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PROJECT REPORT

ON

"CATARACT AND OTHER OCULAR DISEASES DETECTION USING MACHINE LEARNING"

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CERTIFICATE

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ABSTRACT

Ocular diseases refer to a group of conditions that affect the eye and its surrounding structures, which can result in visual impairment, pain, and discomfort, and in severe cases, lead to blindness. These diseases can be caused by various factors such as genetics, environmental factors, and lifestyle choices and can affect individuals of all ages. Common ocular diseases include cataract, glaucoma, age-related macular degeneration, diabetic retinopathy, and dry eye syndrome, which can significantly impact an individual's quality of life and require long-term management. Cataracts, for instance, are characterized by a hazy spot in the eye's lens that results in a gradual deterioration of vision. Symptoms of cataracts include halos surrounding lights, faded colours, distorted or double vision, problems with bright lights, and difficulty seeing at night. These symptoms can lead to difficulties in reading, driving, and recognizing people, as well as an increased risk of falling and depression. The global incidence of cataracts is high, accounting for 33% of visual impairment and 51% of cases of blindness worldwide. Our project aims to develop a machine learning model capable of assessing the severity of cataract and other ocular diseases from fundus images of patients. The model is then incorporated into a web application that provides ophthalmologists with an automated way of assessing the severity of the ocular disease.

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CHAPTER 1

INTRODUCTION

Early fundus screening in ophthalmology is an affordable and effective technique to prevent blindness caused by ocular diseases. However, manual diagnosis can be time-consuming and may result in delayed treatment due to a lack of medical resources. While deep learning has shown promise in ocular disease detection, most studies focus on a single disease, limiting their real-world applicability.

To address these limitations, we used a dataset with annotations for multiple diseases and evaluated various deep neural networks. We found that simply increasing the network's size did not lead to improved performance for multiple diseases.

Furthermore, most existing deep learning models only focus on one eye, while ophthalmologists typically diagnose patients using data from both eyes in clinical situations. Developing a more comprehensive and effective fundus screening system capable of identifying multiple diseases is crucial to meeting the demands of patients with fundus disease.

As per World Health Organization, at least 2.2 billion people worldwide suffer from vision problems, with at least 1 billion cases being preventable. Rapid and automatic disease identification is essential to reduce the burden on ophthalmologists and prevent further damage to patients' vision.

1.1 Types of Ocular Diseases

Ocular diseases are a type of conditions that affect the eye and its surrounding structures. These diseases can cause variety of symptoms and visual impairments, including pain, discomfort, and in severe cases, blindness. Ocular diseases can impact people of any age and have diverse causes, such as genetics, environment, and lifestyle choices.

There are many different types of ocular diseases, each with its own set of symptoms and treatment options. Some of the most common ocular diseases include:

1. Cataract - a condition where the eye's lens becomes cloudy, causing vision to deteriorate. Cataracts can affect one or both eyes and often progress slowly.

2. Glaucoma - Glaucoma is a type of eye condition that damage the optic nerve, leading to vision loss or blindness if left untreated. It is often associated with increased pressure in the eye, called intraocular pressure.

3. Age-related macular degeneration (AMD) - a condition where the macula, which is responsible for central vision, deteriorates. AMD is the leading cause of vision loss in individuals over 60 years old.

4. Diabetic retinopathy - a condition that affects individuals with diabetes, causing damage to the blood vessels in the retina. Diabetic retinopathy will cause vision loss and, in severe cases, blindness.

5. Dry eye syndrome - a condition where the eyes do not produce enough tears, leading to discomfort, irritation, and vision problems.

6. Retinal detachment - a condition where the retina detaches from the underlying tissue, causing vision loss.

7. Conjunctivitis - also known as pink eye, a condition where the conjunctiva, the thin layer of tissue that covers the front of the eye, becomes inflamed. Conjunctivitis can cause redness, itching, and discharge from the eye.

8. Uveitis - Uveitis is the inflammation of the uvea, the middle layer of the eye, which can lead to symptoms such as eye redness, pain, blurred vision, and sensitivity to light. Prompt diagnosis and treatment by a healthcare professional are essential to manage uveitis and prevent potential vision loss.

9. Keratitis - a condition where the cornea, the clear layer in front of the eye, becomes inflamed. Keratitis will cause vision loss and, in severe cases, blindness.

Effective diagnosis and management of these ocular diseases are crucial in preventing vision loss and improving the quality of life for individuals affected by these conditions.

Diseases Our Project focus on

1.1.1 Cataract

The lens of your eye, which is typically clear, becomes clouded by a cataract Most cataracts grow slowly and don't affect your vision at first. Your vision will eventually be hampered by cataracts. Due to white coating it produces, it is one of the easiest abnormalities to spot. Figure 1.1 shows how a realistic depiction of a cataract appears on fundus images. It is extremely simple to see how the lens is clouded.

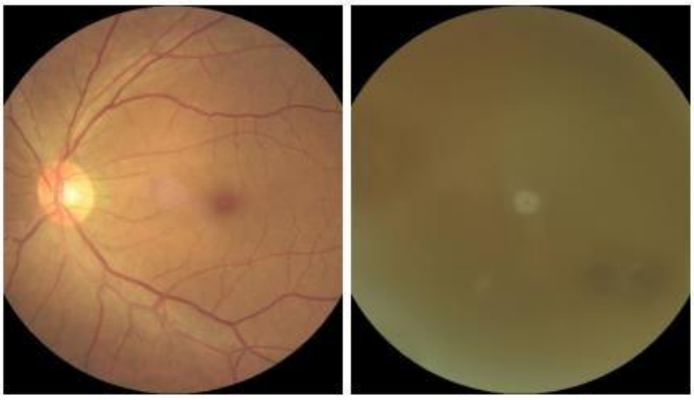


Figure 1.1.1

1.1.2 Age-Related Macular Degeneration

An eye condition known as age-related macular degeneration (AMD) can obstruct the clear central vision required for tasks like reading and driving. "Age-related" simply indicates that it frequently affects older individuals.

"Macular" indicates that it has an impact on the macula, a region of the eye. Figure 1.2 illustrates how AMD appears and is explained. It takes place when the fragile cells of the macula, the small, central region of the retina that controls the center of our field of vision, are harmed and cease to function.

Figure 1.1.2

1.1.3 Myopia

When the eye swells excessively from front to back, myopia develops. Near-sightedness now affects about 41.6% of Americans, up from 25% in 197116. A myopic eye and a normal eye are contrasted in Figure 1.3. As you can see, the retina of the myopic eye (on the right) is more stretched, and its blood vessels are thin. By 2050, it's predicted that myopia would affect nearly half of the world's population.

Figure 1.1.3

1.1.4 Hypertensive Retinopathy

Acute blood pressure elevation typically causes reversible vasoconstriction in retinal blood vessels18. You can observe that HR is not such a common disease. In Figure we can observe how Hypertensive Retinopathy manifests. The Bhaktapur Retina Study is a population based, cross-sectional study to estimate the prevalence of vitreo-retinal diseases among subjects 60 years and above residing in the Bhaktapur district of Nepal. This study was done on 1000 people.

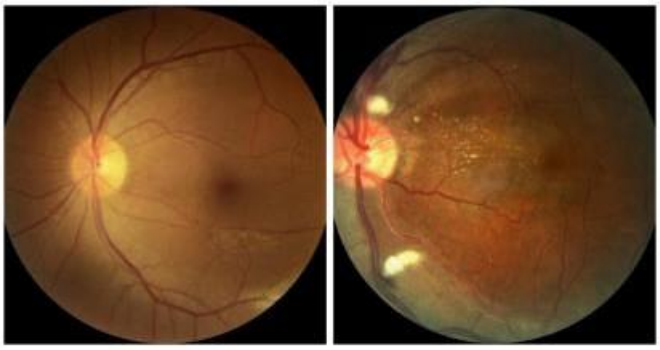


Figure 1.1.4

1.2 Introduction to Fundus Image

The fundus is the interior lining of the eye's posterior segment, which includes the retina, optic disc, macula, and surrounding blood vessels. The fundus image is a non-invasive diagnostic tool that ophthalmologists use to examine the condition of the retina and other structures in the posterior segment of the eye. By examining the details visible in the fundus image, an ophthalmologist can identify various eye conditions, such as diabetic retinopathy, glaucoma, age-related macular degeneration, and cataract.

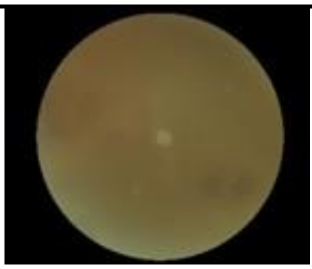
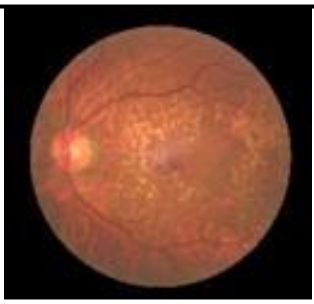
Kinds	Image Example
Diabetes	
Cataract	
Myopia	
Age related Macular Degeneration S(AMD)	

Figure 1.2.1 Types Ocular Disease Fundus

During a fundus examination, the patient's eyes are dilated using eye drops to allow the ophthalmologist to capture a clear image of the fundus. The patient is asked to look straight ahead while the camera is positioned close to the eye to capture the image. The process is painless and takes only a few minutes to complete. The resulting fundus image provides a detailed view of the retina and other structures in the posterior segment of the eye. The image will detect abnormalities such as swelling, bleeding, and lesions that may indicate the presence of an eye disease. Fundus images are also used to track the progress of a disease and monitor the effectiveness of treatment.

1.3 Introduction to Machine Learning

Machine learning is a part of artificial intelligence (AI) that focuses on the development of algorithms and statistical models that allow computer systems to learnand improve their performance on a specific task or set of tasks without being explicitly programmed. The goal of machine learning is to develop computational methods that can automatically learn patterns and relationships in data, and use this knowledge to make predictions or decisions. This makes machine learning an important tool for solving complex problems in a variety of fields, such as computer vision, natural languageprocessing, robotics, and finance.

Various categories of machine learning techniques exist, such as supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. In supervised learning, models are trained using labelled data, where input data is associated with corresponding output labels. The model learns to map inputs to outputs, and can then make predictions on new, unseen data.

Unsupervised learning, in contrast, entails training a model on unlabeled data, where the model must identify patterns and relationships within the data without any predefined labels or guidance. Semi-supervised learning combines elements of both supervised and unsupervised learning by training a model on a mixture of labeled and unlabeled data. Reinforcement learning, on the other hand, involves training a model through iterative trial and error, where the model learns to make decisions that maximize a reward signal. Machine learning finds diverse applications across domains such as image and speech recognition, medical diagnosis, and fraud detection. The rapid growth of big data and advancements in computing power has significantly expanded the potential applications of machine learning.

