To Develop an Optimal Classifier for the Diagnosis of Diabetic Retinal Images using Computational Intelligence Techniques

[1]Ku.Pradnya Bhagwant Sawade, [2]Dr.V.L Agrawal
[1]*Student, Electronic and Telecommunication of HVPM'S College of Engineering and Technology, India*
[2]*Professor, Electronic and Telecommunication of HVPM'S College of Engineering and Technology, India*

***Abstract*— In this paper classification normal and diabetic retina scan images, which uses the FFT transform over the retina images as feature detector and a constructive one hidden layer Generalized feed forward neural network as classification normal and diabetic retina scan images classifier technique is applied to a database consisting of images of 145 having normal and dibetic retina scan images. It is demonstrated that the best recognition rates are 99.70%. Finally, optimal algorithm has been developed on the basis of the best classifier performance. The algorithm will provide an effective alternative method of Classification of Diabetic Retinopathy using Neural Network Approach.**

***Index Terms*—Neural network, Microsoft excel, MatLab, normal and diabetic retina scan images.**

I. INTRODUCTION

Harm in the eye because of diabetes is called Diabetic retinopathy (DR) which might happen because of changes in blood glucose level that might prompt changes in retinal veins. It is typically considered as the most well-known reason for vision misfortune for the beyond 50 years. Diabetic retinopathy is vision alarming that happens in people with well established diabetes with moderate harm to the retina of the eye and a main source of visual impairment among working grown-ups assuming it stays untreated. It tends to be seen during enlarged eye assessment by an ophthalmologist or optometrist. Early detection and proper treatment of DR can help to avoid blindness [1]. DR is broadly classified into proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR). In the event of PDR the blood vessels in the retina of the eye get blocked and avoid flow of blood in the eye. Whereby new, but weak vessels begin to form on the retina which supply blood to the closed area. This status is called neo-vascularization. In the event of NPDR extra fluid will get leaked from the damaged blood vessels along with little amount of blood. This situation leads to the formation of exudates in the retina of the eye.

1. DIGITAL RETINOGRAPHY

1.1Structure of the eye

A typical retina is shown in Figure 1. It comprises of light-detecting cells, an optical nerve head and an organization of veins. Light enters through the understudy of the eye and is then centered around the retina. The focal point assists with catching pictures from various distances and the iris controls how much light entering the eye. In the event that the light is brilliant the iris closes and when it is faint it opens [12]. The retina has a thickness of around 0.5mm and lines within the eyeball and has the undertaking of changing over light that goes through the eyes into a brain signal that is additionally handled by the cerebrum.

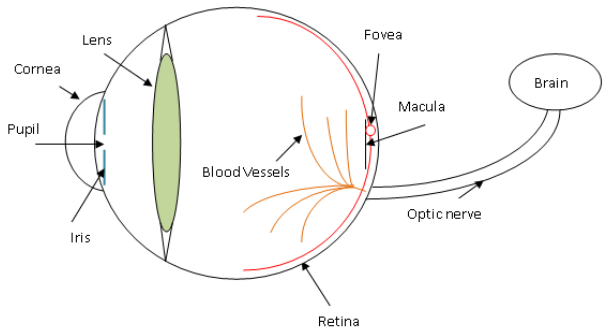


Figure 1 Location of the retina

Blood vessels transport blood throughout the body and in the retina look like thin elongated structures with different widths and lengths. They vary in thickness in the range 50-200μm with a median of 60 μm [13]. The optic nerve head is shown in Figure 1 and has a mean vertical and horizontal diameter of 1.88 and 1.77 mm, respectively [14]. The vessels emanate from the optic nerve head and branch out to cover most of the retina.

Nerves that connect to the brain are all gathered in the optic nerve. The other side of the optic nerve head leads to the brain hence the retina is considered a part of the brain.

1.2 Diseases in the eye

The most common diseases that manifest in the eye are diabetic retinopathy which causes the growth of new blood vessels, age-related macular degeneration, glaucoma and cardiovascular disease. All involve damage to the retina which can be observed in retinograms. Figure 1.2 shows examples of normal and abnormal retinograms. The left image shows a normal retinogram where no damage to the blood vessel network or any other structure is present, whilst the right one shows an abnormal one where the optic disc is in the form of an extended yellow patch.

