Early Detection of Diabetic Retinopathy Based Artificial Intelligent Techniques

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ABSTRACT

The eye is impacted by several disorders, either directly or indirectly. As a result, eye exams are a crucial component of general healthcare. One of the effects of diabetes is diabetic retinopathy (DR), which affects the blood vessels that supply and nourish the retina and causes severe visual loss. One of the prevalent eye conditions and a consequence of diabetes that affects the eyes is diabetic retinopathy. The symptoms of diabetic retinopathy may be absent or minimal. It may eventually result in blindness. Therefore, seeing symptoms early could aid in preventing blindness. This paper aims to research automatic methods for detecting diabetic retinopathy and create a reliable system for doing so. A modified extracted feature for the automatic identification of DR in digital fundus pictures is presented. The properties of exudates, blood vessels, and microaneurysms—three elements of diabetic retinopathy—are reported utilizing a variety of image processing techniques. Back Propagation Neural Networks (BPNN) and Support Vector Machine (SVM) classifiers are used to categorize the phases. SVM, which has accuracy, sensitivity, and specificity of 96.5, 97.2, and 93.3 percent, respectively, is the model that performs the best overall.

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1. INTRODUCTION

The primary focus of artificial intelligence (AI) research in the field of medicine is on creating algorithms and methods that can evaluate whether the behavior of a system represents an accurate illness diagnosis. A person's symptoms and indicators are evaluated to determine the disease or diseases that are causing them through the process of medical diagnosis. The history of the patient and the results of the physical examination are the two primary sources of diagnostic information. [1-2]. DR is a complication of diabetes that affects the eyes. It is brought on by harm to the blood vessels in the tissue at the back of the eye that is light-sensitive (the retina). At first, diabetic retinopathy may not show any symptoms or may only result in modest vision problems. Any person with diabetes, whether type 1 or type 2, can get this ailment, but it could ultimately lead to blindness. The likelihood of developing this sort of eye-related issue increases as diabetes progresses and blood sugar control levels are improved [3-5].

Manual examination of fundus images to check for morphological changes in micro-aneurysm, exudate, vascularization, hemorrhage, and macula is laborious and time-consuming. This check can be done quickly with the help of a computer-aided system and changeability for the observer. This section discusses several techniques for detecting microvascular aneurysms, hemorrhages, and exudates for the definitive detection of non-proliferative diabetic retinopathy [6-8]. Vascular detection techniques for diagnosing proliferative diabetic retinopathy are also discussed. Furthermore, the next section provides a detailed discussion of the trials accessed by the authors for the detection of diabetic retinopathy.

Fundus photography employing desktop analog and digital cameras has been replaced by handheld digital and smartphone-based cameras over the last few decades. Some of these more recent gadgets are now recognized as suitable tools for routine diabetic retinopathy screening by national organizations [9-11]. A skilled technician is still needed to take the retinal pictures using these technologies. Diabetes patients must undergo routine retinal screening in order to identify and treat DR early and reduce the risk of blindness. Different lesions that occur on the retina of a picture can be used to detect DR [12]. A fundus picture with multiple anomalies is shown in Figure 1. The earliest indication of DR is Microaneurysms (MA), which are microscopic blood vessel bulges that manifest as dark red spots on the retina due to the weakened vessel walls. They often manifest as little red spots that are temporal to the macula and are frequently the first clinically discernible retinopathy symptom. The size is less than 125µm, and the margins are sharp. Hemorrhages (HM) are small spots of blood discharge. It appears in larger spots on the retina, whose size is more significant than 125 µm with an irregular margin. The compact middle layers of the retina's retina can experience hemorrhages, which might manifest as spots or blots [13-14].

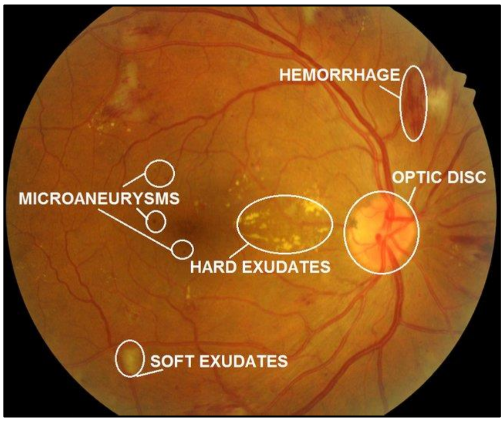


Figure 1. Different types of lesions Retinal fundus image [12].

By utilizing several categorization algorithms, this study intends to create an efficient, reliable, and precise automatic system for the earlier detection of diabetic retinopathy. This project aims to investigate automatic methods for detecting diabetic retinopathy that can enhance the management of the condition before developing a useful screening program for this. First, the paper described creating an entire system for detecting and categorizing diabetic retinopathy utilizing eye fundus images. This system will classify images into two different cases: normal and diabetic retinopathy. The investigation will then concentrate on finding microaneurysms, the first signs of diabetic retinopathy. The proposed work also offers modified derived features for identifying diabetic retinopathy and maculopathy in eye fundus pictures.

