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Diabetic Retinopathy Recognition System Based On GLDM Features And Feed-Forward Neural Network Classifier.

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Diabetic Retinopathy Recognition System based on GLDM Features and Feed-Forward Neural Network Classifier.

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Abstract

Detection and recognition of Diabetic Retinopathy (DR) at the early phase can prevent the risk of gradual damage in the retina and vision loss. Many works have been introduced for automatic DR recognition and diagnosis in recent years. To date, there are still some issues that are required to work on to improve the quality and the performance of automatic DR recognition systems. Therefore, this paper introduces a machine learning-based approach for DR diagnosis and recognition by proposing texture analysis features of the GLDM technique (Contrast, Angular Second Moment, Entropy, Mean, and Inverse Difference Moment) feature and feed-forward neural network classifier. The proposed method has achieved a recognition accuracy of 95% according to undertaken experiments and performance analysis.

1. Introduction

Detecting disease at an early stage is an effective way in the path of treatment and having fast recovery (Kaur and Singh, 2018). Diabetes is a disease of the body lacking insulin that leads to increases in the amount of glucose in the blood (Ashwin et al., 2019). Diabetes can hurt the heart, retina, nerves, and kidneys. Diabetic Retinopathy (DR) is a problem of diabetes that affects the blood vessels of the retina causing swelling and leaking fluids and blood. DR could result in vision loss at its progressive stage. DR is responsible for 2.6% of people's blindness around the world. Regularly checking up on the retina via retina screening is an important step for patients who suffer from diabetes. That is essential to diagnosis and treatment of DR at an early stage. So what is concerned

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the most is to diagnose if a diabetes patient undergoes DR or not. DR is diagnostic via detecting the presence of different kinds of lesions on an image of the retina. These lesions appeared in the form of micro aneurysms (MA), hemorrhages (HM), soft and hard exudates (EX). The initial sign of DR is Micro aneurysms (MA) and observed as small red round marks on the retina because of the vessel's walls' weakness. Hemorrhages (HM) are present as larger dots on the retina having a size is greater than 125 µm with an irregular margin. HM has two kinds which are flame (superficial HM) and blot (deeper HM).

Plasma leakage could cause bright-yellow spots to appear on the retina identified as hard exudates, as they are existent on the outside retina and have sharp margins. Swelling of the nerve fiber could cause white spots to the presence on the retina having oval shape or round named as Soft exudates or cotton wool. MA and HM appear as red lesions while being soft and hard exudates (EX) appear as bright lesions (Alyoubi et al., 2020; Bourouis et al., 2018; Ganesan et al., 2014). Part of studies has categorized the DR into five stages based on the presence of these lesions, which are defined as no DR, mild DR, moderate DR, severe DR, and proliferative DR. However, what concerns us most is to diagnose DR in order to avoid blindness. So, it is most important to know if the patient has DR or not to go through the treatment procedure, especially at its early stage, for rescuing the patient's vision. This study concentration is on the classification of retinal images into normal and abnormal (DR images). The conventional process of evaluating retinal fundus images in DR diagnosis is difficult and susceptible to error or ophthalmologists'' fatigue. Recently using artificial intelligence and machine learning techniques, there have been growing efforts in order to develop an accurate automated recognition system for DR which can help in preventing complete blindness and reducing ophthalmologists' workload (Qu et al., 2017).

Studies for DR detection and recognition have been divided into two groups: machine learning classifier-based approaches (Ahmad, 2019; Behera and Chakravarty, 2020; David, 2020; Deepa and Narayanan, 2020; Ghaffar et al., 2020) and deep learning-based approaches (Dutta et al., 2018; Gargeya and Leng, 2017; Li et al., 2019; Pan et al., 2020). Machine learning classifier-based approaches pass through several levels to achieve an effective diabetic retinopathy system. In machine learning, classifier-based approaches, a lot of image pre-processing methods, features extraction approaches, and machine learning recognition approaches were adopted and utilized, and developed (Rahim et al., 2020). Image processing approaches are continuously used as a method of computer-aided disease detection, where eye diseases are part of them. Image pre-processing means improving retina images quality and saving characteristics of images. Feature extraction is the process that comes after the pre-processing stage to extract many valuable and reliable features from images to be used then in the recognition stage (Rahim et al., 2020).

