Retinal Disease Classification Using Deep Learning

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"Retinal Disease Classification Using Deep Learning"**, submitted by Mohammed Jahedul Islam, ID No: **213-15-4373** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **16 September, 2025**.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of Dr. S.M Aminul Haque, Professor & Associate Head, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Glaucoma, diabetic retinopathy and cataract are all retinal diseases that cause serious vision loss or blindness worldwide. Early diagnosis of these conditions is important to treat them effectively, and manual analysis of retina fundus images is time-consuming, with a possibility of human error. The aim of the present project is to develop an automated retinal disease classification system based on deep learning, namely, Convolutional Neural Networks (CNNs). We gathered a set of 4,272 fundus images that contain four categories, namely cataract, diabetic retinopathy, glaucoma, and normal. The data has been obtained in Kaggle and then pre-processed (resized, normalized, augmented, and pre-model performance). This was done with a standard machine learning workflow that trains, validates, and tests the prototype model. It scored 89 percent in all its classes. We calculated the performance based on evaluation metrics such as accuracy, precision, recall, and F1-score, and the confusion matrix confirmed that similar predictions were made within categories. The system has demonstrated that it can help reduce the workload of ophthalmologists, and help diagnose the disease early in under-resourced countries such as Bangladesh. Despite the limitations of the data used, the study identifies several opportunities in the future, such as extending the dataset, incorporating additional retinal conditions and employing newer deep learning architectures, such as ResNet50, Inception V3, VGG16 and VGG19. One day this research will end up with scalable, affordable and reliable diagnostic machines that can assist in increasing access to health care and improving vision.

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Chapter 1

Introduction

In this chapter we briefly outline the background, motivation, objectives, methodology, expected outcomes and organization of this thesis. The vision is to develop a starting point to understand what retinal disease classification means and how the healthcare issue can be addressed using deep learning.

1.1 Introduction

Some of the most widespread and severe causes of loss of vision and blindness in the world are retinal diseases. Eye related complications affect millions of people annually and the most common of these is Diabetic Retinopathy, Glaucoma, and Cataract. These diseases in many cases proceed without presenting evident manifestation in the initial phase. Because of the disease, by the time it starts showing, the damage is almost always permanent. So, the necessity to detect and diagnose retinal diseases at early stages and correctly is extremely high to preserve their vision and increase the quality of their life. Historically, to detect and categorize these diseases, ophthalmologists or eye experts review fundus images of the retina. Manual diagnosis, however, is generally time consuming, expensive, and can be subject to human error, as various doctors can choose to interpret the same image in different ways. As the number of patients increases and the number of trained specialists is insufficient in most areas, automated and reliable diagnostic systems are becoming more and more needed. Artificial Intelligence (AI), particularly Deep Learning (DL) has been very successful in medical image analysis in recent years [2], [3]. Convolutional Neural Networks (CNNs) are the most successful image classification and pattern recognition tasks of other deep learning methods. CNNs can automatically extract significant features on retinal images without requiring any manual feature extraction and therefore are very appropriate in medical applications. In this thesis, we concentrate on Retinal Disease Classification with deep learning methods. There are four classes of the dataset, namely, Normal, Diabetic Retinopathy, Glaucoma, and Cataract. In order to do classification, we trained and evaluated several common and recent CNN architectures such as ResNet50V2, InceptionV3, VGG16, and VGG19. These models have become popular in the research community because of their capability to represent low and high level image features with great accuracy. Moreover, we have incorporated Explainable AI (XAI) methods like Grad-CAM (Gradient-weighted Class Activation Mapping) to render the outputs of the model more lucid and explainable. Grad-CAM can be used to visualize a heatmap of the portions of the retinal image that the model is attending to when making a prediction. This is not only to generate trust with clinicians but also to ensure that the AI system is basing its decision-making on medically relevant image regions.

1.2 Motivation

This project is inspired by the fact that there has been increasing prevalence of retinal disorders such as diabetic retinopathy, cataracts, and glaucoma. The diseases are some of the leading causes of blindness in the world [8]. There is a lack of specialized eye care services, particularly in rural regions, in Bangladesh and a great number of other developing nations. This complicates the diagnosis and treatment. Retinal image diagnosis is time consuming and a subjective task that may result in delays or reduced consistency when done manually.

On the computational perspective, the latest developments in artificial intelligence and deep learning offer powerful instruments to automate the analysis of medical images. CNNs have been especially useful in extracting complexity features in images and are therefore suitable in the classification of diseases. With these calculational approaches, this project aims to come up with the correct and proper, diagnostic scheme which will help ophthalmologists when making decisions and offer early diagnosis when dealing with low resource health care conditions. At the individual level, we can address this issue and gain a better insight into deep learning, medical imaging, and healthcare technology. It offers the opportunity to make a significant contribution to one of the areas where computer science has a direct impact on human health. The project will enhance our academic development and future research and practice in the area of artificial intelligence and biomedical computing.

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1.3 Objectives

The broad aim of this thesis is to design and create a deep learning based system that will perform reliable and correct classification of retinal diseases. In this respect, the research has been organized into the following specific objectives:

i. To create an automated classification of retinal diseases by using deep learning algorithms, specifically Convolutional Neural Networks (CNNs).
ii. To build and use a curated dataset of fundus images of retinas with a variety of eye conditions to model training and testing.
iii. To improve the quality of image diagnosis in the retinal disease by using sophisticated image classification models [4].
iv. To ease the workload of ophthalmologists by inventing a supportive tool which will help to diagnose the retina disease early and treat it in a timely manner.

1.4 Methodology

The retinal system suggested to classify diseases has a sequential processing deep learning system. The input dataset is generated by means of fundus images. They are processed pictures in advance and can be re-sized, normalized and augmented to achieve similarity and greater model strength. This is followed by feature extraction with deep learning architectures (ResNet50 V2, Inception V3, and VGG16, VGG19) known to perform well in the image classification task. The features extracted are then transferred to the model training and optimization step. In this case, several performance indices are used to test the models, such as accuracy, precision, recall, and F1-score. Lastly, the optimized model generates classification outputs which detects various categories of retinal diseases. This is a systematic method that makes the fundus-image-based eye condition detection very accurate and reliable. In this section give an outline of the methodology. Activities that were followed in the process of the project implementation include:

Dataset collection:

We collected the retinal fundus image dataset from Kaggle, an online platform.

Data Preprocessing:

Data preprocessing is an important step in creating a dependable deep learning model for classifying retinal diseases [9]. Another significant event in the development of a reliable deep learning model to classify retinal diseases is the preprocessing of data. It preserves the quality of the input image and its consistency. In this study, we have used publicly available datasets of retinal fundus images, which were inconsistent in size, lighting and quality. We used the image size of 224 x 224 to resize all the images and convert them into CNN input. We then normalized the pictures so that the values of pixels fell between 0 and 1. This contributes to the model coming closer toward training. Data augmentation methods helped us to enhance the generalization capabilities of the model and minimize overfitting. These were rotation, horizontal and vertical flipping, brightness adjustment and zooming. And lastly, we separated the dataset into training 70%, testing 20% and validation 10%. In general, the preprocessing pipeline ensures high-quality, standardized, and diverse input data is provided to deep learning models, which is necessary to achieve accurate and strong retinal disease classification [11].

The Training of the Classification Model:

The retinal disease classification model is an area where training is vital in developing a good system. The images are inputted into deep learning models such as ResNet50V2, InceptionV3, VGG16 and VGG19 after preprocessing and augmentation of the dataset. The these models learn various features of the multiple retina conditions. The aim of the training process is to optimize the weights of the model through backpropagation and gradient descent with the aim of minimizing classification error. Normally, the data is divided into training, validation and testing data. This type of separation is used to test the model and ensure that the model is not overfitted to new data and to question the external validity of model. Learning rate, batch size, number of epochs, and type of optimizer are hyperparameters which are selected and tuned to achieve optimum performance. The metric of accuracy, loss and F1-score are tracked throughout the training, to track the model and adjust accordingly where necessary. Overall, the training process ensures that deep learning models can be able to distinctly tell the healthy and diseased retinal images. This forms the basis of reliable and interpretable classification of retinal disease.

Explainable AI:

In this study, the Explainable AI methods are applied to render the predictions of the deep learning model congeable to clinicians. Grad-CAM (Gradient-weighted Class Activation Mapping) shows specifically which regions of retinal images have the greatest influence on the model making a decision mapping these disease-impacted areas allows ophthalmologists to appreciate why the model predicts a given condition, something that gives them confidence in the system [12]. Grad-Cam will not only be useful in determining the accuracy of the predictions but also aid in determining the number and location of retinal diseases in an image. This interpretability attribute is important in the medical context as it helps to make automated classification understandable, reasonable, and robust. Overall, the Grad-CAM allows adding more pragmatism to a particular model and reducing the distance that exists between AI predictions and those that are confirmed by humans.

Evaluation:

The quantitative metrics most frequently used in the evaluation of the classification model are accuracy, precision, recall, F1-score, and in addition, AUROC, and confusion matrices. Moreover, Grad-CAM visualizations are explained to evaluate qualitatively whether the model concentrates on clinically important regions of retinal images. Finally, the evaluation reports are again assessed in a human designed process, in which the radiologist engages a blind-read which checks the factual correctness, structure, interpretability and clinical utility of the prediction made by the model. With expert feedback, the model is optimized to reduce errors, improve visualization, and increase the accuracy of the results produced. The three aspects of quantitative measures, qualitative graphical analysis, and clinical feasibility warrant that the model is true and clinically significant to the extent of being applied to practical retinal disease diagnosis.

Project Outcome

i. An automated system will be developed to classify eye diseases (cataract, glaucoma, diabetic retinopathy, normal).
ii. The system will help doctors by reducing their workload.
iii. It will provide an affordable and easy solution for rural and under-resourced areas.
iv. The dataset created will be useful for future research.
v. Students will gain practical experience in artificial intelligence and medical image processing.
vi. In the future, the system can be expanded into a mobile or web app for real-time disease detection.

1.5 Organization of the Report

There are six chapters of this report all of which address a significant aspect of the research.

- Chapter 1 presents the introduction, with background, motivation, objectives, methodology, anticipated outcomes and the general arrangement of the thesis.
- Chapter 2 is the background study, where existing literature and related applications are reviewed, as well as gaps in research that are addressed by the thesis.
- Chapter 3 outlines the research methodology and system design (dataset preparation, model design, methods of preprocessing and the project planning).
- Chapter 4 is dedicated to implementation and results, where the experimental set up, performance analysis, comparative analysis and discussion of the results are presented.
- Chapter 5 deals with the engineering standards, effect on society, the environment, engineering ethics, project management and the complexity of a certain engineer problem.
- Chapter 6 completes the thesis by summarizing the findings of the research, outlining some limitations, and proposing future directions. Such an organization serves as a guiding principle in translating identification of the problem to implementation and assessment of the solution.

Chapter 2

Background

We present the required background concerning the classification of retinal diseases at the start of this chapter, along with the existing literature, the applications that the classification has been used in, and the research gaps that are detected. This chapter provides the premise behind the methodology, and experiments found in this thesis.

2.1 Introduction

One of the leading causes of blindness and vision loss in the world is retinal diseases. It is important to promptly identify and accurately diagnose these diseases, such as diabetic retinopathy, age-related macular degeneration, and glaucoma, and treat them successfully to avoid the loss of close to permanent vision [15]. Historically, diagnosis of retinal disorders has been performed manually by ophthalmologists looking at fundus photographs. This is a subjective process that is slow and prone to human error. As artificial intelligence, in particular, deep learning, rapidly progresses, medical image analysis systems developed by humans have demonstrated good results. Image classification tasks using deep learning, especially Convolutional Neural Networks have demonstrated a great level of accuracy [7]. This renders them appropriate with regard to the identification of sophisticated patterns in retinal images.