2. RELATED WORK

To satisfy the demand for screening the growing number of diabetic patients, the number of certified ophthalmologists must rise concurrently with the significant rise in the number of people with diabetes. This makes it easier to devise strategies for automating DR detection. The computer-aided diagnostic system could greatly reduce the strain currently placed on ophthalmologists. Researchers widely use computer-aided detection methods because they can reliably and effectively identify diabetic retinopathy. Numerous scientific studies on evolution have been published over the last ten years [15]. Rao et al., 2015 [16] proposed a method in which structural and energy features are taken into account and then analyzed to classify them as a glaucoma image. The power distribution was applied to the cup-to-disc ratio to find these critical texture energy features. Finally, the extracted energy features are applied to the multilayer neural network (MLP) and backpropagation (BP) for efficient classification by considering the extracted energy features of the normal subject. While the accuracy of the MLP-BP (ANN) rating was 90.6%. Naive Bayes' classification accuracy was equal to 89.6%.

Kashyap et al., 2017 [17] Introduced an inexpensive and small mobile outcome finding system based on the ANN algorithm for the early identification of DR. The retina is photographed using a condensing lens on a cell phone. The DWT parameters are utilized in this method as a feature vector. The initial scan of the DR is then decided using an artificial neural network detection algorithm. The experiment's findings demonstrate that to shorten the analysis time, the finite numbers of the retinal picture are retrieved with an accuracy of 63 percent and a retrieval rate of 57 percent. Chakraborty et al., 2020 [18] proposed an approach based on supervised learning using an ANN to improve diabetic retinopathy diagnosis results. The feedback propagation neural network is the ANN architecture that was used in this study. The obtained accuracy for the suggested method is 97.13%.

Jadhav et al., 2021 [19] evaluated retinal anomalies as a novel method for creating automated detection of DR. Contrast Limited Adaptive Histogram Equalization (CLAHE) was used to improve the retinal fundus picture. The second step was an open and closed watershed transformation to get rid of the optic disc. The blood vessels were then removed and segmented using a gray level threshold. The images were categorized into normal, previous, intermediate, or severe using a Deep Belief Network (DBN)-based classification algorithm. The results show that the suggested Modified Gear and Steering based Rider Optimization Algorithm (MGS-ROA) had an accuracy that was 30.1% better than NN, 32.2% better than KNN, and 17.1% better than SVM and DBN. Elsharkawy et al., 2022 [20] developed a technique to use structural 3D retinal scans to diagnose DR early. This technique automatically segments all retinal layers of the 3D-OCT scans based on past shape knowledge. After segmenting the volume of OCT B-scans, unique texture features are derived for DR diagnosis from the segmented layers. Every layer is subjected to the Markov-Gibbs random field (MGRF) model to derive the 2nd-order reflectivity. An artificial neural network (ANN) is fed the retrieved feature for each layer to perform layer-by-layer classification in a 3D volume using the extracted Gibbs energy feature.

3. THE PROPOSED METHODOLOGY

The proposed automated solution for diabetic retinopathy would help people see better by saving time and money. Appropriate automation (i.e., decision support systems) can help prevent complications from diabetic retinopathy and lower the chance of blindness by enabling earlier preventative interventions to safeguard vision. Detecting and managing diabetic retinopathy might benefit substantially from a decision support system for clinical diagnosis. In contrast to human analysis, which takes more time, an automatic method will let an ophthalmologist (or optometrist) diagnose diabetic retinopathy (and its detailed classification) more effectively and rapidly. The advancement of efficient image processing methods for identifying diabetic retinopathy is a popular research topic that has attracted the attention of several researchers. Most researchers concentrate on developing and presenting a precise approach or procedure for examining eye fundus images to identify particular aspects of diabetic retinopathy. Even though this field of research has made enormous strides, there are still gaps or opportunities for progress. The strategies suggested in this study will most significantly improve image processing in a number of ways, including by offering a precise method for accurately recognizing signs of diabetic retinopathy. The proposed system block diagram is illustrated in Figure 2. There are three key processes in a diabetic retinopathy detection system: several pre-processing, extraction of features, and classification. As shown in Figure 3 the methods for DR have been developed to improve DR detection. We propose a combination of pre-processing, feature extraction, and classification techniques to improve DR detection.

3.1. DATA ACQUISITION

In this suggested strategy, the blood vessel was found using the DRIVE dataset [21]. DR screening program served as the foundation for the creation of the DRIVE database. There are 40 label photos and 40 color fundus images in it. Of these, seven have mild early DR and 33 are DR-free. Each image is taken at a resolution of 768 by 584 pixels with 8 bits per color plane. Also we used Kaggle dataset to train the model for end-to-end framework for diabetic retinopathy detection [22]. Kaggle dataset, 35126 color fundus pictures, each 3888 by 2951 pixels in size. According to the severity of diabetic retinopathy, it contains photos from five different classes (DR).

