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AN AUTOMATIC GRADING SYSTEM OF SEVERITY LEVEL FOR DIABETIC RETINOPATHY USING CNN CLASSIFIER

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ABSTRACT

The human eye is an organ that reacts to light and has several purposes. As a sense organ, the human eye allows vision. The retina is a light-sensitive layer at the back of the eye that covers about 65% of its interior surface. Rodand cone cells in the retina allow conscious light perception and vision including colour differentiation and the perception of depth. A disease called diabetic retinopathy which is affected in the retina to the diabetic patients suffering with the diabetes more than 10 years. Diabetic Retinopathy (DR) is the utmost common diabetic eye disease and a leading reason of blindness. It is caused due to injury in the blood vessels of the retina. The brittle blood vessels may enlarge and leak fluid which is called as exudates. Exudates are fluids, cells, or other cellular substances that are slowly discharged from blood vessels usually from inflamed tissues. It can be a clear fluid which is composed of serum, fibrin, and white blood cells. Diabetic retinopathy is identified by the ophthalmologists by the dilation method. The dilation method is meant by pouring eye drops into the patient's eye and it causes irritation to the patients. In order to protect the patients from the irritation and blindness, an automatic method is developed to detect these exudates and to measure the severity of the diabetic retinopathy. The exudates are detected by using the JSEG algorithm and the severity level grading is done by using Cascade Neural Network (CNN) classifier algorithm.

Keywords: diabetic retinopathy, exudates, principle component analysis, cascade neural network classifier.

INTRODUCTION

Diabetes is a major issue in our life caused due to increase in the sugar level content of our body because of lack of insulin. High blood sugar (glucose) enhances the risk of eye troubles from diabetes. In fact, diabetes is the leading reason of blindness in adults of ages 20 to 74. For diabetes, this high blood sugar causes the lens of the eye to enlarge, which changes the observing ability of the eye. To correct this category of eye troubles, the glucose level should be controlled. It may endureas long as three months after the glucose level is well controlled for the vision to completely get back to normal. Blurred vision may also be a sign of more dangerous eye problem with diabetes. The three major eye problems that can arise for the people with diabetes are cataracts, glaucoma, and retinopathy. Diabetic eye disease signifies to a group of eye problems which people with diabetes may face as a difficulty of diabetes. All can cause severe vision loss or even blindness. Diabetic retinopathy is the utmost ordinary diabetic eye disease steering to the vision loss. It is caused by variations in the blood vessels of the retina.

For certain people with DR, blood vessels may enlarge and leak fluid. For some other people, abnormal new blood vessels nurture on the surface of the retina. The retina is the perceptive tissue at the rear of the eye. A healthy retina is essential for good vision. Blood vessels harmed from DR can cause vision loss in two modes: Fragile, abnormal blood vessels can arise and oozeblood into the centre of the eye so that the vision is blurred. This is called proliferative retinopathy and is the most progressed stage of the disease.

Fluid can ooze into the center of the macula which is the part of the eye where sharp and straight-ahead vision occurs. The fluid causes the macula swelling to blur the vision. This condition is known as macular edema. It can happen at any stage of DR, even though it is more likely to occur as the disease proceeds. About half of the people with proliferative DR also have macular edema.

Diabetic retinopathy has four stages: 1. Mild Non-proliferative Retinopathy- This is the earliest stage, where them icroaneurysms occur. They are small swelling that may break and allow blood to leak into nearby tissue. 2. Moderate Non-proliferative Retinopathy- As the disease progresses, some of the blood vessels that nurture the retina are clogged. 3. Severe Non-proliferative retinopathy-Many of the blood vessels are clogged, denying several areas of the retina with their blood supply. These areas of the retina deliver signals to the body to grow new blood vessels for sustenance. 4. Proliferative Retinopathy –This is the advanced stage, where the signals sent by the retina for sustenance cause the growth of new blood vessels. These additional blood vessels are abnormal and fragile. They grow near the retina and near the surface of the clear, vitrifiedgel filled inside of the eye. These blood vessels do not cause any symptomor vision loss. However, they have thin, breakable walls. If they oozeblood, dangerous vision loss and even blindness can result.

The premature signs of DR are oozing blood vessels, retinal enlargement (macular edema), pale fatty sedimentson the retina–signs of oozingblood vessels, harmednerve tissue and any modifications to the blood vessels.

