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SYSTEMATIC MODEL FOR GLAUCOMA EYE DISEASE DETECTION USING DEEP LEARNING

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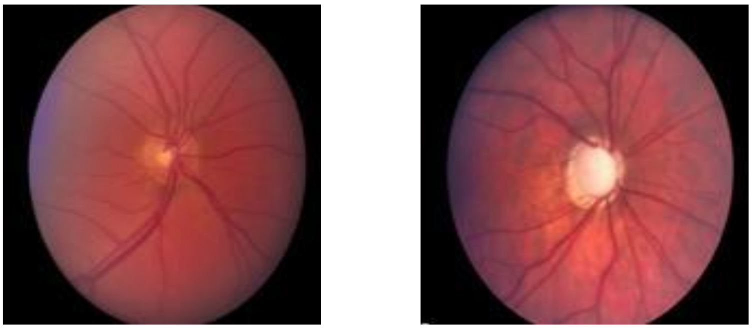
Abstract--- **Nowadays, there are numerous causes for visual impairment. Eye diseases which are evident in the retina can be spotted through a systematic and structured ophthalmologic examination. Subsequent rise of the patients with these diseases due to population growth, aging made the number of Ophthalmologists a controlling factor. Glaucoma is a type of deep-rooted disease which leads to vision loss thus making it irreparable. Therefore, this disease has to be detected at an early or intermediate stage for timely treatment. Various models have been developed based on image processing or deep learning to detect Glaucoma but the systems have either been computationally complex or of insufficient accuracy. In the proposed system, structured learning which makes use of the edge information of the fundus image is used for OD detection. Finally, the convolutional neural network (CNN) is used to check if it is glaucoma affected eye or not. Thus detecting Glaucoma at early stage with system producing the increased accuracy, specificity and sensitivity.**

Keywords - **Convolutional Neural Network, Hough Transform, Optic Cup, Optic disk, Principal Component Analysis, Watershed Segmentation**

I. INTRODUCTION

Glaucoma is an irreversible eye disease that deteriorates the visual ability of humans. The fast-paced rise in the disease has provoked the development of a novel system for early Glaucomatic eye detection. Glaucoma can result in permanent vision loss if there is excessive pressure inside the eyes inflicting damage to the optic nerve. Therefore it is a necessity that it is detected at an initial stage to prohibit further development. Typically, Intraocular Pressure (IOP) measurement, Optic Nerve Head (ONH) and Function-Based Visual Field Test (FBVFT) methods of Glaucoma detection preside over other methods. Though, IOP points as a notable symptom; it can't be globally implemented as it involves various clinical measurements. On the other hand, FBVFT commands sophisticated tools which are expensive and uncommon. Unquestionably, manual ONH process requires a lot of resources. Major ONH methods use specific criteria like Vertical Cup to Disc Ratio (CDR), Rim to Disc Area Ratio (RDR), Disc Diameter and NRR for the detection of Glaucoma. Methods based on CDR are largely used when a higher CDR shows greater risk in Glaucoma. Fundoscopy is prominent Biomedical imaging techniques to analyze the retina. Lately, analyses that make the most of features related to Spatial temporal including the morphological values of Optic Cup, Optic Disc and Neuro-Retinal Rim (NRR) etc in order to detect Glaucoma in fundus images are done.

However, this technique poses difficulties such as appropriate pre-processing, accurate ROI segmentation, scarcity of generalized threshold and post segmentation. These issues limit efficiency of the major existing approaches. Apart from this the segmentation of Optic cup and optic disc, the removal of nerves from the OD and OC for clarity in analysis is rigorous. Therefore, these approaches compound computational complexity. As a possible alternative, methods of deep learning have attracted extensive observation.



(A)Normal Eye **(B) Glaucoma Detected**

Fig 1. Description of Optic Nerve

II. RELATED WORKS

The detection of glaucoma has, by far, mostly been done with the aid of image processing techniques and a few deep learning algorithms or image processing techniques coupled with clinical assessment. A particular method of deep learning to acquire added information relevant to the image, and a screen test to detect glaucoma from the fundus image directly was introduced in a model. It uses a method that combines the hierarchical context of the global fundus image and the local optic disc in depth for the automatic glaucoma detection. The final screening result adds the Output probabilities of different streams.

