A PROJECT REPORT

ON

“ Automatic Detection of Pathological Myopia And High Myopia Using Fundus Images ”

Submitted By

Samrudhi Manchekar.

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In partial fulfillment for the award of the degree

Of

Bachelor of Engineering

Of

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Sinhgad Institutes

RMD SINHGAD SCHOOL OF ENGINEERING

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2024 – 25

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Guided by

Mrs. Sweta Kale .

DEPARTMENT OF INFORMATION TECHNOLOGY

RMD SINHGAD SCHOOL OF ENGINEERING

SAVITRIBAI PHULE PUNE UNIVERSITY

2024 – 2025

Sinhgad Institutes

DEPARTMENT OF INFORMATION TECHNOLOGY

Certificate

This is to certify that,

34	Samrudhi Manchekar
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43	Siddharth Patil

have successfully completed this project report entitled “Automatic Detection of Pathological Myopia And High Myopia Using Fundus Images”, under my guidance in partial fulfillment of the requirements for the degree of Bachelor of Engineering in the Department of Information Technology of Savitribai Phule Pune University during the academic year 2024-25.

Date: -

Place: -

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Internal Examiner External Examiner

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ABSTRACT

Myopia is a growing global public health issue, with high myopia increasing the risk of pathological myopia, potentially leading to irreversible vision loss. Early detection and timely intervention are essential to prevent myopia progression. Digital technologies, such as automated detection systems, can address these needs by enabling screening and risk assessment. This project focuses on the automatic detection of pathological and high myopia using fundus images and Convolutional Neural Networks (CNNs). The system processes retinal images to classify them as normal, pathological myopia, or high myopia, providing an efficient tool for early diagnosis, improving clinical workflows, and enhancing outcomes for individuals at risk, particularly youth.

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1. INTRODUCTION

This project focuses on developing an automated system for detecting pathological and high myopia using fundus images, utilizing Convolutional Neural Networks (CNNs). The technology is intended to aid healthcare practitioners by automating the detection of myopia-related illnesses, decreasing the need for manual screenings, which are time-consuming and error-prone. This technique is especially advantageous to young people, as myopia is growing more common among them as a result of factors such as excessive screen usage and indoor activities. Early diagnosis and monitoring of myopia with this technique can assist to reduce long-term health concerns by providing early treatments.

The system's primary features include picture preprocessing to eliminate noise, feature extraction to detect important indications of myopia, such as retinal thickness and blood vessel patterns, and classification using CNN models to estimate the severity of the problem. This technique enables a precise and consistent diagnosis, allowing ophthalmologist to treat early and perhaps avoid serious problems such as eyesight loss. Furthermore, by employing a simple user interface, this system may be easily implemented in a variety of healthcare settings, offering a scalable and efficient approach for myopia diagnosis. This technology development promises to increase healthcare accessibility and general eye health, particularly among younger people.

a. AIM

Enable the early detection of pathological myopia and high myopia in fundus pictures, enabling for earlier intervention and therapy to prevent progression or consequences. Create methods and systems that can correctly and reliably distinguish between normal and abnormal situations in fundus pictures, lowering the risk of misdiagnosis. Provide ophthalmologist with quantifiable measures and assessments of myopia severity, allowing them to observe changes over time and customize treatment accordingly.

b. MOTIVATION

To develop the ‘Automatic Detection of Pathological Myopia and High Myopia system’, we were motivated by our visit to a hospital where we spoke with an eye specialist. She provided us with valuable information about the condition, explaining the diagnostic process, and treatment options available. We observed how the specialist used lenses and other diagnostic tools to evaluate patients eye conditions, which highlighted the limitations of manual diagnosis. This interaction made us realize the importance of developing an automated system that could assist specialists by providing an accurate and efficient tool for detecting myopia. Our aim is to create a system that can support medical professionals, enhancing both diagnostic accuracy and accessibility for patients.

c. OBJECTIVE

- Create innovative pre-processing algorithms to improve image quality, rectify distortions, and emphasize key features while reducing noise and artefacts.
- Identify and extract relevant features from fundus images, including optic disc parameters, retinal thickness, blood vessel patterns, and myopia-related indicators.
- Optimize machine learning algorithms, including deep neural networks, for feature training.
- Create an intuitive interface for healthcare professionals to interact with.

2. LITERATURE SURVEY

The paper [1], titled "Deep Learning in Image Classification using Dense Networks and Residual Networks for Pathologic Myopia Detection", authored by Zein Rasyid Himami, Alhadi Bustamam, and Prasnurzaki Anki from Universitas Indonesia and published in 2021, addresses the growing concern of pathologic myopia, which can lead to irreversible vision loss. The problem statement is centered on the need for automated, accurate, and cost-effective detection methods for pathologic myopia due to the global shortage of specialists. The objective is to develop a reliable deep learning model for diagnosing pathologic myopia using fundus images. This study applies two convolutional neural network (CNN) architectures ResNet-50 and DenseNet-201 to identify the optimal model configuration and preprocessing techniques, aiming to enhance classification accuracy and reliability. The reason for choosing these architectures lies in their ability to manage complex image patterns and improve learning with deep networks. The **system overview** involves image preprocessing, data augmentation, and training using two dataset splits (70:20:10 and 60:20:20) and three optimizers (SGD, RMSprop, Adam) to identify the most effective configuration. The conclusion from this research demonstrates that the DenseNet-201 architecture with Adam optimizer provides the best results, achieving high accuracy (97%), sensitivity (93%), and specificity (100%) in pathologic myopia detection. A disadvantage of this approach includes potential resource demands for implementing these deep networks, and further work could involve testing against a standardized dataset for robust comparisons and expanding the system to detect other ocular diseases from fundus images.

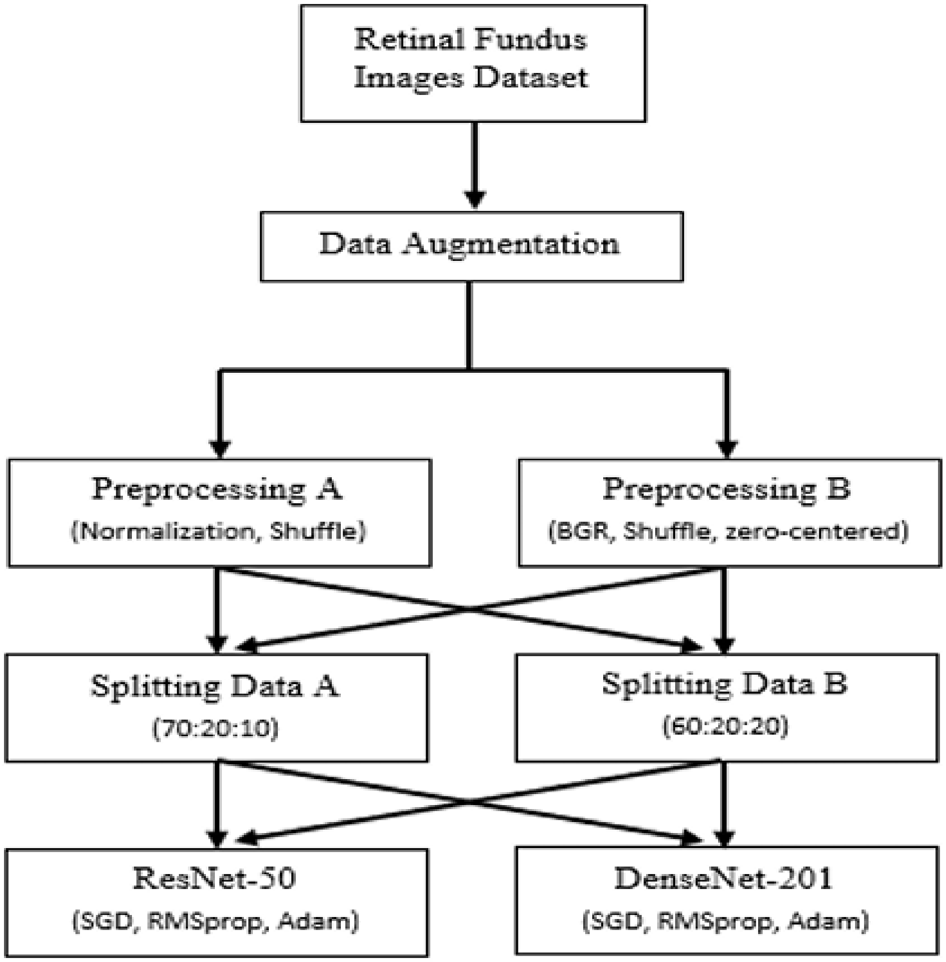

Figure1: System architecture of Deep Learning in Image Classification using Dense Networks and Residual Networks for Pathologic Myopia Detection

The proposed method in this paper utilizes deep learning for detecting pathologic myopia from retinal fundus images. The method begins with data acquisition from the Ocular Disease Intelligent Recognition (ODIR) dataset, containing 612 fundus images categorized into normal and pathologic myopia classes. For improved model robustness, data preprocessing and augmentation techniques are applied, where preprocessing includes scaling and normalization or converting RGB to BGR, and augmentation involves transformations like zooming, flipping, rotating, and shifting. The data is split into training, validation, and test sets using two configurations (70:20:10 and 60:20:20 ratios) to evaluate model performance. The method applies two CNN architectures ResNet-50 and DenseNet-

201 to extract image features and classify them. DenseNet, which connects each layer to every subsequent layer, enables cumulative knowledge sharing, while ResNet employs residual learning to prevent vanishing gradients and accelerate learning. These models are fine-tuned with three optimizers Stochastic Gradient Descent (SGD), RMSprop, and Adam to identify the best-performing configuration. The models are then evaluated using metrics like accuracy, sensitivity, and specificity, and DenseNet-201 with Adam optimizer on a 70:20:10 split demonstrates the highest accuracy and robustness for detecting pathologic myopia.

The paper [2] titled "Pathologic Myopia Detection and Visualization Based on Multi-Scale Deep Features by PMnet Tuned with Cyclic Learning Rate Hyperparameter" is authored by Pammi Kumari and Priyank Saxena and was published in 2023. It addresses the challenge of accurately detecting pathologic myopia (PM), a severe retinal condition, to prevent irreversible vision impairment. The objective is to develop an automated system using PMnet, a CNN designed specifically for fundus images, to classify pathologic and normal retinal images. The study employs an autoencoder for feature extraction and PMnet, optimized with Cyclic Learning Rate (CLR) to improve efficiency and reduce training time. This model leverages CLR to enhance accuracy by eliminating manual learning rate adjustments and incorporates saliency heatmaps for visualizing affected retinal areas. The research concludes that PMnet, especially with CLR, offers high classification performance, demonstrating superior accuracy and efficiency compared to ResNet-50. However, the limitation is that the model only performs binary classification due to the lack of a comprehensive labeled dataset for grading PM severity, suggesting future work to enhance grading capabilities for clinical practice.

