Early Detection of Diabetic Retinopathy with Neural Network

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Abstract--- The aim of this paper is to design a computationally intelligent method to determine exudates, the Non-Proliferative Diabetic Retinopathy (NPDR) symptom which is considered to be the initial stage of retinopathy disease. If NPDR is not identified at its earlier stage, it may lead to Proliferative Diabetic Retinopathy (DR), the complicated stage of retinal symptom that may leads to blindness. In this work an automatic computer aided detection system is proposed which screen a large number of people to identify the DR in its earlier stage for proper treatments. In this work, analysis mainly considers three stages which include removal of optic disc and normalization done by histogram processing; texture information extracted using Gray Level Co-Occurrence Matrix (GLCM) and classification is done with the help of Improved Multilayer Perceptron Neural Network (IMPNN) in early stages. Hence the proposed intelligent approaches aid the ophthalmologists with accurate and efficient detection of abnormalities in fundus images. Through this system, the abnormal retinal images can be identified in its initial stage and an accurate assessment of retinal disease is possible.

Keywords--- Diabetic Retinopathy, Neural Networks, IMPNN, Preprocessing, Deep Learning.

I. INTRODUCTION

Diabetic retinopathy, a chronic, progressive eye disease, has turned out to be one of the most common causes of vision impairment and blindness especially for working ages in the world today [1]. It results from prolonged diabetes. Blood vessels in the light-sensitive tissue (i.e. retina) are mainly affected in diabetic retinopathy. The non-proliferative diabetic retinopathy (NPDR) occurs when the blood vessels leak the blood in the retina. The Proliferative DR (PDR), which causes blindness in the patient, is the next stage to NPDR.

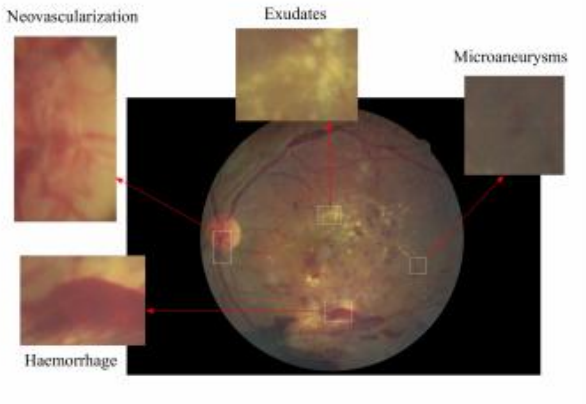

Fig. 1: Example Eye Image of the Proliferative Diabetic Retinopathy

Additional new blood vessels will begin to grow on the surface of the retina. Due to their abnormal and fragile nature, retinal hemorrhages and ruptured blood vessels are created in this stage which will lead to permanent vision loss

The progress of DR can be categorized into four stages: mild, moderate, severe no proliferative diabetic retinopathy, and the advanced stages of proliferative diabetic retinopathy. In mild NPDR, small areas in the blood vessels of the retina, called microaneurysms, swell like a balloon. In moderate NPDR, multiple microaneurysms, hemorrhages, and venous beading occur, causing the patients to lose their ability to transport blood to the retina. The third stage, called severe NPDR, results from the presence of new blood vessels,

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which is caused by the secretion of growth factor. The worst stage of DR is the proliferative diabetic retinopathy, as illustrated in Fig. 1 in which fragile new blood vessels and scar tissue form on the surface of the retina, increasing the likelihood of blood leaking, leading to permanent vision loss.

At present, retinopathy detection system is accomplished by involving a well-trained physician manually detecting vascular abnormalities and structural changes of retina in the retinal fundus images, which are then taken by dilating the retina using vasodilating agent. Due to the manual nature of DR screening methods, however, highly inconsistent results are found from different readers, so automated diabetic retinopathy diagnosis techniques are essential for solving these problems.

