

**Diabetic Retinopathy Using Convolution Neural Network
(CNN)**

*A Project report submitted in partial fulfillment of the requirements for
the award of the degree of*

**BACHELOR OF TECHNOLOGY
IN
ELECTRONICS AND COMMUNICATION ENGINEERING**

Submitted by

S.Sudheer(318126512105)

S.Balaji(318126512099)

R.Mounika(318126512097)

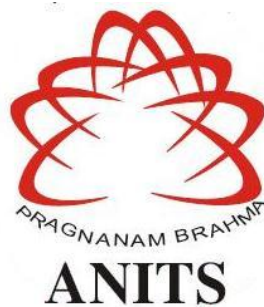
S.Sravan (318126512100)

Under the guidance of

Mr.V.Vijay Kumar Raju M.Tech,(Ph.D) &

Mrs.P.Devi M.Tech,(Ph.D)

Asst.Professor ECE



DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

**ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY AND SCIENCES
(UGC AUTONOMOUS)**

*(Permanently Affiliated to AU, Approved by AICTE and Accredited by NBA & NAAC with 'A' Grade)
Sangivalasa, bheemili mandal, visakhapatnam dist.(A.P)*

2021-2022

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CERTIFICATE

This is to certify that the project report entitled "DIABETIC RETINOPATHY USING CONVOLUTION NEURAL NETWORK" submitted by S.SUDHEER (318126512105), S.BALAJI (318126512099), R.MOUNIKA (318126512097), S.SRAVAN (318126512100) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in ELECTRONICS & COMMUNICATION ENGINEERING of Andhra University, Visakhapatnam is a record of bonafide work carried out under Project guide guidance and supervision.

Project Guide: 1

Mrs.P.Devi

Asst. Professor

Department of ECE

ANITS

Assistant Professor
Department of E.C.E.

Anil Neerukonda

Institute of Technology & Sciences
Sangivalasa, Visakhapatnam-531 162

Project Guide: 2

Mr.V.Vijay Kumar Raju

Asst. Professor

Department of ECE

ANITS

Assistant Professor
Department of E.C.E.

Anil Neerukonda

Institute of Technology & Sciences
Sangivalasa, Visakhapatnam-531 162

Head of the Department

Dr.V.Rajyalakshmi

Professor & HOD

Department of ECE

ANITS

Head of the Department
Department of ECE

Anil Neerukonda Institute of Technology & Sciences
Sangivalasa - 531 162

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PROJECT STUDENTS

S.SUDHEER (318126512105)

S.BALAJI (318126512099)

R.MOUNIKA (318126512097)

S.SRAVAN (318126512100)

ABSTRACT

Diabetic Retinopathy (DR) is the most common cause of blindness of the eye depend on diabetes. However, due to slow progression, the disease shows few signs in early stages, hence making disease detection a difficult task. For this reason, early detection of diabetic retinopathy is of critical importance. Therefore, a fully automated system is required to support the detection and screening process at early stages.

The manual diagnosis process of DR retina fundus images by ophthalmologists is time, effort, and cost-consuming and prone to misdiagnosis unlike computer-aided diagnosis systems. Recently, deep learning has become one of the most common techniques that has achieved better performance in many areas, especially in medical image analysis and classification. In this project, we propose a CNN approach to diagnosing DR from digital fundus images and accurately classifying its severity. We used a network with CNN architecture and data augmentation which can identify the intricate features involved in the classification task such as micro-aneurysms, exudate and hemorrhages on the retina and consequently provide a diagnosis automatically and without user input.

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LIST OF ABBREVIATIONS

DR	Diabetic Retinopathy
PDR	Proliferate Diabetic Retinopathy
NPDR	Non-Proliferate Diabetic Retinopathy
GUI	Graphical User Interface
SDR	Severe Diabetic Retinopathy
ADDR	Automatic Detection of Diabetic Retinopathy
MA	Microaneurysms
WHO	World Health Organization
CAD	Computer Aided Organization
PPS	Pre-Processing Stage
LVQ	Learning Vector Quantization
NARX	Nonlinear Autoregressive
GPU	Graphical Processing Unit
LM	Levenberg Marquardt Algorithm
Rprop	Resilient Backpropagation
GUIDE	Graphical User Interface Development Environment
M-file	MATLAB file

Chapter 1: Introduction

1.1 MOTIVATION

In recent times, India and other parts of the world have been faced with an increase in age and society related diseases like diabetes. According to recent survey, 4% of the country population has been diagnosed of diabetes disease alone and it have been recognized and accepted as one of the main causes of blindness in the country if not properly treated and managed. Early detection and diagnosis have been identified as one of the ways to achieve a reduction in the percentage of visual impairment caused by diabetes with more emphasis on routine medical check which the use of special facilities for detection and monitoring of the said disease. The effect of this on the medical personnel need not be over emphasized, it has lead to increase work load on the personnel and the facilities, increase in diabetes screening activities just to mention a few. A lot of approaches have been suggested and identified as means of reducing the stress caused by this constant checkup and screening related activities among which is the use medical digital image signal processing for diagnosis of diabetes related disease like diabetic retinopathy using images of the retina.

Diabetes is a disorder of metabolism. The energy required by the body is obtained from glucose which is produced as a result of food digestion. Digested food enters the body stream with the aid of a hormone called insulin which is produced by the pancreas, an organ that lies near the stomach. During eating, the pancreas automatically produces the correct amount of insulin needed for allowing glucose absorption from the blood into the cells. In individuals with diabetes, the pancreas either produces too little or no insulin or the cells do not react properly to the insulin that is produced. The buildup of glucose in the blood, overflows into the urine and then passes out of the body. Therefore, the body loses its main source of fuel even though the blood contains large amounts of glucose.

Basically, there are three types of diabetes, Type 1 Diabetes, is caused as a result of auto immune problem. The immune system of the body destroys the insulin producing beta cells in the pancreas leading to no or less production of the required insulin by the pancreas. Type 2 Diabetes is a result of malfunctioning of the beta cell itself. This malfunction includes non-production of insulin or a situation known as insulin resistance. In insulin resistance, the muscles, fat and other cells do not respond to the insulin produced. Type 3 is known as gestational diabetes and only occurs during pregnancy. During this stage, the body resist the effect of insulin produced. The effect of diabetes on the eye is called Diabetic Retinopathy (DR). It is known to damage the small blood vessel of the retina and this might lead to loss of vision. The disease is classified into three stages viz: Non-Proliferate Diabetic Retinopathy

(NPDR), Proliferate Diabetic Retinopathy (PDR) [1]. In PDR phase, the arteries in the retina become weakened and leak, forming small, dot like Haemorrhages. These leaking vessels often lead to swelling or edema in the retina and decreased vision. In the NPDR phase, circulation problems cause areas of the retina to become oxygen-deprived or ischemic. New fragile, vessels develop as the circulatory system attempts to maintain adequate oxygen levels within the retina. This phenomenon is called neovascularization. Blood may leak into the retina and vitreous, causing spots or floaters, along with decreased vision. In the SDR phase of the disease, there is continued abnormal vessel growth and scar tissue, which may cause serious problems such as retinal detachment and glaucoma and gradual loss of vision.

This research work is one of the methods of applying digital image processing to the field of medical diagnosis in order to lessen the time and stress undergone by the ophthalmologist and other members of the team in the screening, diagnosis and treatment of diabetic retinopathy. This work determines the presence of NPDR and PDR or otherwise in a patient by applying techniques of digital image processing on fundus images taken by the use of medical image camera by medical personnel in the hospital.

1.2 AIM

The primary aim of this project is to develop an automated diabetic retinopathy screening system, a detection of Micro aneurysms in digital fundus photographs is needed. Micro aneurysms are the first clinical sign of diabetic retinopathy. The number of micro aneurysms is used to indicate the severity of the disease. Early micro-aneurysm detection can help reduce the incidence of blindness.

The secondary aim includes developing a MATLAB based Graphic User Interface (GUI) tool to be used by the ophthalmologist in marking fundus images. The marked images are to be used for the development of DR grading and database system for this present and future work.

1.3 OBJECTIVE

This project develops an automatic system that can aid in the detection of diabetic retinopathy. As the number of diabetes affected people is increasing worldwide, the need for automated detection methods of diabetic retinopathy will increase as well. To automatically detect diabetic retinopathy, a computer has to interpret and analyze digital images of the retina. Automatic detection of Diabetic Retinopathy (ADDR) is a fully automated system for detection of Diabetic Retinopathy (DR).

Chapter 2: Literature Review

Most of the currently available methods divide MA detection into two consequent stages: candidate extraction and classification. Usually, the first step of candidate extraction is image pre-processing to reduce noise and improve contrast. After pre-processing, specific image segmentation is used to extract as much regions as possible that probably correspond to MAs. In the second step, the resulting candidates are labelled as true or false ones using a supervised learning based method. This classification requires a training set to establish the boundaries of the classes. The training set consists of pairs of feature vectors and class labels. Feature vectors are ordered sets of certain property values, mostly geometrical or colour descriptors that may help to distinguish MA's[2] from other objects.

2.1 Diabetic Retinopathy (DR)

Diabetes is a disease that occurs when the pancreas does not secrete enough insulin or the body is unable to process it properly. Insulin is the hormone that regulates the level of sugar (glucose) in the blood. Diabetes can affect children and adults. Patients with diabetes are more likely to develop eye problems such as cataracts and glaucoma, but the disease's effect on the retina is the main threat to vision. Most patients develop diabetic changes in the retina after approximately 20 years. The effect of diabetes on the eye is called diabetic retinopathy as shown in Fig.2.1.

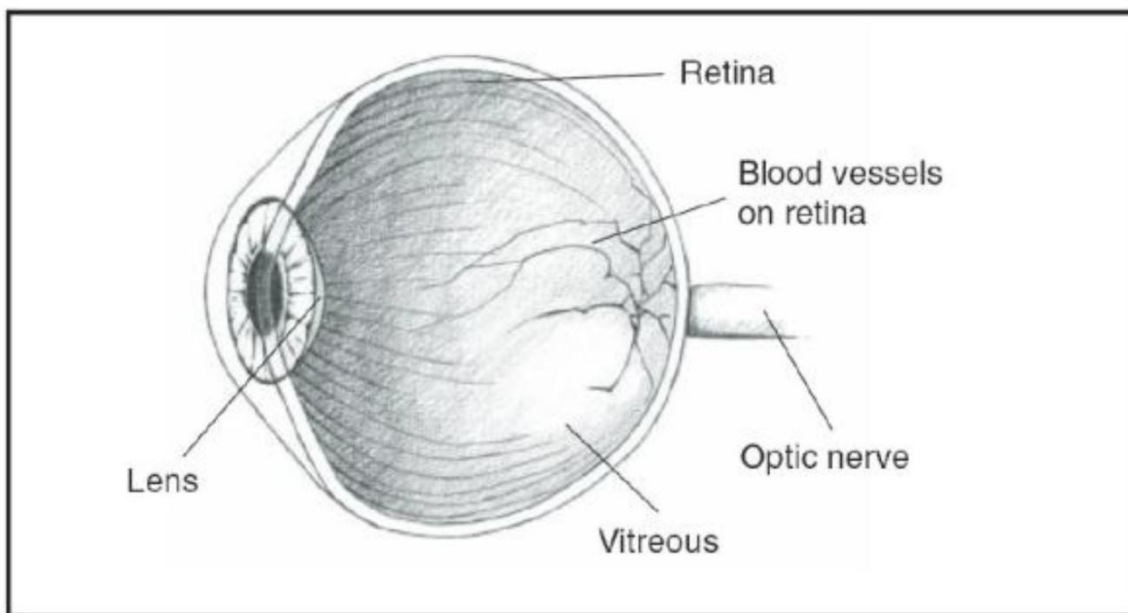


Fig. 2.1 Cross sectional view of human eye

Diabetic Retinopathy (DR) is the damage of the retina caused by diabetes. It is a sight threatening disease that develops in most of the patients with long-standing illness.

Diabetic retinopathy is the leading cause of vision loss amongst the working age population of the developing and the developed countries. Diabetic patients are 25 times more probable to become blind than non-diabetic patients. Diabetic retinopathy is a complication of diabetes to the retina and to the blood vessels.

