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Analysing Diseases Baesd on Fundus Examination

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ABSTRACT

In our rapidly evolving world, the increasing prevalence of eye diseases such as glaucoma, papilledema and diabetic retinopathy has highlighted the importance of early and accurate diagnosis to effectively treat and prevent vision loss. This project aims to harness the power of deep learning techniques to automate the detection and classification of these important eye diseases by analysing retinal fundus images. The system uses a comprehensive dataset that includes normal, glaucoma, papilledema, and diabetic retinopathy cases. Our main goal is to develop a robust and reliable tool that can help healthcare professionals in the early diagnosis and monitoring of these eye diseases. This innovation has the potential to significantly improve patient outcomes and reduce healthcare costs. Fundus examination is a non-invasive procedure that allows the doctor to visualize the retina, optic nerve and other structures at the back of the eye. It is an important tool for diagnosing and monitoring a variety of eye diseases, including glaucoma, papilledema and diabetic retinopathy. Convolutional neural networks (CNNs) are a type of machine learning model that is very well suited for image classification and segmentation tasks. In recent years, CNNs have been used to develop models for the automatic detection and diagnosis of eye diseases based on fundus images.

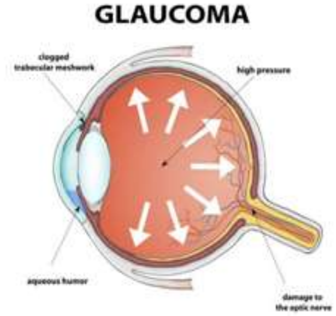
Keywords: Fundus, Glaucoma, Diabetic Retinopathy, Papilledema, CNN, Deep learning.

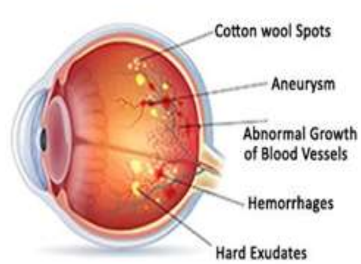
INTRODUCTION

This project delves into the application of fundus image analysis for the detection of sight-threatening pathologies including glaucoma, papilledema, and diabetic retinopathy. By leveraging deep learning techniques, we aim to develop a robust diagnostic tool that assists healthcare professionals in the early and accurate identification of these prevalent eye diseases. This translates to a significant reduction in human error during image review, a crucial aspect for overworked ophthalmologists. The increasing global burden of these conditions, with estimates suggesting 6 million cases of diabetic retinopathy, 4 million glaucoma cases, and 2 million papilledema cases in India by 2030, underscores the necessity for such an automated system. Ultimately, this project aspires to contribute towards improved clinical outcomes, reduced healthcare costs, and potentially, the prevention of vision loss.

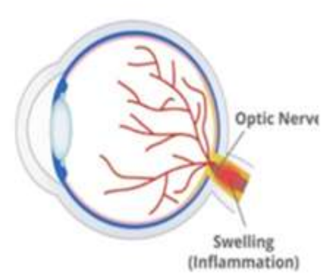
FUNDUS:-The posterior ocular fundus encompasses the retina, macula, and optic disc. Photoreceptor cells within the retina transduce light into neural impulses relayed via the optic nerve. The macula lutea's central fovea facilitates sharp central vision. The optic disc serves as the exit point for the optic nerve, receiving nourishment from the posterior vasculature. Fundus examination is crucial for diagnosing and monitoring various eye disease.

