AUTOMATED DIABETIC RETINOPATHY DETECTION SYSTEM

A DESIGN PROJECT REPORT

Submitted by

NAVEEN KUMAR E

PRASANNA R

SANTHOSH S

in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

K. RAMAKRISHNAN COLLEGE OF TECHNOLOGY

(An Autonomous Institution, affiliated to Anna University Chennai and Approved by AICTE, New Delhi)

SAMAYAPURAM – 621 112

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(AUTONOMOUS)

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BONAFIDE CERTIFICATE

Certified that this project report titled **"AUTOMATED DIABETIC RETINOPATHY DETECTION SYSTEM"** is the bonafide work of **NAVEEN KUMAR E (811721104072), PRASANNA R (811721104080), SANTHOSH S (811721104089)** who carried out the project under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or anyother candidate.

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Submitted for the viva-voce examination held on …………….

INTERNAL EXAMINER	**EXTERNAL EXAMINER**

DECLARATION

We jointly declare that the project report on **"AUTOMATED DIABETIC RETINOPATHY DETECTION SYSTEM"** is the result of original work done by us and best of our knowledge, similar work has not been submitted to **"ANNA UNIVERSITY CHENNAI"** for the requirement of Degree of **BACHELOR OF ENGINEERING**. This project report is submitted on the partial fulfilment of the requirement of the award of Degree of **BACHELOR OF ENGINEERING**.

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ACKNOWLEDGEMENT

It is with great pride that we express our gratitude and indebtedness to our institution, "**K. Ramakrishnan College of Technology (Autonomous)**", for providing us with the opportunity to do this project.

We extend our sincere acknowledgment and appreciation to the esteemed and honorable Chairman, **Dr. K. RAMAKRISHNAN**, **B.E.,** for having provided the facilities during the course of our study in college.

We would like to express our sincere thanks to our beloved Executive Director, **Dr. S. KUPPUSAMY, MBA, Ph.D.,** for forwarding our project and offering an adequate duration to complete it.

We would like to thank **Dr. N. VASUDEVAN, M.TECH., Ph.D.,** Principal, who gave the opportunity to frame the project to full satisfaction.

We thank **Dr. A. DELPHIN CAROLINA RANI, M.E., Ph.D.,** Head of the Department of **COMPUTER SCIENCE AND ENGINEERING,** for providing her encouragement in pursuing this project.

We wish to convey our profound and heartfelt gratitude to our esteemed project guide **Mrs. M. MATHUMATHI, M.E., (Ph.D.,)** Department of **COMPUTER SCIENCE AND ENGINEERING,** for her incalculable suggestions, creativity, assistance and patience, which motivated us to carry out this project.

We render our sincere thanks to the Course Coordinator and other staff members for providing valuable information during the course.

We wish to express our special thanks to the officials and Lab Technicians of our departments who rendered their help during the period of the work progress.

ABSTRACT

Diabetic Retinopathy (DR) is a severe complication of diabetes that can lead to blindness if not detected and managed early. Traditional DR screening methods are often labor-intensive and costly, highlighting the need for an efficient and automated solution. This project, Automated Diabetic Retinopathy Detection, introduces a system leveraging machine learning and image processing techniques to analyze retinal images and identify DR symptoms. The system follows a multi-stage architecture, including data acquisition, Gaussian filtering for noise reduction, feature extraction, and DR classification using a machine learning model. Driven by user inputs, the system supports personalized analysis while features like automated report generation and data logging enable comprehensive tracking and insights. Additionally, the inclusion of a visualization module enhances user interaction by offering in-depth analytics on disease severity and progression trends. This automated approach aims to streamline DR diagnosis, making it faster, more accessible, and cost-effective, ultimately aiding in early detection to reduce DR progression and improve patient outcomes, especially in underserved areas with limited specialist care.

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LIST OF ABBREVIATIONS

ABBREVIATIONS

AI	-	Artificial Intelligence
CNN	-	Convolution Neural Network
CGM	-	Continuous Glucose Monitor
DR	-	Diabetic Retinopathy
LIME	-	Local Interpretable Model-agnostic Explanation
ROC	-	Receiver Operating Characteristic
SHAP	-	Shapley Additive Explanation

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Automated Diabetic Retinopathy Detection is a project focused on developing a machine learning-based system to detect diabetic retinopathy (DR), a diabetes-related eye disease that can lead to blindness if left untreated. This condition requires early detection for effective treatment, but traditional screening methods are time-consuming, costly, and require skilled ophthalmologists. The goal of this project is to create an automated, accessible, and cost-effective solution for DR screening.

The system architecture includes several stages, beginning with data acquisition, where retinal fundus images are collected for analysis. The images are preprocessed using techniques like Gaussian filtering to enhance quality and reduce noise. Key features indicative of DR, such as microaneurysms, hemorrhages, and exudates, are then extracted from the images. A machine learning model, such as a Convolutional Neural Network (CNN), is trained to classify the images based on DR severity, identifying stages from mild to proliferative DR.

Following classification, the system generates a report detailing the results, including the detected DR stage and recommendations for follow-up. Data is logged and visual analytics are provided to help healthcare providers interpret trends and insights. This automated approach has the potential to make DR screening more efficient and accessible, especially in underserved and remote areas, helping to reduce the incidence of vision loss among diabetic patients by enabling timely diagnosis and treatment.

1.2 PROBLEM STATEMENT

The Diabetic Retinopathy (DR) is a progressive eye disease caused by complications of diabetes, which can lead to vision impairment and blindness if not diagnosed and treated in its early stages. According to global health statistics, the prevalence of diabetes is on the rise, leading to an increasing number of DR cases. Traditional methods of diagnosing DR involve manual examination of retinal images by trained ophthalmologists, which is time-consuming, costly, and resource-intensive. This makes regular screening inaccessible, particularly in remote and underserved regions where healthcare infrastructure is limited. The lack of timely diagnosis and limited accessibility to specialized care contributes to a high risk of preventable blindness among diabetic patients. Therefore, there is an urgent need for a cost-effective, accurate, and scalable solution that can detect DR automatically, allowing for early intervention and reducing the burden on healthcare systems. The Automated Diabetic Retinopathy Detection project aims to address this challenge by developing an automated machine learning-based system capable of analyzing retinal images to detect signs of DR. This system will enable faster, affordable, and more accessible DR screening, supporting early diagnosis and improving patient outcomes, particularly for those in low-resource settings.

1.3 OBJECTIVES

The Automated Diabetic Retinopathy Detection project seeks to leverage cutting-edge technologies to address the critical need for efficient and accessible healthcare solutions for diabetic patients. Diabetic retinopathy is a progressive eye disease that affects individuals with diabetes and can lead to permanent vision loss if not diagnosed and treated early. Traditional methods of detecting diabetic retinopathy require expert knowledge and can be time-consuming, making it difficult to provide timely care to all patients, especially in remote or under-resourced areas.

This project aims to develop a robust system that can analyze retinal fundus images to detect DR with high accuracy, using machine learning algorithms such as deep learning and convolutional neural networks (CNNs). The system will be trained on a large dataset of annotated images, enabling it to learn and recognize patterns associated with various stages of the disease. By automating the diagnostic process, the project intends to support healthcare providers in diagnosing diabetic retinopathy more quickly and reliably, ultimately enhancing patient outcomes.

Additionally, this automated tool can assist in screening large populations, offering a scalable solution that can be integrated into existing healthcare infrastructures, ensuring that individuals at risk of DR receive timely and appropriate care. The long-term vision for this project is to make the detection and monitoring of diabetic retinopathy more accessible, reducing the burden on healthcare professionals and ensuring better management of diabetic eye health globally.

1.4 IMPLICATION

The implications of the "Automated Diabetic Retinopathy Detection" project are far-reaching, with significant potential to impact both the healthcare system and patient outcomes. By automating the detection of diabetic retinopathy, the project could streamline the screening process, enabling healthcare facilities to handle larger volumes of patients more efficiently. This would be especially beneficial in underserved or rural areas where access to specialists and advanced diagnostic tools may be limited. The system's ability to quickly and accurately identify early signs of diabetic retinopathy could lead to earlier intervention, preventing the progression of the disease and potentially reducing the incidence of blindness among diabetic patients. Furthermore, the project has the potential to reduce the workload of ophthalmologists and other healthcare professionals, allowing them to focus on more complex cases or provide care to more patients. The project could enhance the overall quality of care and foster better long-term health outcomes for individuals living with diabetes. The automated system could also serve as a valuable educational tool for medical professionals, assisting them in refining their diagnostic skills and staying updated on the latest advancements in retinal image analysis.

Additionally, the ability to scale the solution globally means that the project could play a critical role in addressing the growing burden of diabetic retinopathy, particularly in developing countries where access to specialized care is often limited.This project represents a step toward the integration of artificial intelligence into medical diagnostics, paving the way for more innovative and efficient healthcare solutions.

1.5 SCOPE OF THE PROJECT

1. Develop an automated system that can accurately detect and classify the stages of diabetic retinopathy from retinal images, minimizing the need for manual analysis and reducing human error in diagnosis.

2.Implement preprocessing techniques such as Gaussian filtering to enhance image quality, allowing the model to better identify critical features related to diabetic retinopathy.

3. Use advanced feature extraction methods and machine learning algorithms to analyze retinal images and generate accurate predictions of diabetic retinopathy levels.

4.Generate detailed PDF reports based on model predictions, including information on the detected level of diabetic retinopathy, which can be easily shared with patients and healthcare providers.

5. Provide visualization and analytics capabilities to enhance understanding of the detection results, allowing users to explore the intensity and context of diabetic retinopathy progression.

CHAPTER 2

LITERATURE SURVEY

2.1 TITLE: EXPLAINABLE AI FOR DIABETIC RETINOPATHY DETECTION: A STEP TOWARDS TRUSTWORTHY AI IN HEALTHCARE

AUTHORS: S. H. Lee, J. K. Kim, H. Park.

YEAR: 2023

Proposes a framework to integrate explainable AI (XAI) into the detection of diabetic retinopathy (DR). The primary goal is to address the trust issues associated with AI's "black-box" nature in healthcare. The authors propose using explainable techniques like Local Interpretable Model-agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) to provide interpretable visualizations of AI decision-making. These methods help healthcare professionals understand why an AI model makes certain predictions, thereby increasing trust and transparency in AI-driven diagnoses. The paper suggests that this approach can enhance clinical decision-making by allowing doctors to confidently integrate AI outputs into patient.

2.2 TITLE: EFFICIENT TRANSFER LEARNING APPROACH FOR DIABETIC RETINOPATHY CLASSIFICATION USING FUNDUS IMAGES

AUTHORS: H. Gupta, P. K. Roy, S. Dey.

