

Eye Disease Prediction Based on Retinal image

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Abstract— The main aim of the paper is to develop a general framework for the recognition of diseases such as Rhegmatogenous RD, Maculopathy, Hypertension, Heart Attack, Diabetic Retinopathy, Artery vein occlusion, normal and Stroke in the human body based on retinal images. Fundus images show disease-related information. The pre-processing steps include the accurate segmentation of the retinal vessel thus distinguishing the vessels into arteries and veins. With the advent of Deep Learning, it is possible to recognize images with the help of Convolution Neural Networks (CNN). As CNN works well for images, the diseases can be predicted more accurately than any other method. The VGG 16, VGG 19, Resnet50, and Densenet architectures are used to find the diseases based on retinal images. .

Keywords--- Retinal fundus image, CNN, Preprocessing, VGG16, VGG 19, Resnet50, Densenet Architecture.

I. INTRODUCTION

The eye is an important sensory organ in the human body. It receives light and converts it to nerve impulses and those are transmitted to the brain through the optic nerve and so providing images to us. The retina converts the incoming light into a signal to the brain so it is also an extension of the brain system. Retina plays a major role in which any abnormalities in the retinal function would result in any diseases. Recent advancement in technology gives us high-resolution retinal images. By diagnosing those images, illness could be predicted in the human body. In our work, retinal images are given as input which follows some preprocessing methods which are fed into the CNN approach as a preprocessed image. The CNN approaches are VGG16, VGG19, Resnet50, Densenet, and so on. As a result, the predicted diseases such as heart attack, Rhegmatogenous RD, Maculopathy, hypertension, stroke, artery vein occlusion, diabetic retinopathy, and many other diseases. This prediction of disease would help clinical sectors to identify the illness soon before any big problem so that person could be treated with proper treatment. This prediction of disease by using retinal

images through the CNN approach gives us good accuracy and reliable easy solution for the diseases in the human body.

A. OVERVIEW OF EYE

Three important layers in the eye present the flat against each other. The sclera is the white part of the eye that surrounds the cornea. This forms around 80 percent of the eyeball's surface area, covering from the cornea to the optic nerve. It is the dense connective tissue of the eyeball, which forms the "white" of the eye. The front surface of the eye is the clear layer so-called the cornea. It not only allows light to enter the eye for vision, and provides around a quarter percent of the focusing power of the eye.

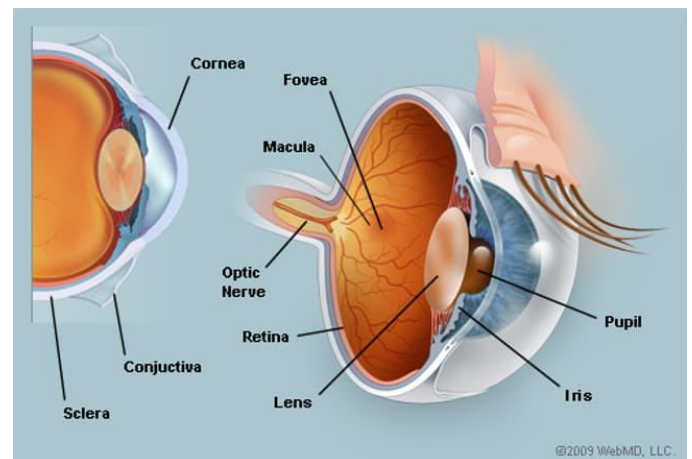


Fig 1. Overview of an eye.

II. LITERATURE SURVEY

Karthikeyan S et al [1] In this research work, collected real-time fundus images from DIARETDB0, HRF Image Database and STARE and grouped into twelve categories to classify the disease. The work is processed by VGG19 Deep Learning Architecture. Initially, the model was optimized around 50 epochs to get maximum accuracy and the prediction of their model gave around 95.63 % of training accuracy and 92.21% of validation accuracy.

Yu Wang et al [2] proposed to bring the image quality good and improvise the model with high accuracy using Random Implication Image Classifier Technique (RICT) algorithm. The pre-processing involves a median filter to remove the noise so as to reduce the loss. The system gives better accuracy of 96.7 percent.

R. Bhavani et al [3], In this work gives the prediction of diseases using the technique of comparison of Central Retinal Equivalent of Vein (CRVE) and Central Retinal Equivalent of Artery (CRAE) measurement. The proposed framework includes Retinal image acquisition, Preprocessing (Grayscale conversion, noise removal), vessel segmentation (Features extraction, Vessel tracking), vessel classification, and disease prediction. Supervised feature extraction method such as median filter is used to get accuracy.

Niloy Sikder et al [4] proposed a study handled the Diabetic retinopathy (DR) dataset using Digital Image Processing (DIP) and Machine Learning (ML). DR is chosen because most grownup people lead to loss of vision so detection of this disease reduces the blindness rate around the world by around 90% and more. In this paper, The work is carried out by an ensemble learning algorithm by extracting the information from retinal images which resulted in a 91% classification accuracy.