Blood vessels are continuous patterns with little curvature, originated from optic disc and have a tree shape branching. The mean diameter of the vessels is about 100 μm , that is 1/40 of retina diameter. Optic disk or optic nerve head is the bright yellowish disk, from which, blood vessels and optic nerve fibers emerge. Optic disk transmits electrical impulses from the retina to the brain. It measures 1.5 to 2 mm in diameter. Macula is the central area of the retina, temporal to the optic disk. It is responsible to have fine central vision and color vision. The center of macula is called fovea as shown in Fig.2.1.1 This region of the retina is the most sensitive region. The diameter of the macula is about 4 to 5 mm.

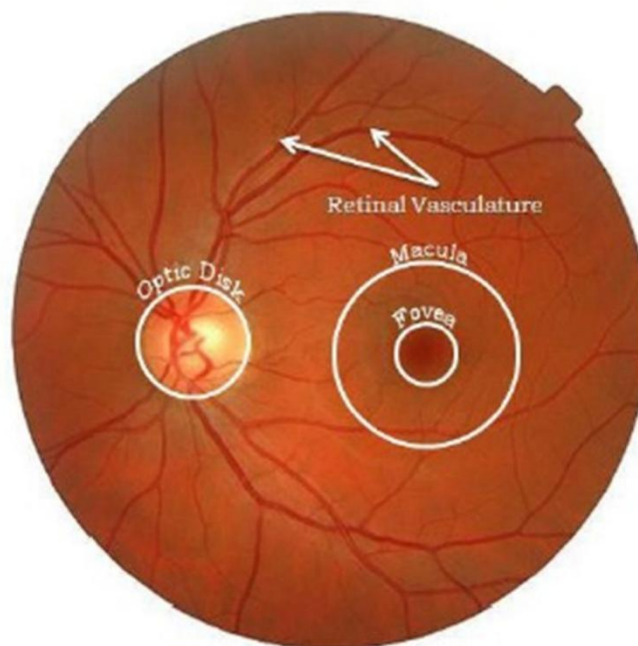


Fig. 2.1.1 Anatomy of eye

Diabetic retinopathy is caused by both the forms of diabetes that is (diabetes mellitus) and (diabetes insipidus). It is a very asymptomatic disease in the early stages and it could lead to permanent vision loss if untreated for long time. The problem here is the patients may

not know about it until it reaches advanced stages. Once it reaches advanced stages vision loss becomes inevitable. As diabetic retinopathy is the third major cause of blindness particularly in India, there is an immediate requirement to develop efficient diagnosis method.

The main stages of diabetic retinopathy are nonproliferative diabetic retinopathy (NPDR) and proliferative retinopathy (PDR). NPDR is the early stage of Diabetic retinopathy. Nonproliferative diabetic retinopathy (NPDR) is a micro vascular complication of diabetes mellitus that can lead to irreversible visual loss. In this case, at least one microaneurysm with or without the presence of retinal haemorrhages, hard exudates, cotton wool spots, or venous loops are present.[3]

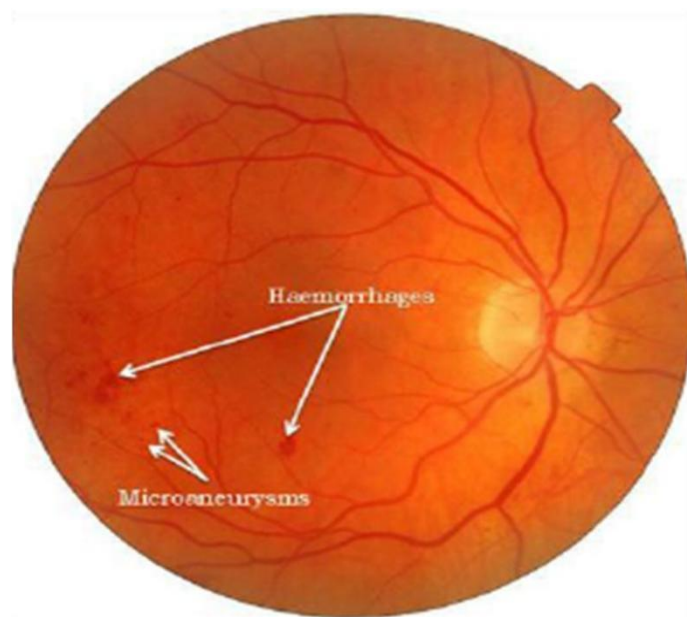


Fig 2.1.2 Retinal image having some Microaneurysms and Haemorrhage

Microaneurysms are the first clinical abnormality to be noticed in the eye. They may appear in isolation or in clusters as tiny, dark red spots or looking like tiny haemorrhages within the light sensitive retina as shown in Fig.2.1.2

Their sizes ranges from 10-100 microns i.e., less than 1/12th the diameter of an average optics disc and are circular in shape, at this stage, the disease is not eye threatening.

In NPDR, depending on the presence and extent of the features such as haemorrhages, hard exudates, microaneurysms or cotton wools spots due to leakage of fluid and blood from the blood vessels [4].

NPDR can be classified into

i) Normal.

In Normal NPDR, microaneurysms are small areas of balloon-like swellings in the retina's tiny blood vessels as shown in Fig 2.1.3

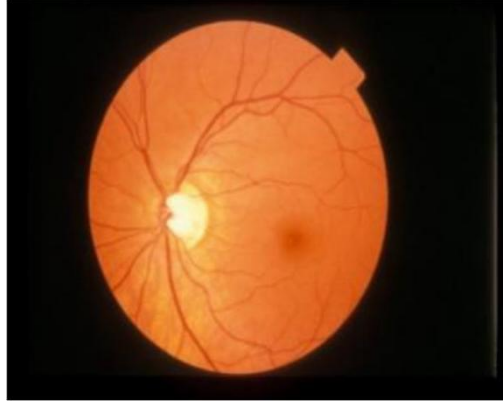


Fig 2.1.3 Normal image

ii) Exudate

In Exudate as the disease progresses, some blood vessels that nourish the retina are blocked and which many more blood vessels are blocked shown in Fig 2.1.4



Fig 2.1.4 Exudate image

iii) Haemorrhage

PDR is the advanced stage whereby signals are not sent by the retina to the brain for the lack of blood supply and this triggers the growth of new blood vessels. In PDR number of Haemorrhages is more. Haemorrhages occur in the deeper layers of the retina and are often called “blot” haemorrhages because of their irregular shape as shown in Fig.2.1.5, As the disease progresses, microaneurysms will be ruptured. This results in retinal haemorrhages either superficially or in deeper layers of the retina.



Fig 2.1.5 Haemorrhage image

2.2 The effect of diabetic retinopathy (DR)

The effect of diabetic retinopathy on vision varies widely, depending on the stage of the disease. Some common symptoms of diabetic retinopathy are listed below, however, diabetes may cause other eye symptoms.

- Blurred vision (this is often linked to blood sugar levels).
- Floaters and flashes
- Sudden loss of vision

2.3 Microaneurysms (MA)

Microaneurysms are the dilation of retinal capillaries. They are round intra-retinal lesions ranging from 10 to 100 micrometers in size and red in colour. The cross-section of a microaneurysm exhibits a Gaussian distribution. Fig.2.3 illustrates examples of different microaneurysms taken from color retinal images. The top part shows their original format while the bottom depicts them in the green channel (so their shape is more visible) [5].



Fig 2.3 Retinal image with microaneurysm marked

2.4 Need of automatic detection of DR.

Diabetic Retinopathy (DR) is an eye disease that can lead to partial or even complete loss of visual capacity, if left undiagnosed at the initial stage. Retinal lesions associated with diabetes are used to evaluate different stages and the severity of this disease. Microaneurysms are among the earliest signs of diabetic retinopathy they arise due to high sugar levels in the blood. According to WHO (World Health Organization) there will be 79 million people with diabetes by 2030, making the India Diabetic capital of the world. Among the patients below the age of 30 years, when first diagnosed with diabetes, the prevalence of retinopathy is 17% during the first 5 years[6]. This increases to 97% after 15 years of diabetes. Amongst the patients above the age of 30 years, 20% have showed signs of retinopathy immediately after diagnosed and this increased to 78% after 15 years of diabetes.

The ratio of ophthalmologists to the number of Diabetic patients is very low. Ophthalmologists in India are insufficient to support the growing Diabetic population. India has 1 Ophthalmologists per 1, 00,000 patients and this ratio is even smaller for rural settings. Today Diabetic Retinopathy is the 3rd cause of blindness in India.

Medical imaging allows scientists and physicians to understand potential life-saving information using less invasive techniques. This automated algorithm indicates places in the image that require extra attention from the physician because they could be abnormal. These technologies are called Computer Aided Diagnosis (CAD).

**Chapter 3:
Implementation of DR
Detection Method**

3.1 Basic system level block diagram

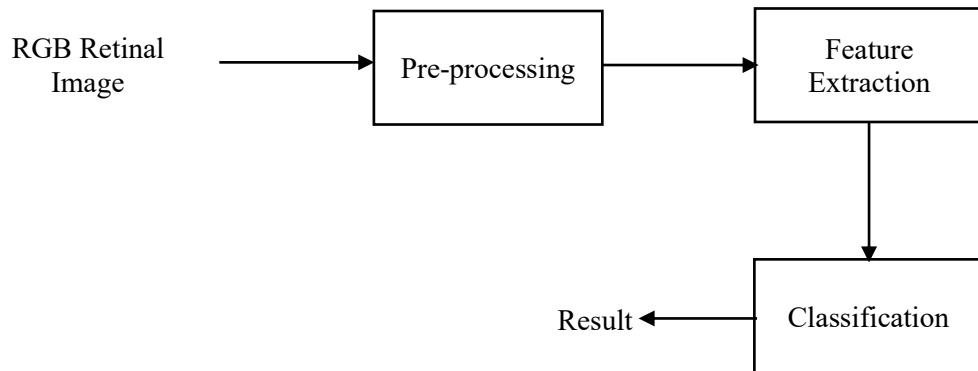


Fig 3.1 Basic system level block diagram

Automatic detection of Diabetic Retinopathy (ADDR) is a fully automated system for detection of Diabetic Retinopathy (DR). Figure shows the block diagram of ADDR. Input to this system is a fundus image which is part of human eye that can be seen through the pupil. Fundus image [1,4] is the interior surface of the eye, opposite the lens, and includes the retina, optic disc, macula, Blood vessels and fovea. As the quality of the image is not satisfactory because of noise, bad contrast, uneven illumination etc. pre-processing is used to get better results.

The methodology is made up of three fundamental parts,

i. Pre-processing

The aim of pre-processing is to attenuate the noise, to improve the contrast and to correct the non-uniform illumination. In the RGB images, the green channel exhibits the best contrast between the vessels and background while the red and blue ones tend to be more noise. Hence green channel is used for further processing.

ii. Feature Extraction

Objective of Feature Extraction is to select all Micro aneurysms present in the pre-processed image. Micro aneurysms appear as isolated patterns and are disconnected from the vessels. The features of micro aneurysms can be extracted based on shape, size and intensity

level. Micro aneurysms are dark reddish in colour, they appear as small red dots of 10 to 100 microns diameter and are circular in shape.

iii. Classification

After the detection of Micro aneurysms, classification groups the eye images as either diseased or normal depending on the count of detected micro aneurysms.

