PERFORMANCE ANALYSIS OF VARIOUS CLASSIFIERS FOR RETINAL IMAGE IDENTIFICATION

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Abstract—The most common reason for blindness is diabetic retinopathy. Now it is diagnosis by human supervision or interaction using colour retinal images. The proposed system is aimed to diagnose the type of diseases in the retina and to automatically detect and segment retinal diseases without human supervision. The system will diagnose the disease present in the retina using a neural network based classifier. The extent of the disease in the retina can be identified by extracting the textural features of the retina. The system has the ability to diagnose the diseases like Diabetic Retinopathy and Drusen.

Keywords—LVQ, PCM, FAR, FRR, SOM, Tele-ophthalmology

I INTRODUCTION

The retina is an important field in the medical treatment of pathologies. By observing the changes of blood vessels in the retina, clinicians can diagnose many diseases. Among them hypertension, arteriosclerosis, and blindness caused by diabetes are the most common. Variety of computerized techniques especially designed for retinal images has been proposed to identify retinal images effectively. These techniques help to collect and assess information provided by retinal images more effectively. Tele-ophthalmology holds a great potential to improve the quality and affordability in health care. It can reduce the need for travel and provide the access to a super specialist. Ophthalmology is a largely image based diagnosis which lends itself easily to telemedicine. Neural network based classifier helps the proposed system to diagnose the diseases in the retina. By extracting the features of the retina the spread of disease in the retina can be identified.

II RETINAL IMAGES

Image segmentation - Survey and registration

Fundus images using the fundus camera are used for the diagnosis and treatment of several disorders affecting the retina and the choroid. For better diagnosis and planning of treatment these images should be processed. Retinal image segmentation is greatly required to extract certain features that may help in diagnosis and treatment. The retinal image registration is very useful in extracting the motion parameters that help in composing a complete map for the retina as well as in retinal tracking.

III PROPOSED SYSTEM

In the novel classifier the Linear Vector Quantisation is used to cover the brightness and vascularity problems in the existing systems. The classification problems preferred to attack the discrimination problem directly rather than indirectly by first estimating the class densities and by then estimating the discrimination function from the generative models through Bayes’s rule. In this paper, we derive a discriminative training procedure based on Learning Vector Quantization (LVQ) where probabilistic models is used to express the codebook. The likelihood-based distance is justified by the Kullback-Leibler distance. Here we present experiments in the fraud detection domain, where models of calling behavior are used to classify mobile phone subscribers to normal and fraudulent users. This is an extension work in clustering probabilistic models with the Self-Organizing Map (SOM) algorithm. In contrary to the real nature of the problem, the classical approach to classification solves the problem by first estimating the class specific densities and by then calculating the posterior probabilities of classes, which defines the discrimination function. This paper consider a learning codebook-based classifier.

The training algorithm is derived from the LVQ algorithm, which classify data samples by nearest neighbour (in the Euclidean distance sense) classification with regard to labelled codebook vectors.

The classifier may be used as a maximum likelihood classifier, and the resulting codebook may be used as a fixed kernel base used for further training.

Block Diagram

The pre-processing involves in enhancing the image for feature enhancement. In this paper brightness adjustment is considered. Though the minimum distance discriminate function approach seems to work well for images under the same illumination conditions, in practice, we find a large variance among the images obtained. This variation is due to the intrinsic attribute of lesions, decreasing color saturation at the lesion boundary or lighting variation over an image, etc. As a result, the color of lesion patches in some regions of an
image may appear dimmer than the background color that is located in another region, these lesions would be wrongly classified as “background” instead of “lesion”. In brightness adjustment procedure, only the darker regions have their brightness enhanced. Those regularly illuminated regions remain unchanged by this adjustment procedure.

\[ y = \beta x^a \]

\[ x = \text{pixel value of the original input image}, \]

\[ y = \text{pixel value after brightness adjustment} \]

\[ B = \text{inmax}^{1-a}, \quad \text{in max is value of upper limit intensity (brightness) of input image desired in transform function where,} \quad 0 \leq c \leq 1. \]

This paper considered two feature; size difference in blood vessel thickness and different color components available on the retinal image. Mainly this two feature can be used for classification of images into normal and abnormal.