1.4 Introduction to Deep Learning

Deep learning is a specific branch within machine learning that harnesses artificial neural networks to acquire knowledge from data and make informed predictions or decisions. Its design is inspired by the structure and functioning of the human brain, where interconnected layers of neurons collaborate to process information and execute intricate tasks. Deep learning algorithms leverage multiple layers of artificial neurons to extract and learn progressively intricate features from data. These layers can be seen as a cascading sequence of abstract representations, with each layer constructing upon the preceding one to construct more intricate and abstract interpretations of the input data.

Deep learning offers a notable advantage in its capacity to autonomously discern intricate patterns and connections in data, eliminating the requirement for explicit feature engineering or manual adjustments. This attribute makes deep learning highly suitable for tasks like image and speech recognition, natural language processing, and independent decision-making. Deep learning has exerted a profound influence on numerous domains, including computer vision, robotics, natural language processing, and healthcare. Within the healthcare sector, deep learning has found applications in diverse areas, encompassing medical image analysis, drug exploration, disease diagnosis and prognosis, as well as personalized treatment planning.

Deep learning has shown remarkable results in healthcare applications, particularly in the field of medical image analysis. One of the most significant challenges in medical image analysis is accurately and efficiently detecting and diagnosing diseases from medical images such as X-rays, CT scans, and MRIs. Deep learning models have been used to achieve state-of-the-art performance on a wide range of medical image analysis tasks, including detecting lung nodules in chest X-rays, identifying tumors in brain MRI scans, and predicting diabetic retinopathy from fundus images of the eye.

In addition to medical image analysis, deep learning has also been used for natural language processing applications in healthcare. For example, deep learning models can be used to analyze electronic health records to identify trends and patterns in patient data, or to extract relevant information from clinical notes and free-text reports. Another area where deep learning has shown promise in healthcare is personalized treatment planning. By analyzing large amounts of patient data and medical records, deep learning models can help predict the efficacy of different treatment options for individual patients, and assist physicians in making more informed treatment decisions.

Overall, the applications of deep learning in healthcare are vast and diverse, and hold great promise for improving patient outcomes, reducing healthcare costs, and advancing medical research and innovation.

1.5 Machine Learning in Health Care

The integration of machine learning in healthcare holds immense potential to transform the approach to disease diagnosis, treatment, and prevention. Within the realm of eye care, machine learning algorithms are being developed to assist in detecting, diagnosing, and managing various ocular conditions, including glaucoma, diabetic retinopathy, and age-related macular degeneration. A significant advantage of employing machine learning in eye care lies in its capability to swiftly and accurately analyse vast volumes of data. For instance, machine learning algorithms can examine fundus images of the eye to identify early indications of disease, such as alterations in the optic nerve or retinal blood vessels.

Another significant advantage is the capacity to enhance patient outcomes through the provision of personalized and precise care. Machine learning algorithms can be trained on extensive datasets to identify patterns and correlations in patient data, enabling more accurate diagnoses and treatment recommendations. Apart from diagnosis and treatment, machine learning can also optimize healthcare operations and resource distribution. For instance, algorithms can aid hospitals and clinics in optimizing scheduling, staffing, and resource allocation to improve patient outcomes while simultaneously reducing costs.

The main challenge in implementing machine learning in eye care is the need for high-quality and accurately labelled datasets. The availability of large and diverse datasets is critical to train machine learning algorithms and ensure their accuracy and generalizability. Furthermore, there are also concerns around data privacy and security when it comes to sharing sensitive patient data. Despite these challenges, the field of machine learning in eye care is rapidly advancing, with new models and techniques being developed and tested. In addition to fundus imaging, other imaging techniques such as optical coherence tomography (OCT) and visual field tests are also being explored for their potential in machine learning-based diagnosis and management of ocular diseases. IN summary, the application of machine learning in eye care has the potential to significantly improve the accuracy and efficiency of diagnosis and treatment of ocular diseases. By leveraging large datasets and advanced algorithms, machine learning can help healthcare providers deliver more personalized and precise care, ultimately improving patient outcomes and reducing healthcare costs.

1.6 Python for Machine Learning and its Libraries

Python has gained popularity as a programming language for machine learning owing to its user-friendly nature, simplicity, and extensive range of open-source libraries. These libraries offer readily available code snippets that enable the development of intricate machine learning models without the necessity of creating everything from scratch. Numerous well-known Python libraries exist for machine learning, including:

1. NumPy: Numpy is a library for numerical computations in Python. It provides a powerful N-dimensional array object, with functions for array manipulation, mathematical operations, and linear algebra.

2. PandasPandas is a widely used Python library that facilitates data manipulation and analysis tasks. It offers efficient data structures for storing and manipulating large datasets, along with a comprehensive set of functions for tasks such as data cleaning, merging, and reshaping. With Pandas, users can effectively manage and process data to extract meaningful insights from it.

3. Matplotlib: Matplotlib is a plotting library that provides a wide range of visualization options for data analysis. It allows users to create line plots, scatter plots, bar charts, histograms, and more.

4. Scikit-learn: Scikit-learn is a popular library for machine learning in Python. It provides a variety of algorithms for classification, regression, clustering, and dimensionality reduction, with tools for data preprocessing, model evaluation, and model selection.

5. TensorFlow: TensorFlow is a machine learning library that is open-source and has been developed by Google. It offers a range of tools and resources for constructing and training deep neural networks, as well as deploying models on various platforms, including mobile and web. TensorFlow is widely used in the machine learning community for its versatility and robustness.

6. Keras: Keras serves as a high-level application programming interface (API) that operates atop TensorFlow, enabling the construction of deep learning models. It offers a user-friendly interface for developing intricate neural networks and facilitates swift prototyping of novel models. Keras is renowned for its ability to streamline the process of building and experimenting with deep learning architectures.

1.7 Project Introduction

The project is a machine learning-based approach to automate the process of ocular disease detection from fundus images. The project utilizes the Convolutional Neural Network (CNN) architecture to classify different ocular diseases including diabetic retinopathy, age-related macular degeneration (AMD), glaucoma, and cataract. The objective of the project is to offer a cost-effective and automated solution for early identification and diagnosis of ocular diseases, aiming to prevent blindness and enhance patient outcomes. The implementation of the project entails utilizing the Python programming language alongside essential libraries such as Keras, TensorFlow, and OpenCV to develop a CNN model and perform pre-processing on fundus images. The dataset employed for training and evaluating the model comprises a collection of labeled fundus images obtained from individuals affected by diverse ocular diseases.

The CNN model proposed in this project comprises several convolutional and pooling layers, followed by a fully connected layer for classification purposes. Through training on the dataset, the model acquires the ability to discern distinctive features among various ocular diseases. Subsequently, its accuracy and performance are assessed using an independent test set. The project holds promise in terms of enhancing the efficiency and precision of ocular disease diagnosis, alleviating the workload on ophthalmologists, and ultimately enhancing patient outcomes.

1.8 Problem Statement

The problem statement for this project is to develop a deep learning model that can accurately detect multiple ocular diseases, including cataract, glaucoma, age-related macular degeneration, and diabetic retinopathy, from fundus images. The aim is to provide an automated and efficient way of detecting ocular diseases in early stages, which can aid in timely diagnosis and treatment, preventing blindness and improving the overall quality of life for patients. The challenge lies in developing a robust and accurate model that can handle the variability in the fundus images and effectively differentiate between the different ocular diseases.

1.9 Objectives of the Project

1. The objective is to create a Convolutional Neural Network (CNN)-based deep learning model capable of accurately identifying multiple ocular diseases from fundus images.

2. To increase the efficiency and speed of ocular disease diagnosis by providing an automated and accurate way of detecting ocular diseases in early stages.

3. The aim is to provide assistance in the prompt identification and treatment of ocular diseases, with the ultimate goal of preventing vision loss and enhancing the well-being of patients.

4. The aim is to develop a robust and accurate model that can handle the variability in the fundus images and effectively differentiate between the different ocular diseases.

5. The objective is to assess the performance of the developed model using suitable metrics and compare its effectiveness with existing methods and models utilized for detecting ocular diseases.

6. The goal is to create a user-friendly web application that integrates the developed model, allowing ophthalmologists to conveniently upload fundus images and receive automated disease diagnosis through an intuitive interface.

CHAPTER 2

LITERATURE SURVEY

A literature survey in a project is a section that allows various analysis of research made in the field of interest and the result which are already been published by considering various parameters of the project. It is the most important phase of the project as it gives direction for the implementation of the project. The detailed analysis of the methodologies and the techniques used by the researchers should be noted. This chapter describes the key features emphasized by the papers that have been surveyed.

2.1 Deep Learning for Ocular Disease Recognition: An Inner-Class Balance

The authors aim to address the challenge of imbalanced datasets in ocular disease classification and propose an approach to improve accuracy through inner-class balance.

The paper starts by introducing the problem of ocular disease recognition and the importance of accurate classification for effective diagnosis and treatment. The authors highlight the imbalanced nature of ocular disease datasets, where certain disease classes may have significantly fewer samples than others, leading to biased learning and reduced accuracy.

The authors suggest an inner-class balancing strategy to address this problem. They use transfer learning using the VGG-19 model after loading the dataset and associated pictures into the model. They seek to increase learning and classification accuracy by balancing the dataset to ensure an equal quantity of samples for each class.

The study conducts separate training on left and right eye images, leveraging the pre-trained VGG-19 model to capture the unique characteristics and patterns associated with each eye. Binary classifications are then performed using the trained models. The results demonstrate high accuracy rates for different disease classifications, including pathological myopia, cataract, and glaucoma, compared to normal cases.

2.2 Ocular Diseases Detection Using Recent Deep Learning Techniques

Jing et al. developed a CNN-based ensemble model to detect one or more ocular diseases in fundus images. Their approach makes use of transfer learning and ensemble learning strategies to overcome the issue of a small dataset. An Efficient Net model for feature extraction and neural networks for multi-label classification make up the model's two components. The model was tested using the ODIR dataset, and the findings revealed that the EfficientNetB3 outperformed other models and could perform well even with fewer data, with an accuracy of 90% and an AUC of 67%.

Junjun proposed a CNN-based multi-label ocular disease classification model to address the correlation between left and right eyes. They used a dense correlation network (DC Net) with three modules: feature extraction using ResNet CNNs, Spatial Correlation Module (SCM) for feature correlation, and classifier for classification and score generation. The model achieved the best performance with ResNet-101 for feature extraction and SCM, with an AUC of 92.7%.

