

GLAUCOMA DETECTION USING FUNDUS IMAGES OF THE EYE

Submitted in partial fulfillment of the requirements
for the award of Bachelor of Technology degree in Bio-
Medical Engineering

by

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**DEPARTMENT OF BIOMEDICAL ENGINEERING
SCHOOL OF BIO & CHEMICAL ENGINEERING**

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INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

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APRIL-2022

DECLARATION

We Divya R, Krisha H here by declaration the Inter disciplinary project Report entitled "Glaucoma Detection Using Fundus Images Of The Eye" done by our under the guidance of Ms.ASabarivani,M.Tech.,(Ph.D.,) (Internal) is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

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This is to certify that this Inter disciplinary project Report is the bonafide work of DIVYA R(39240016), KRISHA H (39240022) who carried out the inter disciplinary project entitled "GLUACOMA DETECTION USING FUNDUS IMAGES OF THE EYE" under my our supervision from December 2021 to April 2022

INTERNAL GUIDE

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ABSTRACT

Digital images are obtained from the retina and graded by trained professionals. Progression of diabetic retinopathy is assessed by its severity, which in turn determines the frequency of examinations. However, a significant shortage of professional observers has prompted computer assisted monitoring. The condition of the vascular network of human eye is an important diagnostic factor in retinopathy. The Inter disciplinary project proposes the Retinal image analysis through efficient detection of vessels and exudates for retinal vasculature disorder analysis. It plays important roles in detection of some diseases in early stages, such as diabetes, which can be performed by comparison of the states of retinal

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LIST OF ABBREVIATION

DWT	- DISCRETE WAVELET TRANSFORM
GLCM	- GRAY LEVEL CO-OCCURRENCE MATRIX
NN	- NEURAL NETWORK
CNN	- CONVOLUTIONAL NEURAL NETWORK
LDP	- LOCAL DIRECTIONAL PATTERN
OD	- OPTIC DISC
RRGA	- RECUSIVE REGION GROWING ALGORITHM
PCNN	- PULSE – COUPLED NEURAL NETWORK

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Retinal vessel segmentation are the implementation of screening programs for glaucomatic retinopathy, evaluation of the retinopathy of prematurity, detection of macular a vascular regions, detection of arteriolar narrowing, measurement of vessel tortuosity to characterize hypertensive retinopathy, measurement of vessel diameter to diagnose hypertension, cardiovascular diseases, and computer-assisted laser surgery. Other indirect applications include automatic generation of retinal maps for the treatment of age-related macular degeneration, extraction of characteristic points of the retinal vasculature for temporal or multimodal image registration, retinal image mosaic synthesis, identification of the optic disc position, and localization of the fovea. Furthermore, the network of retinal vessels is distinctive enough to each individual and can be used for biometric identification, although it has not yet been extensively explored. Vessels, fovea, and optical disk are the three most important structures of the human retina and are mostly used for several applications, such as retinal image registration, illumination correction, as well as pathology detection inside the retina. Detection of these important structures manually is time consuming and depends on the expertise of the user. The segmentation of blood vessels from fundus photographs can be difficult for a number of reasons. Some of the corrupting sources are related to the acquisition process and kind of imagery, and others are intrinsic features of retinal image.

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY

2.1.1 Literature survey

TITLE: Glaucoma Detection Using Fundus Images of The Eye(2019)

a)AUTHOR: Juan Carrillo; Lola Bautista; Jorge Villamizar; Juan Rueda; Mary Sanchez; Daniela rueda

b)TECHNOLOGY: glaucoma detection, disc segmentation, veins segmentation, cup segmentation, image processing

c)DRAWBACKS: Less accuracy ,Less effective ,More complexity

2.1.2 Literature survey

TITLE: Glaucoma Detection from Retinal Fundus Images(2020)

a)AUTHOR: Rahul Krishnan, VarunSekhar, Sidharth J, Gautham S and Gopakumar G

b)TECHNOLOGY: Optic disc Segmentation, Optic cup Segmentation, Image processing, Glaucoma detection, SVM Classifier, Region growing

c)DRAWBACKS: Less accuracy,Less effective ,More complexity

2.1.3 Literature survey

TITLE: An Exploratory Study for Glaucoma Detection using Densely Connected Neural Networks(2020)

