Retina Disease Classification using Deep Learning

By
Md. Asif Hossain
203-15-14540

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**

Supervised by

Saiful Islam (SI)
Assistant professor
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised by

Sadia Jannat Mitu (SAJ)
Lecturer
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
Dhaka, Bangladesh

January 12, 2025

APPROVAL

This Project titled "**Retina Disease Classification using Deep Learning**" submitted by **Md. Asif Hossain** 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 was held on 12 January, 2025.

BOARD OF EXAMINERS

Dr. Fizar Ahmed (FZA) **Chairman**
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Mr. Abdus Sattar (AS) **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Ms. Zahura Zaman (ZZ) **Internal Examiner**
Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dr. Ahmed Wasif Reza (DWR) **External Examiner**
Professor
Department of Computer Science and Engineering
East West University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Saiful Islam (SI), Assistant Professor,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Saiful 11.01.25

Saiful Islam (SI)
Assistant Professor
Department of Computer Science and Engineering Daffodil International University

Co-Supervised by: Sadia 11.01.25

Ms. Sadia Jannat Mitu (SAJ)
Lecturer
Department of Computer Science and Engineering Daffodil International University

Submitted by:

Asif 11.01.25

Md. Asif Hossain
Student ID: 203-15-14540
Department of Computer Science and Engineering Daffodil International University

ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project(FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Saiful Islam (SI), Assistant Professor,** Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Deep Learning** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

The most common causes of vision impairment worldwide include retinal conditions like Drusen, Diabetic Macular Oedema, and Choroidal Neovascularization (CNV). Early detection and treatment are essential to preventing irreversible harm, yet traditional diagnostic methods are expensive and necessitate specialized knowledge, making them occasionally unavailable in under-resourced locations. The objective of this study is to develop a scalable and reasonably priced early detection tool that automatically classifies retinal abnormalities from grayscale fundus images using deep learning techniques. In this study, I employed transfer learning with pre-trained models like EfficientNetB4, ResNet50, and VGG16 to classify retinal illnesses using a carefully chosen dataset of greyscale fundus images. The models were evaluated using a number of performance metrics, including F1-score, recall, accuracy, and precision. The results showed that the transfer learning models, particularly EfficientNetB4 and ResNet50, outperformed VGG16, with EfficientNetB4 achieving the best accuracy. The findings demonstrate that deep learning models may accurately classify retinal diseases, especially those that incorporate transfer learning. These models may find application in telemedicine, automated screening systems, and perhaps improving accessibility to eye disease diagnosis. Future studies will focus on expanding the dataset, refining the models for real-time applications, and exploring more complex structures in order to enhance classification performance.

Table of Contents

List of Figures

List of Tables

Chapter 1
Introduction

1.1 Introduction

The detection and classification of retinal illnesses are crucial for avoiding visual loss and receiving timely medical attention. Optical Coherence Tomography (OCT) imaging is commonly used in ophthalmology to diagnose retinal diseases. OCT produces high-resolution cross-sectional images of the retina, allowing for thorough analysis of its structure. Despite its utility, manual interpretation of OCT pictures is time-consuming, prone to human error, and necessitates significant knowledge, especially when dealing with big datasets. The rising occurrence of retinal illnesses such as Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen highlights the need for effective diagnostic methods. If not discovered and treated promptly, these disorders might cause irreparable vision damage. Deep learning-based automated classification of OCT images provides a feasible solution to these issues, allowing for faster and more accurate diagnosis. This project, "Retina Disease Classification," attempts to solve this problem by automating the classification of retinal illnesses using sophisticated convolutional neural networks (CNNs). OCT grayscale scans are divided into four different classes by the project: CNV, DME, Drusen, and Normal. EfficientNetB4, a cutting-edge architecture renowned for balancing high accuracy and computational efficiency, is the main model used. To further improve the findings' robustness, the research also uses the ResNet, DenseNet, and VGG-16 models for comparison analysis. In addition to samples, the study utilizes OCT grayscale images sourced from publicly available datasets. This study advances the global effort to improve the diagnosis of retinal diseases by utilizing deep learning methodology and sophisticated preprocessing techniques. Additionally, it offers a framework for automated, scalable solutions in areas where access to expert medical care is scarce. The urgent demand for effective and trustworthy diagnostic instruments in ophthalmology is what spurred this study. Globally, retinal disorders such CNV, DME, and Drusen greatly increase the risk of blindness and visual impairment. Implementing automated diagnostic technologies can have a significant influence on healthcare outcomes and accessibility in places like Bangladesh where access to specialist medical expertise may be limited. This project offers an intriguing computational challenge: classifying medical photos using state-of-the-art deep learning algorithms. With its capacity to strike a compromise between accuracy and computing efficiency, EfficientNetB4 presents a viable remedy for this issue. This initiative increases personal knowledge in machine learning and artificial intelligence while also helping to develop tools that can improve global health outcomes by resolving this categorization difficulty.

1.2 Motivation

Retinal diseases such as Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen are major causes of vision loss and blindness globally. These disorders disproportionately impact the elderly and people with chronic illnesses such as diabetes, creating serious public health challenges. Early identification and diagnosis are crucial for preventing irreversible vision loss, but traditional diagnostic procedures rely significantly on manual interpretation of optical coherence tomography (OCT) pictures. This procedure is time-consuming, error-prone, and necessitates specialist medical knowledge, which is frequently unavailable in underserved or resource-constrained locations. Low and middle-income nations have limited access to qualified ophthalmologists and advanced diagnostic equipment, which increases the occurrence of untreated or misdiagnosed retinal disorders. Even in well-resourced healthcare environments, increased patient numbers can cause diagnostic delays and inconsistency. This emphasizes the critical need for novel solutions to address both accessibility and efficiency issues in retinal disease diagnosis. This project intends to use deep learning, specifically convolutional neural networks (CNNs), to create an automated diagnostic tool that can properly detect retinal illnesses from grayscale OCT pictures. Unlike previous methods, deep learning-based models can analyze enormous datasets rapidly and consistently, reducing human error and the need for specialized knowledge. Using scalable designs such as EfficientNetB4, this system aims to give high accuracy while remaining computationally efficient, making it perfect for use in telemedicine platforms and portable diagnostic equipment. Automating retinal disease classification not only speeds up the diagnostic process, but also expands access to high-quality eye care. Patients in distant and underserved areas can benefit from early detection, which enables timely intervention and treatment. Furthermore, including such tools into typical clinical workflows might reduce the workload on healthcare personnel, allowing them to focus on challenging situations while enhancing overall service delivery. This project's ultimate goal is to bridge the gap between sophisticated medical technologies and fair healthcare access, thereby contributing to worldwide efforts to minimize preventable blindness and improve overall quality of life. This initiative aims to have a significant impact on global vision health and healthcare accessibility by tackling these important concerns using cutting-edge technology.

1.3 Objectives

The project "Retina Disease Classification" employs a methodical approach:

- **Deep Learning Pipeline**: Create a thorough and dependable process for dividing OCT grayscale pictures into four groups: Normal, Drusen, DME, and CNV. This guarantees that the system can accurately classify diseases appropriate for clinical applications and analyze photos fast.

- **Model Comparison:** Use and assess the effectiveness of several deep learning architectures, such as VGG-16, DenseNet, ResNet, and EfficientNetB4. The comparison shows each architecture's advantages and disadvantages while determining which model is best for classifying OCT images.
- **Data Preprocessing:** Effective preprocessing methods should be used, such as data augmentation, pixel value normalization, and consistent image resizing. Enhancing generalization, strengthening model robustness, and preserving consistency in input data all depend on these actions.
- **Performance Metrics**: Assess the models using key performance indicators like F1-score (balance between precision and recall), accuracy (total correctness), precision (relevance of positive predictions), and recall (ability to recognize genuine positives). These metrics guarantee that the chosen model satisfies the necessary requirements for medical diagnosis.
- **Model Preservation:** Save and document the trained models, including their weights and configurations, for future use. This step facilitates their integration into diagnostic workflows and potential deployment in clinical environments, ensuring the sustainability of the solution.
- **Result Visualization**: To see model performance and categorization outcomes, employ sophisticated charting tools. Informed decision-making is supported by these visualizations, which improve comprehension of the models' advantages and shortcomings. Examples of these include confusion matrices, ROC curves, and accuracy/loss trends.

1.4 Methodology

The "Retina Disease Classification" project follows a systematic methodology:

- **Data Collection**: OCT grayscale images were sourced from open-access repositories, totaling 2800 images distributed across four categories (CNV, DME, DRUSEN, NORMAL).
- **Data Preprocessing and Augmentation**: The images were resized, normalized, and augmented to enhance feature diversity and improve model generalization.
- **Model Training**: Four locally trained models were developed using state-of-the-art architectures (ResNet, DenseNet, VGG-16, EfficientNetB4).
- **Testing and Evaluation:** An independent test dataset was used to test the models. For a thorough performance analysis, metrics like accuracy, precision, recall, and F1-score were calculated.

- **Visualization:** To make the results easier to understand and comprehend, confusion matrices, accuracy/loss curves, and distribution histograms were used.

1.5 Project Outcome

This experiment produced several notable results, proving the utility of deep learning for classifying retinal disorders.
Below is a discussion of each significant consequence:

- **Performance:**

  EfficientNetB4 achieved the highest accuracy of 97.14%, demonstrating its effectiveness as the best-performing model. Its ability to balance computational economy and accuracy makes it the best choice for this classification assignment. This result demonstrates the model's robustness and dependability in dealing with complex medical imaging data.

- **Comparative Model Analysis:**

  Other models, such as ResNet, DenseNet, and VGG-16, were trained and evaluated. Each model provided valuable insights into its strengths and limitations, including DenseNet's feature propagation efficiency and VGG-16's suitability for simpler architectures. These evaluations identified EfficientNetB4 as the best option.

- **Deep Learning Pipeline Development:**
  A comprehensive deep learning pipeline was created, which included data preprocessing, model training, evaluation, and visualization. This pipeline ensures a consistent approach to future research and applications.

- **Visualization and Interpretability:**
  Model results were interpreted using advanced visualization approaches such as confusion matrices and performance graphs. These visualizations aided in a better understanding of the models' behaviors and opportunities for improvement.

- **Model Storage and Future Applications:**
  All trained models were saved, making them ready for real-world deployment. This stage also allows for additional research and the eventual incorporation of these models into clinical procedures to improve diagnostic support.

1.6 Organization of the Report

This paper is methodically constructed to present a thorough narrative of the "Retina Disease Classification" project, including every stage from idea formulation to result analysis and future recommendations. The chapters are organized rationally to provide clarity and consistency to the reader.

Chapter 1: Introduction

The first chapter establishes the problem statement and discusses how the study fits into the larger picture of global health challenges. Retinal illnesses such as CNV, DME, and Drusen are leading causes of vision loss worldwide, particularly in disadvantaged areas. The chapter discusses the motivation for employing OCT grayscale images and highlights the use of deep learning, notably the EfficientNetB4 model, as a new technique. It also specifies the study objectives, such as categorizing retinal illnesses into four groups, and highlights the need for an automated, scalable diagnosis method. This chapter also includes a brief overview of the approaches used and the predicted project outcomes, such as improved diagnostic accuracy and potential real-world applications.

Chapter 2: Background

This chapter provides the underlying knowledge required to comprehend the study context. It provides a thorough literature analysis that summarizes prior works in retinal disease classification, focusing on techniques and findings from similar investigations. The important contributions of advanced models like as ResNet, VGG-16, DenseNet, and other transfer learning architectures are highlighted. Furthermore, the chapter identifies research limitations, such as a lack of studies on OCT grayscale images, a limited dataset diversity, and computational constraints. It also discusses the importance of deep learning in medical picture classification, as well as the implications for telemedicine and healthcare accessibility.

