Eye Disease Recognition Using Deep Learning

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APPROVAL

This Project titled "Eye Disease Recognition using Deep Learning" submitted by Rakibul Hossain, Student ID: 0242310005103036 AND 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 6th July, 2024

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DECLARATION

We hereby declare that, this thesis has been done by us under the supervision of **Prof Dr. Sheak Rashed Haider Norri, Professor & Head, Department of CSE** Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Eye disorders pose a significant global health challenge, often causing permanent vision loss if not detected and treated promptly. Recent advancements in medical image analysis, particularly through deep learning techniques like Convolutional Neural Networks (CNNs), show promise in early and accurate detection of ocular diseases. This paper reviews pioneering developments in using deep learning for recognizing ocular diseases, focusing on exploring the potential of CNNs in ocular disease diagnosis. It emphasizes the creation and thorough evaluation of deep learning models trained on diverse datasets to proficiently identify various ocular pathologies, such as diabetic retinopathy, glaucoma, and cataracts. Through meticulous architectural design, training methods, and optimization strategies, these models achieve impressive accuracy rates, highlighting the transformative potential of deep learning in ophthalmology. Beyond technical aspects, the research acknowledges the broader benefits of early disease detection, including preventing vision loss and improving quality of life. It also discusses ethical considerations and practical implementation challenges in healthcare settings. the study underscores the game-changing impact of deep learning in ocular disease recognition, offering a promising future for enhancing eye healthcare globally.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

1.1. Introduction

The amazing creation of natural design that is the human eye is how we see the world. It is nevertheless vulnerable to a number of illnesses and diseases that if missed or mistreated, can cause irreversible vision loss and endanger general health. Eye conditions include glaucoma, diabetic retinopathy, and cataracts pose a serious threat to world health. For effective medical management and the maintenance of visual function, early and accurate detection of these diseases is essential. Our investigation into "Eye Disease Detection" is motivated by the significant effects these illnesses have on both individuals and communities. Take the common occurrence of cataracts, which is the primary cause of blindness worldwide. Millions of individuals worldwide suffer from cataracts, which cause their vision to gradually deteriorate every year.

Most of the time, people are unaware of the condition until it becomes quite disruptive to their everyday life. In a similar vein, glaucoma and diabetic retinopathy imperceptibly worsen vision, which may be avoided or lessened with prompt diagnosis. Our drive comes from deep learning, a branch of artificial intelligence, and its transformative potential, not just from the need for quick detection. Deep learning algorithms are a promising way to improve the accuracy and efficiency of ocular illness detection since they can automatically extract patterns and features from large datasets. Our objective is to transform the diagnosis and identification of these disorders by utilizing deep learning, which will lead to major breakthroughs in the field of ocular healthcare. The use of transfer learning in the field of identifying eye diseases is the main topic of this research study. The main goal is to create an intelligent system that can correctly identify and classify ocular illnesses from medical photographs.

By using transfer learning, we want to make use of the information and feature representations gleaned from large image datasets, which will enable accurate and efficient illness detection. Convolutional neural networks (CNNs), in particular, are the focus of the suggested method's fine-tuning for the identification of ocular disorders. Using the pretrained model, the system uses eye pictures as input to extract pertinent information. The specific eye condition is then identified by feeding these extracted variables into a classification

model. We can greatly improve the efficacy and efficiency of eye disease detection systems by utilizing the abundance of information stored in pretrained models. In order to diagnose

eye diseases, this study compares and assesses a number of pretrained models and transfer learning strategies.
The outcomes of the experiment demonstrate how well transfer learning works to detect and classify three different eye conditions with great efficiency and accuracy. This report's format is to offer a thorough synopsis of our study process. The backdrop of eye illness detection, our research methods, experimental results, societal impact, and conclusions are covered in detail in the following chapters. Every segment adds to a comprehensive comprehension of how deep learning might transform the identification of eye diseases and its wider consequences for the medical field.

1.2 Motivation

The motivation for utilizing transfer learning in the identification of ocular diseases stems from its capacity to augment the efficacy, precision, and flexibility of the detection apparatus. We can drastically cut down on the amount of time and computing power needed for model building by using pre-trained models. The pre-trained models possess the ability to learn generalized features that are useful for the particular purpose of detecting eye diseases. Moreover, transfer learning tackles the problem of restricted data accessibility, which is prevalent in instances of uncommon ocular disorders or distinct variations within ocular conditions. The system is able to adjust to real-world variances and complexities that are frequently seen in clinical settings because it makes use of the robust and invariant properties that pre-trained models have gained. The capacity of transfer learning to support ongoing development is another important benefit.

The system may remain current with new diseases and evolving trends in eye health by incorporating fresh data and insights into the model. This flexibility guarantees that the method for detecting eye diseases will continue to be useful and effective in the future. All

things considered, transfer learning provides a thorough and beneficial method for improving the diagnosis of eye diseases, which in turn leads to better healthcare outcomes and the preservation of visual function.

1.3 Rationale of the Study

Eye illnesses, which comprise a broad range of conditions affecting the eyes, significantly impair people's visual health and general well-being. These illnesses pose a threat to world health since, if left untreated, they can result in irreversible eyesight loss. Understanding the kind, frequency, and effective treatment of eye illnesses is critical to maintaining visual function and the general well-being of people impacted. The motivation is clear when looking at research on eye disease detection. One of the most amazing biological wonders of the human race, the eye is our main sense organ. It is nevertheless prone to a number of illnesses and conditions that can impair visual acuity and cause irreversible vision loss. For a number of strong reasons, this susceptibility makes comprehensive research into eye illnesses imperative.

First and foremost, there are many different ways that ocular disorders can present themselves. Examples include cataracts, glaucoma, diabetic retinopathy, and age-related macular degeneration. These ailments may significantly affect a person's capacity for normal vision and daily function. Researchers want to identify the distinctive features of these illnesses—such as their etiology, course, and symptoms—through research on them. Developing successful plans for disease prevention, early diagnosis, and control requires an understanding of these concepts. Moreover, bettering medical intervention and treatment depends on research into eye illnesses. To avoid visual loss and improve the general quality of life for those impacted, prompt identification and treatment of these disorders are essential. Scholars strive to create novel diagnostic instruments and therapeutic strategies that might lessen the effects of ocular disorders, minimize financial damages, and maximize resource use in the medical field.

