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SPECIAL ISSUE ON RECENT RESEARCH CHALLENGES IN BIO-MEDICAL APPLICATIONS

A Decision Support System for Detecting the Stages of Diabetic Retinopathy by using Fundus Images

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Retinal images can be classified by an improved Computer Aided Clinical and Decision Support System using Neural Network is presented in this paper. The Optic Disc features such as thickness of vessels (blood, main and branch), diameter of vein, cup area have been extracted by applying a variety of neural network techniques for classification purpose. By using SVM classifier, percentage of False Acceptance rate and False Rejection rate are noticed to be very less when compared with different classifiers. The proposed system has established 98.45% accuracy. The load of experts can be decreased considerably using automatic disease recognition system by preventing the referrals to those cases which requires instant attention. The proposed system decreases the time utilization and applies additional efforts on screening patients' diseases turn out to be normal.

Key words: Median Filtering, Abnormality detection, diabetic retinopathy, SVM.

Diabetic Retinopathy is one of the main causes of the blindness in people who are suffering by Diabetic Mellitus for a prolonged period of time. Diabetes causes an excess amount of glucose to remain in the blood, which may cause the blood vessels to damage[1,2]. Leakage of blood and fluid by the damaged vessels affects the surrounding tissues and causes problems in the vision. The small blood vessels in the retina are damaged. This is called diabetic retinopathy. Diabetes also increases the possibility of getting several eye related problems[8, 9]. The retina is responsible for converting the light and images as nerve signals that are sent to the brain.

The Fig 1a shows the Normal vision and Fig 1b shows the vision that is being affected by Diabetic Retinopathy. The innermost light sensitive membrane of the eye is called retina, which is present at the back portion of the eye. When the eye is focused, the light from an object outside the eye is imaged on the retina. To put it more simply, retina transforms the light rays into electrical impulses and make it move along with the optic nerve to reach the visual cortex in the brain. Here three-dimensional image is generated by combining the images from left and right eyes. As a result, this allows us to perceive depth and distance. The eye cannot communicate with the brain without the help of the retina. Only by means of retina the eye can communicate with the brain, to make the vision possible[6, 16].

Existing work

Macular edema and Microaneursym are some of the causes of Diabetic Retinopathy. Macular edema occurs when fluid and protein deposits collect on or under the macula of the eye (a yellow central area of the retina) and causes it to thicken and swell (edema)[4,3,14] The swelling may affect a person's vision, as the macula is near the center of the retina. This area holds tightly packed cones that provide

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Fig 1a. Normal Vision

Fig 1b. Vision affected by Diabetic Retinopathy

sharp, clear central vision to enable a person to see. Macular edema is swelling and thickening of the macula (the central portion of the retina). This condition is called diabetic macular edema[7,11, 17]. Figure 2 depicts the Macular Edema

It is one of the common causes of vision loss in patients with diabetes of prolonged time period. Patients with diabetic macular edema experience reduced vision in the form of blurring, darkening or distorted images. Often the amount of retinal and macular edema, and associated symptoms, will be unequal between the two eyes. Microaneurysms are small blood clots that occur due to burst of the capillaries. They are very difficult to detect in retinopathy images[5, 6, 10].

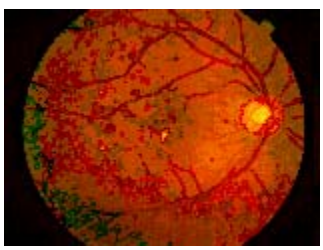

Fig. 2. Macular Edema

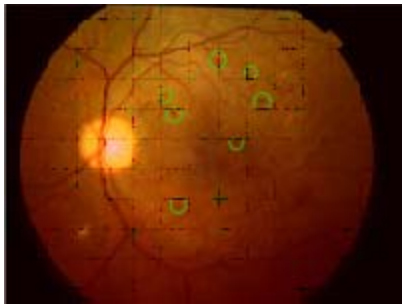

Fig. 3. Microaneurysm

Hemorrhages are bigger clots.A retinal microaneurysm is a tiny area of blood protruding from an artery or vein[3, 16]. They may open and leak blood into the retinal tissue surrounding it. Figure 3 depicts the Microaneurysm.

The Limitations of the Existing work are it is very difficult to detect small or faint hard exudates and high computational complexity of overall detection.