3.2 Pre-Processing Stage (PPS)

In detecting abnormalities associated with fundus image, the images have to be pre-Processed in order to correct the problems of uneven illumination problem, nonsufficient contrast between exudates and image background pixels and presence of noise in the input fundus image. Aside from aforementioned problems, this section is also responsible for color space conversion and image size standardization for the system. This section, which is Pre-Processing stage, can be regarded as the bedrock of this research work. The block diagram of the sub sections that constitute the Pre-Processing stage (PPS) is as shown in Fig.3.2

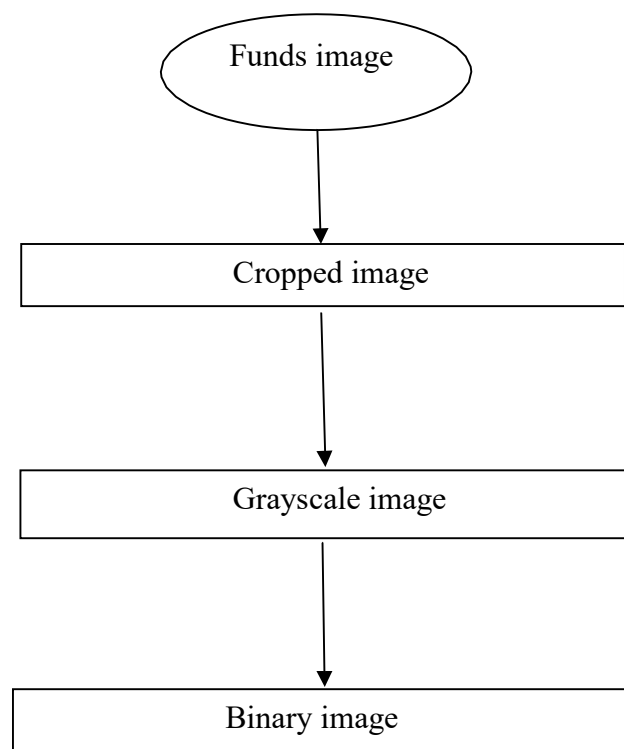


Fig. 3.2 Flow chart of Pre-Processing stage.

3.2.1 Color Fundus Image

The input fundus image is an RGB image. This image is a retinal fundus image of patient. This fundus image can be either normal or defected. We used this image as input image. We have to apply some processes to this image to detect the diabetic retinopathy. In our database, there are such 30 fundus images in which 10 images are normal, 10 images are haemorrhage and remaining 10 are exudates. The Fig.3.2.1 shows the input fundus image.

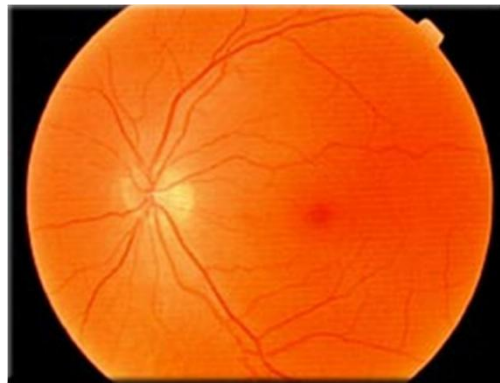


Fig. 3.2.1 Input fundus image

The command used for read image in matlab is explained below.

Syntax

```
A = imread(filename, fmt)
```

Description

`A = imread(filename, fmt)` reads a grayscale or color image from the file specified by the string `filename`. If the file is not in the current directory, or in a directory on the MATLAB path, specify the full pathname.

The text string `fmt` specifies the format of the file by its standard file extension. For example, specify 'gif' for Graphics Interchange Format files. To see a list of supported formats, with their file extensions, use the `imformats` function. If `imread` cannot find a file named `filename`, it looks for a file named `filename.fmt`.

3.2.2 Cropped image

The input image must have to crop at specific size, because the whole part of fundus image is not defected. So we have to choose only the area near the pupil. Only this area more affects the patients vision ability. Fig.3.2.2 shows the cropped image

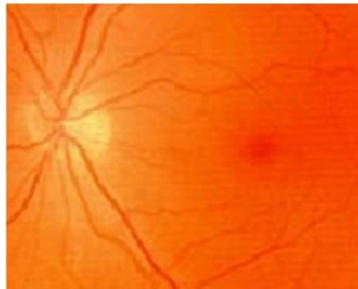


Fig. 3.2.2 cropped image

The command used for cropping image in matlab is explained below.

Syntax

```
I1 = imcrop(I, rect)
```

Description

`I = imcrop` creates an interactive Crop Image tool associated with the image displayed in the current figure, called the target image. `I1 = imcrop(I, rect)` crops the image `I`. `rect` is a four-element position vector `[xmin ymin width height]` that specifies the size and position of the crop rectangle.

3.2.3 Grayscale image

The Grayscale image exhibits the best contrast between the vessels and background while the red and blue ones tend to be more noise. Hence Grayscale image is used for further processing. the retinal blood vessels appear darker in the gray image, shown in Fig 3.2.3

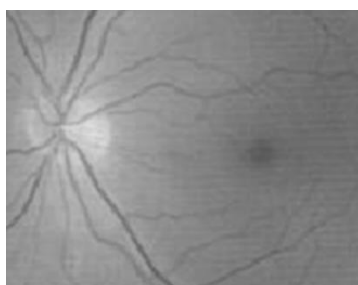


Fig 3.2.3 Grayscale image

The command used for cropping image in matlab is explained below.

Syntax

$$I = \text{rgb2gray}(\text{RGB})$$

Description

$I = \text{rgb2gray}(\text{RGB})$ converts the true color image RGB to the grayscale intensity image I. `rgb2gray` converts RGB images to grayscale by eliminating the hue and saturation information while retaining the luminance.

3.2.4 Binary image

For scanning this image we have to convert image into bitwise binary image. In binary image we provide level on which the image divides in two parts i.e. black part and white part. In which the black part shows the defected part of eye. The converted binary image shown in Fig.3.2.4

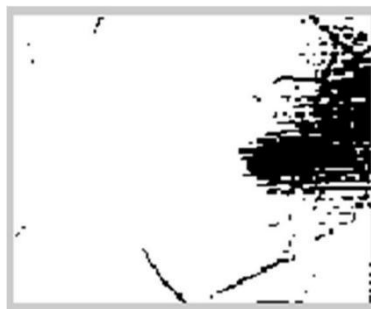


Fig.3.2.4 Binary image

The command used for cropping image in matlab is explained below.

Syntax

$$I1 = \text{im2bw}(I, \text{level})$$

Description

$I1 = \text{im2bw}(I, \text{level})$ converts the grayscale image I to a binary image. The output image I1 replaces all pixels in the input image with luminance greater than level with the value 1 (white) and replaces all other pixels with the value 0 (black). You specify level in the range [0,1], regardless of the class of the input image. The function `gray thresh` can be used to compute the level argument automatically. If you do not specify level, `im2bw` uses the value 0.5.

3.3 Feature extraction

This block finds the pixel locations where the magnitude of the gradient of intensity is larger than a threshold value. Feature Extraction is used to select all Micro aneurysms present in the binary image. Microaneurysms appear as isolated patterns and are disconnected from the vessels. The features of micro aneurysms can be extracted based on shape, size and intensity level. Micro aneurysms are dark reddish in color, they appear as small red dots of 10 to 100 microns diameter and are circular in shape.[2,6]

For scanning the binary image we define a variable 'c'. The black color in the binary image has 0 values. Depending on this value we calculate the value of 'c'. Steps of scanning process is given below

- For scanning first we have to find the size of binary image.
- From the found size we get the number of rows and column of binary image.
- Then we assign variable 'c' to zero value.
- We scan total image by scanning the first row and first column up to the last column of image. If the scanned value is zero then increment the previous value of 'c' by one. If it is not zero then value of 'c' remains as it is.
- Next we scan the second row and first column up to the last column of image. If the scanned value is zero then increment the previous value of 'c' by one. If it is not zero then value of 'c' remains as it is.
- The above process is repeated to the last row of the image.
- As this way we get the final value of 'c'.

Depending upon the value of 'c', we decide type of Diabetic Retinopathy. If the value of 'c' is greater than 5000 then the type of Diabetic Retinopathy is **Haemorrhage**. If the value of 'c' is less than one then the type of Diabetic Retinopathy is **Normal**.

To find the exudate type of Diabetic Retinopathy we use 'Neural Network toolbox'. Neural Network Toolbox™ provides functions and apps for modeling complex nonlinear systems that are not easily modeled with a closed-form equation. The neural network toolbox is explained in detail in chapter 4.

- For the exudates type we first calculate mean of the grayscale image.
- After that we find standard deviation of matrix element which computes standard deviation of the values in grayscale image.
- Depending upon the value of 'c', mean, standard deviation we form a matrix.

- Then Neural network toolbox is initialised and simulated.
- By this way we get the value which is further rounded off.
- If this value is greater than one then this is **Exudates** type of Diabetic Retinopathy.

3.4 Classification

The classification of Diabetic Retinopathy is done on the basis of value of 'c'. The diabetic retinopathy is classified in three types.

1. Normal

If the value of 'c' is less than one then this is Normal DR.

2. Haemorrhage

If the value of 'c' is greater than 5000 then this is Haemorrhage DR.

3. Exudates

If the rounded value is greater than one then this is Exudate DR

3.5 Flowchart and Algorithm

3.5.1 Flowchart

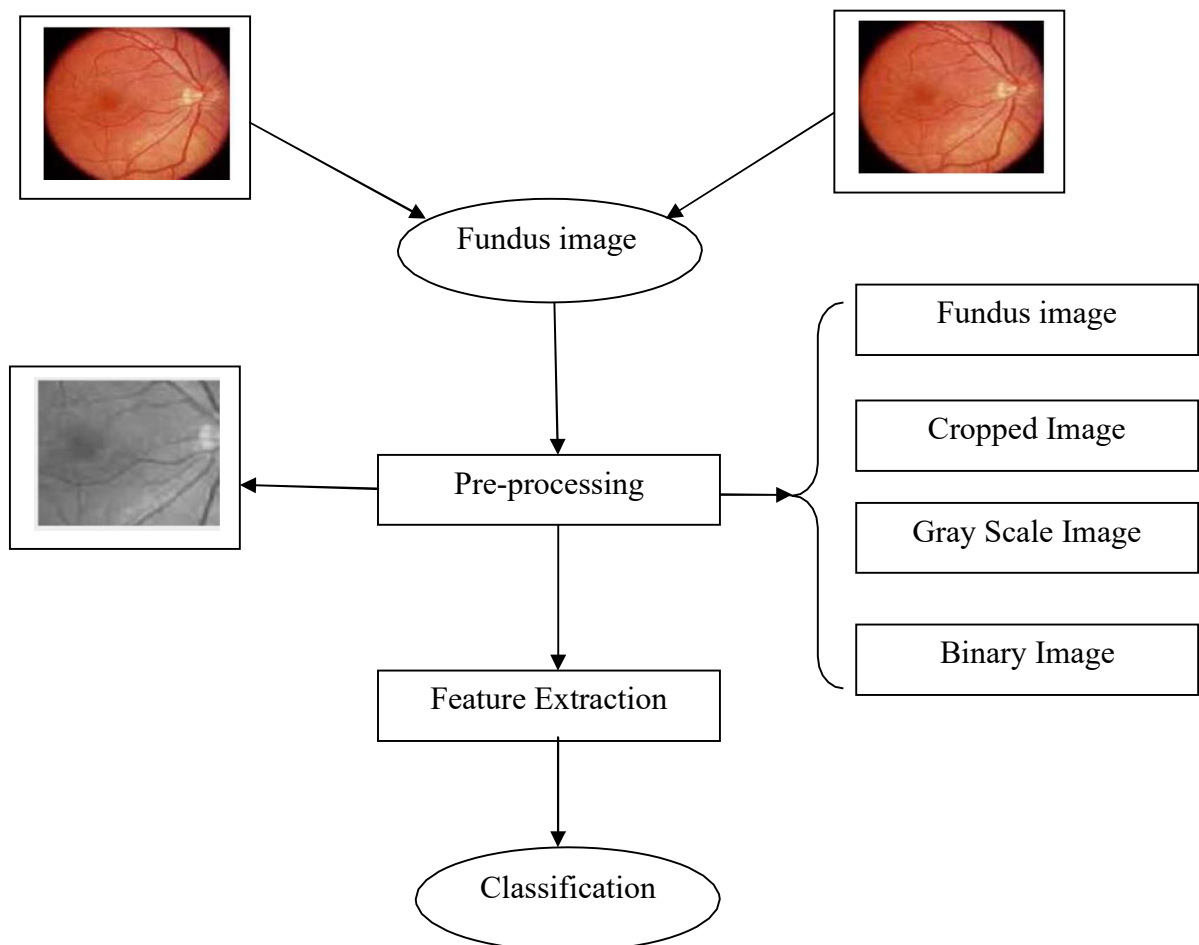


Fig 3.5.1 Flowchart

3.5.2 Algorithm

1) Initialization:

1. Let, i = input image number
2. I = convert 'i' from no to string
3. $I1$ is concatenate string horizontally of I and '.jpg'

2) Read Image

1. Read image from $I1$

3) Processing

1. $I3$ = crop image of $I2$ with four element position vector $X_{min}=50$, $Y_{min}=45$, $width=150$, $height=120$. Plot $I3$ image.
2. $I3$ image is convert into binary at level of 0.45 and assigned to $I4$. Plot $I4$ image.