1.4 Research Questions

1.Which Eye conditions can be effectively identified and categorized by deep learning models?

2.How does the accuracy of deep learning-based ocular disease detection methods compare to conventional diagnostic approaches?

1.5 Expected Outcome

My main aim is to achieve the publication of this research paper in a respected journal. The ultimate objective is to offer significant assistance in enhancing disease management strategies, enhancing our understanding of disease dynamics, and promoting the creation of sustainable methods within the realm of eye disease recognition.

1.6 Project Management and Finance

Project Management

The primary aim of this project is to establish an efficient machine learning platform that utilizes transfer learning for the accurate identification of ocular diseases. Pre-trained models including CNN, VGG19, ResNet, and Mobile net will be examined in order to gauge the system's disease detection abilities. The project will be divided into discrete stages that will all have their own deadlines. These stages will include data gathering, model training and refining, system construction, testing, and deployment. Data scientists, software engineers, machine learning engineers, and ophthalmology specialists will make up the project team. In order to handle possible issues including a lack of training data, inaccurate disease diagnosis, and technical roadblocks in system development, risk management will be essential.

To effectively mitigate these issues, plans for risk mitigation will be developed for each identified risk. There will be quality assurance procedures in place to guarantee the dependability of the system. To evaluate the accuracy, responsiveness, and adaptability of the system to novel illness patterns, extensive testing and validation will be carried out.

Funding agencies, healthcare groups, and ophthalmologists will be important players in this endeavor. The initiative will aggressively solicit feedback from interested parties and offer frequent updates on its status.

Finance

The financial strategy includes budgetary considerations for all project phases, which include system development, testing, deployment, and data gathering. It also includes compensation for team members and costs associated with obtaining necessary computer resources. Potential funding sources include government grants, healthcare groups, and people interested in expanding the technology for identifying eye diseases. The project's economic

viability will be evaluated through a thorough cost-benefit analysis. This analysis will compare the system's advantages such as better illness management and the possibility of better patient outcomes against the expenses related to its creation and upkeep. The system's effect on disease detection rates and healthcare expense savings will be used to compute the Return on Investment (ROI). The project's economic viability will be evaluated through a thorough cost-benefit analysis. This analysis will compare the system's advantages such as better illness management and the possibility of better patient outcomes against the expenses related to its creation and upkeep. The system's effect on disease detection rates and healthcare expense savings will be used to compute the Return on Investment (ROI).

1.7 Report Layout

In this report, each chapter is analyzed from different perspectives, and every chapter comprises comprehensive coverage of multiple components. The report is structured as follows:

In Chapter 1,

Introduction Here, Eye diseases can be identified with Fundoscopy image and why it is necessary. My thesis's introduction, motivation, study rationale, and projected conclusion were all presented.

In Chapter 2,

Background I talk about the conditions surrounding our thesis. We've worked on four different models here. I discussed their principal ailment. I also discussed 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, data gathering procedures, statistical analysis, and implementation needs at this time.

In Chapter 4,

Experimental results and discussion Here, I thoroughly examined the entire procedure and the results of the experiment. I went into considerable detail regarding my experimental results, my experimental description, and my experimental summary.

In Chapter 5,

Summary, Conclusion, recommendation, and implication for future research. Here I explored the social influence on our society in this chapter. Society’s Impact, Ethical Issues, and a Long-Term Plan

In Chapter 6,

Summary, Conclusion, Recommendation & Implication for Future Research. The final concepts of the project are discussed in this chapter. This chapter is in charge of displaying the entire project report in accordance with suggestions. I also talked about the study's summary, conclusion, and implications for future research

CHAPTER 2

BACKGROUND STUDY

2.1 Introduction

In this research, to create a reliable and efficient system for identifying disorders in ocular images, I set out to use the power of transfer learning in this research. My goal is to greatly improve the accuracy and efficiency of eye disease detection by utilizing the power of deep learning models, namely CNN (Convolutional Neural Networks), Resnet (Residual Neural Networks), VGG19, and Mobile Net. My motivation comes from the need to address the issues surrounding the identification of ocular diseases, specifically the lack of labeled data and the requirement for accurate and scalable detection techniques. This study essentially focuses on applying transfer learning methods to the field of eye illness identification. Our goal is to develop a system that excels in the prompt and accurate diagnosis and management of eye disorders by utilizing pre-trained models such as CNN, Resnet, VGG19, and Mobile Net and customizing them to the unique requirements of eye disease identification.

2.2 Related Works

"Deep Learning for ocular Disease Recognition: An Inner-Class Balance" is a work that explores the use of LeNet5, AlexNet, and custom models as the foundation for deep learning techniques for eye disease recognition. It makes use of an eye disease Kaggle dataset. LeNet-5's stated accuracy is roughly 73%, AlexNet's 87%, and the best custom model's 90–95%. "Application of Deep CNN Networks in eye Disease Detection" investigates the use of Convolutional Neural Networks (CNNs) for eye disease detection, and exclusively diagnoses Glaucoma and Normal class. The models that are used are CNN modifications and VGG-19. The dataset used in this study was obtained from Kaggle's extensive public resource, ODIR (Ocular Disease Intelligent Recognition). "Source and Camera Independent Ophthalmic Disease Recognition from Fundus Image Using Neural Network" presents a convolutional neural network (CNN) model for eye disease recognition; the CNN model achieves an F-score of approximately 85%, a Kappa score of 31%, and an AVC value of 80.5%. The study's data was gathered from the ODIR-5K dataset, which comprises color fundus photographs and doctors' diagnostic keywords from 5000 patients. "An Automatic Ocular Disease Detection Scheme from Enhanced Fundus Images Based on Ensembling Deep CNN

Networks" suggests a technique utilizing an ensemble of deep CNN architectures such as ResNet50, InceptionResNetV2, and others.

EfficientNetB0 and EfficientNetB2 for the identification of eye diseases. This study used a huge dataset on ocular diseases that included paired fundus photos of five thousand patients from different Chinese hospitals. With an accuracy of 86.08% on upgraded images, the ensemble method performs better, demonstrating its efficacy in the diagnosis of ocular diseases. A technique utilizing the EfficientNet and DenseNet architectures is presented in the publication "Ocular Diseases Detection using Recent Deep Learning Techniques". With a particular learning rate parameter, the top-performing model, EfficientNetB7, attained an accuracy of 88.85%. The Ocular Disease Intelligent Recognition (ODIR) dataset, which comprises fundus photos from 5,000 patients gathered by Shanggong Medical Technology Co., provided the data for this investigation.

