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Analysis of Glaucoma in Fundus Images Using LSTM-RNN Classifier

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ABSTRACT

Glaucoma is a disorder disease caused due to high fluid pressure in optic nerve, it cause loss of vision and damaged optic nerve subsequently, in this paper proposed methodology for an automatic detection of glaucoma using digital image based on contourlet transforms. Then the image is used transform the contourlet and the component features are obtained ranked based method, The Contourlet Transform consists of the signal into components of different band of frequency. Correntropy based Feature Extraction. The normal and glaucoma image are decomposed into number of parameters features. These features are the classification of normal and glaucoma images using long short time memory recurrent neural network LSTM-RNN classifier. The accuracy of classification proposed method is 99.9%.

Keywords: Fundus images, Contourlet transform, LSTMRNN.

1. INTRODUCTION

Glaucoma is disorders disease eyes, these main causes optic nerve will be damage that the information carries from the eye to the brain. Glaucoma blindness second-leading because, it's cause of no pain and no symptoms produce until noticeable vision loss occurs. It have two types of glaucoma, these are open-angle glaucoma and narrow angle glaucoma. Open-angle glaucoma is to reduce your peripheral vision, it have no symptoms, then permanent vision problem. Open angle glaucoma another name is narrow-angle glaucoma, this type of glaucoma to produces sudden symptoms. That symptoms are such as eye pain, headaches, vision loss, red eyes, halos around lights, and vomiting. In glaucoma forms of occurs optic cup in all directions with a regional based preference on the stage of the disease. Inferior region is generally first affected, followed by superior then temporal and nasal region is the last to be affected.

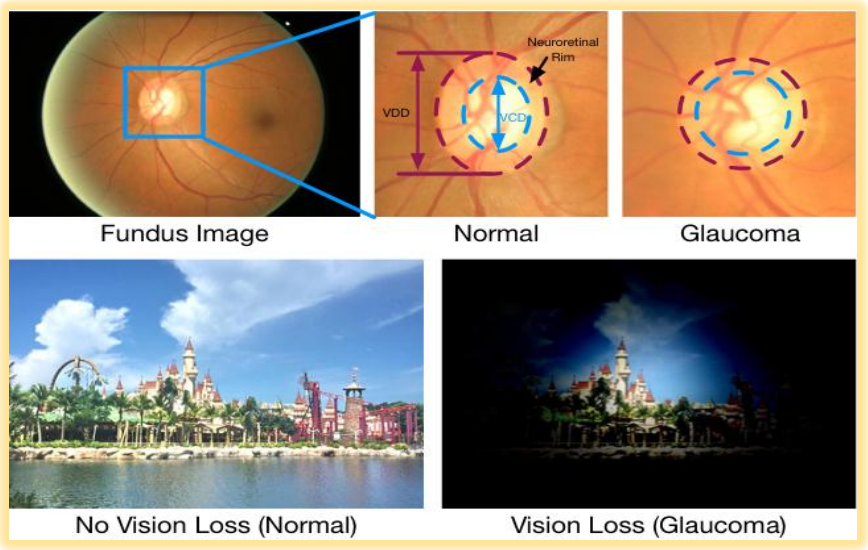

Figure 1: Normal and glaucoma images

An overall cup size of enlargement is called cupping while a focal enlargement of cup leads to notching. Since first affected inferior and superior tissues. The Vertical cup to disk diameter ratio of common measurement used to quantify such deformations in the OD. To indicate a high value of CDR the presence of glaucoma in an eye. Figure 1 to mark difference between a normal and a glaucoma eye and reflected in the corresponding CDR values. The Main problem of glaucoma is vision loss.

2. METHODOLOGY

A. Image dataset

The dataset of fundus images consists of a total of 200 images. It is divided into 100 training and 100 testing images. All images were collected at Aravind eye hospital, Coimbatore from visitors to the hospital, with consent. Glaucoma patient selection was done by clinical investigators and the based on clinical findings during examination. Selected patients were 30- 80 years of age, and equal number of males and females. In this dataset, fundus region of image has been only extracted from the original image. To eliminating the surrounding non-fundus region of image, and obtain an image size of approximately 2047 x 1760 pixels.