In the recognition or diagnosing phase, one classifier model of machine learning techniques can be trained using the extracted features. Classifier model trained to learn how to distinguish and recognize retina-images with diabetic retinopathy disease. However, machine learning-based approaches do not require a large dataset of retina images for the learning or training stage; do not require high computation power, and a big saving location to process images data. On the contrary, deep learning-based approaches encompass embedding features extractions step practically in the recognition and classification phase. Deep learning is a common and interesting topic of machine learning, where features are extracted automatically from the data of input by the adopted model. Besides, deep learning studies are keeping on introducing good image pre-processing methods to ensure obtain a good quality of images' characteristics for the features extraction. Lots of deep learning approaches were introduced for DR detection and recognition. However, deep learning approaches required a huge and various amount of data in order to obtain a good performance as well as great computation power. Implementing deep learning models is challenging when a small range of data is existing only (Rahim et al., 2020).

2. Related Work

A computer-aided diagnostic (CAD) system based on DR detection and classification has been introduced by many studies, for discriminating between the normal retina and abnormal retina with DR (Qu et al., 2017). A good DR recognition method depends on employing an effective characteristics mining technique besides to significant classifier on the retina images to diagnose DR. In order to achieve accurate recognition results, this study has come over recent studies for DR recognition for highlighting the latest problems and drawbacks. Ganesan et al. (2014) proposed a method to improve the automated detection and diagnosis of DR using race transforms with a new functional set as a feature extraction technique since it can simulate the human perception to an image.

For features classification, they utilized two classifiers separately as a comparison, firstly used SVM classifier with quadratic, polynomial, radial basis function kernels; secondly utilized probabilistic neural network (PNN) optimized by genetic algorithm (GA) to adjust the classification parameter of PNN. The adopted datasets were in-house databases and MESSID or open databases. The achieved accuracy was 99.41% for PNN-GA and 99.12% for GA-SVM quadratic kernels. Janney et al. (2015) developed an algorithm that uses Gray Level Co-occurrence Matrix (GLCM) technique based feature extraction in conjunction with the Fuzzy c-Means (FCM) clustering algorithm and

K-Nearest Neighbors (KNN) classifier. FCM and morphological reconstruction techniques are used for exudates segmentation and detection while the KNN classifier was utilized to recognize the type of disease.

However, their method achieved an accuracy of 96%, specificity of 94%, and sensitivity of 90%. Likewise, Kaur and Singh (2018) developed a method for well-timed diabetic retinopathy diagnosis and classifications via using curvelet transform and support vector machine (SVM) classifier based on a standard database existing on the internet. In their work, the retinal fundus images were enhanced by applying the curvelet transform. Also, canny edge detection algorithm and morphological operations were applied sequentially, to obtain eyeball from the retinal image background and extract features from the curvelet image. After feature selection, a multi-SVM classifier was used to classify the retinal fundus images into normal, Proliferative Diabetic Retinopathy (PDR), and Non-Proliferative Diabetic Retinopathy (NPDR).

Nevertheless, they noticed that the number of exudates was detected in their work is more than that of the procedure without enhancement. The accuracy, sensitivity, and specificity of their method were 97.78, 96.77, and 100% correspondingly. The computation time was approximately 45.854221second. In the same aspect, Bourouis et al. (2018) introduced a diabetic Retinopathy detection framework, in which a Fisher kernel is generated from scaled Dirichlet mixture distributions (SDMM) model, to be positioned within SVM. That was to derive a probabilistic SVM kernel instead of standard kernels to tackle the retinal images classification problem. In contrast, the overall accuracy was 90.87%. Likewise, Merlin and Shan (2015) suggested a fuzzy logic-based SVM scheme and 5-D vector collected of gray-level as well as intensity histogram-based features for representation of pixel, within segmentation and detection method of the blood vessel in retinal images, evaluated via utilizing the publicly available databases which are DRIVE and STARE datasets. GS and Mohideen (2017) used the RBF-kernel-based Support Vector Machine (SVM) classifier to the diabetic retinopathy diagnosis system.