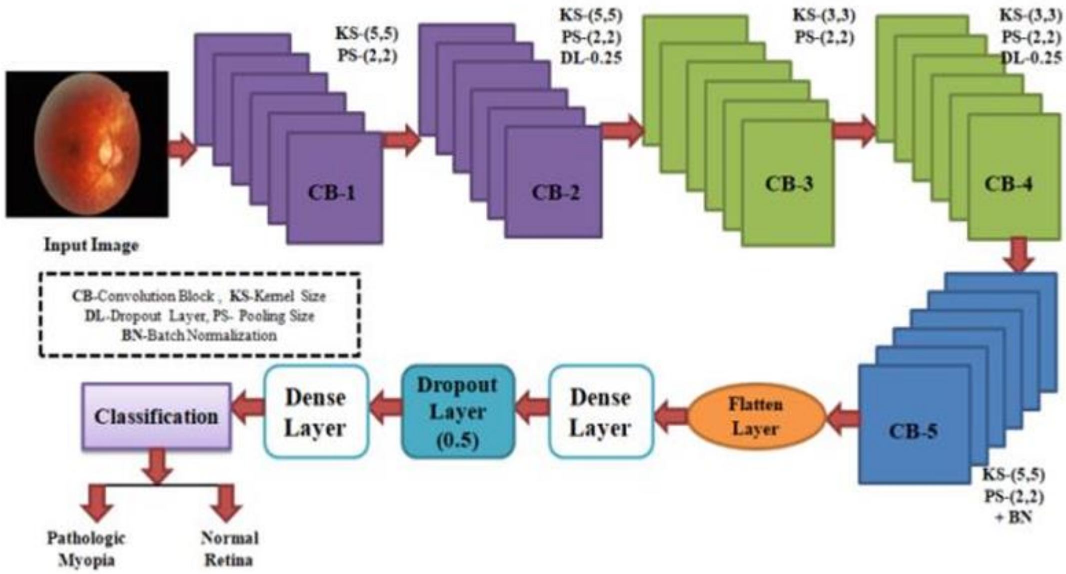

Figure 2 : Used Method in Pathologic Myopia Detection and Visualization Based on Multi-Scale Deep Features by PMnet Tuned with Cyclic Learning Rate Hyperparameter

The proposed framework introduces PMnet, a convolutional neural network specifically designed for detecting pathologic myopia (PM) in fundus images, utilizing a multi-stage approach. First, images are preprocessed to standardize dimensions, and an autoencoder extracts critical features, which are then fed into PMnet for classification. To optimize training, Cyclic Learning Rate (CLR) is used, allowing the model to automatically adjust the learning rate, which accelerates convergence and minimizes manual tuning. PMnet classifies images as either pathologic or normal, and saliency heatmaps highlight the affected areas in PM images, aiding in visualization and interpretation. This framework aims to deliver high accuracy and speed, making it suitable for practical application in early PM detection.

The paper [3] titled "Detection and Classification of ‘Myopia Epidemic’ Using Image Processing and Machine Learning to Prevent Fatal Road Accidents" is authored by A.E. Narayanan, M. Praveen, M. Ishwarya, N. Sagana, and S. Kaviarasan and was published in 2023. The study addresses the issue of road accidents caused by poor vision among drivers, particularly myopia, a condition that can impair distant vision. The objective is to develop a device that detects myopia in drivers to aid traffic authorities in identifying those who may require vision correction, thus reducing accidents. The research uses Convolutional Neural Networks (CNN) for image processing and classification due to CNN's strength in feature extraction and accuracy in medical image analysis. The system captures and processes 3D stereoscopic images of the eye, converting them into grayscale images and using GLCM and GLRLM techniques for texture extraction, with CNN classifying the images as myopic or non-myopic. The study concludes that this system, with an accuracy of up to 97% during testing, can significantly contribute to road safety by assisting law enforcement in identifying drivers with vision impairments. However, the disadvantages include possible limitations in detecting mild cases of myopia and dependence on high-quality image inputs for accurate results, indicating room for improvement in future versions.

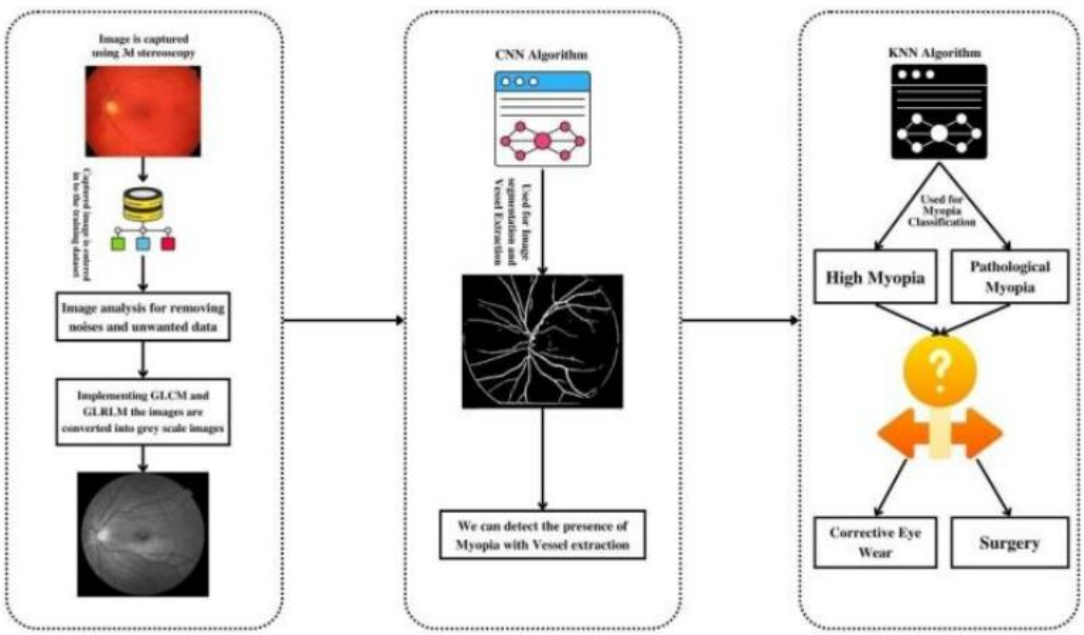

Figure 3 : Proposed architecture in Detection and Classification of Myopia Epidemic Using Image Processing and Machine Learning to Prevent Fatal Road Accidents

The proposed framework in the paper involves creating a device using 3D stereoscopy to capture high-resolution images of the driver's eye. This device includes a webcam with a zoom lens that captures detailed eye images, which are then processed through several stages. First, images are converted to grayscale to enhance texture and clarity. Next, **Gray** Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM) techniques are applied to extract texture features like surface roughness and uniformity. After preprocessing, the Convolutional Neural Network (CNN) is used to classify images as myopic or non-myopic based on retinal vessel patterns. The framework's output helps determine if the driver requires corrective lenses or surgery, thereby assisting traffic authorities in assessing drivers' vision fitness, aiming to prevent accidents.

The paper [4] titled "Automatic Diagnosis of Cataract and Myopia Through Fundus Images" is authored by Wajeeha Ahmed, Farheen Afzal, Bisma Shahid, and Abd Ur Rehman and was published in 2023. The problem statement highlights the increasing prevalence of cataract and myopia, which, if undiagnosed, can lead to blindness. The objective is to use deep learning, specifically transfer learning with ResNet-18 and ResNet-50 models, to automatically classify fundus images for early detection of these conditions. Future scope includes improving diagnostic accuracy and expanding the model to other ocular diseases. ResNet-18 and ResNet-50 algorithms were chosen for their high accuracy and ability to leverage pre-trained models, making them suitable for medical image classification. The system overview involves preprocessing fundus images, resizing them to standard dimensions, and applying transfer learning on ResNet models to classify images into cataract, myopia, or normal categories. The study concludes that ResNet-18 achieved an accuracy of 98.9%, while ResNet-50 achieved 97.8%, showing promise for clinical use in automatic diagnosis. However, the limitations include dependency on high-quality images for optimal performance, which may hinder its application in diverse clinical settings.

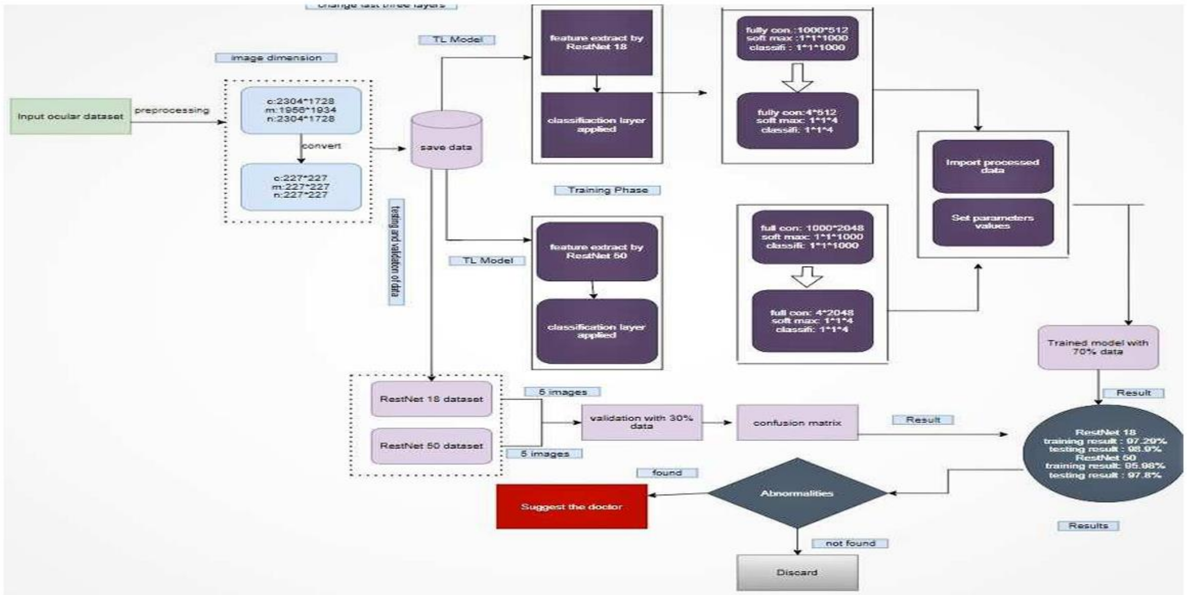

Figure 4 : Proposed Architecture of Automatic Diagnosis of Cataract and Myopia Through Fundus Images

The proposed framework in the paper uses fundus images to automatically diagnose cataract and myopia, employing transfer learning on ResNet-18 and ResNet-50 models. First, the images from a publicly available dataset are preprocessed, resized to a uniform dimension, and noise is removed to ensure clarity. Using transfer learning, the last three layers of ResNet-18 and ResNet-50 are modified to suit the classification task, adapting the pre-trained model for high accuracy in medical image classification. The framework then classifies each image into one of three categories—cataract, myopia, or normal—based on feature extraction and image analysis by the ResNet models. This approach achieves high diagnostic accuracy, demonstrating potential for use in early detection of these conditions in clinical settings.

The paper [5] titled "Automatic Screening of Pathological Myopia Using Deep Learning" was authored by Haonan Qin, Wei Zhang, Xiujuan Zhao, and Zhicheng Dong, and published in 2023. The study addresses the issue of Pathological Myopia (PM), a significant cause of visual impairment globally, and the need for an efficient, automatic screening system for early detection. The primary objective of this research is to develop an AI-based system that can identify PM directly from retinal fundus images using advanced Convolutional Neural Networks (CNNs). The study utilizes transfer learning and ensemble learning to enhance model accuracy and performance across various neural network architectures, including lightweight and large networks like MobileNet and ResNet. The chosen algorithms enable efficient extraction of complex features from high-dimensional medical images, supporting accurate classification. A system overview reveals that it combines CNN-based feature extraction and classification modules, which identify PM characteristics automatically. Results demonstrate a high performance with an accuracy of 99.7% and sensitivity of 99.5%, indicating robust reliability. The study concludes that this AI-driven screening system holds great potential in clinical settings, particularly in PM prevention and management. However, limitations such as focusing solely on PM without a broader range of retinal diseases and the limited dataset suggest that future work should expand these aspects to improve the model's generalizability.

