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FUNDUS IMAGE CLASSIFICATION USING HYBRIDIZED GLCM FEATURES AND WAVELET FEATURES

T. Shanthi, R.S. Sabeenian, K. Manju, M.E. Paramasivam, P.M. Dinesh and R. Anand
Department of Electronics and Communication Engineering, Sona College of Technology, India

Abstract

We find the usefulness of computers in every field including medical field. Scanning the affected part has become a standard study. Diagnosing a disease at the right time, i.e. early detection, from the study of images enables the physician to take right decision and provide proper treatment to the patient. With the alarming growth of population, it is difficult for every individual patient to get a second opinion from medical expert. In these situations, computer-aided automatic diagnosis system will be much helpful. Diabetic retinopathy is a disorder that arises from increase in blood glucose level. Based on the severity, it has been distinguished into four stages. Diagnosing diabetic retinopathy at an early stage from retinal images and providing proper treatment will save the patient from severe vision loss. The proposed method adopts hybridized GLCM features and wavelet features to classify the fundus images according to the severity of the disease. The method is tested with fundus images collected from Indian Diabetic Retinopathy Dataset.

Keywords:

Fundus Image, GLCM, WDM Features, Diabetic Retinopathy, Classification

1. INTRODUCTION

A picture describes a scene efficiently and conveys the information in better way. Human beings are good at interpreting details from an image [1]. More than 90 percentage of data communicated to brain is visual data. Human brain responds and process visual data 60,000 times better than any other form of data. Image processing systems needs representation of image in digital form. Latest inventions of high end cameras and imaging techniques make this possible at an ease [2]. A digital image is a two dimensional array of numbers, where the numbers represent the intensity values of the image at various spatial locations. These pixels possess spatial coherence which can be inherited by performing arithmetic operations like addition, subtraction etc. [3]. The statistical manipulations of the pixel values help to develop an image processing techniques for variety of applications. Image classification is a process in which a machine is used to classify the images utilizing the spatial relativity of the pixels [4].

Computer-assisted medical services are growing at a fast pace. Diagnosing a disease correctly is equivalent to providing 50% of the required treatment. Most of the loss in human life is because of incorrect diagnosis of disease or diagnosing a disease at its final stage [5]. Recently a growing number of research projects have been initiated in medical science where computers play a crucial role. Automatic diagnosis of certain diseases will be of great service to mankind. Computer assisted diagnosis is the need of the hour as more number of patients require the service of experts for their advice and for taking proper treatment [6]. Automated diagnosis system helps the physicians to diagnose the disease correctly and saves a lot of time. It also helps the persons to get a second opinion at an ease [7]. According to the report from World Health Organization (WHO), India had 69.2 million people suffering with diabetes in 2015 and the diabetic population is expected to rise to 98 million in 2030. The annual death rate of diabetic patients in India is about 1 million. This alarming situation calls for immediate attention and redress. About 90% of people with diabetes for long period of time are at higher risk of developing diabetic retinopathy. The number of patients per ophthalmologist is very high in the order of 1 lakh patients per ophthalmologist [8]. In this context, automation in diagnosis facilitates the process of diagnosis in an efficient manner. An automatic system will be of immense help to the doctors in saving their precious time so that more attention can be paid to the people at high risk [9]. Diagnosis of diabetic retinopathy (DR) at an early stage and taking right treatment can save the patients from severe vision loss. This paper discusses the automatic diagnosis of diabetic retinopathy (DR) through the analysis of DR fundus images using combination of GLCM and WDM features [10].

Fig.1. Vision of Normal person and DR Patient

1.1 LITERATURE REVIEW

Image classification is an analytical approach to categorize objects in an image or the whole image into classes or themes. Image processing is seldom carried out without image classification. Exemplary researches have been and are being carried out in image processing in general, but specifically in image classification [11].

In [12], the author present methods of classification are described. Feature extraction and classifiers are two important components of an image classification system. Features should be selected properly and with due relevance. The purpose of employing a classifier is to get enhanced accuracy in classification. Pioneer researchers have proposed new approaches to extract features of interest and thereby to reduce the computation time.

In [13], the author have attempted to detect diabetic retinopathy automatically using a back propagation neural network. The network was evaluated with 179 images obtained from 32 normal subjects and 147 diabetic patients. The images of size 700×700 were captured using Canon fundus camera. Red free images were obtained by extracting green plane from the input color image. The network has three layers, input layer with 400 nodes, hidden layer and output layer with 4 nodes. Recognition rates for the detection of hemorrhages, vessels, and exudates were 73.8%, 91.7% and 93.1% respectively.

