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Improving Efficiency of Diabetic Retinopathy Classification Using Machine Learning

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ABSTRACT: Diabetic macular edema results from abnormal accumulation of fluid in the central retina and indicates compromised function in one or both of the blood—retinal barriers. It is a common sequel of many ocular conditions and the main cause of visual loss in diabetic retinopathy. Diagnosis of diabetic macular edema is best made by slit lamp bio microscopy of the posterior pole using a contact lens. It is however insensitive to small changes in retinal thickness, for example, a subtle CSME is difficult to appreciate, or small intra retinal cystoid spaces or subtle epiretinal changes. Fundus Fluorescein Angiography (FFA) can assess macular edema qualitatively and OCT provides quantitative measurement of foveal thickness. Therefore, the patho- physiologial aspect of can be determined by FA and anatomical features such as the extent of retinal thickening and the retinal layer involved can be assessed best using OCT.Fluorescein angiography has been available as an aid in the diagnosis and assessment of many ophthalmic conditions since its introduction by Novotny and Alvis in 1961 including diabetic maculopathy. It is useful in demonstrating the leakage of fluid, consequent to the breakdown of the blood retinal barrier. Simple leakage on angiogram may not always be associated with retinal thickening in the macula. Reports suggest that actual macular thickness is better correlated with loss of visual acuity. It is in all probability more important in a case of a doubtful macular ischemia, when the foveal perfusion is in question was useful in differentiating between cystoids macular edema and ischemic maculopathy and whether laser therapy indicated. Optical coherence tomography (OCT) provides valuable information about retinal thickness and extent of retinal edema in DME. It is also helpful in monitoring the response to treatment in DME (Laser and/ or Intravitreal Triamcinolone Acetonide injection/Anti VEGF). The role of OCT in assessment and management of diabetic retinopathy has become significant in understanding the vitreoretinalrelationshipandtheinternalarchitectureof the retina. In patients with refractory DME, taut posterior hyaloid membrane (TPHM) is readily recognized by OCT scan. Focal vireo-retinal adhesions, sub foveal subretinal fluid, and the axial distribution of fluid in an edematous macula that cannot be identified on clinical examination can also be evident on OCT. In this work, we are proposing the use of machine learning to improve the classification accuracy of diabetic retinopathy.

KEYWORDS: Retinopathy, clinical, ophthalmology, machine learning, classification

I. INTRODUCTION

The main eye condition associated with diabetes is called diabetic retinopathy and is, the main cause of blindness. The earliest signs of this disease include damage to retinal blood vessels and then the formation of lesions such as exudates and red spots. Such lesions are normally detected manually by clinicians in intensive and time-consuming processes. Computer- aided detection and grading of such conditions could facilitate an immediate and accurate diagnosis. Whilst some progress has been made to detect these diseases, there is no complete system for automated detection and grading of diabetic retinopathy and this is hindering the development of automated methods to support assessment of diabetic eye disease. The aim of this work is to develop computer algorithms that can be used in the medical screening system for evaluating the condition of the retina leading to successfultreatment.

This work comprises five stages:

1) image pre-processing
2) retinal structureextraction
3) hard exudatedetection
4) red lesiondetection
5) grading of diabetic retinopathy.

The aim of image pre-processing is to prepare the image with better quality where shade correction using morphological processes and contrast enhancement using fuzzy logic-based

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method are applied to the image. In the retinal structure extraction, multi-scale morphological technique and classification procedure are proposed for blood vessel detection. Vasculature loop-based method for the optic disc localisation is proposed, while for fovea localisation, a method based on its features and geometric relationships with the other retinal structures is developed. These methods have the advantage of lower computational complexity and competitive performance compared to the existing relatedmethods.

A novel coarse to fine strategy is proposed to detect hard exudates, where a local variation operator is used to calculate the standard deviation around each pixel followed by automated thresholding, morphological operations, and classification to segment coarsehard exudates. To fine-tune the result of coarse hard exudates, two region-based segmentation techniques are investigated to detect fine hard exudates.

The significance of this method is manifested by its superior performance, lower computational complexity (compared to the current state of the art) and the ability to deal with a variety of image qualities. A novel red lesion detection method is proposed using mathematical morphology to segment candidate red lesions followed by refining them from traces of retinal structures and then a classification based on red lesion features is used to detect red lesions with high degree of discrimination between genuine red lesions and artefacts and as a result its detection performance has proved to be favourable.

