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Diabetic Retinopathy Detection Using GLCM, Shi-Tomasi Corner Detection, and Random Forest Classifier

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Abstract: Patients with diabetes may develop clots, lesions, or hemorrhages in the area of the retina that is sensitive to light. This disease is known as diabetic retinopathy. High blood sugar causes blood vessels to become blocked, which encourages the production of new vessels and the creation of structures that resemble mesh. Evaluating the branching retinal vasculature is crucial for ophthalmologists to diagnose the condition effectively. In the process of assessing diabetic retinopathy, fundus scans of the eye undergo pre-processing and segmentation. For image preprocessing, various steps are undertaken, including enhancement, retinal mask extraction, blood vessel segmentation, optic disk extraction, and extraction of lesion candidate regions. To extract the branching blood vessels, thresholding technique is applied. Following this, morphological operations and adaptive histogram equalization are then applied to improve the image quality and remove areas that were falsely segmented. The proliferation of optical nerves was observed to be significantly greater in diabetic or affected patients compared to healthy individuals. Using a hybrid technique combining the Shi-Tomasi Corner Detector and GLCM, additional features are recovered from the lesion candidate. A random forest classifier is used to categorize the existence of diabetic retinopathy. Two datasets—DIARETDB1, a typical Diabetic Retinopathy Dataset, and a dataset from a medical facility including fundus scans of both normal and affected retinas—are used to assess the effectiveness of the proposed strategy. The experimental findings show how well the proposed method works in comparison to conventional approaches. When evaluated on the DIARETDB1 dataset, the model achieves an accuracy of 98.7% and a precision of 97.2%.

Keywords: *GLCM, DIARETB1, Shi-Tomasi and RF etc.*

1. Introduction

A medical disorder known as diabetic retinopathy (DR) [1] affects people who have diabetes. There are two forms of diabetic retinopathy: the more advanced form is called Proliferative Diabetic Retinopathy (PDR), and the milder form is called Non-Proliferative Diabetic Retinopathy (NPDR). Exudates are the first indication of DR because they show NPDR. Patients with NPDR may initially have fuzzy vision, but as the condition worsens, the retina starts to grow new blood vessels, which have a major influence on vision. Blood clots or blobs can develop in the retina as a result of these aberrant blood vessels' propensity to leak or bleed. One of the main contributing factors to the development of DR is damage to the network of arteries that feed the retina with nutrients. In advanced stages of PDR, the blood vessels may become completely blocked, resulting in the formation of lesions. The most visible lesions that occur are microaneurysms and haemorrhages. Microaneurysms are the first observable symptoms of DR and appear as small round-shaped red dots in the fundus.

Currently, DR is primarily detected by trained ophthalmologists through manual assessment of fundus images. On the other hand, rapid and precise detection of the condition is required by automated DR screening systems. To construct such systems with high accuracy, a variety of techniques, including novel unsupervised ones, have been developed. For tasks like pixel-level exudate identification in retinal pictures and fovea detection, deep-learning-based algorithms are applied. One kind of deep neural network made up of several layers of linked neurons is called a convolutional neural network (CNN) [2]. Every neuron in a layer of a CNN is linked to every other neuron in the layer below it. In the context of DR detection and segmentation, among other areas of image classification, CNNs have found extensive use.

Numerous techniques have been investigated in the field of diabetic retinopathy analysis to recognize and identify retinal vessels and other disease-related aspects.

The WELR (Wavelets and Edge Location Refinement) method has been utilized to extract retinal vessels, achieving high true positive (TP) and false positive (FP) rates and accuracy scores [3]. Another effective method for vessel identification is AMT (Adaptive Median Thresholding) [4], which can provide reliable results.

The configuration of the retinal blood artery network poses problems for preterm newborns, including poor contrast, significant noise, and inferior picture quality. The goal of the research has been to create techniques for removing the

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RBVN from this particular population [5].

Techniques like centerline and bit plane identification can also be used to identify retinal vessels [6]. For vessel extraction, multidirectional morphological bit plane techniques have been used.

For the detection of exudates, methods like morphological compact tree (MCT) have been utilized [7]. Effective application of histogram analysis to the detection of exudate in retinal images has also been investigated.

These various methods and techniques contribute to the accurate recognition and analysis of diabetic retinopathy features, including retinal vessels, exudates, and other lesions. Researchers continue to explore new approaches and algorithms to enhance the effectiveness and efficiency of diabetic retinopathy diagnosis and monitoring.