Although DR can damage retina without showing any indication at the preliminary stage [2], successful early-stage detection of DR can minimize the risk of progression to more advanced stages of DR. The diagnosis is particularly difficult for early-stage detection because the process relies on discerning the presence of microaneurysms, retinal hemorrhages, among other features on the retinal fundus images. Furthermore, accurate detection and determination of the stages of DR can greatly improve the intervention, which ultimately reduces the risk of permanent vision loss.

Earlier solutions of automated diabetic retinopathy detection system were based on hand-crafted feature extraction and standard machine learning algorithm for prediction [3]. These approaches were greatly suffer due to the handcrafted nature of DR features extraction since feature extraction in color fundus images are more challenging compared to the traditional images for object detection task. Moreover, these hand-crafted features are highly sensitive to the quality of the fundus images, focus angle, presence of artifacts, and noise. Thus, these limitations in traditional hand-crafted features make it important to develop an effective feature extraction algorithm to effectively analyze the subtle features related to the DR detection task.

In recent times, most of the problems of computer vision have been solved with greater accuracy with the help modern deep learning algorithms, Convolutional Neural Networks (CNNs) being an example. CNNs have been proven to be revolutionary in different fields of computer vision such as object detection and tracking, image and medical disease classification and localization, pedestrian detection, action recognition, etc. The key attribute of the CNN is that it extracted features in task dependent and automated way. So, in this paper, we present an efficient CNN architecture for DR detection in large-scale database. By considering this, in this work a Improved Multilayer Perceptron Neural Network is proposed which outperforms other state-of-the-art network in early-stage detection and achieves state-of-the-art performance in severity grading of diabetic retinopathy detection.

II. RELATED WORKS

Conway et al. [4] researched the job of hemoglobin level in anticipating proliferative retinopathy among 426 Type 1 diabetes patients. They utilized stereo fundus photography to decide the nearness of proliferative retinopathy, trailed by Cox relative risks displaying with stepwise relapse to decide the relationship of hemoglobin level with proliferative retinopathy. They found that higher hemoglobin level predicts the rate of proliferative retinopathy, however the affiliation differs by sex, being straight and positive in men and quadratic in ladies.

T Chandrakumar., et al., [5] proposes to utilize Deep Convolution Neural Network for all dimension of diabetic retinopathy stages. Genuine Positive rate are additionally improved. Moreover utilized Augmentations are required for the pictures to taken from various cameras with various field of perspectives. The upside of this technique is to locate the better and improved approach to grouping the fundus pictures. It has less exactness since it utilizes the

Convolutional Neural Network.

Garcia [6] thought about the precision of four neural system variations: Multilayer Perceptron (MP), Radial Basis Function (RBF), Support Vector Machine (SVM) and Majority Voting (MV). The underlying applicants were distinguished utilizing a nearby thresholding method dependent on the mean pixels of the whole picture contrasted with mean power in a little window around a pixel. As per their trials, the RBF was recommended as the favoured classifier among each of the 4.

Microaneurysms (MAs) detection was investigated in [7]. Here local rotating cross- sectional profile analysis was used. Features such as shape, symmetry, contrast and sharpness are classified with the help of Naive Bayes classifier. The major drawback while using this method is that even though it is able to identify vessel bifurcations and crossings, some false positives come from optic disc. Optic disc removal which is required in order to provide better result was not performed in this method.

In [8] used ensemble-based system for the detection of microaneurysm and for the grading of diabetic retinopathy. Here different preprocessing and different feature extraction methods are combined in order to detect the presence of microaneurysm. Inspite of its improved result, some of its stages are misclassified on detection.

III. PROPOSED METHODOLOGY

In this paper, retinal images obtained using fundus photographs are examined in order to diagnose the earlier retinopathy symptoms. Here, initially color normalization and optic disc removal is carried out using histogram processing technique. Color normalized images are further used in order to extract certain features namely color and texture. In the feature extraction method, texture is extracted with the help of Gray-Level Co-Occurrence Matrix (GLCM) method. At last, classification method namely Improved Multilayer Perceptron Neural Network (IMPNN) in early stages is used to detect the normal and abnormal images. From the result obtained, the grading of retinopathy can be made.

