An Automatic Detection of Eye Disease Using Deep Learning

Authors
Aizaz Khan
Jawad Ahmad
Mustafa

Supervisor: Dr Awais Adnan

Final Year Project Report submitted in partial fulfilment of the requirements for the Degree of BS-DS (Honors)

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PAKISTAN

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Certificate of Approval

We, certify that we have read the report titled: **An Automatic Detection of Eye Disease Using Deep Learning**, by **Aizaz Khan**, Jawad Ahmad, and Mustafa and in out opinion, this work meets the criteria for approving the report submitted in partial fulfilment of the requirements for BDS (Hons.) at Institute of Management Sciences, Peshawar.

Supervisor: Dr Awais Adnan
Assistant Professor

Signature: ______________

Coordinator BCS (Hons.): Dr. ZahidUllah
Assistant Professor

Signature: ______________

Coordinator R&DD: Dr. Saleem Gul
Associate Professor

Signature: ______________

Declaration

We, **Aizaz Khan**, **Jawad Ahmad**, and **Mustafa** hereby declare that the Final Year Project Report titled: **An Automatic Detection of Eye Disease Using Deep Learning** submitted to R&DD by our own original work. We are aware of the fact that in case, our work is found to be plagiarized or not genuine, R&DD has the full authority to cancel my Final Year Project and we will be liable to penal action.

Aizaz Khan
Jawad Ahmad
Mustafa
BSDS
Session: 2019-2023

Dedication

We would like to convey our heartiest appreciation to Allah who is the king of kings and the master of the universe for guiding us throughout this entire journey of completing our final year thesis. We are so grateful to the Holy Prophet Muhammad (SAWW) for showing us the right path and the true meaning of human life.
We would to extend our dignified gratitude to our final-year project supervisor Dr. Awais Adnan for their guidelines and encouragement throughout this whole journey. Their expertise in the field and valuable feedback have allowed us to explore more and gave back to the community. Our research one aspect was to help people and reduce the risks of different eye diseases through early detection of this problem.
We are also grateful to our parents who supported us in difficult times and were always motivated to pursue education at a good institute and provide service to society. They provided us with the platform to learn and get knowledge from one of the best institutes in Peshawar.
We are also very thankful to our motherland Pakistan for providing us an incredible opportunity to live with freedom and utilize our knacks for the benefit of this county.
This thesis was submitted in partial fulfillment of the requirements for the Degree of BS. Data Science at the Institute of Management Sciences Peshawar, Pakistan in the Session 2019-23.

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All the praise to Allah that induced the man with intelligence, knowledge and wisdom. Peace and blessing of Allah be upon the Holy Prophet who exhort his followers to seek for knowledge from cradle to grave.

Foremost, I would like to express my sincere gratitude to my supervisor **Dr Awais Adnan** for his continuous support, patience, motivation, enthusiasm, and immense knowledge. His guidance helped me throughout the project. Last but not the least, I would like to thank my parents for supporting me morally and spiritually throughout my life.

Abstract

In our research work, we have analyzed and processed Fundus images of more than 5K with the Deep Learning algorithm (CNN). Our convolutional neural network (CNN) algorithm has accomplished a performance accuracy of 91% based on the given Fundus dataset. We have also utilized various image preprocessing methods to nurture the efficiency of our deep learning algorithm to perform well on this huge dataset. Then we have shown the classification report of each disease in which the Recall value of glaucoma is higher which is 91% and the F1 score value of cataract is 85% among all. We have minimized the loss function value which was high initially but as we increased the number of epochs it becomes down to less than 0.2.

The model is further deployed on the web application to show the result of the predictions in the interface. The user can upload his/her image and the system will predict with better precision that the person has glaucoma or cataract eye disease.

Chapter 1

Introduction

Our eye is an integral part of the human due to its significant role in vision, light sensitivity, and complex structure. It allows us to see the beautiful world around us and interact with it in useful ways. The core function of the eye is to provide us with the vision to observe different shapes, colors, and people to gather insights about the world.

The human eye is a complex organ with several interconnected components functioning together to facilitate our vision. Due to its complex structure, it is significant to take good care of our eyes to reduce the risks of eye diseases. Eye care is crucial in all stages of life, from childhood to old age, everyone should prioritize routine eye exams to measure their eye health and effectively reduce the chances of different eye diseases. Good vision also contributes a lot to daily activities such as driving, working, reading, etc. We can nurture our eye health and improve our quality of life by taking care of our eyes. The eye is a very significant sensory organ that is essential to our daily activities. The importance of the eye is illustrated by the following: The fundamental purpose of the eye is to deliver vision, which is the sense that affects humans the most. Our eyes provide us the ability to sense the world around us, to appreciate the beauty of our surroundings, and to collect visual data that aids in navigation, object recognition, and environmental interpretation.

The eyes play an important role in nonverbal communication. They allow us to communicate our feelings to others, make eye contact, and perceive their emotions. Eye contact is a crucial part of social interactions and is a powerful tool for establishing rapport and conveying empathy. Safety and awareness: Our eyes help keep us secure and alert to possible dangers around us. They aid in object detection and reaction, enabling us to avoid collisions and confidently traverse our surroundings.

Learning and Education: Vision is essential to both of these processes. Clear vision facilitates efficient reading, writing, and visual comprehension, which facilitates learning and participation in educational materials.

Given the significance of the eyes, maintaining their health is imperative. Here are some pointers for keeping your eyes healthy: Regular Eye Exams: Arrange for routine eye exams with an ophthalmologist or optometrist. These examinations can identify disorders including eye diseases, visual issues, and other possible issues at an early stage when they are easier to treat.

When participating in activities that could result in eye injury, such as sports, construction work, or DIY projects, safeguard your eyes by donning the proper protective eye-wear. To protect your eyes from ultraviolet (UV) rays, use sunglasses with UV protection.

To prevent infections, practise good hygiene by thoroughly washing your hands before touching your eyes or putting on contact lenses. Do not massage your eyes too much because doing so can irritate them or introduce bacteria. Maintain a balanced diet full of fruits, vegetables, and omega-3 fatty acids for a healthy lifestyle. These vitamins and minerals support healthy eye health.

Rest Your Eyes: Take regular breaks from activities that need sustained focus, such as reading or using digital devices, to allow your eyes to recover. Observe the 20-20-20 principle: Look away from the screen once every 20 minutes and concentrate for 20 seconds on anything that is at least 20 feet away. Proper Lighting: To prevent eye fatigue, make sure that your living and working spaces are well-lit. Use drapes, shades, or anti-glare filters to reduce excessive glare from screens or direct sunlight. Contact lens care: If you wear contacts, make sure to clean and sanitise them according to your eye doctor's recommendations. As directed, replace your contact lenses, and stay away from using them for extended periods of time.

1.1 Overview

It is quite a hectic job to identify eye pathology utilizing images in medical settings. Any condition or drawback to that harms the eye's capability to work correctly or badly affects the human eye's visual acuity which is referred to as an ocular disease. Almost everyone experiences vision problems at some point in their lives. Others require the care of an expert, while others are minors that don't visible on claims or maybe any other treatment at the doorstep. Globally, Fundus problems are the main reason why people become blind. The most prevalent eye issues which common are age-related degeneration, the cataract, and the glaucoma, and diabetic Retinopathy (DR). By 2030, there will be more than 400 million people with DR, according to related studies. These eye conditions are now a significant global health problem. Most significantly, the ophthalmic disease is fatal and may cause lifelong blindness. Early diagnosis of these conditions can prevent vision deterioration in clinical settings. However, there is a significant mismatch in the number of ophthalmologists and patients. Additionally, manual Fundus examination takes a lot of time and is highly dependent on the expertise of the ophthalmologist, which hampers large-scale Fundus screening. Therefore, automated computer-aided diagnostic methods are essential for identifying eye diseases. .

Glaucoma is a common eye disease where the human optic never (connected the eye to the brain becomes severely damaged). It is caused by fluid which increases pressure in the inner part of the human eye. Glaucoma can lead to severe blindness in the future if it's not diagnosed at the early stages. Mostly cataracts happen due to normal changes in the human eye as the person gets older with the passage of time. When we are young, the lens of our eye is crystal clear but with time the protein in the eye start breakdown. This makes a cloudy area on our lens which is commonly known as a cataract. Glaucoma and cataracts are the major eye diseases in Pakistan. It is because of several factors which include an aging population, lack of awareness and screening, limited access to hospitals in far-flung areas, and socioeconomic factors.

Due to the latest advances in deep learning (ML) and machine learning technology have made it possible to design new algorithms for automating the identification of eye diseases like glaucoma screening using colorful images and OCT dataset captured. To differentiate between glaucoma patients and healthy patients, the suggested machine learning models in these studies, however, only included one type of image, which is very different from the actual clinical diagnosis by ophthalmologists. In order to diagnose glaucoma, only a small number of machine learning models have been described employing multi-modality images.

In actuality, there is no developed method for disease detection in hospitals. In our line of business, we wish to automatically identify the various ailments. We have taken into account the varied eye conditions. In doing so, it will make it easier for people to recognise their eye condition in the best way possible. We have included more confiscated systems in order to give us a nice living and make our lives easier for us in the long run due to the significant improvement in many areas of AI. In order to avoid problems with our eyes, we must take proper care of ourselves. More individuals will depend on these systems in the age of AI.

The researchers of AI in this area will have more nice prospects if they take a good look at what we see. Additionally, it is mentioned that if we require more leaders to join the bandwagon and identify numerous issues for us in this area of AI. Therefore, it is advised to regularly check your eye health every day and once a month. It's also crucial to give accurate information so that the eye experts in this field can assist us with these kinds of problems. In our research, we place a lot of emphasis on the need to describe the eye's condition so that various diseases can be identified.

Humans are commonly affected by glaucoma, which is primarily concerned with diseases and is known to identify problems over time. When the human eye's optic nerve is harmed, this disease develops.

Under the category of AI, deep learning is a novel subset of machine learning technology. The idea is that DL makes it possible to train computer algorithms using convolutional neural networks, which are complex mathematical functions with millions of parameters and huge amounts of data (CNN). This network draws its inspiration from how brains can change the strength of synaptic connections between neurons to understand intricate patterns in data. Similar to the visual brain, deep learning employs networks with several layers of artificial & neurons in the middle between the input and the output. These fake neurons are trained to recognize a hierarchy of progressively more complicated feature detectors. In recent years, AI and DL with CNNs has quickly advanced and shown promise in the medical industry for complex pattern detection from large datasets. For instance, it has been demonstrated that DL systems perform as well as or better than board certified specialists when it comes to the automated classification of DR, retinal disorders, glaucoma, as well as other illnesses such as malignant melanoma, tuberculosis, and lung cancer. These intriguing experiments highlight DL potential for automated image processing.

Artificial intelligence (AI) is being used in a variety of ways by researchers to better treat eye illnesses and provide for better eye healthcare. Here are a few of the methods they are employing: Diagnosis and screening: AI systems can examine medical imagery like retinal scans to accurately identify and categorise eye illnesses. Researchers can create algorithms capable of spotting patterns and anomalies linked with certain eye disorders by training AI models on vast datasets of annotated photos.

Risk evaluation and prognosis: AI algorithms can be used to determine a person's risk of contracting a specific eye illness based on a variety of variables, such as genetic predisposition, medical history, and lifestyle.

Artificial intelligence (AI) tools like computer vision and robots can help ophthalmic surgeons during difficult eye procedures. With the help of real-time guidance, accurate measurements, and enhanced visualisation provided by AI-enhanced surgical systems, surgeons may perform operations more accurately and with better results. Robotic devices that are AI-powered, for instance, can assist in delicate operations like cataract surgery or retinal detachment repair.

AI can help with continuing eye disease treatment and monitoring. AI algorithms can follow the development of diseases, assess the effectiveness of treatments, and send prompt notifications for any changes or potential consequences by analysing data from wearable devices, such as smart glasses or contact lenses. This can improve long-term treatment outcomes by allowing patients to actively participate in their own care. The main causes of cataract, a frequent eye condition, include ageing, genetics, and environmental variables. The following are some important causes of cataract prevalence:

Age: Age is the main factor causing cataract development. The proteins in the lens of the eye can gradually degrade and clump together as people age, causing the lens to become cloudy and opaque. This process naturally takes place over time and is frequently connected to aging

In research work, we aim to build an automatic system to predict eye diseases using the cutting-edge technology of Deep Learning (DL). Previously, people have used various traditional machine learning (ML) approaches to forecast eye disease, which are not reliable solutions. The project aims to facilitate the laboratory people, and for this purpose, we want to develop a web application to display the results on the screen. The automatic system will forecast whether a person has eye disease or not. The Deep Learning (DL) methods utilized in our research work will allow the researchers to explore the medical imaging field.

1.2 Problem Statement

Although a considerable amount of work has already been done in the area of "eye disease detection", the majority of researchers have used traditional machine learning, it lacks features, large datasets, and designing interface, therefore it is intended to develop an efficient, cost-effective system to crystal clear recognize different eye diseases just like glaucoma and cataract.

1.3 Scope

Glaucoma and Cataracts are the two major causes of blindness in Pakistan. Early detection of the disease can lower the risk factors. In this project, we propose a cost-effective solution for eye disease problems. In local hospitals, there is no automatic system to detect eye diseases via the web application, and all eye disease tests are expensive. There are numerous eye disease tests performed in hospitals which can be avoided or reduced to fever thus it will save time and effort of ophthalmologists.

1.4 Objectives

1. To forecast various eye diseases (glaucoma and cataract) using deep learning techniques.

2. To build web application and to display the ultimate results.

3. To inform users about eye-related diseases through a simple, user-friendly interface.

4. To reduce the risks related to different eye diseases by early detection of the disease.

5. To provide a cost-effective solution for the local hospitals to save time, money and reduce the number of tests in the laboratories.

6. To replace traditional machine learning (ML) techniques which don't provide efficient results with deep learning (DL) models for better solution.

1.5 Tools

In our research work we have utilized Deep learning models are used including TensorFlow and Keras for the implementation of models. The Kaggle platform is used Python coding and a user-friendly web application is designed using Flask.

