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Detection of Various Diseases using Retinal Image

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Abstract:- The project gives the people an insight of how fundus image processing can be used for identifying various human disease. A review of human diseases that can be diagnosed using fundus image is done. The changes in eyes especially the retina acts as the objective measure which captures the change in cell using which the detection is performed. The aim of this project is to show the importance of retinol images in finding various human disorders. Retinol is nothing but a derivative of vitamin A which plays a crucial role in human body like vision, growth regulation etc. Changes in the level of retinol can cause diseases in human. The severity of disease may range from simple metabolic disorders to dangerous cardiovascular disease.

The development in technology has enabled us to use fundus images in finding diseases like Diabetic retinopathy, Glaucoma, Age macular degeneration and cardiovascular diseases without involving the medical experts directly.

Keywords:- *Fundus Image, Retinol, Diabetic Retinopathy, Gluacoma, Age Macular Degeneration, Cardiovascular Disease.*

I. INTRODUCTION

Vision is arguably the most important of the five senses, as it provides us with crucial information about the world around us. The eye allows us to navigate our environment, recognize objects and people, and perform tasks ranging from reading to driving. Our ability to see shapes, colors, and distances greatly influences our daily lives and interactions with others. Understanding the structure and function of the eye is essential for maintaining eye health and diagnosing. The primary function of the eye is to detect light and convert it into electrical signals that the brain can interpret as images.

The eye disease if not treated early it leads to blindness which is one of the major issue .Majorly found eye diseases are Diabetic Retinopathy (DR), Age-related Macular Degeneration (AMD), Glaucoma, macular hole, central serous retinopathy, retinal detachment, retinal vasculitis which occur due to the structural changes in the blood vessels of human retina.

Most people will eventually have eye problems. While minor eye conditions can be treated easily at home and resolve on their own, more serious conditions require medical attention from qualified professionals. Only when these eye conditions are correctly identified in their early stages can their progression be halted. There are many different symptoms that can be seen with these eye conditions. If Cardiovascular diseases is not treated at early stage it can cause death in a short period of time. Cardiovascular disease is majorly caused due to hardening of arteries and high blood pressure . Regular eye exams are important for detecting any issues early and preserving vision for a lifetime.

A. Related Theories

Retinol and its derivatives are essential for normal vision, as they play crucial roles in the function of photoreceptor cells in the retina. Abnormalities in retinol metabolism or signaling pathways can contribute to various visual disorders, such as nyctalopia.

Regular screening with retinal imaging helps identify individuals at risk of vision-threatening complication and facilitates timely intervention to prevent Diabetic Retinopathy.

Retinal imaging can aid in the identification of individuals at risk of developing glaucoma, known as glaucoma suspects. OCT measurements of RNFL thickness and optic nerve head parameters can help distinguish between healthy eyes and those with early signs of glaucomatous damage. Early detection of glaucoma suspects allows for timely initiation of monitoring and preventive measures to preserve vision.

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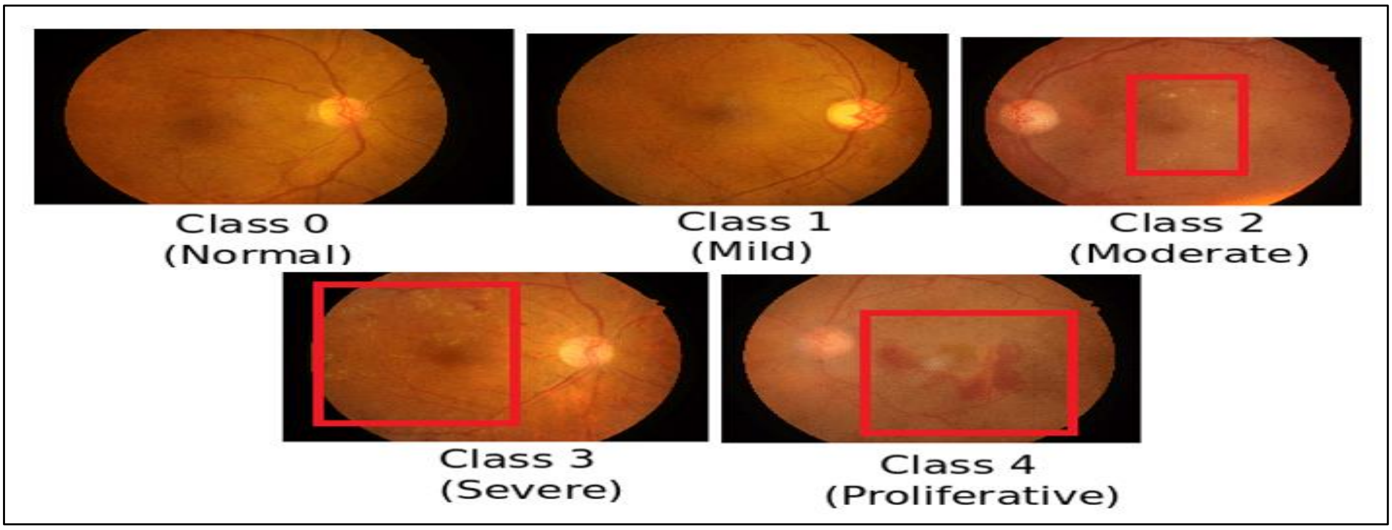