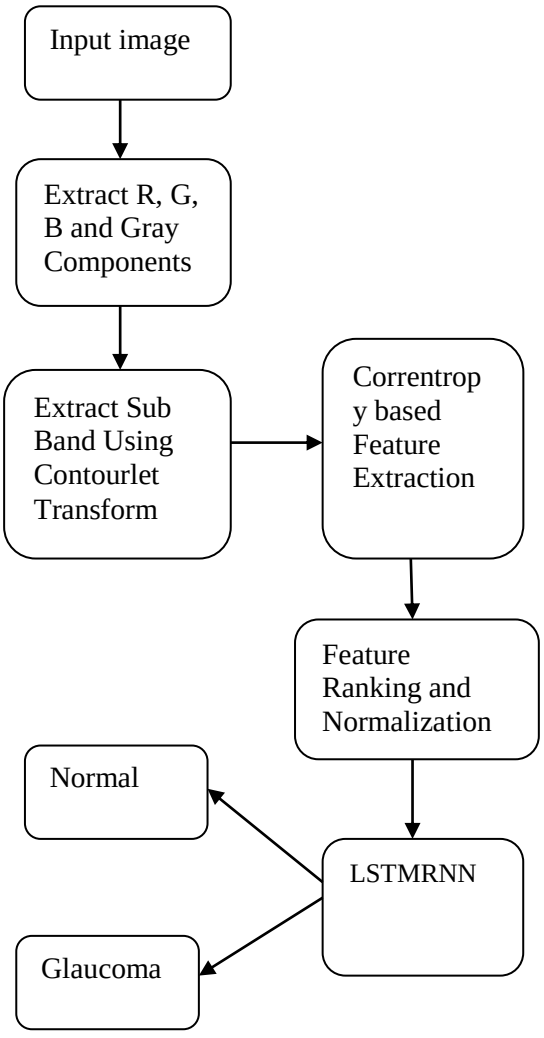

Figure 2: Block diagram of an automatic detection of glaucoma using LSTMRNN

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B. RGB Image Representation

In the RGB image, the basic color components Red, Green, and Blue. These images are represented in the RGB model of color as red, green and blue using 8-bit monochrome standard. The RGB color image has corresponding value of 24bit/pixel 8 bit for each color band (red, green and blue).

3. PROPOSED METHODOLOGY

The contourlet transform decomposes the signal into different level frequency bands parameters. The block diagram of proposed methodology is shown in Fig. 2. The R, G, B components and gray scale of images are subjected to contourlet transform. The R, G, B components of image consists of varies types of gray pixel intensities. The R, G, B parameters presents in the information are used to extract features for automated analysis of glaucoma.

A. Contourlet Transform

Contourlet transforms can be form a multi resolution angle tight frame designed to efficiently approximate images and it make of smooth regions separated by smooth boundaries. The contourlet transform has a fast implementation based on a Laplacian pyramid decomposition followed by directional filter algorithum applied on each band sub band. The contourlet transform uses a double filter, and this bank structure can be getting the smooth contours of images. In this double filter bank, the process of Laplacian pyramid is first used to capture the point will be discontinuities, and then a directional filter bank is used to can be form those point discontinuities into linear structures.

The Compute 1D Fourier transform of each row r of x; X(r;$\boldsymbol{\Omega}$) and columns c of x; X($\boldsymbol{\Omega}$,c) and calculate the spectrum magnitudes mean row as follows:

$$X_{R=}\frac{1}{N_{RW}}\sum_{r=0}^{N_{RW}} X(r,\Omega)$$

$$X_{C=}\frac{1}{N_{C\Omega}}\sum_{c=0}^{N_{\Omega}} X(\Omega,c)$$

Where N_{RW}= number of rows

N_{CL}= number of columns

Perform boundary detection on X_R and X_c and build the corresponding filter bank $\left\{\epsilon_1^R,\left\{\epsilon_m^{N_R}\right\}_{m=1}^{N_R}.\right\}$ and $\left\{\epsilon_1^C,\left\{\epsilon_m^C\right\}_{m=1}^{N_c}.\right\}$ respectively. Where, N_R and N_c are the number of mean row and column sub band.

Filter the row of x is $\left\{\epsilon_1^R,\left\{\epsilon_m^{N_R}\right\}_{m=1}^{N_R}.\right\}$ which provides $\{N_R+1\}$ output images.

Filter {N_R+1} output images along the columns with $\{\epsilon_1^C, \{\epsilon_m^C\}_{m=1}^{N_c}.\}$ this provides {N_R+1}, {N_{C+}1 output images.

B. Feature extraction

An important role of Nonlinearity tests play in system analysis and modeling because involved in analysis and modeling complexity. The correntropy has been used as feature in the proposed methodology. We have extracted correntropy from the decomposed components of contourlet transform. The correntropy is discussed as follows. Correntropy is a measurement of non-linear kernel based similarity which has both statistical and temporal information. It measures to nonlinear domain of multiple delayed correlation samples of the signal. The correntropy based nonlinear features can be used to measure the texture distribution in the decomposed image components. The correntropy CE(G) for lag G can be expressed as

$$CE(G) = \left(\frac{1}{X-G+1}\right)^2 \sum_{x_1,x_2=G}^{X} \gamma(t[x_1,x_2] - t[x_1-G, x_2-G])$$

Where t[x1, x2] is the 2D signal, X is number of rows and columns, and the Gaussian kernel function expressed as

$$\gamma(t[x_1,x_2] - t[x_1-G,x_2-G]) = \frac{1}{\sqrt{2\pi}\varepsilon} \exp\left[-\frac{(t[x_1,x_2] - t[x_1-G,x_2-G])^2}{2\varepsilon^2}\right]$$

Where the Gaussian kernel parameter width is controlled by e. The number of correntropy features depends on the value of G. In this study, we have considered G = 3 and extracted three correntropy features from each decomposed contourlet transform parameters and in the computation of correntropy factors.

