Automatic diabetic retinopathy detection using deep learning mechanism

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ABSTRACT

Diabetes retinopathy describes retinal disease which influenced by diabetes on the eyes. The fundamental danger of the disease can prompt visual impairment. Location the disease at beginning time can safeguard the patients from loss of vision. The significant motivation behind this paper includes automatically distinguish and additionally to group the seriousness of diabetic retinopathy. At to start with, the sores on the retina particularly veins, exudates and micro aneurysms are removed. Highlights, for example, territory, edge and tally from these sores are utilized to group the phases of the disease by applying simulated neural system (ANN). We utilized 214 fundus pictures from DIARECTDB1 and nearby databases. This literature dicovers framework can give the order exactness of 96% and it underpins an incredible help to ophthalmologists.

Parameters

Parameters used for optimization includes Accuracy, sensitivity and specificity

Simulation and Result

Simulation is conducted in MATLAB using image processing and neural network toolbox. The proposed mechanism shows improvement in terms of classification accuracy by the margin of 10%. This is a significant difference enhancing recognition rate.

Keywords: Diabetic retinopathy, MSVM, Accuracy, Specificity, sensitivity,

I. INTRODUCTION

Restorative picture diagnosis assumes a noteworthy part of research for human services purposes. Diabetic retinopathy is a diabetes inconvenience that influences eyes. It can be happened on the grounds that enough rate of insulin in the body isn't discharged legitimately by the pancreas [1]. In the event that a man has diabetes for a long time or more, he or she has the greater likelihood to endure diabetic retinopathy [2]. DIABETES RETINOPATHY normally demonstrates no side effects or vision issues at beginning time of the disease. Be that as it may, it can lead visual impairment in the long run. The most punctual clinical indication of DIABETES RETINOPATHY is the identification of microaneurysms (MAs). They are shaped because of the spillage of blood from hair like. MAs are little, red specks and spread on the shallow retinal layers. At the point when the dividers of MAs get burst, hemorrhages (HMs) happen. The little HMs like MAs are called speck and smear HMs. Fragment hemorrhages that happen in the more shallow nerve fiber layer are called flame shaped hemorrhages. The more spillage from harmed vessels can cause exudates (EXs). They are normally yellow in shading and sporadic formed on the retina. The EXs vary from MAs and HMs from splendor. MAs and HMs are dull sores and EXs are splendid [3]. The more genuine DIABETES RETINOPATHY demonstrates one of the side effects of venous beading (VB), revascularization and intra-retinal small scale vascular irregularities (IRMA). These are variations from the norm of the veins that supply the retina of the eye. Amid the year 1990 to 2010, DIABETES RETINOPATHY turned into the fifth most regular purposes behind visual weakening and visual impairment. In 2010, more than 33% of evaluated 285 million individuals Details of proposed system are discussed in the 4 section. Rest of the paper is organized as under: section 2 gives literature survey of techniques used to detect DIABETES RETINOPATHY, section 3 gives the phases associated with proposed system, section 4 gives the performance analysis, section 5 gives conclusion and future scope and last section gives the references.

overall enduring diabetes had manifestations of DIABETES RETINOPATHY. The Forth National Health Examination Survey in Thailand detailed that 7.7% of females and 6.0% of guys had the pervasiveness of DM. To treat DM and its entanglements, a high spending plan is connected in Thailand [4]. Visual deficiency, the fundamental danger of DIABETES RETINOPATHY, can be spared by early discovery and treatment. DIABETES RETINOPATHY can be identified amid a widened eyes exam by an ophthalmologist or optometrist, regularly prompt time, cost and exertion devouring. The computerized identification of DIABETES RETINOPATHY can help ophthalmologist by advantaging quick, solid and exact location. In this manner, therapeutic picture investigation winds up one of the essential territories of research for diabetic retinopathy. Numerous analysts in the writing researched characterization of DIABETES RETINOPATHY utilizing the retinal pictures. Saifuddin and Vijayalakshmi [5] acquainted a novel strategy with find exudates and group shading eye fundus pictures. They