Grading of diabetic retinopathy is a very important stage after the detection of retinal lesions to evaluate their severity and to decide appropriate treatment. The most reliable medical approaches to diabetic retinopathy grading were investigated to build a novel computer-aided model for automated grading based on the clinical criteria and results of the earlier lesion segmentation. This model quantifies the nature, extent and spatial distribution of all the detected features and provides a clinical grading assessment. This is among the first of such models published and a such the novelty is considered to be one of the main contributions of this work.

In this paper, we have compared various systems for DR image processing, and identified the algorithms used for a given application, the next section describes the algorithms in brief. Finally, we conclude the paper with some interesting observations about the compared algorithms and proposed the future work which researchers can perform in order to further analyse these algorithms.

II. LITERATUREREVIEW

Kozak et al showed that both FFA and high-resolution OCT are highly sensitive techniques and correlate well in detection of Macular edema. However, there is a small chance that when performed alone they might miss existing subtle macular edema.[7]

Lucio et al concluded that the cross-sectional area of retinal tissue between the plexiform layers in cystoid macular edema, as imaged by OCT, is the best indicator of visual function at baseline. Further prospective treatment trials are needed to investigate this parameter as a predictor of visual outcome after intervention [8].

Yeung L et al revealed that pathologic changes on SD-OCT correlated well with FFA findings. Loss of inner retinal layers was specifically correlated with capillary non perfusion and severe ischemia. Judgment of whether management of Diabetic macular edema based on fine retinal structural changes influences clinical outcomes must be reserved pending further investigation with prospective trials [9].

Horrii et al provide a novel interpretation of flourescein pooling and OCT characteristics of cystoid spaces and serous retinal detachment in diabetic macular edema and suggested several mechanisms by which the blood retinal barrier is disrupted and concomitant edematous changes develop[10]

Turgut et al concluded the presence of serous macular detachment and high HbA1c levels in the patients with diabetic CME may be indirectly suggestive of retinal pigment epithelium dysfunction documented by OCT and FFA [11].

Ota et al correlate the spectral domain OCT findings of serous retinal detachment (SRD) and hyper reflective dots may be associated with the sub foveal deposition of hard exudates during follow up [12].

Irimia et al concluded that OCT contributes in understanding the anatomy of diabetic macular edema and the intra retinal damage and it is the technique of choice for the follow up of diabetic macular edema and for monitoring the effect of therapies [13].

III. PROPOSED SYSTEM

The overall diabetic retinopathy detection process may be broken down into three sub -processes:

1. Image/signal acquisition and processing this sub-process involves capturing an image of the retina and converting it to a digital format.
2. Detection of exudates: a computer system is used to verify and identify the exudates

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3. Representation: the unique features of the retina are presented as a template.

The image acquisition and processing phase is the most complicated. The speed and ease with which this sub-process may be completed largely depends on user cooperation. To obtain a scan, the user must position his/her eye very close to the lens. To safeguard the quality of the captured image, the user must also remain perfectly still at this point. Moreover, glasses must be removed to avoid signal interference (after all, lenses are designed to reflect). On looking into the scanner, the user sees a green light against a white background. Once the scanner is activated, the green light moves in a complete circle (360 degrees). The blood vessel pattern of the retina is captured during this process. Generally speaking, three to five images are captured at this stage. Depending on the level of user cooperation, the capturing phase can take as long as one minute. This is a very long time compared to other biometric techniques. The next stage involves data extraction. One very considerable advantage of retinal recognition becomes evident at this stage. As genetic factors do not dictate the pattern of the blood vessels, the retina contains a diversity of unique features. This allows up to 400 unique data points to be obtained from the retina. For other biometrics, such as fingerprints, only 30-40 data points (the minutiae) are available. During the third and final stage of the process, the unique retina pattern is converted to an enrolment template. At only 96 bytes, the retina template is considered one of the smallest biometric templates. The block diagram of the designed retina recognition system is given in Fig.4.1. The image recognition system includes retina image acquisition and recognition. During image acquisition, the retina image in the input sequence must be clear and sharp. Clarity of the retina's minute characteristics and sharpness affects the quality of the iris image. A high- quality image must be selected for retina recognition. The retina recognition includes pre-processing and neural networks. In pre- processing, the retina is extracted from an eye image and normalized. Normalized image after enhancement is represented by the feature vector that describes gray-scale values of the retina image. For classification neural network is used. Feature vector becomes the training data set for the neural network.