Features such as the mean area of the segmented region, mean intensity, the number of segmented regions, and solidity, were extracted which showed significant differences between normal and diabetic retinopathy groups. However, the proposed SVM classifier gave sensitivity, specificity, and accuracy values of around 92%. Amin et al. (2018) proposed a method that utilized an automated technique for DR detection and classification. A region of interest was enhanced using a local contrast improvement approach; an adaptive threshold method with mathematical morphology was utilized to segment the region of lesion accurately. For better classification, features fusion is done based on the geometrical and statistical features. Sharma et al. (2019) proposed convolutional neural networks (CNN) for DR detection and classification based on severity by utilizing color fundus images. Though the proposed model showed satisfactory results on the Kaggle dataset, giving accuracy around 47.04% for 5 class classification, the proposed system was introduced for further enhancement. Afrin and Shill (2019) proposed a system for automatic DR detection and DR stages classification from retinal images, in which blood vessels area, micro aneurysms count, exudates area, contrast, and homogeneity features are detected and fed into the Fuzzy classifier.

However, the Fuzzy classifier classified images based on STARE, DIARETDB0, and DIARETDB1 databases with an accuracy of 95.63%. Ashwin et al. (2019) presented a method for DR Detection and classification using a pre-processing model and AdaBoost as a supervised machine learning classifier along with Artificial Neural Network (ANN) classifier; the procedure of features extraction was obtained by utilizing Gray Level Co-occurrence Matrix (GLCM) and carried out based on Contrast, energy, homogeneity, ASM (angular second moment), and dissimilarly. Although Artificial Neural Network achieved good accuracy 84.21% in this outcome compared to AdaBoost accuracy 0.620, this study suggested collecting more data samples of fundus images as well as increasing input features to improve the model performance and accuracy.

Li et al. (2019) performed a study for DR classification; their study employed a deep convolutional neural network (DCNN) that was based on fractional max-pooling instead of max-pooling layers. Also, the SVM classifier trained on each class highlighted the distribution boundary. Kaggle dataset of 34,124 training images was used for images training, 1,000 for images validation (build model), and 53,572 for images testing. Conversely, their study accomplished a recognition rate of 86.17% for five categories of DR stages or severity, and 91.05% for binary class with normal and abnormal DR. Behera and Chakravarty (2020) used widespread features extraction techniques scale-invariant feature transform (SIFT) and speeded up robust features (SURF) on each retinal images to find feature matrix of a region of exudates. Also, the SVM technique is utilized for the classification step and DR prediction.

Though, the study recommended using new features that can be applied to acquire the best classification. On the other hand, Techniques of texture analysis are generally adopted for texture features extraction, where they are divided into three groups: statistical, structural, and model-based techniques. The texture is defined as an associated set of frequently occurring sets of pixels in an image. Texture offers knowledge about the deviation in the surface intensity (Reed and Dubuf, 1993).

Garcia et al. (2012) introduced GLCM, GLDM, and GLRLM techniques for recognizing the abdominal aortic aneurysm after endovascular repair. Ali et al. (2016) used GLCM mapping to detect anomalies in MR images of the spine. Likewise, Chevrefils et al. (2007) utilized statistical and spectral texture characteristics in order to segment intervertebral discs of scoliotic spines automatically from MRI. Hashia and Mir (2018) highlighted the performance for each of GLRLM, GLCM, and GLDM concerning intervertebral discs abnormalities classification.

