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DIAGNOSIS RETINOPATHY DISEASE USING GLCM AND ANN

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ABSTRACT

The diabetes mellitus is a chronic disease. It has high incidence all over the world. It has many complications such as peripheral neuropathy, cardiac and renal problems and retinopathy, but the diabetic retinopathy considers one of the major problems, which causes retinal damage and leading blindness. Unless we avoid the danger of rapid diagnosis and accurate continuity to monitor any developments that may occur. In addition, distinguish them from other diseases that may affect the eye and which occur for other reasons. Therefore, it is necessary for ophthalmologists to accurately diagnose this disease in order to avoid any error may occur.

In this paper, we suggest an algorithm for retinopathy diseases diagnosis to help doctors diagnose diabetes mellitus and distinguish between the health's conditions from the infected condition. The algorithm based on two stages; the first Stage, depends on converting the image to grayscale and improving the contrast of the image using the Contrast Limited Adaptive Histogram Equalization (CLAHE). Then analysis the image by using the Grey Level Co-occurrence Matrix (GLCM) to extraction the image features. The second stage extracting the qualities from the color image by converting (RGB) color space in to (HSV) color space and using color moment algorithm and extract the feature based on color. The features extracted from Qualities gave strong results. The features will be to Neural Network, which enables us to diagnose the cases of, normal and abnormal with high accuracy; our algorithm accuracy is 97%. Our dataset collected from various sources, including local and international, in this paper used (283) images.

Keyword: *GLCM, Retina, Diagnosis, Feature Extraction, Diabetic, ANN.*

1. INTRODUCTION

The prettiness of eye is like an old camera, which includes the cornea, iris, pupil and lens, and images that focus on the thin retina on the back of the eye. The light-sensitive retina acts as a camera film, and the images are sent by the optic nerve to the brain where it interprets images. The retina is very active and complex tissue feed by blood, a precise network of blood vessels. The inner layer of the retina Blood vessels and optic nerve are the main components of the retina structure as shown in Figure.1 [1, 2].To avoid traditional manual classifying it needs an automatic method for analysis technique. Retinal fundus images deliver necessary information about retinal and several systemic and non-systemic diseases[3].The infiltration of liquid from damaged blood vessels in the retina causes swelling and hinder its normal functions. If the swelling is in the central area, it will cause sugar spots, and gradual weakening in central vision and even blindness. which affects both eyes at the same time and can block blockage in capillary blood vessels in the retina, but more If a blockage occurs, the oxygen supply step to the retina and the body tries to repair the condition by forming new blood vessels from the retina.

The ophthalmologist when he studies images is retinal imaging with a digital camera with a flare that ensures clear color images of the retina and may occasionally cause temporary restlessness in

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the eye. After flashing, the eye may become more sensitive to light. Capture and analysis of retinal images to monitor changes can be measured from retinal images[4].the accuracy of image processing depends on algorithms in the accuracy of image processing. It is a sort of screening technique that can be relied upon to determining the infection. In addition, the imaging has the essential role in the detection of retina select and correct the bottom of the image[5, 6] . The Contrast Limited Adaptive Histogram Equalization (CLAHE) used for enhancing the image and the GLCM algorithm and color moment algorithm to extract strong features so the accuracy of the diagnosis increased [7]. Early diagnosis of diabetic retinopathy enables timely treatment. It can ease the burden of the disease on the patients and their families by maintaining a sufficient quality of vision and preventing severe vision loss and blindness[8].The diabetic patient's trust follows specialist guidelines to reduce the risk of developing diabetic retinopathy, and when diagnosed with diabetic retinopathy, it is necessary to check once every 12 months, at least once every 3 months, depending on the degree of disease[4].The Symptoms may be in chuffed signs of the appearance of dark spots or openings in the visual field. In addition, vision cloudy, confused, or dark or double vision, difficulty in night vision or increased sensitivity to .Light as well as. Frequent changes in the degrees of prescription glasses and see glowing halos around the lights and lines or threads generally, during the early stages of diabetic retinopathy such as (micro-aneurysms (Mas), hemorrhage exudates), are Considered abnormalities[7, 9, 10] .as we show in Figure (2)where deferent in structure between (A)normal retina and (B) Abnormal retina. The first detectable abnormalities according to medical expert are micro-aneurysms (Mas) which are small round shape red spot on the retinal capillary. They cause intra-retinal hemorrhage [11-13]. About 30 %.It seems to be of benefit even to those who have normal lipid levels. The prevalence of diabetes for all age groups around the world is estimate at 2.8 percent in 2000 and 4.4 percent in 2030. Which means that the total number of people with diabetes is expected to rise from 171 million in 2000 to 366 million in (2030). World Health Organization (WHO) predicts 135 million people worldwide diabetes will rise this to 300 million from 2025.Statistics for its occurrence will increase the number to double by 2050. The number of people with diabetes. Who treated by the doctor is about 24,000, per year[3, 14, 15].There are many methods which designed to be appropriate for Determination diabetic diseases especially retina eye diseases, therefore; it is necessary to analyze these different methods[7]. In this paper, an algorithm to analyze a digital image for detecting retinal diseases is suggested. The analysis of images requires several steps, the first essential step is analyzing a digital image after preprocessing for detecting if the retina normal or abnormal by extracting the features that distinguish between them, the features that are extract from them by analyzing the (texture and color and) retinal. Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to enhance the contrast of images, We used GLCM algorithm and color moment to Compute and analyze the images of normal and abnormal states to extract this features .The neural network used to diagnose the normal and abnormal (diabetic retinopathy). In our study, we do not need to use segmentation stage we depended on extract robustness features to diagnosis normal and abnormal (diabetic retinopathy). This method was greater challenge because no one discover their.