In [14], the author classify DR images with the accuracy of 93% by segmenting vessels, exudates and microaneurysm from the fundus image. The algorithm has been tested with the publicly available DRIVE, DIARTDB1 and MESSIDOR databases by using at trained SVM classifier.

1.2 FUNDUS IMAGE DATASET DESCRIPTION

The IDRID is a treasure of considerable number of retinal images representing all grades of Diabetic Retinopathy (DR), Diabetic Macular Edema (DME), and healthy retina. A digital fundus camera, namely, Kowa VX-10 alpha (Fig.2) was used to register the images. The images were taken in such a manner that the focus was centred near macula with 500-field of vision. The camera captured the fundus images with a resolution of 4288×4288 pixels. The images were produced in JPG format. Each image occupied a storage space of 800 KB.

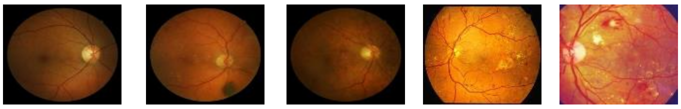

Fig.2. Fundus images showing healthy retina and retina with different grades of diabetic retinopathy

Rest of the article is organized as follows. Section 2 presents the method proposed in this paper. Section 3 describes in detail about the experimentation and discussions. Conclusion is provided in section 4.

2. METHODOLOGY USED

An image classification algorithm needs a feature extraction followed by a classifier. The classifier in this paper is fed with two sets of features and then followed by hybrid features. GLCM and WDM are the features used in this paper.

2.1 PREPROCESSING

In the proposed method, the fundus image from IDRID database is taken as the input. The input image is preprocessed so that it enhances the result in further steps. In preprocessing stage, the input image of size 4288×2848 is resized to 150×150. The clarity of the blood vessels are prominent in the green channel of the image. Hence the green component is extracted from the original RGB image as shown in Fig.3. These preprocessing steps mentioned are used to improve the overall quality of the image.

2.2 GLCM FEATURES

The Gray Level Co-occurrence Matrix method - likewise often named as the Spatial Gray Level Dependence Matrix (SGLDM) Method. This method is based on the intensity values of the image. The features when fed to the machine learning algorithm performs the classification effectively [1] [2].

The second-order statistics are attained by considering a set of pixels related to each other in positive three-dimensions. The Gray Level Cooccurrence matrices provide rare mathematical statistics on the texture. Texture feature calculation use the content of the GLCM to give a measure of the variation in intensity at the pixel of interest. GLCM matrix is a square matrix that has same number of rows and same number of columns. GLCM matrix is N×N matrix, where N denotes the number of possible gray levels in an image. For example, a 3-bit image will have a GLCM matrix of size 8×8. The rows and columns are the gray values (0-7). GLCM matrix of image depends on the direction and offset values. The direction can be anyone among the eight possible directions as shown in the Figure1. The offset represents distance between pixels.

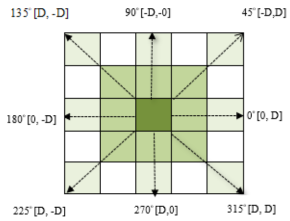

Fig.3. Co-occurrence Matrix

This paper utilizes 8 different features that are computed from GLCM Matrix [13]. These 8 features are elaborated as follows.

2.2.1 *Entropy:*

Entropy measures the disorder or complexity of an image. If the entropy is large when the image is not texturally uniform and if the texture is complex, then entropy becomes high. Energy and entropy are inversely proportional to each other, it means if entropy is high, energy will be low and vice-verse. Entropy can be calculated for image $f(x,y)$ using the following equation,

$$Entropy(E)=\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)*\log(f(x,y)) \tag{1}$$

2.2.2 *Contrast:*

Contrast measures the spatial frequency of an image and different moment of GLCM. It is difference between the highest and the lowest values of a contiguous set of pixels. Contrast can be calculated for image $f(x,y)$ using the following equation,

$$Contrast(C)=\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}(x-y)^2 f_{xy} \tag{2}$$

2.2.3 *Mean:*

Mean is the normal value of the whole amount of data. Mathematically,

$$Mean(M)=\frac{\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)}{M\times N} \tag{3}$$

2.2.4 *Standard Deviation:*

The standard deviation is the square root of variance divided by the entire number of samples. Mathematically expressed as,

$$SD=\sqrt{\frac{\sum|x-\mu|^2}{N}} \tag{4}$$

2.2.5 *Variance:*

This statistic measures the heterogeneity and it is strongly correlated with first order statistical variable such as standard deviation. Variance can be calculated for image $f(x,y)$ using the following equation,

$$Variance(V)=\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}(i-\mu)^2 f_{xy} \tag{5}$$

where μ is the mean of an input image.

