Deep Learning Architecture for diabetic retinopathy categorization based on segmented fundus image characteristics.

Report submitted to SASTRA Deemed to be University as the requirement for the course.

CSE300 -MINIPPROJECT

Submitted by

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SASTRA
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SASTRA

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Bonafide Certificate

This is to certify that the report titled "**Deep Learning Architecture for Diabetic Retinopathy Categorization based on Segmented Fundus Image Characteristics**" submitted as a requirement for the course, CSE300 **MINI PROJECT** for B.Tech. is a bonafide record of the work done by **Suggula Jyothsna (Reg. No.: 123003243, CSE), Garlapati Dhanalakshmi (Reg. No.: 123003286, CSE), and Chappidi Manogna (Reg. No.: 123003047, CSE)** during the academic year 2021-22, in the School of Computing, under my supervision.

Signature of Project Supervisor :

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Date : 25-06-2022

Mini Project *Viva voce* held on 29/06/2022

Examiner 1 **Examiner 2**

List of Figures

Abbreviations

DR	Diabetic Retinopathy
CNN	Convolution Neural Network
PDR	Proliferative Diabetic Retinopathy
NDPR	Non-Proliferative Diabetic Retinopathy
AI	Artificial Intelligence
MPC	Maximal principal Curvature
AHE	Adaptive Histogram Equalization

Abstract

Artificial intelligence (AI) is useful in medical image processing for disease diagnosis. Diabetes results in diabetic retinopathy (DR), an eye disease. For diabetics, the formation of clots, and lesions in the light-sensitive part of the retina, is a problem. Vision loss is caused by damaged blood vessels. Most individuals can prevent visual loss if they receive prompt treatment for DR. As a result, it is critical to identify the severity of DR in order to provide therapy recommendations. The suggested method begins with pre-processing of retinal fundus pictures and then moves on to segmentation. The maximum principal curvature approach is used for the extraction of blood capillaries. The approaches used to reduce falsely segmented sections include Equalization of adaptive histograms and morphological aperture. The convolution neural network (CNN) is a deep learning technology used to identify defects in fundus pictures of retina of the eye. This study looks into how computer-assisted systems can reliably classify retinal fundus images. When compared to the usual method, the suggested algorithm yields superior results.

Keywords : Diabetes-related retinopathy, Hessian matrix,Maximum principal curvature,Convolutional neural network ,Congestion.

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CHAPTER 1
SUMMARY OF THE PAPER

Title : Deep Learning Architecture for Diabetic Retinopathy Categorization based on Segmented Fundus Image Characteristics
Journal Name : Biomedical Signal Processing and Control
Publisher: Elsevier
Year: 2021

Diabetes affects many individuals nowadays, and diabetic patients confront a medical disease known as Diabetic Retinopathy(DR). DR is the most common cause of visual loss in adults of working age. NPDR, the milder form, and PDR, the more advanced form, are the two kinds of DR. Patients with NPDR have blurry vision at first, but as the condition progresses, new blood vessels sprout in the retina, affecting vision. Blood clots in the retina are caused by abnormal blood vessels. Blood Vessel damage is the major cause of DR. Vessel blocking , lesion formation appears as microaneurysms and hemorrhages. Currently, diabetic retinopathy can be detected by a trained ophthalmologist by manually assessing the fundus images. So, an automated DR system is needed to detect the disease accurately.

Steps to detect Diabetic Retinopathy:
1.Image Preprocessing
2. Segmentation
3. Convolution Neural Networks (CNN).

1.1 Dataset:

The DIARETDB1 dataset was used in this experiment, and it contains 89 retinal fundus images, 84 of which are aberrant and 5 of which are normal. To increase the image count, we use augmentation techniques on the dataset. By rotating the dataset images horizontally, vertically, and horizontal-vertically, we get 255 abnormal images and 93 normal images.

1.2 Image pre-processing:

Input images undergo preprocessing, which includes:

1. Resizing each image size into 336 x 448px.
2. Coloured images are converted into grayscale images.
3. Grayscale images are sent for segmentation.