YEAR: 2022

Proposes an efficient transfer learning-based approach for classifying diabetic retinopathy (DR) using fundus images. The authors aim to improve the accuracy and efficiency of DR detection while minimizing the need for large annotated datasets, which is a common challenge in medical image analysis. The proposed approach leverages pre-trained deep learning models that have been trained on large image datasets (e.g., ImageNet). By utilizing transfer learning, the authors fine-tune these models on a smaller, domain-specific dataset of retinal images to classify DR into various stages of severity (such as normal, mild, moderate, severe, and proliferative DR).

2.3 TITLE: DETECTION USING CNNS WITH DATA AUGMENTATION AND OPTIMIZATION TECHNIQUES

AUTHORS: P. N. Sharma, R. Kumar, S. Verma.

YEAR: 2022

Proposes an approach for detecting diabetic retinopathy (DR) using Convolutional Neural Networks (CNNs) enhanced with data augmentation and optimization techniques. Recognizing the challenge of limited annotated data in medical imaging, the authors suggest using data augmentation methods such as rotations, translations, and zooming to artificially expand the dataset, which helps improve model robustness and generalization. Additionally, they incorporate advanced optimization techniques to enhance the training process, ensuring the model converges efficiently and improves accuracy. The proposed method aims to achieve high-performance DR detection.

2.4 TITLE: AUTOMATED DIABETIC RETINOPATHY GRADING SYSTEM BASED ON DEEP LEARNING

AUTHORS: M. A. Khan, N. Sharif, M. Y. Javed, S. Anwar.

YEAR: 2021

Proposes an automated system for grading diabetic retinopathy (DR) using deep learning techniques. The authors focus on developing a deep learning-based approach to automatically assess and grade the severity of DR in retinal images, which is crucial for timely diagnosis and treatment. The system uses Convolutional Neural Networks (CNNs) to analyze retinal fundus images and classify the severity of DR into different stages, such as mild, moderate, severe, or proliferative DR. The proposed model is trained on large annotated datasets of retinal images, allowing it to learn the distinguishing features of DR across various stages. The paper highlights the effectiveness of deep learning in automating DR grading by eliminating the need for manual inspection, which is time-consuming and requires expert knowledge.

2.5 TITLE: AUTOMATIC DIAGNOSIS RETINOPATHY USING MACHINE LEARNING

AUTHORS: Piumi Liyana Gunaeardhana, Raviru Jayathilake, Yasiru Withanage.

YEAR: 2020

Diabetic Retinopathy is a popular cause of diabetes, causing vision-impacting lesions of the retina. Blindness may be avoided by early detection. The ophthalmologist's manual approach of diagnosing diabetic retinopathy is expensive and time consuming. At the same time, unlike computer assisted diagnostic systems, it may cause misdiagnosis. Deep learning has recently become one of the most effective approaches that has obtained better efficiency in the analysis and classification of medical images. In medical image analysis, convolutional neural networks are more commonly used as a deep learning approach and they are extremely effective.

2.6 TITLE: THE AUTOMATED DIABETIC RETINOPATHY DETECTION BASED ON BINOCULAR SIAMESE-LIKE CNN

AUTHORS: Xianglong Zeng, Haiquan Chen , Yuan Luo.

YEAR: 2019

Diabetic retinopathy (DR) is an important cause of blindness worldwide. However, DR is hard to be detected in the early stages, and the diagnostic procedure can be time-consuming even for the experienced experts. Therefore, a computer-aided diagnosis method based on deep learning algorithms is proposed to automatedly diagnose the referable diabetic retinopathy by classifying color retinal fundus photographs into two grades. In this paper, a novel convolutional neural network model with the Siamese-like architecture is trained with a transfer learning technique. The proposed model accepts binocular fundus images as inputs and learns their correlation to help to make a prediction.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Current systems for diabetic retinopathy detection typically follow a structured but largely manual process. First, patient demographic information and retinal images are collected in a clinical setting, often through fundus photography. This data is then manually labeled or annotated by healthcare professionals, who determine the severity of diabetic retinopathy based on established criteria. Once features are identified, the images are graded according to the severity of the diabetic retinopathy, often following the International Clinical Diabetic Retinopathy Disease Severity Scale.. After the evaluation, a report summarizing the findings, diagnosis, and recommendations for treatment is generated manually and existing systems usually lack advanced visualization tools.

3.1.1 DISADVANTAGES

Limited Adaptability to Diverse Patient Populations: Traditional manual systems often struggle to adapt to variations in retinal images across diverse patient populations. Factors such as differences in retinal pigmentation, imaging conditions, or varying degrees of disease severity can affect the appearance of retinopathy indicators. Since these systems rely on the expertise of healthcare providers rather than adaptable machine learning models, it can be challenging to standardize diagnosis across diverse cases, leading to potential disparities in detection accuracy among different patient groups.

Inconsistent Accuracy in Early Detection: Existing systems are limited in their ability to consistently detect early or subtle signs of diabetic retinopathy. Human examiners may overlook faint microaneurysms or minor hemorrhages, especially in early stages where indicators are less obvious. This lack of sensitivity in early detection reduces the system’s overall accuracy and can delay intervention, potentially allowing the disease to progress to more severe stages before it is identified and treated.

3.2 PROPOSED SYSTEM

The proposed "Automated diabetic retinopathy detection" follows a structured workflow that leverages machine learning and image processing to identify diabetic retinopathy in retinal images. It begins with data acquisition, where retinal images are collected from patients using fundus cameras. These images are then subjected to preprocessing using Gaussian filtering, which reduces noise and enhances key features in the images, making it easier to detect abnormalities

This extracted data is passed into a machine learning model likely a deep learning model like a convolutional neural network (CNN) that has been trained to recognize patterns associated with different stages of diabetic retinopathy. Based on its analysis, the model classifies the retinal images into categories indicating the presence and severity of the disease. The results from the model are then used for report generation, producing an automated report that details the findings and provides a recommendation on whether the patient needs specialist intervention. This report is logged in a data log for record-keeping, to enhance usability, the system includes a visualization module that provides healthcare providers with detailed analytics views, illustrating the model's performance metrics and detection patterns. This proposed system aims to deliver a streamlined, accurate, and accessible tool for early detection of diabetic retinopathy, supporting timely interventions and improving patient outcomes.

3.2.1 ADVANTAGES

Improved Diagnostic Accuracy and Speed: By automating the detection process using machine learning and image processing techniques, the system can quickly and accurately identify diabetic retinopathy levels. This reduces the dependency on manual diagnosis, enhances consistency, and allows for faster detection, ultimately helping healthcare providers make timely treatment decisions.

Enhanced Data Visualization and Insight: The architecture includes a visualization and detailed analytics view, which enables users to better understand the severity and progression of diabetic retinopathy. This feature not only aids healthcare providers in making more informed decisions but also helps in communicating results effectively to patients, improving overall patient care.

3.3 SYSTEM ARCHITECTURE

The system architecture begins with the data acquisition module, where high resolution retinal images are captured using specialized fundus cameras. These images serve as the raw input for the system, providing the necessary data to detect signs of diabetic retinopathy. Once the images are acquired, they proceed to the preprocessing stage, which applies Gaussian filtering to reduce noise and enhance image quality. This step ensures that key features are more visible, making it easier for the system to detect abnormalities.

After preprocessing, the images enter the feature extraction module, where specific characteristics associated with diabetic retinopathy, such as microaneurysms, hemorrhages, and exudates, are identified. These extracted features are essential for accurate analysis, as they provide critical information about the disease's presence and severity.

The extracted features are then fed into a machine learning model—often a deep learning model like a convolutional neural network (CNN)—which has been trained on extensive labeled datasets of retinal images. The model uses these features to classify the images into different categories, indicating the presence and severity of diabetic retinopathy. Based on the classification results, the system moves to the report generation module, where an automated report is created.

This report provides a summary of findings, including the risk level and recommendations for specialist intervention if needed. To facilitate data management and analysis, the system incorporates a data log to store processed images, extracted features, and generated reports.

This logged data can be retrieved through the data extraction module, which allows healthcare providers and researchers to access specific datasets. The architecture also includes a visualization, which provides detailed analytics and performance metrics, helping healthcare providers gain insights into detection patterns.

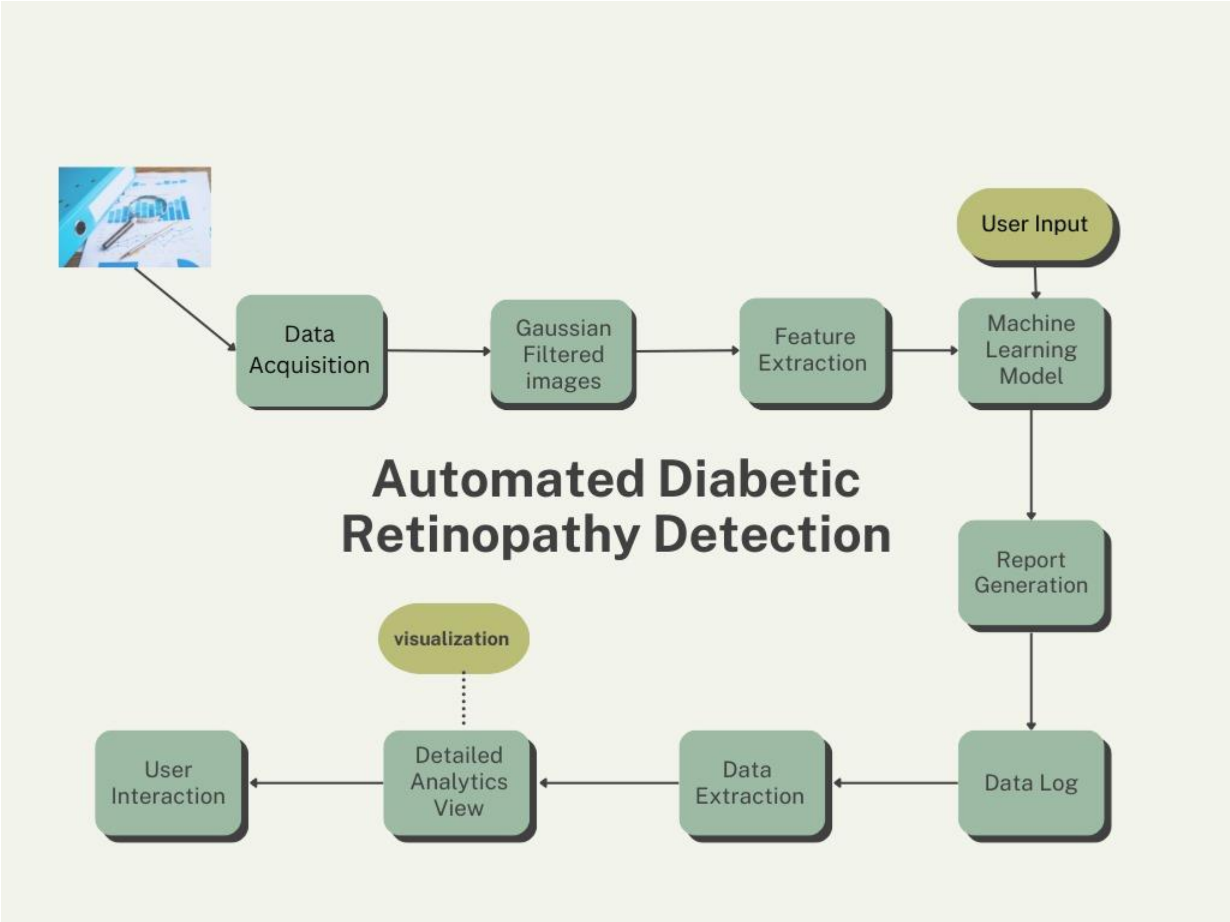


Fig. 3.1 Architecture Diagram

3.4 SEQUENCE DIAGRAM

The sequence diagram illustrates a high-level view of how the different components interact to achieve the automated detection of diabetic retinopathy, along with the generation of reports and visual insights. The system includes several stages, beginning with data acquisition, where retinal fundus images are collected for analysis. The images are preprocessed using techniques like Gaussian filtering to enhance quality and reduce noise. Key features indicative of DR, such as microaneurysms, hemorrhages, and exudates, are then extracted from the images. A machine learning model, such as a Convolutional Neural Network (CNN), is trained to classify the images based on DR severity, identifying stages from mild to proliferative DR.