GLAUCOMA





Diabetic Retinopathy



Papilledema

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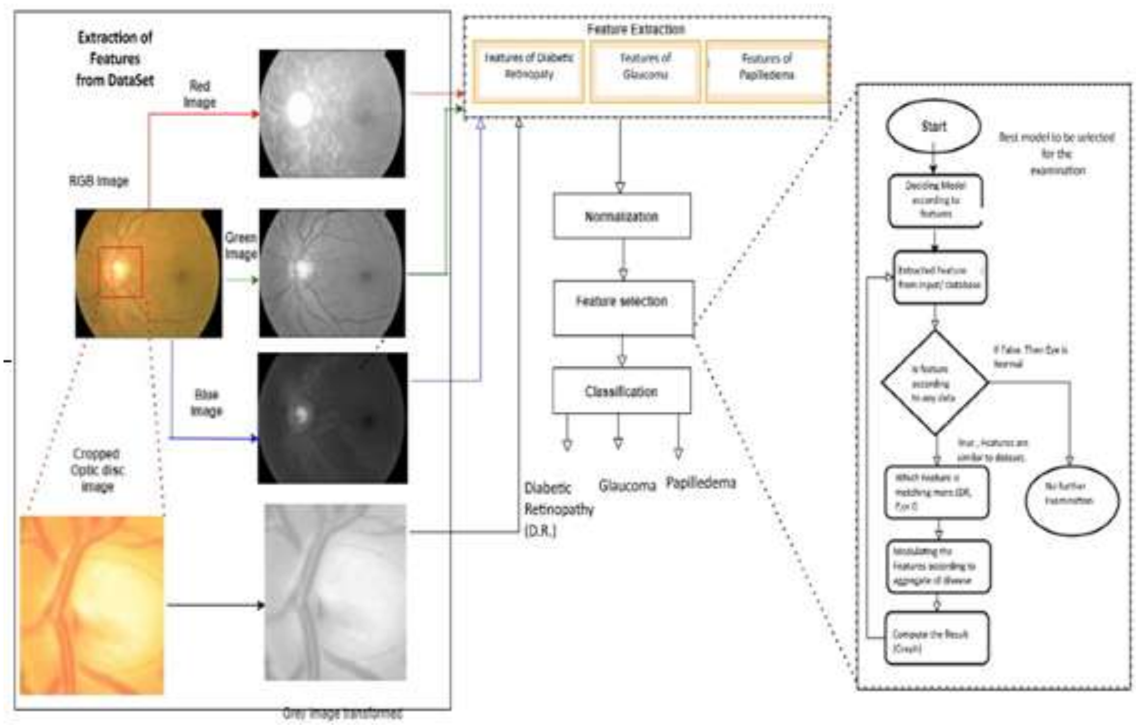
Here this project analyses and detects 3 Ocular Fundus Disease:-

a) Glaucoma, a group of eye diseases damaging the optic nerve, is a leading cause of blindness. Early detection and treatment are crucial for vision preservation
b) Increased intracranial pressure (ICP) exceeding 250mmHg in adult's triggers papilledema, optic nerve head swelling. This signifies potential severe conditions and can lead to vision loss if not addressed. Persistent ICP disrupts axoplasmic flow, causing nerve edema. Chronic pressure induces axonal loss and ischemic optic atrophy.
c) Hyperglycemia in diabetes precipitates retinopathy, a leading cause of working-age adult blindness. Laser therapy or injections can impede vision loss. Chronically elevated blood sugar disrupts retinal function, causing micro vascular blockages and subsequent leakage or hemorrhage. Ischemic retina triggers neovascularization, with fragile vessels prone to further bleeding.

SYSTEM ARCHITECTURE & METHODOLOGY

A) SYSTEM ARCHITECTURE: -



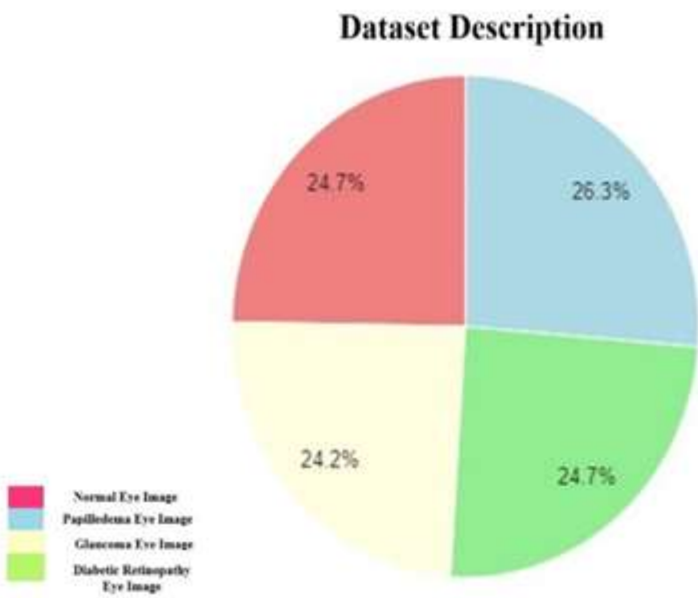
The architecture depicted shows a block diagram of a system for the automatic diagnosis of papilledema, diabetic retinopathy and glaucoma based on retinal fundus images [1]. Fundus examinations are necessary because they provide a view of the back of the eye, which includes the retina, optic nerve, and blood vessels. This allows doctors to recognise signs of eye diseases, such as Glaucoma, Diabetic Retinopathy, Papilledema.