However, in machine learning classifiers approaches, an accurate automated diabetic retinopathy system can be accomplished only by suggesting a method that can identify and detect a wide range of DR signs that encompass various fundus images characteristics. Various studies have been proposed in the last decade trying to explore valuable techniques for detecting and identifying worthy features of eye fundus images that can guide to precise DR detection and recognition Garcia et al. (2012). Despite the big progress in the numbers of DR diagnosis proposed studies in recent years, there are still gap and drawbacks need to be improved (Cao et al., 2018; Ahmad, 2019; Li et al. 2019; Shaharum et al. 2019; Behera and Chakravarty, 2020; David, 2020; Deepa and Narayanan, 2020; Ghaffar et al., 2020; Rahim, et al., 2020). This study aims to improve the performance of the automatic diabetic retinopathy diagnosis system by proposing a feed-forward neural network classifier on the features of the grey level difference method (GLDM) (Hashia and Mir, 2018).

The rest of the paper is organized as follows: the proposed method is discussed in section 2, and the results are discussed in section 3. Finally, the paper is concluded in section 4.

3 .Proposed method

In this paper, the diabetic retinopathy recognition method is introduced based on feed-forward neural network classifier on GLDM features of retina images. The framework of the proposed method is depicted in Figure 1**.** The proposed method consists of three phases, image segmentation, features extraction, and classification phase. Firstly, the Tyler Coye algorithm is used for blood vessel segmentation in retinal images. GLDM technique is proposed for points of features extraction and feed-forward neural network technique (FFNN) for features recognition.

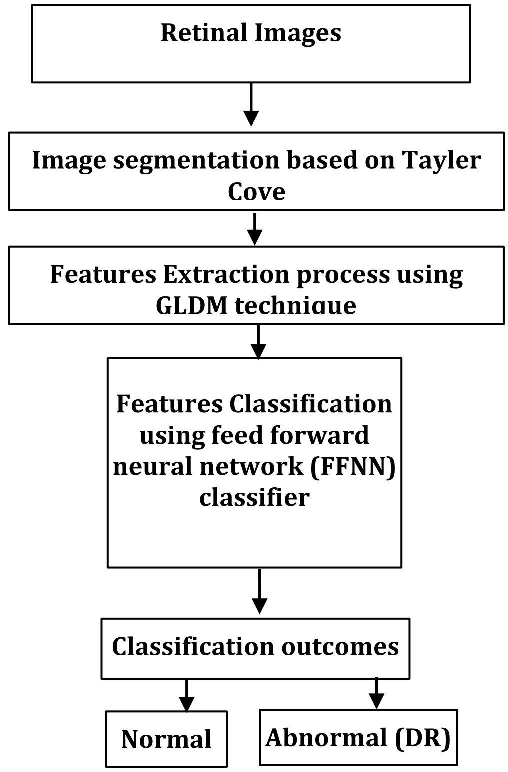

Fig.1- framework of proposed DR diagnosis method.

2.1 Tyler Coye algorithm

The first stage in this work is blood vessel segmentation in the retina image; it is done by using the Tyler Coye algorithm. After reading the retina image, through PCA of weighted Lab color model the RGB image is converted into grayscale. The whole process is done through at first resizing the image to have a width of 20. Then using PCA to discover or catch the primary and secondary axis in the color spaces of RGB and CIELAB. Using PCA to compute the mean value of the image is performed and after that generating the full resolution of the original image onto the primary axis using the nearest point. Scaling this new luminance image to utilize the full range so that in the case of RGB Image, the image is mapped to the max and min of the original RGB image and then map that to [0,1]. In the case of LAB space, The Luminance L of the original L channel is mapped into new values and then converts the image to a grayscale image.

Then, performing contrast enhancement by adaptive histogram equalization. Following that, background exclusion is achieved by subtracting the average filtered image. The fair threshold level is extracted based on (Bandara and Giragama, 2017), for the Binarization process. Lastly, the smaller components are excluded by taking into account the size of each connected component. Figure (2) show the flow diagram of the Tyler Coye algorithm.