In this proposed work, the focus is on studying recent deep learning architectures, implementing various data augmentation techniques and fine-tuning to increase the classification performance of multiple ocular diseases. The suggested model uses a bespoke multi-class classifier and the Inception-v3 deep learning architecture for feature extraction and tweaking. The model is trained and evaluated using fundus pictures for various ocular disorders from the publicly accessible EyePACS dataset. Several data augmentation strategies are used to enhance the model's performance. According to the experimental findings, the suggested model is 80% accurate in identifying four eye diseases: diabetic retinopathy, glaucoma, macular degeneration, and hypertensive retinopathy. The model performs better than existing techniques for the diagnosis of several eye disorders in terms of accuracy and F1 score. This proposed work can contribute towards the early detection and diagnosis of ocular diseases, which can help in timely treatment and prevention of vision loss.

2.3 Ocular Eye Disease Prediction Using Machine Learning

A Convolutional Neural Network (CNN) is a type of Deep Learning algorithm that can take in an image as input, identify different objects and features within the image, and distinguish between them. Compared to other classification algorithms, a ConvNet requires less pre-processing of the data. In traditional methods, the filters or features are hand- designed, but with ConvNets, the network can learn these features through training. The use of convolutional layers allows the network to effectively capture spatial and temporal information within the image. This results in a better fit to the image dataset, as the number of parameters involved is reduced, and the learned features can be reused.

The goal of the convolution operation is to extract significant features such as edges from the input image. ConvNets can have more than one convolution layer, with the first layer capturing low-level features such as edges, colors, and gradients, and additional layers learning higher-level features. The combination of Convolutional Layers and Pooling Layers forms each layer of the Convolutional Neural Network. Depending on the complexity of the images, the number of layers may be increased to capture more detailed low-level features, but this comes at the expense of more computational power.

2.4 Eye Disease Identification Using Deep Learning

The accurate diagnosis of eye diseases requires a thorough analysis of various symptoms and signs. In order to address this issue, we propose a novel approach that involves the use of digital image processing techniques such as segmentation and morphology, as well as deep learning methods such as convolutional neural networks (CNNs) to create an automated eye disease identification model that is based on visually observable symptoms.

Specifically, our proposed method focuses on the identification and categorization of four different eye diseases, namely crossed eyes, bulging eyes, cataracts, and uveitis and conjunctivitis. By utilizing advanced deep learning techniques, our model is able to detect these eye diseases accurately and quickly, which can aid in the early detection of eye disorders and prompt patients to seek out an ophthalmologist for further screening and treatment.

2.5 Ocular Disease Detection Using Advanced Neural Network Based Classification Algorithms

In this paper, the focus is on ocular disease detection using advanced neural network-based classification algorithms. The objective of the research is to explore the effectiveness of these algorithms in accurately identifying ocular diseases. The paper provides insights into the methodology employed for developing and implementing these algorithms. The findings of the study, along with their implications, are also discussed. Overall, the paper aims to contribute to the field of ocular disease detection by leveraging advanced neural network techniques.

The study focuses on developing and implementing these algorithms to achieve accurate detection results. The paper highlights the methodology used and presents the key findings of the research.

2.6 A Review of Deep Learning Methods Applied to Ocular Diseases Recognition and Detection

Artificial intelligence is revolutionizing many fields, including ophthalmology, by utilizing deep learning models to improve the detection of clinical signs and diagnosis of optical conditions. This has the potential to increase the accuracy of diagnoses and benefit a larger number of patients. Deep learning models have been applied primarily to eye fundus images and optic coherence tomography and have shown impressive performance in detecting conditions such as glaucoma, diabetic retinopathy, age-related macular degeneration, and diabetic macular degeneration. To facilitate the development of these models, international challenges have been held to provide large eye imaging datasets and expert annotations for segmentation and diagnosis. Moreover, these models are becoming more interpretable, thus providing clinicians with valuable information. This review summarizes the current state-of-the-art deep learning models used for ophthalmic images, datasets, and challenges in the field of optical diagnosis.

2.7 Detection of Ocular Diseases Using Ensemble of Deep Learning Models

Deep learning models have shown high competence in image processing and are used to detect diabetic retinopathy, glaucoma, and age-related macular degeneration, which are the primary causes of vision impairment and blindness in India. To address the issue of late detection of these diseases, an automated system is proposed using deep learning models to identify them in their early stages. The dataset used is augmented with data augmentation techniques to increase the amount of data available. VGG16, DenseNet201, and ResNet50 are applied to the dataset with various train-test split ratios, and an ensemble model is built using all three models. The ensemble model outperforms individual models in predicting fundus images and provides an accuracy of 72.8% for both 60-40% and 70-30% train-test splits. The proposed method is expected to aid in the early detection of ocular diseases, ultimately improving patient outcomes.

2.8 Optimized Convolution Neural Network Based Multiple Eye Disease Detection

The authors address the significance of early detection and accurate diagnosis of eye diseases to prevent vision loss. They propose the use of CNNs, a powerful deep learning technique, to automate the detection process and improve accuracy.

The study focuses on improving the accuracy and efficiency of disease detection by optimizing the CNN architecture. The authors propose a novel architecture that combines feature extraction, dimension reduction, and classification into a single network. The optimized CNN is trained using a large dataset of eye images and evaluated using performance metrics such as accuracy and sensitivity. The results demonstrate the effectiveness of the proposed approach in detecting multiple eye diseases with high accuracy.

The authors also address the issue of class imbalance in the dataset by employing a combination of oversampling and under sampling techniques. This helps to ensure that the CNN is trained on a balanced representation of different eye diseases, leading to improved detection performance. Additionally, the paper discusses the importance of preprocessing techniques such as image resizing and normalization for enhancing the performance of the CNN.

2.9 Machine Learning Technique for Detection of Ocular Disease

The study aims to develop an accurate and efficient system for identifying various eye diseases using machine learning algorithms.

The paper explores different machine learning techniques, including support vector machines (SVM), k-nearest neighbors (KNN), random forest (RF), and artificial neural networks (ANN). The authors discuss the preprocessing steps involved in preparing the ocular images, such as image enhancement and normalization. Feature extraction techniques are also employed to extract relevant information from the images.

With performance indicators including accuracy, precision, recall, and F1 score, the authors assess the effectiveness of the suggested machine learning models. The outcomes show that the machine learning method is very accurate and efficient in identifying eye disorders.

The proposed approach offers a promising solution for automated and reliable diagnosis, which can assist healthcare professionals in making informed decisions and providing timely treatment for patients with ocular diseases.

2.10 A Benchmark of Ocular Disease Intelligent Recognition: One Shot for Multi-Disease Detection

Early screening of ophthalmic diseases using fundus imaging is an effective and cost-efficient way to prevent blindness. However, manual diagnosis is time-consuming and may delay treatment due to a lack of medical resources. Deep learning techniques have shown promising results in diagnosing single ophthalmic diseases, but multi-disease diagnosis on binocular fundus images is more clinically relevant. To address this, a dataset containing 10,000 fundus images from 5,000 patients with eight ophthalmic diseases was created for benchmark experiments using state-of-the-art deep neural networks. Results showed that simply increasing the scale of the network did not improve multi-disease classification, and a well-structured feature fusion method was needed to combine the characteristics of multiple diseases. The goal of this work is to advance research in the field of ophthalmic disease diagnosis.

2.11 Very Deep Convolutional Networks for Large- Scale Image Recognition

This study focuses on convolutional network depth on image recognition accuracy at a large scale. This study uses small 3x3 convolution filters and finds that increasing the depth to 16-19 weight layers can significantly improve performance compared to prior approaches. The results of this study were used in the ImageNet Challenge 2014, where the team achieved first and second place in the classification and localization tracks. Additionally, the study demonstrates that the representations generated in this way can generalize well to other datasets and achieve state-of-the-art results. The two best-performing ConvNet models used in the study have been made publicly available to support further research in deep visual representations in computer vision.

Table 2.1 Literature Survey

Defined problems in papers	**Observations**
Balancing of Dataset	In this work, the dataset were balanced by utilising an equal amount of data for each class, and the VGG-19 model was used to train the classes. When the dataset was appropriately balanced, the accuracy of individual classes increased. After training, the work sought to determine the proper class. It demonstrates that each of those left and a right eye picture was trained separately using the pre-trained VGG-19 model.
Detection of one or more disease	Images of the fundus may reveal one or more diseases when used in an ensemble model based on convolutional neural networks (CNN). The process initially splits up each image's multilabel classification issue into two separate problems for each label. Second, transfer learning and ensemble learning strategies are used to overcome the issue of a limited dataset.

Pre-Handling in Conv Net compared to other grouping techniques.	This examines and contrasts the pre-handling strategies employed by Convolutional Neural Networks (Conv Nets) with alternative grouping strategies. It covers how pre-handling methods may improve Conv Nets performance by enhancing feature extraction and lowering overfitting. Examples include picture scaling, normalisation, and data augmentation. The results show how crucial these methods are for enhancing Conv Nets' functionality across a range of applications.
To accurately diagnose eye diseases	It is necessary to examine a variety of symptoms. We present a novel approach to provide an automated eye illness detection model utilising visually discernible symptoms, combining deep learning techniques like convolution neural network with digital image processing techniques like segmentation and morphology.
Early screening and diagnosis of ocular diseases	This study presents four deep learning-based models, including Resnet-34, EfficientNet, MobileNetV2, and VGG-16, trained on the ODIR dataset containing 5000 fundus images. These state-of-the-art image classification algorithms enable precise categorization of ocular tumors, leveraging the improved picture categorization abilities of deep learning.
Role of AI	Artificial intelligence is significantly influencing several fields of medicine, and ophthalmology is no exception. Deep literacy techniques have been effectively used, in instance, to identify clinical indicators and classify ocular diseases. In this work, the most recent deep literacy techniques employed in ophthalmic pictures, databases, and

	Implicit difficulties for optical opinion are discussed.
Usage of deep learning models	In this work, glaucoma, age-related macular degeneration (ARMD), and diabetic retinopathy (DR) are among the frequent eye disorders that are detected using four deep learning models. These models show extraordinary mastery of image processing operations. There is a recommendation to create an automated system using deep learning models for the early diagnosis of these eye conditions given that DR, glaucoma, and ARMD are the main causes of vision impairment and blindness in India.
Early detection and diagnosisof ocular disease	Four deep learning models utilized are excellent at processing images are used to identify glaucoma, age-related macular degeneration, and diabetic retinopathy (DR) (ARMD). In India, the main causes of vision loss and blindness are DR, glaucoma, and ARMD. For the purpose of identifying these eye disorders in their early stages, an automated system built using deep learning models is suggested.
Enabling a platform for the doctors and patients	In this work, we provide a platform that, via a base system, connects patients, medical devices, ophthalmologists, and intelligent eye disease analysis tools. By efficiently integrating discriminative data from a different domain and combining pre-learned SVM (Support Vector Machine) classifier at the same time, our system is able to train the quick prediction model. The platform supports an integrated ecosystem that makes it possible to screen for and monitor eye diseases in an effective and affordable manner.

