Automatic Detection of Abnormalities in Retinal Blood Vessels using DTCWT, GLCM Feature Extractor and CNN-RNN Classifier

Revathi Priya Muthusamy, S. Vinod, M. Tholkapiyan

Abstract--- ***In worldwide, retinal diseases are found to be frequent cause of blindness for working age population in western countries. So, early diagnosis can prevent the blindness. We develop a system for the early diagnosis of retinal disease. The images with different colour variation inside the eye is compared by using images taken laser camera with high definition. These images are termed as fundus images. The feature extraction of the fundus images can be obtained by usingthe software toolMATLAB. Automatic screening will help to quickly identify the condition of the patients in a more accurate way. The 4-level discrete wavelet transform is used to decompose the image into various sub-bands. The textural features had been calculated using GLCM features, and the classification is done by using CNN-RNNNeural networks. The processed output will be displayed using Matlab GUI. Experimental result proves that the abnormality in the blood vessels andexudates can be effectively detected by applying this method on the retinal images. 76% of test cases are correctly classified.***

Keywords--- ***Retinal, Fundus Image, MATLAB, DTCWT, GLCM, CNN-RNN.***

I. INTRODUCTION TO RETINA AND BLOOD VESSELS

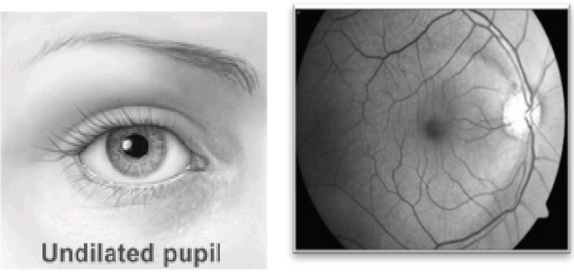

Fig. 1: Undilated Pupil and Fundus image

Retina is the tissue which senses light, it lies in the backside of the eye. Retinal relays the images to the brainA healthy retina helps us to read, drive and see finer details around us. (7). A disease in retina affects this tissue and may even causeblindness.The most common retinal disease are Glaucoma, diabetic retinopathy, floatersand the retinitis pigmentosa.**Fundus Imaging**-Fundus Imageis captured using a camera which isattached with a specialized low-power microscope.Ophthalmologists can use these retinal images for diagnosis and treatment of eye diseases.

II. IMAGE PROCESSING USING DTCWT, GLCM AND RNN

Fig. 2: Flowchart-Image processing of abnormalities in Retina

Image Pre-processing

In this step, the retinal image is taken as a input and processed to RGB plane separation. Preprocessing consists of de-noising and enhancement steps. De-noising refers to the process employed for removing the noise that exists in the image; enhancement indicates a process used for increasing the image contrast. Here, the input image has speckle noise.(1) The speckle noises generally degrades segmentation process and decreases image quality. It will increase the difficulties of image segmentation. So the speckle noise should be removed to achieve the accurate segmentation. For removing the speckle noise, median filter is exploited for removing the speckle noise. The filter process is given below. Median filter is used to de-noising and smoothen the image without removing edges or sharp features in the images (3). After de-noising, the input image is re-sized to the particular dimension. The input image has separated into red, green and blue planesfrom this the green plane is taken as a input for next level processing.

Feature extraction: Dual Tree - Complex Wavelet Transform (DTCWT), enhanced directional selectivity and phase information properties of redundant CWT results in the super-resolved image. By using dual tree wavelet transform , the input image had been decomposed into sub-bands, these sub-bands is further fed as a input for GLCM (Grey level co-occurrence matrix) feature extraction which is an texture based feature descriptor.

Manuscript received June 10, 2019.

RevathiPriyaMuthusamy, Computer Science and Engineering, Vel Tech Multi Tech Dr.RangarajanDr.Sakunthala Engineering College, 42, Alamathi Road, Avadi, Thiruvallur, Chennai, Tamil Nadu, India. (e-mail: revathipriya@yahoo.com)

S. Vinod, Assistant Professor, Computer Science and Engineering, Vel Tech Multi Tech Dr.RangarajanDr.Sakunthala Engineering College, 42, Alamathi Road, Avadi, Thiruvallur, Chennai, Tamil Nadu, India. (e-mail:svinod@veltechmultitech.org)

Dr.M. Tholkapiyan, Professor, Department of Civil Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Tandalam, Chennai, India. (e-mail:m.tholkapiyan@gmail.com)

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Blue Eyes Intelligence Engineering
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The grey level co-occurrence matrix of all sub-band's are calculated to arrive atresulting values which can be processed to arrive at the
Final result of the feature vector.

In the above proposed method, DT-CWT dualtree - complex wavelet transform has to be first employed onto theraw image and we can obtain the sub-images at six different directions. After which the GLCM calculation is done for each sub image and thus the final resultant feature vectoris constructed. Thisexperimentalresultsshows that this proposed method can achieve better accuracy with high texture classification than otherconventional method and has the property of robustness.