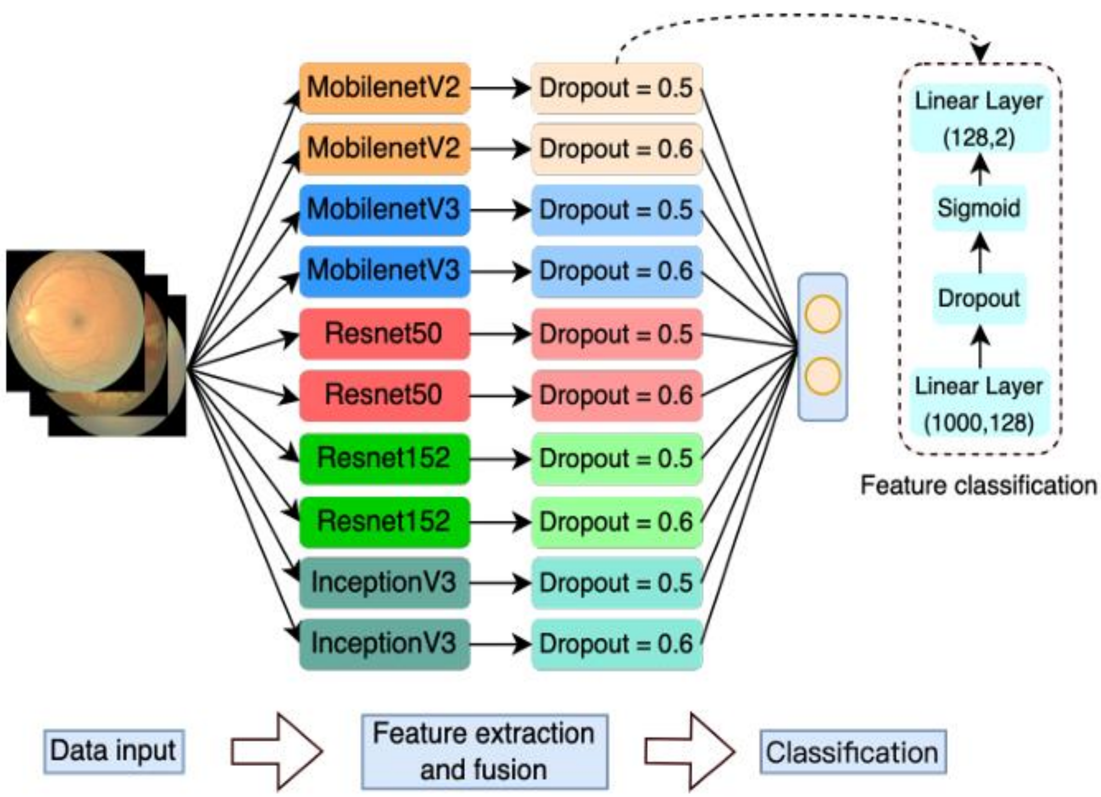

Figure 5 : Used Method in Automatic Screening of Pathological Myopia Using Deep Learning

The proposed framework for automatic pathological myopia (PM) screening comprises two main components: feature extraction and classification. The feature extraction component utilizes a Convolutional Neural Network (CNN) with its top layer removed, enabling the system to learn and detect critical pathological features of PM directly from fundus images. This feature extraction is enhanced through transfer learning (leveraging pre-trained knowledge from the ImageNet dataset) and ensemble learning (combining multiple CNN models) to improve accuracy and capture complex image features at different semantic levels. The classification module then uses a customized neural network to analyze these features and determine if an image indicates PM. The framework integrates both lightweight networks (like MobileNet) and larger networks (like ResNet), balancing performance with computational efficiency, especially for resource-constrained devices, and achieves high accuracy by fine-tuning these model ensembles.

The paper [6] titled "Automatic Detection of Pathological Myopia and High Myopia on Fundus Images", authored by Siying Dai, Leiting Chen, Ting Lei, Chuan Zhou, and Yang Wen, was published in 2020. The problem statement addresses the challenge of differentiating between pathological myopia (PM) and high myopia (HM), which is essential in clinical diagnostics but difficult due to their visual similarity on fundus images. The objective of the study is to develop an automated deep learning method that not only detects myopia but also distinguishes between PM and HM accurately. The future scope includes refining the model for broader clinical applications and enhancing its capability to classify other types of ocular conditions. The study utilizes a two-branch deep learning network with ResNet18 as the backbone, combined with Binary Cross-Entropy (BCE) loss and Triplet loss functions to improve differentiation between PM and HM. The choice of ResNet18 is motivated by its effectiveness in reducing computation complexity while maintaining accuracy. The system overview consists of two branches: one for identifying normal vs. abnormal images, and the other for distinguishing between PM and HM, with BCE and Triplet loss applied in the classification branches. The conclusion indicates that the model achieves high accuracy, precision, and sensitivity, making it an effective tool for aiding myopia diagnosis. A disadvantage is the model’s dependency on a private dataset, which limits the generalizability of the results across diverse clinical datasets.

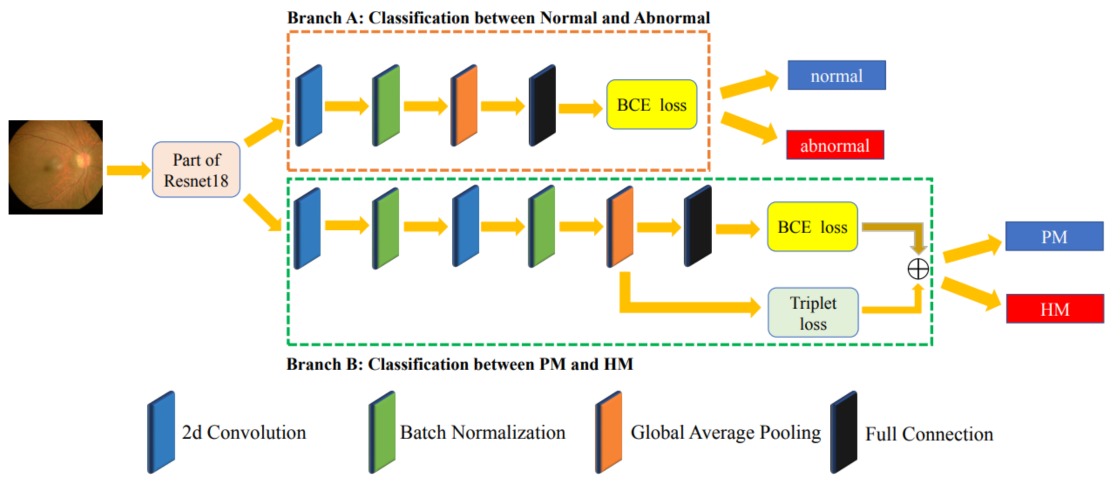

Figure 6 : Proposed Architecture Automatic Detection of Pathological Myopia and High Myopia on Fundus Images

The proposed method for detecting and differentiating pathological myopia (PM) and high myopia (HM) from fundus images employs a two-branch deep learning network architecture based on ResNet18. The network first classifies images into normal and abnormal (myopic) categories using the initial branch, and then the second branch further distinguishes between PM and HM for the abnormal cases. To improve accuracy, the method combines Binary Cross-Entropy (BCE) loss for the normal-abnormal classification with Triplet loss for the PM-HM classification, a technique typically used in face recognition to separate similar classes by increasing the distance between them. The model is trained and tested on a private dataset, with preprocessing steps that include resizing images and applying random transformations such as flipping and rotation for robustness. The combined loss functions and dual-branch approach enable the network to perform precise classifications, with experimental results showing high performance in accuracy, precision, and sensitivity, especially in distinguishing PM from HM, addressing a significant challenge in automated myopia diagnostics.

3. PROBLEM STATEMENT

The problem statement, "Automatic detection of pathological myopia and high myopia using fundus images" focusses on the creation of a computer-based system or algorithm that can identify and classify the cases of pathological and high myopia using fundus photographs. This system intends to automate the detection process, hence increasing diagnostic accuracy and efficiency.

4. SOFTWARE REQUIREMENT & SPECIFICATION

1. Functional Requirements:
   - User Registration: Users must register using their personal information. Once registered, the administrator verifies their identity and grants them access to the system.
   - CNN Algorithm for Detection: The method employs CNN to evaluate fundus pictures and identify myopia via image classification.
   - Data Loading: The system will import and process picture datasets for analysis.

2. External Interface Requirements:
   - User interface: The system will provide an easy to learn user interaction, which can include process for entering data and facilitating users output view.
   - Hardware Interfaces: It should have minimum 8GB RAM and Intel i5 processor to manage Computational Needs of CNN. A capacity of 40GB on the hard disk drive must also be reserved for storage.

3. Software Interfaces:
   - Operating System: Windows 10
   - IDE (Integrated Development Environment): You will need for coding is Anaconda Navigator as it is good with python the code language.
   - Programming Language: As the high-performance libraries are crucial to machine learning tasks, Python 3.8 is introduced as native programming language.

4. Non-Functional Requirements:
   - Efficiency: The system must have high performance levels with nearly instantaneous image processing, and timely responses.

- Reliability: The system is designed in a modular way allowing it to fail and be debugged, without affecting the entire system.
- Protection: Lets multiple levels of security through checks to confirm and verify legitimate users from using data.

5. System Requirements:
    - Software: The system needs SQLite for the database and Jupyter Notebook as an IDE.
    - Hardware: An Intel i3 or higher system, 8GB of RAM and minimum disk space availability is mandatory for optimum performance.

The system specification resulted in what will be a robust, secure and user-friendly CNN-based myopia detection tool that is able to properly handle the computational requirements of image processing.

5. FLOWCHART

The flowchart describes the steps for diagnosing pathological and high myopia in fundus pictures. It starts with image upload, then preprocessing to increase quality. Key characteristics, such as retinal thickness and optic disc form, are extracted. A CNN identifies the pictures as normal, abnormal, or excessive myopia. The findings are displayed and saved to a database for future use, ensuring efficient and precise detection.

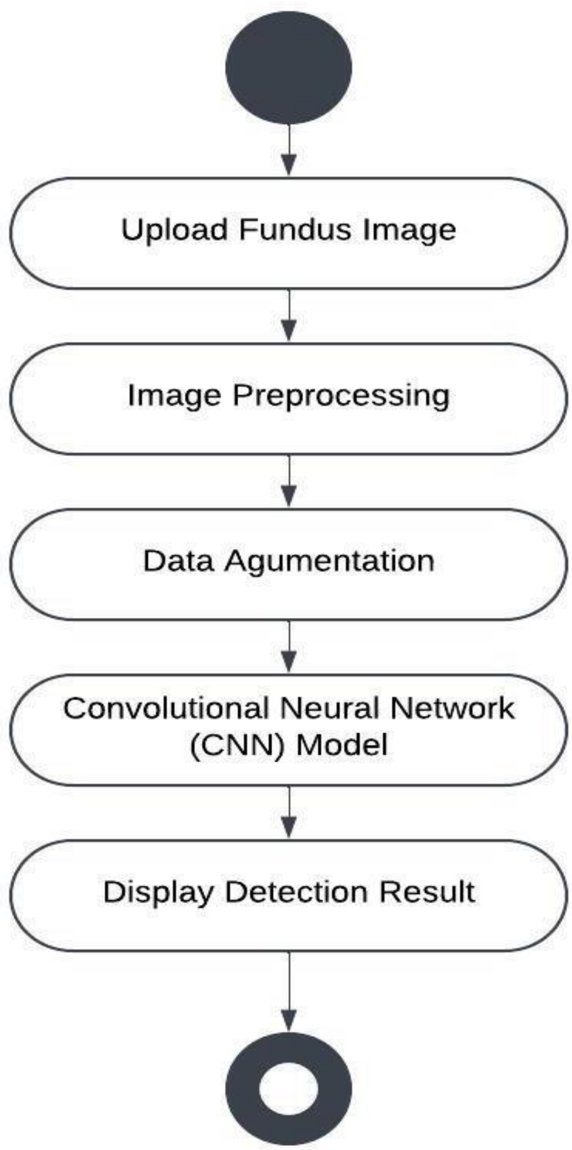

Figure 7: Flowchart of myopia detection

6. PROJECT REQUIREMENT SPECIFICATION

1. Software Requirements:

- Python: The project relies on Python due to its robust libraries for deep learning and image processing. Python’s dynamic nature and comprehensive ecosystem make it an ideal choice for developing CNN-based applications.
- Anaconda Navigator: Anaconda Navigator is chosen as it provides a user-friendly interface and simplifies the management of packages, environments, and IDEs (like Jupyter Notebook and Spyder) essential for scientific computing and machine learning tasks. This setup enhances coding efficiency and debugging during the development process.
- SQLite: In this project, SQLite is used to create a sqlite file where user data and fundus image analysis results are stored.

