AI-Driven Detection and Classification of Retinal Disease Using Deep Learning

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Certificate

We accept the work contained in the report titled "AI-Driven detection and classification of Retinal Disease using Deep Learning", written by Rana Ahmed Mehmood & Syed Farrukh Sajjad Bukhari as a confirmation to the required standard for the partial fulfillment of the degree of Bachelor of Science in Artificial Intelligence.

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Abstract

This study examines that diabetic retinopathy, a significant cause of vision impairment in individuals with diabetes, could plausibly be identified earlier through the analysis of retinal images via important automated methods given that manual screening may well suggest inconsistent results, particularly when detecting subtle abnormalities such as microaneurysms, hemorrhages, and exudates. Moreover, the evidence may indicate that these critical diagnostic challenges support the need for a deep-learning–based system that demonstrates the use of EfficientNet-B3 and ResNet-18 architectures for multi-level classification. However, findings may show both models trained on retinal fundus data achieve strong results. Thus, results could indicate accuracies of 95 percent with EfficientNet-B3 and 94 percent with ResNet-18. Furthermore, the study may suggest the system provides an intuitive web interface that enables users to upload retinal images and obtain classification results. In light of the significant findings, this critical system could demonstrate that automating the detection workflow may support reduced clinical workload, increased screening precision, and expanded access to important reliable eye-care diagnostics, particularly in underserved communities. Nevertheless, findings may indicate this key study could support timely identification and continuous monitoring of diabetic retinopathy, helping reduce the global impact of the disease and improving patient outcomes.

Acknowledgments

All glory be to Allah Almighty, who enabled us to expand our knowledge and also provided us with the devotion and wisdom to work and plan with great passion. We owe all of our academic work and struggles to our dear parents and respected teachers; without them, we are nothing. We would like to convey our heartfelt gratitude to our project supervisor Ms. Aima Zahoor and co-supervisor Dr. Adil Khan for their helpful suggestions and guidance during the project.

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November 28^{th}, 2025

"AI has the potential to transform medicine and healthcare, but we must remember that it's our creativity, dedication, and hard work that will ultimately make this transformation possible."

—Dr. Lily Peng

[1]

[1] Quote attributed to Dr. Lily Peng, Google Health.

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Acronyms and Abbreviations

DSA	Data Structure and Algorithms
OOP	Object Oriented Programming
PF	Programming Fundamentals
SE	Software Engineering
SQL	Structured Query Language
UNESCO	United Nations Educational, Scientific and Cultural Organization
XML	Extensible Markup Language

Chapter 1

Introduction

Diabetic retinopathy (DR) is one of the most harmful and progressive eye complications that may be essentially related with the essential pathophysiology of diabetes mellitus. However, the condition can insidiously occur, slowly affecting the vision and eventually leading to total blindness in case the necessary clinical care is not provided. In addition, due to the ever-growing rate of the diabetic disease spread across the world, the DR burden is becoming more and more viewed as a burning health issue. Since early detection is the most crucial aspect, the proposed project will help to cope with the growing need of effective screening methodologies and will consider the most advanced technologies. In turn, these methods can be used to improve clinical diagnosis. Nevertheless, long-term patient outcomes and constant monitoring could indicate great progress.

1.1 Project Background

Diabetic retinopathy (DR) is a microvascular complication of diabetes mellitus, where the pathological alterations of the vascularities in the retina occur due to the impaired glucose metabolism. The chronically increased systemic glucose level causes damage to the retinal capillaries causing endothelial leakage, intraretinal edema and the resulting structural impairment. DR is usually asymptomatic in its initial phases, although, in advanced stages, patients can be affected by an unremitting and incurable visual loss. DR is one of the major causes of blindness in the world. Epidemiological statistics show that about 80 per cent of patients with diabetes who have had the disease at least ten years develop some sort of DR and virtually all patients with type 1 diabetes and a significant fraction of the patients with type 2 diabetes are at higher risk.[1]. Figure 1.1 illustrates the contrast between normal vision and vision affected by DR.

Figure 1.1: a. Normal b. Vision affected by Diabetic Retinopathy

Diabetic Retinopathy

Diabetic Retinopathy is divided into two major types:

1. **Non-Proliferative Diabetic Retinopathy (NPDR)**
NPDR is the first and relatively weaker stage of the disorder. In this phase the retinal vessels are weakened and they can form small swellings called as miosis aneurysms that can release fluid into the tissue surrounding the retina which may result in swellings of the macro.[2]. Symptoms may be short but makes early detection challenging.

2. **Proliferative Diabetic Retinopathy (PDR)**
PDR is the progressive and vision threatening type of DR. Lack of blood encourages development of diseased and frail blood vessels throughout the retina and extending to the vitreous chamber. These boats are likely to tear and cause hemorrhagic, scarring, retinal detachment and nerve injury to the eye. PDR also has a high chance of causing permanent blindness without prompt treatment.[3].

• Fundus Image:
Fundus image is the captured photo of the internal eye part, captured through fundus cameras equipped with optical magnification. These images clearly gets key retinal structures, including the optic disc, macula, and both central and peripheral retinal regions [4].

• Retinal Abnormalities:
Common retinal abnormalities of DR include:

- Microaneurysms
- Hemorrhages
- Exudates

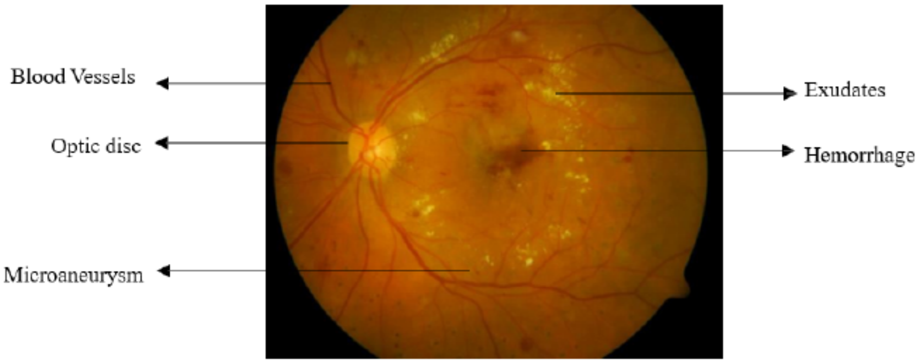


Figure 1.2: Retinal Abnormalities

• **Microaneurysms:**
These are small, localized outpouchings of weakened retinal capillaries. This often represent the firstly detectable signs of DR. It may leaks small amount of blood or fluid into nearest tissues.

• **Hemorrhages:**
Retinal hemorrhages occurs when damaged blood vessels breaks, allowing blood to spread within retinal layers. While some hemorrhages remain silent, others may interfere with visual clarity, particularly if seen near the macula.

• **Exudates:**
As DR progresses, protein and lipid-rich fluid may avoid from compromised vessels and deposit within the retina. This appears as yellowish or whitish lesions of irregular size and shape and are strong indicators of macular damage linked to vision disability.

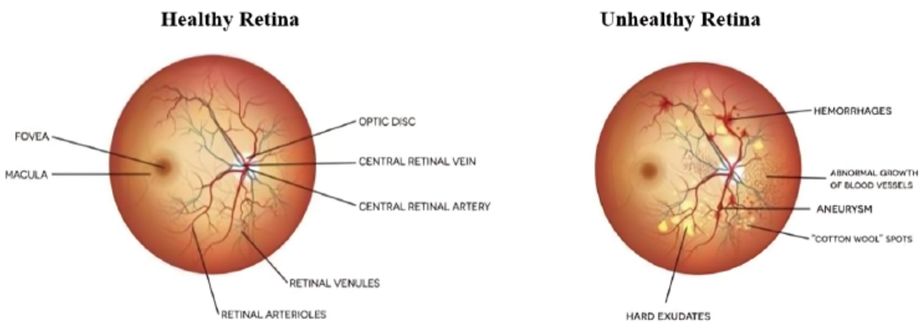


Figure 1.3: Healthy vs Unhealthy Retinal Image

1.2 Problem Description

Even with the progress made in medical imaging and treatment, Diabetic Retinopathy is one of the conditions that are hard to identify at an early stage because it manifests itself with few symptoms. Traditional diagnosis uses human retina visualization in the form of manual test by trained ophthalmologists, which is time-consuming, subjective, and relies on the availability of experts. As the number of diabetics in the world grows very fast, manual screening will not be sufficient to fulfill the mass requirements of healthcare. Due to this, a lot of people get DR diagnoses when their vision has been deteriorated to an observable or irreversible extent. Moreover, it is crucial that constant monitoring is needed but frequently impossible in resource-restricted areas. The DR progression can be silent and thus, the use of only manual evaluation can be dangerous due to late treatment. Hence, scalable, automated, and correct screening tools have to be developed to help in early detection, severity rating, and effective clinical decision-making [5]. Key challenges include:

- Classification of retinal images into Normal, Mild, Moderate, Severe, and Proliferative DR categories.
- Achieving improved diagnostic performance compared to previous methods.

1.3 Project Objectives

Our goal is to design and evaluate a deep learning–based framework capable of automatically detecting Diabetic Retinopathy and classifying its severity from retinal fundus images [6]. The specific objectives include:

- **Develop a Deep Learning Model:** Building an advanced neural network which will be capable of getting meaningful retinal features for accurate DR detection.
- **Automated Detection and Severity Classification:** Making a system that not only shows the presence of DR but also categorizes its clinical stage.
- **Assist Healthcare Professionals:** Provide a supportive diagnostic tool that enhances clinical decision-making and screening efficiency.
- **Improve Patient Outcomes:** Enable earlier changes through timely identification of disease that helps to prevent severe visual disability.
- **Advance Medical Image Analysis Research:** This paper will make a contribution to the overall research on automated retinal imaging by delving into and improving deep learning technologies.

1.4 Project Workflow

The methodology that has been used in this project is outlined below:

1.4.1 Model Development

- **Data Collection and Preprocessing:**Get large, labeled retinographic images databases, such as those available in the APTOS collection in Kaggle [7]. The preprocessing procedures are to be used to improve the quality and consistency of the images..
- **Model Development:** Use the latest Convolutional Neural Network architectures, i.e.: ResNet -18 and EfficientNet, to take advantage of the latest state-of-the-art performance improvements.[8]. The models were trained using transfer learning and adjusted to the diabetic retinopathy severity classification, as shown below. Figure 1.4.
- **Training:** The convolutional neural network architectures are trained using augmented datasets to reduce the overfitting. Hyperparameter and model setup optimization is performed to optimize both model robustness and classification accuracy.
- **Validation and Testing:** Determine performance by using independent image sets that were not observed in the training stage, and they are thus used to ensure the generalization ability and stability of the model.

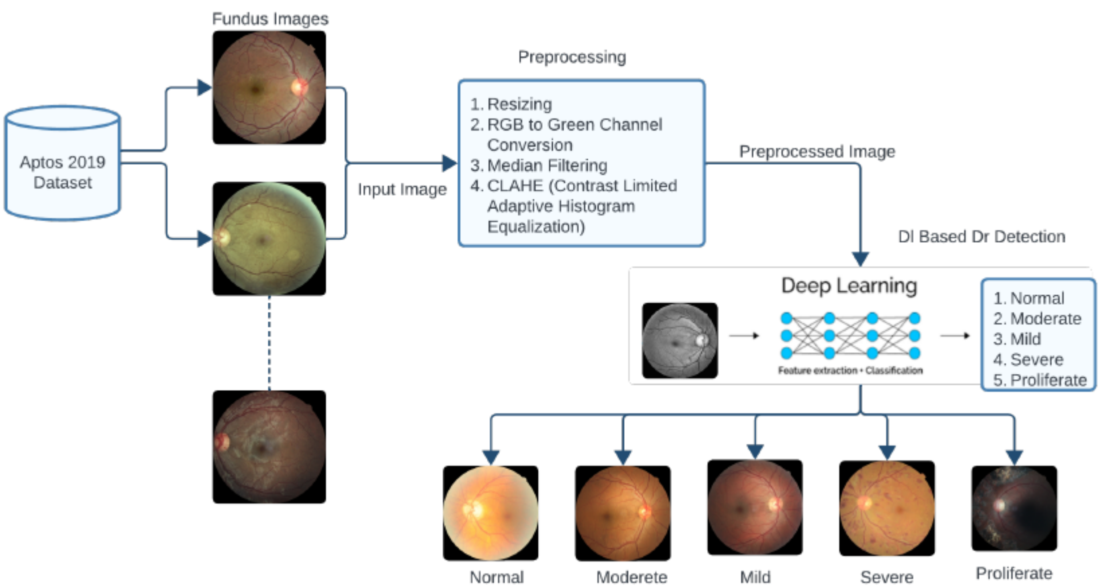


Figure 1.4: Project Workflow

1.4.2 Web-Based Platform

- This paper suggests that a simple web-based software be developed that would allow patients to post retinal scans and then get automatic screening on the level of diabetic retinopathy.
- The evolution of a safe backend system to manage images, inference, and delivery of results should be in line with the current privacy laws.

1.5 Project Scope

The objectives of the study are to formulate, assess and integrate a regionally deployed deep learning-based classification system to perform automated screening of diabetic retinopathy. The scope involves pre-process of the data, training of the model, evaluation of the performance and the implementation of the model in a controlled environment. The project does not go to large-scale implementation, real-time clinical deployment, integration, and acquisition of hardware and primary data collection. It presupposes an annotated data which can be used to train and test. Having a well defined scope, the project focuses on methodological rigor and technological feasibility and does not go over the mentioned goals.