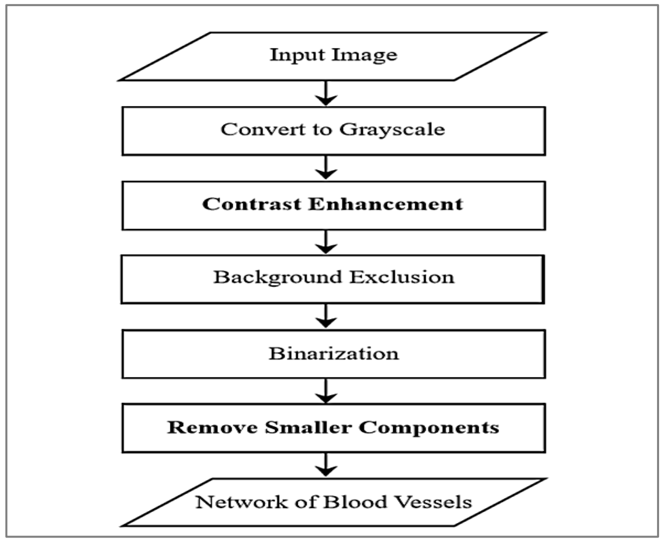

Fig.2- Flowchart of the Tyler Coye algorithm (Bandara and Giragama, 2017).

2.2 Feature extraction utilizing texture analysis

The texture is defined as an associated set of frequently occurring sets of pixels in an image. The texture is identified as a correlated set of frequently appearing sets of pixels in an image. Texture offers knowledge about the deviation in the surface intensity (Reed and Dubuf, 1993). In this work, statistical texture analysis is used as a texture feature description. Texture features have been extracted based on the statistical distribution of the pixel intensity at the prior allocated location relative to the other pixels in the image matrix (Van et al., 1985). The features of statistical texture analysis: GLDM technique has been used in this study and described below.

2.2.1 Grey Level Difference Method (GLDM)

GLDM technique has the ability to recover the first-order statistics of local property values. GLDM is based on the presence of the two pixels that have a known difference in grey level values and are separated by the displacement (‘δ). Let p(x, y) refer to the digital picture function. For any predefined displacement δ = (Δx, Δy), where x and y are integers, let pδ(x, y) = | p(Δx, Δy) − p(x + Δx, y + Δy) | and DF(i/δ) be the predicated probability-density function identified by the formula:

$$DF(i/\delta) = \mathrm{PF}(p_\delta(x,y) = i).$$

Four possible formulas of the displacement δ are taken into account in this procedure and are: (0, d), (− d, d), (d, 0), (d,-d) where d is the inter-sample spacing distance (Hashia and Mir, 2018). In this paper, five of the GLDM texture features are computed and extracted according to table 3.

Feature	Formula
Contrast	$\sum_{i=0}^{Ng-1} (i)^{2*}\mathrm{DF}(\mathrm{i}/\delta)$
Angular second moment	$\sum_{i=0}^{Ng-1} (DF(i/\delta))^2$
Entropy	$\sum_{i=0}^{Ng-1} (DF(i/\delta)*log(DF(i/\delta))$
Mean	$\sum_{i=0}^{Ng-1} i^*(DF(i/\delta))$
Inverse difference moment	$\sum_{i=0}^{Ng-1} \frac{(DF(i/\delta))}{i^2+1}$

Table 1- five GLDM features matrix (Hashia and Mir, 2018).

In this study, a feature vector of 30 features is taken from every single fundus input image of retina, and for each one of GLDM features in Table 1. Gaining five feature vectors for every image, which is 30 ×5 matrix. However, in order to get more recognizable features for each image of retina, feature selection operation is performed on the computed features' vectors of GLDM based on choosing the more recognizable feature that has max value. By this technique, the overall accuracy of FFNN on GLDM features is improved.

1.3 Feed Forward Neural Network Technique (FFNN) Classifier

The neural network technique is created based on layers of neurons where neurons among layers are connected to each other. Every neuron is a computational entity, the input value of a neuron is multiplied by the corresponding set of learnable weight parameters, computing the summation of multiple values, converts the summed values using the activation function, the output of the converted value is computed. The neural network model consists of the input layer which is the first layer, every entity in the input layer has one value of predictors for a specific observation. The input layer sends all values of predicators that are related to specific observations to every neuron in the first hidden layer.

