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Submission date: 09-May-2023 01:25PM (UTC+0530)
Submission ID: 2088397245
File name: Proj_report_p1.pdf (1.05M)
Word count: 1796
Character count: 9728

ABSTRACT

Diabetic individuals experience ophthalmological distress known as diabetic retinopathy as a result of blood, hemorrhages formed in retina's sensitive area. Because of increase in blood sugar, vascular blockage occurs. This causes the growth of new vessels, which results in the development of mesh-like structures. Ophthalmologists must evaluate the branching retinal vasculature in order to provide an accurate diagnosis. Pre-processing is applied to eye images before segmentation. The maximal curvature technique, that uses Hessian matrix's Eigenvalues. Following that, segmentation is carried out to improve and remove incorrectly segmented sections. When compared to healthy people, those with diabetes or affected showed a substantially higher proliferation of optical nerves. For classification purposes, we trained the classifier using a convolution neural network (CNN). Convolution and pooling layers make up the CNN's classification architecture for the two classes. Dataset used DIARETDB1. Comparing suggested algorithm to more established methods, experimental findings demonstrate superior results. When tested on the DIARETDB1 dataset, the model produced results with a precision and accuracy of 97.2% and 98.2%, respectively.

Keywords: Pre-processing, Segmentation, ResNet, Classification

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CHAPTER-1
INTRODUCTION

Title: Classifying Diabetic Retinopathy based on fundus eye images using Deep Learning.

Journal Name: Biomedical

Publisher: ELSEVIER

Year: 2022

1.1 Introduction

The eye-related consequence of diabetes is designated diabetic retinopathy. The tissue in the rear eye is affected when blood vessels in that area undergo damage. All diabetics are in tremendous risk of developing DR, that results in blindness. Early treatment of this condition can prevent it from advancing to total blindness. DR is identified early enough; laser therapy may be used to treat it in order to prevent or postpone future vision loss. When the problem reaches the PDR stage, however, new blood vessel formation and leakage start and cannot be controlled, which results in permanent vision loss. Retinal images are utilized in the diagnosis in DR.

The retinal photograph is evaluated by ophthalmologists, and search for any exudates, microaneurysms, or hemorrhages. Initial symptoms of DR is exudates. These lesions, also referred to as white lesions. The presence of the optic disc in retinal vision may make it difficult to identify these symptoms. The bright, spherical feature of a retina is optic disc. The retinal disc must be taken out in order to use image processing methods to find exudates.

1.2 Convolutional Neural Networks

Over the past few decades, Deep Learning has become a very potent technology due to its ability to handle massive amounts of data. Especially for pattern recognition, hidden layer technology is far more common than traditional approaches. Most popular deep learning network is convolutional neural networks.

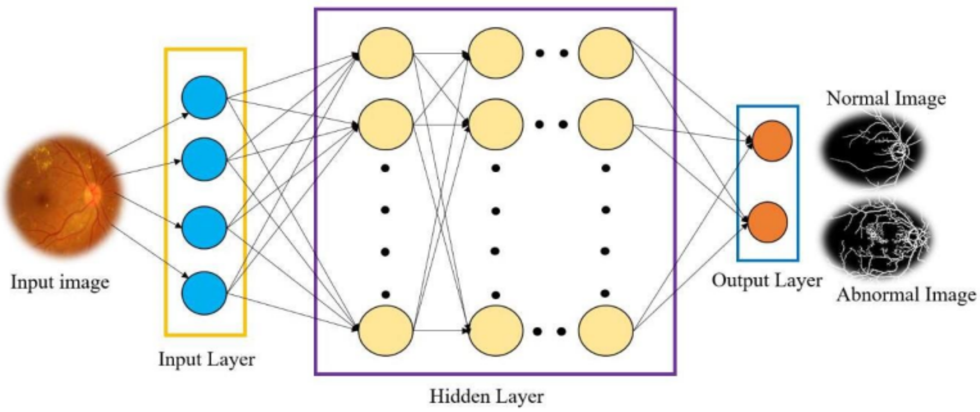


Fig 1. Convolutional Neural Network

Convolution activates various parts of the input images by applying a chain of convolutional filters, one after another.