C. Feature Selection

Feature selection an important role in performance of this project. The highly determine features are selected using Student's t-test algorithm for further analysis. The t-test typically two classes on the basis mean value. The t-test to assume normal distribution of feature sets corresponding value. And have two different classes' features. These Features are ranked based on the t value. Features with higher t value are more discriminatory and are chosen for performance evaluation process. We have obtained four contourlet transform parameters, these parameters from each image and computed three correntropy features from each single decomposed component. Hence, twelve entropy features are computed from each image. All these features are further processed using Student's t-test process.

D. Feature Standardization

In this process, the standardized features with zero mean and standard deviation units. The process is known as z-score normalization. The normalization is done by subtracting mean from the data and dividing the resultant with standard deviation. The normalized data have zero mean and unit deviation.

4. LSTMRNN CLASSIFIER

Long Short-Term Memory (LSTM) networks are an extension for recurrent neural networks, and it's basically extends their memory. Therefore it is well suited to learn about from important experiences that have very long time memory in between. The units of an LSTM are used building units for the layers of a RNN, and then this method often called an LSTM network. LSTM's enable RNN's to remember of inputs over a period of time will be long. This is because LSTM's contain their data information in a memory that is much like the memory of a computer. And the LSTM can read, write and delete information from its memory. This memory can be seen as a gated cell of the memory, where gated means that the cell decides whether or not to can store or delete information of the memory based on the importance it assigns to the information of the data. It can be determine importance process through weights, which are also learned by the algorithm

5. RESULTS AND DISCUSSION

This paper extracted 12 entropy features from each R, G, and B channels and gray scale image.

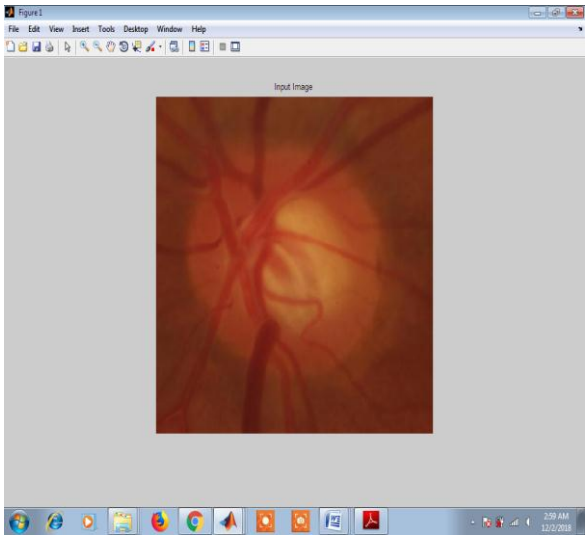

Figure 3: Input image

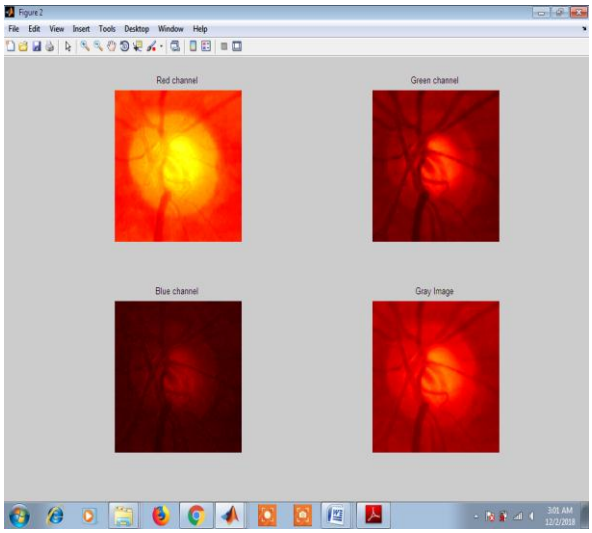

Figure 4: RGB image

Figure 5: Contourlet transform image

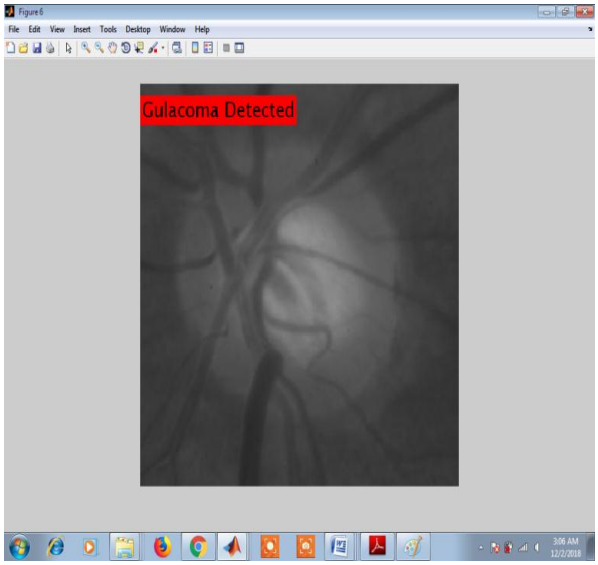

Figure 6: Glaucoma detector image

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6. CONCLUSION

In this paper successfully developed an automated analysis of glaucoma system. The Contourlet transform based correntropy features are extracted from fundus images. And classification accuracy is high, and efficient.

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