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ANN and SVM to recognize Texture features for spontaneous Detection and Rating of Diabetic Retinopathy

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Abstract—The higher levels of blood glucose most often causes a metabolic disorder commonly called as Diabetes, scientifically as Diabetes Mellitus. A consequence of this is a major loss of vision and in long terms may eventually cause complete blindness. It initiates with swelling on blood vessels, formation of microaneurysms at the end of narrow capillaries. Haemorrhages due to rupture of small vessels and fluid leak causes exudates. The specialist examines it to diagnose and gives proper treatment. Fundus images are the fundamental tool for proper diagnosis of patients by medical experts. In this research work the fundus images are taken for processing, the neural network and support vector machine are trained for the proposed model. The features are extracted from the diabetic retinopathy image by using texture based algorithms such as Gabor, Local binary pattern and Gray level co-occurrence matrix for rating the level of diabetic retinopathy. The performance of all methods is calculated based on accuracy, precision, Recall and f-measure.

Keywords—Diabetic Retinopathy (DR), SVM, Neural Networks (ANN), Gabor, Statistical, LBP

I. INTRODUCTION

Diabetic retinopathy is widespread cause for weakening the vision and even loss of eyesight. The working age population gets influenced due to it. The research work has been done on diabetic retinopathy models non-invasive and widely available techniques to identify the disease severity level, timely treatment and management of disease to keep the vision loss away The need to develop the machine aided tool is to detect the disease severity at early stage with appropriate cost. Machine–aided disease diagnoses in retinal images ease the huge examination of populace suffering from diabetes mellitus to aid practitioner to utilize the time effectively. The current development in technologies in machine learning techniques, communication systems and increased computational power gives opportunity to the biomedical engineers and computer scientist to design a tool to assist the medical experts [1]. To develop and test the digital examination programs and automated algorithm the prerequisite is retinal images with great variation. The swelling of blood vessels leaking blood due to increase blood glucose level causes the non-proliferative diabetic retinopathy. The proliferative diabetic retinopathy causes permanent blindness due to formation of new vessel network which are brittle in nature. They start leaking blood in the retina which may cover the fovea. It is the next stage of NPDR. The non-proliferative DR is categorised as Mild, Moderate and severe, based on type of the lesion present at this stage. At the early stage the puff like structure appears at the end of narrow capillaries termed as microaneurysms [2]. This stage is initiation of DR, termed as mild NPDR. If left untreated it progresses in next stage the microaneurysms increases in number in all quadrants, causes moderate NPDR. In the progression, the blood vessels start leaking blood and it spreads in the retina causing haemorrhages, the injured blood vessel starts leaking the fluid in the retina forms Exudates, appears as yellowish white spots in the retina, leads to severe NPDR. The blood vessel are injured, so for retina nourishment the new vessels are formed ,but the newly formed vessels are brittle, easily leak out blood through it, causing vitreous haemorrhage leads to proliferative diabetic retinopathy, can cause permanent blindness. Presently the medical experts detect the vascular deformity and structural changes in retinal images. The retina is dilated by the use of vasodilating agent to produce image with enhanced contrast. The methods are invasive techniques which has certain limitations. Because of manual nature of DR examination methods incompatible results are obtained. Therefore existing problem can be solved by using automated investigation of diabetic retinopathy.

This work involves a technique for diabetic retinopathy detection and rating. The work is classified as; first one is feature extraction using Gabor, GLCM and Local binary pattern. While the second stage incorporates classification of DR images based on extracted features using SVM and ANN. The above research work is further organized as follows: Section II contains the Dataset used for problem analysis, section III contains the relevant literature followed by proposed methods for implementation as discussed in section IV. The experimental setup and results are discussed in section V leading to conclusion in section VI.