Another model uses a structured analysis and interpretation of data for the automatic segmentation, calculation and evaluation of AS-OCT structures. The system estimates initial markers in the eye. These markers allow the segmentation of chief clinical structures, and then they are used to regain normal clinical parameters. Following this the initial markers are refined. Clinicians make use of these parameters for assessment of the eye anatomy and they are used in glaucoma screening-based algorithms for the detection of angle closure.

A third method uses a stacked Auto-Encoder jointly with CNN. Functionally it inherits the features of the Convolutional Auto-Encoders. It achieves deep feature extraction followed by learning then classification. GlaucoNet implements a CAE model that gathers deep features and integrates numerous features to perform classification. Structurally, it embodies 3 Convolutional layers and 2 Fully Connected layers. The convolutional layer retrieves the features and learns with it, whereas the fully connected layers play the role of the classification layer to execute the classification between Glaucomatic and Non-Glaucomatic fundus images.

III. EXISTING SYSTEM

The proposed system focuses on both Cup-to Disk Ratio (CDR) and various features to advance the accuracy of glaucoma. This system includes preprocessing of high-resolution fundus images (datasets) which includes the following steps: RGB to Gray scale conversion, Normalization, Noise removal and Contrast enhancement. Morphological Hough Transform Algorithm (MHTA) is intended for optic disc segmentation. For the separation of optic cup intensity based elliptic curve method is used. Then the CDR value and feature extraction can be estimated. Finally, classification is performed with combination of Naive Bayes Classifier and K Nearest Neighbor (KNN). These classification techniques improve the classification process based on severity of disease and damage to optic fiber. The storage time is reduced due to reduction in the features used. The accuracy using Navies Bayes Classifier is about 75.4 and using hybrid classifier is about 78.91.But the major drawback in the aforementioned techniques and methods result in several problems which lack in several areas like accuracy of detection mechanism, absence of appropriate selection method in case of noise removal and segmentation process and not imposing any constraints to the classification mechanisms. Even after developing a sophisticated model it lacked good accuracy of detection of glaucoma.

IV. PROPOSED SYSTEM

This paper proposes a technique for Optic Disk detection in a structured manner of learning. The method uses the fundus image of the eye and works on the edge information. The image enhancement is done using adaptive histogram equalization, morphological processing is performed followed by watershed segmentation. It is different from the classical methods of capturing edge information such as the use of edge detectors. When the conventional edge detectors are used it detects the vascular edges on the fundus image as well apart from just the optic disc edges retrieving redundant information. Here, for segmentation of Optic Disc the Hough transform is used. Finally, the Convolution neural network (CNN) classifier is used to check the fundus image is normal or abnormal.

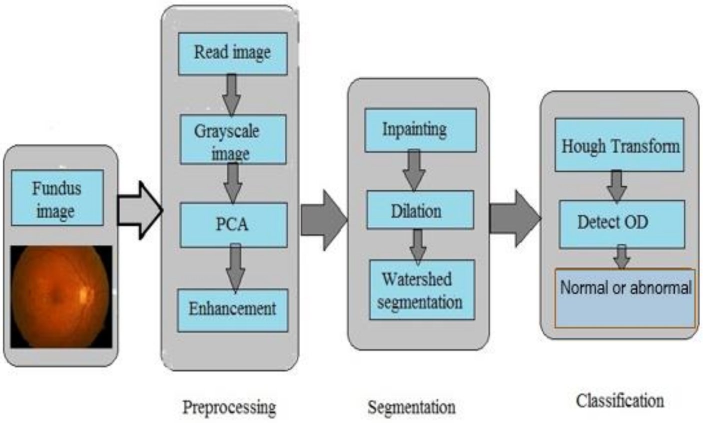


Fig 2. Simple Block Diagram of Proposed Model

V. WORKING METHODOLOGY

The first stage is preprocessing. The fundus image undergoes grayscale conversion which is then applied to principle component analysis. PCA is used in dimensionality reduction.