Early detection and treatment of these diseases can help prevent vision loss. Fundus examinations are painless and relatively quick. During a fundus examination, the pupils are dilated with eye drops. A healthcare professional then shines a bright light into your eyes and examines the back of the eye using a special magnifying lens.

This system Architecture depicts the works in segments such as, first pre-processing the fundus image. To do this, the image is cropped to focus on the optic disk and the image intensity is normalized. Features are then extracted from the image. These features are characteristics of the image that can be used to detect the presence of a disease. In the case of diabetic retinopathy, features such as micro aneurysms (small bulges in the blood vessels) and haemorrhages (bleeding) can be extracted. In the case of glaucoma, features that can be extracted include changes in the shape of the optic nerve and the presence of optic nerve haemorrhages. Once the features have been extracted, they are used to train a classification model. This model is a computer program that has been trained to recognize the presence of a disease based on the extracted features. The classification model can then be used to classify new retinal fundus images as normal or abnormal.

The Architecture can further be divided into 4 main categories which comprises of Dataset Description, Image Preprocessing, Main Model, and the database description where the meta data is stored (Login & Registration Credentials) .

I) DATASET DESCRIPTION

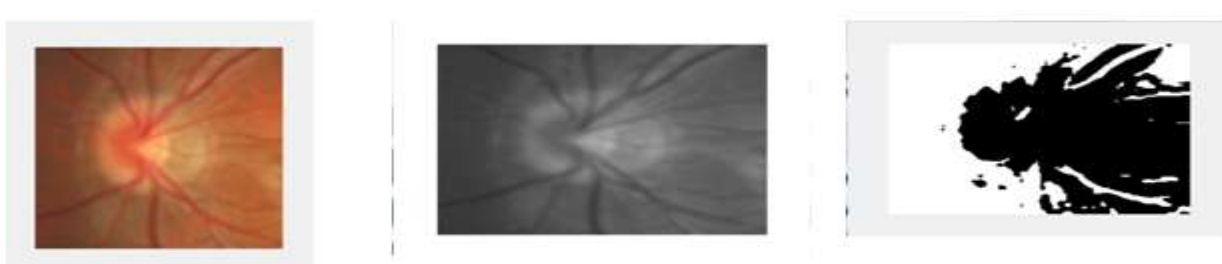


a) **Glaucoma (24.7%):** This slice contains images of eyes with glaucoma (glaucoma). Glaucoma is a group of eye diseases that damage the optic nerve, which can lead to loss of vision.
b) **Diabetic retinopathy (26.3%):** This section includes images of eyes with diabetic retinopathy. As you mentioned, this is a complication of diabetes that affects the blood vessels in the retina.
c) **Normal eye (49%):** This section likely represents images of healthy eyes with normal skin color around them. The description "light red or pink" suggests that these are images where the whites of the eye and the skin around the eye appear normal."

II) Image Preprocessing :

a) Display Images:

- Converts the grayscale and threshold images to a Tkinter-compatible format using Image.fromarray andImageTk.PhotoImage.
- Displays the grayscale image (img2) and the thresholder image (img3) as Tkinter labels.
- Displays the grayscale image (img2) and the thresholded image (img3) as Tkinter labels.



(a) (b) (c)
Original Fundus Image Preprocessed Fundus Images

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III) Feature Extraction :

i) Training Phase:

- Retinal Image: This is the input data used to train the system.
- Preprocessing: The retinal image undergoes preprocessing steps to prepare it for further analysis.
- Segmentation of Features: The image is segmented to identify relevant features such as blood vessels and the optic nerve.
- Feature Extraction: Features are extracted from the preprocessed image.
- Classification: The system is trained to classify the image into different categories, such as glaucoma, papilledema, or diabetic retinopathy.

ii) Testing Phase:

- Input Image (Fundus Image): This is the image that the system will classify.
- Preprocessing: Similar to the training phase, the input image is preprocessed.
- Feature Extraction: Features are extracted from the preprocessed image.
- Classification: The system classifies the image based on the features it has extracted.

B) METHODOLOGY:-

I) DATA DISTRIBUTION

The usual split is 80% for training and 20% for testing. This means that with 4035 images, approximately 3228 would be used for training and 807 for testing.

These data sets are available on Kaggle.