1. TensorFlow
2. Keras
3. OpenCV
4. Kaggle and Jupyter Notebook
5. Flask

Chapter 2

Background Study

Deep Learning (DL) with CNNs has gained popularity in recent years and demonstrated strengths[1] in pattern recognition from large datasets in the medical imaging field. Guangzhou et al. [2] diagnosed open-angle glaucoma by using the Forest algorithm with a k-fold cross-validation value of 10. They used OTC machine, known as OCT dataset, and colorful images. In this research, they enrolled 208 glaucoma and 149 normal eye pictures and obtained color images.

They used multiple supervised learning techniques, including Decision Tree, Random Forest, Nave Bayes, and neural network algorithms, in reference [3], to analyze eye disease based on multiple features, including patient age, clinical observations, and illness history. The data set contains 3000 observations and 10 attributes that can be used to predict the eye disease glaucoma. When compared to more complex neural networks and the Naive Bayes algorithm, they achieved the best prediction accuracy of 90% with Random Forest and Decision Tree.

Gauri et al. [4] have taken glaucoma, retina, and cataract into consideration to detect eye diseases using classification algorithms including logistic regression, random forest, gradient boosting, and support vector machines. The prediction accuracy was evaluated using the ROC value for various eye-related diseases. The gradient boosting algorithm has achieved an accuracy of 90% for cataract-related eye disease among all other algorithms. The supervised algorithms logistic regression and random forest, on the other hand, performed well, with accuracy rates of 89% and 86%, respectively.

Nouf et al. [5] used multiple supervised algorithms to classify the glaucoma eye disease, including support vector machines (SVM), K-nearest neighbors (KNN), Naive Bayes, decision trees, multilayer perceptron (MLP), random forests, and convolutional neural networks (CNN). In comparison to Random Forest and MLP, the CNN has achieved a better accuracy of 84%, while that of RF and MLP is 77%, thus showing that using deep learning techniques provides better results compared to traditional machine learning approaches in medical imaging.

Chen et al. [6] studied eye-related diseases based on fundas photography using the convolutional neural network to forecast various types of eye diseases. They demonstrated that traditional approaches perform very poorly for multi-class classification Fundus images. To the privacy issues of patients, it is capable of training large DCNNs, but rather they utilized a lightweight deep learning approach called MobileNetV2 and transfer learning to figure out various eye issues in patients. Based on this experiment, they accomplished an average accuracy of 96%, a sensitivity of 0,9, and a specificity of 97% with a dataset consisting of only 250 feature images.

Ashrafi et al. [7] studied seven types of eye disease and used various methods of ML and DL algorithms such as DCNNs and SVM for eye problem detection. They used Principle Component Analysis (PCA) for feature selection along with t-distributed stochastic neighbor embedding methods for better feature selection. The seven types of eye diseases are classified as cataracts, Trachoma, conjunctivitis, cornea, ulcer, Ectropion, Periorbital, cellulitis, and Bitot's. Based on the experiment, they showed the average accuracy achieved for DCNNs was 98%, compared to SVM having a sensitivity of 97% and a specificity of 99% in this research work.

Md. Shakib et al. [8] utilized the fundus images of the ODIR dataset widely available on Kaggle. The dataset contained 5000 images and divided the eye diseases into eight classes with unbalanced data. To balance the dataset, they trained VGG-19 on foundational images and converted the multi-class classification into binary classification. The higher accuracy achieved by VGG-19 was 90% for normal versus glaucoma and 94% for normal versus cataract. Based on their findings, models achieved better results once the data was balanced in the ODIR dataset.

Ling et al. [9] studied eye screening, which has more significance and highly contributes to the detection of diabetic Retinopathy disease. In order to facilitate the screening, they developed a deep learning (DL) system called DeepDR. The DeepDR can recognize diabetic Retinopathy in its early-to-late stages. DeepDR was trained on a massive real-time dataset of field images. They used the local dataset containing 200,136 field pictures of 52,004 patients for evaluation purposes. The areas under the curves (AUC) received for mild, moderate, severe, and proliferative are 0.94, 0.95, 0.96, and 0.97, respectively.

R. Naveen et al. [10] used traditional image processing techniques in MATLAB to extract blood vessels from the images. The core aim of this research was to forecast diabetic Retinopathy, an eye disease. They utilized the histogram equalization method using the CLAHE algebra with the computer vision (CV) framework. The accuracy achieved in this research work was 98% and accurately predicted diabetic Retinopathy from fundus images.

Guangzhou et.al [2] developed ML algorithm for glaucoma diagnosis with open-angle of glaucoma for 3D OCT dataset and images. For the purpose, they used 400 images and thickness, and the deviation maps were formed using a segmentation algorithm. Transfer learning and convolutional neural network (CNN) were used using k-fold cross-validation of 10. The model performance was checked using the Auc metric and CNN achieved an AUC value of .94 using k-fold value of 10.

Stefan et.al [11] studied the nerve fiber layer and ganglion cells with the inner Plexiform layer which are widely responsible for to monitor the glaucoma. Initially, machine learning (ML) methods were used which majorly relied on segmentation imaging. They developed a DL method and classified healthy or glaucoma disease from the dataset. The deep learning algorithm CNN outperformed logistic regression. The ROC value achieved by CNN was 0.94.

Illavarason et.al [12] captured eye images and made a quick diagnosis of cerebral palsy disease in kids. They used a dataset of 40 samples from kids having an age range from 3-11 years. The major cause of cerebral palsy is the misalignment of the eye. The system developed used check the precision by classifying the abnormal concern of CP using machine learning. The best accuracy was achieved through Neural Network Classifier classification which was 94%. The specificity rate was 0.98 and the sensitivity rate was 0.91 in this research work.

Linglin et.al [13] used a deep convolutional neural network (DCNN) to detect and grade cataract disease directly, it also gives visualization of some of the feature maps. . The proposed model DCNN was cross-validated on a large number of population-based fundas images up to 5600 accumulated from the hospital. The DCNN showed better performance and achieved an accuracy of 93% using this local hospital dataset of fundus images. The Proposed model can also be used to detect other eye diseases in the future.

Yang et.al [14] used a support vector machine, back propagation neural network, and ensemble method and extracted independent chararactristics such as wavelet, sketch, and texture features from the images. The cataract was classified into four classes non-cataractic, normal, or extremely high. The best accuracy achieved by the ensemble classifier was 93%.

Dong et.al [15] applied the max entropy technique to analyze the images. They used several classification algorithms to detect and identify the extracted features. For comparison of features extraction by deep learning and wavelet from retinal vascular, support vector machines and softmax were used for cataract classification. The cataract images were classified into normal, slight, severe, and average. They achieved the best accuracy from Softmax and the results suggested that deep learning was most effective for eye disease detection.

Qian et.al [16] classified various components of cataracts in the lens, they used supervised training of CNN training the 420 images of cataracts on a lens taken it from slit lamps. They predicted this sort of classification of cataracts more easily in the future and it would help the eye expert applied numerous operations to various categories of cataracts within short intervals to prevent cataracts.

Masum et.al [17] proposed a novel deep neural network named cataractNet used for automatic cataract detection and it required fever parameters and layers for training. The computational resource utilization and running time of CataractNet are deduced as a compared to CNN. They used an overall of 1130 cataract and non-cataract picture using Adam Optimizer. The accuracy and F1 score achieved by the model was 99

Tasmina et.al [18] suggested an effective solution to recognize cataracts from the iris images, the iris portion has been extracted using a contour detection process from the binary mask picture. They worked on two sorts of structure features Gray level co-occurrence matrix and histogram texture features were got from the image. The random forest accomplished the high accuracy of 97%.

Gupta et.al [19] trained data on various machine learning algorithms and performed binary classification on oscular images. They used support vector machines, random forest, decision tree, logistic regression, XG boost, naıve Bayes, KNN, and light gradient boosting. The light gradient boosting algorithm outperformed compared to other classification algorithms.

Md Kamrul Hasan et.al [20] has utilized the ODIR database of 5000 patients of all ages images with CNN model meta-architecture containing inceptionV3, Xception and DenseNet121 using the the framework of Tensorflow Deep learning library for object recognition. The model has achieved the validation accuracy 98% on the above mentioned data.

Table 2.1: Sample Comparison Table

S.No	Title	Techniques	Dataset	Eye Diseases	Evaluation
1	Research ref [01]	RF, CNN	357 Images	open-angle glaucoma	ROC for CNN= 0.94 RF combined with CNN = 0.96
2	Research ref [02]	LR, RF, Gradient Boosting and SVM	1K	cataract, glaucoma retinal	Gradient boosting accuracy 90%
3	Research ref [03]	SVM, CNN, MLP, Naïve Bayes, DT, KNN	2k	Glaucoma	MLP 77% CNN achieved accuracy 84%
4	Research ref [04]	MobileNetV2 and transfer learning, DCNN	250 Images(kaggle)	Glaucoma, Pathological Myopia	Accuracy achieved 96%
5	Research ref [05]	DCNNs and SVM, PCA for feature selection	1753 images	Seven eye diseases	DCNN model Accuracy 98%
6	Research ref [06]	VGG-19	5k(Kaggle)	Eight classes	VGG-19 accuracy 90%
7	Research ref [07]	DeepDR (Detect early-to-late stages	200,000	Diabetic Retinopathy	AUC achieved 0.94%

Table 2.2: Sample Comparison Table

S.No	Title	Techniques	Dataset	Eye Diseases	Evaluation
8	Research ref [08]	Images processing, Histogram Equalization (MATLAB)		Diabetic Retinopathy	Accuracy 98%
9	Research ref [09]	Data Augmentation/CNN	00 images	Glaucoma	AUC 0.96
10	Research ref [10]	U-Net, Mnet, ensamble	Online	Glaucoma	Roc value 0.92
11	Research ref [11]	CNN	888samples training	Glaucoma	CNN 0.94 AUC
12	Research ref [12]	Neural Network Classifier	40 samples	–	Accuracy 94%
13	Research ref [13]	Deep Convolutions Neural Network	5600 images	Cataract	Accuracy 93%
14	Research ref [14]	Ensemble learning Support vector machines Neural network	- -	cataract	Ensemble accuracy 93%

Table 2.3: Sample Comparison Table

S.No	Title	Techniques	Dataset	Eye Diseases	Evaluation
15	Research ref [15]	Softmax and SVM	- -	Multiclass cataract	Softmax best accuracy
16	Research ref [16]	SqueezNet	420 images	cataract	Accuracy 96%
17	Research ref [17]	CataractNet	1k images	cataract	F1 score 99%
18	Research ref [18]	Random Forest	- -	cataract	Accuracy 97%
19	Research ref [19]	Classification algorithms knn, xgboost, light gradient boost etc.	- -	cataract	Better performance light gradient boosting
20	Research ref [20]	g Deep Learning and Random Forest Classifier	101 colour fundus images	glaucoma	Random Forest accuracy of 99

Chapter 3

System Requirements, Architecture and Design

3.1 The Functional Requirements

- **Image Capture:**
  The system must be capable to capture high-quality images of the eye using various imaging modalities such as Fundus camera, optical coherence tomography (OCT), and ultrasound.
- **Image Processing:**
  The system must have the capability to process and analyze the captured images using various image processing techniques such as image enhancement, segmentation, augmentation, and feature extraction. The system should also be able to detect problems and features associated with various eye diseases such as diabetic Retinopathy, glaucoma, and cataract.
- **Diagnosis:**
  The system must be efficient to provide a diagnosis of the detected disease based on the analyzed images and other patient-specific insights. The diagnosis should include the type of disease, the severity of the condition, and any suggestions for treatment.
- **Reporting:**
  The system must be able to produce reports of the diagnosis for the patient. The reports should be easily understandable and should include detailed images, diseases, and any recommendations for the treatment of that specific eye disease.

- **User Interface:**
  The system should have a user-friendly interface (web application) that is easy to use for both the patients and the healthcare-related people. The interface should allow the patient or technicians in the laboratory to use the system and see the results of different eye diseases.

3.2 Non-Functional Requirements

- **Accuracy:**
  The system must maintain a good level of accuracy in predicting and diagnosing different eye diseases. This can be achieved through routine validation of the system using a huge dataset of images.

- **Speed:**
  The system must be capable of fastly processing the images to provide a diagnosis in a timely manner. This is particularly significant in clinical settings where patients may be waiting for a diagnosis.

- **Security:**
  The system must be secure to protect patient data from unauthorized access. This includes ensuring that patient data is stored that only authorized persons have access to the overall system.

- **Scalibility:** The system must be capable to tackle large number of patients and images. This is particularly vital in clinical settings where the system may be used by multiple healthcare hospitals.

- **Reliability:**
  The system must be reliable and able to operate continuously without any failure. This includes ensuring that the application is robust against power outages and other unexpected problems.

- **Maintainability:**
  The system should be easy to maintain as technology advances in the future. This includes ensuring that the web application is modular and can be easily updated with new image processing algorithms and other features as they become available in the market.

3.3 System Architecture and Design

The system architecture tells us about the overall layout of the computer system which contains the hardware, software, and network components of the system. Design and requirements are also the key elements of crafting the system architecture. The flow diagram Figure 3.1 of the system shows the overall steps involved from image capturing to data preprocessing, building a model, and finally making a web application to display the results.