Implementation of the proposed system

The flow sequence of the proposed approach is shown in Figure 4. The proposed method consists of Preprocess, Feature Extraction, Feature Selection, Classification and Decision making.

Preprocess

The preprocess is done using a sharpening filter named Gabor filter. The Gabor filter can be used to make a sharper appearance of an image[12, 15]. These filters emphasize fine details in the image exactly the opposite of the low-pass filter. The working of Gabor filter and low pass filter are similar. Gabor filter is used in the brightest parts of the image, where the signal-to-noise ratio is higher. Gabor filtering can also cause small, faint details to be greatly exaggerated.

Figure 5 shows the image of the retina after preprocessing and its corresponding Histogram. The Retina edges can be detected using the function

$$H(p,q,f,\theta)=\exp\left\{-\frac{1}{2}\left|\frac{p'^2}{\delta_{p'}^2}+\frac{q'^2}{\delta_{q'}^2}\right|\right\}\cos\left(2\pi f p'\right)$$

Where

$$q' = p\cos\theta + q\sin\theta$$

$$p' = p\sin\theta + q\cos\theta$$

Where θ is the orientation of Gabor Filter

By using the various methods of Artificial Intelligence, the extracted features are classified.

Feature extraction

The anatomical structures like Retinal blood vessels, macula, optical disk, blood vessel thickness and vein diameter are extracted. In this work three features such as Retinal blood vessel thickness, optical Disc parameters and vein diameter have been focused and estimated. The Optic disk is the brightest portion than all the other features and it is almost circular and measures about 1800 µm. Retinal vasculature originates in optic disc. Features are extracted from the retinal fundus images of size 576x720 pixels. Localized statistical features are computed by dividing the image into sub-images. More localization of the image will yield accurate features. In this proposed system fundus images are divided into sub images of size 36x90 pixels, which will result in a feature vector of size 128. It extracts four statistical features such as mean, variance, skewness and kurtosis. The total size of the feature vector is 512. These features are computed as follows.

a. Mean $= \dfrac{\sum_{i=1}^{N} x_i}{N}$ where N is the number of $\bar{x}$ data points and n is the order of the moment

b. Variance $= \dfrac{\sum_{i=1}^{N} \left(x - \bar{x}\right)^2}{N}$

c. Skewness $= \dfrac{1}{N}\left(\dfrac{\left(x-\bar{x}\right)}{\sigma}\right)^3$ and

d. Kurtosis $= \dfrac{1}{N}\left(\dfrac{\left(x-\bar{x}\right)}{\sigma}\right)^4 - 3$

After feature extraction, each image is transformed into a feature vector and are represented as {f1, f2, f3… fn, Image Category} where each fi is a continuous feature and Image category is the pre-defined category of the image.

