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PROJECT REPORT

On

HEART ATTACK RISK PREDICTION USING RETINAL IMAGES

Submitted in partial fulfilment for the award of degree

of

Master of Computer Applications

By

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DEPARTMENT OF COMPUTER APPLICATIONS

MANGALAM COLLEGE OF ENGINEERING, ETTUMANOOR

(Affiliated to APJ Abdul Kalam Technological University)

APRIL 2025

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CERTIFICATE

*This is to certify that the Project titled **"Heart Attack Risk Prediction Using Retinal Images"** is the bonafide record of the work done by **Parvathy Mohanan (MLM23MCA-2037)** of Masters of Computer Applications towards the partial fulfilment of the requirement for the award of the **DEGREE OF MASTERS OF COMPUTER APPLICATIONS by APJ ABDUL KALAM TECHNOLOGICAL UNIVERSITY**, during the academic year 2023-25.*

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ABSTRACT

Cardiovascular disease (CVD) remains the leading cause of morbidity and mortality worldwide. Early detection and risk assessment of cardiovascular diseases are important for effective prevention and timely intervention. An analysis of deep learning methods used for prediction of CVR based on RFI. Since it is an extension of central nervous system, the retina gives an exceptional chance for safe medical diagnosis. Using multiple types of retinal fundus images together with the patient and clinical data, we developed a new deep learning model for prediction of several vital parameters for cardiovascular diseases. With CNN, it is possible to extract relevant features from retinal images without involving any manual procedures. The main aim of our study is to predict hypertension, diabetes and hyperlipidemia, which are risk factors for cardiovascular diseases. Our deep learning model achieves incredible accuracy in identifying high-risk individuals by identifying changes in brain vessels, microaneurysms, and other signs of pathology. Additionally, the model provides good information about the relationship between the visibility of the eye and the severity of these problems. We also consider ways of interpreting predictive models which help us understand how retinal changes relate to CV risk based on pathophysiological mechanism. Such research can lead the doctors on how to improve themselves if possible and intervene earlier for the sake of preventing this health condition.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

ABBREVIATION		FULL FORM
CVD	-	Cardiovascular disease
CNN	-	Convolutional Neural Networks
AI	-	Artificial Intelligence
CT	-	Computer Tomography
OCT	-	optical coherence tomography
RNN	-	recurrent neural networks
DFD	-	Data Flow Diagram

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Cardiovascular disease (CVD) is a leading cause of death and disability worldwide, affecting millions of people every year. The nature of these diseases is such that they are often preventable, especially when detected early. Early identification of risk factors such as hypertension, diabetes, and unhealthy lifestyle habits can significantly reduce the burden of cardiovascular diseases. In recent years, the intersection of clinical medicine and artificial intelligence (AI) has emerged as a powerful tool to improve cardiovascular disease detection and management. One of the most intriguing areas of research in this domain is the connection between retinal images and heart disease. The retina, being an extension of the central nervous system, shares similar blood vessels with the heart. Changes in these retinal blood vessels can indicate a person’s overall cardiovascular health, revealing early signs of conditions such as hypertension, diabetes, and even heart disease. Studies have shown that abnormalities in retinal blood vessels, such as microaneurysms, hemorrhages, and changes in vessel caliber, are indicative of underlying cardiovascular problems. This connection highlights the potential of using retinal imaging as a non-invasive and cost-effective method for predicting heart disease.

1.2 INTRODUCTION

Cardiovascular diseases, particularly heart disease, remain the primary cause of death globally. This underscores the importance of early detection and effective management to reduce the risk of life-threatening complications. The proposed system aims to utilize cutting-edge machine learning and artificial intelligence techniques to predict heart disease accurately. Machine learning, particularly through neural networks such as Convolutional Neural Networks (CNN), has shown great promise in analyzing complex health data and making predictions. This research leverages vast amounts of data, such as retinal images, to predict cardiovascular health and potentially prevent heart attacks before they occur. In today’s healthcare landscape, the need for simple, non-invasive, and accurate diagnostic tools is growing. Traditional diagnostic methods can be costly, invasive, and often require specialized equipment. By incorporating AI and machine learning algorithms, this research focuses on making cardiovascular disease prediction tools more accessible and effective. The goal is to create a system that not only predicts heart disease but also tailors predictions to each individual's unique health profile, ultimately contributing to BB personalized medicine and better preventive care.

1.3 PROBLEM STATEMENT

The primary focus of this research revolves around identifying and predicting the various factors that contribute to cardiovascular diseases. Heart-related illnesses such as heart attacks, strokes, and other cardiovascular conditions remain leading causes of death globally. Traditional methods of diagnosing heart disease often involve expensive procedures such as ECG, blood tests, and angiography, which may not always provide accurate or timely informationThe research proposes using advanced machine learning techniques, particularly Convolutional Neural Networks (CNNs), to analyze large sets of health data and provide more accurate predictions of heart disease risk. The aim is to bridge the gap between the current diagnostic methods and the need for a more precise, accessible, and non-invasive solution to predict heart disease.

1.4 MOTIVATION

Cardiovascular disease remains a top global health concern, making early detection a critical factor in reducing mortality and improving quality of life. Traditional diagnostic methods such as ECG, angiography, and blood tests often involve high costs, invasive procedures, and limited accessibility, particularly in low-resource settings. Advances in Artificial Intelligence (AI) and Deep Learning present an opportunity to develop a more affordable, non-invasive method for detecting heart disease risk. Retinal images, which capture the state of blood vessels in the eye, offer a unique and valuable insight into a person's cardiovascular health. Changes in retinal blood vessels are often linked to conditions such as hypertension, diabetes, and heart disease, making them a valuable indicator for early detection. This research leverages AI tools such as Inception v3, CNN, and AdaBoost algorithms to analyze retinal images and predict heart disease risk with a high degree of accuracy. The goal is to make early predictions about heart attack risk, enabling timely intervention and improving patient outcomes. By offering a more accessible and accurate method for heart disease detection, this research could have a transformative impact on healthcare, particularly in regions with limited medical resources.

1.5 SCOPE

Heart disease is one of the leading causes of mortality worldwide, emphasizing the need for early detection and prevention. This project aims to develop an AI-driven heart attack risk prediction system using retinal fundus images. By leveraging deep learning models such as Inception v3, Convolutional Neural Networks (CNN), and AdaBoost, the system can efficiently analyze retinal images to identify patterns and abnormalities associated with cardiovascular diseases.A key advantage of this approach is its non-invasive nature, making it a highly accessible screening tool for early heart disease detection. Traditional cardiovascular risk assessments often rely on factors such as blood tests and electrocardiograms, but this system offers a novel alternative by utilizing retinal imaging. The dataset used consists of thousands of labeled retinal fundus images, ensuring a well-trained model capable of accurate predictions.Future enhancements to this project could involve integrating additional patient health data, such as blood pressure, cholesterol levels, and lifestyle factors, to further refine risk assessment accuracy. The potential applications of this system extend to hospitals, telemedicine platforms, and large-scale health screening programs. By providing a scalable and accessible solution for heart disease prevention, this project has the potential to significantly impact global healthcare by enabling early intervention and reducing mortality rates.

CHAPTER 2
LITERATURE REVIEW

2.1. Prediction of Multiple Adverse Health Conditions from Retinal Images.

Author(s): Lakshmi Kala Pampana, Manjula Sri Rayudu

The paper Prediction of Multiple Adverse Health Conditions from Retinal Images by Lakshmi Kala Pampana, Manjula Sri Rayudu published in the IEEE Bangalore Humanitarian Technology Conference (B-HTC) 2020.During the recent years, lifestyle related diseases and disorders such as stress, hypertension and diabetes are increasing at a rapid rate in the middle aged population also These disorders may have greater likelihood of developing multiple adverse health conditions like cardiovascular strokes, cerebrovascular strokes, kidney failures, depression etc. Preventive diagnosis measures are required to diagnose these adverse health hazards in the middle aged group. These days the health care sector is equipped with sophisticated instruments to diagnose the abnormalities in specific organs using different modalities like Computer Tomography(CT), Magnetic Resonance Imaging(MRI), Positron Emission Tomography(PET), Ultrasonography scans, X-Ray, etc. Retinal vascular imaging has its popularity in diagnosing several ocular diseases viz, Diabetic Retinopathy(DR), Age related Macular Degeneration(AMD), Edema, Glaucoma, etc using the latest advancements in Artificial Intelligence with the aid of modalities like Retinal Fundoscopy, Optical Coherence Tomography(OCT), confocal scanning laser ophthalmoscope (cSLO). As per the clinical based studies, the retina shares similar physiological and anatomical features with vital organs hence it is million worthwhile to say that retinal vascular imaging could predict the multiple adverse health conditions like Cardiovascular(CVD), Cerebrovascular(CVS), Chronicle Kidney Diseases(CKD), Breast Cancer and Pulmonary Diseases.

2.2. Disease Prediction based on Retinal Images.

Author(s):S.N. Shivappriya,Harikumar Rajaguru, M.Ramya,U. Asiyabegum, D.Prasant

The paper Disease Prediction based on Retinal Images by S.N. Shivappriya,Harikumar Rajaguru, M.Ramya,U. Asiyabegum, D.Prasanth published in the 2021 Smart Technologies, Communication and Robotics (STCR).The human eye serves as a window to various health conditions, particularly those affecting the cardiovascular and nervous systems. Retinal fundus imaging has emerged as a powerful tool in medical diagnostics, enabling the detection of various disorders such as diabetes, hypertension, and heart disease. The major objective of this research is to establish a framework that can effectively identify these diseases by analyzing retinal fundus images. Retinal fundus images provide detailed views of blood vessels, including both arteries and veins, which are highly correlated with brain and heart functioning. Changes in the structure and morphology of these vessels can serve as indicators of underlying health conditions. The ability to distinguish between arteries and veins is crucial for diagnosing diseases related to the circulatory system. By leveraging advanced deep learning techniques, this project aims to automate the identification and classification of such anomalies. Following the preprocessing and segmentation stages, the images undergo analysis using Convolutional Neural Networks (CNNs). CNNs are highly effective in image classification tasks as they can automatically learn and extract relevant features from images.The CNN model used in this project is trained to recognize key features associated with diseases by analyzing differences in retinal structures. These features include the thickness, curvature, and branching patterns of blood vessels, which are significant indicators of various medical conditions.

