Classification of Diabetic Retinopathy using Neural Network Approach

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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 multilayer perceptron 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 of 116 are used for network training, and the remaining images of 29 are used for cross validation. It is demonstrated that the best recognition rates are 100% for the training as well as cross validation. Furthermore The Average Classification Accuracy of MLP Neural Network comprising of one hidden layers with 12 PE's organized in a typical topology is found to be superior (100 %) for Training . 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.

IndexTerms **- Neural network, Microsoft excel, MatLab, normal and diabetic retina scan images**
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I. INTRODUCTION

Damage in the eye due to diabetes is called Diabetic retinopathy (DR) which may occur due to changes in blood glucose level that may lead to changes in retinal blood vessels. It is normally considered as the most common cause of vision loss for the past 50 years. Diabetic retinopathy is vision frightening that occurs in persons with long standing diabetes with progressive damage to the retina of the eye and a leading cause of blindness among working adults if it remains untreated. It can be perceived during dilated eye examination 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 consists of light-sensing cells, an optical nerve head and a network of blood vessels. Light enters through the pupil of the eye and is then focused on the retina. The lens helps to capture images from different distances and the iris controls the amount of light entering the eye. If the light is bright the iris closes and when it is dim it opens [12]. The retina has a thickness of about 0.5mm and lines the inside of the eyeball and has the task of converting light that passes through the eyes into a neural signal that is further processed by the brain.
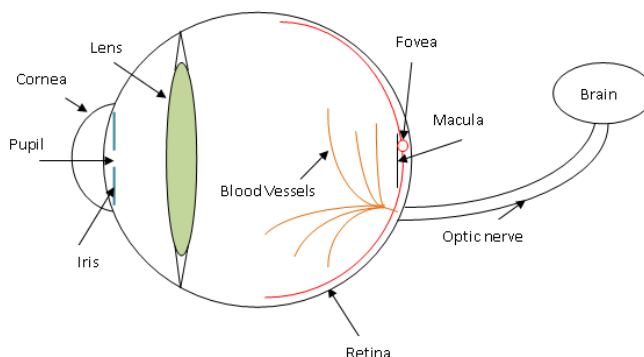

Figure 1. Location of the retina.

      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.

The macula is located at the centre of the retina and is considered the area with the highest visual acuteness (Figure 1) [15]. The fovea as shown in Figure 3 is located in the centre of the macula area and is the point where light rays are focussed which produces fine details for sharp vision [16, 17].

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 dots initiate from the fovea area and expand to different areas of the macular region. They are produced from weakening of vessel walls of the smallest vessels called capillaries. Haemorrhages differ from microaneurysms as they become larger and become flame shaped and expand towards other anatomical structures in their surroundings [21]. xudates 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, therefore monitoring the disease progression via population screening will allow for timely and effective treatment. Screening programs are now taking place in various countries and early detection is only possible through automated analysis since there is too much workload for manual detection [15,11]. The machine analyses the retinal images of patients and if abnormalities are found, a retinal specialist carries out a detailed diagnosis . Screening should be performed at regular intervals such as every six months to a year. When diabetic retinopathy is identified from screening, successful treatment can be performed by laser surgery and strict glucose control. Blindness cannot be reversed once it has occurred due to diabetic retinopathy but further damage to the retina can be avoided. The laser treatment is called photocoagulation where the laser is directly applied to the leaking microaneurysms so that further haemorrhaging is avoided. a larger part of the retina to reduce the need for oxygen and further damage. Photocoagulation reduces the risk of blindness before blindness has occurred [22].

1.3 Contribution

In this project work, the digital retinal fundus images are classified into diabetic or non-diabetic; Diabetic image contains mild to severe signs of non-proliferative DR and nondiabetic does not contain any microaneurysms (MA). The method proposed

in this work is to correctly assign the class to which a retinal fundus image could be classified using one rule classifier and back propagation neural network (BPNN) techniques.

1.4 Advantages

1) Diabetic Retinopathy diagnosis is an arduous task that needs to be executed scrupulously. The computerization of this system will be extremely advantageous.

2) Clinical judgments are usually made based on medical practitioner's perception and wisdom rather on the technical information available in the database.

3) It is not easy for a doctor to have expertise in every subspecialty. This leads to unwanted prejudices, mistakes and unnecessary medical expenses that might affect the quality of service provided to patients.