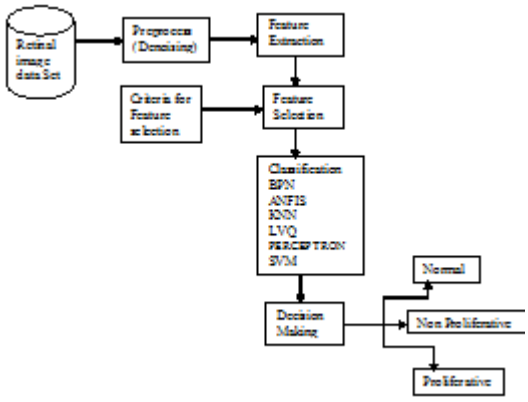

Fig. 4. Flow Sequence of the proposed Approach

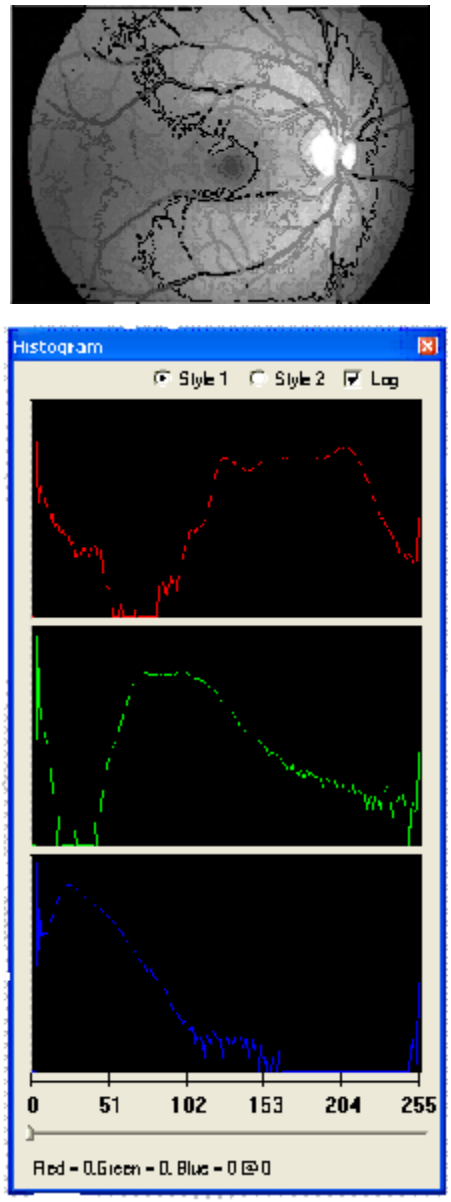

Fig. 5. Preprocessing of the Retinal Image and its corresponding Histogram

Feature selection

With no quality data, there are no quality mining results. So, in order to reduce the hypothesis space for the classifiers and to reduce the average classification error, feature selection is performed using CfssubsetEval, a correlation based method. This method evaluates the worth of a subset of features considering the individual predictive ability of each feature along with the degree of redundancy between them. Subsets of features that are highly correlated with the class while having low inter-correlation are preferred. Optical Coherence Tomography (OCT) is a high resolution technique used for measuring the total retinal thickness and Retinal nerve Fiber layer (RNFL) thickness. In Figure 7 the regions for measuring are deducted.

Support vector machines

Support Vector Machines (SVMs) are relatively new learning process influenced by growth in statistical learning theory and an adequate enhancement in the power of computer processing. It is one of the useful techniques for classification of data. It is a non probabilistic binary linear classifier, used in supervised learning methods that analyze data and recognize patterns. The purpose of SVM is to generate a model based on training data sets and predicts to calculate the target values of the test data. The vectors can be separated with maximum distance and minimum errors by using a hyper plane. An optimal hyper plane can be obtained by the SVM using an iterative training algorithm. By using SVM, an error function can be reduced and it helps to locate a linear separating hyper plane with the maximal margin in this higher dimensional space. It requires that each data instance is represented as a vector of real numbers. Scaling before applying SVM is very important. The most important benefit of scaling is to prevent the dominations of attributes in smaller numeric ranges over greater numeric ranges. The following are the basic kernels

Linear: $K(a_i, a_j) = a_i^T a_j$

Polynomial: $K(a_i, a_j) = (\gamma a_i^T a_j + r)^d, \gamma > 0$

Radial basis function (RBF) $K(a_i, a_j) =: \exp(-\gamma \Pi a_i - a_j \Pi^2), \gamma > 0$

Sigmoid: $K(a_i, a_j) = \tanh(\gamma a_i^T a_j + r)$

Here ,r and d are kernel parameters. The selected kernel for SVM classifier is the Radial Basis Function. Localized and finite responses can be produced by the SVM classifier across the whole range of the X axis. SVMs are effective in a wide range of Bioinformatics problems. From the extracted features, the classification of the retinal image as normal or abnormal (Non proliferative or Proliferative) can be identified. The false acceptance rate of SVM classifier is less than most well known classifiers. It also provides optimal False Rejection Rate (FRR) and False Rejection Rate (FRR) and thus it gives a higher accuracy

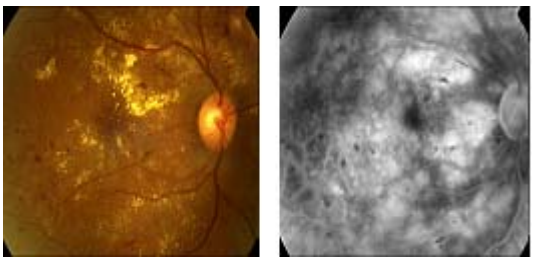

Fig. 6. Abnormal retinal image and its corresponding image for selecting the features