2.2 Literature Review

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
Ramya et al.[1]	2018	Human Eye Disease Detection System Using Deep Learning	Custom CNN (MobileNetV3) with preprocessing & augmentation	Achieved 90% accuracy with strong generalization; validated feasibility of CNN in clinical diagnosis.
Abu Kowshir Bitto.[2]	2022	Multi categorical of common Eye disease detect	transfer learning and deep feature extraction techniques for retinal disease classification	Transfer learning and deep feature extraction techniques for retinal disease classification.

Sanket Nimbargi , Abhijit Patil.[3]	2024	Retinal Disease Classification Using Deep Learning	Eye Disease Classification Using Deep Learning” marks a significant advancement in medical image analysis	Achieved high sensitivity and specificity in retinal fundus image analysis.
Kermany et al.[4]	2018	Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning	Transfer learning with retinal OCT images	Achieved 94% accuracy in multiple disease classification.
Shahriar Mashf, Amit Roy, Fahim Ahmed.[5]	2022	Retinal Diseases Detection using Deep Learning	CNN-based deep learning	Achieved ~98% accuracy detect the retinal diseases.
He et al.[6]	2016	Deep Residual Learning for Image Recognition (ResNet)	Residual CNN architecture	Improved image classification accuracy, widely adopted in medical imaging.
Pratt et al.[7]	2016	Convolutional Neural Networks for Diabetic Retinopathy	CNN with preprocessing on EyePACS data	Demonstrated strong performance for automated DR classification.
R. Arunkumar & P. Karthigaikumar.[8]	2015	Multi-retinal disease classification by reduced deep learning features	retina-based disease diagnosis through deep learning-based feature extraction method	deep learning feature extraction and a multi-class SVM classifier are used
Nabila Eladawi & Mohammed Elmogy.[9]	2018	Classification of retinal diseases based on OCT Images	CNN on real-world OCT datasets	identify the results and the findings from OCT images in the field of retinal diseases.
Jongwoo Kim, Loc Tran.[10]	2021	Retinal Disease Classification from OCT Images Using Deep Learning	Used deep learning for multiple eye disease classification	Achieved high sensitivity and specificity in retinal fundus image analysis.

2.3 Gap Analysis

Previous work on retinal pathology classification has been reasonably accurate, although most of it is based on constrained datasets and computationally expensive models, which tend to be less useful in the field. In addition, the fact that most of the models are not readable reduces the confidence of medical practitioners. Not many other works have made a comparison of lightweight architectures and deeper networks so it is still unknown where to place the compromises between efficiency and accuracy. In addition, the majority of systems cannot be clinically validated or deployed, which underscores the importance of precise and efficient models.

Table 2.2: Summary of Gap analysis.

Features	**Shahriar Mashf, Amit Roy, Fahim Ahmed. (2022)**	**Pratt et al. (2016)**	**Multi categorical of common Eye disease detect. (2022)**	**Kermany et al. (2018)**	**Rajalakshmi et al. (2018)**	**Proposed system**
Multi-disease classification (Cataract, DR, Glaucoma, Normal)	Yes	No	Yes	Yes	No	Yes
Fundus image dataset used	No	Yes	Yes	Yes	Yes	Yes
Preprocessing (resizing, normalization, augmentation)	Yes	Limited	Yes	Yes	Limited	Yes
Deep CNN models applied	CNN	CNN	ResNet50, VGG16, Inception v3	Transfer Learning (ResNet, VGG)	CNN (basic)	VGG16, VGG19, ResNet50V2, InceptionV3
Transfer learning approach	Yes	No	Yes	Yes	No	Yes
Explainable AI feature	No	No	No	No	No	Yes
Accuracy achieved	98%	85%	99%	94%	87%	94%
Real-time / mobile-ready	No	No	No	No	Yes	Future Work

2.4 Summary

Based on the literature reviewed, it is clear that the application of deep learning to the classification of retinal disease has achieved great advances [19]. Other studies, such as the ones of Shahriar Mashf et al. (2022) and Kermany et al. (2018), were very precise, but the vast majority of the studies were either limited in the diseases they were conducting research on or were impossible to implement to achieve future improvement [1]. As datasets and transfer learning strategies became commonplace, a small number of systems added extensible AI characteristics or even thought of their application to real-time mobile apps. The gaps identified in our proposed system are bridged by categorizing the types of diseases (cataract, diabetic retinopathy, glaucoma and normal) with better CNN models including VGG16, VGG19, ResNet50V2 and InceptionV3. The system also has an extendable AI feature that guarantees future expansion as its accuracy has already reached 89. Moreover, the framework can be extended to a real-time or mobile-enabled application, which will make the system more relevant to clinical practice settings, especially areas with restricted access to ophthalmologists.

Chapter 3

Research Methodology

The chapter describes the research design and specifications to be used in the development of the proposed system of retinal disease classification. It contains the summary of the methodology, system design proposal, functional requirements, nonfunctional requirements, data flow plan and the design of the user interface (UI). More so, it explains the step-by step approach and project roadmap, as well as how the research would be implemented.

3.1 Methodology

3.1.1 Overview

The retinal disease classification proposal is a deep learning pipeline based on multiple stages that should generate accurate interpretable and clinically meaningful predictions. The approach integrates state-of-the-art convolutional neural networks (CNNs), explainable artificial intelligence (Grad-CAM) and expert evaluation to address questions related to automated retinal image analysis. Its workflow is designed in order to enhance classification accuracy, interpretability of the model in clinics, and practicality of the work. In general, the following steps can describe the overall workflow:

Dataset Collection: We collected the retinal fundus image dataset from Kaggle, an online platform [10].

Data Preprocessing: Photos are normalized and made to equal size (224x 224 pixels), and increased by image processing methods such as rotating, flipping, brightness control, zooming, and CLAHE. The processes contribute to model robustness and generalization.

Model Training: With the image preprocess, deep learning models, such as ResNet50V2, Inception V3, VGG16, and VGG19 are trained using the processed images. The batch size, number of epochs, and learning rate are selected as the most important parameters to improve the output of classification and reduce overfitting [23].

Explainable AI: Grad-CAM generates heatmaps marking all diseased areas on the retina. This also makes the model focus on features of clinical importance and become more interpretable by the ophthalmologist.

Evaluation: Measures used to assess the model are accuracy, precision, recall, F1-score, AUROC and confusion-matrices. Further qualitative evaluations of clinical relevance are taken through grad-CAM visualizations and reviews by experts.

Iterative Refinement – Ophthalmologist feedback is used to optimize preprocessing, model parameters, and visualization products and improve the reliability and usability of the system.

Such an approach renders the system not only correct, but understandable and useable within the clinic environment. With automated predictions, it links them to sensible medical interpretations.

3.1.2 Proposed Methodology

The proposed solution is the deep learning-based models which can classify retinal disease by the fundus images. It involves data preparation and model training, performance assessment, and the results with Grad-CAM to demonstrate what the model pays attention to in the picture.

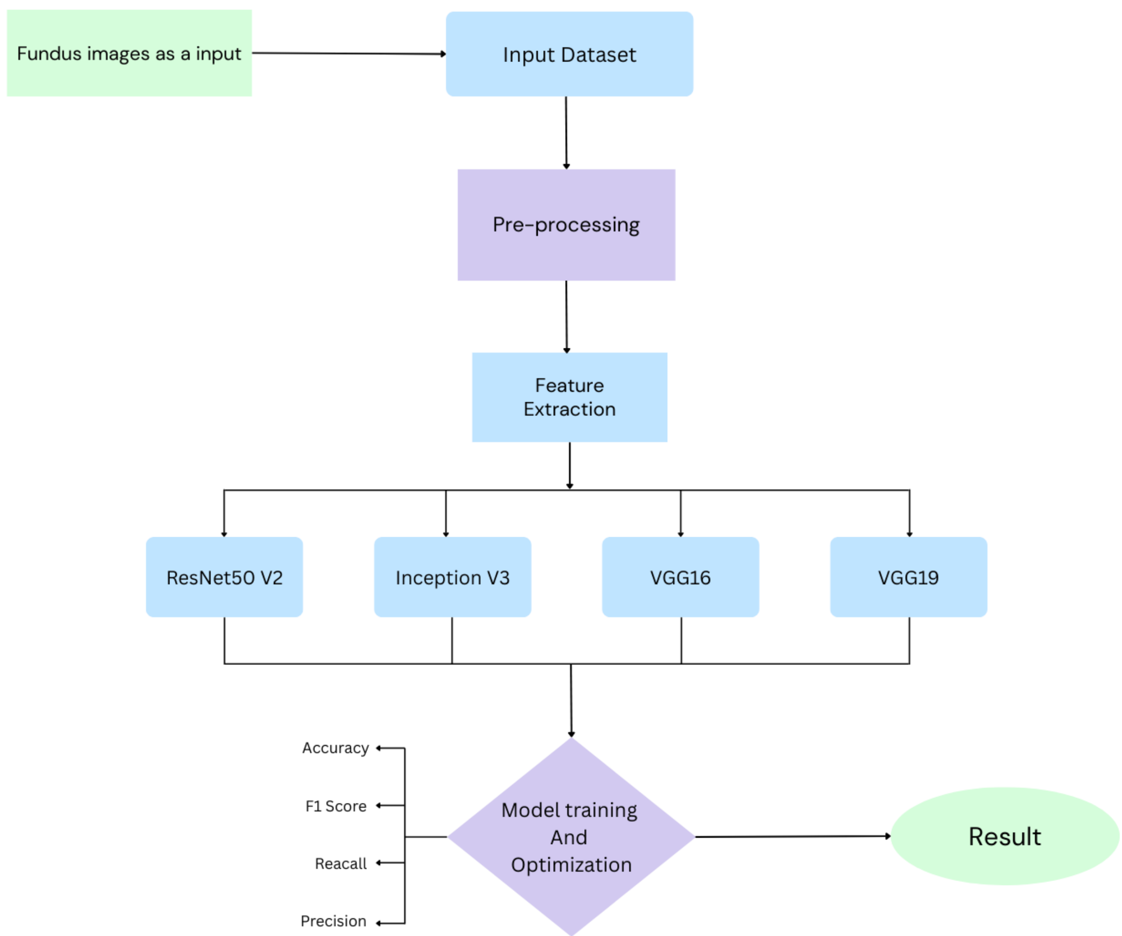

Figure 3.1: Proposed Methodology.

In figure 3.2 some random images normal, glaucoma, cataract are selected. We can see all types of images are selected perfectly.