Design Constraints

- **Data Privacy and Security:** Patient images must be protected in accordance with established medical and digital privacy regulations.
- **Accessibility:** The system should support diverse healthcare environments, including rural or low-resource settings with limited technological infrastructure.
- **Accuracy and Reliability:** Diagnostic consistency and high classification precision are essential to minimize erroneous predictions and associated clinical risks.

Chapter 2

Literature Review

The chapter is a systematic review of the current literature related to the Diabetic Retinopathy (DR) detection using deep learning and other machine-learning-based methods. The analyzed studies are all used to demonstrate the progress in the deployment of data sets, preprocessing guidelines, feature-extraction procedures, and classification effectiveness. It is through the critical assessment of available contributions that the conceptual and methodological scaffold on which the present project is based will be established.

2.1 Deep Transfer Learning for Multi-Class Diabetic Retinopathy Severity Classification

The present research study focuses on a Deep Transfer Learning-based Computerized Diagnostic System (DTL-CDS) which is aimed at grading the severity of DR in a variety of categories. The authors use the IDRiD data to adapt and evaluate several state-of-the-art inductive transfer-learning models, i.e., Inception 3, ResNet34, EfficientNet -B 0, VGG16, and Xception to automate the classification of the DR severity. The first one is to increase the accuracy of diagnosis by increasing feature extraction and narrowing down the classification layers [9].

Segmentation Method

To strengthen the discriminative performance and reduce the over-fitting, the suggested models include a global average pooling layer

Model

The final layer is a softmax classifier, which allows multi-step DR classification. Comparative studies with existing researches show high performance with the DTL-CDS showing 99.36-percent of accuracy, and 0.986-percent precision, 0.986-percent recall, an F1-score of 0.986, and an area under the receiver operating characteristic curve of more than 0.990-percent, which has a strong potential of automated screenings of DR and clinical decision support.

2.2 BP and SVM-Based Diagnosis of Diabetic Retinopathy

The current paper presents a diagnostic model that is focused on detecting microaneurysms (MAs), an early diabetic retinopathy visual appearance. The data analysis process involves the use of the median filter to clean up fundus images and extract MA-specific features in terms of intensity, morphology and dimensionality. A support vector machine (SVM) classifier is then used to classify the images into four levels of severity, namely normal, mild, moderate, and severe with a result of 83% accuracy, 74% sensitivity and 100% specificity. [10].

Segmentation Method

The segmentation is followed by isolating the MAs between retinal vessels and the background structures using the threshold techniques. The Canny edge detector also enhances the definition of the boundaries, and it is possible to identify the MAs with the help of geometric descriptors like roundness, circularity, and perimeter.

Model

The procedure has been based on using the SVM algorithm that builds an ideal separating plane on the severity classes. The strength of its ability in dealing with multidimensional medical-image data combined with its strong performance in SVM indicates the appropriateness of the combination of the backpropagation neural networks and SVM in early DR detection, thus the significance of a hybrid approach to learning in medical diagnostics.

2.3 Multi-Headed CNN and Vision Transformer-Based Model for Early Detection of Diabetic Retinopathy

In the context of contributing to tackle the problem of early DR detection, this paper presents a hybrid design that combines multilayered convolutional neural networks (CNNs) and vision transformers. CNNs are capable of identifying localized spatial features, transformers are able to gather wider contextual information about images as a whole, which makes it easier to interpret lesions in a holistic manner[11].

Segmentation Method

This multi-scale feature representations leads to a better separation of the minor stages of DR, especially at the early stages of the disease development.

Model

The system is capable of providing enhanced predictive reliability by merging CNN and transformer outputs. The model shows the effectiveness of the hybrid deep-learning methods in the complex medical-image classification and opens up the promising opportunities of the model in the early DR detection and clinical risk assessment.

2.4 Retinopathy-Based Multistage Classification of Diabetes

The presented work describes a non-invasive diagnostic pathway to the DR staging using retinal imaging[1].

Segmentation Method

After the definition of the relevant retinal areas, the features are then obtained and then separated by a random-forest algorithm to distinguish between non-proliferative (NPDR) and proliferative (PDR) stages.

Model

The method provides a classification error of up to 90%, which demonstrates that it is possible to use conventional machine-learning models to aid in clinical DR diagnosis and staging.

2.5 Auto-Segmentation of Retinal Blood Vessels Using Image Processing

In the current study, Malak T. Bantan presents a mechanism of vessel-segmentation with the automation which should be used to diagnose diabetic retinopathy (DR) and glaucoma. The experiment uses a small sample (45 fundus photos) and demonstrates how preprocessing has such an influential effect on the accuracy of segmentation[12].

Segmentation Method

Before segmentation, the fundus images are converted into grayscale format, contrast enhancement, intensity normalization, histogram equalization, and complements of the images are done. These processes boost the edges of vessels and dampen the noises in the background.

Model

According to the segmentation scheme, the accuracy ranges to 94, the specificity is 97 and the sensitivity is 69.

2.6 Diabetic Retinopathy Detection Using Deep Learning and Data Augmentation Techniques

Gulshan et al. (2016)[13] used experienced deep-learning network with more than 128 000 fundus images in the training to detect referable DR. Their model achieves an area below the receiver operating characteristic curve (AUC) of 0.991, which is similar to that of expert ophthalmologists, hence the strong feasibility of the deep-learning-based methodologies in the area of large-scale screening of DR.

Segmentation Method

The system works on end-to-end deep CNN capable of learning diagnostic features directly from raw fundus images.

Model

The architecture of Inception-v3 that undergoes supervised learning and extensive data augmentation enables binary classification of referable and non-referable cases of DR.

2.7 Hybrid Deep Learning and Ensemble Models for Retinal Disease Classification

Pratt et al. (2016)[14]introduce a collection of convolutional neural networks that have been trained with the EyePACS to measure the severity of DR. The ensemble structure suppresses the variance and solidifies the predictability, especially when used on the early stages of the disease symptoms.

Segmentation Method

Although the lesion-level segmentation is not involved, the traditional preprocessing measures, including normalization and contrast enhancement, are made to prepare the images to work with a classification task.

Model

Several convolutional neural networks are then individually trained and then combined through ensemble methods. The resulting architectures consist of convolutional, pooling and fully connected architectures thus making possible categorical classification of five discrete grades of DR severity.

2.8 Transformer-Enhanced Retinal Vessel Segmentation Using Attention Mechanisms and Multi-Scale Fusion

In their article, Kim, Eesaar, and Chong (2024)[15] suggest a transformer-based segmentation network that is designed with specific focus on the analysis of blood-vessels in the retina.

Segmentation Method

Fundus images are processed through multi-scale learning modules. Transformers capture global vessel connectivity, while CBAM and JPU enhance structural continuity and fine-grained segmentation.

Model

Testing on the CHASE-DB1 benchmark gives a mean intersection-over-union (IoU) of 0.8047, recall of 0.7254, precision of 0.8492, F1-score of 0.7824, and specificity of 0.9892, outperforming a number of existing vessel-segmentation algorithms.

2.9 Vision Transformer-Based Recognition of Diabetic Retinopathy Grade

Wu, Hu, Xiao, Chen, and Liu (2021)[16] explore an untainted Vision Transformer (ViT) model in grading DR.

Segmentation Method

There is no explicit segmentation done and Vision Transformers are trained to learn global contextual representation on the whole image by means of patch-based attention mechanisms.

Model

The model claims a relative accuracy of 91.4, and corresponding values of specificity, sensitivity, precision, and AUC show good competitiveness to the developed CNN-based methods.

2.10 DR Classification Using OCTA and Deep Learning

Ryu et al. (2021)[17] study a fully automated system of DR classification that uses optical coherence tomography angiography (OCTA) images. The paper compares classical machine-learning methods with CNN-based architectures at different resolutions of scans and depth of retinal slabs with ultra-widefield angiography as a standard in diagnostic.

Segmentation Method

The preprocessing of OCTA images is done to standardize the quality of scans and enhance the inter-image consistency; individual and combination of superficial, deep and full retina slabs are analysed without doing direct lesion segmentation.

Model

The CNN-based classifier shown strong diagnostic performance while highlighting OCTA as a viable modality for automated DR analysis.

Table 2.1: Performance metrics of the OCTA-based DR detection model

Metric	**Performance**
Accuracy	91% – 98%
Sensitivity	86% – 98%
Specificity	94% – 99%
AUC	0.919 – 0.976

2.11 Summary of Literature Review

Table 2.2: Comparative Analysis of Diabetic Retinopathy Detection Methods

Year	Paper Name	Dataset	Preprocessing	Feature Extraction / Model	Accuracy / Metrics
2019	Deep Neural Network for Diabetic Retinopathy Detection [18]	APTOS (Kaggle)	Image cropping and resizing	ConvNet, Logistic classifier	74%
2020	Identification of Diabetic Retinopathy through Machine Learning [12]	MESSIDOR	Color space conversion, edge zero padding, median filtering, adaptive histogram equalization	SVM, KNN, RF	78%
2021	A deep learning system for detecting diabetic retinopathy across the disease spectrum [19]	466,247 images (121,342 patients)	Real-time image quality assessment	Lesion detection and grading	90.1%
2021	Classification of Diabetic Retinopathy in Eye Fundus Images Based on Retinal Lesion Detection [6]	Kaggle EyePACS	Image resizing, removal of black edges	DenseNet121, Xception, ResNet50	73–90%
2021	Severity Classification of Diabetic Retinopathy Using Ensemble Learning [20]	APTOS 2019 BD	Handling duplicates with different labels	GLCM, XGBoost (10-fold CV)	92%
2021	Deep Transfer Learning for Multi-Class Diabetic Retinopathy Severity Classification [9]	IDRiD	Image normalization, augmentation	Inception V3, ResNet34, EfficientNetB0, VGG16, Xception	99.36% (AUC $>$ 0.99)
2021	BP and SVM-Based Diagnosis of Diabetic Retinopathy [10]	Fundus images (custom dataset)	Median filter, noise removal, Canny edge detection	SVM classifier with MA segmentation	83% (Se=74%, Sp=100%)
2022	Multi-Headed CNN and Vision Transformer for Early DR Detection [11]	EyePACS	Normalization and augmentation	Hybrid CNN + Vision Transformer	94% (high sensitivity)
2024	Transformer-Enhanced Retinal Vessel Segmentation[kim2024]	DRIVE, STARE, CHASE$_D B1$	Contrast enhancement, resizing	Transformer + CNN attention segmentation	Dice $\approx$ 0.82–0.85
2021	Automated Deep Learning Detection of DR using OCT Angiography[ryu2021octa]	OCTA scans (45 images)	Gray-scale conversion, histogram equalization	CNN on OCTA features	Acc: 91–98%, Se: 86–98%, Sp: 94–99%, AUC: 0.919–0.976

Chapter 3

Requirement Specifications

This chapter outlines the requirements that guide the development of the proposed Diabetic Retinopathy (DR) detection system. The primary objective is to design a solution that balances diagnostic accuracy with accessibility, allowing medical professionals and screening programs to benefit from automated DR assessment. The specifications aim to integrate clinical screening needs with modern computational techniques, ensuring early detection and effective monitoring across various healthcare environments.

3.1 Existing System

The existing methods of diabetic retinopathy (DR) detection are relying on classification of initial retinal defects to a large extent. Though the methods are used in clinical assessment, they are frequently specifically adapted to sets of data, which limits their applicability to heterogeneous populations and imaging cases. They are therefore not able to provide full-fledged anomaly detecting that would be sufficient to be used in the real world. Although there has been improvement in preprocessing and classification techniques, several reported systems have an average accuracy of about 85% [8].

In addition, morphological abnormalities that occur during an advanced stage of the disease process can be difficult to detect with only one segmentation or classification method.

As a result, a growing need to have integrated, scalable frameworks that would be able to synthesize the various retinal properties and improve the accuracy of the diagnosis at every grade of severity is emanating.

3.2 Proposed System

The proposed system proposes a multistage diabetic retinopathy (DR) classifier aimed to correct the weaknesses of the existing models. It is used to classify the retinal images into five clinical severity scores-Normal, Mild, Moderate, Severe, and Proliferative DR-and therefore allows a more finer evaluation of the disease progression. Although similar preprocessing steps are utilized as in the previous research works, the current algorithm continues the segmentation and feature extraction processes[21].

Unlike traditional systems, which focus on the identification of microaneurysms only, this model uses other types of lesions, such as hemorrhages, to increase its diagnostic ability. The feature set includes the quantitative lesion measures (e.g. lesion count and lesion area), and statistical and textual features (e.g. variance, energy, and correlation). These composite factors improve the level of classification and make it easy to stage retinal images reliably. The proposed system can be described architecturally as illustrated in Figure 3.1.

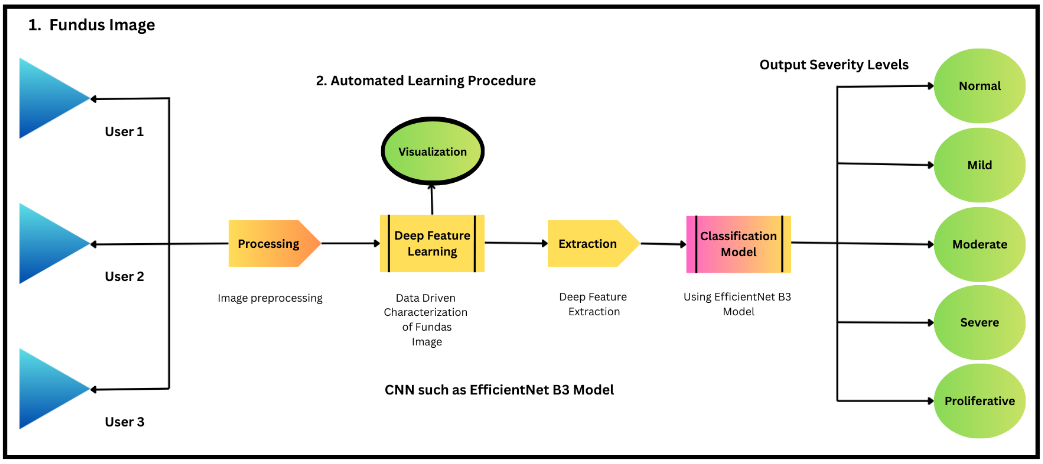


Figure 3.1: System Architecture

3.3 Feasibility Study

It is necessary to conduct a feasibility analysis to assess the practicability of the implementation of a deep-learning-based diabetic retinopathy detection system. This evaluation will include the technical readiness, data availability, resource requirements, development risks and implementation constraints. Knowing these aspects makes it easy to establish the reliability of the system in the real-life healthcare situations.