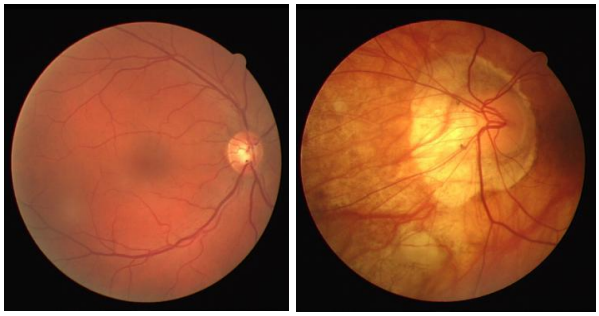


Figure 1.2. Example of retinograms.

Left: Normal retinogram with no signs of disease. Right: Abnormal retinogram. Damage has been caused on the optic disc which is shown as the expanded yellow patch and differs from the normal optic disc shown in the left retinogram. The difference in colour between these two images is a normal variation.

Diabetic Retinopathy affects 80% of people with diabetes worldwide. It is one of the leading causes of blindness in the United States [18, 19] and the second leading cause of blindness in the western world [19].During pre-proliferative diabetic retinopathy the retinal arteries are weakened and start to leak and form haemorrhages [20]. Microaneurysms (Figure 1.2) which are small red dots are also formed along with dot-haemorrhages. These red dabs start from the fovea region and grow to various region of the macular district. They are created from debilitating of vessel dividers of the littlest vessels called vessels. Hemorrhages contrast from microaneurysms as they become bigger and become fire molded and grow towards other physical designs in their environmental elements [21]. exudates are also formed which are yellow patches with sharp edges. They are plasma protein precipitation or lipoprotein deposits [19] that have been caused by retinal vessel bleeding and appear as white lesions (dots) that have the same size as microaneurysms but can become larger by merging with their neighbouring exudates. At this stage, swelling or Oedema is caused in the retina which impairs vision [12]. Proliferative diabetic retinopathy causes severe bleeding and leakage of blood and an increase of exudates around the macula [20]. This stage is very dangerous for the central vision since retinal exudation expands to the fovea region and causes arterial and capillary closing. White patches called cotton wool spots are also formed. Some areas of the retina become oxygen deprived or ischemic and whilst the circulatory system attempts to maintain adequate oxygen levels, new vessels start to grow which causes changes in vessel diameter leading to changes in the blood vessel network. These new vessels are called neovascularisations [22]. During the final stage, an increase of new blood vessels occurs that causes blindness by either a number of haemorrhages occurring or by retinal detachment from connective tissues of new vessels [19]. Age-related Macular Degeneration (AMD) has two forms: I) Dry AMD where visual acuity is slowly lost and ii) Wet AMD where a growth of vascular structure into the macula is caused. The increase in vascular permeability causes fluid to be gathered underneath the retina which leads to permanent visual loss . Glaucoma involves raised pressure within the eye, causing damage to the optic nerve. Cardiovascular disease which causes deep white spots in the retina, widening of retinal veins and thinning of retinal arteries is another form of disease which manifests in the retina [11].

