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Predictive Analysis of Diabetic Retinopathy

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Abstract

Diabetic Retinopathy is human eye disease which causes damage to retina of eye and it may eventually lead to complete blindness. Detection of diabetic retinopathy in early stage is essential to avoid complete blindness. Many physical tests like visual acuity test, pupil dilation and optical coherence tomography can be used to detect diabetic retinopathy but are time consuming and affects patients as well. This project focuses on detecting the presence of diabetic retinopathy by performing different classifiers such as Artificial Neural Network (ANN), back propagation levenberg-marquardt, Support Vector Machine (SVM), Radial Basis Function Networks (RBFN) using features drawn from output of different retinal image processing features, like diameter of optic disk, lesion specific micro aneurysms, exudates etc. These data set consists of details about patients for Analysing if the patients have Diabetic retinopathy or not. The data set was obtained from University of California Irvine Machine Learning Repository and some real time data sets. The purpose of this project is to identify the efficient classifier in predicting the diabetic retinopathy. Depending upon the test result we evaluate the essential parameters like accuracy, specificity and Performance.

Keywords: Diabetic retinopathy, Back propagation, Support vector machine, Radial Basis Function Networks, MATLAB.

INTRODUCTION

According to a study, diabetic retinopathy (DR) had affected many people of age 40 and older. They have advanced DR that could lead to severe vision loss. Diabetic Retinopathy is human eye disease which causes damage to retina of eye and it may eventually lead to complete blindness. Detection of diabetic retinopathy in early stage is essential to avoid complete blindness. Early detection and treatment of DR can provably decrease the risk of severe vision loss by over 90%. Thus, there is a high consensus for the need of efficient and cost-effective DR screening systems. The major reasons for this screening and treatment gap include insufficient referrals, economic hindrances and insufficient access to proper eye care. Telemedicine, with distributed remote retinal fundus imaging and grading at either local primary care offices or centralized grading remotely by eye care specialists, has increased access to screening and follow-up necessary treatment. The feasibility of DR screening, and several algorithms have been developed for detection of lesions such as exudates, haemorrhages and microaneurysms. Micro-aneurysms are considered to be the primary indicators of DR. Diabetic retinopathy is caused by diabetes mellitus which manifests itself in the eye retina. Diabetic eye disease is one of the most frequent causes of complete blindness in many countries. The detection of retinal pathologies became much easier using automated retinal image analysis whereas other methods like dilation of eye pupil is time consuming and patient has to suffer for some time. Diabetic retinopathy occurs when high blood glucose damages the small vessels that provides nutrients and oxygen to the retina. These features are then used in a system comprising of different learning algorithms like Back propagation neural network, RBFN and SVM. In the dataset analysis we have used the different 20 attributes from the predicted image. This dataset contains features extracted from the Messidor image set to predict whether an image contains signs of diabetic retinopathy or not. All features represent either a detected lesion, a descriptive feature of an anatomical part or an image-level descriptor.

PREVIOUS METHODS

Xiaohui Zhang and Chutatape Opas used local contrast enhancement preprocessing and Improved FCM (IFCM) in Luv colour space to segment candidate bright lesion areas. A hierarchical Support Vector Machines (SVM) classification structure was applied to classify bright non-lesion areas, exudates and cotton wool spots [1]. The comparative exudate classification using Support Vector Machines (SVM) and neural networks was also applied. They showed that SVM are more practical than the other approaches [2]. The global report says 422 million adults suffer from diabetes and 1.5 million deaths are directly related to diabetes. The World Health Organization published another report regarding blindness prevention due to Diabetes. Diabetes is a vital health condition globally, where, more than 75% of people above 20 years will be having retinopathy complications [3]. The segmentation utilizes local threshold and the method performance showed a sensitivity of 85%. Niemeijer evaluated a system for automatic detection. The system was developed from RGB fundus images taken on patients with diabetes in larger extent [4]. Big blood clots called hemorrhages are found. Hard exudates are yellow lipid deposits which appear as bright yellow lesions. The bright circular region from where the blood vessels emanate is called the optic disk. The fovea defines the centre of the retina and is the region of highest visual acuity [5].The different procedures adopted for in diabetic retinopathy are given in [6]-[10] and [15]-[19].