3.3.1 Risk Involved

Data Quality

- The prediction model performance will depend on the existence of high-resolution, heterogeneous and accurately annotated repositories of retinal images.
- Lack of data quality may create class imbalance, error in annotation or demographic bias, which compromises predictive reliability.
- Adoption of sound data acquisition and verification procedures is urgent to reduce the diagnostic errors.

Technical Challenges

- Implementing and optimizing deep learning architectures such as EfficientNet-B3 and ResNet18 require specialized knowledge in machine learning and software engineering.
- Key challenges include:
  - Avoiding model overfitting during training
  - Securing sufficient GPU or cloud computing resources
  - Ensuring efficient inference during high user-load scenarios
- Developing an interactive web-based interface demands expertise in technologies such as React, HTML5, CSS3, JavaScript, and Bootstrap.
- Additional challenges involve:
  - Seamless integration between frontend and backend systems
  - Responsive design across devices
  - Maintaining platform stability and usability
- Backend deployment may rely on microservice architectures using Flask to manage API requests, run model predictions, and securely process uploaded images.

Privacy and Security

- Since medical imaging data is highly sensitive, the system must enforce strict confidentiality and comply with data protection regulations.
- Unauthorized access, data leaks, or ethical misuse could result in legal and institutional repercussions.

Integration and Testing

- Incorporating the trained model into the web platform requires careful coordination between software components and the deployed API.
- Continuous system testing ensures:
  - Accuracy and consistency of model predictions
  - Smooth communication between backend services and user interface
- Automated testing and user-centered evaluations support early detection of system faults and improve operational reliability.

Addressing these considerations increases the likelihood of delivering a dependable system capable of supporting clinical workflows and large-scale screening initiatives.

3.3.2 Resource Requirement

Developing an AI-driven DR detection system requires coordinated software and hardware resources capable of supporting intensive image processing and model training tasks.

3.3.3 Software Requirements

Table 3.1: Software Requirements

Component	Description
Language	Python 3.8+
Libraries	PyTorch/TensorFlow, Keras, NumPy, Pandas, Scikit-learn
Modeling Tools	Google Colab, Jupyter Notebook, PyCharm
Web Framework	Flask or FastAPI for backend
Frontend	HTML, CSS, JavaScript
Version Control	Git, GitHub

3.3.4 Hardware Requirements

Table 3.2: Hardware Requirements

Resource	Minimum	Recommended
RAM	8 GB	16–32 GB
Processor	Quad-core CPU or higher	i7 9 gen or higher
GPU	Not required (for training only)	NVIDIA GPU (Colab/Cloud or local CUDA)
Storage	10 GB	10+ GB for datasets and logs
OS	Windows/Linux/Mac	Any with Python 3 support

3.3.5 Cloud Tools

Cloud-based platforms such as Google Colab and Kaggle Kernels may be utilized for large-scale training, GPU acceleration, and collaborative experimentation.

3.4 Functional Requirements

The functional requirements define the intended behavior and operational capabilities of the system:

1. **Image Input and Validation:** Accept retinal images in standard formats (JPEG, PNG, TIFF) and validate image resolution, dimensions, and quality prior to processing.
2. **Automated Detection with EfficientNet-B3:** Apply a fine-tuned EfficientNet-B3 model to detect DR-related abnormalities with high diagnostic confidence.
3. **5-Level DR Severity Classification:** Categorize each analyzed image into Normal, Mild, Moderate, Severe, or Proliferative DR based on learned decision boundaries.
4. **Multistage Classification Logic:** Integrate model outputs with clinical interpretive logic, acknowledging lesion characteristics such as type, density, and spatial distribution.
5. **Pre-processing Steps:** Implement preprocessing operations such as adaptive histogram equalization, median filtering, and illumination correction to enhance image clarity.
6. **Segmentation:** Apply segmentation methods to isolate lesions including microaneurysms, hemorrhages, and exudates, supporting downstream analysis.
7. **Feature Extraction:** Retrieve morphological, statistical, and textural descriptors from segmented regions to enrich prediction accuracy.
8. **User Interface:** Develop a streamlined and responsive web interface enabling clinicians to upload images, review results, and monitor patient records.
9. **Output Display:** Present diagnostic results, probability scores, and classification summaries, with an option to generate downloadable reports.

3.5 Non-Functional Requirements

Non-functional requirements describe the performance, quality, and operational expectations of the system:

1. **Scalability:** The system must accommodate increasing user demand and image-processing volume without degradation.

2. **Performance:** Image analysis and classification should be completed within a clinically acceptable time frame.

3. **Reliability:** Outputs must remain consistent, accurate, and reproducible across multiple test conditions.

4. **Usability:** The interface should minimize cognitive load, requiring little to no specialized training for effective use.

3.6 Use Case

Use case modeling helps explain how different system components interact with end users. These scenarios illustrate typical workflows by detailing user actions and corresponding system responses. The use case representation is illustrated in Figure 3.2.

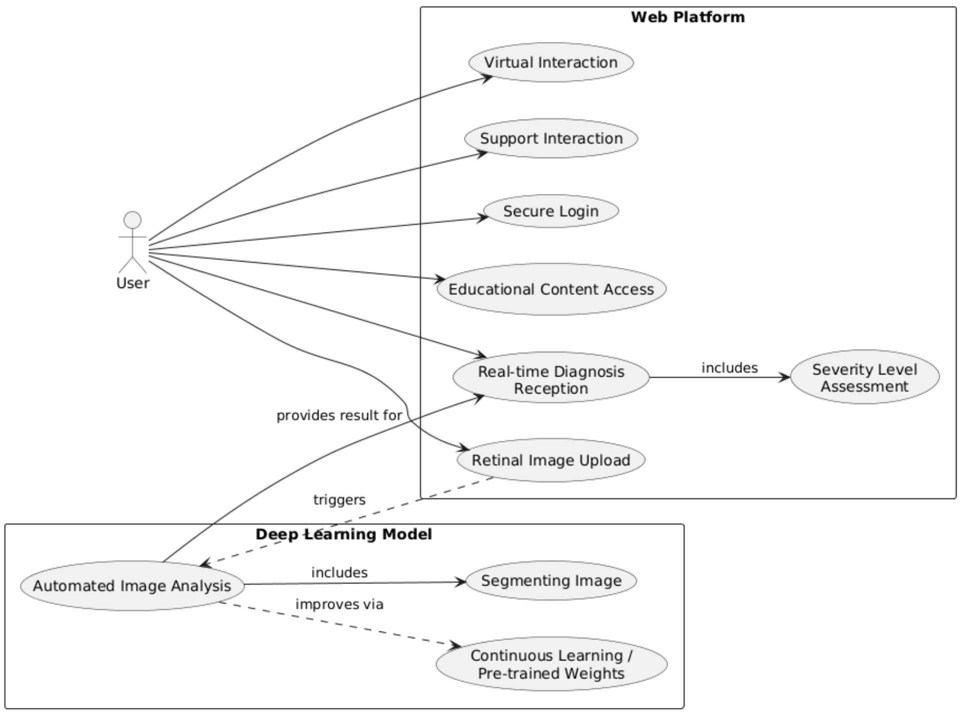


Figure 3.2: Use Case Diagram

User

- **Account Registration:** Users may create an account to customize access and store screening history.

- **Secure Login:** Returning users authenticate using secure credentials before accessing system features.
- **Retinal Image Upload:** Users upload images through an intuitive drag-and-drop interface. The system validates image quality before processing.
- **Real-Time Diagnosis Reception:** After image submission, users receive DR predictions and processing status updates.
- **Severity Level Assessment:** The platform clearly presents the predicted DR stage along with interpretive guidance.
- **Educational Content Access:** Users may view curated resources regarding DR symptoms, prevention practices, and treatment pathways.

Deep Learning Model

- **Automated Image Analysis:** The system triggers model execution immediately upon input receipt, applying trained algorithms to evaluate disease presence and severity.
- **Continuous Learning:** The model may incorporate new annotated data to enhance accuracy and reduce misclassification over time.
- **Image Segmenting:** Lesion-level segmentation assists clinicians by highlighting suspicious regions and supporting interpretability.

3.6.1 Use Case 1: Signup

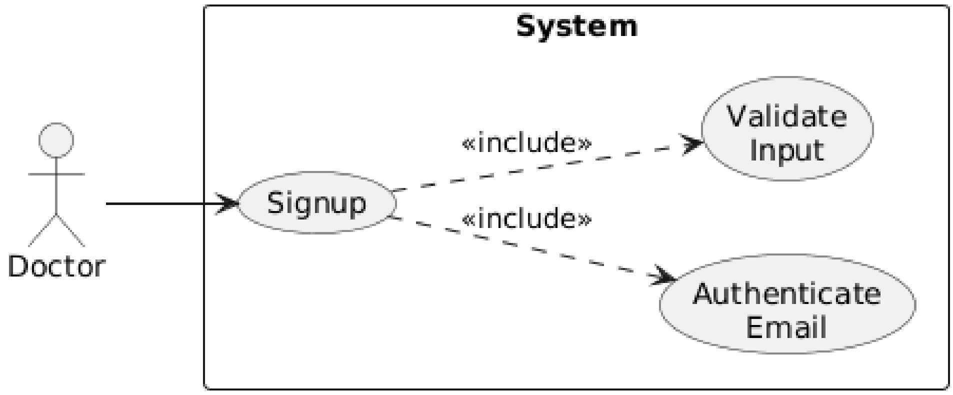


Figure 3.3: SignUp Use Case Diagram

Use Case Description: Signup

Table 3.3: Use Case Description: Signup

Use Case ID:	UC-0001
Use Case Name:	Signup
Actors	Doctor
Description	Doctor can sign up on the website by providing a valid email and password. This use case ensures secure registration through form validation and user input checks.
Trigger	Patient/Doctor clicks on Sign up button.
Normal Flow	**Actor** Doctor clicks on the Application Doctor gives a valid email and password. **System** System displays the Signup form System stores the Signup Information.
Alternative Flow	A toast displaying an error message upon the following reason. 1. Incorrect email/password

3.6.2 Use Case 2: SignIn

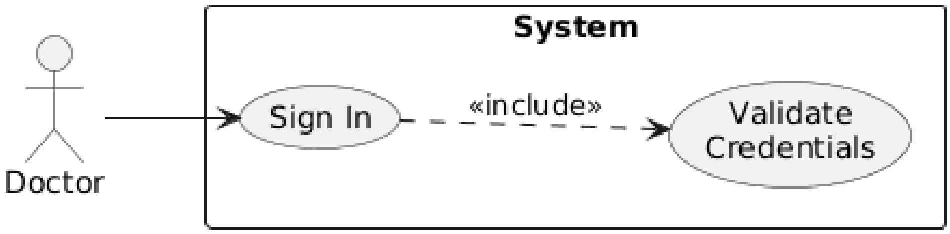


Figure 3.4: SignIn Use Case Diagram

Use Case Description: SignIn

Table 3.4: Use Case Description: SignIn

<table>
<tr><td>Use Case ID:</td><td>UC-0002</td></tr>
<tr><td>Use Case Name:</td><td>Sign in</td></tr>
<tr><td>Actors</td><td>Doctor</td></tr>
<tr><td>Description</td><td>Doctor can login to the website by providing valid credentials. This use case ensures secure authentication, allowing access only to authorized users.</td></tr>
<tr><td>Trigger</td><td>Patient/Doctor clicks on login button.</td></tr>
<tr><td>Normal Flow</td><td><table>
<tr><td>Actor</td><td>System</td></tr>
<tr><td>Doctor clicks on the website</td><td>System displays the login form</td></tr>
<tr><td>Doctor gives a valid email and password</td><td>System shows the homepage after successful login</td></tr>
</table></td></tr>
<tr><td>Alternative Flow</td><td>A toast displays an error message upon the following reason: 1. Incorrect email/password</td></tr>
</table>

3.6.3 Use Case 3: Upload Image

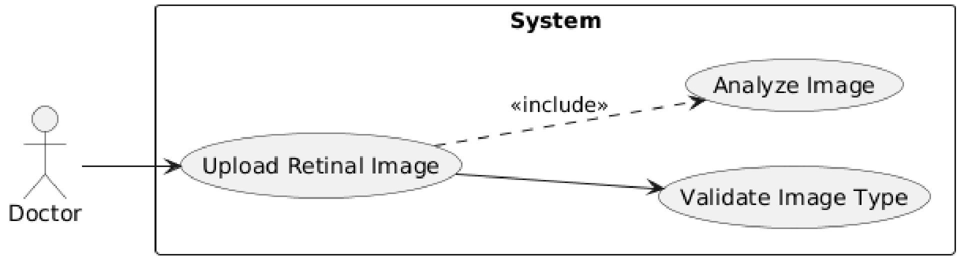


Figure 3.5: Upload Image Use Case Diagram

Use Case Description: Upload Image

Table 3.5: Use Case Description: Upload Image

<table>
<tr><td>Use Case ID:</td><td colspan="2">UC-0003</td></tr>
<tr><td>Use Case Name</td><td colspan="2">Upload Retinal Image</td></tr>
<tr><td>Actors</td><td colspan="2">Doctor</td></tr>
<tr><td>Description</td><td colspan="2">The doctor is able to upload a retinal image through the system's user interface. This image is intended for diagnostic analysis and further processing by the system.</td></tr>
<tr><td>Trigger</td><td colspan="2">Doctor selects an image to upload</td></tr>
<tr><td rowspan="3">Normal Flow</td><td>Actor</td><td>System</td></tr>
<tr><td>Doctor clicks on choose file button</td><td>System displays file explorer to select an image</td></tr>
<tr><td>Doctor selects an image from gallery</td><td>System uploads the image for test</td></tr>
</table>