3.2. PREPROCESSING

Pre-Processing stage is the phase that can be viewed as the foundation of this study. Before the images can be utilized to identify anomalies related to fundus images, they must be pre-processed to address difficulties with uneven illumination, insufficient contrast, and the presence of noise. The next crucial step is merging the three color channels—red, green, and blue—into a single channel gray-scale image. Grey scale conversion is carried out utilizing principal component analysis (PCA) instead of choosing the green channel merely for its potential gray-scale representation, as followed by many prior academics. PCA is an effective tool for data analysis.

Since the histogram in these places is heavily concentrated, conventional Adaptive histogram equalization (AHE) tends to overamplify the image's contrast in various areas that are close to constant. AHE might thus lead to noise amplification in nearly constant locations. AHE technique, limits the contrast amplification to lessen the issue of noise amplification. This work used CLAHE to increase the image contrast. This is to highlight the DR features.

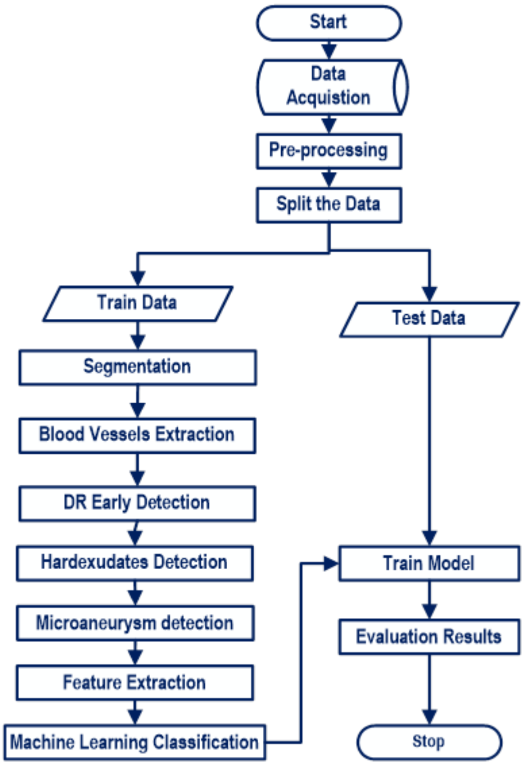


Figure 2.General block diagram of the proposed methodology.

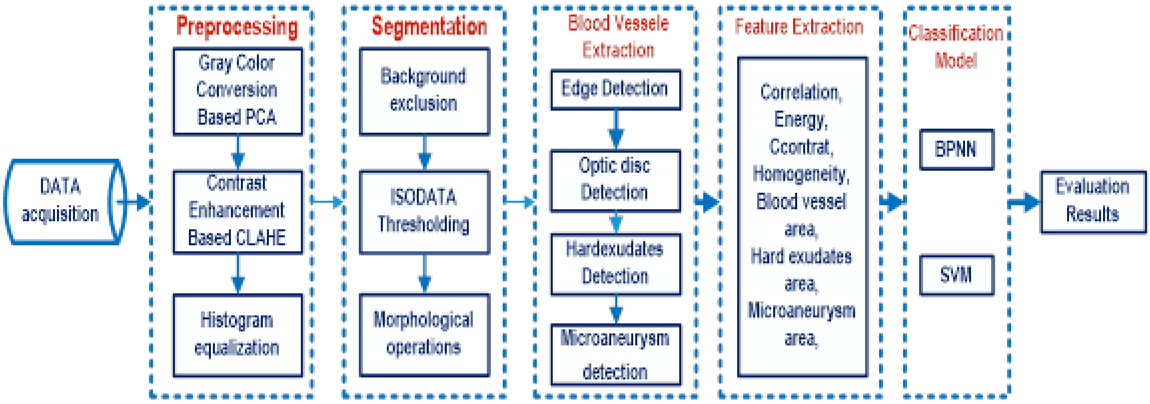


Figure 3. Flow Chart of the proposed DR detection using Image Processing

3.3. SEGMENTATION

Image segmentation provides essential information or data for automatic image analysis requirements. Because it enables the appropriate output to be generated from the pixels of interest. The original intensity image from the average filtered image is subtracted in the suggested algorithm to achieve background exclusion. One of the classification-based techniques for picture segmentation is the Iterative Self-Organizing Data Analysis Technique (ISODATA) technique. ISODATA is a widely used unsupervised classification technique in remote sensing and the analysis of medical pictures [23]. As seen in Figure 4, the goal is to divide nonhomogeneous regions into two subregions. The greatest way to improve threshold segmentation is through morphological operation, which eliminates noise and filters out smaller zones. The block diagram of morphological operations is shown in Figure 5.