a)AUTHOR: Silvia Ovreiu; Irina Cristescu; Florian Balta; Elena Ovreiu

b)TECHNOLOGY: glaucoma, early glaucoma, deep learning, densely connected neural networks, detection

c)DRAWBACK: Less accuracy,Less effective ,More complexity

2.1.4 Literature survey

TITLE: Analysis of CDR of Fundus Images for Glaucoma Detection(2018)

a)AUTHOR: Shivangi C. Patel; Manish I. Patel

b)TECHNOLOGY: Fundus Image; Glaucoma; Optic Disc; Optic Cup; CDR

c)DRAWBACKS: Less accuracy,Less effective ,More complexity

2.1.5 Literature survey

TITLE: Automated Detection of Suspected Glaucoma in Digital Fundus Images

a)AUTHOR: NamitaSengar; Malay Kishore Dutta; RadimBurget; Martin Ranjoha

b)TECHNLOGY: Suspected Glaucoma, Hemorrhages, fundus Image

c)DRAWBACKS: Less accuracy,Less effective ,More complex

2.1.6 Literature survey

TITLE: A Statistical Robust Glaucoma Detection Framework Combining Retinex, CNN, and DOE Using Fundus Images(2020)

a) AUTHOR: Wheyming Tina Song; Ing-Chou Lai; Yi-Zhu Su

b) TECHNOLOGY: Glaucoma, CNN, DOE, robust, Retinex

c) DRAWBACKS: Less accuracy less effective more complexity

CHAPTER 3

AIM AND SCOPE

3.1 AIM

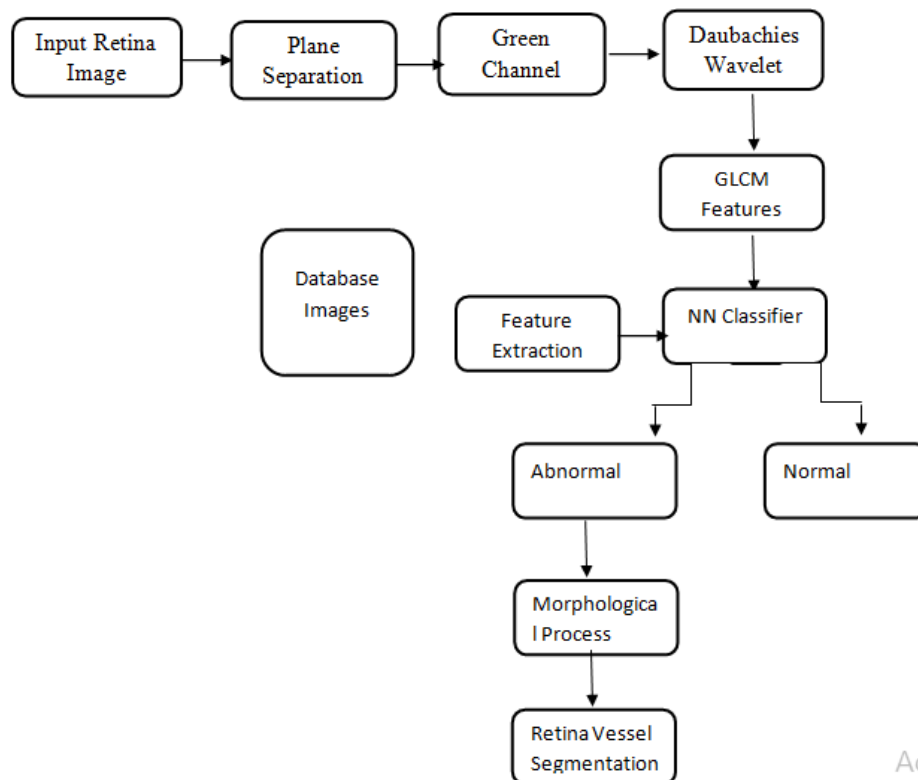
Aim of the inter disciplinary project is to create an artificial intelligent model which classifies glaucoma is affected or not using fundus eye images with deep learning technique.

3.2 SCOPE OF THE INTER DISCIPLINARY PROJECT

The main contributions of this inter disciplinary project therefore are

- Data Analysis
- Dataset Preprocessing
- Training the Model
- Testing of Dataset

3.3 BLOCK DIAGRAM:



Activat
Go to Set

CHAPTER 4

EXPERIMENTAL METHODS AND ALORITHMS

4.1. BLOCK DIAGRAM EXPLANATION:

4.1.1. *GLCM Features*

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, secondorder and higher-order statistics.