Fig 1: Model Different Stages of Severity of Eye Disease Shown in Retinol Fundus Image

Retinal imaging biomarkers derived from retinol images can predict the risk of AMD progression and visual outcomes. Parameters such as drusen volume, geographic atrophy (GA) area, and subretinal fluid (SRF) on OCT scans may serve as prognostic indicators for disease severity and likelihood of developing advanced AMD, such as neovascular AMD (wet AMD).

Retinal imaging can detect microvascular changes in the retinal arterioles and venules, such as arteriolar narrowing, venular dilation, and the presence of retinopathy lesions. These alterations in retinal vessel morphology are associated with systemic cardiovascular risk factors, including hypertension, diabetes, dyslipidemia, and atherosclerosis. Retinal vessel abnormalities may serve as biomarkers for assessing cardiovascular risk and predicting the development of cardiovascular disease (CVD) events.

B. Network Design

We implement this model as a convolutional neural network. The input images are received as raw pixel values in input layer of convolutional neural network. The dimension of input layer and dimension of input images will be corresponding. Learnable filters known as kernels are applied to the input image in the convolutional layer. Feature extraction is done by filters using multiplication and summation within the small regions of the input image. Output provided by this layer is known as Feature map. An activation function is applied after every convolutional layer. computational complexity is reduced by using the pooling layer.