- **Kaggle**: Kaggle is a platform for data science competitions and has a community-driven area for sharing datasets. You can search for "eye image dataset" or specific terms such as "glaucoma dataset" to find relevant datasets

II) IMAGE PRE-PROCESSING:-

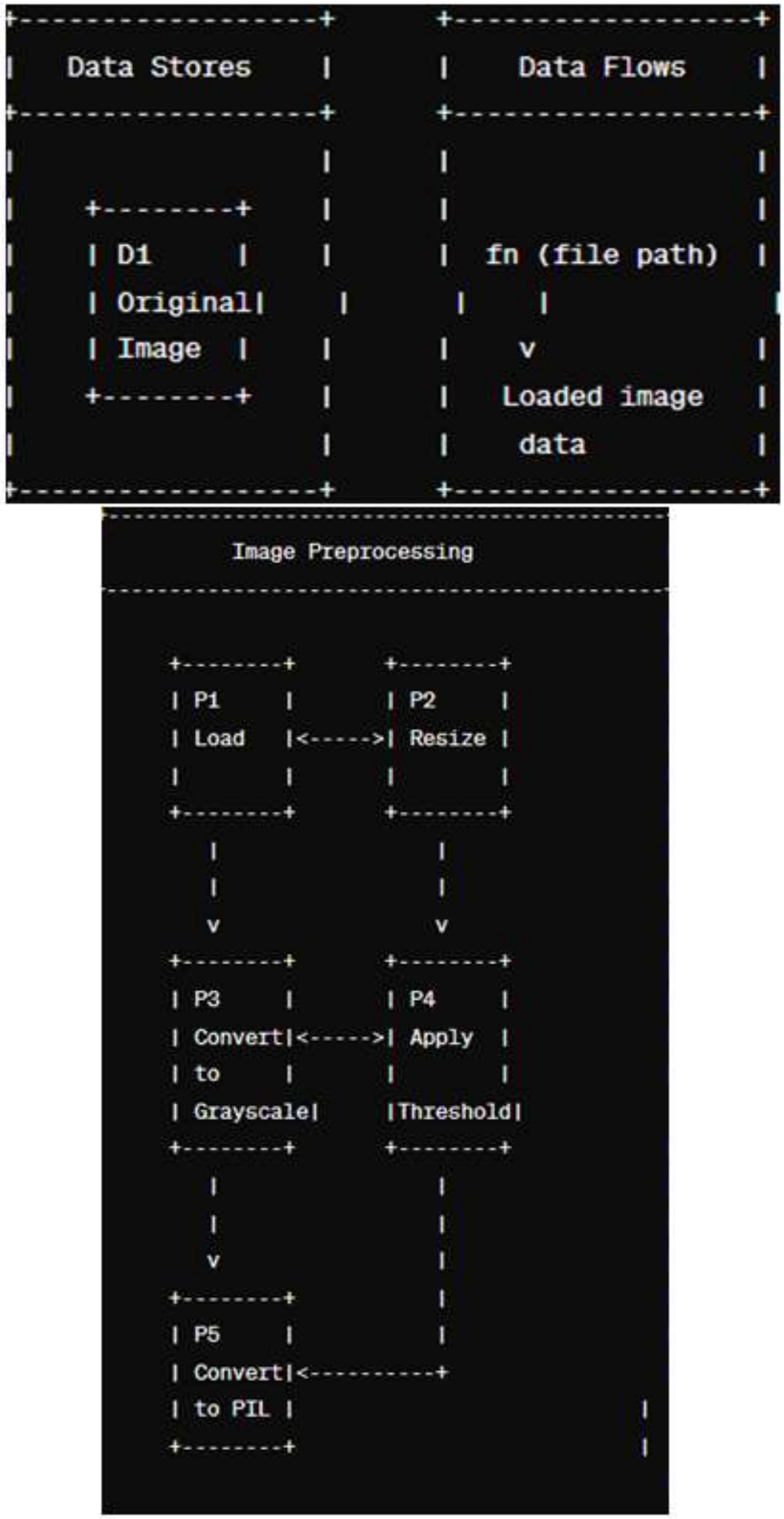
a) Read and resize image:

- Reads an image file specified by the global variable fn using PIL's Image.open.
- Resizes the image to a predefined size of 200x200 pixels.
- Convert to grayscale:
- Converts the resized image to grayscale using OpenCV's cv2.cvtColor.
- Changes the size of the grayscale image back to the original dimensions.

b) Thresholding:

- Applies Otsu's thresholding method with cv2.threshold to segment the grayscale image into a binary image.
- Otsu's method automatically calculates the threshold based on the image histogram.
- The cv2.THRESH_BINARY_INV flag is used to invert the binary image so that the foreground pixels become white and the background black.