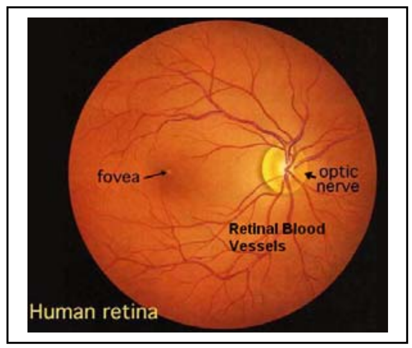

Figure 1: Structure of retina

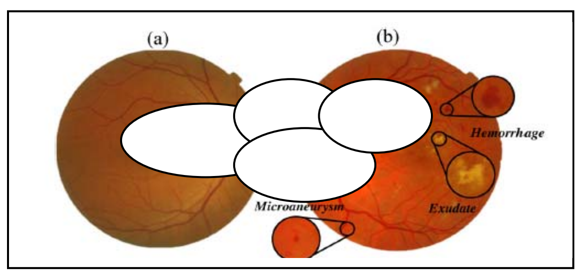

Figure 2: (A) Normal (B) Abnormal (Diabetic Retinopathy)

1.2 Our Objective:

The aims of this paper is to design and implementation of a computer-aided for help the Ophthalmologists to diagnosis the retinal diseases of the treatment efficiency, which is fully automated. Diagnosis of retinal through the analysis of the 2D digital retina images and extraction features from it reliably and automatically. After that case classification into the normal and abnormal retina. This help to optimize therapy, intensify the patient-physician relationship. In order to achieve these objectives, several aims are set out as follow:

1. The designed system simulates the behavior of a specialist Ophthalmologists.
2. The tentative results show that these expert systems act a lot better than a non-experienced doctor.
3. Extract new information from the image.
4. Develop predicate system to determine the patient may suffer from retinopathy from either color image or a grey level image obtained from the retina of the patient. These types of images are called fundus images.
5. Decrease the time required for the management of retinopathy cases.
6. Professional determination of the affected areas of the eye by an efficient algorithm

2. RELATED WORK

Many researchers have conducted many studies and researchers in medical image diagnosis to solve retinal diseases based on many features such as according to differences in color and intensity. According to **Merlin and et al** [16].They presented a new supervised method for blood vessels detection in digital retina image. Their method used a fuzzy logic based on support vector machine scheme for pixels group, a compute vector composed of intensity histogram and gray level based on features extraction for pixels representation. Then get a result estimated 96%according to the measure evaluation sensitivity, specificity and accuracy. However, in their method the researcher relied on a large number of qualities in the stage of extraction of qualities and therefore work full load on the next stage (the stage of classification). Therefore takes a lot of time in the classification process, which affects the measurements of precision and performance improvement of the system. **Kumar and et al** [17].They present method for classification the normal and abnormal (DR).their method based on segmentation the optic disc and extract the blood vessels depending on the histogram by using tow median filters. Then in the classification stage (diagnosis) to distinguish between the normal forms abnormal (DR), based on aggregate the lesion extracted from each image the result accuracy was estimated as 80%. But here the researcher used to extract the qualities through the color only, which requires him to add a lot of help to get more accurate, such as extraction of the vessels and separation and calculation, as well as determine the area of the optical disk and identify them alone and distinguish through color and also extract feature to the exudates and hemorrhage and separation by color, As well as more time and thus affect the process of improving the tool. The system also evaluates through the following measures of privacy, sensitivity and accuracy, respectively. **Manoj and et al** [18]. They suggest an algorithm to classification and detect of (DR).relied on segmentation image by using (Pillar-K means algorithm). their system apply K-mean algorithm optimized after Pillar .to improve the accuracy and computation time for all the enhancement features of the image in all color space.