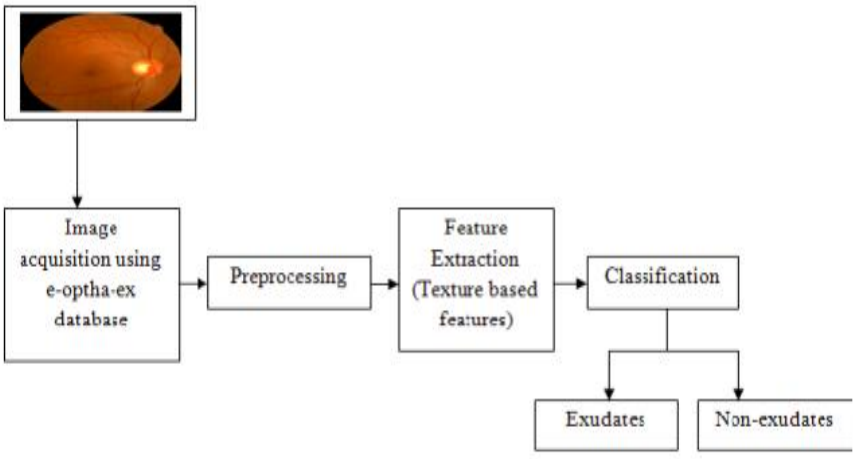

Figure 2: Block Diagram of the Methodology Used to Detect DR Related Lesions in the Retina

The basic block diagram describing the flow of analysis of diabetic retinopathy symptom is shown in Figure 2.

a. Image Acquisition

In comparison to a direct examination, retinal details may be easier to visualize in fundus photographs. Fundus imaging is the 2D picture of the 3D retinal tissue. It is captured using specialized fundus cameras consisting of a flash enabled camera with a highly intricate microscope attached to it. The camera gives a magnified and upright view of the fundus. It views 30° to 50° of retinal area with a magnification of 2.5x; using zoom or auxiliary lenses 15°

area and 5x magnification can be obtained; similarly 140° can be obtained with a wide angle lens which minifies the image by half.

b. Preprocessing

The qualities of retinal images that are obtained using fundoscopy may differ due to non-uniform illumination of images. This may also occur due to number of other factors such as eye movement and retinal color variations. Hence color normalization is a necessary procedure that needs to be performed before image analysis in order to make the image intensity uniform. In this paper, the green channel from the RGB color image is taken and histogram specification18 approach is used in it to normalize the color of retinal images. Histogram specification approach is used to equalize the level of the original image by changing its intensity values. In histogram specification approach, a reference image was taken and its histogram was generated. Then the histograms of all other images are generated and it is tuned to match with the reference image histograms. The location of optic disc is about 3mm to the nasal side of the macula and it is the only part in the retina which is insensitive to light and hence it is said to be called as blind spot. Optic disc is the bright region present in the retina; hence it can be misclassified as drusen or noise during image analysis. Hence removal of optic disc is essential before proceeding on to feature extraction. Initially optic disc segmentation is performed at its preprocessing stage with the help of edge based detection method. Edge detection is used to identify the image pixels that are on the optic disc of the retinal image. Hough transform is used in this process to find the parameters of a particular shape from its edge points. Once the optic disc segmentation is done, removal of optic disc is carried out.

c. Feature Extraction

Image texture provides useful knowledge about the spatial arrangement of color or intensities in the retinal image. In order to classify the color normalized images; several features need to be extracted from the retinal images. In this paper, color and texture based feature extraction is considered. Grey-Level Co-Occurrence Matrix (GLCM) method is used to extract the texture features during feature extraction. GLCM also called as Grey Tone Spatial Dependency Matrix is a combination of how often different pixel brightness values appearing in a retinal image. Using histogram calculation, only the intensity distribution can be known. Hence co-occurrence matrix is used here to know the relative position of pixel with respect to each other. GLCM represents the probability of occurrence of a pair of grey levels (i,j) which separated by a particular displacement d for an angle θ. GLCM determines the relation between two pixels namely reference pixel and neighboring pixel. The sum of all entries given in the GLCM i.e., the number of pixel combinations will be smaller for a given window size.