2.2.6 *Homogeneity:*

Homogeneity is the consistency in the arrangement of an input image $f(x,y)$. If the arrangement of an input image follow a regular pattern then it is said to be homogenous. Mathematically can be expressed by the following equation,

$$Homogenous(H)=\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}\frac{f_{xy}}{1+|x-y|^2} \tag{6}$$

2.2.7 *RMS Contrast:*

Root Mean Square (RMS) measure the standard deviation of the pixel intensities. It does not depend upon any angular frequency or spatial distribution of contrast of an input image. Mathematically it can be expressed as

$$RMS\ Constrast(RC)=\sqrt{\frac{1}{MN}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}(I_{ij}-\bar{I})^2} \tag{7}$$

where, I is the normalized pixel intensity values between 0 and 1

2.2.8 *Smoothness:*

The input image $f(x,y)$ is highly correlated between the adjacent pixels then we can say the image are autocorrelated (the autocorrelation of input data with itself after shifting one pixel). The autocorrection of input image can be calculated by the following equations.

$$autocorrelation\ f(x,y) = \iint f(x,y) * f(x+\bar{x})(y+\bar{y})dxdy \qquad (8)$$

2.3 WDM FEATURES

The wavelet Decomposition matrix is obtained by using wavelets. The advantage of wavelet features is that the image can be analysed at different resolutions. The Haar wavelet is used in this paper. The first level of decomposition gives one approximate component, diagonal component, vertical and horizontal components. As the approximate component contains more information, it is used as input for the next level of decomposition. This process continues for further level of decomposition. The input matrix is divided into 2×2 cells as $\begin{bmatrix} x_1 & x_2 \\ x_3 & x_4 \end{bmatrix}$ and the wavelet decomposed matrix is obtained as

$$W_P = \begin{bmatrix} W_{AP} & W_{VP} \\ W_{HP} & W_{DP} \end{bmatrix} \qquad (9)$$

where, W_{AP} is approximation component = $1/4(x_1+x_2+x_3+x_4)$, W_{vp} is vertical component = $1/4(x_1+x_2-x_3-x_4)$, W_{HP} is horizontal component = $1/4(x_1-x_2+x_3-x_4)$, W_{DP} is diagonal component = $1/4(x_1-x_2-x_3+x_4)$. From each level of wavelet decomposition matrix, the covariance matrix and correlation matrices are computed.

3. EXPERIMENTS AND DISCUSSIONS

The features are fed to the classifiers individually and then in mixed combination. The accuracies obtained using GLCM feature spaces is provided in Table.1. The accuracy obtained from variance and homogeneity were higher than other features. The accuracies obtained using WDM feature spaces is provided in Table.2. The accuracy obtained from W_4 and W_5 are higher than other features. These high performing features are combined and fed to the classifier. The accuracies obtained using hybrid feature spaces is provided in Table.3. The accuracy obtained from homogeneity and fourth level WDM is higher than other features

Table.1. Accuracy results using GLCM feature spaces

Class	E	C	M	SD	V	H	RC	S
DR Grade 0	76.6	75.6	85.3	77.4	**87.2**	**88.8**	79.6	77.1
DR Grade 1	82.5	84.1	**92.2**	78.3	84.4	**86.2**	80.1	78.4
DR Grade 2	75.1	83.5	89.8	94.8	**96.9**	**95.8**	87.5	91.9
DR Grade 3	84.6	87.6	84.8	90.5	**97.9**	**93.9**	92.7	88.4

Table.2. Accuracy results using WDM feature spaces

Class	W_1	W_2	W_3	W_4	W_5	W_6
DR Grade 0	82.63	87.65	**95.32**	**97.43**	92.29	87.83
DR Grade 1	82.56	88.13	92.23	**98.34**	**94.43**	86.22
DR Grade 2	85.17	83.52	94.80	94.87	**96.90**	95.82
DR Grade 3	84.60	87.61	96.82	96.59	**97.99**	93.91

Table.3. Accuracy results using hybrid feature spaces

Class	V-W_3	V-W_4	H-W_3	H-W4
DR Grade 0	82.63	94.43	95.32	97.43
DR Grade 1	88.56	93.90	92.23	98.34
DR Grade 2	85.17	97.99	94.80	94.87
DR Grade 3	84.60	87.61	96.82	96.59
Average	85.24	93.48	94.79	**96.80**

4. CONCLUSIONS

A lot of research work is available for image classification problem but most of the cases are binary classification. The proposed work aims at providing multiclass classification with satisfactory results. In future the proposed work can be further extended to include more classes with minimum loss and maximum classification accuracy. The proposed method is tested with individual features and then with the hybrid features. The noticeable characteristic of the method proposed is that it is very simple to implement with promising results. The results can be improved further by adopting better classifiers.

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