

Cardio-Eye Connection: Retinal Eye Imaging for Heart Attack Risk Prediction

Ambati Shashisri¹; Dr. Y Mohana Roopa²; Indrakanti Shiva³;
Bhukya Soundarya⁴

¹B.Tech, Department of CSE Institute of Aeronautical Engineering Hyderabad, India

²Professor, Department of CSE Institute of Aeronautical Engineering Hyderabad, India

³B.Tech, Department of CSE Institute of Aeronautical Engineering Hyderabad, India

⁴B.Tech, Department of CSE Institute of Aeronautical Engineering Hyderabad, India

¹(0009-0005-4170-9969); ²(0000-0002-8528-9637); ³(0009-0003-3972-7717); ⁴(0009-0000-5258-6021)

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Abstract: Cardiovascular diseases (CVDs) remain a leading cause of global mortality. Early identification of individuals at risk is crucial for effective intervention and prevention. Recent advancements in ophthalmology have revealed a potential link between retinal vascular changes and systemic vascular diseases, particularly coronary artery disease. Retinal imaging, a non-invasive technique, allows for the visualization and analysis of the retinal microvasculature. By examining features such as vessel caliber, tortuosity, and bifurcations, researchers can identify potential indicators of systemic vascular dysfunction. Machine learning models, particularly convolutional neural networks (CNNs), enhance the predictive analysis of these features. This study presents a methodology combining retinal imaging with machine learning to predict heart attack risk, validated through extensive evaluations and demonstrating significant potential for clinical applications.

Keywords: Cardiovascular Disease, Retinal Image, Machine Learning, Convolutional Neural Network.

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I. INTRODUCTION

Cardiovascular disease is a major global health problem, causing common illness, important mortality and high healthcare costs. CVD is not a single condition, but rather a group of diseases and these diseases affect the sensory, heart and vascular systems. Stroke, high blood pressure and coronary heart disease are among the conditions in this group.

Doctors consider several factors in diagnosing retinal problems, including age, heart disease history and blood pressure. Fundus image examination offers an analytically important, non-intrusive method for detecting these abnormalities and this approach eases early diagnosis. The healthy retina and fully functioning optic nerve are necessary for these images. Thinning retinal blood vessels are a potential sign of a serious eye condition. This condition is known as diabetic retinopathy.

Retinal hemorrhage is bleeding in the retina and vitreous hemorrhage is bleeding in the eye's vitreous humor. Myocardial infarction can cause ventricular septal aneurysms. It can also cause atrial septal aneurysms of varying sizes. Aneurysms can have several shapes. These include saccular, fusiform and focal

bulges. Meaningful exudates, fluids containing purulent exudate, leukocytes, serum and decaying cells, are also clearly visible. Hard and soft exudates are the two main types of clinically important exudates and hard exudates usually appear early in the development of CVD.

Image processing techniques play a vital role in identifying such irregularities in fundus of the retina images. For instance, intensity thresholds are applied to segment the retinal fundus image and isolate blood vessels. Clustering, a machine learning method, is utilized to differentiate exudates from the fundus image. The thresholding segmentation method is specifically employed for segmenting microaneurysms. By analyzing retinal images, this method aims to detect potential indicators of heart attack risk. Since the retinal layer is an augmentation of the focal sensory system, it provides a unique view into the body's vascular system.

Exudates are fluids that leak from blood vessels into surrounding tissues, composed of proteins, solids, and cells. They can result from cuts, infections, or inflammation. Microaneurysms are tiny bulges that form on the walls of capillaries. That could potentially cause fluid leakage, resulting in intra-reticular swelling. Bleeding: Retinal bleeding occurs

when blood vessels rupture. In the case of a retinal detachment, which can be caused by diabetes, the retina may tear or rupture. Hypertension, head wounds or variations in air pressure.