3.6.4 Use Case 4: Patients Records

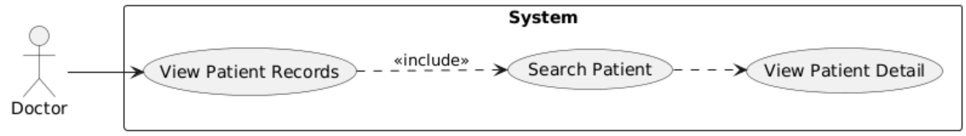


Figure 3.6: Patient Record Use Case Diagram

Use Case Description: Patient record

Table 3.6: Patient record use case description

<table>
<tr><td>Use Case ID:</td><td>UC-0004</td></tr>
<tr><td>Use Case Name</td><td>Patients Record</td></tr>
<tr><td>Actors</td><td>Doctor</td></tr>
<tr><td>Description</td><td>The doctor can access and view the medical records of their respective patients. The system allows doctors to either browse through all records or search for a specific patient by name.</td></tr>
<tr><td>Trigger</td><td>Doctor clicks on patient record link</td></tr>
<tr><td>Normal Flow</td><td><table>
<tr><td>Actor</td><td>System</td></tr>
<tr><td>Doctor clicks on patient record link</td><td>System displays all the patient records</td></tr>
<tr><td>Doctor searches for a specific patient</td><td>System displays only the records of the searched patient</td></tr>
</table></td></tr>
<tr><td>Alternative Flow</td><td>No patient record is found</td></tr>
</table>

3.6.5 Use Case 5: Patient's Medical Report

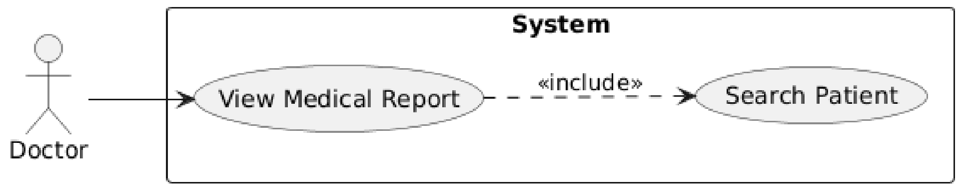


Figure 3.7: Patients Medical Report Use Case Diagram

Use Case Description: Patient Medical Report

Table 3.7: Patient Medical Report use case description

<table>
<tr><td>Use Case ID:</td><td>UC-0005</td></tr>
<tr><td>Use Case Name</td><td>Patients Medical Report</td></tr>
<tr><td>Actors</td><td>Doctor</td></tr>
<tr><td>Description</td><td>The doctor can view detailed medical reports of individual patients. This functionality allows the doctor to access relevant diagnostic and treatment information by selecting the patient's profile or card.</td></tr>
<tr><td>Trigger</td><td>Doctor clicks on a patient's card in order to see the medical report</td></tr>
<tr><td>Normal Flow</td><td><table><tr><td>Actor</td><td>System</td></tr><tr><td>Doctor clicks on patient's card</td><td>System displays the medical report of that specific patient</td></tr></table></td></tr>
</table>

3.6.6 Use Case 6: Generate PDF

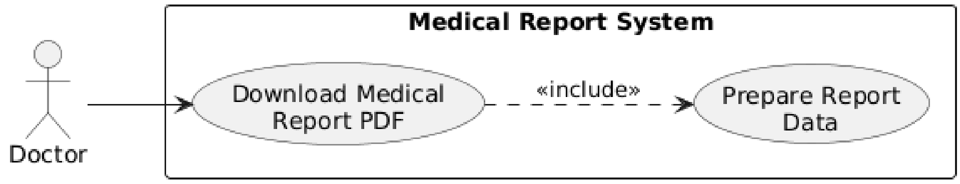


Figure 3.8: Generate PDF Use Case Diagram

Use Case Description: Generate PDF

Table 3.8: Generate PDF use case description

Use Case ID:	UC-0006	
Use Case Name	Generate PDF	
Actors	Doctor	
Description	The doctor can download a patient's medical report in PDF format. This allows for easy storage, printing, or sharing of the report as needed for medical or administrative purposes.	
Trigger	Doctor clicks on the PDF button to download the medical report.	
Normal Flow	**Actor**	**System**
	Doctor clicks on the PDF button.	System downloads the medical report.

3.7 Sequence Diagram

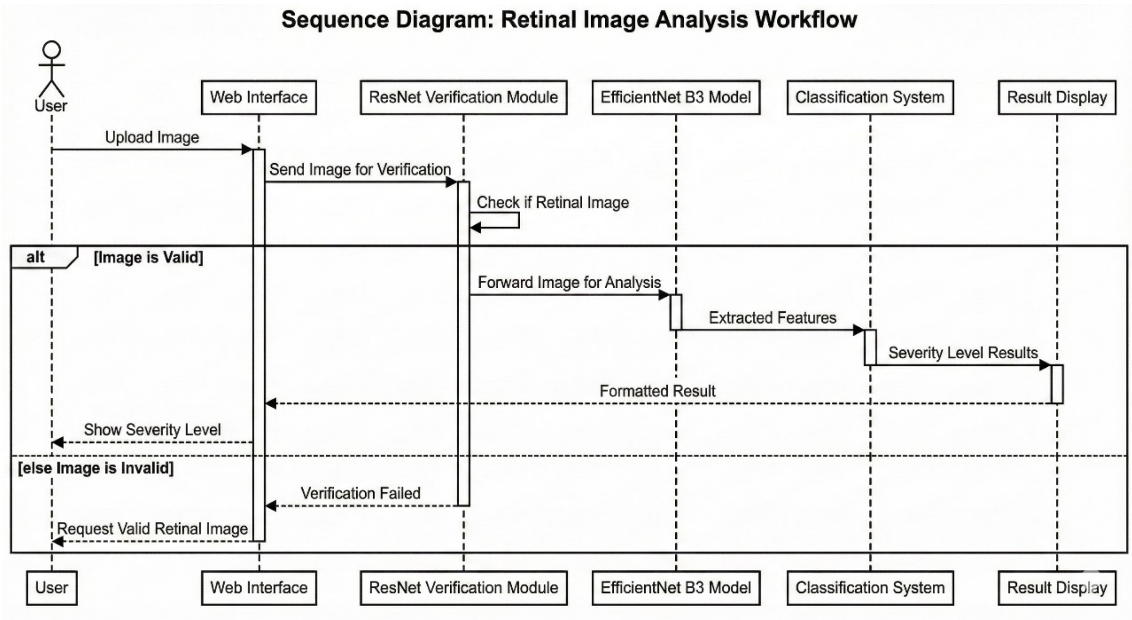


Figure 3.9: Sequence Diagram of DR Detection System

Chapter 4

Design

This chapter defines the stringent systematic design process that was used in the building of the Diabetic Retinopathy (DR) Detection and Classification System. The goal is to put theoretical understanding, machine learning principles and software engineering principles into a working device that can be integrated into real clinical practice. The design components explained in this section form the framework of the further implementation, assessment, and future scalability.

4.1 System Architecture

The accommodated system architecture is designed with the aim of automated DR detection and stratification of its severity through the latest deep-learning models. It is made up of several mutually organizing subsystems that have specific stages of data intake, analytical work, or interaction with the user, which together give rise to valid and valuable diagnostic results.

4.1.1 Subsystems

The key subsystems are below:

1. **Web Interface Subsystem:**
    - The main interaction medium between the clinicians and the end users of the system is a browser based interface, which is developed using React.js. The auxiliary technologies, HTML, CSS, and JavaScript, ensure the smooth navigation, laminar image uploading, responsive designs, and the general intuitive user interface.
2. **Image Preprocessing and Validation Subsystem:**

- First image cleaning is performed with the use of denoising, normalization, resizing, and contrast, with libraries like Albumentations and PIL. ResNet based validation module is also included to ensure that uploaded files are of retinal fundus images that may be subjected to diagnostic analysis.

3. **Segmentation and Feature Extraction Subsystem:**

   - The system performs the targeted retinal structure segmentation of the retinal structure, followed by automated feature extraction using the EfficientNet-B3 architecture. The features obtained form structured inputs in the downstream classification model.

4. **Severity Classification Subsystem:**

   - EfficientNet-B3 will classify images into five DR severity levels: No DR, Mild, Moderate, Severe, and Proliferative DR.

5. **Result Presentation and Education Subsystem:**

   - The interface shows model predictions, the confidence scores alongside the explanatory narratives of each severity stage in a readable and understandable format. In addition, it provides the educational materials that outline the symptoms, treatment types, and prophylaxis in order to increase patient knowledge.

6. **Backend Processing Subsystem:**

   - This was done using Flask. This manages a server side execution.

4.2 Design Constraints

The process of creating a medical diagnostic system requires the possibility of observing rigorous compliance with numerous practical and ethical design limitations as they are following.

1. **Resource Utilization:**

   - Inference and training of deep-learning are both computationally extensive. This leads to the fact that both the EfficientNet -B3 and ResNet model should be fine-tuned to ensure that the through put is high and the performance is not compromised due to the available resources (GPU and memory).

2. **Accuracy and Reliability:**

- Since the system influences the medical decision-making, it should be characterized by a high level of sensitivity, specificity, and the general diagnostic qualities. The use of cross-validation, the right data balancing, and performance benchmarking helps to overcome the threat of misclassification.

3. **Usability:**

   - The platform should be user-friendly to the audience with different degrees of technical skills. A user-friendly, user guided and properly organized interface will ensure that clinicians are able to post pictures and generate outcomes without having to be trained to use it.

4. **Response Time:**

   - Real-time or near real-time inference is essential for practical clinical use. The system design must therefore reduce latency by optimizing backend processing, performing parallel computations where possible, and minimizing network delays.

4.3 Design Methodology

The design methodology is guided by clearly defined objectives that ensure alignment between model performance, system usability, and clinical applicability:

1. **Accurate Diabetic Retinopathy Detection:**

   - **Objective:** Build a deep learning model capable of reliably detecting DR in retinal fundus images.
   - **Strategy:** Train EfficientNet-B3 on a large diverse dataset and improve generalization using augmentation, regularization, and hyperparameter tuning until satisfactory diagnostic performance is achieved.

2. **Multistage Severity Classification:**

   - **Objective:** Distinguish between five severity levels to support informed treatment planning.
   - **Strategy:** Use hierarchical features extracted by EfficientNet-B3 and optimize classification thresholds using cross-validation and ensemble-based refinements.

3. **Early Diagnosis and Monitoring:**

   - **Objective:** Support timely medical intervention and continuous patient follow-up.

- **Strategy:** Deploy the model through a web application, enabling repeated screenings and comparisons over time.

4. **User-Friendly Web Interface:**

    - **Objective:** Facilitate smooth and intuitive user interaction.
    - **Strategy:** Develop a structured React.js-based interface that simplifies uploading, reviewing, and interpreting results.

5. **Segmentation and Feature Extraction:**

    - **Objective:** Highlight critical DR-related retinal abnormalities.
    - **Strategy:** Apply segmentation pipelines that isolate hemorrhages, microaneurysms, and other lesion regions before extracting statistical, morphological, and textural features.

4.4 High-Level Design

The high-level system design incorporates several integral components:

1. **System Architecture:**

    - Combines a web-based user interface with a backend inference engine. EfficientNet-B3 performs DR classification, while ResNet validates uploaded images as retinal scans.

2. **Data Input:**

    - Accepts high-resolution retinal fundus images obtained from diagnostic imaging sources.

3. **Pre-processing:**

    - Standardizes and enhances image quality using processing techniques such as median filtering, adaptive histogram equalization, and green-channel extraction.

4. **Segmentation:**

    - Identifies and isolates retinal abnormalities including microaneurysms and hemorrhages to strengthen classification performance.

5. **Feature Extraction:**

    - Analyzes segmented regions to derive morphological, statistical, and textural data relevant to disease assessment.

6. **Multistage Classification:**
   - Categorizes images into five DR severity levels using EfficientNet-B3's learned representations and optimized prediction thresholds.
7. **Output:**
   - Produces visual and textual diagnostic feedback, highlighting predicted severity and potential risk factors.
8. **User Interface:**
   - Provides an accessible React.js-based platform enabling clinicians to upload images, receive predictions, and interact with educational resources.

4.5 Data Flow Model

Once the system is initialized, uploaded fundus images undergo preprocessing, segmentation, feature extraction, and classification. This structured flow improves reliability and standardization across varied datasets.