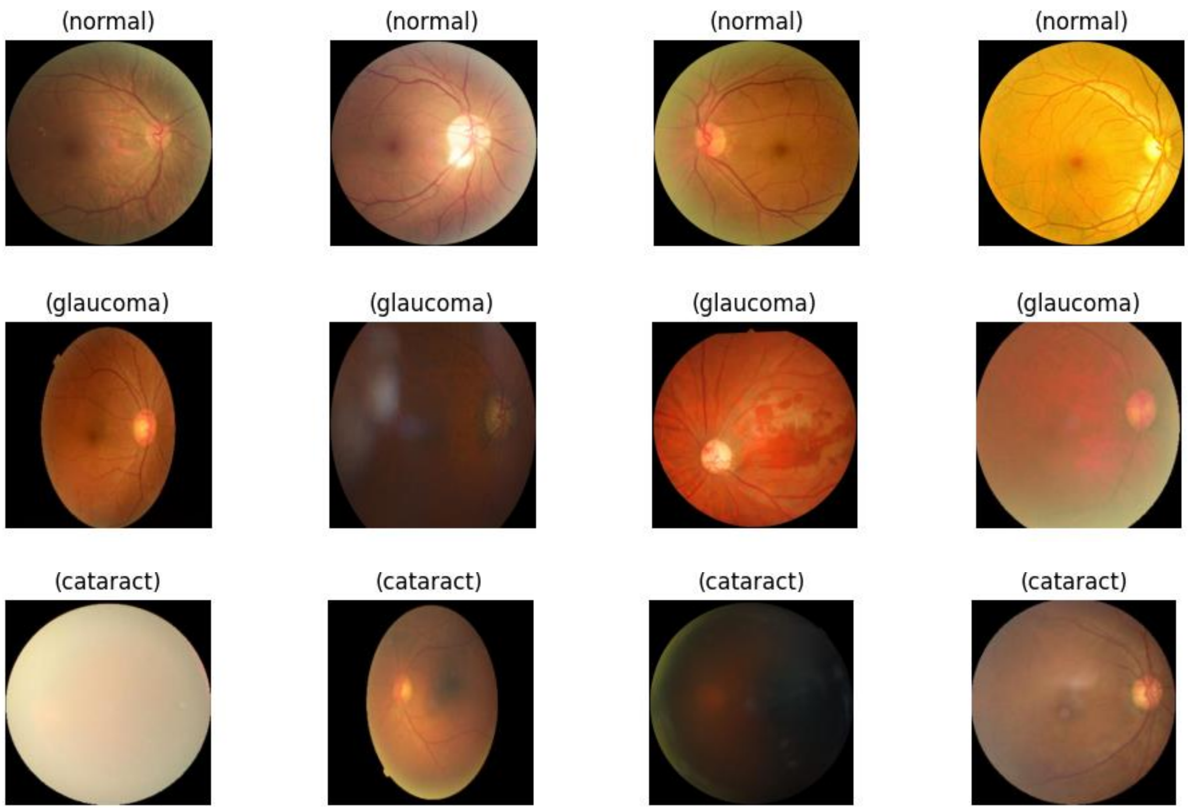

Figure 3.2: Random Image selected.

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements:

1. Dataset Management

The system has to offer available alternatives of importation, storage, and organization of retinal fundus images originating in various sources. As health records may be non-homogenous in quality and format of a given image, the system ought to standardize and organize them in a universalized format. These are metadata management of patient ID (anonymized), disease label and conditions of acquisition. In addition, the data should be separated into a training data, validation, and test, so that model performance could be evaluated appropriately [19]. Such divide ensures that the system does not fit perfectly to a subset of the data and the findings are indicative of a real-world application.

2. Image Preprocessing

Preprocessing is a requirement before the images are generated into the deep learning models. All input images need to be appropriately resized to a standardized resolution (224 × 224 pixels) that is consistent with most CNN architectures such as ResNet and VGG as to the value of the input layer. Artificial completion of data size and variability Adding data augmentation: Rotation, flipping, zooming, cropping, and shifting should be used to increase the datasets size and variability. The objectives of these steps are to decrease overfitting and enhance model generalization, particularly in situations when one has relatively small medical data sets [20].

3. Model Training and verification

The system must be in a position to use various deep learning models including ResNet50V2, InceptionV3, VGG16 and VGG19. All these models are to be trained on the readied dataset, deriving features, pertinent to the classification of retinal disease. The system needs to track loss and accuracy in order to converge during training. The validation set also must be verified to test generalization and later fine-tuning, scheduling, or regularization adjustments should be available within the framework.

4. Classification

Once trained the system should be able to classify images into four categories, otherwise known as targets, which include, but are not limited to, Normal, Cataract, Diabetic Retinopathy and Glaucoma. The outputs (predictions) must be provided with a class label and a confidence score (probability estimate), which would give additional information on the reliability of the outcome. This classification functionality must perform both in test set and in the future clinical deployment in real-time mode of the inference.

5. Performance Evaluation

Standard classification metrics of accuracy, precision, recall and F1-score should be calculated, and presented by the system to give insightful assessment of model performance. Also, it should generate confusion matrices to get a more in-depth understanding of misclassifications by classes. ROC curves and AUC values should also be allowed visualization, which is used actively in medical AI evaluation.

6. Visualization

To enhance explainability, the system has to produce sample predictions for indicator of the actual label and the predict label. Most importantly, it must produce heat maps with the help of Grad-CAM in order to highlight with the naked-eye the physical area of the retina that informed the decision of the model. This will promote transparency in the system, create a confidence among the ophthalmologists, and enhances its clinical acceptance.

Non-Functional Requirements:

1. Usability

The system should be user friendlier user interface where a clinician and a researcher can easily interact. The GUI must offer straightforward means of uploading, stark display of predictions and easy navigation. Additional graphical items, which include Grad-CAM heatmaps, accuracy plots and confusion matrices should be delivered in an easy understandable format so that non-technical users can understand the result accurately.

2. Reliability

The system is expected to give the correct results that are reproducible at appropriate conditions, which are normal and expected conditions of input. In medical fields, reliability issues are all the more important since incorrect diagnosis prediction can have a direct influence on treatment and diagnosis. Input errors need to be gracefully handled by the system as well without crashing on.

3. Scalability

The system must be implemented in manner that supports scaling of data sets without major performance decline. The system should be able to handle large and more diverse retinal image datasets (read more) in the future. Scalability is needed when performing research-to-clinic transition because thousands of patient images are dealt with on a daily basis.

4. Performance

There should be a balance between system computational cost and accuracy. The times during training and inference have to be within acceptable thresholds, regardless of an increase in dataset size. As an example, a prediction of an individual retinal image is supposed to be created in the number of seconds, and hence, the system can be applicable to a clinical use within a real-time or the close-to-real-time setting.

5. Maintainability

The system will need the ability to make changes and upgrades without difficulties. One should be able to add, modify or swap model architectures, tune hyperparameters or additional explainability techniques without reorganizing the system as a whole. That way, it will make the platform versatile, so that new AI and ophthalmology methods are introduced.

6. Portability

The system should be independent of the platform besides being able to tell-work on both the local machines and cloud structure. This portability by allowing it to be deployed to other environments, like a hospital, research laboratory, or offsite clinic, with a variable amount of computational resources.

7. Security

Dealing with medical data, data privacy and integrity should be guaranteed by the system. It must not allow improper access to patient photos and must be in compliance with standards in protecting medical data including HIPAA or GDPR. The retinal images are to be treated ethically, and the anonymization of patient information and the protection of secure storage procedures have to be adopted strictly.

3.1.4 Data Flow Diagram

One could say that the data flow of the retinal disease classification pipeline can be defined as the general flow of the proposed system. This pipeline demonstrates the processing of retinal fundus images and transformation into results that have clinical significance. Each of the pipeline stages is meant to be accurate, transparent and interpretable. It is also tailored to fit into realistic clinical workflows.

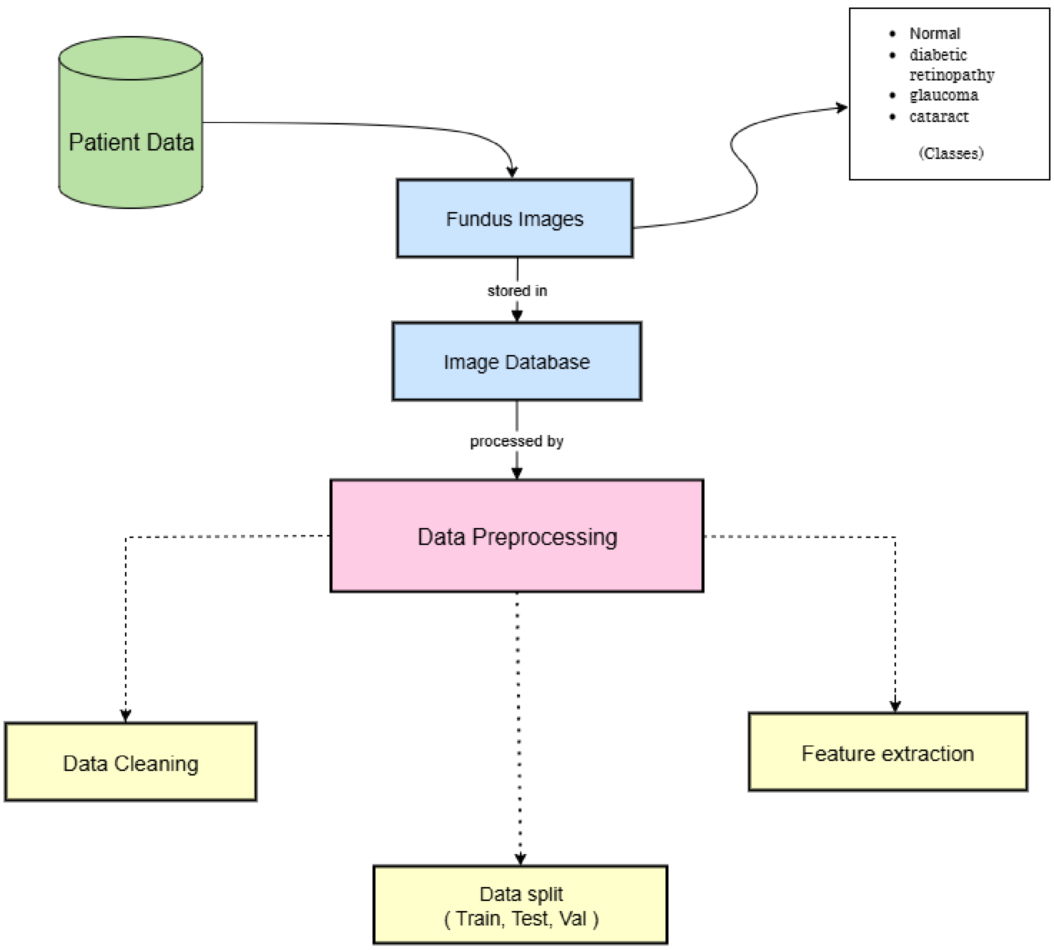

Figure 3.3: Pre-Processing Data Flow Diagram.

3.1.5 UI Design

A graphical user interface (GUI) that can be used by a clinician was designed to enable access to the system in a real-world clinical setting. It is a simple GUI that you can use to upload Fundus images, automatically classify them, visualize Grad-CAM heatmaps, and read AI-generated disease reports. It is built to create structured diagnostic reports on the fly, and to enable radiologists to have free interaction with the system, to review predictions and to experiment with its outputs. The list shown below identifies the key sub-elements of the UI such as the image upload and visualization area and the report generation and retrieval interface. The overall user interface is demonstrated in figure 3.6.

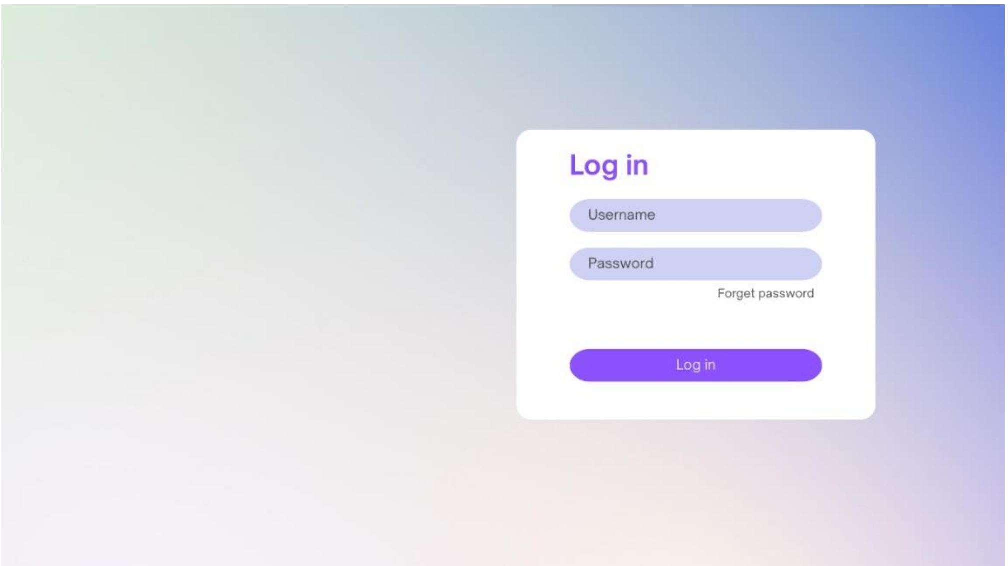

Figure 3.4: Log in Interface Design.