(A)Grayscale Conversion:

The color of a pixel in an image is given by the combination of colors Red, Green, and Blue (RGB). The representation of RGB color values is three dimensional and illustrated by the attributes of lightness, chroma and hue. The grayscale image has been represented using 8-bit values in two dimensions using luminance. The luminosity method is adopted here. The intensity of a pixel value of a grayscale image ranges from 0 to 255. By converting the RGB values i.e., 24 bit into grayscale value i.e., 8 bit a color image is converted into a grayscale image. To convert any color image to a grayscale image of its intensity then their first values of the primaries in linear intensity encoding through gamma_expansion must be obtained. Finally, merge certain proportions of green, red and blue (Green being the highest proportion, then red, then blue).

(B)Principle Component Analysis:

Principal component analysis (PCA) is a method that evaluates a data table in which data are described by many quantitative inter-correlated dependent variables. Its aim is to retrieve the significant information from the data to display it as a set of new orthogonal variables called principal components, and to show the similarity pattern between the observations and the variables. The primary aim of principal component analysis (PCA) is dimensionality reduction of the data that has multiple variables with correlation but also maximum possible retention of the variation. This is achieved by the transformation of the variables to a new set of variables in a manner such that retaining the variation in the actual variables declines as we advance downwards in the order. Therefore, the maximum variation in the initial components is retained by the 1st PC. The principal components are orthogonal as they are the eigenvectors of a covariance. The Eigen vectors and Eigen values are the vectors and numbers connected to square matrices. The Eigen-decomposition matrix helps in analyzing the structure of the matrix based on correlation, covariance and cross-product matrices.

PCA consists of the following steps:

STEP 1: Loading the data by arranging a data set as an $m \times n$ matrix, where m is the number of measurement types and n is the number of trials.

STEP 2: Demean the original dataset by calculating the covariance matrix of the dataset.

STEP 3: Acquiring the eigenvector(s) associated with the greatest Eigen value(s).

STEP 4: Transform the original dataset using the Eigen vector(s).

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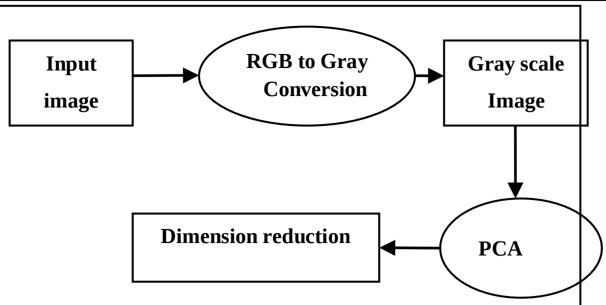


Fig 3. ER Diagram for Preprocessing

(C) Image Enhancement:

Adaptive histogram equalization is performed to improve the global contrast of images. Alternatively, to applying histogram equalization, contrast-limited adaptive histogram equalization (CLAHE) can be performed. The former operates on the whole image, the latter works on certain sections of the image, called **tiles.** In order for the histogram of the output region to approximately match a specified histogram, adaptive histogram equalization enhances the contrast of each tile. Once equalization is done it joins the neighboring tiles using bilinear interpolation to eliminate boundaries that are induced artificially.

(D)Inpainting and Dilation:

Image inpainting is the technique of reconstructing missing sections of an image so that viewers are unable to observe that these regions have undergone restoration. This technique is commonly used to eliminate undesirable objects from an image or to revive damaged areas of old photos. The two kind of morphological operations are dilation and erosion. Pixels are added to the boundaries of objects in an image in dilation whereas pixels are removed from object boundaries. The number of pixels added or removed from the objects in an image varies based on the size and shape of the structuring element that is used in the image processing.

(E) Watershed Segmentation:

- **Gradient Method:**

The gradient method is used prior to watershed transform segmentation for preprocessing of the grayscale image. The gradient magnitude at the object edges contains the high pixel values whereas in all other portion it contains the low pixel values. During watershed transform there is a risk of over segmentation due to formation of watershed ridge lines along the edges of the object. The topological gradient approach can be used for segmentation results along with which the attenuation of over segmentation can be done. Here, the main edges of the processed image are identified and then the calculation of the watershed takes place for the gradient detected which an added advantage of this method.