The Gray Level Coocurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. The approach has been used in a number of applications, Third and higher order textures consider the relationships among three or more pixels. These are theoretically possible but not commonly implemented due to calculation time and interpretation difficulty.

4.1.2. *WAVELET & GLCM FEATURES*

4.1.2.1 *STATIONARY WAVELET TRANSFORM:*

Wavelet Transform is a type of signal representation that can give the frequency content of the signal at a particular instant of time or spatial location. Stationary wavelet transform decomposes the image into different subband images, It splits component into numerous frequency bands called subbands. They are LL, LH, HL, and HH subbands. A high-frequency subband contains the edge information of input image and LL subband contains the clear information about the image. Upsampling of coefficients will be performed for factor 2 after each row and column decomposition process to make lossless representation of edge details

4.1.2.2 *ONE-STAGE FILTERING:*

For many signals, the low-frequency content is the most important part. It is the identity of the signal. The high-frequency content, on the other hand,

imparts details to the signal. In wavelet analysis, the approximations and details are obtained after filtering. The approximations are the high-scale, low frequency components of the signal. The details are the low-scale, high frequency components. The filtering process is schematically represented as in Fig. 4.1

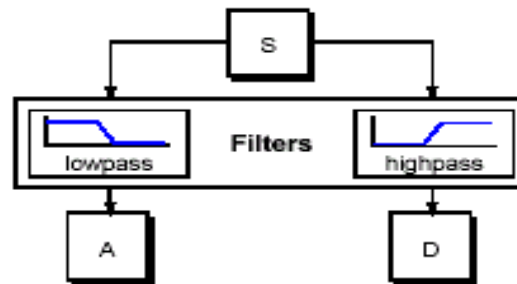


Fig. 4.1 Single stage filtering

The original signal, S , passes through two complementary filters and emerges as two signals. Unfortunately, it may result in doubling of samples and hence to avoid this, down sampling is introduced. The process on the right, which includes down sampling, produces DWT coefficients.

4.1.2.3 TYPES OF WAVELET:

There are different types of wavelets. They are (i) Haar wavelet (ii) Morlet wavelet (iii) Mexican-hat wavelet (iv) Daubechies wavelet (v) Shannon wavelet.

(i) Haar wavelet: It is a bipolar step function. The Haar wavelet is discontinuous in time and it has good localization property in time and frequency domain.

(ii) Morlet wavelet: The Morlet wavelet is obtained by multiplying the Fourier basis with a Gaussian window.

(iii) Mexican-hat wavelet: Mexican-hat wavelet is a second-order derivative of the Gaussian function. The two-dimensional Mexican-hat is popularly known as the Laplacian operator. The Laplacian operator is widely used in edge detection.

(iv) Daubechies wavelet: The Daubechies wavelet bases are a family of orthonormal compactly supported scaling and wavelet functions that have maximum regularity for a given length of the support of the quadrature mirror filters.

(v) Shannon wavelet: The Shannon wavelet has poor time resolution, but its frequency localization is excellent.

4.1.3. PIXEL LEVEL IMAGE FUSION

Multi focus image fusion is performed with pixel level fusion rule called maximum method. The low frequency subband coefficients are fused by selecting coefficient having maximum spatial frequency. It indicates the overall active level of an image. The high frequency subband coefficients are fused by selecting coefficients having maximum LDP code value.

4.2. DOMAIN OVERVIEW

Deep neural networks are now the state-of-the-art machine learning models across a variety of areas, from image analysis to natural language processing, and widely deployed in academia and industry.

These developments have a huge potential for medical imaging technology, medical data analysis, medical diagnostics and healthcare in general, slowly being realized. We provide a short overview of recent advances and some associated challenges in machine learning applied to medical image processing and image analysis. Long before deep learning was used, traditional machine learning methods were mainly used. Such as Decision Trees, SVM, Naïve Bayes Classifier and Logistic Regression.

These algorithms are also called flat algorithms. Flat here means that these algorithms cannot normally be applied directly to the raw data (such as .csv, images, text, etc.). We need a preprocessing step called Feature Extraction.

The result of Feature Extraction is a representation of the given raw data that can now be used by these classic machine learning algorithms to perform a task. For example, the classification of the data into several categories or classes. Feature Extraction is usually quite complex and requires detailed knowledge of the problem domain. This preprocessing layer must be adapted, tested and refined over several iterations for optimal results.