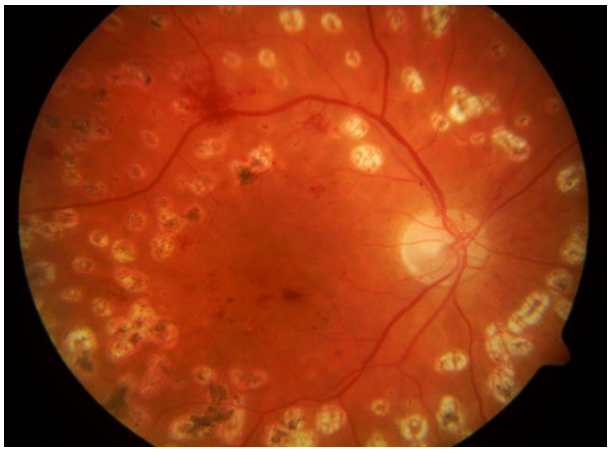
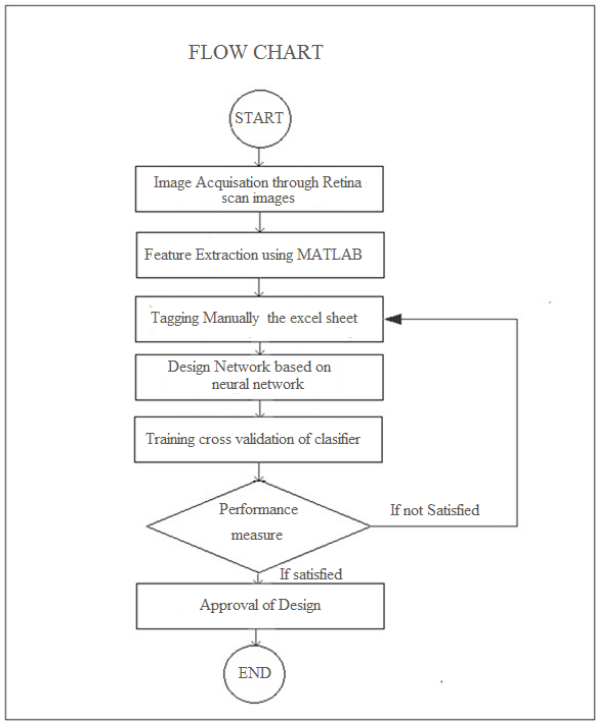


Figure 1.3. Severe diabetic retinopathy

Untreated diabetic retinopathy will cause blindness thusly checking the illness movement by means of populace screening will take into consideration convenient and successful treatment. Screening programs are currently occurring in different nations and early identification is just conceivable through robotized investigation since there is a lot of responsibility for manual recognition [15,11]. The machine examinations the retinal pictures of patients and in the event that irregularities are found, a retinal expert does a definite conclusion . Screening ought to be performed at ordinary stretches like at regular intervals to a year. At the point when diabetic retinopathy is recognized from screening, effective treatment can be performed by laser medical procedure and severe glucose control. Visual deficiency can't be turned around whenever it has happened because of diabetic retinopathy yet further harm to the retina can be kept away from. The laser treatment is called photocoagulation where the laser is straightforwardly applied to the spilling microaneurysms so that further draining is stayed away from. a bigger piece of the retina to decrease the requirement for oxygen and further harm. Photocoagulation reduces the risk of blindness before blindness has occurred [22].

III. ALGORITHM



In this paper to study classification of dabatic and non diabatic retina images Using Neural Network Approaches.. Data acquisition for the proposed classifier designed for the classification of diabatic retinopathy using neural network approach. Image data will be Collected from the different- different ophthalmologest hospital.The most important un correlated features as well as coefficient from the images will be extracted .In order to extract features, statistical techniques, image processing techniques, transformed domain will be used.

IV. NEURAL NETWORKS

Following Neural Networks are tested:
Feed-Forward Neural Networks

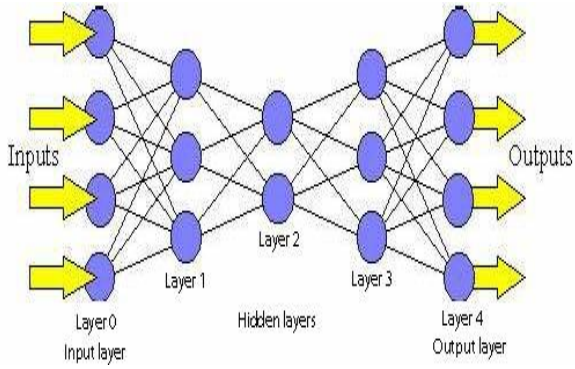


Figure 3.1. A feed-forward network.

Feed-forward networks have the following characteristics:

1. Perceptrons are arranged in layers, with the first layer taking in inputs and the last layer producing outputs. The middle layers have no connection with the external world, and hence are called hidden layers.
2. Each perceptron in one layer is connected to every perceptron on the next layer. Hence information is constantly "fed forward" from one layer to the next., and this explains why these networks are called feed-forward networks.
3. There is no connection among perceptrons in the same layer.