- **Marker Controller Method:**

The watershed transform cannot be directly applied to gradient images as it produces over segmentation due to noise which divides the regions into many segments. Over segmentation can be controlled using the marker which is defined as the attached component in an image. Markers are broadly divided into two- internal for object and external for boundary and these are used for modification of the gradient images. The marker-controlled watershed segmentation does the segmentation along the closed contours making it a powerful and versatile technique. In this internal marker are attached to the region of interest and external markers are attached to the background. After this the edges of the watershed regions are properly arranged along the appropriate ridges thus demarcating the object from its neighbors.

Algorithm:
Segmentation is used to mark the background locations and foreground objects. The following procedure for Marker-controlled watershed segmentation:
Step 1: Calculate a segmentation function in an image whose dark regions are the region of interest.

Step 2: Find the connected pixels or blobs within the object for computing foreground markers.

Step 3: Find the pixels which are not part of the objects for computing background markers.

Step 4: Segmentation function is modified in such a way that the foreground and background markers have only minimal.

Step 5: Calculate the watershed transform for modified function.

(F)Edge Detection technique:

Edge detection is the key tool for image segmentation where the original images are transformed into edge images by exploiting the changes in grey tones. Edge detection is the most recognized approach for identifying the discontinuities in luminance values and detects and outlines the boundaries and background of an object in an image. There are points, line and edges (occur on the boundary between areas) discontinuities which can be detected using spatial masks.

(G)Hough transforms:

The technique of isolating the desired features of a particular shape which is specified in some parametric form in an image is called Hough Transform. By using this basic curve like lines, circles, ellipses etc can be detected.

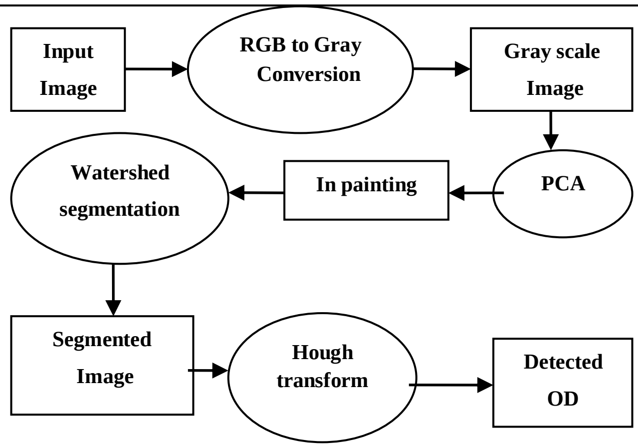


Fig 4. ER Diagram for Segmentation Process

(H)Classification:

In this the edge map is performed to obtain a binary image. The approximation of the boundary of OD is done by circle Hough Transform. Finally, CNN (Convolutional Neural Network) classifier is used to check the fundus image is normal or abnormal.

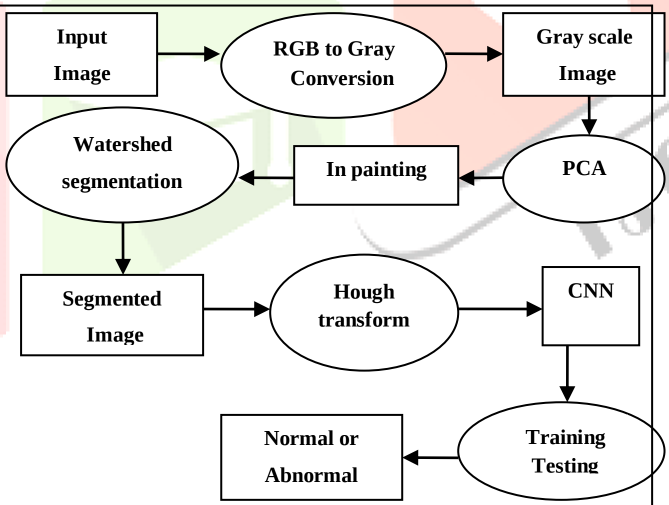


Fig 5. ER Diagram for Classification Process

- **Convolution Neural Network (CNN):**

A Convolution Neural Network (CNN) process the information as the nervous system of human do like brain thus it's a systematic model for information processing. The main element of the model is information processing novel structure system. It comprises of numerous interconnected processing components (neurons) working unitedly to resolve specific problems. It is a clad of artificial neural networks. Neural networks learn by example. A Neural network is configured in an application-specific manner, such as data classification or pattern recognition, through a learning process.