2. Hardware Requirements:

   Processor: An Intel i3 processor or higher is necessary for handling the computational load of training and running CNN models.

   RAM: A minimum of 8GB RAM is required to efficiently process images and execute machine learning algorithms.

   Hard Disk: At least 20GB of storage space is needed to store image datasets, processed data, and application files.

3. Operating System:

   The system will be developed on and must run on Windows 10 or higher to ensure compatibility with required software and hardware resources.

By following these project specifications, the system will be able to identify myopia utilizing advanced image processing and machine learning techniques, while also running smoothly and efficiently on the appropriate hardware and software configuration.

7. PROPOSED SYSTEM ARCHITECTURE

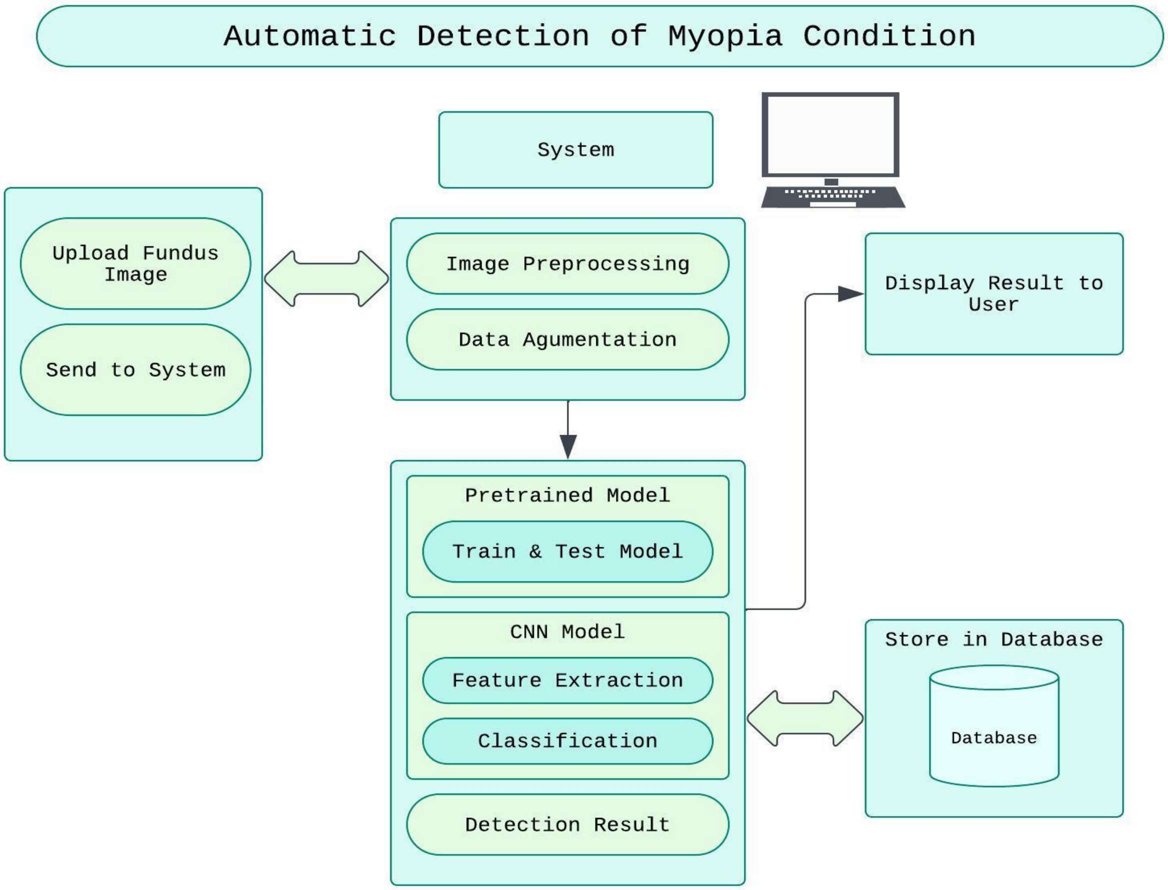

Figure 8 : System Architecture

- Components of the System Architecture:
- Upload Fundus Image: The user uploads a fundus (eye) image, which serves as input data for the system.
- Send to System: The uploaded image is sent to the system for further processing.
- Image Preprocessing: The system processes the raw images to make them suitable for analysis. This step involves:
    - Noise Removal: Any irrelevant noise or blur in the images is removed to enhance clarity.
    - Data Cleaning: The method standardises photos for reliable feature extraction.

    - Image transformation : Image transformation involves converting data into forms that the CNN can readily analyse. This involves resizing photos and altering colour contrast as appropriate.

  This step ensures that the images are clear, of high quality, and free from distortions, which is critical for precise detection.

- Data Augmentation: Techniques are applied to increase the amount and diversity of training data (e.g., rotating, flipping, or scaling the image) to help the model generalize better.
- Pretrained Model: A model that has been previously trained on a similar dataset is used, which saves time and can improve performance. This model undergoes additional training and testing on myopia data. The system splits the data to train and test the model's performance to ensure it correctly detects myopia.
- CNN Model: A Convolutional Neural Network (CNN) is employed for deep learning analysis, with two main functions:
- Feature Extraction: Important features are automatically extracted from the image for further processing.
- Classification: Based on extracted features, the model classifies the image to determine if myopia is present.
- Detection Result: The output of the classification is the detection result, which indicates the presence or absence of myopia.
- Display Result to User: The final detection result is displayed to the user.
- Store in Database: The detection result is saved in the database for record-keeping or future reference.

8. HIGH LEVEL DESIGN

The project's high-level design is concerned with the architectural and functional blueprint of the system for Automatic Detection of Pathological Myopia and High Myopia Using Fundus Images. This design explains the primary components, their relationships, and data flow inside the system, which is based on picture categorization using Convolutional Neural Networks (CNNs).

The Data Flow Diagram (DFD) gives a high-level perspective of the system, demonstrating how fundus pictures are processed from input to output.