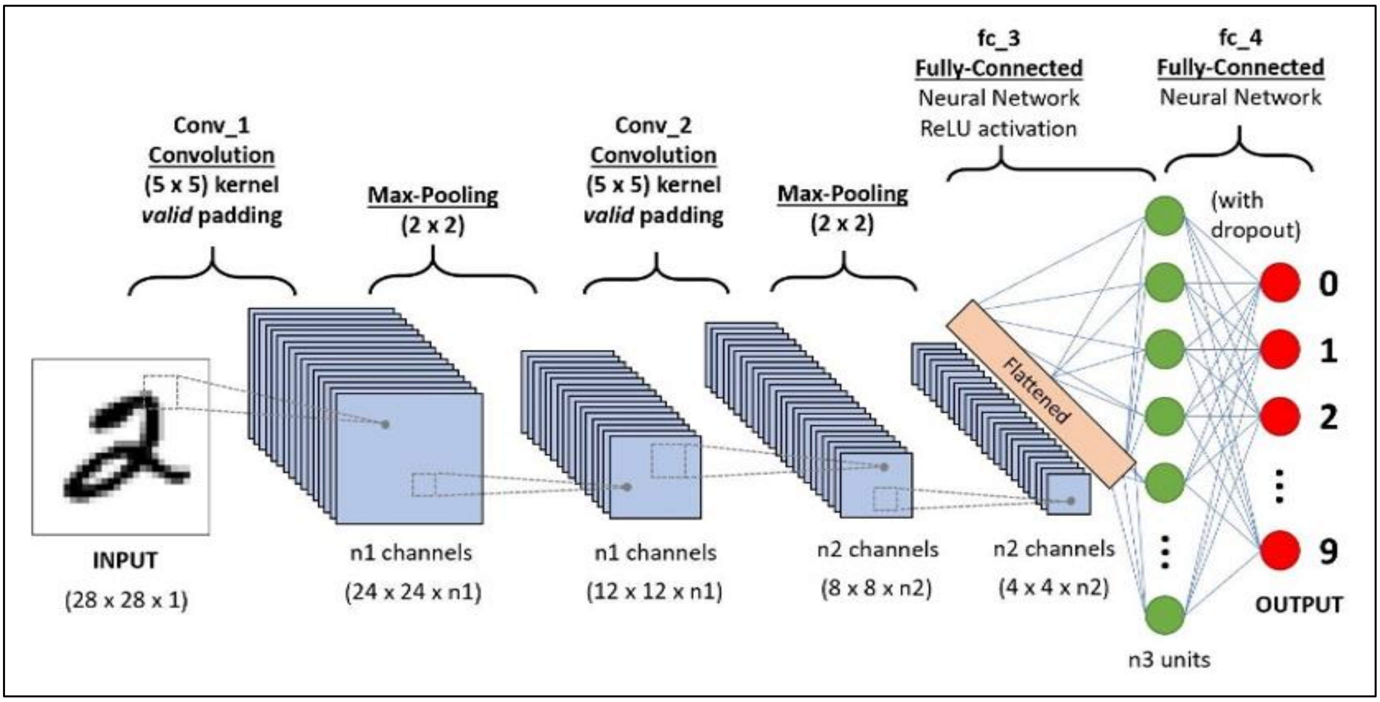

Fig 2: The Architecture of Convolutional Neural Network and how the Image is being Processed in Different Layers

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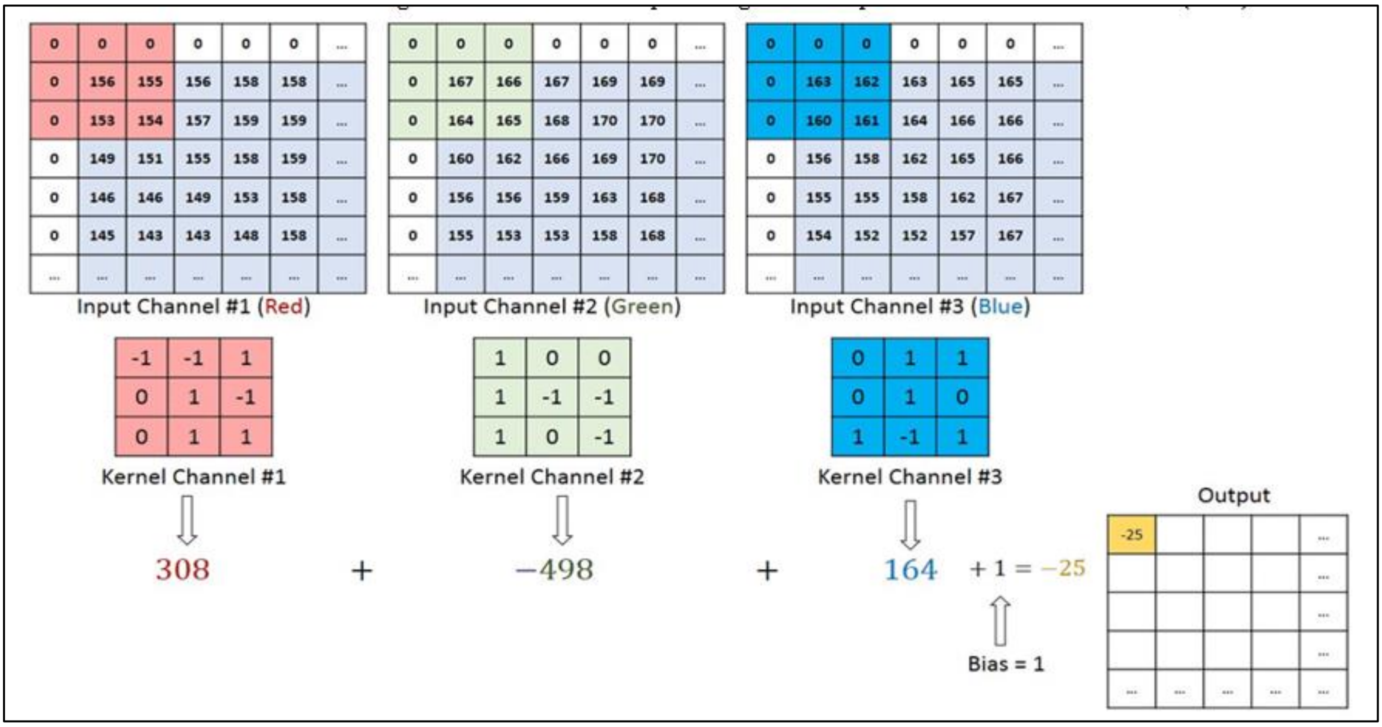

Fig 3: Convolutional Operation using 3x3x3 Kernel on MxNx3 Image Matrix

Convolution operation is performed by an element of convolutional layer called filter and is represented as 3x3x1 matrix during matrix multiplication because stride length is 1 kernel shifts between its position. Even though kernel has multiple channels like RGB the depth of the image remains same as the input image. The result gives us 1-depth feature output when Kn and In stack undergoes matrix multiplication.