Now, let us represent the mathematical model for thresholding:



The threshold operation can be represented as follows:
& \text{if } I(x, y) > T \\
& \text{otherwise}

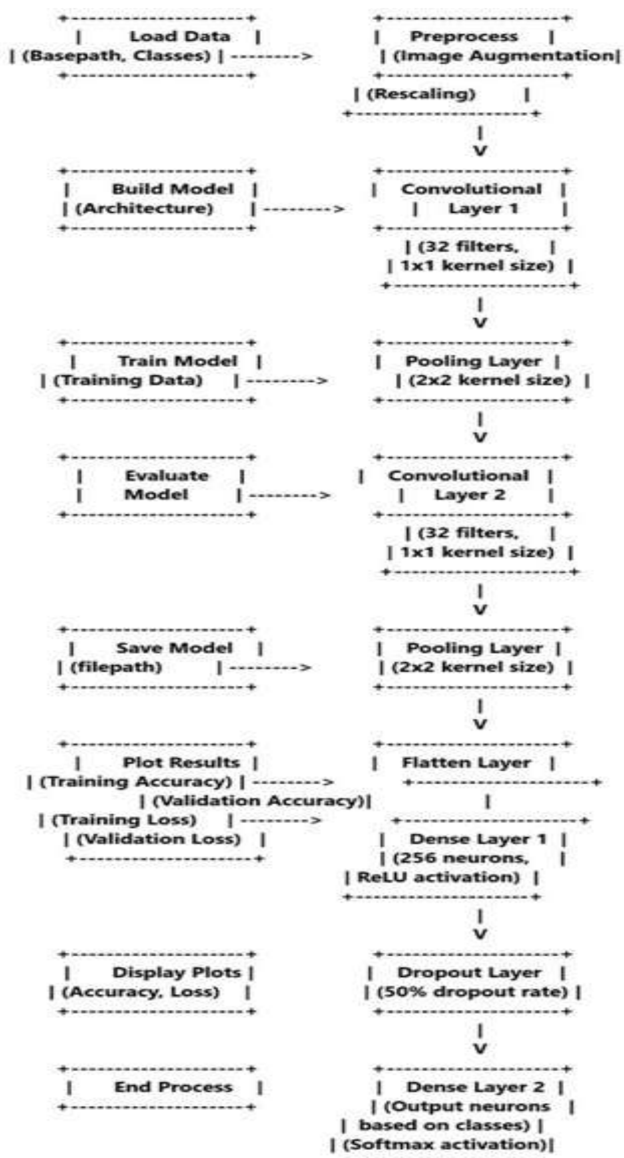
- \end{cases} \]
- Here \(O(x, y) \) stands for the pixel intensity of the binary image at the coordinates \((x, y) \). If the pixel intensity in the grayscale image is greater than the threshold value \(T \), the corresponding pixel in the binary image is set to 255 (white); otherwise it is set to 0 (black).

III) Main Model Description :

A) Imports and Setup:

- numpy: Numerical computation library for handling arrays and mathematical operations.
- Sequential, Convolution2D, MaxPooling2D, Flatten, Dense, Dropout from tensorflow.keras.layers: These are classes for building the CNN architecture.
- Optimizers from tensorflow.keras: This provides various optimization algorithms like Stochastic Gradient Descent (SGD).
- ImageDataGenerator from keras. Preprocessing. image: Used for data augmentation and preprocessing.
-
- h5py: Used for saving the trained model to a file.
- matplotlib.pyplot: Used for plotting accuracy and loss graphs.

B) Model Architecture:



The CNN model is initialized as a Sequential model.

- Model architecture:

- The CNN model is initialized as a sequential model.
- Three convolutional layers are added, each followed by a ReLU activation function and a max-pooling layer to extract features and reduce dimensionality.
- The flattening layer converts the 2D feature maps into a 1D vector.
- Two fully linked (dense) layers with ReLU activation are added, and a dropout layer is added to prevent over fitting.
- The output layer consists of 5 neurons (classes) with softmax activation for multi-class classification.

C) Compilation:

- The model is compiled with SGD optimizer, categorical cross entropy loss function and accuracy metric.
- Data augmentation:

Image Data Generator is used to generate augmented training data by applying random transformations such as rotate, shear, zoom and flip.

D) Loading the data:

- The training and test data are loaded from directories using the flow_from_directory method, specifying the target size, batch size and class mode. class mode specified.

E) Training:

- The model is trained using the fit_generator method with the training data generator. During training, validation data is provided for evaluation.

