International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 06 Issue: 12 | December - 2022 Impact Factor: 7.185 ISSN: 2582-3930

Detection of Diabetic Retinopathy in Fundus Images Using SVM

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Abstract - One of the main causes of blindness in the industrialised world, diabetic retinopathy is a consequence of diabetes brought on by alterations in the retina's blood vessels. Patients who have diabetic retinopathy are protected from losing their vision by early identification. The automatic detection of diabetic retinopathy using the support vector machine algorithm is the sole goal of this project. The major objective is to automatically assess any fundus image for non-proliferative diabetic retinopathy. The fundus image that is used as the project's input is sent to the preprocessing stage for noise removal. It separates blood vessels, microaneurysms, and hard exudates during the image preprocessing stage. The feature extraction procedure is applied to the preprocessed image. The SVM classifier receives the retrieved image and uses it to determine each fundus image's retinopathy grade. Additionally, the classifier will determine whether or not the image has diabetic retinopathy. In order to help individuals identify diabetic retinopathy early on, this research suggests a computer-assisted diagnosis based on the digital processing of fundus images. A library of 400 fundus pictures that have been classified using a 4-grade scale for non-proliferative diabetic retinopathy has been used to evaluate this concept. As a result, we were able to forecast data with a 90% accuracy.

It has also been assessed how resilient the algorithm is to changes in its parameters.

I. Introduction

One of the most serious eye conditions affecting people with long-term diabetes is diabetic retinopathy. Even if a sizable portion of the population is afflicted, testing is still conducted manually by skilled specialists in the real world, which is a time-consuming process that frequently results in misunderstandings and delayed results, which ultimately postpone treatment. The severity of diabetic retinopathy emphasises the identification of the two subtypes: Haemorrhages and Exudates. These are taken from patient fundus pictures and used in the preprocessing stage. Then, a grey level co-occurrence matrix is to be used to extract the texture features. Following the presentation of the segmented fundus picture to the SVM classifier, GLCM features are computed. For the purpose of detecting diabetic retinopathy, we must extract both dense and sparse features during the feature extraction stage. The need for instruments to aid in the diagnosis of diabetic retinopathy has increased due to the rising number of diabetic retinopathy cases worldwide. Significant time and effort savings will result from the automatic identification of diabetic retinopathy. Additionally, a number of image pre-processing methods have been suggested for the detection of diabetic retinopathy. Nevertheless, despite all of these earlier studies, automated identification of diabetic retinopathy still has to be improved. Thus, bias-free computer-based automatic segmentation can offer quick and simple segmentation of retinal blood vessels. There has been numerous research on the segmentation of blood vessels in general, but few of them have focused specifically on retinal blood vessels. Seven groups of methods have been taken into consideration in order to review the techniques suggested for vessel segmentation in retinal images: matching filters, vessel tracking, morphological processing, region growth, multiscale, supervised, and adaptive thresholding approaches. Segmenting retinal blood vessels has been widely employed in a variety of contexts. In the implementation of screening programmes for diabetic retinopathy, the evaluation of retinopathy of prematurity, the detection of the foveal avascular region, and the detection of arteriolar narrowing, for instance, changes in the retinal blood vessel appearance are an important indicator for various ophthalmologic and cardiovascular diseases, such as diabetes, hypertension, and arteriosclerosis.

II . Literature Survey

[1] Diabetic retinopathy (DR) is associated with eye unwellness caused by the complication of polygenic disease and we tend to ought to discover it early for effective treatment. As polygenic disease progresses, the vision of a patient could begin to deteriorate and cause diabetic retinopathy.

[2]This technique uses an ensemble system of bagged and boosted call trees and utilises a feature vector supporting the orientation analysis of gradient vector field, morphological transformation, line strength measures, and Dennis Gabor filter responses.

[3] This paper presents a supervised technique for vessel detection in digital retinal pictures. The employment of digital pictures for disease designation can be used for early detection of Diabetic Retinopathy.

[4]Automatic segmentation of the vasculature in retinal pictures is very important within the detection of diabetic retinopathy that affects the morphology of the vessel tree.

[5] We give an algorithmic program for the automatic detection of the retinal tube network which mixes differential filters, for line extraction, with morphological operators, used for filling vessel segments.