2.3 Cardiovascular Disease Prediction from Retinal Images using Machine Learning

Author(s): Biji Rose; S Kavya; S Rachana; E Manisha

The paper titled Cardiovascular Disease Prediction from Retinal Images using Machine Learning by Biji Rose, S Kavya, S Rachana, and E Manisha, published in the 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), explores how retinal imaging and machine learning can aid in the early detection of cardiovascular diseases (CVDs), specifically hypertension and heart attacks.Cardiovascular diseases significantly impact the microvascular structure and function, particularly through conditions such as hypertension. The human eye serves as a window to various health conditions, particularly those affecting the cardiovascular and nervous systems. Retinal fundus imaging has emerged as a powerful tool in medical diagnostics, enabling the detection of various disorders such as diabetes, hypertension, and heart disease. The major objective of this research is to establish a framework that can effectively identify these diseases by analyzing retinal fundus images. Changes in retinal blood vessels serve as indicators of these conditions. The paper highlights how retinal images, captured using a fundus camera, reveal abnormalities in the vascular structure that can indicate early signs of cardiovascular damage. Traditional methods of diagnosing such conditions rely on clinical observations and invasive techniques, whereas this research focuses on utilizing machine learning and artificial intelligence (AI) for early detection.The methodology employed in the study involves collecting retinal images of individuals diagnosed with hypertension and heart attacks. Machine learning techniques are then used to analyze these images by extracting morphological characteristics of the retinal blood vessels. To enhance the accuracy of diagnosis, the vessel segmentation method is applied, which removes interference data—elements unrelated to the retinal vasculature—so that only crucial morphological details remain.

2.4 Diagnosis Of Cardio Vascular Diseases Using Retinal Fundus Scans Via Deep Learning

Author(s): Pryadarshne D; Sai Ruthvik Madireddy; M.P. Vaishnnave; Mercy Paul

The paper titled Diagnosis Of Cardio Vascular Diseases Using Retinal Fundus Scans Via Deep Learning by Pryadarshne D; Sai Ruthvik Madireddy; M.P. Vaishnnave; Mercy Paul published in the 2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE).Cardiovascular disease (CVD) remains a leading global health concern, necessitating early and accurate detection methods for effective intervention. This study presents a groundbreaking approach to CVD detection leveraging deep learning techniques applied to retinal fundus scans. Retinal fundus images provide detailed views of blood vessels, including both arteries and veins, which are highly correlated with brain and heart functioning. Changes in the structure and morphology of these vessels can serve as indicators of underlying health conditions.Retinal fundus scans offer a non-invasive, cost-effective, and easily accessible source of information for potential CVD risk assessment. The utilization of deep learning algorithms, such as Convolution Neural Networks (CNNs), has demonstrated remarkable promise in identifying subtle pathological changes within the retinal vasculature and optic nerve. This study reviews the current state of research on CVD risk prediction and highlights the potential of retinal fundus scans as a valuable diagnostic tool. The integration of deep learning methods facilitates the automatic extraction of intricate features from retinal images, enabling the development of accurate and efficient CVD detection models. By examining retinal vasculature, microaneurysms, hemorrhages, and other relevant features, these models can aid in early risk stratification and timely intervention. Furthermore, this study delves into the challenges and future prospects of this novel approach, emphasizing the importance of large, diverse datasets, model interpretability, and the integration of clinical data to enhance predictive accuracy

2.5 Detection and Prediction of Cardiovascular Disease Using Fundus Images with Deep Learning

Author(s): Victoria Willis; Bing Zhou; Qingzhong Liu

The paper Detection and Prediction of Cardiovascular Disease Using Fundus Images with Deep Learning by Victoria Willis; Bing Zhou; Qingzhong Liu published in the 2024 20th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD).The research focuses on using retinal fundus imaging, a non-invasive and cost-effective method, to assist in detecting and predicting cardiovascular risks. Fundus imaging captures detailed images of the retina, which can provide insights into vascular health. Since routine eye exams are common and widely accessible, leveraging these images for cardiovascular assessments presents a practical solution, particularly in cases where other medical data may not be readily available.The authors propose the utilization of deep learning techniques, specifically convolutional neural networks (CNNs) and transfer learning, to analyze fundus images. CNNs are widely recognized for their effectiveness in image processing tasks, as they can extract important features from medical images and identify patterns indicative of disease. Transfer learning, a technique that applies pre-trained models to new tasks, is also explored in the study to enhance the model's performance and reduce the computational cost of training from scratch.A key aspect of the study involves evaluating various transfer learning models and comparing their effectiveness in CVD detection and risk prediction. The researchers aim to determine which models provide the highest accuracy and efficiency in analyzing fundus images for cardiovascular assessment. By utilizing deep learning in this context, the study presents a promising avenue for improving early diagnosis and preventive care for individuals at risk of cardiovascular disease.This research is particularly significant as it addresses the challenge of limited availability of comprehensive medical data by relying solely on fundus images. If successful, the proposed methods could be integrated into standard eye exams, making CVD screening more accessible and cost-effective. The findings of this study have the potential to advance the field of medical imaging and artificial intelligence in healthcare, offering a new perspective on non-invasive cardiovascular risk assessment.

2.6 Prediction of Cardiovascular Diseases with Retinal Images Using Deep Learning

Author(s): Tumu Vineetha; Danda Rami Reddy; Kandimalla Mahendra; Ballanki Dhana Lakshmi

This paper Prediction of Cardiovascular Diseases with Retinal Images Using Deep Learning by Tumu Vineetha; Danda Rami Reddy; Kandimalla Mahendra; Ballanki Dhana Lakshmi published in the 2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI).The study leverages convolutional neural networks (CNNs) in conjunction with the MobileNet architecture to analyze retinal images with high accuracy. CNNs are renowned for their ability to extract intricate features from images, making them well-suited for medical image analysis. MobileNet, a lightweight deep learning model optimized for mobile and edge devices, enhances computational efficiency while maintaining high performance. By integrating these two architectures, the study aims to create a robust model capable of accurately identifying CVDs from retinal scans.A critical aspect of this research is the dataset used, which has been carefully curated to represent diverse clinical conditions. The preprocessing techniques applied to the dataset ensure enhanced model robustness and reliability. Image augmentation techniques, such as contrast enhancement, noise reduction, and normalization, are utilized to improve the model's generalization ability. This meticulous preprocessing helps the model handle variations in retinal images caused by different patient demographics, imaging devices, and pathological conditions.The study highlights the potential benefits of this deep learning approach in medical diagnostics. By enabling faster and more cost-effective CVD screening, the proposed system can assist healthcare professionals in early detection, risk stratification, and preventive measures. The model's ability to process retinal images efficiently suggests that it could be integrated into routine screenings, particularly in remote or resource-limited settings where access to cardiologists is scarce.Despite its promising results, the research acknowledges certain challenges, such as the need for extensive validation before clinical implementation. Ensuring that the model performs accurately across different patient populations and imaging conditions is crucial for its adoption in real-world medical practice.

CHAPTER 3

PROPOSED SYSTEM

To develop a deep learning-based system that utilizes retinal fundus images to predict cardiovascular risk (CVR) and identify high-risk individuals at an early stage. This system will leverage convolutional neural networks (CNNs) to automatically extract significant features from retinal images and combine them with clinical data to predict cardiovascular diseases.

Fundus images are captured using specialized ophthalmic imaging devices. These images serve as a rich source of information on the health of retinal vessels and microstructures.Retinal fundus images are processed to enhance quality and remove noise. This may involve image normalization, resizing, and contrast enhancement.A convolutional neural network (CNN) is employed to automatically extract relevant features from the retinal fundus images. CNNs are particularly effective at detecting visual patterns such as changes in retinal vasculature, microaneurysms, and other pathologies that may indicate cardiovascular issues. This multimodal approach enhances the model's ability to predict cardiovascular risk accurately by considering both visual and clinical health parameters.The deep learning model will be trained on a large dataset of labeled retinal images and corresponding clinical data. Supervised learning techniques, such as cross-entropy loss, will be used to train the model.A user-friendly interface will be developed for healthcare providers, where they can upload retinal images and input clinical data. The system will return a cardiovascular risk assessment, along with explanations of the results based on the retinal image features and clinical parameters.The system will be deployed on a secure cloud infrastructure to ensure scalability and real-time access. It will also be monitored regularly to ensure its performance remains optimal and to update it with new datasets for better prediction accuracy.

By combining retinal imaging with clinical data, the system can detect early signs of cardiovascular risk, enabling early intervention. The system provides a non-invasive means of assessing cardiovascular risk using retinal fundus images, reducing the need for more invasive diagnostic procedures.Scalability: The model can be scaled to handle large populations, making it suitable for widespread use in healthcare settings.The proposed system for cardiovascular risk prediction using deep learning methods on retinal fundus images and clinical data represents an innovative approach to cardiovascular disease prevention.

CHAPTER 4

METHODOLOY

The methodology for developing a deep learning-based system for cardiovascular risk (CVR) prediction using retinal fundus images and clinical data is outlined in the following steps:

1. Data Collection

1.1 Retinal Fundus Images

- **Data Source**: Retinal fundus images will be collected from publicly available datasets such as the **EyePACS**, **Kaggle Diabetic Retinopathy**, or other ophthalmic datasets. Alternatively, data from hospitals or medical research institutions could be used with proper consent and ethical clearance.
- **Image Acquisition**: Fundus images are captured using specialized cameras such as **fundus cameras** or **optical coherence tomography (OCT)** devices. These images provide detailed information about the retinal vasculature, microaneurysms, and other pathologies associated with cardiovascular risk.

2. Data Preprocessing

2.1 Image Preprocessing

- **Normalization**: The retinal images will be normalized to ensure consistency in image size and pixel values, typically resizing images to a standard size (e.g., 224x224 pixels).
- **Noise Removal**: Preprocessing techniques such as median filtering or Gaussian smoothing will be applied to remove any noise and enhance image quality.
- **Contrast Enhancement**: Adaptive histogram equalization or other contrast enhancement techniques will be applied to improve the visibility of important structures (e.g., blood vessels, microaneurysms).

2.2 Clinical Data Preprocessing

- **Data Cleaning**: Missing values will be handled using imputation techniques (e.g., mean imputation, KNN imputation).
- **Normalization**: Numerical clinical data (e.g., blood pressure, cholesterol levels) will be normalized to a standard scale to prevent model bias due to large differences in the range of clinical features.
- **Categorical Encoding**: Categorical features (e.g., gender, smoking history) will be encoded using one-hot encoding or label encoding.

3. Feature Extraction Using Convolutional Neural Networks (CNNs)

3.1 CNN Architecture

- **Pretrained Models**: For the feature extraction from retinal images, a **pretrained CNN model** like **ResNet-50**, **VGG16**, or **InceptionV3** will be used. These models are capable of learning hierarchical features from the images without the need for manual feature engineering.
- **Fine-tuning**: Pretrained models will be fine-tuned on the retinal image dataset to adapt to specific characteristics of retinal vasculature, microaneurysms, and other relevant features for cardiovascular risk prediction.
- **CNN Layers**: The architecture will consist of convolutional layers for feature extraction, followed by pooling layers to reduce dimensionality, and fully connected layers for classification.

3.2 Image Augmentation

- **Data Augmentation**: Techniques such as random rotations, flipping, and scaling will be applied to augment the dataset, reducing overfitting and improving model generalization.