Divers of functions along with values of predicator are computed in every neuron in the first hidden layer. Then, the outputs of the first hidden layer are sent to the second hidden layer, where divers of activation functions is computed with the values of predictors, and so forth to the layer of the final output which is the prediction. Neural network models learn by iteratively comparing their predictions with the observed results or outputs and then perform modifying to their weights to improve their prediction.

In this paper, the features vectors of GLDM are fed into FFNN supervised learning method. The proposed FFNN method is built with one hidden layer and 150 neurons. The output layer consists of two layers that determine the target classes (normal, and abnormal (DR)). The most important parameters in the network is set as follows, rate of learning is set number 1 as a value, epochs assigned value of 20000, the maximum number of iterations, infinity time of training. Besides, data division function, the transfer function is used as ''tansig', linear activation function is implemented for the output layer (Purelin), using the function of performance (msc). The training function adopted here is (Scaled conjugate gradient), the weight and the bias is generated randomly. After training the network, it was tested using a testing dataset; the obtained results are discussed in the results section.

2. Results and discussion

In this paper a method of FFNN neural classifier on the statistical features of GLDM technique has been proposed for diabetic retinopathy (DR) recognition. The proposed approaches have been evaluated quantitatively using the DRIVE dataset. DRIVE dataset consists of 40 fovea centered color retinal images. DRIVE images have been taken for 33 people with nondiabetic retinopathy and 7 people with early mild diabetic retinopathy. The images were captured by a Canon CR5 nonmydriatic 3CCD camera (Canon, Japan) with a FOV of 45 degrees (Huang et al., 2016). The 40 images of the dataset have been divided into 20 images for the training set and 20 images for the testing set, randomly. The results were calculated utilizing means of accuracy, where the accuracy is the part of true outcomes, either true positive or true negative, in a population, according to (Janney et al., 2015).

Accuracy = (TN + TP)/ (TN+TP+FN+FP), TN – True negative and FP – False Positive.

At first, the image segmentation process has been performed, in which the blood vessels are segmented from RGB retinal images using the Tyler Coye algorithm because of its effectiveness for fundus retina image segmentation according to previous studies (Bandara and Giragama, 2017). Figure 3 illustrates some of the segmentation results. For the features extraction phase, features of texture analysis have been captured based on the statistical distribution of the pixel intensity at the prior allocated location relative to the other pixels in the image matrix. Statistical texture analysis features called GLDM based technique is proposed and feature vector has computed for every binary segmented retina image.

For proposed GLDM technique, the obtained features have been computed for four directions: (0 °, 45°, 90° & 135°). In the GLDM technique, five features have been extracted Contrast, Angular Second Moment, Entropy, Mean, and Inverse Difference Moment feature. For every GLDM feature in Table 1 and for four directions: (0 °, 45°, 90° & 135°), feature vector of 30 features is extracted from each fundus input image of retina. Gaining five feature's vectors for every image, which is 30 ×5 matrix. Yet, to get more recognizable feature of retina image, feature selection operation is executed on the computed features' vectors of GLDM based on choosing the more recognizable feature that has max value. By this technique and based on our experiments, the overall accuracy of FFNN on GLDM features is improved from 88% to 95%.

Fig. 3- Some of the retinal segmented images using the Tyler Coye algorithm on the Drive images dataset.

For the recognition and diagnosing phase, the five captured features of the GLDM technique (shown in table 1) were fed into the FFNN classifier. The accuracy of the FFNN classifier has been examined according to prior explained adjusting parameters of the neural network in section 2.3. The obtained accuracy is 95% for the testing dataset, see Figure 4, of which can see the neural network training details. While Figure 5 shows the ROC plot, to demonstrate how good the FNN has match data since it depicts the relation rate between false positive and true positive in the context of thresholding outputs varied from 0 to 1. Where in such a plot the greatest classifiers have a line extend from the left corner of the bottom to the left corner of the top or could be close to that. Figure 6 presents the percentage of correct and incorrect classification using a confusion matrix, where the green area refers to the rates of correct classification and the red area refers to incorrect classification.