Quicker and more effective training is made possible by the rectified linear unit (ReLU), which keeps positive values while translating negative values to zero. This is commonly referred to as activation because only the active properties are carried over to the subsequent layer.

Pooling processes are carried out repeatedly across tens or hundreds of levels, each layer learns to recognize different traits.

1.3 Methodology

The image is pre-processed by scaling it down to 512x512 and turning it into grayscale to make it homogeneous. The image is resized again during CNN. A 336 x 448 input image is processed by CNN using many layers of convolution and maximum pooling. Ten 9X9 filters make up the first convolutional layer, which is thenceforth by single 2X2 max-pooling layer. Ten 6X6 filters make up the second convolution layer, which is followed by a 3X3 max pool layer.

subsequently a fully connected layer with output size 2, a layer for batch normalization, a layer for SoftMax, and then a classification layer that makes use of ReLU activation. 20 epochs are used for training the neural network. (An epoch is a round of neural network training that uses all of the training data.) The segmented image is analyzed by the model in such a way that it is classified as abnormal if there is an abnormal proliferation of blood vessels. The segmented image is categorized as normal if there are no abnormal blood vessel growths seen.

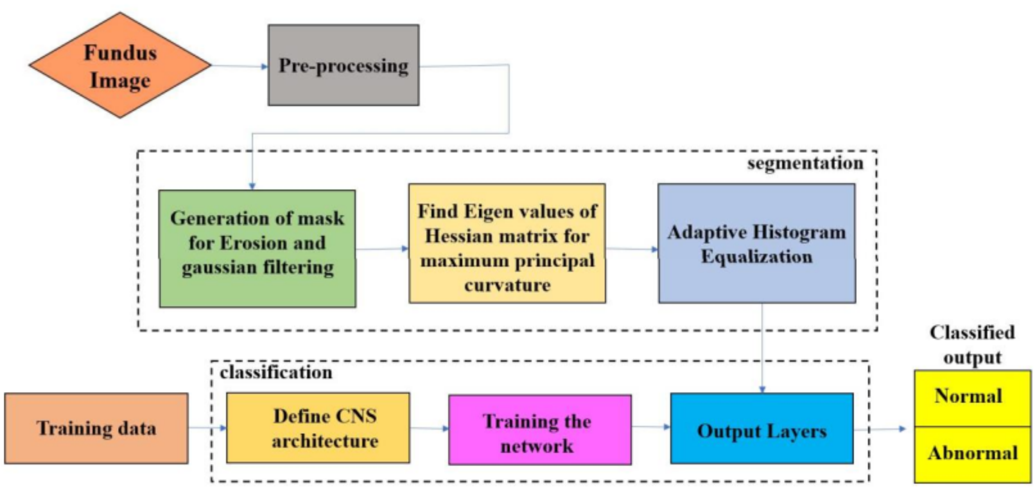


Fig2.Methodology

1.4 Dataset Information

There are 89 images in the dataset. A 50-degree view was used to capture these fundus scans. Each image is 1150 × 1152 pixels in size.

The augmentation is done with respect to 45-degree, 90- degree, 135-degree 180-degree, 225-degree and 270-degree horizontal flipping.

Data set URL: "https://www.it.lut.fi/project/imageret/diaretdb1/"

CHAPTER 2

2.1 Merits of Base Paper

- The photos are correctly categorized, with an accuracy of 98.2% and a precision of 97.2%.

- A CNN model is created from scratch, and the necessary procedure is thoroughly explained.

2.2 Demerits of Base Paper

- Using operators for feature extraction, segmentation can be condensed into a single step.