performed discovery of exudates from districts utilizing scientific morphology and ordered exudates and non-exudates by connecting with multilayer perceptron (MLP) classifier. They detailed 100% precision for the tried dataset. Nayak and Bhat [6] presented a strategy that utilized morphological preparing and surface investigation. They removed hard exudates, veins and discover territory, border and differentiation. At that point, they grouped typical, NPDIABETES RETINOPATHY and PDIABETES RETINOPATHY utilizing the counterfeit neural system (ANN) and showed order exactness 93%. Sargunar and Sukanesh, [7] identified exudates and veins utilizing morphological methods. Their proposed technique characterized the DIABETES RETINOPATHY seriousness in light of region, edge and hurst coefficient. Their technique's exactness was estimated as 85%. MahenDiabetes retinopathyan, Dhanasekaran and Narmadha [8] concentrated on a robotized strategy to identify exudates applying morphological handling and figured the dark level matric of the separated exudate. Their grouping is finished utilizing Probabilistic Neural Network (PNN) classifier. In any case they didn't report exactness of the framework. Shahin et al. [9] overviewed a framework to distinguish the veins, exudates, microaneurysms and figure the territory of these extricated injuries. In addition they discover the entropy and homogeneity to order by applying manufactured neural system (ANN) and accomplished precision more than 92 %.

II. LITERATURE SURVEY

This section provide in depth into the techniques used to detect diabetic retinopathy at early stage. [6]uses the contrast enhancement, morphological filtering and segmentation technique to detect hard exudes from the various input image. The system utilizes Contrast Limited Adaptive Histogram Equalization (CLAHE) technique to enhance the image and top hat transform to enhance the blood vessels. After that filtering is to be done and pattern recognition techniques are utilized to recognize the diseases. [7] SVM classifier based system is to be utilized in this paper to diagnose DIABETES RETINOPATHY affected patient. It utilizes test fundus to contribute to SVM classifiers.

Technique discussed by [9] provides mechanism to detect diabetic retinopathy by the use of Deep learning. Considerably large dataset is used for this purpose. Data Diabetes retinopathyiven artificially intelligent deep learning mechanism is used to derive training and testing images for distinguishing normal image from DIABETES RETINOPATHY image. However, mechanism used lacks preprocessing mechanism including noise handling within the automatic detection of DIABETES RETINOPATHY and multiclass classification. Several other techniques of data mining in healthcare are surveyed by [10]. Algorithms associated with data mining provides the filtering mechanism[11], [12] to ensure the better classification of result. By analyzing discussed techniques, best possible technique can be selected for future enhancement. Low cost medical image processing mechanism is proposed by [13]. Field programmable field array is merged along with the processor for analyzing the complex diseases like DIABETES RETINOPATHY. [14] Utilizes microneurysm segmentation that is automatically done by using mathematical morphology. It does not work on predefined set of directives. Sensitivity and specificity can also be further improved .[8] uses multiclass SVM classifier[15], [16] that assure classification phase . It can ensure unwavering analysis of human observer and also presents supervised classifier that uses testing sets to obtain results. [17]classifies the DIABETES RETINOPATHY stages using automated system having feature classifier. It detects the disease by extracting features using image processing method and classifies them accordingly. [18] SVM and MDA methodologies are surveyed in this paper and also their utilization for detecting diabetic retinopathy are explained.

3. PROPOSED SYSTEM

Entire simulation is divided into phases.

i. Preprocessing: at preprocessing stage resizing operation is performed since input layer of the network requires predefined size. Size of 77x100 and channel of size 3 is required, indicating RGB image. Gaussian Filtering is used to tackle noise(Denoising) if any within the image.

ii. MSVM for segmentation and Classification: Multi class SVM is used to extract critical and non critical segments from within the training images. After extracting the features, classification is performed on test image.