Ophthalmologists usually give diagnoses of multi-disease on binocular fundus image.	Ophthalmologists frequently diagnose multiple diseases during fundus screening, so we released a dataset with eight diseases to better reflect the real medical environment. This dataset contains 10,000 fundus images from both eyes of 5,000 patients and contains information on eight different diseases. We used several cutting-edge deep neural networks to conduct benchmark studies on it. We discovered that just expanding the network's size would not produce satisfactory results for classifying several diseases.
Effect of the convolutional network depth on its accuracy in the large- scale image recognition setting.	In this study, we examine how the convolutional network's depth affects its accuracy in the context of large-scale picture recognition. Our key contribution is a detailed analysis of networks with increasing depth utilising an architecture with extremely tiny (3 3) convolution filters, which demonstrates that raising the depth to 16–19 weight layers may significantly outperform existing setups.
Black box phenomenon	First off, DL algorithms are difficult to describe in terms of ophthalmology. This is the "black box phenomenon," which may eventually cause physicians to embrace this technology less readily. In reality, "who is liable to suffer the legal repercussions of an adverse event owing to an erroneous forecast given by an artificial intelligence algorithm? If a machine thinks similarly to a human ophthalmologist who may make errors? These extremely complicated medical legal problems are still pending.

The early identification of ocular disease	In this research, we suggested a method for automatically diagnosing OD, where detection is carried out in two phases. The Mobile Net architecture is utilised for feature extraction since users of smartphones and iPhones without home computers may use it. Other architectures like VGG and RESNET are slower than the one being utilised.
To examine the anomalies related to diseases that affect the eye.	The monitoring and identification of different ophthalmological illnesses depends heavily on a fundus picture. Using ensemble neural architectures, this article suggests a unique Multi-Disease Classification Framework (MDCF). The first job in the suggested approach is to preprocess the dataset using techniques like contrast enhancement, oversampling, scaling, and normalisation.
Retinal pathologies are the most common cause of childhood blindness	It is vital and crucial to diagnose illnesses quickly and automatically in order to lighten the strain of ophthalmologists. Ophthalmologists use direct or indirect vision of the eye and its surrounding tissues to diagnose disorders using pattern recognition. Due to its reliance on the fundus of the eye and its inspection, the application of deep learning algorithms in the area of ophthalmology is suitable. We first examine the various characteristics of lesions and outline the basic procedures of data processing. Then, we determine the hardware and software required to implement deep learning solutions. Finally, we look at the experimental concepts used to assess the different approaches.

Doctor-patient ratio	The doctor-patient ratio in India is 1:10,000 according to research. In both industrialized and developing nations, diabetic retinopathy, which is the primary cause of blindness among individuals of working age, is mostly brought on by a person's diabetes. In this article, automated methods for detecting diabetic eye illness are systematically reviewed from a number of angles, including I datasets that are currently accessible, ii) picture pre-processing methods, iii) deep learning models, and iv) performance assessment metrics.
Early diagnosis of eye diseases is essential to prevent irreversible vision loss.	In this study, the classification of fundus pictures into cataract, glaucoma, and retinal disorders is the main objective. In a number of issues including illness categorization, the Convolution Neural Network-Recurrent Neural Networks (CNNRNN) model has shown to be successful.
Recent Tele Medicine Emergence	The major objective is to give them better care at a reduced cost. People in metropolitan locations can still manage an eye exam, but it gets more challenging for those in rural areas. Due to the widespread use of mobile phones throughout the nation, telemedicine is now possible.
Speedy diagnosis of eye disease	The objective of this work is to create a comprehensive framework for storing diagnostic data in an international standard format to facilitate the prediction of eye illness diagnosis based on symptoms utilising decision tree algorithms, such as cataract, glaucoma, and retinal.

CHAPTER 3

DESIGN AND METHODOLOGY

Systems design is the process of defining the architecture, modules, interfaces, and data for a system to satisfy specified requirements. Systems design could be seen as the application of systems theory to product development. There is some overlap with the disciplines of systems analysis, systems architecture and systems engineering. If the broader topic of product development "blends the perspective of marketing, design, and manufacturing into a single approach to product development," then design is the act of taking the marketing information and creating the design of the product to be manufactured.

Systems design is therefore the process of defining and developing systems to satisfy specified requirements of the user.System Design focuses on how to accomplish the objective of Design Document is a required document for every project. It Should include a high- level description of why Design Document has been created, provide what the new system is intended for or is intended to replace and contain detailed descriptions of the architecture and system components of based on the user requirements and the detailed analysis of the existing system, the new system must be designed. It is the most crucial phase in the developments of a system. System design is the phase that bridges the gap between problem domain and the existing system in a manageable way.

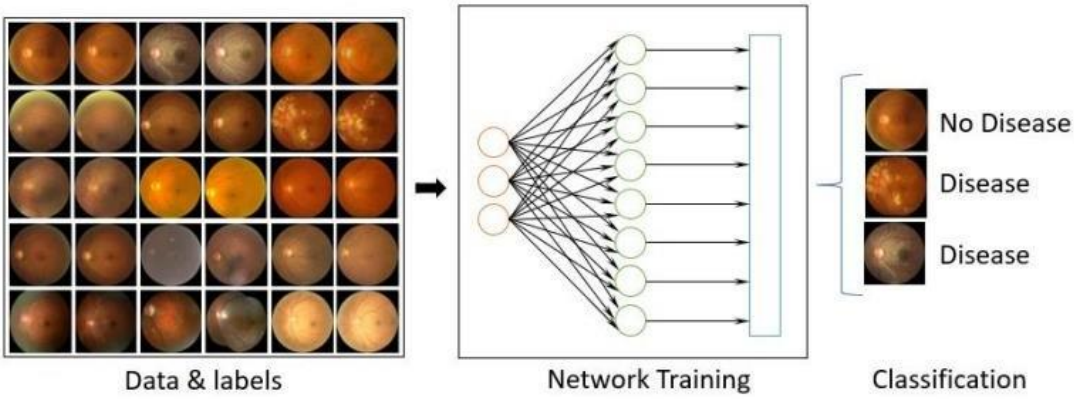


Figure 3.1 Design

3.1 System Architecture

Architecture for ocular disease detection using CNN consists of several components. The first component involves the acquisition of fundus images of the eye, which are then pre-processed using maximum entropy transformation to enhance the image quality. The pre-processed images are then fed into a convolutional neural network (CNN) for feature extraction. The CNN is optimized using a flower pollination optimization algorithm (FPOA) to improve its speed and accuracy.

The output of the CNN is then passed on to a multiclass support vector machine (MSVM) classifier for disease classification. The proposed CNN-based multiple disease detection (CNN-MDD) system is tested using an online dataset, the Ocular Disease Intelligent Recognition (ODIR) dataset. The performance of the CNN-MDD system is evaluated in terms of precision, accuracy, specificity, recall, and F1 score, which are compared to other optimized models.

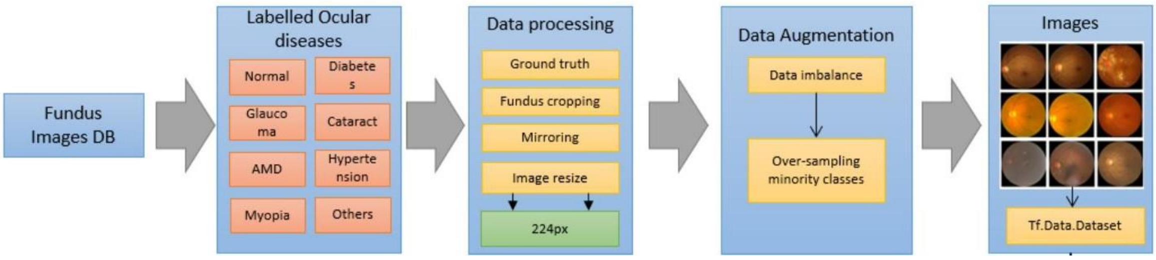


Figure 3.2 System Architecture to obtain images

Architecture for ocular disease detection using CNN typically involves the following steps:

1. Image Acquisition: The first step is to acquire retinal fundus images using an ophthalmic camera. These images are then pre-processed to enhance their quality and remove any artifacts or noise.

2. Image Augmentation: The next step is to augment the images by applying various transformations, such as rotation, scaling, and flipping, to increase the diversity of the dataset.

3. Convolutional Neural Network (CNN): The pre-processed and augmented images are then fed into a CNN. The CNN consists of multiple layers of convolutional and pooling operations that extract features from the images. The final output is a vector of probabilities that indicates the likelihood of each class.

4. Training and Optimization: The convolutional neural network (CNN) is trained using a sizable dataset of annotated images. To optimize the network's performance, the weights of the CNN are adjusted using an optimization algorithm, such as stochastic gradient descent (SGD). The goal of this optimization process is to minimize the loss function, which measures the discrepancy between the predicted outputs of the CNN and the actual labels of the images. By iteratively updating the network's weights based on the gradient of the loss function, the CNN learns to make more accurate predictions over time.

5. Validation and Testing: The trained CNN is then validated on a separate dataset to ensure that it is not overfitting to the training data. Finally, the performance of the CNN istested on a test dataset to evaluate its accuracy in detecting ocular diseases.

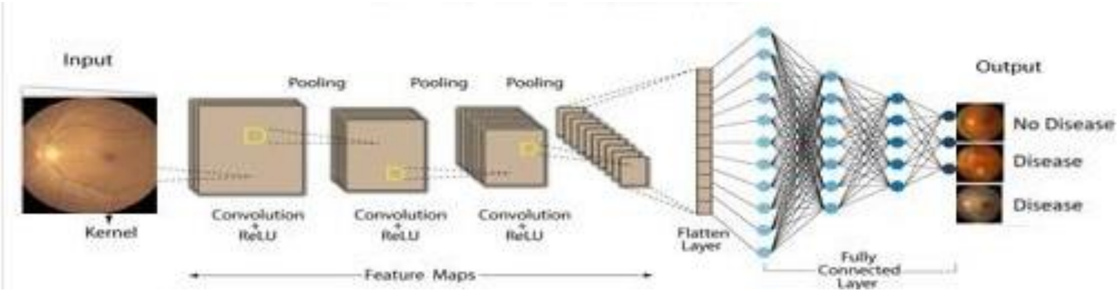


Figure 3.3 CNN Architecture

In this image, we can see that the pre-processed and augmented retinal fundus images are fed into a CNN, which consists of multiple convolutional and pooling layers. The output of the CNN is then flattened and fed into a fully connected layer, which produces the final output of probabilities for each class. The weights of the network are optimized using an optimization algorithm, such as stochastic gradient descent (SGD), and the performance of the CNN is evaluated on a test dataset.