Materials and Methods:

In our research process, we used Back propagation, SVM, RBFN for the analysis of Diabetic Retinopathy for the best prediction of the algorithm[20][21].The datasets were taken from eye images of the patients.

Preprocessing is a technique used to reduce the redundant information present in the image / signal. The preprocessing methods that are used in signals are described in [11]-[14].Independent component analysis methods described in [22]-[27] may also be used with this method for extraction of original image components and hence to get better accuracy.

METHODOLOGIES

A. Levenberg-Markquardt(Back Propagation):

Artificial neural network has an extensive relationship with medical applications and in addition to that this classifier has an advantage of low cost digital hardware realizations. Sigmoid function is used as the activation function in the Back-propagation algorithm. Levenberg-Markquardt is selected as a learning rule for implementing the back-propagation training algorithm. Though this learning rule takes more memory space, this is the fastest supervised algorithm. It finds the local minimum and not the global minimum and will far off the minimum like the steepest descent method which is described in Figure 1. The local minimum of a function f(x) that is a sum of squares of nonlinear function is given by the equation (1).

$$F(x) = \frac{1}{2}\sum_{i=0}^{m}[f_i(x)]^2 \qquad (1)$$

Training gets stopped when any of these conditions occurs:

- The maximum number of epochs (repetitions) is reached.
- The maximum amount of time is exceeded
- Performance is minimized to the goal.

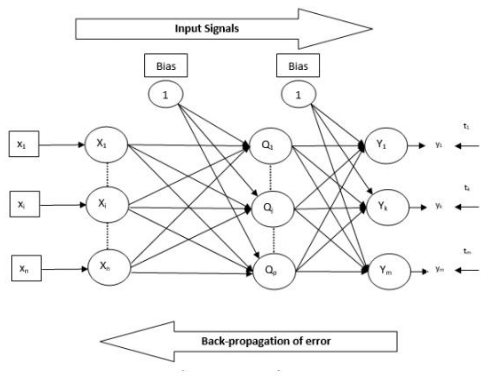

Figure 1. Back Propagation

B. Support Vector Machine

Support vector machine training process is applied to analyse training data to find an optimal way to classify images into their respective classes namely PDR, NPDR or Normal. SVM is a robust technique for data classification and regression. SVM models search for a hyperplane that can linearly separate classes of objects. Support vector machine is used to discriminate the various categories. Classification parameters are calculated using support vector machine learning. The training process analyse training data to find an optimal way to classify images into their respective classes. The training data should be sufficient to be statistically significant. The support vector machine learning algorithm is applied to produce the classification parameters according to calculated features. The derived classification parameters are used to classify the images. The image content can be discriminated into the various categories in terms of the designed support vector classifier. To fit nonlinear curves to the data, SVM make use of a kernel function to map the data into a different space where a hyperplane can be used to do the separation which is described in Figure 2. SVM can be applied to non-linear classification using nonlinear kernel functions to map the input data onto a higher dimensional feature space in which the input data can be separated with a linear classifier. Kernel function *K(x,y)* represents the inner product *ϕ(x),ϕ(y)* in feature space. In this work, we have used polynomial kernel which is given by the equation (2).