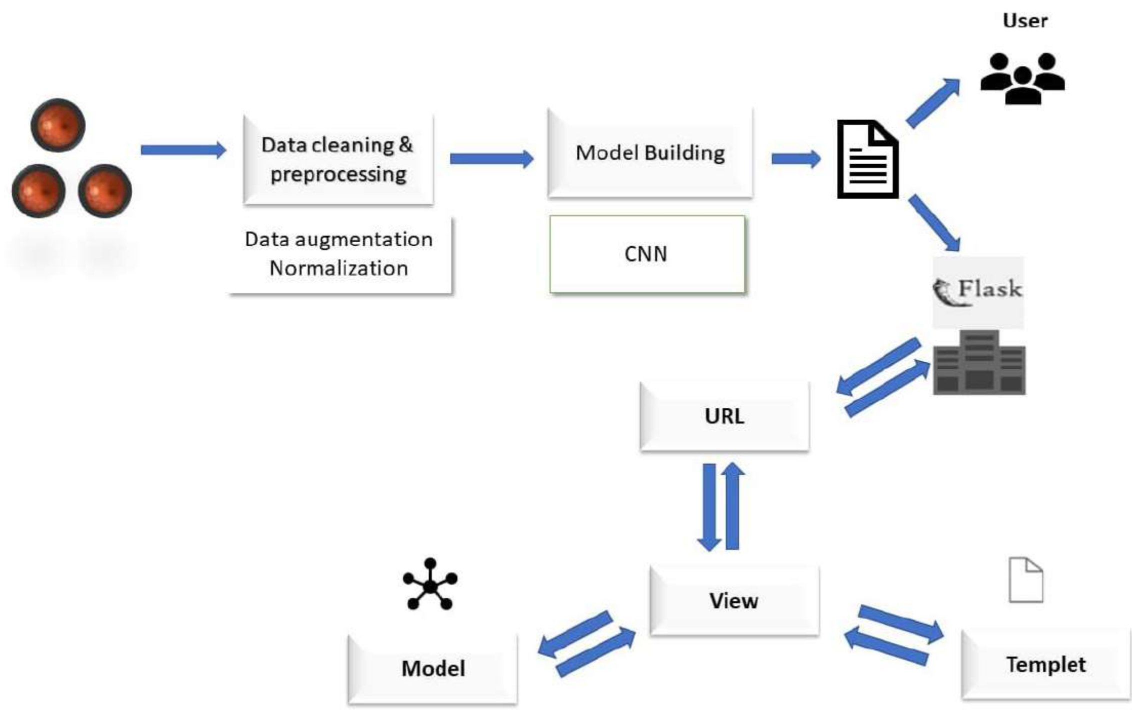

Figure 3.1: Flow Chart

3.4 Use-Case: 01

A use case is a diagram in software engineering which shows that how many actors are associated with the software application that is developed. The below illustrations show how these actors will interact with the system to perform some actions. Figure 3.2 shows the use case of an admin and the use case description is mentioned in the table.

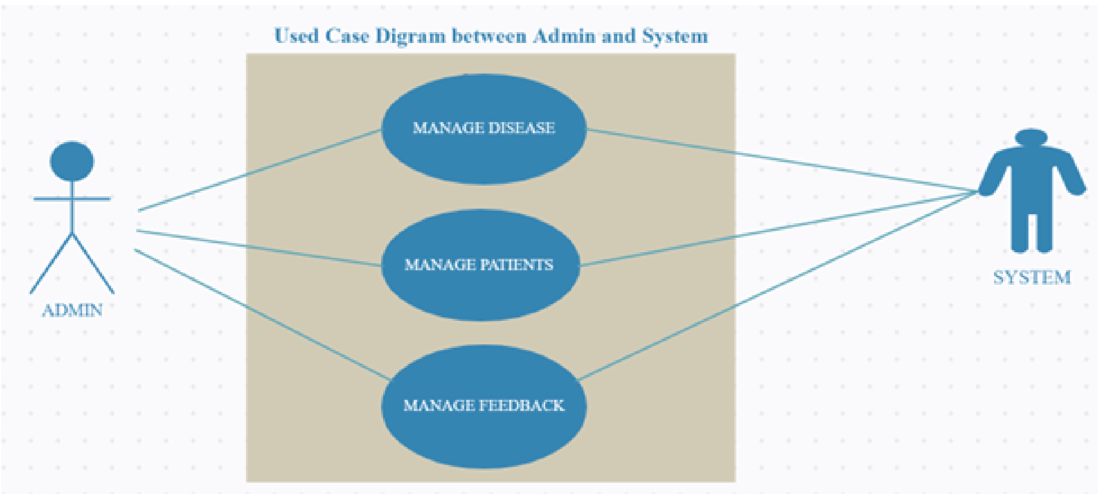

Figure 3.2: Use-case 01

System	Flask, TensorFlow
Admin	Admin can login into the system using his/her ID and password
Add Dataset	Admin can add and update the model, can add new dataset to the model
View Dieseses	Admin can view various diseases details
User	You can chose fundus image for PC storage
Diseases Prediction	The lab assistant can take the eyes picture from the patient using OCT (optical Coherence tomography) and upload it to the system to predict the patient disease based CNN model and generate report

Table 3.1: Table of Use Case Description of the web application

3.5 Use-Case: 02

In the below use case diagram Figure 3.3 the interaction between the user and system is illustrated along with the use case description table.

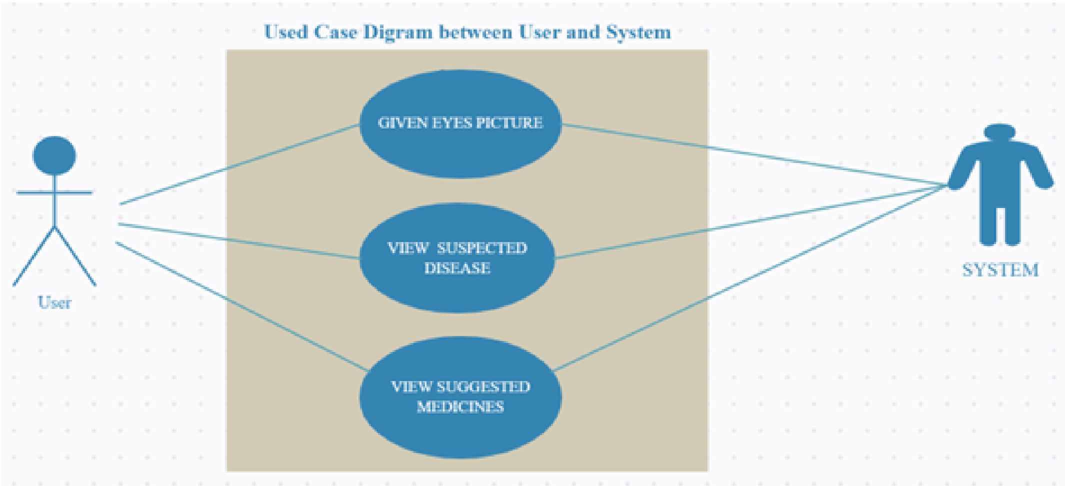

Figure 3.3: Use-case 02

System	Flask, TensorFlow
Admin	Admin can login into the system using his/her ID and password
Add Dataset	Admin can add and update the model, can add new dataset to the model
View Dieseses	Admin can view various diseases details
User	You can chose fundus image for PC storage
Diseases Prediction	The lab assistant can take the eyes picture from the patient using OCT (optical Coherence tomography) and upload it to the system to predict the patient disease based CNN model and generate report

Table 3.2: Use Case Description Table

3.6 System Sequence Diagram:

In the sequence diagram tells us about the message passed between different objects in the system. In our work, the data will pass in the following way which is vividly illustrated in Figure 3.4, the user or patient will come to the hospital to check his/her eye disease test and then the Fundus image will be captured through the OTC machine in the hospital. The Fundus image will be uploaded into the web application to check whether a person has eye disease or not. The application works on a deep learning model which will further classify three types of diseases as Glaucoma or Cataracts as an ultimate result of the system will generate.

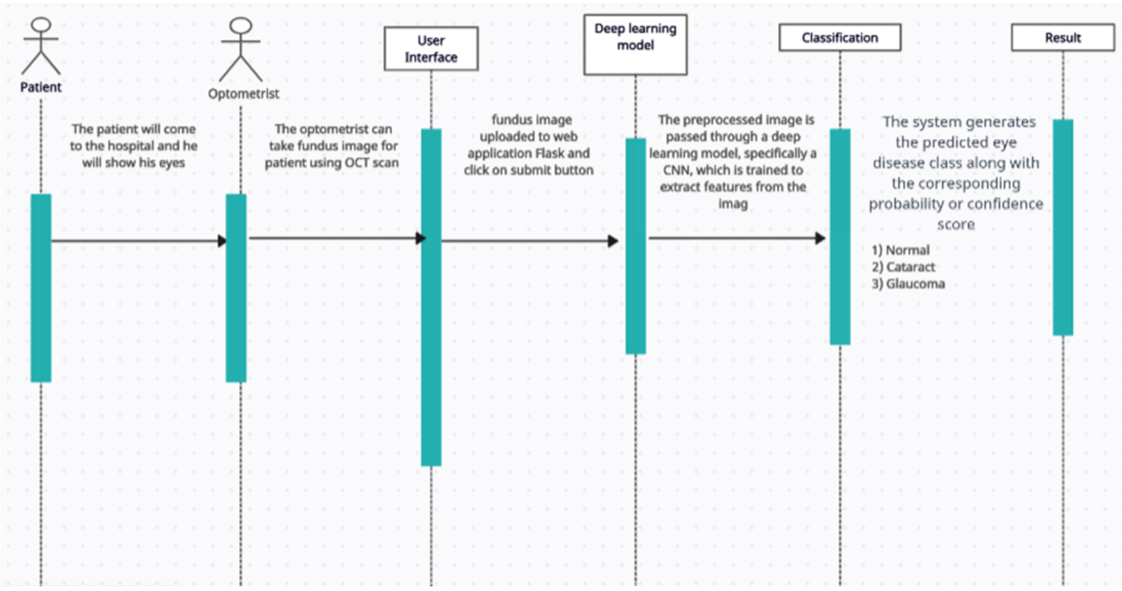

Figure 3.4: System Sequence Diagram

3.7 The Data Flow Diagram (DFD):

The Data Flow Diagram shows the movement of data in the overall system. It also refers to the flow of data in the system that how the information will carry in the system as a visual representation. Figure 3.5 illustrates the data flow diagram which includes how data is collected and processed using the CNN model with max pooling and other parameters. Later on, the model is deployed on the web application to show the final result of different eye diseases through a user-friendly interface. Below are the following steps involved in Data Flow Diagram.

- The user will upload the eye image captured from the OCT machine to check whether he/she has any eye disease.
- The system will process the image using various data processing techniques including data augmentation and normalization etc.
- The Convolutional Neural Network model is utilized to process this huge amount of images.
- The user will see the results of the eye disease test through a user's friendly interface along with the probability of other eye diseases.

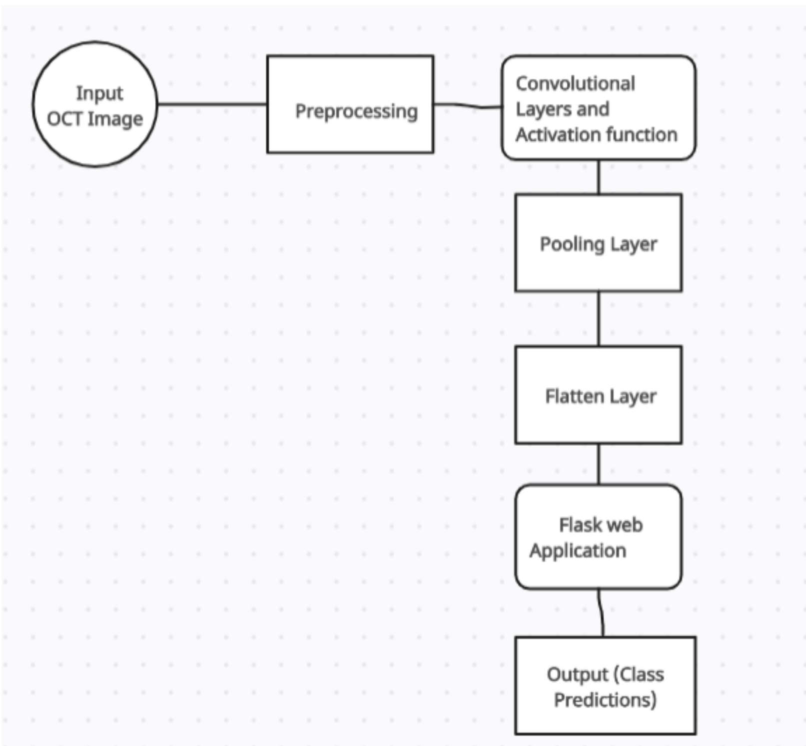

Figure 3.5: Caption

3.8 Convolutional Neural Network:

The network receives images with a resolution of 224x149 pixels as input in the system. The structure is designed based on three sets which contain convolution, activation, and max pooling layers that are stacked together. There are fully two interconnected hidden layers and valid padding is also used in the convolutional layers. Figure 3.6 gives the architecture of the system along with the convolutional neural network utilized for this work.

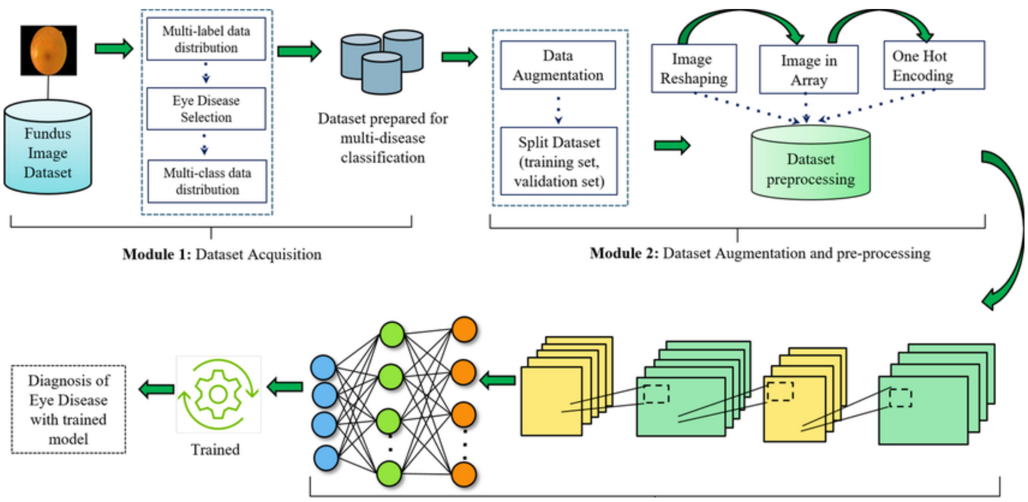

Figure 3.6: The overall Architecture along with Convolutional Neural Network

Chapter 4

Methodology

In this section we introduce various methods and techniques utilized for this research work on eye disease. The flow chart diagram 4.1 illustrates the overall methodology of the system which starts from obtaining Fundus images from the OTC machine followed by data preprocessing steps and deep learning model training. The model has then been deployed on a web application using Flask.