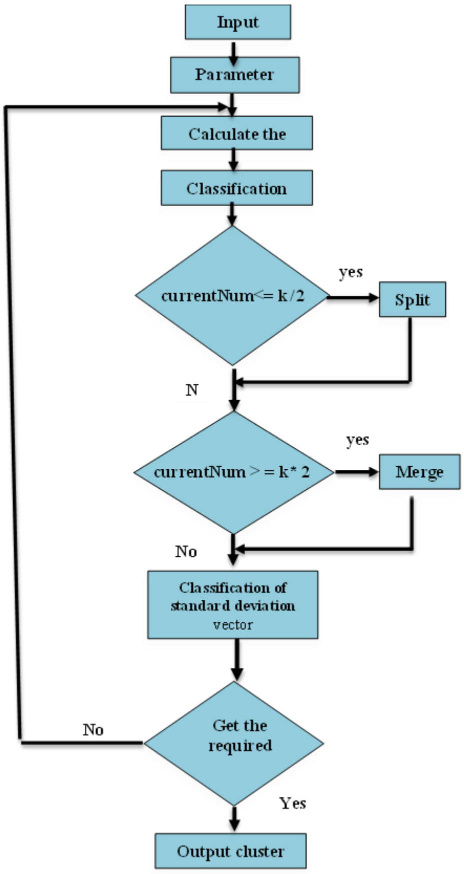


Figure 4. Block diagram of the ISODATA algorithm.

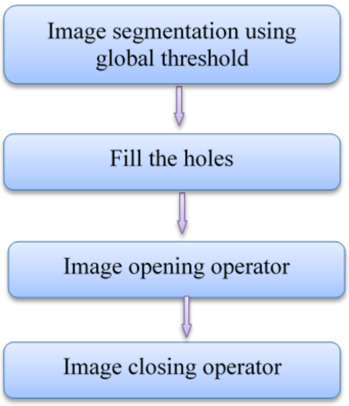


Figure 5. Morphological operation's block diagram.

3.4 BLOOD VESSEL DETECTION

The image is subjected to three distinct sized and ellipse-shaped structural pieces, measuring 5x5, 11x11, and 23x23, in alternate sequential filtering (three times opening and closing). The output image is then subtracted from the source image. There are numerous minor sounds in the subtracted image. Area parameter noise elimination eliminates the noises. After that, a threshold value is used to binarize the resulting image. Finally, a calculation is made to determine how many pixels the blood vessel region covers

3.5 MICROANEURYSM DETECTION

The RGB value's green component is used to extract microaneurysms. CLAHE is used for improved contrast. After that, noise is removed using a median filter. For morphological operation, a structural element with the dimensions 7x7 is used. After applying the morphological operation erosion, the image is reversed. Morphological closure is utilized to connect the blood vessel segments that are not connected. The image has then undergone binarization. The blood vessel, hemorrhage, and microaneurysm will all be identified together in the binarized image since they all have nearly equal intensity levels. Microaneurysms have been extracted utilizing contour areas since they are smaller in size.

3.6 FEATURE EXTRACTION

The practice of feature extraction reduces the amount of resources needed to adequately describe a sizable data set. The Modified feature extracting method is presented by adding the Gray Level Co-Occurrence Matrix (GLCM) feature to increase the sensitivity of the overall process. This work extracts four important features, correlation, energy, contrast, and homogeneity, from diabetic retinopathy images. The blood vessel area, area of hard exudates, and Microaneurysm area are also selected for improvement in the detection. Some important modified features are defined below.

$$Correlation = \frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i,j)p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y} \quad (1)$$

$$Contrast = \sum_{i=0}^{N-1}\sum_{i=0}^{N-1}(\boldsymbol{i}-\boldsymbol{j})^{\mathbf{2}}\boldsymbol{p_{ij}} \quad (2)$$

$$\text{homogeneity} = \sum_{i=0}^{N-1}\sum_{i=0}^{N-1}\frac{p_{ij}}{1+|i-j|} \quad (3)$$

$$Energy = \sum_{i=0}^{N-1}\sum_{i=0}^{N-1}\boldsymbol{p_{ij}^2} \quad (4)$$

3.7 ANNS AS CLASSIFICATION MODELS

The neural networks have become a crucial classification technique. Consequently, three classifiers were utilized in this study to diagnose hepatitis illness. Training and testing are the two phases of classification, a supervised learning process. The classifier is trained from a set of examples known as the training set during the training phase. During the testing step, the classifier is tested on cases it has never seen before. Two well-known classifiers are discussed in this subsection.

- ***Back Propagation Neural Network (BPNN)***

The three fundamental layers for each dataset division make up the proposed network, as shown in Figure 6. The input layer, which connects the network to its surroundings, has seven cell neurons (which represent the collected attributes) as nodes. The classification's accuracy depends on how many levels there are and how many neurons there are in each level. In this study, the use of two hidden layers, the first with five neurons and the second with five neurons, led to the best accuracy. The output layer, the third and final layer, determines the class to which the individual belongs based on the features generated in the inputs. There are two neuronal cells in it. One class per cell, representing those who are not infected with DR, is represented by each cell. People with DR are shown in the other cell.