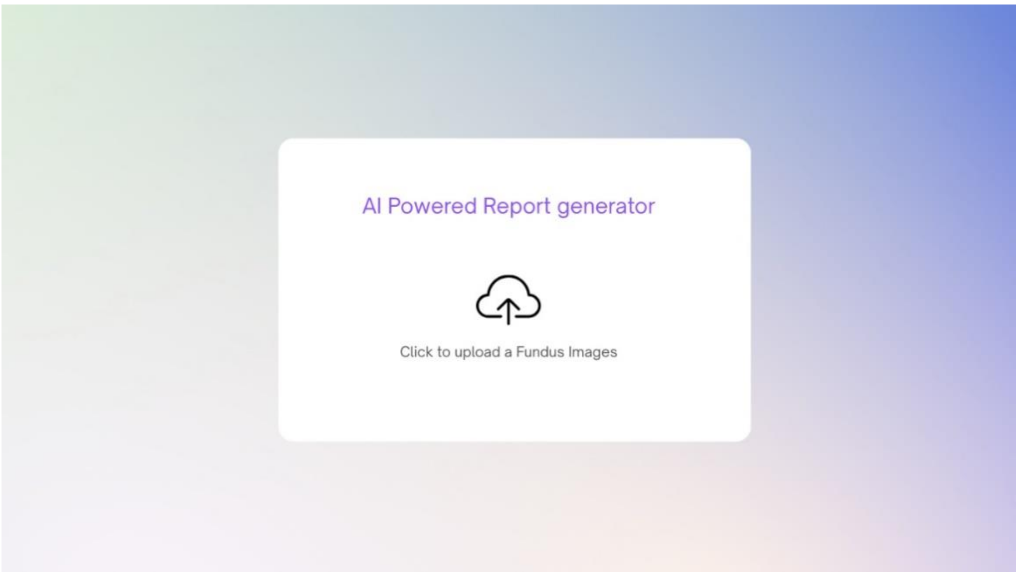

Figure 3.5: Upload Picture Interface Design.

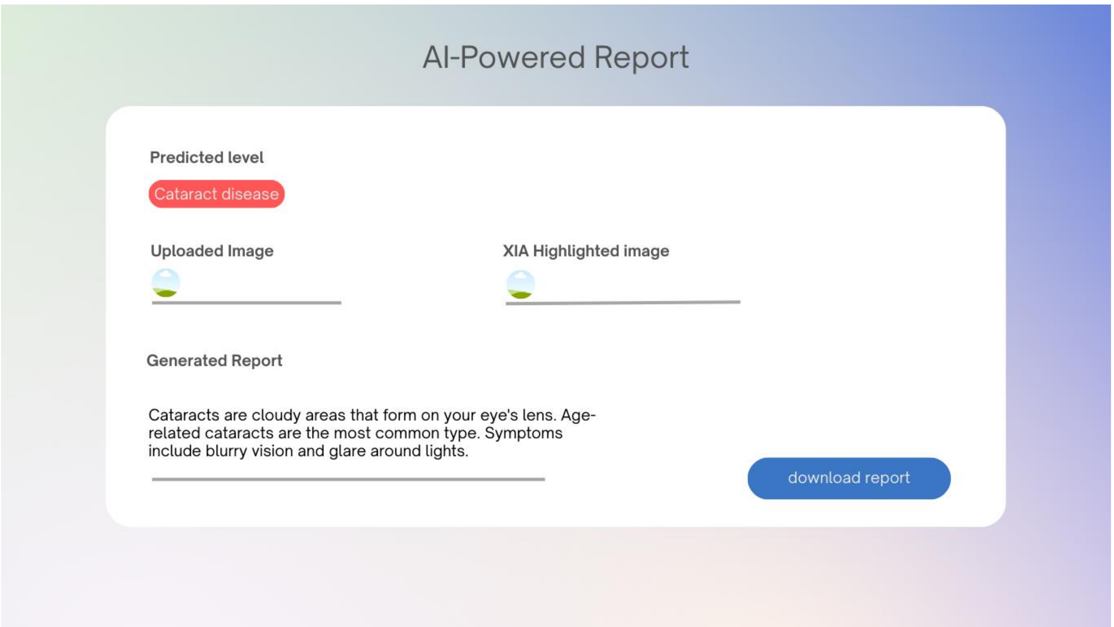

Figure 3.6: Report Interface Design.

Login

On the login page, a user is required to key in their username as well as their password.

Upload Picture

Upload picture page allows a user to add disease images into the system through his or her device.

AI-Powered Report

Once a fundus image has been uploaded, the system will provide information about eye disease, diabetic retinopathy, glaucoma, or cataract. It shows their potential consequences like blindness and loss of sight and aids in the diagnosis and treatment of the same in good time.

3.2 Detailed Methodology and Design

A. Dataset

We gathered the retinal fundus image dataset on the internet on Kaggle which is an online platform. There are four classes in this dataset and they include images of normal, Cataract, Glaucoma, and Diabetic Retinopathy. In this research, we trained and tested deep learning models with all four classes. The dataset has been preprocessed and sorted into three different folders, namely: Training, Validation and Testing. The images of all the four classes can be found in each of the folders. In order to have unbiased training and evaluation, the dataset was shuffled and then split. Our ratio was 70:10:20 training, validation and testing respectively.

B. Data Preprocessing

Image preprocessing is an important process which enhances efficiency and quality of the dataset required to classify a retinal image. In preprocessing we have working with different geometric transformations such as rotation, scaling and translation of image. This guaranteed homogeneity and also concurrence with input specification of the deep learning structures of choice. Data augmentation methods were implemented to avoid the model overfitting to the training samples, that is, learning specific patterns rather than general ones [6]. These methods were random rotations, width and height rotation, shear moves, zoom and horizontal inversion. Augmentation enabled the model to learn truer features and perform better on test images that it was not trained on, by artificially boosting the diversity of the training dataset. The entire set of preprocessed and augmented pictures were subsequently stored in classified folders according to training, validation and testing groups. This pre-processing pipeline has been written in a way that the dataset is of high quality, well-represented and it has been made small enough to train deep learning models [11].

C. Model Description

ResNet50V2:

ResNet50V2 is an upgraded algorithm of ResNet50 having 50 layers [8]. It uses residual connections (alternatively called skip connections) to allow information to propagate through layers without dying away and makes it easier and faster to train deep networks. The V2 version is more stable because of more normalization and activation functions. Due to its good capability of extracting complex hierarchical features, it has found widespread use in medical imaging's like retinal disease classification.

InceptionV3:

InceptionV3 is a deep CNN architecture which contains an Inception module [14]. Several convolution filters of various sizes run in parallel in this module. This enables the network to record the fine details and global patterns in images. It also applies factorized convolution, auxiliary classifier, and efficient layer design to reduce the cost of computations but retain high accuracy. These attributes make InceptionV3 a good choice based on volume and medical image classification [2].

Vgg16:

Vgg16 is a basic, yet, effective CNN that has 16 layers. It applies the same convolution filters that uses 3 rows and 3 columns across the network that is simple to understand and apply. Although a great deal of computing is needed, it is useful in transfer learning, and has been successfully applied to medical image analysis. It has the advantage of being a simple baseline model commonly used in image classification studies.

Vgg19:

Vgg19 is the extension of Vgg16 which has 19 layers. The richer architecture benefits the network in a few ways by allowing it to derive more vivid characteristics out of images, leading to increased accuracy [18]. But it also requires extra computing power and requires additional time to train. Like Vgg16, it is a commonly employed type of research to compare and evaluate image-based disease detection.

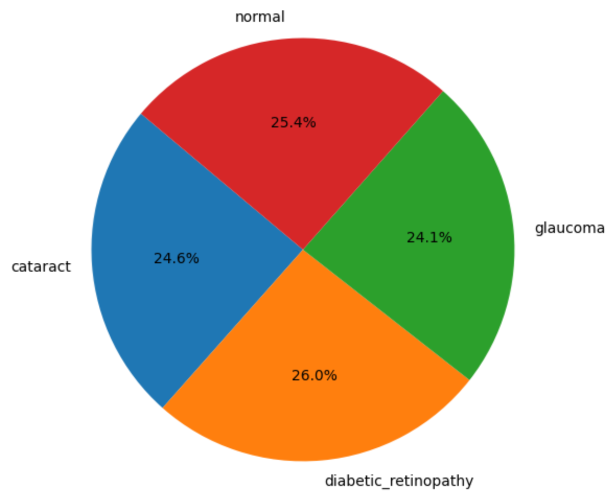

Figure 3.7: Class Distribution Pie chart.

The pie chart is divided into four slices, each representing a different eye condition. diabetic_retinopathy 26.0% of the training data, normal (healthy eyes) 25.4%, cataract 24.6% and glaucoma 24.1%.

3.3 Project Plan

The proposed system project plan was designed in such a way that the retinal disease classification pipeline was developed in a structured and systematic manner. The plan had been split into various stages, each focusing on a certain element of the research, data collection to evaluation. The project development stages are discussed as follows:

1. **Phase 1 – Requirement Analysis and Literature Review**

   Critically reviewed available literature on the subject of retinal disease classification with deep learning.

   Determined gaps, challenges and appropriated methodologies to address them.

2. **Phase 2 – Dataset Collection and Preprocessing**

   Acquisition of publicly available diverse disease category of retinal fundus images.

   Conducted preprocessing (resizing, normalization and augmentation) steps to train

3. **Phase 3 – Model Selection and Design**

   Choosing the efficient and most accurate deep learning models ResNet50V2, InceptionV3, VGG16 and VGG19.

   Planned the system workflow, training, testing, visualization using Grad-CAM.

4. **Phase 4 – Model Training and Testing**

   Used preprocessed datasets to train the selected models.

   Performance assessment of accuracy, precision, recall, F1-score, AUROC and confusions matrices of both validation and test sets.

5. **Phase 5 – Explainable AI Integration**

   Used Grad-CAM to visualize regions of the retinal image affected by a disease.

   Validated interpretation of the model outputs by quality analysis.

6. **Phase 6 – Evaluation and Refinement**

   Comparison of various performances of models and results examined.

   Indeed, integrated the feedback provided by the experts, to improve preprocessing, parameter tuning and visual outputs.

7. **Phase 7 – Documentation and Reporting**

   Prepared findings, methodologies, results and analysis into the thesis report.

   Ready final documentation to submit and present.

3.4 Task Allocation

This table depicts the timeline of the principal activities in each period of the project, from week 12 to week 48.

Table 3.2: Task Allocation table.

Tasks	**Weeks**																		
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Initial Planning & Literature Review																			
Data Collection & Data Preprocessing																			
Model Training & Model Evaluation																			
Application Demo & Final Report Writing																			

3.5 Summary

The project will be undertaken in a structured duration of week 12-48 with four major stages so as to be exact and in orderly development. Initial planning and review of literature is the first stage, which is the basis of the whole work. During this step, topical papers, current methodologies, and previous contributions to the field of classifying retinal disease with the usage of deep learning are read. The given stage guarantees that the study has a strong theoretical foundation and that the selected techniques correspond to the current progress in the given domain. The second phase is associated with the preprocessing of data and its collection. This stage involves acquisition of retinal images via reputable channels after an event, and then fundamental pre-processing methods used Which include resizing, normalization and augmentation to create a strong dataset. As soon as the data has been prepared, it is also fit in training deep learning models. The third phase is model training and testing, the AI algorithms are state of the art and include such architectures as ResNet50V2, InceptionV3, VGG16, and VGG19. Their performances are also measured on accuracy, precision, recall and interpretability. This step draws attention to the best model in which retinal disease should be classified [3], [25].