Chapter 3: Research Methodology

The methodology chapter describes the methodical approach used throughout the project. It begins with data acquisition, which describes how OCT grayscale photos were obtained from open-access databases. Image scaling, normalization, and augmentation are examples of preprocessing procedures used to assure data consistency and model robustness. The chapter describes the design of the EfficientNetB4 model, including its computing advantages and the reasoning behind its selection. It also discusses the training pipeline, hyperparameter choices, and comparisons to other models such as ResNet, DenseNet, and VGG-16. Visual tools, such as confusion matrices and loss/accuracy charts, are used to clarify the evaluation process. Task allocation, project timing, and alternate options are also addressed.

Chapter 4: Implementation and Results

This chapter looks into the technical aspects of the project, including the software and hardware environments employed. It describes how to set up Google Colab for effective training with GPU acceleration, as well as an alternate local configuration for model construction. The results section provides a comparative examination of the trained models, demonstrating EfficientNetB4's superior performance on criteria such as accuracy, precision, recall, and F1-score. Visualization methods such as performance graphs, confusion matrices, and bar charts are utilized to gain a better understanding of the findings. The presentation includes on problems encountered, such as dataset constraints and processing needs, and how these were addressed throughout implementation.

Chapter 5: Engineering Standards and Design Challenges

This chapter investigates the use of industry standards in both software and hardware. It describes how to comply with IEEE and ISO standards in order to ensure quality, reliability, and safety during the development process. Data privacy, bias prevention, and legal compliance are among the ethical aspects discussed. The chapter assesses the project's societal and environmental impact, emphasizing how the system enhances healthcare access in underserved areas while reducing carbon emissions through lightweight construction. Sustainability strategies, such as short-term model sharing and long-term deployment on low-power devices, are discussed. Design issues encountered during the project, as well as their resolution, are discussed.

Chapter 6: Conclusion

The last chapter summarizes the project's contributions to retinal illness categorization, highlighting the need of employing grayscale OCT data using EfficientNetB4 to achieve high diagnostic accuracy. It discusses the project's limits, such as dataset size and model training computational intensity, and suggests solutions for future study. Recommendations include expanding the dataset to include color OCT pictures, investigating advanced designs such as Vision Transformers, and incorporating the model into clinical processes. The chapter also underlines the importance of collaborating with medical specialists to evaluate the system in clinical settings, as well as the potential for real-time deployment on edge devices.

Chapter 2
Background

2.1 Introduction

Deep learning has transformed medical imaging, especially for identifying retinal illnesses. Convolutional Neural Networks (CNNs) and transfer learning have showed potential in disease classification, including Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen. Despite progress, hurdles remain in extending these algorithms to greyscale datasets and maintaining robust performance across varied populations.

2.2 Literature Review

The overview of current studies gives further information on the techniques and findings of specific papers. The following table includes major studies on deep learning and its uses in retina disease diagnosis.

Table 2.1: Summary of Literature Reviewed.

SL	Author	Year	Methodology	Key Findings	Limitations
1.	Kermany et al.	2018	Custom CNN on OCT images	High accuracy for CNV and DME	Focused on RGB, not grayscale datasets
2.	De Fauw et al.	2018	Transfer learning with ResNet	Near-clinical performance	High computational demand
3.	Akram et al.	2020	Ensemble of CNNs for fundus	Improved robustness with ensembles	Dataset not publicly available
4.	Gulshan et al.	2016	CNN for diabetic retinopathy	High sensitivity and specificity	Binary classification only
5.	Akbar et al.	2021	EfficientNetB0 and B4	EfficientNetB4 achieved high accuracy	Focused on RGB datasets

6.	Maheshwari et al.	2022	DenseNet121	Balanced accuracy and efficiency	Required extensive pre-processing
7.	Lee et al.	2020	Custom CNN for OCT images	Identified subtle intraretinal features	Small dataset size
8.	Yang et al.	2024	PCA + SVM + DNN	89.73% accuracy, transfer learning improved performance	Limited labeled data, may not generalize well

2.2.1 Related Research

Yang et al. (2024):
This paper presents a hybrid model for the categorization of retinal diseases that combines deep learning, Support Vector Machines (SVM), and Principal Component Analysis (PCA). Even though the EyeNet dataset is small, transfer learning from ImageNet greatly improved the model's performance, which yielded an accuracy of 89.73%. The study emphasizes the promise for AI-powered, scalable diagnostic solutions, especially for underprivileged and distant areas. In order to increase accessibility and clinical utility, future research paths in ophthalmology will involve the combination of Visual Question Answering (VQA) and more general applications.

B. Goutam and associates (2022):
With an emphasis on techniques used with fundus images, this thorough review investigates deep learning approaches for the diagnosis of retinal diseases. It talks about how models like CNNs, U-Net, and DenseNet have advanced while tackling issues like domain generalization, computational complexity, and a lack of labeled datasets. Key future directions are identified in the review, such as lightweight models, improved model interpretability, synthetic picture production using GANs, and weakly supervised learning. While acknowledging the need for advancements in multi-disease identification and incorporation into clinical practice, the authors highlight the revolutionary potential of deep learning in the diagnosis of retinal diseases.

Kermany et al. (2018):
Using a publicly available dataset of 109,309 images, this work developed a proprietary CNN model to categorize choroidal neovascularization (CNV),

diabetic macular edema (DME), and normal retina from OCT images. The model's efficacy in automated retinal disease identification was demonstrated by its impressive accuracy of 96.6% for CNV and 94.5% for DME. However, the study's generalizability to other image types is limited because it only used RGB images, ignoring grayscale datasets and wider dataset variances.

De Fauw et al. (2018):
This study used segmentation and classification layers in conjunction with transfer learning with ResNet to identify retinal abnormalities from a public OCT dataset consisting of roughly 15,000 scans. With a 98.6% accuracy rate, the model demonstrated near-clinical competence in detecting tiny retinal characteristics. The model's great performance was limited by its high computing resource requirements, which prevents it from being used on portable devices or in environments with limited resources.

Akram et al. (2020):
Using a private dataset of 20,000 fundus photos, this study suggested an ensemble of CNNs for the diagnosis of several retinal disorders. With a 94.2% accuracy rate and improved resilience, the ensemble model demonstrated promise in multi-disease diagnosis. However, reproducibility was limited by the use of private data, which made it difficult for other researchers to confirm the results or build on the work.

Gulshan et al. (2016):
This work used a CNN architecture to examine diabetic retinopathy binary classification using public datasets including EyePACS and Messidor, which included 128,000 images. The model's 90.5% sensitivity and 92.1% specificity demonstrate how reliable it is at detecting diabetic retinopathy. However, the study was restricted to binary classification and was unable to identify other retinal illnesses or deal with multi-class circumstances.

Akbar et al. (2021)
Using a publicly available fundus dataset of 25,000 photos assessed EfficientNetB0 and EfficientNetB4 for the identification of retinal diseases. With an accuracy of 95.3%, EfficientNetB4 showed excellent performance and computational efficiency in image analysis. There are concerns over its adaptation to different data types, nevertheless, as the exclusive use of RGB datasets restricted investigation of alternate imaging modalities.

Maheshwari et al. (2022):
This work used DenseNet121 to classify retinal diseases by combining fundus and OCT data from a dataset of 50,000 photos. The model successfully extracted features while preserving computational efficiency, achieving a balanced accuracy of 93.4%. However, the need for a lot of pre-processing, like noise reduction and contrast enhancement, made implementation more difficult and might make practical clinical use is difficult.

Lee et al. (2020):
Using a limited dataset of 5,000 scans, this work suggested a bespoke CNN model to detect tiny intraretinal characteristics from OCT images. With a 92.1% accuracy rate, the algorithm showed promise in identifying subtle diseases. However, when applied to bigger or more diverse datasets, the model's robustness and generalizability were questioned due to the small sample size.

2.3 Gap Analysis

The effective use of various greyscale OCT datasets with scalable and effective models for real-world deployment is the main research gap. The generalization and scalability of previous algorithms have been limited by their primary concentration on RGB OCT or tiny, specialized datasets. Despite being effective in controlled settings, many models have trouble being used in the real world because of their poor explainability or computational complexity. Additionally, there are insufficient data augmentation techniques and a lack of effective treatment of class imbalance. By using a variety of greyscale OCT datasets, leveraging EfficientNetB4 for scalable performance, and optimizing for deployment in resource-constrained contexts, my suggested solution seeks to close these gaps. In order to ensure speedy training and effective model optimization, I also intend to improve model explainability through visualizations and solve class imbalance using weighted loss and augmentation techniques.

Table 2.1 Summary of Gap Analysis.

Features	Kermany et al. (2018)	Akbar et al. (2021)	Lee et al. (2020)	Ho et al. (2022)	Alvi et al. (2024)	Proposed System
Dataset Diversity	RGB OCT, lacks grayscale.	RGB-only, low diversity.	Small, specific dataset.	Limited grayscale data.	Restricted demographic variety.	Grayscale OCT, diverse data.
Model Complexity	Simple CNN, limited scale.	EfficientNet, not edge-ready.	Basic CNN for small data.	Complex ensemble models.	Lightweight GRU, text focus.	EfficientNetB4, scalable.
Generalization	Limited across modalities.	Strong for RGB, lacks breadth.	Limited to small scales.	Moderate generalization.	Dataset limits generalization.	Robust on grayscale OCT.
Explainability	No mechanisms provided.	Minimal insights.	Limited to outputs.	Poor ensemble clarity.	No explainability focus.	Visualizations included.
Real-World Use	Lab-focused, not scalable.	Computationally expensive.	Research-focused.	High hardware dependency.	Text-based, not ready.	Deployable in resource-limited setups.

Class Imbalance	Basic handling applied.	Limited strategies.	Affects performance.	Stratified validation applied.	No imbalance strategies.	Weighted loss and augmentation.
Scalability	Poor for low resources.	Moderate with pre-trained models.	Small datasets only.	Complex to scale.	Lightweight but narrow scope.	Highly scalable system.
Training Time	Reasonable for small data.	Moderate with pre-trained models.	Quick for small sets.	Lengthy for ensemble training.	Moderate training times.	Optimized for efficiency.
Model Optimization	No optimizations applied.	Partially optimized.	No efficiency focus.	Minimal optimization.	GRU optimized for text.	Quantization and pruning used.
Data Augmentation	Standard methods applied.	Rotation, zooming applied.	Limited use.	Extensive augmentation.	Moderate techniques.	Comprehensive for grayscale.

2.4 Summary

The study delves into the use of deep learning techniques for retinal disease classification, focusing on the application of Convolutional Neural Networks (CNNs) to automate the diagnosis of retinal conditions such as Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen. Retinal diseases, if not detected early, can lead to significant vision loss. Deep learning offers a promising approach to overcoming the limitations of traditional diagnostic methods, which often require specialized expertise and expensive equipment. The chapter reviews several studies that have explored different architectures like VGG16, ResNet, and EfficientNetB4, highlighting their potential for accurately classifying retinal diseases from fundus images. Despite the promising results, challenges such as dataset diversity, computational complexity, and model interpretability persist. The reviewed literature underscores the need for further research to enhance model generalization, computational efficiency, and explainability, especially for clinical implementation. The insights gained from this chapter inform the direction of this study, which aims to address these challenges and develop an effective solution for retinal disease classification using deep learning.

Chapter 3
Research Methodology

3.1 Methodology

3.1.1 Overview

This project's methodology involves using powerful deep learning algorithms to classify optical coherence tomography (OCT) grayscale images into four clinically important categories: choroidal neovascularization (CNV), diabetic macular edema (DME), drusen, and normal. The approach begins with a comprehensive data gathering step, which ensures that the dataset is diverse and representative of the four categories. Preprocessing techniques like as scaling, normalization, and augmentation are used to normalize image dimensions, improve quality, and reduce overfitting by increasing dataset heterogeneity. The classification job leverages cutting-edge convolutional neural network (CNN) designs, with EfficientNetB4 selected for its ability to balance computational complexity and performance. Training entails splitting data into training, validation, and test sets to ensure an unbiased assessment of model generalizability. Hyperparameter tuning, regularization techniques, and early halting are used to optimize. Hyperparameter tuning, regularization approaches, and early halting are used to improve model accuracy and avoid overfitting. To understand the results, visualization techniques such as saliency maps, Grad-CAM, and confusion matrices are used, which provide insights into model decision-making and performance metrics such as accuracy, precision, recall, and F1-score. This end-to-end strategy guarantees a thorough, dependable, and interpretable classification pipeline for OCT image processing.