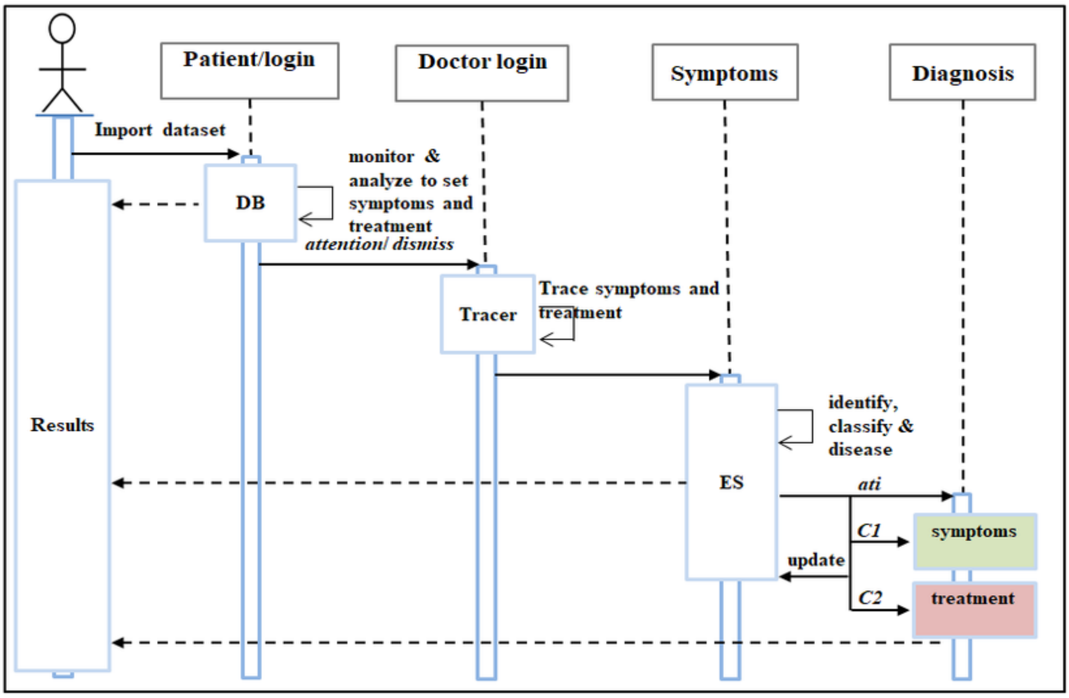


Fig. 3.2 Sequence Diagram

3.5 CLASS DIAGRAM

The class diagram provides a static view of the Colorectal Cancer Risk Prediction System, illustrating the classes and their relationships within the system. Through the class diagram, stakeholders can understand the structure of the Colorectal Cancer Risk Prediction System, including the entities involved and their associations, facilitating comprehension of its organization and design.

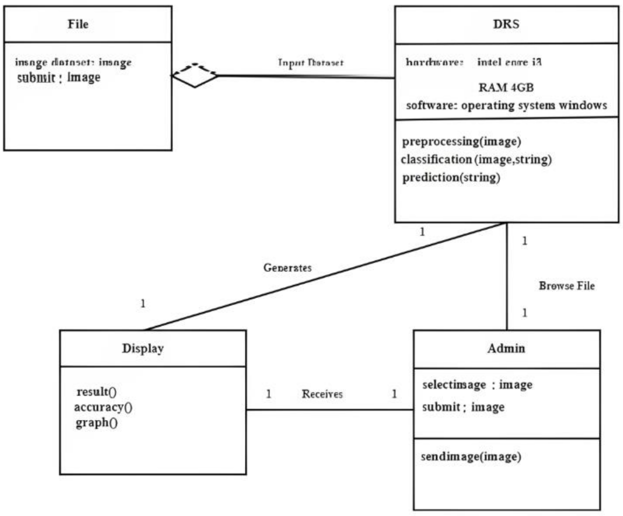


Fig. 3.3 Class Diagram

3.6 FLOW DIAGRAM

The flow diagram provides a visual representation of the process flow within the Colorectal Cancer Risk Prediction System, illustrating the sequence of steps involved in data preparation, risk prediction, and result delivery.

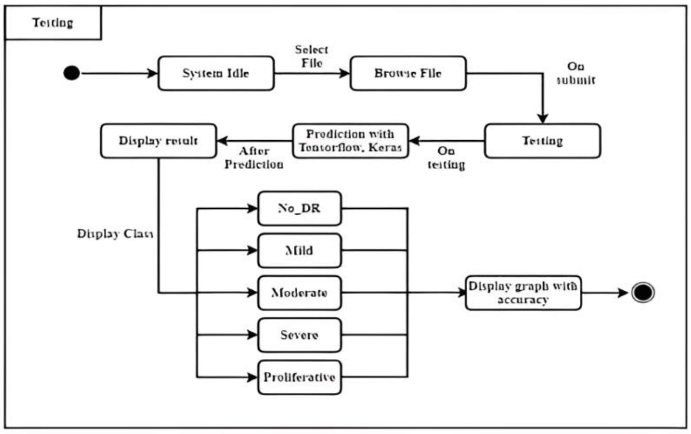


Fig. 3.4 Flow Diagram

Through the flow diagram, stakeholders can understand the procedural flow of the Colorectal Cancer Risk Prediction System, including the steps involved in processing input data, performing risk prediction, and presenting results, facilitating comprehension of the system's workflow.

CHAPTER 4

THEORETICAL CONSIDERATIONS

4.1 HISTORICAL INTRODUCTION

Diabetic Retinopathy (DR) has been a critical concern in ophthalmology due to its significant impact on global blindness. First identified in the mid-19th century, DR has been associated with prolonged diabetes, leading to damage to retinal blood vessels. Over time, advancements in imaging technologies and medical interventions have improved the diagnosis and management of DR.

Early Techniques:

Initial diagnostic methods relied on direct ophthalmoscopy, where ophthalmologists visually inspected the retina using handheld devices.

Limitations included subjective interpretation and the inability to detect subtle abnormalities.

Advancements in Retinal Imaging:

The advent of fundus photography in the mid-20th century provided a more objective means of examining the retina. High-resolution images became the standard for documenting disease progression.

Introduction of fluorescein angiography allowed detailed visualization of blood vessels but required invasive procedures.

Shift Toward Automation:

The integration of machine learning into medical imaging started in the late 1990s, with basic algorithms developed to identify retinal features.

Deep learning revolutionized the field in the 2010s, with convolutional neural networks (CNNs) achieving exceptional accuracy in detecting and classifying DR.

Despite advancements, DR screening remained challenging due to:
Shortage of trained ophthalmologists, particularly in rural or underdeveloped regions.
High variability in human diagnosis, especially in early stages of DR.
Increasing global diabetes prevalence, creating a demand for scalable and consistent solutions.

4.2 OVERVIEW OF THE DIABETIC RETINOPATHY DETECTION SYSTEM

The Automated Diabetic Retinopathy Detection system is a comprehensive framework designed to streamline the identification and classification of DR. It leverages machine learning to analyze retinal images and provides actionable insights for medical professionals.

System Architecture

The system follows a modular architecture, starting with data acquisition and preprocessing and progressing through feature extraction, classification, and reporting. Each module is designed to handle a specific aspect of the detection process, ensuring modularity, scalability, and efficiency.

Functionality

Input: High-resolution retinal images from patients, captured using fundus cameras.

Processing Pipeline: Preprocessing ensures image quality and uniformity. Feature extraction highlights disease-relevant patterns, such as microaneurysms and exudates. Classification assigns a severity level based on extracted features.

Output: A detailed report including severity level, heatmaps of affected areas, and treatment recommendations.

Applications

Primary Diagnosis: Helps clinicians detect early signs of DR, reducing the risk of blindness.

Screening Programs: Facilitates large-scale screening in populations with high diabetes prevalence.

Research: Provides insights into DR trends, aiding in epidemiological studies.

The system's ability to integrate with healthcare applicability and impact.

4.3 COMPONENTS

Pre-processing Module:

- **Tools:** OpenCV for image processing tasks such as resizing, filtering, and normalization.
- **Goal:** Prepares images for analysis by ensuring uniformity and clarity.

Feature Extraction Module:

- **Framework:** TensorFlow or PyTorch for implementing CNNs.
- **Methodology:** Extracts features such as vessel patterns and lesion characteristics.

Classification Model:

- **Type:** Deep learning-based classifier

(e.g., ResNet, InceptionNet).

- **Role:** Predicts severity levels using feature maps generated during preprocessing.

Report Generator:

- **Tools:** Python libraries like ReportLab or LaTeX for generating professional-grade PDFs.
- **Features:** Includes severity scores, heatmaps, and treatment recommendations.

Integration and Scalability:

The modular design allows seamless integration with existing healthcare systems. Ensures scalability for larger datasets and multiple users.

4.4 FEATURES OF THE DETECTION SYSTEM

The system is designed with advanced features to ensure reliability, scalability, and user-friendliness.

Key Features

- **Automated Detection and Classification:**
  Leverages deep learning for accurate and unbiased analysis.
  Categorizes DR into five severity levels: No_DR, Mild, Moderate, Severe, and Proliferative_DR.

- **Real-Time Processing:**
  Efficient algorithms ensure minimal latency, making it suitable for clinical workflows.
  GPUs accelerate image processing and classification.

- **Heatmap Visualization:**
  Highlights affected regions in the retina, aiding in interpretation and treatment planning.
  Ensures transparency in the decision-making process.

- **Customizable Reports:**
  Generates reports tailored to individual patients, with options to include additional lifestyle recommendations.
  Format optimized for both digital sharing and hard copy use.