DR can be noticed from dilated retinal images. Dilated images are taken by dropping chemical solution into patients' eye. This permits the ophthalmologists to see

ARPN Journal of Engineering and Applied Sciences

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beyond the inside of eyes to examine for signs of the disease. An extra ordinary magnifying lens is used to investigate the retina and optic nerve for indications of wound and other eye problems. After the assessment, the detailed vision may stay blurred for several hours. Tonometry is an instrument which computes the pressure inside the eye. These methods cause irritation to the patient. Hence, an automated method is developed for detection of exudates from the non-dilated colour fundus retinal images using morphological process. The image containing exudates are shown in Figure-1.

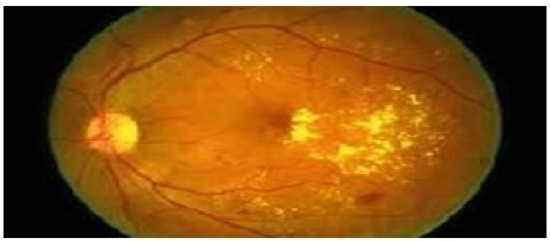

Figure-1. Image containing exudates.

An automated method was proposed using FCM technique for exudates segmentation and morphological methods for reconstruction (Akara Sopharak *et al.* 2008). The exudates were detected using the neighbourhood connected component labeling and the severity level is assessed by the Support Vector Machine classifier (Mahendran Gandhiand R. Dhanasekaran, 2014).The exudates are detected using the Contour technique for locating the optic disc and weighted FCM for segmenting the exudates (Giri Babu Kande *et al.* 2008).Athresholding approach is used to detect the lesions, optic disc and vascular network and a neural network classifier was then used to assess the severity level of the disease(Krishnan and kumar, 2008). A method uses morphological operators to detect the microaneurysms, Haemorrhages, Exudates and blood vessels but the severity level of the diabetic retinopathy was not examined (Sai Prasad Ravishankar *et al.* 2009).Three different types of Neural Networks were examined and compared to detect Exudates in retinal images. Those types of neural networks are Multi-Layer Perceptron, Radial basis function networks and Support vector machine classifiers (Maria Garcia *et al.*2009).The author proposed an innovative method using the GA/PSO method for feature extraction and Probabilistic Neural Network (PNN) Classifier for the classification of Normal, NPDR and PDR (Mookiah M.R.K *et al.* 2013).A new method was used to detect macula swelling by analysing multiple view retinal fundus images. The method used three stages as pre-processing technique, registering multiple retinal fundus views and a dense pyramidal optical flow is calculated to build a naive height map of the macula (Giancardo.L *et al.*2011). The computational intelligence and pattern recognition were used to analyse the diabetic reinal fundus image along with machine learning techniques (Alireza Osare *et al.* 2009).The mathematical morphology was implemented in two stages for detecting exudates in retinal color fundus images as coarse and fine detection (Daniel Welfer *et al.* 2010). The exudates were detected by using Fuzzy Morphology (Atif Bin Mansoor *et al.* 2008). A novel integrated approach was implemented using dynamic thresholding and an edge detector was applied to detect the sharp edges of the exudates (Sagar *et al.* 2007).A Multi-space clustering is used to differentiate hard exudates and soft exudates (Keerthi Ram C. and Jayanthi Sivaswamy, 2009). An automated method was proposed in which sobel edge detector combined with thresholding to produce the best qualitative segmentation to detect choroidal neovascularisation from retinal fluorescein angiograms in exudative age related Macular Degeneration(Brankin.E *et al.* 2006). A thresholding technique based on the assortment of areas to detect exudates was applied. A patch of size 256 x 192 pixels is chosenover the area of interest. Soft exudates were detected using Global thresholding, and the hard exudates are detected by local thresholding (Phillips.R.P *et al.*1993).A method was introduced to detect main features of fundus images such as optic disc, fovea, exudates and blood vessels. Hough transform was used to find the optic disc. Fovea was detected by using its spatial relationship with the optic disc. Exudates were found using grey level variation and their contours were discriminated by means of morphological reconstruction techniques and the blood vessels were highlighted using bottom hat transform and morphological dilation after edge detection (Noronho *et al.* 2006). The morphological operators and SVM classifier were used to detect the exudates and itsseverity level. Morphological operators were used for the detection of exudates and SVM classifier was used to measure the severity of the disease diabetic retinopathy (MahendranGandhi and R. Dhanasekaran, 2013).A new automated method in which exudates are identified by FCM and its severity level is assessed by means of CNN Classifier (Mahendran Gandhi *et al.* 2014). The author reported a method using color features on a Bayesian statistical classifier to classify each pixel into lesion or non-lesion classes (Wang *et al.* 2000). The author detected the exudates using morphological operator and determined the severity level of the disease using PNN classifier (Mahendran Gandhi *et al.* 2014).