1.2.1 Gaussian Filtering:

It's a linear filtering technique that reduces the amount of noise in an image. Smoothing is done by blurring the image using a function called Gaussian function or Gaussian Blur. Gaussian filter blurs the edges and decreases the contrast unlike other filters. In this function x is origin distance and sigma is the standard deviation.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

Fig 1.1 Gaussian Function Formula

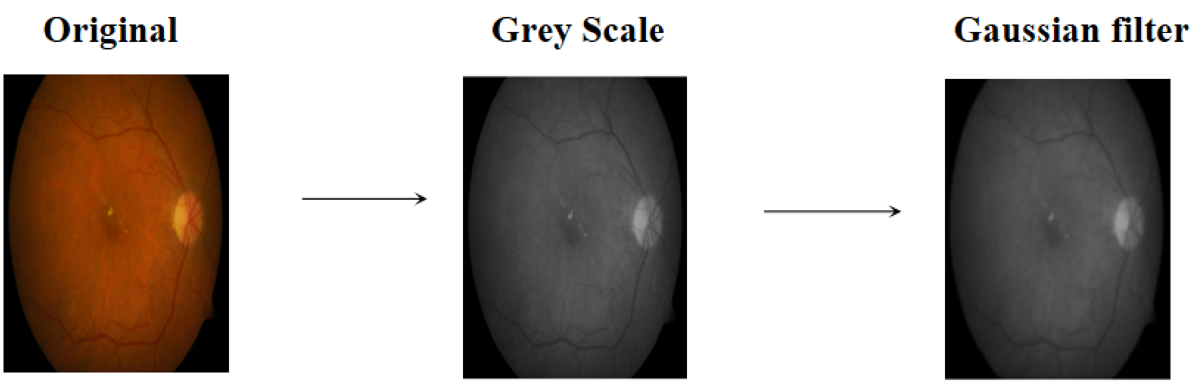


Fig 1.2 Pre-processing

1.3 Segmentation:

Pre-processed images are sent for following segmentation techniques to extract blood vessels from the fundus images. We have implemented maximum principal curvature technique for extracting the blood vessels.

1.3.1 Maximum Principal Curvature:

The dark lines/edges on the light background are detected by maximum principal curvature. The eigenvalues of the Hessian for a particular pixel can be used to calculate principal curvature. Curvature is the amount of bend of a curve. The maximum and minimum values of a curvature at a particular point are called principal curvatures. Maximum principal curvature is the largest eigenvalue from hessian matrix.

Hessian Matrix : A square matrix of second-order partial derivatives of a scalar-valued function or scalar field is referred to as a Hessian. It is calculated for every pixel in the image that is being processed.

$$H_x = \begin{bmatrix} \dfrac{\partial^2 f}{\partial x_1^2} & \dfrac{\partial^2 f}{\partial x_1 \partial x_2} \\ \dfrac{\partial^2 f}{\partial x_1 x_2} & \dfrac{\partial^2 f}{\partial x_2^2} \end{bmatrix}$$

Fig 1.3 Hessian Matrix

The maximum principal curvature technique provides better results in extracting blood vessels compared to the other methods.

1.3.2 Adaptive Histogram Equalization : It is a technique utilized to improve contrast in images and increase the definition of edges in each region of an image.

- Firstly, we must know about histogram equalization which is a technique in which a histogram is constructed with the intensity at each position and then according to the threshold, the intensity is equalized such that the contrast increases.
- But this technique induces more noise by raising the contrast of unnecessary regions . To avoid this, we divide the image into certain blocks and then histogram equalization is performed adaptively for each block divided to improve the contrast.

Maximum Principal Curvature **AHE**

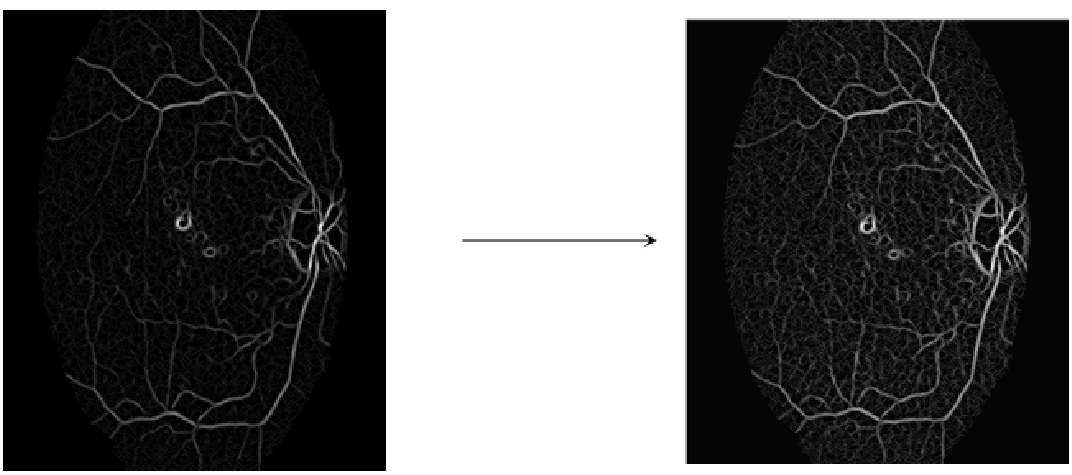


Fig 1.4 MPC and AHE

Thresholding segmentation –

We have used the thresholding segmentation method in our project for better results compared to other methods.

