Survey On Diabetic Retinopathy Detection Using Artificial Neural Networks

[1]Anila V M, [2] Seena Thomas
[1]M.Tech Student, [2]Associate Professor
[1]Departmentof Computer Science and Engineering,
[1]LBS Institute of Technology for Women, Thiruvananthapuram, India

Abstract*— *Diabetic Retinopathy is an eye disease caused by the complication of diabetes. Diabetes progresses it results the deterioration of patient's vision and leads to diabetic retinopathy. Therefore early detection of diabetic retinopathy through regular screening will control the progress of the disease.Neural networks are used to find and diagnose the disease. Digital color fundus imaging is commonly used to detect the diabetic retinopathy. In this paper techniques for diabetic retinopathy detection using artificial neural network like Probabilistic Neural Network, Bayesian classification and Support Vector Machine are described.

Index Terms*— *Diabetic Retinopathy, Probabilistic Neural Network(PNN), Support Vector Machine(SVM), Radial Basis Function (RBF), Fundus Images

I. INTRODUCTION

Diabetes is a group of metabolic diseases in which a person has high blood sugar, either because the body does not produce enough insulin, or because the cells do not respond to the insulin that is produced. Diabetic retinopathy is one of the common complications of diabetes. It is a severe and widely spread eye disease. It damages the small blood vessels in the retina resulting in loss of vision. The risk of the disease increases with age i.e., middle aged and older diabetic patients are prone to Diabetic Retinopathy. Non-proliferative diabetic retinopathy is an early stage of diabetic retinopathy. In this stage, tiny blood vessels within the retina leak blood or fluid. The leaking fluid causes the retina to swell or to form deposits called exudates. Proliferative diabetic retinopathy, PDR is an attempt by the eye to grow or resupply the retina with new blood vessels (neovascularization), due to widespread closure of the retinal blood supply. Unfortunately, the new, abnormal blood vessels do not re-supply the retina with normal blood flow, but bleed easily and are often accompanied by scar tissue that may wrinkle or detach the retina.

The process of Automatic Diabetic Retinopathy detection involves detection and segmentation of the abnormal features from the input images. The input image from the retinal image database is preprocessed to extract the grayscale or green component of the image, noise removal and to enhance the contrast of the image for further processing. The next step is to localize the retinal components such as Optic Disc, Fovea and blood vessels. In the next step, abnormal features such as micro-aneurysms, hemorrhages and hard exudates and cotton-wool spots are extracted. These features are analyzed with different techniques to perform severity classification of the disease as normal, mild, moderate, severe Non proliferative Retinopathy (NPDR) and Proliferative Retinopathy (PDR).

II. DIABETIC RETINOPATHY DETECTION AND SEVIERITY CLASSIFICATION

1. Pre-processing for contrast enhancement and removal of noise: The main aim of preprocessing methods is to achieve image normalization by attenuation of intensity variations in the input images. The original images contain non-uniform spatial variations across the image.
2. Detection, Localization of the Optic Disc and its segmentation: This process consists of finding approximate optic disc center. Circular Hough transform and Principal Component Analysis are the methods used to detect the optic disc and active contour model to segment the optic disc.
3. Retinal vascular tree segmentation: Retinal vasculature segmentation is done by applying morphological operators and edge detection.
4. Abnormal Feature Extraction : After the optic disc, fovea and blood vessel network localization the exudates, hemorrhages and microaneurysms are extracted from the images
5. Classification of different stages of Diabetic Retinopathy: After the features are extracted, according to the extent of features extracted, classification is done using different types of classifiers, such as neural networks, support vector machines. Efficiency of the classifier is calculated in terms of its efficiency to classify normal images into normal and abnormal images as abnormal.
6. Evaluation of the performance of classifier: Several parameters such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are calculated. These parameters are calculated by comparing the classifier outcome with the number of normal and abnormal images from the database.

III. LITERATURE SURVEY

Various eye disease detection image processing, neural network algorithms are proposed in past. Many important eye diseases as well as systemic diseases manifest themselves in the retina. While a number of other anatomical structures contribute to the process of vision, this review focuses on retinal imaging and image analysis.