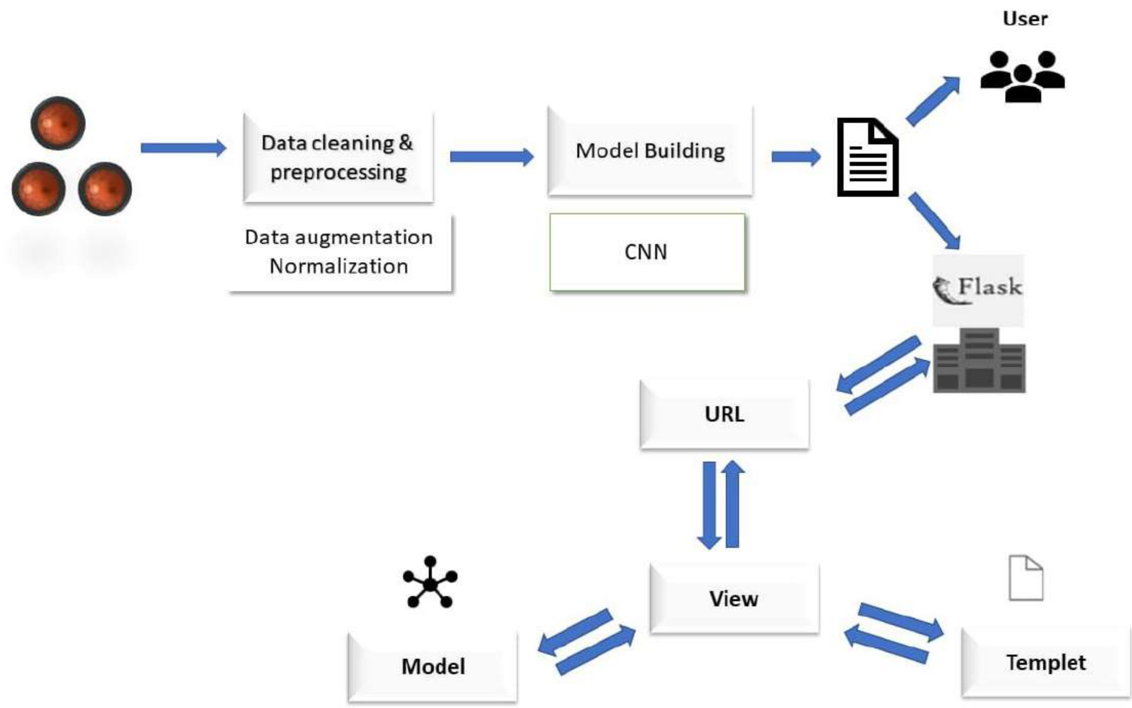

Figure 4.1: Flow Chart and Methodology

4.1 Dataset

To prepare our data for forecasting various diseases, we have accumulated images from a local hospital in our town of round about a total of 5203 different images. These images are further divided into three major categories which include Normal eye images, Glaucoma, and Cataracts. The dataset also contains the train and validation datasets. Figure 4.2 illustrates the following types of eye diseases sample dataset.

For the purpose of deep learning-based eye illness identification, we have assembled a comprehensive dataset with more than 5000 photos. These photos were taken from a nearby hospital, guaranteeing a wide representation of the many eye conditions seen in actual clinical settings. The dataset is a useful tool for developing, testing, and validating deep learning models that aim to automatically diagnose eye diseases.

The dataset includes images of a wide range of eye ailments, including cataracts, glaucoma, age-related macular degeneration, and diabetic Retinopathy. Because of this diversity, our deep learning model is exposed to a wide range of aberrations and visual patterns linked to various eye disorders.

With more than 5000 photos, our collection offers an abundance of information for reliable training and validation. The dataset's size helps to reduce the chance of overfitting and makes sure the model can generalise successfully to previously undiscovered photos. The photos in our collection were taken from a nearby hospital and depict actual clinical situations. This makes sure that the dataset is pertinent to the difficulties that medical practitioners encounter when detecting and treating eye illnesses. The dataset's clinical relevance improves our deep learning model's adaptability and potential impact in real-world healthcare settings.

The dataset was created in accordance with stringent ethical standards, protecting patient privacy, and maintaining patient confidentiality. According to the relevant data protection and privacy laws, all required consents and approvals have been received in order to use the photographs for research.

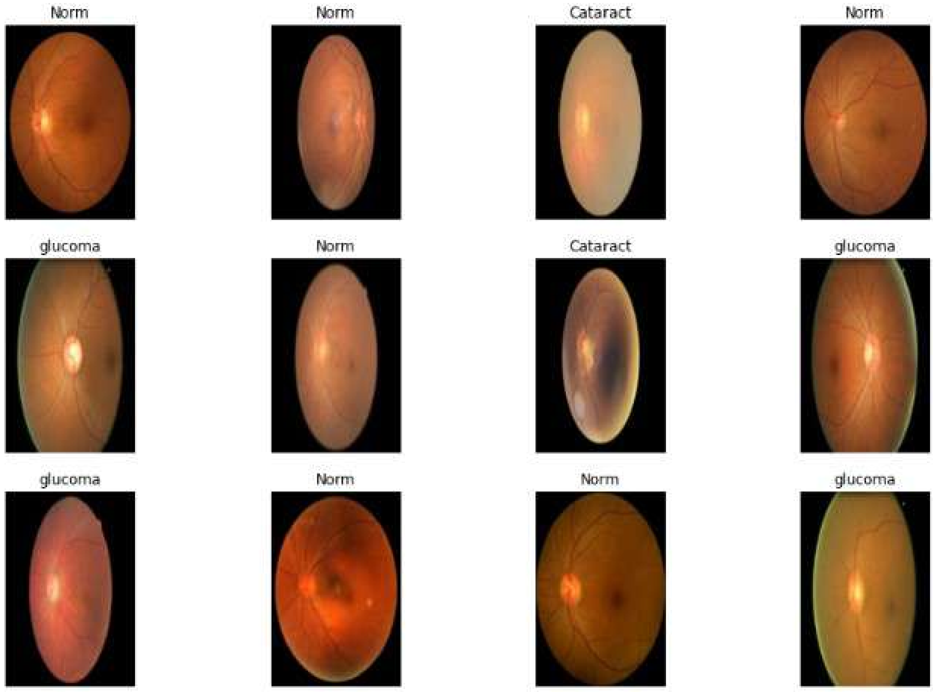

Figure 4.2: Sample Dataset

4.2 The Data Cleasing Steps

Data preprocessing or cleansing is an integral part of a deep learning project it nurtures the performance of a deep learning model by cleansing, transforming, and formatting the unformat data into a suitable format that can be used by the model easily. By using appropriate techniques of data wrangling we can accomplish better precision for our model.

Xuguo et.al [21] showed that using various image processing techniques can nurture the process and helps us to extract relevant features for the given problem easily. They have combined principle component analysis known as PCA with different genetic algorithms for the fast selection of feature extraction.

Many computer vision and image analysis jobs depend heavily on picture preprocessing. It entails using a variety of approaches to improve an image's quality, reduce noise, fix distortions, and extract important elements. Here are some explanations on why preparing images is crucial.

There are numerous types of data preprocessing methods that can be utilized or applied to the Fundus images of the eye. It includes:

- **Image Cropping**
  During image preprocessing, the cropping image technique is used to remove unimportant backgrounds or edges from an image. It ensures to filter out all other unnecessary things and focuses only on the region of interest for example retina or iris.

- **Normalization of Image**
  Image normalization is also an important technique for scaling the pixels of the images to a standard range such as in the format of [0,1] or [-1.1] to make sure that our model is not affected by contrast or lighting. Koo et.al [22] in his work they have proposed a system to nurture the image recognition precision through image normalization and extraction techniques commonly called the preprocessing phase. They focused on the electronic object to recognize major characteristics due to its material specificity. They focused on the electronic object to recognize major characteristics due to its material specificity. By applying transformations like rotations, flips, or translations, these approaches produce modifications of the original image. Data augmentation broadens the range of training data, enhancing the robustness and generalizability of machine learning models.

- **Enhancement of Image**
  For image enhancement, there are many techniques to apply such as histogram equalization or contrast stretching to nurture the features to be more visible in the image. Goel et.al [23] showed various image enhancement (techniques like contrast enhancement, histogram equalization technique, and filtering techniques using Matlab) to enhance the image quality and obtain a better-quality image. In the majority of cases, the medical images of various categories always suffer from the chaos of noises and shortage of contracting.

- **Resizing the Image**
  To ensure the model can tickle images of various sizes we transform the image into a standard resolution that is 256x256 to achieve better outcomes.

- **Annotation of Image**
  Label the eye disease images with appropriate class labels like normal or diseased in order to train our model and to effectively recognize various types of eye diseases.

- **Data Augmentation:**
  There are different data augmentation utilized such as image rotation, and flipping to artificially enhance the diversity and size of the images dataset. Data Augmentation helps to enhance the performance of our machine learning algorithms by providing a robust training data. Shorten et.al [24] showed that using data augmentation techniques improved the size and the overall quality of the data and we can build better deep learning algorithms based on these techniques.

  One of the major challenges in automatic eye disease detection is the storage of a diverse dataset available to train the model. This is due to a lack of high-resolution images of the eye and variation in the appearance of the disease.

  There are numerous data augmentation techniques that can be applied to eye disease images.

  - **Rotation:**
    By rotating the eye disease images at various angles helps the model to recognize and familiar with different features of the eye irrespective of their orientation. For instance, an eye disease might appear when rotates the image at different angles.

  - **Scaling:**
    By resizing the images can assist the model to recognize various features of eye diseases at different scales. For example, an eye may disease a cataract that is only visible when we zoomed in on the image.

  - **Flipping:**
    By moving the images vertically and horizontally helps the model to know more about different features irrespective of the position of the eye image.

  - **Brightness and Contrasting:** By changing the contrast and brightness of the eye disease Fundus images can help the model recognize various features in different conditions of the lighting.

– **Adding Noise:**
Sometimes we also add noise to the Fundus images so that the model recognizes features irrespective of the presence of the noise in the image. Thus adding noise in the images of eye disease will boost the precision of the model by accurately predicting the desirable outcomes. Figure 4.3 illustrates various data preprocessing steps involved in this research work. Singh P et.al [25] proposed a better technique in their research work to remove the corrosive Gaussian additive noise from the computed tomography images along with all other details. They proposed the system by accumulating the the technique of method noise with a deep learning (DL) based framework of the CNN model.

It is essential that image preprocessing should be done with sound care and consistency, as errors in the preprocessing part lead to poor precision of the model. In order to adopt good image preprocessing techniques or to utilize them you must have a good understanding of the data and the problem you are interested to solve.

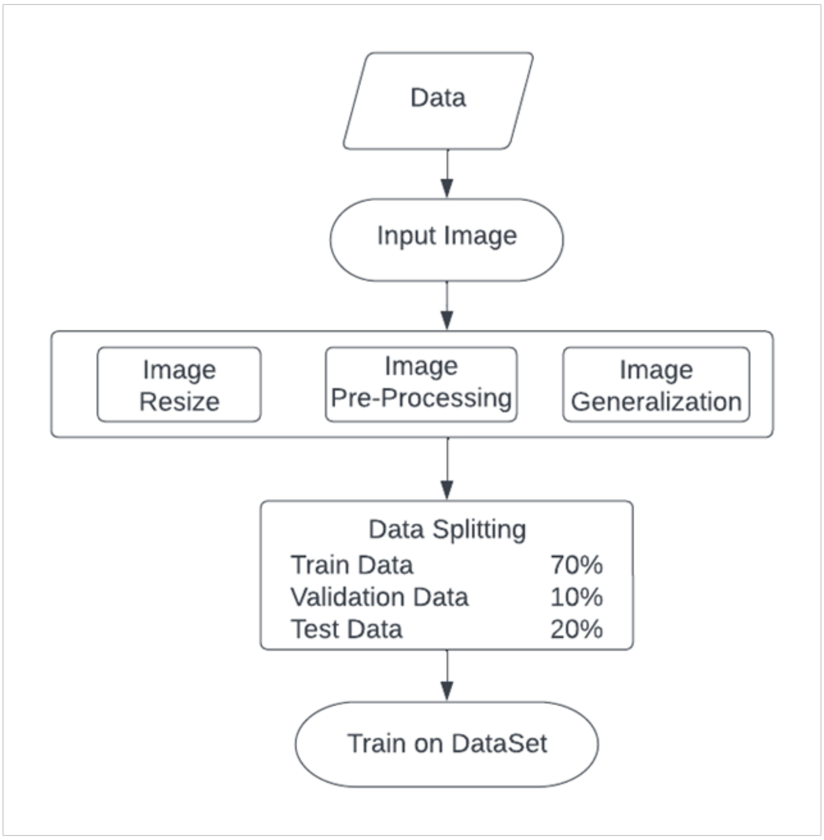

Figure 4.3: Preprocessing of Data

4.3 Splitting The Data

Data Splitting is a common practice to separate the entire dataset into two portions. One is for the training of our Neural Network Model and the other part is for the testing of the model. The most commonly used practice for splitting the data is to divide it into two parts 70% to train our model and the rest of the data is used 30% for test purposes.

Training data is used to train our model by providing a huge number of labeled eye diseases fundus images. The model used these images to recognize various types of characteristics in the Fundus images dataset. During the testing phase, we evaluate the precision or accuracy of our model based on the trained dataset to make the prediction.

Reitermanová et.al [26] mentioned the detailed insights of the existing sampling techniques which can be applied for data splitting. The supporting experimentation contain the benefits of using the selected data separation methods and the involvement of artificial neural network backpropagation.

For various reasons, data splitting—or partitioning a dataset into training, validation, and testing sets—is crucial.