Zhentao Gao et al [5] with their dataset collected from different databases predicted a four-degree classification task. Inception-V3 network is used as a diagnostic model and their performance is evaluated with various mainstream CNN models. By using the DCNN approach, the model predicted an accuracy of around 91.2%.

Toufique Ahmed Soomro et al., in their work [6] demonstrates the Deep Learning model and compared the techniques with each other and highlights the different contributions of work among the papers and depicted the limitations and advantages of each paper.

Ansh Saxena et al [7] provides researchers a platform for medical diagnosis using images. In the paper, They presented the analysis of classification methods collected from the dataset from some databases. It shows the pre-trained CNN models like Xception, VGG16, VGG-19, ResNet-50, DenseNet-121, and DenseNet-169, and their performance observed from the classification report.

T. Johnlayoni et al [8] presents the work involves a methodology to preprocess the dataset and achieve high accuracy. The input retinal image is preprocessed to convert RGB to Grayscale conversion and a median filter is applied to remove noises to maintain the image quality. Then the preprocessed image follows the vessel segmentation process and the disease is predicted by measuring the CRAE and CRVE values by using the SVM algorithm.

D.Selvathi et al [9] in their work proposed a method to classify the diseases using some algorithm and predict the disease using thermal images. The preprocess steps involve a Gray Level Co-occurrence Matrix to texture conversion from gray images. The preprocessed image is fed into the algorithm and finally gives an output with an accuracy of around 86.22%.

Gorana Gojic et al [10] in this work compared the existing work and its performance to improve its action for segmenting the vessels and showed the high performing predictor for diagnosis purpose.

Vikram Ragunath et al [11] proposed a work compares the existing work and improvised model by segmenting the optic disc and cup and undergoing the retinal image extraction and then classifying it into Glaucoma sickness.

Pedro Costa et al [12] developed a new method to overcome the drawback in the existing methodology based on the multiple instance learning (MIL) framework. The method gives better performance and high accuracy compared with the existing works.

Denial Utami Nurul Qomariah et al [13] proposed an Automatic Detection system that helps for quick detection of DR and uses high-level features for the prediction of disease. Through this technique, The model was developed and gave a better accuracy of around 95.83%.

Bambang Krismono Triwijoyo et al [14] detail Convolutional Neural Networks (CNN) that helps in recognizing retinal images. The dataset used here is the STARE color image dataset and it is divided into various categories as 15 classes.

Mobeen-Ur-Rehman et al [15] implemented automated tools to predict Diabetic Retinopathy. A customized 5 layered CNN model is proposed. The customized model gives good results when compared with the pre-trained models.

This work uses various masking techniques for the segmentation process and data of ten hypertensive retinopathy patients is evaluated. The best way to identify retinal problems is color image segmentation, according to M Anna Latha et al [16].

Keita Saito et al [17] proposed a simple CNN model, built for classification of various heart diseases images. This CNN model is directly trained with that class images. Pre-trained networks like Alex Net and Google Net are used in the applications of image processing. This CNN model achieves higher image classification with less training time.

Qiu et al [18] explains in his work, an innovative methodology to detect DR lesions at the pixel level. A multi-

scale Convolution Neural Network (CNN) is designed to make full use of multiple different scales with complementary image information.

R. Hannah Roseline et al [19] details Retinal Image Analysis (RIA) as the key element in the early detection of diseases. In this work, the detection of blood vessels is effective, when deep Neural Networks (NN) are used for segmentation and Support Vector Machine (SVM) is used for classification of various diseases.

Aya Adel et al [20] explores his work to automatically detect Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), DRUSEN, and NORMAL class in Optical Coherence Tomography (OCT) images. This deep learning classification model has two transfer-learning architecture and Support Vector Machine (SVM) instances to classify the retinal diseases correctly in the retinal OCT dataset.

III. DATA SET

The Data set is of seven categories such as heart attack, Rhegmatogenous RD, Maculopathy, Hypertension, stroke, artery vein occlusion, and diabetic retinopathy. The dataset is collected from three databases such as STARE, DRIVE, CHASE.

TABLE I . COMPARISION OF CNN ARCHITECTURES
The input image of artery vein occlusion, heart attack, diabetic retinopathy, hypertension, stroke, hematogenous and maculopathy is shown in the table. These input images are preprocessed and finally classification takes place and its accuracy are shown in the table.

NAME	DIABETIC RETINOPATHY	HEART ATTACK	HYPERTENSION	ARTERY VEIN OCCLUSION																																								
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IV.METHODOLOGY

Image acquisition is the process of retrieving images from various sources. Pre-processing the data means handling the input image. It is the primary step in executing the model. Images sizes and resolutions are highly varied. The 3 channels of pictures are RGB. This RGB colour is converted to a greyscale then standardization is followed to make the data rescaling. Median Filter Algorithm is used so that images are noise-free so that the model can be trained and predicted correctly. The pre-processed image is saved for further processes. Save the pre-processed record. Each of the pre-processed pictures is saved in the record alongside their classes. Finally, the saved images are used to feed into the Convolutional Neural Network. By following this process, the Prediction of various diseases are done through four deep learning algorithms such as VGG16, VGG19, RESNET50, DENSENET121.