- **Data Logging and Analytics:**
  Stores data securely for follow-up care and longitudinal studies.
  Provides insights into DR trends through statistical and visual analytics.

- **Accuracy:** State-of-the-art models ensure high diagnostic precision.

- **User-Centric Design:** Focused on usability for both medical professionals and patients.

CHAPTER 5

MODULE DESCRIPTION

5.1 DATA ACQUISITION AND PREPROCESSING MODULE

Purpose: This step is all about preparing the retinal images so that they are suitable for analysis. High-quality images are essential for accurate detection of diabetic retinopathy, and preprocessing ensures that these images are standardized and free from noise.

Key Processes:

- **Data Collection:** Retinal images are obtained either from clinical settings or publicly available datasets like Eye PACS or Kaggle. These datasets provide a variety of image types, which helps build a robust model.
- **Noise Reduction:** Using Gaussian filtering helps remove noise from images. This makes underlying retinal features such as blood vessels and lesions more distinct, which is crucial for accurate analysis.
- **Image Resizing:** Images are resized to a standard resolution. This ensures that every image has the same size, which is important for training machine learning models and reducing computational complexity.
- **Normalization:** The pixel intensity values are adjusted (normalized) so that the lighting and contrast are uniform across all images. This helps the model focus on the relevant features instead of being affected by variations in lighting conditions.
- **Contrast Enhancement:** This step makes small abnormalities like microaneurysms (tiny bulges in blood vessels) or exudates (fatty deposits) more visible, which are key indicators of diabetic retinopathy.

Outcome: The images are now clean, consistent, and optimized for further analysis, setting a strong foundation for accurate feature extraction.

5.2 FEATURE EXTRACTION MODULE

Purpose: The goal here is to automatically identify and extract features in the retina that are indicative of diabetic retinopathy, such as microaneurysms, hemorrhages, and exudates.

Key Features Extracted:

- **Microaneurysms:** These are tiny, balloon-like bulges in the blood vessels of the retina, often the first signs of diabetic retinopathy.
- **Hemorrhages:** Leaks of blood that appear as dark spots in the retina, indicating damage.
- **Exudates:** Fatty deposits caused by damage to the retina.
- **Vascular Abnormalities:** Changes in the structure of the blood vessels, which worsen as diabetic retinopathy progresses.

Tools Used: Convolutional Neural Networks (CNNs) are used to automatically analyze the patterns in the image pixels. This deep learning method can extract complex features without requiring manual intervention.

Outcome: The result is a set of feature maps that highlight the areas of the retina most likely affected by diabetic retinopathy, enabling the model to detect even subtle signs.

5.3 MACHINE LEARNING MODEL MODULE

Purpose: This module is responsible for classifying the retinal images into different stages of diabetic retinopathy based on the features extracted.

Classification Categories:

- **No_DR:** No signs of diabetic retinopathy.
- **Mild:** Early-stage retinopathy with minimal changes.
- **Moderate:** Noticeable changes requiring medical attention.
- **Severe:** Significant retinal damage with high risk of vision loss.
- **Proliferative_DR:** Advanced stage with abnormal blood vessel growth.

Model Used: Deep learning models like ResNet or VGGNet are specifically fine-tuned for retinal image analysis. These models are capable of learning complex patterns in the data to make highly accurate classifications.
Outcome: The model produces highly accurate severity classifications, helping clinicians make informed decisions about patient care.

5.4 REPORT GENERATION MODULE

Purpose: The goal here is to convert the system's output into a user-friendly, interpretable report.
Report Features:

- **Severity Level & Confidence Scores:** The report provides the classification result(severity of diabetic retinopathy) along with a confidence score, showing the model'scertainty in its diagnosis.
- **Heatmaps:** These highlight the areas of the retina that are affected by the disease, providing a visual representation of the analysis.
- **Treatment Recommendations:** Based on the severity of the retinopathy, the system can suggest follow-up actions or treatments.

Outcome: A well-structured PDF report that healthcare providers can use for diagnosis and treatment planning. The report is also suitable for sharing with patients.

5.5 DATA LOG MODULE

Purpose: This module securely stores the processed images and results for future reference, ensuring that they are organized and accessible.
Key Features:

- **Organized Storage:** Data is organized by patient ID, severity level, and timestamp,making it easy to retrieve later.
- **Security:** The data is encrypted, ensuring that it's stored securely and access is restricted to authorized users.

Outcome: A secure and well-structured data repository that supports future patient follow-ups, research, and system evaluation.

5.6 DATA ANALYTICS VIEW MODULE

Purpose: To offer a comprehensive analysis of the system's performance and insights into diabetic retinopathy trends.

Key Features:

- **Metrics:** Includes detection rates, accuracy of the model, and prevalence rates across different populations.
- **Graphical Tools:** The system can display visual data like heatmaps, pie charts, and line graphs to highlight trends and metrics.

Outcome: Healthcare administrators and researchers gain insights into disease patterns, system performance, and potential areas for improvement.

5.7 USER INTERFACE MODULE

Purpose: To create an intuitive interface that allows users to easily interact with the system.

Key Features:

- **Upload Options:** Users can upload retinal images for analysis.
- **Real-Time Status Updates:** The system provides feedback on the progress of the analysis, notifying users if there are any errors or issues.
- **Downloadable Reports:** Users can download detailed reports that include severity levels, heatmaps, and treatment recommendations.

Outcome: Improving the system's accessibility and effectiveness.

CHAPTER 6

SYSTEM SPECIFICATION

6.1 HARDWARE REQUIREMENTS

- **Processor**: Minimum Intel i5 or AMD Ryzen 5 for fast computation.
- **RAM**: At least 8GB, preferably 16GB for handling datasets smoothly.
- **Storage**: 256GB SSD or more for faster read/write operations.
- **Graphics Card**: Optional but recommended for visualization and model training (e.g., NVIDIA GTX 1650).
- **Operating System**: Windows, macOS, or Linux (Ubuntu recommended).
- **Peripherals**: Keyboard, mouse, and a reliable internet connection for software installation and research.

6.2 SOFTWARE REQUIREMENTS

Operating System

Windows 10 or later

macOS Catalina or later

Linux (Ubuntu, CentOS, etc.) with GNOME or KDE desktop environment

Programming Languages and Libraries

Python 3.x with libraries such as NumPy, pandas, scikit-learn, Matplotlib, and TensorFlow for data analysis and machine learning

Integrated Development Environment (IDE)

Anaconda or Miniconda for environment management (optional)

Jupyter Notebook or Jupyter Lab for data exploration and model development.

PyCharm or Visual Studio Code as the primary Python IDE

6.3 SOFTWARE DESCRIPTION

PANDAS:

- PANDAS is a powerful data manipulation library in Python.
- It provides data structures and functions to work with structured data efficiently.
- Organizes patient demographic details, medical history, and diabetic retinopathy severity levels in a structured format (Data Frame).
- PANDAS is Saves model predictions and analysis results for reporting and future reference..

MATPLOTLIB.PYPLOT:

- MATPLOTLIB.PYPLOT is a versatile plotting library for Python.
- It allows users to create various types of plots, including line plots, scatter plots, histograms, and more.
- MATPLOTLIB.PYPLOT is widely used for visualizing data and results in scientific computing and data analysis.
- Plots metrics like ROC curves and confusion matrices to assess the accuracy and reliability of the machine learning model..
- Saves generated plots as image files (PNG, JPEG) that can be embedded in PDF reports for clear and informative presentations.

SEABORN:

- A statistical data visualization library based on Matplotlib.
- Simplifies the creation of complex visualizations with a high-level interface.
- Offers built-in themes to improve plot aesthetics easily.

- Integrates seamlessly with Pandas DataFrames for enhanced data analysis.
- Seaborn can create more sophisticated plots, like box plots or violin plots, to analyze the distribution of different diabetic retinopathy severity levels in the dataset.

SKLEARN (SKLEARN):

- SKLEARN, also known as scikit-learn, is a comprehensive machine learning library for Python.
- It provides simple and efficient tools for data mining and data analysis.
- SKLEARN includes various algorithms for classification, regression, clustering, dimensionality reduction, and more.
- It offers a consistent API and extensive documentation, making it easy to use for both beginners and experts.
- SKLEARN is widely used in academia and industry for building machine learning models and conducting experiments.

STREAMLIT:

- An open-source app framework for machine learning and data science.
- Allows for rapid prototyping of interactive web applications.
- Simplifies the deployment of machine learning models as web apps.
- Offers easy integration with Python scripts, enabling real-time updates
- Supports customization of UI components like sliders, charts, and buttons.

CHAPTER 7

MODULE IMPLEMENTATION

7.1 MODULE IMPLEMENTATION DETAILS

The Automated Diabetic Retinopathy Detection System is a cutting-edge solution designed to address the challenges of early detection and severity classification of diabetic retinopathy, a leading cause of blindness. The system leverages advanced image processing, machine learning, and user-friendly interfaces to provide a seamless end-to-end workflow. The process begins with data acquisition, where high-quality retinal images are collected from clinical databases or public repositories. These images undergo preprocessing techniques such as noise reduction, contrast enhancement, and normalization to ensure consistency and highlight critical retinal features like blood vessels, microaneurysms, and hemorrhages. Following preprocessing, the system performs feature extraction using Convolutional Neural Networks (CNNs), which automatically detect and map relevant patterns indicative of diabetic retinopathy.

The extracted features are fed into a machine learning model, which classifies the images into five severity levels: No_DR, Mild, Moderate, Severe, and Proliferative_DR. This classification process is optimized for high accuracy and reliability, ensuring that even subtle abnormalities are detected. The results are compiled into a comprehensive report, including visual heatmaps, confidence scores, and treatment recommendations. All processed data and results are securely stored in the data log for future reference, enabling efficient patient follow-ups and research. Finally, the system features an intuitive user interface, allowing users to upload images, monitor analysis progress, and download detailed reports. The streamlined flow ensures that the system delivers quick, accurate, and actionable insights, empowering healthcare professionals and improving patient care.

