classify the retinal images, the study applied multiple state-of-the-art methodologies: CNN, VGG16, Mobilenet, and ResNet.

One of the strengths of this work is the use of a larger dataset and a wider range of methodologies compared to previous studies, which produced a detailed analysis and comparison. The performance of each model was carefully examined: Our proposed model CNN was trained using the Adam optimizer, further reaching an impressive accuracy of 86.16%. One more popular model known as VGG16 achieved a relatively acceptable accuracy of 76.84%. MobileNet taking into account the fact that it takes less time for the proper computations, scored slightly higher than CNN and reached 87.44%. But the ResNet was proved to be the best model which gives 90.52% accuracy in our experiment. ResNet had a particularly high performance and explained this by the fact that it uses identities of volumes and subspaces of the following layer and previous layer images for connection, so it can work with deeper networks without dealing with vanishing gradients. This structural advantage makes ResNet well-suited for extracting high-level features from the retinal images and hence is very beneficial in detailed medical image analysis.

In this study, the accuracy has been improved compared to previous studies made on ocular disease identification and confirms that models like ResNet can help in achieving tremendous advancement in identification accuracy. This work, which adopts a large dataset and applies several machine learning approaches, including ResNet, points in the direction of making ocular disease diagnosis efficient and accurate.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

Detection and diagnosis of eye diseases, facilitated by machine learning, has positive implications for health practitioners and their patients. The early identification of eye diseases will enable medical practitioners to implement timely interventions and treatments that may halt the further progression of such conditions and preserve patients' vision. Earlier disease detection could also facilitate more effective management strategies and reduce the need for invasive or expensive procedures. This is a study that could have a potential impact on society by enabling the early detection of diseases, management, and care for patients to improve vision health, and quality of life in individuals affected by diseases of the eye. Over time and as the technology continues to evolve, it could become even more profoundly influential and long-lasting in its impact within the field of ophthalmology.

5.2 Impact on the environment

Detection of eye diseases is usually done with the help of sophisticated technologies in the form of imaging devices, computers, and servers where the data is processed. Another important aspect regarding the value of preventing blindness and other forms of vision impairments concerns improving the quality of life for affected individuals and reducing the environmental burden accompanying their treatment. Detection of eye diseases is usually done with the help of advanced technology: imaging devices, computers, and data processing. These devices consume a lot of energy, and it is very significant. The sources of energy for these technologies must be clean and environmentally friendly, for instance, renewable energy, such as solar or wind energy. It is also important to work out ways of reducing consumption by efficient hardware and software design.

5.3 Ethical Aspects

In my efforts regarding eye disease detection, I always pay much attention to the maintaining private information of an individual and also following strict ethical standards upon which our civilized society is built. I am deeply committed to the well-being of others in this world and beyond, and my act ensures this. Information I utilize varies from different sources on eye health, and to the best of my ability, I have tried to make sure my professional activities do not harm individuals or threaten society. In my research on detecting eye diseases, I have only utilized my computing systems and the internet; I have not accessed any data from outside sources or equipment that would impugn in any manner an ethical violation in my research. I execute my work with extreme determination for integrity, legality, and transparency in performing my duties and adhering to the highest codes of ethics as I pursue knowledge advancement and healthcare improvements within ophthalmology.

5.4 Sustainability Plan

The project targeted the classification of ocular diseases by image analysis. To get high accuracy, I preprocessed the eye images into structured data and measured the precision using deep learning algorithms. In the course of my work, I closely analyzed a dataset with about 4217 photographs of eyes. Because I have worked with quite a large amount of information, I can be confident about the stability and reliability of my methodology. Since I was able to identify diseases in such a large dataset of eye images, my work is a good reference that accredited organizations can use for similar projects in the future, hence increasing the relevance of such work for a longer period.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

In my research, I searched for both types of data: those with and without diseases. It was a big challenge for me; information gathering took four months, and forming a framework took four months more or so. I used deep learning to make my work effective, and estimating diseases through images is a concept, I think, that can be availed by all. I did my task step by step, trying to make my working uniform in general. The continuing parts of my cause are also explained below.

Step 1: Avail free online data.

Step 2: I have stored the data in separate categories according to Conditions.

Step 3: For ease of access, I opted for online data.

Step 4: I changed the data from images to pre-processing data.

Step 5: Methods CNN, VGG16, and RESNET 15 V2, Mobile net will be used in this paper.

Step 6: Optimizers are Adam and Admax.

Step 7: I re-checked the results that we got.

I have given importance to the quality of my work by following the above-mentioned processes. Simultaneously, I am assured that my contributions will help people in the future.

6.2 Conclusions

The research was done essentially with the use of machine learning in general, with the inclusion of the technique of transfer learning in analyzing ocular diseases. This dataset used in this paper comprises images of the retina from Fundoscopy-both diseased and healthy eyes. Pre-trained models that once were on voluminous datasets related to this domain helped in the research with their use in transfer learning to make sure that accuracy was not compromised in any way. Also, various algorithms process the data collected. In this work, many methodologies such as CNN, VGG16, Mobile Net, and RESNET were used. Distinctively, the distinctive part of this research from the earlier works in the related literature is the use of a bigger dataset and a wide range of methodologies being adopted. The study results showed that CNN performed at an accuracy of 86.1% when the Adam optimizer was employed. VGG16 had an accuracy of 76.84%, mobile net showed an accuracy of 87.44%, and on its part, RESNET did remarkably on the graph when it comes to accuracy: 90.52%. It has to be noted that RESNET proved the most accurate methodology as was shown in the other methodologies presented here in the study.

On the whole, in comparison with the results of earlier series of research within the framework of eye disease identification, the report demonstrates better accuracy that might serve as a testimony to the fact that major breakthroughs in this highly important field of study are at hand.

6.3 Implication for Further Study

Completion does not signify the end of the journey for a research paper. There are flaws and gaps in my work. I am firm in believing that with an increased dataset, I can do more about the subject matter. I will do this by increasing the data available and experimenting with a wider range of algorithms to open a path towards future development. I hope that, at some point in the future, this work shall form part of my daily routine, seeking continuous improvement in the quality of the data and results issued from my research.

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