In this paper, JSEG segmentation is presented for the automatic detection of exudates from the non-dilated retinal images. Since dilation is not required for this process, it reduces the effects of those mydriatic drugs. The non-dilated retinal images are fed as input to the Pre-Processing stage. It corrects the problem of illumination variation that occurred during image acquisition. The pre-processing stage involves colour space conversion, image restoration and enhancement. The result of this stage is fed to the segmentation stage. JSEG algorithm is used for segmentation. The feature of the segmented image is extracted by the Principle Component Analysis (PCA) and the CNN classifier makes use of this classifier to detect the severity.

ARPN Journal of Engineering and Applied Sciences

METHODOLOGY

The methodology of the proposed work shown in the Figure-2 starts from the acquisition of non-dilated retinal images, which are fed as input to the pre-processing stage. The preprocessing stage includes image enhancement, filtering and color space conversion. The preprocessed image is applied with JSEG algorithm to detect the exudates with respect to the macula for identifying the severity level of diabetic retinopathy.

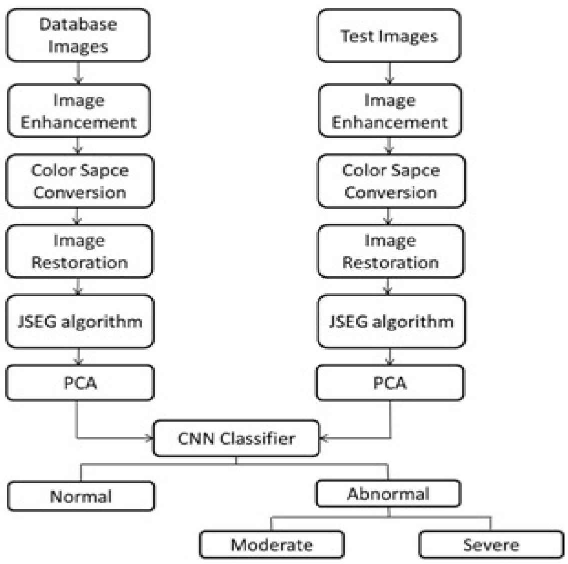

Figure-2. Methodology of proposed work.

Image acquisition

The first stage of any image processing technique is the Image acquisition stage. Digital image acquisition is the process of capturing the digital images. The images for this work are collected from the STARE and MESSIDOR databases. The non-dilated retinal image shown in the Figure-3 is fed as input to the pre-processing stage.

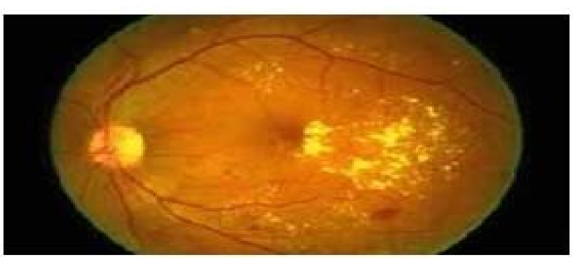

Figure-3. Original image.

Preprocessing

Preprocessing stage is composed of enhancement, restoration and color space conversion. Image enhancement is the process of adjusting digital images so that the quality of the images is improved and they are more suitable for display or further image analysis. The objective of image enhancement is to improve the interpretability or perception of evidence in images for human viewers, or to offer better input for other computerized image processing techniques. The RGB image is entirely enhanced before the process. Image enhancement is done by histogram equalization and the enhanced image is shown in Figure-4(a). The histogram formation is done by means of three steps:

- Separate the color image into red channel, blue channel and green channel.
- Take histogram for each channel.
- Plot the three channels in same axis.

Converting color space is the main step in this process. RGB image is converted into Lab color space. Lab is a color-opponent space in which L states the dimension for lightness and (a) and (b) denote the color-opponent dimensions, based on nonlinearly compacted CIE XYZ color space coordinates. The image converted into Lab color space is shown in the Figure-4(b) and it is used here to approximate human vision. This Lab color space image is converted into the gray scale image.