The article "Novel Approach for Detection of Retinopathy" by Ltd. from many Chinese hospitals presents a strategy for segmenting blood vessels in retinal images by combining the canny edge detection technique with Contrast-Limited Adaptive Histogram Equalization (CLAHE). The Digital Retinal Images for Vessel Extraction (DRIVE) database was used to test the study's data. The suggested method's ability to extract vascular patterns more effectively than more conventional edge detection techniques is the main focus of the paper; however, a measured accuracy rate for the method is not provided.

Glaucoma Detection from Fundus Camera Image" focuses on the detection of glaucoma using fundus camera images. The methodology involves using image processing techniques to calculate the Cup to Disc Ratio (CDR). The dataset used consists of 45 retinal fundus images obtained from Arvind Eye Hospital, Pondicherry. The research reports a detection accuracy of 93.5% using fuzzy logic for diagnosis and classification. The single layer perceptron method is used in the cataract detection system, which is designed to classify eye conditions into normal, immature cataract, and mature cataract categories. The research reports that this detection system achieves an accuracy of 85%. Direct data collection from cataract patients using a smartphone makes the study practical and accessible.

2.3 Comparative Analysis and Summary

The study evaluated the performance of a number of machine learning algorithms for the purpose of detecting eye diseases. Convolutional Neural Networks (CNN), VGG19, ResNet,

and Mobile Net V2 were the models that were compared. Of these models, the ResNet model in conjunction with the Adam optimizer yielded the highest accuracy rate of 90.52%. This indicates that ResNet v2 is a highly effective model for image recognition tasks, including the detection of eye diseases.

Table 2.3: 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%

The study focused on using transfer learning within deep learning for the purpose of eye disease recognition. The developed system uses pre-trained models that have been specifically fine-tuned for the task of identifying eye diseases. During the testing phase, the Resnet model exhibited the highest accuracy rate in disease detection. This suggests that deep learning, particularly transfer learning, can effectively identify eye diseases. The CNN model achieved an accuracy rate of 86.61%, which is lower than the Resnet model but still a high accuracy rate of 90.52%. The Mobile net model achieved an accuracy rate of 87.44%, which is higher than CNN but lower than Resnet, indicating that Mobile net also performs well for this task, but not as well as Resnet15.

This study aims to provide a precise and efficient method for applying transfer learning to the identification of eye diseases. Specifically, by using pre-existing deep learning models and refining them with a specialized dataset of eye disease images, the researchers hope to improve the robustness and accuracy of ocular disease recognition. This approach is expected to overcome the difficulties caused by a lack of labeled data and increase the efficiency and scalability of disease detection in the context of eye diseases. 4217 images were sourced for this research's dataset. In summary, the study focuses on the application of transfer learning techniques to the detection of eye diseases.

2.4 Scope of the Problem

In order to use machine learning for the diagnosis of eye diseases through transfer learning, the following task definition can be used: the main goal is the precise and effective identification of different eye diseases. This involves identifying and evaluating a variety of ailments that frequently affect the eyes visually. The task involves analyzing medical images of the eye to detect disease signs. Relevant features must be extracted from these images using machine learning techniques that must be developed and applied. The main challenge is the application of transfer learning, which entails adapting pre-trained models (like VGG19, ResNet, Mobile net, and CNN) to the particular task of eye disease detection.

The scope of the project also encompasses the evaluation and comparison of different machine learning algorithms in terms of their accuracy in disease detection. This comparative analysis aims to identify the most suitable algorithm for the given task. Another challenge is the development of a user-friendly interface that allows users, including healthcare professionals and patients, to upload eye images for disease identification. Users should receive real-time feedback from the system regarding the presence and type of eye disease detected in the images. Furthermore, integrating the disease detection system with existing healthcare management systems is crucial to provide a comprehensive solution for managing eye diseases. The system should be designed to handle a large volume of users and images while maintaining its performance. It should also be adaptable to accommodate emerging diseases and changing disease patterns, ensuring its effectiveness in identifying novel and previously unrecognized eye disease patterns.

2.5 Challenges

Applying machine learning techniques to detect ocular diseases using transfer learning can pose various difficulties, similar to those encountered in papaya fruit disease detection. These challenges include the collection of diverse and extensive datasets of ocular images, encompassing both healthy and diseased cases. Ensuring the quality, angle, and lighting conditions of the images is consistent can significantly influence the model's performance. Accurate labeling of images with the corresponding ocular diseases necessitates expertise in ocular pathology. Moreover, training deep learning models like CNN, VGG19, Mobile net and ResNet is computationally intensive and time-consuming, which can pose resource

challenges. Overfitting, where the model performs well on the training data but poorly on new, unseen data, is a potential risk, particularly when data is limited. The model's capacity to generalize effectively to detect previously unidentified ocular disease patterns is crucial but can be hampered by insufficient training data on specific disease patterns. Additionally, achieving real-time disease detection, especially for a large volume of individuals or images, can be complex and may require efficient model deployment and resource management. Integrating the disease detection system with existing healthcare or medical management systems may introduce compatibility and integration issues. Lastly, the model's performance may be influenced by environmental factors, such as variations in lighting conditions or the timing of image capture, impacting the accuracy and reliability of disease detection. Addressing these challenges in ocular disease recognition using deep learning is paramount to developing a reliable and effective system for disease diagnosis and management.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

In this research, I employed various techniques as one typically would in any scientific study. I incorporated insights and innovative approaches from previous researchers who had explored this subject matter. Detailed explanations of the initial phases and concluding aspects of my project will be provided in the upcoming sections.

I gathered information from various accessible Google and Internet sources. Data clearing, data resizing, data argumentation has been done in pre-processing. In the following data extraction, I completed data training and testing. I used Deep Learning as a method to advance our work, as well as CNN, VGG19, Mobile net and Resnet 15 to establish the classification outcome.