F) Saving the model:

- The trained model is saved in a file in HDF5 format.

G) Evaluation:

- The model is evaluated using the test data to calculate the test accuracy and also using the training data to calculate the training accuracy.

H) Plotting:

- Matplotlib is used to plot training and testing accuracy and loss across epochs.
- Now to create a mathematical model and equations, we can mathematically represent each step of the CNN architecture. For example:

I) Convolutional layer:

- Explanation: - Convolutional layers are the building blocks of a CNN. They apply a series of filters to the input image to extract features. Each filter learns to recognize a particular pattern or feature from the input.
- In the convolution operation, the filter (also known as a kernel) is passed over the input image and the dot product between the filter weights and the corresponding pixel values in the receptive field is calculated.
- The result of a convolution layer is a feature map that represents the presence of features recognized by the filters at different spatial locations of the input image.
- Mathematical representation:

$$\text{Output}=\sigma(\textstyle\sum_{i,j}(W_{ij} * X_{ij}+b))$$

Wij: Filter weights, **Xij:** Input pixels, **b**: Bias term, **σ**: Activation function.

J) Pooling Layer:

- Explanation: Pooling layers are used to reduce the feature maps obtained from the convolutional layers, thus reducing their spatial dimensions and the number of parameters in the network.
- Max-pooling is the most common pooling operation, where the maximum value within each local region of the feature map is retained and the rest is discarded.
-
- Mathematical representation:

Output(i,j)=Max(X2i,2j,X2i,2j+1,X2i+1,2j,X2i+1,2j+1).

Here**, X2i,2j** represents the values in a **2x2** region of the input feature map

- Pooling makes the learned features more robust to input variations, reduces computational complexity and controls over fitting.
- In max-pooling, the output at each spatial position (i,j) in the pooled feature map is calculated as the maximum value within a local neighbourhood:

K) Fully Connected Layer:

- Explanation: Fully connected layers, also known as dense layers, are used to perform classification based on the features extracted from the convolutional layers. Each neuron in a fully connected layer is connected to each neuron in the previous layer, forming a dense matrix multiplication. The output of a fully connected layer is the result of applying an activation function to the weighted sum of the inputs from the previous layer.
- Mathematical representation& its Elaboration: -

Output=**σ (W·X+b)**

W: weight matrix, **X**: input vector, **b**: bias term**, σ**: activation function.
Let X be the input vector for the fully connected layer, W the weight matrix and b the bias vector. The output Y is calculated as follows: $Y=\sigma(W\cdot X+b)$
Where $W\cdot X$ is the dot product of the weight matrix and the input vector, b is added element by element and σ is the activation function.
These equations represent the mathematical operations that are performed in each layer of the CNN.

iii) Database Description

a) Importing sqlite3 Module:

- import sqlite3: This statement imports the SQLite database module so that the Python program can interact with SQLite databases.
-

b) Defining variables:

- Email = tk.StringVar(): This line defines a Tkinter StringVar object to store the email entered by the user.
- password = tk.StringVar(): This line also defines a Tkinter StringVar object to store the password entered by the user.
-

c) Advantages of SQLite:

- Ease of Use: SQLite is easy to set up and use, making it ideal for small to medium-sized projects.
- Serverless: SQLite is a serverless database engine, meaning it doesn't require a separate server process to operate. This simplifies deployment and reduces overhead.
- Embeddable: SQLite databases are self-contained, allowing them to be embedded directly into applications without requiring a separate database server installation.
- Cross-Platform: SQLite databases are compatible across different platforms and operating systems, making them highly portable.
- Transactional: SQLite supports ACID (Atomicity, Consistency, Isolation, Durability) transactions, ensuring data integrity and reliability.