- ***Support Vector Machine (SVM)***

It is a supervised machine learning method to classify data points in a high-dimensional space by increasing the distance between classes. Our initial objective is to identify which eye has diabetic retinopathy and which is healthy because SVM is a binary classifier. Following the initial classification, our next objective is to reapply the SVM. It will once more distinguish between diabetic retinopathy that is non-proliferative or in the early stages and that is proliferative or in a severe state. This time, it is exclusively used on those who are already harmed.

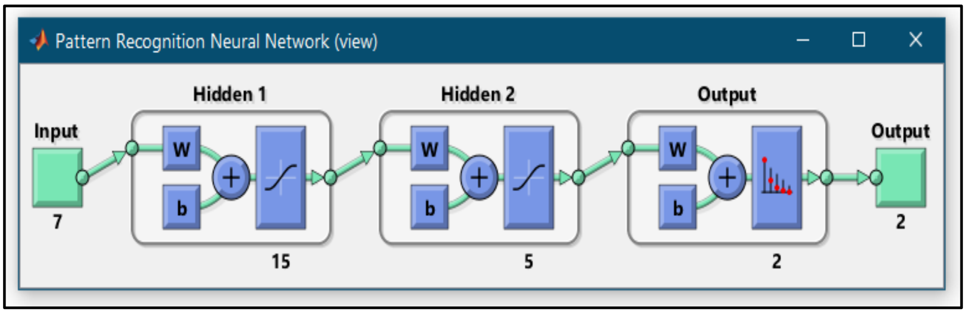


Figure 6. Structure of proposed BPN.

4. RESULTS DISCUSSION

In this work, we evaluate our work in terms of Accuracy, Sensitivity, and specificity. And the evaluation metrics are calculated and compared with several related works which are referenced. We used a computer with a respectable configuration as an experimental setup to carry out our work, Diabetic Retinopathy Classification from Retinal Images using Machine Learning Approach. As an experiment for this work, we employed the configuration; Intel Core i7 5 generation processor, 8GB RAM, 1TB Hard-disc, 2GB graphics card. The image resolution that was captured is 1280x1024 in 24bit JPEG format. An eye's color image is used as the input image before being transformed into a grayscale image. The effectiveness of the suggested method is assessed using all 40 photos from the DRIVE database divided into 50% for training and 50% for testing sets (20 training and 20 test images) to detect the blood vessel based on image processing. While in machine learning we have used 100 fundus images from Kaggel database (80 with DR and 20 No DR) to classify the DR based on BPNN and SVN. Figure 7a displays an example of a digitized retinal color fundus picture. In this work, proposed Grey scale conversion is done based on PCA, also the Contrast Enhancement based CLAHE shown in Figure 7c. The outcomes of using the average filter on the gray-scale images are shown in Figure 7d. By deleting the undesired pixel, the stage improves the global threshold segmentation. The average filter is applied by the proposed approach using a window size of 9x9 pixels. The outcomes of using the average filter on the gray-scale images are shown in Figure 7e. The three phases in this stage are to fill the holes, open the operator, and close it. As shown in Figure 7e and 7f, the final step in this procedure is to transform the image created by the morphological operations into a binary image.

DR can be identified following blood vessel excision. The most advanced stages of the suggested algorithm are produced by this step. Then, sensitivity, accuracy, and specificity are employed as the final evaluation criteria for the suggested algorithm's accuracy. Table 1 provides the accuracy percentages for the DR Detection using Image Processing. The most common performance metric is a classification error %. However, a false negative in identifying diabetic retinopathy might have disastrous consequences. As a result, it is necessary to look into different performance criteria for these models. The dice A measure of similarity called a coefficient is frequently employed in medical image processing to assess how well segmentation algorithms perform when given truth-based data on a preset surface [24]. The Jaccard index evaluates the difference or dissimilarity between the two photos and is comparable to the dice index used to determine how similar two sets of photographs are [24]. To compute this, use the formula,