2.1 Our Contribution:

The concept of extraction features and classification is paly important role important in development of (DR) for diagnosis the normal and abnormal such as [16]. However, in their method the researcher relied on a large number of qualities in the stage of extraction of qualities and therefore work full load on the next stage (the stage of classification). Therefore, takes a lot of time in the classification process, our contribution is summarized below:

1. Rely on extracting strong qualities by depend on GLCM algorithm in gray level. In addition, depending on color moment algorithm to extract features in color in this paper we extract the features in (color and textural).
2. We relied on the use of strong qualities in the stage of extraction of qualities without resorting to the separation of the area of injury, and this is a huge challenge where there is no discovery of this method by other researchers.
3. We used (HSV) color space instead of (RGB) color space to extract storing features in color. As we discuss the details in the next section.

3. METHODOLOGY

The image processing technology was used in our proposed algorithm starting from image enhancement, image analysis features extraction and classification (diagnosis).

3.1 Contrast

The contrast limited adaptive histogram equalization (CLAHE), is transformed value to enhance the contrast of grayscale. It works on

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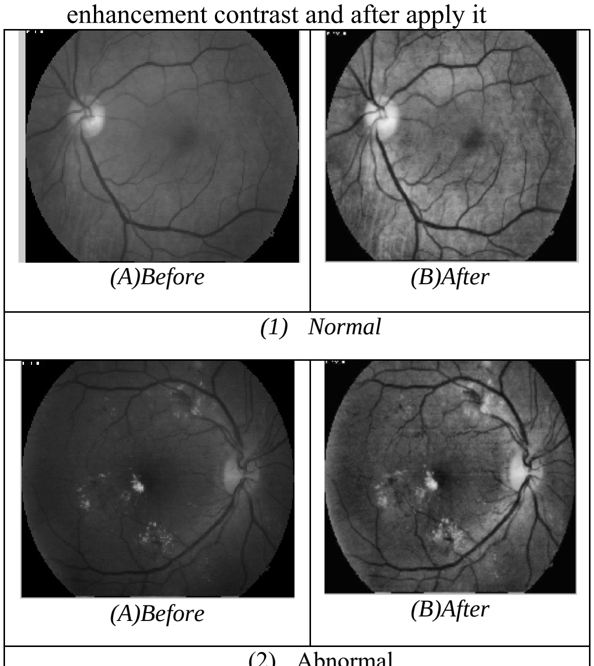
small regions in the image, called tiles, instead of all-region in the image. So that the histogram specific to the distribution parameter approximately matches the histogram of the output region[19] . The weak density caused by bad contrast. To improve the contrast in order to get the best performance and get a lot of information about diseases. Enhancement contrast by using an algorithm of contrast limited adaptive histogram equalization (CLAHE), to enhancement contrast of gray level image through transform values using this algorithm. Contrast limited adaptive is using to improve color retina image. Contrast images it is to recognize retinal blood vessels area, micro-aneurisms, and optic disk through the fragmentation of the main features in color in the retina of the eye [20-22]. As shown in Figure.4 display the deferent in the image grayscale before apply (CLAHE) to enhancement contrast and after apply it



Fguer 3: (1) Normal. (2) Abnormal. images

3.2 Grey Level Co-occurrence Matrix (GLCM)

GLCM very important Methods for calculation statistics technical analysis. It is an analysis methodology for image and convert it to using the template grayscale and extraction features. It storage a matrix (i, j, G) depended on (G). Where (G) is acting number of gray level, (0, 1,…....G-1). And (i,j) is acting the pair of pixels. To compute GLCM of an image. By using a displacement vector (d) determined by its orientation θ and radius δ. Every element of the matrix acts the likelihood of connected occurrence of density levels(i. j) at a specific distance (d) and an angle θ. Relying on a type of values of (d) and θ angles is (such as 0°, 45°,90° and135) [23, 24]. We compute textural features from grey level by using GLCM algorithm .In our suggested method, there are (5) texture features extracted; Correlation, homogeneity, energy, dissimilarity and Information measure of correlation1.These features are extracted and analyzed using deferent distances and direction[25]

3.2.1 Correlation:

The Correlation features views the linear dependency of the grayscale amount in the matrix. It presents how a reference pixel is related to its neighbor, zero is uncorrelated, 1is perfectly correlated. Presents how a reference pixel is related to its neighbor, zero is uncorrelated, 1is perfectly correlated.

$$f_2 = \sum_{i=0}^{Nr-1} \sum_{j=0}^{Nr-1} p_{d,\emptyset}(i,j) \frac{(i-\mu_x)(j-\mu_y)}{\sigma_x \sigma_y} \quad (1)$$

Where standard deviations of p_x and p_y μ_x, μ_y and σ_x, σ_y are the means.