2.3 Literature Survey

Author Name	*Year of publication*	*Model used*	*Accuracy*	*Advs of used model*	*Dataset used*
Santosh Kumar	2019	Maximum Principal Curvatures Based (OPCB) segmentation that has been optimised	96%	effective blood vessel extraction from retinal fundus pictures. superior to alternative segmentation techniques with empirical support	STARE and DRIVE
R. Manjula	2019	Multi-scale analysis, the Gaussian approach, and the mathematical morphology method	94%	Utilising Spark and Hue Over Big Data, predict diabetes data	DIARETDB1
Nogol Memari	2019	fuzzy level sets and c-means clustering	96.1%	enables a data point to be a member of many clusters with varying degrees of affiliation. Flexibility, Robustness, Interpretability	CHASE DB1
Dulanji Lokuarachchi	2019	Incorporating various morphological operations allows for accurate detection.	94.59%	used to separate the blood vessels from retinal image segments	DIARETDB1
Renoh Johnson Chalakkal	2018	the mathematical morphology method	97.26%	Automatic segmentation and identification of the fovea and optic disc in retinal images	DIARETDB1
Wejdan L. Alyoubi	2020	Convolutional neural networks.	96.5%	Used for DR classification	DIARETDB1

Shailesh Kumar	2020	Operation in mathematical morphology. Watershed transforms.	93%	Segmenting the optic disc makes use of the watershed transform.	DIARETDB0 DIARETDB1
Payal Shah	2020	AI algorithm	98.5%	DR early detection and preventing blindness.	MESSIDOR
Darvin Yi	2018	Alex Net and Google Net	95%		MESSIDOR-1
D. Jude Hemanth	2020	Utilising CNN to process images with histogram equalisation and classification	94%		MESSIDOR

2.4 Methodology and Work carried out

The proposed effort includes three stages for categorizing diabetic retinopathy.

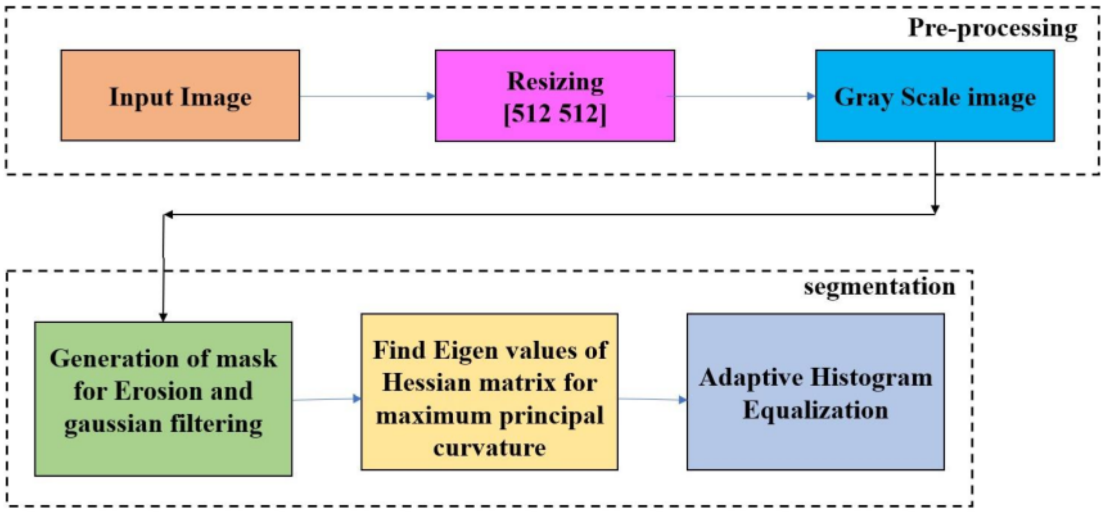


Fig 3. Preprocessing and Segmentation

Stage-1:

Pre-processing is preliminary phase. Using MATLAB, image is scaled down to 512X512 and turned into grayscale.

Stage-2:

Segmentation comes after stage one. For feature extraction, we employed the Adaptive Histogram Equalization. When a function is evaluated at a critical point, the determinant of the Hessian matrix equals the Gaussian curvature of the function viewed as a manifold.