On the other side are the artificial neural networks of Deep Learning. These do not need the Feature Extraction step. The layers are able to learn an implicit representation of the raw data directly and on their own. Here, a more and more abstract and compressed representation of the raw data is produced over several layers of artificial neural-nets. This compressed representation of the input data is then used to produce the result. The result can be, for example, the classification of the input data into different classes.

4.3.SYSTEM ANALYSIS (Existing Systems)

4.3.1.Back ground detection and subtraction

4.3.2.Anatomy detection

4.3.3.Candidate extraction

4.3.4.Recursive region growing algorithm

4.3.1 BACK GROUND DETECTION AND SUBTRACTION

Back ground region of the fundus is the portion of the image where no retinal anatomy or lesions present, it consists of only the retinal layer of the fundus so it is an unwanted portion of the fundus image for screening of the MS. The detection of any anatomy or lesion present on the fundus image becomes simple, if we can detect and subtract the back ground region from the fundus image. By removal of back ground information we are left with only the retinal anatomy and lesions on the fore ground image of the fundus.

4.3.2 ANATOMY DETECTION

As mentioned in the above section, the major false candidates for exudates are 1. Optic disc and 2. region between two near blood vessels. So we need to detect Optic disc and blood vessels to reduce the false alarms. We used the local variance based method [6] to detect the OD on the fundus image. The local

variance at the Optic Disc location is high compared to the other fundus image. In this method, we compute the local variance of the fundus image in patch wise for the entire image. The region with the maximum value of the local variance is considered as the OD region. Finally we calculated and applied a threshold range consists of maximum value of the local variance; to detect the region consists of OD.

4.3.3CANDIDATE EXTRACTION

We applied a global threshold to detect the hard exudates candidates. The global threshold value is selected by conducting many experiments such that the candidates include all the hard exudates present in the fundus image. The exudates candidate regions consists of exudates, traces of optic disc and small region in between major blood vessels.

4.3.4RECURSIVE REGION GROWING ALGORITHM

The recursive region growing algorithm (RRGA) for detection of bigger exudates, the bigger exudates are not detected completely as the size of bigger exudates are comparable to that of the kernel size of the median filter. In case of the bigger exudates only some portion of the exudates are detected so we used the RRGA to detect the complete exudate. RRGA algorithm, which is based on comparison of local pixel properties (like grey level intensity, color, texture etc) in the defined local region

4.4 DRAWBACKS OF EXISITNG SYSTEM

- In this method intrinsic characteristics of retinal images make the blood vessel detection process difficult.
- Poor Edge detection.
- Less accuracy
- It is not suitable for all lighting condition images

4.5 PROPOSED SYSTEMS

Retinal image analysis for glaucoma tic retinopathy detection based on,

- Kirsch's template based edge Enhancement
- Morphological filtering

- Object Classification with Connected component analysis
- Neural networks segmentation

4.6 ADVANTAGES

- Accurate retina vessel and execute detection
- Better efficiency and less sensitive to noise
- It is useful to detect glaucoma in an early stages

4.7 ALGORITHM

4.7.1 NEURAL NETWORKS (NN)

Neural Network segmentation relies on processing small areas of an image using an artificial neural network^[23] or a set of neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network. A type of network designed especially for this is the Kohonen map.

Pulse-Coupled Neural Networks (PCNNs) are neural models proposed by modeling a cat's visual cortex and developed for high-performance biomimetic image processing. In 1989, Eckhorn introduced a neural model to emulate the mechanism of cat's visual cortex. The Eckhorn model provided a simple and effective tool for studying small mammal's visual cortex, and was soon recognized as having significant application potential in image processing. In 1994, the Eckhorn model was adapted to be an image processing algorithm by Johnson, who termed this algorithm Pulse-Coupled Neural Network. Over the past decade, PCNNs have been utilized for a variety of image processing applications, including: image segmentation, feature generation, face extraction, motion detection, region growing, noise reduction, and so on. A PCNN is a two-dimensional neural network. Each neuron in the network corresponds to one pixel in an input image, receiving its corresponding pixel's color information (e.g. intensity) as an external stimulus. Each neuron also connects with its neighboring

neurons, receiving local stimuli from them. The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. Through iterative computation, PCNN neurons produce temporal series of pulse outputs. The temporal series of pulse outputs contain information of input images and can be utilized for various image processing applications, such as image segmentation and feature generation. Compared with conventional image processing means, PCNNs have several significant merits, including robustness against noise, independence of geometric variations in input patterns, capability of bridging minor intensity variations in input patterns.