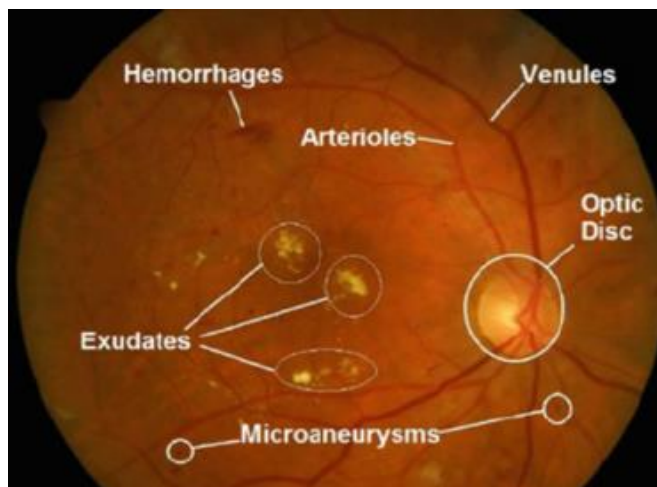


Fig 1 Retinal Characteristics.

II. LITERATURE SURVEY

Cardiovascular disease (CVD) is not only a significant contributor to the rising costs of healthcare globally but also a leading cause of disability and mortality [1]. Among diabetics, CVD is the foremost cause of death, with hypertension further complicating the situation [2]. The problem of blindness in the industrial age, with an emphasis on diseases including glaucoma, diabetic retinopathy, and progressive macular degeneration. Their method entails locating contaminated pixels in retinal images, which allows for timely intervention [3]. The primary aim of their study is to establish a foundational framework for diagnosing various health issues, including hypertension, insulin resistance, and cardiovascular events [4].

This review seeks to explore and document the retinal connections associated with these critical health conditions, drawing on data from multiple clinical studies [5]. One study investigates the retinal vascular function in asymptomatic individuals, categorizing them according to their Framingham Risk Score, into risk groups [6].

One more Research paper by combining correlation filters with measurements based on the eigenvalues of the hessian matrix, retinal vascular segmentation using the average of synthetic precise filters and hessian matrix offers an effective technique [7]. Scale-Invariant Feature Transform and Accelerated Robust Features were used in the research mentioned above. Transform and Speeded Up Robust Features were used to identify the regions of exudates in each of the visual fields. It combines a theory of recreational activities and with medical conditions, and forecasting important problems such as diabetes [8] and cardiovascular complication.

The segmentation of blood vessels is addressed in another study, which proposes using the Fuzzy C-Means (FCM) technique, Gabor transform function, and ant colony optimization [9]. Tests conducted on fifteen high-resolution retinal images demonstrated that this method outperformed existing techniques [10].

The presence of retinal vessels is a crucial factor in assessing CVD, and the methods employed to measure these vessels can indicate the existence of underlying diseases [11]. Additionally, one study utilizes a set of quantitative methods to analyze the outcomes of multimodal image fusion. The primary objective of the Discrete Wavelet Transform-Intuitionistic Fuzzy Sets approach is to combine the characteristics of intuitionistic fuzzy sets with a unique discrete wavelet transform [12].

III. RELATED WORK

It is proposed to predict Cardio Vascular Disease using the Convolutional Neural Network (CNN). The Flow diagram illustrates the proposed system (fig. 2). The main idea of the author argues that the government should provide more support and resources for stroke survivors and their families. Heart failure, angina, coronary heart disease (CHD), and hypertension. One of the conditions that might impact the eyes is diabetic retinopathy (DR).

The CVD provides substantial insights for effectively utilizing machine learning. Approaches to Learning. Different classification models can be employed to predict how. Individuals suffering from a specific condition will exhibit similar behavior in the future. Our: The objective of this work is to develop a model for cardiovascular disease. The system was designed to assist in addressing the ongoing humanitarian crisis. Response: These prediction algorithms can be incredibly beneficial. In directing initial measures to effectively handle diseases, the organization aimed to establish a comprehensive management plan. Current context. The data is split into two sets: one for training and the other for testing. In the suggested framework. This suggested model makes use of the CNN algorithm. Machine learning is used for teaching the data. Methods: The testing models were used to evaluate the test values. Commonly used measures include accuracy, recall, f1 score, and support. This method is used to predict the accuracy of machine learning methodologies are used to train the data for Cardio Vascular Disease.