Classification

The classification is done by using neural networks, here we will be using combination of convolutional neural networks with Recurrent Neural networks concepts (2). CNN detects patterns and makes sense out of them. CNN has Hidden layers called convolution layers, convolutional layers transforms the signal and passes on to the next layer. With each convolution layer, we specify the number of filters. Filters are used detect the patterns. The pattern may be edges, corners, circles or squares. More sophisticated objects like ear, eyes can be detected. The output of the Convolution layer is passed as input to the filters of the next layer.

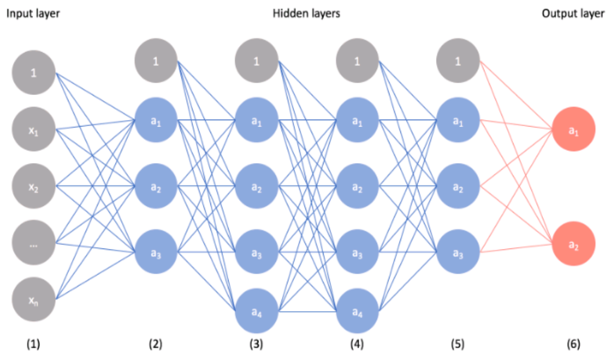

Fig. 3: Convolutional neuralnetwork

The main use of Recurrentneural network is in the field of image recognition. The RNN is a network which has recurrent network connections. The traditional feed forward neural network does not provide good results for Times series/ sequential data such as Stock prices, video streams etc.They do not model memory.(6)RNN captures information from sequences and time series data. They can work with variable size input and work with variable size data.The concepts of Convolution neural network is also incorporated by adding recurrent connections to each convolutional network layer. This can also be called asrecurrent convolution layers (RCL).

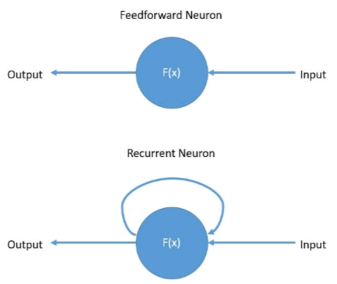

Fig. 4: Basic structure of a Recurrent Neuron

RNN recursive formula

$S_t = F_w(S_{t-1}, X_t)$.

X_t- Input at time step t

S_t- State at time step t

F_w - Recursive Function

RNN learns using Back propagation through time. RNN uses three to four layers maximum.

Dataset

The dataset downloaded form the database ofIndian Diabetic Retinopathy Image Dataset (IDRiD)and two public datasets STARE and DRIVEwere used.

III. EXPERIMENTS AND RESULTS

100 images were used for training the tool using the training function TRAINSCG. We can evaluate our techniques by calculating three metrics: (i) Root-Mean Square Error (RMSE) (ii) Pearson Correlation Co-efficient (CC) and (iii) Concordance Correlation Co-efficient (CCC). The Concordance Correlation Coefficientcalculates and measures the agreement betweenthe two variables using the below expression:

$$\rho_c = \frac{2\rho\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2 + (\mu_x - \mu_y)^2}$$

Where ρ isPearson correlation co-efficient, σ 2 x , σ 2 y variance of the predicted , ground truth value respectively , μx, μy –respective means. The highest CCC value can be used to select the strongest method.

Table 1: Comparison of Performance

Method	RMSE	CC	CCC
Baseline [13]	0.117	0.358	0.273
CNN	0.121	0.341	0.242
CNN+D	0.113	0.426	0.326
CNN+A	0.125	0.349	0.270
CNN+AD	0.118	0.405	0.309
CNN+RNN - tanh	0.111	0.518	0.492
CNN+RNN - ReLU	**0.108**	**0.544**	**0.506**

Table 1.Comparison of Performance between: (i) Baseline method (ii) CNN having Single framewith different regularization levels (iii) CNN having Single framewith RNN A = Data AugmentationandD = Dropout.

Table 2: CNN RNN performance with increasing no. of layers

Method	RMSE	CC	CCC
CNN+RNN - W=100 - 1 layer	0.107	0.553	0.481
CNN+RNN - W=100 - 2 layers	0.111	0.514	0.459
CNN+RNN - W=100 - 3 layers	**0.106**	**0.565**	**0.489**