Each block finds its histogram equalizes. Contextual limiting is employed to minimize noise amplifiers. As a result, AHE may cause noise to be amplified in near-constant regions. After segmentation augmentation of the dataset is done. We have used python for augmentation. The augmentation is done with respect to 45-degree, 90- degree, 135-degree 180-degree, 225-degree and 270-degree horizontal flipping. With this we have achieved a total of 2234 images.

Stage-3:

The third stage is classification. ResNet-50, SoftMax Classifier are employed. And the images are classified into Normal and Abnormal.

ResNet-50 and its Architecture

In order to solve the Vanishing gradient problem, ResNet-50 is helpful. (The gradient information cannot be propagated by networks to the input layers of the model.). ResNet-50, a version of the ResNet model,that contains 48 convolutional layers, 1 max-pooling layer & an average pooling layer. ResNet-50 is pre-trained CNN.

Max pooling, with stride two, appears soon after convolution, kernel with size 7X7 and 64 distinguished kernels with stride of size 2, delivering 1 layer. Then comes a layer of convolution, subsequently a 1X164 kernel, then 3X364 kernel, and lastly a 1X1256 kernel. In this process, the three aforementioned layers are processed three times for an aggregate of nine layers. Later, a kernel with 1X1,128, eventually kernel of 3X3128 and ultimately with kernel 1X1512. There are 12 levels, after this step is processed four times. Then arrives a kernel having size 1X1256, then two additional kernels with 3X3256 and 1X11024; this sequence happens six times providing 18 layers. Then two additional kernels 3X3512 and 1X12048 are incorporated along with 1X1512 kernel. Three successive cycles of this method deliver nine layers. A typical pool follows, and the layer concludes with a fully linked layer with 1000 nodes. Finally, a SoftMax function is present and provides an additional layer. 50 layers deep convolutional network: 1 + 9 + 12 + 18 + 9 + 1.

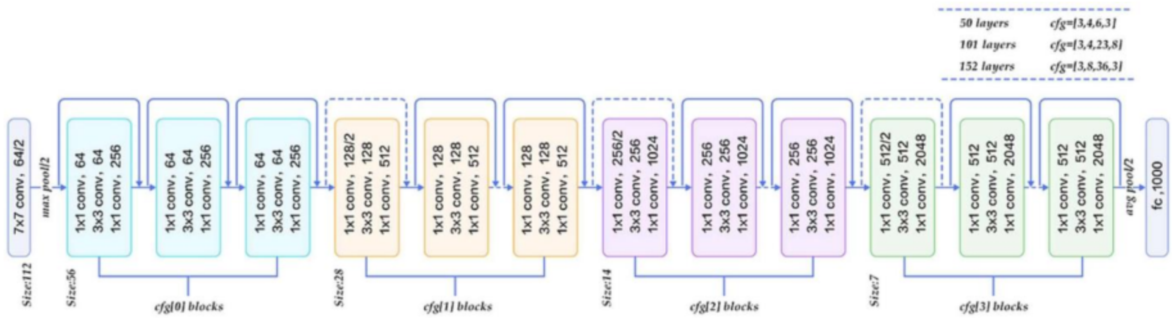


Fig 4, ResNet Architecture (Ref.No:8)

Confusion Matrix:

An analysis of a model's performance of test data is summarized by confusion matrix. It is frequently used to assess how well categorization models work. These models try to predict a categorical label for each input event. The matrix shows true and false categorizations.