This method divides the pixels in an image by comparing the pixel's intensity with a specified value (threshold).

It is useful when the required object has a higher intensity than the background (unnecessary parts).

The thresholding method converts a grey-scale image into a binary image by dividing it into two segments.(Required and not required sections).

In this method you replace the image's pixels with either white or black. If the intensity of a pixel at a particular position is less than the threshold value, you'd replace it with black.

If the intensity is higher than the threshold value you'd replace it with white.

Obtained binary image also contains noise, in order to remove the noise morphological opening is performed to remove the noise and to obtain clear segmented image.

1.3.3 Morphological Opening: Morphological Operation is a procedure which processes images from their shapes.It is of 2 types dilation and erosion.

It uses a structural element that focuses on the shape and size of larger objects and ignores smaller objects.We have used erosion,which removes the unwanted pixels from image boundaries based on the structural element given as input.

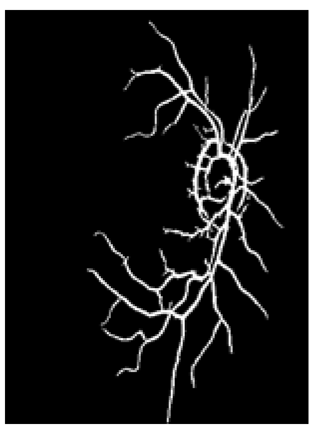


Fig 1.5 Segmented Image

1.4 Convolution Neural Networks (CNN):

A Convolution Neural Network is a deep learning algorithm which can take in an input image, assign importance to various aspects/objects in the image and be able to differentiate one from another.

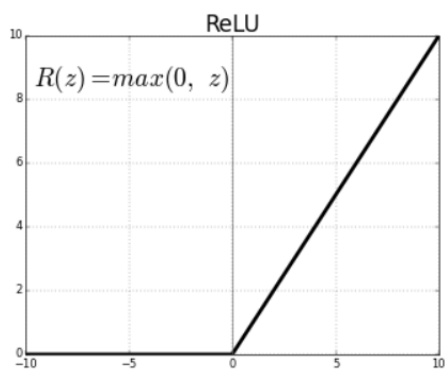
CNN make use of filters (also known as kernels) to detect what features such as edges are present throughout the image

Input Image Layer-The image of size 336*448 is taken as input to the image input layer .This layer consists of the number of nodes equal to the number of pixels of data of the image.

Convolution Layer - Convolution is a mathematical operation applied to the input that converts the input matrix into a single value by multiplication through a filter. The output is a feature matrix.

Max Pooling Layer - Pooling layers are similar to convolution layers but they perform a specific function to reduce the dimensionality of the network. These use filters which extract maximum features from the matrix.

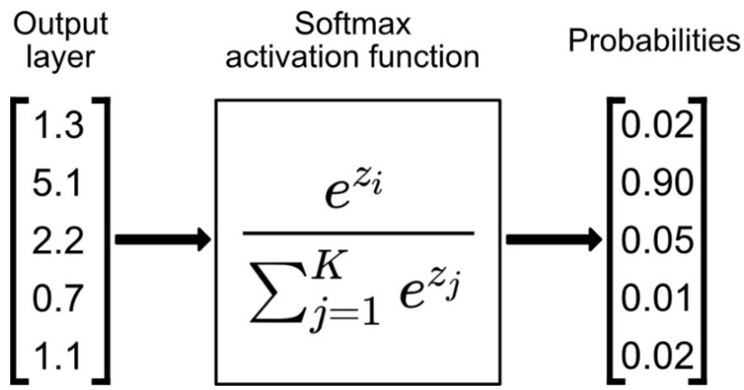
ReLU Layer - The rectified linear activation is a piecewise linear function that will output the input directly if its positive otherwise it will output zero. It has become the default activation function for many types of neural networks because a model that uses it is easier to train and often achieves better performance.



Fully Connected Layer- This layer helps to establish the connections between each and every node in one layer are connected to all the neurons in the other layer which helps to mix the signals from every neuron.This layer's input is the output from the convolution layer and this will be in the last few layers in the network.

Batch Normalization Layer-This layer normalizes the data not only to the input data but also the data after each and every layer which makes each layer to perform more independently without depending more on the other layers.