4. Multimodal Data Fusion

4.1 Combining Retinal Features and Clinical Data

- **Feature Concatenation**: The extracted features from retinal images (obtained through CNN) will be concatenated with clinical data such as blood pressure, glucose levels, and cholesterol levels. This creates a multimodal feature vector.
- **Feature Normalization**: To ensure consistency, both the image-derived features and the clinical data will be normalized before fusion.

4.2 Fusion Techniques

- **Early Fusion**: The retinal image features and clinical data will be combined at an early stage by merging both sets into a single vector before feeding it to the deep learning model.
- **Late Fusion**: Alternatively, separate models for image data and clinical data can be trained and then combined at the final decision-making stage. This involves training independent CNN models for images and fully connected layers for clinical data, and fusing their outputs before making the final prediction.

5. Model Training and Evaluation

5.1 Training the Deep Learning Model

- **Model Architecture**: The combined features (retinal images + clinical data) will be fed into a deep learning model, consisting of fully connected layers or recurrent neural networks (RNNs) for prediction. A **multilayer perceptron (MLP)** is suitable for this fusion, or a **deep neural network (DNN)** may also be used.
- **Loss Function**: A suitable loss function such as **binary cross-entropy** (for binary classification, i.e., high-risk vs. low-risk) or **categorical cross-entropy** (for multi-class classification) will be used.
- **Optimizer**: **Adam optimizer** or **SGD (stochastic gradient descent)** will be used to optimize the model.
- **Training**: The model will be trained using a split dataset (typically 70% for training, 30% for validation/testing) using cross-validation to avoid overfitting.

5.2 Evaluation Metrics

- **Accuracy**: Percentage of correct predictions out of total predictions.
- **Precision, Recall, and F1-score**: These metrics will be used to assess the model's performance, particularly in predicting high-risk individuals.
- **AUC-ROC Curve**: The **Area Under the Receiver Operating Characteristic Curve (AUC-ROC)** will be calculated to evaluate the model's ability to discriminate between high-risk and low-risk individuals.
- **Confusion Matrix**: This will help in visualizing the performance of the model in terms of false positives, false negatives, true positives, and true negatives.

6. Model Interpretability

6.1 Explainability Techniques

- **Grad-CAM**: Grad-CAM (Gradient-weighted Class Activation Mapping) will be applied to visualize the regions of retinal fundus images that contribute most to the model's prediction. This helps healthcare professionals understand which retinal features are associated with cardiovascular risk.
- **SHAP Values**: **SHAP (SHapley Additive exPlanations)** values will be used to interpret the contribution of clinical data features and the retinal image features in the model's decision-making process.

6.2 Pathophysiological Insights

- The system will analyze how changes in retinal vessels, microaneurysms, and other abnormalities correlate with cardiovascular risk factors (e.g., hypertension, diabetes). The interpretability framework will allow clinicians to understand the relationship between retinal abnormalities and underlying cardiovascular diseases.

7. System Deployment

7.1 User Interface

- **Front-End Design**: A web or desktop interface will be developed for healthcare professionals. They can upload retinal fundus images and input patient clinical data for prediction.
- **Real-Time Processing**: The backend of the system will process the images and data in real-time, providing predictions and risk assessment results to the user.

7.2 Continuous Learning

- The system will include a feedback loop for clinicians to provide feedback on predictions, which can be used to further fine-tune and improve the model over time.

This methodology outlines a comprehensive approach to developing a deep learning-based system for predicting cardiovascular risk using retinal fundus images and clinical data. By combining state-of-the-art image processing techniques with clinical data analysis, the system can provide accurate, early detection of cardiovascular risks, supporting healthcare providers in making informed decisions for patient care and intervention.

CHAPTER 5
SYSTEM ARCHITECTURE

The system architecture for heart attack risk prediction using retinal eye images is designed to process medical images, extract relevant features, and classify individuals based on their risk levels. The architecture integrates deep learning models, specifically Inception v3 and CNN, along with the AdaBoost algorithm to enhance classification accuracy.

The workflow of the AI-based heart attack risk prediction system consists of the following stages:

1. **Image Input & Acquisition:**

Retinal fundus images are collected from medical datasets containing labeled images of patients with different cardiovascular risk levels.Images are preprocessed to ensure uniformity and quality for model training.

2. **Preprocessing & Feature Extraction:**

Images undergo JPEG decoding, resizing (299×299 pixels), and normalization to prepare them for deep learning processing.Inception v3 extracts hierarchical features from the images, identifying important patterns related to retinal vascular changes.CNN (Convolutional Neural Networks) detects microaneurysms, hemorrhages, and other abnormalities associated with hypertension, diabetes, and cardiovascular diseases.

3. **Classification & Risk Prediction:**

The extracted features are passed through AdaBoost, which improves model performance by combining multiple weak classifiers into a strong one.

The system classifies patients into three categories:

- **High-risk** (significant retinal abnormalities indicating possible cardiovascular issues).
- **Low-risk** (mild abnormalities with potential long-term impact).
- **Normal** (no visible signs of heart disease in retinal images).

4. **Output & Interpretation:**

The final risk prediction is displayed to healthcare professionals, allowing for early diagnosis and preventive measures.

The system can be integrated into hospitals, telemedicine platforms, and health screening programs for real-time risk assessment.

The system is trained on a large dataset of retinal fundus images, including cases with and without cardiovascular disease indicators. The dataset characteristics include:

- Total Images: Over 6,000 labeled retinal images.
- Image Types: Color fundus images showing different cardiovascular conditions.
- Labels: Each image is categorized as high-risk, low-risk, or normal.
- Preprocessing Steps:
  - Resizing to 299×299 pixels (for compatibility with Inception v3).
  - Normalization (standardizing pixel values to stabilize training).
  - Data Augmentation (cropping, flipping, brightness adjustment) to increase training diversity.

The dataset is divided into:

- 80% for Training (to teach the model).
- 10% for Validation (to tune model performance).
- 10% for Testing (to evaluate accuracy and real-world applicability).

3.1 CLASSIFICATION

How Inception v3 and CNN Are Used for Feature Extraction

- **Inception v3 Architecture:**

A deep learning model designed for **image classification and feature extraction**.

It extracts **spatial patterns** from images, identifying complex retinal abnormalities.

It consists of **convolutional layers** that detect fine details in retinal vessels.

- **Convolutional Neural Networks (CNNs):**

CNN **learns hierarchical features** from retinal images.

Detects **low-level features** (edges, textures) and **high-level features** (microaneurysms, vascular narrowing).

Helps in **accurate classification** of risk levels.

Role of AdaBoost in Improving Classification Accuracy

- AdaBoost is used to **improve the final classification performance**.
- It **combines multiple weak classifiers** (Inception v3, CNN layers) into a strong classifier.
- Helps in refining predictions by **reducing false positives and false negatives.**

Different Risk Categories (Classification Labels)

5. **High-Risk:**
    - Severe **retinal vascular abnormalities**, including hemorrhages and vessel narrowing.
    - Strong indication of potential **heart disease, hypertension, or diabetes.**
6. **Low-Risk:**
    - Mild **vascular changes**, indicating a **potential risk** that requires monitoring.
7. **Normal:**
    - No visible **retinal changes** linked to cardiovascular conditions.

3.2 EXPIERIMENT

Dataset & Preprocessing Techniques

- The dataset contains **over 6,000 images**.
- Preprocessing includes:
    - **JPEG decoding** to extract pixel data.
    - **Resizing images** to 299×299 pixels.
    - **Normalization** (scaling pixel values for stable model training).
    - **Data Augmentation** (random cropping, brightness adjustment).

Training Process

- The model is trained using **deep learning techniques:**

  - **Inception v3 for feature extraction.**
  - **CNN for image classification.**
  - **AdaBoost for improving accuracy.**
- **Training Hyperparameters:**
  - **Learning Rate:** 0.01
  - **Batch Size:** 100
  - **Training Steps:** 6000
- **Training & Validation Strategy:**
  - **80% Training Data** (Model learns from labeled images).
  - **10% Validation Data** (Hyperparameter tuning).
  - **10% Testing Data** (Model evaluation on unseen images).

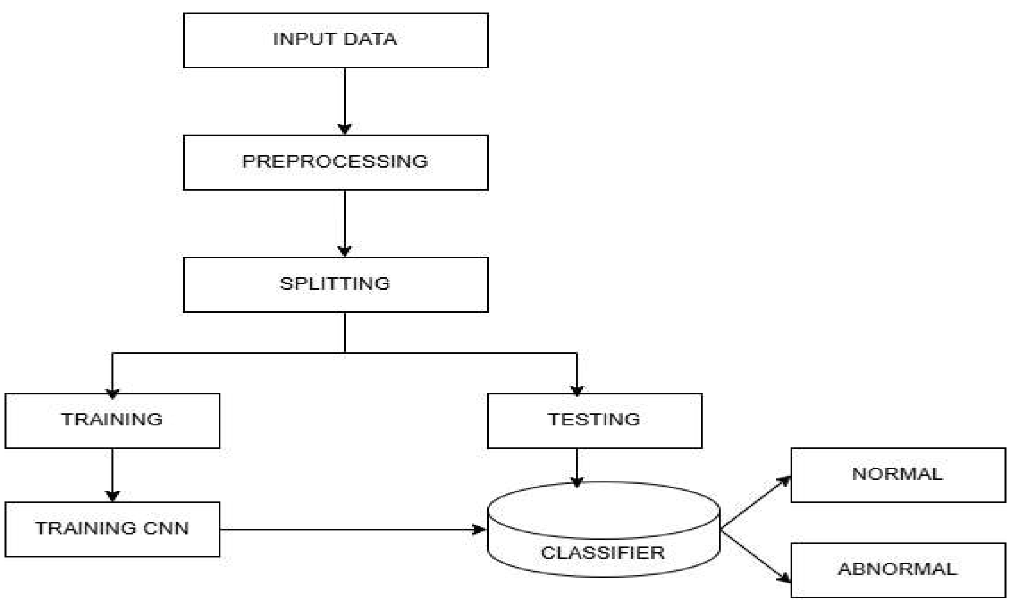

Fig 5.1 System Architecture

CHAPTER6

MODULES

This cardiovascular risk prediction system is designed to streamline the process of risk assessment based on retinal fundus images and clinical data. The system will consist of three primary modules: Admin, User, and Doctor. Each module has specific roles and functionalities that contribute to the efficient operation of the system. Below is the detailed description of each module.

1. Admin Module

The **Admin Module** is responsible for managing the system's overall functionality, user roles, and maintaining system integrity. Admin users are the highest-level users who have full access to the system's data and operations.

Key Features:

User and Doctor Management:

a. **User Registration**: The admin has the ability to review and approve user accounts, ensuring only valid users have access to the system.
b. **Doctor Registration**: Admin can register and manage doctors, ensuring they are authorized to provide consultations and assessments.
c. **View User and Doctor Profiles**: Admin can view the profiles of both users and doctors, including personal information and activity logs.