CNNs are a mathematical construct comprised of convolutional layers, pooling layers and fully-connected layers (3 sorts of layers) which are stacked to form CNN architecture. The first two layers perform feature extraction whereas the third layer maps the extracted features into the final output, essentially classification. The basic functionality of the CNN is split into four key areas. The pixel values of the image are presented in the first layer called input layer. By calculating the scalar product between the weights the middle layer (convolutional layer) are connected to local regions of input layer therefore it determines the output of neurons. This layer uses the 'kernel'. Kernels are a set of parameters that are learnable and are applied in convolution operations. When it goes through a convolutional layer, the layer brain process information.

In the convolutional layer the convolution of each filter across the input takes place to generate a 2D activation map. A scalar value is produced by obtaining the element-wise product of the input tensor and the kernel giving an output feature map. To ensure that this operation is performed on every element zero padding is done along the corner elements. Another key feature is parameter sharing that helps in reduction of the number of parameters in the whole system making computation more efficient. The input is weighted into the input layer in as a multidimensional vector. This is then distributed to the hidden layers for further computation. The hidden layers perform complex computations on the input data and produce a net input which is then run through an activation function to give the actual output. The last layer in the network is the output layer that produces the desired output for an input. Neural networks are arranged as layers which consist of large number of Interconnection called nodes which contains activation function. Patterns are given to the input layer which communicates with the one or more hidden layers that in turn connected to the output layer. The hidden layer is the place for actual processing through a system of weighted connections. The following representation shows the dimension of input layer (N, N), filter (F, F) and the output layer (N-F+1, N-F+1).

The output of the linear function is then fed to the non-linear activation function such as rectified linear unit (ReLu) which uses an element wise activation function like sigmoid to the output produced by the previous layer of the activation. A typical down sampling is given along the spatial dimensionality of the input in the pooling layer to reduce the number of parameters within that activation. It aims to reduce the dimensionality and in turn the complexity of the model. The most common form of pooling is max pooling which extracts a fixed array of parameters, selects the maximum parameter and discards the rest. This is commonly performed by a filter of size 2x2 and a stride. The fully-connected layers will perform an equivalent number of duties that is in standard ANNs and planned accordingly to produce class scores from the activations which is used for classification. The output feature maps are transformed to one dimension which is connected to one or more fully connected layers. There are same number of output nodes and the classes in the fully connected layer. It's also suggested that ReLu, an activation function, could also be used between these layers to improve performance.

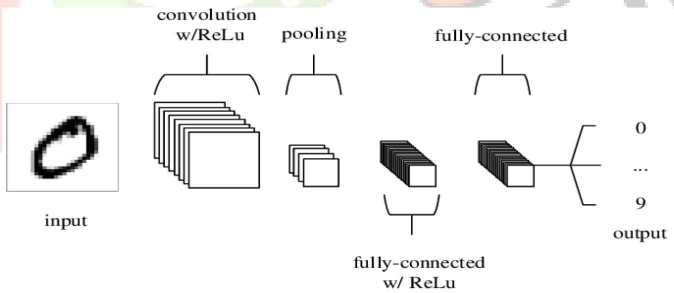
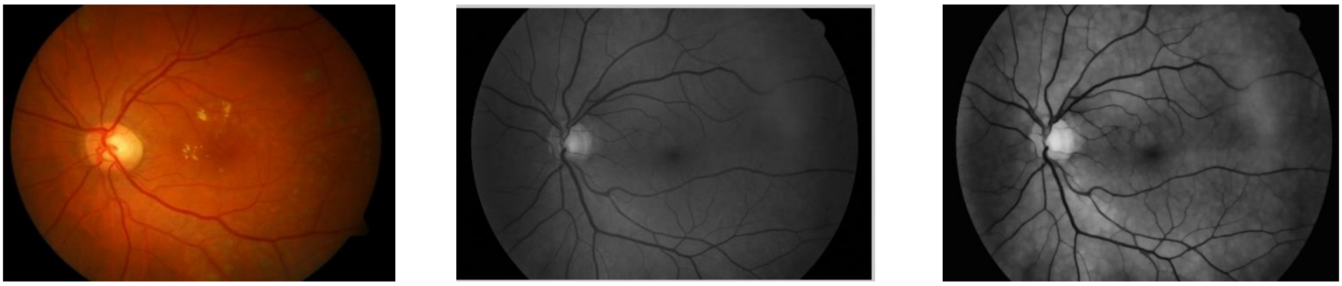