High level features such as edges are extracted by performing convolution operation. convolutional layer is not limited to convets. The responsibility of capturing low level features is of conv layer like gradient orientation, color etc. understanding of image is obtained due to the added layers in dataset because of high level features which provide a network to have a clear picture of the datasets. This operation is performed in two forms one, where the dimension of convolved feature is reduced. second, here the dimension remains the same or increases we obtain these results by using valid padding and same padding.

To obtain convolved matrix of dimension 5x5x1 we apply 3x3x1 kernel above the 6x6x1 image when it is merged with 5x5x1 image and this is known as same padding. when the above process is done without padding, we obtain a matrix which is of the dimension 3x3x1 and which is equal to the dimension of the kernels hence, it is called valid padding. until the complete width is examined for a particular stride value the filter is said to move to the right. Till traversal of the image the filter moves from starting of the image to the end maintaining the same stride value.

➢ *The Requirements Listed Below must be Met by the Data Training in Our CNN Model:*

- Our dataset shouldn't contain any missing values.
- The dataset needs to be clearly separated into training and testing sets. Neither the training nor the testing sets should include any irrelevant data from outside of our model domain. If the dataset is an image dataset, all of the images need to be the same size because an uneven distribution of image sizes in our dataset can reduce the neural network's efficiency.
- Before feeding the photos into the convolution layer, they should be changed to black and white format because reading the images in RGB would need a 3-D NumPy matrix, which would speed up execution.
- Before putting the database's contents into the neural network, any damaged or fuzzy photos ought to be removed. Now that we understand the guidelines for pre-processing input, let's get straight to how a convolutional neural network operates.

II. METHODOLOGY

A. Data Acquisition:

As the dataset collected where from different source and resolution and even the degree of noise was reduced and lighting was maintained the dataset obtained is of high accuracy because the images in dataset are of different resolutions, they are varying from 2592x1944 to 4752x3168 pixels. Thus, a few preprocessing stages have been completed. Following these preparation steps, 500 photos in all were chosen from the Kaggle dataset. Of these 500 photos, 70 percent are used for system testing and the remaining 30 percent are used for training.

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B. Initialization of the Hyper Parameter:

We initialized the hyperplane values before to creating the network layers. The initial learning values (α), mini-batch size, learning-rate decay-schedule, learning rate factor, and momentum value (θ) are all set to 0.9. For VGG16, the initialization values of the alpha values are 0.0001, 0.0001, and 0.001, respectively. For VGG16, the learning-rate decay schedule was stair-wise, while the decay schedule for Inception Net is exponential. For VGG16, the learning-rate-decay factor was 0.10. For VGG16, the initial learning rate decay factor was 20.

C. Pre-Processing:

The preprocessing measures we used to attain high accuracy were as follows: CNN uses a dataset of fundus photos, each with a different aspect ratio and size. The image is Resized and downsized to 256x256 images as it is considered as the primary step to perform preprocessing Before giving data into the architecture for classification, Convert the photos before adding data to the architecture for categorization filter is applied to remove any unwanted noise in the image. The fundus pictures' microaneurysms (MA) and vessels are highlighted in monochrome images known as data. The swelling is caused by microaneurysms (MA) on the side of a blood artery. MA is a crucial indicator of DR.by using filtering algorithm like histogram equalization Microaneurysm candidates was able to perform high contrast adjustment in fundus image. Zero-padding is used to resize the image by filling with black pixels.

D. Training Algorithm:

Selection of an appropriate loss function to quantify the difference between the model's predictions and the ground truth labels. For binary classification tasks (presence/absence of a retinal disorder), binary cross-entropy loss is commonly used. Choose Based on the calculated loss function, select an optimization strategy to update the model's parameters iteratively. An optimization technique that is frequently utilized is stochastic gradient descent (SGD). Tune hyperparameters such as learning rate, momentum, and weight decay to optimize the convergence of the training process. Feed batches of retinal images and corresponding labels into the network. Use the selected optimizer to minimize the chosen loss function by updating the network's weights and biases through backpropagation. Monitor training metrics such as loss and accuracy on the training and validation sets to track the model's performance and detect overfitting. Train the network for multiple epochs (iterations over the entire dataset) until convergence or until performance plateaus.