Softmax Layer-This layer converts the data into the probabilistic data which gives the probability of the class that it belongs to. A sample example of how the softmax function works is given below.



Classification Layer-This layer classifies the label of the label of the class based on the probabilities given by the previous layer.

Training is done through a series of layers. First layer is a convolution layer which has a total of 10 9x9 filters. Then comes a 2x2 max pooling layer. Second convolution layer has a total of ten 6x6 filters followed by a 3x3 max pooling layer. Then the fully connected layer of output size 2 as images are normal and abnormal. After that batch normalization, soft max and lastly the classification layer is used as an output layer which uses Re Lu activation. The model is trained with an 80-20 split which means it divides 80% of the data used for training and 20% for validation. While training the network learning rate of 10e-05 and 20 epochs are used.

If proliferation of blood vessels in segmented images is excessive, it is considered abnormal; otherwise, it is considered normal. If the proliferation of blood vessels in segmented images is excessive, it is considered abnormal; otherwise, it is considered normal.

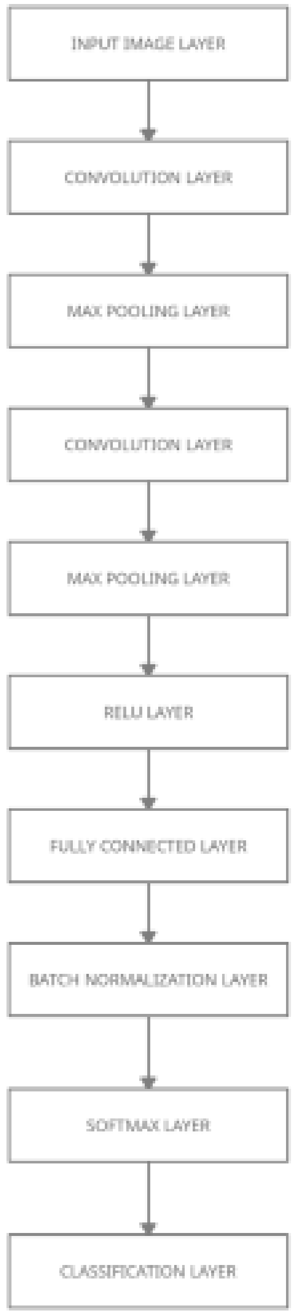


Fig 1.6 CNN Architecture

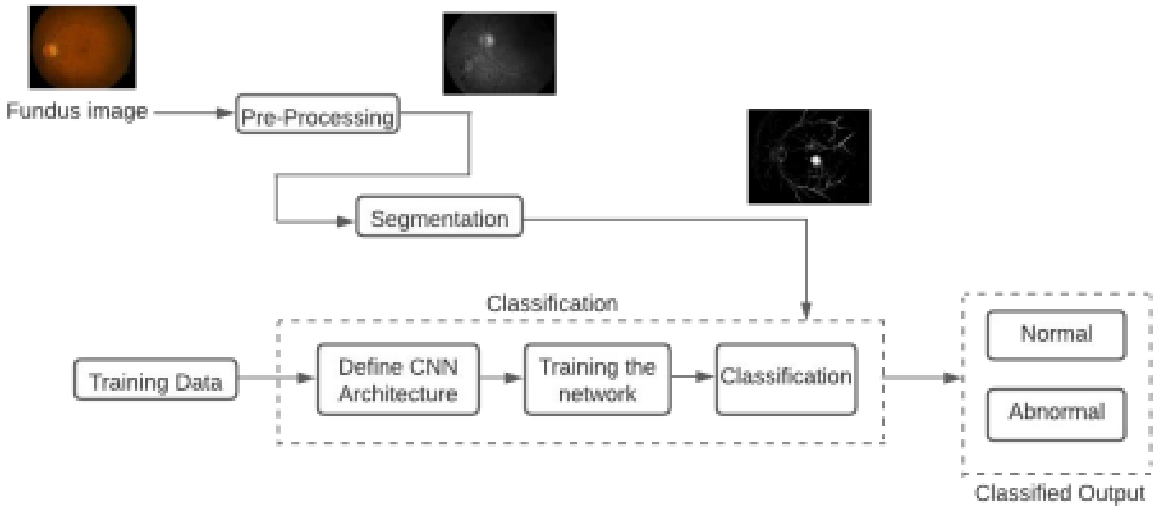


Fig 1.7 Proposed Methodology

Proposed Algorithm -

1. Read the input images from the specified dataset.
2. Perform augmentation to increase the dataset size.
3. **PREPROCESSING**
    a. Convert all the colored images to grayscale format.
    b. Apply a gaussian filter to blur the images.
    c. Generate an image mask.
    d. Use an octagonal structural element of radius 24.
    e. Perform morphological erosion operation to erode the image.