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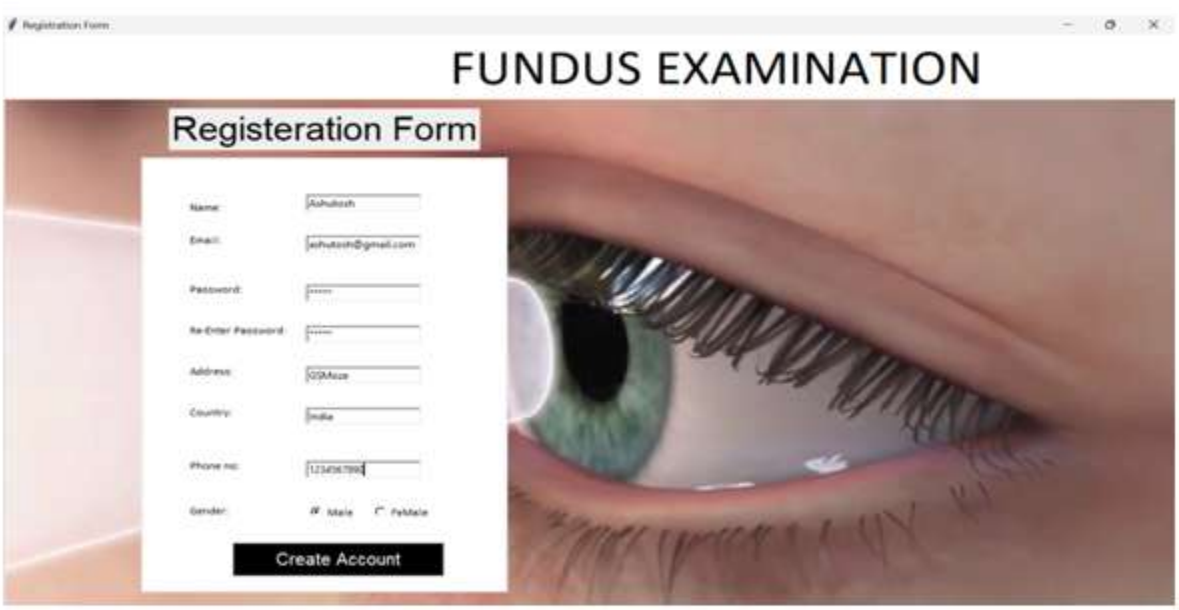
- Performance: For many use cases, SQLite offers excellent performance due to its lightweight design and efficient storage format.
- Widely Supported: SQLite is widely supported and integrated into various programming languages and frameworks, including Python, making it a popular choice for development.

RESULTS & DISCUSSIONS

Result will be shown in the statistical graph of accuracy vs percentage which shows the mild, moderate, severe these are levels of Diabetic Retinopathy, Glaucoma, Papilledema. We conclude that Convolutional neural networks have the potential to revolutionize the way that eye diseases are diagnosed and managed. d. In recent years, CNN models have been shown to achieve state-of-the-art accuracy in the detection and diagnosis of eye diseases from fundus images. CNN models have the potential to be highly accurate. CNNs can be used to develop automated systems for fundus image analysis, which can help clinicians to diagnose eye diseases earlier and more accurately. Thus, we detected some gaps in existing systems to fulfill that gaps we have much scope to work on it.

STEP 1: Home Page (Once the Code is executed this page will be popped up):-

STEP 2: If the user has not registered, they have to register first:-



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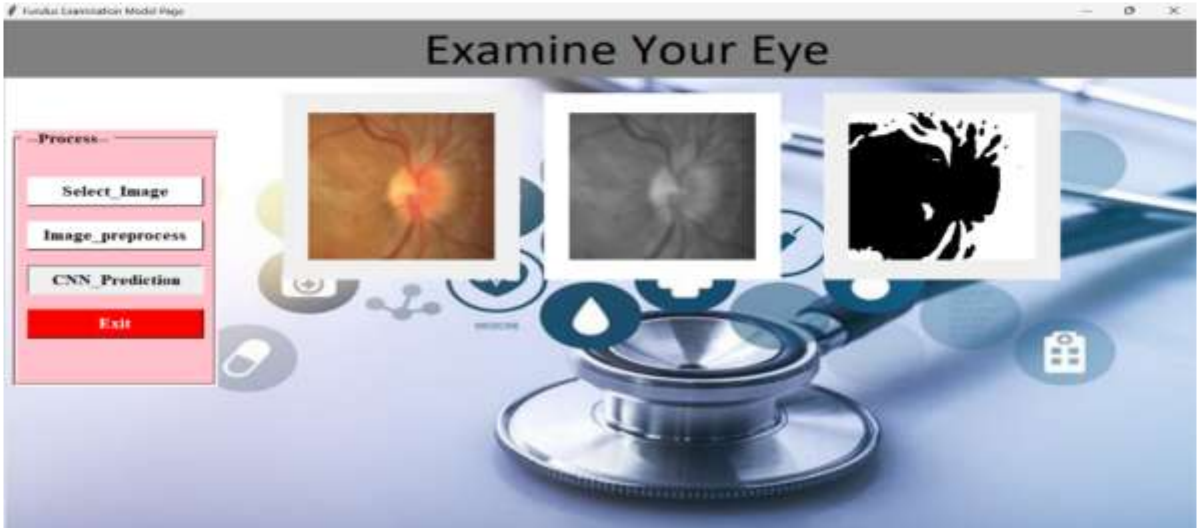
STEP 3: - Login Page (USER has to login into there account)