➤ Data Collection

The data is collected using the retinal dataset. The retinal images we utilize are sourced from a comprehensive dataset that includes various anatomical features of the eye, such as the optic disc, macula, and the posterior pole. These images are captured using advanced imaging techniques that allow for detailed visualization of the retinal structure. The fundus images provide a view of the internal surface of the eye, which is crucial for identifying abnormalities in the retinal vasculature.

The dataset comprises a collection of images that will be used for both training and testing our predictive models. One of the advantages of using retinal images is that they are generally easier to differentiate compared to traditional imaging modalities. The distinct features of the retinal vasculature, such as the diameter of blood vessels and the presence of anomalies, can be more readily identified in these images.

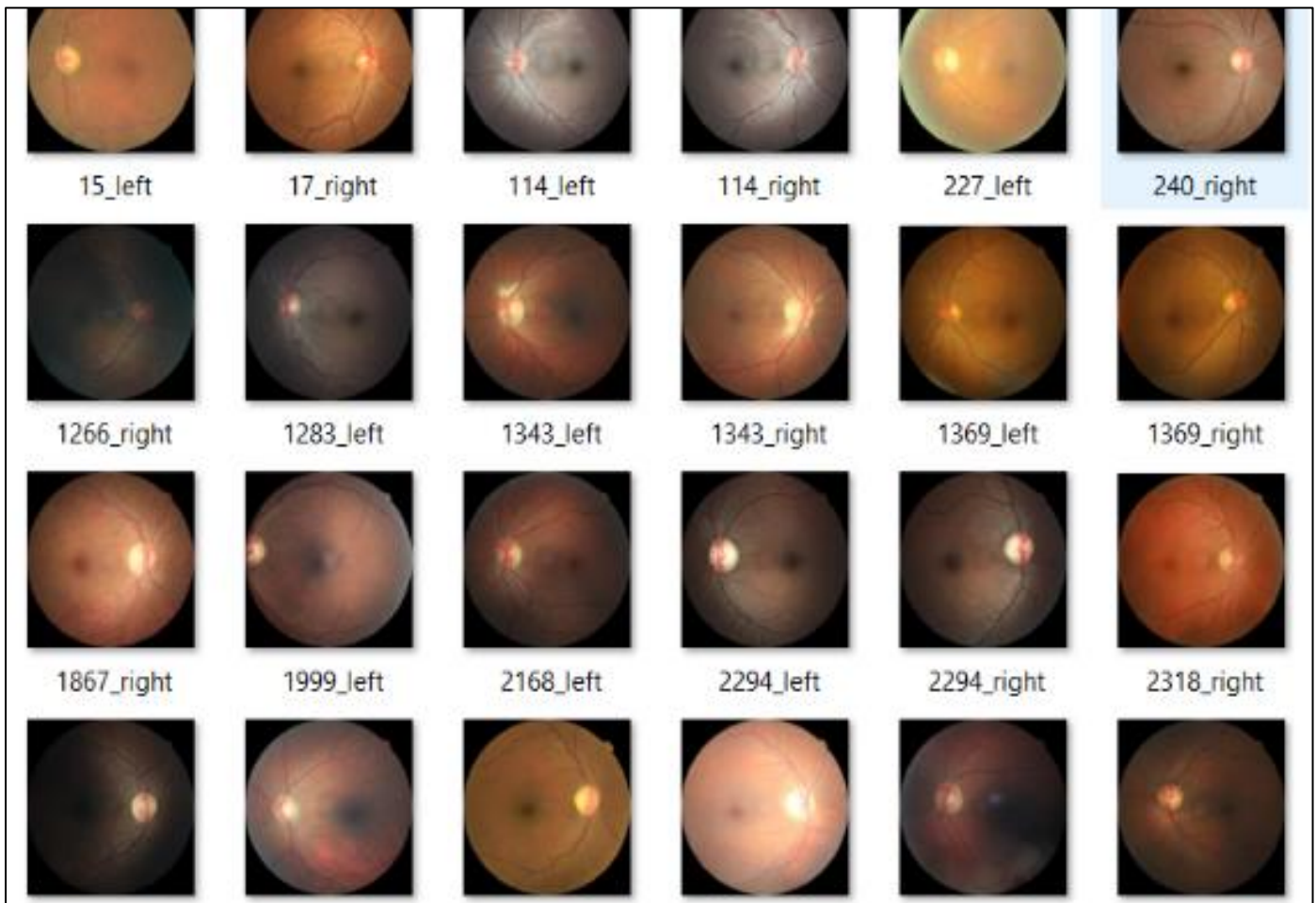
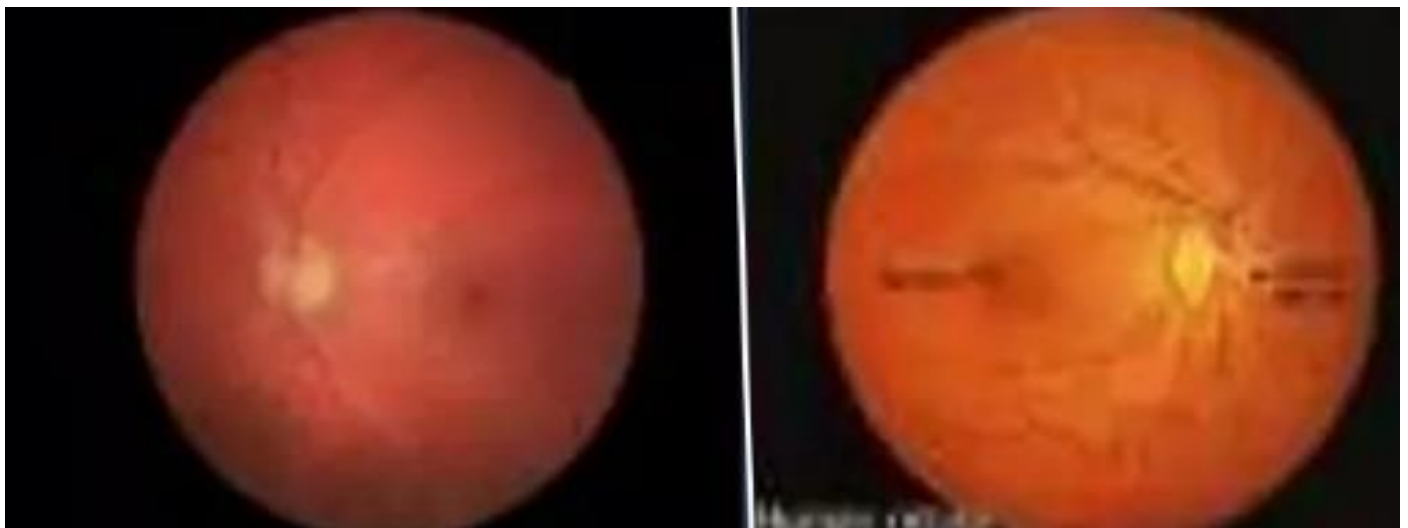


Fig 2 Retinal Dataset

➤ Data Preprocessing

The preprocessing method is employed to enhance images in a manner that increases the likelihood of successful subsequent analyses. This process improves the visual quality of retinal images by refining the high-frequency components, which is essential for highlighting important features. Image sharpening involves applying a filter that emphasizes edges and fine details within the photograph. Specifically, this technique utilizes a high-pass filter that isolates high-frequency

information from the original image. The original image is first processed through this high-pass filter, which removes lower frequency components, allowing for the enhancement of sharpness and detail. After filtering, a scaled version of the high-pass filtered image is combined with the original image to create a sharpened output. This approach effectively accentuates the edges and intricate details, making it easier to identify critical features in the retinal images that are relevant for further analysis and diagnosis.