4) Scanning Process

1. Let, $[j, k]$ is the size of image $I4$.
2. 'c' is assigned to zero i.e., black part.
3. For j , i.e., row varies from 1:120 and for k , i.e., column varies from 1:150
4. If $I4 [j, k]$ is equal to value zero then value of 'c' is incremented by 1, otherwise no change.
5. This stage is repeated up to last row and last column of $I4$. We get the final count of c .

5) Classification

1. If $c > 5000$, then display type of DR is hemorrhage.
2. Else, $I5$ is the conversion of $I3$ into grayscale image. Plot $I5$ image.

6) Neural Network Initialization

1. Let, m is the mean of $I5$ image and s is the standard deviation of $I5$ image.
2. Let, p is matrix of three element vector of value of c , m , s .
3. Initialize feed forward network with 'tansig' and 'purelin'.
4. Set train parameter of network.

Epochs= 1000;

Goal = 0.01;

5. Train the neural network.
6. Simulate the neural network with p.
7. For approximation simulated value is multiplied by 10 and rounded off.

7) Classification

1. If this value is greater than 1 , then type of DR is Exudates. Else,
2. Type of DR is Normal.

8) END

3.6 Software and tools used for algorithm

I have used MATLAB simulation software for implementation of ADDR algorithm. MATLAB (matrix laboratory) is a numerical computing environment and fourth-generation programming language. Developed by Math Works, MATLAB allows matrix manipulation, plotting of function and data and implementation of various algorithms. We have used MATLAB 2021 version for achieving my project goals. I have used Neural Network toolbox. It allows me for creation of various required function and GUI (Graphical user interface).

**Chapter 4:
Neural Network
Toolbox**

4.1 Neural Network Toolbox

Neural Network Toolbox™ provides functions and apps for modeling complex nonlinear systems that are not easily modeled with a closed-form equation. Neural Network Toolbox supports supervised learning with feed forward, radial basis, and dynamic networks. It also supports unsupervised learning with self-organizing maps and competitive layers.

With the toolbox you can design, train, visualize, and simulate neural networks. You can use Neural Network Toolbox [7] for applications such as data fitting, pattern recognition, clustering, time-series prediction, and dynamic system modeling and control. To speed up training and handle large data sets, you can distribute computations and data across multicore processors, GPUs, and computer clusters using Parallel Computing Toolbox™.

Key Features

- Supervised networks, including multilayer, radial basis, learning vector quantization (LVQ), time-delay, nonlinear autoregressive (NARX), and layer-recurrent
- Unsupervised networks, including self-organizing maps and competitive layers
- Apps for data-fitting, pattern recognition, and clustering
- Parallel computing and GPU support for accelerating training (using Parallel Computing Toolbox)
- Preprocessing and postprocessing for improving the efficiency of network training and assessing network performance
- Modular network representation for managing and visualizing networks of arbitrary size
- Simulink blocks for building and evaluating neural networks and for control systems applications.

4.2 Network Architectures

Neural Network Toolbox supports a variety of supervised and unsupervised network architectures. With the toolbox's modular approach to building networks, We can develop custom network architectures for your specific problem. We can view the network architecture including all inputs, layers, outputs, and interconnections.[8] Supervised Networks Supervised neural networks are trained to produce desired outputs in response to sample inputs, making them particularly well-suited to modeling and controlling dynamic systems, classifying noisy data, and predicting future events. Neural Network Toolbox includes four types of supervised networks: feedforward, radial basis, dynamic, and learning vector quantization.

Feedforward networks

Feedforward networks have one-way connections from input to output layers. They are most commonly used for prediction, pattern recognition, and nonlinear function fitting. Supported feedforward networks include feedforward back propagation, cascade-forward back propagation, feedforward input-delay back propagation, linear, and perceptron networks. Feedforward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear relationships between input and output vectors as shown in Fig.4.2.

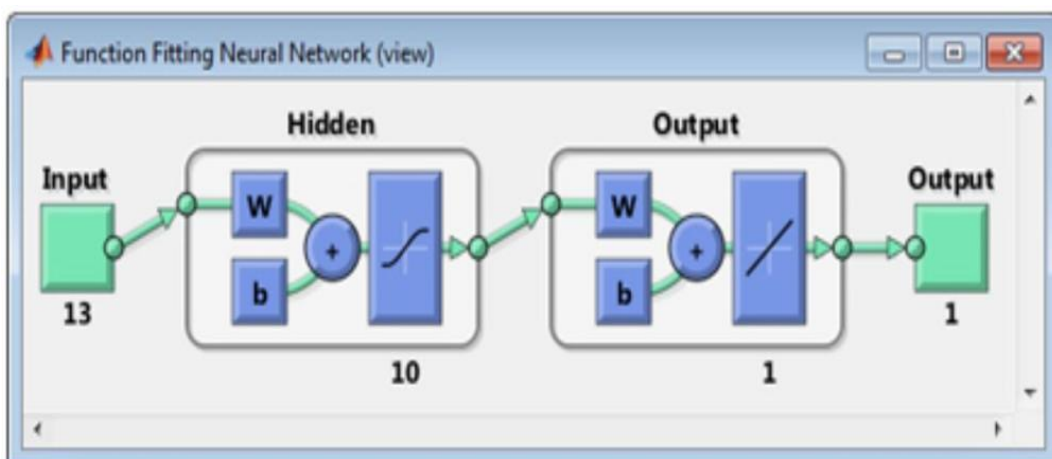


Fig.4.2 Feed Forward Network

4.3 Transfer function used in neural network

1) tansig

Hyperbolic tangent sigmoid transfer function as shown in Fig.4.3.

Graph and Symbol-

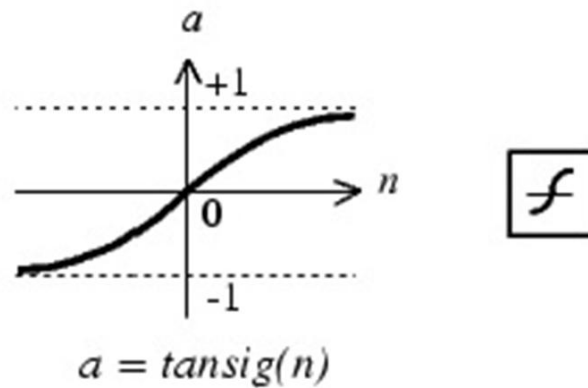


Fig.4.3 Tan-sigmoid transfer function

Description-

tansig is a neural transfer function. Transfer functions calculate a layer's output from its net input. Sigmoid output neurons are often used for pattern recognition problems.

2) purelin

Linear transfer function as shown in Fig.4.3.1.

Graph and Symbol-

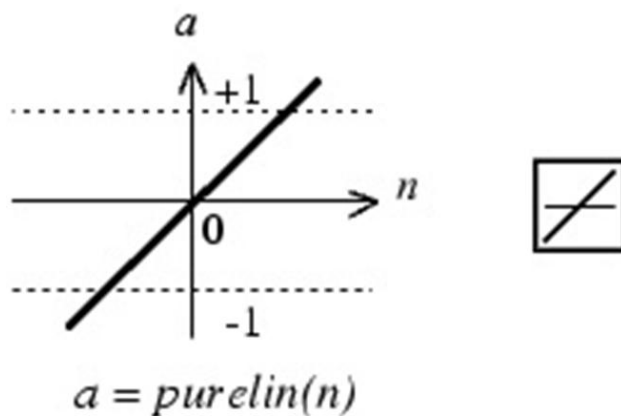


Fig.4.3.1 Linear transfer function

Description-

purelin is a neural transfer function. Transfer functions calculate a layer's output from its net input. linear output neurons are used for function fitting problems.

4.4 Training Algorithms

Training and learning functions are mathematical procedures used to automatically adjust the network's weights and biases. The training function dictates a global algorithm that affects all the weights and biases of a given network. The learning function can be applied to individual weights and biases within a network. Neural Network Toolbox supports a variety of training algorithms, including several gradient descent methods, conjugate gradient methods, the Levenberg-Marquardt algorithm (LM) [9], and the resilient backpropagation algorithm (Rprop). The toolbox's modular framework lets you quickly develop custom training algorithms that can be integrated with built-in algorithms. While training your neural network, you can use error weights to define the relative importance of desired outputs, which can be prioritized in terms of sample, time step (for time-series problems), output element, or any combination of these. You can access training algorithms from the command line or via apps that show diagrams of the network being trained and provide network performance plots and status information to help you monitor the training process. A suite of learning functions, including gradient descent, Hebbian learning, LVQ, Widrow-Hoff, and Kohonen, is also provided.

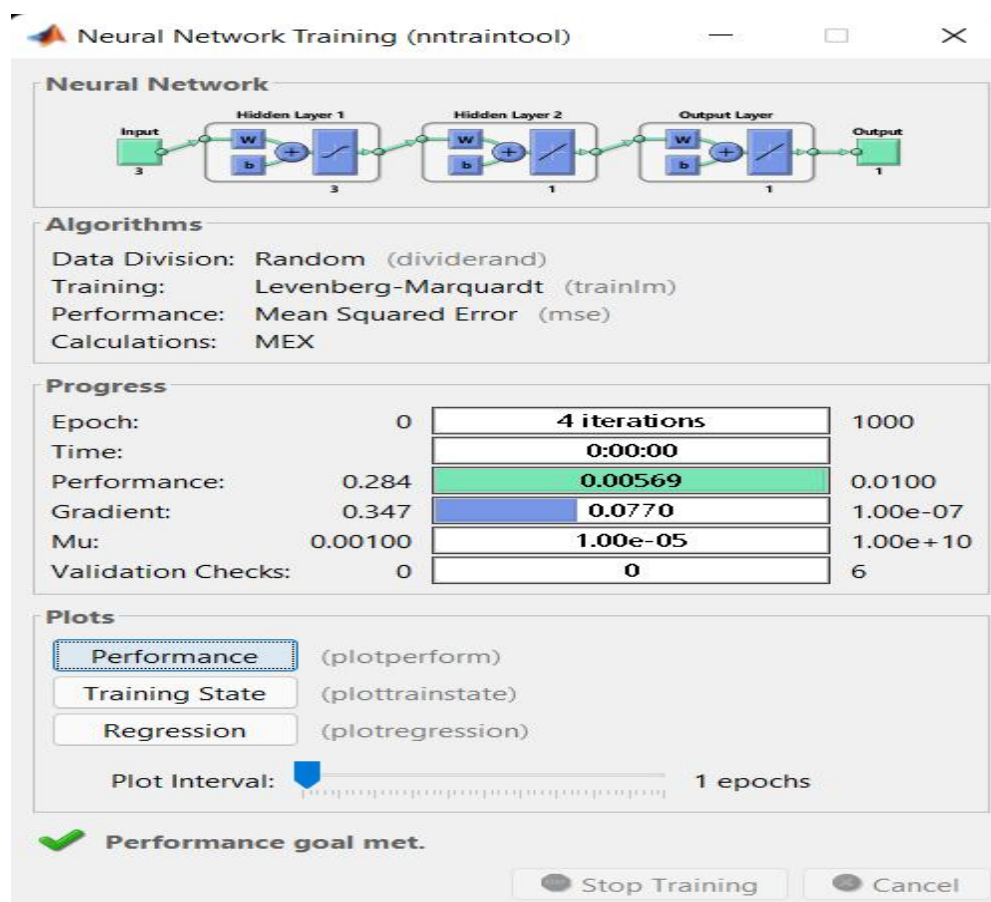


Fig.4.4 Neural Network training Tool

4.5 Commands used for neural network

```
m(i)=mean2(I5)
```

Description

Average or mean of matrix elements

$m(i) = \text{mean2}(I5)$ computes the mean of the values in A.