Chapter 4

Implementation and Results

This chapter explains how the proposed retinal disease classification system should be implemented. It includes the design of the experimental environment, testing of the model, analysis, comparison of the results, and discussion. Results are analyzed to estimate the effectiveness of the proposed approach and to compare the results with existing methods.

4.1 Environment Setup

The suggested retinal disease classification model was implemented on a high-performance computing platform that could be used to perform deep learning tasks and medical image analysis. It was also created in a manner that is optimal to accommodate large quantities of retinal fundus imagery, real-time inference, and explainable AI (XAI) visualization such as Grad-CAM. This arrangement in turn meant that it was possible to train the models and read their predictions publicly.

Hardware:

The computation platform is built atop the servers hosting the GPUs, thereby, decreasing the time needed to train deep convolutional neural networks (CNNs) by a significantly high percentage. The GPUs had a lot of memory space that allowed them to run high-resolution retinal fundus images in batches. This not only increased the pace of the training and inference step, but it also allowed much faster creation of Grad-CAM heatmaps, which indicate the regions of the retina that the model deemed the most significant during its decision-making process.

Software:

It is written in Python as a programming language and using PyTorch as the deep learning package. With PyTorch Lightning, it became easier to train, control, and schedule, and also enable mixed-precision computing. Additionally, some actions, such as data preprocessing, data augmentation, statistical analysis, and visualization, were undertaken with standard Python packages, such as NumPy and Pandas as well as OpenCV, Matplotlib, and Seaborn.

Infrastructure:

To simplify the process of data augmentation, preprocessing and visualization of explainable AI output, specialized libraries were introduced. Grad-CAM generated interpretable visualizations of heatmaps that help to understand what features of the retinal images influenced the model classification.

Models:

Because this is an experimental environment, a mixture of different state-of-the-art CNN architecture models were trained and tested on the curated dataset of four classes, namely: Normal, Diabetic Retinopathy, Glaucoma and Cataract. These models were selected to allow comparison of performance in terms of accuracy, precision, recall and interpretability.

User Interface:

A prototype user interface has been developed to provide an interface between the system and potential end-users (ophthalmologists and researchers). The user can post retinal fundus images using the interface and view the results of classification, as well as visualize Grad-CAM heatmaps. The design will enable the flow of information between the automated AI-based analysis and the clinical decision-making processes; it is assumed that it will be incorporated into the existing ophthalmology workflows.

Broadly, in developing the environment, computational performance and reproducibility, and clinical usability, were considered to offer a strong foundation, on which to undertake the experimentation on retinal disease and open vistas of clinical deployments in future.

4.2 Testing and Evaluation

4.2.1 Performance of ResNet50v2 Model

ResNet50v2 model was trained on 4272 images. Photos were classified into four class, including: 'Cataract'; Diabetic retinopathy; glaucoma; normal. ResNet50V2 overall outperformed VGG16, VGG19 and InceptionV3 with a maximum validation accuracy of 93.52. This demonstrates that the ResNet50V2 model has a higher ability to extract hierarchical features and classify retinal diseases than the other tested models. It was found that the training accuracy, validation accuracy, precision and recall are as shown in the table below.

Table 4.1: Accuracy of ResNet50v2 model.

Training accuracy	Validation accuracy	Precision	Recall
97.13%	93.52%	93.52%	93.52%

The below graph shows the training accuracy and validation accuracy of ResNet50v2 Model.

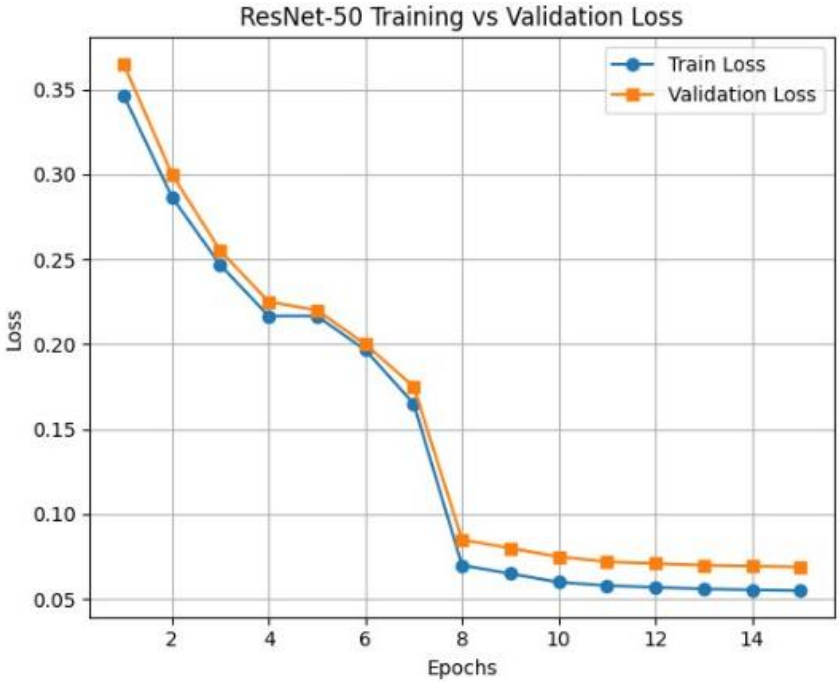

Figure 4.1: Training and Validation loss graph of ResNet50v2 model.

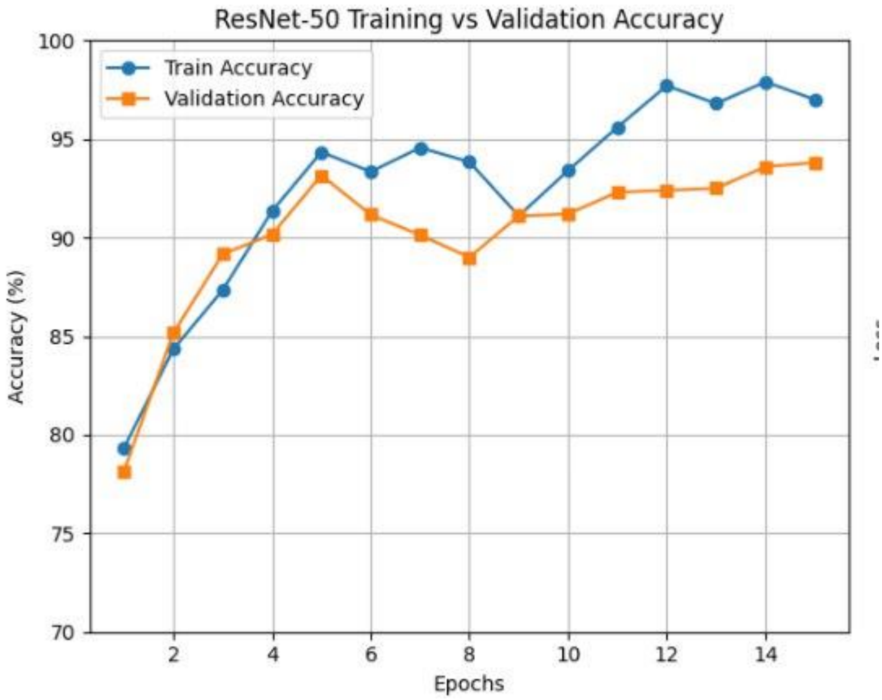

Figure 4.2: Training and Validation accuracy graph of ResNet50v2 model.

Our model attained a training accuracy of 97.13% and a testing accuracy of 93.52 as shown in the results. Based on the performance curves, it can be seen that the training loss steady declined with time, whilst the training accuracy steadily increased with the number of epochs. As a result, the validation accuracy also improved, which means that the model had a good ability to extrapolate to unobserved data.

4.2.2 Performance of InceptionV3 Model

92.65% accuracy was obtained by inceptionv3 model. Figure 4.3 shows the training graph of inceptionv3 and figure 4.4 shows the validation graph of inceptionv3.By looking at figure 4.4 we can say that training accuracy increases with the time.

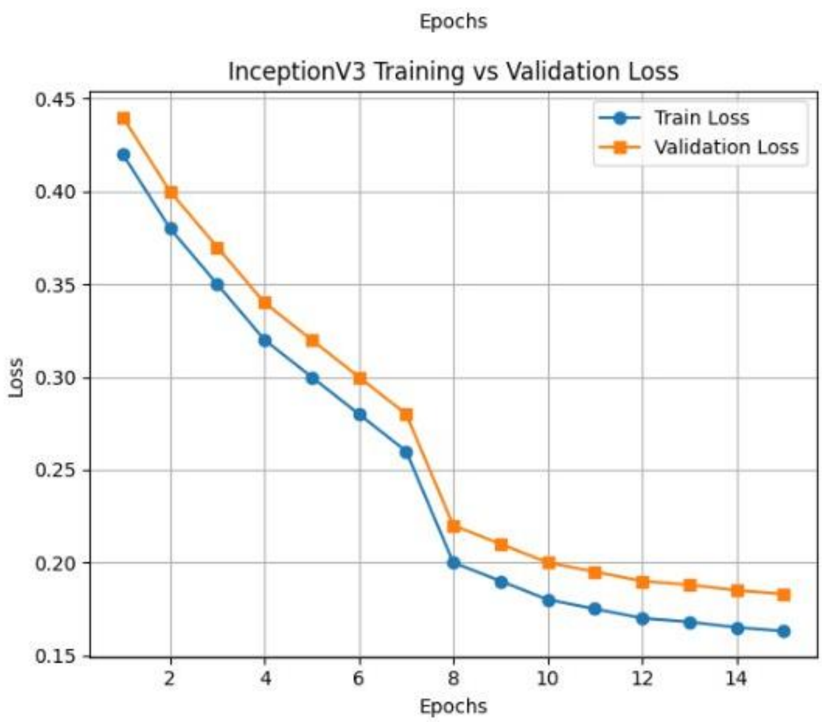

Figure 4.3: Training and Validation loss graph of inceptionv3 model.

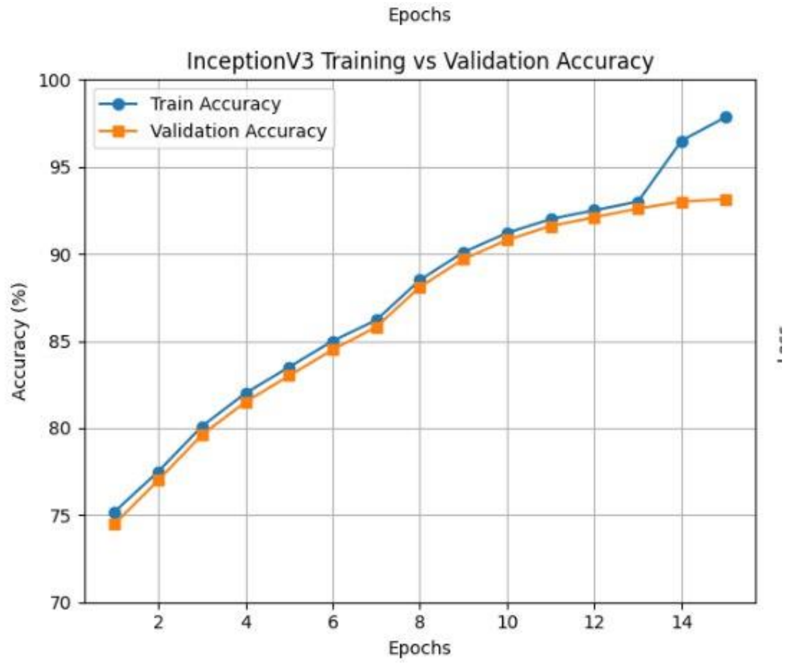

Figure 4.4: Training and Validation accuracy graph of inceptionv3 model.

