An approach to Enhance Automatic Diagnosis of Diabetic Retinopathy and Classification by Hybrid Multilayer Feed forward Neural Networks by Genetic Algorithm

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ABSTRACT- For a particularly long time, Automatic diagnosis of diabetic retinopathy from digital fundus images has been an active research topic in the medical image processing community. This paper describes what is the diagnosis of Diabetic Retinopathy by various image processing techniquesand how proposed work can be help to enhace it further. In the beginning section introduction provides the terminology related to DR like fundus images with different types of stages in Diabetic Retinopathy as NPDR(Non Proliferative DR) and PDR(Proliferative DR) levels. Further sections describes different features extraction of Fundus images like exudates, microaneurysms, optic Disc, macula, blood vessels, texture properties like entropy ect. as a responsible parameters for DR with image processing. Brief description of Genetic algorithm and Multilayer feed forward neural network is given. Next section describes how proposed algorithm for classification of Diabetic retinopathy on feature vector can be applicable to train the artificial neural network. This elaborates how Genetic algorithm can be utilized on the training dataset of multilayer feed forward Neural Network . Last section covers the comparing the proposed algorithm with present algorithm to enhance further to expect better results. Finally conclusion on rework and references are included with their reference numbers.

1. INTRODUCTION

Diabetes has become one of the rapidly increasing health threats worldwide [21]. Proper and early treatment of diabetes is cost effective since the implications of poor or late treatment are very expensive. Fundus imaging has an important role in diabetes monitoring since occurrences of retinal abnormalities are common and their consequences serious. However, since the eye fundus is sensitive to vascular diseases, fundus imaging is also considered as a candidate for non-invasive screening. The success of this type of screening approach depends on accurate fundus image capture, and especially on accurate and reliable image processing algorithms for detecting the abnormalities. Numerous algorithms have been proposed for fundus image analysis by many research groups [13, 6, 9, 15, 18]. However, it is impossible to judge the accuracy and reliability of the approaches because there exists no commonly accepted and representative fundus image database and evaluation protocol.

In the type 1 diabetes, the insulin production in the pancreas is permanently damaged, whereas in the type 2 diabetes, the person is suffering from increased resistance to insulin. The type 2 diabetes is a familial disease, but also related to limited physical activity and lifestyle [21]. The diabetes may cause abnormalities in the retina (diabetic retinopathy), kidneys (diabetic nephropathy), and nervous system (diabetic neuropathy) [14]. The diabetes is also a major risk factor in cardiovascular diseases [14].

The diabetic retinopathy is a micro vascular complication of diabetes, causing abnormalities in the retina, and in the worst case, blindness. Typically there are no salient symptoms in the early stages of diabetic retinopathy, but the number and severity predominantly increase during the time. The diabetic retinopathy typically begins as small changes in the retinal capillaries. The first detectable abnormalities are mircroaneurysms (Ma) (Fig. 2.1(a)) which are local distensions of the retinal capillary and which cause intra retinal hemorrhage (H) (Fig. 2.1(b)) when ruptured. The disease severity is classified as mild non-proliferative diabetic retinopathy when the first apparent microaneurysms appear in the retina [19]. In time, the retinal edema and hard exudates (He) (Fig. 2.1(c)) are followed by the increased permeability of the capillary walls. The hard exudates are lipid formations leaking from