In GLCM feature calculation (Table 1.), the NPV denotes the neighbor pixel value and RPV denoted the reference pixel value. The features such as Contrast, Correlation, Variance and Angular second moment can be calculated from the GLCM matrices. Contrast is defined as the difference in the visual property of an image that makes an object in the image to be distinguishable from other objects. Correlation gives information about linear dependence between two pixels that are related to each other. Angular second moment or energy is the sum of squares of entries made in the GLCM.

d. Classification Using Improved Multilayer Perceptron Neural Network (IMPNN)

The MLP is a most popular multilayer feed-forward neural network. The adopted neurons configuration, shown in Figure 1, includes 6 neurons, 10 neurons and 3 neurons in input, hidden and output layers, respectively. For prediction problems, The MLP is generally trained with a Back Propagation (BP) learning algorithm by computing the connection weights and biases. The BP learning algorithm, which is largely depends on selection of initial values of weights for faster convergence and a minimum

generalization error, is an extension of the Least Mean Square (LMS) rule. Many training algorithms have been reported in the literature to optimize the generalization errors and convergence speed of the MLP. Recently, extensive research and significant progress have been made in the area of nonlinear system. However, when a neural system is used to handle unlimited examples, including training and testing data, an important issue is how well it generalizes to patterns of the testing data, which is known as generalization ability. Many algorithms have been proposed so far to deal with the problem of appropriate weight-update by doing some sort of parameter adaptation during learning. Singhal and Wu illustrated the application of extended Kalman algorithm which converged quickly compared to BP algorithm but required more computation [9]. Sarkalehm and Shahbahrami suggested several training algorithms such as Gradient Decent algorithm (GDA) with adaptive Learning Rate, Resilient and Levenberg-Marquardt algorithms for MLP to classify Paced Beat (PB), Atrial Premature Beat (APB) and NSR [10]. Suykens and Vandewalle determined output weights of single hidden layer MLP classifier using SVM method [11].

In fact the gradient-based training algorithms often require large iterations so as to evade from being spellbound in local optima and tuning of learning rate. Numerous modifications have been suggested to overcome the limitations of the gradient-based algorithm. The evolutionary approaches such as Genetic algorithm, Ant Colony Optimization, artificial bee colony, Cuckoo search, PSO are usually being used in avoiding local minima and improving convergence rate of training algorithm [12-14]. In latest years, swarm intelligence algorithm such as PSO has been applied to solve real life problems in the area of optimization [14].

Particle swarm optimization

The PSO algorithm replicates social intelligence of particle swarm namely flock of birds and school of fishes. PSO is most popular among other evolutionary algorithms because of ease of implementation and requirement of tuning of few parameters. PSO has recently been employed in the field of an optimization problem such as training of neural network [15].

In many literatures, the PSO has been proposed as an effective tool for training neural networks [16]. The basic PSO often get trapped in local optima and resulted in poor convergence. To efficiently control the local search and convergence to the global optimum solution, weights are introduced in addition to the time varying inertia weight factor in PSO to estimate the new velocity of each particle and particles are reinitialized whenever they are stagnated in the search space [17].

The particle of the PSO possesses two characteristics namely position and velocity. A solution of any optimization problem contains updating of personal position and velocity in response with cognitive and social experience [14].