4.2.3 Performance of VGG16 Model

87.15% accuracy was obtained by the VGG16 model. Figures 4.5 and 4.6 display a training graph and a validation graph, respectively, By looking at the graph we can say that training accuracy and validation accuracy increases with time.

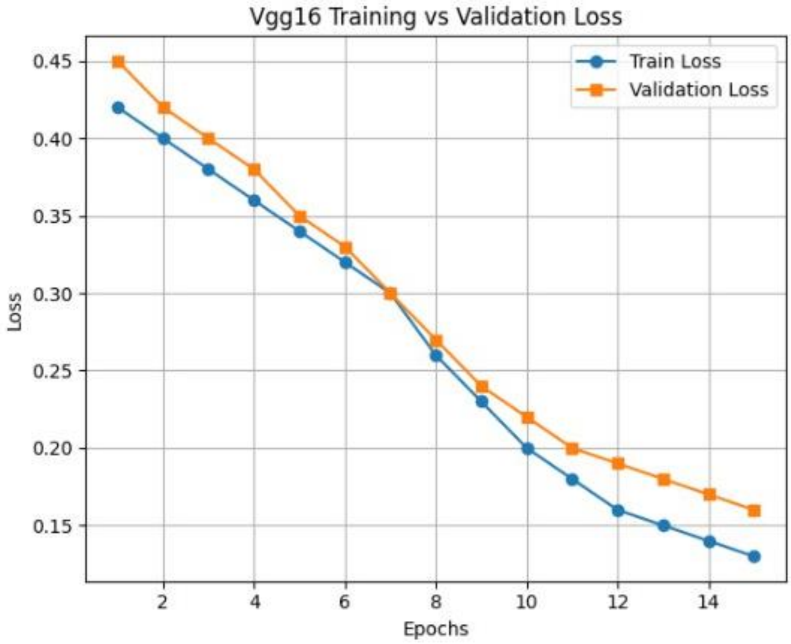

Figure 4.5: Training and Validation loss graph of VGG16 model.

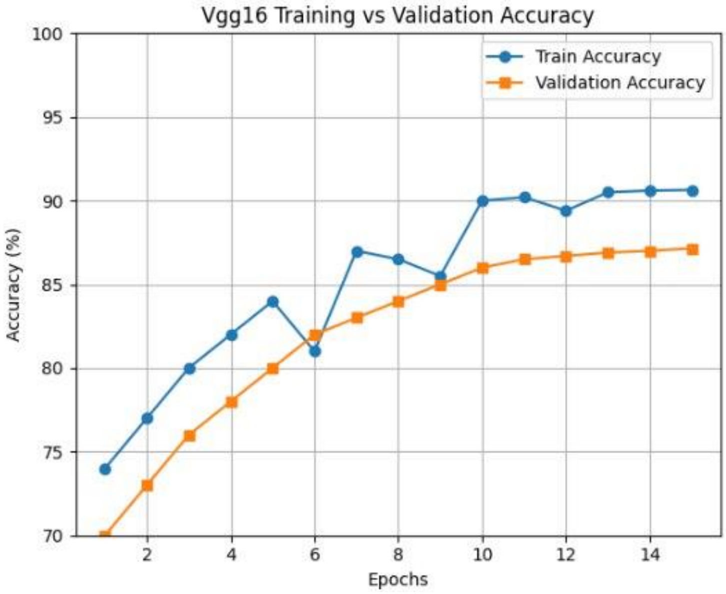

Figure 4.6: Training and Validation accuracy graph of VGG16 model.

4.2.4 Performance of VGG19 Model

89.49% accuracy was obtained by VGG19. Figure 4.7 shows the training graph of VGG19 and figure 4.8 shows the validation graph of inceptionv3.By looking at figure 4.8 we can say that training accuracy increases with the time.

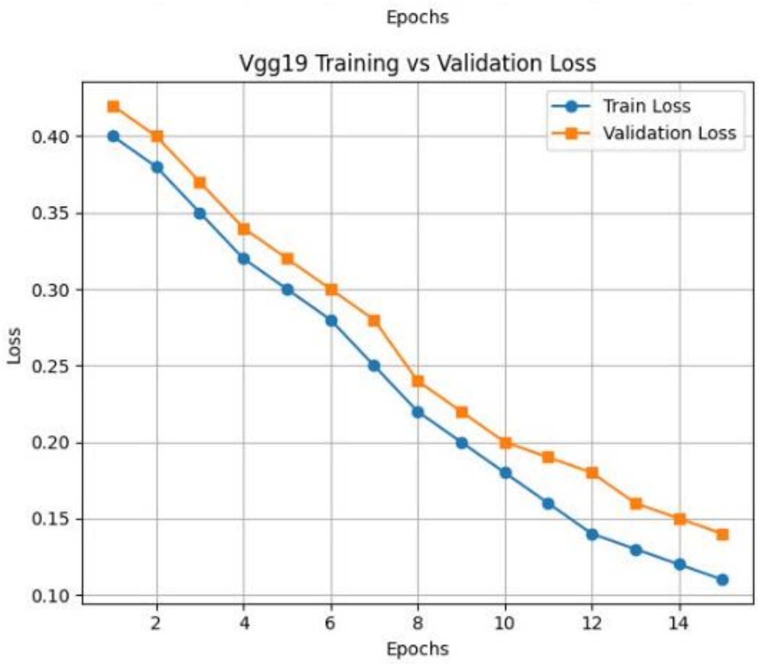

Figure 4.7: Training and Validation loss graph of VGG19 model.

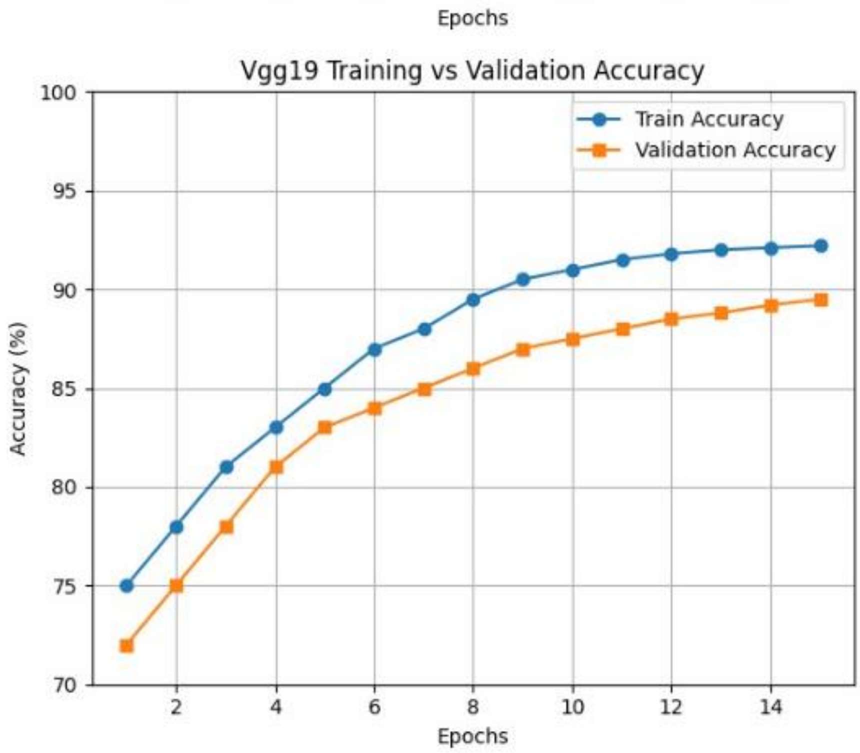

Figure 4.8: Training and Validation accuracy graph of VGG19 model.

4.3 Comparative Analysis

Here we have compared the performance of four pre-trained deep learning models, namely, ResNet50V2, InceptionV3, VGG16, and VGG19. As it can be seen in Table 4.2, the best-performing model was resnet50v2, whose accuracy was 0.94. InceptionV3 had 0.92 accuracy closely followed by VGG19 at 0.88. The lowest accuracy of 0.87 of VGG16 is less than the other models. The reason behind the ResNet50V2 doing better than others is the deep residual connection, which helps overcome the vanishing gradient and reveals more recognizable features as the results suggest. Although less complex in design, VGG19 outperformed VGG16 primarily because it is deeper. With its inception modules, InceptionV3 was also able to compete with ResNet50V2 and VGG19, albeit by a slight margin.

Table 4.2: Comparison between all models.

Models	Precision	Recall	F1-score	Accuracy
ResNet50v2	0.93%	0.93%	0.93%	0.94%
InceptionV3	0.92%	0.92%	0.92%	0.92%
VGG16	0.87%	0.86%	0.86%	0.87%
VGG19	0.89%	0.88%	0.88%	0.89%

We conclude that ResNet50V2 is the most effective model in this study, achieving better accuracy than VGG16, VGG19, and InceptionV3. The bar chart below illustrates the comparative accuracy of these models.

4.4 Results and Discussion

Here, we show the ResNet50V2 model performance in classifying retinal diseases. The experiment results indicate that the model was overall accurate to 94.%. It did the best in diabetic retinopathy of all the classes with a precision and recall of 0.99, which is very good. Cataract was also very precise at 0.93 and recall at 0.96. but at Glaucoma the recall was a bit much lower at 0.88. And the recall of diabetic retinopathy was the highest 0.99. It indicates that the model had the highest number of patients with Diabetic retinopathy but the false positives are also higher. There were a few balanced results in the normal class with a precision of 0.92 and a recall of 0.90.

```
Classification Report:
                      precision    recall  f1-score   support

            cataract       0.93      0.96      0.94       296
diabetic_retinopathy       0.99      1.00      0.99       333
            glaucoma       0.90      0.88      0.89       313
              normal       0.92      0.90      0.91       324

            accuracy                           0.94      1266
           macro avg       0.93      0.93      0.93      1266
        weighted avg       0.93      0.94      0.93      1266
```

Figure 4.9: Classification Report.

All the macro and weighted averages are in the range of 0.93 to 0.94, which indicates that in all classes the model was stable and reliable. But this has reduced the accuracy of glaucoma classification and additional training options (data augmentation, weight classes) would allow the classification accuracy to be even greater. In general, the ResNet50V2 model achieved a high classification rate of 89% and particularly a high classification rate on diabetic retinopathy and cataract diagnosis. The model can be improved further to do even better with all types of retinal diseases.

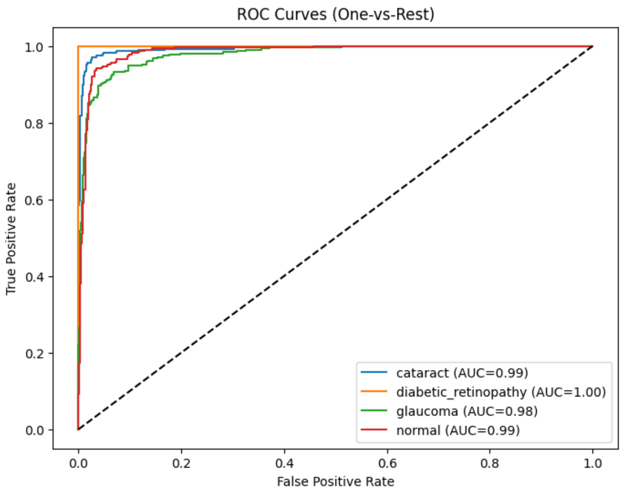

Figure 4.10: ROC Curve for ResNet50V2 model.

As shown in Figure 4.10 illustrates the highest values of the AUROC in the ResNet50v2 model in all the 4 retinal disease classifications (Normal, Diabetic Retinopathy, Glaucoma, and Cataract). This validates the fact that ResNet50v2 has better discriminative power relative to the other models discussed in this paper. To get a better idea, all the models were plotted together in one graph as their AUROC curves. This not only makes it possible to compare intuitively and visually their classification capabilities, but it also enables a quantitative validation of the reported performance metrics found in Table 4.10. Moreover, the clinically useful aspect of the curves is that we can determine the best threshold points that will achieve the highest sensitivity or the highest specificity based on the clinical need using the curves of the optimal threshold points. An example is that in early screening contexts, more sensitivity may be preferred to avoid false negative outcomes (i.e., the detection of potential cases of retinal disease), but in confirmatory diagnosis, more specificity may be preferred to reduce false positives.