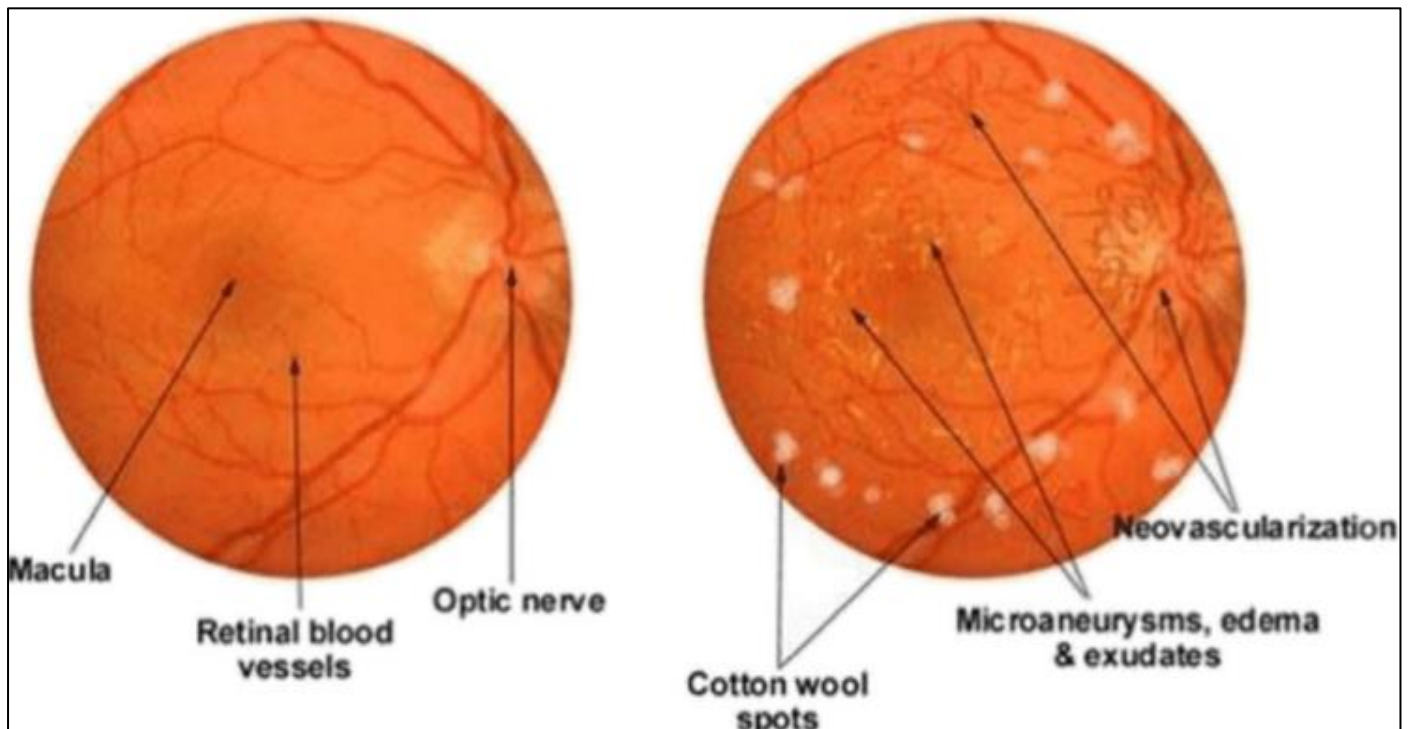


Fig 3 Normal Retina Versus CVD affected Retina

➤ Training

After acquiring the retinal dataset images, a Convolutional Neural Network (CNN) performs several key steps to analyze and classify the images.

Input Layer: A convolutional neural network processes retinal images. Standard-size images are required for datasets. CNN convolutional layers process input images. They use learnable filters via convolution. These filters scan the image. They identify several key features, including edges, textures and patterns.

Convolutional layers process data, identifying progressively complex features. Every convolution operation is followed by one activation function, which introduces non-linearity into the model. This enables the network to learn complex data patterns.