At current iteration time (t), current velocity v_{ij} and new position x_{ij} are modified using equation (1) and equation (2) respectively

$$v_{ij}(t+1) = w(t)v_{ij}(t) + c_1 r_1 \left(p_{ij}(t) - x_{ij}(t)\right) + c_2 r_2 p_{gj}(t) - x_{ij}(t)) \qquad (1)$$

$$x_{ij}(t+1) = v_{ij}(t+1) + x_{ij}(t) \qquad (2)$$

Where $w(t)$, c_1 and c_2 , r_1 and r_2 , $p_{ij}(t)$ and $p_{gj}(t)$, $x_{ij}(t)$ represent inertia weight, cognitive and social acceleration coefficients, random variables, personal best position, global best position and previous personal best position respectively.

The inertia weight may be randomly chosen. In improved PSO, inertia weight can be computed using time linear decreasing method. Equation (3) gives inertia weight as follows:

$$w(t) = w_{max} - \frac{w_{max} - w_{min}}{T} * t \qquad (3)$$

Where w_{max} , w_{min} T and t represent maximum and minimum value of inertia weights, maximum iteration and

current iteration respectively.

The performance of PSO is dependent to the proper tuned parameters that results in the optimum solutions. Normally, cognitive (c_1) and social acceleration coefficients (c_2) are randomly selected to constant values. If value of c_2 is selected higher than value of c_1, the PSO will converge prematurely.

Initially choosing high c_2 and small c_1 will make particles to move towards optimum solution. As optimization progresses, the values of c_1 and c_2 will get modified, which direct the particles to the global solution [18]. The acceleration coefficients are determined according the following equations (4) and (5) [19].

$$c_1(t) = \left(c_1^{'} - c_1^{"}\right) * \frac{i}{i_{max}} + c_1^{"} \quad (4)$$

$$c_2(t) = \left(c_2^{'} - c_2^{"}\right) * \frac{i}{i_{max}} + c_2^{"} \quad (5)$$

Where c_1 and c_1, c_2 and c_2 are minimum and maximum values of cognitive coefficients, minimum and maximum values of social coefficients respectively.

In the simulation, the parameters of PSO algorithm are set initially as shown in Table 1. Each particle possesses fitness value and fitness of the particle is measured by a fitness function. In this approach, mean squared error is used as the fitness function to test the performance of individual particle.

The fitness of kth particle at tth iteration is assessed using equation (6).

$$f_k(t) = \frac{1}{P}\sum_{n=1}^{P}[O_n - O_n^{'}]^2 \quad (6)$$

Where P, O_n and $O_n^{'}$ denote number of training datasets, desired output and actual network output, respectively.

A personal best position pbestk and a global best position gbestk of kth particle will be adapted in tth iteration using equation (6).

$$pbest_k(t) = \begin{Bmatrix} p_k(t) f_k(t) \le f_k(t-1) \\ pbest_k(t) f_k(t) > f_k(t-1) \end{Bmatrix} \quad (7)$$

$$gbest_k(t) = best\{pbest_k(t)\}_{k=1}^{k} \quad (8)$$

IV. EXPERIMENTAL RESULTS

The fundus images are obtained from the database. These images are RGB model images of the fundus.

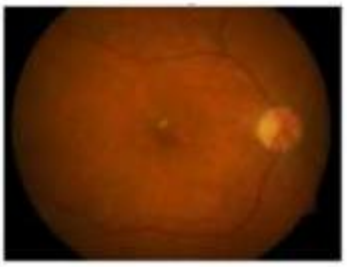

Figure 3: Fundus Image from Database

The images in the RGB model are converted to HSI model in Matlab, in order to work on it in it"s grey scale