[6] Blood vessel segmentation of retinal pictures plays a vital role within the diagnosis of eye diseases. During this paper, we have a tendency to propose automatic unsupervised blood vessel segmentation methodology for retinal pictures.

[7] In this paper, a unique multi -concavity modelling approach is projected to handle

both healthy and unhealthy retinas at the same time.

[8] We propose an automatic vessel segmentation technique. The planned rule starts with the extraction of vessel centerline pixels.

[9] Retinal fundus imaging is widely used for eye examinations. The analysis of the vasculature contains a high importance particularly for detecting cardiovascular diseases.

[10] Colour features were used on Bayesian statistical classifiers to classify each pixel into lesion or non-lesion classes. They have achieved 100% accuracy in identifying all the retinal images with exudates, and 70% accuracy in classifying normal retinal images as normal. DR and normal retina were classified automatically using image processing and multilayer perceptron neural network.

III . Design

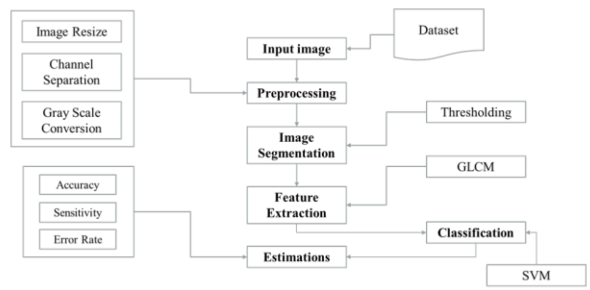

Fig 3: Data Flow Diagram

First the image is obtained, and various methods of preprocessing are applied to the image (resize, grayscale conversion). After this step the fundus image is segmented using thresholding and the GLCM matrix is used to extract necessary features. Which is then classified into different stages by the SVM classifier.

IV . Implementation

There are two types of diabetic retinopathy which are non- proliferative diabetic retinopathy and proliferative diabetic retinopathy, where the proliferative diabetic retinopathy can be further divided into mild, moderate and severe. The grade of retinopathy diagnosis is normally categorised by ophthalmologist based on:

0. Normal (μA=0) and (H=0)

1. Mild NPDR (0<μA 5) and (H=0)

2. Moderate NPDR (5<μA<15 or 0<H<5) and (NV=0)

3. Severe NPDR (15<μA<25) or (5<H<10) or (NV=1)

4. Proliferate DR (μA≥25) or (H≥10) or (NV=1)

where μA is the number of microaneurysms, H the number of haemorrhages and NV the presence of neovascularization.

A. Image Database:

The 1000 eye fundus colour numerical images of the posterior pole that make up the Indian Diabetic Retinopathy Image Dataset (IDRiD database were taken by Indian ophthalmologic departments utilising a colour video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinography with a 45 degree field of view. Medical diagnoses are also included in an MSExcel file for each image. In this study, we employ 148 photos from the department of ophthalmology that are retinopathy-free (stage 0), 26 images with mild NPDR (stage 1), 69 images with moderate NPDR (stage 2), and 136 images with severe NPDR (stage 3).

B . Input Image:

The image acquisition step is the first phase of any vision system. Image acquisition is the process of digitising and archiving an image. After the image has been captured, it can be processed using a variety of techniques to carry out the many vision tasks needed today. First, use functions to capture the input image from the source file. Even with the help of any kind of picture enhancement, the planned tasks might not be possible if the image was not acquired adequately.

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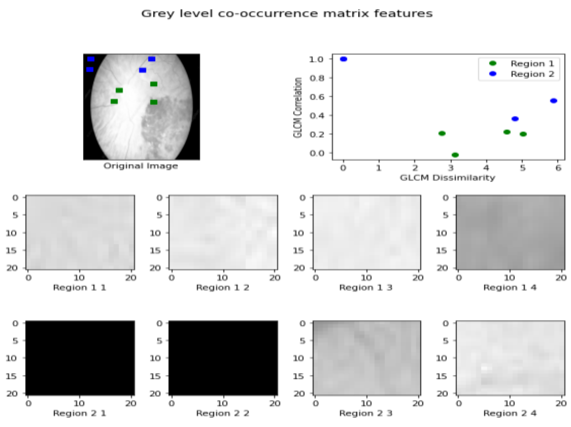

Fig 1: Grey level co-occurrence matrix features

C . Gray conversion:

A grayscale or greyscale digital image is one in which each pixel's value is a single sample, carrying only intensity information, and is used in both photography and computers. These images, commonly referred to as black-and-white, are made up entirely of shades of grey, ranging from black at the lowest intensity to white at the highest.