$$K(x, x') \ (x.x' +1)^{d} \qquad (2)$$

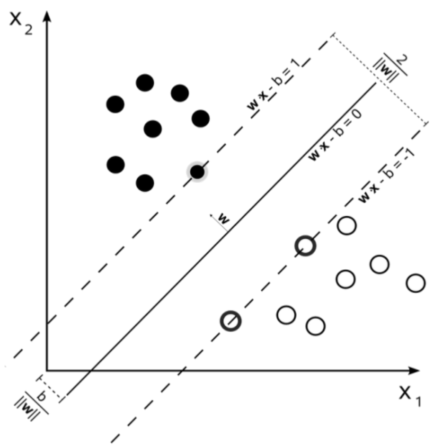

Figure 2. Selection of Hyper planes

C. Radial Basis Functions Neural Network

Radial Basis Functions emerged as a variant of artificial neural network in late 80's. However, their roots are entrenched in much older pattern recognition techniques as for example potential functions, clustering, functional approximation, spline interpolation and mixture models. RBF's are embedded in a two-layer neural network, where each hidden unit implements a radial activated function. The output units implement a weighted sum of hidden unit outputs. The input in RBF network is nonlinear while the output is linear. Due to their nonlinear approximation properties, RBF networks are able to model complex mappings, with perceptron neural networks can only model by means of multiple intermediary layers. In order to use a Radial

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Basis Function Network, we need to specify the hidden unit activation function, the number of processing units, a criterion for modelling a given task and a training algorithm for finding the parameters of the network which is described in Figure 3. Finding the RBF weights is called network training. If we have a set of input-output pairs, called training set, we optimize the network parameters in order to fit the network outputs to the given inputs.

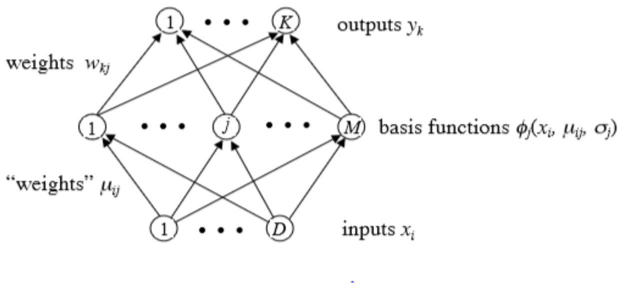

Figure 3. RBFN Architecture

The fit is evaluated by means of a cost function, usually assumed to be the mean square error. After training, the RBF network can be used with data whose underlying statistics is similar to that of the training set.

RESULT ANALYSIS

Diabetic retinopathy is a human eye disease which causes the blindness and early detection helps to avoid it. The three classifiers (Back propagation, support vector machine and the radial basis function networks) have been compared and it is found that the radial basis networks have the best performance. The suitable and efficient classifier for the prediction of diabetic retinopathy is shown in Figure 4.

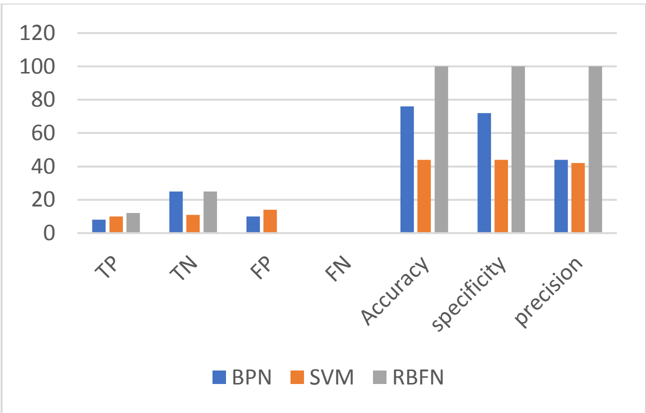

Figure 4. Comparison of Three Classifiers

CONCLUSION

Early detection and timely treatment of DR can slow down the progression of the disease and avert blindness. This paper proposed the predictive analysis of diabetic retinopathy. The SVM classifier has been found with accuracy and specificity of 44%. To overcome the low accuracy, the prediction is done on the back propagation neural network. The back propagation neural network was estimated with accuracy of 87% and specificity of 77%. Though the accuracy of BPN algorithm is average, the number of instances it took for training is low. In order to compensate both, the prediction is done on the radial basis function networks (RBFN). It is estimated with accuracy and specificity of 100% and the number of instance taken for training is also greater than that of back propagation algorithm. Hence, the radial basis function networks are the efficient and best suitable classifier for the prediction of diabetic retinopathy.

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