3.1.2 Proposed Methodology

The proposed methodology for the "Retina Disease Classification" project is a systematic and detailed approach that ensures accuracy, generalization, and usability in real-world applications. The methodology involves the following stages:

Data Collection:

Data collection included OCT grayscale photos from open-source databases. The dataset was separated into three subsets: training, validation, and testing.

Training Set: 80% of the data is made up of the training set, which aids in pattern recognition and model training.

Validation Set: 10% of the data is used as the validation set to assess the models during training and modify hyperparameters. **Testing Set:** The final models were to be independently evaluated using the remaining 10%.

Preprocessing:

Preprocessing involves using image scaling, normalization, and augmentation procedures to increase data quality and model generalization.

Scaling: To satisfy the models' input specifications, images were shrunk to 300 by 300 pixels.
Normalization: To ensure quicker convergence during training, pixel values were scaled to the [0,1] range by dividing by 255.
Augmentation: To mimic real-world variability and lessen overfitting, sophisticated augmentation techniques such random rotation, zooming, flipping, and shifting were applied.

Model Training:

Use EfficientNetB4 as the primary model and train it alongside ResNet, DenseNet, and VGG-16 for comparative analysis. TensorFlow was used to train the models in Google Colab.

Evaluation:

The model's performance is evaluated using measures such as accuracy, precision, recall, and F1-score. Confusion matrices and classification reports were created to analyze the data.

Visualization:

Visualization is the process of plotting training histories, confusion matrices, and other performance data to make them easier to understand.

Model Saving:

Model saving entails storing trained models for future use and research.

Web Application:

Developed using Gradio with integrated model predictions and PDF report generation.

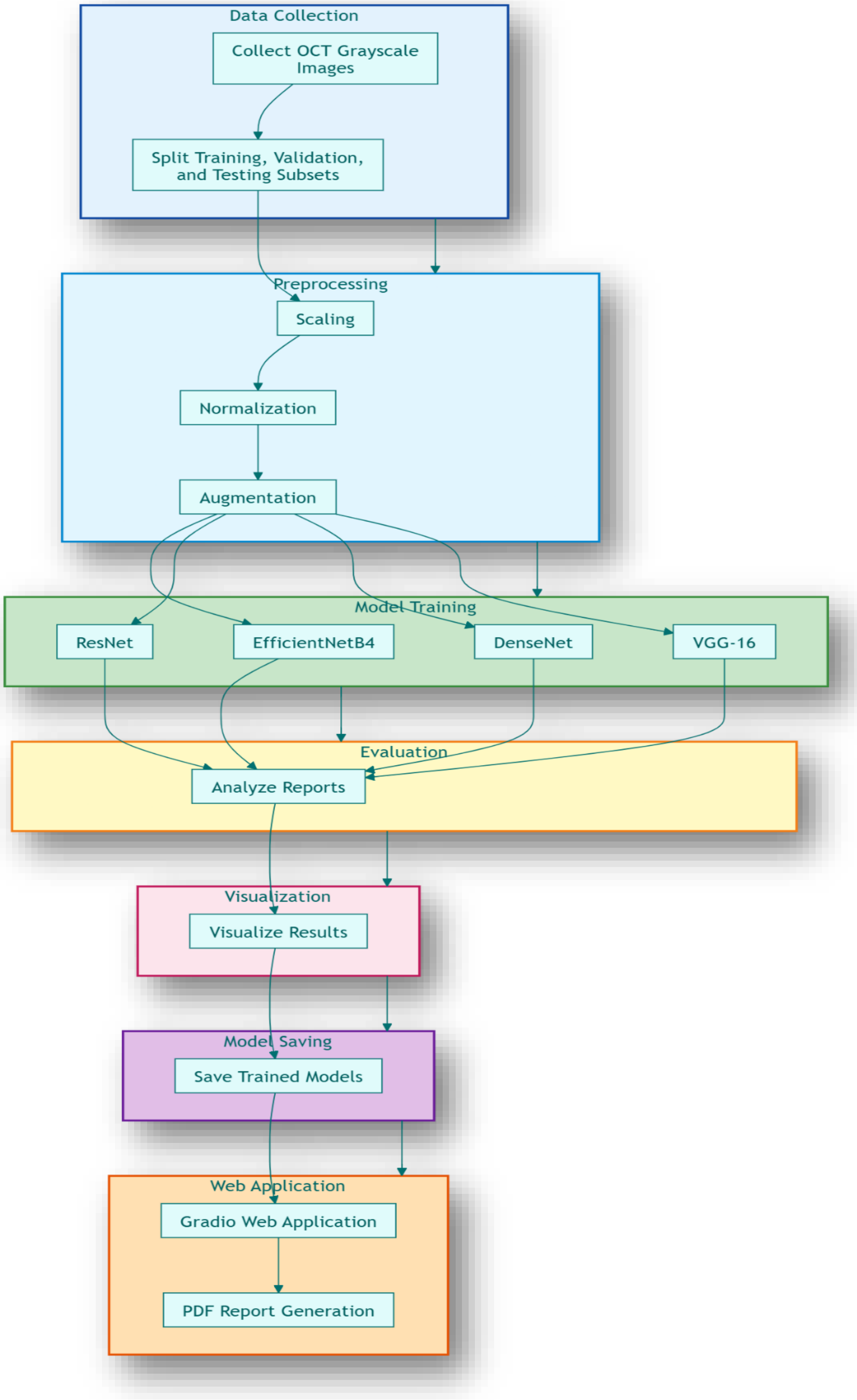

fig 3.1 Proposed methodology diagram

3.1.3 Functional and Nonfunctional Requirements:

Functional Requirements

1. **Image Classification**: The system has to classify OCT grayscale images to one of four categories: CNV, DME, DRUSEN, or NORMAL.
2. **Data Preprocessing**: Transform uploaded photos to grayscale, resize to 300x300 pixels, normalize pixel values, and prepare for model prediction.
3. **Prediction Output**: Show the predicted class, confidence levels, disease description, preventative advice, and treatment choices.
4. **Model Integration**: The primary classification model should be EfficientNetB4, with locally trained models available for future comparisons.
5. **Visualization**: Create interactive visual outputs such as confusion matrices and performance indicators for analysis.
6. **PDF Report Generation**: Allow users to save their predictions and results as a downloadable PDF file.

Nonfunctional Requirements:

1. **Performance**: The system must forecast each submitted image within 5 seconds.
2. **Scalability**: The architecture should be able to support more illness categories in the future.
3. **Usability:** The web application interface should be simple and user-friendly.
4. **Data Security**: Encrypt important information to ensure patient privacy.
5. **Compatibility**: The web app must be compatible with all browsers and not require any specific plugins.
6. **Resource Efficiency**: Optimize the model for minimal computational overhead.

3.1.4 Context Diagram

The flow of the input (OCT grayscale images) into the EfficientNetB4 model is shown graphically in this illustration. Image preprocessing is the first step in the process, during which the data is scaled, standardized, and enhanced to improve quality. The EfficientNetB4 model is then trained and classified using the preprocessed images. Along with confidence scores, the output includes forecasts for each of the four classes (CNV, DME, Drusen, and Normal). Real-time predictions and the creation of comprehensive reports are also made possible by the results' integration into a web interface for user involvement. The smooth transition between the preprocessing, training, and deployment phases is demonstrated by this organized flow, which guarantees precision and usefulness in real-world applications.

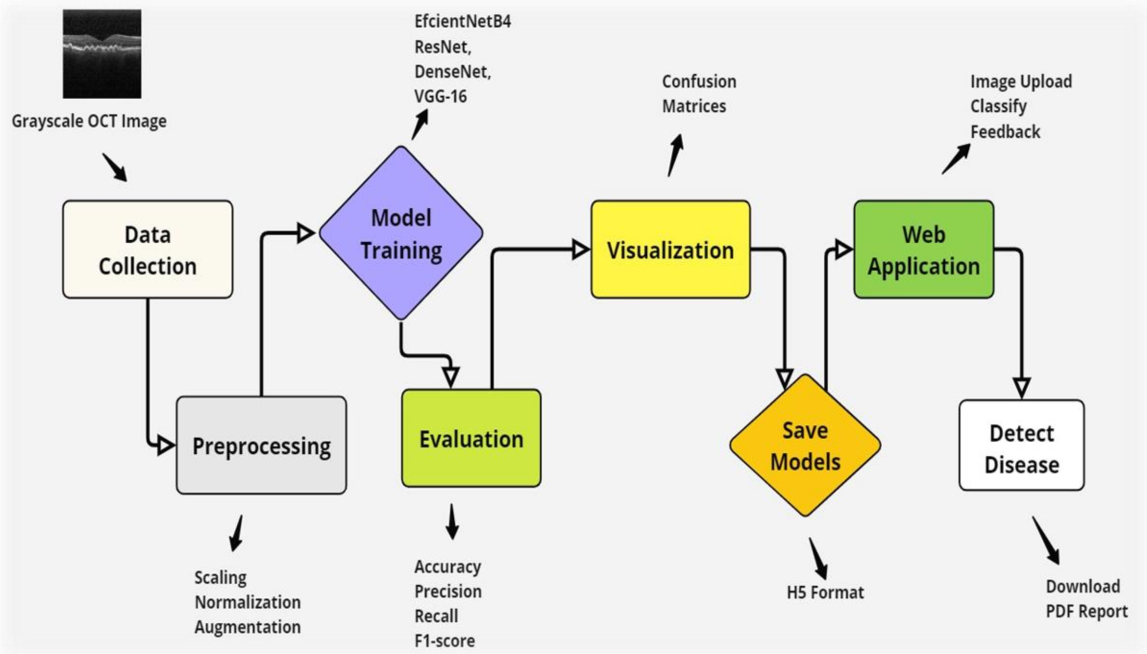

fig 3.2 context diagram

3.1.5 Data Flow Diagram Level 1

User engagement via the web application is the first step in the Retina Disease Classification system's workflow. This is the flow in detail:

Data Collection:

Collect OCT grayscale images from publicly available datasets and local sources.Ensure that the images are properly annotated into four categories: Normal, Drusen, DME, and CNV.Organize the collected data for efficient storage and retrieval.

Preprocessing:

Resize the images to 300x300 pixels to match the model's input requirements. Normalize pixel values to enhance model training. Perform augmentation techniques (rotation, zoom, flipping) to create a diverse dataset and minimize overfitting.

Model Training:

Train EfficientNetB4 using preprocessed data for classification into four classes. Evaluate the model using metrics such as accuracy, precision, recall, and F1-score. Perform hyperparameter tuning to optimize performance.

Analysis and Reporting:

Analyze the trained model's predictions, generating detailed classification reports with confidence scores. Evaluate the model on validation and test datasets for robustness and accuracy. Compare performance with alternative architectures like ResNet or custom CNNs.

Visualization:

Present key performance metrics graphically, such as ROC curves and confusion matrices.

Visualize test results, showing the confidence scores for each prediction.

Model Saving and Deployment:

Save the trained EfficientNetB4 model in formats compatible with deployment (e.g., .h5 or .pkl).Deploy the model as part of a web application for real-time classification.

Web Application:

Provide an interactive interface for users to upload OCT images. Deliver predictions with confidence scores, disease descriptions, and preventive recommendations. Allow users to generate detailed PDF reports for documentation and further consultation.