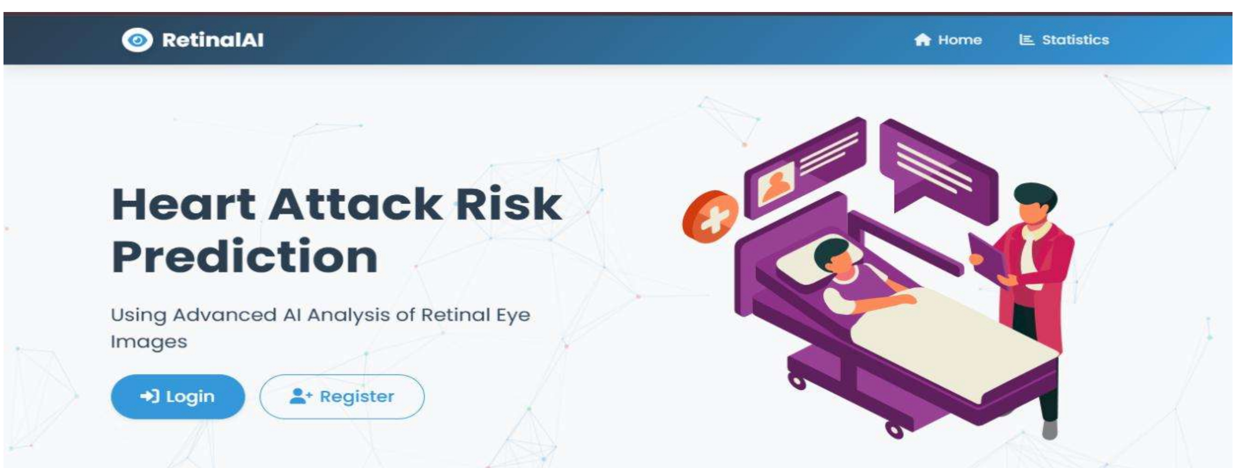

Fig 6.1 Home Page

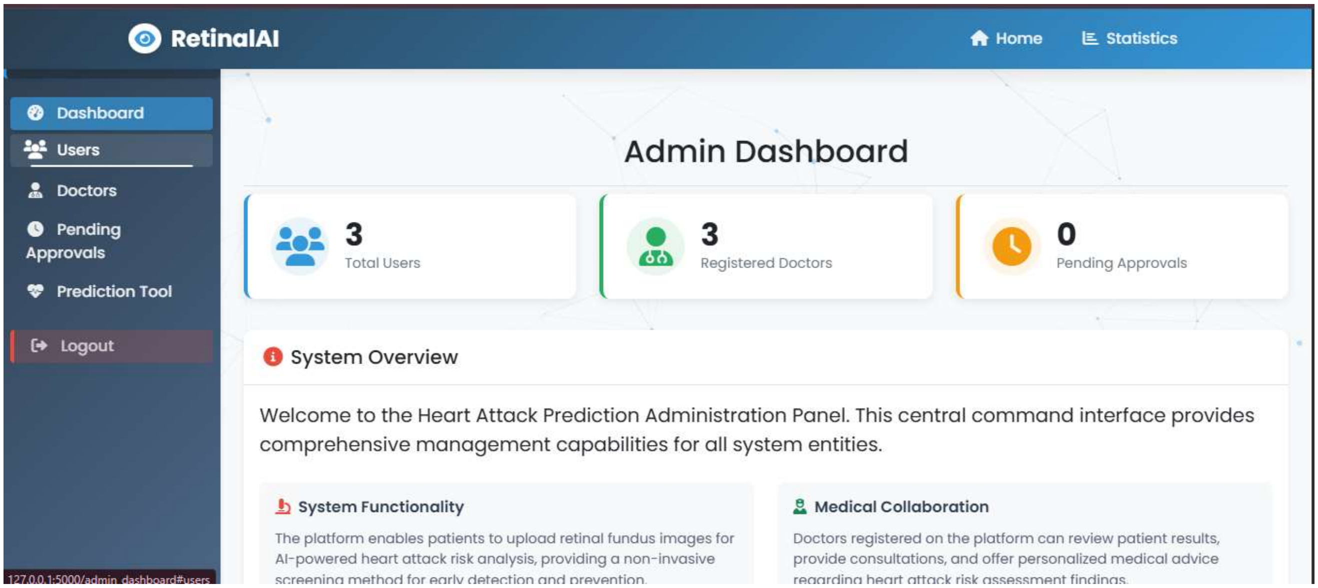

Fig 6.2 Admin Dashboard

2. User Module

The **User Module** provides functionalities for the end-users (patients or individuals seeking cardiovascular risk predictions) to interact with the system.

Key Features:

1. **User Registration & Login**:
    a. **Sign Up**: Users can register by providing personal details such as name, age, gender, contact information, and medical history.
    b. **Login**: Registered users can log into their account using secure authentication methods (e.g., email and password, two-factor authentication).
    c. **Profile Management**: Users can update their personal information and contact details as needed.
2. **Upload Retinal Fundus Images**: Users can upload their retinal fundus images to the system through a simple interface. The system will process these images to extract relevant features for risk prediction.

3. **View Predictions**:
    a. **Risk Prediction**: After uploading the retinal images, users will receive a prediction report

indicating their heart attack risk level. This report is based on both retinal image analysis and their clinical data.

4. **Download Report**:
   a. **Report Generation**: Users can generate detailed reports that include their uploaded retinal images, the results of the cardiovascular risk prediction, and any recommendations based on their risk level.
   b. **Downloadable PDF**: The report can be downloaded in PDF format for reference, consultations, or sharing with medical professionals.
5. **Consult Doctor**:
   Doctor Consultation Request: Users can request a consultation with a registered doctor through the system. The request can include their risk report and any additional questions they may have.