Data splitting enables the division of data into distinct subsets for various stages of model building, which is useful for both model creation and evaluation. The validation set is used to adjust hyperparameters and track performance, while the training set is used to train the model's parameters. The testing set is then used to assess the model's performance in its entirety. This division makes sure that the model is evaluated using hypothetical data, giving a more accurate picture of its generalizability.

When a model performs well on the training data but is unable to generalise to fresh, untried data, overfitting has taken place. You may determine if the model is accurate by dividing the data. The ultimate performance of the model is estimated using the testing set, which is separate from the training and validation sets.

You can get a fair evaluation of the model's true performance in real-world circumstances by assessing it on data that hasn't been seen before. For evaluating the model's effectiveness, choosing where to deploy it, and comparing it to other models or benchmarks, this estimation is essential.

Data splitting enables you to analyse the model's generalizability, or its ability to apply to new data. By putting the model to the test on the testing set, you can learn more about how well it can predict new, untested samples. This evaluation is essential for figuring out the model's dependability and possible utility in practical applications.

The separation of our dataset into 70% for training and 30% for the testing purposes is a good combination or in other words a good balance of having a large amount of data to train the model. Splitting the data is an essential part of any project and must be randomly separated without having any tendency towards biases of the data otherwise we will get low accuracy of the model. The Figure 4.4 shows the splitting of the dataset for train-test. Splitting any sort of dataset mainly depend on the size of the dataset and the specific problem we want to solve. Even if the dataset is small enough a separation of 80-20 or 60-40 can be a good balance.

Figure 4.4: Splitting of Dataset

4.4 Model Implementation

- **Convolutional Neural Network**

Convolution Neural Network is a popular deep learning algorithm and is widely used for image classification tasks. It is made up of a combination of layers that process the input Fundus image by applying a series of filters to extract different features from the Fundus image dataset.

The foremost layers of a CNN model utilize simple filters to detect basic image characteristics and edges. On the other hand, the later layers utilize advanced complex filters to recognize high-level features of shapes and patterns. Xin et.al [27] proposed a system of the creative criterion of deep neural networks for the minimum classification error. According to their work, the cross entropy and the M3CE are combined and analyzed to get better outcomes. Their experimentation results showed that the M3CE can improved the cross entropy

From the perspective of eye disease detection, the CNN's model can be trained to recognize particular features in images. For instance, if a person has glaucoma the CNN model can be trained to find out the features of cupping of the optic nerve that is seen in the majority of cases of this disease. Similarly in cataract disease, a CNN model can be trained on the fundas images dataset to recognize the cloudy appearance of the human lens.

Using Deep Learning techniques has several benefits in terms of feature extraction for image classification problems. As compared to manual feature extraction the CNN model can tickle high dimensional data of images that's why CNN is well suited for medical-related tasks and extract relevant features for us in less time.

Another good edge of using a CNN's model is it can handle a large amount of data and gives us generalized outcomes. The formula for convolution operations is given below:

$$s[t] = (x * w)[t] = \sum_{a=-\infty}^{\infty} x[a]w[a+t]$$

In this equation s = feature map, x= input image, w= kernel. A convolution refers to a mathematical terminology for a function that is got by combining two other functions. It shows that how other functions can change the overall structure of the function. For instance, let's say that the image is represented by "x" the image which is a two-dimensional (2D) array of pixels along with distinct color channels.

Here we have utilized the kernel which is "w" which is basically a feature detector through which we get the output by applying the feature map. The entire convolution operations are responsible for measuring the fundus image edges. In our CNN model, the first and the second layers are made of 32 3x3 filters. While on the other hand, the third convolution layer is composed of 64 3x3 filters.

Using ReLU is essential to utilize in the eye disease detection in CNN models because of its non-linearity functionality and the capability to capture advanced patterns in the problem. It offers numerous functionalities including computational efficiency, extracts relevant features, and simplicity. Still, there are many alternatives exist but ReLU will stand out as a popular choice.

Function	Equation	Range	Derivative Equation
ReLu	$f(x) = \begin{cases} 0; x<0 \\ x; x \geq 0 \end{cases}$	0, $+\infty$	$f'(x) = \begin{cases} 0; x<0 \\ 1; x \geq 0 \end{cases}$

Max Pooling and Dropout Neural Net Models are significant techniques in our CNN models for the eye disease detection problem. Max pooling deduces the spatial dimensions and nurtures to effectively used the computational resources. On the other hand, the Dropout prevents the model from overfitting and improves generalization thus enhancing the robustness of the model. These techniques contribute much to feature extraction and lower the risk of overfitting the model. By applying these techniques to the CNN architecture our model becomes more efficient and capable of detecting eye disease with greater accuracy. The Figure 4.5 and figure 4.6 illustrates the max pooling and dropout neural net model.

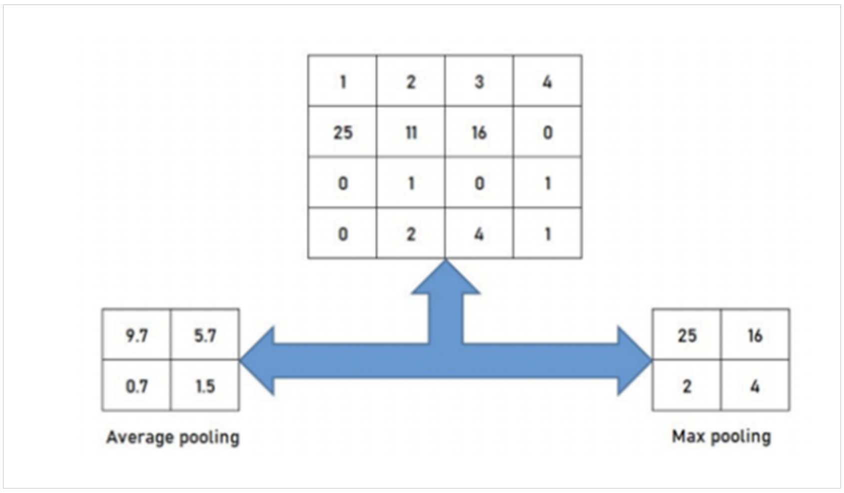

Figure 4.5: Finding Average and Max Pooling From Image Pixel

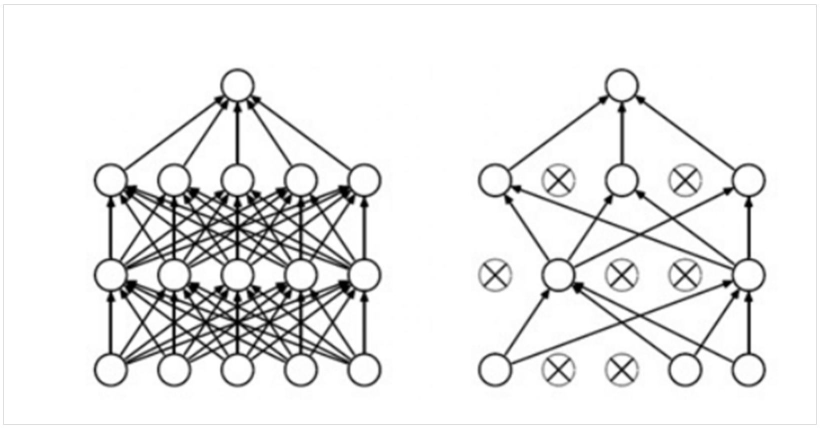

Figure 4.6: Dropout Neural Net Model

Our model has been trained on a Tensorflow fame model (CNN) to extract multiple features from the fundus images. we also know that the CNN model has three different layers: the Conv Layer, the pooling 13 layer, and the fully interconnected layer. So we had our three Conv2D layers. While each Conv layer was stacked with a Max-pooling layer and an activation layer. Next, a flattened layer is used to turn the data into a single dimension to feed it to the forward layer. Then a dropout layer is used to deduce overfitting problems. Weilong Mo et al [29] developed a system for image recognition model-based ensemble learning and CNN structure to filter out the issue of of a single convolution network classifier maybe being more vulnerable to error or any other unreliable outcomes prediction.

Finally, a fully interconnected layer was added. We also used the softmax Activation function at the output to generate a probabilistic distribution of our outcome. This is the overall flow in the model: ConV2D $\rightarrow$ ActivisionFunction $\rightarrow$ MaxPooling $\rightarrow$ (Previous three layers continue for two cycles) $\rightarrow$ Flatten $\rightarrow$ FC architecture of the CNN that is utilized for the eye disease problem. The overall architecture of extractor feature is listed in the Figure 4.7.

4.5 Model Evaluation

There is an abundance of evaluation measures to check the precision of our deep learning models. It is an integral part of any machine learning project to effectively monitor the precision of the model. In case our model fails to perform as expected then we can reverse the steps and can nurture the model's accuracy. Müller et.al [28] in his work proposed guideline details for standardized image segmentation measures to nurture the quality of the model precision. They have discussed numerous evaluations of the model including the dice similarity, Jaccard similarity, Rand index, the area under the curve graph (ROC), etc.

A confusion matrix is a tool widely used to measure the precision of a classification model. The matrix displays the number of true positive, true negative, false positive, and false negative values predicted by our model. These values can be utilized further to measure different performance metrics, such as precision, recall, and overall accuracy, which can be used to check the model's efficiency in detecting different eye diseases. Some common performance measure matrices are listed below.

1. **The Confusion matrix:**
   The matrix gives us a notion of the no of true positives, true negatives, false positives, and false negatives for a binary classification task.

2. **The Precision:**
   Precision is the No of true positives divided by the number of true positives plus false positives. It measures the proportionality of correct outcome predictions made by our model that are correct.

3. **Recall:**
   Recall is the no of true positives divided by the number of true positives plus false negatives. It calculates the proportionality of actual positive diseases that were identified accurately by the model.

4. **F1 Score:**
   F1 Score is the harmonic mean of precision and recall. It is a measure of a model's accuracy.

5. **ROC Curve:**
   ROC (Receiver Operating Characteristic) curve is a visual representation of the performance of a classification algorithm. It is used to plot the true positive rate Vs. the false positive rate.

6. **AUC (Area Under the Curve:**
   AUC is the area under the ROC curve. It ranges from 0 to 1, with higher values indicating better performance.

7. **Accuracy:**
   It's the proportion of correct predictions out of all predictions made. It's generally a good metric to use when the classes are balanced but it can be misleading when they are imbalanced.

4.6 Web Application Interface

To detect various eye diseases using deep learning a web application is designed using Flask, a Python Web Framework. The application facilitates the users to upload Fundus images and get predictions about the presence of glaucoma or cataract disease.

Due to the increasing number of eye diseases early detection is needed through a user-friendly interface to nurture the healthcare unit. The system is designed based on a deep learning model to effectively process the Fundus images of the human eye. We have utilized different image preprocessing techniques as mentioned above such as normalization, augmentation, and removal of noise to improve the precision of our deep learning model.

The accuracy of the application has been measured by using a separate test data. By comparing the outcomes generated by the web application with the correct labels provided to us by ophthalmologists, we have measured its sensitivity, specificity, and overall precision.

Chapter 5

Results and Discussions

In this chapter we have displayed our findings for this research work on eye disease using deep learning. Our Convolution Neural Network (CNN) model trained on more than 5K Fundus images has predicted the outcomes with high accuracy of 91% on this dataset. From Figure 5.1 we trained our CNN model on 485,277 parameters of fundus images with max pooling.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 222, 147, 32)      896

 max_pooling2d (MaxPooling2D  (None, 111, 73, 32)      0
 )

 conv2d_1 (Conv2D)           (None, 109, 71, 64)       18496

 max_pooling2d_1 (MaxPooling  (None, 54, 35, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 52, 33, 64)        36928

 max_pooling2d_2 (MaxPooling  (None, 26, 16, 64)       0
 2D)

 conv2d_3 (Conv2D)           (None, 24, 14, 120)       69240

 max_pooling2d_3 (MaxPooling  (None, 12, 7, 120)       0
 2D)

 conv2d_4 (Conv2D)           (None, 10, 5, 150)        162150

 max_pooling2d_4 (MaxPooling  (None, 5, 2, 150)        0
 2D)