The aim of image restoration is the noise removal and to recover the original quality of the images. The simplest possible approach for noise removal is filtering techniques such as low-pass filter or median filter. Here, the median filter is applied to the gray scale image because it preserves edges while removing noise under specific conditions. In a median filter, a window slides horizontally the image, and the median intensity measurement of the pixels within the window becomes the output intensity of the pixel being treated. Similarly every pixel value is swapped with the median of all the pixels which are under the shape of neighbours called the window. The window slides, entry by entry, over the entire image. Median is just the middle value after all the entries in the window are organized statistically. For an even amount of entries, there is more than one probable edian. The result of the image restoration is shown in the Figure-4(c).

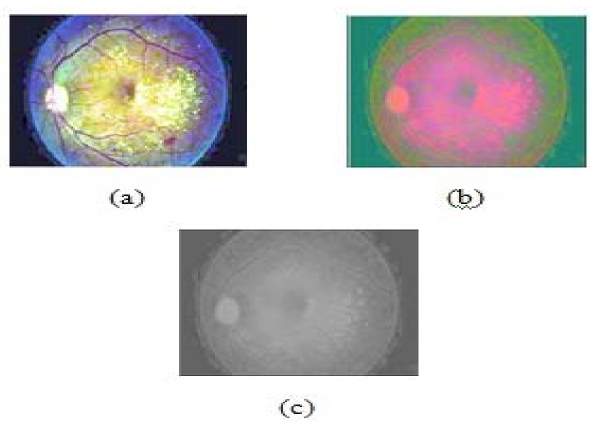

Figure-4. (a) Enhanced image (b) LAB color space image (c) Filtered image.

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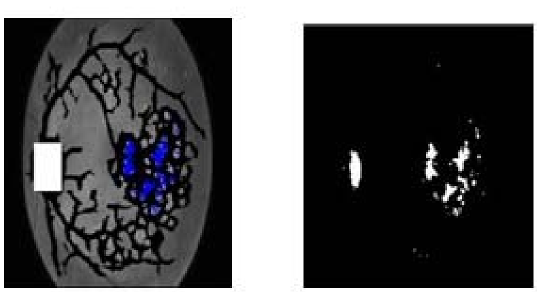
ARPN Journal of Engineering and Applied Sciences

Image segmentation

The pre-processed image is applied with the JSEG algorithm. The image segmentation involves subdividing an image into essential parts, or separating definite aspects of an image. The unsupervised segmentation method of color-texture regions in images and videos is called as JSEG. The objective of this algorithm is to segment images and video into uniform color texture regions (Viswanatha V M *et al*., 2011).

JSEG algorithm

The concept of the JSEG algorithm is to carry out the segmentation process by means of two portions: colour quantization and spatial segmentation. The colour quantization quantizes colours in image into numerous representative classes which are used to differentiate regions in the image. The quantization method is realized in the colour space without considering the spatial distribution of the colours. The corresponding colorclass labels are replaced with the original pixel values and then a class-map of the image is created. In the second portion, spatial segmentation performs on the class-map instead of regarding the corresponding pixel color similarity. The criterion are described in detail (Luciano CássioLulio et al., 2011). The segmented image is given in the Figure-5.



(a) (b)

Figure-5. (a) Exudate detected image. (b) Segmented image.

Feature extraction

Principal component analysis (PCA) is a numerical method that uses orthogonal change to transform a set of remarks of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The quantity of principal components is fewer than or equal to the number of unique variables. This transformation is defined in such a way that the leading principal component has the prime possible variance and each consequent component in turn has the utmost variance possible under the constraint that it is orthogonal to the preceding components. Principal components are ensured to be independent if the data set is jointly and normally scattered. PCA is sensitive to the comparative scaling of the original variables.

PCA is statistically defined as an orthogonal linear conversion that alters the data to a new coordinate system such that the extreme variance by some projection of the data comes to lie on the leading coordinate, the second greatest variance on the second coordinate, and so on.