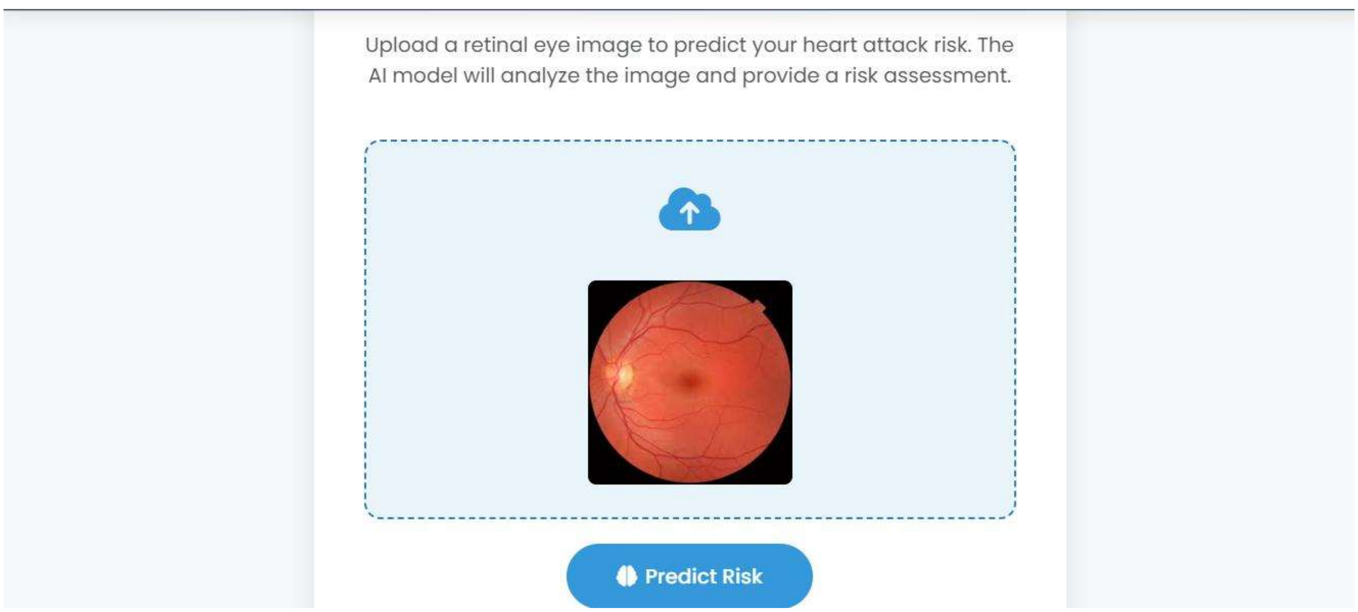

Fig 6.3 Upload Retinal Image

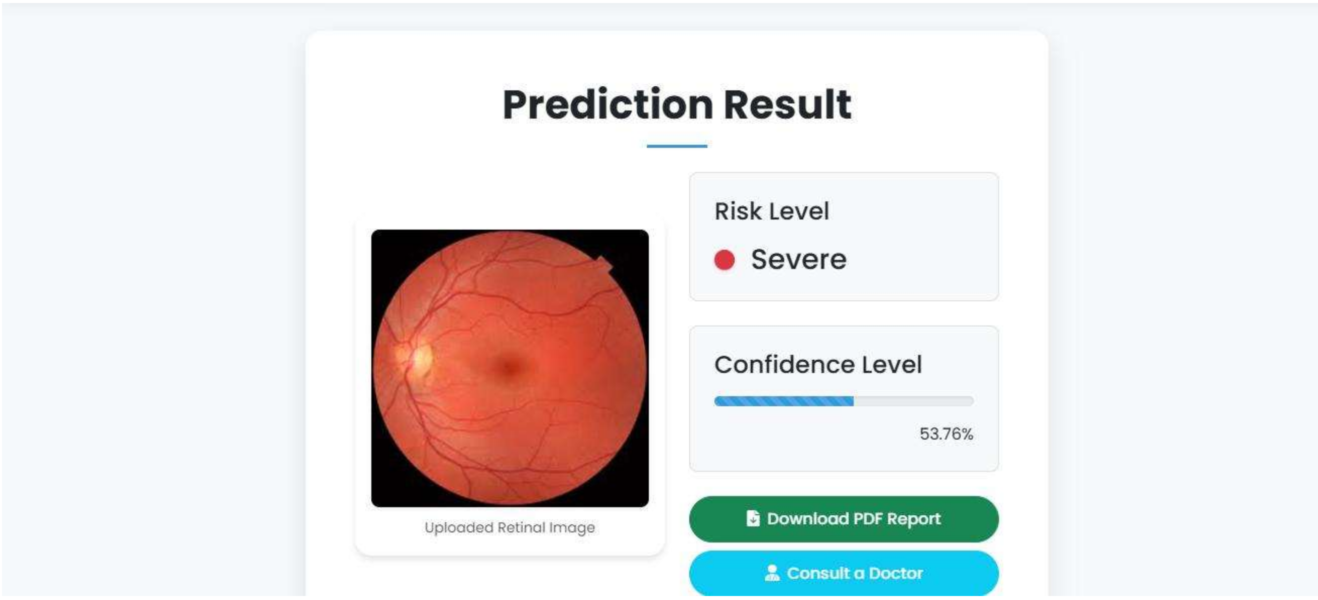

Fig 6.4 Prediction Result

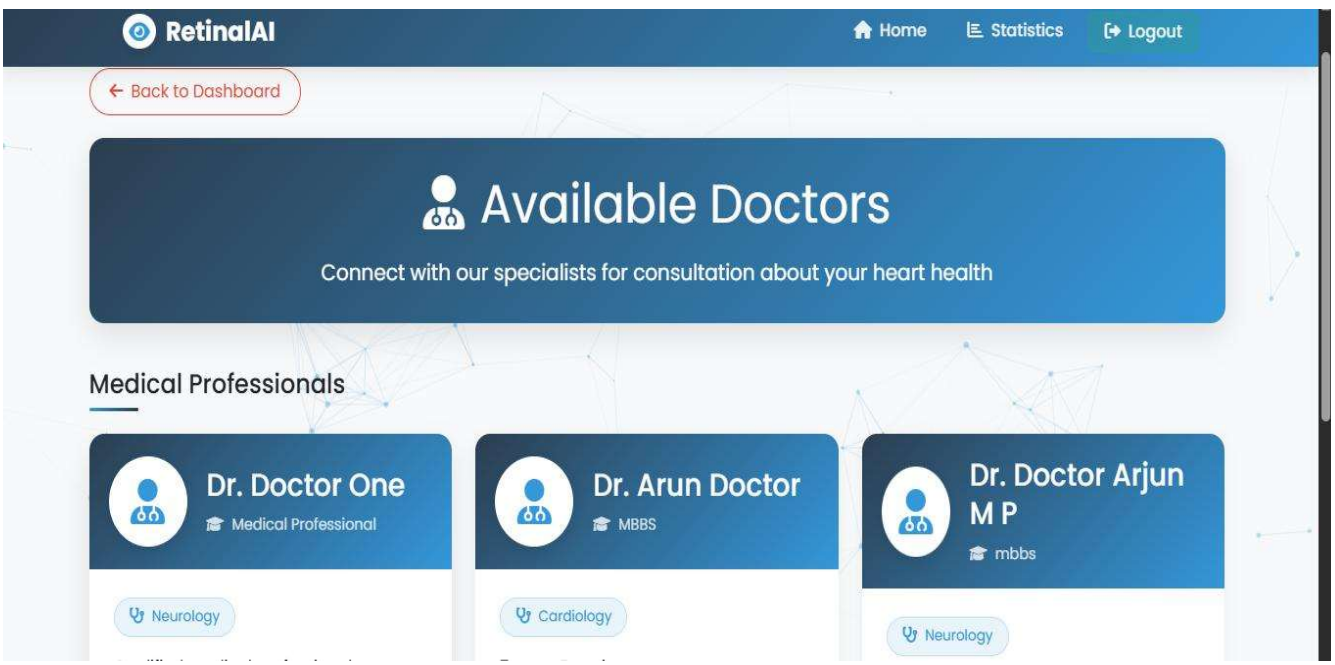

Fig 6.5 Consult Doctor

3. Doctor Module

The **Doctor Module** enables medical professionals to assess users' cardiovascular risk, provide consultations, and interpret retinal image-based predictions for personalized medical advice.

Key Features:

1. **Doctor Registration & Profile Management**:
   a. **Sign Up/Registration**: Doctors can register to the platform after validation and approval by the admin. They provide necessary credentials and expertise details.
   b. **Profile Management**: Doctors can manage their professional profiles, including specialties, contact details, and available consultation slots.
2. **Consultation Management**:

   View User Requests: Doctors can view and manage consultation requests from users. This includes reviewing the user's risk report and any uploaded retinal images before the consultation

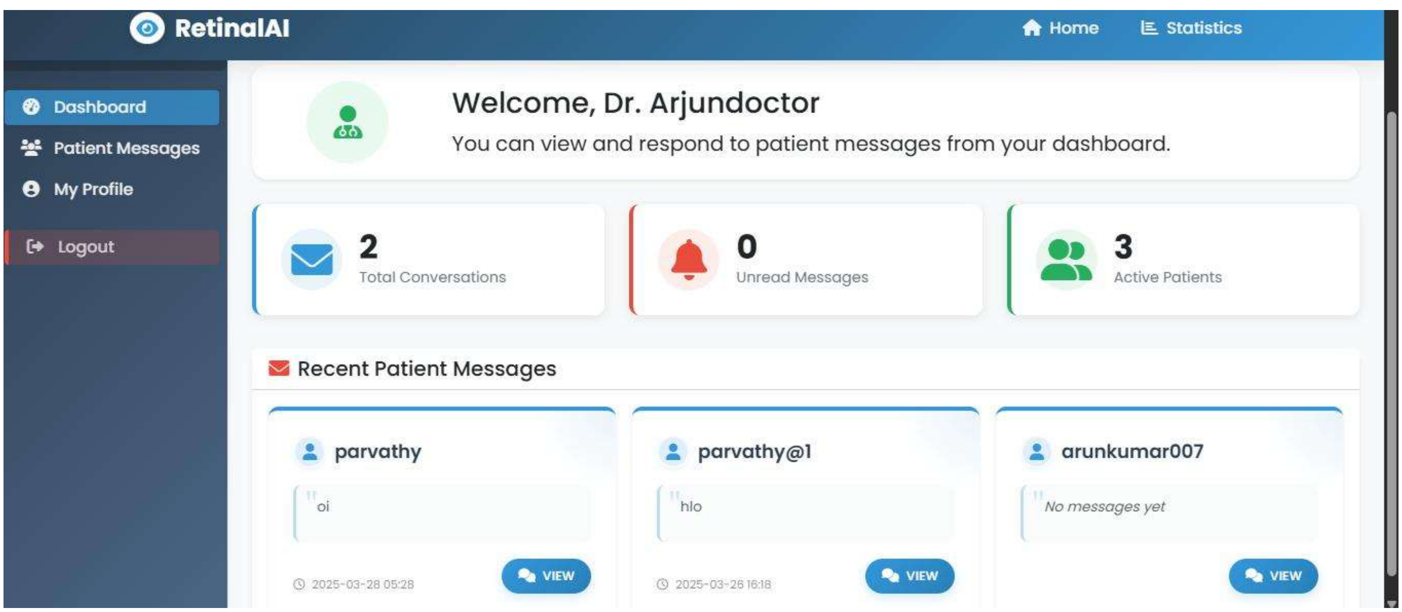

Fig 6.6 Doctor Dashboard

CHAPTER 7

DIAGRAMS

7.1 DFD (Data Flow Diagram).

A **Data Flow Diagram (DFD)** is a graphical representation used to visualize the flow of data within a system. It shows how data moves from input to output through various processes, data stores, and external entities. DFDs are widely used in system analysis and design to understand the functionality and data handling of a system.

Key Components of a DFD:

1. **Processes (Circles or Rounded Rectangles)**
   - Represent actions or functions that transform incoming data into outgoing data.
   - Each process should have a unique name and number for identification.
2. **Data Flows (Arrows)**
   - Show the movement of data between processes, data stores, and external entities.
   - Labeled with the name of the data being moved.
3. **Data Stores (Open-ended Rectangles or Parallel Lines)**
   - Represent repositories of data that are used and stored by processes.
   - They do not transform data but allow data to be stored or retrieved.
4. **External Entities (Squares or Rectangles)**
   - Represent sources or destinations of data outside the system being analyzed.
   - Also called terminators or actors.

Levels of DFDs:

1. **Level 0 (Context Diagram):**Shows the system as a single process with all external entities and major data flows.High-level overview with no internal details.
2. **Level 1:**Breaks down the main process into sub-processes.Shows more detail about the internal functions of the system.
3. **Level 2 and beyond:**Further decomposes processes into smaller, more detailed subprocesses.