Fig 6. CNN Structure with Convolutional, Pooling &Fully Connected Layers

VI. RESULT AND DISCUSSION

The result obtained by using segmentation and CNN algorithm produces the increased accuracy, specificity and sensitivity. The results and outcomes of the two main processes, image processing and classification are displayed below. The given input image goes through various steps of image processing before classification. The given input image is first converted to a grayscale image after which it undergoes enhancement and morphological processing. The inpainting process is done for restoration and then watershed segmentation is performed.



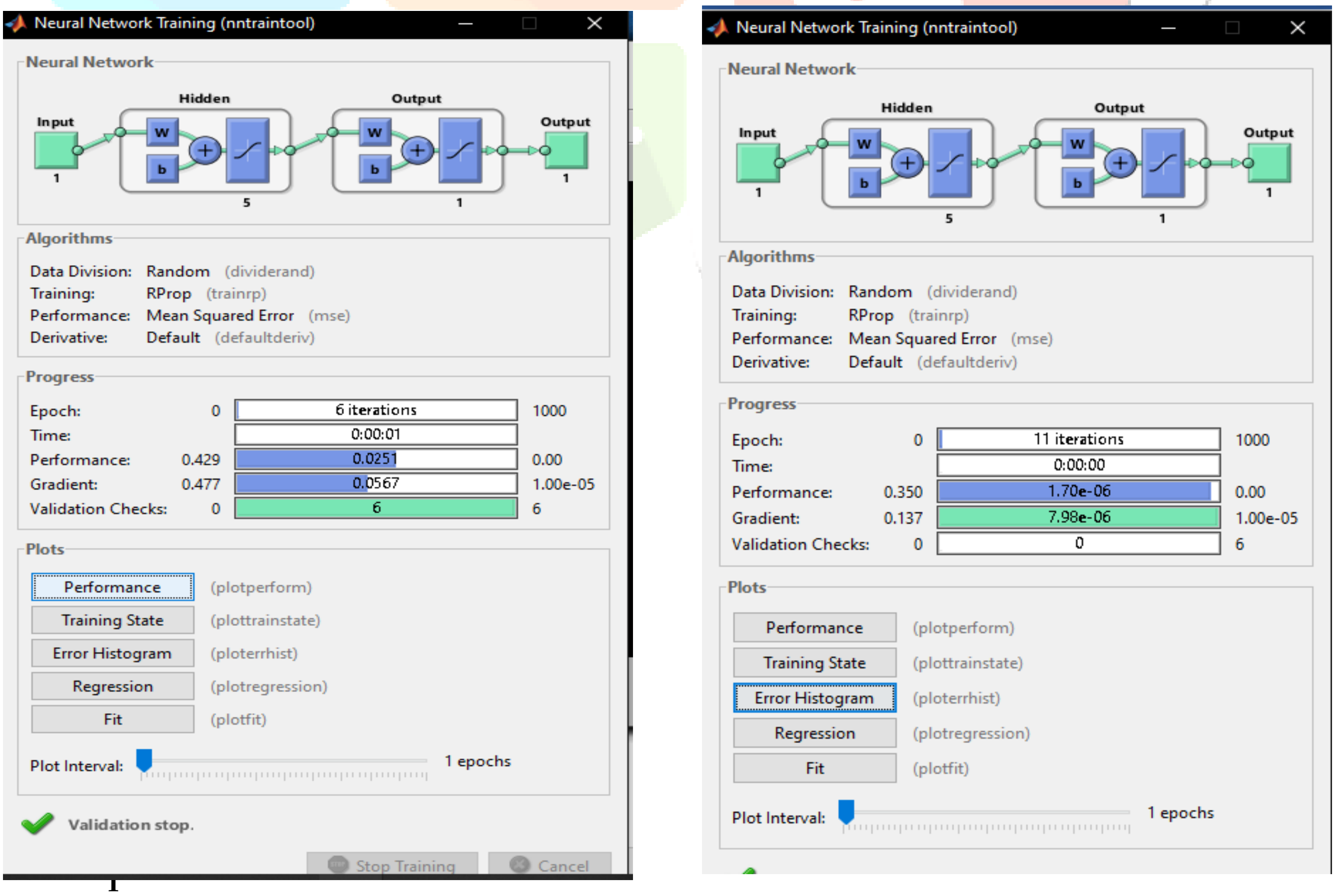
(A) Input Image B) Grayscale Image C) Enhanced Image