The input image A can be numeric or logical. The output image $m(i)$ is a scalar of class double.

```
s(i)=std2(I5)
```

Description

Standard deviation of matrix elements

$s(i) = \text{std2}(A)$ computes the standard deviation of the values in A.

A can be numeric or logical. $s(i)$ is a scalar of class double.

```
p=[c;m;s]
```

Description

By using this command we get the network for a three-element input vector

```
net = newff(P,T,[S1 S2...S(N-1)],{TF1 TF2...TFN1})
```

Description

several arguments in newff. TF_i Transfer function of i th layer. (Default = 'tansig' for hidden layers and 'purelin' for output layer.) The transfer functions TF_i can be any differentiable transfer function such as tansig, logsig, or purelin.

Example

Here is a problem consisting of inputs P and targets T to be solved with a network.

```
P = [0 1 2 3 4 5 6 7 8 9 10];
T = [0 1 2 3 4 3 2 1 2 3 4]
net = newff(P,T,5);           // Here a network is created with one hidden layer of five
neurons.
Y = sim(net,P);             //The network is simulated and its output plotted against the
targets.
plot(P,T,P,Y,'o')
net.trainParam.epochs = 50; // The network is trained for 50 epochs. Again the network's
output is plotted
net = train(net,P,T);
Y = sim(net,P);
plot(P,T,P,Y,'o')
```

Algorithm

Feed-forward networks consist of Nl layers using the dotprod weight function, net sum net input function, and the specified transfer function.

The first layer has weights coming from the input. Each subsequent layer has a weight coming from the previous layer. All layers have biases.

The last layer is the network output. Each layer's weights and biases are initialized with initn. Adaption is done with trains, which updates weights with the specified learning function. Training is done with the specified training function. Performance is measured according to the specified performance function.

```
net.trainParam.epochs
net.trainParam.goal
```

Description

By using these command we set the training parameters and training will stop when any of these conditions occurs:

The maximum number of epochs (repetitions) is reached.

Performance is minimized to the goal

```
net=train(net,p,t)
```

Description

Train trains a network net according to net.trainFcn and net.trainParam. Train (net,P,T,Pi,Ai) takes

net - Network

P - Network inputs

T - Network targets (default = zeros)

```
y=sim(net,p)
```

Description

sim simulates neural networks.

net - Network

P - Network inputs

Chapter 5: Results

5.1 Graphical User Interface (GUI)

A graphical user interface (GUI) can be describe as a graphical display that contains devices, or components, that enable a user to perform interactive tasks without creating a script or type commands at the command line . These components can be push buttons menus, toggle buttons, toolbars, checkboxes, radio buttons and sliders etc. [10]. Data can also be display in graphical form or plots or groups. The user need not know the details of the task. A simple GUI supported by MATLAB with its rich sets of tools is as shown in Fig 5.1

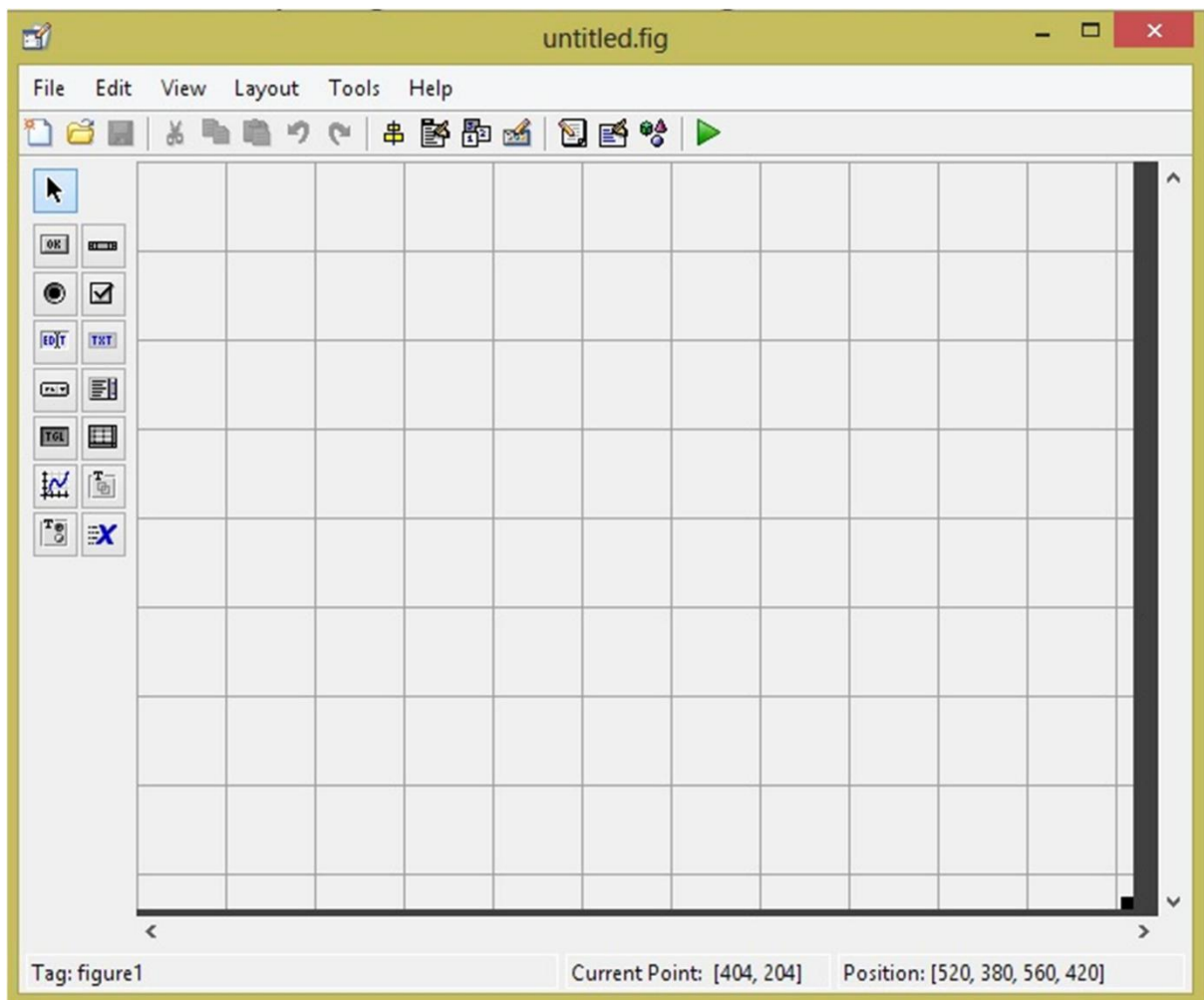


Fig.5.1 GUI supported by MATLAB

Creating a GUI using MATLAB's Graphical User Interface Development Environment (GUIDE) is divided into two relatively managed and independent tasks.

- 1) GUI Component layout
- 2) GUI Programming

In GUI component layout, the GUIDE enables the user to layout the GUI as required. It involves clicking and dragging of the components from the components palette to the layout area. These components can be aligned, resize, set tab order etc by using other tools are accessible from the Layout Editor. Saving this GUI layout generates an M-Files (MATLAB) file which helps to control how the GUI works. This and subsequent activities constitute the GUI Programming tasks. The generated M-file provides code to initialize the GUI when launched and contains a framework for the GUI callbacks; the routines that execute in response to user-generated events such as a mouse click. Adding codes to the callbacks function using the M-file editor enable the GUI perform intended operations. Since part of the aim of this research work is to design a GUI to assist in fundus image for this present and future work in this field, GUI was created.[11]

➤ **Main GUI window**

Main GUI shown in Figure 3.2 consists of 4 different push buttons, 2 different text box, and four display area [12]. The user input the fundus image by using the push button 'Select image' and this image is loaded into an axes one display area. Pre-processing and feature extraction is done by 'Process' push button and display result of pre processing in axes 2 to 4 display areas. Result of feature extraction display in text one and two.