LEVEL 0 CONTEXT DIAGRAM

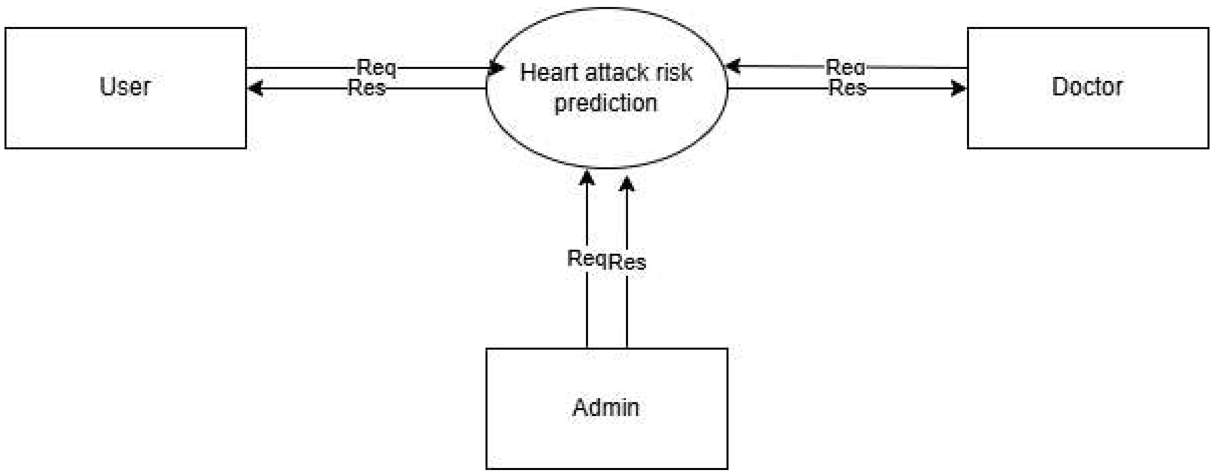

Fig 7.1.1 Level 0

ADMIN

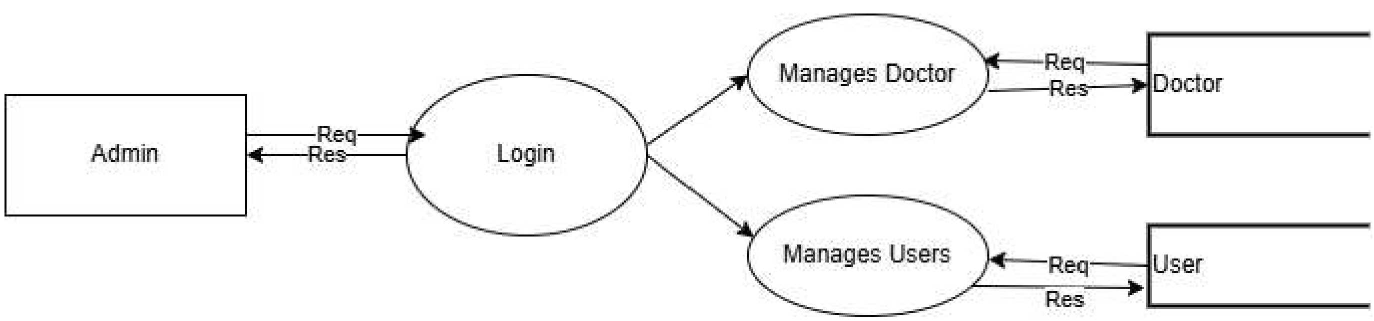

Fig 7.1.2 Level 1 Admin

USER

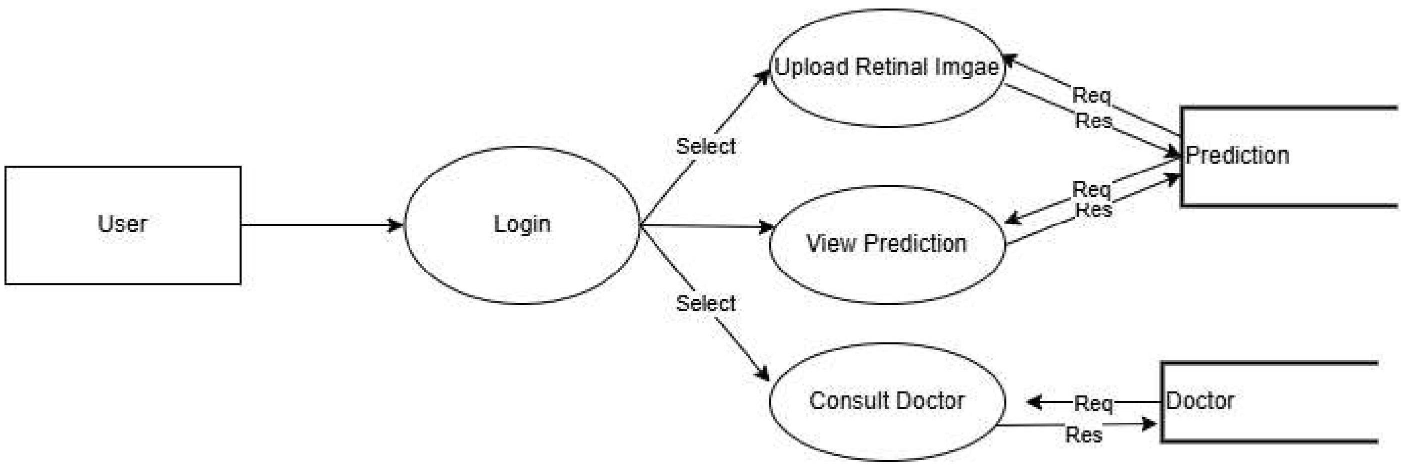

Fig 7.1.3 Level 1 User

DOCTOR

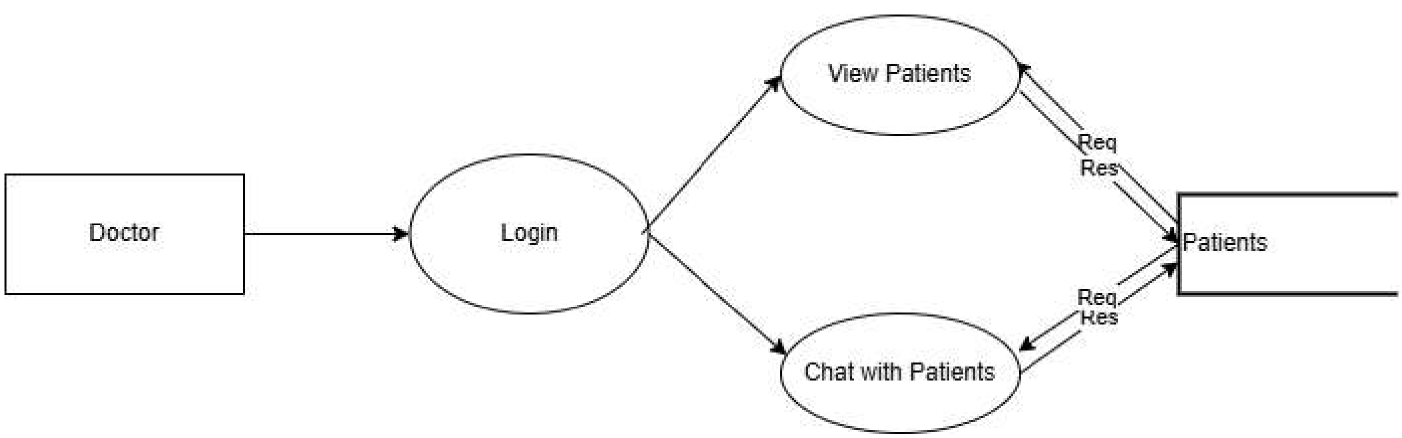

Fig 7.1.4 Level 1 Doctor

7.2 Class Diagram

A class diagram offers a static view of a system, illustrating the types of objects involved and their relationships. Each class consists of objects and may inherit properties from other classes.This diagram helps in visualizing, describing, and documenting various aspects of a systemwhile also assisting in the development of executable software code. It represents essentialelements such as attributes, functions, classes, and relationships, giving a comprehensiveoverview of the software architecture. To enhance clarity, these components are organized intoseparate compartments, making it easier for developers to interpret and work with. Since a classdiagram includes classes, interfaces, associations, collaborations, and constraints, it iscategorized as a structural diagram in system modeling.

A class diagram is structured into three distinct sections, each serving a specific purpose:

Upper Section: This section contains the name of the class, which represents a group of similar objects that share common attributes, relationships, operations, and semantics. The class name is typically placed at the top to provide a clear identifier for the entity it represents.

Middle Section: The middle section defines the attributes of the class, describing its characteristics or properties. These attributes help define the qualities of the class and contribute to distinguishing one object from another within the system.

Lower Section: This section includes the methods or operations associated with the class. These methods are listed line by line, specifying the actions that the class can perform. They define how a class interacts with data and other components within the system, showcasing its behavior and functionality.

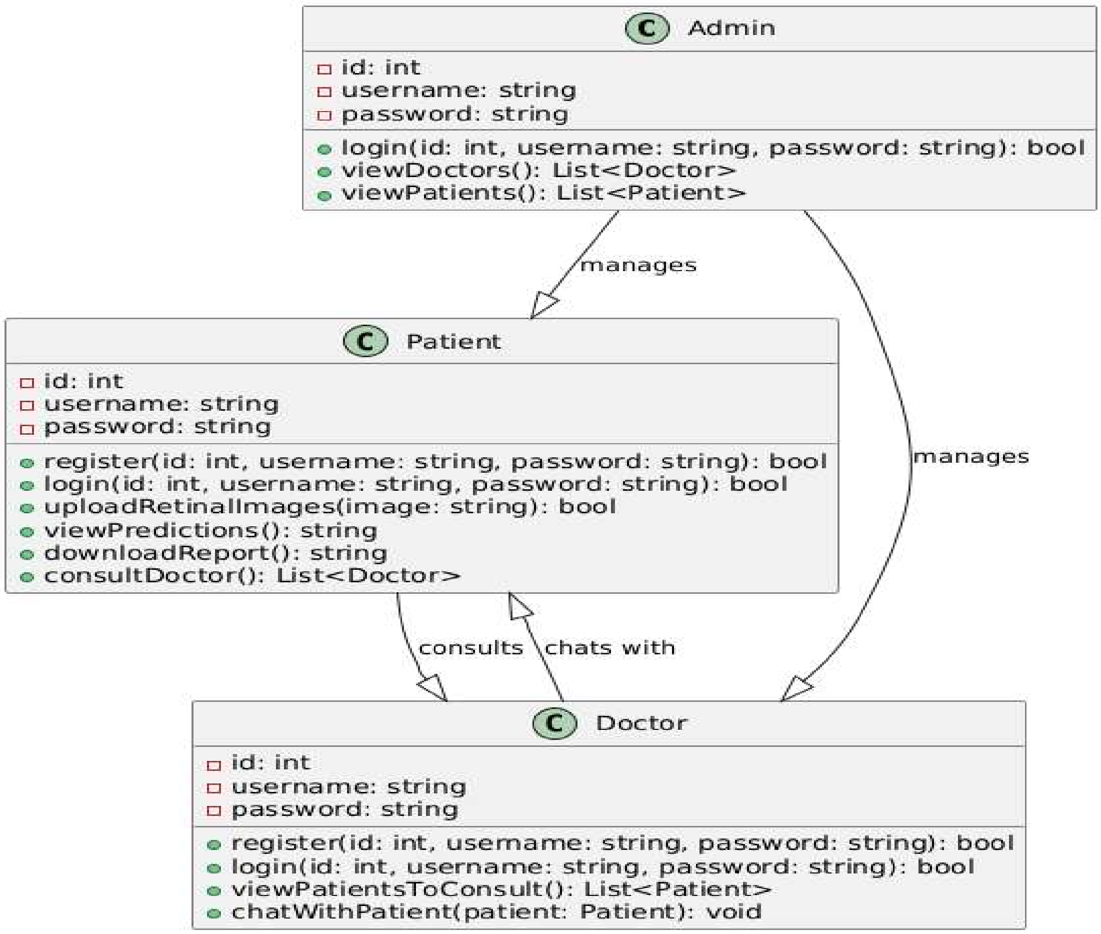

Fig 7.2.1 Class Diagram

7.3 Use Case Diagram

A use case diagram is a visual representation of the interactions between various components of a system. It is used in system analysis to define, explain, and organize system requirements. The term "system" refers to any application, software, or process that is either under development or already operational. Unified Modeling Language (UML), a widely adopted notation for modeling real-world systems, includes use case diagrams as a fundamental tool. A use case represents a specific task or functionality that an actor can perform within the system. Each use case is depicted as an oval, with the function or task written inside it.

Key Components of a Use Case Diagram:

1.Actors: An actor represents an external entity that interacts with the system. Actors can be users, roles, or other systems that either provide inputs to or receive outputs from the system.They are typically represented by a stick figure in the diagram.

2. Use Cases: A use case represents a selected function or motion within the device that offers a measurable outcome. It's essentially a venture or function that the actor can perform using the system. Each use case is represented by an oval, with the characteristic written inside it.

3.System Boundary: The device boundary is a rectangle that encapsulates all the use instances for a system. It defines the scope of the machine, showing which functions are a part of it and that are outside interactions.

4. Relationships:

• Association: A stable line connecting an actor to a use case, displaying that the actor is involved in that use case.

• Include: Shows that a use case is usually referred to as as a part of every other use case. For instance, "Login" may be covered in a couple of use cases because it's a prerequisite foraccessing various components of the machine.