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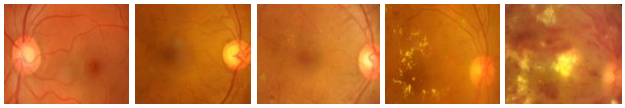
II. IDRiD DATASET FOR DR GRADING

Here, IDRiD (Indian Diabetic Retinopathy Image Dataset [1] is used for detection and rating of Diabetic retinopathy.
This dataset is mainly designed with DR rating ground truths. It comprises the images with all types of lesions present in diabetic retinopathy as well as normal images. It also describes the severity of disease and diabetic macular oedema. It enables to design and development of efficient algorithm.
The different phases are shown in figure 1. Figure 1(a) shows Normal eye image with on symptoms of DR. figure 1(b) shows the mild NPDR image with only few number of microaneurysms, In moderate NPDR the increased number of microaneurysms and few haemorrhages are shown in figure 1(c) . The figure 1(d) Severe NPDR shows microaneurysms, haemorrhages and exudates appearing in yellowish white colour in the image. The figure 1(e) shows the Proliferative diabetic retinopathy, it includes venous bleeding and vitreous haemorrhage, leading to permanent blindness.



(a) (b) (c) (d) (e)

Figure1: Phases of diabetic Retinopathy

Diabetic retinopathy dataset with different grades of DR consists of
1. Original colour fundus images in jpg format.
2. Ground truth Labels for Diabetic Retinopathy in csv file.

Table -1: Diabetic Retinopathy Grading

Disease Severity Level	Findings
Level-0 Normal eye	No deformity present
Level-1 Mild – NPDR	Few number of Microaneurysms are visible
Level – 2 Moderate– NPDR	Microaneurysms in more number and small haemorrhages
Level – 3 Severe – NPDR	number of haemorrhages are more Exudates are visible Venous bleeding
Level – 4 PDR	Neovascularization Vitreous haemorrhage

III. RELATED WORK

V Raman et al. [2] Finds the deformity in the image by finding abnormal features from retinal fundus image using machine aided algorithms. It emphasizes on detection of Optic disc, Blood vessels and abnormal features like microaneurysms, haemorrhages and exudates. Based on these features classification is done as mild, moderate and severe NPDR and PDR by the use of machine learning techniques. [3] Singh &Tripathi presented analysing of image for early diagnosis of Diabetic retinopathy by using image processing techniques. T.A. Soomro[4] presented image enhancement technique, proposed threshold based static wavelet transform along with morphological operations for retinal images and blood vessels are enhanced using contrast limited adaptive histogram equalization.K. Malathi and R. Nedunchelian[5] proposes two types of filters. The Gaussian based filter is used for noise removal present in the images. And the other filter is Haar filter used to detect the diabetic retinopathy. The position of optic disc is automatically detected by using the blood vessel's identical expected directional pattern. D. K. Prasad, L. Vibha and K. R. Venugopal[6]. Proposed segmentation of blood vessel, microaneurysms and exudates. The algorithm is applied by dividing the image into four quadrants and further haar wavelet transform is applied on extracted features. By using principal component analysis the better features are selected, and back propagation neural network and one rule classifier is used for classifying the images as DR or non DR. M. Usman Akram et al [7] proposes the extension M-mediods based modelling approach combined with Gaussian mixture model in an ensemble to for a hybrid classifier so as to increase accuracy. It incorporates the descriptor based on shape, intensity and statistics for lesion detection. Winder, R. John[8] a literature survey for detection of diabetic retinopathy is done based on different methods for pre-processing, localization and segmentation of optic disc by considering colour fundus images. Haleem, Muhammad Salman[9] presented a survey report about advanced methods for extraction of anatomical features to help in early diagnosis of glaucoma. The comparative study of different techniques is carried out for glaucoma analysis. Cemal Kose et al [10] present inverse segmentation method for diabetic retinopathy detection. As the direct segmentation gives poor results, it exploits the homogeneity of healthy portion area. It deals with variation in structure of unhealthy portion. Adarsh. P and D. Jeyakumari [11] presented that the feature vector is built using area of lesions and texture features. Further the feature vector is applied as input to multiclass support vector machine for classifying the images into different categories of diabetic Retinopathy.

IV. IMPLEMENTATION

The implementation approach is presented in this section. The features are extracted by using Gabor, LBP and GLCM techniques. Further the detection and grading is done by using Neural network and SVM.

A. Gabor Features Extraction

These are very effective means for extracting the feature and their analysis. It works on the frequency pattern of a particular region. By using Gabor filter at different orientations and different frequencies maximum features can be extracted. Gabor filter is sinusoidal for a given frequency and orientation and it is modulated using Gaussian function with the capability of multi-resolution decomposition,it is due to its localization in Spatial and frequency domain.