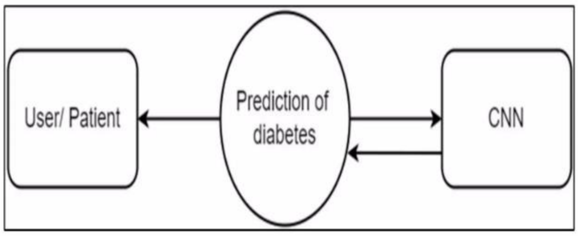


Fig.7.1 Data Flow Diagram Level-0

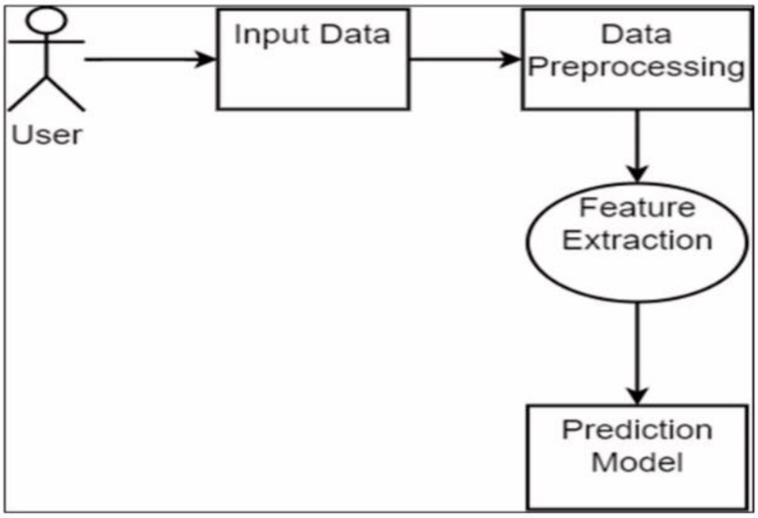


Fig.7.2 Data Flow Diagram Level-1

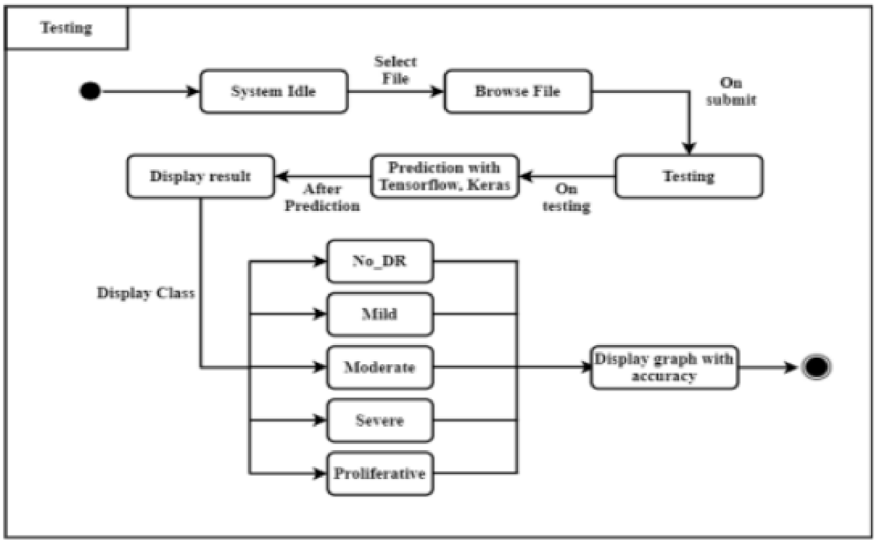


Fig.7.3 Data Flow Diagram-Level-2

7.1.1 DATA ACQUISITION AND PREPROCESSING MODULE

Purpose:

The foundation of any machine learning system lies in the quality and consistency of input data. For this project, data acquisition and preprocessing aim to prepare retinal images, ensuring they are clean, standardized, and optimized for further analysis.

Data Collection:

Retinal images were sourced from publicly available datasets like EyePACS and Kaggle. These datasets contain a diverse range of images with varying levels of diabetic retinopathy severity.Clinical settings provided additional images to enhance the dataset's diversity and robustness. Each image was labeled according to its severity level (No_DR, Mild, Moderate, Severe, Proliferative_DR).Challenges like image quality inconsistencies were addressed during preprocessing.

Noise Reduction:

Gaussian filtering was applied to suppress noise while preserving important retinal details such as blood vessels and lesions.

The kernel size and sigma values were fine-tuned to ensure optimal noise removal without affecting critical features.

Normalization:

Pixel intensity values were normalized to a range of 0 to 1 to minimize the impact of varying lighting conditions.

This step ensured that the model focused on the patterns in the retina rather than inconsistencies in brightness or contrast.

Contrast Enhancement:

Histogram equalization techniques were used to improve the visibility of subtle abnormalities like microaneurysms and exudates.

Outcome:

The preprocessing pipeline produced high-quality, standardized images that facilitated accurate feature extraction and model training, laying a strong foundation for the system's success.

Fig.7.4 Data Pre-processing Diagram

7.1.2 FEATURE EXTRACTION MODULE

Purpose:

To identify and extract disease-relevant patterns from retinal images, such as microaneurysms, hemorrhages, and exudates, which are indicative of diabetic retinopathy.

Key Features Extracted:

- **Microaneurysms:** Detected using pixel-level patterns representing small, balloon-like bulges in blood vessels. These are often the earliest signs of DR.
- **Hemorrhages:**Identified as dark spots in the retina caused by blood vessel leaks. Morphological techniques and CNN layers helped distinguish them from other structures.
- **Exudates:**Bright, fatty deposits were highlighted using edge-detection algorithms and CNN feature maps.
- **Vascular Abnormalities:**Structural changes in blood vessels were detected using a combination of segmentation techniques and deep learning layer.

Tools Used:

A Convolutional Neural Network (CNN) was implemented for automated feature extraction. This eliminated the need for manual feature engineering, allowing the model to learn patterns directly from the data.Pre-trained models like ResNet were fine-tuned to improve feature detection accuracy and reduce computational effort.

Outcome:

The feature extraction module produced detailed feature maps highlighting disease-relevant regions, enabling accurate classification in the subsequent steps.

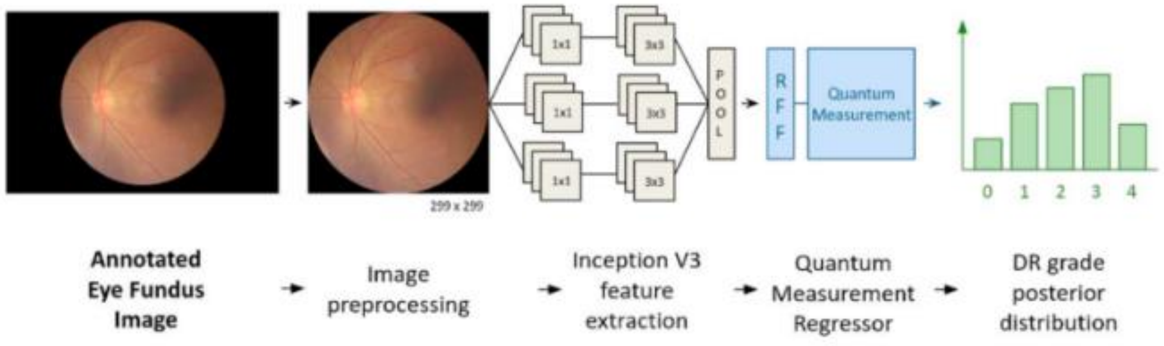


Fig.7.5 Feature Extraction

7.1.3 MACHINE LEARNING MODEL MODULE

Purpose:

To classify retinal images into severity levels of diabetic retinopathy based on extracted features.

Implementation Details

- **Model Architecture:**A deep learning architecture based on ResNet-50 was employed. This model's residual connections helped mitigate vanishing gradient issues during training.The model was fine-tuned on the retinal image dataset, with additional layers added to adapt it specifically for DR classification.
- **Training Process:** Images were split into training, validation, and testing sets in an 80:10:10 ratio. Data augmentation techniques, such as rotation, flipping, and brightness adjustments, were applied to improve model generalization.A categorical cross-entropy loss function was used, with the Adam optimizer for efficient gradient updates.
- **Classification Categories:**

  The model classified images into the following categories:

  No_DR: Healthy retina.

  Mild: Early signs of retinopathy.

  Moderate: Clear damage requiring medical intervention.

  Severe: High-risk damage.

  Proliferative_DR: Advanced retinopathy with abnormal vessel growth.

Outcome:

The trained model achieved high accuracy, producing reliable predictions for diabetic retinopathy severity, thereby supporting clinical decision-making.

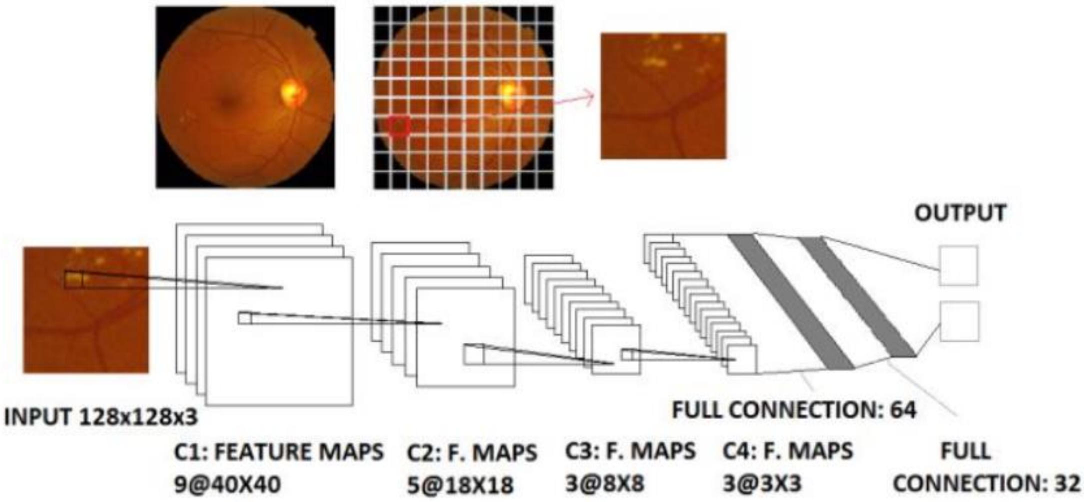


Fig.7.6 Implementation Diagram

7.1.4 REPORT GENERATION MODULE

Purpose:

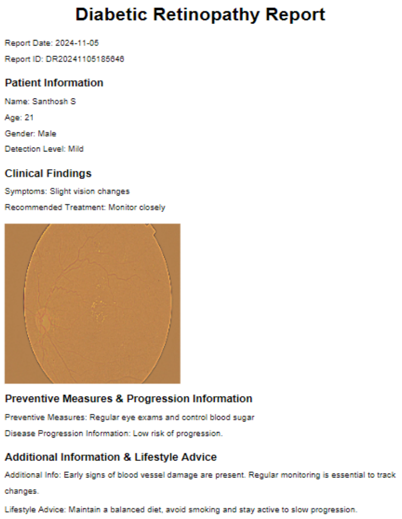
To present the system's output in a structured, user-friendly format suitable for clinicians and patients.

Report Features:

- **Severity Level & Confidence Scores:**The classification result, along with a confidence percentage, was displayed to convey the model's certainty.
- **Heatmaps:**Grad-CAM (Gradient-weighted Class Activation Mapping) was used to generate heatmaps. These visualized the regions most indicative of disease, aiding in result interpretation.
- **Treatment Recommendations:**Each severity level was paired with evidence-based treatment suggestions.
- **PDF Generation:**Libraries like ReportLab and LaTeX were used to create professional-grade reports.