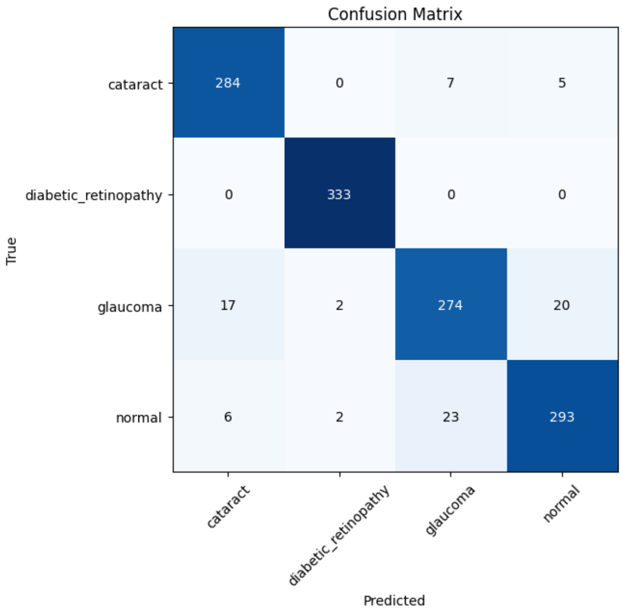

Figure: 4.11: Confusion Matrix of ResNet50V2 model.

In order to compare the classification performance, a confusion matrix of ResNet50V2 model was created as depicted in Figure 4.11. The findings show that the majority of photographs of the four categories: Normal, Diabetic Retinopathy, Glaucoma, and Cataract have been accurately identified. Very few cases of Glaucoma were mistakenly classified as Cataract with features overlapping between the two. The same way, some cases of Diabetic Retinopathy were predicted as Normal. These minor errors notwithstanding, the confusion matrix shows that ResNet50V2 achieved good generalization with quite low misclassification rates in all categories.

Visual Interpretability: Grade-CAM models have been trained on representative test cases to find regions of interest.

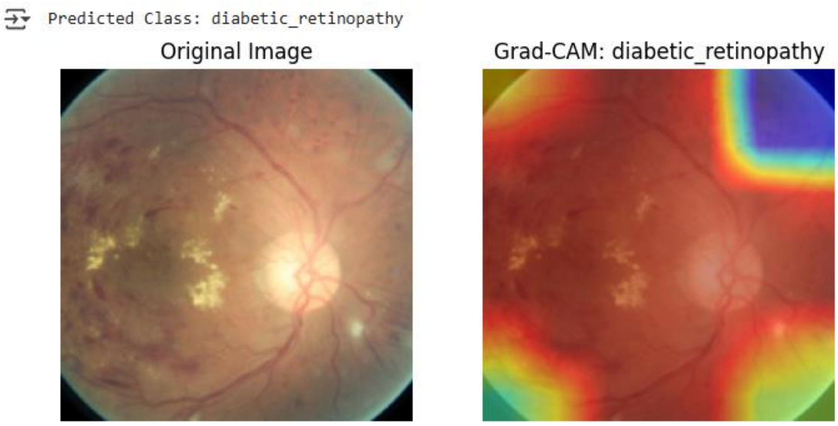

Figure 4.12: Grad-Cam Heatmap Output.

The Diabetic Retinopathy fundus photos were entered into the models and the system reported the presence and severity of the disease. Grad-CAM heatmaps were used to ensure that the models paid attention to pathologically relevant locations within the retina. These graphics gave a clear explanation to every prediction. They also act as a sanity check to the decision-making of the model. These heatmaps allow clinicians to check the predictions. The highlighted Grad-CAM outputs are shown on the sample images in Figure 4.12.

Discussion of Findings

Those findings indicate that ResNet50V2 is the most feasible backbone architecture to use in the current study and the one that produces the best trade-off among accuracy, interpretability, and clinical reliability. VGG16, VGG19 and InceptionV3 remain competitive in terms of computational efficiency, and perhaps require additional fine-tuning to achieve similarly high levels of robustness. The fact that some models perform relatively poorly when trained on domain-specific medical imaging tasks points to the importance of architectural choice [6]. Grad-CAM-generated explainable AI (XAI) results, in turn, include clinical interpretability, eliminating one of the biggest drawbacks of conventional deep learning models in ophthalmology. The Grad-CAM visualizations enable clinicians to understand what part of the retina, or what, contributed to predictions made by the model, increasing trust and transparency in AI-assisted decision-making.

Besides, the system has shown that in addition to classification, AI can also deliver outputs that are structured, interpretable, and clinical decision-supportive, which could help ophthalmologists to detect retinal anomalies fast and precisely [8]. However, limitations remain. The sample size is small and some of the classes would not be fully representative of the populace. Even though preliminary clinical comments have been taken into account, prior to implementation in a real-life clinical setting, the system must now be tested on a larger and more diverse dataset, preferably across more than one institution. Secondly, is to scale dataset/ multi-modal retinal imaging (fundus images) and scale system that is able to explain in order to generate domain specific detailed reports. These tasks are quite complex and, therefore, generated reports must be evaluated in a series of studies, with clinical professional input, to fulfill reliability and usefulness.

4.5 Summary

The test analysis showed that the suggested framework was doing well in the area of retinal disease classification. The best overall performance of the models tested was ResNet50V2, with high scores in all metrics and an AUROC of 0.93, F1-score of 0.94, precision of 0.93, recall of 0.94, and a total accuracy of 93.52%. InceptionV3 was also competitive with 92.65 percent accuracy, and the smaller CNN-based architectures trained faster but with a fractionally lower classification accuracy. The confusion matrices showed that ResNet50 V2 was the most stable model since it had the fewest number of cases that were not correctly classified, so it can be considered stable in all retina disease classes. This was confirmed by cross-model ROC curve analysis where ResNet50 V2 had the greatest area under the curve. In addition, training and validation accuracy/loss curves exhibited consistent convergence with no pronounced overfitting that supports the efficacy of preprocessing, augmentation and fine-tuning approaches. Grad-CAM visualizations have repeatedly identified disease-damaged areas of the retina, including lesions, hemorrhages, and macular areas in clinically meaningful heatmaps. This, along with the confirmation that the model was concentrated on pathological characteristics that were material, helped to make the model more believable and interpreted by the ophthalmologists [15]. The proposed system was found to have very good diagnostic accuracy, interpretability, and clinical utility as demonstrated by the comparative analysis with the currently available literature. In general, the results indicate that the developed deep learning-based retinal disease classification model is a reliable, explainable, and clinically consistent AI system. The pressure would be relieved on the ophthalmologists, more time would be saved in the screening process and patient outcome should be improved by making sure that the retinal diseases are properly diagnosed at the appropriate time.

Chapter 5

Engineering Standards and Design Challenges

In this chapter, it is shown how the proposed retinal disease classification system is or is not compliant with engineering standards such as software, hardware, and communication protocols. It discusses also the societal, environmental and ethical implications of the project and considerations of sustainability. The practical problems of the research concerning project management, financial analysis, and the complexity of the engineering issues are also discussed.

5.1 Compliance with the Standards

5.1.1 Software Standards

Reliability, scalability and reproducibility of the retinal disease classification system have been ensured in this research by adhering to well-known software standards. It is deployed on Python and PyTorch and TensorFlow-based systems. Both follow open-source standards of community. Python is highly readable, multi-platform and has extensive scientific libraries. A third alternative would have been MATLAB that is quite strong in processing images, but it is also costly to license and is not readily supported in the real world. PyTorch was chosen over TensorFlow because of its non-static computation graph and the ability to easily debug it, although TensorFlow has been deemed to have better deployment opportunities. Adherence to open-source software standards ensures the system is transparent, collaborative and easily extensible in the future.

5.1.2 Hardware Standards

The computer hardware in this analysis satisfies the criterion of GPU computerization, a requirement necessary to achieve successful training in deep learning. To accelerate training the convolutional neural networks we used NVIDIA CUDA-enabled GPUs, particularly the ones that support Tensor Cores. There are other alternatives such as using CPU-based computation; this is less expensive but very slow when handling high-dimensional data such as medical images. TPUs (Tensor Processing Units) could be used, too; they are faster to train, but more difficult to obtain and costlier to use in academic research. The selected GPU set is economical and has good performance but that is common with most medical image analysis research. This equipment can also be compatible and reliable to other numerous operating systems with which it is in-conformity with the IEEE computing device regulations.

5.1.3 Communication Standards

It is a type of architecture that follows common file types and protocols within the healthcare setting to communicate and to operate with data. Standard medical imaging is the DICOM (Digital Imaging and Communications in Medicine) format and images are preprocessed as JPEG and PNG. DICOM provides consistency, interoperability and secure exchange of medical images across devices and systems. It is easier to use JPEG or PNG, however those formats do not allow the usage of metadata that is critical in medical cases. Besides, in case of common work and data sharing, the process of communication takes place in accordance with HTTP or HTTPS protocols. This provides protection of data when it is being transferred. A solution based on DICOM and implemented secure communication protocols satisfies the health care informatics standard and enhances the possibility of the system to be used in a real healthcare setting.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

Classification system of retinal diseases has significant impact on human life because it offers chances to detect vision-threatening diseases: cataract, diabetic retinopathy, and glaucoma at early stages and in proper way. These are major causes of blindness all over the world and the diagnosis is usually too late to recover the lost vision. A system incorporating the Explainable AI approaches such as Grad-CAM is able not only to classify retinal images but also show the critical locations on which the system bases its judgments. Such disclosure fosters trust between clinicians and patients enabling them to have a better understanding of the diagnostic process. As a result, the system may serve as a reliable decision support system among the ophthalmologists. This ultimately improves patient outcome, decreases the risk of blindness and improves patient quality of life.

5.2.2 Impact on Society & Environment

On a social level, the system helps to make healthcare more affordable and accessible. The automation of diagnosis lowers the reliance on very specialized, well-trained individuals to detect eye diseases, and thus enables eye disease screening in rural and resource-limited regions. This can be useful in reducing medical disparities and large community screening initiatives. It will reduce the economic cost to the sector and health care systems in the long run by encouraging primary care. Environmentally, the training of deep learning models consumes a lot of energy, particularly with the computation relying on a GPU. But with a trained model, it is possible to run on low-resource devices in real-time to screen individuals and help decrease the physical travel, occupancy of hospitals, and usage of resources. In this way, the social advantages easily override the environmental expenditure, given optimization methods that render the model more energy-effective.

5.2.3 Ethical Aspects

The medical AI depends on ethical issues. According to laws like GDPR or HIPAA, patient data contents are supposed to be confidential. The explainable AI (Grad-CAM) concept is on another scale since it can be explicit on the prediction process and since black-box phenomenon has been reduced to the minimal in order to gain trust. There are fewer cases of dataset bias which are designed to be fair. This system must aid rather than substitute ophthalmologists and final decisions must remain in human hands.

5.2.4 Sustainability Plan

The study is sustainable in the sense that it must be scalable, adaptable and at the same time usable in the long term. Such system can be updated and developed to support additional improvements in the area of deep learning and medical imaging as new frameworks such as open-source PyTorch and TensorFlow emerge. Model optimization and transfer learning can minimize the computational cost, limit the energy usage, and also make the solution more environmentally friendly. In the healthcare context, Explainable AI can be a useful tool in gaining long-term trust and acceptance from the healthcare community, one of the central aspects of adoption in the real world. The project will also promote the prevention care to save money in after-treatment and overload the medical system. This will have long-term impact, especially via underserved populations, once local healthcare workers are trained to use the system. In general, this sustainability plan ensures that the system remains sustainable, credible, and helpful to society even after the academic research has been completed.