The retina recognition system includes two operation modes: training mode and online mode. At first stage, the training of recognition system is carried out using greyscale values of retina images. After training, in online mode, neural network performs classification and recognizes the patterns that belong to a certain retinal image.

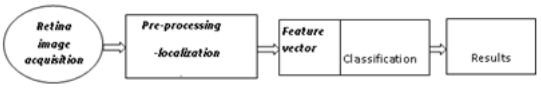

Fig. 4.1 A block diagram of the retinopathy recognition system

The starting point of the project was the creation of a database with all the images that would be used for training and testing. The image database can have different formats, but the images in this thesis are

.jpg and. bitmap format. This meant that they have same sizes and same resolutions, and then the value of the images pixel taken after the gray scaling and scale down stages, and combined in a .dat file acting as a database for the program.

Extracted RGB retina images are transformed to greyscale images. A grayscale image is simply one in which the only colours are shades of grey. The reason for differentiating such image from any other sort of the color image is that less information needs to be provided for each pixel. In fact a gray color is one in which the red, green, and blue components all have equal intensity in RGB space, and it is necessary to specify a single intensity value for each pixel, as opposed to the three intensities needed to specify each pixel in all color images. Often, the grayscale intensity stored as an 8-bit integer giving 256 possible different shades of gray from black to white. Grayscale images are very common, in part because much of today's display and images capture hardware can only support 8-bit images. In addition, grayscale images are entirely sufficient for many tasks so no need to use more complicated and harder to process colour images.

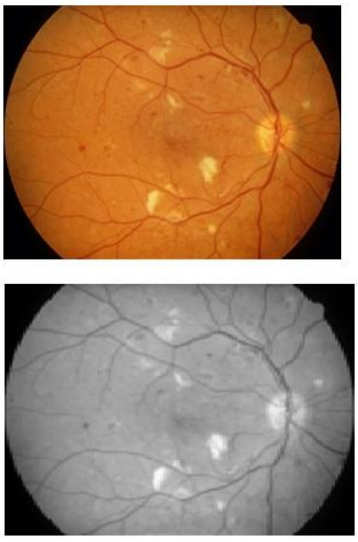

Fig.4.RGB(a)andgreyscale(b)ofretina image

International Journal of Advances in Engineering and Management (IJAEM)
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Figure 4 (a) shows coloured RGB retina image and after transforming the grayscale image of retina (b) . Obtained greyscale image is scaled. Scaling is defined as the increase or reduction of image size by a fixed ratio We first smooth the image by convolution with a spatially resolution. However, for a scale down by a specific factor in the respective directions. The image width to height ratio of thereduced results remain equal to that of the original image width to height ratio. Scaling is applied for decrease of input data size.

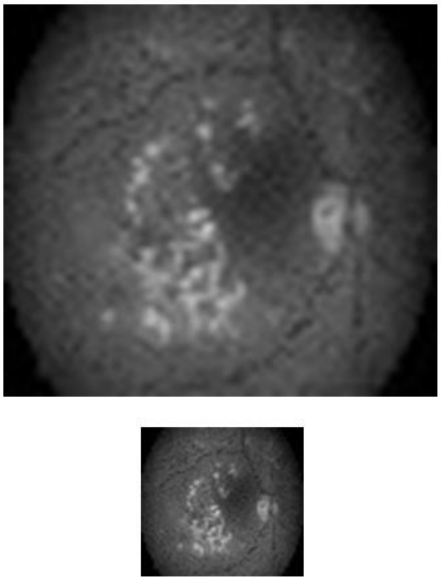

Figure 5 Scale Down of Retina Image Scaled image is segmented and averaged. This operation is based on averaging pixel values within segments of a pattern, thus yielding one average pixel value per segment. The output of each segment is forming feature vector and entering to the neural network input.

The neural network based diabetic retinopathy recognition system is modelled in Matlab. Figure 6 describes the network structure of recognition system. The network is initially trained without noise for a maximum of 10000 epochs or until the network sum-squared error falls beneath 0.01. P = double(P)

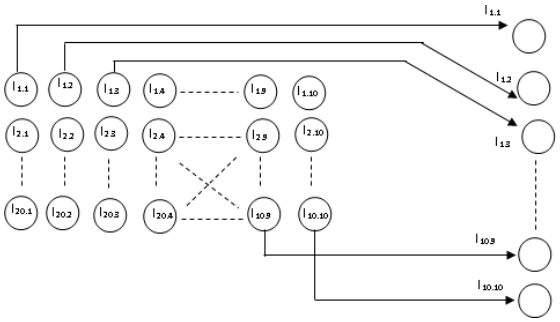

Fig.6Initializationtheparametersof Neural Networks

DR recognition uses a three-layer neural network to learn and recognize pattern (Input, Hidden, and Output layer). The retina image is digitized and transformed into grayscale values. These greyscale values are input for neurons of input layer. The output of the input neurons are input of the hidden layer, each possible answer is represented by a single output neuron. As in most networks, the data is encoded in the links between neurons.