By increasing the efficiency and precision of DR diagnosis, these automated technologies hope to help medical personnel quickly diagnose and treat the ailment. It's crucial to remember that, even if these techniques appear promising, more investigation and validation are required to guarantee their dependability in actual clinical situations.

The contribution of the proposed algorithm lies in its comprehensive approach to assessing diabetic retinopathy through fundus scans. By combining various pre-processing and segmentation techniques, it effectively extracts key features and classifies the presence of diabetic retinopathy. Here are the key contributions of the algorithm:

- **Preprocessing and Segmentation:** The algorithm performs essential pre-processing steps such as image enhancement, retinal mask extraction, blood vessel segmentation, optic disk extraction, and lesion candidate region extraction. These steps help to isolate and extract relevant regions of interest from the fundus scans.
- **Branching Blood Vessel Extraction:** The algorithm employs a thresholding technique to extract branching blood vessels from the fundus scans. This step is crucial as the proliferation of optical nerves, observed to be significantly greater in diabetic or affected patients, serves as an important characteristic for diabetic retinopathy assessment.
- **Image Enhancement and False Segmentation Elimination:** Morphological operations and adaptive histogram equalization methods are used to remove incorrectly segmented areas and improve the quality of the fundus images. As a result, further analysis and categorization are more accurate and reliable.
- **Feature Extraction:** GLCM (Gray Level Co-occurrence Matrix) [8] and Shi-Tomasi Corner Detector [9] are used in combination to extract additional features from the lesion candidate areas. This combination allows for the extraction of relevant texture and corner-based features, capturing important patterns and irregularities associated with diabetic retinopathy.
- **Classification using Random Forest:** Based on the features that were extracted, a random forest classifier is used to determine whether diabetic retinopathy is present or not. Robust classification results and ease of handling complicated datasets are well-known characteristics of random forests.

By integrating these contributions, the proposed algorithm offers a comprehensive and effective solution for the assessment of diabetic retinopathy. It combines image processing techniques, feature extraction methods, and a powerful classification model to achieve high accuracy and precision in diagnosing diabetic retinopathy using fundus scans.

The study begins by providing a comprehensive literature review in Section 2, highlighting the relevant research in the field. The materials and methods used in the research paper are presented in Section 3. In Section 4, the proposed methods are explained in detail. The results of the MATLAB-based simulation are presented and analyzed in Section 5. Finally, the paper concludes with a summary of the findings and conclusions in Section 6.

2. Literature Review

Considerable studies have been devoted in the last few decades to the efficient segmentation of retinal blood vessels and the classification of retinal images according to the degree of diabetic retinopathy (DR) [10].

In traditional DR analysis, an automatic retinopathy classification approach based on Artificial Neural Networks (ANN) has been proposed [12]. This technique utilizes morphological operations to distinguish between exudates and blood vessels. Techniques such as Genetic Algorithms (GA) and Fuzzy C Means (FCM) have been employed to achieve maximum accuracy. Excellent reliability in predicting hard exudates in DR images has been demonstrated by fuzzy logic (FL). A multi-scale line detecting system has been used to analyze retinal vascular features [11]. An algorithm named DR analysis with the utilization of Machine Learning (DREAM) has been developed, incorporating a Gaussian mixture model and nearest neighborhood approach with a classifier based on Singular Vector Machine (SVM) [5]. Retinal image pre-processing has been done using global thresholding [6]. To increase accuracy, morphological component analysis (MCA) was applied to vessel segmentation in the DRIVE and STARE datasets [7]. Zago et al. [13] utilized the

VGG16 model [14] to detect red lesion patches in diabetic retinopathy images and achieved promising results. They classified the images as either having diabetic retinopathy or not based on the detected red lesions, achieving an impressive AUC of 0.912 on the Messidor dataset [15]. The DDR dataset was first presented by Li et al. [16] with the goal of localizing lesions in the images and classifying them into the five phases of diabetic retinopathy. They employed the SE-BN-Inception model [17] for stage classification and achieved the highest accuracy of 82.84%. For lesion localization, they utilized Faster RCNN [18] and attained a mean Average Precision (mAP) of 9.2.