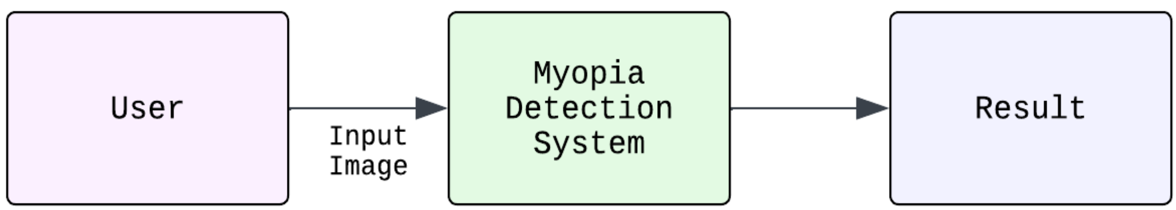

Figure 9 : Data Flow Diagram 0

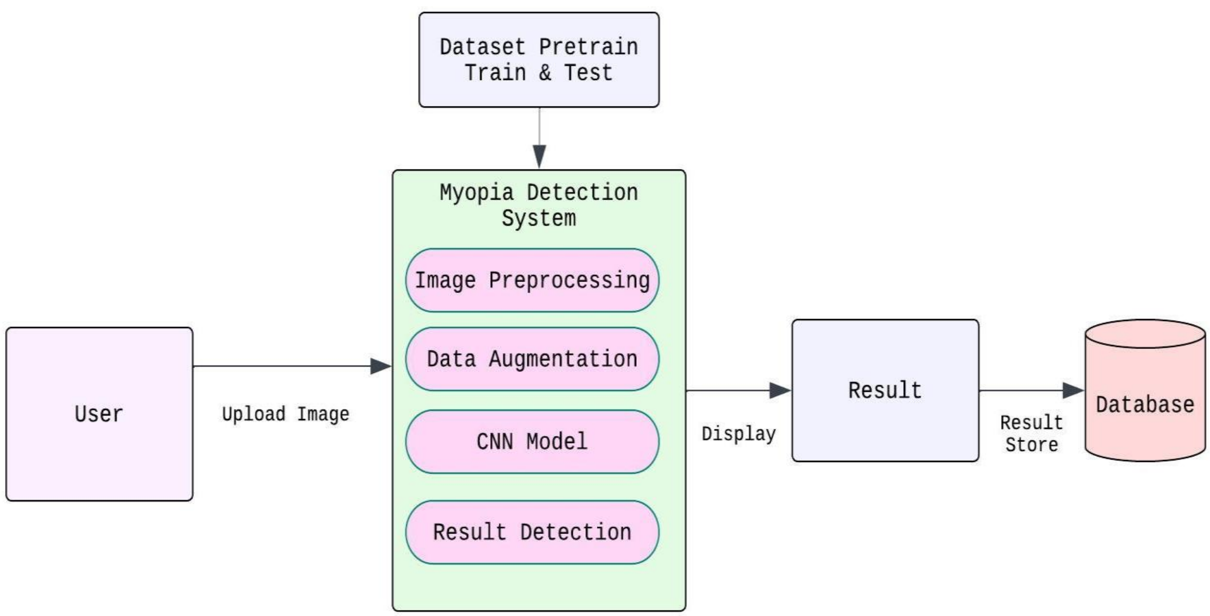

Figure 10 : Data Flow Diagram 1

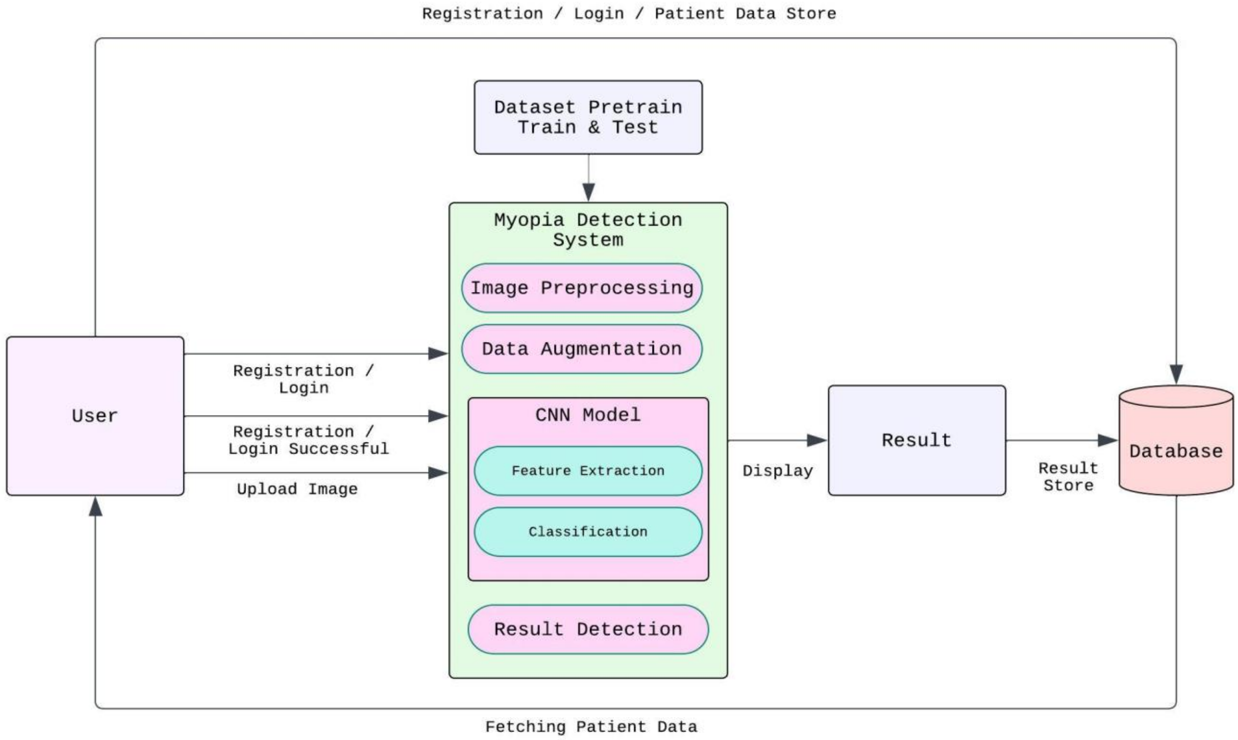

Figure 11 : Data Flow Diagram 2

The ERD illustrates the relationships between various entities in the system, including:

- User Entity: Stores information about users, such as personal details and login credentials.
- Image Data Entity: Contains data related to uploaded fundus images.
- Detection Results Entity: Stores information about the classification results, including whether a case of myopia is detected and its severity.
- Admin Entity: Manages the user verification and overall system maintenance.

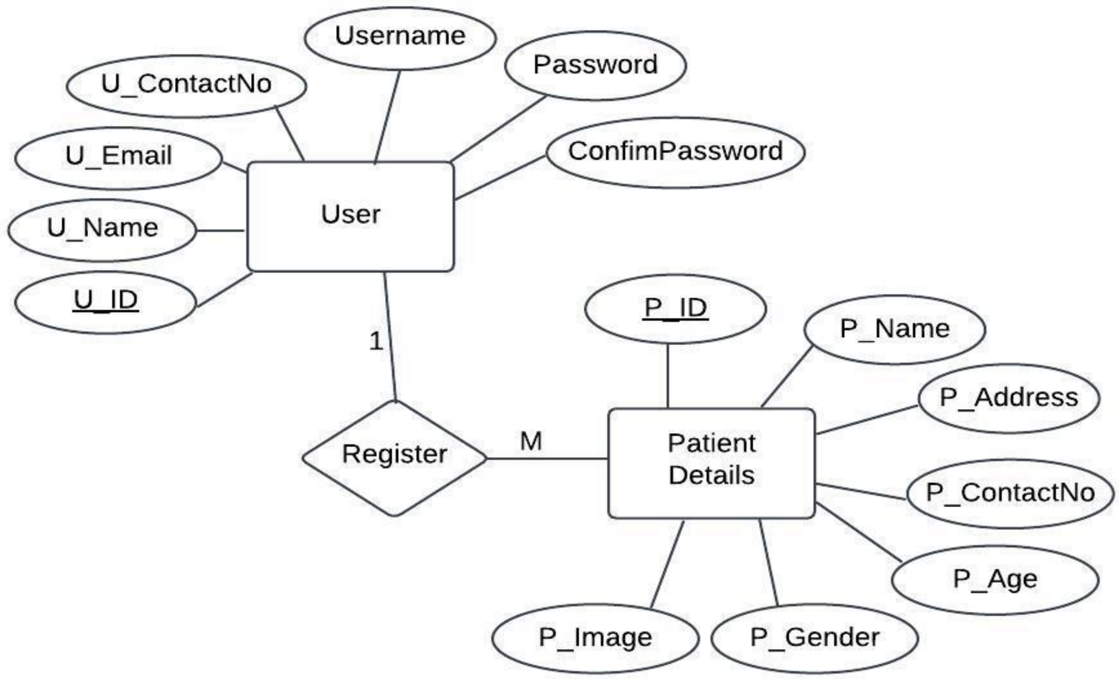

Figure 12: Entity Relationship Diagram

UML Diagrams

- Class Diagram: The class diagram represents the static structure of the system, showing classes, attributes, methods, and the relationships between them. Key classes include:
    - User: Handles user registration and login.
    - Fundus Image: Manages the uploaded images, including their preprocessing and feature extraction.
    - CNN Model: Represents the core CNN responsible for classifying the fundus images.
    - Result: Stores the results of the classification, including the severity of myopia detected

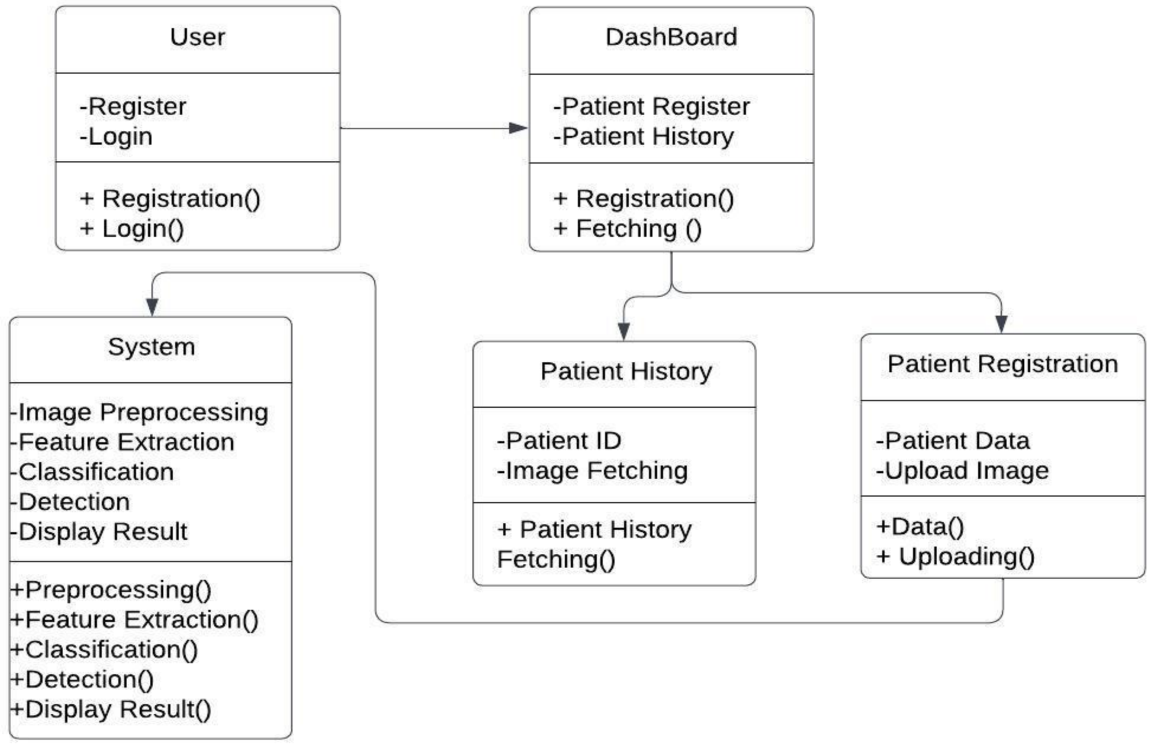

Figure 13: Class Diagram

Use Case Diagram: The use case diagram shows the interactions between users (patients, doctors, or healthcare professionals) and the system:

- User Registration and Login: Users must first register and be verified before accessing the system.
- Upload Fundus Images: Users can upload retinal images for analysis.
- View Results: The system returns the results of the myopia detection.

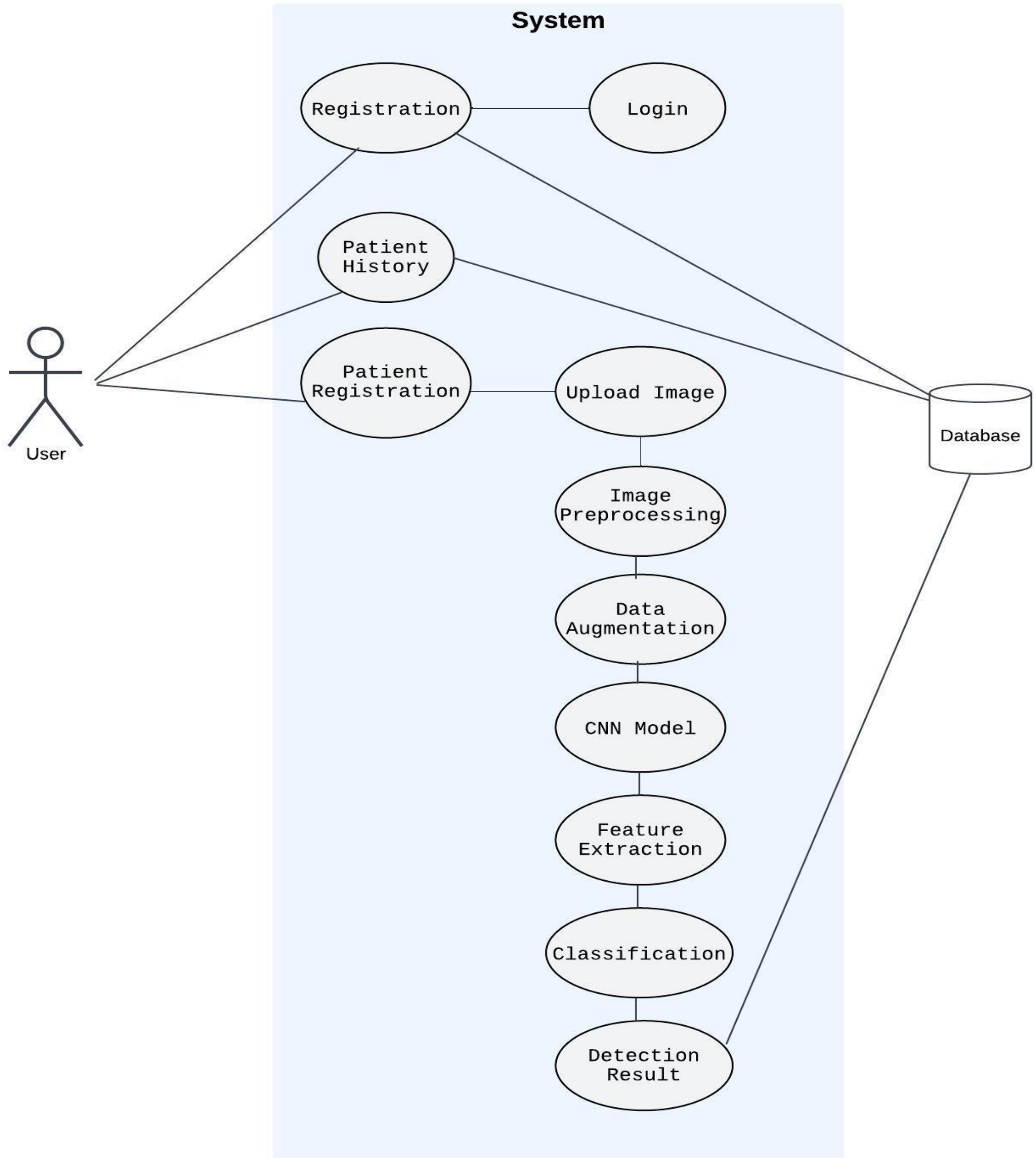

Figure 14: Use Case Diagram

Sequence Diagram: The sequence diagram visualizes the interactions between objects over time. It highlights:

- User uploading a fundus image.
- System preprocessing the image and feeding it to the CNN for classification.
- CNN returning the classification result to the user.