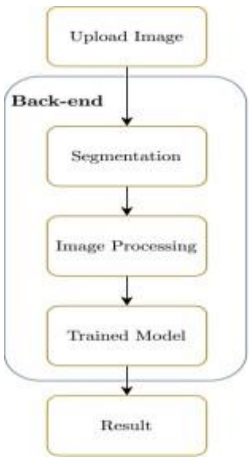


Figure 3.4 Proposed Model

CHAPTER 4

SYSTEM REQUIREMENTS SPECIFICATION

Hardware:

- Processor: 1GHz or faster
- Memory: 4GB or above
- A high-performance CPU and GPU are needed to train the CNN effectively. The CPU is used for pre-processing, data management, and model evaluation, while the GPU is used for training the CNN due to the massive parallelism required.

Software:

- Several software tools and libraries are needed to develop and train the CNN model. These include an image processing library, deep learning frameworks such as TensorFlow or PyTorch, and a programming language such as Python.

Pre-processing tools:

- Various pre-processing techniques may be required to prepare the dataset for training the CNN model, including image normalization, resizing, and augmentation.

Training parameters:

- The CNN model's hyper parameters, such as learning rate, number of epochs, batch size, and optimizer, must be selected appropriately to ensure optimal performance.

Evaluation metrics:

- Standard metrics such as accuracy, precision, recall, and F1 score can be used to evaluate the performance of the CNN model.

Functional Requirements:

- Should be able to access and process retinal fundus images.
- Should be able to perform pre-processing of images using maximum entropy transformation.

- Should be able to extract features using a convolutional neural network (CNN) optimized with the flower pollination optimization algorithm (FPOA).
- Should be able to optimize hyper parameters using FPOA for training the CNN.
- Should be able to classify the type of disease using a Multiclass Support Vector Machine (MSVM) classifier.
- Should be able to automatically detect the type of disease from retinal fundus images.

Non-functional Requirements:

- Should have a user-friendly interface for medical professionals to interact with.
- Should be scalable to accommodate large datasets of retinal fundus images.
- Should have a high level of accuracy and performance in disease detection.
- Should be secure and protect patient data privacy.
- Should have a fast response time to enable timely diagnosis and treatment of ocular diseases.

CHAPTER 5

IMPLEMENTATION

The implementation of this project involves several steps, including:

Data Collection: The first step is to collect a dataset of retinal fundus images with corresponding labels indicating the presence or absence of various ocular diseases.

Data Pre-processing: The collected data is then pre-processed by resizing the images to a fixed size, normalizing the pixel values, and augmenting the data to increase the size of the dataset.

Training and Validation Split: The pre-processed data is then split into training and validation sets to train and evaluate the CNN model.

Model Architecture: A CNN model is designed with multiple convolutional and pooling layers to extract features from the input images.

Training the Model: The model is trained on the training dataset using backpropagation algorithm with a suitable loss function and optimizer.

Hyper parameter Tuning: The hyper parameters of the CNN model, such as learning rate, number of epochs, batch size, etc., are tuned to optimize the model's performance.

Model Evaluation: The trained CNN model is evaluated on the validation dataset to measure its accuracy, precision, recall, and F1 score.

Testing: Finally, the trained model is used to predict the presence or absence of ocular diseases in new retinal fundus images.

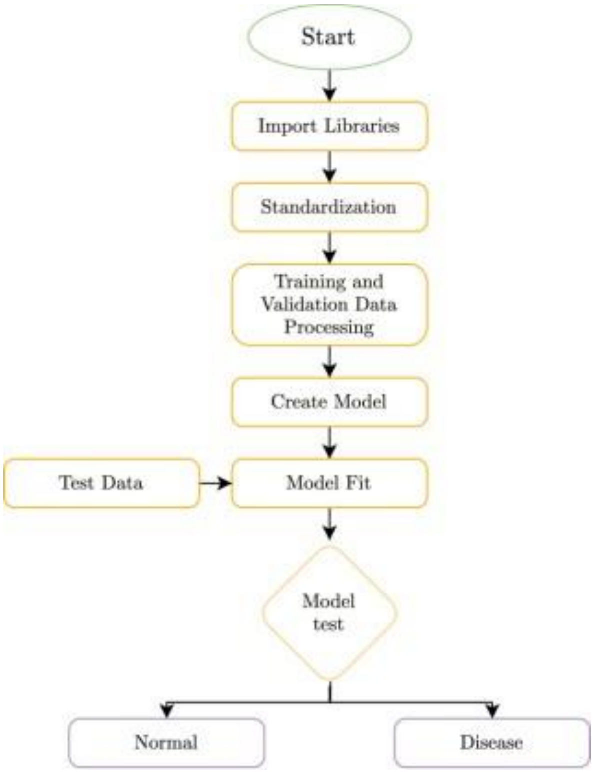


Figure 5.1 Software Flow Diagram

5.1 Data Collection

Fundus image data can be collected using various types of cameras, including handheld, tabletop, and slit-lamp cameras. These cameras are specially designed to capture high-resolution images of the fundus, which is the interior surface of the eye that includes the retina, optic disc, macula, and blood vessels. Fundus cameras use different imaging technologies, such as traditional film photography, digital photography, and scanning laser ophthalmoscopy (SLO). In digital photography, the camera captures the image and stores it in a digital format, which can be easily transferred to a computer or other device for analysis. In SLO, a laser beam is used to scan the fundus, and the reflected light is used to create an image.

Fundus images can be collected from patients with or without dilating eye drops, although dilating drops may be necessary to obtain a clear image of the fundus. The images are typically taken by a trained ophthalmic photographer or technician and can be reviewed by an ophthalmologist or other medical professional for diagnosis and treatment of ocular diseases. In recent years, automated fundus imaging systems have also been developed, which use artificial intelligence algorithms to analyse the images and detect ocular diseases.

5.2 Dataset

The Ocular Disease Intelligent Recognition (ODIR) system was employed in this investigation to gather the data. The ODIR challenge is a structured ophthalmic dataset of 5,000 patients including age, color fundus images of the left and right eyes, and doctors' diagnostic keywords that Shanggong Medical Technology Co., Ltd. has gathered from various hospitals and medical facilities in China. There are a total of 6,392 photos in this competition, with 2,873 of them being normal, 1,608 of them being diabetic, 284 of them being glaucoma, 293 of them being cataracts, 266 of them being age-related macular degeneration, 128 of them being hypertension, 232 of them being pathological myopia. The six eye disorders in our studies were Normal, Glaucoma, Cataract, Age Related Macular Degeneration, Hypertension, and Pathological Myopia. We worked on scenarios 6 and 8 of ocular diseases. Figure displays several sample pictures.

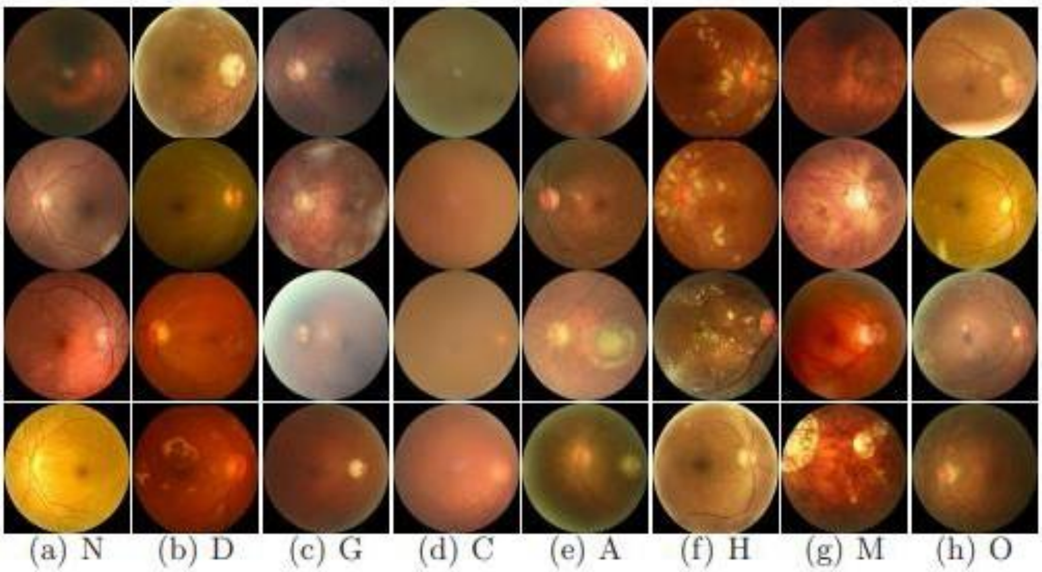


Figure 5.2 Images from each categories. Each column of images comes from the same category, i.e. Normal (N), DR (D), Glaucoma (G), Cataract (C), AMD (A), Hypertension (H), Myopia (M), and Others (O).

5.3 Data Pre-processing

Initially, TensorFlow dataset objects were used to resize images while the model was being trained. This strategy, nevertheless, turned out to be ineffective, resulting in sluggish training with epochs lasting up to 15 minutes. To fix this, a separate function that resizes photographs before constructing the TensorFlow dataset was developed. This makes resizing a one-time operation and saves the scaled data in a distinct location. Following a number of tests, it was found that scaling pictures to 250x250 pixels offered a reasonable compromise between training speed and accuracy metrics, and this size was used for subsequent tests.

The data presented a problem in labelling the photos.csv file because the labels applied to both eyes as a whole, even if each eye may have a separate ailment. To fix this, a mapping between diagnostic keywords and illness labels was made to enrich the dataset, ensuring that each eye was given the correct name. Images containing annotations that had nothing to do with the particular condition were eliminated. By replacing the picture files with letters denoting the various illnesses, label information was included. File renaming has shown to be a quick process, and labelled files may be used to construct TensorFlow datasets by extracting the label information from the file names.

Given the short dataset, the validation set was made by randomly choosing 30% of the available photos, assuring representative data for testing the model without adding bias.

Minority classes in the training set were subjected to data augmentation procedures in order to balance the dataset. Techniques including random zooming, rotating, and flipping the horizontal and vertical directions were used. Before building the TensorFlow dataset object, data augmentation was done with the use of programmes like OpenCV. Contrast-limited adaptive histogram equalisation (CLAHE) was a possibility for picture enhancement, but it was eventually rejected because of the considerable noise it added.