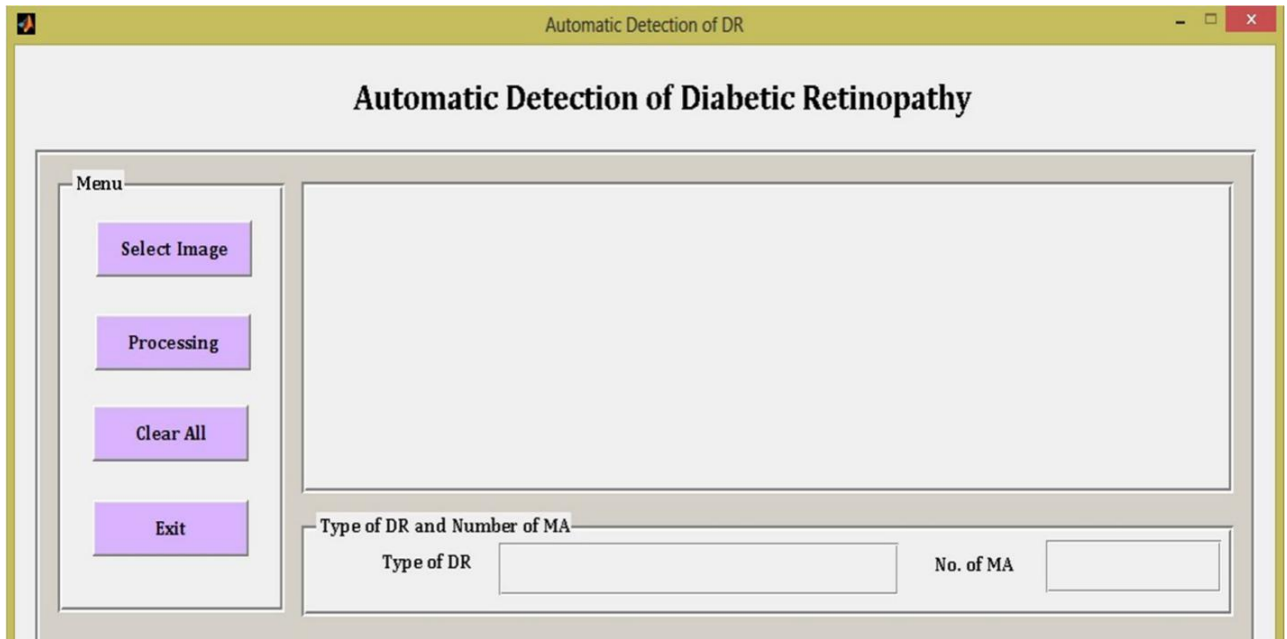


Fig.5.1.1 Main GUI window

➤ **GUI window with selected input image**

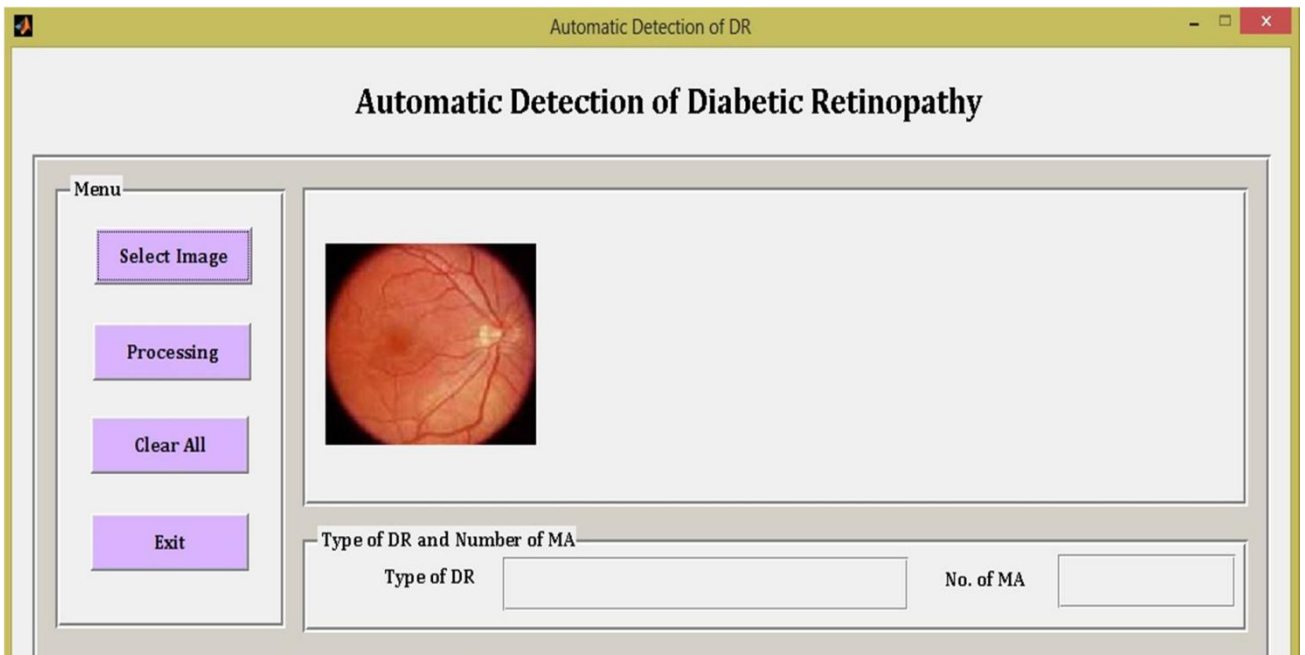


Fig.5.1.2 GUI window with selected input image

➤ **GUI window after processing**

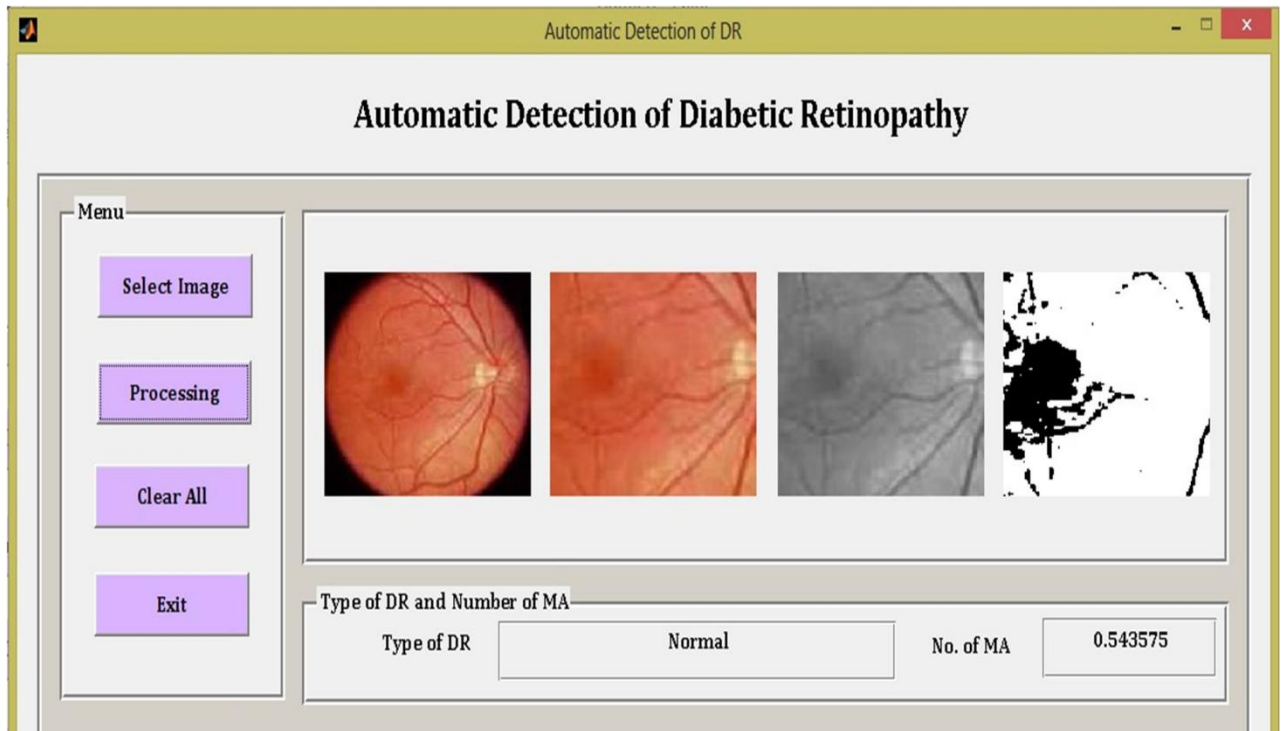


Fig.5.1.3 GUI window after processing

5.2 Results and analysis

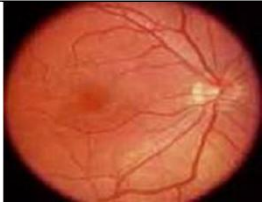



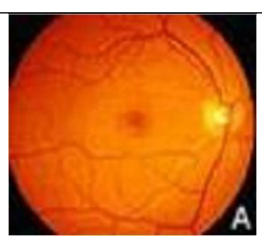



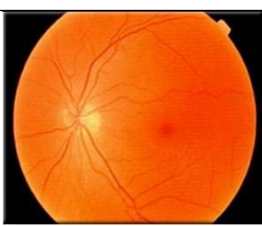
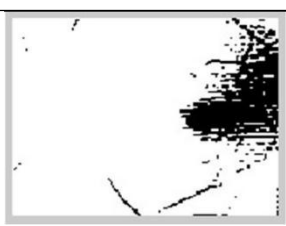
This chapter starts with presentation of result obtained from diagnosis of thirty (30) fundus images which were used for detection and diagnosis.

Result Obtained

The result obtained from the diagnosis of DR by this research work is as shown in the Following table. Thirty images (10 normal images and 20 abnormal images) Detection for abnormalities is centred on detecting red spot disease and bleeding.

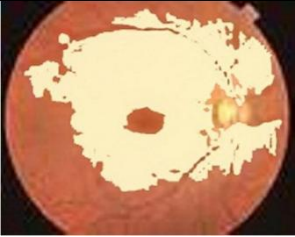
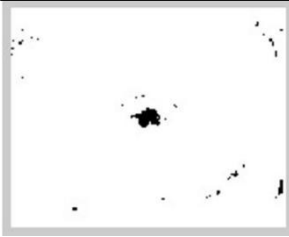


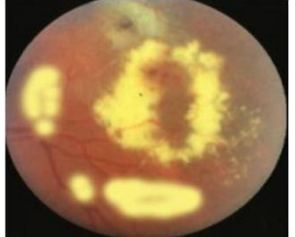


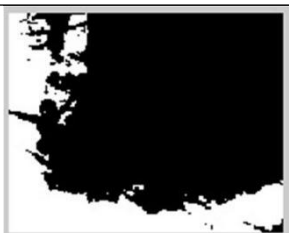


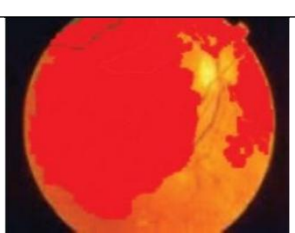

5.2.1 Results for normal image

Table no 5.2.1 Result of Normal images

S.No.	Input Image	Binary Image	Type of DR (No.of MA)
1			Normal (0.04247)
2			Normal (0.08644)
3			Normal (0.47895)
4			Normal (0.051261)
5			Normal (0.5678)

5.2.2 Result for abnormal images

Table no 5.2.2 Result of abnormal images

S.No	Input Image	Binary Image	Type of DR (No.of MA)
1			Exudates (7.0181)
2			Exudates (8.37845)
3			Exudates (9.80943)
4			Hemorrhages (11771)
5			Hemorrhages (14951)
6			Haemorrhages (15406)

5.2.3 Performance Plots

The Performance plots for Normal, Exudates, Hemorrhages are shown in the Fig.5.2.3.

For Normal the mean square error value is 0.00025922 at 5th epoch as shown in the Fig.5.2.3(a)

For Exudates the mean square error value is 0.00071047 at 3rd epoch as shown in the Fig.5.2.3(b)

For Hemorrhages the mean square error value is 0.0017519 at 3rd epoch as shown in the Fig.5.2.3(c)