A single perceptron can classify points into two regions that are linearly separable. Now let us extend the discussion into the separation of points into two regions that are not linearly separable. Consider the following network:

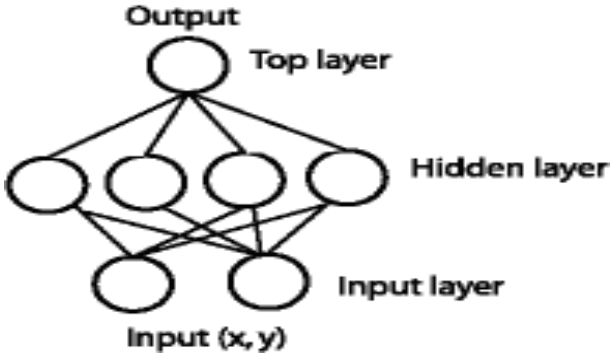


Figure 3.2. A feed-forward network with one hidden layer

The same (x, y) is fed into the network through the perceptrons in the input layer. With four perceptrons that are independent of each other in the hidden layer, the point is classified into 4 pairs of linearly separable regions, each of which has a unique line separating the region.

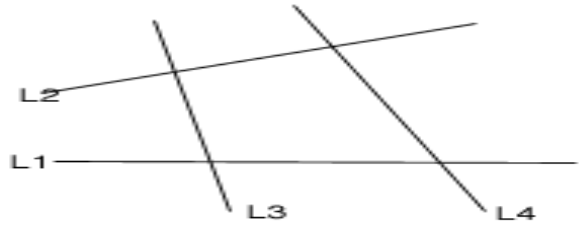


Figure.3.2 lines each dividing the plane into 2 linearly separable regions.

The top perceptron performs logical operations on the outputs of the hidden layers so that the whole network classifies input points in 2 regions that might not be linearly separable. For instance, using the AND operator on these four outputs, one gets the intersection of the 4 regions that forms the center region.

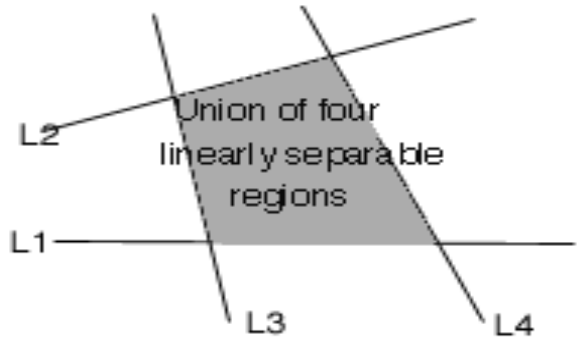


Figure3.3 Intersection of 4 linearly separable regions forms the center region.

By varying the number of nodes in the hidden layer, the number of layers, and the number of input and output nodes, one can classification of points in arbitrary dimension into an arbitrary number of groups. Hence feed-forward networks are commonly used for classification.

3.1Learning rules of Neural Network

3.1.1 Quick propagation (QP):

Quick propagation (QP) is a heuristic modification of the standard back propagation algorithm. Fahlman introduced QP in 1998. QP is not essentially faster than back propagation even though for some application it may prove faster. QP is more susceptible to instability and may stick to local minimum than back propagation. QP changes the network weights after each case. It is a batch update algorithm

QP works with the assumption that the error surface is locally quadratic, with the axes of hyper-ellipsoid error surface associated with the weights. If this is true, then the minimum of the error surface can be found after only a couple of epochs. Certainly, the assumption is not generally valid, but if it is close to true, the algorithm can converge to the minimum very quickly. On the first epoch, the weights are changed using same rule as the back propagation, based upon the local gradient and the learning rate. The basic QP formula has a number of limitations. If the error surface is not concave, the algorithm can deviate from the desired value. If gradient changes a little or not at all, Then the changes can be extremely large. If the zero error is encountered, a weight will stop changing permanently. On the first epoch, QP updates weights similar to back propagation. Subsequently, weight changes are calculated using the quick propagation equation.

$$\Delta w(t) = \frac{s(t)}{s(t-1)-s(t)}\Delta w(t-1)$$

.... (19)

The system is numerically unstable if *s(t)* is very close, equal or greater than *s(t-1).* Since *(t)* is expressed along the direction of weight gradient, such conditions can oly occur if the slope becomes constant, or becomes steeper. In such cases, the weight update formula is

$$\Delta w(t) = \varepsilon\alpha\Delta w(t-1)$$

.... (20)

Where α denotes on acceleration constant

V. RESULT SIMULATION

The Best Neural network with maximum accuracy is shown below:

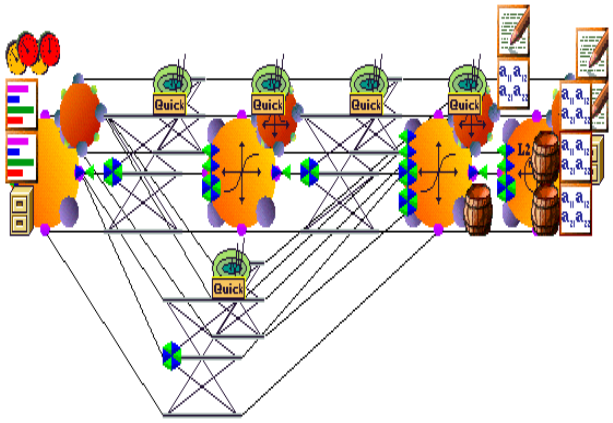


Figure 4.1 The Best Neural network with maximum accuracy

Training Report of the Best Classifier:

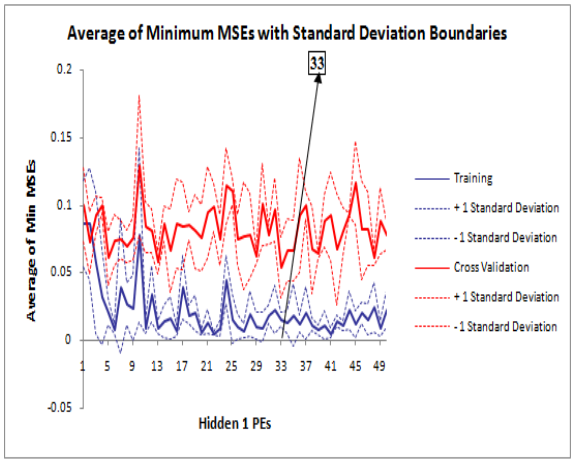


Figure 4.2: Average of Minimum MSEs with Standard Deviation Boundaries

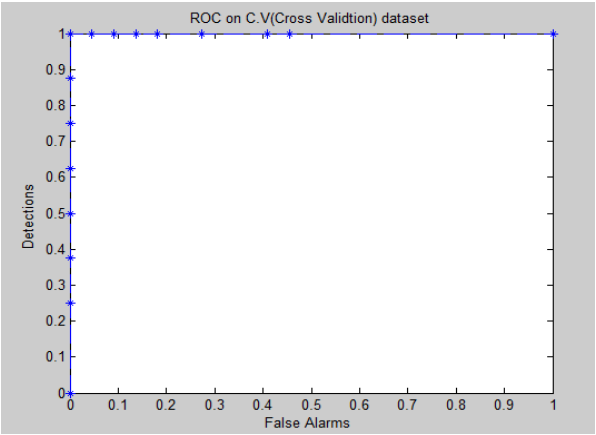
Test on Cross validation (CV):

Output / Desired	*NORMAL*	*DIABATIC*
NORMAL	8	0
DIABATIC	0	22

Table 1: Test on Cross validation (CV)

Performance	*NORMAL*	*DIABATIC*
MSE	0.01903138	0.019007516
NMSE	0.097319558	0.097197527
MAE	0.088134937	0.094955021
Min Abs Error	0.001800706	0.006470327
Max Abs Error	0.498109347	0.499925863
r	0.95397242	0.953133212
Percent Correct	100	100

Table 2: Performance Measures for cross validation



Area underROC curve = 1.000000

Test on Training:

Output / Desired	*NORMAL*	*DIABATIC*
NORMAL	29	1
DIABATIC	0	85

Table 3: Test on Training

Performance	*NORMAL*	*DIABATIC*
MSE	0.013816186	0.016711712
NMSE	0.073263456	0.08861764
MAE	0.064400846	0.076116281
Min Abs Error	0.000371286	3.76694E-05
Max Abs Error	0.994043115	1.00181068
r	0.963725332	0.957029497
Percent Correct	100	98.8372093

Table 4: Performance Measures for training

VI. CONCLUSION

From the results obtained in FFT domain it concludes that the GFF Neural Network with QP (Quick Prop) and hidden layer 1 with processing element 33 gives best results of 99.70% Accuracy.

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