3.2.2 Energy:

It measures the symmetry of an image. When pixels are very analogous, the

(ASM) value will be greater.

$$f_3 = \sum_{i=0}^{Nr-1} \sum_{j=0}^{Nr-1} p_{d,\emptyset}(i,j)^2 \quad (2)$$

$$\mu_x = \sum_{i=0}^{Nr-1} \sum_{j=0}^{Nr-1} i * p_{d,\emptyset}(i,j) = \sum_{i=0}^{Nr-1} \sum_{j=0}^{Nr-1} j * p_{d,\emptyset}(i,j) \quad (3)$$

$$\sigma_x = \sqrt{\sum_{i=0}^{Nr-1} \sum_{j=0}^{Nr-1} (i-\mu)^2 * p_{d,\emptyset}(i,j)} = \sqrt{\sum_{i=0}^{Nr-1} \sum_{j=0}^{Nr-1} (j-\mu)^2 * p_{d,\emptyset}(i,j)} \quad (4)$$

3.2.3 Homogeneity:

That measures the local homogeneity of an image

$$f_4 = \sum_{i=0}^{Nr-1}\sum_{j=0}^{Nr-1} \frac{1}{1+(i-j)^2} p_{d,\emptyset}(i,j) \qquad (5)$$

Where Nr is the greatest level in gray level image, P (i, j) is GLCM matrix. Features calculating by multiply (4) angles with (5) textural feature. As the equations (1), (2), (3), (4), (5).

By using our algorithm .We obtain a vector with (20) features by used GLCM.

3.3 Colour Moments (CM)

Color is one of the most important features of image color space principally subject to define color feature such as RGB, LUV and HSV[26]. Color moments is consider one of the simplest until now very effective features. The color descriptors are principally parameters statistical calculated from several color space bands, such as means, standard deviation (STD), and Skewness of HSV or RGB[27].

$$\emptyset_i = \frac{1}{D}\sum_{j=1}^{D} g_{ij} \qquad (6)$$

$$\psi_I = \left(\frac{1}{D}\sum_{j=1}^{D}(g_{ij}-\phi_i)^2\right)^{\frac{1}{2}} \qquad (7)$$

$$\lambda_I = \left(\frac{1}{D}\sum_{j=1}^{D}(g_{ij}-\phi_i)^3\right)^{\frac{1}{3}} \qquad (8)$$

Where Φ is The Mean, ψ is The Standard Deviation and λ is The Skewnees.

In the outer method, we used HSV color space instead of RGB color space. (Hue, Saturation, and Value) represents a column of the matrix output respectively. The mean may calculated by using equation (6) for each one HSV bands. The standard deviations may calculated by using equation (7) for each one HSV bands. The skewness may calculated by using equation (8) for each one HSV bands. There are (9) features obtained from (Mean, STD, Skewness).

4. THE PROPOSED ALGORTHIM

In this paper, we proposed new algorithm to diagnose the (normal and abnormal) of Retina disease. Our algorithm consist of four stages. First stage is acquisition images .The second stage is pre-processing, which include three phases. The first phase; is creates mask and background, the second phase; is enhancement image (increase the contrast) and the third phase; is remove noises from (RGB) images (by using Gaussian filter). The third stage is analysis textural of images and extraction feature then we have to select the robustness features. The fourth stage is diagnosis stage which diagnosis the normal and abnormal retina by using neural network. As shown in Figure (4).

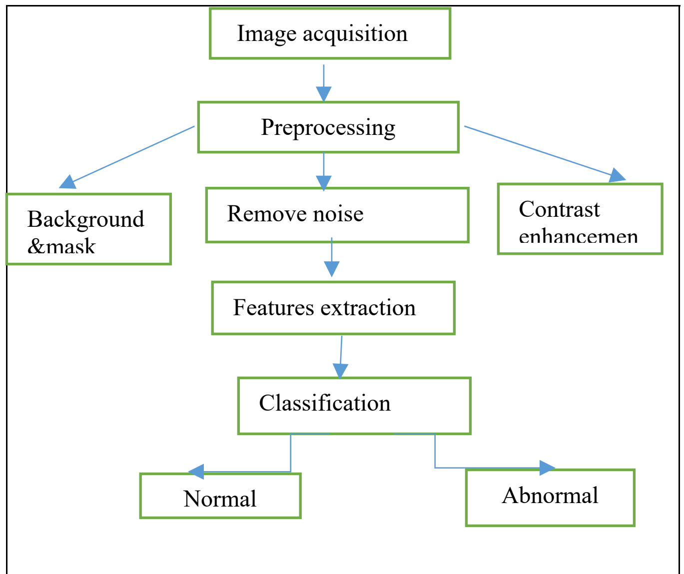


Figure 4:.Algorithm Flowchart

4.1 Image Acquisition

In this paper, we had collected images as dataset for our research from different resources locally and globally .The local resources from (AL-Ramadi Teach–Hospital), the dataset includes (300) images the normal (129) and abnormal (171) images. (AL-Habubi Teach–Hospital), the dataset includes (41) images (10) normal image and (31) abnormal images. The globally resources from OCT and DIRETDB1, the dataset include (283) images the normal (141) and abnormal (143) images. The total of all dataset were.(994)

In this paper, we used (283) images.