Outcome:

A polished, detailed report that provides both diagnostic and treatment insights, suitable for clinical use and patient communication.



Diabetic Retinopathy Report

Report Date: 2024-11-05

Report ID: DR20241105185646

Patient Information

Name: Santhosh S

Age: 21

Gender: Male

Detection Level: Mild

Clinical Findings

Symptoms: Slight vision changes

Recommended Treatment: Monitor closely

Preventive Measures & Progression Information

Preventive Measures: Regular eye exams and control blood sugar

Disease Progression Information: Low risk of progression.

Additional Information & Lifestyle Advice

Additional Info: Early signs of blood vessel damage are present. Regular monitoring is essential to track changes.

Lifestyle Advice: Maintain a balanced diet, avoid smoking and stay active to slow progression.

Fig.7.7 Report Generation.

7.1.5 DATA LOG MODULE

Purpose:

To securely store processed images and diagnostic results for future use.

Implementation Details

- **Organized Storage:**Data was organized in a hierarchical structure,Metadata included timestamps, severity levels, and preprocessing parameters.
- **Categories :** Stores all the generated reports into the separate folder for further Visualizations.

Outcome:

A secure, organized repository that supports follow-ups, and system evaluations.

7.1.6 DATA ANALYTICS VIEW MODULE

Purpose:

To provide a comprehensive analysis of system performance and diabetic retinopathy trends.

Implementation Details

- **Performance Metrics:**Accuracy, precision, recall, and F-scores were calculated to evaluate the model.Detection rates and false positive rates were analyzed for each severity level.
- **Visualization Tools:**Graphical representations like heatmaps, pie charts, and line graphs illustrated trends and performance metrics.

Outcome:

The analytics module enabled insights into disease prevalence and future improvements.

Fig.7.8 Analytics View

7.1.7 USER INTERFACE MODULE

Purpose:

To ensure seamless interaction between users and the system.

Implementation Details

Features:

- **Image Upload:** A drag-and-drop interface allowed users to upload retinal
- **Report Download:** Reports were made available as downloadable PDFs.

Technology Used:

The UI was implemented using Kivy, offering a minimalistic design with intuitive navigation.

Outcome:

An user-friendly interface that simplifies system and enhances user experience.

CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

The Automated Diabetic Retinopathy Detection System offers a reliable and efficient solution to one of the most pressing challenges in ophthalmology: the early detection and management of diabetic retinopathy. By combining advanced image preprocessing techniques, feature extraction through deep learning, and classification using robust machine learning models, the system ensures accuracy and consistency in diagnosis. Its ability to generate comprehensive, user-friendly reports with actionable insights makes it a valuable tool for clinicians and healthcare administrators. The secure data logging feature further facilitates patient follow-up and research opportunities, while the user-friendly interface ensures accessibility for non-technical users. Overall, this system bridges the gap between technology and healthcare, providing a scalable and effective tool to combat vision loss caused by diabetic retinopathy.

8.2 FUTURE ENHANCEMENT

Integrating the diabetic retinopathy detection system with wearable health devices like smartwatches or continuous glucose monitors (CGMs) offers a more comprehensive and real-time approach to managing diabetes and its complications. By analyzing data trends from these devices, such as blood glucose levels, and correlating them with retinal changes detected in images, the system can provide actionable insights. Alerts can be sent to patients when abnormal readings indicate potential risks, prompting them to schedule retinal checkups. Additionally, historical data from wearable devices can be used to generate personalized recommendations for lifestyle adjustments, making disease management more proactive. This integration creates a seamless ecosystem where real-time monitoring complements periodic screenings, empowering patients and clinicians to take timely actions to prevent disease progression.

8.2.1 INTEGRATION WITH NATIONAL HEALTHCARE SYSTEMS

Expanding the system to integrate with national healthcare databases positions it as a powerful tool for large-scale public health management. Such integration enables population-wide screenings for early detection of diabetic retinopathy, streamlining diagnosis and reducing the burden on healthcare providers. Real-time reporting ensures that detection results are accessible to both clinicians and policymakers, enabling better resource allocation and strategic planning. Additionally, anonymized data collected from the system can contribute to medical research, driving innovations in diabetic retinopathy treatment and AI model refinement. By embedding the system within national healthcare infrastructures, it can reach underserved populations, significantly improving public health outcomes and reducing the prevalence of diabetic retinopathy.

8.2.2 REAL-TIME VIDEO RETINAL SCREENING

Incorporating real-time video analysis into the system could revolutionize the screening process. Instead of static image uploads, patients or technicians could stream live retinal videos for immediate processing. The system could frame-by-frame analyze the video to detect diabetic retinopathy signs dynamically, providing an even more accurate assessment. Real-time analysis would be particularly beneficial during clinical examinations, enabling instant feedback and reducing waiting times for diagnosis. This innovation could also assist in monitoring disease progression more effectively by capturing more comprehensive data than static images alone.

APPENDIX A

PYTHON CODE FOR A MACHINE LEARNING MODEL

```
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import EarlyStopping

# Define the model
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(5, activation='softmax'))  # Assuming 5 classes for severity
levels

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])

# Data augmentation and preprocessing
train_datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)
train_generator = train_datagen.flow_from_directory(
    'path_to_dataset',
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical',
    subset='training'
)
```

```
validation_generator = train_datagen.flow_from_directory(
    'path_to_dataset',
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical',
    subset='validation'
)

# Train the model
early_stopping = EarlyStopping(monitor='val_loss', patience=5)
model.fit(train_generator, validation_data=validation_generator, epochs=50,
callbacks=[early_stopping])

# Save the model
model.save('diabetic_retinopathy_model.h5')
```

PYTHON WEB APPLICATION CODE(STREAMLIT)

```
import streamlit as st
import numpy as np
import cv2
from keras.models import load_model
from fpdf import FPDF
import tempfile
import base64
from datetime import datetime, timedelta
import os
from pathlib import Path
import pdfplumber
import pandas as pd
import plotly.express as px
import re
```

```
import plotly.graph_objects as go

# Load the pre-trained model
model_path =
r"A:\code\Dp3\diabetic_retinopathy_detection\models\diabetic_retinopathy_mode
l.h5"
model = load_model(model_path)

# Function to apply Gaussian filtering
def apply_gaussian_filter(image):
    return cv2.GaussianBlur(image, (5, 5), 0)

# Function to resize image for processing
def resize_image(image, size=(512, 512)):
    return cv2.resize(image, size, interpolation=cv2.INTER_AREA)

# Function to preprocess image for the model
def preprocess_image(image):
    image = resize_image(image, (224, 224))  # Resize to the model's input size
    image = image.astype('float32') / 255.0  # Normalize to [0, 1]
    return image

# Function for diabetic retinopathy detection using the model
def detect_diabetic_retinopathy(image):
    processed_image = preprocess_image(image)
    prediction = model.predict(np.expand_dims(processed_image, axis=0))
    severity_levels = ["No_DR", "Mild", "Moderate", "Severe", "Proliferate_DR"]
    predicted_level = severity_levels[np.argmax(prediction)]
    return predicted_level

# Function to create heatmap overlay based on blood vessel analysis
def create_heatmap_overlay(image):
```

```
    resized_image = resize_image(image, (224, 224))

    # Create a heatmap based on the detection level
    intensity_map = {
        "No_DR": 0,
        "Mild": 0.25,
        "Moderate": 0.5,
        "Severe": 0.75,
        "Proliferate_DR": 1.0
    }

    level = detect_diabetic_retinopathy(resized_image)
    intensity_value = intensity_map.get(level, 0)

    heatmap = np.full((224, 224), intensity_value * 255)
    heatmap = cv2.applyColorMap(heatmap.astype(np.uint8),
cv2.COLORMAP_JET)
    combined_image = cv2.addWeighted(resized_image, 0.6, heatmap, 0.4, 0)
    heatmap_img_path = "heatmap_overlay.png"
    cv2.imwrite(heatmap_img_path, combined_image)
    return heatmap_img_path

    if st.button("Visualize Reports"):
    if pdf_files:
        df = extract_data_from_pdf(pdf_files)
        if not df.empty:
            st.write("Extracted Data from Reports:")
            st.dataframe(df)

            # Basic visualization of the data
            fig = px.bar(df, x='Name', y='Age', color='Detection Level',
                         title="Patient Age and Detection Level")
```

```
st.plotly_chart(fig)

# Severity Distribution Pie Chart
severity_counts = df['Detection Level'].value_counts()
fig_pie = px.pie(
    values=severity_counts.values,
    names=severity_counts.index,
    title="Distribution of Diabetic Retinopathy Severity",
    color_discrete_sequence=px.colors.qualitative.Set3,
    hole=0.3
)
fig_pie.update_traces(textposition='inside', textinfo='percent+label')
st.plotly_chart(fig_pie, use_container_width=True)
```