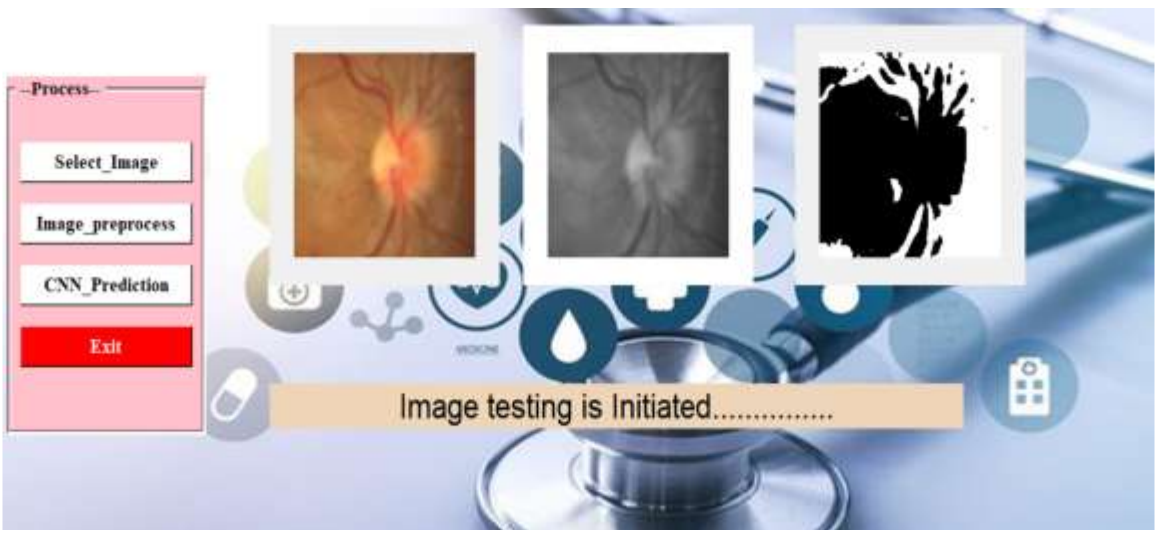
STEP 4:- Once you have Login into your account you will be redirected to main page:-

STEP 5:- Now USER has to select the Fundus Inage and UPLOAD it :-

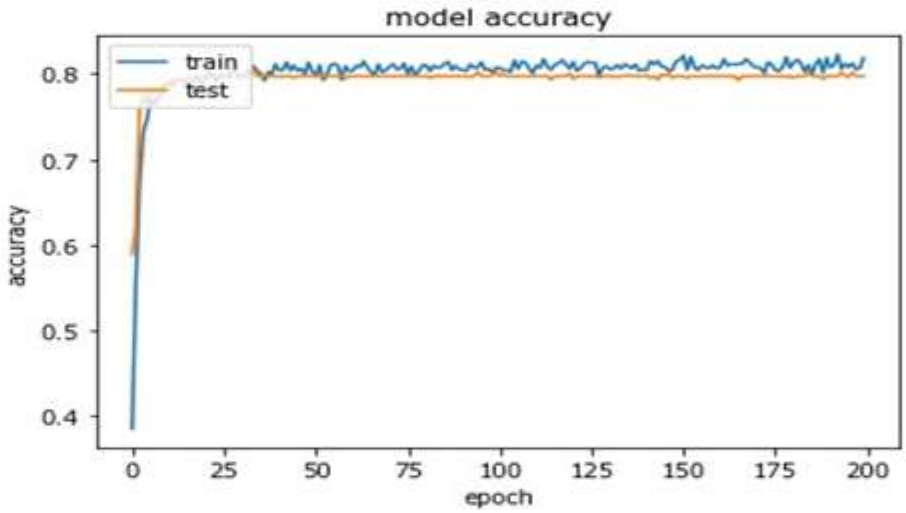
STEP 6:- Click the Image_Preprocessing Button and this will be shown:-



STEP 7: Now Click CNN_Prediction Button and and the model will we initiated :-



STEP 8:- This Output will be popped up:



As the model accuracy is 95% and after training the model on different epoch this Model Accuracy is evaluated and can be seen. The Epoch is change to obtain high accuracy and for better performance this can be seen as the model is trained again and again.

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