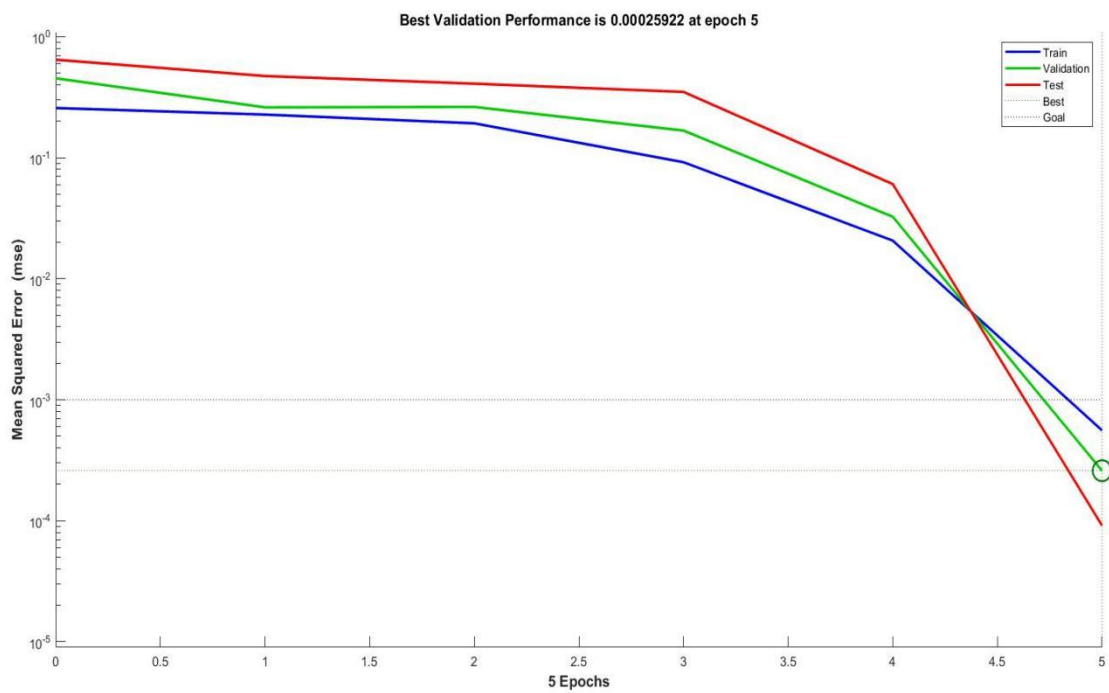


Fig.5.2.3(a) Performance Plot of Normal DR

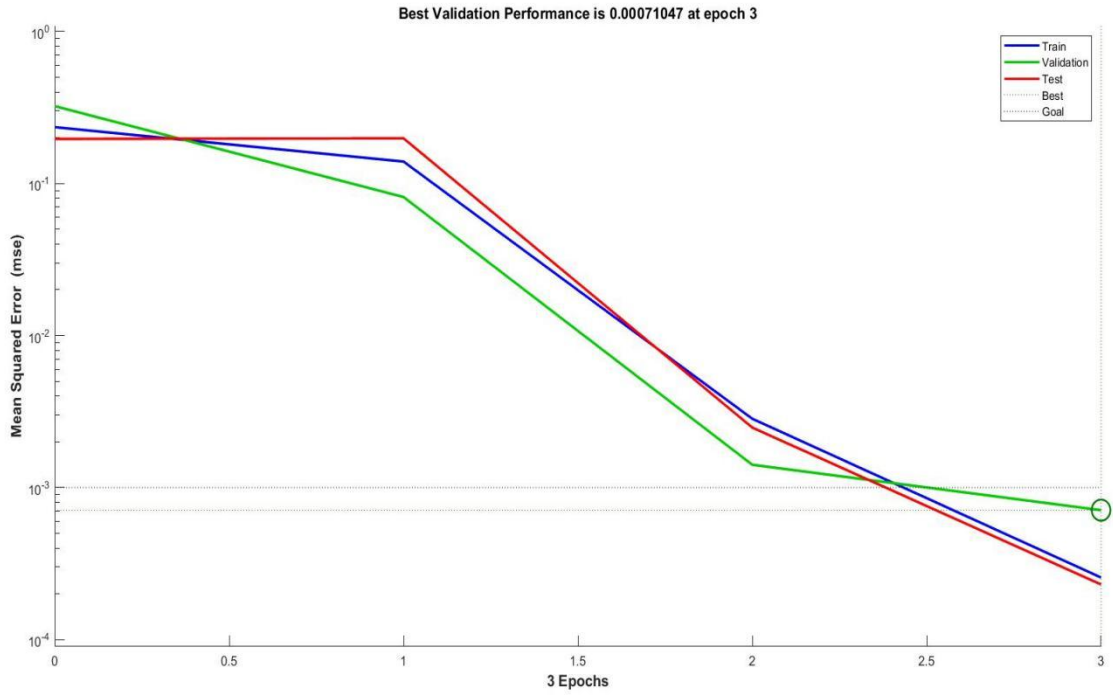


Fig.5.2.3(b) Performance Plot of Exudates

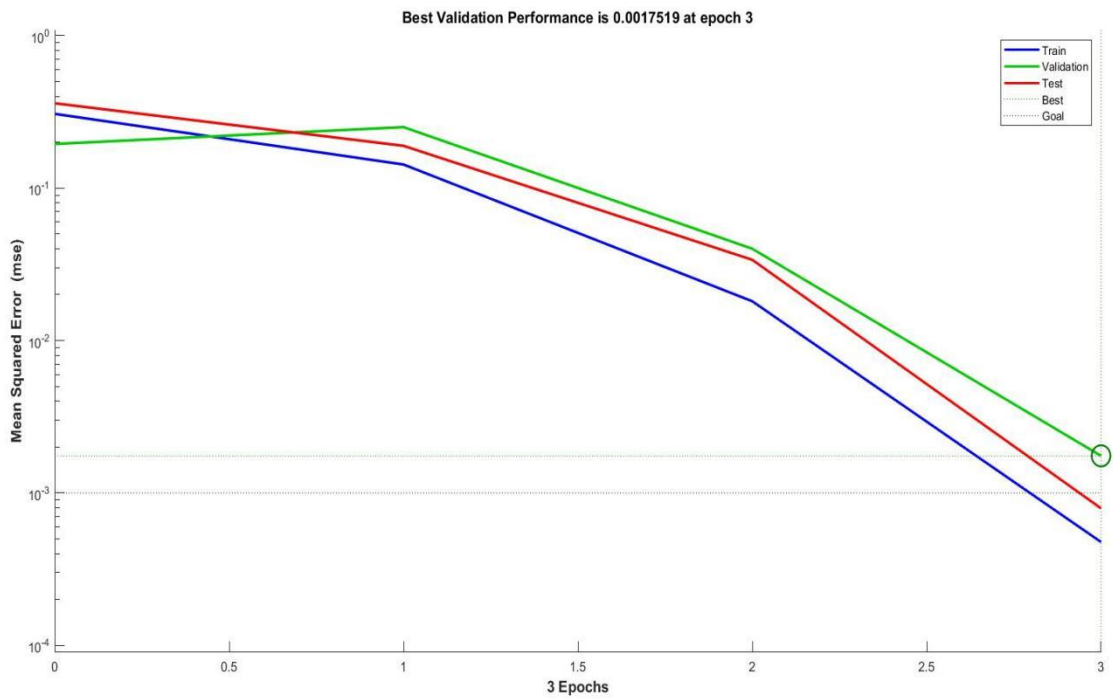


Fig.5.2.3 (c) Performance Plot of Hemorrhages

5.3 Analysis

General classification involves classifying an image as normal or abnormal. This involves the presence or otherwise of any of the disease mentioned in the previous sections above. From this the specificity and sensitivity of the system is determined. Sensitivity refers to the percentage of abnormal fundus image classified as abnormal by the method while specificity can be defined as percentage of normal fundus image classify as normal.

**Chapter 6:
Conclusion and
Future scope**

6.1 Conclusion

As stated earlier in Chapter 1 of this report the aims of this work are:

- a) Development of a system that will be able to identify patients with from colour fundus image
- b) The different diabetic retinopathy diseases that are of interest include red spots and bleeding both falls between NPDR and PDR stages of the disease.
- c) Development of a MATLAB based Graphic User Interface (GUI) tool to be used by the ophthalmologist for taking fundus images. The fundus images are to be used for the development of DR detection and database system for this present and future work.
- d) By using CNN we observe the MA values for different types of lesions i.e. Normal, Exudates and Haemorrhages
 - For Normal DR, MA values less than 1.
 - For Exudates DR, MA values range from 1 to 10.
 - For Haemorrhages DR, MA values greater than 10.

6.2 Future scope

The present research work detects Diabetic retinopathy. Other diseases are also to be incorporated into this research work in order to complete the whole DR diagnosis. Ours only focus on red spot and bleeding, diseases like new vein growth will still need to be diagnosed as part of future work.

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**PAPER
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An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Diabetic Retinopathy Using Convolution Neural Network (CNN)

¹V.V.K.Raju, ²P.Devi

¹S.Sudheer, ²S.Sravan, ³R.Mounika, ⁴S.Balaji

¹Department of ECE,

¹ANITS, Visakhapatnam, India

Abstract : Diabetic Retinopathy (DR) is the foremost usual cause of diabetics-related visual deficiency. The is a infection, however, presents few signs within the early stages due to its slow course, making illness location challenging. As a result, recognizing diabetic retinopathy at an early organize is significant. As a result, a fully mechanized framework is fundamental to help within the early recognizable proof and screening prepare. Not at all like computer-aided conclusion frameworks, Ophthalmologists must manually determine DR retina fundus images, which takes time, effort, and money, as well as inclined to misdiagnosis. Profound learning has as of late been one of the foremost well known methodologies for making strides execution in a assortment of areas, especially therapeutic picture investigation and classification. In this exertion, we show a CNN approach for diagnosing DR and precisely reviewing its seriousness from computerized fundus pictures. We make a arrange with CNN design and information increase that can perceive the complex components included within the system of classification assignment, such as micro-aneurysms, exudates, & hemorrhages on the retina, as well as providing a determination consequently as well as without the required for human input.

IndexTerms-Levenberg Marquardt Algorithm, Resilient Backpropagation, Learning Vector Quantization, Autoregressive, Microaneurysms.

I. INTRODUCTION

Years have passed since then, and India, in addition to other countries, of the world have seen a surge in age-related and societal diseases such as diabetes. According to a recent survey, diabetes has been diagnosed whereas 4% of the country's population, and it has been identified as a result, if not properly treated and controlled, it is a major cause of blindness in the country. It has long been recognised that early detection and diagnosis are critical. as a result, there are ways to reduce the percentage of visual impairment caused by diabetes, with a greater emphasis on routine medical checks and the use of special facilities for disease detection and monitoring. It is unnecessary to exaggerate the impact on medical workers. It has led to an increase in work load on staff and facilities, as well as an increase in diabetes screening activities, to name a few. Many approaches have been proposed and identified as ways to reduce the stress caused by this constant check-up and screening-related activities, one of which is the use of medical digital image signal processing for diagnosis of diabetes-related diseases such as diabetic retinopathy using retinal images.

Diabetes is a metabolic illness. The body obtains its energy from glucose, which is formed as a result of food digestion. The pancreas, an organ located near the stomach, produces the hormone insulin, which helps digested food enter the bloodstream. The pancreas creates the precise amount of insulin required for glucose absorption from the blood into the cells during eating. The pancreas either generates too little or no insulin in people with diabetes, or the cells do not react appropriately to the insulin that is generated. The glucose in the blood builds up, overflows into the urine, and eventually exits the body. As a result, the body's primary source of nutrition is depleted, despite the fact that the blood contains a lot of glucose Type 1 diabetes is caused by an auto immune issue and is one of three forms of diabetes. The body's immune system destroys the insulin-producing beta cells in the pancreas, resulting in the pancreas producing no or very little insulin. The dysfunction of the beta cell is the cause of Type 2 Diabetes. Non-production of insulin or a condition known as insulin resistance are examples of this dysfunction. Muscles, fat cells, and other cells do not respond to the insulin produced in insulin resistance. Kind 3 diabetes, often known as gestational diabetes, is a type of diabetes that exclusively arises during pregnancy. During this time, the body is resisting the effects of the insulin that has been produced. Diabetic Retinopathy is the result of diabetes on the retina (DR). It is known to cause damage to the retina's tiny blood vessels, which can result in eyesight loss. The disease is classified into three stages viz: Non-Proliferate Diabetic Retinopathy Page 3 (NPDR), Proliferate Diabetic Retinopathy (PDR).Thearteries in the retina weaken and leak during

the PDR phase, resulting in tiny, dot-like hemorrhages. Swelling or edoema in the retina, as well as reduced vision, are common side effects of leaking vessels. Circulation difficulties lead parts of the retina to become oxygen-deprived or ischemic during the NPDR phase. As the circulatory system tries to maintain enough oxygen levels within the retina, new weak vessels form. Neovascularization is the term for this phenomenon. Blood may flow into the retina and vitreous, resulting in spots or floaters as well as a reduction in vision. Within the SDR phase of the illness, there's proceeded irregular vessel development and scar tissue, which may cause genuine issues such as retinal separation and glaucoma and continuous misfortune of vision. This investigate work is one of the strategy of applying computerized picture preparing to the field of restorative determination in arrange to reduce the time and push experienced by the ophthalmologist and other individuals of the group within the screening, determination and treatment of diabetic retinopathy. This work decide the nearness of NPDR and PDR or something else in a understanding by applying methods of advanced picture preparing on fundus pictures taken by the utilize of therapeutic picture camera by a therapeutic faculty within the clinic.

II. LITERATURE SURVEY

MA detection is usually divided into two stages: candidate extraction and classification, according to the majority of currently available approaches. Image pre-processing to reduce noise and improve contrast is usually the initial step in candidate extraction. Following pre-processing, picture segmentation is utilized to extract as many regions as feasible that are likely to be MAs. In the second stage, employing a supervised learning-based algorithm, the candidates are labeled as true or false. This categorization necessitates the use of a training set to define the class borders. The training set is made up of feature vectors and class labels in pairs. Feature vectors are ordered sets of particular attribute values, usually geometrical or color descriptors, that can be used to differentiate MAs from other objects.

III. PROPOSED METHODOLOGY

3.1 Basic System level block diagram

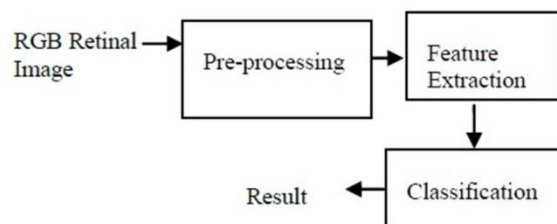


Fig 1: Basic system level block diagram

The Automatic Diabetic Retinopathy Detection System (ADDR) is a completely automated Diabetic Retinopathy Detection System (DR). The ADDR block diagram is shown in the diagram. A fundus picture, which is a component of the human eye that can be viewed via the pupil, is fed into this system. The retina, optic disc, macula, blood vessels, and other structures on the internal surface of the eye, opposite the lens, are included in the fundus image. Because the image quality is poor due to noise, poor contrast, uneven illumination, and other factors, pre-processing is performed to improve the findings.

The suggested technique is made up of three parts,

1. Pre-Processing:

The purpose of pre-processing is to reduce noise, improve contrast, and adjust for non-uniform lighting. The green channel in RGB photos has the best contrast between the vessels and the background, whereas the red and blue channels have more noise. As a result, the green channel is employed for additional processing.

2. Feature Extraction:

Objective of Feature Extraction is to select all Micro aneurysms present in the pre- processed image. Micro aneurysms appear as isolated patterns and are disconnected from the vessels. The features of micro aneurysms can be extracted based on shape, size and intensity level. Micro aneurysms are dark reddish in color, they appear as small red dots of 10 to 100 microns diameter and are circular in shape.