APPENDIX B

SCREENSHOTS

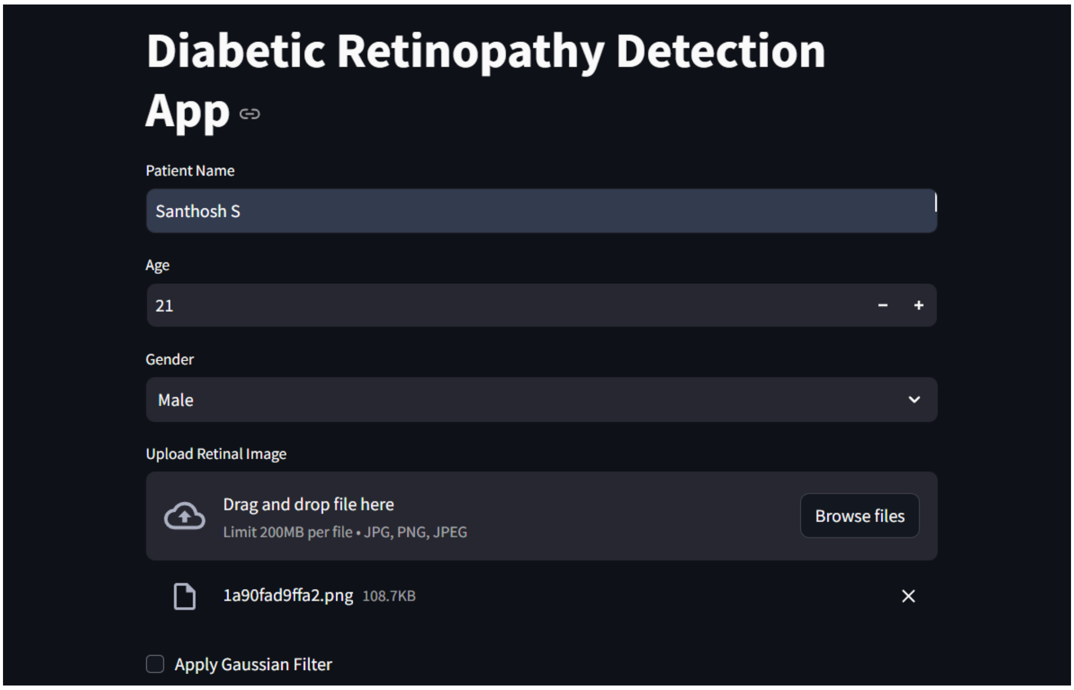


Fig.B1 User Input

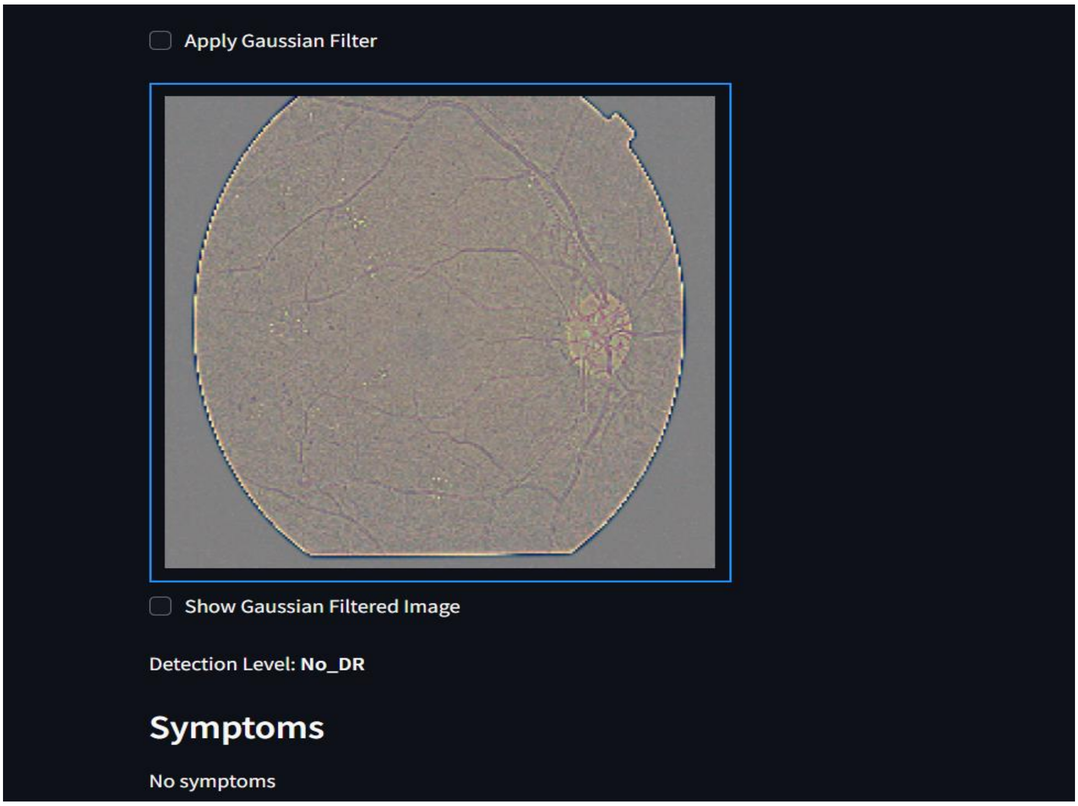


Fig.B2 Guassian Filtered image

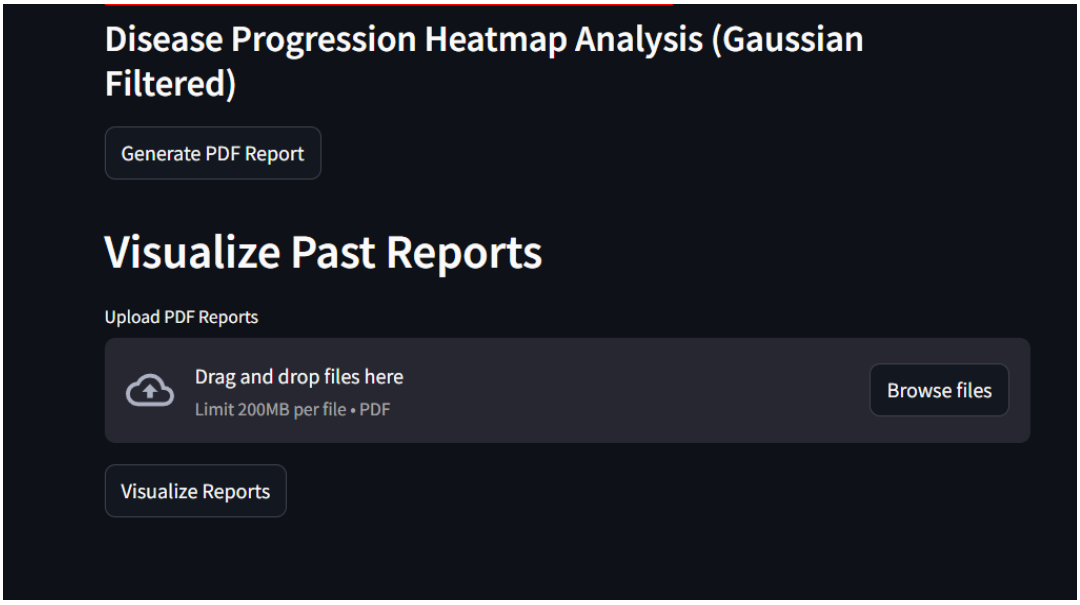
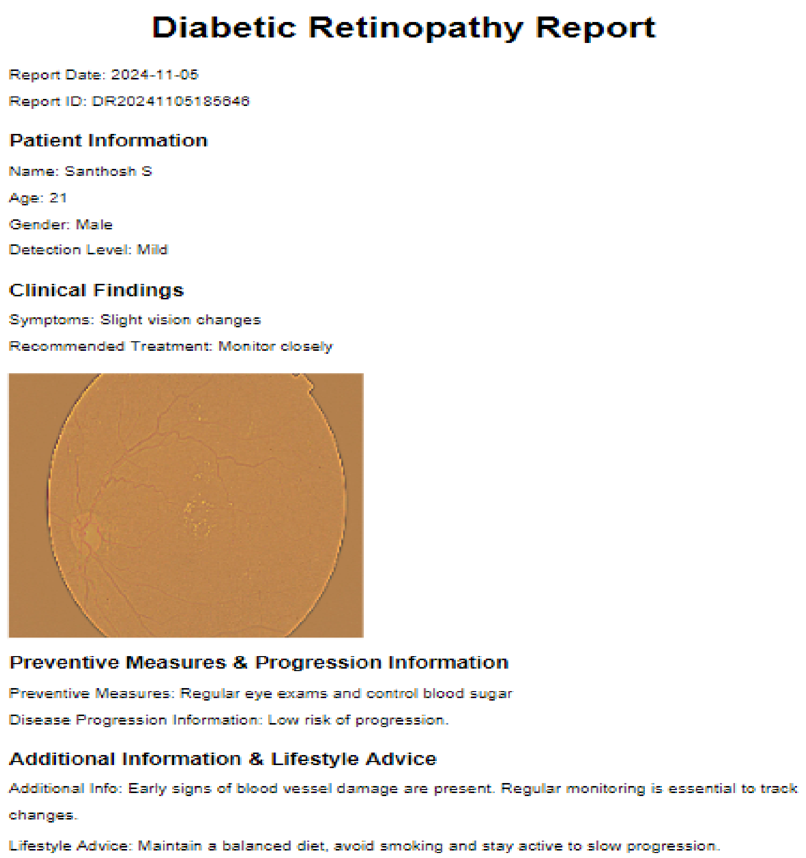


Fig.B3 Options



Diabetic Retinopathy Report

Report Date: 2024-11-05

Report ID: DR20241105185646

Patient Information

Name: Santhosh S

Age: 21

Gender: Male

Detection Level: Mild

Clinical Findings

Symptoms: Slight vision changes

Recommended Treatment: Monitor closely

Preventive Measures & Progression Information

Preventive Measures: Regular eye exams and control blood sugar

Disease Progression Information: Low risk of progression.

Additional Information & Lifestyle Advice

Additional Info: Early signs of blood vessel damage are present. Regular monitoring is essential to track changes.

Lifestyle Advice: Maintain a balanced diet, avoid smoking and stay active to slow progression.

Fig.B4 Report Generation

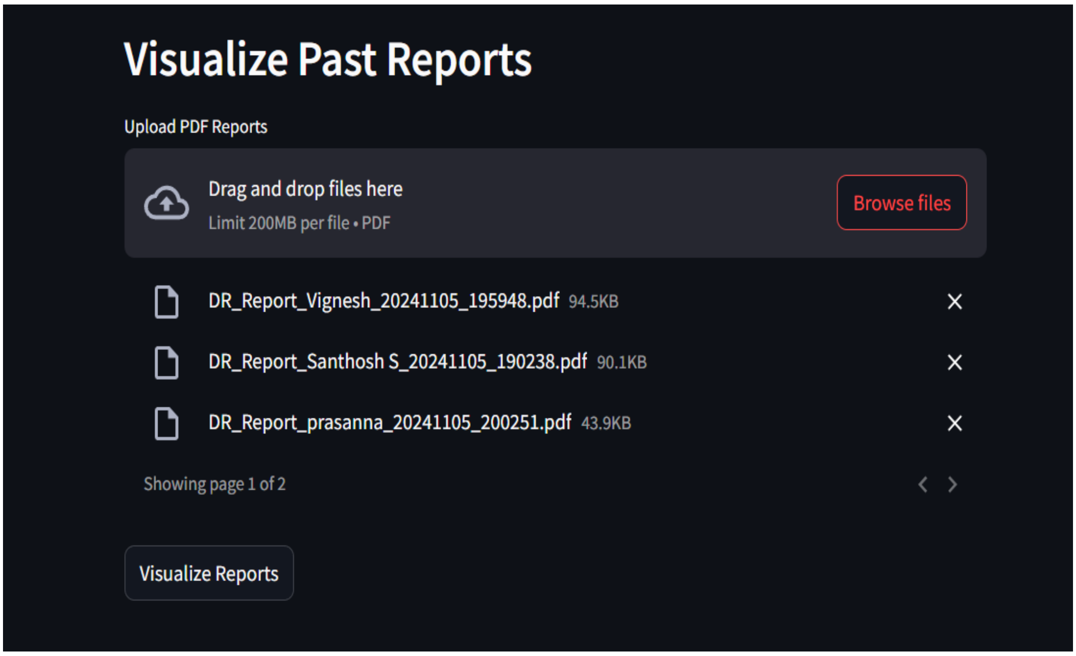


Fig.B5 Upload past reports

	Name	Age	Detection Level
0	Arul	22	Mild
1	pragatheesh	20	Proliferate_DR
2	prasanna	21	Proliferate_DR
3	Santhosh S	21	Severe
4	Vignesh	20	Severe