		Predicted Class	
		Abnormal	Normal
Observed Class	Abnormal	TP	FP
	Normal	FN	TN

TP	**True Positive**	**Accuracy = (TP+TN)/(TP+TN+FP+FN)**
FP	**False Positive**	**Precision = TP/(FP+TP)**
TN	**True Negative**	**Sensitivity = TP/(TP+FN)**
FN	**False Negative**	**Specificity = TN/(TN+FP)**

Fig 5. Confusion matrix

CHAPTER-4
RESULTS

4.1 Sample Images:

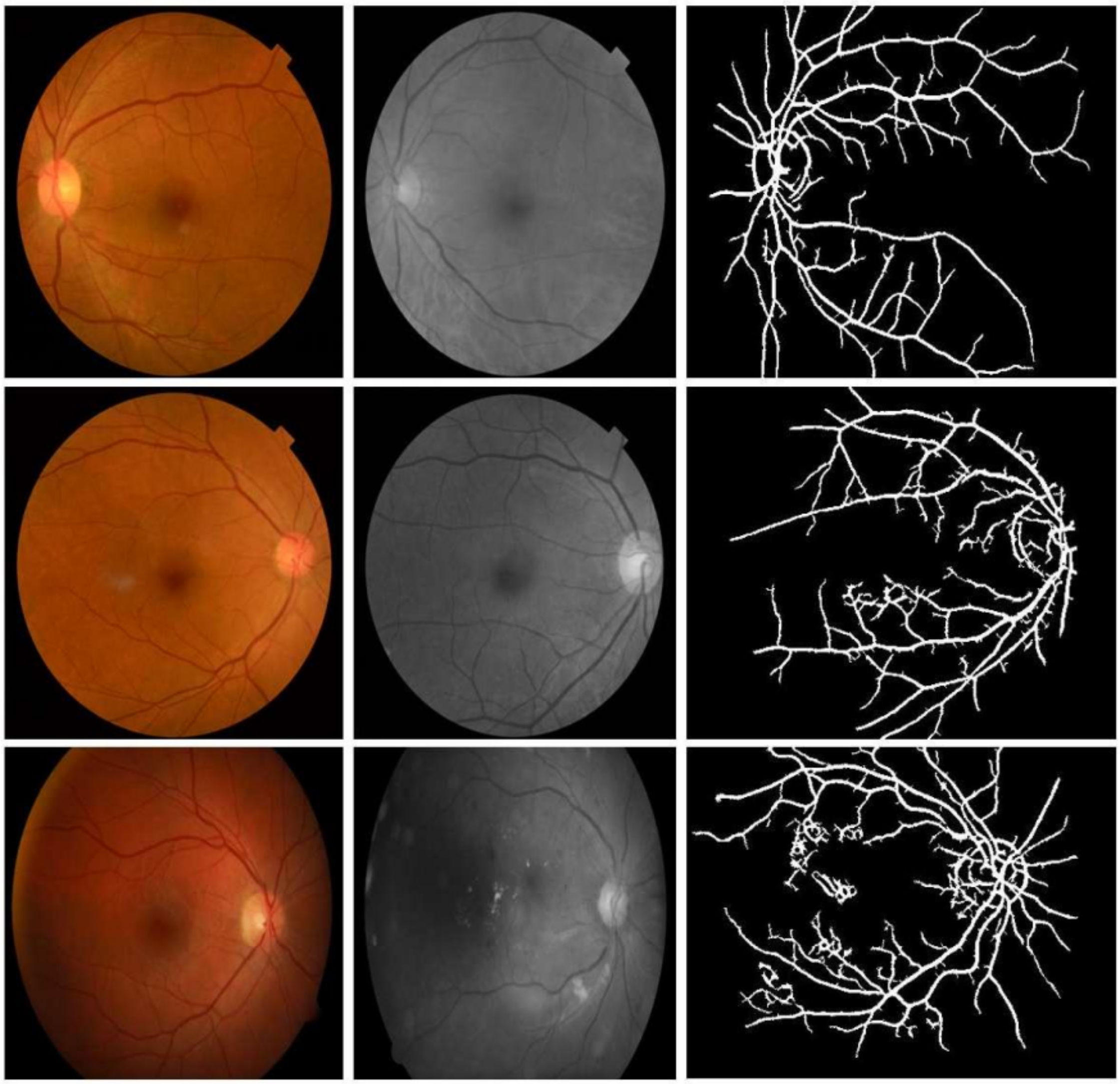


Fig 6. Original Images *Fig 7. Grayscale Images* *Fig 8. Segmented Images*

The above images are taken from DIARETDB1.
Images after resizing and converting into grayscale.
Gray scaled images are given as input to segmentation process then we get above images as output.