The tf.data API was used to generate the TensorFlow dataset object. The tf.data is offered by this API.Abstraction of a dataset that represents a list of items, where each element is made up of one or more components. A training example containing image and label tensor components corresponds to an element in the image pipeline. 32 batches were used as the batch size to reduce overfitting. In order to ensure that the model learns from a variety of examples, the dataset was additionally shuffled using the shuffling dataset feature, which randomly chooses components from a buffer.

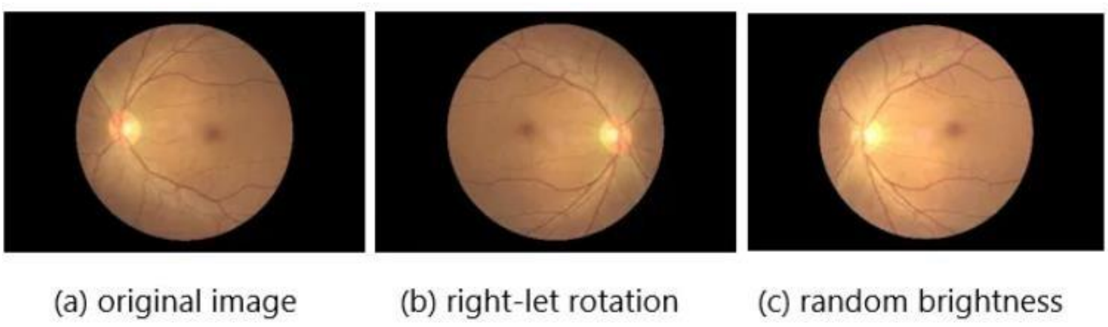


Figure 5.3 Exemplary data augmentation results

5.4 Building Convolution Neural Network

A CNN architecture for ocular disease detection typically involves a more detailed design to capture specific features and patterns relevant to ocular diseases. Here is a more comprehensive description of CNN architecture for ocular disease detection:

1. Input Layer: The input layer receives the image data, which is typically a grayscale or color image of the eye. The size of the input image may vary depending on the specific dataset or application.

2. Convolutional Layers: The convolutional layers consist of multiple filters or kernels that convolve over the input image, extracting local features. Each filter performs element-wise multiplications and summations to produce a feature map. The number of filters in each convolutional layer determines the depth of the feature maps.

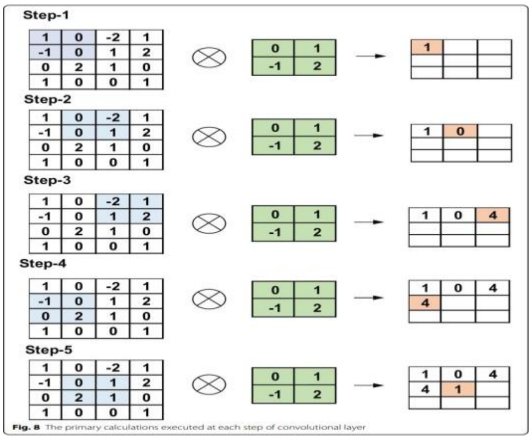


Figure 5.4 CNN Operations

3. Activation Function: After each convolutional layer, an activation function like ReLU (Rectified Linear Unit) is applied element-wise to introduce non-linearity. This helps the network learn complex and non-linear relationships between the input image and the extracted features.

4. Pooling Layers: Pooling layers are typically inserted after the activation function to downsample the feature maps and reduce the spatial dimensions. Max pooling is a common choice, where the maximum value in each pooling window is selected as the representative value for that region. This helps in achieving spatial invariance and reducing the computational complexity.

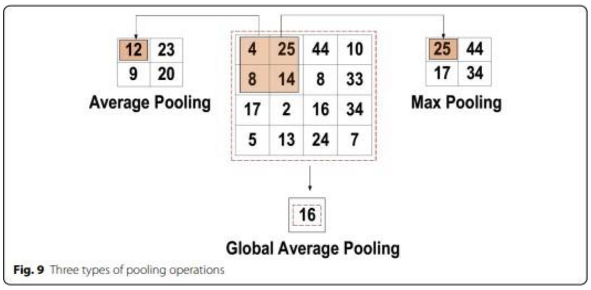


Figure 5.5 Pooling operations

5. Additional Convolutional and Pooling Layers: The above steps of convolution, activation, and pooling are repeated multiple times to capture increasingly abstract and complex features. Deeper layers can learn more global and high-level representations.

6. Dropout: To prevent overfitting and improve generalization, dropout regularization method can be used. Dropout randomly sets a fraction of the neuron outputs in the previous layer to zero during training, which forces the network to learn redundant representations and reduces inter-dependencies between neurons.

7. Flatten Layer: After the convolutional and pooling layers, a flatten layer is used to reshape the output into a one-dimensional vector. This prepares the data for the fully connected layers.

8. Fully Connected Layers: These layers connect every neuron from the previous layer to every neuron in the subsequent layer, learning higher-level representations. The fully connected layers typically have a decreasing number of neurons to reduce the computational complexity. Activation functions like ReLU or sigmoid can be applied to each neuron.

9. Output Layer: The number of neurons in the final, fully connected layer of neural network topologies is often equal to the number of classes or illnesses to be recognised. Depending on the particular issue being treated, the activation function for the output layer is chosen. Class probabilities are typically generated using the softmax activation function in multi-class classification applications. The network provides probabilities for each class, indicating the chance that an input belongs to each, by using softmax activation.

10. Training: The network is trained using a labeled dataset through a process called backpropagation. The weights and biases of the network are adjusted iteratively using optimization techniques such as gradient descent, minimizing a defined loss function. The

training dataset is split into training and validation sets to monitor the model's performance and prevent overfitting.

11. <u>Evaluation</u>: Once trained, the model can be evaluated on a separate test dataset to assess its performance and generalization ability. Metrics such as accuracy, precision, recall, and F1 score can be used to evaluate the model's performance in detecting ocular diseases.

5.5 Snippet Code for CNN Model

```
IMG_SIZE = 50
LR = 1e-3
MODEL_NAME = 'odir-{}-{}.model'.format(LR, '2conv-basic')


1 usage
def label_img(img):
    df = pd.read_csv('df.csv')[['filename','target']].set_index('filename
    return eval(df.loc[img][0])

1 usage
def create_train_data():
    training_data = []Z
    for img in tqdm(os.listdir(TRAIN_DIR)):
        label = label_img(img)
        print('##############')
        print(label)
        path = os.path.join(TRAIN_DIR,img)
        print(path)
        img = cv2.imread(path,cv2.IMREAD_COLOR)
        img = cv2.resize(img, (IMG_SIZE,IMG_SIZE))
        #img = cv2.resize(img,None,fx=0.5,fy=0.5)
        training_data.append([np.array(img),np.array(label)])
    shuffle(training_data)
    np.save('train_data.npy', training_data)
    return training_data
```

Figure 5.5 Training module

```python
def process_test_data():
    testing_data = []
    for img in tqdm(os.listdir(TEST_DIR)):
        path = os.path.join(TEST_DIR,img)
        img_num = img.split('_')[0]
        print(img_num)
        img = cv2.imread(path,cv2.IMREAD_COLOR)
        img = cv2.resize(img, (IMG_SIZE,IMG_SIZE))
        testing_data.append([np.array(img), img_num])

    shuffle(testing_data)
    np.save('test_data.npy', testing_data)
    return testing_data
```

Figure 5.6 Testing module

```python
convnet = max_pool_2d(convnet, 3)

convnet = conv_2d(convnet, 32, 3, activation='relu')
convnet = max_pool_2d(convnet, 3)

convnet = conv_2d(convnet, 64, 3, activation='relu')
convnet = max_pool_2d(convnet, 3)

convnet = fully_connected(convnet, 1024, activation='relu')
convnet = dropout(convnet, 0.8)

convnet = fully_connected(convnet, 8, activation='softmax')
convnet = regression(convnet, optimizer='adam', learning_rate=LR, loss='ca

model = tflearn.DNN(convnet, tensorboard_dir='log')

if os.path.exists('{}.meta'.format(MODEL_NAME)):
    model.load(MODEL_NAME)
    print('model loaded!')

train = train_data[:-1]
test = train_data[:-10]

X = np.array([i[0] for i in train]).reshape(-1,IMG_SIZE,IMG_SIZE,3)
Y = [i[1] for i in train]
print(X.shape)
test_x = np.array([i[0] for i in test]).reshape(-1,IMG_SIZE,IMG_SIZE,3)
test_y = [i[1] for i in test]
print(test_x.shape)
```

Figure 5.7 CNN Model Creation

5.6 Code Snippet for Web Application

```
import shutil
import os
import sys
import json
import math
from PIL import Image
from flask import Flask, render_template, request
import cv2  # working with, mainly resizing, images
import numpy as np  # dealing with arrays
import os  # dealing with directories
from random import shuffle  # mixing up or currently ordered data that mig
from tqdm import \
    tqdm  # a nice pretty percentage bar for tasks. Thanks to viewer Danie
import tflearn
from tflearn.layers.conv import conv_2d, max_pool_2d
from tflearn.layers.core import input_data, dropout, fully_connected
from tflearn.layers.estimator import regression
import tensorflow as tf
import matplotlib.pyplot as plt
from PIL import ImageTk, Image

# global b
app = Flask(__name__)
@app.route('/')
def index():
    return render_template('index.html')

@app.route('/cnn', methods=['GET', 'POST'])
def cnn():
    if request.method == 'POST':
        dirPath = "E:\\Ocular Disease Recognition\\static\\images"
        fileList = os.listdir(dirPath)
        for fileName in fileList:
            os.remove(dirPath + "\\" + fileName)
        fileName=request.form['filename']
        dst = "E:\\Ocular Disease Recognition\\static\\images"

        shutil.copy("E:\\Ocular Disease Recognition\\test\\"+fileName, dst

        verify_dir = 'E:\\Ocular Disease Recognition\\static\\images'
        IMG_SIZE = 50
        LR = 1e-3
        MODEL_NAME = 'odir-{}-{}.model'.format(LR, '2conv-basic')
    ##    MODEL_NAME='keras_model.h5'
        def process_verify_data():
            verifying_data = []
            for img in tqdm(os.listdir(verify_dir)):
                path = os.path.join(verify_dir, img)
                img_num = img.split('-')[0]
                img = cv2.imread(path, cv2.IMREAD_COLOR)
```

```
convnet = input_data(shape=[None, IMG_SIZE, IMG_SIZE, 3], name='i

convnet = conv_2d(convnet, 32, 3, activation='relu')
convnet = max_pool_2d(convnet, 3)

convnet = conv_2d(convnet, 64, 3, activation='relu')
convnet = max_pool_2d(convnet, 3)

convnet = conv_2d(convnet, 128, 3, activation='relu')
convnet = max_pool_2d(convnet, 3)

convnet = conv_2d(convnet, 32, 3, activation='relu')
convnet = max_pool_2d(convnet, 3)

convnet = conv_2d(convnet, 64, 3, activation='relu')
convnet = max_pool_2d(convnet, 3)

convnet = fully_connected(convnet, 1024, activation='relu')
convnet = dropout(convnet, 0.8)

convnet = fully_connected(convnet, 8, activation='softmax')
convnet = regression(convnet, optimizer='adam', learning_rate=LR,

model = tflearn.DNN(convnet, tensorboard_dir='log')

if os.path.exists('{}.meta'.format(MODEL_NAME)):
    model.load(MODEL_NAME)
    print('model loaded!')
```

Figure 5.8 Home Routes and CNN Routes

CHAPTER 6

TESTING

Software testing is a process conducted to assess the quality of a software product or service and provide stakeholders with relevant information. It offers an unbiased perspective to the business, enabling them to understand and mitigate potential risks associated with software implementation. One of the test procedures involves executing a program or application with the aim of identifying any errors or issues. Testing is an iterative process because when a defect is rectified, it may reveal further failures caused by deeper flaws or even introduce new ones. product testing can give users or sponsors unbiased, independent information regarding the caliber of the product and the danger of its failure. As soon as there is executable software (even if it is only half developed), testing may begin. When and how testing is done are frequently dictated by the general strategy used to software development.