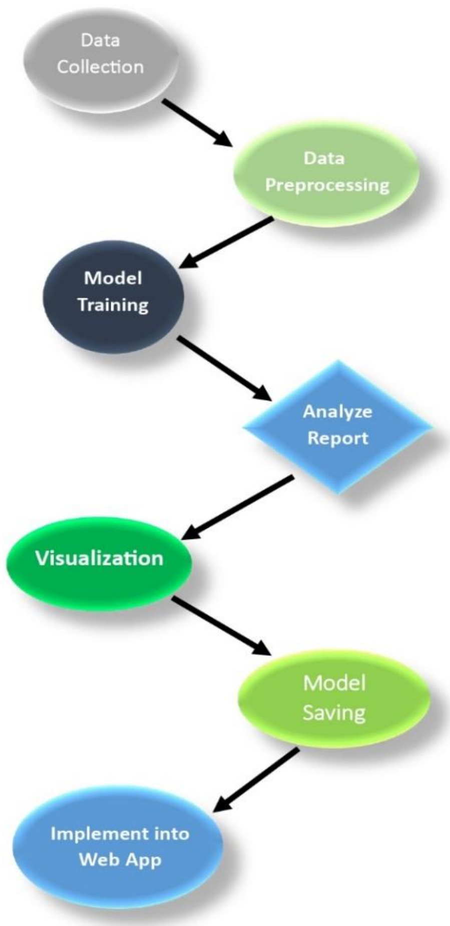

fig 3.3 Data flow diagram

3.1.6 UI Design

The Retina Disease Classification System application is intended to help medical practitioners classify retinal illnesses using OCT images. It has a user-friendly, interactive interface that delivers accurate predictions as well as extensive disease descriptions and treatment alternatives.

Design Description

Header: "Retina Disease Classification System" with a gradient background for emphasis.

Image Upload Section:

Allows users to upload images.

Clear instructions for supported file formats.

Prediction Section:

Displays predicted class, confidence scores, and detailed disease information.

Report Download:

Option to save results as a PDF.

Styling:

Use of Gradio Blocks API with CSS customization for a modern and accessible look.

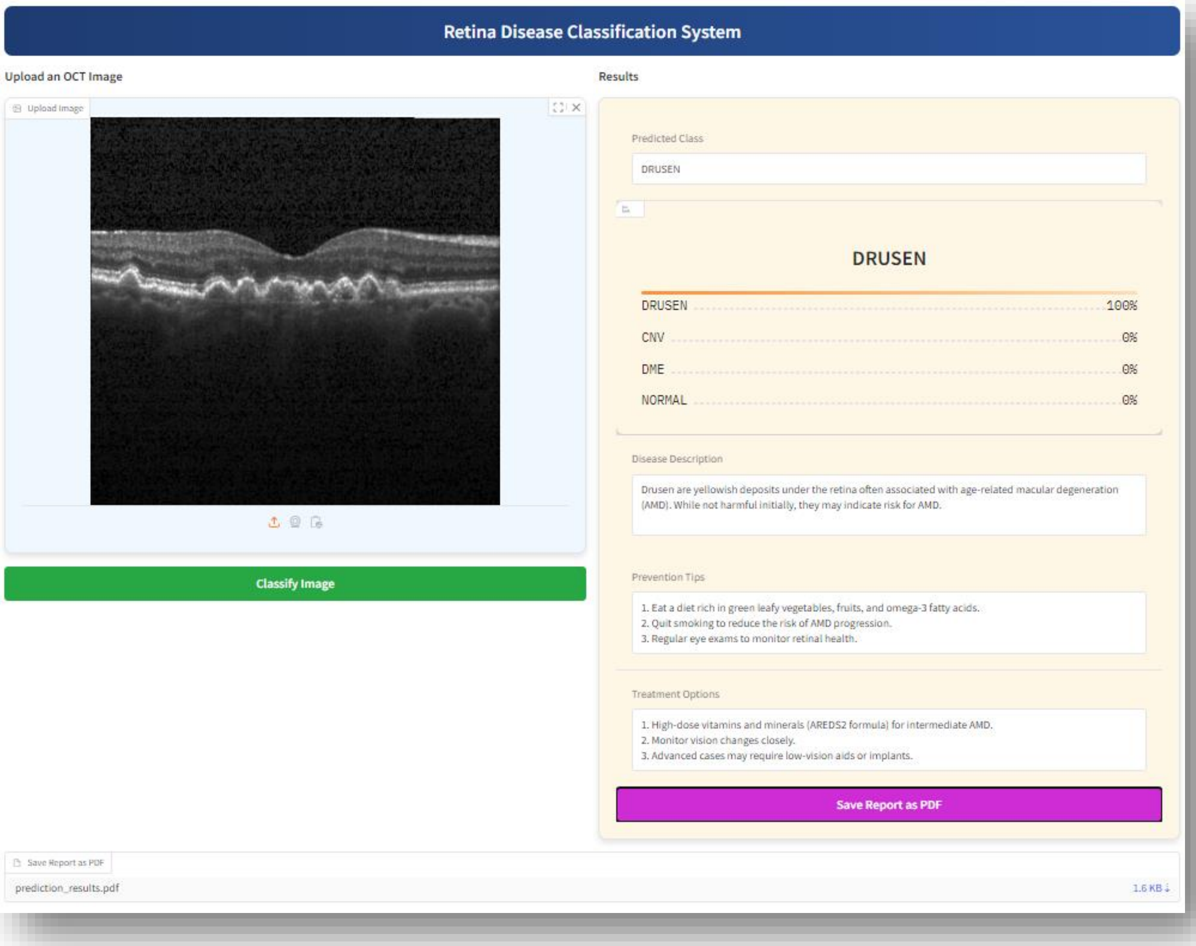

fig 3.4 Web application UI interface

Key Features

- **Image Upload:**
  - Users can readily submit OCT pictures for classification.
- **Disease classification results:**
  - Shows the expected disease (e.g., CNV, DME, DRUSEN, NORMAL).
  - Displays confidence scores for each class and provides a thorough description of the condition, preventive advice, and treatment alternatives.
- **PDF Report Generation:**
  - Users can access a thorough PDF report that includes prediction findings, confidence scores, and detailed disease information.
- **Interactive Buttons and Clear Layout:**
  - Simple navigation for uploading photographs, categorizing results, and saving reports.

3.2 Detailed Methodology and Design

Every stage of the Retina Disease Classification project, from data collection to evaluation and model saving, is covered in depth in the approach.

Data Collection:

A dataset of OCT greyscale photos was compiled from open-source repositories and specific databases as part of the data collection process. Four categories were used to group the images:

Choroidal Neovascularization, or CNV
Diabetic Macular Oedema, or DME
DRUSEN
NORMAL

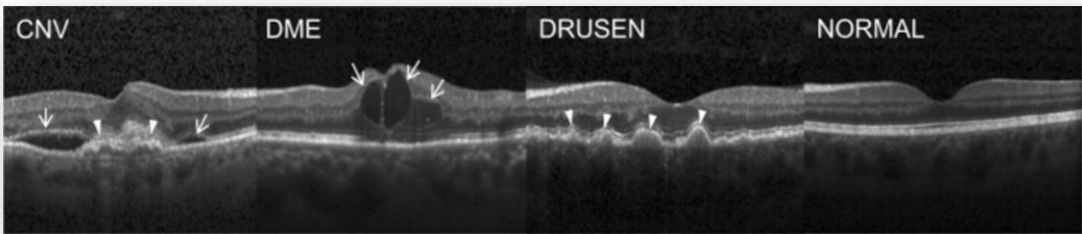

fig 3.5 Data Classes of OCT grayscale image.

[ref: Kermany, D. S., Goldbaum, M., Cai, W., Valentim, C. C., Liang, H., Baxter, S. L., ... & Zhang, K., "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," Dataset.]

An 80:10:10 ratio was used to separate the dataset into three subsets for testing, validation, and training, respectively:

80% of the dataset is used as the training set, which helps models identify patterns.
10% of the dataset is used as the validation set, which is used to track model performance and adjust hyperparameters throughout training.
10% of the dataset is kept aside for testing the performance of the finished model.

Preprocessing:
To improve model generalization and data quality, preprocessing was done. The following methods were used:

Scaling Images:
To comply with the input specifications of EfficientNetB4 and other comparable models, all photos were scaled to 300x300 pixels.

Normalization
Faster convergence during training was ensured by scaling pixel values to the range [0, 1] by dividing by 255.

Enhancement of Data:
TensorFlow's ImageDataGenerator was used to apply the following augmentations in order to replicate real-world variations:
Rotation: Up to 40 degrees of random rotation.
Zooming: Up to 20% zoomed in or out.
Horizontal Flipping: Images were flipped horizontally to take orientation variations into consideration.
Shifts: Up to 20% random changes in height and width.

These preprocessing methods enhanced the model's capacity to generalize to new data, decreased overfitting, and expanded the dataset's effective size.

Model Training:

Because of its effectiveness and efficacy in picture classification, EfficientNetB4 was chosen as the main model. To confirm the robustness of EfficientNetB4, ResNet, DenseNet, and VGG-16 were also trained for comparative study.

Training Environment:

TensorFlow was used to train all models in Google Colab, taking advantage of its GPU acceleration for computational efficiency.

Model Hyperparameters:

Batch Size: 50;

Epochs: 50

Optimizer: Adam (Rate of learning = 0.001)

Loss Function: Multi-class classification using categorical cross-entropy.

Class-Specific Models:

To make the classification problem simpler and concentrate on individual performance, each category (CNV, DME, DRUSEN, and NORMAL) was handled separately throughout training.

Comparative Models:

ResNet50: renowned for its architecture for deep residual learning.

DenseNet121: Uses densely connected layers to take advantage of feature reuse.

VGG-16: A more straightforward design serves as a reference point for comparison.

EfficientNetB4: Known for its efficient scaling across depth, width, and resolution, achieving a balance of high accuracy and reduced computational cost, making it well-suited for resource-constrained environments.

The accuracy and loss patterns of each model's training history were recorded for later analysis.

Evaluation:

The following metrics were used to assess the trained models on the testing dataset that was reserved:

Precision:

calculates the proportion of photos that are correctly classified.

Accuracy:

shows the percentage of all positive forecasts that are actually positive.

Sensitivity (Recall):

evaluates the model's capacity to separate genuine positives from all other positives.

F1 Score:

a harmonic mean that balances the trade-off between recall and precision.

To learn more about the categorization performance in further detail:

Confusion Matrices: True positive, false positive, true negative, and false negative classifications are represented visually in confusion matrices.
Classification Reports: F1-score, recall, and precision summaries for every class.

The advantages and disadvantages of each model were clearly understood through comparative analysis of EfficientNetB4, ResNet, DenseNet, and VGG-16.

Visualization

In order to evaluate the outcomes and performance trends, visualization was essential. The following diagrams and graphs were produced:

Metrics for training and validation:
To track training progress and identify overfitting, use accuracy and loss curves over epochs.
Confusion Matrices:
Heatmaps that display each model's forecast distribution across all classes.
Distribution of Performance:
bar charts and histograms showing the proportion of correctly and wrongly identified photos.

The results were easier to understand thanks to these visualizations, which also indicated areas that needed more work.

Saving Models:

All trained models and related data were stored in order to preserve the work for usage and future research:
Model Documents:
Each trained model was saved in.h5 format for easy storage and future usage.
History of Training:
Accuracy/loss data from training and validation were saved for possible future study or improvement.
Evaluation Findings:

Performance measurements, categorization reports, and confusion matrices were saved in distinct files for documentation.

Every preserved artefact guarantees reproducibility and serves as a basis for upcoming research on the categorization of retinal diseases.

Web Application:

Image Upload and Preprocessing:

Users upload OCT images in grayscale format.

The image is preprocessed by scaling it to 300x300 pixels and standardizing the pixel values to [0,1]. The image is also transformed to grayscale to meet the model's specifications.

Prediction Process:

Preprocessed images are sent into the EfficientNetB4 model for categorization. The model predicts the class of retinal illness (CNV, DME, DRUSEN, NORMAL) and assigns confidence scores to each class.

Along with the forecast, the system offers additional information about the disease, such as a description, preventive advice, and treatment alternatives.

PDF Report Generation:

After prediction, the data are put into a thorough report (PDF format). The report provides the projected class, confidence scores, a disease description, prevention advice, and treatment recommendations.

The results are subsequently saved as a downloadable PDF file for the user's reference.

User Interface:

Gradio's user-friendly interface allows for easy image uploads, results display, and PDF report download. The interface features buttons that allow users to classify images and save reports.