Fig 7. Preprocessed Images

(A) Watershed Segmentation (B) Hough Transform (C) Segmentation of OD &OC

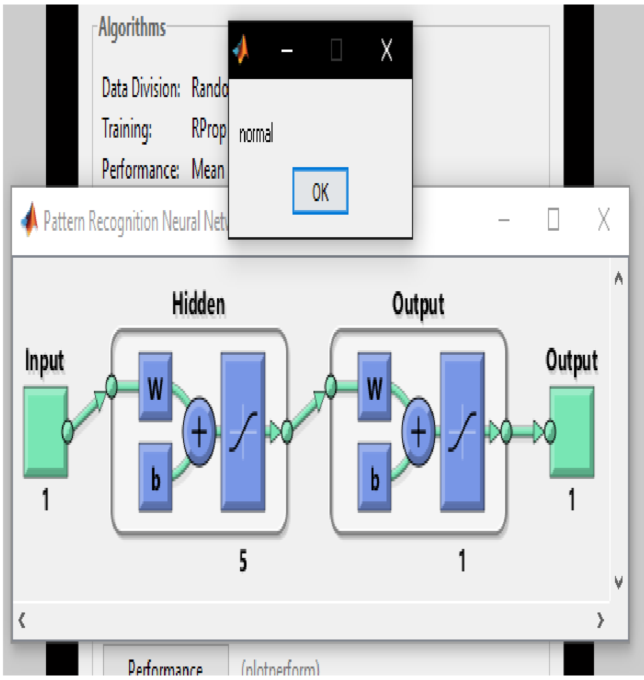
Fig 8. Segmentation Process

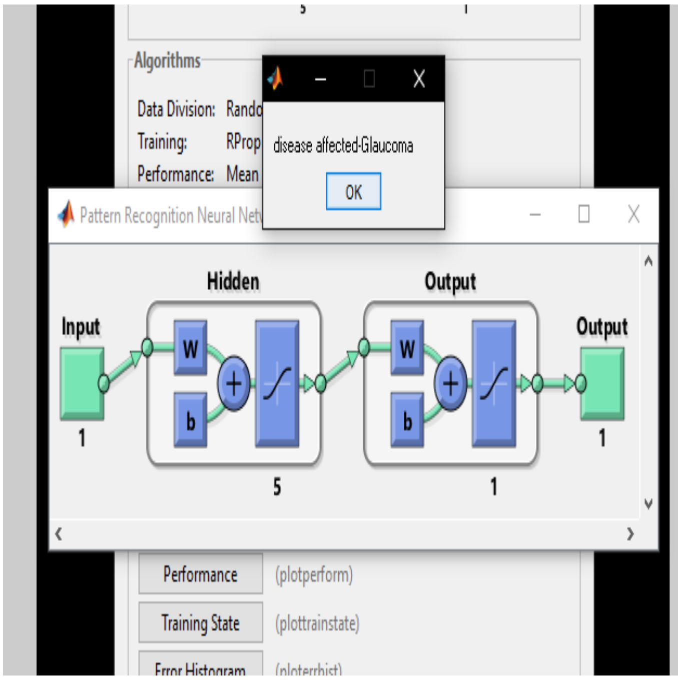
Then the Hough transform is performed on the given images for segmentation of the optic cup and optic disc which in turn further used for the classification of the image.



raining the Neural Network (B) Testing the Neural Network

Fig 9. Classification Process





(A)Result of image unaffected by Glaucoma **(B) Result of image affected by Glaucoma**

Fig 10. Neural Network Process

Accuracy can be calculated using the overall performance of the segmentation and classification process. The result can be specified as True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) which can be computed using pixels in an image as reference.