Being a linear filter, it analyses whether there are any specific frequencies present in a specific direction in the region of interest. Studies [12],[13] shows that the Gabor filter has been very useful for the detection of texture frequency and its orientation.

$$g(x,y) = \frac{f^2}{\pi\gamma\eta} exp\ (-\frac{x'^2+\gamma^2y'^2}{2\sigma^2})exp\ (j2\pi fx' + \varphi) \quad (1)$$

$$where,\ x' = xcos\theta + ysin\theta$$
$$y' = xsin\theta + ycos\theta$$

Where *f - represents* the frequency of the sinusoidal factor, θ- is the orientation; φ-phase offset σ -standard deviation,
γ- is the spatial aspect ratio, it specifies the ellipticity of support of Gabor function. Here in the proposed algorithm forty Gabor filters in 5 scales and 8 orientations are selected.

B. Local Binary Pattern

It was introduced by Ojala in 1996 as a texture descriptor operator. The basic idea to develop LBP was that, by using two complimentary measures such as gray scale contrast and local spatial patterns two dimensional surface textures can be described. For the computation of LBP, the uniform pattern is used so that the separate labels are used for each even pattern and all non-uniform patterns are labeled under a single label. All the uneven patterns are accumulated in a single bin yield an LBP operator [14],[15]. Each bin of LBP can be regarded as micro-texton.
The LBP follows the following steps for implementation:

- The window under test is portioned into cell (e.g. 16x16 pixels per cell).
- Comparison of each pixel in each cell is done with all its 8 neighbourhoods; follow the pixels along circle, i.e. clockwise and anticlockwise.
- For higher pixel value greater than that of neighbourhood write "0", else, write "1". The output obtained is 8-digit binary number
- Calculate the histogram for the cell for the knowledge of frequency of each number occurring (i.e. each combination of pixels which are higher than centre and which are smaller than centre).The histogram is a 256 dimensional feature vector for a gray scale image.
- The histogram is normalized.
- As the fundus image is combination of micro pattern, the histograms of all cells are concatenated, to form a single histogram, which gives the feature vector for complete window.

C. Statistical Features

The image texture possesses features such as grey-tone linear dependencies, distinction, nature and number of boundaries present and homogeneity. Haralick et al. extracted various texture features by introducing the probabilities by making use of GLCM. It is defined by two
"A two-dimensional histogram of grey levels for a pair of pixels, which are separated by fixed spatial relationship" [16].

$$g(i,j) = (i,j)^{th} entry\ in\ GLCM$$

$$Energy = \sum_{i=1}^{L}\sum_{j=1}^{L} g(i,j)^2 \quad (2)$$

$$contrast = \sum_{i}\sum_{j}(i-j)^2 g(i,j) \quad (3)$$

$$Entrpy = \sum_{i=1}^{L}\sum_{j=1}^{L} g(i,j)logg(i,j) \quad (4)$$

$$Variance = \sum_{i}\sum_{j}(i-\mu)^2 g(i,j) \quad (5)$$

$$homogenity = \sum_i \sum_j \frac{1}{(1-j)^2} g_{ij} \quad (6)$$

Where μ is the mean of $g(i,j)$

Energy gives measure of symmetry, when pixels are analogues. It gives texture disorders. Entropy also measures complexity in the image. Contrast measures the spatial frequency present in the image. Variance gives the measure of homogeneity and the difference from mean [17].
Different statistical features considered here are contrast, correlation, Energy and Homogeneity.

D. Support Vector Machines

It is a supervised machine learning model, associated with the learning algorithms that investigate the data for classification and regression analysis. In n- dimensional space each data item is plotted with value of each feature as a value of particular coordinate. The hyper plane further differentiates the two classes. In the set of training examples the data belong to either one class or the other. A model constructed using SVM training algorithm allots new examples to either one group or the other. It makes it as a non-probabilistic binary linear classifier.SVM model presents examples as points in space; they are mapped such that the examples of separate groups are split by clear gap that is as broad as possible. The same space is then maps new examples and predicted to belong to the group based on side of gap they fall [18].While performing the linear classification, SVM effectively perform the non-linear classification by implicitly mapping their inputs to high-dimensional feature space. The supervised learning is not possible if the data is not labeled, for which the unsupervised learning approach is required. It tries to find natural clustering of data to groups along with mapping new data to these formed groups.