4.2 Preprocessing

The fundus image color repeatedly looks imperative lighting differences poor quality and content noise in order to decrease these

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inadequacies, we need to make all the images had the same environments to get the real results for all the images to extract strong pixel features for diagnosis step, through using image processing technology, pre-processing content three steps.

1) Create mask and background.
2) Contrast enhancement.
3) Remove noise on image color.

4.2.1 Create mask and background

To create the mask and background, the image must convert into a binary image then compute maximum value and minimum value of vertical circle, compute maximum value and minimum value of horizontal circle. Then find the center of the circle by calculate value of center by using the equation of circularity, to determine the white area that including the circular and its center and the outer perimeter is black area, which represented a background. Resized original images into (200*200) pixels then convert into gray scale. As shown in Figure 4-5.

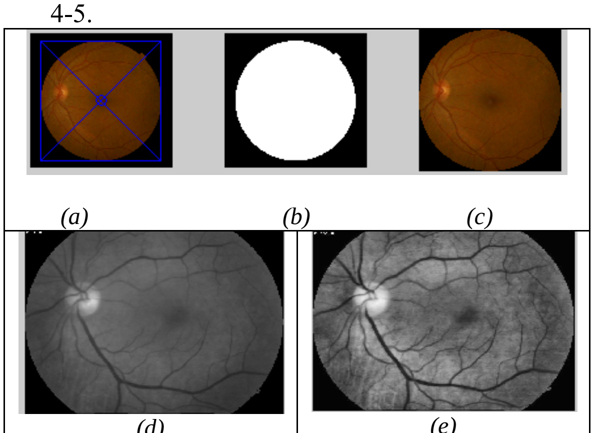

*Figure 5: shows preprocessing stage. For normal image. (a) Fined the center of retina. (b) create mask and background (c) resized images in to (200*200) pixels .(d) convert into gray level .(e) apply Contrast Limited Adaptive Histogram Equalization,*

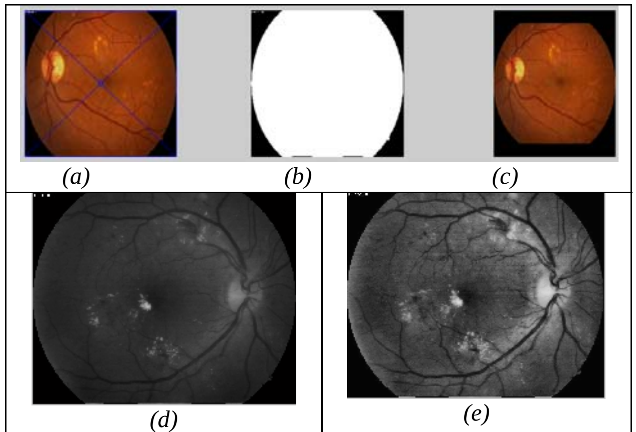

*Figure 6: shows preprocessing stages .for Abnormal image. (a) Fined the center of retina. (b) create mask and background (c) resized images in to (200*200) pixels .(d) convert into gray level .(e) apply Contrast Limited Adaptive Histogram Equalization.*

4.2.2 Removing the noise

To get a better result we must remove the noise from the image in order to reduce the noise from image we used Gaussian filter to remove the noise then we used image adjustment for image enhancement as shown in Figure 6.

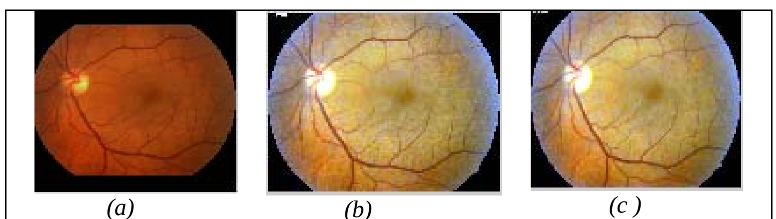

Figure.7: (a) origin image (b) applying Gaussian filter (c) applying adjustment enhancement.