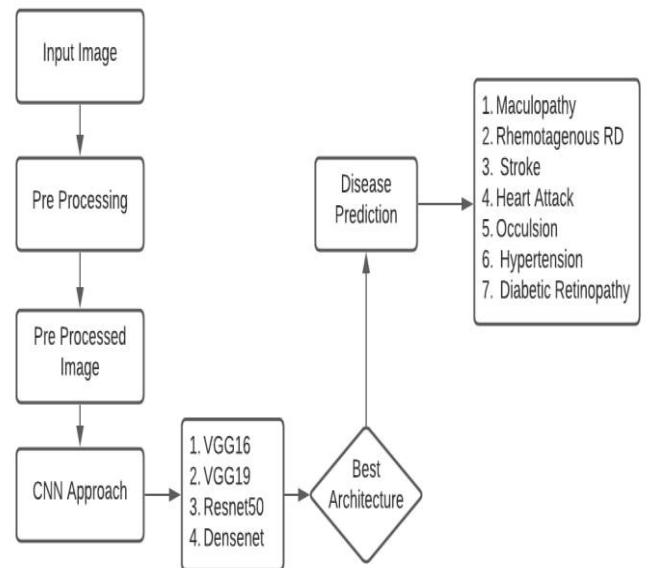


Fig 2. Block Diagram

V. ARCHITECTURE

1. VGG16 NETWORK ARCHITECTURE
2. VGG19 NETWORK ARCHITECTURE
3. RESNET50 NETWORK ARCHITECTURE
4. DENSENET ARCHITECTURE:

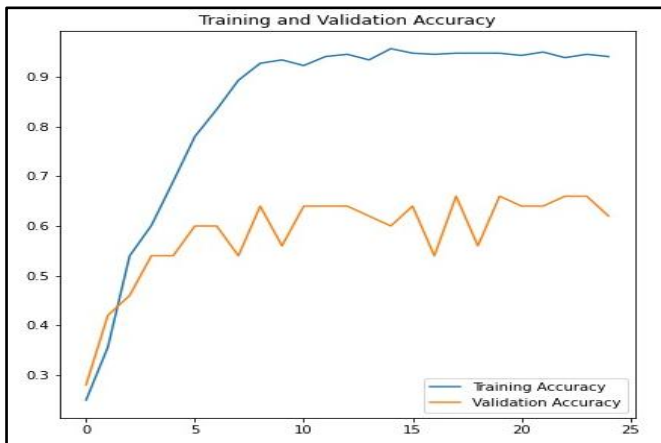


Fig.3. gives 98% Training accuracy of the model

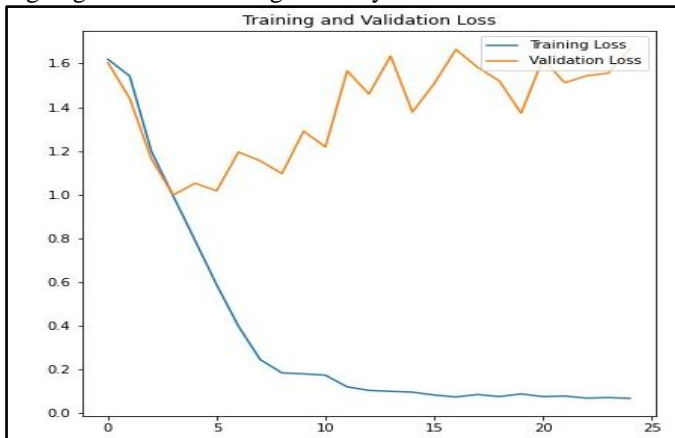


Fig 4 Training and validation loss graph

VI.CONCLUSION

Our project has anticipated the characterization of the retinal eye by predicting the diseases in the human body using retinal images of the human eye utilizing the CNN approach. This work used four different architectures namely Vgg16, Vgg19, Resnet 50, Densenet 121 and by comparing its classification report and observing recall, precision, sensitivity, and accuracy of that model and finally chose the VGG 19 as best architecture among those four because the sensitivity score of all the diseases was found to be high. As a result, the trained

model predicted whether the person is affected or not by giving input as a retinal image and it follows pre-process methodology and finally gives us the output. the classes are categorized into seven diseases such as Rhegmatogenous RD, Maculopathy, stroke, hypertension, heart attack, diabetic retinopathy, artery vein occlusion. . the input image is classified into any one of these diseases and gives us the output. The CNN approach is used and finally, it gives us a good accuracy of 68%.

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