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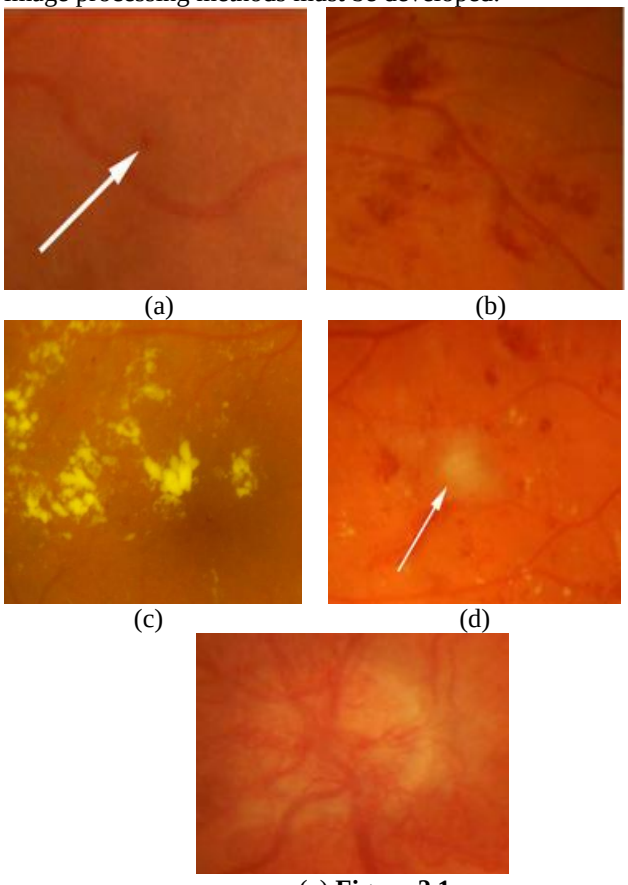
these weakened blood vessels. This state of the retinopathy is called moderate non-proliferative diabetic retinopathy [19]. However, if the above-mentioned abnormalities appear in the central vision area (macula), it is called diabetic maculopathy [21]. As the retinopathy advances, the blood vessels become obstructed which causes micro infarcts in the retina. These micro infarcts are called soft exudates (Se) (Fig. 2.1(d)). When a significant number of intra retinal hemorrhages, soft exudates, or intra retinal micro-vascular abnormalities are encountered, the state of the retinopathy is defined as severe non-proliferative diabetic retinopathy [19].

The severe non-proliferative diabetic retinopathy can quickly turn into proliferative diabetic retinopathy when extensive lack of oxygen causes the development of new fragile vessels [19]. This is called as neo-vascularisation (Fig. 2.1(e)) which is a serious eye sight threatening state. The proliferative diabetic retinopathy may cause sudden loss in visual acuity or even a permanent blindness due to vitreous hemorrhage or tractional detachment of the central retina. After diagnosis of diabetic retinopathy, regular monitoring is needed due to the progressive nature of the disease. However, broad screenings cannot be performed due to the fact that the fundus image examination requires attention of medical experts. For the screening, automatic image processing methods must be developed.



(a) (b) (c) (d) (e) **Figure 2.1**

Figure 2.1: *Abnormal findings in the eye fundus caused by the diabetic retinopathy: (a) microaneuryms (marked with an arrow), (b) hemorrhages, (c) hard exudates, (d) soft exudate (marked with an arrow), and (e) neovascularization.*

2.1 Current evaluation practices

In medical diagnosis, the medical input data is usually classified into two classes, where the disease is either present or absent. The classification accuracy of the diagnosis is assessed using the sensitivity and specificity measures. Following the practises in the medical research, the fundus images related to the diabetic retinopathy are evaluated by using sensitivity and specificity per image basis. Sensitivity is the percentage of abnormal funduses classified as abnormal, and specificity is the percentage of normal fundus classified as normal by the screening. The higher the sensitivity and specificity values, the better the diagnosis. Sensitivity and specificity can be computed as [22]:

$$\text{Sensitivity (SN)} = TP/TP + FN,$$
$$\text{Specificity (SP)} = TN/TN + FP \quad (1)$$

where *TP* is the number of abnormal fundus images found as abnormal, *T N* is the number of normal fundus images found as normal, *FP* is the number of normal fundus images found as abnormal (false positives) and *FN* is the number of abnormal fundus images found as normal (false negatives). Sensitivity and specificity are also referred to as the true positive rate (TPR) and true negative rate (TNR), respectively.

2.2 Automatic methods

As mentioned previously, the diagnosis of diabetic retinopathy can be divided into the following two categories:

1. Screening of the diabetic retinopathy
2. Monitoring of the diabetic retinopathy

Most automatic systems approach the detection directly using shape, color, and domain knowledge of diabetic retinopathy findings, but the abnormalities can also be found indirectly

by detecting changes between two fundus images taken from the same eye in different time moment [11, 17]. The direct approach contributes to screening of the disease, where indirect approach contributes to both screening and monitoring of the diabetic retinopathy. Both approaches use roughly the following stages for finding abnormalities in fundus images: 1) image enhancement 2) candidate diabetic retinopathy finding detection 3) classification to correct diabetic retinopathy category (or hypothesis rejection).

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The automatic methods either use the vital domain information provided by the normal fundus parts or remove them due to their similar color and shape appearance with abnormal fundus findings.