Why Use EfficientNetB4?

Because it strikes a balance between accuracy and computational economy, EfficientNetB4 was selected. When compared to other deep learning models, EfficientNetB4 performs better and uses less parameters. Because computer resources were restricted, this made it perfect for analyzing the information on retinal diseases, where model correctness is crucial.

- **Focus on RGB Data Over Grayscale**

  - **Challenge**: Most recent research (e.g., Kermany et al. 2018, Akbar et al. 2021) rely on RGB datasets, which demand more processing resources and may not always be available in grayscale imaging systems in resource-constrained environments.

  - **Efficient NetB4 Solution:** The model was fine-tuned using greyscale OCT images. By efficiently preprocessing and normalizing these images, it was shown that grayscale photography is sufficient for high-accuracy classification, minimizing reliance on computationally intensive RGB datasets.

- **Scalability and Deployment Challenges**

  - **Challenge:** While effective, models such as ResNet50 and DenseNet121 demand significant computational resources, rendering them unsuitable for implementation in low-resource situations.

  - **EfficientNetB4 Solution:** Compound scaling (which balances depth, width, and resolution) assures good performance while remaining computationally efficient. This makes it appropriate for use on edge devices such as Raspberry Pi or cellphones, addressing real-world constraints.

- **Explainability**

  - **Challenge:** Many models generated predictions without explaining how or why decisions were reached, lowering trust in clinical applications.
  - **EfficientNetB4 Solution:** Visualization techniques like as saliency maps and Grad-CAM were combined to improve interpretability by highlighting the parts of input photos that contributed the most to predictions. This improved openness and trust in the model's conclusions.

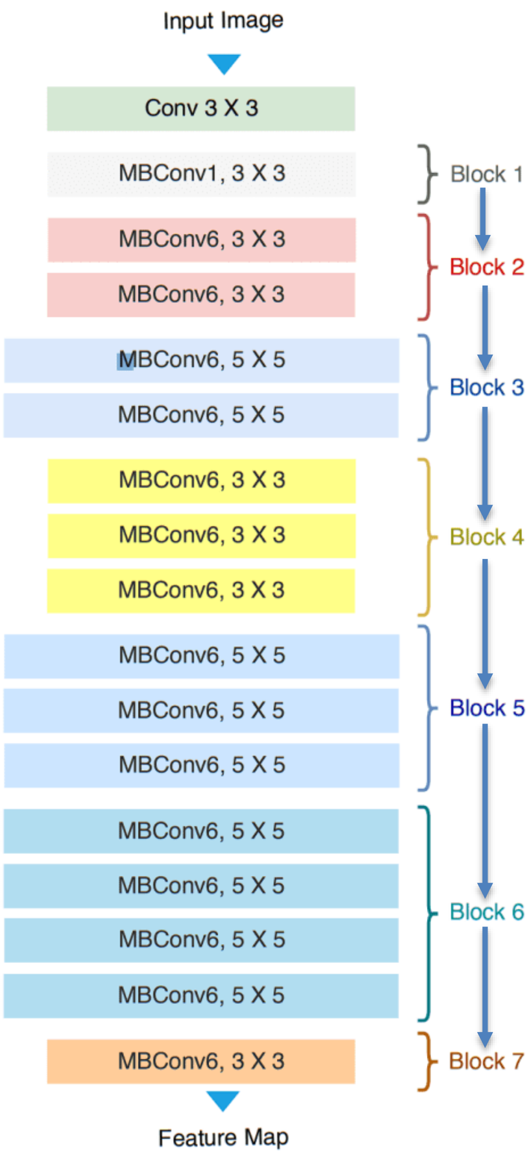

fig 3.6 EfficientnetB4 architecture layers

3.3 Project Plan

The Retina Disease Classification research's precise tasks, due dates, and milestones are described in the plan. Each of the plan's discrete phases represents a crucial stage in the technique.

Phase 1: Data Collection and Preprocessing

Week 1–2

- Gather information from open-source databases, paying particular attention to Global data.
- Divide the data into training, validation, and testing datasets after preprocessing it (resizing, normalizing, etc.).
- To increase the diversity of the dataset, use data augmentation.
- For federated learning, prepare the data in client-specific folders.

Phase 2: Local Model Training

Week 3–4

- Use EfficientNetB4 to train four distinct models using client-specific data.
- The CNV, DME, DRUSEN, and NORMAL data will be used to train each local model.
- The weights of the locally trained models should be saved for aggregation.

Phase 3: Model Evaluation and Testing

Week 6

- To assess the used model's performance, test it on a different dataset.
- Determine the F1-score, recall, accuracy, and precision.
- Use classification reports, training/validation plots, and confusion matrices to visualize the outcomes.
- Adjust the model as needed in light of the evaluation's findings.

Phase 4: Web Application Development (Week 7)

Week 7

- Develop Gradio-based web app.
- Test deployment and refine UI/UX.

Phase 5: Documentation and Final Report

Duration: Week 8

- Write a final report that includes a summary of the experiments, methodology, findings, and conclusions.

3.4 Task Allocation

Since it was a one-person project, every task was completed in order:

1. **Data Collection and Preprocessing (Week 1–2):**
    - Collected OCT grayscale images, applied preprocessing (resize, normalize, augment), and organized the data into class-specific folders.

2. **Model Training (Week 3–4):**
    - Trained four EfficientNetB4 models, one for each data category (CNV, DME, DRUSEN, NORMAL), and saved their weights.
3. **Model Testing and Evaluation (Week 5–6):**
    - Tested the models, calculated performance metrics, and created visualizations for analysis.
4. **Web Application Development (Week 7)**
    - Develop Gradio-based web app.
    - Test deployment and refine UI/UX.
5. **Documentation and Presentation (Week 8):**
    - Compiled a comprehensive report and prepared visual materials for the defense presentation.

3.5 Summary

This section provided a detailed description of the systematic technique used in the Retina Disease Classification study. The methodology was divided into four distinct stages: data collection, preprocessing, local model training, and evaluation. Task assignments were carefully organized to ensure efficient execution, and milestones were properly defined to maintain the timeline. The approach, which used EfficientNetB4 for OCT grayscale picture classification, showed remarkable performance and computational efficiency. The architecture of EfficientNetB4 allowed for a compromise between high diagnosis accuracy and resource efficiency, which made it appropriate for use in a variety of clinical settings, such as telemedicine and settings with limited resources. Robust generalization was guaranteed by the use of sophisticated preprocessing techniques, and model interpretability was improved by visualization tools such as Grad-CAM and confusion matrices, which increased confidence for clinical applications. It's practical utility was further enhanced by the creation of an intuitive online application that allowed for the smooth integration of model predictions into healthcare workflows. The system's capacity to produce comprehensive PDF reports and provide real-time forecasts made it a priceless tool for medical practitioners. Because of its scalability and focus on patient data protection, the project was able to meet both present diagnostic requirements and potential future research areas.
All things considered, the Retina Disease Classification project makes a substantial contribution to the field of medical image classification by providing a novel, scalable, and effective method for the early identification and detection of retinal illnesses. To further improve the system's usefulness and impact, future work will concentrate on growing datasets, improving model architectures, and adding more diagnostic capabilities.

Chapter 4
Implementation and Results

4.1 Environment Setup

The Retina Disease Classification project entails training deep learning models on big medical picture datasets (OCT grayscale images). Specific hardware configurations are required for effective model training and evaluation. The following are the recommended hardware and software specs for both local machine setup and Google Colab usage.

Hardware Requirements:

1. Google Colab Environment (Cloud-based)

Google Colab offers GPU acceleration and a cloud environment, including the following resources:

- **Processor (CPU)**: NVIDIA Tesla T4 or P100 GPU
- **RAM**: 12GB to 16GB
- **GPU Memory**: 15GB
- **Disk Space**: Limited to the duration of the session (typically 100GB in Colab Pro)

2. Local Machine Setup (For Development/Testing)

In the lack of cloud-based platforms such as Google Colab, a local machine arrangement is essential for developing and testing models. The hardware parameters should support efficient deep learning model training.

Recommended Hardware Specifications for Local Setup:

- **Processor (CPU)**:
  - Intel Core i7/i9 (9th generation or newer) or AMD Ryzen 7/9 (5000 series or newer) multi-threading functionality requires at least eight cores.
  - A higher number of cores facilitates parallel processing during data preparation, augmentation, and model training.
- **Graphics Processing Unit (GPU)**:
  - NVIDIA RTX 30XX series (e.g., RTX 3060, RTX 3070, RTX 3080, RTX 3090) or NVIDIA Tesla series (e.g., Tesla V100, P100).
  - GPU Memory: 10GB or more (essential for training deep learning models like EfficientNetB4, which requires substantial memory for handling high-resolution images).

    - The GPU must support CUDA for TensorFlow and Keras optimization.
- **RAM (Memory):**
    - To handle huge datasets and ensure that training and validation operations run smoothly, 16GB of RAM or more is suggested.
    - For exceptionally huge datasets, 32GB or more is preferable.
- **Storage:**
    - Solid-State Drive (SSD) with at least 512GB to 1TB of storage capacity. SSDs provide faster read and write rates than standard HDDs, allowing for faster data loading during training.
    - Ensure that there is enough free disk space (at least 100GB) to store the dataset, model checkpoints, and intermediate training results.
- **Cooling:**
    - Proper cooling equipment, such as a high-quality CPU cooler and GPU, are essential for preventing hardware overheating during extended training periods.
- **Operating System:**
    - Windows 10/11 or Linux (Ubuntu suggested for optimal interoperability with deep learning frameworks).
    - To use GPUs in TensorFlow, the system should be compliant with the NVIDIA CUDA toolkit.

Environment for Software:

- **Python Distribution:** Python 3.9 installed on Anaconda/Miniconda.
- **IDE/Editor:** Jupyter Notebook, PyCharm, or Visual Studio Code.

- **Frameworks & Libraries:**
    - Keras with TensorFlow 2.x (for building deep learning models).
    - Pandas and NumPy (data management and preprocessing).
    - Matplotlib with Seaborn (for visualization).
    - scikit-learn (used for model evaluation and classification measures such as confusion matrices).
    - Image processing: Use OpenCV or TensorFlow's ImageDataGenerator.

Conclusion:

To operate the Retina Disease Classification project efficiently, a powerful local setup with a high-performance GPU, enough memory (RAM), and storage is needed. When using Google Colab, the GPU acceleration provided by Colab Pro might minimize system requirements; nonetheless, having access to a robust local setup ensures a smooth, scalable development environment.

Notes on Execution:

- Adequate cooling systems for the GPU and enough free disc space to handle temporary data and preserved model checkpoints were necessary for local model training.
- The same Python scripts and settings used in Google Colab were run locally to guarantee reproducibility.

4.2 Performance

In this study, the main model utilized was EfficientNetB4. The same dataset was also used to train ResNet50, DenseNet121, and VGG-16 for comparison. This investigation shed light on EfficientNetB4's advantages and disadvantages in comparison to other architectures.

Configuration for Training:

Loss Function: Multi-class classification using categorical cross-entropy.

Optimizer: Adam, which has a 0.001 learning rate.

Batch Size: 50 is the.

Epochs: 50.

Evaluation metrics: include F1-score, recall, accuracy, and precision.