E. Testing:

Testing involves running a system to find any flaws, missing requirements, or requirements that differ from the real requirements. A software engineer must comprehend the fundamental idea underlying software testing before implementing techniques to create efficient test cases. Every test ought to be able to be linked back to the needs of the client. Black-box testing is the process of testing an application without having any knowledge of its internal workings. Assess the trained model's capacity for generalization and look for possible problems like overfitting or underfitting by evaluating it on the validation set. Adjust model hyperparameters or architecture based on validation performance if necessary. Once satisfied with the performance of the validation set, evaluate it on the held-out test set to obtain an unbiased estimate of how well it functions in actual situations. Determine assessment measures including recall, accuracy, precision, and F1-score., and area.

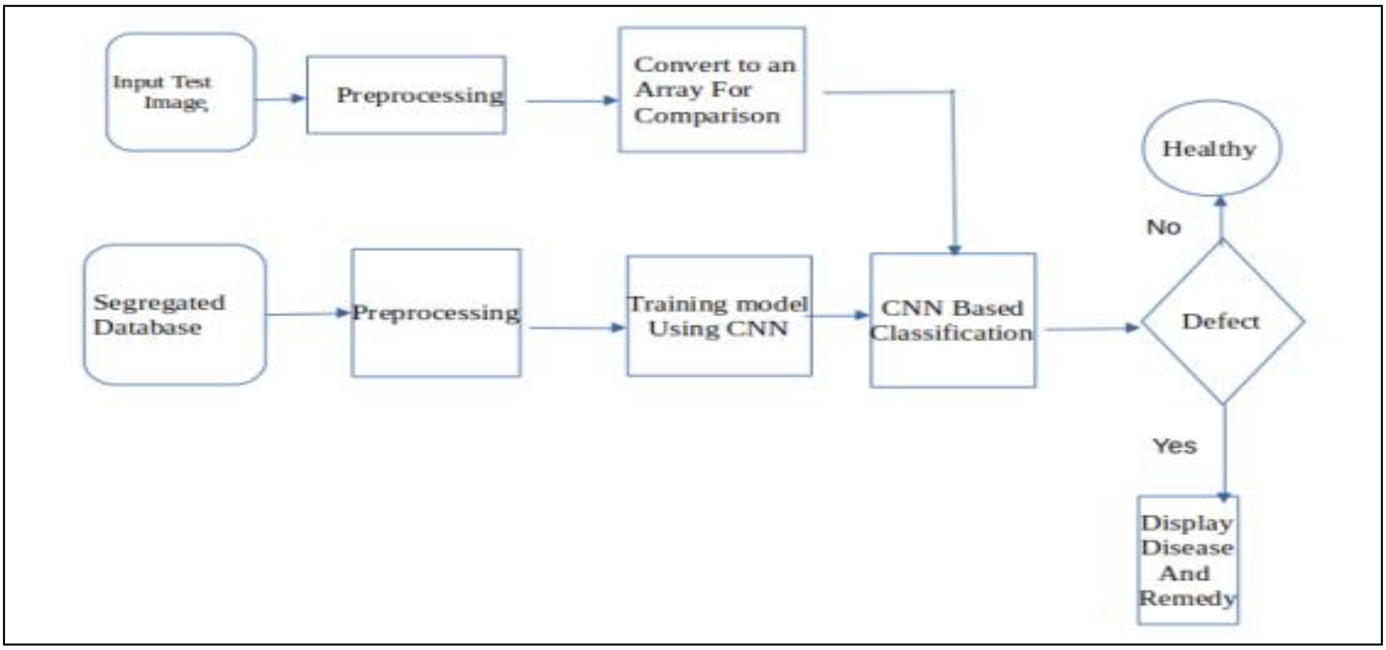

Fig 4: Flowchart of Retinol Disorder as Biomarker for Detection of Human Disease

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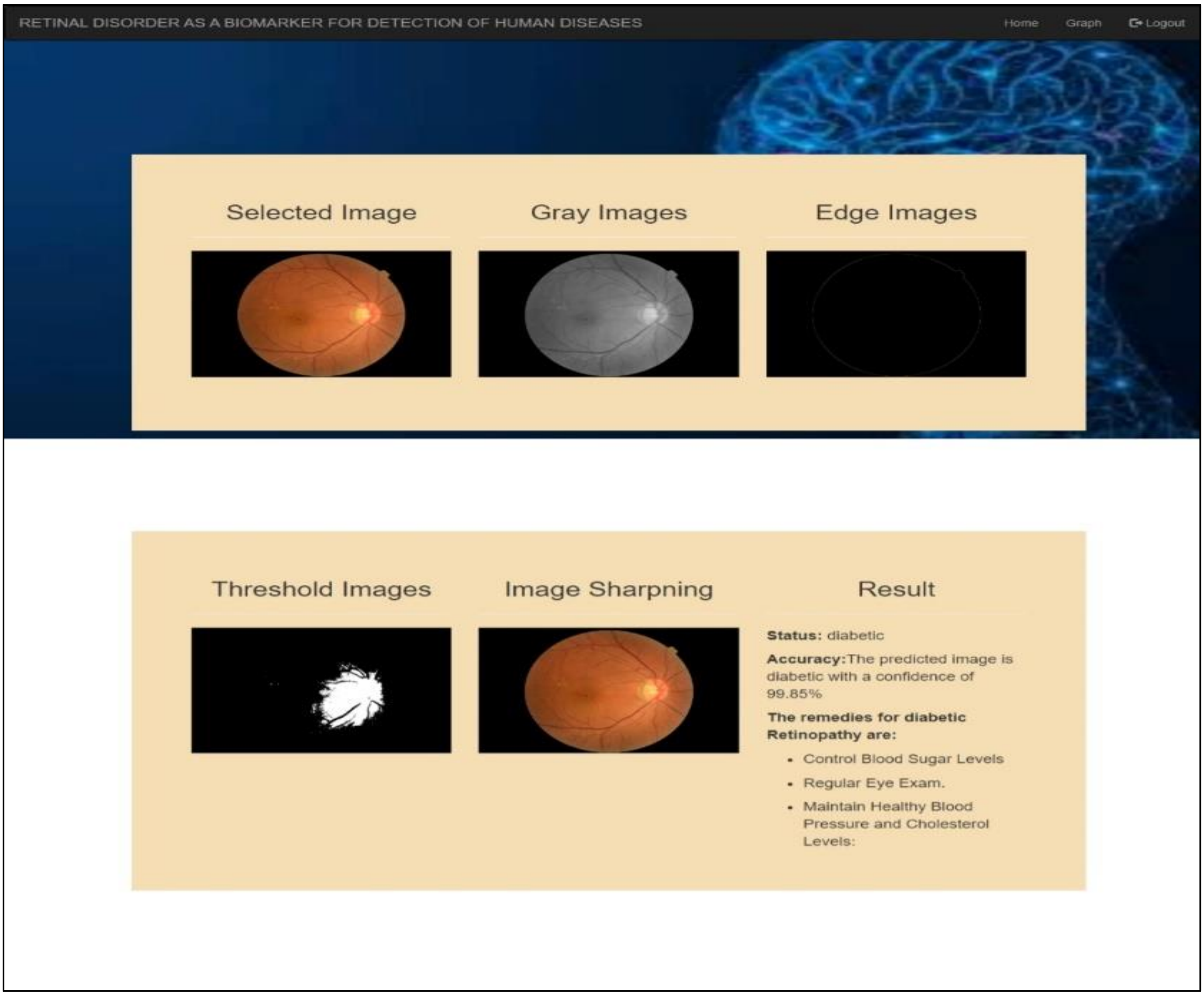

Fig 5: The dataset is Tested and the Image Passes through Following Stages Like Gray Image, Edge Image, Threshold Image, Image Sharping and Finally the Output is Obtained Detecting the Disease

III. CONCLUSION

The association between retinal disorders and various human diseases serves as a promising biomarker, offering valuable insights into systemic health. The intricate network of blood vessels and the shared embryological origin with the brain make the retina a window to broader physiological conditions. Detecting retinal abnormalities may aid in early diagnosis and monitoring of diseases such as diabetes, hypertension, cardiovascular disorders (low severity or high severity), glaucoma. The growing significance of retinopathy as a possible biomarker for human illness identification presents a promising avenue for advancing diagnostic and prognostic approaches in healthcare. The exploration of retinol disorder as a biomarker is done using convolutional neural network. This proposed system will help people to get treatment for disease at early stage reducing the severity of the disease.

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