A modified version of RFCN [20] was used by Wang et al. [19] to identify the phases of diabetic retinopathy and to pinpoint certain features such as microaneurysms (MA) and hemorrhages (HM). They combined the outcomes of their two RFCN models. Their approach attained a high mAP of 92.15 for localization in their proprietary dataset. They achieved an accuracy of 92.95% in categorization [20]. These approaches demonstrate the utilization of various techniques, such as ANN, morphological operations, GA, FCM, FL, SVM, and MCA, in the analysis and classification of retinal images for DR diagnosis. With the goal of increasing the precision and effectiveness of DR evaluation, each technique concentrates on a distinct facet, such as vessel segmentation, exudate identification, and tortuosity analysis. It's crucial to remember that the studies listed above only make up a small portion of the substantial research done in this area; further developments and improvements are still being investigated.

Limitations:

Despite the advancements in vessel segmentation techniques, accurately segmenting retinal vessels in images with low contrast, noise, or artifacts can still be challenging.

The proposed methods often rely on specific datasets, and their performance may vary when applied to different datasets with variations in image quality, resolution, and characteristics of diabetic retinopathy cases.

The interpretation of DR severity solely based on vessel analysis may overlook other important features and indicators present in retinal images, such as microaneurysms, hemorrhages, or exudates.

3. Materials and Methods

3.1. GLCM

A statistical technique called the GLCM [21] is used to extract textural information from images. The GLCM is basically a matrix that displays the joint probability distribution of two pixel intensities at a given distance and direction in the image. It was first developed as a texture analysis technique. The number of instances of a pair of gray-level values at a specific relative location in the image is represented by each element in the matrix. Due to the symmetry of the matrix, the probability of a pair of values occurring at position (i,j) is the same as at position (j,i).

The construction of a GLCM comprises four essential steps. Firstly, the image is preprocessed to remove any noise or artifacts that may impact the computation of the co-occurrence matrix. Secondly, the image is quantized into a discrete set of gray-level values (usually 8 or 16 levels). Thirdly, a distance d and direction θ are selected to determine the relative position of the pairs of pixels whose gray-level values are to be compared. Typically, four directions (0°, 45°, 90°, and 135°) and a range of distances are chosen. Lastly, counting the instances in which a pair of pixel values (i,j) appears in the image at a distance d and direction θ yields the co-occurrence matrix. By dividing each element by the total number of pairings at that distance and direction, the GLCM is normalized.

It is possible to extract several texture properties from an image using the GLCM, such as homogeneity, contrast, energy, and entropy. The GLCM is used to compute these features in the following way:

- ***Contrast:*** measures the local variations in gray-level values of the image. It is defined as:

$$Contrast = \sum_{i,j} (i-j)^2 P(i,j) \tag{1}$$

  where$P(i,j)$ is the normalized co-occurrence matrix.

- ***Energy:*** measures the uniformity of gray-level values in the image. It is defined as:

$$Energy = \sum_{i,j} P(i,j)^2 \tag{2}$$

- ***Homogeneity:*** measures the closeness of the distribution of gray-level values to the diagonal elements of the GLCM. It is defined as:

$$Homogeneity = \sum_{i,j} \frac{P(i,j)}{(1+|i-j|)} \tag{3}$$

- ***Entropy:*** measures the randomness or uncertainty of the distribution of gray-level values in the image. It is defined as:

$$Entropy = -\sum_{i,j} P(i,j) \log_2\big(P(i,j)\big) \tag{4}$$

GLCM is a widely used method in computer vision, remote sensing, medical imaging, and other domains where texture characteristics are extracted from images in an easy-to-use and efficient manner.

3.2. Shi-Tomasi Corner Detector

The Shi-Tomasi corner detector is a popular method for detecting corners in images. Based on the eigenvalues of the image's second-moment matrix, it is an adaptation of the Harris corner detector.

Let $I(x, y)$ represent the pixel's intensity at (x, y) position in the picture. The Shi-Tomasi corner detector uses the eigenvalues of the matrix M, which are specified as follows, to calculate a score for each pixel (x, y):

$$M = \sum w(x,y)[\nabla_I(x,y)\nabla_I(x,y)^T] \quad (5)$$

Where $w(x, y)$ is a window function that weights pixels around (x, y), and $\nabla_I(x, y)$ is the gradient of the image at (x, y).

The eigenvalues of the matrix M are given by:

$$\lambda_1, \lambda_2 = \frac{1}{2}\left[trace(M) \pm \sqrt{\left(trace(M)^2 - 4 * det(M)\right)}\right] \quad (6)$$

where$trace(M) = \lambda_1 + \lambda_2$ is the sum of the eigenvalues and $det(M) = \lambda_1\lambda_2$ is the determinant of the matrix.