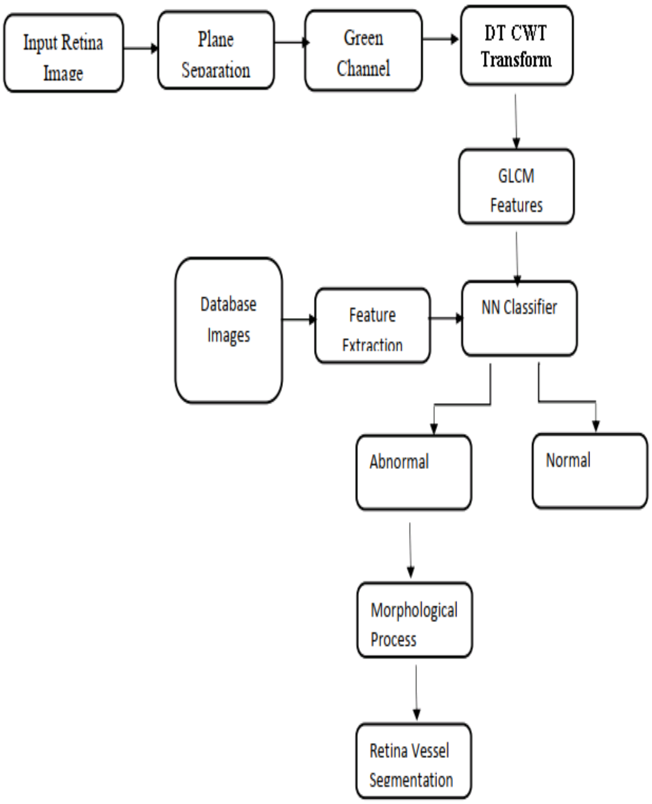

Fig. 5: Process flow diagram of Image processor with Pre-processing, feature extraction and Classifier.

IV. DEEP LEARNING USING MATLAB SOFTWARE

Requirement Specification:

(i). Retinal Images for Training and Quality testing.

(ii). Software Requirement

- MATLAB 7.5 and above versions
- Deep Learning Toolbox

MATLAB software can be used to in Image processing such as to remove the noise in image, produce high resolution image from low quality image using Convolution nueral network.

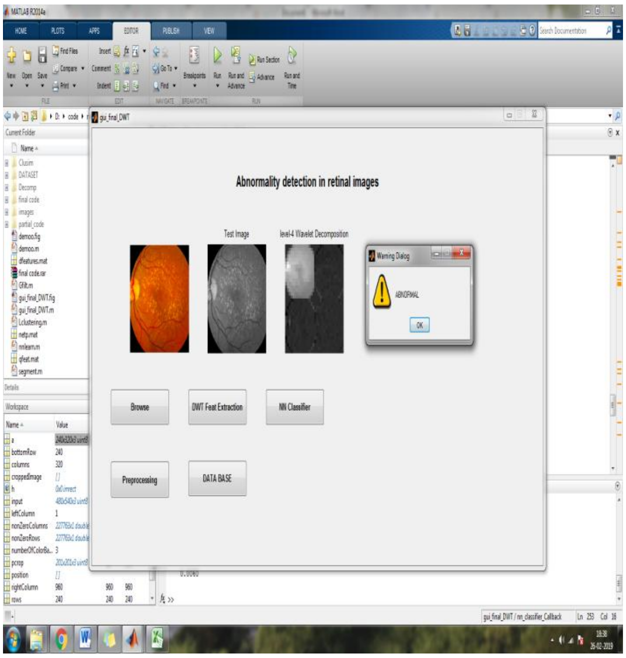

Fig. 6: MATLAB GUI of the proposed system

V. CONCLUSION

In this work, we have pre-processed the image to separate the Green plane of the image, de-noised and fed the signals to DTCWT and GLCM feature extraction process followed by the CNN-RNN neural network for classification. The Network is prior trained with the dataset using Deep learning techniques of MATLAB functions for the detection of normal and abnormal images. The output is displayed in MATLAB GUI.Our model has achieved better performance compared to other state-of-the-art image processing systems.

REFERENCES

1. Detection and Classification of Retinal Diseases in Spectral Domain Optical Coherence Tomography Images based on SURF descriptors,2018 IEEE International Conference on System, Computation, Automation and Networking (ICSCAN)
2. Retinal Vessel Segmentation via A Coarse-to-fine Convolutional Neural Network,2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)
3. Segmenting Retinal Vessels with a Multi-scale ModifiedDolph-Chebyshev Type I Function Matched Filter,2018 4th International Conference on Science and Technology (ICST)
4. Feature Extraction Method of Retinal Vessel Diameter,Conference: 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)
5. Color Retinal Image Enhancement Based on Luminosity and Contrast Adjustment, IEEE Transactions on Biomedical Engineering (Volume: 65 , Issue: 3 , March 2018)
6. How deep neural networks can improve emotion recognition on video data, 2016IEEE International Conference on Image Processing (ICIP).
7. Diabetic Retinopathy and Diabetic Macular Edema.
8. Steven R. Cohen, Thomas W. Gardner. Developments in ophthalmology, 2016.
9. A Retinal Image Enhancement Technique for Blood Vessel Segmentation Algorithm. A. M. R. R. Bandara, P. W. G. R. M. P. B. Giragama 2017 IEEE International Conference on Industrial and Information Systems (ICIIS), Peradeniya, Sri Lanka, 2017, pp. 1-5
10. Detection of diabetic retinopathy using computational model of human visual system. MasoudKhazaeeFadafen*, Nasser Mehrshad, Seyyed Mohammad Razavi, Department of Electrical and Computer Engineering, University of Birjand, Birjand, Iran. Biomedical Research 2018,ISSN 0970-938X
11. Mobile assisted diabetic retinopathy detection using deep neural network, 2018 Global Medical Engineering Physics Exchanges/Pan American Health Care Exchanges (GMEPE/PAHCE).

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