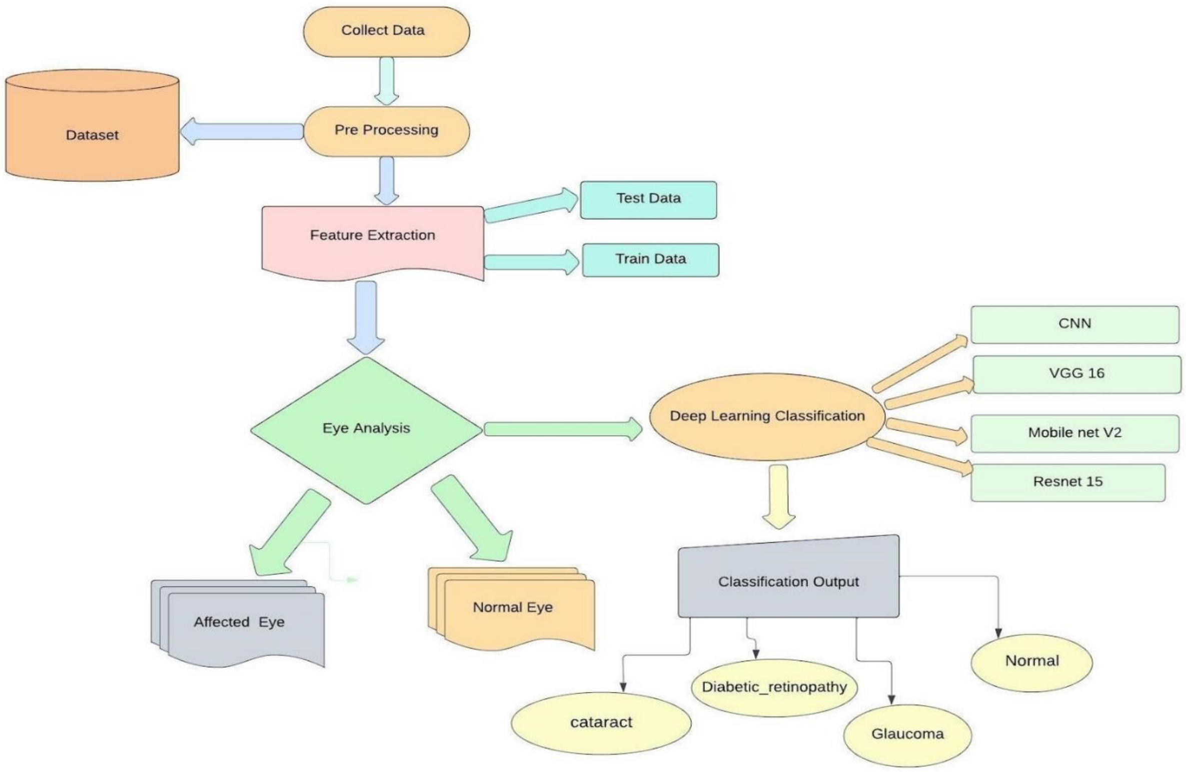

Figure 3.1: Working Procedure.

3.2 Research Subject and Instrumentation

Eye Disease Recognition using Deep Learning, the title of our thesis proposal. Disease detection is a major area in the study right now. I employed certain deep learning models in our study technique since I used some mathematical functions in my proposed model. Working with a deep learning model will be incredibly challenging for me because A strong PC, GPU, and other components are needed. the equipment and technology required to introduce our product are listed below -

Hardware and Software:

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

Tools for Development:

- Windows 10 is the latest version of Windows.
- Python 3.7.13 is required.
- TensorFlow version 2.8.0 Backend
- NumPy.
- Pandas.

3.3 Data Collection Procedure

In this study, the Eye Disease Intelligent Recognition (ODIR) dataset is utilized. Known as one of the most comprehensive datasets available publicly on Kaggle, it's used for identifying various eye diseases. After gathering data from online resources, I categorized it into four classes.

3.4 Statistical Analysis

I took 4217 photos from online platform for my experiment. I've separated them into two different groups. I used 80% data for training and 20%data for testing. The two groups that I have classified into four groups are as follows: Normal, Cataract, Diabetic retinopathy, Glaucoma.

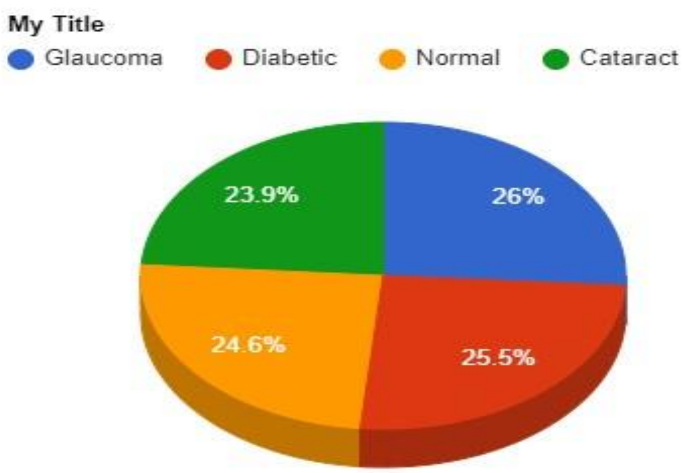

Fig 3.4.a: Categories Of Ocular Disease

These statistics represent the categories within the eye data, with 26% of eyes affected by Glaucoma, 25.5% by Diabetic conditions, 24.6% classified as normal, and 23.9% suffering from Cataracts. My dataset comprises information on various eye diseases, and the distribution of data based on these diseases, as well as data related to healthy eyes, is visualized in the graph below.