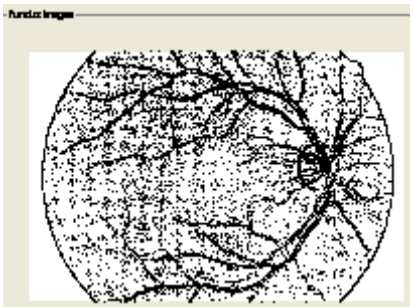

Fig. 7. Feature Selection

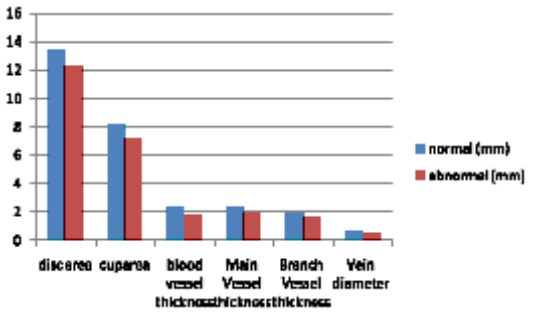

Fig. 8. depicts the normal and abnormal values for the various parameters

percentage compared to other methods of classification.

RESULTS AND DISCUSSION

Table 1 The measurement of optic disc measurement of the disc and cup area, blood vessel thickness, main vessel thickness and branch vessel thickness and vein diameter of the retinal images of both normal and abnormal images.

The Analysis is applied to the entire 90 sample by age group varying from 26 years to 65 years. As a first step, measurements have been made on the normal subjects (Free from diabetics). The same procedure is repeated for abnormal images such as diabetic affected patients. Figure 8 depicts the normal and abnormal values for the various parameters.

Comparative analysis

Relative examination of the future approach with some existing approaches is present in this section. Computing the False Acceptance rate (FAR) and False Rejection rate (FRR) is the common way to measure the retinal image classification accuracy. FAR and FRR are the percentage of inaccurate acceptances and inaccurate rejection. The Table 2 gives the percentage of the recognition rates and the accuracy rates of the various classification techniques. The following equation is used to calculate the accurate measurement of the overall approach,

$$Accuracy = 100 - \left[\frac{(FAR / FRR)}{2}\right]$$

Table 1. The measurement of optic disc measurement of the disc and cup area, blood vessel thickness, main vessel thickness and branch vessel thickness and vein diameter of the retinal images of both normal and abnormal images

S.No	1	2	3	4
Age Group (Years)	26-35	36-45	46-55	56-65
Types of Images	Normal and Abnormal Images			
Number of Subjects	90 Sample (Both normal and abnormal)			
Optic Disc measurement				
Disc Area normal (mm)	7.817	13.368	19.41	25.889
Disc Area abnormal (mm)	5.744	12.249	16.077	24.07
Cup Area normal (mm)	2.744	8.258	12.906	19.393
Cup Area abnormal (mm)	2.724	7.238	14.228	21.938
Blood Vessel thickness normal (mm)	2.14	2.336	2.623	2.799
Blood Vessel thickness abnormal (mm)	1.463	1.801	2.345	2.645
Main Vessel thickness normal (mm)	2.001	2.338	2.439	2.541
Main Vessel thickness abnormal (mm)	1.6	1.97	2.371	2.663
Branch Vessel thickness normal (mm)	1.658	2.022	2.274	2.354
Branch Vessel thickness abnormal (mm)	1.527	1.594	2.315	2.627
Vein diameter normal (mm)	0.529	0.627	0.794	1.058
Vein diameter abnormal (mm)	0.529	0.532	0.649	0.474

Table 2. Performance comparison of various classification techniques

Classification Methods	FAR (%)	FRR (%)	Accuracy (%)
Proposed Method (SVM)	10.84	2.16	98.45
Back Propagation Network (BPN)	32.56	3.14	94.91
Adaptive Neuro Fuzzy Inference systems (ANFIS)	42.62	3.54	93.69
Linear vector Quantization (LVQ)	19.33	2.68	96.33
K-Nearest Neighbor (KNN)	31.76	3.03	94.79
Perceptron	37.23	3.65	92.55

CONCLUSION

In the computer aided diagnostic system, neural network is used to classify the retinal images and it is validated with many samples and experts. The classification of the retina as normal or abnormal has been improved by using SVM classifier and multiple feature analysis.The proposed system can be used as a secondary observer in the clinical decision making