 conv2d_5 (Conv2D)           (None, 4, 1, 164)         98564

 flatten (Flatten)           (None, 656)               0

 dense (Dense)               (None, 150)               98550

 dense_1 (Dense)             (None, 3)                 453

=================================================================
Total params: 485,277
Trainable params: 485,277
Non-trainable params: 0
_________________________________________________________________
```

Figure 5.1: CNN Architecture with Max Pooling Layers

From figure 5.2 shows the actual Vs. predicted classification of outcomes. Here our model has accurately predicted the target classes of diseases with a 100.0% confidence interval. For instance, as we can see the prediction that the actual class was Cataract or Normal and our model accurately predicted with a confidence of 100% similarly the confidence value for glaucoma prediction was 88.86%.

Figure 5.2 shows the striking performance of our model through a visual comparison of the results' actual and projected classification. The outcomes show that our model had a 100.0% confidence interval for correctly predicting the target classes of disorders. This extraordinary degree of confidence inspires confidence in the accuracy of our model's predictions.The model's success in accurately identifying cases of glaucoma and its flawless prediction of Cataract or Normal cases speak loudly about its effectiveness. The strong degree of confidence in these forecasts adds to the validity and dependability of our model's findings.

These results from Figure 5.2 support our model's potency in the realm of disease classification. Our model has considerable promise for assisting medical professionals in diagnosing and treating patients more successfully by properly forecasting disease outcomes, notably for Cataract or Normal cases and glaucoma.

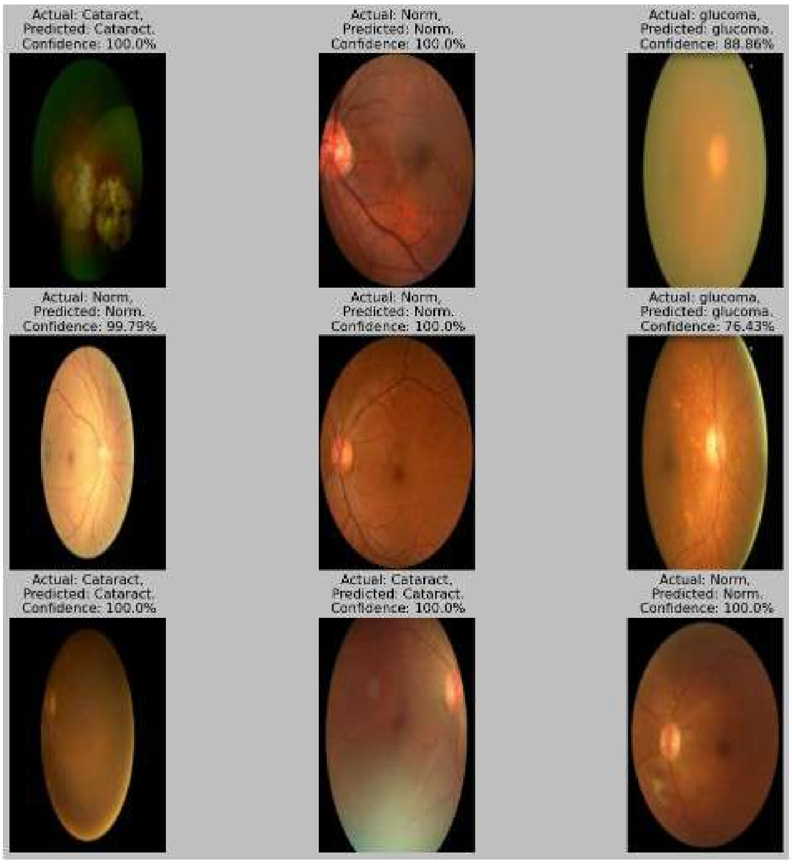

Figure 5.2: Results of Actual Vs Predicted Classes

The confusion matrix shows the summary of our model predictions based on different classes of eye disease. Here we can see a large number of predictions are correct with lie on the diagonal side of the matrix Figure 5.3.

The predictions made by our model for various classifications of eye illnesses are comprehensively summarised in the confusion matrix, which is shown in Figure 5.3. By displaying the distribution of accurate and inaccurate predictions, it provides insightful information about the performance and accuracy of our model.

When we examine the confusion matrix, we see that a significant portion of the predictions match the diagonal side of the matrix. This diagonal depicts the predictions that our model correctly made, demonstrating its high level of classification accuracy for different eye illnesses. The fact that this diagonal contains a sizable percentage of predictions shows how well the model distinguishes between the various disease groups.

Moreover, the off-diagonal elements in the matrix represent instances where our model's predictions diverged from the actual classes. These errors in prediction provide crucial information about the areas where our model may require further improvement or refinement. By analyzing the patterns and frequencies of miss-classifications, we can identify specific disease classes that may present more challenges for the model. This knowledge enables us to focus on enhancing the model's performance in accurately classifying those particular classes.

The consistency of our model's performance is demonstrated by the distribution of accurate predictions along the confusion matrix's diagonal. It shows that our model has successfully internalised and generalised from the training data, allowing it to produce reliable forecasts for a wide variety of eye disease classes. The medical industry will greatly benefit from this performance because precise disease classification is essential for efficient diagnosis and treatment planning.

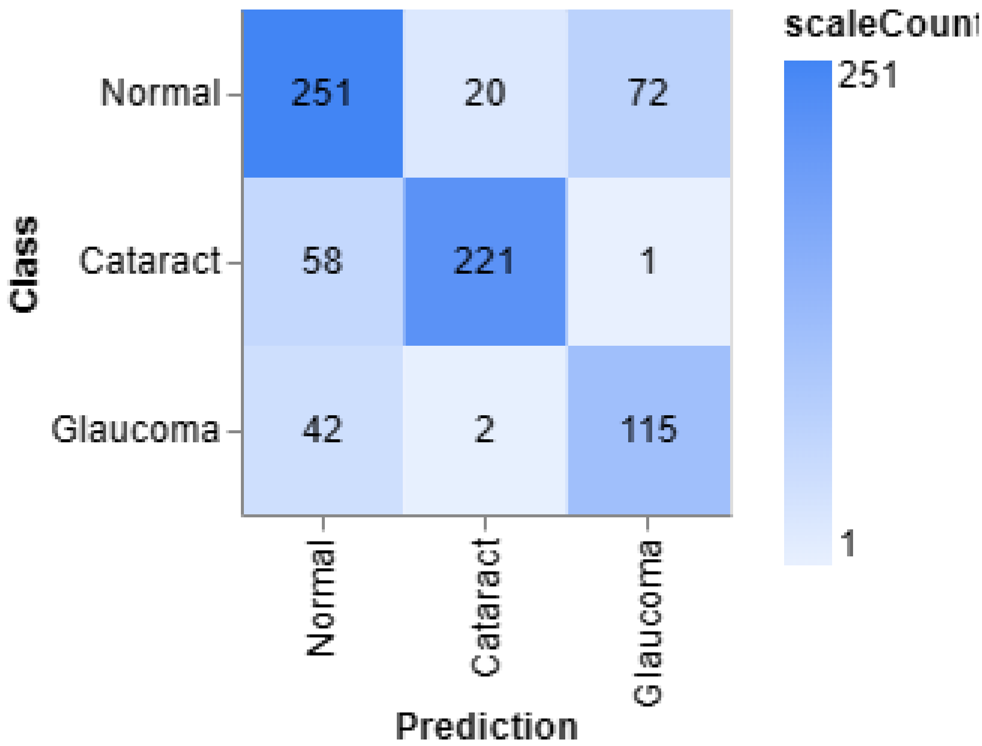

Figure 5.3: Confusion Matrix of Different Classes

The recall value of glaucoma is the highest which is 91 while the Cataract value of the F1 score is higher compared to all and also its accuracy is also higher which is 79. The below figure 5.4 illustrates the classification report of different eye diseases.

The classification report offers a thorough study of numerous performance measures for various eye conditions. It sheds light on the advantages and disadvantages of our model's predictions by highlighting the recall values, F1 scores, and accuracies related to each disease class.

The greatest recall value for the glaucoma class, at 91, is one interesting finding from the classification report. This shows that our approach has a significant ability to accurately detect cases of glaucoma, reducing the likelihood of false negatives. For glaucoma, a high recall value is very important since it guarantees that the model can accurately capture positive cases and aid in the early detection and treatment of this potentially serious condition.

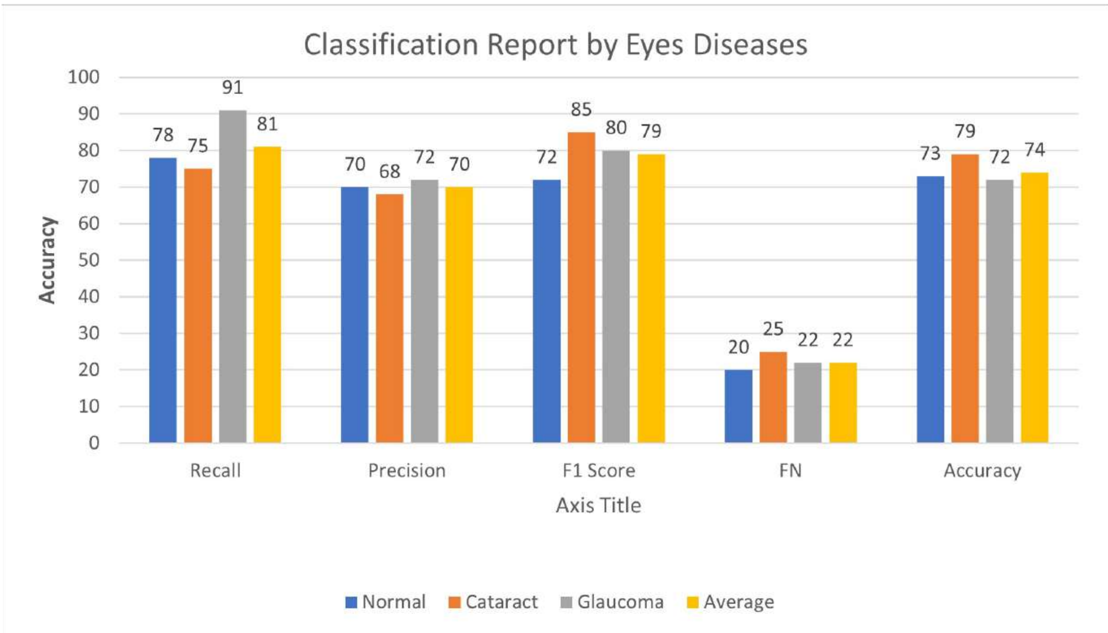

Figure 5.4: Classification Report of Different Diseases

Based on the Classification report, we have also calculated different evaluation metrics for each separate disease class of glaucoma, cataract, and normal. Figure 5.5 shows the individual classification report of cataracts. Here we can see the F1 Score value of cataract disease is 0.85 followed by its accuracy of 0.79 and the Recall value which is 0.78 of the given Fundus images dataset.