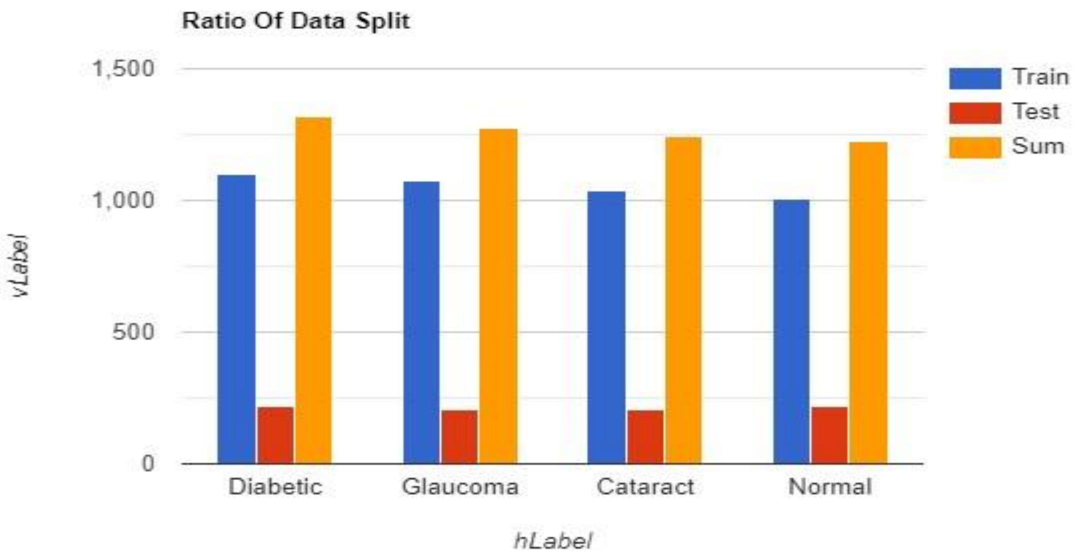

Figure 3.4.b: Ratio of Data Split.

This figure illustrates the proportion of the overall data collection, along with the data allocated for training and testing, as well as the total data count.

Table 3.4 Total of all different Eye image

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 process of identifying ocular diseases entails examining every image in the input image dataset. The identification process is predicated on classifying the diseases into distinct groups, such as Normal, Cataract, Diabetic Retinopathy, or Glaucoma, which has been verified by science. Our suggested method is based on deep learning techniques because deep

learning encompasses a wide range of algorithms, models, and strategies. Specifically, I experimented with four main models: VGG16, Convolutional Neural Network, Resnet, and Mobile Net, which are highly relevant to my proposed project.

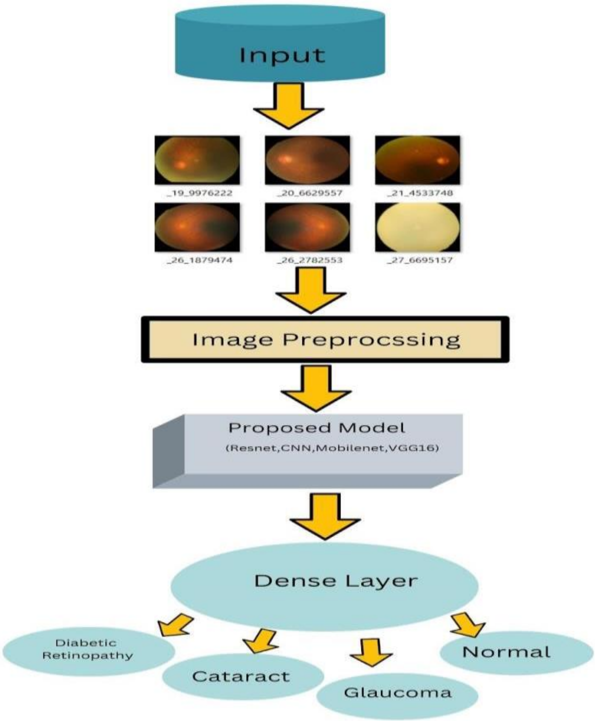

Figure 3.5.1: Proposed Method's Architecture.

3.5.a VGG16

VGG-16 is a deep convolutional neural network (CNN)It consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. VGG-16 is known for its simplicity and effectiveness in image classification tasks. It uses 3x3 convolutional filters, ReLU activation functions, and max-pooling layers with 2x2 pools. Originally designed for 1000-class image classification it can be adapted for other tasks by modifying the number of output neurons. While computationally expensive, VGG-16 has been influential in the field of deep learning and computer vision.

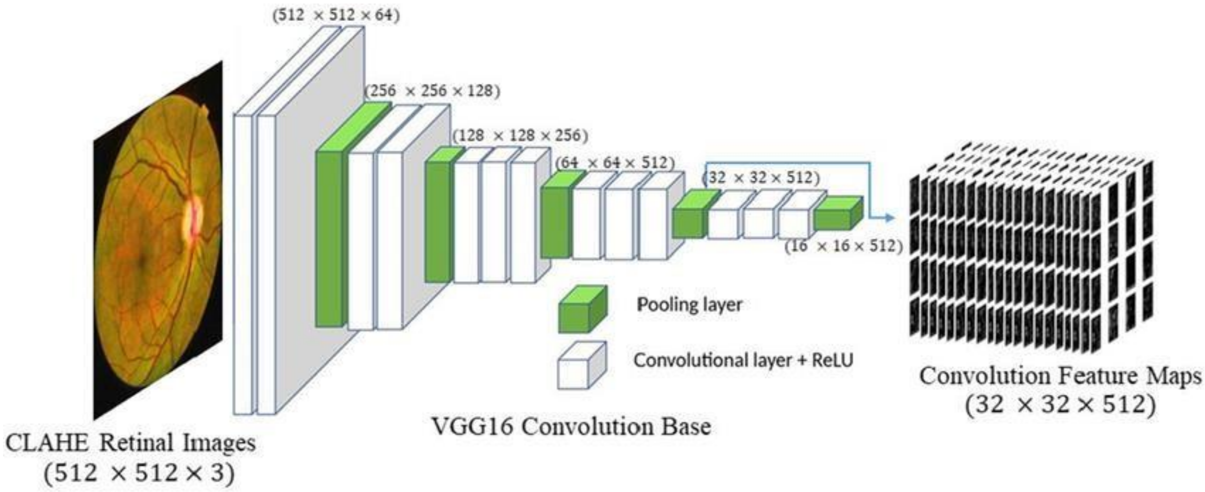

Figure 3.5.a: Architecture of VGG16

(i)VGG-16 model takes an input image, typically with dimensions of 224x224 pixels (though variations can be used), in the form of a three-channel RGB image (Red, Green, and Blue).

(ii)VGG-16 consists of 13 convolutional layers with 3x3 filters and ReLU activation functions.

(iii)VGG-16 includes max-pooling layers.Max-pooling is typically performed using 2x2 pooling windows with a stride of 2.

(iv), VGG-16 has three fully connected layers with 4096 neurons each.