4.5.1 Data Flow Diagram (DFD)

Level 1:

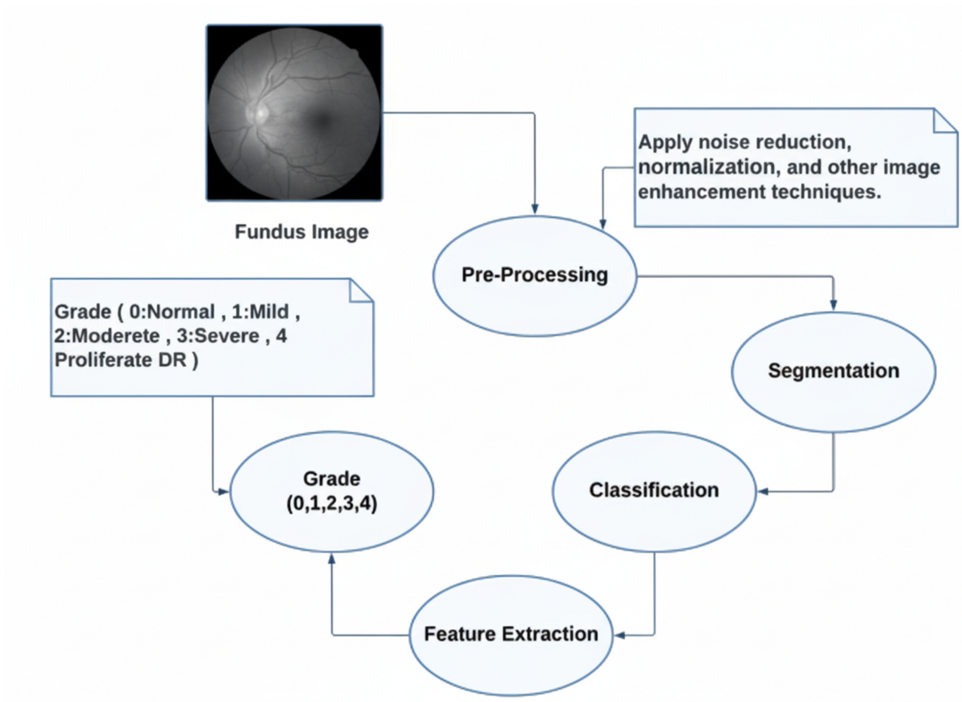


Figure 4.1: Level 1 Data Flow Diagram

Each uploaded image progresses through preprocessing, segmentation, classification, and result presentation, as depicted in Figure 4.2.

4.5.2 Pre-processing

Image quality issues such as poor illumination, motion blur, uneven focus, or reflections can negatively affect automated diagnosis. Approximately 10% of fundus images contain artifacts that hinder grading. Preprocessing therefore plays a crucial role in normalizing illumination, correcting contrast, reducing noise, and enhancing retinal structures to support accurate feature extraction and classification.

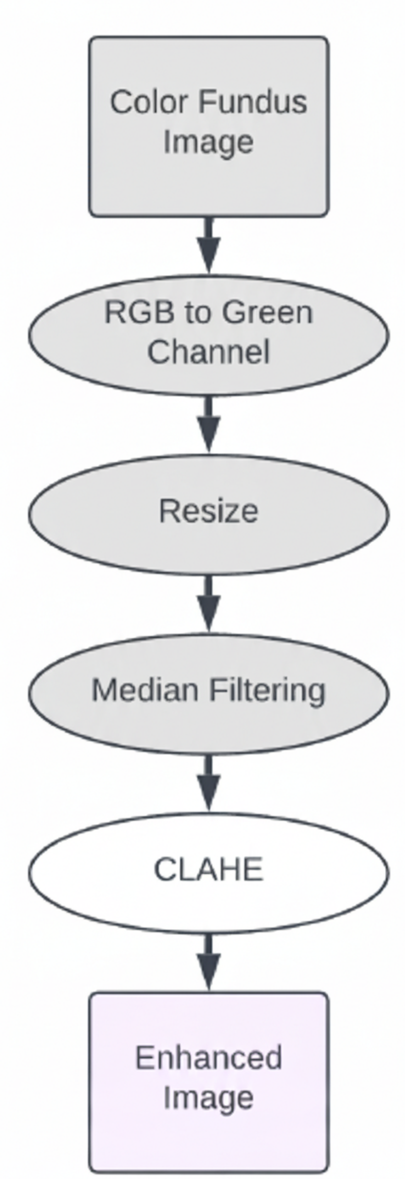


Figure 4.2: Pre-processing Data Flow

The preprocessing pipeline includes several sequential steps:

RGB to Green Channel Conversion

Retinal abnormalities are more distinguishable in the green channel than in red or blue channels. Thus, after converting the image to grayscale, the green channel is isolated to improve vessel and lesion visibility, as shown in Figure 4.4.

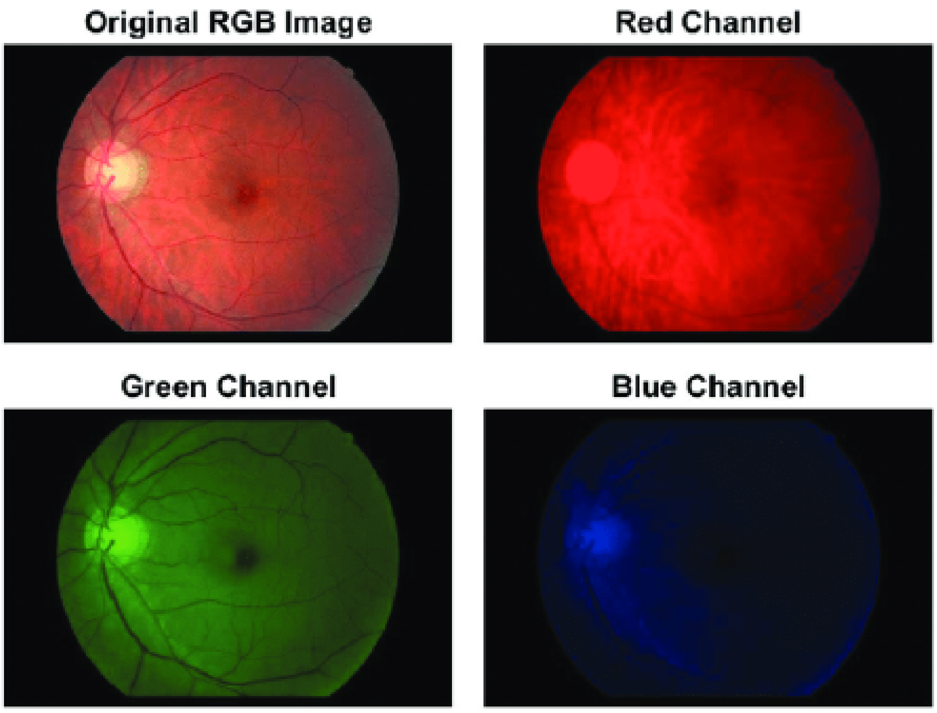


Figure 4.3: Three Color Channel Comparison

Image Resizing

To maintain consistency across datasets and models, images are resized to a standard resolution of **1024** $\times$ **1024** pixels.

Median Filtering

A nonlinear median filter removes impulse noise while preserving edges, making it well suited for retinal image denoising especially when dealing with salt-and-pepper noise patterns.

CLAHE (Contrast-Limited Adaptive Histogram Equalization)

CLAHE enhances local contrast by applying adaptive histogram equalization to small image tiles, improving structural visibility without over-amplifying noise. Collectively, preprocessing steps substantially improve diagnostic clarity.

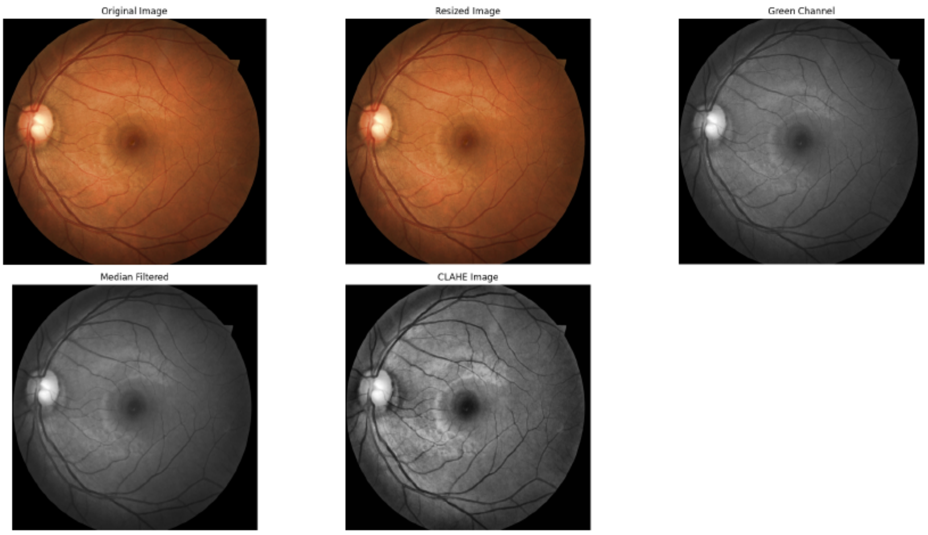


Figure 4.4: Preprocessed Image Output

4.5.3 Segmentation

After preprocessing, lesion segmentation is performed to isolate clinically relevant retinal structures.

Vessel Detection and Removal

Blood vessels are extracted using CLAHE, morphological filtering, and thresholding operations. Removing vessels from the image simplifies the task of identifying red lesions such as microaneurysms or hemorrhages [1].

Microaneurysm and Hemorrhage Segmentation

Microaneurysms and hemorrhages are differentiated based on structural characteristics, smaller circular lesions are classified as microaneurysms, while larger irregular regions are labeled as hemorrhages. Morphological opening further eliminates vessel fragments.

4.6 Classification

Classification involves training a model to distinguish between disease stages based on extracted image features. During training, patterns and descriptive feature boundaries are learned; during testing, these learned boundaries are applied to unseen images for prediction.

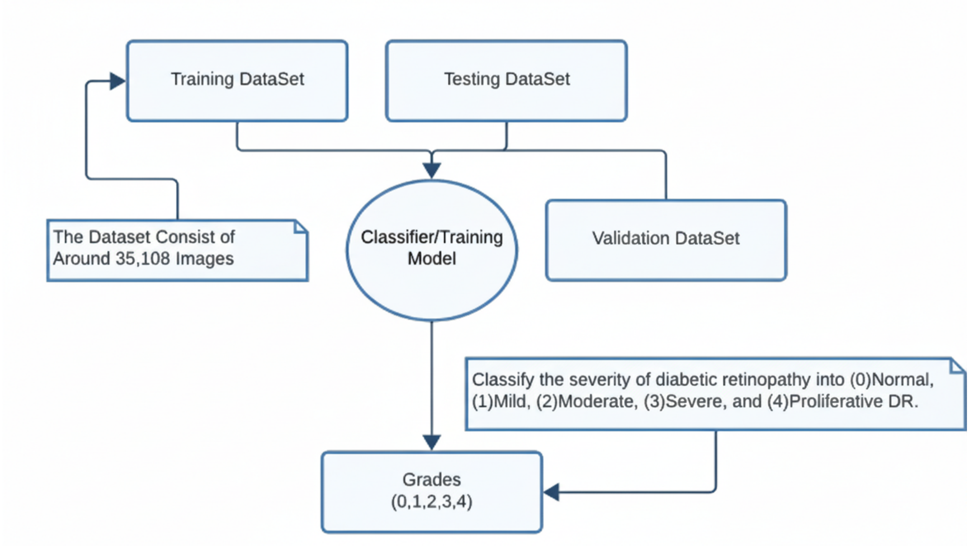


Figure 4.5: Classification Model Pipeline

Figure 4.5 illustrates the flow of training, validation, and testing data toward generating final severity predictions.

Implementation Steps

The implementation workflow for the DR classification system includes:

1. **Define Severity Stages**
   - Establish classification categories based on clinical guidelines:
     (a) Normal
     (b) Mild NPDR
     (c) Moderate NPDR
     (d) Severe NPDR
     (e) Proliferative DR (PDR)
2. **Feature Extraction and Augmentation**
   - Extract deep visual features using EfficientNet-B3
   - Improve dataset diversity using augmentation techniques provided by Albumentations
3. **Retinal Verification and Training**

- Employ ResNet18 to confirm image authenticity as retinal
- Train EfficientNet-B3 on labeled datasets using supervised learning

4. **Evaluate Deep Learning Models**
   - Compare architectures such as EfficientNet-B3 and ResNet18
   - Tune hyperparameters using metrics including sensitivity, specificity, and overall accuracy

5. **Diabetic Retinopathy Classification**
   - Deploy the trained EfficientNet-B3 model to classify uploaded images
   - Provide outputs that support diagnosis, monitoring, and treatment planning