D . Image Resize:

Scaling is the process of resizing a digital image in computer graphics and digital imaging. In video technology, up scaling or resolution enhancement are terms used to describe the enlargement of digital content. A vector graphic image can be resized without sacrificing image quality by utilising geometric transformations on the graphic primitives that make up the image. Raster graphics images must be scaled by creating a new image with more or less pixels. When the number of pixels is reduced (scaling down), there is typically a noticeable quality reduction. Raster graphics scaling is a two-dimensional example of sample rate conversion from the perspective of digital signal processing, which is the conversion of a discrete signal from a sampling rate to another.

E . Segmentation:

For the diagnosis of eye problems, the segmentation of blood vessels in retinal images is essential. In this work, we offer a technique for automatically and unsupervised blood vessel segmentation in retinal images. Using the vessel enhanced intensity feature and the green channel intensity, a multidimensional feature vector is first created using a morphological operation.

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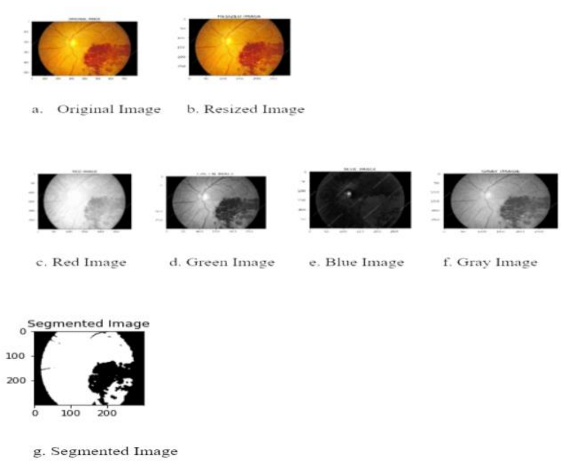
F . Feature Extraction - GLCM:

Image analysis methods include the Gray Level Co-occurrence Matrix1 (GLCM) and related texture feature calculations. The GLCM is a tabulation of the frequency with which various combinations of grey levels co-occur in an image or image portion given an image made of pixels each with an intensity (a distinct grey level). Calculations of texture features utilise the information in the GLCM to provide a measurement of the intensity variation (also known as image texture) at the pixel of interest. Energy, entropy, contrast, homogeneity, correlation, shade, and prominence are examples of features.

G . SVM Classification:



SVM is a collection of supervised learning tools used for data regression and classification. They have two key advantages over more recent algorithms like neural networks: greater speed and improved performance with fewer samples. The algorithm is hence excellent for classification issues. It classifies the training samples into different groups. The test samples are mapped to similar feature spaces while these training samples are regarded as points in the feature space. Following that, it is designated as belonging to one of the classes. A maximal splitting hyper plane between two classes is created by SVM. The categorization error is reduced as a result.The input can be partitioned into a hyperplane and is mapped into a high-dimensional feature space containing linearly non-separable data. The SVM learning calculates the parameters that are used for the classification. The training procedure examines the training data to determine the best strategy for classifying the images into appropriate groups. The SVM's kernel function maps the data into different feature spaces. The non-linear classification is carried out using the SVM using the non-linear kernel functions. SVM is also known as a binary classifier because it primarily accepts the values +1 and -1. A straight line is used to distinguish between two distinct classes in two-dimensional domains.The stages of diabetic retinopathy are categorised by the equation for the straight line, $wx+b=0$, which is followed by $wx+b>0$ for positive class and $wx+b0$ for negative class.