Based on the segmentation of blood vessel and the detection of the microaneurysms in the fundus image of the retina. First, the blood vessel network is ubiquitous to all retinal images and can provide a wealth of health and disease information. The second, microaneurysms, is a lesion particularly associated with diabetic retinopathy – a disease of the retina resulting from diabetes. This is polished off with some more recent and sophisticated techniques in wavelet and fractal analysis of the vessel network. First we will consider the literature based on blood vessel segmentation. Many methods for retinal vessel segmentation have been reported. These can be divided into two groups: rule-based methods and supervised methods. In the first group, methods like vessel tracking, mathematical morphology, matched filtering, model-based locally adaptive thresholding or deformable models are used for vessel segmentation. On the other hand, supervised methods are those based on pixel classification (implementing some kind of classifier). Supervised methods are based on pixel classification, which consists on classifying each pixel into two classes, vessel and non-vessel. Classifiers are trained by supervised learning with data from manually-labeled images.

Gardner et al. [1] proposed a back propagation multilayer neural network (NN) for vascular tree segmentation. After histogram equalization, smoothing and edge detection, the image was divided into 20 × 20 pixel squares (400 input neurons). The NN was then fed with the values of these pixel windows for classifying each pixel into vessel or not. Each pixel in the image was classified by using the first principal component, and the edge strength values from a 10 × 10 pixel sub image centered on the pixel under evaluation, as input data. Niemeijer et al. [2] implemented a K-nearest neighbor (kNN) classifier. A 31-component pixel feature vector was constructed with the Gaussian and its derivatives up to order 2 at 5 different scales, augmented with the gray-level from the green channel of the original image. The assumption that vessels are elongated structures is the basis for the supervised ridge-based vessel detection method presented by Staal et al. [3].

The PNN architecture is composed of many interconnected processing units or neurons organized in successive layers. The input layer unit does not perform any computation and simply distributes the input to the neurons in the pattern layer. On receiving a pattern *x* from the input layer *x*, the neuron of the pattern layer computes its output. Each category may contain many training patterns (training vectors) whose dimension is equal to the number of input factors, and taking a set of specific values of input factors. The training vectors are imported from sample data and hence they are not always necessarily representative of all existing patterns for that class. However, this is the advantage of PNN, in that it can generalize to allow recognition of a new pattern of a class [3].

Soares et al. [4] used a Gaussian mixture model Bayesian classifier. Multiscale analysis was performed on the image by using the Gabor wavelet transform. The gray-level of the inverted green channel and the maximum Gabor transform response over angles at four different scales were considered as pixel features. SVM is a robust technique for data classification and regression. Support vector machine (SVM) for pixel classification as vessel or nonvessel. They used two orthogonal line detectors along with the gray-level of the target pixel to construct the feature vector.

ANN maybe provided with the digitized data of various scotomata from visual field analysis such as accurate defects, hemianopias, etc. Once the network has been trained to recognize the digitized visual fields, an example of a scotoma which has not previously been seen can be presented. Even though this may not be exactly the same as any of the scotomata in the training set the neural network will be able to provide a probability of the scotoma belonging to one of the outputs-for example, accurate defect. The ANN can therefore categories data which are inherently variable as most images of biological systems are, for example, fundus photographs.[5]

The network used was a back propagation network in which there as feedback mechanism allowing the network to retrain itself on data for adjustment of the internal weights. Transfers between each layer (the input layer, output layer, and hidden layer)are governed by a transfer function and the back propagation controlled by a learning function both of which can be varied to optimize performance. The memory of a network is stored in the connection weights, the numbers of which are determined by the number of elements in the hidden layer. Increasing the number of elements in the hidden layer increases the number of possibilities that the network can learn, while reducing the number forces the network to try to generalize. The optimum number of weights for a particular problem must be determined [6].