3. Classification:

Following the detection of micro aneurysms, categorization labels the eye pictures as diseased or normal based on the number of micro aneurysms found.

3.2 Pre-Processing Stage (PPS):

The photos must be Pre-Processed in order to correct difficulties such as uneven illumination, insufficient contrast between exudates and image backdrop pixels, and the presence of noise in the input fundus image for detecting anomalies connected with fundus images. Apart from the aforementioned issues, this area is also in charge of the system's color space conversion and image size standardization. This portion, which is the Pre-Processing step, might be considered the foundation of this study. The Pre-Processing stage is represented by a block diagram of the sub parts that make up the level (PPS).

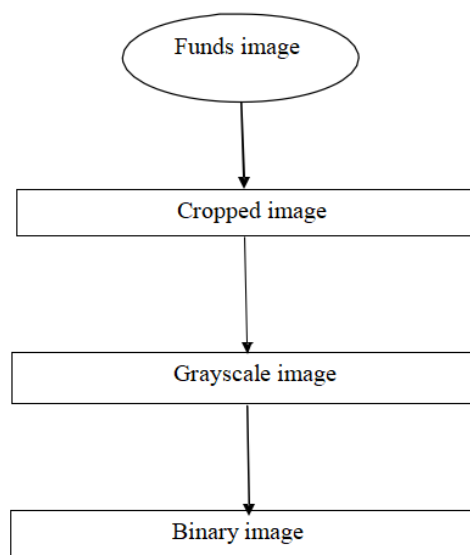


Fig 2: Block diagram of Pre-processing stage

3.2.1 Color Fundus Image

The input fundus image is an RGB image. This image is a retinal fundus image of patient. This fundus image can be either normal or defected. We used this image as input image. We have to apply some processes to this image to detect the diabetic retinopathy. In our database, there are such 30 fundus images in which 10 images are normal, 10 images are hemorrhage and remaining 10 are exudates. The fig.3.2.1 shows the input fundus image.

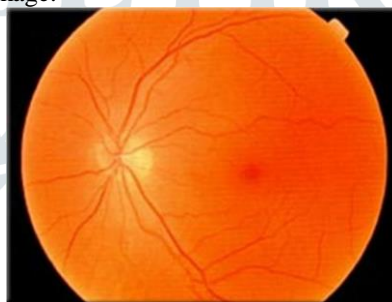


Fig 3: Input Fundus Image

3.2.2 Cropped Image

The input image must have to crop at specific size, because the whole part of fundus image is not defected. So we have to choose only the area near the pupil. Only this area more affects the patient's vision ability.

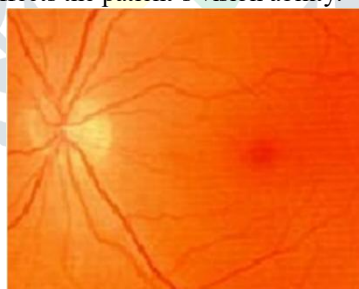


Fig 4: Cropped Image

3.2.3 Grayscale Image

The grayscale image has the best contrast between the vessels and the background, whereas the red and blue images have a lot of noise. As a result, for further processing, a grayscale image is used. In the grey image, the retinal blood vessels seem darker.

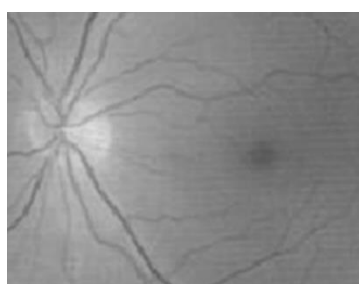


Fig 5: Grayscale Image

3.2.4 Binary Image

To scan this image, we must first transform it to a bitwise binary image. We provide a level in binary images where the image is divided into two halves, black and white. The defective part of the eye is shown by the black area. Figure shows a binary image that has been transformed.



Fig 6: Binary Image

3.3 Feature Extraction

This block locates pixel locations where the gradient of intensity magnitude is greater than a threshold value. To pick all Micro aneurysms in the binary image, Feature Extraction is utilized. Microaneurysms show as distinct patterns that are not related to the vessels. Micro aneurysms can be classified depending on their shape, size, and severity level. Micro aneurysms are little red dots with a diameter of 10 to 100 microns and a circular shape that are dark reddish in colour.

For scanning the binary image, we define a variable 'c'. The black color in the binary image has 0 values. Depending on this value we calculate the value of 'c'. Steps of scanning process is given below

- For scanning first we have to find the size of binary image.
- From the found size we get the number of rows and column of binary image.
- Then we assign variable 'c' to zero value.
- We scan total image by scanning the first row and first column up to the last column of image. If the scanned value is zero then increment the previous value of 'c' by one. If it is not zero then value of 'c' remains as it is.
- Next, we scan the second row and first column up to the last column of image. If the scanned value is zero then increment the previous value of 'c' by one. If it is not zero then value of 'c' remains as it is.
- The above process is repeated to the last row of the image.
- As this way we get the final value of 'c'.
- Depending upon the value of 'c', we decide type of Diabetic Retinopathy. If the value of 'c' is greater than 5000 then the type of Diabetic Retinopathy is **Hemorrhage**. If the value of 'c' is less than one then the type of Diabetic Retinopathy is **Normal**.
- We employ the 'Neural Network Toolbox' to determine the exudates type of Diabetic Retinopathy.
- Neural Network Toolbox™ contains functions and apps for modeling complex nonlinear systems that are difficult to model using closed-form equations.
- For the exudates type, we first compute the grayscale image's mean, then find the standard deviation of the matrix element, which computes the standard deviation of the grayscale image's values.
- We create an a matrix based on the value of 'c', mean, and standard deviation.
- After that, the Neural Network Toolbox is set up and simulated.
- In this manner, we obtain a value that has been further rounded off.
- If this value is larger than one, the Diabetic Retinopathy is Exudates type.

3.4 Classification

The classification of Diabetic Retinopathy is done on the basis of value of 'c'. The diabetic retinopathy is classified in three types.

1. Normal
If the value of 'c' is less than one then this is Normal DR.
2. Hemorrhage
If the value of 'c' is greater than 5000 then this is Hemorrhage DR.
3. Exudates
If the rounded value is greater than one then this is Exudates DR.

IV. SOFTWARE AND TOOLS USED

For the implementation of the ADDR method, I used MATLAB simulation. MATLAB is a fourth-generation programming language and numerical computation environment. MATLAB is a software programme developed by Math Works that allows you to manipulate matrices, plot functions and data, and perform numerous algorithms. To complete my project, I used the MATLAB

2021 version. The Neural Network Toolbox was utilized. It enables me to create a variety of required functions and user interfaces (Graphical user interface).

V. NEURAL NETWORK TOOLBOX

5.1 Network Architecture

A wide range of supervised and unsupervised network architectures are supported by Neural Network Toolbox. You can create custom network architectures for your specific problem using the toolbox's modular approach to network building. The network architecture, which includes all inputs, layers, outputs, and linkages, may be viewed. Networks that are supervised Supervised neural networks are well-suited to modelling and regulating dynamic systems, classifying noisy data, and predicting future events because they are trained to produce desirable outputs in response to sample inputs. Feedforward, radial basis, dynamic, and learning vector quantization are the four types of supervised networks available in Neural Network Toolbox.

5.2 Feed forward Networks

From the input to output layers, feed forward networks have one-way connections. Prediction, pattern recognition, and nonlinear function fitting are the most prevalent applications. Feed forward back propagation, cascade-forward back propagation, feed forward input-delay back propagation, linear, and perceptron networks are all supported feed forward networks. One or more hidden layers of sigmoid neurons, followed by an output layer of linear neurons, are common in feed forward networks. The network can learn nonlinear interactions between input and output vectors thanks to multiple layers of neurons with nonlinear transfer functions.

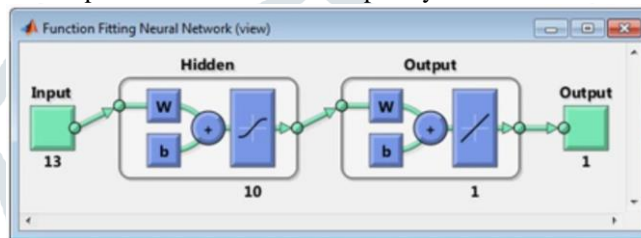


Fig 7: Feedforward Network

5.3 Transfer Functions used in Neural Network

1. tansig

Hyperbolic tangent sigmoid transfer function
Graph and Symbol

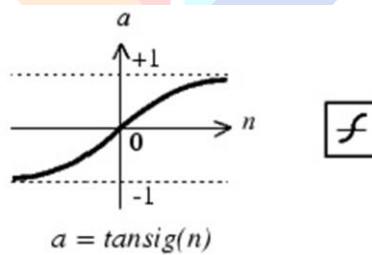


Fig 8: Tan-sigmoid transfer function

Tansig is an example of a neural transfer function. Transfer functions compute the output of a layer based on its net input. Pattern recognition problems are frequently solved using sigmoid output neurons.

2. Purelin

Linear transfer function
Graph and Symbol

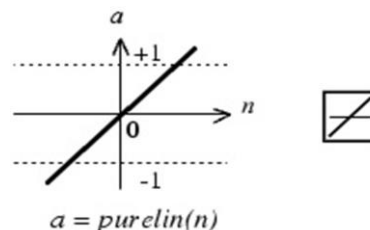


Fig 9: Linear transfer function

A neuronal transfer function is purelin. The output of a layer is calculated using transfer functions. For function fitting difficulties, linear output neurons are used.

VI. THE CNN ARCHITECTURE

The network has an input layer that accepts images with a resolution of 512x512 pixels as input. The architecture is made up of five sets of convolution, pooling, and dropout layers that are stacked one on top of the other. Following that are two sets of fully connected hidden and feature pooling layers. The final output layer is then added.

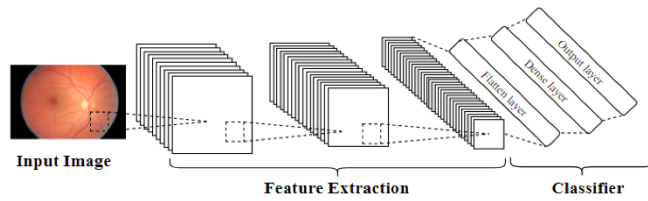


Fig 10: Layered Structure of CNN

VII. RESULTS & ANALYSIS

This chapter starts with presentation of result obtained from diagnosis of thirty (30) fundus images which were used for detection and diagnosis.

The result obtained from the diagnosis of DR by this research work is as shown in the Following table. Thirty images (10 normal images and 20 abnormal images) Detection for abnormalities is centered on detecting red spot disease and bleeding.

Sr.no.	Input image	Binary image	Type of DR
1			Normal
2			Normal
3			Normal
4			Normal
5			Normal

Fig 11: Results of Normal Images

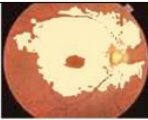
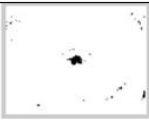


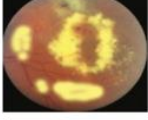

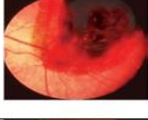





Sr.no	Input image	Binary image	Type of DR
1			Exudates
2			Exudates
3			Exudates
4			Hemorrhages
5			Hemorrhages
6			Hemorrhages

Fig 12: Results for Abnormal Images

VIII. CONCLUSION

- Development of a system that will be able to identify patients with from color fundus image
- The different diabetic retinopathy diseases that are of interest include red spots and bleeding both falls between NPDR and PDR stages of the disease.
- Development of a MATLAB based Graphic User Interface (GUI) tool to be used by the ophthalmologist for taking fundus images. The fundus images are to be used for the development of DR detection and database system for this present and future work.
- In line with the aims and objectives of this research work, this research group is able to develop a MATLAB GUI based system.

IX. FUTURE SCOPE

The present research works detects Diabetic Retinopathy. Other diseases are also to be incorporated into this research work in order to complete the whole DR diagnosis. Ours only focus on red spot and bleeding, diseases like new vein growth will still need to be diagnosed as part of future work.

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