4.3 Features Extraction

In this paper we compute the features by using GLCM (Grey Level Co-occurrence Matrix) and color moments (CM) algorithms the robustness features are (5) feature from GLCM algorithm (Correlation, homogeneity, energy, dissimilarity and Information measure of correlation1) in gray level in (0, 45, 90 and 135) angles and (3) feature from CM algorithm (means, standard deviation, and skewness) in color through (HSV) color space instead of (RGB) color space. In this step we depended on (color and textural) features. We depended on robustness features to recognize the

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normal and abnormal for the next step, without need to segmenting the injuring to detect the normal and abnormal in this work is huge challenge there no one other researchers do this method.

4.4 Diagnoses

In our proposed algorithm, we used neural network to diagnoses between normal and abnormal states. Where the neural network gives high accuracy in training stage accuracy is 100% and testing stage accuracy is 97%. As we shows in Figure 8.

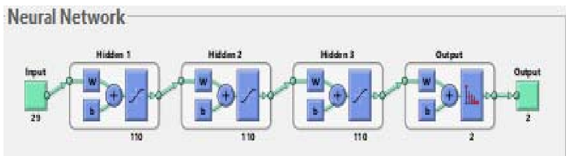

Figure 8: Structure of neural network.

Shows the network structure with one input layer, three hidden layers and two-output layer. It is 29×110×110×110×2 network structure. The input vector is twelve. The output vector is two. This thesis uses the above ANN architecture, feed forward back propagation learning algorithm to generate, train and test the neural network for melanoma lesion diagnosis. MATLAB software with its neural network toolbox is used. Data sets are portion into two subsets, training set and testing set. The network gives high accuracy when train equal to 100% and test equal to 97% with simple training time equal to (0.4 seconds) at 129 epochs, with best training performance is 1.26e-08at epoch 129 as shown in Figure9.

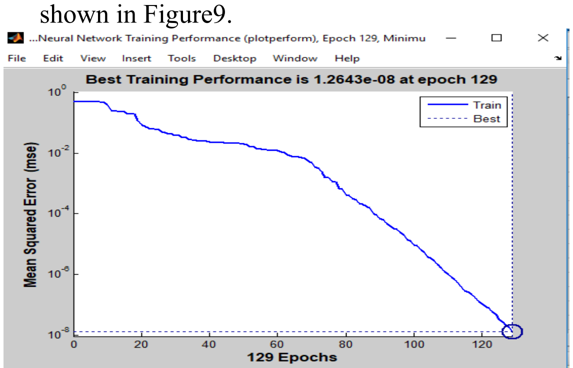

Figure 9: Neural network training

Table.1 shows the accuracy results for the training and testing stage by using color features only, texture features only and texture combine.

Table 1: Shows The Accuracy Results For The Training And Testing Stage.

No .of image	Type of feature	Accuracy of Classification	
		Training %	Testing %
283 images	Color feature	100	88
	Texture feature	100	78
	Color& texture	100	97
	Total accuracy resulting from ANN by using color and texture features		97%

The suggested algorithm has an accuracy of 97% for recognition of retina to classify the normal and abnormal .

5. THE RESULT

In this paper, we have collected image color from different resources locally and global .the local resources from AL-Ramadi Teach – Hospital, the dataset includes (300) images the normal (129) and abnormal (171) images.AL-Habubi Teach – Hospital, the dataset includes (41) images the normal (10) and abnormal (31) images. The global resources from OCT, DIRETDB1, the dataset include (284) images the normal (141) and abnormal (143) images. The total of all database was (994). Ophthalmologists classified these images in the database, depending on lesions kind (hemorrhage, exudates, and micrynersims) an images content one of this lesion is classified, as abnormal Otherwise is normal. Matlab in the 64-bit system with 2.50 GHz core i7 processor and 8 GB of RAM, run with MS Win.10 operating system. The proposed has been tested on all images in the dataset to diagnostic

In our experiments, we used (283) images divided into (183) images for training stage Where the result accuracy was 100%.And the number of images in testing stage are (100) images where the results accuracy of our proposed algorithm was 97%. In Fig (5), (6) shows the preprocessing stage in gray level Normal and abnormal image.Fig(7) shows remove the noise stage for normal and abnormal image. The confusion matrix shows the errors in the classification. Figure (10) and Figure (11) show the confusion matrix for training and

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testing cases, which illustrate the classification results of the neural network for normal retinal and abnormal retinal (retinopathy). In Table (1) shows, the accuracy result from classification stage when comparative between the color features and texture features in accurses result and improvement the performance of system. When combined the color and textural features. We get a higher accuracy and improve the performance of the system than the color alone and textural alone. As shown in Table (2-3) shows the results from GLCM and CM for normal and abnormal, respectively these features gave the best results for diagnosis. The Table (4), (5) shows the result for training and testing for combining the color and textural features to classify the normal and abnormal (DR). Table (6) shows the comparative our method with other researchers in diagnosis normal and abnormal (DR) retinal.