The Shi-Tomasi corner detector computes a score for each pixel (x, y) based on the smaller of the two eigenvalues:

$$\mathbb{R} = \min(\lambda_1, \lambda_2) \quad (7)$$

The score $\mathbb{R}$ measures the corner response at the pixel (x, y) and is used to determine whether the pixel is a corner or not. A high score indicates that the pixel is a corner, while a low score indicates that the pixel is not a corner.

To extract features from an image using the Shi-Tomasi corner detector, the following steps can be performed:

1. Compute the gradient of the image using a derivative filter.
2. Compute the matrix M for each pixel using the gradient information and a window function.
3. Compute the eigenvalues of the matrix M for each pixel.
4. Compute the corner response $\mathbb{R}$ for each pixel based on the eigenvalues.
5. Apply a threshold to the corner response to determine which pixels are corners.
6. Extract the corner locations and use them as features for further processing.

Using the unique corner structures found in retinal images, the Shi-Tomasi corner detector for image feature extraction in the field of diabetic retinopathy detection enables the extraction of corner features that can help distinguish and categorize various features related to the condition.

4. Proposed Methodology

When it comes to diabetic retinopathy, lesions are found using the GLCM and Shi-Tomasi Corner detector. Then, feature extraction techniques are used to retrieve pertinent data from the lesions, which is then used to create patterns using a Random Forest classifier. The feature extraction procedure is explained as follows:

- ***Lesion Detection:*** Using preprocessing methods, the initial step is to identify the lesions in the retinal images. These algorithms identify potential lesion locations based on corner points, which are areas of interest that indicate the presence of lesions.
- ***Lesion Segmentation:*** The next step is to segment or separate the lesions from the healthy retinal tissue surrounding them when they have been identified. This may be accomplished by creating lesion masks or binary images that show the extent of the lesions using a variety of segmentation approaches, including thresholding, region growth, and active contour models.
- ***Feature Extraction:*** Upon acquiring the lesion zones or masks, pertinent properties of the lesions are captured through the application of feature extraction algorithms. These features may consist of:
- ***Texture features:*** These features capture the spatial arrangement and patterns within the lesions. GLCM texture features and Shi-Tomasi Corner detector texture features are applied, which quantify properties like contrast, entropy, and homogeneity.
- ***Random Forest Training:*** A Random Forest classifier is trained using the features that have been retrieved from the lesion areas. The association between the retrieved features and the matching patterns or classes of lesions is discovered by the classifier. To train the Random Forest model, the labeled features must be supplied together with the matching lesion patterns (such as severity levels).
- ***Pattern Generation:*** The Random Forest classifier may be trained and then used to produce patterns in previously undetected lesion areas. Based on the patterns it learnt during the training phase, the classifier forecasts the pattern or degree of severity of the lesions. By classifying the lesions into distinct groups or degrees of severity, these patterns

allow for more investigation and comprehension of the diabetic retinopathy situation.

By combining the GLCM and Shi-Tomasi Corner detector, feature extraction techniques, and the Random Forest classifier, this approach allows for the extraction of relevant information from the detected lesions to generate patterns. These patterns can aid in the characterization and classification of the lesions, offering important information on the degree and course of diabetic retinopathy.

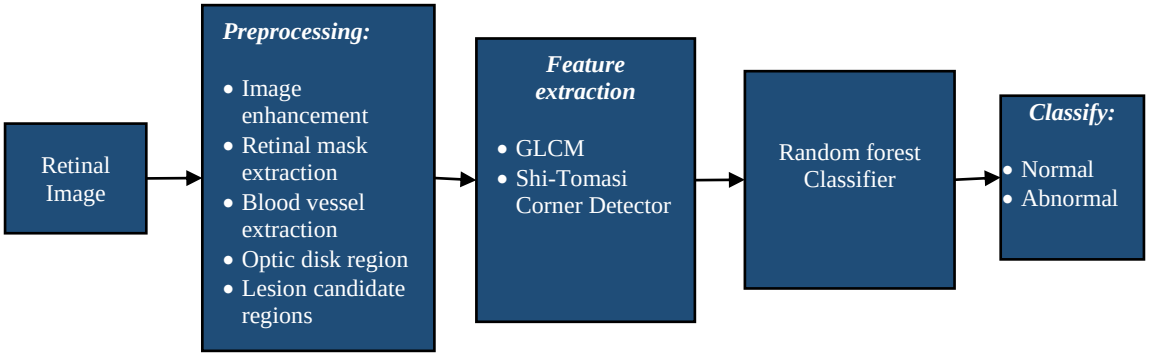


Fig. 1. Proposed diagram for Diabetic retinopathy

4.1. Preprocessing

In the context of diabetic retinopathy analysis, preprocessing retinal images usually entails many procedures, such as optic disk extraction, blood vessel extraction, and retinal mask extraction. This is a broad description of these procedures:

1. ***Retinal Mask Extraction***

- ***Preprocessing:*** The retinal image is preprocessed to enhance its quality and reduce noise. Common techniques include denoising, contrast enhancement, and normalization.
- ***Thresholding:*** The preprocessed image is then subjected to a thresholding approach that turns it into a binary image where pixels are classed as background or foreground (retinal structures).
- ***Region Growing:*** Starting from seed points within the retinal region, a region growing algorithm is applied to expand the initial region and include neighboring pixels that exhibit similar characteristics. This helps in delineating the retinal boundaries and obtaining the retinal mask.
- ***Edge Detection:*** As an alternative, the edges of the retinal structures may be found using edge detection methods like Canny edge detection, which can then be utilized to produce the retinal mask.

2. ***Blood Vessel Extraction***

- ***Preprocessing:*** Similar to retinal mask extraction, the retinal image is preprocessed to enhance vessel visibility and reduce noise.
- ***Thresholding:*** The preprocessed image is thresholded to produce a binary vessel map, in which foreground pixels indicate vessels.
- ***Morphological Operations:*** To improve the vessel map, morphological procedures like opening and closing are used. Opening can remove small noise and thin vessel segments, while closing can bridge gaps in vessel segments.

3. ***Optic Disk Extraction***

- ***Preprocessing:*** The retinal image is preprocessed to enhance the optic disk's visibility and reduce noise.
- ***Optic Disk Detection:*** The optic disk area can be located and extracted using a variety of techniques. A variety of machine learning-based systems that learn to distinguish optic disk regions, template matching techniques that use a predetermined disk template, and edge identification algorithms (e.g., Canny edge detection) to identify the disk's edges.
- ***Circular or Elliptical Fitting:*** A precise determination of the optic disk border can be achieved by applying an elliptical or circular fitting method once the optic disk region has been identified.
- ***Optic Disk Segmentation:*** The optic disk region can be further segmented to differentiate it from the surrounding retinal structures.

To improve the optic disk extraction, this may include using additional image analysis methods or morphological processes.

The precise algorithms and methods used for blood vessel extraction, optic disk extraction, and retinal mask

extraction can change depending on the needs of the research or clinical setting, the features of the retinal images, and the experience of the practitioners or researchers.

Algorithim-1:

Retinal mask extraction:

Input: Retinal image

// Preprocessing

Preprocess the retinal image (e.g., denoising, contrast enhancement, normalization)

// Thresholding

Utilize a thresholding approach to create a binary image from the preprocessed image.

// Region Growing

Select seed points within the retinal region

Initialize an empty mask

For each seed point:

Add the seed point to the mask

While there are nearby pixels with comparable features:

Add the neighboring pixel to the mask

// Edge Detection (Alternative approach)

Apply an edge detection algorithm (e.g., Canny edge detection) to detect the edges of retinal structures

Create a binary mask using the detected edges

Output: Retinal mask

Algorithm - 2:

Blood vessel extraction

Input: Retinal image

// Preprocessing

Preprocess the retinal image (e.g., denoising, contrast enhancement, normalization)

// Thresholding

Apply a thresholding technique to create a binary vessel map

// Morphological Operations

Apply morphological opening and closing operations to refine the vessel map

// Machine Learning Approaches (Alternative approach)

Train a CNN using labeled retinal images to segment blood vessels

Apply the trained CNN to segment blood vessels in the retinal image

Output: Blood vessel segmentation

Algorithm - 3:

Input: Retinal image

// Preprocessing

Preprocess the retinal image (e.g., denoising, contrast enhancement, normalization)

// Optic Disk Detection

Apply an optic disk detection algorithm:

Use edge detection (e.g., Canny edge detection) to identify edges of the optic disk

// Circular or Elliptical Fitting

Fit a circle or ellipse to the detected optic disk region to determine the boundary

// Optic Disk Segmentation

Refine the optic disk extraction, if needed, using morphological operations or additional image analysis techniques