Fig.B6 Basic Visualization

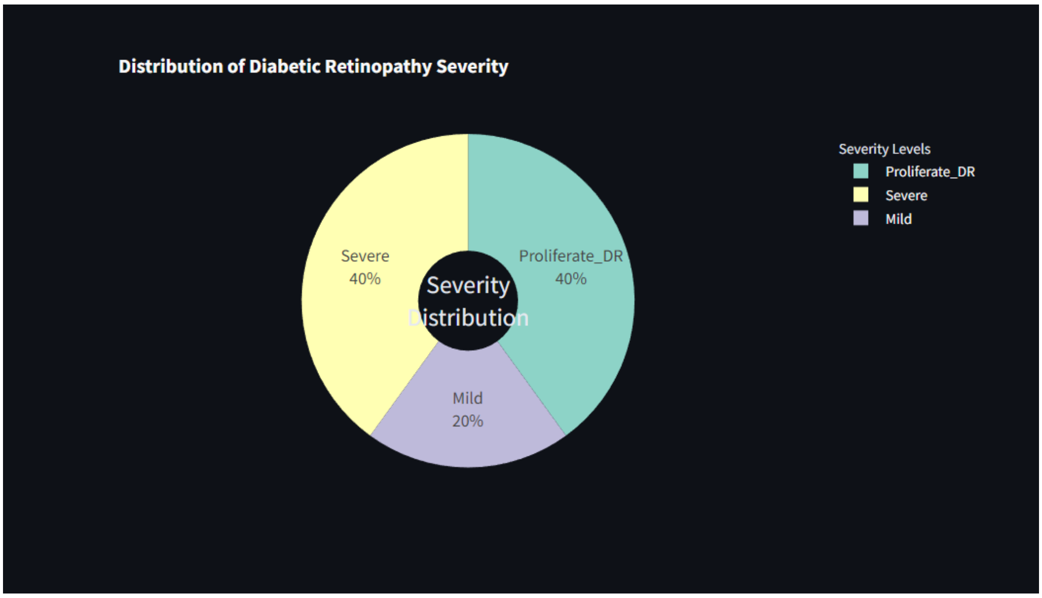


Fig.B7 Severity Distribution

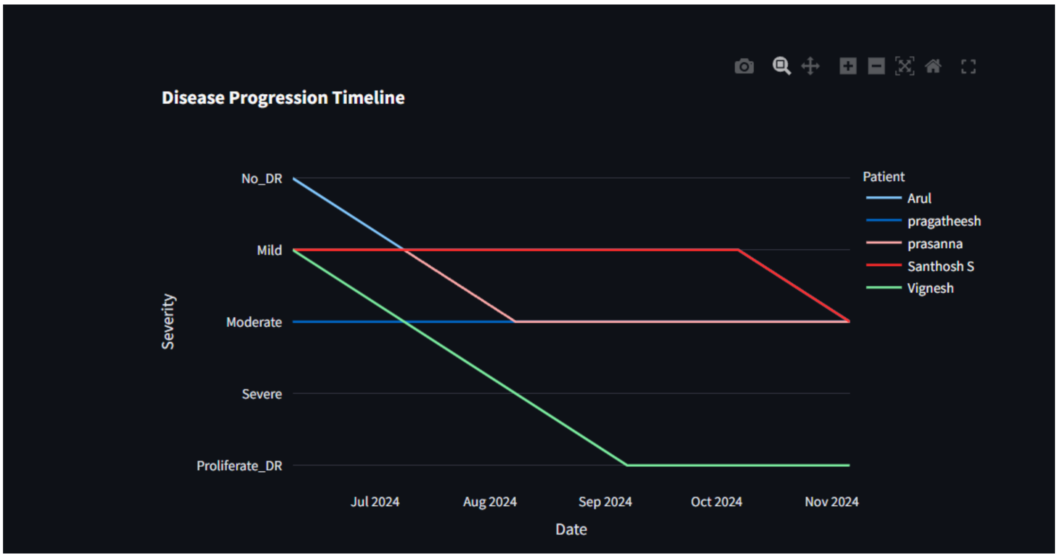


Fig.B8 Progression Timeline

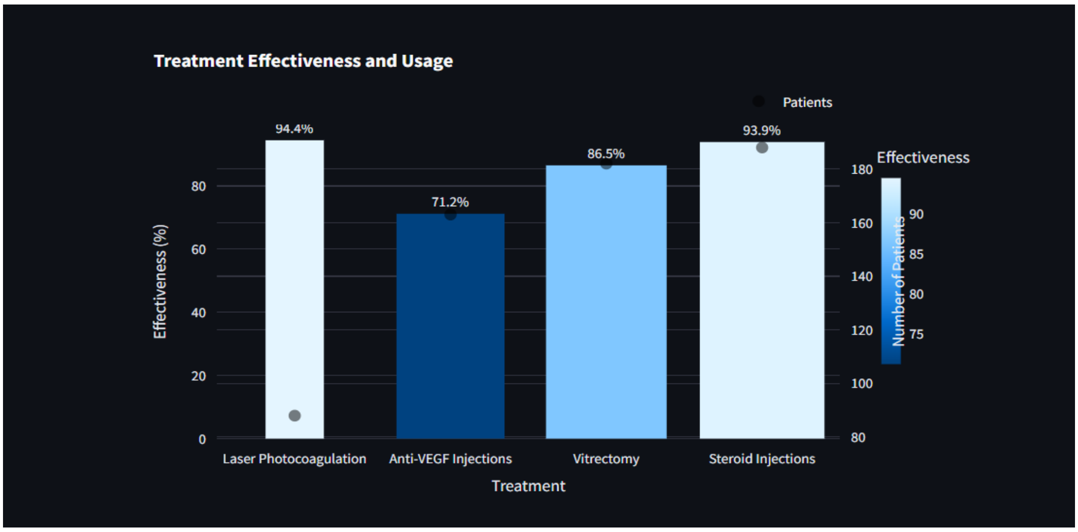


Fig.B9 Treatment Effectives and usage

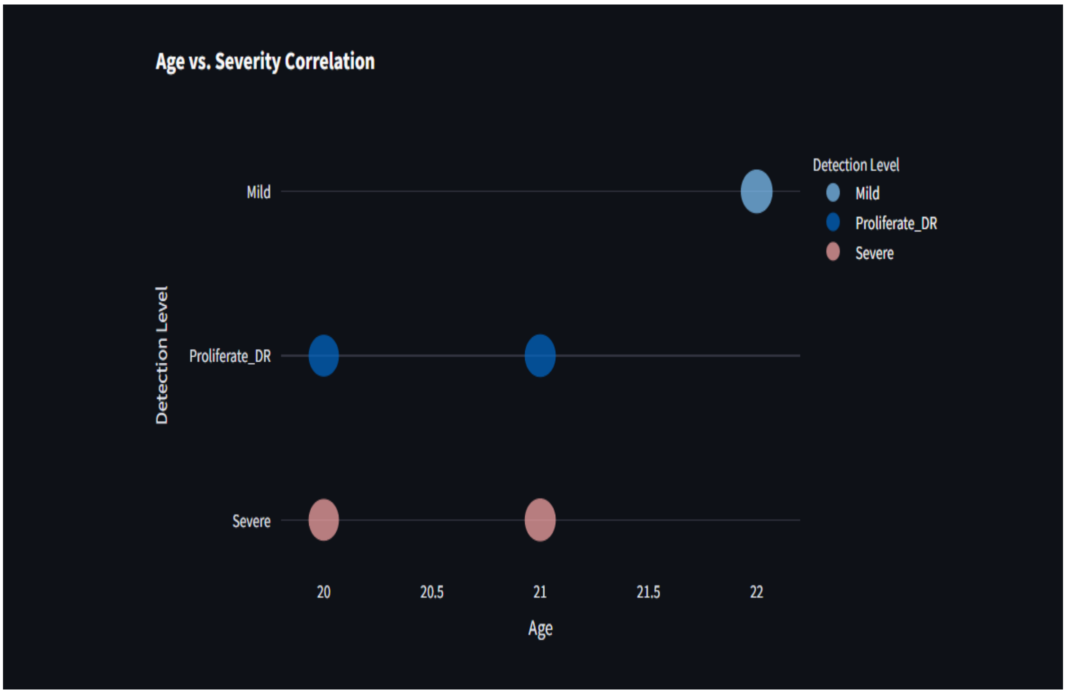


Fig.B10 Age Vs Severity Correlation

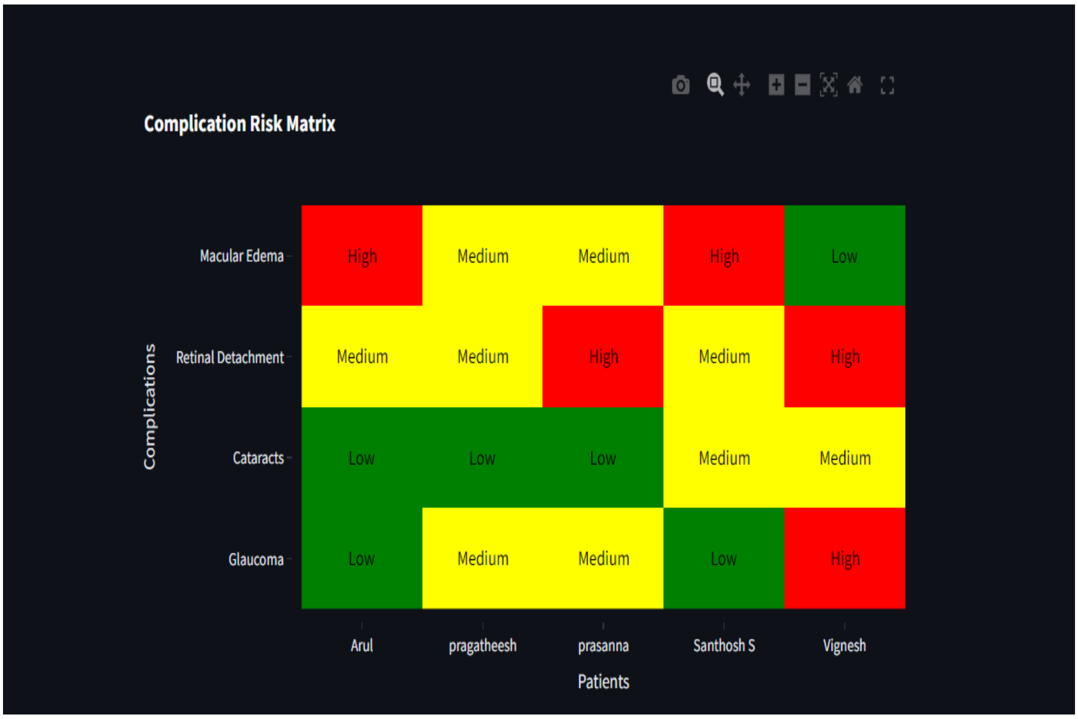


Fig.B11 Complication Risk Matrix

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