4. **SEGMENTATION**
    a. Hessian matrix is used to find out the eigen values.
    b. These values are used to find maximum principal curvature of the images.
    c. Image contrast is increased using AHE.
    d. Thresholding segmentation is used to remove unwanted regions.

5. **CNN ARCHITECTURE**
    a. CNN model defined in the base paper is analyzed.
    b. Flowchart containing CNN layers (Fig 1.6) is drawn and code is generated.
    c. Segmented images are sent for training (split of 80-20).

6. **CLASSIFICATION**
    a. Images are classified as abnormal and normal from the model created.
    b. Accuracy and graph for the designed model is generated.

CHAPTER 2

MERITS AND DEMERITS

There are several techniques for diabetic retinopathy some of them are listed below, mentioning the merits and demerits of the proposed technique over each of the existing techniques.

Santosh et al. [1] proposed “segmentation with pre-processing and post-processing”. In this method segmentation starts with input preprocessing and after post processing. Post processing is done by using maximal principal curvature, it takes less time and produces remarkable accuracy but the segmentation techniques are minimal. So, to get maximum accuracy maximal principal curvature alone is not enough, we have to use some more segmentation techniques as detailed in our proposed work.

Gehad et al. [2] introduced the “blood vessel segmentation approach”, used to extract retinal image vessels for retinal image analysis. It employs mathematical morphology to increase blood vessels while suppressing background noise, and it employs k-means clustering to improve the image. The DRIVE dataset was used to evaluate this methodology, which yielded a 95.10 percent accuracy. The accuracy was satisfying but k-means cannot handle the noisy data and the number of clusters should be mentioned in advance. The segmentation technique in the proposed model can handle any type of noise.

R.Manjula et al. [4] “employed image processing techniques to enhance and measure the dimensions of the retinal blood vessels”. For segmentation, three methodologies are used: the Gaussian approach, mathematical morphology, and multi-scale analysis. The Gaussian filter approach distinguishes between broad and narrow blood arteries. This is a more successful method, although it is only suitable for thick vessels. Thin vessels are recognised with high accuracy using mathematical morphology. The multi-scale analytic technique recognises both thick and thin vessels without any noise. Because it is primarily focused on vessel size, this approach delivers less accuracy than the maximal primary curvature technique.

Memari et al. [5] employed an “automatic retinal vessel segmentation that utilizes fuzzy c-means clustering”, Adaptive histogram equalization is utilized to improve variance in retinal images. Noise is condensed using a mathematical morphological technique and matching filters Gabor and Frangi. The original blood vascular network is extracted using fuzzy-c methods. For segmentation refinement, an integrated level set approach is applied. The accuracy of this approach was 96.1% on average. But fuzzy-c clustering takes more iterations to get better results which is time consuming.

Budai et al. [6] tried to "reduce the running time of the algorithm", compared with the Frangi approach, he tried to minimize the calculation time without disturbing high accuracy and sensitivity. Besides being heavy work in front of them the authors avoided potential issues such as thick vessel specular responses, constructing this strategy. They employed DRIVE and STARE, two public databases with an accuracy of 95.72 percent and 93.86 percent, accordingly. Super pixels-based segmentation, watershed segmentation, and active contour approaches are among the segmentation methods used here.

Renoh et al. [14] proposed "a unique unsupervised method", to identify the OD and fovea in a retinal picture and then segment it The recommended approach consists of three steps: coarse ONH centre detection, fine-tuned ONH centre detection with boundary detection, and fovea detection. They demonstrated how to recognise the optic disc (OD) in retinal images automatically using histogram-based template matching and the greatest sum of vessel information. Optic Disk detection accuracy was 95 percent, while fovea detection accuracy was 97.26 percent. These segmentation approaches cannot handle fundus pictures of varying sizes or images with noise.

Merits:

1. The proposed methodology produces significant detection accuracy.
2. Works well for different sizes of fundus images.
3. Able to differentiate even more noise present in the images.

Demerits:

1. Consumes more time to get better results.
2. Misclassification of images if the normal and abnormal images look more similar.
3. Need accurate segmentation of image for correct classification of image.