3. PROPOSED ALGORITHM

Proposed algorithm for the enhancement of DR is given as below in **figure 3.1**
Step 1. Input Fundus Image
Step 2. Various Feature Extraction by applying image processing Tools.
Step 3. Creation of feature vector of input image
Step 4. Classification with HybridMLFFNN

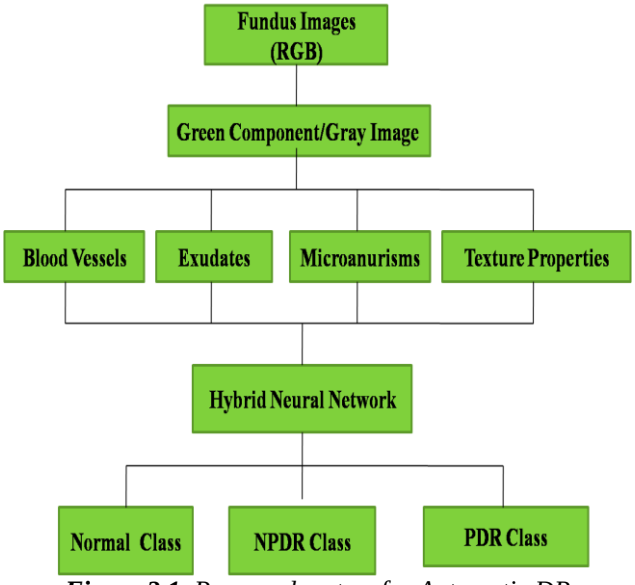
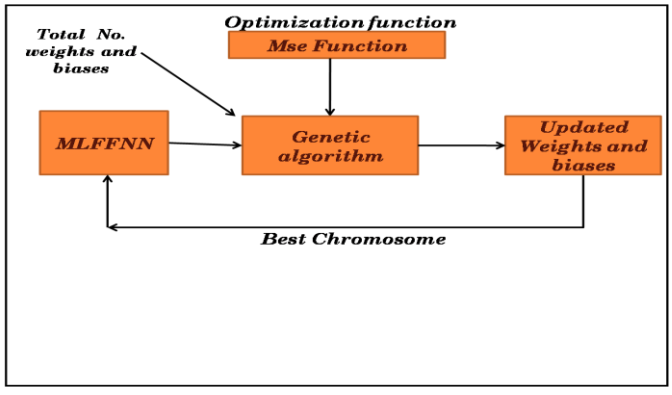


Figure 3.1 *Proposed system for Automatic DR*

3.1 Hybrid Multi Layer Feed Forward Neural Network

Hybridization of HybridMLFFNN is be done by two step learning process can be called as *Neural-genetic network learning algorithm is as in figure below*



First learning stage (Proposed Step):-
Genetic Algorithm
1. Initialize a population of chromosomes
2. Calculate the fitness value for each chromosome according to Mean square function objective function (MSE)
3. Apply crossover and mutation to produce new chromosome
4. Replace new generation as current generation
5. Stop first learning stage

Second learning stage:-
Multilayer Feed forward neural network[24][25]

- Set the best chromosomes (obtained from GA) as the initial weight and bias vector.
- Apply this best set of chromosomes as a optimized weight and bias to train the multilayer feed forward neural network.

3.2 Training of ANN

The ANN is a feed-forward back propagation network and uses supervised learning to train the neural network. Supervised learning is by providing the ANN with input data and matches them with output results. Its weights would adjust according to its learning rules as it undergoes training before being tested for accuracy. The ANN used for classification in this project as shown in the **figure 3.2** below.

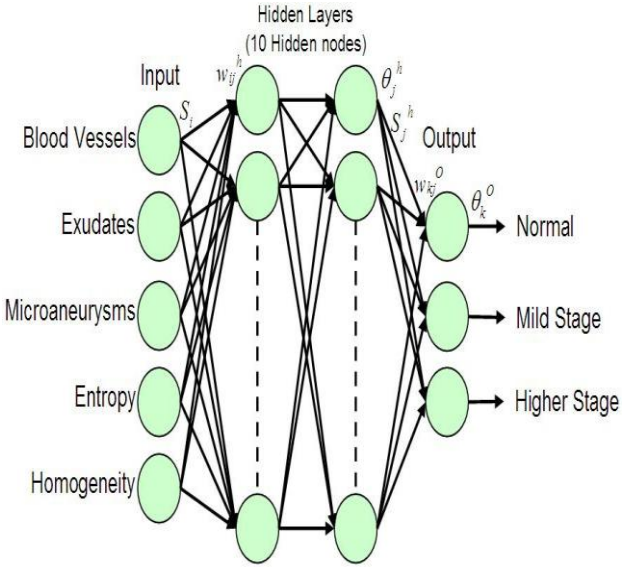


Figure 3.2 ***Four-layer feed-forward neural network classifier***

The input layer is made up of nodes to accept the 5 data values while the subsequent layers process the values using activation function. There are 10 neurons for each "hidden layer" and the trained network would output binary numbers which represent the different stages.