II. PROPOSED ALGORITHM
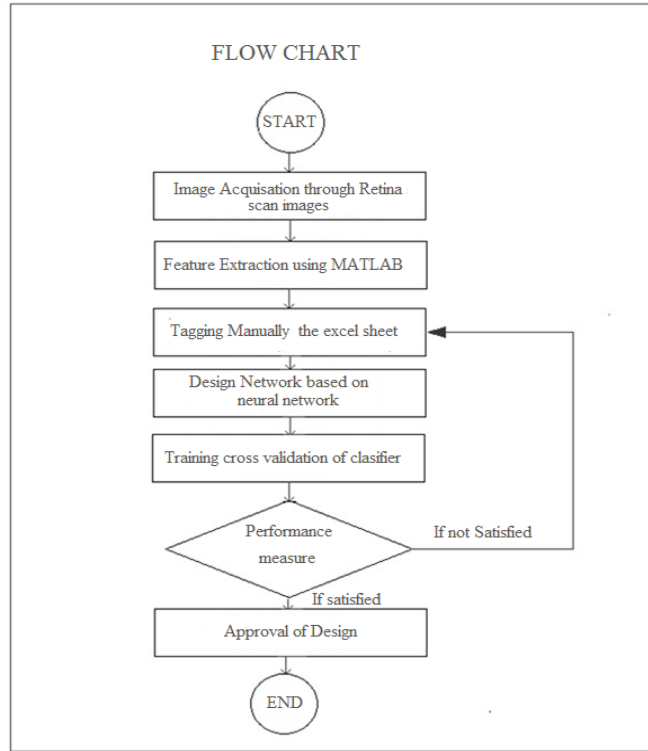
in this paper to study classification of dabatic and non diabatic retina images Using Neural Network Approaches.. Data acquisition for the proposed classifier designed for the classification of diabatic retinopathy using neural network approach. Image data will be Collected from the different- different 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.

III. NEURAL NETWORK

Following Neural Networks are tested:

Multilayer perceptron (MLP)

The most common neural network model is the multi layer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. A graphical representation of an MLP is shown below:
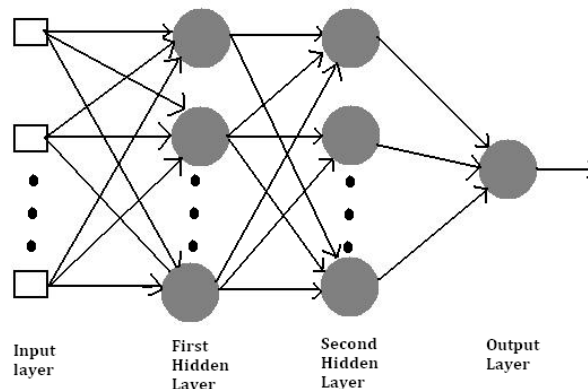

Figure 2.2: The Structure Of Neural Network Model MLP.

The MLP and many other neural networks learn using an algorithm called back- propagation. With back-propagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back-propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training".

3.1 Learning 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. It computes the average gradient of the error surface across all the cases before updating the weights at the end of an epoch.

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. On successive epochs, the quadratic assumption is used to obtain the minimum.

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.

$$\Delta w(t) = \frac{s(t)}{s(t-1)-s(t)} \Delta w(t-1) \qquad \qquad .... (19)$$

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 only occur if the slope becomes constant, or becomes steeper. In such cases, the weight update formula is

$$\Delta w(t) = \varepsilon \alpha \Delta w(t-1) \qquad \qquad .... (20)$$

Where α denotes on acceleration constant

IV. RESULTS SIMULATION

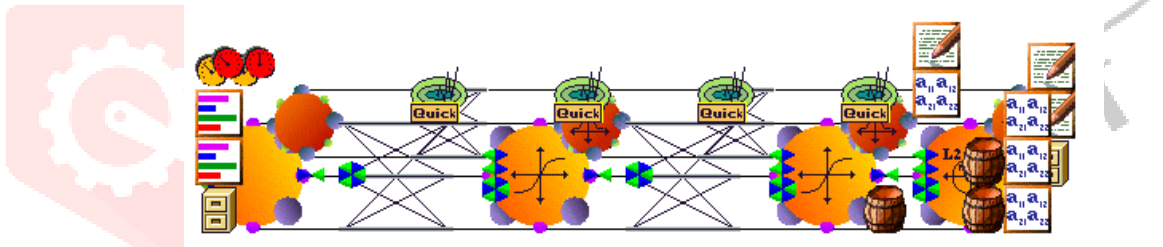The Best Neural network with maximum accuracy is shown below:

Figure   4.1 The Best Neural network with maximum accuracy
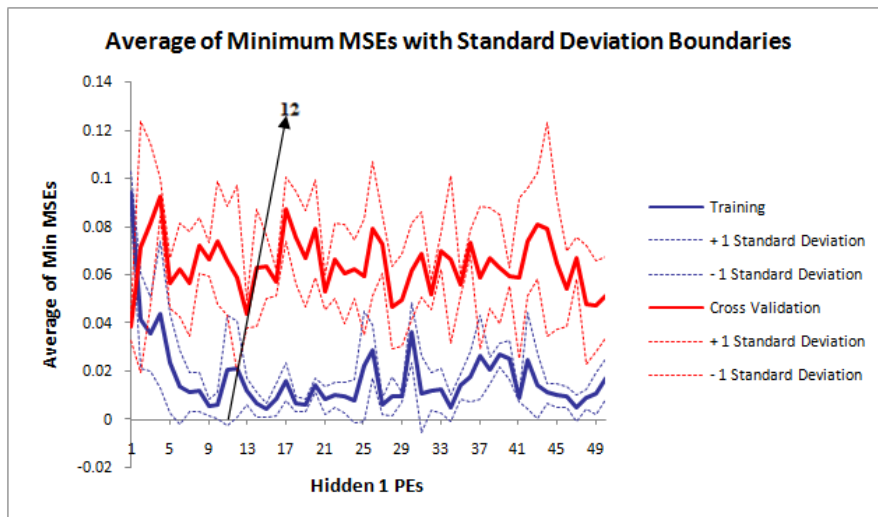
Training Report of the Best Classifier:

Figure 4.2: Average of Minimum MSEs with Standard Deviation Boundaries

Best Networks	Training	Cross Validation
Hidden 1 PEs	47	12
Run #	1	3
Epoch #	746	374
Minimum MSE	0.001249137	0.015664086
Final MSE	0.001249137	0.015897488

Table 1: Processing Element Training Data Set

Test on Cross validation (CV):

Output / Desired	NAME(NORMAL)	NAME(DIABATIC)
NAME(NORMAL)	8	0
NAME(DIABATIC)	0	22

Table 2: Confusion matrix of Cross validation (CV)

Performance	NAME(NORMAL)	NAME(DIABATIC)
MSE	0.026357515	0.026703892
NMSE	0.134782747	0.136553994
MAE	0.095081608	0.09561794
Min Abs Error	0.001526066	0.000458386
Max Abs Error	0.48041589	0.517609526
r	0.931958693	0.930934048
Percent Correct	100	100

Table 3: Performance Measures for cross validation

ROC curve besed on best classifier result :
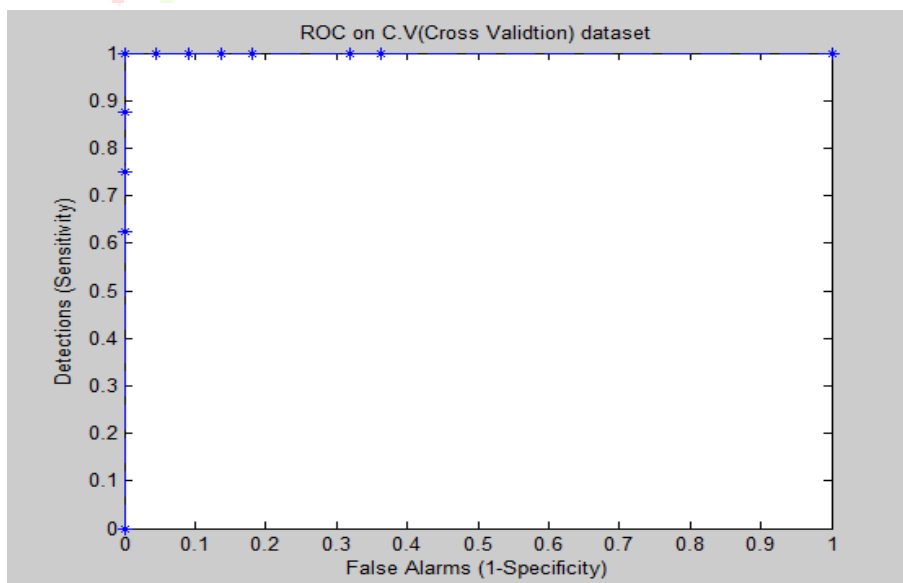
Area under ROC curve = 1.000000

Test on Training:

Output / Desired	NAME(NORMAL)	NAME(DIABATIC)
NAME(NORMAL)	29	0
NAME(DIABATIC)	0	86

Table 4: confusion matrix of Training

Performance	NAME(NORMAL)	NAME(DIABATIC)
MSE	0.000684046	0.000710832
NMSE	0.003627308	0.003769349
MAE	0.021037087	0.021500819
Min Abs Error	0.000904207	0.000183683
Max Abs Error	0.062228827	0.056450487
R	0.99826734	0.998193079
Percent Correct	100	100

Table 5: Performance Measures for training

IV. CONCLUSION

From the results obtained in FFT domain it concludes that the MLP Neural Network with QP (Quick Prop) and hidden layer 1 with processing element 12 gives best results of 100% in Training as well as in Cross Validation.

V. ACKNOWLEDGMENT

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