Pooling layers, which often use max pooling, reduce the size of feature maps following convolutional layers. This considerably reduces the data's spatial dimensions, substantially decreasing the computational load, improving overfitting control greatly and effectively retaining key features. After several convolutional and pooling layers, the high-level feature maps are flattened into a single one-dimensional vector. This readies all the data for the following fully connected layers. At least one fully connected layer processes the flattened vector; additional layers may also be used. These three analytically important layers combine the features learned by the convolutional layers. This process produces highly accurate final predictions. CNN output layers use an activation function to produce final predictions. This layer outputs the probability of each class's possessing the input image.

The retinal images are input to the CNN. To guarantee uniform dataset presentation, images are usually resized to a consistent dimension. With learnable filters, the CNN performs convolutions on input images. These filters analyze the image to detect several features, such as edges, textures and patterns. Each convolutional layer extracts an increasing number of more complex features as data moves through the network. Activation functions follow convolution operations to add non-linearity to the model. Complex data patterns are learned by the network as a result. Convolutional layers are followed by analytically important pooling layers. These layers, often using max pooling, greatly down-sample the feature maps. This considerably reduces the spatial dimensions of the data by a large amount, substantially decreasing the computational load and improving control over overfitting while preserving all of the most important features. Following three convolutional and two pooling layers, the high-level feature maps are flattened into a one-dimensional vector. This process precisely prepares the data and this thoroughly prepared data is then immediately ready for subsequent fully connected layers. The vector, considerably flattened, is passed through a minimum of one densely connected layer, or possibly more.

➤ Evaluation

After training, the Convolutional Neural Networks is tested to determine how well it performs on a different validation or test dataset. Measures like recall, accuracy, precision, and F1 score are frequently employed to assess how effectively the model classifies the retinal images.

➤ Classification

After evaluation, the model classifies the image as either low risk, normal, or high risk of heart attack risk. The result of the classification will be used to help patients who suffer from the Cardio Vascular disease.

IV. RESULTS

Setting Up the Environment: The first step in executing the project involves setting up the Python environment where the application will run. Open the Anaconda Navigator application on your system. Once Anaconda Navigator is

open, navigate to the Environments tab and select or create the environment named flask_env. This specific environment is pre-configured to contain all the required libraries and dependencies for running a Flask-based application. Activating this environment ensures that the application has access to the necessary tools for its execution.