Neural network used for recognition of retinal images has three layers: input, hidden and output layers. Fig. 4.6 describes the neural network structure used for recognition of retinal images. The neuron in the first layer receives input signal. The first layer is used for distributing input signals. These signal are multiplied to weight coefficients and entered to the neurons of second layer. In second layer activation function is applied to transform output signal of neurons of second layer. Exponential sigmoid function is used as activation function in neurons of second and third layer. The output signal of second layer will be input for the neurons of the third layer. The determination of output signal of third layer is performed as like as second layer. After determined output signal the training of neural network start. Figure 7 describes Matlab results of used Neural Network structure.

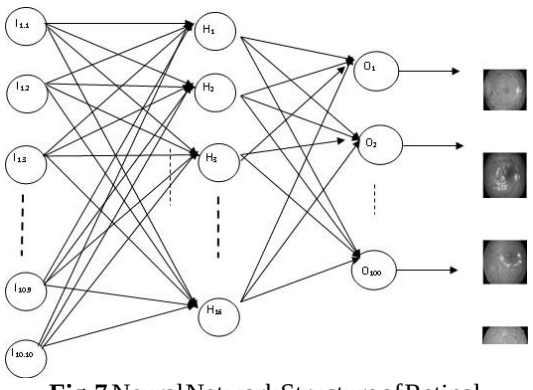

Fig.7 Neural Network Structure of Retinal Recognition Results.

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For training of neural network backpropagation algorithm is applied. Training of neural network used recognition of retinal images is shown in Figure. 7. As shown in figure training is performed for 500 epochs, with accuracy of 0.001. 221 epochs are used for training and the required accuracy of training is obtained.

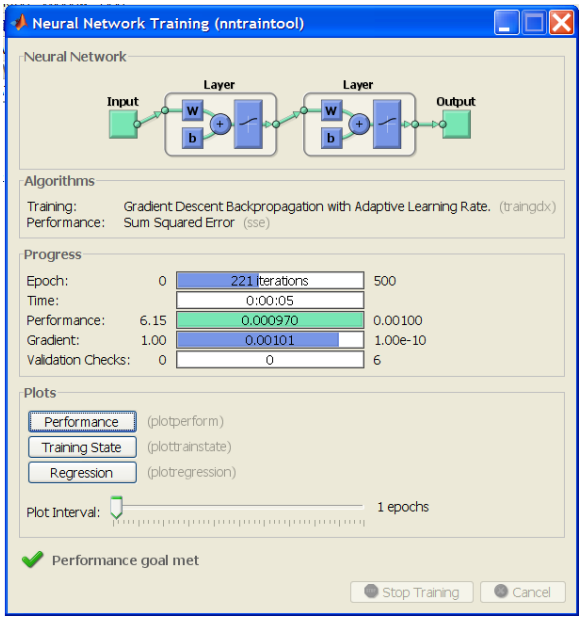

Fig.8 Matlab graphic editor demonstrating neural networktraining

Figure 8 demonstrates Matlab graphical editor describing the learning process of neural networks.

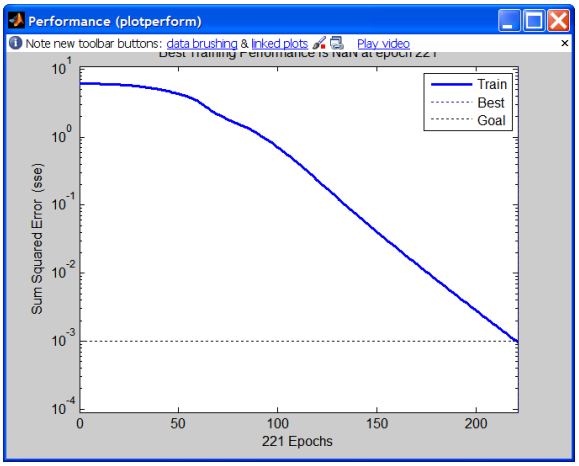

Figure 8 Performance of Neural network training

Figure 8 demonstrates Matlab performance editor that shows us plots the training, validation, and test performances given the training record TR returned by the function train.