$$jaccard(x, y) = \frac{|x \cap y|}{|x| + |y| - |x \cap y|} \quad (5)$$

$$Dice(x, y) = \frac{2|x \cap y|}{|x| + |y|} \quad (6)$$

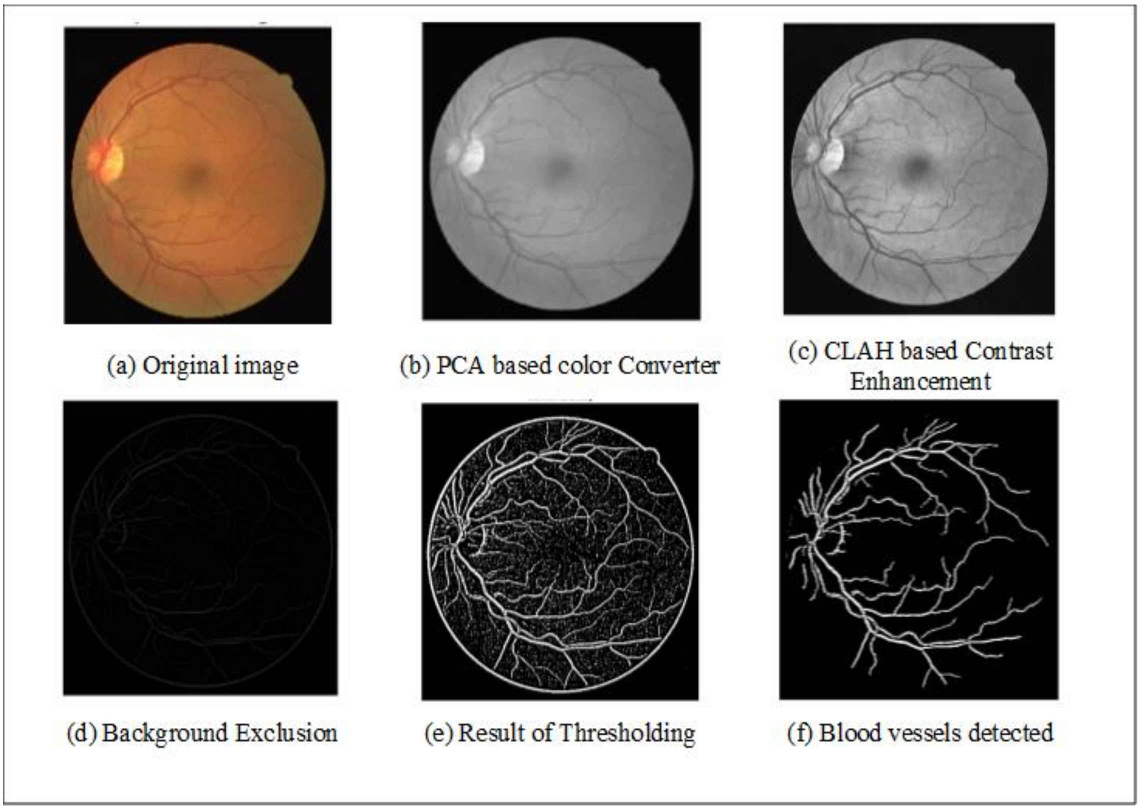


Figure 7. Experimental Result

Table 1. Performance result of Drive database for the proposed DR detection method.

image number	Accuracy	Specificity	Sensitivity	Jaccard	Dice
1	0.946914778	0.958195794	0.831759511	0.582982168	0.736561889
2	0.948424051	0.962970591	0.82092335	0.619768975	0.765256014
3	0.944875136	0.968088007	0.73523242	0.570740802	0.726715447
4	0.957379682	0.982864162	0.705837781	0.603725203	0.752903555
5	0.953488302	0.977338086	0.722761387	0.59279896	0.744348753
6	0.947248151	0.971203046	0.725090298	0.572260585	0.727946233
7	0.936319554	0.95495784	0.750994959	0.518691589	0.683076923
8	0.947142078	0.967669305	0.729085209	0.542699074	0.703570882
9	0.949348406	0.967475653	0.743801653	0.543398082	0.704158037
10	0.954794521	0.974551195	0.73449698	0.572141587	0.727849949
11	0.940277609	0.961407491	0.725380006	0.520919943	0.685006394
12	0.936440781	0.947139019	0.823236223	0.527934093	0.691043017
13	0.944672081	0.96738674	0.735050684	0.565001906	0.722046285
14	0.928654988	0.934615524	0.860891405	0.493818135	0.661148936
15	0.939122924	0.949615794	0.802998221	0.485595022	0.653738084
16	0.945199418	0.959319583	0.802927059	0.569496691	0.725706138
17	0.944453873	0.958773022	0.78913543	0.5452899	0.705744469
18	0.943005213	0.955423677	0.79869186	0.526142062	0.68950601
19	0.954912717	0.966998139	0.821307223	0.601761383	0.751374568
20	0.953576191	0.964078575	0.821265197	0.565397492	0.722369232
Mean	0.945812523	962503562	0.7774043343		

Following the aforementioned procedures, a new eye image that detects blood vessels, as well as images of hemorrhages or exudates, is obtained. Images of hemorrhages or exudates are detected using a set of feature values extracted from a blood vessel. The feature values extracted are; Blood vessel area, Area of hard exudates, Microaneurysm area, Contrast, Homogeneity, Correlation, and Energy. The complete list of features of the NDR testing image from the DRIVE database is shown in Figure 8