3.5.b Mobile Net V2

MobileNetV2 employs depth wise separable convolutions, dividing a typical convolution into depth wise and pointwise types. It judiciously applies ReLU6 non-linearities in bottleneck layers, avoiding them in narrower layers to conserve information. The network's layers are structured for optimal performance, with initial layers concentrating on detailed aspects and later layers on broader features. Due to its scalable design, MobileNetV2 excels in a range of tasks, such as image classification and object detection, and adapts seamlessly across various platforms from mobile devices to desktops.

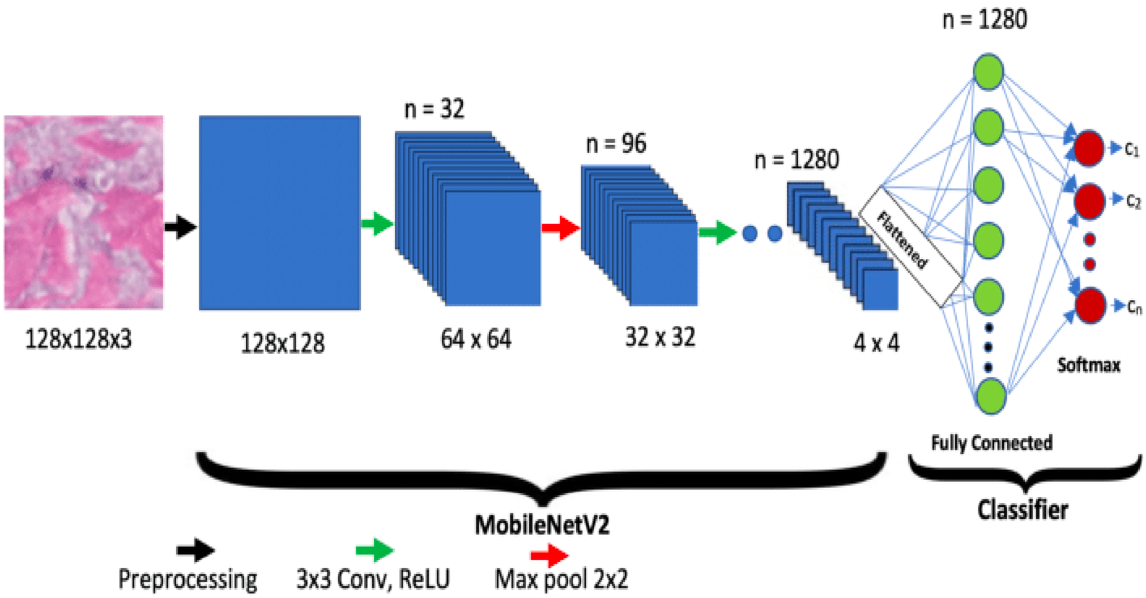

Figure 3.5.b: Architecture of Mobile net V2

3.5.c Convolutional Neural Network (CNN)

Compared to fully connected neural networks, CNNs offer unique benefits for image recognition. A traditional CNN structure comprises four different types of layers: convolutional layers, pooling layers, normalization layers, and fully connected layers. The diagram below illustrates a typical CNN designed for image classification.

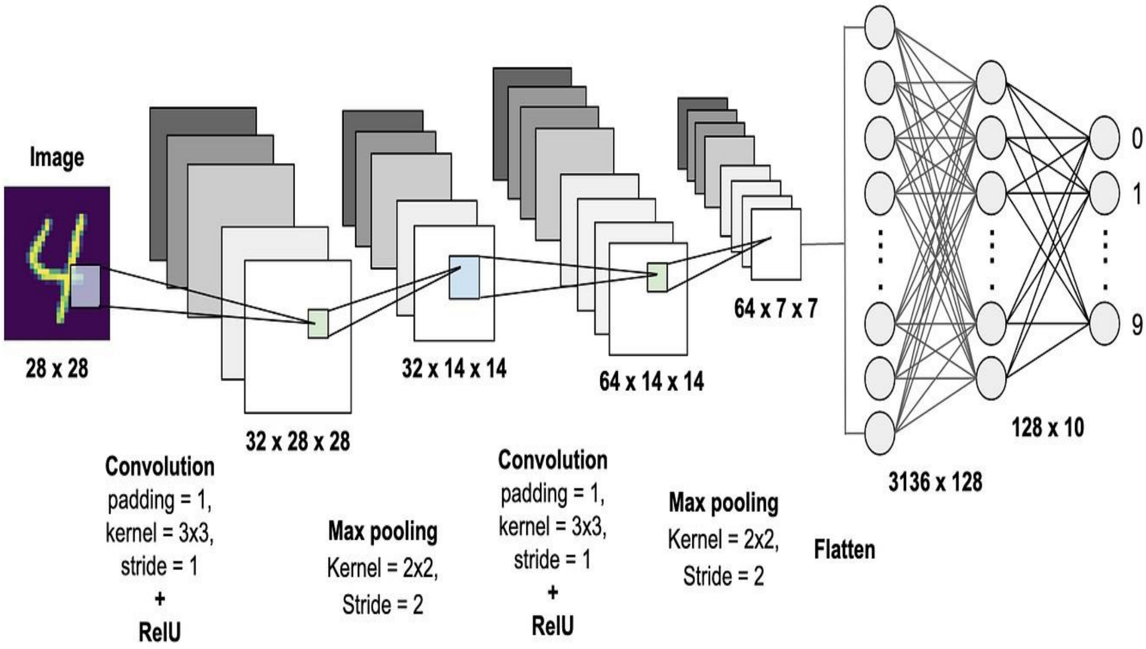

Figure 3.5.c: CNN for image recognition flowchart

3.5.d. Resnet

ResNets (Residual Networks) is another name for ResNets. ResNet is a type of CNN used in image recognition. ResNet's initial application was Deep Residual Learning for Image Processing. ResNets of various depths, such as ResNet-50 and ResNet-152, can be constructed. The number at the end of ResNet indicates the number of layers or the depth of the networks.

We chose ResNet-50 for our implementation, which is a deep convolutional neural network with 50 layers.