CHAPTER 3

SOURCE CODE

Augumentation.m

```
srcF = dir('C:\Users\jyoth\Desktop\mini project\codes\A\*.png');
for i=1:length(srcF)
 filename =
strcat('C:\Users\jyoth\Desktop\mini project\codes\A\',srcF(i).name);
Test_Image = imread(filename);
 I = flip(Test_Image,1); %Flipped Vertically
 name1 = strcat('V_',srcF(i).name);
 path1 = strcat('C:\Users\jyoth\Desktop\mini project\codes\A\',name1);
imwrite(I,path1)
 name2 = strcat('H_',srcF(i).name);
 path2 = strcat('C:\Users\jyoth\Desktop\mini project\codes\A\',name2);  I2
= flip(Test_Image,2); %Flipped Horizontally
 imwrite(I2,path2)
 name3 = strcat('HV_',srcF(i).name);
 path3 = strcat('C:\Users\jyoth\Desktop\mini project\codes\A\',name3);  I3
= flip(I,2); %Flipped Horizontally+Vertically
 imwrite(I3,path3)
end
```

DR_Normal.m

```
srcF = dir('C:\Users\jyoth\Desktop\mini project\codes\A\*.png');
mkdir('Normal_final');
for i=1:length(srcF)
 filename =
strcat('C:\Users\jyoth\Desktop\mini project\codes\A\',srcF(i).name);  Test_Image =
imread(filename);
 segIm = vesselSegPC(Test_Image);
 path =
strcat('C:\Users\jyoth\Desktop\mini project\codes\Normal_final\',srcF(i).name);
imwrite(segIm,path);
end
```

vesselSeg.m :

```
function [segImage] = vesselSegPC(inputImage)

%Generation of image mask
mask = im2bw(inputImage,20/255);
se = strel('octagon',24);
erodedmask = im2uint8(imerode(mask,se));


%Apply gaussian filter to the image where s=1.45
img3= imgaussfilt(inputImage(:,:,2) ,1.45);
%Finding lamda - principal curvature
lamda2=prinCur(img3);
maxprincv = im2uint8(lamda2/max(lamda2(:)));
maxprincvmsk = maxprincv.*(erodedmask/255);

%Contrast enhancement.
newprI = adapthisteq(maxprincvmsk,'numTiles',[8 8],'nBins',128);
thresh = isodata(newprI);
vessels = im2bw(newprI,thresh);

%Filtering out small segments
vessels = bwareaopen(vessels, 1500);
segImage = vessels;
```

prinCur.m :

```
function lamda2=prinCur(Image)

%Image : Input Image
%Here we obtain parameters for Hessian metrx in every pixel and find eigen %values
of the hessian matrix using lamdafind function

% Obtain parameters for hessian matrix
 [ga, gb] = gradient(double(Image));
 [gaa, gab] = gradient(ga);
 [gab, gbb] = gradient(gb);



 [row,col]=size(Image);
lamdaplus = zeros(row,col);
lamdaminus = zeros(row,col);

%finding eigen values of hessian matrix [gaa gab;gab gbb]

for r = 1:row
 for c = 1:col
```

```
 [lamdaplus(r,c),lamdaminus(r,c)]=lamdafind(gaa(r,c),gbb(r,c),gab(r,c));  end
end

lamda2 = lamdaplus;
end
```

lamdafind.m :

```
function [lamdaplus,lamdaminus]=lamdafind(gaa1,gbb1,gab1) %This function
is used to find eigen values of hessian matrix and output %maximum and
minimum eigen value as lamdaplus and lambaminus

H=[gaa1 gab1;gab1 gbb1];

%Obtain eigen values

            8
lamda=eig(H);

%Obtain maximum and minimum lamda values
if lamda(1)>lamda(2)
 lamdaplus = lamda(1);
 lamdaminus = lamda(2);
else if lamda(1)<lamda(2)
 lamdaplus = lamda(2);
 lamdaminus = lamda(1);
 else
 lamdaplus = lamda(1);
 lamdaminus = lamda(2);
 end
end
end
```

isodata.m :

```
function [level,MAT,MBT]=isodata(I)
I = im2uint8(I(:));

 [hist_counts,hist_N]=imhist(I);
hist_counts(1)=0;
ii=1;
mum=cumsum(hist_counts);
Th(ii)=(sum(hist_N.*hist_counts))/mum(end);
Th(ii)=round(Th(ii));

mum2=cumsum(hist_counts(1:Th(ii)));
MBTT=sum(hist_N(1:Th(ii)).*hist_counts(1:Th(ii)))/mum2(end);
```

```
mum3=cumsum(hist_counts(Th(ii):end));
MATT=sum(hist_N(Th(ii):end).*hist_counts(Th(ii):end))/mum3(end);
ii=ii+1;
Th(ii)=round((MATT+MBTT)/2);

while abs(Th(ii)-Th(ii-1))>=1
 mum2=cumsum(hist_counts(1:Th(ii)));
 MBTT=sum(hist_N(1:Th(ii)).*hist_counts(1:Th(ii)))/mum2(end);
 mum3=cumsum(hist_counts(Th(ii):end));
 MATT=sum(hist_N(Th(ii):end).*hist_counts(Th(ii):end))/mum3(end);
 ii=ii+1;
 Th(ii)=round((MATT+MBTT)/2);
 Thresholddd=Th(i);
end

levell = (Thresholddd - 1) / (hist_N(end) - 1);
MATT = MATT / (hist_N(end) - 1);
MBTT = MBTT / (hist_N(end) - 1);
end
```