4.7 Activity Diagram

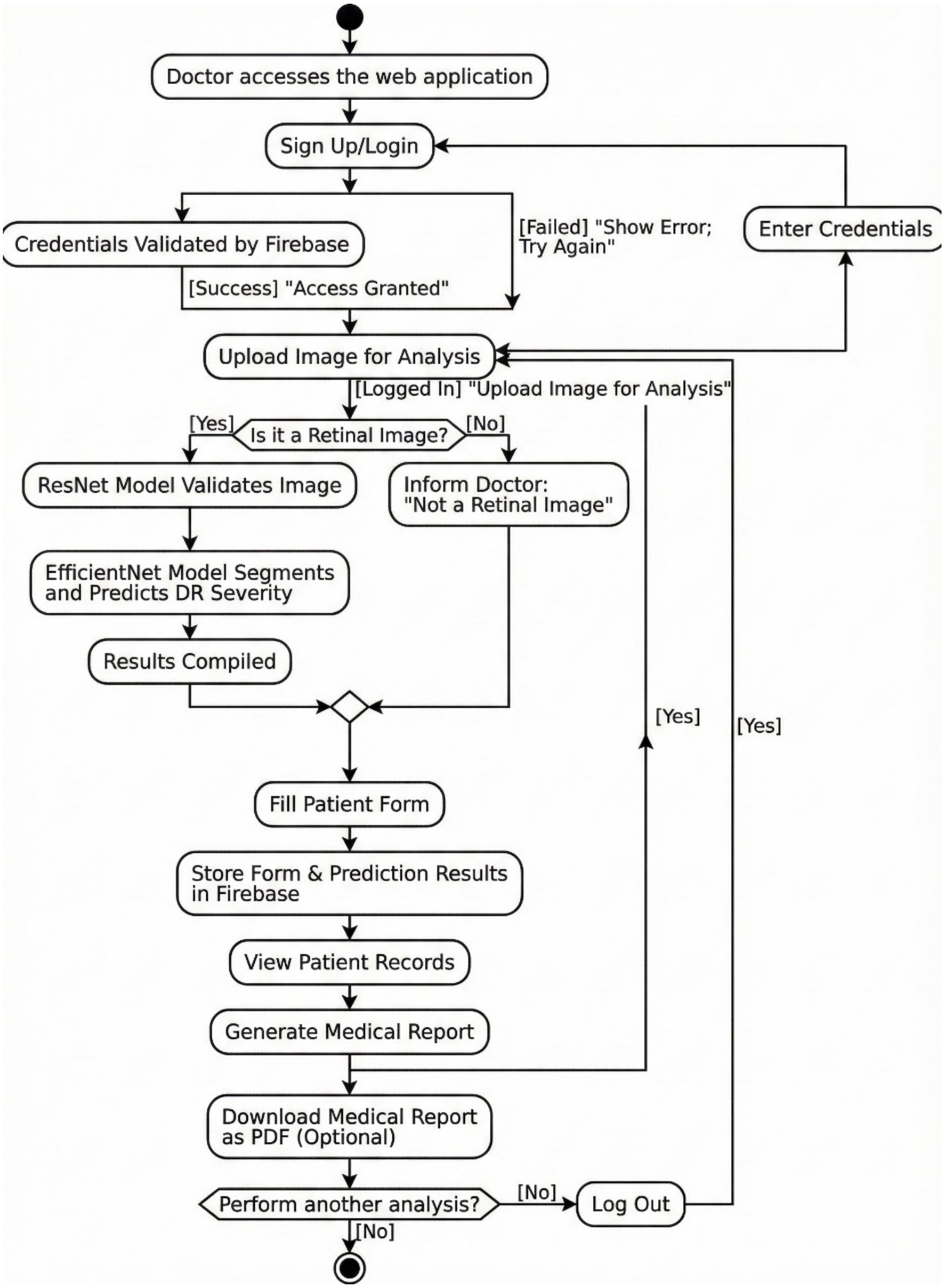


Figure 4.6: Activity Diagram Representing Doctor Interaction

Chapter 5

System Implementation

The implementation phase is the period between the theoretical design to the functional development. In this stage, the conceptual design, algorithms, data structures, and interface specifications are converted into a combined, working application. The chapter presents the outline of the development, configuration, and deployment of the proposed diabetic retinopathy detection system to offer reliable real-time diagnostic support.

5.1 Internal Components

In this section, the actual design of the system is explained and how individual modules are created to constitute the final working product. Every component has a purpose of being implemented to provide efficiency, accuracy and usability within the diagnostic workflow.

5.1.1 User Authentication

- The account creation and login options are secured to allow the user authentication.
- Credential protection and controlled access maintain the user confidentiality.

5.1.2 Patient Record Management

- The users are given the power to create, update, search, and arrange patient medical records.
- Persistent and cloud based data storage and swift retrieval is done using Firebase.
- Search functionality has been added that separates records according to the names of the patients.

5.1.3 Retinal Image Upload and Analysis

- The users can post retinal fundus images to assist in automatic diagnostic analysis.
- Pictures are fed through a backend of the Flask based on segmentation and classification.
- Clinical decision support is presented with the display of analytical results and system interpretations.

5.1.4 Export to PDF

- The PDF medical reports can be downloaded and used to generate documentation and sharing.
- The system increases accessibility, portability and integration into clinical workflow.

5.2 Dataset

The main dataset used to train and test the model is the set of around 35,108 labeled fundus images, which are obtained on the competition on the subject Blindness Detection on the Kaggle, as shown on the graph in Figure 5.1. All the images are marked on a five-point diabetic retinopathy severity scale: 0(Normal), 1(Mild), 2(Moderate), 3(Severe), and 4(Proliferative Diabetic Retinopathy). These categories are written down in a corresponding CSV file and form the basis of the supervised learning structure applied in classification. This data was utilized to train EfficientNet -B3 to grade the severity but ResNet -18 was used to verify if an uploaded image is retinal before sending it to the classification model.

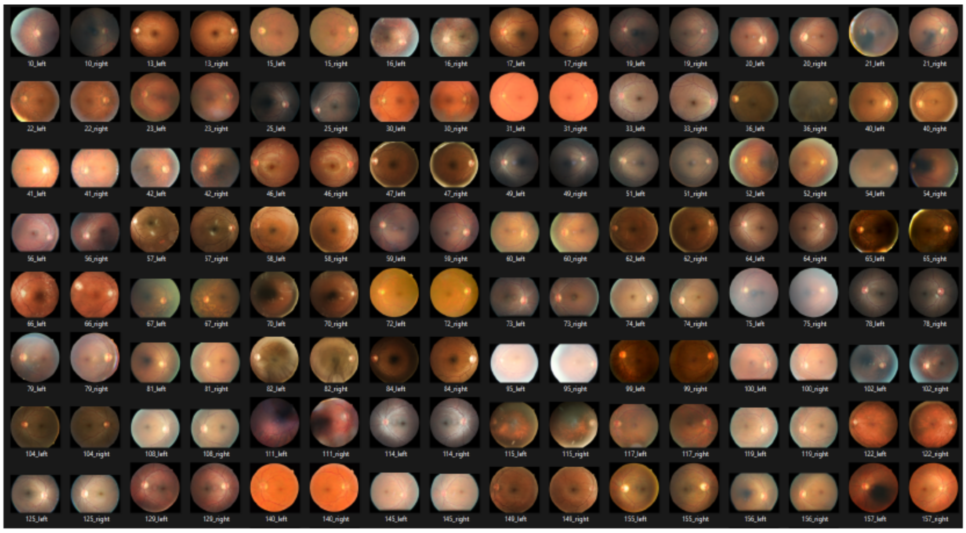


Figure 5.1: Diabetic Retina Dataset

A1 | fx | 10_

	A	B	C
296	343_right	0	
297	348_left	1	
298	348_right	1	
299	349_left	0	
300	349_right	0	
301	352_left	3	
302	352_right	3	
303	355_left	0	
304	355_right	0	
305	356_left	0	
306	356_right	0	
307	358_left	0	
308	358_right	0	
309	360_left	2	
310	360_right	2	
311	363_left	0	
312	363_right	0	
313	364_left	0	
314	364_right	0	
315	367_left	4	

Figure 5.2: Severity Scale in CSV File

Open source Non-Retinal Images: Another dataset that included the quotidian visual images e.g. cars, flowers and animals was used to train the non-retinal image detector. This method ensures that the system first checks the correctness in uploaded uploads in the form of fundus pictures and then proceeds to the treatment of diabetic retinopathy (DR).

5.3 Functionalities of the Components

All the elements of the system are in support of the primary goal of creating an automated, precise, and scalable diagnostic model of the early diagnosis of diabetic retinopathy.

5.3.1 Training Model

The central classification model in this system is EfficientNet-B3.

EfficientNet Overview

EfficientNet is a group of convolutional neural network designs proposed by Google as a way of achieving high predictive accuracy with low computation costs. These models are depth, width, and resolution uniform and therefore can be optimally performed on a wide range of hardware configurations.

EfficientNet-B3 Variant

EfficientNet-B3 provides a trade-off between computational power and representational power. Its improved depth and property features make it well applicable in complicated visual recognition situations, e.g. lesion detection in fundus images.

Architecture Characteristics

EfficientNet models are based on compound scaling and they use depthwise separable convolutions, squeezeandexcitation modules and multi-stage feature fusion. Both the finer-grained and high-level patterns of the retinal patterns can be extracted through this architecture.

Pre-trained Weights

The system uses the transfer-learning approach through initializing EfficientNet-B3 using ImageNet pre-trained weights. Such weights hasten convergence and enhance the classification accuracy through the transfer of the old visual representations to the DR dataset.

Output Layer

The last completely connected layer has 1536 input features and five output nodes that represent the classes of the DR severity: Normal, Mild, Moderate, Severe and Proliferative. This change makes the model architecture follow the classification goal.

On the whole, EfficientNet-B3 was chosen because of its excellent performance, ability to generalise as well as its applicability to medical image classification.

Config.py

- Global configuration parameters are saved in the module, and they include the computational device, learning rate, weight decay, batch size, and the number of epochs, as well as the checkpoint name and training model.
- The strategies of data augmentation are defined through the Albumentations library.

- The numerical identifiers are converted into human understandable severity levels.

Train.py

- Training, validation and testing data are loaded using the DRDataset class.
- EfficientNet, CrossEntropyLoss and Adam optimizer are initialised in the architecture.
- The process of iterative training moves on with simultaneous checks of validation performance and systematic recording of measures.
- Checkpoints are maintained based on the given configuration preferences.

Utils.py

- Prediction, evaluation of accuracy and preservation of checkpoints are done easily using reusable helper functions.
- It has the ability of saving and loading trained model weights.

Dataset.py

- The DRDataset class has been implemented in a way that allows the loading of pairs of image and labels in a structured manner.
- Implements required PyTorch dataset methods: `__len__` and `__getitem__`.
- It will read image paths and severity labels from CSV files.

ImageDetection.py

- Retinal and non-retinal image classification data sets are used separately.
- It uses ResNet18, which is trained on Cross-Entropy loss and SGD as an optimizer.
- Training of a binary image verification model is done and the checkpoints are saved.

5.4 User Interface Modules

The following data shows the key system screens and user interactions:

5.4.1 Login

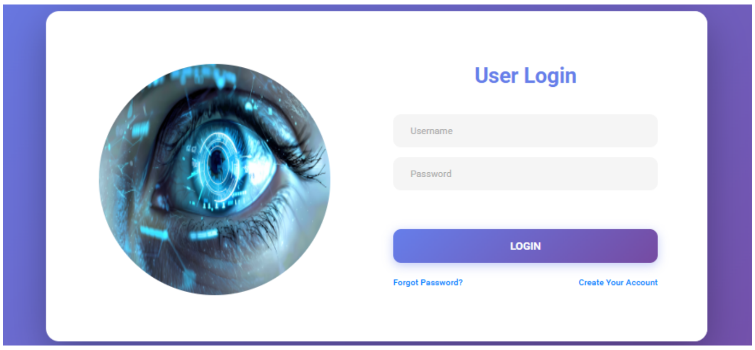


Figure 5.3: Login Screen

5.4.2 Signup

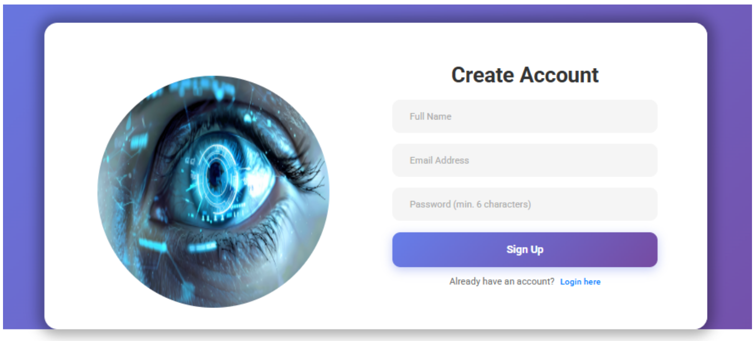


Figure 5.4: Signup Interface

5.4.3 Forgot Password

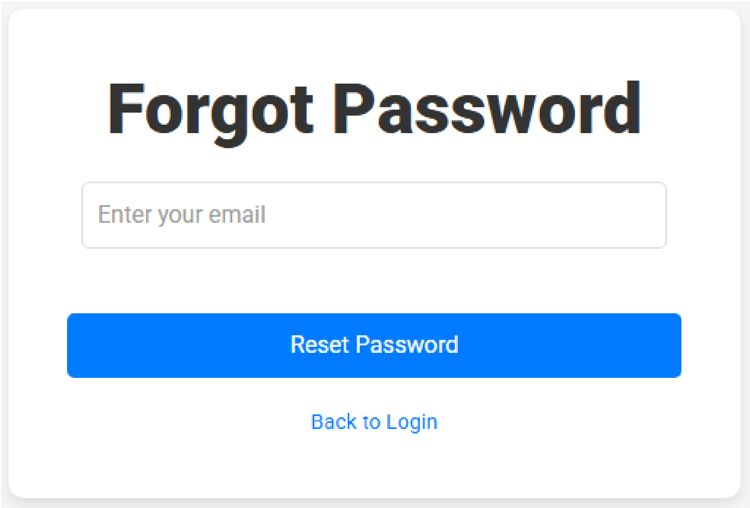


Figure 5.5: Password Reset Page

5.4.4 Patient Form

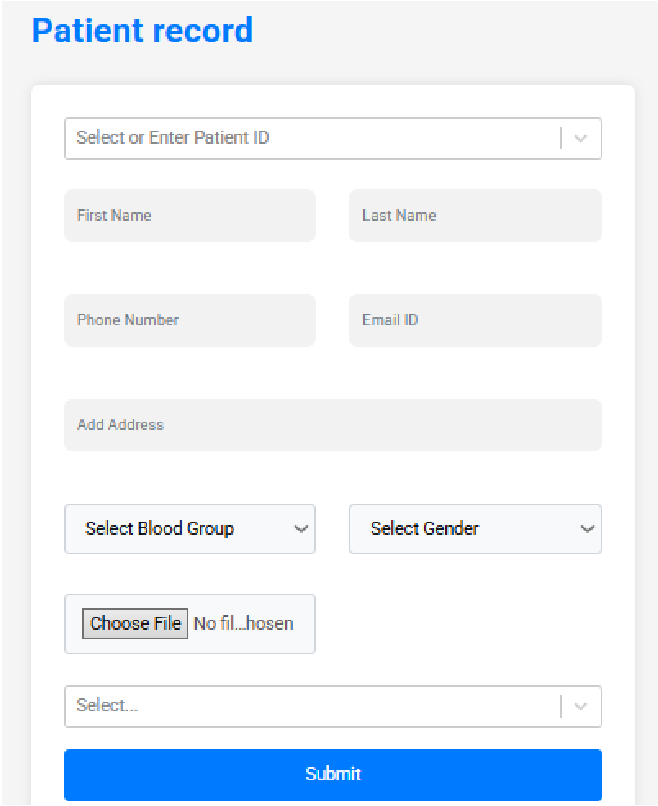


Figure 5.6: Patient Information Form

5.4.5 Patient Record

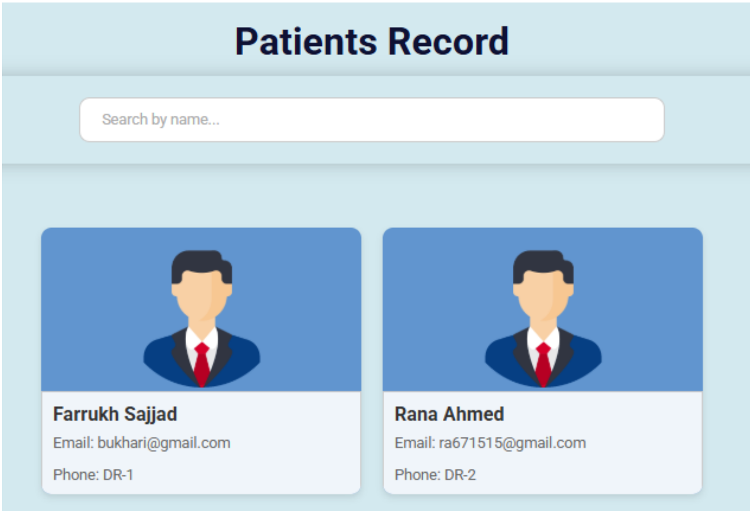


Figure 5.7: Patient Records Dashboard

5.4.6 Patient History

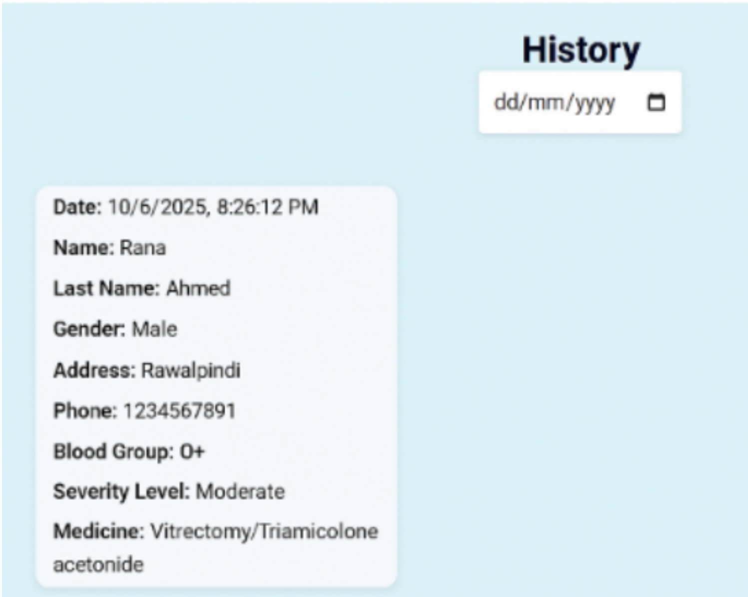


Figure 5.8: Patient Visit History

5.4.7 Record of Specific Patient

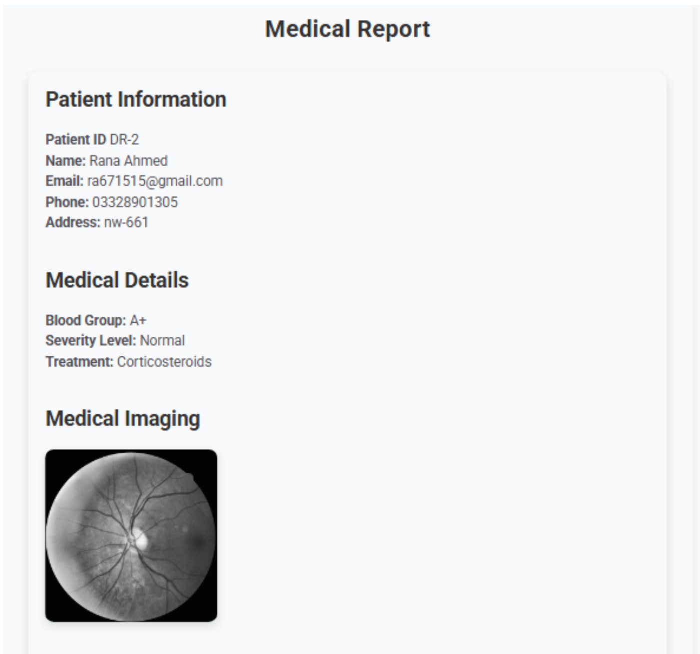
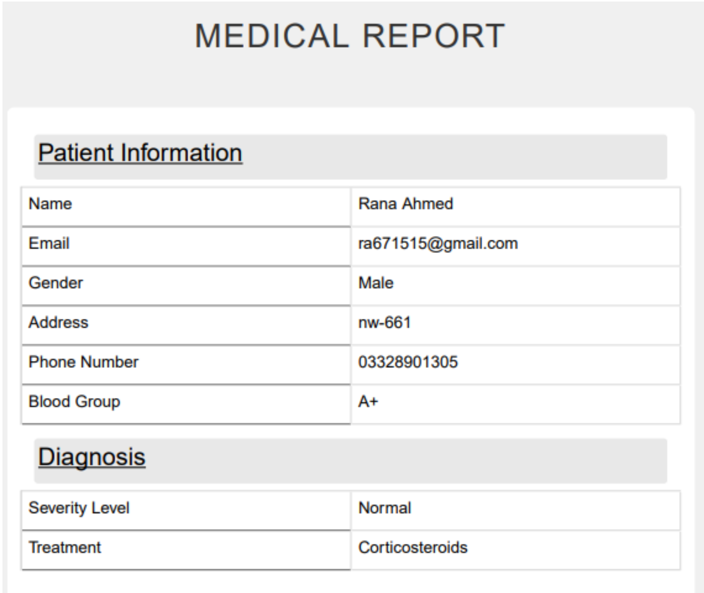


Figure 5.9: Individual Patient Report View

5.4.8 Generated PDF


MEDICAL REPORT

Patient Information

Name	Rana Ahmed
Email	ra671515@gmail.com
Gender	Male
Address	nw-661
Phone Number	03328901305
Blood Group	A+

Diagnosis

Severity Level	Normal
Treatment	Corticosteroids

Figure 5.10: Exported Medical Report

5.5 Image Upload and Prediction Workflow

Web Interface: Flask is used to control router routing, request processing and communication with the prediction model. The uploads of images are taken through POST requests and inferred.

Python Backend

1. Import PyTorch, PIL, NumPy, Albumentations, and EfficientNet modules.
2. Uses ResNet18 to check whether the uploaded file is a retinal image.
3. Fundus images to EfficientNet-B3 model for severity classification.

CORS Enablement: Cross-Origin Resource Sharing (CORS) is turned on to allow communication between the browser-based applications when served out of different domains and the Flask server. **Image Transformation Pipeline:** Images uploaded undergo resizing, segmentation, normalization and conversion to tensors before making a inference.

Model Loading: EfficientNet-B3 architecture is set up with pre-trained weights and is set up to classify five severity levels.

Prediction Route: The `/predict` end point accepts uploaded images, makes an inference and sends the results of the classification in a form of JSON.

Upload Non-Retinal Image

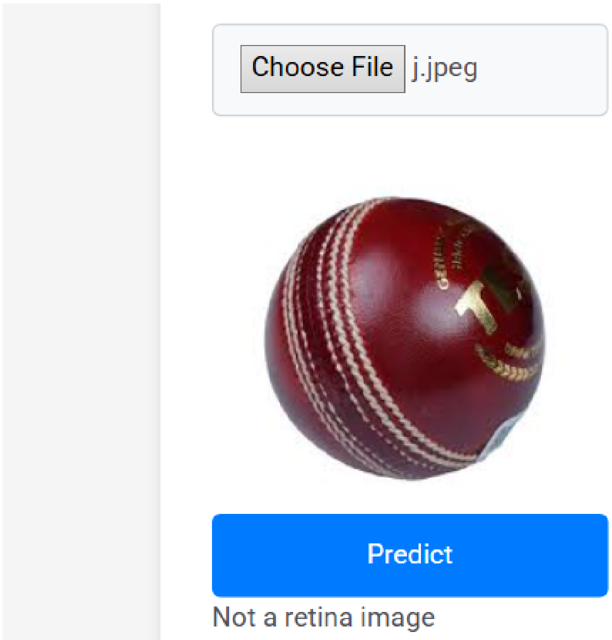


Figure 5.11: Non-Retinal Image Upload Test

Upload Retinal Image

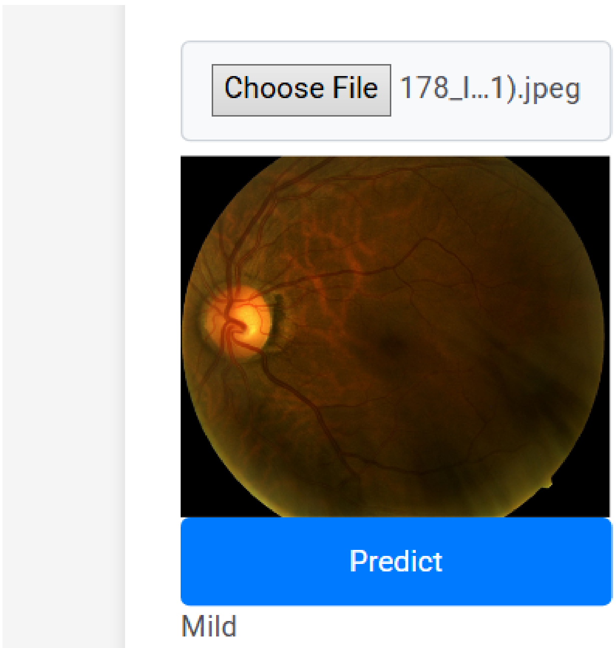


Figure 5.12: Retinal Image Upload Interface

Predict Image

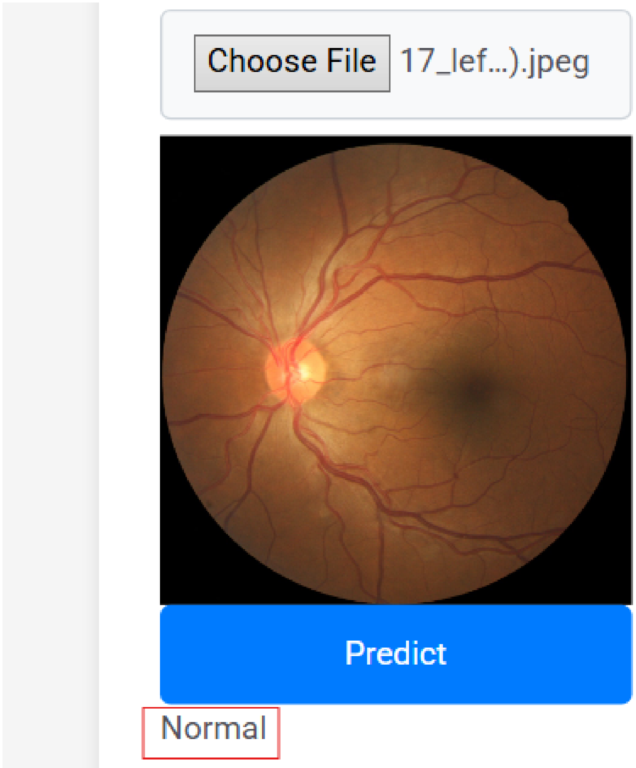


Figure 5.13: Predicted Severity Result

Chapter 6

System Testing and Evaluation

System testing forms an important step in validating the reliability, stability and performance of the proposed application before it can be used at the real world. At this stage, the system goes through a series of strict tests to determine the possible shortcomings, check on the expected results as well as to establish the effectiveness of every part of the system under various environments. When thorough testing is carried out, it is necessary to be sure that the final product is not only able to fulfil functional requirements, but is also able to operate consistently, efficiently, and precisely.

6.1 Testing Approaches

In performing a holistic evaluation of the system, a number of testing methodologies have been used. These approaches focus on one aspect of system behaviour, functionality and usability. The following methods were included into the process of testing:

- Documentation Testing
- GUI Testing
- Model Testing
- Black Box Testing
- Boundary Value Analysis

6.2 Documentation Testing

Some of the benefits of documentation testing include ensuring that all the system needs are clearly defined, traceable and properly reflected during the implementation. In a project devoted to automated Diabetic Retinopathy detection, accurate documentation is an essential requirement to provide an opportunity to detect, classify the severity and verify the machine-learning models. This includes the ResNet18 model which is to be used to verify retinal images and the EfficientNetB3 model that will be used to determine the severity of the disease.