The total number of pixels which are estimated as a part of the segment with respect to the reference image which are actually used for processing is called **True Positive.**

The total number of pixels which are estimated as a part of the segment with respect to the reference image which are actually not used for processing is called **False Positive.**
The number of pixels estimated in the segments that wrongly indicates that the required condition or attribute is absent in the segment is called **False Negative.**

In reference to the context, **Specificity** is defined as the percentage of showing result as no glaucoma for individuals who actually don't have glaucoma (also referred to as "real negative" rate) i.e., the test should have the capability to properly identify an individual as disease-free.

Sensitivity is defined as the percentage of showing result as glaucoma for individuals who actually have glaucoma (also referred to as “real positive” rate) i.e., the capacity of a test to accurately identify a person as diseased.

Formulae

$$\textbf{Sensitivity} = \frac{TP}{(TP + FN)} = \frac{\text{Number of true positive cases}}{\text{Number of all positive cases}}$$

$$\textbf{Specificity} = \frac{TN}{(TN + FP)} = \frac{\text{Number of true negative cases}}{\text{Number of all negative cases}}$$

$$\textbf{Accuracy} = \frac{(TN + TP)}{(TN+TP+FN+FP)} = \frac{\text{Number of correct cases}}{\text{Number of all assessments}}$$

where

TP = True Positive
FP = False Positive
TN = True Negative
FN = False Negative

This approach obtained accuracy of 91.52%, specificity of 72.61% and sensitivity=88.29%.The tabular column below shows that the proposed system gives an improved accuracy, sensitivity and specificity over the existing system. The existing system uses machine learning algorithms such as Naïve Bayes Classifier and KNN algorithm and the convolutional neural network algorithm is a far more suitable algorithm for image classification especially in terms of efficiency and accuracy.

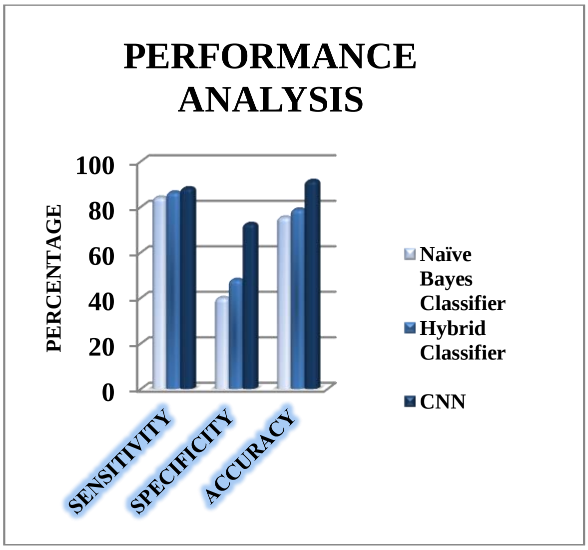


Fig11. Parameter Comparison of Existing and Proposed System

	CLASS-IFIERS	SENSIT-IVITY	SPECIF-ICITY	ACCU-RACY
EXISTI-NG SYSTEM	Naïve Bayes Classifier	84.16	40	75.4
	Hybrid Classifier (Naïve Bayes + KNN)	86.41	48	78.91
PROPO-SED SYSTEM	Convoluti-onal Neural Network	88.29	72.61	91.52

VII. CONCLUSION

Glaucoma is a deep-rooted irreparable eye disease that is initially asymptomatic but if left undetected and untreated can lead to loss of vision. To enable quick and reliable detection of the disease, this model proposes an efficient approach. This reduces the man power and easy prediction of the disease. It advocates supervised learning methods for the edge detection of OD. The fundus image of the eye is subjected to various steps of image processing in order to obtain results with high precision. This model allows dimensionality reduction, watershed segmentation, segmentation of the Optic Disc and Optic up using Hough transform. The processed images are then fed to the Convolutional Neural Network (CNN) which performs high accuracy of 91.52% classification of images into two categories: Glaucoma affected eye or Normal eye. Thus, the proposed system automatically detects glaucoma for early treatment, with minimal effort from the healthcare frontline, thereby reducing time consumption and required medical resources.

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