E. Neural Networks

Neural networks are being used to innumerable real world problems with varying complexities**.** Many complex problems can be solved by using neural networks. Biological nervous system of human brain is base for neural networks. They are the complex network of neurons or nodes. The neural networks are classified as feed forward network and recurrent network. The connections of the biological neuron are modeled as weights. An excitatory connection is reflected by positive weight. And inhibitory connections by negative values.

The modifications are made to all inputs by weights and summed. It is called linear combination. Finally to control the amplitude of the output an activation function is used.

For example, usually the allowable output range is betweenn 0 and 1, or it can be −1 and 1[19].The learning rule, architecture and transfer function affects the actions of neural network [20].

It serves many tasks such as Pattern recognition, data classification and application, predictive modeling, adaptive control and applications which are trained through the dataset.

V. EXPERIMENTAL RESULTS

F. *Dataset Selection and Pre-processing:*

DR image training dataset is selected. For 70% training 100 images were considered and 141 images are considered for testing.

The same number of images (141 no.) is considered for training as well as testing.

Then for preprocessing, the median filter is used for noise removal.

G. *Features Extraction*

From the preprocessed training images Gabor, LBP and statistical features are extracted and the classification is done using neural network and SVM and accuracy is measured.

Neural networks and SVM are trained with various features for diabetic retinopathy detection and grading. The performance of SVM and Neural Network classifiers have been evaluated the sample grading outputs obtained by both classifiers are tabulated as below:

Table-II: Correct Classification by all algorithms with SVM Classifier.

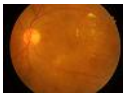
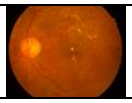
Target Image	Image	Ground truth	Gabor	GLCM	LBP
IDRiD_001		3	3	3	3
IDRiD_002		3	3	3	3
IDRiD_016		2	2	2	2

Table-III Correct Classification by any of the two algorithms with SVM Classifier

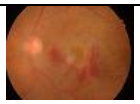
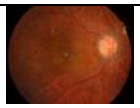
Target Image	Image	Ground truth	Gabor	GLCM	LBP
IDRiD_005		4	4	2	4
IDRiD_009		3	3	3	0
IDRiD_020		2	2	4	2

Table-IV: Correct Classification by anyone algorithm with SVM Classifier

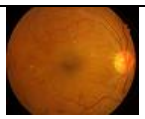
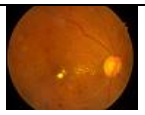
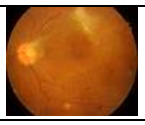
Target Image	Image	Ground truth	Gabor	GLCM	LBP
IDRiD_023		3	3	1	0
IDRiD_029		2	2	3	3
IDRiD_032		4	4	2	3

Table-V: Correct Classification by all algorithms with Neural network Classifier

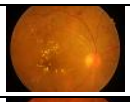
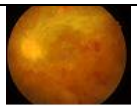
Target Image	Image	Ground truth	Gabor	GLCM	LBP
IDRiD_001		3	3	3	3
IDRiD_003		2	2	2	2
IDRiD_015		4	4	4	4

Table-VI: Correct Classification by any two algorithms with Neural network Classifier

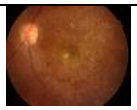
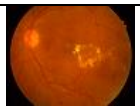
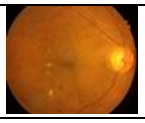
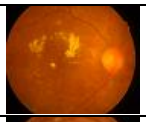
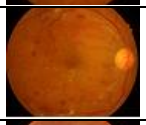
Target Image	Image	Ground truth	Gabor	GLCM	LBP
IDRiD_008		4	4	4	3
IDRiD_042		2	2	2	4
IDRiD_049		3	3	4	3

Table-VII: Correct Classification by one algorithm with Neural network Classifier

Target Image	Image	Ground truth	Gabor	GLCM	LBP
IDRiD_017		4	3	3	4
IDRiD_027		4	3	3	4
IDRiD_045		2	2	1	2

Further the performance is assessed depending on four parameters namely accuracy, precision, recall and F measure[21]. These parameters are defined using four measures; True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN)