4.2 Sample Augmented Images:

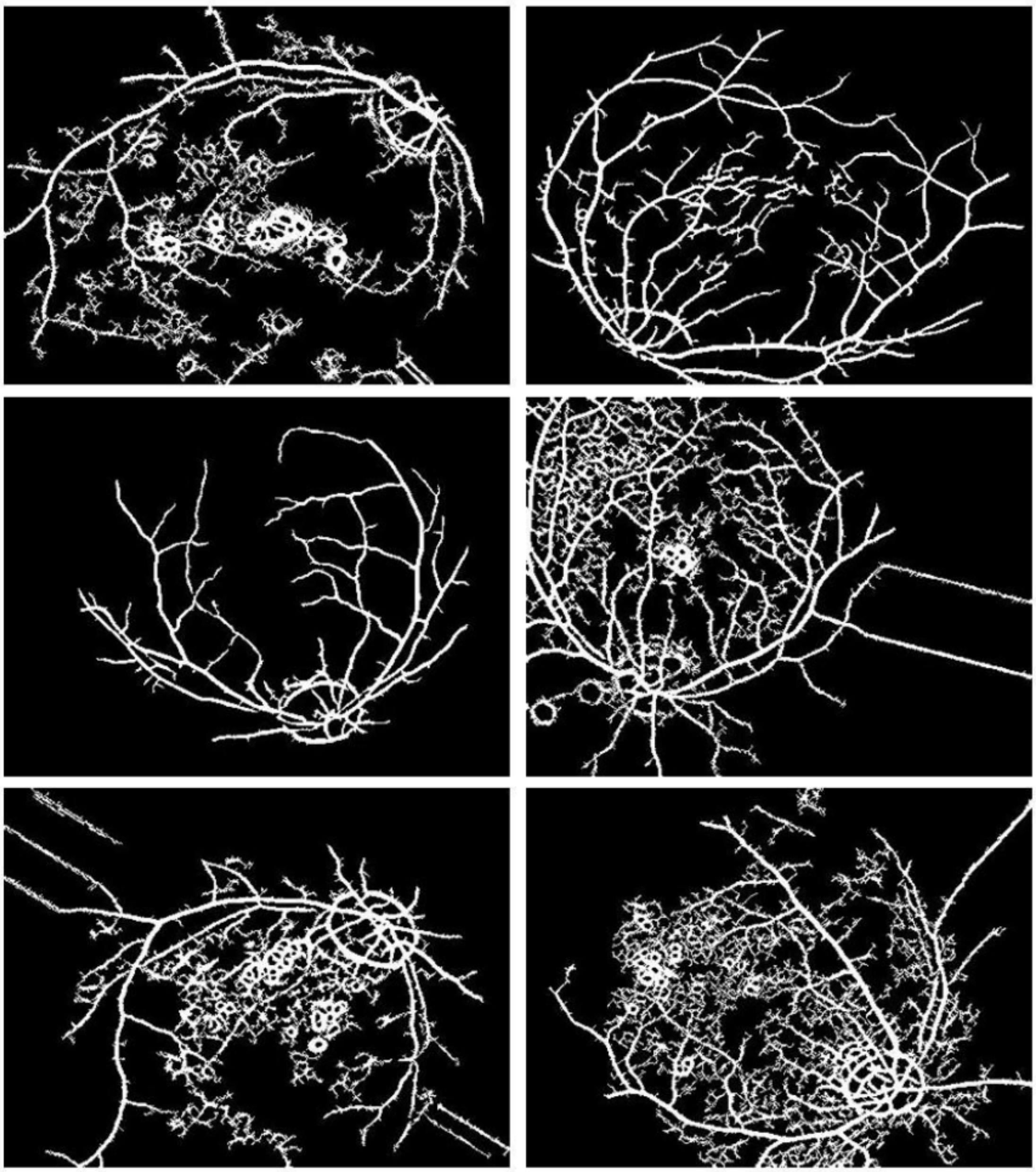
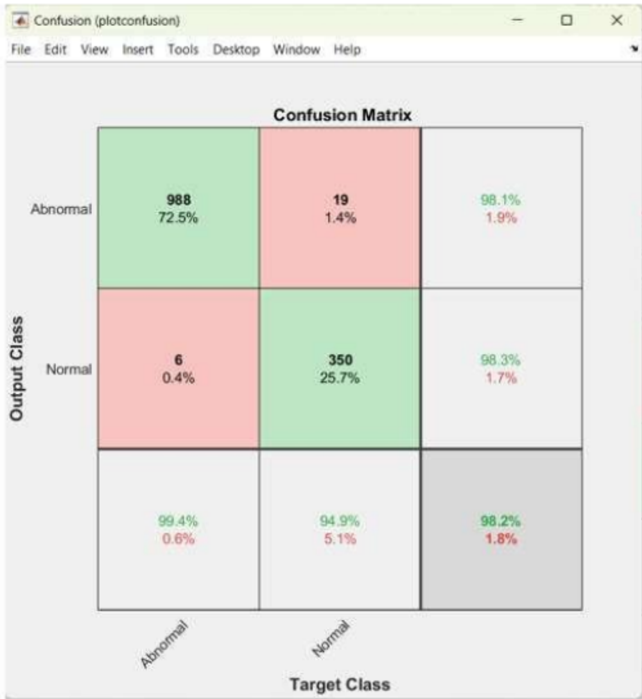