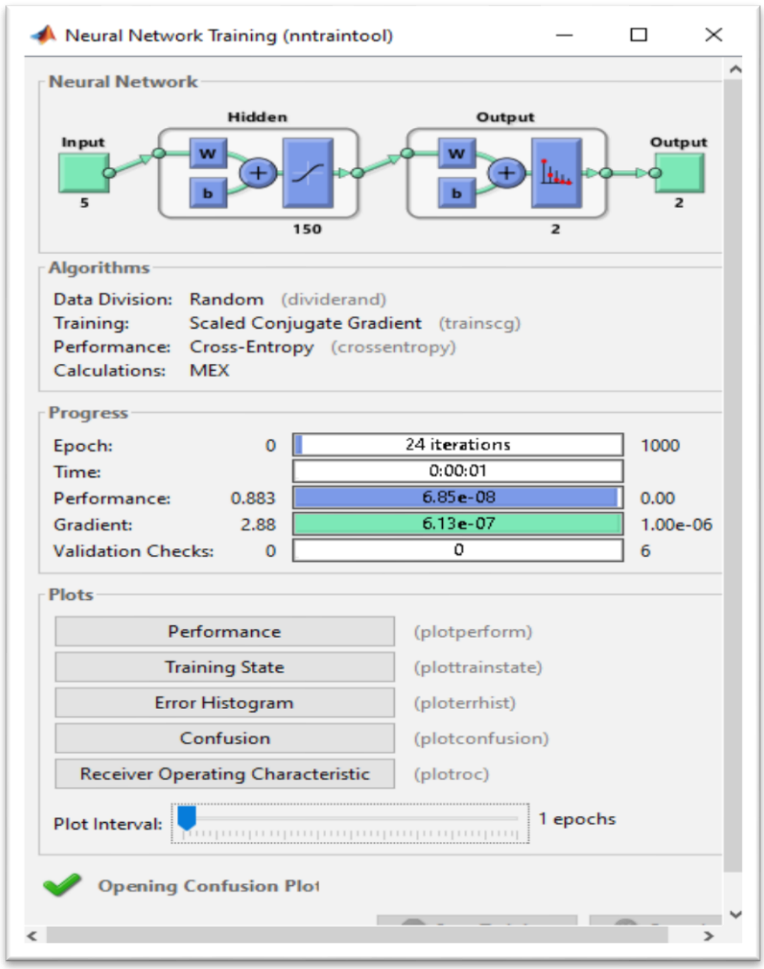

Fig. 4- The neural network training.

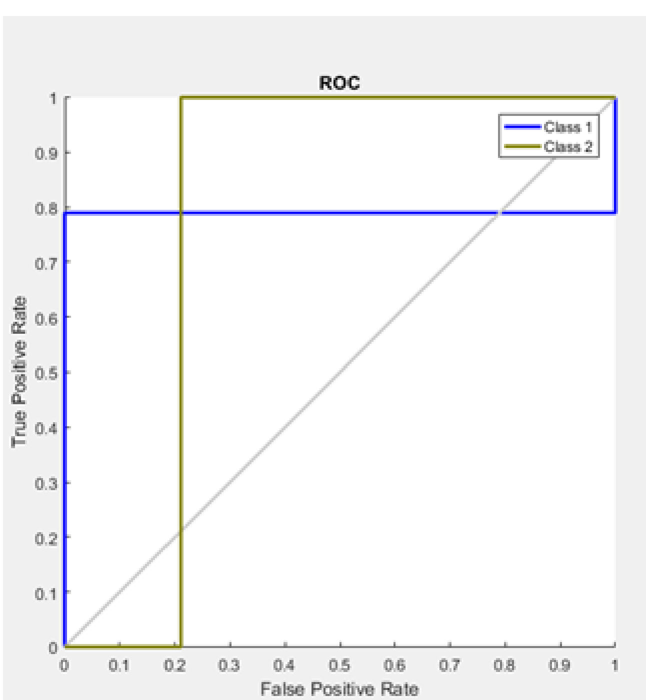

Fig.5- the relation rate between false positive and true positive in the context of thresholding outputs.