True Positive: The DR detection matches with actual tagged data
True Negative: classifier and ground truth matches absence of DR
False Positive: classifier tags a normal case as a DR image.
False Negative: Classifier tags DR image as a normal image.
Accuracy: It is defined as the ratio of number of correctly classified images to total number of images.

$$Accuracy = \frac{(Tp+Tn)}{N} \quad (7)$$

Total number of cases are N
Precision is the ratio of correctly classified cases to the total observations.

$$precision = \frac{Tp}{(Tp+Fp)} \quad (8)$$

Recall or it is also called as sensitivity, is the ratio of correctly classified all cases to the all observations in actual class.
It is trivial to achieve recall of 100% by returning all documents in response to any query. Therefore, recall alone is not enough but one needs to measure the number of non-relevant documents also, for example by also computing the precision.
The recall is defined as:

$$Recall = \frac{Tp}{(Tp+Fn)} \quad (9)$$

F1 score is calculated by taking weighted score of precision and Recall. It takes into account both values; false positive and false negative. F1-score plays an important role for uneven class distribution. Precision and Recall are important, if the false positives and false negatives are very different.

$$F1\ score = 2 * \frac{(Recall*Precision)}{(Recall+Precision)} \quad (10)$$

We have evaluated the performance of diabetic retinopathy detection and grading on IDRiD (Indian Diabetic Retinopathy Image Dataset [1]. The DR images are labeled in five groups as
Grade – 0: Normal eye
Grade – 1: Mild – NPDR
Grade – 2: Moderate – NPDR
Grade – 3: Severe – NPDR
Grade – 4: PDR
We have considered 70% training data for evaluating the performance. Tables VIII to XI depict the results obtained.

Table -VIII: Accuracy with 70% Training data

Algorithm	Neural Networks	SVM
Gabor	65.9574	74.4681
Statistical	43.2624	57.4468
LBP	51.773	51.0638

Gabor features with SVM gives better accuracy of 74.4681% as compared to neural networks and other features extraction techniques.

Table -IX: Precision with 70% Training data

Algorithm	Neural Networks	SVM
Gabor	0.6751	0.803
Statistical	0.4493	0.5634
LBP	0.5314	0.4983

Table -X: Recall with 70% Training data

Algorithm	Neural Networks	SVM
Gabor	0.6911	0.815
Statistical	0.4342	0.5626
LBP	0.5291	0.4829

Table -XI: F-Measure with 70% Training data

Algorithm	Neural Networks	SVM
Gabor	0.683	0.809
Statistical	0.4416	0.563
LBP	0.5303	0.4905

By considering the training data same as testing data the results are obtained the as depicted in tables XII to XV

Table -XII: Accuracy

Algorithm	Neural Networks	SVM
Gabor	85	**100**
Statistical	56	70
LBP	63	56

Gabor features with SVM classification can correctly detect and classify the diabetic retinopathy in different severity grades.

Table -XIII: Precision

Algorithm	Neural Networks	SVM
Gabor	0.8521	**1**
Statistical	0.5668	0.7224
LBP	0.6402	0.545

Table -XIV: Recall

Algorithm	Neural Networks	SVM
Gabor	0.85	**1**
Statistical	0.56	0.7
LBP	0.63	0.56

Table -XV: F-Measure

Algorithm	Neural Networks	SVM
Gabor	0.851	**1**
Statistical	0.5634	0.711
LBP	0.6351	0.5524

VI. CONCLUSIONS

The undertaking explores different texture based features for grading diabetic retinopathy images. The gabor algorithm excels to statistical and LBP algorithm when compared for both classifiers namely, neural network and support vector machine (SVM). Further, the analysis of performance reports that the combination of gabor features using SVM maximize the accuracy as 74.5%. In addition, the precision recall and F1 score are also better. The results with SVM and neural network are compared using all three algorithms.

For IDRiD clinical dataset, the SVM classifier could classify 50% of images correctly graded by all algorithms, 29% of images correctly graded by any two algorithms and 20% of images correctly graded by one of the algorithm. Whereas the neural network classifier could classify 44% of images correctly graded by all algorithm,28% of images correctly graded by any two algorithms and 28% of images correctly graded by one of the algorithm. This proves that the SVM outperforms compared to neural network. However being a crucial clinical decision, it is recommended that the average of grading score and rounding will certainly make it possible to reduce the misclassification.

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