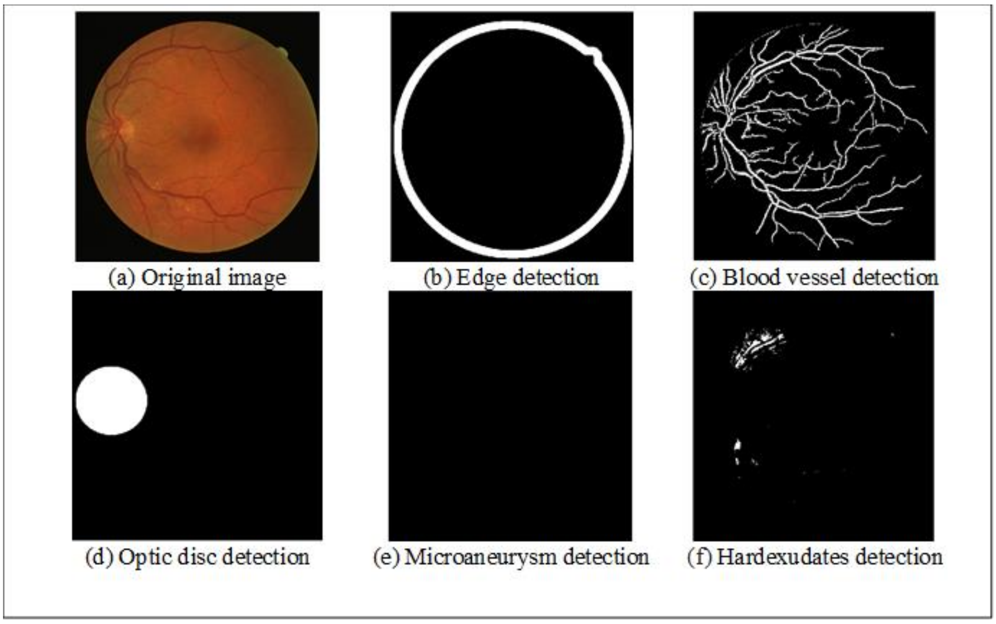
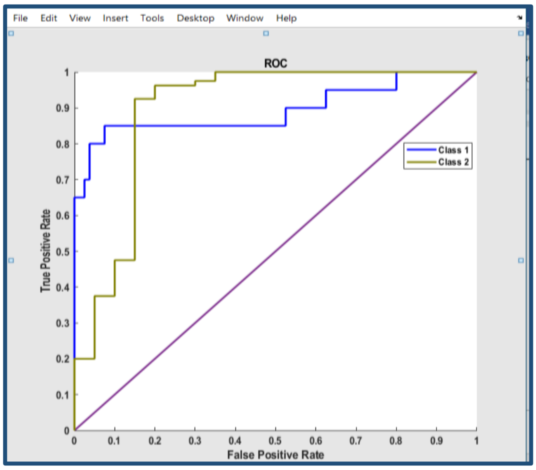


Figure 8. Features extracted of 01_testing image from Drive database.

The linear transmission function is the activation function in BPNN's input layer and output layer. Tan-sigmoid is the activation function employed in the hidden layer. The performance of the BPNN during the training phase is shown in Figure 9. When the system is tested by the training group itself for every database division, the performance of (MSE) Mean Square Error is less than 1×10^{-6} and the accuracy of the correct classifications is 100%. The response receiver operating characteristics (ROC) curves for systems using different classifier and feature combinations are shown in Figure 10. The blue line represents the suggested method's retinal change detection sensitivity (100%) on the test set of 100 photos.



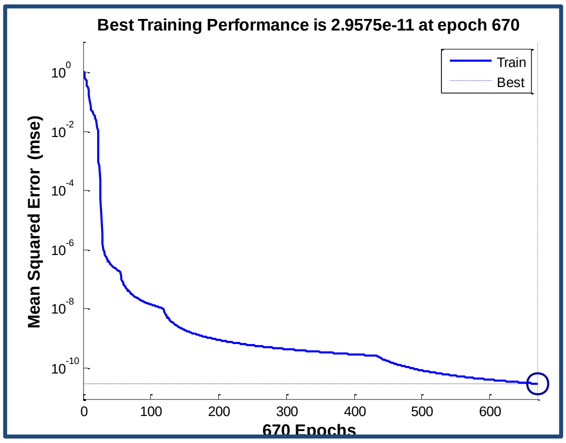


Figure 9. Training performance of BPN for two-class for 100 sample of kaggle database.

Figure 10. ROC Curve.

The image is divided into two classes using Support Vector Machines (SVM), such as Diabetic Retinopathy eye and healthy eye. Our initial objective is to identify which eye has diabetic retinopathy and which is healthy because SVM is a binary classifier. Our next job is to employ the Support Vector Machine once more after the initial categorization. This time, it is exclusively used on those who are already harmed. It will once more categorize which cases of non-proliferative (early stage) and proliferative diabetic retinopathy (in the severe stage). Applying BPNN classifiers to assess the images in this model led to the discovery of a classification confusion matrix, as shown in Figure 11.