• Extend: Represents optionally available behavior or an extension of a use case. For example, "Add Discount" may amplify the "Make Purchase" use case, which means it only takes place beneath certain conditions.

• Generalization: Illustrates inheritance among actors or use cases. If two actors proportion a not unusual conduct, one actor might be a specialized version of the alternative.

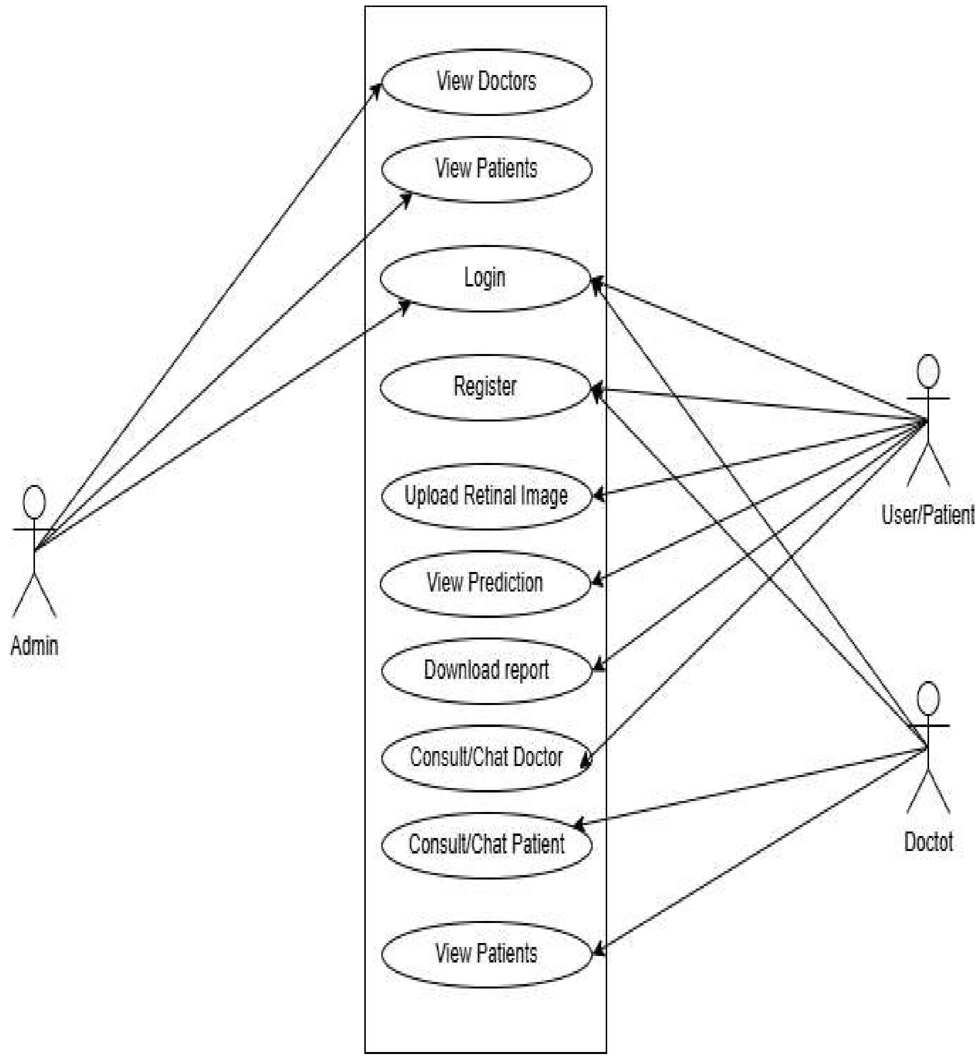

Fig 7.3.1 Use Case Diagram

CHAPTER 8

TESTING

Testing is a crucial phase in the development of the Cardiovascular Risk Prediction System, ensuring that all components of the system work as intended and meet the specified requirements. Testing involves evaluating the functionality, performance, security, and usability of the system, and validating the accuracy of the risk prediction model.

The testing of this system can be categorized into different types, including **unit testing**, **integration testing**, **system testing**, **user acceptance testing**, and **model testing**. Below is an overview of the testing strategies for each module and the overall system.

1. Unit Testing

Objective: Verify that individual components of the system function correctly.

Steps:

- **Test Individual Modules**: Unit tests focus on specific functions or components such as:
    - **User Authentication**: Test user registration, login, and password reset functionalities.
    - **Image Uploading**: Test the uploading process, including file size limits, format validation, and error handling for invalid images.
    - **Retinal Image Preprocessing**: Ensure preprocessing functions like resizing, noise reduction, and contrast enhancement work correctly.
    - **Risk Prediction Model**: Test the CNN model for feature extraction and predictions. This ensures that the model processes the input data (images and clinical parameters) and outputs predictions correctly.

2. Integration Testing: Ensure that different modules work together correctly.

Steps:

- **Test Data Flow**: Ensure smooth integration between modules such as user registration, image uploading, preprocessing, and risk prediction.
- **Backend & Frontend Integration**: Test the interaction between the front-end user interface (UI) and the back-end services, including image upload and data submission.
- **Database Integration**: Verify that data flows correctly between the user interface, backend

processing, and the database. For example, check that retinal images, clinical data, and prediction results are properly stored and retrieved from the database.

3. System Testing

Objective: Test the entire system's functionality as a whole, ensuring that all components interact correctly.

Steps:

- **End-to-End Workflow Testing**:
  - Test the complete workflow of the system from user registration, image uploading, prediction generation, to consultation and report generation.
  - Ensure that each component works as expected when the system is fully functional.
  - For example, test if a user uploads an image, receives a prediction, downloads a report, and requests a doctor consultation.
- **Performance Testing**:
  - **Load Testing**: Simulate multiple users uploading images and generating predictions simultaneously to ensure the system can handle high traffic.
  - **Stress Testing**: Push the system beyond normal operational capacity to identify potential weaknesses and breakpoints.
- **Security Testing**:
  - **Authentication and Authorization**: Verify that only authorized users (doctors, admins, users) have access to their respective modules.
  - **Data Privacy**: Ensure that personal and medical information is securely handled and that sensitive data (e.g., retinal images, clinical data) is encrypted during storage and transmission.

4. Model Testing

Objective: Evaluate the accuracy, performance, and robustness of the deep learning model used for cardiovascular risk prediction.

Steps:

- **Model Accuracy**:
  - **Cross-validation**: Use techniques like k-fold cross-validation to test the model's accuracy on different subsets of the data and ensure that it generalizes well.
  - **Metrics**: Evaluate the model using metrics such as **Accuracy**, **Precision**, **Recall**, **F1-score**,

and **ROC-AUC** to assess its performance on cardiovascular risk prediction.

- **Test Data**:
  - **Testing with unseen data**: Evaluate the model's predictions on a test dataset that was not used during training. This ensures that the model can predict accurately on new, unseen data.
  - **Clinical Data Integration**: Test the model by incorporating real clinical data (e.g., blood pressure, cholesterol) alongside retinal images and verify its ability to provide correct predictions.
- **Model Robustness**:
  - **Adversarial Testing**: Test how the model handles noisy, low-quality, or corrupted retinal images to ensure its robustness in different real-world conditions.

5. User Acceptance Testing (UAT)

Objective: Ensure the system meets the requirements and expectations of the end-users.

Steps:

- **Test User Interface (UI)**:
  - Ensure the UI is intuitive and easy to navigate. This includes testing the image upload process, the clarity of prediction results, and the layout of the reports.
- **Test Doctor Consultation Workflow**:
  - Verify that doctors can easily view predictions, consult with users, and generate reports. Ensure that users can communicate with doctors and schedule appointments without issues.
- **User Feedback**:
  - Conduct a usability test with actual users (patients) to collect feedback on the system's functionality, speed, and ease of use. Based on the feedback, fine-tune the system to enhance user experience.
- **Real-World Testing**:
  - Perform UAT with a small group of target users (e.g., healthcare professionals, patients) to simulate real-world usage. This helps uncover issues related to user workflow, accessibility, and feature usability.

6. Regression Testing

Objective: Ensure that new code changes (e.g., bug fixes, feature additions) do not break existing functionality.

Steps:

- **Re-test Existing Features**: Whenever there are updates or changes to the system (e.g., bug fixes, new features), regression tests are run to ensure that previously working features are still functional.
- **Automated Regression Testing**: Automated tests can be written for common workflows to quickly validate the system after updates or deployments.

7. Load and Stress Testing

Objective: Test the system's performance under normal and extreme conditions.

Steps:

- **Simulate High Traffic**: Create simulated traffic by mimicking a large number of concurrent users uploading images and generating predictions.
- **Measure Response Time**: Evaluate how quickly the system processes requests, especially when handling large image files or a significant number of users.
- **Identify Bottlenecks**: Use performance testing tools to identify any system bottlenecks, such as slow database queries or CPU-intensive operations in the model.

Testing the system is a comprehensive process that includes several types of tests to ensure the system's functionality, accuracy, performance, and usability. By conducting thorough unit, integration, system, model, and user acceptance testing, you ensure that the system meets the required specifications and provides reliable, accurate predictions for cardiovascular risk based on retinal images and clinical data.
Testing also helps identify and fix potential issues, enhance system performance, and ensure a smooth user experience, ultimately leading to a robust and reliable healthcare application.

CHAPTER 9
ADVANTAGES AND DISADVANTAGES

ADVANTAGES

1.Non-Invasive

Traditional heart disease detection methods, such as ECG, angiography, and blood tests, require physical hospital visits, trained professionals, and expensive equipment.AI-based retinal image analysis is a non-invasive technique, meaning it does not require blood samples or invasive procedures.This approach is particularly beneficial for developing countries and rural areas, where specialized cardiologists and expensive tests may not be readily available.

2. Faster Diagnosis Using AI

Manual diagnosis of heart disease involves doctors reviewing multiple tests and patient history, which takes time.AI-powered models analyze retinal images in seconds, providing instant risk assessments.This real-time diagnosis allows early intervention, reducing the risk of life-threatening cardiovascular events.Doctors can use AI as a decision-support tool, helping them prioritize high-risk patients and speed up treatment planning.

3. High Accuracy with Deep Learning Models

Traditional machine learning models (e.g., Logistic Regression, Decision Trees) rely on numerical data like age, cholesterol, and blood pressure, achieving 70-85% accuracy.Deep learning models like CNN with Inception v3 + AdaBoost achieve 96-97% accuracy by analyzing retinal blood vessel patterns, microaneurysms, and hemorrhages that are early indicators of heart disease.CNNs are automated feature extractors, meaning they learn directly from retinal images without requiring manual feature selection.

4. Cost-Effective Screening Solution

Traditional cardiovascular tests (e.g., echocardiograms, MRIs, or blood tests) can be expensive.Retinal imaging combined with AI provides a low-cost, quick, and efficient alternative for preliminary screening.