MLPs are feed-forward neural networks trained with the standard back-propagation algorithm. It is shown that a network having a single layer of threshold units could classify a set of points perfectly if they were linearly separable. For a set of N points, a two-layer network of threshold units with N- 1 unit in the hidden layer could exactly separate an arbitrary dichotomy data. Multilayer perceptrons (MLPs) are feed forward neural networks (FF NNs) trained with the standard back propagation algorithm. They are supervised networks so they require a desired response to be trained. Most NN applications involve MLPs. They learn how to transform input data into a desired response, so they are widely used for pattern classification. They are very powerful pattern classifiers. With one or two hidden layers they can approximate virtually any input–output map. They efficiently used the information contained in the input data [7].

IV. CONCLUSION

Automated analysis of retinal images is an ongoing active field of research. Since there are large number of diabetic patients yet not screened are under the danger of vision degradation or loss. In this research work some of the simpler and some of the more recent analytical tools bought to analyses retinal images have been discussed. We have seen that standard image processing techniques that may be found in any good text on general image processing can go a long way to detecting certain features/lesions in retinal images and produce seemingly good results. The proposed methods are able to detect the microaneurysms from the fundus image without the need of doing fundus fluorescence angiography and it is simple, flexible and robust. Vessel segmentation has been done using two pixel feature, still an appreciable accuracy is attained. The advantage of the automated detection method using neural network is less computation time, so that an ophthalmologist can concentrate on more severe patients rather than testing every patient. With such a screening system a person with little training can able to do testing of patient so it is not necessary to have expert ophthalmologist. Since this system is able to detect microaneurysms at earliest stage there will be remarkable cost saving in treatment.

V. ACKNOWLEDGMENT

We are greatly indebted to our principal Dr. K. C. RAVEENDRANATHAN, Dr. SHREELEKSHMI R., Professor, Head of the Department of Computer Science and Engineering, Mr. MANOJ KUMAR G., Associate Professor, Department of Computer Science and Engineering, LBS Institute of Technology for Women who has been instrumental in keeping my confidence level high and for being supportive in the successful completion of this paper. We would also extend our gratefulness to all the staff members in the Department; also thank all my friends and well-wishers who greatly helped me in my endeavor. Above all, we thank the Almighty God for the support, guidance and blessings bestowed on us, which made it a success.

REFERENCES

[1] G. G. Gardner, D. Keating, T. H.Williamson, and A. T. Elliott, “Automatic detection of diabetic retinopathy using an artificial neural network: A screening tool,” Br. J. Ophthalmol., vol. 80, pp. 940–944, 1996.

[2] J. Staal, M. D. Abràmoff, M. Niemeijer, M. A. Viergever, and B. v. Ginneken, “Ridge based vessel segmentation in color images of the retina,” IEEE Trans. Med. Imag., vol. 23, no. 4, pp. 501–509, Apr. 2004.

[3] T. Walter, J.C. Klein, P. Massin, and A. Erginay, “A contribution of image processing to the diagnosis of diabetic retinopathy-detection of exudates in colour fundus images of the human retina” , IEEE Transactions on Medical Imaging , Vol. 22(10), pp. 1236 – 1243, 2002.

[4] João V. B. Soares, Jorge J. G. Leandro, Roberto M. Cesar Jr.,Herbert F. Jelinek, and Michael J. Cree, Retinal Vessel Segmentation Using the 2-D Gabor Wavelet and supervised Classification IEEE TRANSACTIONS ON MEDICALIMAGING, VOL. 25, NO. 9, SEPTEMBER 2006

[5] Frédéric Zana and Jean-Claude Klein, Segmentation of Vessel-Like Patterns Using Mathematical Morphology and Curvature Evaluation ,IEEE TRANSACTIONS ON IMAGEPROCESSING, VOL. 10, NO.7, JULY 2001

[6] H. Li, O. Chutatape. “Automatic Location of Optic Disc in Retinal images”. IEEE ICIP, 2001, pp. 837-840.

[7] H. Li and O. Chutatape. “Fundus image features extraction”. Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 4,2000, pp.3071 -3073.