There are three stages of diabetic retinopathy:

1 Mild DIABETES RETINOPATHY,

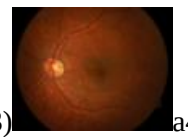
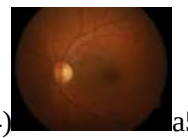
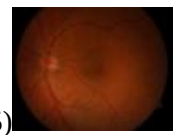
2. Moderate DIABETES RETINOPATHY

3. Severe DIABETES RETINOPATHY(proliferative)

Actually, proliferative is the most widely recognized diabetic retinopathy, speaking to 80% of all cases.

3A. Image database

The image dataset used consist of 3 categories of 200 eye fundus. Resizing operation manually as well as automated mechanism is posted upon to fit into the input layer of the network. The images were captured and resized to 77x100 with 3 colour channels.

(a1)  (a2)  (a3)  a4)  a5) 

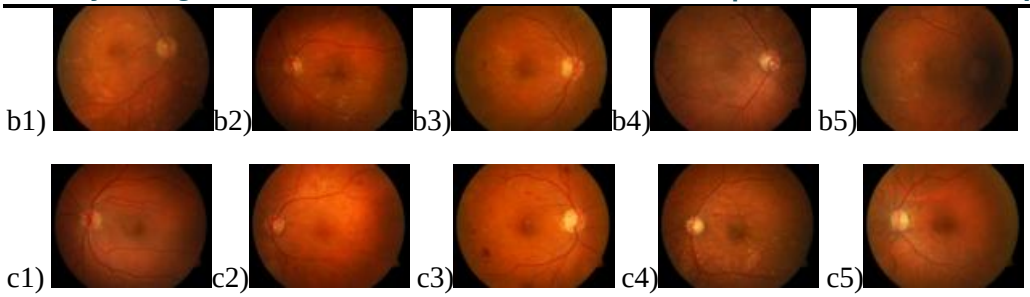


Fig. 1.a) mild retinopathy images: (b) moderate retinopathy images, (c) proliferative retinopathy images.

The 200 pictures are bundled in 3 sets, one for each ophthalmologic division, utilizing the png format. In addition, an Excel record with therapeutic conclusions for each picture is given. In this work, we utilize the pictures of only one ophthalmologic division containing 48 pictures with mild retinopathy, 48 with moderated and 48 with severe DIABETES RETINOPATHY

3B) Pre-Processing

Preprocessing mechanism used in this literature contains noise handling along with resizing operation. noise handling is done using Gaussian filtering mechanism. This filter is capable of handling impulse noise along with smoothening operation. Equation 1 gives the operation of filtering along with smoothening.

$$G_{Smoothened_{image}} = \frac{1}{2\pi\alpha^2} e^{(a^2+b^2)\frac{1}{2\alpha^2}}$$

Equation 1: Gaussian Filtering

'α' is slandered deviation, 'a' is distance from horizontal axes and 'b' is a distance of origin from vertical axes.

After handling noise, resizing operation is done. Resizing is done to present the uniform data to the input layer. Resizing is done using equation 2.

$$Resized_G = Resize\left(G_{Smoothened_{image'}}, [70\ 100]\right)$$

Equation 2: Resized image

This resized imageset obtained is passed to the network for further processing.

3B) Training with Deep Learning

Training operation begin by receiving the imageset from the pre-processing phase. To create a new network, proposed mechanism used inbuilt layers with input layer accepting images of 77x100 with 3 channels. Training parameters is defined using training option command using deep learning toolbox. Train network function is used to finally train the network. Flow of network definition is given as under