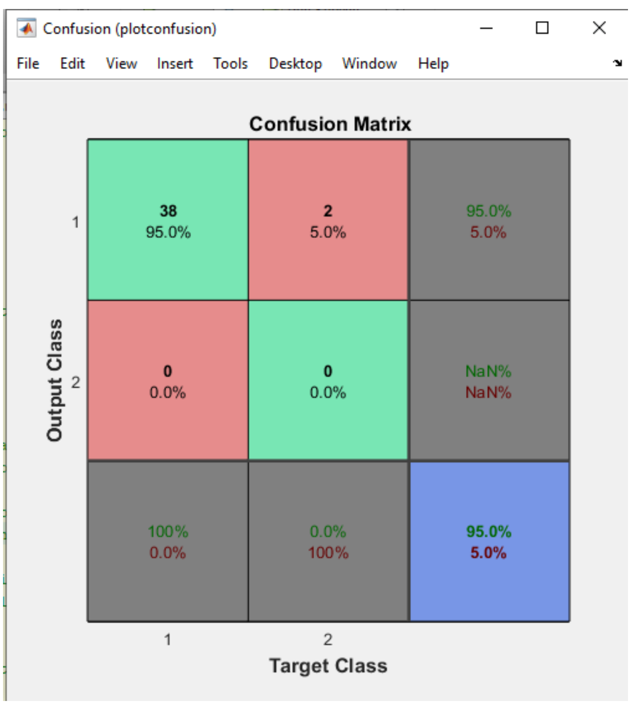

Fig. 6-the percentage of correct and incorrect classification using confusion matrix

The performance of our proposed method has been compared with existed methods based on overall accuracy acquired as illustrated in table 2. As seen from comparative analysis in table 2, that our presented study has good performance in comparison with other researches mentioned in table 2. It can conclude that GLDM texture analysis features that come up with five statistical features contrast, Angular Second Moment, Entropy, Mean, and Inverse Difference Moment, can extract and capture worthy characteristics in retina images for DR. Combined with good performance of FFNN classifier that presented a good ability to recognize the extracted features of GLDM, gaining a good accuracy result of (95%) on test dataset.

Name	**Technique**	**Overall Accuracy**	**Classification Type**
GS and Mohideen (2017)	RBF-kernel based SVM	92.4%	normal / abnormal (binary class)
Sharma et al. (2019)	CNN	74.04 %	5 CLASS
Li et al. (2019)	Deep convolutional neural network (DCNN)	86.17%,	5 CLASS
		91.05%	normal / abnormal

			(binary class)
Shaharum et al. (2019)	Artificial neural network (ANN) + two types of feature; mean of pixel and area of the pixel	90% (with 30 hidden neurons in the neural network)	normal / abnormal (binary class)
Tavakoli et al. (2020)	Combination of matching Based approach following with concept of deep learning and CNNs	90%	normal / abnormal (binary class)
Kamble and Kokate (2020)	RBF neural network classifier	71.2% on 130 DIARETDB0 dataset, 89.4% on 89 DIARETDB1 dataset	normal / abnormal (binary class)
Proposed Method	**proposed FFNN-GLDM**	**95% on Drive dataset**	**normal / abnormal (binary class)**

Table 2-Comparison analysis with state-of art studies.

3. Conclusion

This paper proposed a method for automatic DR recognition system based on textures analysis features of the GLDM technique and FFNN neural network classifier. Because of GLDM good performance in detecting and capturing five features (Contrast, Angular Second Moment, Entropy, Mean, and Inverse Difference Moment feature) in compatible with FFNN neural network classifier, our proposed method has achieved good accuracy results (95%) on testing data in comparison with recent studies for DR recognition. However, our method still needs further improvements regards introducing a technique for features selection in order to enhance the overall accuracy, considering additional datasets for retinopathy recognition, as well as adopting hybrid classification method to recognize DR from NON-DR.

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Conflicts of Interest: The authors declare no conflict of interest.

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