Output: Optic disk region

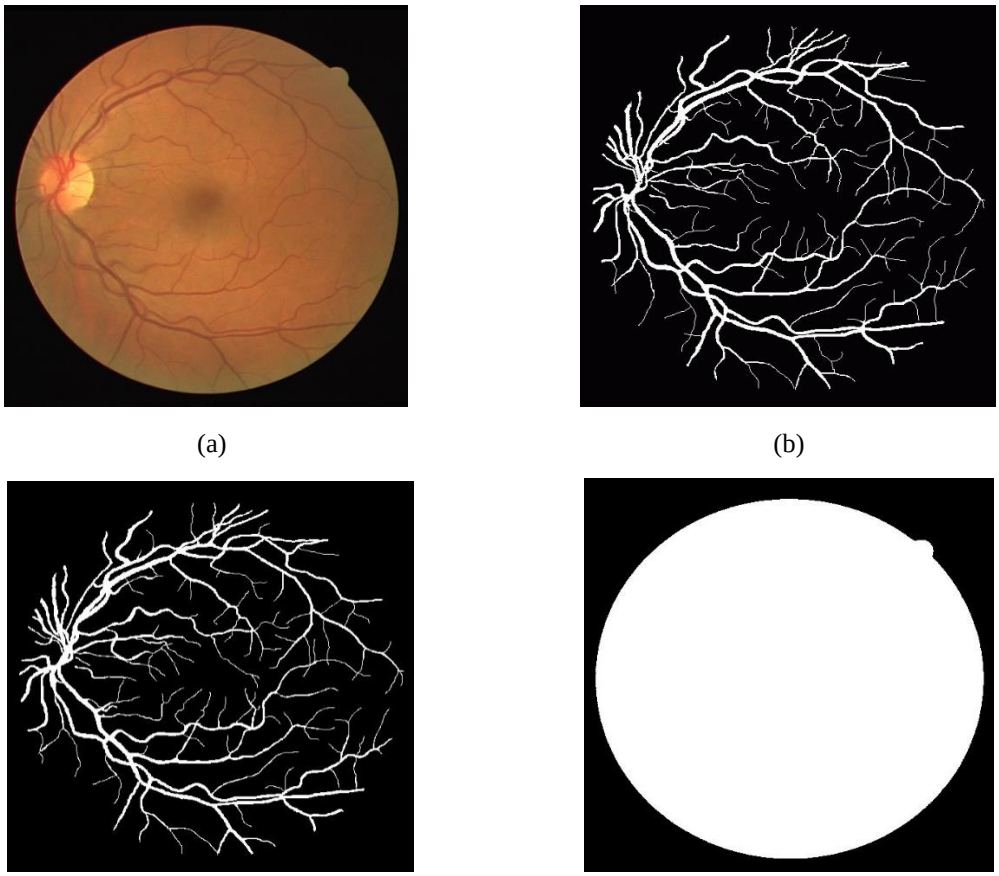
5. Simulation and Results

5.1. Databases

Image databases are a vital tool for developing retinal image processing algorithms because they enable researchers to assess and contrast newly created techniques with state-of-the-art research findings. Better algorithms are developed as a result of them. Several databases we used for our work are shown in this section.

5.1.1. DRIVE Image Database

The Drive image database includes 40 color fundus images, 7 of which show pathologies. Images are acquired with a non-mydriaticretinograph (Canon RC5) with a 45-degree field of view (FOV). They are saved in JPEG format, with a size of 768×584 pixels. The image base is divided into two sets (20 images for training and the rest for testing). Manual segmentation of the vascular network is performed by two experienced ophthalmologists [51].



(a) (b)

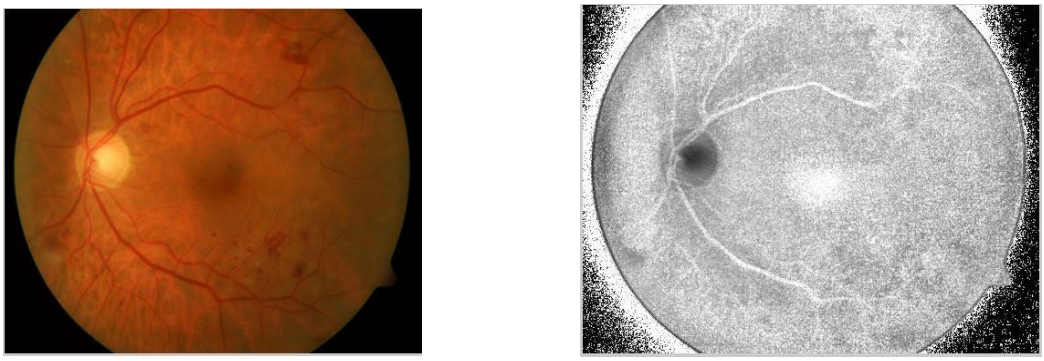
(c) (d)