The confusion matrix shows the accuracy and errors of classification as shown in Figure (10) and the confusion matrix for training and testing cases shown in Figure (11) which illustrate the classification results of the neural network for normal and abnormal.

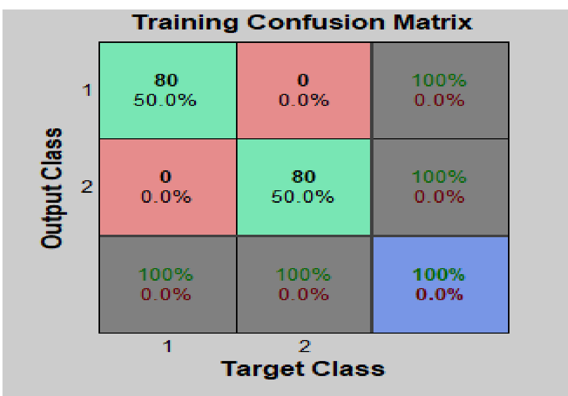

Figure 9:Confusion Matrix For Training

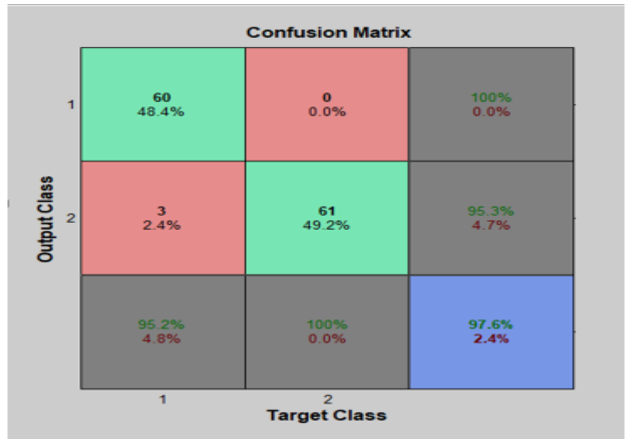

Figure 9: Confusion Matrix For Testing

Tables (4-5) shows the accuracy of classification results from NN classifier.

Table 4: *Accuracy Of Classification For Training Stage*

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Retinal eye	Classification Result %
Normal case	100%
Abnormal case	100%

Table 5: Accuracy Of Classification For Testing Stage.

Retinal eye	Classification Result %
Normal case	97%
Abnormal case	97%

Table (6): Shows the comparative our method with other researchers in diagnosis normal and abnormal (DR) retinal.

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Table 6: Shows The Comparative Our Method With Other Researchers In Diagnosis Normal And Abnormal (DR) Retinal.

Researchers	Data Type	Diagnosis methods	Accuracy Result
Nayak, et al 2009 [28]	331 fundus images	Support vector machine (SVM)	85.9%
Rama, et al 2013 [29]	100 fundus images	Intuitionistic fuzzy histon segmentation	93.4%
Merlin,et al 2015 [16]	DRIVE,STARE	Fuzzy logic based on SVM	96%
Haleem,et al 2015 [30]	104 fundus image	Neural network	92%
Kumar, et al 2016 [18]	268	An aggregation of the lesion extracted form image	Sensitivity 80% Specificity 50%
Dai,et al 2017[31]	MESSIDOR,ONHSD,DRIONS, datasets	Principle component analysis (PCA)	91%%
Our proposed	**283 fundus image**	**Neural network**	**97%**

The performance of the proposed algorithm is evaluated in terms of specificity, sensitivity and accuracy. As the following: [32]

Sensitivity: Is the ratio of the real number of positive detection for disease type to the total number of the image containing the disease. It may calculated by the following equation :

$$Sen. = \frac{TP}{(TP + FN)} \dots\dots\dots (9)$$

Specificity: Is the ratio of the real number of negative detection for disease type to the total number of the image containing non-disease. It is calculated by the following equation.

$$Spec. = \frac{TN}{(FN + TP)} \dots\dots\dots (10)$$

Accuracy: It is used to degree the probability that the diagnostic test is performed correctly. They are calculate as in the following equations :

$$Acur. = \frac{(TP + TN)}{(TP + FN + FP + FN)} \dots\dots\dots (11)$$

Our research we get Sensitivity (95.2%)Specificity (100%), and Accuracy (97%).

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Table 2: Shows The Features Of Normal Images.