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Program interface

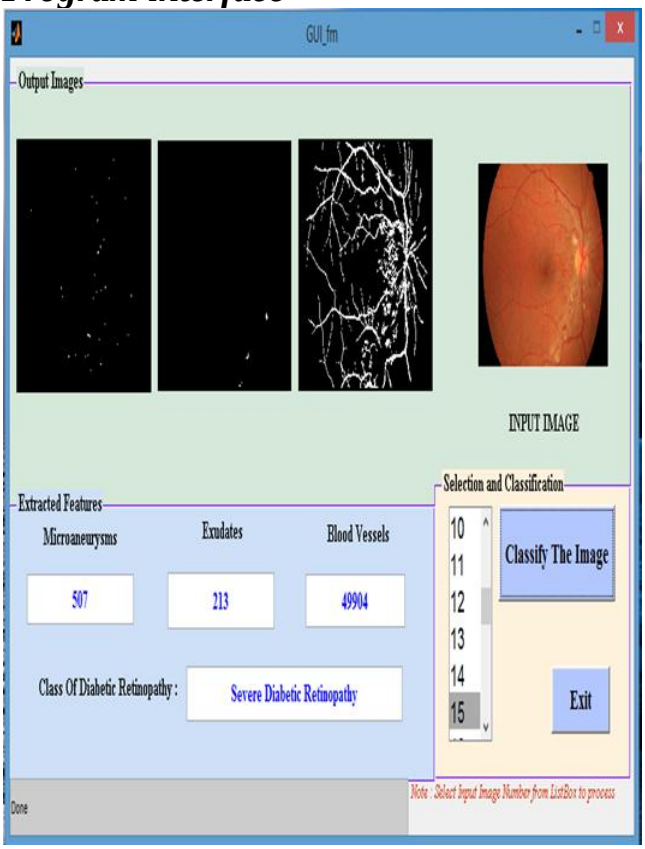

Figure 3.3 Program Interface

4. CONCLUSIONS

The neural network depends on the training conditions (hidden node number, learning rate, momentum, and initial weight and bias). The minimum size used to recognize the type of DR. This technique can be used to detect the DR stage. The learning time depends strongly on the resolution of image, hidden nodes and training pixels. The proposed genetic algorithm presented to suitable network, which was able to perform well within the specified tolerance e.g. zero failure rate for MLP net. As far as training procedures are concerned, we have identified some important learning phenomenon e.g. the effect caused by learning rate, number of hidden units, training of under units, training sets, etc. Thus, the ratio of reduction on the number of epoch's can be least or equal to 50% if we used the genetic algorithm. Integrating the genetic algorithm with MLP network, the following observations are the conclusions can be drawn:

The results of neural network learning are sensitive to the initial value of the weight and bias vector. A genetic algorithm is employed to perform global search and to seek a good starting weight vector for subsequent neural network learning algorithm. The result is an improvement in the convergence speed of the algorithm. Comparison with various techniques given in table 4.1.

Comparison Table

Technique	Features	Dataset Training/ Testing	Sensitivity & Specificity	Percentage of Correct Classificat-ion
Adaptive Neuro-Fuzzy Inference System Approach	Blood Vessels, Area of Exudates, Entropy, Homogeneity	**120 / 80**	**0.68864**	**68%**
SVM (Support Vector Machine)	Blood Vessels	**250 / 217**	**99.45% / 100%**	**98.92%**
Tree Type Classifier-(RF) Random Forest	Blood Vessels, Haemorrhages	**39 / 28**	**0.875 / 1**	**88.46%**
Gaussian bayes Classifier	F0veal Avascular zone (FAV)	**315**	**95%/ 98%**	**98%**
Hybrid Neural Network using GA	Blood Vessels, Microaneurysms, Exudates, Entropy, Homogeneity	**50 / 24**	**0.833%**	**83%**

Table 4.1 Comparison Table

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