Similarly the classification report for the glaucoma disease is given in Figure 5.6 which shows the highest value of Recall which is 0.91 and F1 Score value of 0.8. The precision 0.72 and overall accuracy of Glaucoma Disease.

The cataracts individual categorization report, as shown in Figure 5.5, offers particular evaluation measures for this specific disease class. These metrics provide important information about how well our algorithm performed in correctly recognising cataracts in the dataset of fundus images that was provided.

For cataracts, the F1 Score, a balanced indicator of memory and precision, reaches a value of 0.85. With regard to cataract cases, this score demonstrates a fair balance between accurately identifying true positives and reducing false positives. A higher F1 Score indicates that our algorithm makes more trustworthy and accurate predictions for cataracts, which helps identify the condition more successfully.

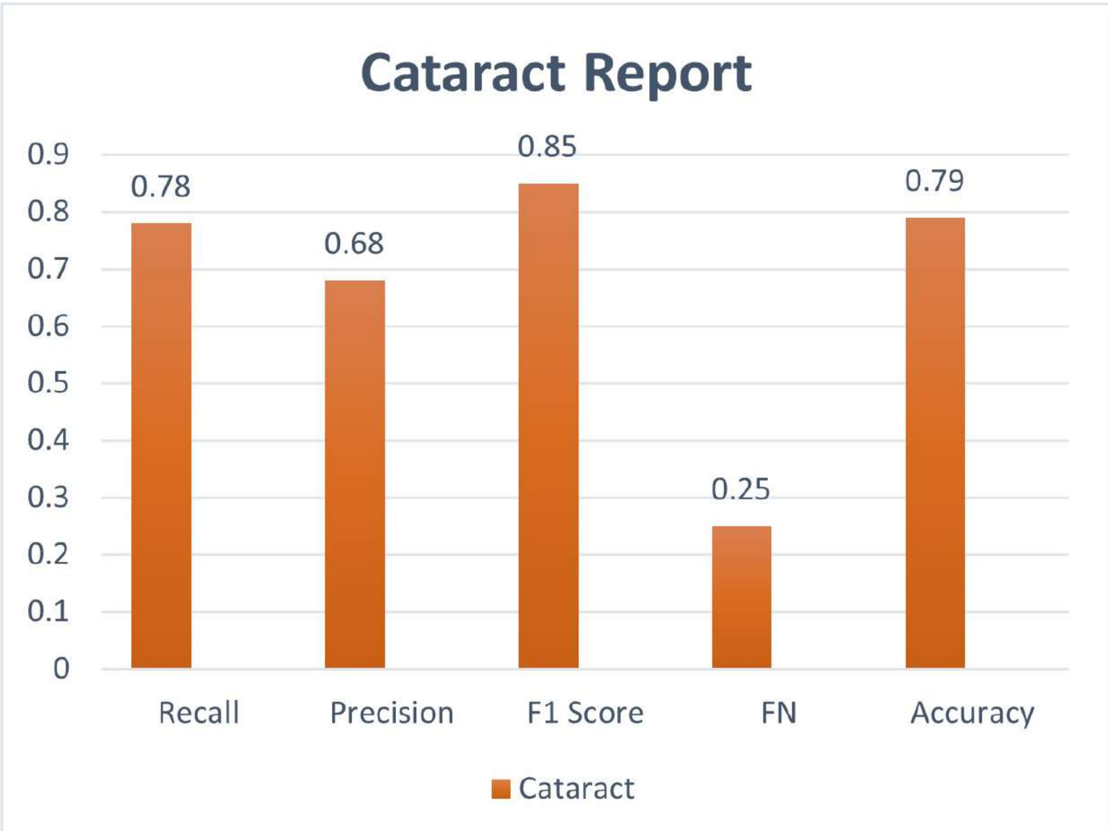

Figure 5.5: Classification Report of Cataract Disease

Similarly the classification report for the glaucoma disease is given in Figure 5.6 which shows the highest value of Recall which is 0.91 and F1 Score value of 0.8. Figure 5.6's classification report for the glaucoma condition includes particular evaluation metrics that give insight on how well our algorithm performed in detecting glaucoma cases. These metrics provide important information about how well the model categorises glaucoma in the dataset.

The report's recall value for glaucoma is 0.91. This score denotes the model's capacity to accurately detect a large percentage of glaucoma cases while minimising the probability of false negatives. Our algorithm is effective at correctly recognising positive cases of glaucoma, as shown by its recall value of 0.91, allowing for early detection and the right kind of therapy.

The categorization report for glaucoma offers important information into how well our model performs in relation to this class of diseases. The model's ability to precisely identify glaucoma patients within the dataset is demonstrated by its high recall value and F1 Score. These indicators illustrate the model's dependability in aiding doctors in the early detection and diagnosis of glaucoma, permitting prompt interventions and providing the best possible care for patients.

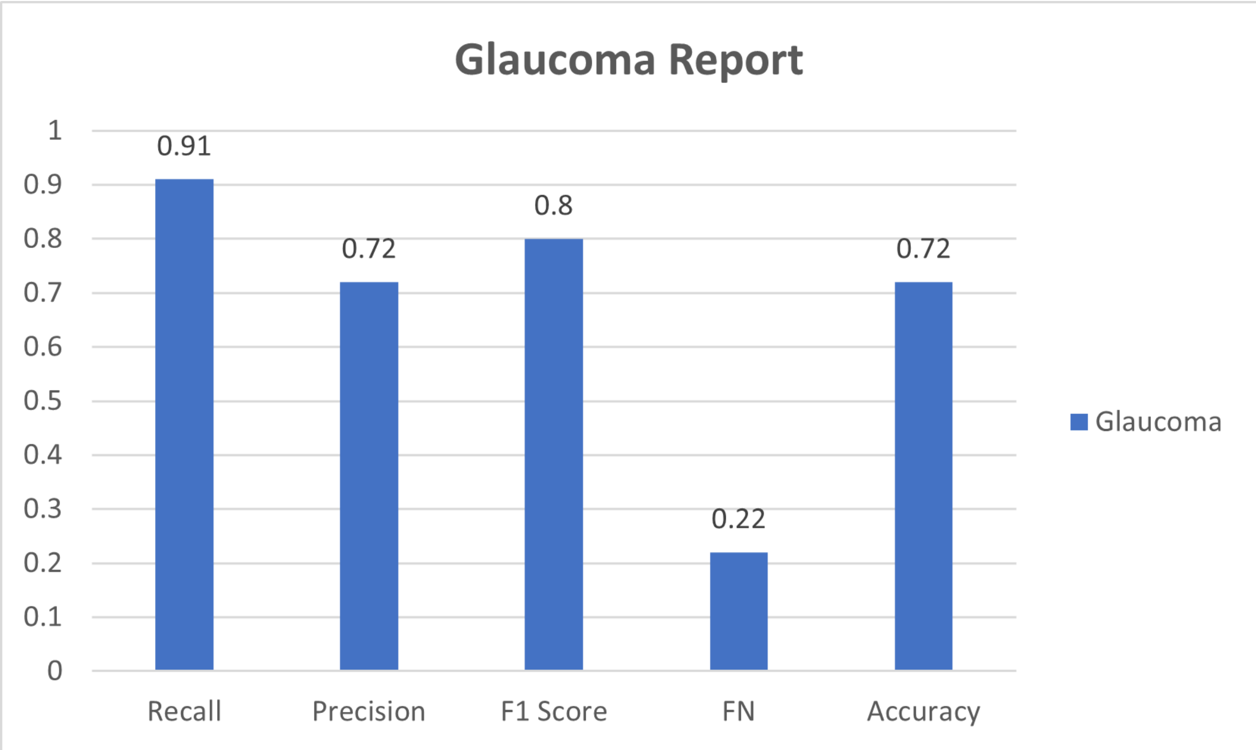

Figure 5.6: Classification Report of Glaucoma Disease

Figure 5.7 shows the normal images of the classification report which seems like a balance report as all the evaluation metrics values are around about 72-75% based on our model predictions. According to our model predictions, Figure 5.7's classification report for normal photos shows a balanced performance across several evaluation parameters. According to the report, the model's accuracy, precision, recall, and F1 Score for typical photos hover between 72 and 75 percent. This shows that our model performs consistently and dependably when correctly categorising normal photos from the dataset.

The model's capacity to successfully distinguish and accurately identify instances that belong to the normal category, leading to accurate disease classification, as demonstrated by the balanced evaluation metrics in the classification report for normal images.

Figure 5.7 shows the normal images of the classification report which seems like a balance report as all the evaluation metrics values are around about 72-75% based on our model predictions.

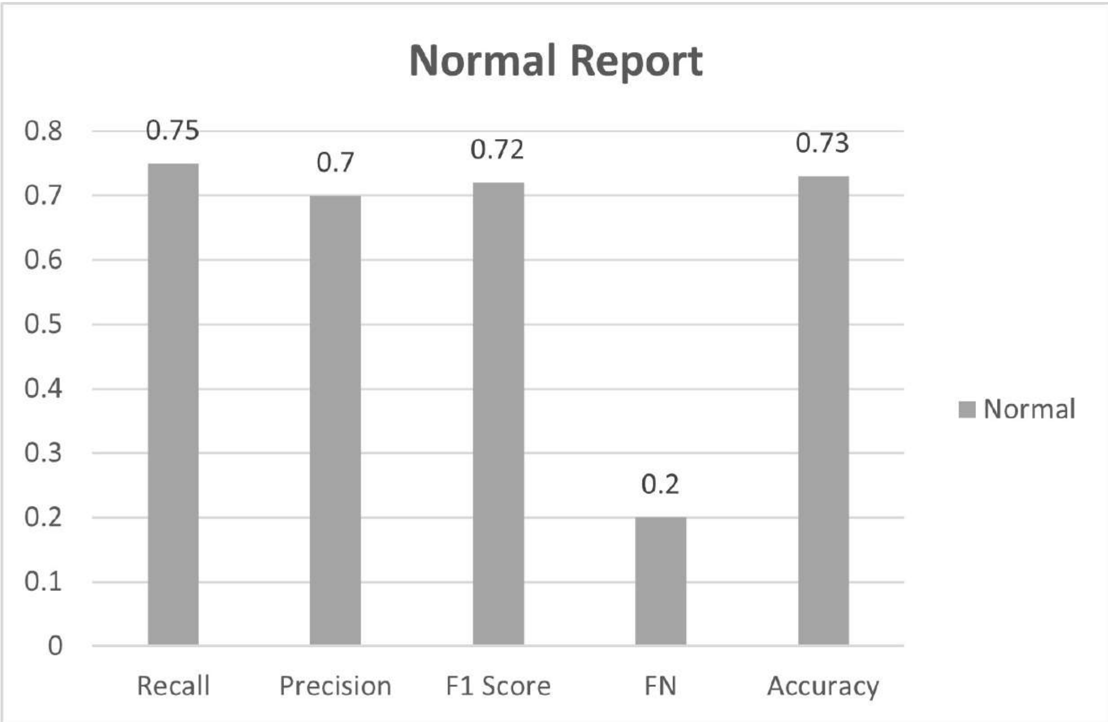

Figure 5.7: Classification Report of Normal Images

Then we have calculated the training accuracy Vs Validation accuracy and here we can see from the graph that accuracy is above 90% for this fundus images dataset with more than 90 epochs figure 5.8 illustrates the training accuracy Vs. Validation accuracy of the model. Thus it shows good accuracy that our model has predicted very well by forecasting the outcomes as the number of epochs increased.

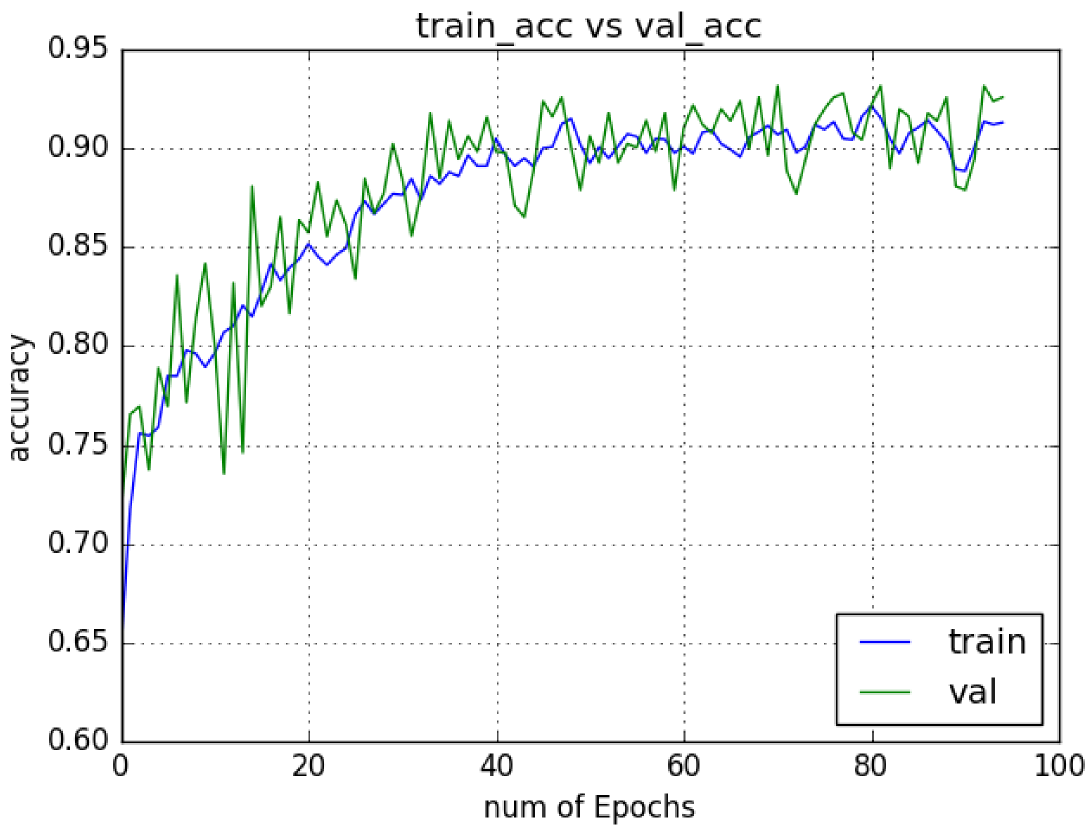

Figure 5.8: Training Accuracy Vs Validation Accuracy

A high value of the loss functions means that our machine learning model has performed poorly thus selecting a specific loss function for your model is critical to train an accurate machine learning model. Here figure 5.9 shows that initially, the loss function value was very high beyond 0.6 but as the number of epochs increases the loss function value starts decreasing and at its is less than 0.2 which indicates a good impression that our model has performed very well.

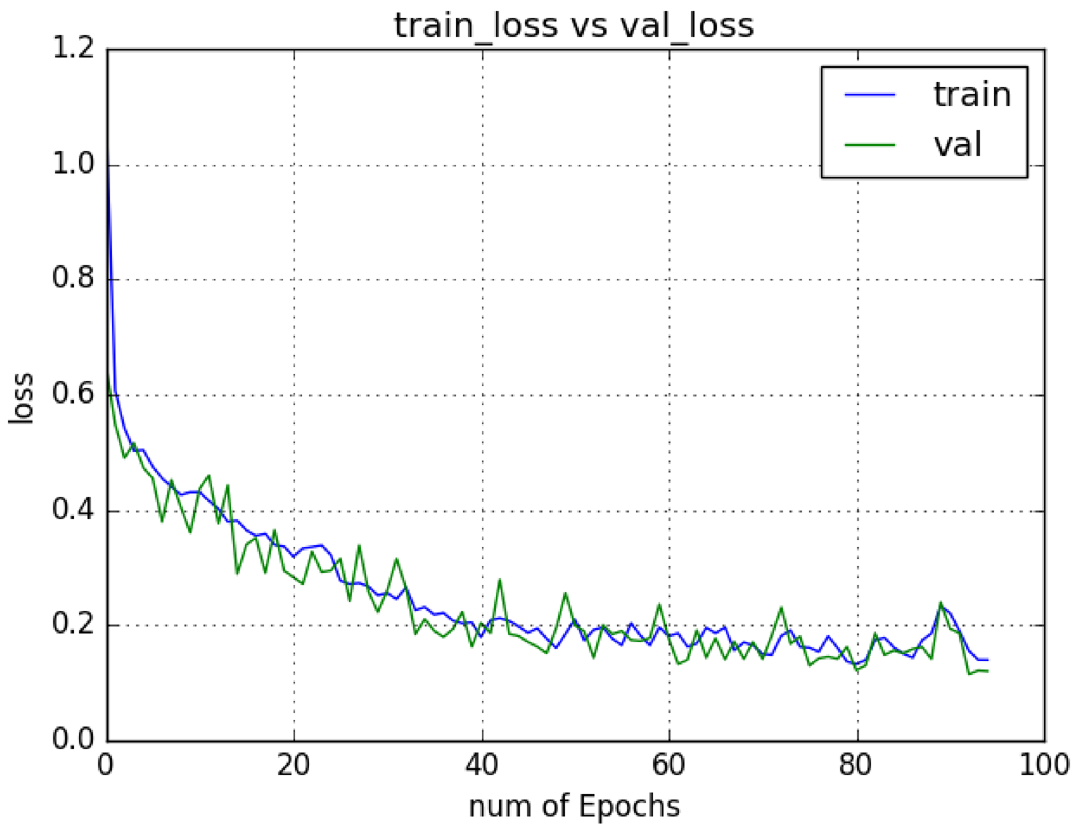

Figure 5.9: Training Loss Vs Validation Loss

We also have deployed our deep learning model of CNN on a web application using a Flask to facilitate people utilizing this user-friendly interface for their eye disease detection. Figure 5.10 shows the interface of a web application in which the user or laboratory person will upload the Fundus image of the eye. There we have two major characteristics for uploading the image: First, we can upload an image from our system or we can directly upload an image from the internet online just we need to copy the link of the given Fundus image and paste it here into the web application:

It provides two functionalities to end users:

- Upload Fundus image from your system
- Upload Fundus image URL online or from any site

By enabling users to upload fundus pictures directly from their systems and the ease of publishing fundus image URLs online or from any site, our ground-breaking solution for eye illnesses revolutionizes the practise of ophthalmology. We have developed a user-friendly platform with these features that enables quick and precise glaucoma and cataract detection.