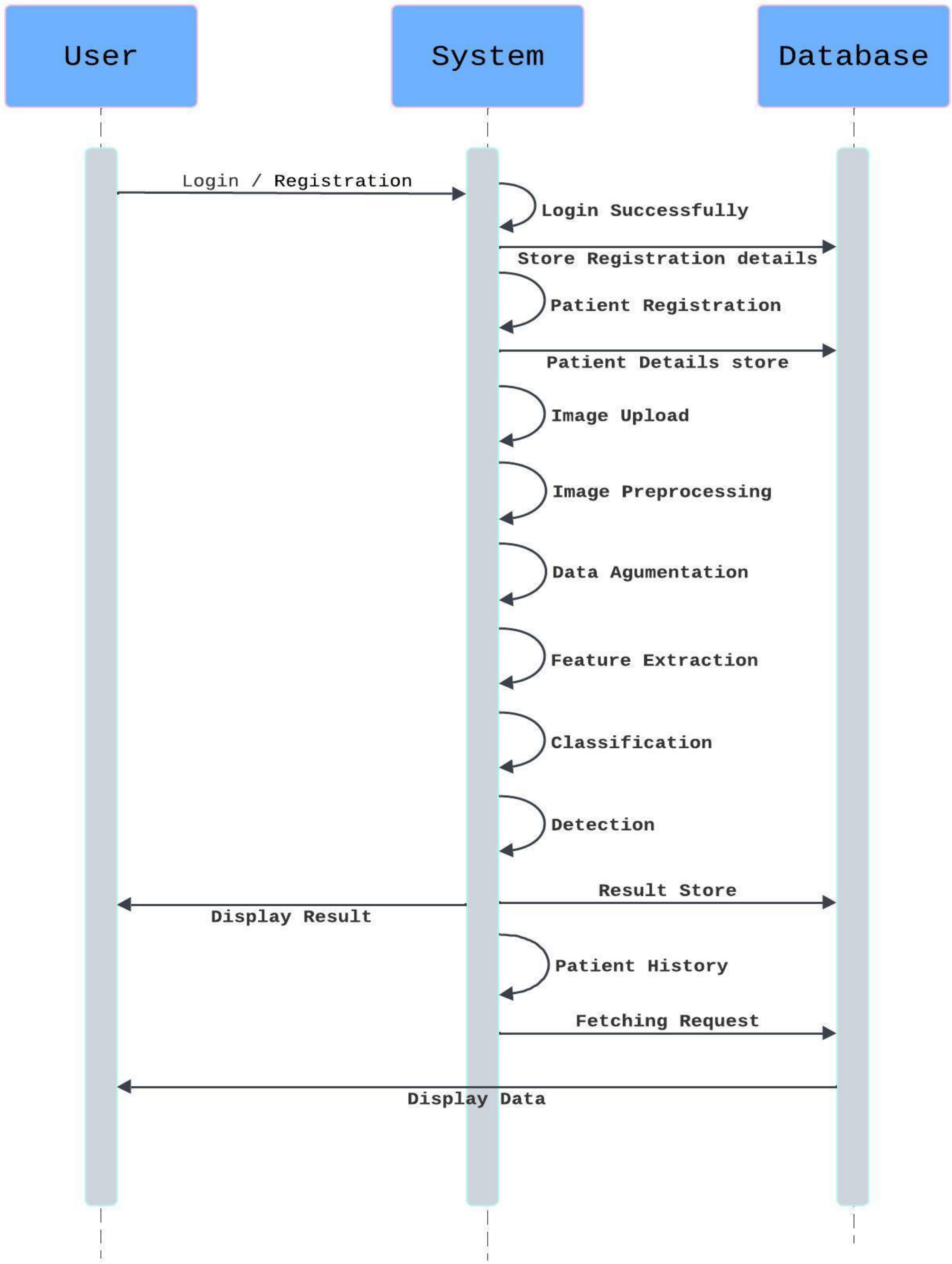

Figure 15 : Sequence Diagram

9. SYSTEM IMPLEMENTATION

The system's methodology can be divided into key steps that ensure a smooth flow from input to output, using CNN for myopia detection:

1. Upload Image & Send to System

    - Upload Image: The user (e.g., a doctor or technician) uploads a fundus (retinal) image to the system. This image serves as the primary input for the detection model. It is essential to use a high-quality image to ensure accurate analysis.
    - Send to System: Once uploaded, the image is sent to the system, where it undergoes a series of preprocessing and analysis steps. The system receives the image as input data to prepare it for further processing.

2. Image Preprocessing

    - Purpose: Image preprocessing is performed to improve the quality and consistency of images, making them suitable for the machine learning model. The quality of input data can significantly impact model performance, so preprocessing ensures optimal image clarity and uniformity.
    - Techniques: Common preprocessing techniques include:
        - Resizing: Adjusting the image dimensions to a fixed size suitable for the model.
        - Normalization: Scaling pixel values to a range (e.g., 0-1) to standardize input.
        - Noise Reduction: Removing irrelevant noise or artifacts that may affect model accuracy.
    - Outcome: A cleaned, standardized image that is ready for data augmentation or direct model input.

3. Data Augmentation

- Purpose: Data augmentation artificially increases the size and diversity of the training dataset, helping prevent overfitting and enhancing the model's ability to generalize to new data.
- Techniques: Common data augmentation techniques include:
    - Rotation: Rotating the image by various angles.
    - Flipping: Horizontally or vertically flipping the image.
    - Scaling: Zooming in or out on the image.
- Outcome: A diverse set of images generated from the original image, improving the model's ability to recognize myopia across varying conditions.

4. Training & Testing of Data

- Data Split: The dataset is divided into training and test sets. The model is trained using a labeled dataset of fundus images.
- The model is validated on a separate set of images to ensure generalization and accuracy in predictions.
- Training Set: Used to train the model, enabling it to learn patterns associated with myopia detection.
- Test Set: A separate set used only after training is complete, to evaluate the model's final performance.
- Loss Function: Cross-entropy loss is used for classification tasks to measure the difference between predicted and actual labels.
- Optimization: The Adam optimizer is used to update the weights of the CNN during training. Adam combines the benefits of both momentum and RMSprop, making it ideal for handling sparse gradients.
- Training Process: During training, the model learns to identify and differentiate features associated with myopia by minimizing error through backpropagation.

- Validation Process: The model’s accuracy and other metrics are monitored on the validation set to ensure it’s generalizing well and not just memorizing the training data.
- Outcome: A well-trained model that can accurately classify fundus images.

5. CNN Model for Feature Extraction & Classification

- Feature Extraction: The CNN (Convolutional Neural Network) model extracts key features from the input images, such as shapes, textures, and patterns, which are essential in identifying the condition of the eye.
    - Convolution Layers: These layers apply filters to the input image to detect local patterns, such as edges, which help in recognizing structures in the eye.
    - Pooling Layers: Pooling layers reduce the spatial size of the data, preserving important features while reducing computation.
- Classification: After feature extraction, the CNN classifies the image into one of three categories:
    - Normal Eye: No signs of myopia.
    - High Myopia Eye: Indicates severe myopia, characterized by certain retinal changes.
    - Pathological Myopia: A more advanced condition that includes structural damage and higher risk of complications.

6. Detection of Category

    - Classification Decision: Based on the probabilities from the CNN model, the system determines the most likely category for the eye condition.
    - Output: The final detection result is prepared, indicating whether the image belongs to the "Normal," "High Myopia," or "Pathological Myopia" category.

7. Display Result

    - User Interface: The result is displayed to the user

8. Store Result, User Information & Patient Information in Database

    - Result Storage: The detection results are stored in a structured database for record-keeping and future analysis

This system implementation process ensures that the model is effective, user-friendly, and secure, offering accurate myopia condition detection in a real-world setting.

10.TEST CASES

Below are the key test cases for validating the system for Automatic Detection of Pathological Myopia and High Myopia Using Fundus Images. These test cases ensure the system’s functionality, reliability, and performance across different scenarios.

GUI Testing -

01	Test Case	Login Screen - Sign up
	Objective	Click on sign up button, then check all required/mandatory fields by leaving all fields blank.
	Expected Result	All required/mandatory fields should display with the symbol .*The instruction line “* field(s) are mandatory” should be displayed.
02	Test Case	Create a Password >> Text Box Confirm Password >> Text Box
	Objective	Check the validation message for Password and Confirm Password fields.
	Expected Result	Correct validation message should be displayed accordingly, or “Password and confirm password should be the same” in place of “Password mismatch”.

Table 1: GUI Testing

Login Test case:

Test Case Id	Test Case	Test Case I/P	Actual Result	Expected Output	Test Case Criteria
01	Enter the wrong username or password click on submit button	Username and password	Error comes	Error should come	Pass
02	Enter the correct username or password click on submit button	Username and password	Accept	Accept	Pass

Table 2 : Login Test Case

Registration Test case:

Test Case ID	Test Case	Test Case I/P	Actual Result	Expected Result	Test Case Criteria (P/F)
01	Enter the number in username, middle name, last name field	Number	Error Comes	Error Should Come	Pass
	Enter the character in username, middle name, last name field	Character	Accept	Accept	Pass
02	Enter the invalid email id format in email id field	kkgmail.com	Error Comes	Error Should Come	Pass
	Enter the valid email id format in email id field	kk@gmail.com	Accept	Accept	Pass
03	Enter the invalid digit number in phone no field	99999	Error Comes	Error Should Come	Pass
	Enter the 10 digit number in phone no field	9999999999	Accept	Accept	Pass

Table 3 : Registration Test Case

Test Cases :

Test Case ID	Test Case Description	Input Data	Expected Output	Actual Output	Status
1	User Registration	User details	Successful registration, user saved in the database	Registration successful	Pass
2	User Login	Valid Username and Password	Successful login	Logged in successfully	Pass
3	Invalid User Login	Invalid Username/Password	Error message: "Invalid credentials"	Error message displayed	Pass
4	Upload Fundus Image	Valid image file	Image uploaded and stored successfully	Image uploaded successfully	Pass

5	Upload Invalid Image File	Invalid image file format	Error message: "Invalid file type"	Error message displayed	Pass
6	Image Preprocessing	Fundus image	Image processed, resized, and enhanced	Image processed successfully	Pass
7	Myopia Detection – Normal Case	Fundus image without myopia	Output: "Normal"	Output: "Normal"	Pass
8	Myopia Detection – Pathological Myopia Case	Fundus image with PM	Output: "Pathological Myopia Detected"	Output: "Pathological Myopia"	Pass
9	Myopia Detection – High Myopia Case	Fundus image with high myopia	Output: "High Myopia Detected"	Output: "High Myopia"	Pass
10	System Response Time for Image Upload and Detection	Fundus image	Process completed within 3 seconds	Process completed in 2.5 sec	Pass
11	Data Storage - Detection Results	Results	Data saved in the database	Data saved successfully	Pass
12	User Logout	Click Logout	Successful logout	Logged out successfully	Pass
13	Image Upload with No Image Selected	No image selected	Error message: "Please select an image to upload"	Error message displayed	Pass