Well-kept documentation also makes it easier to plan tests systematically, provides a regression testing, and makes it easier to make improvements in the future, perhaps by improving algorithms or re-modeling interface elements. It supports the fact that upgrades do not undermine modules that were previously working and provides a point of reference in determining the gains made in diagnostic accuracy or processing efficiency.

In addition, structured documentation encourages better debugging, maintainability, and structured system development. It creates clarity with regard to system architecture, data flow, model behaviour and design decisions. Finally, documentation testing enhances the overall integrity and sustainability of Diabetic Retinopathy Detection System, which would guarantee its future reliability, clinical suitability, and applicability in a real healthcare environment.

6.3 GUI Testing

The following is an important role that Graphical User Interface (GUI) testing is to test usability, responsiveness and visual fidelity. As the system is designed to operate in a clinical and screening setting, it should be able to offer a user-friendly interface and reduce the number of errors made by a user. GUI testing is used to evaluate the functionality of interface elements and their correct representation of what goes on in the back-end processing.

In this, there is the scrutiny of button functionality, verification of file-upload processes, testing of navigation, and ensuring the display of diagnostic findings is made clear and consistent. Common user behaviors, including creating retinal images, finding patient records, creating reports and evaluating predictions, are performed and compared with the expected results.

Moreover, GUI testing ensures the smooth connection between the parts of the interface and the machine-learned pipeline. As an example, the image verification model of ResNet18 and the severity classification model of EfficientNet-B3 should both provide the output of the model to the interface without breaking it. This is because through GUI testing, inconsistencies, layout problems, or other interaction problems will be detected, and healthcare professionals may be able to use the system with confidence, efficiency, and without unnecessary complexity.

A strictly tested interface eventually improves user experience and increases the appropriateness of the system to clinical workflow, especially in situations of early screening and disease-monitoring.

6.4 Model Testing

Measuring performance of machine-learning is an essential part of system testing, particularly in medical systems where the diagnostic quality of the system has a direct impact on patient outcomes. The accuracy and the confusion matrix were used to analyse the performance of the models in classifying the retinal images with respect to the severity of the disease.

6.4.1 Accuracy

Accuracy refers to the ratio of the cases correctly predicted to the number of samples that are to be considered. Although accuracy provides an overall measure of model performance, it fails to reflect the imbalance of the classes, as well as the dissimilar outcomes of a misclassification, as both are of paramount importance in medical screening.

In this system, EfficientNet3 was used to categorize the severity of diabetic retinopathy, and ResNet18 confirmed the presence of uploaded images of retina. The accuracy was obtained using the following expression:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

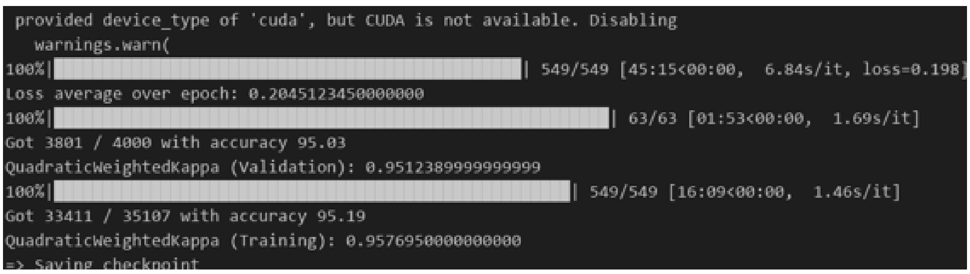


Figure 6.1: Model Accuracy Achieved

Model Accuracy for Retinal Image Classification

The `ImageDetection.py` module enforces a custom dataset engine that is tailored so that it can distinguish between retinal and non-retinal images. The given classification framework is based on the ResNet18 model, which was trained on the CrossEntropyLoss objective, and optimized with the help of the Stochastic Gradient Descent (SGD). Also, the model checkpoints are stored as per the specified configuration parameters thus enabling progress monitoring and recovery during experimentation as shown in Figure 6.2.

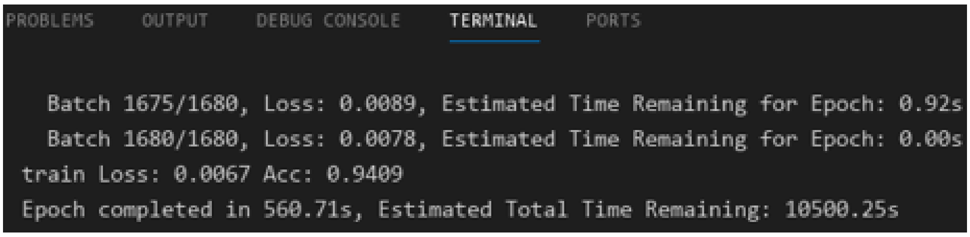


Figure 6.2: Accuracy Achieved Using the ResNet18 Model

6.4.2 Confusion Matrix

The confusion matrix is a basic assessment tool of classification models, that provides an in-depth description of the prediction results. It is a binary forecasting method that illustrates the number of correct labels as well as showing the type of error made by the model by comparing predicted labels and ground-truth values. In its turn, this makes it particularly useful in explaining model behavior in ways that are not associated with aggregate measures of accuracy.

In Figure 6.3, i.e., the element on the first row and the first column means that there were 447 correctly identified images in the No DR category. On the contrary, zero in the first row, second column shows that the images of the No DR category were not falsely identified as Mild. The correct predictions are shown by the elements on the main diagonal but the misclassifications are shown by the off-diagonal cells. In theory, the high-performing model will have high numbers on the diagonal, with low figures on the other cells.

The model has been depicted to be effective especially in the determination of No DR and moderate conditions, as the darker diagonal areas depict. By contrast, the relative lightness of the cells of Mild and PDR class suggests some problems with the differentiation of these stages. In general, the confusion matrix supports the strengths of the model and, at the same time, provides the direction of future work by revealing the misclassification trends.

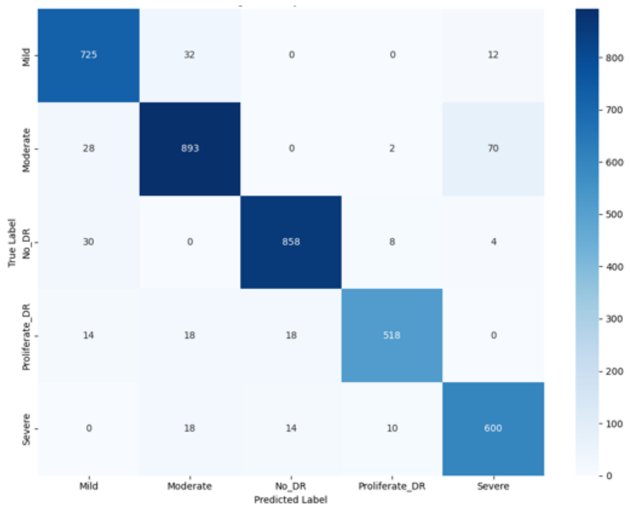


Figure 6.3: Confusion matrix for classification of retinopathy stages using the deep learning model

Confusion Matrix for Retinal and Non-Retinal Images

The confusion matrix obtained in the process of the binary classification task performed with ResNet18 model will be shown in Figure 6.4. This is a matrix that represents the effectiveness of the system to segregate retinal images with non-retinal images. The large horizontal figures are the testimony of strong work, and it is possible to note that the model can be trusted to prove whether an uploaded image can be subject to the further diagnostic analysis.

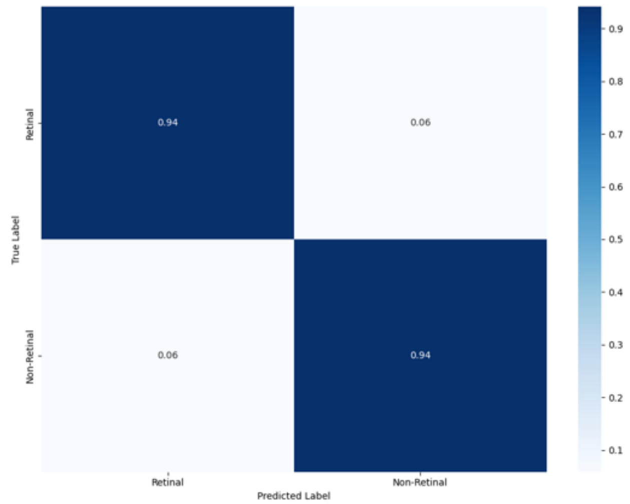


Figure 6.4: Confusion matrix for the detection of retinal images

6.5 Black Box Testing

Retinopathy Detection System Blackbox testing has been critical in verifying the general functionality of the system. This testing paradigm only analyzes the system in terms of its inputs and outputs but not on the internal structure and details of its implementation. Black-box testing guarantees that the application behaves in a certain way, i.e. the application performs like a real user, i.e. the application should be able to perform login, photo upload as well as patient record management and diagnostic output. The approach can be used to confirm usability, reliability, and logical workflow, as viewed by an end-user, and is therefore especially useful in the context of healthcare-oriented applications.

6.5.1 Test Case for Sign-Up

Table 6.1: Test Cases for Signup Functionality

Actions	**Expected Result**	**Test Result**
Use Case	UC-0001	Pass
Enter invalid email	Invalid email	pass
Enter invalid email	Enter correct email/password	pass
Enter password less than 6 digits	Password should be at least 6 characters	pass
Leave all fields empty	Fill all fields	pass
Using already used email	This email is already in use. Please login or use a different email.	pass

6.5.2 Test Case for SignIn

Table 6.2: Test Cases for Login Functionality

Actions	**Expected Result**	**Test Result**
Use Case	UC-0002	Pass
Enter valid email and Password and press Login button	Redirect to home screen	pass
Enter Invalid email	Enter correct email/password	pass
Enter Invalid password	Enter correct email/password	pass
Both fields are empty and press login button	Fill all fields	pass

6.5.3 Test Case for Image Upload

Table 6.3: Test Cases for Image Upload Functionality

Actions	Expected Result	Test Result
Use Case	UC-0003	Pass
Image Upload	Image successfully uploaded	pass
Select Image from File Explorer	File Explorer opens to select image	pass
Upload retinal Image	Verification if it's a retinal image or not	pass
Prediction after uploading retinal Image	Display Prediction: Normal, Mild, Moderate, Proliferate based on the uploaded image	pass

6.5.4 Test Case for Patient Record

Table 6.4: Test Cases for Viewing and Searching Patient Records

Actions	Expected Result	Test Result
Use Case	UC-0004	Pass
View all patient records	All records shown	pass
Searching name that is not in patient records	No patient records found	pass
Click on any patient record	Move to his medical report	pass
Patient having female name	Female icon for them	pass
Patient having male name	Male icon for them	pass

6.5.5 Test Case for Patient Form

Table 6.5: Test Cases for Patient Form Functionality

Actions	Expected Result	Test Result
Use Case	UC-0005	Pass
Enter invalid email format	Please enter a valid email address, starting with an alphabet. The email should be in the format of abc@anydomain.com.	pass
All fields are empty	Please fill all the data fields, select an image	pass
If any one field is empty	Please fill all the data fields, select an image	pass
Enter email which is already in use	Email already exists!	pass

6.5.6 Test Case for Medical Report

Table 6.6: Test Cases for Medical Report Functionality

Actions	**Expected Result**	**Test Result**
Use Case	UC-0006	Pass
View medical report	Medical report displayed	pass
Generate Pdf	PDF generated	pass

Chapter 7

Conclusion

Diabetic retinopathy (DR) is on the increase, and thus it is important to come up with efficient and accurate diagnostic procedures. This paper thus compares a bi-model system, which uses ResNet-18 and EfficientNet-B3 to screen automated DR. ResNet -18 plays the role of a filter in this architecture, where non-retinal images are filtered out as they enter the pipeline, only authentic fundus images remain in the pipeline. After that, EfficientNet-B3 conducts finer severity delineation based on its highly effective feature-extraction tools to detect delicate retinal abnormalities that are related to disease progression.

All of these models together form a consistent and trusted set of workflow in automated DR detection. The inherent technical characteristics of deep-learning methods both increase the accuracy of diagnosis and decrease the reliance on human inspection, which considerably decrease human variability and eradicate the time-consuming processes. The system has potential of enabling the ophthalmologists to intervene at an earlier stage and better manage the disease progression through speeding up the screening processes and enhancing the consistency of the classification.

Finally, this study is a step in the larger direction of using artificial intelligence to minimize avoidable visual impairment in diabetic patients.

Future Work

The current project should be further refined. One such priority area is to increase the scale and the diversity of the training regime, which is necessary to capture more varied datasets, acquired in a wide range of clinical settings, which should improve the generalizability of the model to diverse populations and imaging modalities. Also, future research would need to examine the effectiveness of current architectures like Vision Transformers, EfficientNetV2, and CNNTransformer hybrids, which are more sensitive to delicate retinal changes, in order to establish their ability to enhance diagnostic accuracy.

The existing structure, which is specifically designed to detect diabetic retinopathy, can be modified to detect other retinal disorders, such as glaucoma and age-related macular degeneration, and, as a result, a more effective screening system can be formed. A streamlined version of the model that requires minimal resources, can be run on a mobile or embedded device, would support the point-of-care diagnostics at rural or underserved locations. Moreover, cloud-deployment, electronical medical record system integration, and an implementation of a clinician-feedback loop would enhance scalability and allow the clinical deployment as an AI-assisted diagnostic tool. Such improvements are bound to add more practical value and increase the world eye-health outcomes.

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