Fig. 2. Sample images from the DRIVE database; (a): original image; (b): manual segmentation of the vascular network by the first ophthalmologist (c): manual segmentation of the vascular network by a second ophthalmologist; (d): mask of the original image

5.1.2. Fundus Image

The Fundus Image Registration Dataset, or FIRE, is a collection of 129 retinal images that make up 134 image pairings. Depending on their attributes, these image pairings are divided into three groups. The Nidek AFC-210 fundus camera was used to capture the photos. It has a FOV of 45° in both the x and y dimensions and can capture images with a resolution of 2912×2912 pixels. 39 patients' images were taken at the Papageorgiou Hospital at Aristotle University of Thessaloniki in Thessaloniki.

5.2. Results



(a) (b)

Fig. 3. Preprocessing (a): Original image; (b) improved image

The retinal imaging images were scanned and digitally transformed to generate the Structured Analysis of the Retina (STARE) database. The images in the STARE database were taken with a camera with a 35-degree field of view, and they have a resolution of 700×605 pixels.

Table 1. Comparative results of different datasets using the SVM classifier

Parameters	MESSIDOR	DRIVE	STARE
Accuracy	9.75e-01	8.75e-01	9.25e-01
Error Rate	2.50e-02	1.25e-01	7.50e-02
Sensitivity	1.00e+00	1.00e+00	1.00e+00
Specificity	0.95	0.75	0.85
Precision	0.9524	0.8	0.8696
False Positive Rate	0.05	0.25	0.15
F-Score	9.76e-01	8.89e-01	9.30e-01
MCC	9.51e-01	7.75e-01	8.60e-01
Kappa Statistics	9.50e-01	7.50e-01	8.50e-01

Table 1 presents a comparative analysis of different datasets (MESSIDOR, DRIVE, and STARE) using an SVM classifier for Diabetic Retinopathy detection. The accuracy rates for the datasets are 97.5% for MESSIDOR, 87.5% for DRIVE, and 92.5% for STARE. Correspondingly, the error rates are 2.5%, 12.5%, and 7.5%. Sensitivity is consistently perfect at 100% across all datasets, while specificity varies, being highest for MESSIDOR at 95%, followed by STARE at 85%, and lowest for DRIVE at 75%. Precision values are 95.24% for MESSIDOR, 80% for DRIVE, and 86.96% for STARE. The false positive rate is lowest for MESSIDOR at 5%, higher for STARE at 15%, and highest for DRIVE at 25%. The F-Score is 97.6% for MESSIDOR, 88.9% for DRIVE, and 93.0% for STARE. The Matthews correlation coefficient (MCC) and Kappa statistics further reflect the performance, with MESSIDOR having an MCC of 95.1% and a Kappa statistic of 95%, DRIVE having an MCC of 77.5% and a Kappa statistic of 75%, and STARE having an MCC of 86% and a Kappa statistic of 85%. This comparison highlights MESSIDOR as having the most robust performance across all evaluated metrics.

Table 2. Comparative results of different datasets using the Random Forest classifier

Parameters	MESSIDOR	DRIVE	STARE
Accuracy	9.81e-01	9.17e-01	9.63e-01
Error Rate	1.85e-02	8.33e-02	3.70e-02
Sensitivity	1.00e+00	1.00e+00	1
Specificity	9.63e-01	8.33e-01	9.26e-01
Precision	9.64e-01	8.57e-01	9.31e-01
False Positive Rate	3.70e-02	1.67e-01	7.41e-02
F-Score	9.82e-01	9.23e-01	9.64e-01
MCC	9.64e-01	8.45e-01	9.28e-01
Kappa Statistics	9.63e-01	8.33e-01	9.26e-01