REFERENCES

1. Balint Antal, Andras Hajdu, "Improving Microaneurysm Detection In Color Fundus Images By Using An Optimal Combination of Preprocessing Methods And Candidate Extractors", 18th European Signal Processing Conference (EUSIPCO-2010).
2. Davidson J, T. Ciulla, J. McGill, K. Kles, and P. Anderson, "How the diabetic eye loses vision," *Endocrine*, **32**: pp. 107–116, Nov. 2007
3. Giancardo L ,F. Meriaudeau ,T.P. Karnowski , Y.Li , K.W Tobin , Jr., and E. Chaum , "Automatic Retina Exudates Segmentation Without a Manually Labelled Training Set," in Proc. 2011 IEEE Int. Symp. Biomed. Image: From Nano to Macro, Mar. 2011, pp. 1396–1400
4. Hatanaka Y, T. Nakagawa, Y. Hayashi, Y. Mizukusa., A. Fujita, M. Kakogawa, K. K.M., D. , T. Hara , andH. Fujita,"Cad Scheme To Detect Hemorrhages And Exudates In Ocular Fundus Images," in Proc. SPIE Med. Image. 2007: Comput.-Aided Diagn., Mar. 2007, vol. 6514, pp. 2M1–2M8
5. Huan, H. Wynne W, and L.M Li,"Effective Detection of Retinal Exudates In Fundus Images", in Proc. 2nd Int. Conf. Biomed. Eng. Informant., Oct. 2009, pp. 1-5.
6. Jaafar H, A. Nandi, and W. Al-Nuaimy, "Detection of exudates in retinal images using a pure splitting technique," in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Aug. 2010, pp. 6745–6748.
7. Jerald Jeba Kumar S and Madheswaran M,"An Improved Medical Decision Support System to identify the Diabetic Retinopathy Using Fundus Images", journal of Medical Systems (Springer), Volume 36, number 6,2012
8. Osareh A, M. Mirmehdi, B. Thomas, and R. Markham, "Automated identification of diabetic retinal exudates in digital color images," Br.J. Ophthalmol., Vol. 87, pp. 1220–1223, Oct. 2003.
9. Osareh, B. Shadgar, and R. Markham, "A computational-intelligence-based approach for detection of exudates in diabetic retinopathy images," IEEE Trans. Inf. Technol. Biomed., Vol. 13, no. 4, pp. 535–545, Jul. 2009.
10. Ram K and J. Sivaswamy, "Multi-space clustering for segmentation of exudates in retinal color photographs," in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Sep. 2009, pp. 1437–1440.
11. Ravishankar S, A. Jain, and A. Mittal, "Automated Feature Extraction For Early Detection of Diabetic Retinopathy In Fundus Images," IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2009, pp. 210–217.
12. Sai Deepak Kand Jayanthi Sivaswamy, "Automatic Assessment of Macular Edema From Color Retinal Images" IEEE Transactions on Medical Imaging, Vol. 31, no. 3, March 2012
13. Silberman, R F, N, K. Ahlrich, and L. Subramanian, "Case For Automated Detection of Diabetic Retinopathy", Proc. AAAI Artif. Intell. Development (AI-D'10), pp. 85–90, Mar. 2010.
14. Singh J, G. D. Joshi, and J. Sivaswamy, "Appearance-based object detection in color retinal images," in Proc. Int. Conf. Image Process., 2008, pp. 1432–1435.
15. Thomas Walter, Jean-Claude Klein, Pascale Massin, and Ali Erginary, "A Contribution of Image Processing To The Diagnosis of Diabetic Retinopathy-Detection of Exudates In Color Fundus Images of The Human Retina" IEEE Transactions on Medical Imaging, Vol.21, no. 10, October 2002
16. Verma M, R. Raman, and R. E. Mohan, "Application of tele ophthalmology in remote diagnosis and management of adnexal and orbital diseases," Indian J. Ophthalmol., Vol. 57, no. 5, pp. 381–384, Jul. 2009.
17. Vijayalakshmi R, Silvia RC "Proceedings of IEEE sponsored International Conference on Information Communication and Embedded Systems (Silvia RC ICICES), 2013 ", pp. 978-983 2, March 013