No.	Texture Features												Color features								
	Correlation				Energy				Homogeneity				Hue			Saturation			Value		
	0	45	90	135	0	45	90	135	0	45	90	135	mean	Stander	skewness	mean	Stander	skewness	mean	Stander	skewness
Image 1	0.96024	0.92421	0.947357	0.925094	0.069045	0.065504	0.06775	0.065497	0.4354	0.391641	0.419884	0.396654	0.149403	0.079449	0.106398	0.341346	0.054969	0.920296	0.710241	0.124738	0.63326
Image 2	0.97427	0.95521	0.974694	0.955756	0.06911	0.065576	0.067851	0.065552	0.455375	0.416986	0.452843	0.413935	0.179913	0.09896	0.335911	0.446119	0.047045	1.192554	0.618504	0.095985	1.213239
Image 3	0.97764	0.95703	0.971917	0.957252	0.069459	0.065836	0.068281	0.065803	0.493513	0.44613	0.483816	0.445031	0.13565	0.061113	0.435191	0.591767	0.07753	1.513475	0.408192	0.060957	0.457042
Image 4	0.97681	0.95168	0.967893	0.957044	0.069632	0.066086	0.068399	0.066081	0.471101	0.423883	0.456267	0.430529	0.178983	0.070235	0.027724	0.238756	0.062329	0.51734	0.682078	0.106767	0.825821
Image 5	0.97952	0.96007	0.974349	0.960632	0.069087	0.065545	0.06782	0.065547	0.457736	0.416799	0.451797	0.423948	0.182836	0.06659	0.707454	0.337141	0.056137	1.284731	0.647389	0.107892	0.785493
Image 6	0.96024	0.92421	0.947357	0.925094	0.069045	0.065504	0.06775	0.065497	0.4354	0.391641	0.419884	0.396654	0.149403	0.079449	0.106398	0.341346	0.054969	0.920296	0.710241	0.124738	0.63326

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Table 3: Shows The Features Of Abnormal Images.

No.	Texture Features												Color features								
	Correlation				Energy				Homogeneity				Hue			Saturation			Value		
	0	45	90	135	0	45	90	135	0	45	90	135	mean	Stander	skewness	mean	Stander	skewness	mean	Stander	skewness
Image 1	9.75E-01	9.58E-01	9.73E-01	9.59E-01	1.11E-02	1.06E-02	1.11E-02	1.06E-02	4.45E-01	3.51E-01	4.01E-01	3.54E-01	0.1515	0.0791	0.1208	0.3366	0.0548	0.9027	0.7156	0.126	0.6272
Image 2	0.975635	0.962807	0.974232	0.959374	0.011263	0.010745	0.011292	0.010723	0.447657	0.353584	0.396207	0.351163	0.1832	0.0965	0.343	0.4386	0.0462	1.2231	0.6201	0.098	1.2025
Image 3	0.964666	0.940953	0.958315	0.939804	0.011399	0.010665	0.011218	0.010671	0.460652	0.349577	0.390854	0.35105	0.1366	0.061	0.4018	0.5902	0.0771	1.5312	0.4063	0.0609	0.4538
Image 4	0.962616	0.938057	0.955715	0.937689	0.012435	0.011302	0.012007	0.011365	0.510714	0.375801	0.417397	0.379759	0.1847	0.0694	0.0361	0.2321	0.0621	0.5002	0.6882	0.108	0.8451
Image 5	0.975238	0.942762	0.956963	0.942617	0.011136	0.010613	0.011029	0.010599	0.41757	0.279025	0.299504	0.276203	0.1933	0.0613	0.7175	0.3264	0.0555	1.2568	0.6483	0.1085	0.7826
Image 6	0.978518	0.96723	0.978559	0.967465	0.011292	0.010858	0.011387	0.01089	0.430976	0.346587	0.394143	0.351849	0.1824	0.0917	0.5466	0.4029	0.0597	1.4561	0.579	0.0537	2.1932

6. THE CONCLUSION

We found from our methods .that the image enhancement it the main role in diagnosis. By fixed all image to have the same environments. Special by using CLAHE, which give a good result. Also

Using (29) feature from texture features for GLCM Algorithm by using (20) feature(Correlation, homogeneity, energy, dissimilarity and Information measure of correlation1) for each angled (0, 45, 9,135) in gray level. Moreover, from color features by using color moment we get from it (9) features (mean, STD and skewness). By using (H, S, V) color space instead of (R, G, B) color space. After extracting Qualities that is characterized by strength because, it gave strong results. Can be categorized and diagnosed using the Neural Network, which enables us to diagnose the cases of normal and abnormal cases with high accuracy. Our study we find that it depends on the (H, S, V) color space of (R, B, G) color space and extraction of the feature from the algorithm of the color moment. As well as grayscale and extraction feature from the algorithm (GLCM). This method was based on color and texture. To extract feature that was strong in the diagnosis of cases. That gives us the high accuracy and more effective between normal and abnormal (retinopathy diabetics) cases. Using Neural

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Network is the best classifier that the others such as fuzzy logic.

Correlation				Energy				Homogeneity				Hue			Saturation			Value		
0	45	90	135	0	45	90	135	0	45	90	135	mean	Stande	skewn	mean	Stande	skewn	mean	Stande	skewn

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