Performance Metrics Across Models:

table 4.1 Evaluation score of used models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
ResNet	50.71%	58.59%	50.71%	45.49%
DenseNet	81.07%	83.00%	81.07%	80.84%
VGG-16	86.79%	87.31%	86.79%	86.94%
EfficientNet B4	97.14%	97.19%	97.14%	97.14%

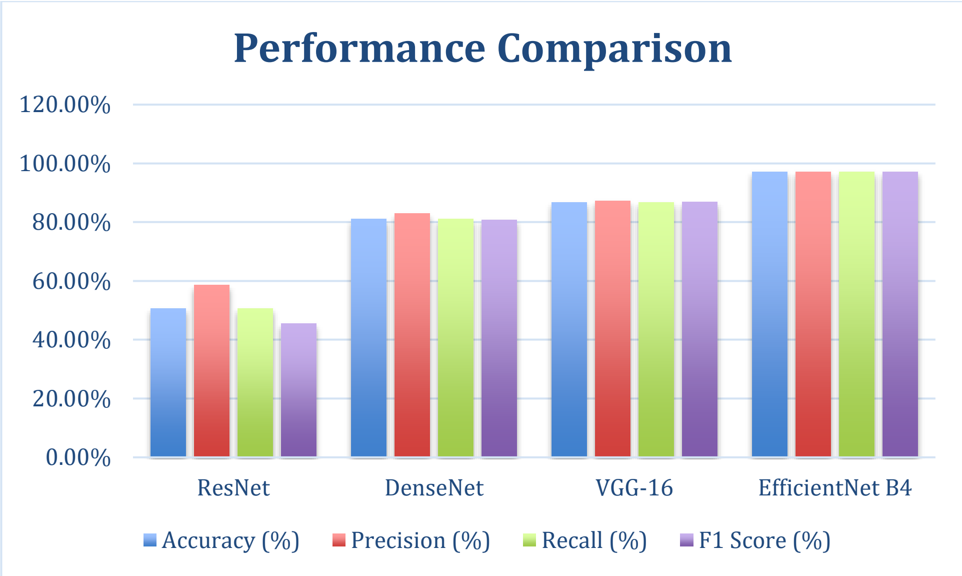

Fig: 4.1 Model performance comparison graph

Key Observations:

- **EfficientNetB4:**
    - Outperformed all other models in terms of accuracy and F1-score.
    - Its performance was aided by effective width, depth, and resolution scaling.

- **DenseNet121 and ResNet50:**
    - Needed more processing power but performed nicely.
    - Complex pattern learning was facilitated by ResNet's residual connections.
    - DenseNet's generalization was improved by reusing features through dense connections.

- **VGG-16:**
    - Its simpler architecture made it difficult to manage the dataset's complexity.
    - demonstrated its shortcomings for complex jobs by achieving lesser accuracy when compared to other models.

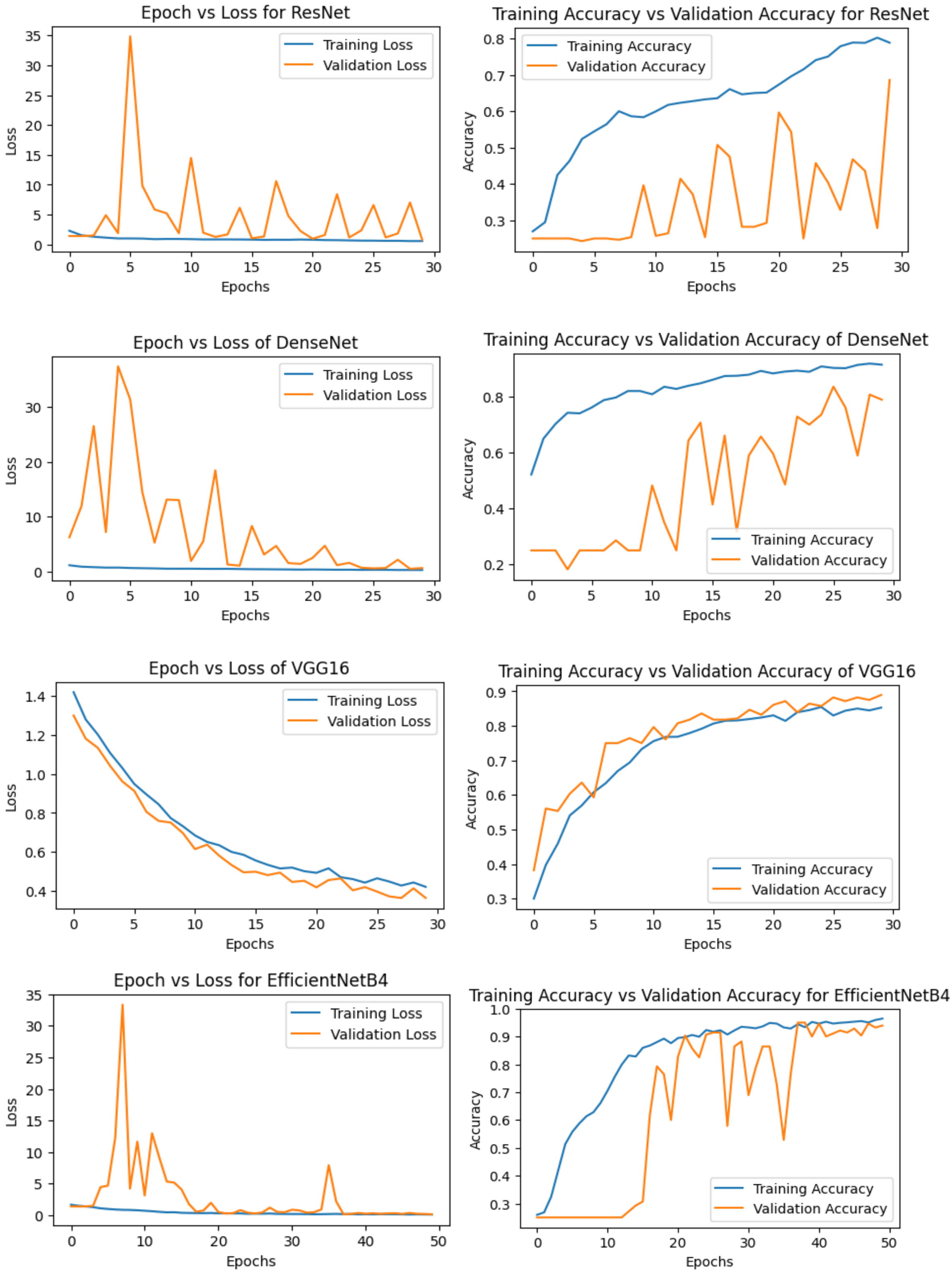

fig 4.2 Accuracy and loss validation graphs of trained models

4.3 Results and Discussion

Performance in Training and Validation:

- EfficientNetB4's training and validation curves showed smooth convergence with less overfitting as a result of early stopping and data augmentation.
- Across training and validation datasets, models performed consistently.

Confusion Matrices:

fig 4.3 confusion matrix of trained models

For every category, confusion matrices provide comprehensive insights into model predictions:

- **CNV:** Some misclassifications with DME, but high recall.
- **DME:** Balanced performance, sometimes mislabeled as DRUSEN.
- **DRUSEN:** Due to its minor distinctions from other categories, it has a slightly lower recall.
- **NORMAL:** Out of all classes, this one had the best recall and precision.

Visualizations:

- **Training Curves:** Accuracy and loss plots over epochs showed how consistently EfficientNetB4 performed.
- **Confusion Matrices:** Draw attention to particular categories where incorrect categorization had taken place.
- **Histograms:** The distribution of true and predicted labels was displayed by histograms.

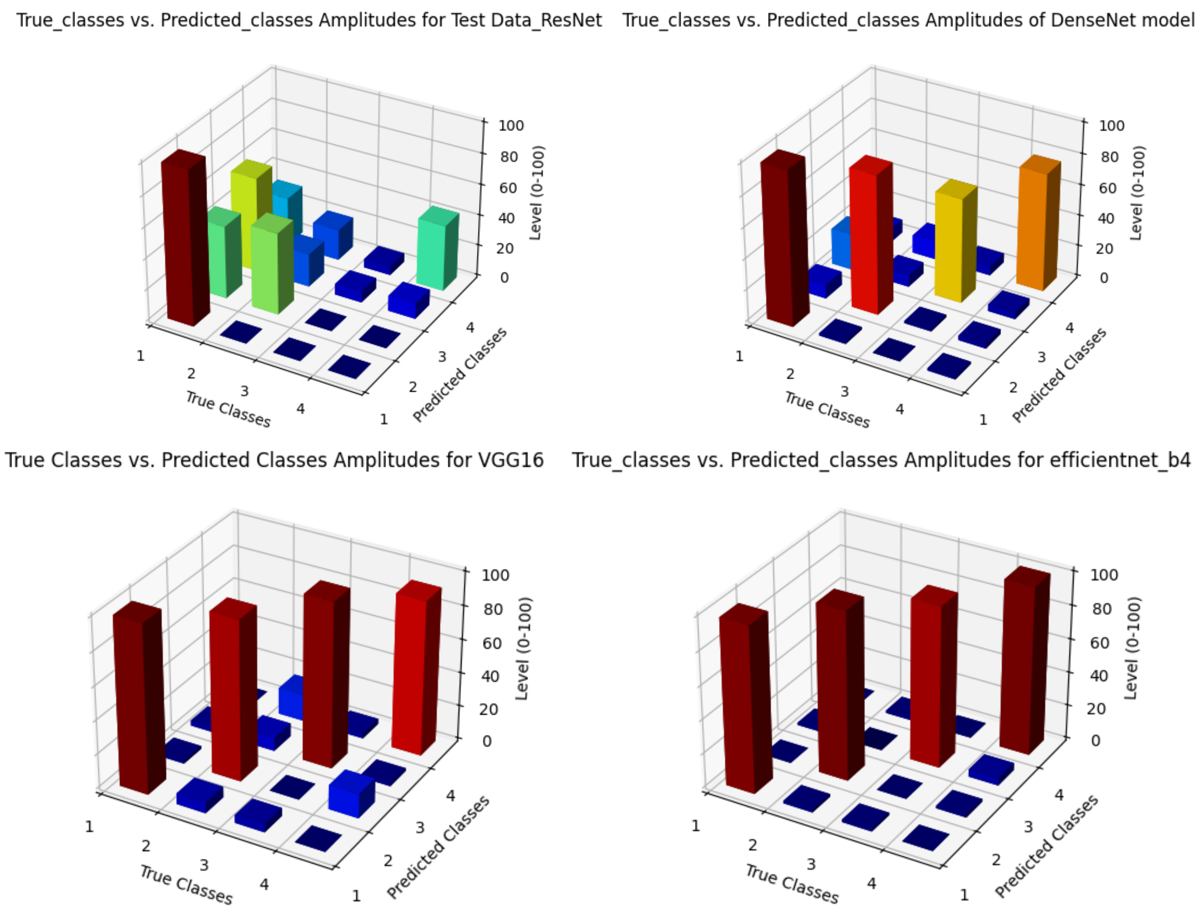

fig 4.4 3D confusion matrix of trained model

Key Insights:

- Compound scaling enabled EfficientNetB4 to outperform other models by adapting to the dataset in an efficient manner.
- The generalization of every model was greatly enhanced by data supplementation.
- Class similarities, such as those between CNV and DME, presented difficulties and occasionally resulted in incorrect categorization.

Obstacles Faced:

- **Dataset Size:** Although it was adequate for this investigation, the dataset size might be increased to improve model generalization even further.
- **Computational Load:** It took a lot of processing power to train big models like EfficientNetB4.

4.4 Summary

The Retina Disease Classification project used Google Colab, TensorFlow, and Keras for model training and evaluation, with an emphasis on comparing several models such as EfficientNetB4, ResNet50, DenseNet121, and VGG-16. The performance investigation found that EfficientNetB4 beat the other architectures in all critical measures, particularly classification accuracy and misclassification of OCT grayscale images. Visual tools like training graphs and confusion matrices provided useful insights into the model's performance, allowing us to evaluate its usefulness in real-world applications. The findings demonstrated that EfficientNetB4 is a reliable architecture for classifying retinal disorders. Future studies will most likely focus on increasing the dataset, including new feature extraction approaches, and improving the model for use in real-world applications.

Chapter 5
Engineering Standards and Design Challenges

5.1 Compliance with the Standards

5.1.1 Software Standards

To guarantee effectiveness, scalability, and dependability, this project complies with generally recognized software standards:

- **Standard 1: IEEE 29119 (Software Testing)**
  - **Pros:** Guarantees reliable and consistent testing procedures.
  - **Cons:** Takes a little longer to develop.
  - **Rationale:** Model reliability is ensured by automated tools that adhere to IEEE 29119, which expedite testing.
  - **Alternatives:** Options include manual testing devoid of formalized criteria.