CHAPTER 5

RESULT ANALYSIS

5.1. LIST OF MODULES

- 5.1.1 Plane separation(green channel selection)
- 5.1.2 DWT
- 5.1.3 GLCM features
- 5.1.4 Neural network classifier
- 5.1.5 Morphological process

5.2 MODULES WORKING FLOW

5.2.1 MODULE 1

PLANE SEPARATION(GREEN CHANNEL SELECTION)

Extracting the Green Component from the RGB Image

An RGB image represents each pixel color as a set of three values, representing the red, green, and blue intensities that make up the color. These intensity values are stored directly in the image array. In MATLAB, the red, green, and blue components of an RGB image reside in a single m-by-n-by-3 array. m and n are the numbers of rows and columns of pixels in the image, and the third dimension consists of three planes, containing red, green, and blue intensity values. For each pixel in the image, the red, green, and blue elements combine to create the pixel's actual color .

For further processing, the green component of the RGB input image is extracted.



Fig. 5.1: (a) Normal Retina image (b) Green component extracted image

5.2.2. MODULE 2:

5.2.2.1.DWT

The discrete wavelet transform (DWT) became superior to use the wavelet rework to the digital international. Filter banks are used to approximate the behavior of the non-prevent wavelet remodel. The sign is decomposed with a immoderate-skip smooth out and a low-bypass clear out. The coefficients of these filters are computed using mathematical evaluation and made to be had to you. See Appendix B for more records about those computations.

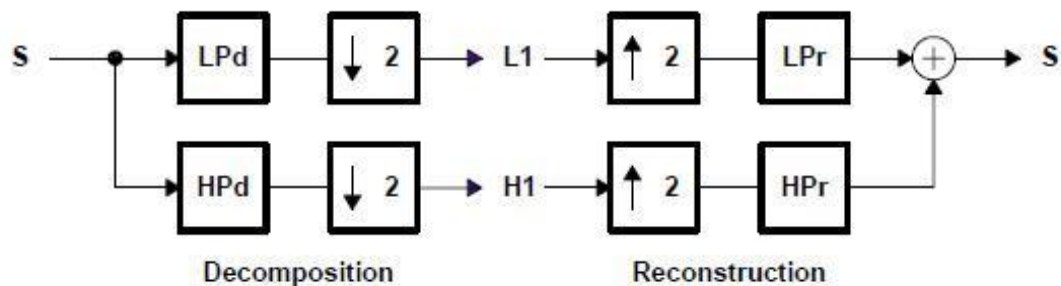


Fig.5.2 Discrete Wavelet Transform

Where,

LP d: Low Pass Decomposition Filter

HP d: High Pass Decomposition Filter

LP r: Low Pass Reconstruction Filter

HP r: High Pass Reconstruction Filter

In this process to compress image from high level to low level we apply Discrete wavelet transform. By using this DWT process we are going to compress the image and we get a good compressed image. This is necessary part to reduce a storage level and easy process

5.2.3. MODULE 3:

5.2.3.1.GLCM:

- Gray level co occurrence matrix used to get features from an image. The image may vary depends on more information like contrast, energy, etc.. The main aim to use this process is to get features from an image.
- This feature extraction plays a major role in training process and after the process the features are classified by using NN. So, this is a one of the necessary process in this inter disciplinary project.

5.2.4. MODULE 4:

5.2.4.1.NN classifier:

Neural Network is one the classification technique. By using this method we can train our code and able to classify the output. In this inter disciplinary project the neural network plays a major role for training and testing period. In that training period we use neural network training our dataset images to the code the images are not treated as it is, it may takes as a features itself so that the dataset images also have pre-processing and feature extraction process. After the training process the NN have a main work in classification after that part we get an accurate output like it is affected or not.

5.2.5. MODULE 5:

5.2.5.1.MORPHOLOGICAL PROCESS

- Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to grey scale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.
- Morphological contain two different processes in it dilation and erosion. These techniques are applied based on the need. These

two have different operations. Erosion is remove the unwanted pixels by using '0' pixel value. Dilation enlarges the pixel values by using '1'.