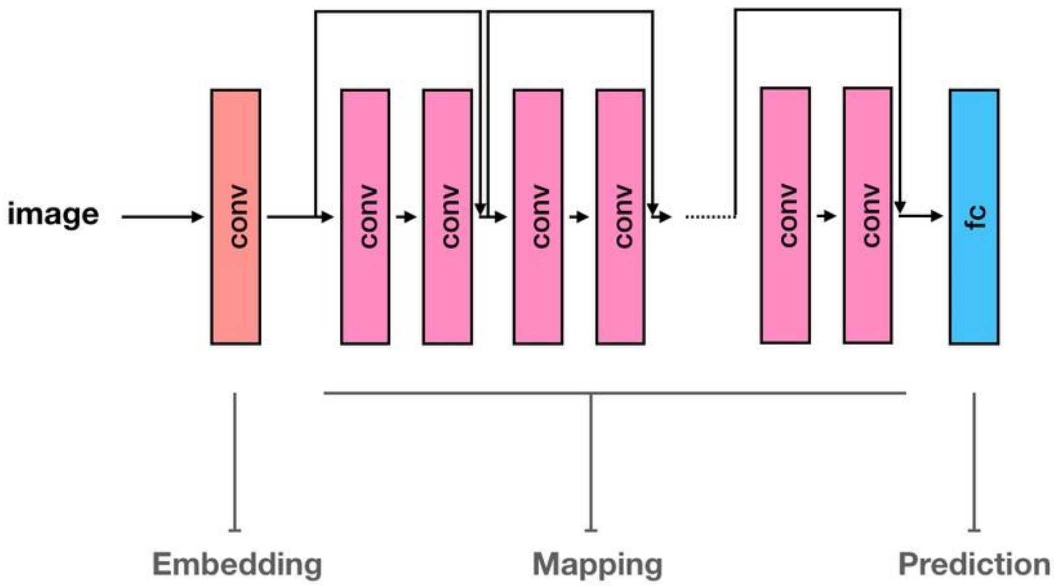

Figure 3.5.d: Architecture of ResNet

3.6 Implementation Requirements

In the domain of deep learning, there are numerous model options designed to serve various purposes. My project proposal includes four different models, all of which have demonstrated exceptional effectiveness in the detection of diseases from image data. My dataset predominantly consists of eye images collected from online sources. These models function by autonomously classifying images, enabling them to identify disease-related patterns with a high degree of accuracy. This precise image classification process ultimately yields the most accurate results for disease identification in my project.

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

Before delving into this section, let's briefly discuss the various algorithms applied in the context of eye disease detection in this project. This chapter will outline the discoveries and outcomes achieved through the implementation of these algorithms. It is important to note that the primary focus of our work revolves around Deep Learning techniques. For the task of image classification in the domain of eye disease detection, we harnessed the power of four key algorithms: VGG16, Convolutional Neural Networks (CNN), Mobile net V2 and Residual Neural Networks 15 (Resnet). The subsequent sections will provide a detailed analysis of the results generated by these models, along with an evaluation of other pertinent metrics. To optimize and minimize loss in our models, we employed a highly effective optimizer called Adam and Admax. By subjecting the models to extensive training on our dataset, we anticipate achieving a remarkable level of accuracy in disease detection. Among the plethora of available optimizer, Adam plays a pivotal role in enhancing the training phase's effectiveness.

In order to effectively train these deep learning algorithm models, it is imperative to utilize a wellequipped PC or laptop with substantial computational power. The training process demands the utilization of a potent Graphics Processing Unit (GPU) to expedite the computations. Initially, we initiated the training of our proposed eye disease detection model on a standard personal computer. However, due to prolonged execution times and the potential for inaccuracies in the results, we decided to transition to Google Colab for the training phase. Google Colab proved to be an invaluable resource, significantly contributing to the successful training of our models for this crucial project in the realm of eye disease detection.

4.2 Descriptive Analysis

The effectiveness of a deep learning classification system can be assessed using a confusion matrix, which provides insights into how many instances have been assigned to each class. Accuracy, as a metric, quantifies the model's correctness by calculating the percentage of accurate predictions made by the model out of all predictions:

Accuracy = (Correct Predictions / Total Predictions) Precision is an important metric that measures the proportion of true positives to the total number of positive predictions made by

the model. It is primarily used for information retrieval: Precision = (True Positives / (True Positives + False Positives)) × 100%

Recall, on the other hand, assesses the model's completeness by calculating the proportion of true positives to the sum of true positives and false negatives:

Recall = (True Positives / (True Positives + False Negatives)) × 100%

The F1-score, often referred to as the F1 score, strikes a balance between recall and precision, taking into account both false positives and false negatives:

F1-Score = ((2 × Precision × Recall) / (Precision + Recall)) × 100%

The False Negative Rate (FNR) indicates the model's rate of incorrectly predicting the negative class:

False Negative Rate = (False Negatives / (False Negatives + True Positives)) × 100%

Negative Predictive Value (NPV) represents the proportion of individuals correctly diagnosed as negative compared to the total number of individuals with negative test results:

Negative Predictive Value = (True Negative / (True Negative + False Negative)) × 100%

Finally, the False Discovery Rate (FDR) is calculated as the ratio of false positives to the sum of true positives and false positives:

False Discovery Rate = (False Positives / (True Positives + False Positives)) × 100%

These metrics collectively provide a comprehensive assessment of the performance and reliability of the deep learning classification system in the context of disease detection.

4.3 Experimental Results

The final outcome holds significant importance in any project. It's well understood that no machine can provide a 100% accuracy rate. While my research yielded promising results, the models I employed occasionally exhibited imprecision. In my pursuit of optimal results, I utilized three different models and employed two distinct types of optimizers. Specifically, I made use of the VGG16, CNN, ResNet 15 and Mobile net 15 V2 models in combination with Adam and Admax optimizers. These two optimizers generated four different sets of results. The Resnet model delivered the highest accuracy at 90.52%, indicating that implementing the Adam optimizer resulted in the best performance. The Mobile net V2 model also performed well with an accuracy of 87.44%. But VGG16 model performed the worst with accuracy 76.84%.

Table 4.3: 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
MobilenetV 2	Adam,Admax	.8742

4.3.1. CNN

I achieved an impressive 86.61% accuracy using a CNN model with the Adam optimizer, as demonstrated in a table. This table is divided into eight columns, detailing training loss, training precision, training recall, training accuracy, and corresponding metrics for testing - test loss, test precision, test recall, and test accuracy.