We do away with the requirement for intricate procedures or expensive equipment by letting customers upload fundus photos from their systems. Using tools like smartphones or digital cameras, this functionality enables people to effortlessly capture photographs and take charge of their eye health. These photographs can then be easily uploaded to our system, where our cutting-edge algorithms and machine-learning strategies are put to use.

The second feature, which allows users to upload URLs for fundus images, gives them even more convenience. They can even get particular photographs from medical databases or pull pertinent images from a variety of web sources. By offering a simpler procedure for acquiring and analysing fundus photos, this tool helps users save time and effort.

Our method uses cutting-edge technologies to precisely identify glaucoma and cataract after the fundus photos are uploaded. Our powerful algorithms use machine learning to classify and recognise symptoms of various disorders by analysing significant characteristics and patterns in the fundus images. Our system uses deep learning approaches to enhance its accuracy and performance over time, adjusting to new data and honing its diagnostic abilities.

The user will upload pictures from the system either glaucoma or cataract disease. The Figure 5.10 and Figure 5.11 shows how to upload image from the system of different eye diseases. The user can either choose to select the image from the system or upload through online just the user will need to copy the URL link of the given website or database and paste it into the upload option of paste URL in the system.

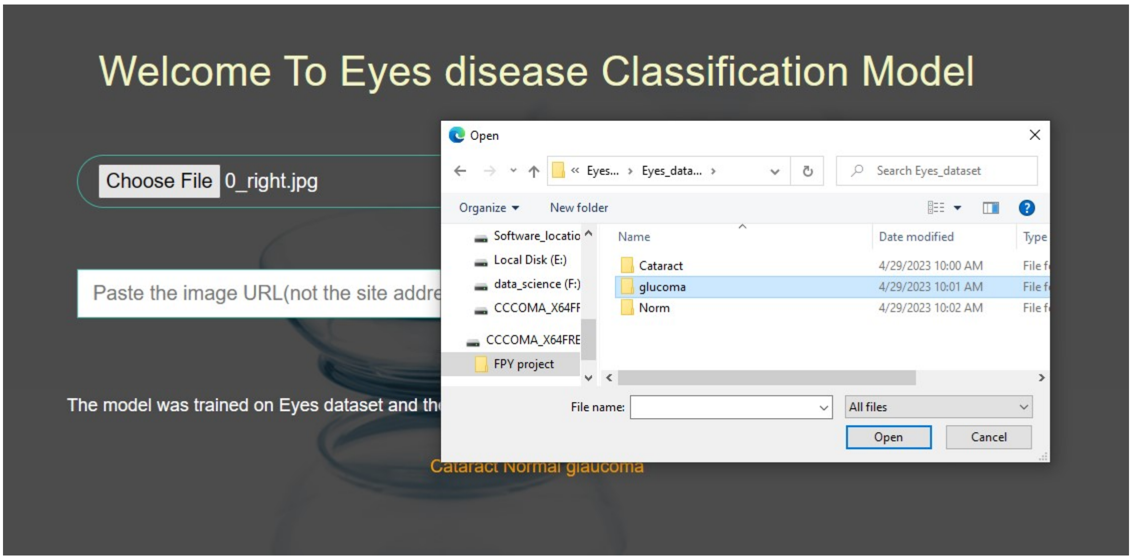

Figure 5.10: Figure 5.10: Upload Images of Eye Diseases

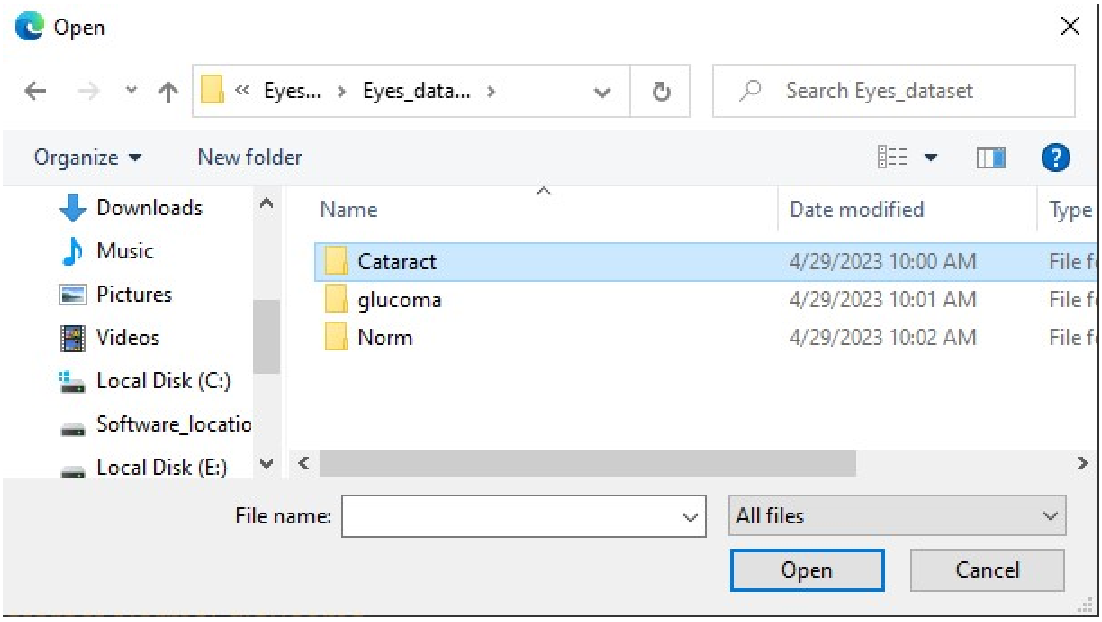

Figure 5.11: Caption

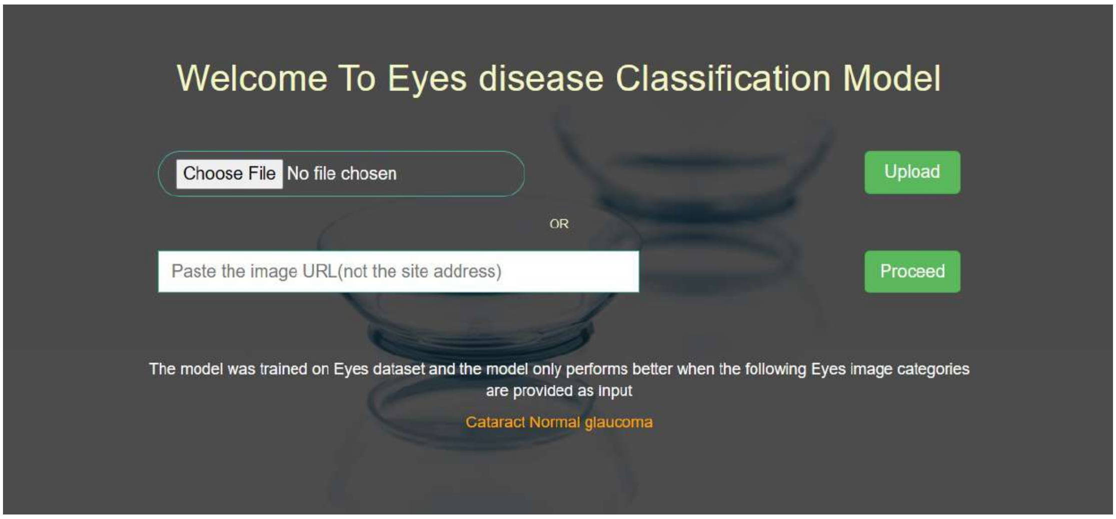

Figure 5.12: User's Friendly Web Application Interface

Once we uploaded the eye images in the application, the system will then analyze and process this Fundus image and will predict the desirable outcomes. The result prediction shows the probability of each class existing whether it is glaucoma or cataract. The model's prediction results are listed below first we have done it for glaucoma in Figure 5.11 and then for the cataract which shows in Figure 5.12 and lastly for the normal Fundus images in Figure 5.13.

The system starts analysing and processing the Fundus image after receiving the ocular images from the application. The system thoroughly evaluates the image to forecast the desired results using sophisticated algorithms. The system's outcome prediction includes the likelihood that each class, such as cataract or glaucoma, will occur. This data enables medical personnel to learn more about the possibility that particular eye disorders will be present, assisting in correct diagnosis and directing suitable treatment strategies. The system's capacity to offer probability estimates improves decision-making and makes it easier to maintain eye health effectively.

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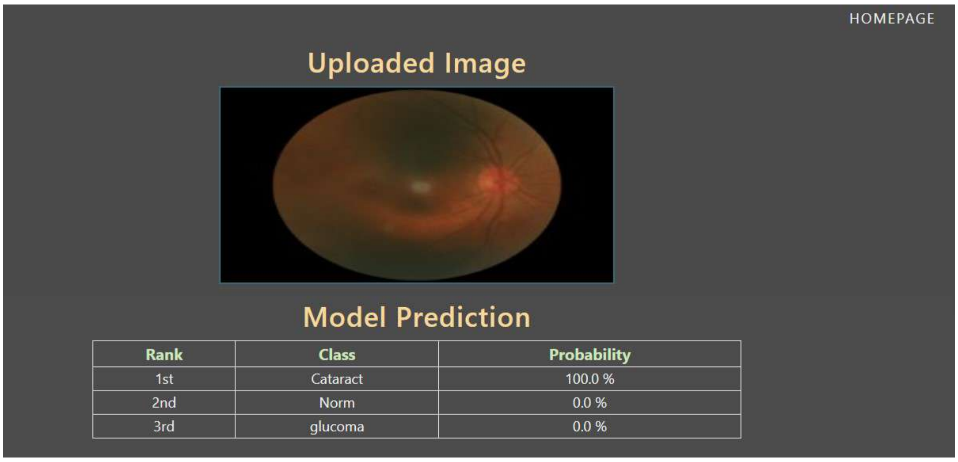

Figure 5.13: Model's Prediction of Cataract Disease

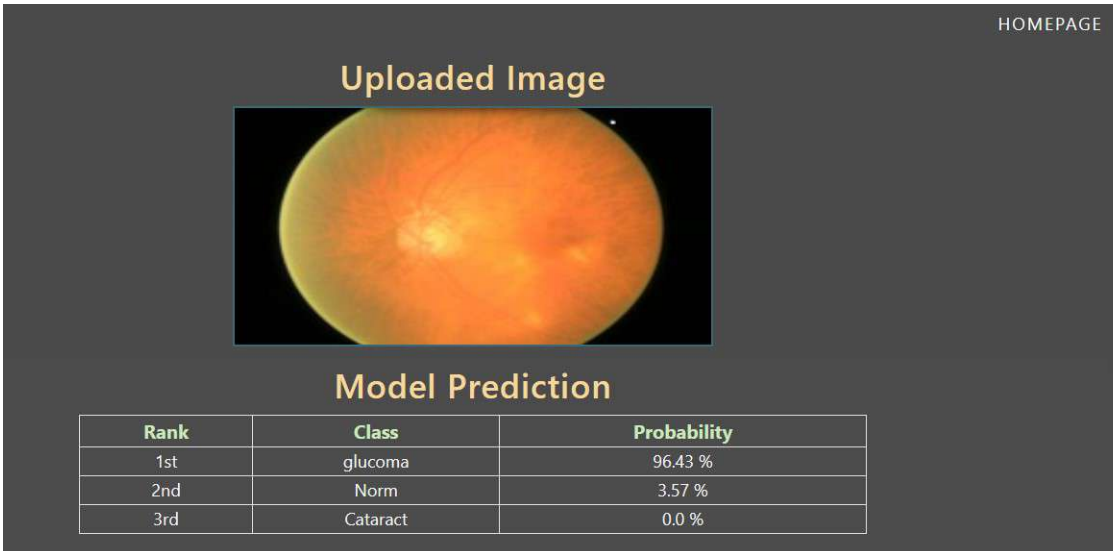

Figure 5.14: Model's Prediction of Glaucoma Disease

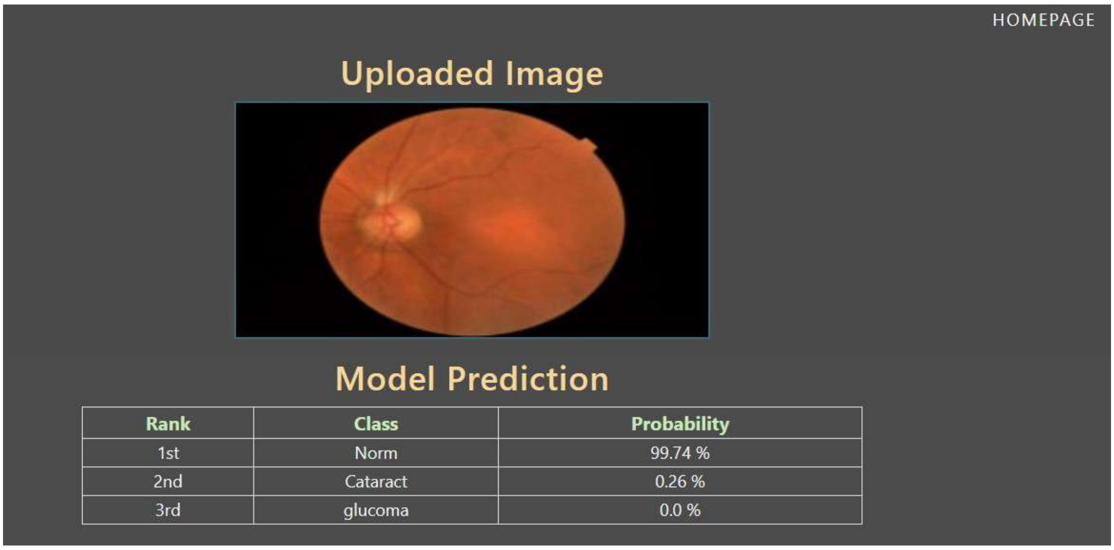

Figure 5.15: Model's Prediction of Normal Eyes

Chapter 6

Conclusions

In this research work we have detected various eye diseases using Deep Learning (DL) techniques to accurately predict the outcomes. We trained our Deep Neural Network Model (CNN) on Fundus images of more than 5K collected from a local hospital having three categories of images which include glaucoma, cataract, and normal Fundus images.

We have used numerous image processing techniques to nurture the performance of our Neural Network Model (CNN) which include data augmentation, normalization, etc.

Our CNN achieved a high accuracy of 91% on this large amount of data by maintaining a low value of cost function which was less than 0.2. Then we generated the classification report of each category of eye disease including the correct predictions of the model with Actual Vs. The predicted class was also predicted accurately. Further, we deployed our Deep Learning model of CNN on a Web Application using Flask to show the results of our model predictions through an application. The user can upload an image of his/her eye from the system or just copy the URL of the Fundus image online and the system will predict whether he/she has glaucoma or cataract. This system will play a significant role in detecting eye diseases at an early stage and help people get better treatment in the hospital on time.

Chapter 7

Future Work

In the future to proceed with this project one step ahead we can add more eye diseases that are widespread in our local demographic by taking relevant datasets into consideration. By using advanced neural network techniques we accurately predict all other eye diseases in the future with high accuracy.

As far as a web application is concerned we add more insights in the interface for users along with recommendations of precautions and treatments etc. We can also add more relevant information to the system by showing graphs and charts of the model performance in the interface directly.

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