5.3.RESULT ANALYSIS

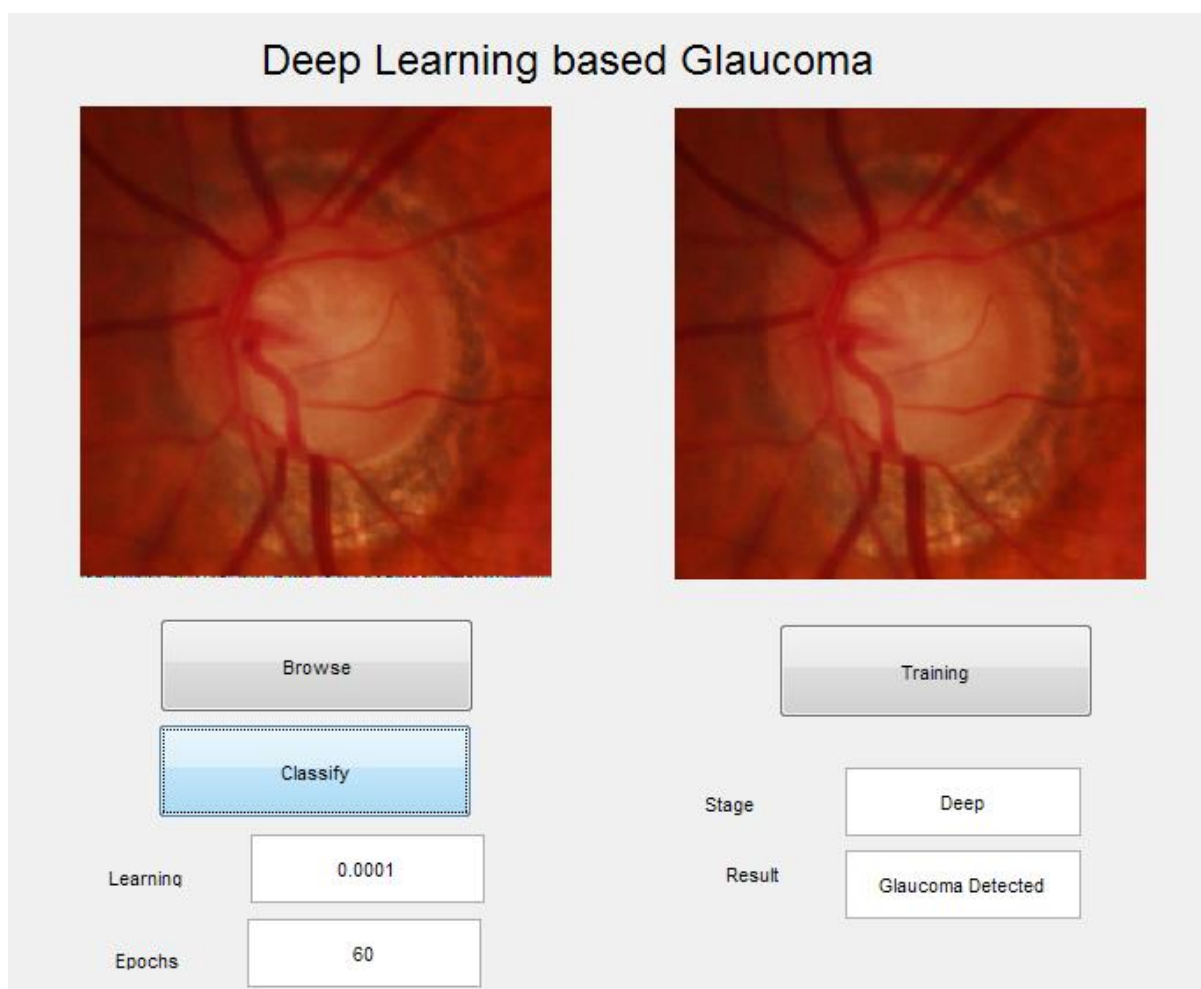


Fig. 5.3

ANALYSIS RESULT				
	NAME	TYPE	ACTIVATIONS	LEARNABLES
1	imageinput 227x227x3 images with 'zerocenter' normalization	Image Input	227×227×3	-
2	conv1 96 11x11x3 convolutions with stride [4 4] and padding [0 0 0 0]	Convolution	55×55×96	Weights 11×11×3×96 Bias 1×1×96
3	relu1 ReLU	ReLU	55×55×96	-
4	norm1 cross channel normalization with 5 channels per element	Cross Channel Nor...	55×55×96	-
5	pool1 3x3 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	27×27×96	-
6	conv2 256 5x5x48 convolutions with stride [1 1] and padding [2 2 2 2]	Convolution	27×27×256	Weights 5×5×48×256 Bias 1×1×256
7	relu2 ReLU	ReLU	27×27×256	-
8	norm2 cross channel normalization with 5 channels per element	Cross Channel Nor...	27×27×256	-
9	pool2 3x3 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	13×13×256	-
10	conv3 384 3x3x256 convolutions with stride [1 1] and padding [1 1 1 1]	Convolution	13×13×384	Weights 3×3×256×384 Bias 1×1×384
11	relu3 ReLU	ReLU	13×13×384	-
12	conv4 384 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]	Convolution	13×13×384	Weights 3×3×192×384 Bias 1×1×384