Table 4.3.1: 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	.45 41	.8460
.4484	.8259	.39 43	.8661

4.3.2 VGG 16

Utilizing the VGG16 model, one of four models tested, we achieved an accuracy of 76.84%. The table provided shows detailed outcomes for the last 10 epochs, with the final four columns specifically presenting the test set's loss, precision, recall, and accuracy.

Table 4.3.2: Test and train result of VGG 16 model with Adam Optimizer

Train Loss	Train Accuracy	Val Loss	Val Accuracy
.918 3	59.51	.9145	58.96
.901 9	61.26	.9008	60.38
.885 5	62.15	.8791	61.92
.868 8	63.66	.8608	64.06
8491	65.80	.8442	66.07
.833 7	68.26	.8285	68.92
.813 8	70.30	.8072	70.58
.790 5	72.85	.7874	73.07
.769 4	74.78	.7675	75.09
.748 7	75.49	.7509	75.92

4.3.3 ResNet 15 V2

Using the Resnet 15 model, one of four models tested, we achieved an impressive accuracy of 90.52%. Which is best accuracy. The table below provides a detailed overview of the performance during the last 7 epochs of training.

Table 4.3.3: 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

4.3.4 MobilenetV2

From Mobile net algorithm I got 87.44% accuracy. These metrics provide insight into the model's performance during the last 7 epochs of training, both on the training and validation datasets.:

Table 4.3.4: 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

4.4 Discussion

Deep learning algorithms were employed in my project, where I proposed four different models. Throughout the training, various loss functions were evaluated, but the final loss function calculation was reserved until all iterations were complete. Prior to initiating the training, the data was divided into training and testing subsets.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

Detecting and diagnosing eye diseases using machine learning can provide significant benefits to healthcare professionals and patients. By identifying eye diseases early, medical practitioners can initiate timely treatments and interventions, potentially preventing the progression of these conditions and preserving patients' vision. Early disease detection can also lead to more effective management strategies, reducing the need for invasive or costly procedures. This research has the potential to positively impact society by enabling early disease detection, improving patient care, enhancing vision health, and ultimately contributing to a better quality of life for individuals affected by eye diseases. As technology continues to advance, the application of these tools in the field of ophthalmology can have a profound and lasting impact on society.

5.2 Impact on Environment

Eye disease detection often relies on advanced technology such as imaging devices, computers, and servers for data processing. Preventing blindness or vision impairment can also contribute to a better quality of life for affected individuals and reduce the environmental burden associated with their treatment. Eye disease detection often relies on advanced technology such as imaging devices, computers, and servers for data processing. These devices can consume significant amounts of energy. It is important to ensure that the energy sources used for these technologies are sustainable and eco-friendly, such as renewable energy sources like solar or wind power. Reducing energy consumption through efficient hardware and software design is also crucial.

5.3 Ethical Aspects

In my endeavors related to eye disease detection, I prioritize the preservation of individuals' privacy and unwavering adherence to ethical standards that underpin our civilized society. I

am deeply committed to safeguarding the well-being of others, both in the present and the future, and ensure that my actions reflect this dedication. The information I utilize originates from diverse sources within the field of eye health, and I have taken meticulous steps to ensure that my professional responsibilities do not pose any harm to individuals or society. Throughout my work in eye disease detection, I have exclusively employed my personal computing systems and the internet, refraining from accessing any external data or equipment that could compromise the ethical integrity of my research. I approach my work with a steadfast commitment to integrity, legality, and transparency, thus upholding the highest ethical standards in the pursuit of advancing knowledge and improving healthcare in the field of ophthalmology.

5.4 Sustainability Plan

This project's main goal was to identify ocular diseases through image analysis. To achieve the highest levels of accuracy possible, I transformed eye images into structured data and utilized deep learning algorithms to evaluate precision. Throughout my work, I carefully reviewed a dataset that included about 4217 eye photographs. Because I processed a significant amount of data, I am confident in the stability and dependability of my methodology. Since I was able to identify diseases in such a large dataset of eye images, my work will be a valuable resource for prestigious organizations looking to use it in future projects, enhancing its relevance and long-term applicability.

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 challenging task for me, and it took me four months to gather information and form the framework. I used deep learning to make my work more effective, and I think that estimating diseases from images is a concept that can benefit everyone. I finished my task gradually, making an effort to keep my work consistent overall. The ongoing aspects of my cause are also detailed below.

Step 1: Use online data freely available.

Step 2: I have stored the data in different categories based on Conditions.

Step 3: For accessibility, I chose to collect online data.

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

Step 5: Using methods. These are CNN, VGG16, and RESNET 15 V2, Mobile net.

Step 6: Optimizers are Adam, Admax.

Step 7: I double-checked the results we received.

I have ensured the quality of my work by following the processes outlined above. At the same time, I am positive that my efforts will help people in the future.

6.2 Conclusion

This research primarily focused on utilizing machine learning, specifically leveraging transfer learning techniques, to detect ocular diseases. The dataset used in this study comprised images of the retina obtained through Fundoscopy, encompassing both healthy and diseased eyes. To ensure precision, the research made use of transfer learning, harnessing pretrained models initially trained on extensive datasets from related domains. Additionally, the collected data underwent thorough processing using a variety of algorithms. In this study, various methodologies were explored, including CNN, VGG16, Mobile net, and RESNET. What distinguishes this research from prior work in the field is the incorporation of a larger dataset and the adoption of a diverse array of methodologies. The study's results demonstrated that CNN achieved an accuracy rate of 86.1% when employing the Adam optimizer, VGG16 achieved 76.84% accuracy, Mobile Net achieved an accuracy of 87.44%, and RESNET performed exceptionally well with an accuracy rate of 90.52%. It's worth noting that RESNET demonstrated the highest accuracy among all the methodologies, making it the most precise approach in this research.

Overall, compared to earlier research in the field of eye disease identification, this report shows improved accuracy, indicating the possibility of major breakthroughs in this important field of study.

6.3 Implication for Further Study

It is a well-known fact that a research paper's journey doesn't end when it is finished. Obviously, there are flaws and gaps in my work. I am adamant that if I had access to a larger dataset, I could go even deeper into the subject matter. My goal is to open the door for future advancement by increasing the amount of data that is available and experimenting with a wider range of algorithms. In the future, I intend to incorporate this work into my everyday routine, always trying to improve the quality of data and the results that result from my research.

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