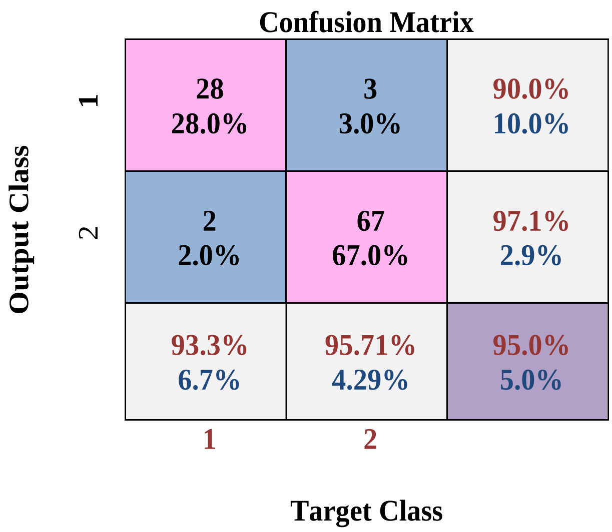


Figure 11. The confusion matrix after applying BPNN classifiers.

Because the objective function in SVM is convex and never trapped in the local maximum, we chose to utilize it. The shape of the separating hyperplane is an optimum hyperplane. The input vector's dimensionality is not a direct determinant of the optimization problem's objective function, which solely depends on the inner products of two vectors. Due to this property, separate hyperplanes can be constructed in high-dimensional spaces. A classification confusion matrix has been discovered after applying SVM classifiers to test the images in this model. In Figure 12, the confusion matrix is displayed.

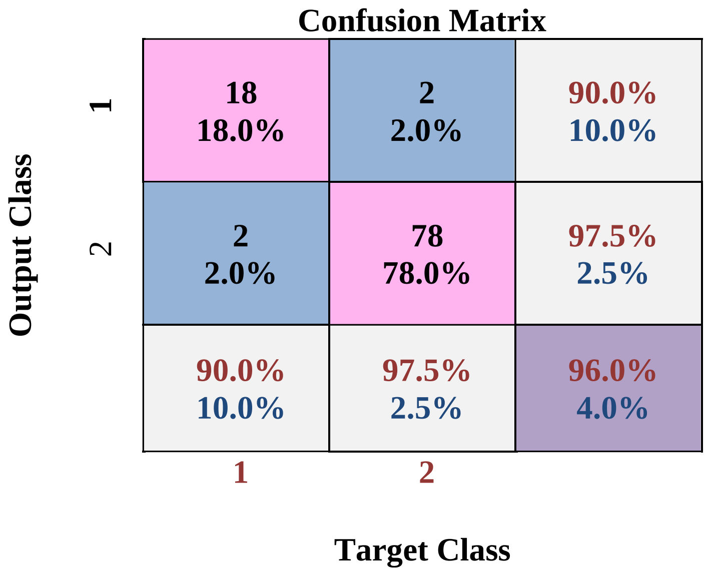


Figure 12. The confusion matrix after applying SVM classifiers.

Performance Comparison with Previous Works

The accuracy of earlier investigations has been increased as much as feasible to get a correct DR detection. Regarding the number of classes, methods employed, features, etc., the assessment metrics are contrasted with the related studies. Table 2 compares the accuracy of each work with the findings of the current investigation.

Table 2. Comparison of Automatic detection of the DR stages by various researcher

Ref.	Algorithm	Accuracy	Specificity	Sensitivity
[16]	MLP-BP	89.6%	---	---
[18]	BPNN	96.17%	96.2%	96%
[19]	MGS-ROA-DBN	93.18%	95.45%	86.36%
[20]	3D-OCT	90.56%	86.98%	98.63%
Proposed	SVM	96%	97.5%	90%
Proposed	BPNN	95%	97.1	93.3%
Proposed	Image Processing	94.58%	96.25%	77.74%

5. CONCLUSION

By utilizing several categorization algorithms, this study intends to create an efficient, reliable, and precise automatic system for the earlier detection of diabetic retinopathy. Be aware that the PCA-based technique produces a vessel-specific image significantly more effectively. Compared to if we had chosen a green image, the histogram of the PCA-based gray image is more evenly distributed and indicates many more intensity levels. This strategy aims to identify some characteristics specifically responsible for diabetic retinopathy. Several morphological functions and reconstructions were employed to obtain these features. The most severe eye abnormalities are exudates, blood vessels, and microaneurysms. So we considered these lesions in our research. It has been discovered through research into related works that using machine learning-based classifiers produces more accurate predictions. Image processing technique, BPNNS, and SVM, are selected for this research. The performance of all three classification techniques was good. However, the findings show that SVM is more efficient than BPNN.

In the future, we intend to use a neural network model to carry out this classification procedure utilizing a larger dataset of diseased eyes. In future studies, the body position (standing or seated) and geometry should be considered in detail. Also, future work will employ more sophisticated computations for image processing to arrange the images more effectively than the classifier in use today. Patients will benefit from the Client Helpline being included in the User Interface.

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