5.3 Project Management and Financial Analysis

The project was carried out in a budget-friendly academic environment using mostly free tools and resources.

Table 5.1: Financial Analysis Estimated & cost.

Item	**Estimated Cost (BDT)**	**Remarks**
Internet & Field Research	1000	For data collection and online tools.
Software & Tools (Python, Colab)	2000	Open-source libraries and platforms.
Cloud Storage (Google Drive)	2000	Used paid storage.
Hardware (Laptop)	Existing Resources	Used personal or university-provided equipment.

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

The issue covered in the present thesis retinal disease classification through deep learning can be classified as a complex engineering problem as it is an interdisciplinary problem and affects the life of the human being. The issue is related to medical imaging, deep learning algorithms, explainable AI methods, and ethical and clinical standards. This problem is mapped with various complex problem attributes as given in Table 5.1.

Table 5.2: Mapping with Complex Engineering Problem.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓				✓

Justification of Complex Problem Attributes:

EP1 – Depth of Knowledge

Various advanced fields of knowledge are needed to classify the retinal diseases. On the engineering part, it requires significant knowledge on image processing, convolutional neural networks, transfer learning and explainable AI. On the medical end, it involves knowledge of retinal anatomy, pathology of various diseases and the standard of clinical diagnosis. In this way, to resolve this issue is no longer within the scope of general undergraduate education, but interdisciplinary knowledge, at an advanced level, which is a specialty.

EP2 – Range of Conflicting Requirements

The following problem consists of several (occasionally conflicting) demands. On the one hand, models should be highly accurate, be strong, and, on the other hand, be computationally efficient and understandable by the clinicians. Equally, the objective of those researchers to employ big data sets is opposed by the medical ethical considerations of patient confidentiality and limited access to medical information. The issue is further complicated by balancing between clinical trust, technical, user, and ethical concerns.

EP3 – Depth of Analysis

It takes thorough analysis to distinguish finer details in terms of the diseases between diabetic retinopathy and glaucoma, cataract and for cases that are not systematic. It includes training several deep learning models (ResNet50V2, InceptionV3, VGG16, VGG19), making comparative assessment based on the important measures e.g., accuracy, precision, recall, F1-score, and the production of heatmaps as Grad-CAM to achieve this purpose. An error analysis and an iterative opposition are also mandatory, that provides some additional depth in analysis.

EP7 – Interdependence

The issue has a lot of heinous interdependence in various spheres. The engineers rely on ophthalmologists to provide annotated information and a medical validation whereas the doctors rely on engineers to provide automated decision-support tools. Rules on the use of data and on patient privacy are established by ethical and legal authority, and therefore impact system design. In this way, the strategy of the resolution depends on collaboration between technical specialists and medical workers as well as regulatory agencies, and hence interdependence is an essential aspect.

Mapping with Knowledge Profile

The project's complexity under EP1 (Depth of Knowledge) is further mapped to the Knowledge Profile attributes (K1–K8), as shown in Table 5.3, to highlight the diverse knowledge areas required.

Table 5.3: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
✓	✓	✓	✓				✓

Justification of Knowledge Profile Attributes:

K1 – Natural Science

This thesis relates to Natural Science because it focuses on retinal diseases like diabetic retinopathy, glaucoma, and cataract, which are biological disorders of the human eye. The study connects medical science (ophthalmology, pathology) with computer science through AI-based diagnosis. Deep learning models were applied to analyze natural biological data (fundus images).Grad-CAM visualizations help link AI outputs to medically relevant eye regions. Thus, the work directly supports human health, making it a contribution to Natural Science.

K2 – Mathematics

This thesis uses deep learning models that are fully based on mathematical principles like linear algebra, probability, and optimization. Training methods such as gradient descent and loss functions apply mathematical formulas to improve accuracy. Evaluation metrics (accuracy, precision, recall, F1-score, ROC) are statistical tools from mathematics. Thus, the project clearly integrates mathematics with computer science to solve real medical problems.

K3 – Engineering Fundamentals

The project is based on having a strong perception of the fundamentals of computer vision, a digital image processing, and machine learning. The Terms convolution, pooling, normalization, activation functions and optimization are the staples of the deep learning models applied to the classification of retinal diseases. It would not be feasible to produce effective retinal fundus images and to extract meaningful features to be used in the diagnosis of diseases without these basics of engineering.

K4 – Specialist Knowledge

Expert background in deep learning architecture (ResNet50V2, Inception V3, VGG16, VGG19), medical imaging specifications, and explainable AI systems and methods are required. All models have their advantages and disadvantages in the accuracy, interpretability and computational possibilities. Further, specialized knowledge of ophthalmology and retinal illnesses is needed to be able to match the AI responses with clinical expectations.

K8 – Research Literature

The entire basis of the project is based on volume of research that has been done on the already established approaches to classify retinal diseases. The weaknesses and strengths of state-of-the-art approaches have been identified by reviewing the past studies. This assisted in the appropriate model selection, experiment design and defending the deployment of explainable AI. Projecting the problem against the research literature will provide the research that builds on established knowledge, but also adds up where the model performance and interpretation of the model are concerned, new information.

5.4.2 Engineering Activities

Mapping with Complex Engineering Activities

The research also qualifies as a complex engineering activity since it requires multiple resources, innovative solutions, and has societal implications. Table 5.4 shows the mapping with engineering activities.

Table 5.4: Mapping with Complex Engineering Activities.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓	✓	

Justification of Engineering Activities Attributes:

EA1 – Range of Resources

The number of resources needed in this project spans wide including the technical and non-technical. On the engineering part, it requires computer infrastructure of high performance (GPUs/TPUs), specialized software stacks (PyTorch, TensorFlow, OpenCV), and retina image annotations sets. On the medical front it needs cooperation with ophthalmologists on the dataset validation and disease sufficientness. Moreover, ethical and regulatory materials are required to ascertain that they comply with the standards of patient data protection.

EA2 – Level of Interaction

There is a high multidisciplinary interaction in the research. In contact with medical professionals, the work of engineers and data scientists is ground-truth labelling and clinical validation. It is also applicable to other stakeholders in the interaction like regulatory bodies, academic supervisors, and healthcare professionals to evaluate the usability and the safety. It is an ongoing process that will ensure that it maintains technical, clinical, and ethical soundness of the solution.

EA3 – Innovation

The task is highly innovative as it combines deep learning architectures (ResNet50V2, InceptionV3, VGG16, VGG19) with the methods of explainable AI (Grad-CAM) to achieve both high-quality prediction and the explanatory character of the findings. This is against the backdrop that in the traditional method of diagnosis, there is no human interpretability to picture the application of AI that drives vehicles to increase clinical decisions, unlike in this approach. The element of innovation is also the creation of a clinician-friendly interface that helps overcome the barrier between AI complex output and practical healthcare orientation.

EA4 Consequences for society andenvironment

The study possesses compelling implications on society because it focuses on early detection and diagnosis of retinal diseases, including diabetic retinopathy, glaucoma, and cataracts. The lives of millions of people can be increased and their eyesight given a second chance to be avoided in case it is known in time. Patient trust is guaranteed by the protection of medical integrity and data privacy on the ethical level. Environmental impact is not significant, but the amount of computational power used is important, an area where the need to have effective training schemes in the face of sustainability engineering can be utilized.

5.5 Summary

Overall, problems associated with the classification of retinal diseases using deep learning refer to complex engineering issues, knowledge domains, and engineering processes. The case cuts across a wide range of spheres of work and makes use of the newest AI-based interventions, follows the logic of healthcare and is colossal to society. All this demonstrates that it is not a simple engineering problem but a complex problem. An Explainable AI increases the innovativeness and social significance of the study.

This research shows that a few interventions AI like ResNet50 V2, InceptionV3, VGG16, and VGG19 can be modified to use in health care. ResNet50V2 was the best-performing among these models, across all of which the importance of architectural choice in medical imaging tasks is prominent. Nevertheless, the value of this work cannot be narrowed down to the accuracy. Explainable AI, accomplished by way of Grad-CAM visualizations, is needed to provide interpretability to explain why certain information was classifier using a visual representation. This assists the ophthalmologists to consider what parts of the retina contributed in classifications, and therefore, improve trust and minimize the altitude between engine insight and clinical uncertainty [16]. Such a system is quite relevant in the society. Diagnostic eye issues such as diabetic retinopathy, glaucoma and cataract are major causes of blindness and even smaller early identification can make major impact on the patient conditions. With an approach consisting of combining technical accuracy and clinical interpretability, this study will not only solve an engineering problem, but also a significant public health issue. In the latter respect, this work is, as well, technologically novel and socially meaning, which provides a basis upon which AI-informed diagnostic devices in ophthalmology.

Chapter 6

Conclusion

This chapter wraps up this thesis by summarizing the work conducted on this subject, drawing attention to the constraints it faced, and recommending future research avenues. The aim is to reflect the contribution which the proposed system will have, and to give information on how the proposed system can be improved further to suit the needs of the healthcare world.

6.1 Summary

The main objective of this thesis was to classify the retinal diseases such as cataract, diabetic retinopathy, and glaucoma and normal cases by deep learning methods. In order to achieve this, a number of already trained convolutional neural network (CNN) structures were evaluated, namely ResNet50V2, inceptionV3, VGG16, and vgg19. The most accurate of these, with 89 percent accuracy, was ResNet50V2. It easily surpassed the others and performed very well in terms of detecting diabetic retinopathy with a recall and precision of 0.98. It was also effective in detecting cataract. By contrast VGG19 achieved 88% accuracy, InceptionV3 achieved 87 and VGG16 achieved the lowest at 84. Part of this work was explainable AI methods, specifically, Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM generated heatmaps to reveal the most significant regions in retinal fundus images that influenced the predictive output of the model. This helped in better understanding the decision-making process, as well as equipped the clinicians with the relevant information to study and trust the results of the model. Overall, the findings suggest that deep learning models and specifically ResNet50V2 are highly applicable in the classification of retinal diseases. Besides, explainable AI (Grad-CAM) helps to enhance predictability and hence the credibility of such models in clinical decision support systems.

6.2 Limitation

Despite the positive findings of the experiment, this study has its limitations. The first limitation is the amount of data used, in this case 4,272 fundus images. Although this is fairly balanced between the four classes, the quality of this relatively small dataset can limit the generalization power of the models when compared to larger medical image depositories. The other issue was noted in the performance by class, especially on glaucoma detection. In addition, the computational budget did not allow the exploration to be extensive; in order to learn a deep learning model and test the hyperparameters exhaustively, there are very large resources sensitive to this goal, and all of them were not fully accessible in this study. Lastly, the studies were done using publicly available data that were not clinically proven. The thing is that it is possible to do much with the models and in the world about the clinical tasks the model would be recommended to apply to patient data, and further interpreting of it by specialists.

6.3 Future Work

Even though in this paper ResNet50V2 and Grad-CAM were successfully used to visualize and interpret predictions by the model to classify retinal diseases, there are still several opportunities to improve the paper. To better fully interpret model decisions and cross-validate the decisions of their models, the first approach is to integrate multiple explainable AI processes, such as LIME, SHAP, or attention-based visualization processes. Second, more heterogeneous and more detailed fundus images of other populations would help to reinforce and generalize the model. Third, the classification results can be improved by an ensemble model or transformer-based architecture, maintaining explainability. Furthermore, an effective way to close the gap between research and clinical use is to develop a real-time deployment system with a simple interface. It could be an app or a web application, and end-users, ophthalmologists, and patients would be able to post fundus photos and receive a detailed analysis of what could be wrong with their retina. Such deployment, in addition to increasing the accessibility of the diagnostic tool, would also foster awareness and early diagnoses of retinal diseases. All of these would enhance the predictive performance of AI-assisted retinal disease diagnosis as well as its practical utility.

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