Table 4: Test cases

11.PROPOSED GUI WORKING MODELS

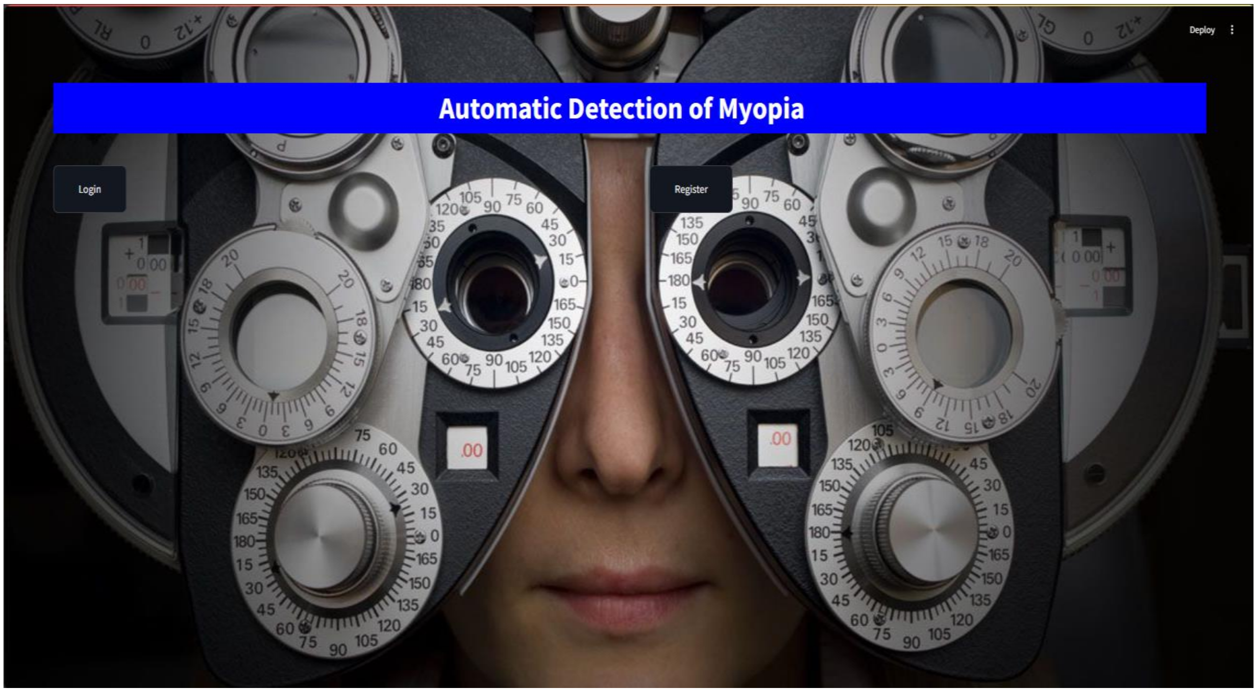

Figure 16: Home Page

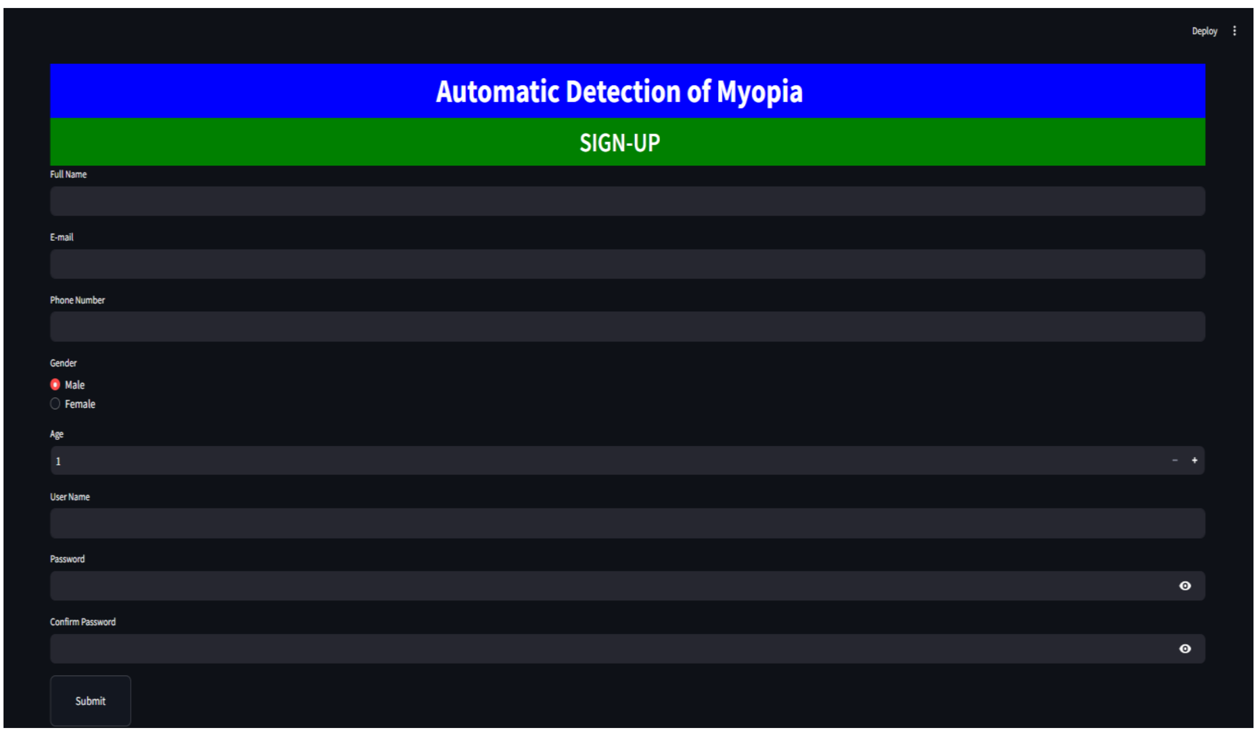

Figure 17: Registration Page

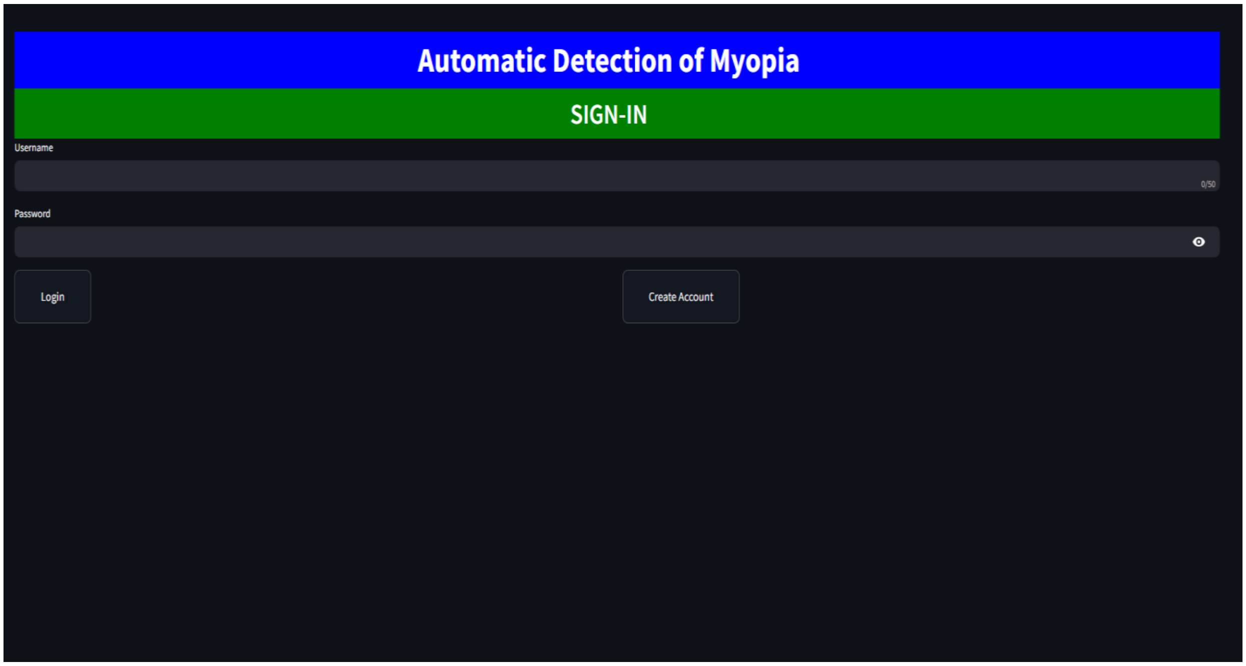

Figure 18: Login Page

Figure 19: Dashboard Page

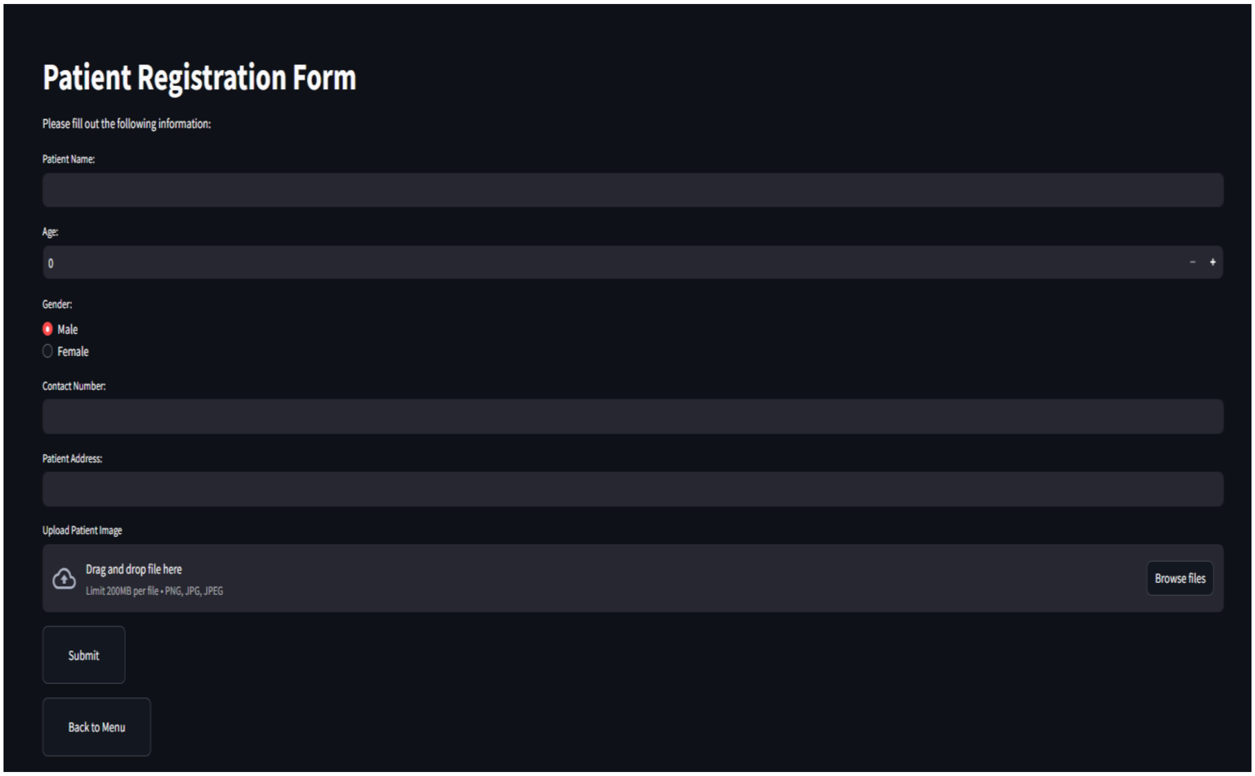

Figure 20: Patient Registration Form Page

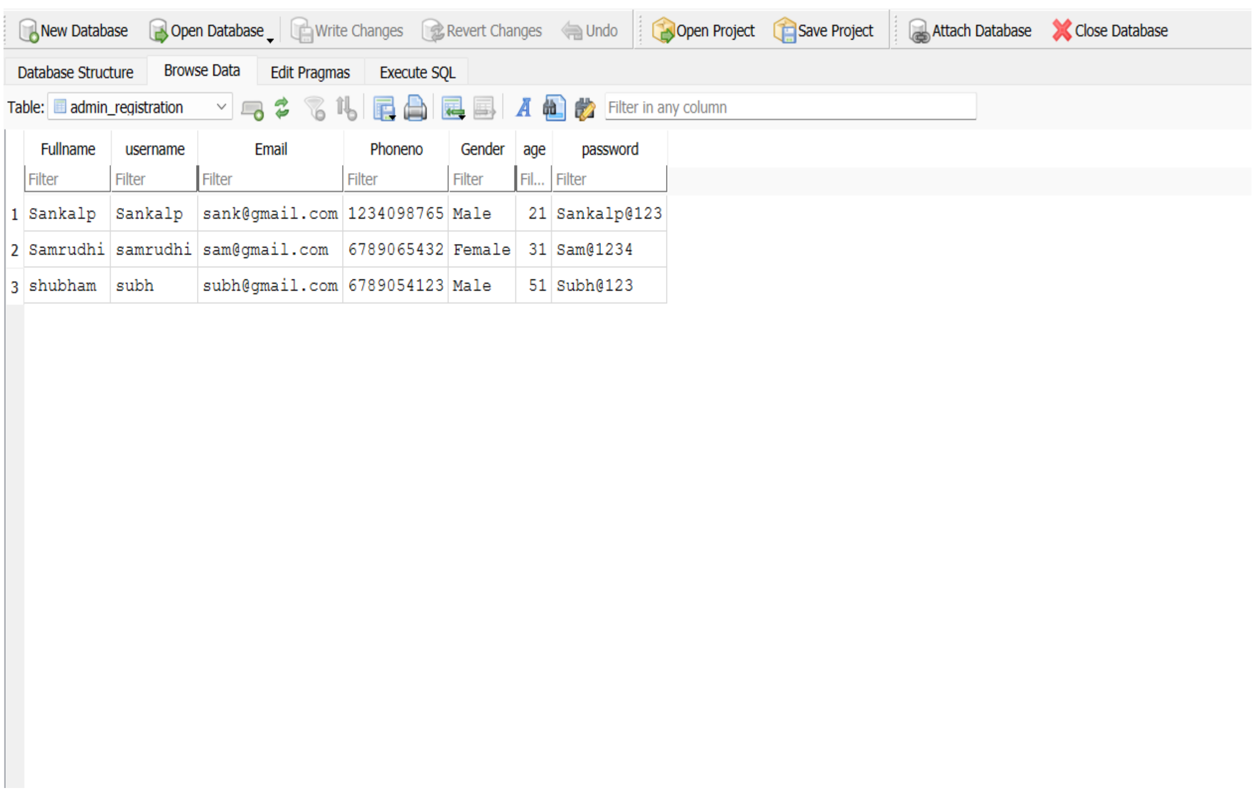

Figure 21: Register Data

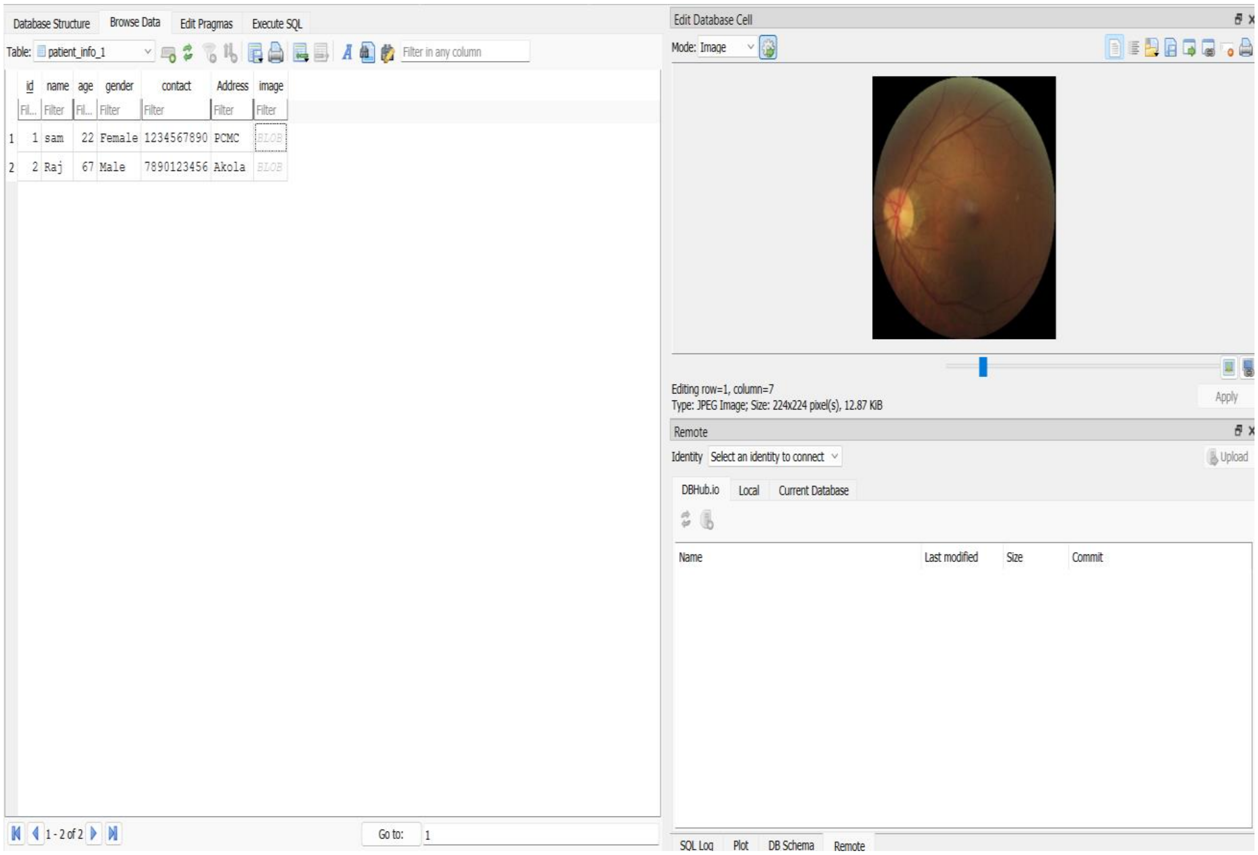

Figure 22: Patient Register Data

12.PROJECT PLAN

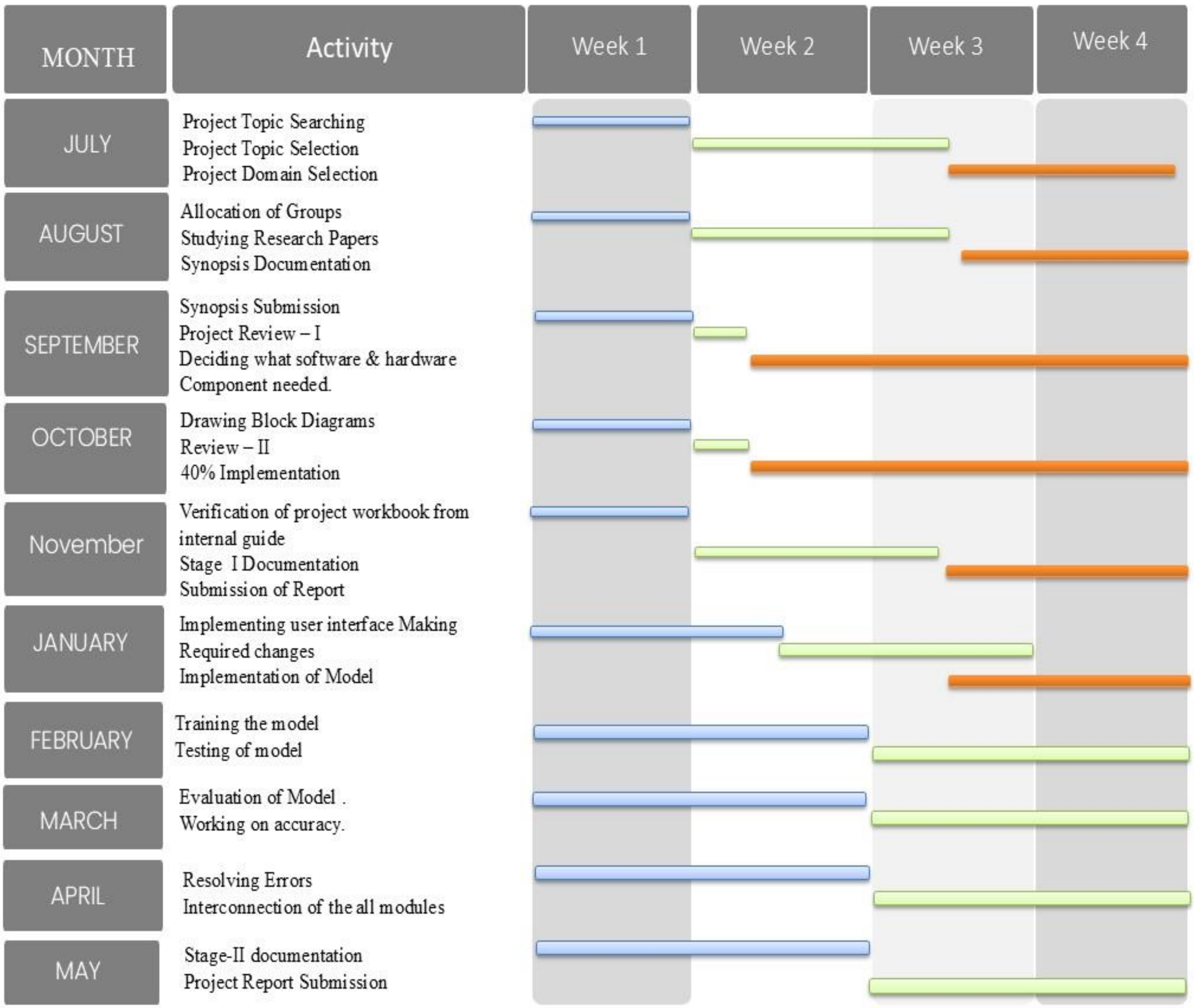

Figure 23: Gantt Chart

13. CONCLUSION

This project will develop an automated system for detecting pathological and high myopia using fundus images and Convolutional Neural Networks (CNNs). The system aims to improve diagnostic accuracy by classifying images into normal, pathological, or high myopia categories, enabling early detection and intervention. It will reduce manual effort, enhance efficiency, and provide a user-friendly tool for healthcare professionals, showcasing the potential in addressing myopia-related vision issues.

14. REFERENCES

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15.APPENDICES