DISADVANTAGES

1. Requires a Large Dataset for Training

Deep learning models learn from vast amounts of labeled data to achieve high accuracy.High-quality, labeled retinal images from patients with and without heart disease are needed to train the model.Medical datasets are often limited, difficult to obtain, and require expert annotations, making the initial training process challenging.If the dataset is too small or unbalanced, the model may not generalize well to real-world patient populations.

2. AI Models May Have Biases If Trained on Limited Data

If the dataset lacks diversity (e.g., contains images only from a specific ethnic group, age group, or gender), the model may not perform well on underrepresented patient groups.Bias in training data can lead to incorrect predictions for certain populations, raising ethical concerns in medical AI.Ensuring a balanced, high-quality dataset is critical to making the AI model fair and accurate for all patients.

3. Real-World Implementation Depends on Hardware and Computational Power

Training deep learning models requires high-end GPUs (e.g., NVIDIA RTX 3060 or higher), which increase costs.Hospitals and clinics may not have the necessary infrastructure to run AI models locally.Cloud-based AI solutions could be an alternative, but they introduce data privacy concerns and depend on stable internet access.Deployment in low-resource settings is challenging due to computational requirements and power limitations.

4. Regulatory & Ethical Concerns

AI-based medical diagnostics face regulatory hurdles and ethical concerns, particularly regarding patient privacy and the responsibility of decision-making.

CHAPTER 10
RESULTS AND CONCLUSIONS

The study on Heart Attack Risk Prediction Using Retinal Eye Images demonstrates the potential of artificial intelligence (AI) and deep learning in transforming cardiovascular disease detection. Traditional diagnostic methods, such as ECG, angiography, and blood tests, are often invasive, time-consuming, and expensive. This research presents a non-invasive, cost-effective, and efficient alternative using retinal fundus images to assess heart disease risk.By leveraging Inception v3, CNN, and AdaBoost, the system effectively identifies vascular abnormalities in retinal images, which serve as early indicators of hypertension, diabetes, and cardiovascular diseases. The model classifies patients into high-risk, low-risk, or normal categories with an accuracy of 96-97%, outperforming many traditional machine learning techniques. The integration of AI in healthcare offers faster diagnosis, reduced hospital workload, and improved patient outcomes.Overall, this study highlights the feasibility and effectiveness of AI-based retinal analysis in early heart disease detection. The model provides a strong foundation for further advancements in AI-driven healthcare solutions, making cardiovascular screening more accessible and efficient.

CHAPTER 11
APPENDICES

```
import os
# import tensorflow as tf
import numpy as np
# from keras.preprocessing import image
from PIL import Image
import cv2
# from keras.models import load_model
from flask import Flask, request, render_template, redirect, url_for, session, flash,
jsonify, send_file
from werkzeug.utils import secure_filename
# from tensorflow.keras.applications.densenet import preprocess_input
import logging
from functools import wraps
from flask_sqlalchemy import SQLAlchemy
from datetime import datetime
import uuid
import io
from reportlab.pdfgen import canvas
from reportlab.lib.pagesizes import letter
from reportlab.lib import colors
from reportlab.platypus import SimpleDocTemplate, Paragraph, Spacer, Image as
ReportLabImage, Table, TableStyle
from reportlab.lib.styles import getSampleStyleSheet, ParagraphStyle
from reportlab.lib.units import inch
from werkzeug.security import generate_password_hash, check_password_hash

app = Flask(__name__)
app.secret_key = 'your-secret-key-here'
app.config['SQLALCHEMY_DATABASE_URI'] = 'sqlite:///heartattack.db'
app.config['SQLALCHEMY_TRACK_MODIFICATIONS'] = False
db = SQLAlchemy(app)

# Models
class User(db.Model):
    id = db.Column(db.Integer, primary_key=True)
    username = db.Column(db.String(80), unique=True, nullable=False)
    password = db.Column(db.String(120), nullable=False)
    created_at = db.Column(db.DateTime, default=datetime.utcnow)
    reports = db.relationship('Report', backref='user', lazy=True)
    messages_sent = db.relationship('Message', backref='sender', lazy=True,
```

```
foreign_keys='Message.sender_id')

    def __repr__(self):
        return f'<User {self.username}>'

class Doctor(db.Model):
    id = db.Column(db.Integer, primary_key=True)
    username = db.Column(db.String(80), unique=True, nullable=False)
    password = db.Column(db.String(120), nullable=False)
    full_name = db.Column(db.String(100), nullable=False)
    specialization = db.Column(db.String(100), nullable=False)
    email = db.Column(db.String(120), unique=True, nullable=False)
    approved = db.Column(db.Boolean, default=False)
    created_at = db.Column(db.DateTime, default=datetime.utcnow)
    about_me = db.Column(db.Text, nullable=True)
    qualifications = db.Column(db.Text, nullable=True)
    phone = db.Column(db.String(20), nullable=True)
    address = db.Column(db.Text, nullable=True)
    messages_received = db.relationship('Message', backref='doctor', lazy=True,
foreign_keys='Message.doctor_id')

    def __repr__(self):
        return f'<Doctor {self.username}>'

class Admin(db.Model):
    id = db.Column(db.Integer, primary_key=True)
    username = db.Column(db.String(80), unique=True, nullable=False)
    password = db.Column(db.String(120), nullable=False)

    def __repr__(self):
        return f'<Admin {self.username}>'

class Report(db.Model):
    id = db.Column(db.Integer, primary_key=True)
    user_id = db.Column(db.Integer, db.ForeignKey('user.id'), nullable=False)
    image_file = db.Column(db.String(150), nullable=False)
    result = db.Column(db.String(50), nullable=False)
    probability = db.Column(db.Float, nullable=False)
    created_at = db.Column(db.DateTime, default=datetime.utcnow)

    def __repr__(self):
        return f'<Report {self.id}>'
```

```
class Message(db.Model):
    id = db.Column(db.Integer, primary_key=True)
    sender_id = db.Column(db.Integer, db.ForeignKey('user.id'), nullable=False)
    doctor_id = db.Column(db.Integer, db.ForeignKey('doctor.id'), nullable=False)
    content = db.Column(db.Text, nullable=False)
    timestamp = db.Column(db.DateTime, default=datetime.utcnow)
    is_read = db.Column(db.Boolean, default=False)

    def __repr__(self):
        return f'<Message {self.id}>'

# Login required decorators
def login_required(f):
    @wraps(f)
    def decorated_function(*args, **kwargs):
        if 'logged_in' not in session or not session['logged_in']:
            flash('Please login to access this page')
            return redirect(url_for('login'))
        return f(*args, **kwargs)
    return decorated_function

def doctor_login_required(f):
    @wraps(f)
    def decorated_function(*args, **kwargs):
        if 'doctor_logged_in' not in session or not session['doctor_logged_in']:
            flash('Please login as a doctor to access this page')
            return redirect(url_for('doctor_login'))
        return f(*args, **kwargs)
    return decorated_function

def admin_login_required(f):
    @wraps(f)
    def decorated_function(*args, **kwargs):
        if 'admin_logged_in' not in session or not session['admin_logged_in']:
            flash('Please login as an admin to access this page')
            return redirect(url_for('admin_login'))
        return f(*args, **kwargs)
    return decorated_function

# Modified to not use TensorFlow
# model = tf.keras.models.load_model('heart_attack_prediction_model.h5', compile=False)
# model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
def get_className(prediction):
    predicted_class = np.argmax(prediction)
    if predicted_class == 0:
        return "No"
    elif predicted_class == 1:
        return "Mild"
    elif predicted_class == 2:
        return "Moderate"
    elif predicted_class == 3:
        return "Severe"
    else:
        return "Proliferate"

INPUT_SIZE = 224  # Update the input size to match the model

def preprocess_single_image(image_path):
    # Instead of actually using TensorFlow model, we'll return a mock prediction
    # This is just for testing the UI without TensorFlow

    # Random prediction between 0 and 4 classes
    mock_classes = 5
    mock_prediction = np.zeros((1, mock_classes))
    mock_class = np.random.randint(0, mock_classes)
    mock_prediction[0, mock_class] = 0.7 + 0.3 * np.random.random()  # Between 0.7 and 1.0
confidence

    # Add some random values to other classes
    for i in range(mock_classes):
        if i != mock_class:
            mock_prediction[0, i] = 0.3 * np.random.random()  # Between 0 and 0.3

    # Normalize to ensure sum is 1
    mock_prediction[0] = mock_prediction[0] / np.sum(mock_prediction[0])

    return mock_prediction

def generate_pdf_report(report):
    buffer = io.BytesIO()
    doc = SimpleDocTemplate(buffer, pagesize=letter)
    styles = getSampleStyleSheet()
    elements = []

    # Title
```

```
title_style = ParagraphStyle(
    'Title',
    parent=styles['Heading1'],
    fontSize=18,
    alignment=1,
    spaceAfter=20
)
elements.append(Paragraph("Heart Attack Risk Prediction Report", title_style))
elements.append(Spacer(1, 0.25*inch))

# Report information
report_info = [
    ["Date", report.created_at.strftime("%Y-%m-%d %H:%M")],
    ["User", User.query.get(report.user_id).username],
    ["Result", report.result],
    ["Probability", f"{report.probability:.2f}%"],
]

# Add tables for report info
table = Table(report_info, colWidths=[2*inch, 3*inch])
table.setStyle(TableStyle([
    ('BACKGROUND', (0, 0), (0, -1), colors.lightgrey),
    ('GRID', (0, 0), (-1, -1), 1, colors.black),
    ('FONTSIZE', (0, 0), (-1, -1), 12),
    ('PADDING', (0, 0), (-1, -1), 8),
    ('ALIGN', (0, 0), (-1, -1), 'LEFT'),
]))
elements.append(table)
elements.append(Spacer(1, 0.25*inch))

# Add image
image_path = os.path.join(app.static_folder, 'uploads', report.image_file)
if os.path.exists(image_path):
    try:
        img = ReportLabImage(image_path, width=5*inch, height=4*inch)
        elements.append(img)
    except:
        elements.append(Paragraph("Image could not be loaded", styles['Normal']))
else:
    elements.append(Paragraph("Image not found", styles['Normal']))

elements.append(Spacer(1, 0.25*inch))
```

```
            if not message.is_read:
                user_messages[user.id]['unread_count'] += 1

    # Add all users who haven't messaged this doctor yet
    for user in all_users:
        if user.id not in user_messages:
            user_messages[user.id] = {
                'username': user.username,
                'messages': [],
                'unread_count': 0
            }

    # Get active users count - all registered users
    active_users_count = len(all_users)

    return render_template('doctor_dashboard.html',
                          user_messages=user_messages,
                          active_users_count=active_users_count,
                          total_conversations=len(users_with_messages),
                          doctor=doctor)
```

CHAPTER 12
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