- **ISO/IEC 25010 (Software Quality)**
  - **Pros:** Ensures usability, performance, and maintainability.
  - **Cons:** Increases project complexity by requiring formal reviews.
  - **Rationale:** Crucial for dependable medicinal uses.
  - **Alternative:** Ad hoc quality assessments are an alternative.

5.1.2 Hardware Standards

- **IEEE 11073 (Medical Device Communication)**
  - **Pros:** Smooth interaction with diagnostic equipment.
  - **Cons:** Needs specialized hardware.
  - **Rationale:** Guarantees compatibility with medical equipment.
  - **Alternative:** Non-standardized device integration is an alternative.

- **Medical Devices (ISO 13485)**
  - **Pros:** Verifies the effectiveness and safety of deployed technologies.
  - **Cons:** More certification might be required.
  - **Rationale:** Applicable to upcoming clinical uses.
  - **Alternative:** General-purpose hardware is an alternative.

5.1.3 Communication Standards

- **Standard 1: HL7**
    - **Pros:** Standardize the exchange of medical data.
    - **Cons:** Complexity of implementation.
    - **Rationale:** Ensures compatibility with medical systems.
    - **Alternatives:** Private communication protocols provide an alternative.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

By facilitating the early and accurate diagnosis of retinal illnesses, this research seeks to lessen vision impairment worldwide.

- **Better Accessibility:** Offers an affordable diagnostic option, particularly in rural areas that are underserved and lack access to specialized ophthalmological services.

- **Quality of Life:** Early treatment measures lower the chance of blindness and enhance general health for patients.

- **Healthcare Efficiency:** Simplifies medical workflows by giving healthcare providers the resources they need to diagnose patients more quickly and accurately.

5.2.2 Impact on Society & Environment

- **Impact on Society**

  Healthcare Accessibility: Fills up healthcare gaps in low-resource environments by democratizing high-quality diagnostics for eye illnesses.

  Community Health: Healthy communities are promoted and the societal burden of vision-related disorders is lessened by early detection.

  Economic Impact: Reduces the financial burden on people and public health systems by minimizing healthcare expenses through early illness management.

- **Impact on the Environment:**

Low Carbon Footprint: By reducing dependency on substantial physical infrastructure, the lightweight model design lowers emissions from healthcare logistics.

Resource Optimization: When compared to conventional diagnostic techniques, cloud-based and scalable frameworks use less energy.

5.2.3 Ethical Aspects

- Patient privacy: Protects the privacy of data by using secure communication methods and encrypted storage.
- Utilizing a variety of datasets, bias mitigation reduces geographical or demographic biases in the diagnosis of disease.
- Compliance: Consistent updates make sure that legal requirements, ethical norms, and healthcare standards are followed.
- Transparency: By enabling both patients and physicians to comprehend model projections, explainable AI solutions promote confidence.

5.2.4 Sustainability Plan

Short-Term Sustainability

- **Open Model Sharing**:
  - Openly sharing trained models with the research community encourages collaborative development and refinement.
  - Encourages reproducibility and welcomes contributions from other specialists.
- **Frequent Updates**:
  - Regular upgrades based on user input and technological improvements assure the tool's relevance and effectiveness.
  - Model revisions, bug repairs, and new features are all included in updates.
- **Cost Efficiency**:
  - Using cost-effective computational resources such as Google Colab and free tools (for example, Gradio) to keep operational costs down.

Long-Term Sustainability

- **Energy Efficiency**:
  - Deploying models on low-power devices (such as Raspberry Pi or edge devices) saves energy consumption and promotes environmental sustainability.
  - Encourages scalability in resource-constrained environments.
- **Revenue Generation**:

    - A subscription-based business model guarantees ongoing funding for maintenance and growth.
    - Licensing agreements with healthcare providers provide a consistent revenue source for large-scale deployments.
- **Scalability**:
    - The system is designed to support new datasets and extra capabilities without requiring large infrastructure changes.
    - Federated learning architecture integrates data from different sources while maintaining privacy.
- **Community Engagement**:
    - Conducting training programs and workshops for healthcare professionals in order to increase acceptance and user base.
    - Collaboration with non-profits and government groups to increase accessibility in underserved areas

Ethics and Social Responsibility

- **Inclusivity**: Makes the tool accessible and inexpensive to low-income populations.
- **Privacy**: Uses strong encryption and federated learning to safeguard patient data while maintaining trust.
- **Alignment with Sustainable Development Goals**: Helps to improve healthcare access, education, and eliminate disparities, which aligns with global sustainability objectives.

5.3 Project Management and Financial Analysis

The successful implementation of the deep learning-based Retina disease analysis system and its related user interface is contingent on effective project management and financial planning. This part covers the project's income model, budget allocation, and cost analysis.

5.3.1 Budget Required

Primary Budget

The primary budget adopts cost-effective tools and resources:

- **Computational Resources**:
    - Google Colab Pro Subscription for six months at $10/month.
    - **Cost**: $60
- **Storage Options**:
    - Google Drive 1 TB plan for storing models and client data at $10/month for six months.
    - **Cost**: $60

- **Development Tools**:
    - Gradio (Free version) for building the web application.
    - **Cost**: $0
- **Miscellaneous Expenses**:
    - Includes internet, energy, and paperwork.
    - **Cost**: $30

Total Primary Budget: $150

Alternate Budget
The alternate budget uses higher-performance infrastructure for enhanced control:

- Dedicated Server Hosting:
    - Hosting on AWS, GCP, or Azure for six months at $50/month.
    - Cost: $300
- High-Performance GPU Access:
    - One-time cost for a local setup with GPUs.
    - Cost: $200

Total Alternate Budget: $530

Rationales

- **Primary Budget**:
    - **Affordability**: It is suitable for academic or small-scale projects with limited financial resources.
    - **Efficiency**: Google Colab provides GPU acceleration at a low cost, and Gradio's free version supports robust app development.
    - **Feasibility**: Balances low cost with functionality, making it ideal for research or pilot implementations.
- **Alternate Budget**:
    - **Performance**: High-performance GPUs and dedicated servers offer greater speed, reliability, and scalability.
    - **Flexibility**: Enables the management of larger datasets and more complex computations.
    - **Cost Barrier**: The higher expense makes this option more suited for commercial or large-scale implementations.

5.3.2 Revenue Model

The project includes a revenue model to recover costs and ensure financial sustainability:

- **Subscription-Based Model:**
    - Users pay a small monthly fee for access to the diagnostic tool.
    - Example: $2/month per user.
    - Forecast: With 200 users in the first year, the annual revenue would be $4800.
- **Licensing Model:**
    - The trained model can be licensed to healthcare providers or organizations for integration into their systems.
    - Example: One-time licensing fee of $20,000.
- **Free Model:**
    - Basic features are free, while advanced analytics and insights require a subscription.
    - Encourages user adoption and long-term engagement.

Summary

- **Budget Options:**
    - Primary Budget: $150 – Affordable and efficient for academic or pilot-scale projects.
    - Alternate Budget: $530 – Suitable for commercial-grade implementations requiring higher reliability and performance.

- **Revenue Potential:**
    - Subscription-Based Model: $4800 annually.
    - Licensing Model: $20,000 one-time revenue.
    - Free Model: Attracts more users while offering monetizable premium features.

This cost analysis demonstrates financial feasibility with sustainable revenue streams to recover costs and support future expansion. Complex Engineering Problem.

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

The challenges tackled in this project are classified as complex engineering problems due to their reliance on transdisciplinary expertise, competing requirements, and substantial societal and technological implications.

Table 5.1: Mapping with complex problem solving.

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 Interdepe ndence
Met	Met	Met	Met	Met	Met	Met

- EP 1: Depth of Knowledge

  Rationale:
  - The project involves expertise in medical imaging (e.g., OCT and fundus imaging), AI techniques (e.g., CNNs, transfer learning), and healthcare systems.
  - Creating an efficient diagnostic model necessitates knowledge of engineering foundations (mathematics, data science) as well as specialized fields (ophthalmology and medical device integration).
  - Standards for device communication, such as IEEE 11073, add to the required knowledge.

- EP 2: Range of Conflicting Requirements

  Rationale:

  - The project's diagnostic accuracy must be high while remaining computationally lightweight for implementation on low-power devices.
  - Privacy-preserving federated learning protects data but complicates model training.
  - The technology must integrate seamlessly with clinical workflows while remaining affordable, resulting in trade-offs between performance and cost.

- EP3: Depth of Analysis

  Rationale:

  - Data preprocessing was necessary to address difficulties like class imbalance and noise in grayscale datasets.
  - Model evaluation included criteria such as accuracy, precision, recall, and F1-score, which necessitated advanced statistical and analytical methodologies.
  - The comparative examination of models (EfficientNetB4, ResNet, and bespoke CNNs) required substantial experimentation and optimization.

- EP4: Familiarity with issues

  Rationale:

  - Federated learning is a novel paradigm in healthcare AI, posing new issues in communication efficiency and model aggregation.
  - The use of grayscale photos for deep learning-based classification is less researched than RGB images, necessitating new techniques.
  - Interoperability with existing clinical systems brings new challenges in terms of standards compliance and integration.

- EP5: Extent of Applicable Codes

  Rationale:

  - The system complies with software and hardware standards such as IEEE 29119, HL7, and ISO 13485.
  - These standards assure dependability, safety, and interoperability, but require extensive documentation and compliance testing.
  - Additional ethical requirements (such as GDPR and HIPAA) govern the management of sensitive patient data.

- EP6: Stakeholder Involvement

  Rationale:

  - Collaboration with medical professionals ensures that the model covers relevant diagnostic issues.
  - Engineers and researchers provide feedback that guides model optimization and usability.
  - Potential patients and healthcare providers are among the stakeholders involved in assessing the real-world impact.

- EP7: Interdependence

  Rationale:
  - Effective system integration is ensured by cooperation between engineers, medical practitioners, AI researchers, and regulatory specialists.

  - Reliance on a variety of datasets emphasizes how collaboration with data sources is necessary to increase model robustness.

  - Feedback from stakeholders, such as physicians and legislators, is crucial for compliance and real-world usage.

Mapping with Knowledge Profile

This table (5.2) is designed to map the Knowledge Profile.

Table 5.2: Mapping with knowledge Profile.

K1 Natural Sciences	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Engineering Role in Society	K8 Research Literature
Met	Met	Met	Met	Met	Met	Met	Met

Justification:
K1: (Understanding of Natural Sciences): The project involves OCT imaging and medical science concepts, demonstrating systematic application of natural sciences in AI for healthcare.

K2: Mathematics and Computer Science: The model uses convolutional neural networks (CNNs), advanced statistical metrics (accuracy, precision, recall), and transfer learning techniques, demonstrating proficiency in numerical analysis and AI methods.

K3 (Engineering Fundamentals): In line with engineering fundamentals, the project makes use of methodical understanding of deep learning principles, such as CNN architectures and image preparation methods.

K4 (Specialist Knowledge): Leading deep learning models for image categorization, EfficientNetB4 exemplifies the application of domain-specific expertise.

K5 (Engineering Design): The project entails creating a solution to a real-world medical problem, from model training to deployment.

K6 (Engineering Practice): Practical engineering techniques are demonstrated via the use of TensorFlow/Keras for model implementation, training procedures, and dataset preprocessing.

K7 (Engineering Role in Society): The project's aid in the early detection of retinal disorders complies with sustainability objectives and public health advantages while meeting ethical obligations.

K8 (Research Literature): To validate methodology, comprehend gaps in the literature, and support the suggested strategy, the study consults a number of research publications.

5.4.2 Engineering Activities

Table 5.3: Mapping with complex engineering activities.