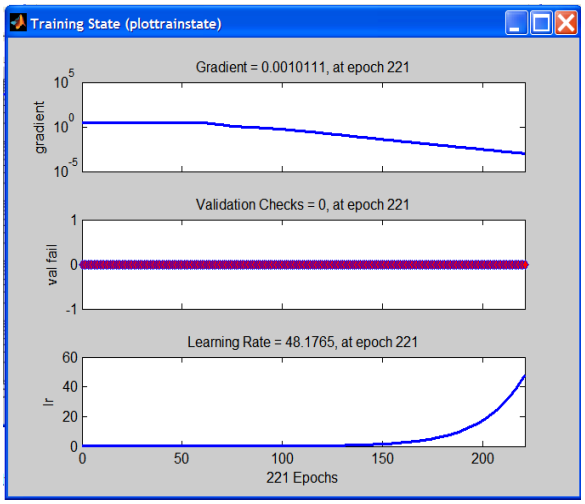

Fig. 9 Training state of neural Network Figure 9 demonstrates Matlab graphical

editor describing the training state of neural networks. The plots describing the values of gradient, validations, and learning rates are given. The results are showcased in the next section

IV. RESULT ANALYSIS

In biometrics based system, the accuracy of implemented algorithms is very important and they must be tested properly. In this thesis DRIVE dataset is used in order to check the validity and accuracy of proposed system. Figure 4.11 shows different images from DRIVE database.

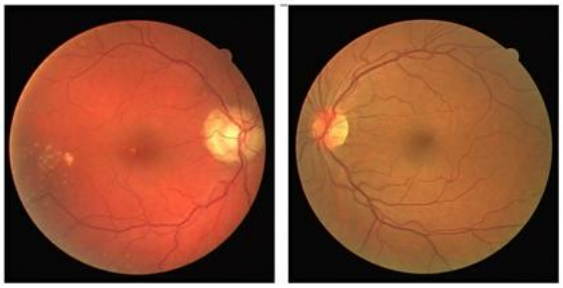

Fig. 4.10 Retina images taken from DRIVE database

DRIVE [41] database is publicly available database to check the accuracy of retinal pattern extraction and these databases also include ground truth for vascular segmentation. Other databases are STARE[42] and VARIA [21]. VARIA is a database that is formed for retinal recognition systems. It includes 233 retinal images with a resolution of 768x584, from 139 different persons. The proposed retinal recognition system is tested on total 40 images. The 40 retinal images from DRIVE database are taken. After NN training the recognition of images have been done. The 97.5%

recognition rate obtained with neural network system. Table I shows the recognition rate of proposed method on DRIVE databases.

The recognition of the same images have been done in [4] also. The same recognition rate obtained by using vascular detection of retinal images.

Table 4.1 Recognition Rate

Database	Total Images	Correctly Recognized	Wrongly Recognized	Recognition Rate
Drive	40	39	1	97.5 %

The simulation results show that Neural Network based system achieves a recognition rate of 100% for DRIVE database. Retinal image consists of a unique pattern in each individual and it is almost impossible to forge that pattern in a false individual. However, its high cost and acquisition related drawbacks have prevented it from making a commercial impact. This thesis presented a retinal pattern based biometric system. In designed system, the acquired retinal image is preprocessed to remove background and noise and then grayscale values of pattern is extracted. A feature vector is formed. This feature vector is used for identification of retinal images. Results demonstrated that the proposed system can be used in a biometric based personal identification system.

V. CONCLUSION

The structure of DR system of retinal images is designed. Preprocessing is applied to transform retina images to greyscale values and extract input features from the retinal images. These features are input signal for Neural Network. Neural Network is applied to classify retina patterns in a recognition step. The structure of Neural Network used retina recognition system is proposed. The operation principle and learning algorithm of neural network-based retina recognition system are presented. For the designed structure the learning algorithm is designed. The Back Propagation is applied to train neural networks. Implementation of DR recognition system is done by using MATLAB package. The located retina images after pre-processing are represented by a data set. Using this data set as input signal, the neural network is used to recognize the retina patterns. The recognition accuracy for trained patterns 97.5%was achieved.

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