13	relu4 ReLU	ReLU	13×13×384	-
14	conv5 256 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]	Convolution	13×13×256	Weights 3×3×192×256 Bias 1×1×256
15	relu5 ReLU	ReLU	13×13×256	-
16	pool5 3x3 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	6×6×256	-
17	fc6 4096 fully connected layer	Fully Connected	1×1×4096	Weights 4096×9216 Bias 4096×1

Fig. 5.4

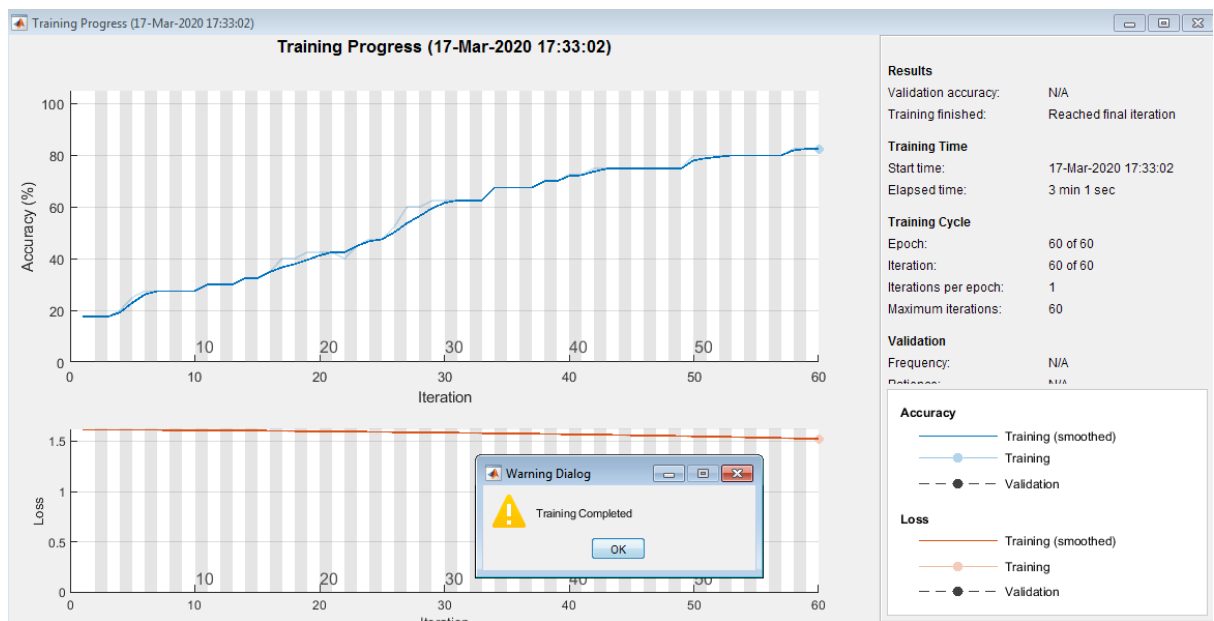


Fig. 5.5

CHAPTER 6

CONCLUSION

6.1 CONCLUSION

To this aim detect diabetic retinopathy by using deep learning concept here we create a graphical user interface for getting input fundus images, analyzing and classifying the output. we comprehensively illustrate the plane separation (green channel selection), wavelet transform and GLCM feature extraction technique, neural network and morphological process to classify the output because of these methods we get a more accuracy, specificity, and the performance also be increased.

6.2 FUTURE ENHANCEMENT

In future we increased the performance of this process and able to get more accuracy.

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