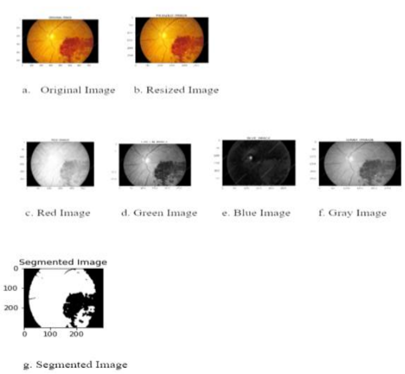


Fig 2: Image Pre-processing

V . Results

The software was used to implement the evaluation of our idea. This initial set of results' main goal is to find any grade of DRNP. All the features from these photographs were used to train an SVM classifier, which was then put to the test using a 10-fold cross-validation procedure.

The performance was also enhanced by choosing the SVM parameters and characteristics that were the most pertinent. Thus, a linear kernel function in the SVM technique was used to achieve the best accuracy for our detector. In this instance, the only input features needed by SVM are the actual and potential numbers of microaneurysms. Table I displays the confusion matrix for the best detector.

The results for accuracy, sensitivity, and specificity are listed in Table II.

The classifier's average accuracy is 85%. The SVM detector and classifier consistently produce better results than their matching Neural Networks counterparts in every several cases. The SVM findings are comparable to those reported in earlier publications [2]. This demonstrates how reliable our suggested SVM implementation is.

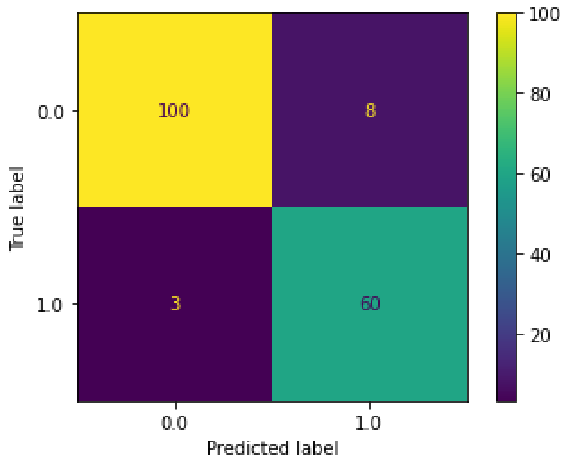


Fig 4: Confusion Matrix

Table 1. Confusion Matrix :-

n = 171	True Positive	False Positive
False Negative	100	8
True Negative	3	60

Table 2. Accuracy Optimised Performance of SVM :-

Metric	SVM
Accuracy	93.56 %
Sensitivity	97.08 %
Specificity	88.23 %

VI . Experimental Analysis

Using a benchmark dataset, computational tests were done to gauge how well the proposed classifiers performed. The proposed SVM was implemented using Spyder software version 2016 run on an Ryzen 7 4800H - CPU 2.4 GHz, on a 64-bit windows 10 operating system.

The accuracy of SVM is 93.35%. Additionally, each algorithm's sensitivity and specificity are examined in order to have a thorough grasp of its performance. High sensitivity values imply a low rate of False Negatives for the algorithm (incorrect negative prediction). High specificity denotes high precision classification of the samples for each class. Confidence interval is the final performance indicator that is used to evaluate the algorithms. The confidence interval delivers the outcome using the range value, unlike other measures that utilise only one value. Basically, the accuracy value will be reflected in the confidence interval result. As an outcome, the SVM result showed a high level of sensitivity of 97.08% and the greatest accuracy value of 93.56%. Likewise, the SVM's range of potential accuracy is from 90.07 to 93.76 with 88.23% Specificity Level.

VII. Conclusion

A presented automated strategy for detecting diabetic retinopathy. The most well-known classifier, SVM, has been extensively researched in this article. Developing a classifier with an ideal or almost ideal accuracy value for DR classification was the objective. Exudates and blood vessels are retrieved as part of the procedure to determine the degree of diabetic retinopathy. The identified features have a significant amount of potential for DRNP classification and detection. SVM has a sensitivity of about 95% for DRNP detection, while DRNP classification accuracy is typically 85%. SVM typically surpasses other machine learning algorithms in terms of accuracy. It could assist professionals in making more informed choices and evolve into a commonly used diagnostic guideline.

VIII. Acknowledgment

We thank Vishwakarma University's Faculty of Science and Technology for providing us with this opportunity to present our study and research to the industry experts. Last but not the least, we would like to thank our friends who supported us and respondents for their active participation, encouragement and willingness to spend time on our proposed system.

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