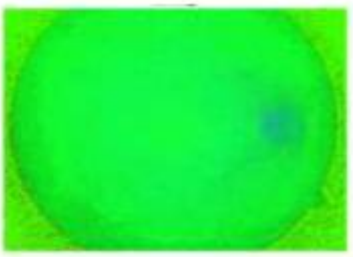

Figure 4: HSI Model

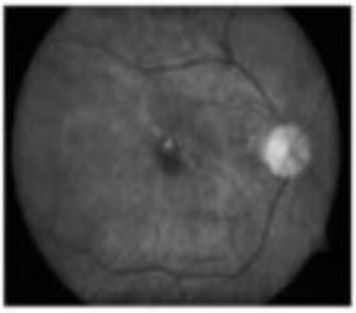

Figure 5: Image after CLAHE

Figure 6: Optimal Disc Segmentation

Figure 7: Classification Result

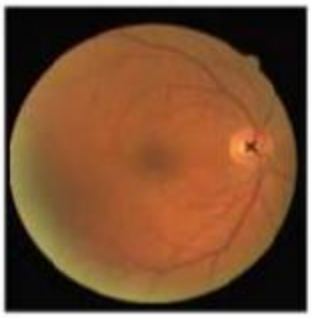

Figure 8: Optic Disc Detection

In this paper, Color normalization using Histogram processing has been used in normal fundus images in order to uniformly redistribute the intensity of images. Usually optic disc present in retinal images will be misclassified as noise. Hence, in the proposed method, optic disc removal is performed with the help of edge based detection method. Detecting exudate after segmenting optic disc will be helpful in order to provide better result. After removing the optic disc, GLCM method is used to extract the texture features of retinal images. After extracting the texture features, SVM classifier is used to detect the exudates from abnormal images. By using SVM classifiers in order to detect exudate regions, classification accuracy of about 92% is achieved. The comparison of vectorised and non-vectorised GLCM feature computation based on their execution and CPU time is taken (Figure 4). Here the computation is performed based on 10 different GLCM inputs and it is shown from the graph that the CPU time consumption in order to gather autocorrelation and contrast features and the execution time for correlation features is low when compared to other features.

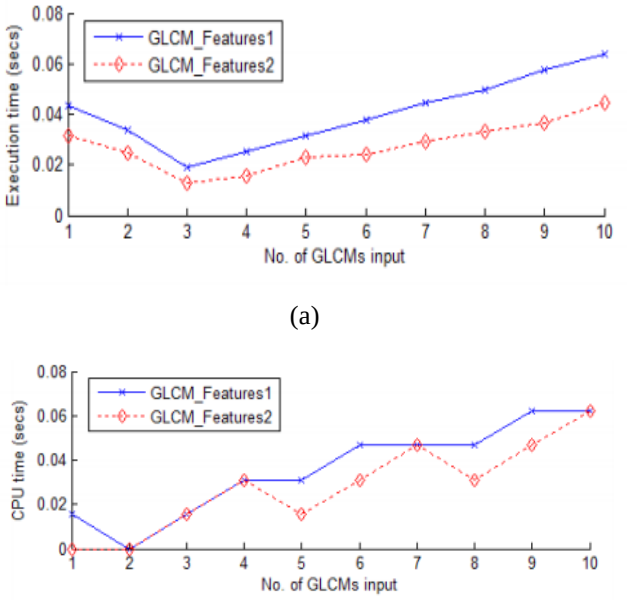

Figure 9: Comparison of Vectorised and Non-vectorised GLCM Features

V. CONCLUSION

This paper proposes an intelligence method for detecting initial lesions that appear in the retina due to diabetic retinopathy. Normal color fundus images considered are of non-uniform illumination. Hence color normalization is performed at its preprocessing stage for the uniform distribution of intensity of color fundus retinal images. Optic disc segmentation is done using Hough transform method. At the next stage, GLCM is used to extract the texture features from the color retinal images. Feature extraction and classification provides better results for the detection of lesions using digital fundus images. Multilayered Perception integrated with particle swarm optimization based classifier is used here to detect abnormal images and it presents better classification accuracy when compared to previous techniques. This method can be used for diabetic retinopathy screening based on the lesion detection. Further test need to be carried out to detect other DR related lesions in the retinal images.

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