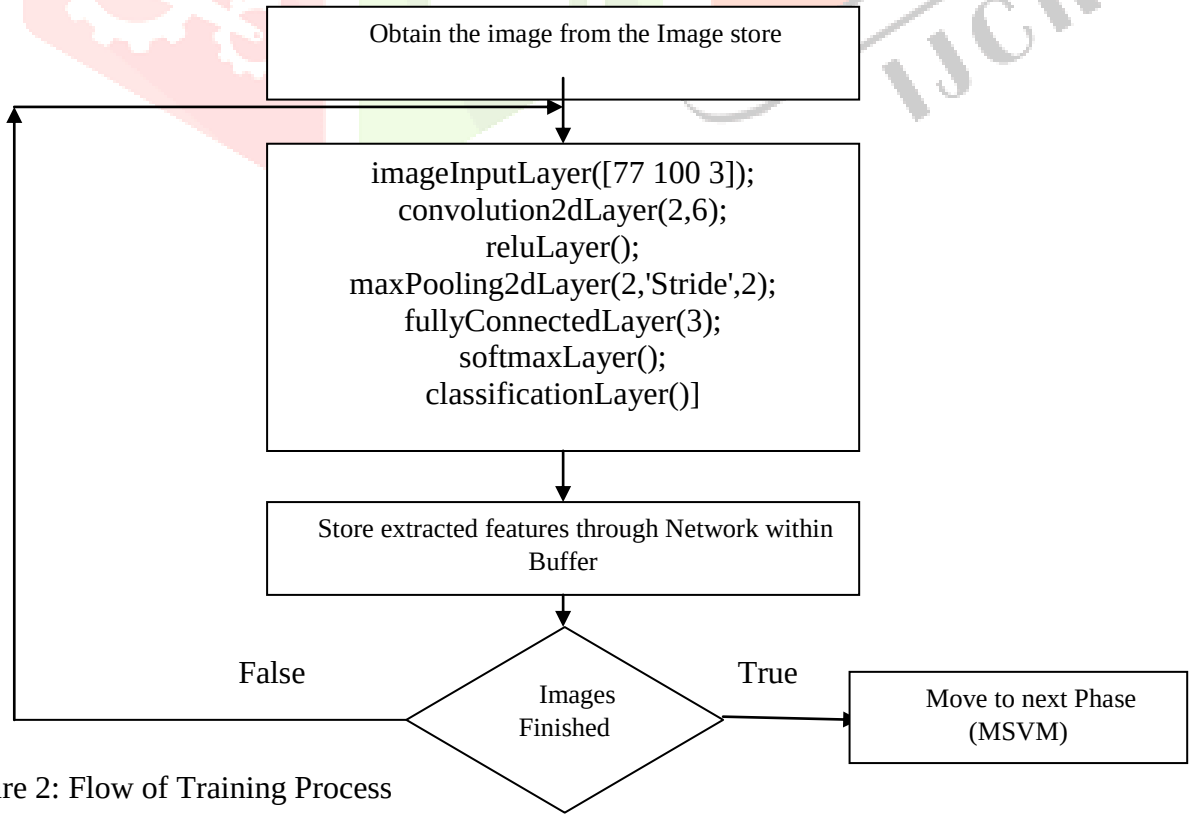


Figure 2: Flow of Training Process

3C) Classification

To perform classification MSVM is used as a last phase. Support vector machine uses rules based environment to correctly reach to the solution of the given problem including outlier detection or unnecessary regions. [20]this system is proposed to resolve unclassified region. MSVM are used to realize the classification results. Optimal hyper planes are defined to determine whether the obtained values of membership functions satisfy the hyper plane(D(x)) or not.

Satisfaction Criteria D(X)>1

One dimensional membership function $m_{i_j}(x,y)$ is defined for determining optimal separating hyper planes $D_j(x) = 0$ as follows

3.2.1 if values of diagonal are equal (i==j)

$$m_{i_j}(x) = \begin{cases} 1 \ for\ D_i(X) > 1 \\ D_i(x) for\ D_i(X) < 1 \end{cases}$$

Equation 3: Rules determining correct class 1 or 2

3.2.2 if values of diagonal are not equal(i≠j)

$$m_{i_j}(x) = \begin{cases} 1 \ for\ D_i(X) < 1 \\ -D_i(x) for\ D_i(X) > 1 \end{cases}$$

Equation 4: Rules determining correct class 1,2 or 3

The procedure of classification is listed as follows

3.2.3 if the pixel value x is such as $D_i(x)>0$ and is satisfied only for that class then it is fed into that class.