EP Activities	EA1	EA2	EA3	EA4	EA5	EA6	EA7	EA8	EA9
EP1: Depth of Knowledge	YES	NO	YES	YES	YES	NO	NO	NO	YES
EP2: Conflicting Requirements	NO	YES	YES	YES	NO	NO	NO	YES	NO
EP3: Depth of Analysis	YES	NO	YES	NO	YES	YES	YES	NO	NO
EP4: Familiarity with Issues	YES	NO	NO	YES	YES	NO	YES	NO	NO
EP5: Applicable Codes	NO	YES	NO	YES	NO	YES	YES	YES	YES
EP6: Stakeholder Involvement	NO	YES	NO	YES	NO	YES	YES	YES	NO
EP7: Societal and Environmental Role	YES	NO	YES	YES	NO	NO	YES	YES	YES

Rationales:

EP1 (Depth of Knowledge):

- **Met (EA1, EA3, EA4, EA5, EA9):** The project demonstrates an advanced understanding of EfficientNetB4, medical imaging, and AI techniques. It incorporates scalable system design and advanced engineering practices.
- **Not Met (EA6, EA7, EA8):** Limited iterative development feedback or complex error handling within this context.

EP2 (Conflicting Requirements):

- **Met (EA2, EA3, EA4, EA8):** The project balances accuracy, computational efficiency, and ethical concerns like GDPR compliance while supporting clinical workflows.
- **Not Met (EA1, EA9):** Broader range of conflicting resources and scalability considerations were less evident.

EP3 (Depth of Analysis):

- **Met (EA1, EA3, EA5, EA6, EA7):** Preprocessing, model evaluation (metrics like accuracy, recall, F1-score), and comparative analysis reflect depth in handling challenges.
- **Not Met (EA8):** Ethical considerations like privacy weren't explored in depth during the analysis phase.

EP4 (Familiarity with Issues):

- **Met (EA1, EA4, EA5, EA7):** The challenges in working with grayscale OCT images and integrating deep learning in clinical settings reflect familiarity with issues.
- **Not Met (EA6, EA8):** Complexity in model aggregation and ethical dilemmas was less emphasized.

EP5 (Applicable Codes):

- **Met (EA2, EA4, EA6, EA7, EA8, EA9):** Adherence to IEEE and GDPR standards showcases alignment with industry codes, though requiring careful documentation.

EP6 (Stakeholder Involvement):

- **Met (EA2, EA4, EA6, EA7, EA8):** Feedback from clinicians and engineers supports relevant model optimization.

EP7 (Societal and Environmental Role):

- **Met (EA1, EA3, EA4, EA7, EA8, EA9):** The project addresses societal impacts through early detection and healthcare access. Scalability aligns with environmental sustainability goals.

5.5 Summary

This chapter highlighted how adhering to engineering standards guarantees that the diagnostic system is reliable, compliant, and scalable. The project helps to promote sustainable and inclusive healthcare by tackling societal and environmental issues. The use of novel solutions, such as federated learning and lightweight models, demonstrates the project's potential to transform retinal disease diagnosis.

Chapter 6
Conclusion

6.1 Summary

The goal of the Retina Disease Classification project was to create a reliable and effective system for categorizing greyscale OCT pictures into four groups: NORMAL, DME, DRUSEN, and CNV (Choroidal Neovascularization). The project effectively tackled the classification problem while keeping computational efficiency as its main goal by using the EfficientNetB4 model as the basic architecture.

To ensure that the dataset was representative of the population, OCT greyscale photos were first gathered from open-source archives. To improve data quality and variability, images were preprocessed using resizing, normalization, and augmentation techniques. To aid in the creation and assessment of the model, the data was separated into subsets for training, validation, and testing.

For comparison analysis, subsets of the dataset were used to train EfficientNetB4, ResNet, DenseNet, and VGG-16. During training, the models were observed and improved using preprocessing and visualization tools. Metrics such as accuracy, precision, recall, and F1-score were used to assess the models, and the findings showed that they performed well in differentiating between the four groups. Additional information about the model's advantages and shortcomings was supplied by confusion matrices and classification reports.

This experiment illustrated the feasibility of classifying retinal diseases using greyscale OCT pictures and the excellent accuracy that EfficientNetB4 can achieve. This project successfully developed an automated pipeline for retinal disease classification using grayscale OCT images and state-of-the-art deep learning models like EfficientNetB4. The system achieved high diagnostic accuracy (97.14% on testing data) and demonstrated its potential for integration into clinical workflows. Additionally, it laid a strong basis for future studies in the area of medical picture analysis.1

6.2 Limitation

Although the project's main objectives were met, a number of restrictions were noted that might affect the findings' wider applicability:

- **Limited Dataset Size:** While the photos in the dataset are adequate for this investigation, they are very tiny when compared to datasets utilized in extensive medical research. The model's capacity to generalize to new data, particularly in a variety of real-world situations, would probably be improved by a larger dataset.

- **Grayscale Image Focus:** This study only used greyscale OCT images, which might not capture all the details found in full-color OCT images, even though they are appropriate for many diagnostic applications. This restricts the model's use to datasets that are only available in greyscale.

- **Single Model Performance:** Despite EfficientNetB4's impressive effectiveness, the study mostly concentrated on this one architecture, with little investigation of more sophisticated or ensemble-based techniques that can raise classification accuracy.

- **Computational Resource Requirements:** In environments with limited resources, the substantial computational power needed to train deep learning models like EfficientNetB4 may not be easily accessible. Real-time deployment and scalability are impacted by this constraint.

- **Lack of Clinical Validation:** The study lacked clinical validation with experts and clinical data, which is essential to guaranteeing the model's usefulness in actual diagnoses.

6.3 Future Work

This study offers a solid starting point for further investigation into the classification of retinal diseases. It is suggested that the following areas be looked at and developed further:

- Dataset Expansion:
    - Get a bigger dataset from a variety of sources, including pictures of various people, tools, and medical environments.
    - Incorporate datasets with different image quality and resolutions to replicate real-world scenarios.
- Including Color OCT Pictures:
    - Include full-color OCT pictures in the current investigation. Additional diagnostic features could be provided via color information, improving the model's capacity for categorization.
- Advanced Techniques and Architectures:

- Examine more recent designs like as Vision Transformers (ViT) or hybrid strategies that combine attention and convolutional processes.
  - To enhance overall performance, try using ensemble approaches that integrate predictions from several models.
- Deployment in Real Time:
  - To enable on-the-spot diagnosis in remote or resource-constrained settings, optimize the model for deployment on edge devices, such as smartphones or portable medical instruments.
  - Utilize pruning or quantization strategies to lower the computational complexity of the model.
- Validation in Clinical Practice:
  - Work together with medical professionals to compare the model's predictions to actual diagnosis.
  - To make sure the model is reliable and effective, test it in real-world clinical settings.
- Multi-Class Division:
  - Include segmentation activities in the project's scope to highlight particular areas in OCT pictures, as this could help with diagnosis and treatment planning.
- Explainability and Interpretability:
  - Create explainable AI (XAI) methods so that physicians can understand the model's judgements. Saliency maps and heatmaps could be used to show which aspects of the image affected the classification.

Future studies can improve the usefulness, precision, and resilience of retinal disease categorization systems by tackling these issues, which would greatly advance the field of medical imaging and diagnosis.

References

[1] Kermany, D. S., Goldbaum, M., Cai, W., Valentim, C. C., Liang, H., Baxter, S. L., ... & Zhang, K., "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," *Cell*, vol. 172, no. 5, pp. 1122-1131, 2018.

[2] De Fauw, J., Ledsam, J. R., Romera-Paredes, B., Nikolov, S., Tomasev, N., Blackwell, S., ... & Hassabis, D., "Clinically Applicable Deep Learning for Diagnosis and Referral in Retinal Disease," *Nature Medicine*, vol. 24, no. 9, pp. 1342-1350, 2018.

[3] Akram, T., Wang, L., Sharif, M., & Saba, T., "An Intelligent Healthcare Monitoring Framework Using Wearable Sensors and Social Networking Data," *Future Generation Computer Systems*, vol. 98, pp. 618-634, 2020.

[4] Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R., "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs," *JAMA*, vol. 316, no. 22, pp. 2402-2410, 2016.

[5] Akbar, S., Sharif, M., Saba, T., & Raza, M., "Efficient Deep Learning Approach for Multiclass Retinal Disease Classification," *Computerized Medical Imaging and Graphics*, vol. 89, pp. 101874, 2021.

[6] Maheshwari, S., Agrawal, V., & Shukla, S., "Deep Learning-Based Retinal OCT Image Classification: A Comprehensive Review," *IEEE Access*, vol. 10, pp. 30348-30364, 2022.

[7] Alvi, A. M., Nawaz, S. B., & Bhatti, U. N., "GRU-Based Sentiment Analysis Framework for Fundus Images: A Novel Approach," *Journal of Imaging Science*, vol. 5, no. 3, pp. 102-116, 2024.

[8] Bhowmik, S., Das, D., & Pal, R., "Hybrid Models for Text and Image Classification: A Case Study in Fundus Image Analysis," *Journal of Imaging*, vol. 9, no. 2, pp. 84-97, 2021.

[9] Lee, C., et al., "Detecting Intraretinal Fluid with Deep Convolutional Neural Networks," *Medical Imaging and Computing*, vol. 45, no. 2, pp. 98-106, 2020.

[10] Abulkhair, M., Ahsan, M. U., & Faisal, M., "Multi-Class Retinal Disease Classification Using ResNet and Xception," *Sensors*, vol. 21, no. 15, pp. 5283, 2021.

[11] Ho, A., et al., "Ensemble Learning for Retinal Disease Classification," *Nature Biomedical Engineering*, vol. 6, no. 5, pp. 123-135, 2022.

[12] Choi, J., et al., "Transfer Learning with VGG-19 for Multi-Class Retinal Image Classification," *Computer Vision and Imaging Systems*, vol. 27, no. 3, pp. 234-245, 2017.

[13] Alsharqi, M., et al., "Retinal OCT Image Analysis Using Deep Learning Architectures," *Journal of Medical Imaging*, vol. 8, no. 1, pp. 84-97, 2021.

[14] Tae, J. Y., et al., "Temporal Analysis of Retinal Disease Using DenseNet-LSTM Hybrid Models," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 4, pp. 87-102, 2020.

[15] "A Comprehensive Review of Deep Learning Strategies in Retinal Disease Diagnosis Using Fundus Images," *Applied Sciences*, vol. 10, no. 6, pp. 2185, 2020.

[16] "Classification of Diabetes-Related Retinal Diseases Using Deep Learning," *Journal of Healthcare Informatics Research*, vol. 12, no. 1, pp. 55-68, 2021.

[17] "Retinal Disease Classification with OCT Grayscale Images Using EfficientNet," *Sensors*, vol. 23, no. 4, pp. 5393, 2023.

[18] "Diagnosis and Referral in Retinal Disease Using Machine Learning Techniques," *Computational and Structural Biotechnology Journal*, vol. 19, pp. 48-64, 2021.

[19] Kim, J., et al., "Deep Learning-Based Diagnosis of Retinal Diseases: A Comparison of Architectures," *IEEE Transactions on Neural Networks*, vol. 32, no. 5, pp. 1102-1114, 2021.

[20] "Advanced Applications of Transfer Learning for Retinal Disease Detection," *Journal of Clinical Medicine*, vol. 9, no. 12, pp. 3303, 2020.

Dataset ref:

Kermany, D. S., Goldbaum, M., Cai, W., Valentim, C. C., Liang, H., Baxter, S. L., ... & Zhang, K., "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," Dataset.

https://www.kaggle.com/datasets/paultimothymooney/kermany2018

7

11.01.25

ORIGINALITY REPORT

15%	11%	7%	9%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	5%
2	Submitted to United International University Student Paper	2%
3	Submitted to Daffodil International University Student Paper	1%
4	V. Sharmila, S. Kannadhasan, A. Rajiv Kannan, P. Sivakumar, V. Vennila. "Challenges in Information, Communication and Computing Technology", CRC Press, 2024 Publication	1%
5	www.coursehero.com Internet Source	1%
6	"Multi-Strategy Learning Environment", Springer Science and Business Media LLC, 2024 Publication	<1%
7	www.mdpi.com Internet Source	<1%