**Learning Vector Quantization**

Learning Vector Quantization (LVQ) constitutes a particularly intuitive and simple though powerful classification scheme. LVQ is very appealing for several reasons such as: the method is easy to implement; the complexity of the resulting classifier can be controlled by the user; the classifier can naturally deal with multiclass problems; and, the resulting classifier is human understandable because of the intuitive classification of data points to the class of their closest prototypes. So LVQ has been used in a variety of academic and commercial applications for example robotics, telecommunication, image analysis etc.

**IV LVQ ALGORITHM**

The Learning Vector Quantization (LVQ) is an algorithm for learning classifiers from labeled data samples. Instead of modeling the class densities, it models the discrimination function defined by the set of labeled codebook vectors and the nearest neighbourhood search between the codebook and data. In classification, a data point \( x_i \) is assigned to a class according to the class label of the closest codebook vector. The training algorithm involves an iterative gradient update of the winner unit. The winner unit \( m^* \) is defined by

\[ c = \arg \min \| x_i - m^k \| \]

The direction of the gradient update depends on the correctness of the classification using a nearest neighbourhood rule in Euclidean space. If a data sample is correctly classified, the model vector closest to the data sample is attracted towards the sample; if incorrectly classified, the data sample has a repulsive effect on the model vector. The update equation for the winner unit \( m^c \) defined by the nearest-neighbour rule and a data sample \( x(t) \) are

\[ m^c(t+1) = m^c(t) + \alpha(t)[x(t) - m^c(t)] \]

where the sign depends on whether the data sample is correctly classified (+) or misclassified (−). The learning rate \( \alpha(t) \in [0, 1] \) must decrease in time. For different picks of data samples from training set, this procedure is repeated iteratively until convergence. The optimized learning-rate LVQ is presented by Kohonen, where for each codebook the learning-rate is optimized individually.

**Result and analysis**

The main challenge of the proposed system is how to reduce the error rates as low as possible and improve the performance of the system by achieving acceptable identification accuracy. The performance of a system is based on measures such as a False Accept Rate (FAR) and False Reject Rate (FRR) are two widely used standard metrics to determine the accuracy. Performance of the systems is measured by their accuracy in identification, which is calculated using false rejection and false acceptance errors. The goal of the proposed system is to reduce

i. False accept rate (FAR)

ii. False reject rate (FRR)

**False accept rate**

False-acceptance rate (FAR) also is referred to as the false-accept rate(FAR), false-match rate(FMR), false-positive rate(FPR) and type II error rate. The FAR measures the percentage of times an individual who should be taken as affected but taken as normal by the system.

Flase reject ratio

False-rejection rate (FRR) also is referred to as the false-reject rate, false-non match rate(FNMR), false-negative rate(FNR) and type I error rate. FRR measures the percentage of times an individual who should be taken as normal but taken as affected.
EXPERIMENTAL RESULT

The results are simulated using matlab to evaluate the performance of the proposed method. Simulation was carried out with 54 abnormal and normal images taken from the drive data base and hospital. Figure below show some tested image.

EXPERIMENTAL RESULT

<table>
<thead>
<tr>
<th>Method</th>
<th>Detected as Abnormal</th>
<th>Detected as Normal</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>39</td>
<td>15</td>
<td>72%</td>
</tr>
<tr>
<td>DEA</td>
<td>41</td>
<td>13</td>
<td>76%</td>
</tr>
<tr>
<td>BAP</td>
<td>36</td>
<td>18</td>
<td>66%</td>
</tr>
<tr>
<td>ODL</td>
<td>46</td>
<td>08</td>
<td>85%</td>
</tr>
<tr>
<td>PSA</td>
<td>49</td>
<td>05</td>
<td>91%</td>
</tr>
<tr>
<td>SVM</td>
<td>50</td>
<td>04</td>
<td>94%</td>
</tr>
<tr>
<td>PCA+SVM</td>
<td>50</td>
<td>04</td>
<td>94%</td>
</tr>
<tr>
<td>MRM</td>
<td>48</td>
<td>06</td>
<td>89%</td>
</tr>
<tr>
<td>NC LVQ</td>
<td>52</td>
<td>02</td>
<td>96%</td>
</tr>
</tbody>
</table>

The accuracy rate of the proposed classifier ie NCLVQ is much higher (96%) than the existing classifiers.

CONCLUSION

Here eight classifiers are analyzed. By making use of these classifiers retinal and non-retinal images can be classified and found the accuracy rates and also create a novel classifier which covers the disadvantage of the existing ones. The accuracy of proposed LVQ classifier is very high.

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