CHAPTER 4

SNAPSHOTS

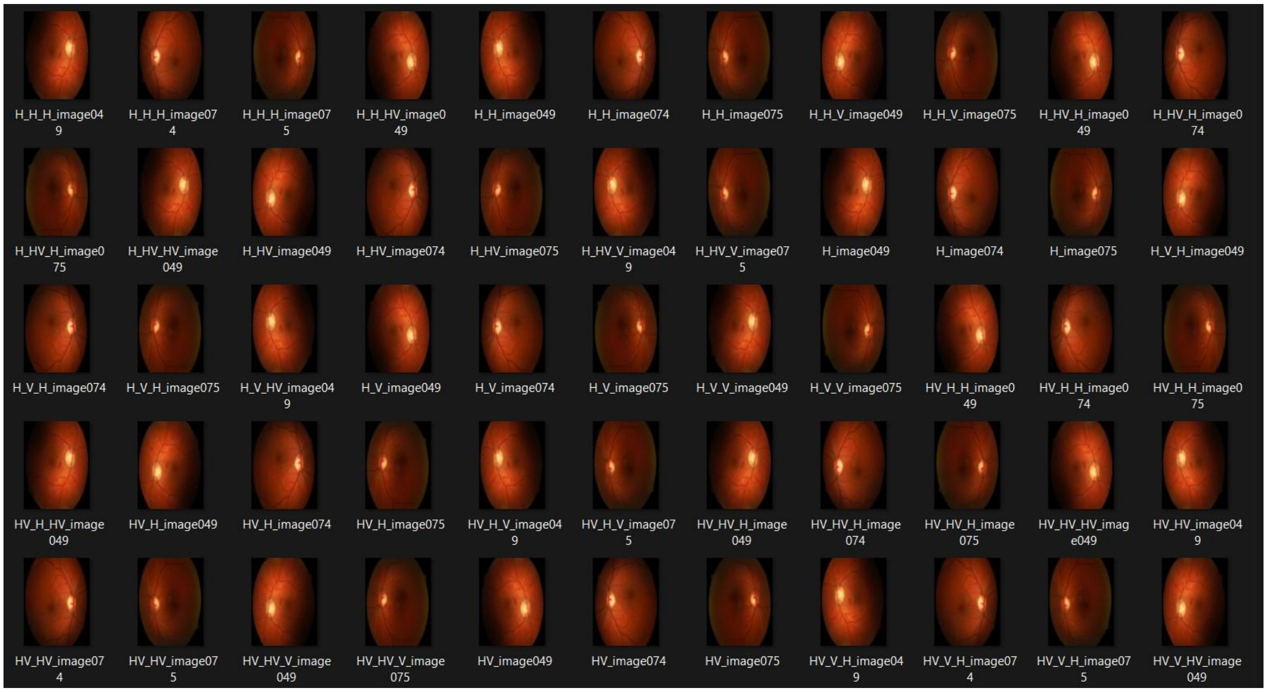


Fig 4.1 Retinal Fundus Images

Fig 4.2 Segmented Fundus Images

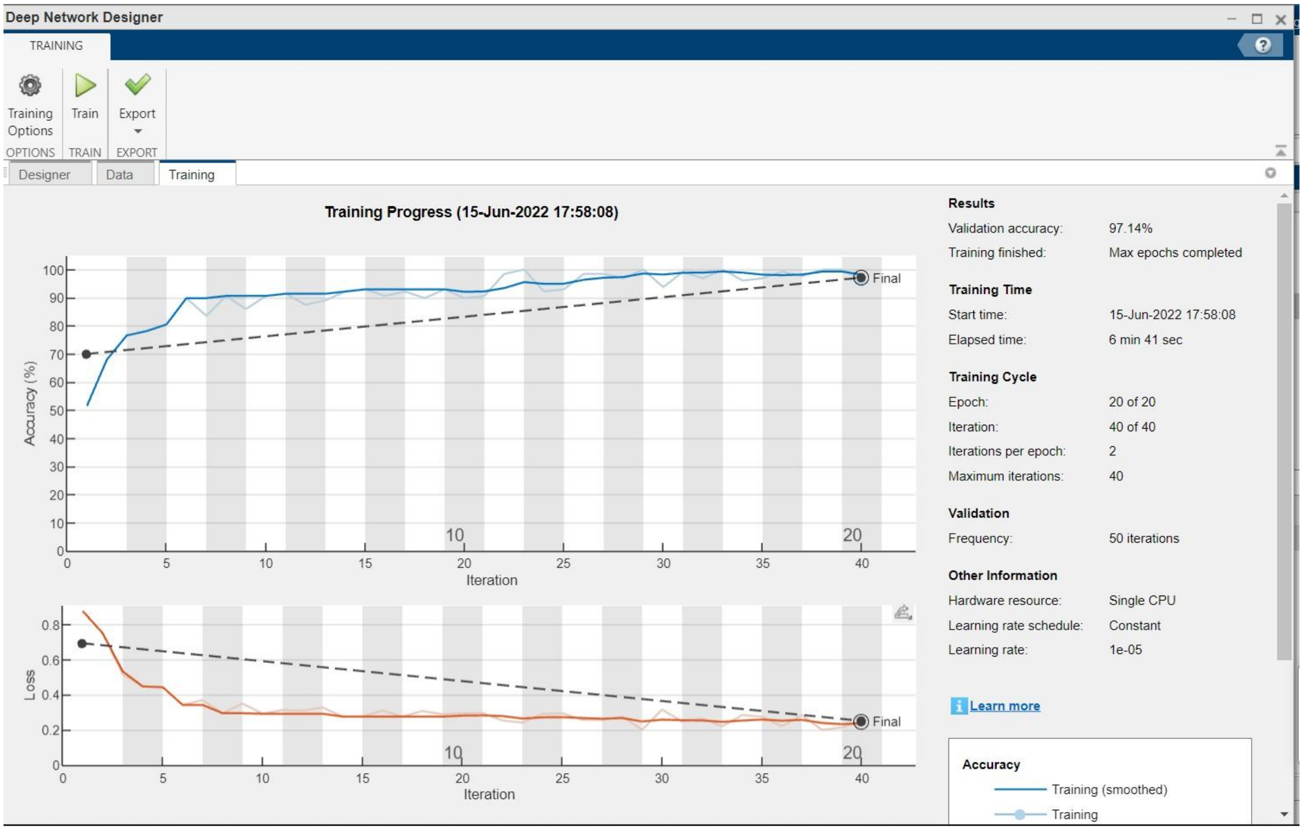


Fig 4.3 Trained Model Output

```
>> image1=imread("Testdata/Abnormal1.png")
>> predict(trainedNetwork_1,image1)

ans =

  1×2 single row vector

    0.7109    0.2891
```

Fig 4.4 Testing the model with Abnormal Image

```
>> image2=imread("Testdata/Normal1.png")

>> predict(trainedNetwork_1,image2)

ans =

  1×2 single row vector

    0.0411    0.9589
```

Fig 4.5 Testing the model with Normal Image

CHAPTER 5
CONCLUSION AND FUTURE PLANS

Conclusion:

In this study, we offer an automated DR system that can accurately detect diabetic retinal disease. The dataset consists of retinal fundus images taken from diaretdb1 dataset. The process starts with pre-processing of the images by converting them into Gray scale images. Then maximum principal curvature technique is applied for blood vessel extraction. For removing and strengthening erroneously segmented sections, adaptive histogram equalisation after that morphological opening is used. After that the segmented images are trained using CNN network. The classifier determines whether the image is normal or abnormal based on the proliferation of blood vessels. The proposed approach produces an accuracy of 97.14%.

Future works:

We are planning to extend our project by determining the period from when the person is suffering with the disease. If any person is diagnosed with diabetic retinopathy, then we will work on how long the person is suffering and how severe the disease is.

CHAPTER 6

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CHAPTER 7

APPENDIX – BASEPAPER

Title:

Deep learning architecture based on segmented fundus image features for classification of diabetic retinopathy.

Citation:

Sraddha Das, Krity Kharbanda, Suchetha M, Rajiv Raman, Edwin Dhas D, Biomedical Signal Processing and Control, Volume 68, 2021, 102600, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2021.102600.

https://www.sciencedirect.com/science/article/pii/S174680942100197X