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Classification of Diabetic Retinopathy using Multilayer Perceptron Neural Network

Fazil Ahmad Khan **Vijay L. Agrawal**

***Abstract* — An eye disease which is assorted in person with diabetes that is occurred by change in blood vessels of the retina is called Diabetic Retinopathy. Retinopathy can occur with all types of diabetes and can cause vision loss if it's not treated on time. In this paper a new classification algorithm is proposed for the Classification of Diabetic retinopathy. In order to develop algorithm 80 retinal scan images of patients have been considered consisting of normal retina image and Infected retina image. With a view to extract features from the retina scan images after image processing, an algorithm proposes (WHT) Wavelet Transform coefficients. The Efficient classifiers based on Multilayer Perceptron (MLP) Neural Network. A separate Cross-Validation dataset is used for proper evaluation of the proposed classification algorithm with respect to important performance measures, such as MSE and classification accuracy. Finally, optimal algorithm has been developed on the basis of the best classifier performance. The algorithm will provide an effective alternative to traditional method of retinal scan images.**

***Key Words* — MLP Neural Network,Matlab,Retina scan images,Microsoft Excel.**

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. 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. As the disease advances, the quantities of the exudates also gain. Figure 1 and Figure 2 show the normal retinal image and DR affected image.2016

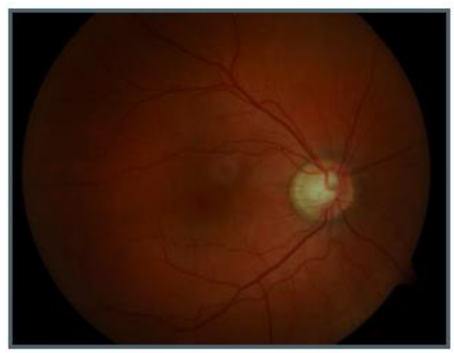


Fig.1. Normal retinal image

Fig.2. Diabetic Retinopathy infected image

Diabetic Retinopathy (DR) is the retinal bruise, caused by elevation of blood sugar levels, which can ultimately lead to vision impairment. According to the World Health Organization, It has been estimated that more than 75% of people who have diabetes for more than 20 years will have some form of Diabetic Retinopathy. Diabetic Retinopathy is asymptotic in the beginning and therefore many diabetic patients are not aware of their condition until it affects their vision. Early and regular screening of DR is therefore very important to prevent further complication or to control the progression of the disease. microaneurysms (MA) appear as tiny reddish dots in the peripheral retinal layers. With the progression of the disease, smaller vessels may close and new abnormal blood vessels begin to grow in the retina and are referred to as proliferative stage. This stage may lead to vision impairment and if not treated properly would eventually turn to vision loss.

Research in the field of medicine suggests that abnormal pressure and glucose levels are a major cause of several critical ailments. Such aberration can lead to other complications in various organs of the body. In this Purposed work we place focus on Diabetic Retinopathy, the former being a disorder in the retina of the eye caused mainly due to Diabetes leading to imperfect/loss of vision and the latter being associated with elevated pressure in the eye causing damage to the optic nerve .Diabetic Retinopathy are asymptomatic in the preliminary stages and findings reveal that treatment may be useful only when detected early. Regular screening of the people who have high risk of the disease may help detect the disease at an early stage. Detecting retinal abnormalities in a large number of images generated by screening programs is a time-, resource and labor – intensive task. Automatic detection of the disease from the retinal images is thus an important area of ongoing research.

Contribution: In this work, the digital retinal fundus images are classified into diabetic or non-diabetic; Diabetic image 1) 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.

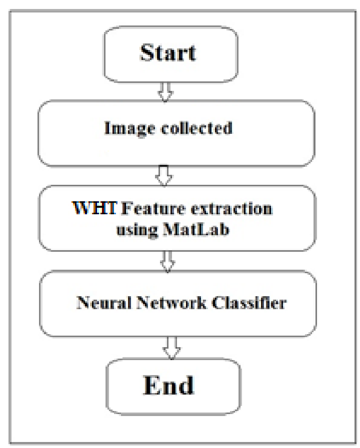
***Advantages*:**

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



It is proposed to study Efficient Classification of Diabetic retinopathy using Neural Classifier. Data acquisition for the proposed classifier designed for the diagnosis of retina shall be in the form of retina Scanned images. Image data will be Collected from the different-different hospitals of the state .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.