Consider a data matrix, X, with zero empirical mean , where each of the n rows represents a different replication of the experiment, and each of the columns provides a particular kind of datum. The empirical covariance matrix between the principal components becomes

$$W^T Q W \propto W^T W \Lambda W^T W = \Lambda \qquad (1)$$

where Λ is the diagonal matrix of eigen values $\lambda_{(k)}$ of $X^T X$

Cascade neural network

Cascade Neural Network is architecture of generative, feed-forward, supervised learning algorithm for artificial neural networks. Cascade initiates with a minimal network, then routinely trains and enhances new hidden units one by one building a multi-layer structure. Connection weights as certain an organizational topology for a network and permit units to transmit stimulation to each other. Input units program the problem being offered to the network. Output units program the network's response to the input problem. Cascade combines two concepts: The first is the cascade architecture comprising hidden units which are added only one at a time. The second is the learning algorithm, which produces and connects the new hidden units. For each new hidden unit, the algorithm tries to exploit the significance of the correlation between the new unit's output and the residual error sign of the network. It begins with a minimal network comprising only of an input and an output layer. Both layers are fully united. The algorithm for CNN classifier is as follows:

Step-1: Train all the link sending at an output unit with a usual learning algorithm until the error of the net no longer decreases.

Step-2: Produce the candidate units which are connected with all input units and with all surviving hidden units. Between the puddle of candidate units and the output units there are no weights.

Step-3: Try to exploit the correlation between the stimulation of the candidate units and the residual error of the net by exercising all the links leading to a candidate unit. Learning will take place with an ordinary learning algorithm. The exercising is stopped when the correlation scores no longer develops.

Step-4: Choose the candidate unit with the determined correlation freeze its incoming weights and add it to the net.

Step-5: To alter the candidate unit into a hidden unit, generate associations between the selected unit and all the output units. As the weights leading to the new hidden unit are frozen, a new everlasting feature detector is attained (V M Viswanatha et al., 2011). This algorithm is repeated until the overall error of the net falls below a given value. Then we calculate the Euclidean distance between two color histograms i and j shown as

VOL. 10, NO. 13, JULY 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

$$D_R(i,j) = \|P_i - P_j\| \quad (2)$$

whereP denotes the color histogram vector. The method of region merge is based on the agglomerative method.

RESULTS AND DISCUSSIONS

The non-dilated retinal fundus input images were collected from DRIVE and MESSIDOR databases. A data set of 220 retinal input images out of which 70 normal images and the remaining 150 abnormal images was collected from DRIVE database. Out of 70 normal images, 30 images were used for training and 40 images were used for testing the classifier algorithm. Out of 150 abnormal images, 60 images were used for training and the remaining 90 images were used for testing the algorithm.

Another data set of 235 retinal input images out of which 75 normal images and the remaining 160 abnormal images was collected from MESSIDOR database. For training 90 images such as 30 normal images and 60 abnormal images are used. For testing the classifier algorithm, 145 abnormal images such as 45 normal images and 100 abnormal images are used. The comparison of the classifier accuracies for the images collected from both the databases is given in Table-1.

Table-1. Comparison of accuracies between the DRIVE and MESSIDOR database images.

Database	**Class**	**No. of Training images**	**No. of Testing images**	**No. of images correctly classified**	**Classifier accuracy** (%)
DRIVE	Normal	30	40	40	100
	Moderate	30	45	42	93.33
	Severe	30	45	43	95.56
Average Classification Accuracy					96.3
MESSIDOR	Normal	30	45	45	100
	Moderate	30	50	48	96.0
	Severe	30	50	49	98.0
Average classification accuracy					98.0

CONCLUSIONS

Diabetic retinopathy is a major issue for the diabetes patients as it makes them to lose their vision. The patients affected by diabetic retinopathy can be prevented from the vision loss if the disease is diagnosed in an earlier stage. To investigate the disease, the symptoms of the disease are detected. The primary signs of the diabetic retinopathy are the exudates which are detected by using JSEG segmentation algorithm. This segmentation algorithm detects the presence and location of exudates with respect to macula. The distance of the location of exudates with respect to macula is useful information to find the severity of the disease. If the exudates will be present far away from the macula, the classifier algorithm confirms the less severity. If the exudates are very closer to the macula then it confirms the more severity. The degree of severity is measured by using CNN classifier and the input features needed for classification are extracted by using PCA. The informations about the severity of the disease and then the localisation of exudates are very useful to the ophthalmologist for diagnosing the disease and apply proper treatments to the patients. The classification accuracies for the images collected from both DRIVE and MESIDOR data bases are found out to be 96.3% and 98% respectively.

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