Fig 9. Augmented Images

Fig.9 shows results of augmentation.

4.3 Sample Confusion Matrix



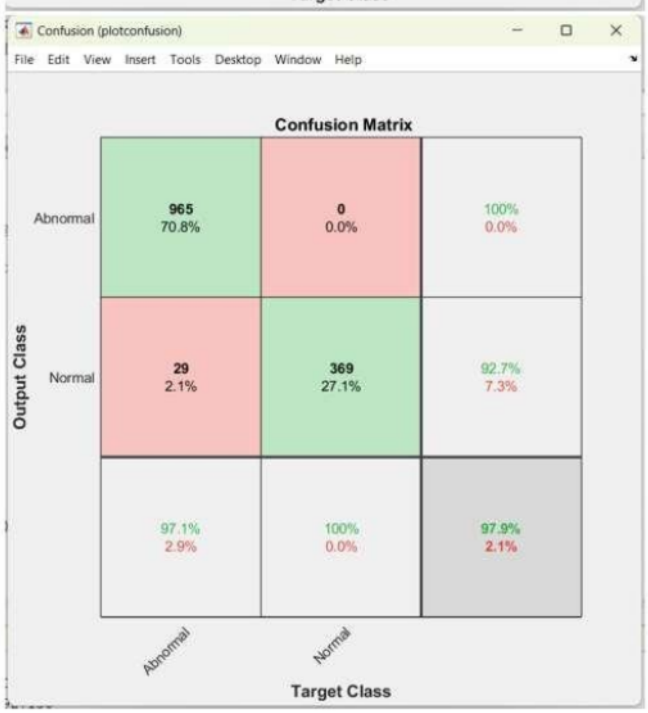


Fig 10. Confusion Matrix

4.4 Sample Validation Results

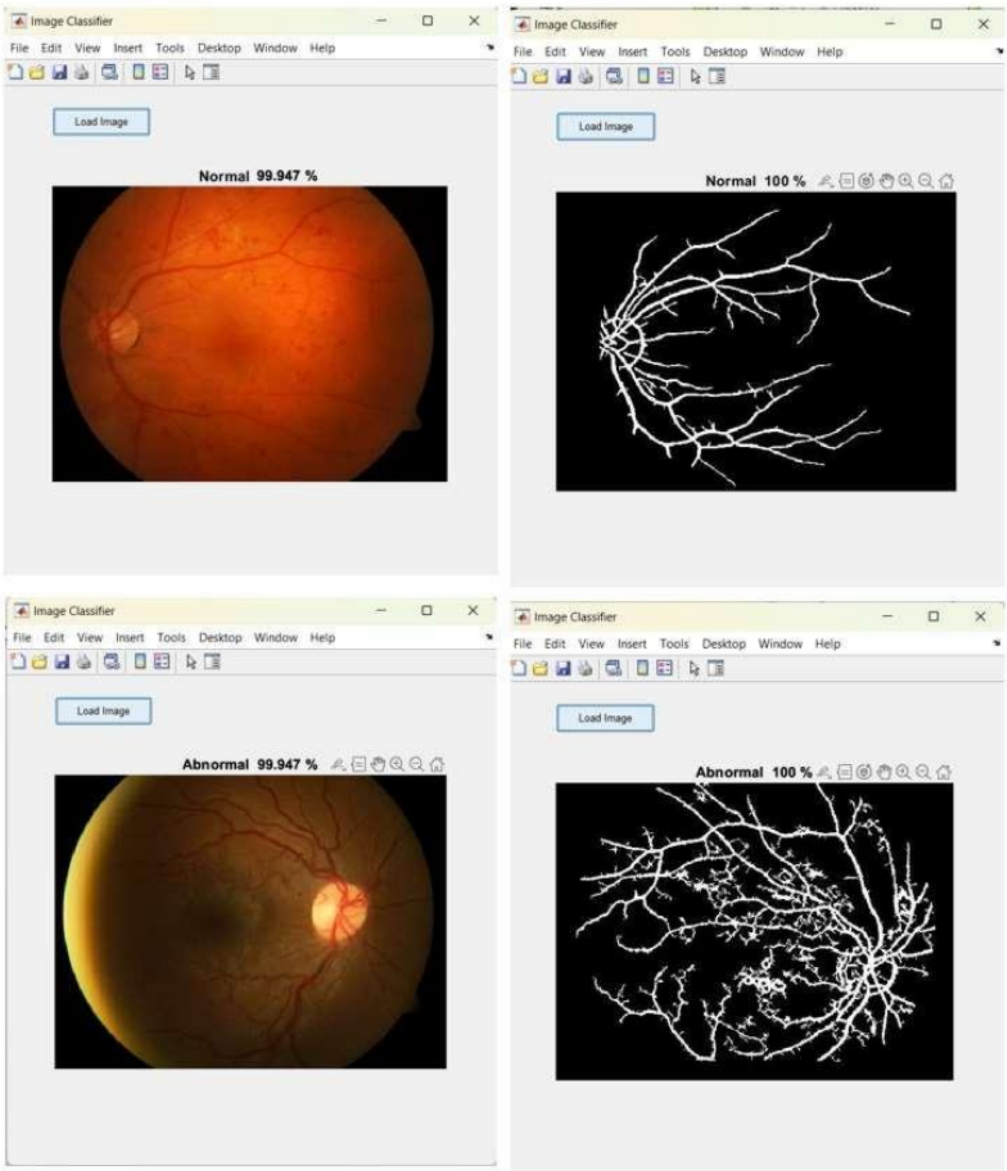


Fig 11. Validation Images

A GUI is created for validation purpose. A image from the dataset is given as input for classification purpose.

CHAPTER 5

CONCLUSION

5.1 Conclusion

- Trained model obtained different accuracies when trained repeatedly.
- The highest accuracy we got for the trained model is 98.2%.
- Precision is 97.2%, Specificity is 91.8%, Sensitivity / Recall is 93.3% , F1 score is 55.7% and accuracy is 98.2%.
- The images are classified as abnormal which means the patient is affected by fundus.

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