6.1 Testing Methods

Black-box Testing: is a software testing technique where the tester is unaware of the internal structure, design, or implementation details of the system being tested. The examiner does not possess knowledge about the framework and does not have access to the source code.. Usually, while performing this, the tester can interact with the device's user interface, presenting the input and checking the output without knowing where and how it is installed.

White-box Testing: is a software testing method where the tester has knowledge of the internal structure, design, and implementation details of the system being tested. In order to conduct a white box test, the tester must understand the internal functionality of the code within the application. To check which unit/part of code behaves incorrectly, the tester will look inside the source code.

6.1.1 Manual and Automation Testing

Manual Testing:

Software faults are checked manually for during manual testing. In order to assure proper behavior, it calls for the tester to assume the position of an end user and make use of the majority of the application's capabilities.

It is evaluated based on the software requirements. To perform Manual Testing, following steps are performed

1. Read and comprehend the project documents and instructions. Additionally, if accessible, review the Application Under Test (AUT).
2. Create test cases that address all of the documentation's requirements.
3. With the team lead and the client (if relevant), go through and baseline the test cases.
4. Execute the test cases on the AUT
5. Report bugs.
6. Once bugs are fixed, again execute the failing test cases to verify they pass.

Automation Testing:

Automation testing, also known as test automation, involves the execution of a test case suite using specialized software tools designed for automation. This approach aims to reduce the need for manual testing by automating various tasks, such as generating comprehensive test reports, comparing expected and actual results, and injecting test data into the System Under Test. Implementing software test automation requires significant investments in terms of finances and resources. However, the objective of automation is not to entirely replace manual testing but to minimize the number of test cases that need manual execution. The automation process follows a series of steps for successful implementation.

1. Test Tool Selection
2. Define scope of Automation
3. Planning, Design and Development
4. Test Execution
5. Maintenance

6.1.2 Unit Testing

Individual software modules or components are checked as part of a form of software testing known as unit testing. The goal is to confirm that each piece of software code operates as intended. Developers do unit testing when creating an application (the coding phase). Unit tests isolate a specific piece of code and validate its accuracy. An singular function, method, process, module, or object might be considered a unit.

Best Unit Testing Practices:

- Independent unit test cases are ideal. Unit test cases shouldn't be impacted by improvements or changes to the requirements.
- One code at a time only.
- Use naming standards for your unit tests that are clear and consistent.
- Before modifying the implementation of any module after making a code change, make sure the module has a corresponding unit Test Case and passes the tests.
- Use a "test as your code" philosophy. You have to examine more pathways for faults the more code you write without testing.

Table 6.1 UTC Cataract Detection

TEST CASE	**UTC-1**
TEST NAME	CATARACT DETECTION
ITEMS BEING TESTED	FUNDUS IMAGE
SAMPLE	IMAGE
EXPECTED OUTPUT	DISEASE NAME (CATRACT)
ACTUAL OUTPUT	DISEASE NAME (CATRACT)
REMARKS	PASS

Table 6.2 UTC Normal Detection

TEST CASE	**UTC-2**
TEST NAME	NORMAL DETECTION
ITEMS BEING TESTED	FUNDUS IMAGE
SAMPLE	IMAGE
EXPECTED OUTPUT	NORMAL

ACTUAL OUTPUT	NORMAL
REMARKS	PASS

Table 6.3 UTC Myopia Disease Detection

TEST CASE	**UTC-3**
TEST NAME	MYOPIA DISEASE DETECTION
ITEMS BEING TESTED	FUNDUS IMAGE
SAMPLE	IMAGE
EXPECTED OUTPUT	MYOPIA
ACTUAL OUTPUT	MYOPIA
REMARKS	PASS

Table 6.4 UTC Age Related Macular Degeneration Disease Detection

TEST CASE	**UTC-4**
TEST NAME	ARM DISEASE DETECTION
ITEMS BEING TESTED	FUNDUS IMAGE
SAMPLE	IMAGE
EXPECTED OUTPUT	ARM
ACTUAL OUTPUT	ARM
REMARKS	PASS

Table 6.5 UTC Abnormalities Disease Detection

TEST CASE	**UTC-5**
TEST NAME	ABNORMALITIES DETECTION
ITEMS BEING TESTED	FUNDUS IMAGE
SAMPLE	IMAGE
EXPECTED OUTPUT	ABNORMALITIES
ACTUAL OUTPUT	ABNORMALITIES
REMARKS	PASS