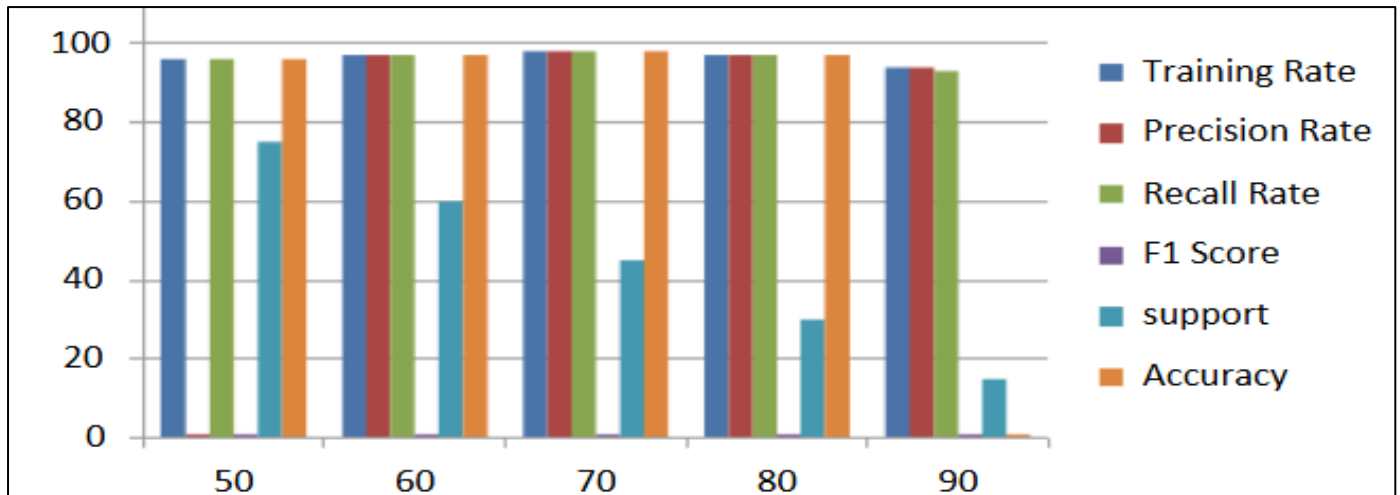


Fig 4 Graphical Representation

Locate the folder labeled "Heart Disease Project", which contains all the source code and assets required for the project. Open the terminal within Anaconda Navigator or any terminal application compatible with the selected environment. Using the terminal, navigate to the directory containing the project files. Copy the contents of the "Heart Disease Project" file into the working directory of your terminal session.

To execute the project, python app1.py command instructs Python to run the file named app1.py, which serves as the main script for the application. If the execution is successful, you will see a message in the terminal indicating that the Flask server has started, along with the local URL where the application is hosted. After successfully executing the project and ensuring the Flask application is running, open a web browser. It consists of login page, classification page and results page.

Home page provides the login window to fill the credentials. Through the login, the user can upload the retinal image which further goes through classification page. It predicts the image contains low risk or high risk of heart attack risk.

➤ Experimental Outcomes.

The proposed system was successfully implemented using Python on a system with an Intel Pentium 2.10 GHz

processor and 4 GB of RAM. The data was obtained from the DIARETDB1 database. This database derives the accuracy values from 89 color fundus photographs, 84 of which show at least mild symptoms and 5 of which are normal.

The proposed system was successfully put into action using. Python is compatible with a system that has an Intel Core i5 2.40 GHz processor. And 8 gigabytes of RAM. This database calculates the accuracy values. From a collection of 286 color fundus photographs, 100 of which capture the eye, can be found at. Mild symptoms, with 100 of them showing high-risk symptoms, are the least severe form of the illness. And 85 of which are considered normal. Performance metrics: recall, f1 score, and support. The significance of the cardio-eye connection lies in its ability to predict the risk of heart attacks. By analyzing retinal eye images (table 1), the researchers were able to gather valuable data for their study. Visual depiction. Of the recall, precision, f1 score, support, and accuracy values. (fig) Based on the experimental findings, it can be concluded. The evaluated measures indicate that the precision is 97%, recall is also 97%, and the f1 score is also 97%. Achieve a score of 97%, and the support value is 60 with an accuracy rate of 97%. Among the available training data, this particular dataset is widely regarded as the most exceptional.

Table 1 Experiment Values

S. No	Training data	Precision rate	Recall rate	F1 Score	Support	Accuracy
1	51	96.0	96.0	0.96	75.0	96.0
2	61	97.0	97.0	0.97	60.0	97.0
3	71	98.0	98.0	0.98	45.0	98.0
4	81	97.0	97.0	0.97	30.0	97.0
5	91	94.0	93.0	0.93	15.0	93.0

V. CONCLUSION

The potential of retinal imaging as a non-invasive tool for predicting heart attack risk. The integration of machine learning techniques enhances the analysis of retinal features, providing a promising avenue for early detection of cardiovascular diseases by expanding the dataset, refining the machine learning models, and exploring the clinical applicability of this approach in routine cardiovascular risk assessment. Our research focuses on machine learning techniques for the accurate prediction of heart attack risk through the analysis of retinal images. We made a trained model to show difference between healthy retinal features and those indicative of cardiovascular disease, leveraging a diverse dataset that plays a crucial role in assessing cardiovascular health. In this study, we evaluated the performance and generalization capabilities of various robust classifiers using two distinct datasets: a publicly available retinal image dataset and a clinical dataset. When we examined multi-class classification within the clinical dataset, retinal dataset maintained its superior performance, outperforming other deep learning classifiers which were recorded at 97%.

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