3.2.4 if $D_i(x) > 0$ and x lies between various classes then classify the data into the class with maximum $D_i(x)$

3.2.5 if $D_i(x) <_= 0$ and x lies between various classes then classify the data into the class with minimum $D_i(x)$

3D) Flow of proposed system

Flow of the proposed system is given as under

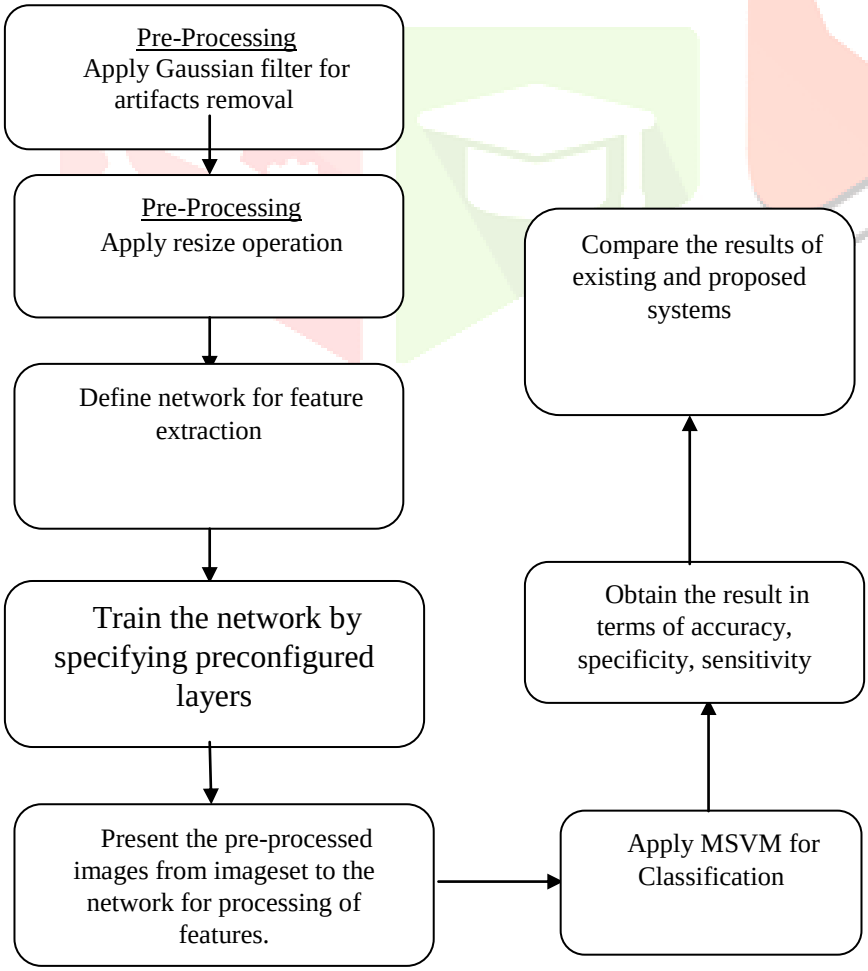


Figure 4: Flowchart showing the flow of operation

4. PERORMANCE ANALYSIS AND RESULTS

The performance of the system is analyzed by the use of parameters such as accuracy, specificity and sensitivity.

Accuracy is obtained by subtracting the actual result from the approximate result. In terms of predictions accuracy is obtained as

$$Accuracy = \frac{Correct_{Pre}}{Total_{Pred}}$$

Equation 5: Accuracy in terms of prediction

Sensitivity is obtained by dividing number of positive predictions to the total true positive rate.

$$\text{Sensitivity} = \frac{Correct_{Positive_{predictions}}}{Total_{Positives}}$$

Equation 6: Sensitivity evaluation formula

Specificity is another parameter used to evaluate correctness of the proposed system. It is given as under

$$\text{Specificity} = \frac{True_{Negitives}}{True\ Positive + False\ Negitive}$$