CHAPTER 7

RESULTS

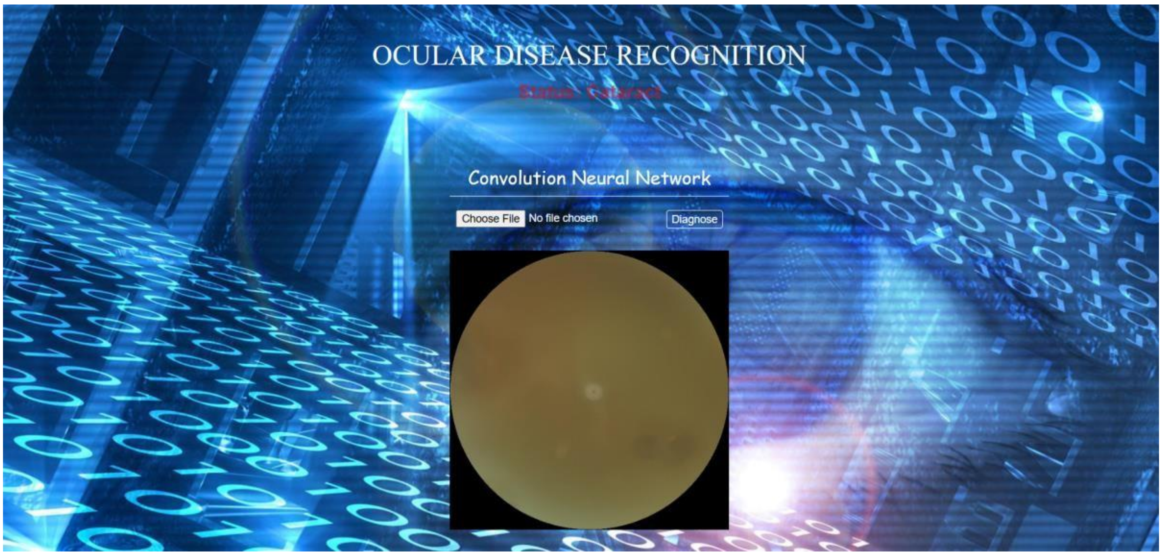


Figure 7.1 Cataract

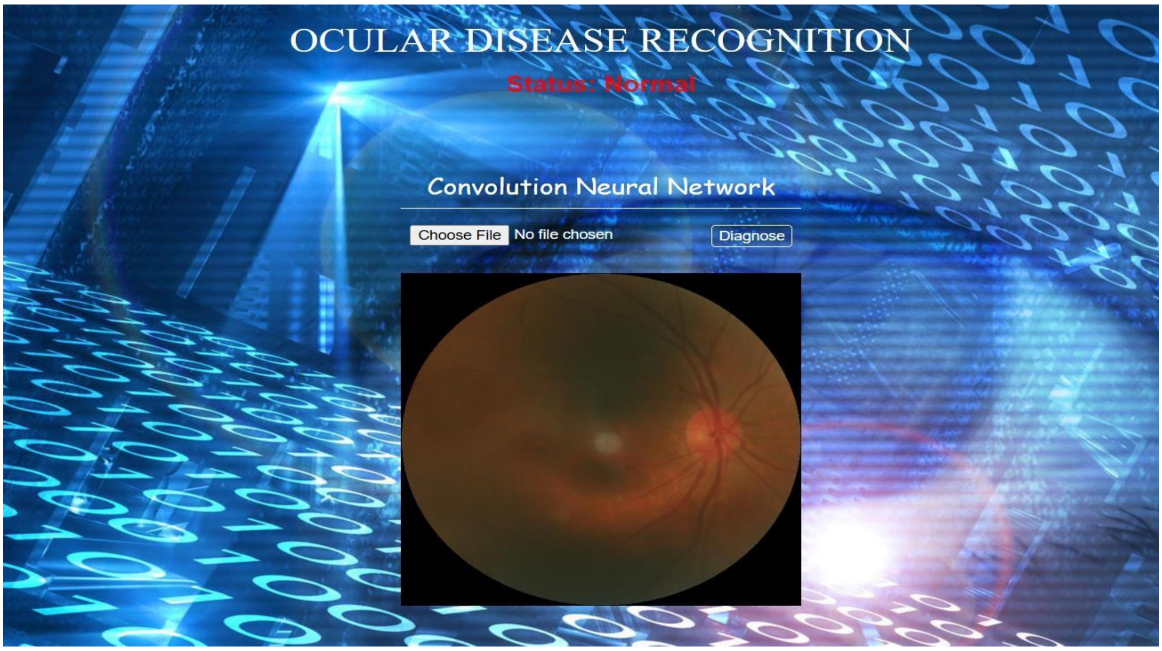


Figure 7.2 Normal

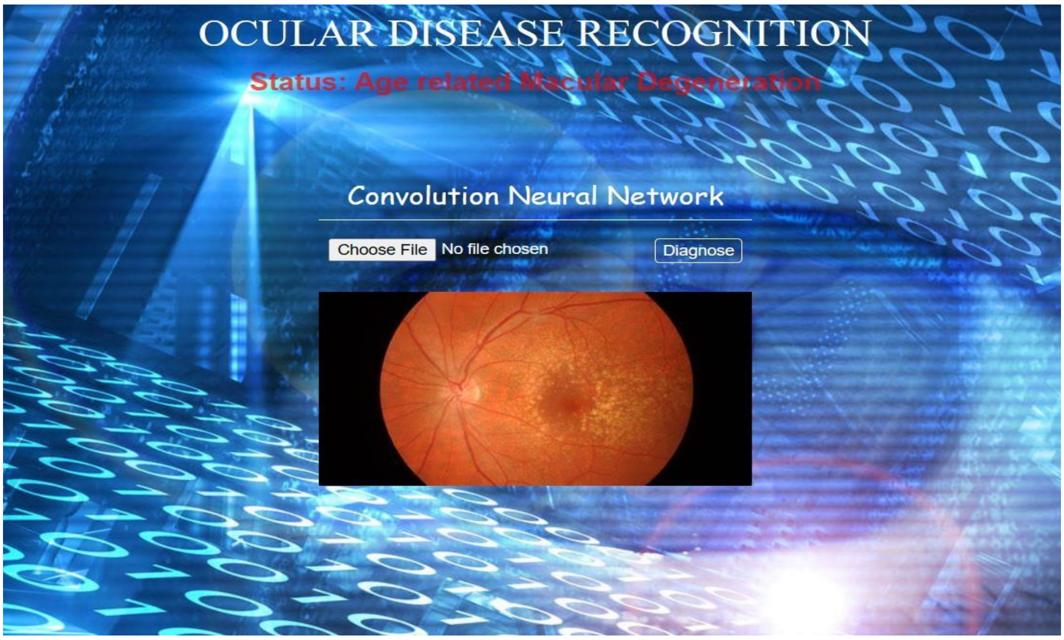


Figure 7.3 Age Related Macular Degeneration

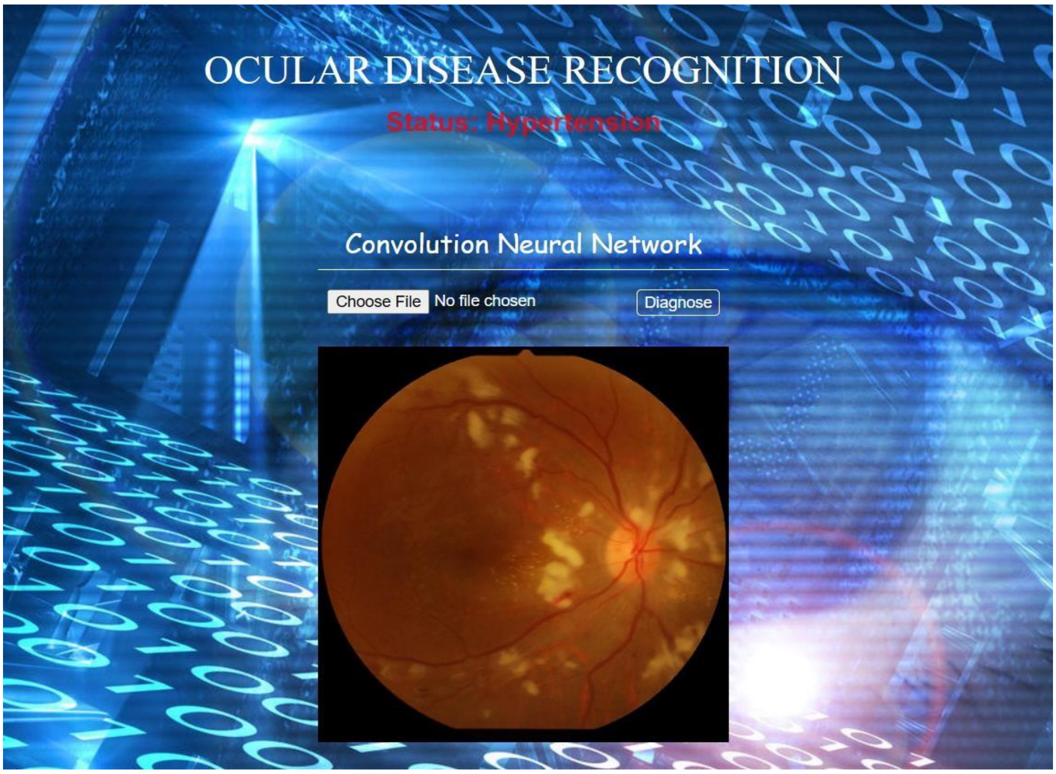


Figure 7.4 Hypertension

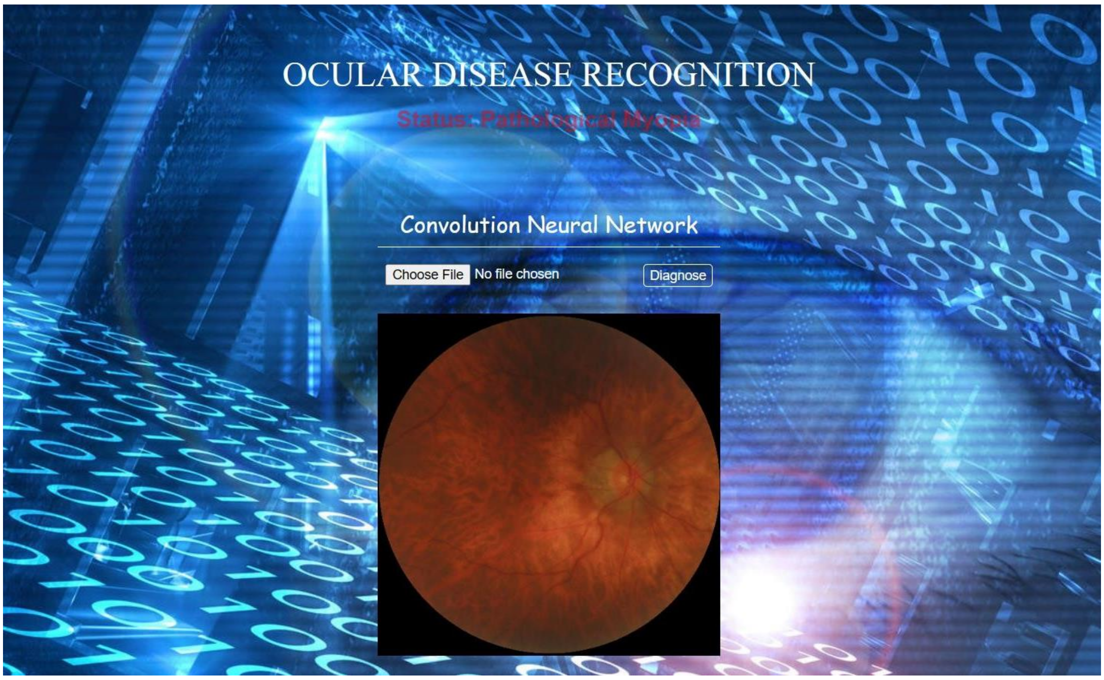


Figure 7.5 Myopia

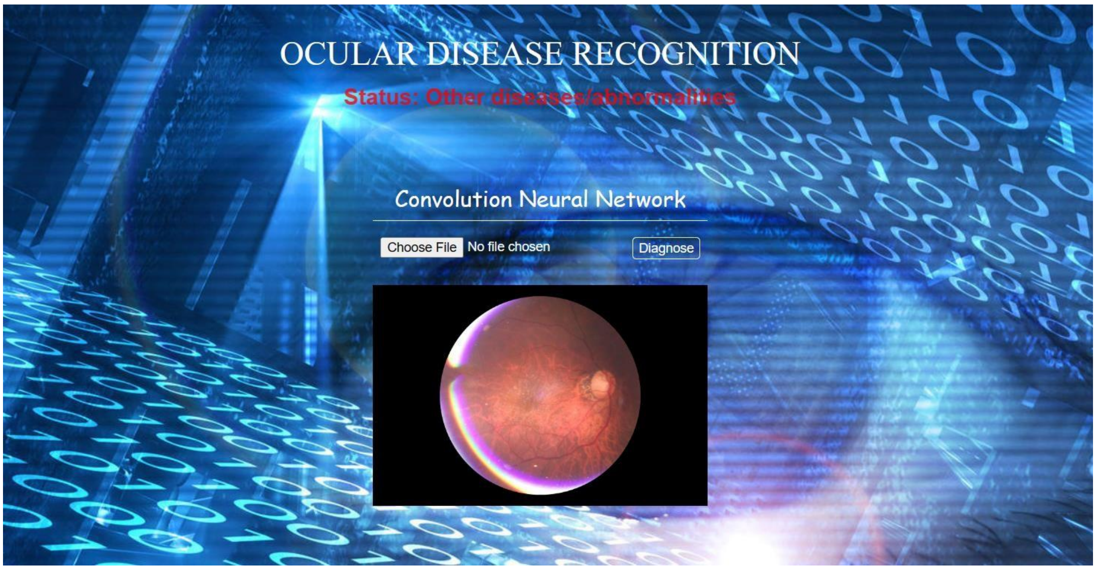


Figure 7.6 Other abnormalities

CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT

8.1 Conclusion

In conclusion, CNNs have shown great potential for ocular disease detection, with high accuracy rates in identifying various diseases, such as diabetic retinopathy, glaucoma, and age-related macular degeneration. The ability of CNNs to automatically extract relevant features without human supervision has made them an ideal choice for processing medical images. Additionally, the use of transfer learning techniques and data augmentation methods has shown promising results in improving the performance of CNNs for ocular disease detection.

However, there are still some challenges and future enhancements that can be made to improve the accuracy and efficiency of CNNs for ocular disease detection. One of the major challenges is the limited availability of labelled medical images, which can affect the performance of the CNNs. The development of more extensive and diverse datasets would help improve the accuracy of CNNs for ocular disease detection.

Another challenge is the interpretability of CNNs, as they can sometimes be regarded as black boxes due to their complex architecture. The development of techniques to explain the reasoning behind the CNNs' predictions would help to increase their acceptance and trust in the medical community.

8.2 Future Enhancements

In terms of future enhancements, the integration of other imaging modalities, such as optical coherence tomography (OCT) and fundus auto fluorescence (FAF), can further improve the accuracy of CNNs for ocular disease detection. The use of multi-modal CNNs can help in the early detection of ocular diseases, which can lead to timely intervention and better patient outcomes.

In addition, there is a need for more diverse datasets that include a wider range of ocular diseases and different populations, to ensure that the CNN models are accurate and effective for all patient groups.

CHAPTER 9

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