1)Neural Networks

Following Neural Networks are tested:

a) 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:

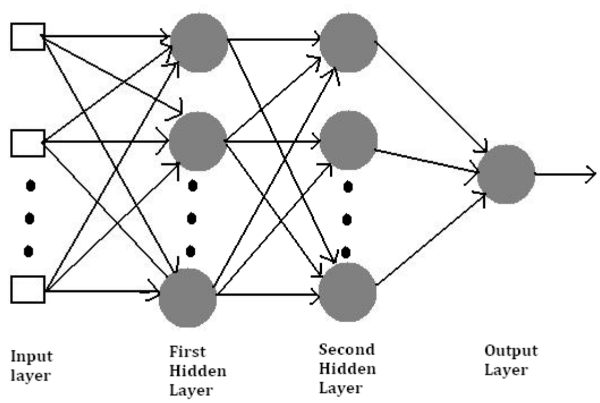


Fig 3. The structure of neural network model multi layer perceptron (MLP)

The MLP and many other neural networks learn using an algorithm called backpropagation. With backpropagation, 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 (backpropagated) 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". [10]

2)Learning Rules used:

- *Momentum*

Momentum simply adds a fraction m of the previous weight update to the current one. The momentum parameter is used to prevent the system from converging to a local minimum or saddle point. A high momentum parameter can also help to increase the speed of convergence of the system. However, setting the momentum parameter too high can create a risk of overshooting the minimum, which can cause the system to become unstable. A momentum coefficient that is too low cannot reliably avoid local minima, and can also slow down the training of the system.

- ***Conjugate Gradient***

CG is the most popular iterative method for solving large systems of linear equations. CG is effective for systems of the form A=xb-A (1) where x _is an unknown vector, b is a known vector, and A _is a known, square, symmetric, positive-definite (or positive-indefinite) matrix. (Don't worry if you've forgotten what "positive-definite" means; we shall review it.) These systems arise in many important settings, such as finite difference and finite element methods for solving partial differential equations, structural analysis, circuit analysis, and math homework.

Developed by Widrow and Hoff, the delta rule, also called the Least Mean Square (LMS) method, is one of the most commonly used learning rules. For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The change in weight from ui to uj is given by: dwij = r* ai * ej, where r is the learning rate, ai represents the activation of ui and ej is the difference between the expected output and the actual output of uj. If the set of input patterns form a linearly independent set then arbitrary associations can be learned using the delta rule.

It has been shown that for networks with linear activation functions and with no hidden units (hidden units are found in networks with more than two layers), the error squared vs. the weight graph is a paraboloid in n-space. Since the proportionality constant is negative, the graph of such a function is concave upward and has a minimum value. The vertex of this paraboloid represents the point where the error is minimized. The weight vector corresponding to this point is then the ideal weight vector.

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- ***Quick propagation***

Quick propagation (Quickprop) [1] is one of the most effective and widely used adaptive learning rules. There is only one global parameter making a significant contribution to the result, the e-parameter. Quick-propagation uses a set of heuristics to optimise Back-propagation, the condition where e is used is when the sign for the current slope and previous slope for the weight is the same.

- ***Delta by Delta***

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III. Simulation Results

1) Computer Simulation

The MLP neural network has been simulated for 80 retina Scan images out of which 56 (70% of total images) were used for training purpose and 24 (30% of total images) were used for cross validation.

The simulation of best classifier along with the confusion matrix is shown below :

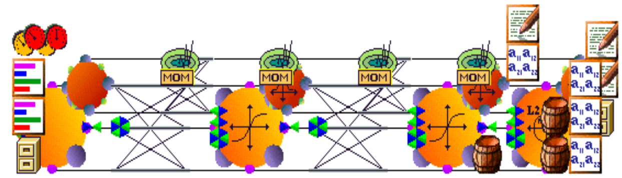

Fig.4 MLP neural network trained with MOM learning rule

IV. RESULT

Output / Desired	*NAME(N.R images)*	*NAME(I.R images)*
NAME(N.R images)	7	3
NAME(I.R images)	3	11

Table I. Confusion matrix on CV data set

Output / Desired	*NAME(N.R images)*	*NAME(I.R images)*
NAME(N.R images)	22	4
NAME(I.R images)	4	26

TABLE II. Confusion matrix on Training data set

Here Table I and Table II Contend the C.V as well as Training data set of Normal retinal image and Infected retinal images.

Performance	***NAME(N.R images)***	***NAME(I.R images)***
MSE	0.163713027	0.368504597
NMSE	0.668494861	1.504727104
MAE	0.309295967	0.499612867
Min Abs Error	0.042212176	0.036217045
Max Abs Error	0.814500637	1.012556711
r	0.643574482	-0.002653575
Percent Correct	66.66666667	75

TABLE III. Accuracy of the network on CV data set

Performance	NAME(N.R images)	NAME(I.R images)
MSE	0.171364875	0.171353493
NMSE	0.6854595	0.685413971
MAE	0.307599623	0.270260544
Min Abs Error	0.007290042	0.003951564
Max Abs Error	0.935546817	1.004779376
r	0.599069321	0.596989152
Percent Correct	84.61538462	84.61538462

TABLE IV. Accuracy of the network on training data set

Here Table III and Table IV Contain the Training and C.V result. Table III show the result or identify the N.R images and I.R images 66.66% and 75% or Table IV show the result or identify both 84.61%.

CONCLUSION

The MLP classifier with MOM learning rule gives performance of 84.61% in both N.R images and I.R images in Training and in Cross validation e N.R images and I.R images 66.66% and 75% identify.

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AUTHOR’S PROFILE

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Fazil ahmad khan
Student of HVPM’S College of Engineering and Technology Amravati (India)