Equation 7: Specificity obtaining formula

The disease detection and prediction is given though accurate classification, result in terms of plots is given as under

For level 1 DIABETES RETINOPATHY imageset accuracy is given as under

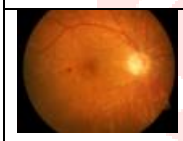
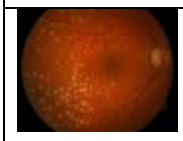
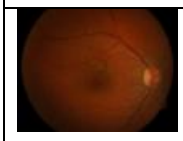
Imageset	Accuracy with Deep Learning and decision tree classifiers(%)	Accuracy with MSVM(%)
	80	91
	82	95
	81	91
	86	94
	84	95

Table 1: Predicted accuracy corresponding to pre-proliferative(Mild) retinopathy(level 1)

In case of level 2 retinopathy image segments are used then classification results are listed as under

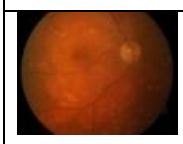
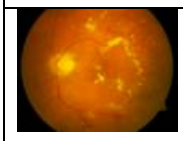
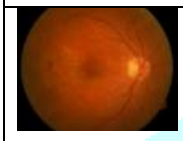
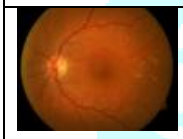
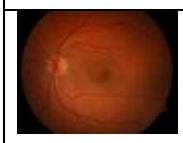
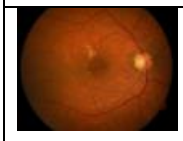
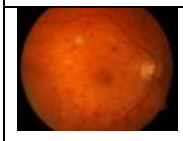
Imageset	Accuracy with Deep Learning and decision tree classifiers(%)	Accuracy with MSVM(%)
	83	92
	81	94
	80	92
	87	94
	82	96

Table 2: classification accuracy for (Moderate)proliferative retinopathy image segments

Results of image set proliferative DIABETES RETINOPATHY is given as under

Imageset	Accuracy with Deep Learning and decision tree classifiers(%)	Accuracy with MSVM(%)
	87	95
	86	96
	85	95
	84	94

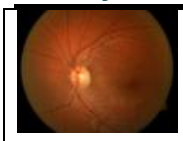
	81	95

Table 3: prediction accuracy of image set Severe or proliferative DIABETES RETINOPATHY.

Result comparison in terms of accuracy ,sensitivity and specificity are given as under

Imageset name	Parameter	Existing (%)	Proposed(%)
Level 1 DIABETES RETINOPATHY(Pre-Proliferative)	Accuracy	85	95
	Specificity	86	84
	Sensitivity	85	92
Level 2 DIABETES RETINOPATHY	Accuracy	85	94
	Specificity	87	82
	Sensitivity	84	93
Level 3 DIABETES RETINOPATHY	Accuracy	83	96
	Specificity	88	82
	Sensitivity	85	94

Classification accuracy of proposed system appears to be more as compared to existing techniques. Multiple classes prediction mechanism showing higher accuracy proving the worth of study.

Results and performance analysis as indicated through the plot shoes that deep learning combined with multi support vector machine yield better result.

5. Conclusion and future scope

We propose a framework for the target of distinguishing and order of DIABETES RETINOPATHY. We utilized 214 fundus pictures from DIARECTDB1 and nearby databases. We identified there injuries specifically veins, exudates and micro aneurysms from input pictures. And afterward removed essential highlights and characterized utilizing ANN classifier. The proposed technique performed up to order affectability of 95%, exactness of 95% and precision 96% separately. The execution time took around 28.064 seconds. As a future work, we can upgrade the classifier execution with more pictures, extricating subtle elements highlights and utilizing diverse classifier. Overall enhancement in terms of accuracy is 10%. The main objective of this research is to check the consistency of classification accuracy when presented with larger datasets which is subsequently increased. In future, e health system that accurately implements the steps described in section 3 can be developed.

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