Table 2 provides a comparative analysis of the performance of a Random Forest classifier on three different datasets (MESSIDOR, DRIVE, and STARE) for Diabetic Retinopathy detection. The accuracy rates achieved are 98.1% for MESSIDOR, 91.7% for DRIVE, and 96.3% for STARE. Correspondingly, the error rates are 1.85%, 8.33%, and 3.7%. Sensitivity is consistently perfect at 100% across all datasets. Specificity values are highest for MESSIDOR at 96.3%, followed by STARE at 92.6%, and lowest for DRIVE at 83.3%. Precision rates are 96.4% for MESSIDOR, 85.7% for DRIVE, and 93.1% for STARE. The false positive rate is lowest for MESSIDOR at 3.7%, higher for STARE at 7.41%, and highest for DRIVE at 16.7%. The F-Score is 98.2% for MESSIDOR, 92.3% for DRIVE, and 96.4% for STARE. The MCC is 96.4% for MESSIDOR, 84.5% for DRIVE, and 92.8% for STARE. Kappa statistics further reflect these trends, with values of 96.3% for MESSIDOR, 83.3% for DRIVE, and 92.6% for STARE. Overall, MESSIDOR exhibits the highest performance across most metrics, followed by STARE, and DRIVE, demonstrating that the Random Forest classifier performs robustly, particularly with the MESSIDOR dataset.

Table 3. Comparative results of different classifiers for the Drive dataset

Parameters	SVM	KNN	RF
Accuracy	0.9494	0.9154	0.9793
Error Rate	0.0506	0.0846	0.0207
Sensitivity	0.9494	0.9154	0.9889
Specificity	0.9494	0.9154	0.8444
Precision	0.9494	0.9154	0.9889
False Positive Rate	0.0506	0.0846	0.1556
F-Score	0.9494	0.9154	0.9889
MCC	0.8987	0.8308	0.8333
Kappa Statistics	0.8987	0.8308	0.8333

Table 3 presents a comparative analysis of different classifiers (SVM, KNN, and RF) applied to the DRIVE dataset for Diabetic Retinopathy detection. The Random Forest (RF) classifier achieves the highest accuracy at 97.93%, with an error rate of 2.07%. The Support Vector Machine (SVM) follows with an accuracy of 94.94% and an error rate of 5.06%, while the K-Nearest Neighbors

(KNN) classifier has the lowest accuracy at 91.54% and an error rate of 8.46%. Sensitivity is highest for RF at 98.89%, compared to 94.94% for SVM and 91.54% for KNN. Specificity is equal for SVM and KNN at 94.94% and 91.54%, respectively, while RF has a lower specificity at 84.44%. Precision mirrors sensitivity, with RF again leading at 98.89%, followed by SVM and KNN at 94.94% and 91.54%, respectively. The false positive rate is lowest for SVM at 5.06%, higher for KNN at 8.46%, and highest for RF at 15.56%. The F-Score follows the same trend as sensitivity and precision, with RF at 98.89%, SVM at 94.94%, and KNN at 91.54%. The MCC is highest for SVM at 89.87%, followed by RF and KNN, both at 83.33%. Kappa statistics reflect these trends with values of 89.87% for SVM, and 83.33% for both RF and KNN. Overall, the RF classifier demonstrates superior performance in most metrics, particularly in accuracy and sensitivity, although it has a higher false positive rate compared to SVM and KNN.

6. Conclusion

In conclusion, the proposed algorithm for assessing diabetic retinopathy through fundus scans demonstrates superior performance compared to traditional approaches. The technique uses many preprocessing stages, such as optic disk extraction, blood vessel segmentation, retinal mask extraction, image enhancement, and lesion candidate region extraction.

A thresholding approach is used to extract branching blood arteries, and then adaptive histogram equalization and morphological opening improve the picture quality while removing sections that were incorrectly segmented. One notable characteristic that is thought to set diabetic or afflicted people apart is the markedly increased proliferation of optical nerves. A hybrid technique of Shi-Tomasi Corner Detector and GLCM (Gray Level Co-occurrence Matrix) is used for feature extraction in order to further investigate the lesion candidate locations. The existence of diabetic retinopathy is then classified using a random forest classifier that receives these features.

Two datasets are used to assess the algorithm's performance: the standard Diabetic Retinopathy Dataset (DIARETDB1) and a dataset from a medical facility that includes fundus images of both normal and afflicted retinas. The experimental findings show that the suggested method is more successful than conventional systems. The model obtains an amazing 97.2% precision and 98.7% accuracy when tested on the DIARETDB1 dataset. These encouraging findings suggest that the suggested methodology has a lot of potential for diagnosing diabetic retinopathy with fundus scans in an accurate manner. It is a useful tool to help medical professionals detect and manage this problem because of its great accuracy and precision. Further research and validation on larger and diverse datasets are recommended to strengthen the algorithm's robustness and generalizability.

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