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RESEARCH ARTICLE

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DIABETIC RETINOPATHY ANALYSIS USING SVM AND LDA

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ABSTRACT
Diabetic retinopathy (DR) is the leading ophthalmic pathological cause of blindness among people of working age in developed countries. The main cause of DR is abnormal blood glucose level height which harms vessel endothelium and accordingly expanding vessel permeability. The main indication of DR is tiny capillary dilations known as micro aneurysms. DR progression also causes neo-vascularization and haemorrhages and macular edema and in later stages retinal detachment. Diabetic retinopathy has turned into an increasingly vital reason for visual impairment. Vision loss can be kept from head of schedule identification of diabetic retinopathy and monitor with regular examination. Basic programmed recognition of retinal anomalies is for micro aneurysms and haemorrhages and hard exudates and cotton wool spot. However there is a more awful instance of retinal abnormality but very little research was done to identify it. It is neo-vascularization where new blood vessels develop because of broad absence of oxygen in retinal capillaries.

Keywords: Diabetic Retinopathy, Fundus Images, Retina, Support vector machine and Linear Discriminant Analysis (LDA).

1. INTRODUCTION

1.1 Diabetic retinopathy (DR)

Diabetic retinopathy (DR) having a condition where retina is damaged due to fluid leaking from the blood vessels into retina where in the extreme cases patient will become blind therefore early detection of diabetic retinopathy is crucial to prevent blindness.

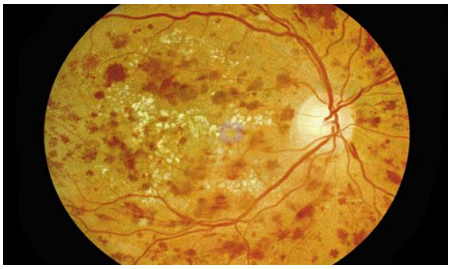


Figure 1: Diabetic Effected Retina

Diabetic retinopathy main stages are Non-Proliferation Diabetes Retinopathy (NPDR) and Proliferate Diabetes Retinopathy (PDR).

1.2 Background or non-proliferative diabetic retinopathy (NPDR): The earliest stage of diabetic retinopathy is non-proliferative diabetic retinopathy (NPDR) with this condition damaged blood vessels in retina begin to leak extra fluid and small amounts of blood into the eye. The deposits of cholesterol or other fats from the blood may leak into the retina where NPDR can cause changes in the eye as it including:

1.3 Micro aneurysms: Small bulges in blood vessels of the retina that often leak fluid.

1.4 Retinal haemorrhages: Tiny spots of blood which leak into retina.

1.5 Hard exudates: Deposits of cholesterol or other fats from blood which leaked into the retina.

1.6 Macular edema: Swelling of the macula caused by fluid leaking from the retina blood vessels and macula does not function properly when it swollen where macular edema is the most common cause of vision loss in diabetes.

1.7 Macular ischemia: Small blood vessels which also called as capillaries close where your vision blurs because of macula no longer receives enough blood to work properly. Many diabetes people have mild NPDR which usually not affect their vision however if their vision is affected and it is the result of macular edema and macular ischemia.

1.8 Proliferative Diabetic Retinopathy (PDR): Mainly proliferative diabetic retinopathy occurs when many of the blood vessels in the retina close and preventing enough blood flow where in attempt to supply blood to the area as the original vessels closed and retina responds as growing new blood vessels which is called neo-vascularization. These new blood vessels are abnormal they do not supply the retina with proper blood flow and new vessels are also accompanied as scar tissue that may cause the retina to wrinkle or detach.

2. TECHNIQUES USED

Following techniques are used in the diabetic retinopathy analysis:

2.1 Linear Discriminant Analysis (LDA): Linear Discriminant Analysis (LDA) is scheme for feature extraction and dimension reduction. It has been used widely in many applications involving highly dimensional data as face recognition and image recognition. Linear Discriminant Analysis easily handles the case where the within-class frequencies are unequal and their performances have been examined on randomly generated test data. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability. Linear Discriminant Analysis (LDA) is a techniques used for data classification and dimensionality reduction.

$S_w = \sum_{i=1}^{k} \sum_{xe \prod i} (x - m_i)\,(x - m_i))^T$ and

$S_b = \sum_{i=1}^{K} n_i$ (m_i -m) (m_i-m)^T,

where

$m_i = \frac{1}{n_i} \sum_{xe \prod i} x$ is the mean of the ith class and

m = $\frac{1}{n} \sum_{i=1}^{k} \sum_{xe \prod i}$ x is the global mean in discriminant analysis, two scatter matrices, called within-class (Sw) and between-class (Sb) matrices are defined to quantify the quality.

2.2 Support Vector Machine (SVM): It is primarily a classifier in which Width of the edge between the classes is the enhancement paradigm that is empty area around the decision boundary characterized by the distance to the nearest training patterns. These are called support vectors. The support vectors change the prototypes with the main distinction between SVM and traditional template matching strategies is that they describe the classes by a decision limit. This decision boundary is not simply characterized by the minimum distance function. The concept of (SVM) Support Vector Machine was introduced by Vapnik. The objective of any machine that is capable of learning is to achieve good generalization performance, given a finite amount of training data. The support vector machines have proved to achieve good generalization performance with no prior knowledge of the data. The principle of an SVM is to map the input data onto a higher dimensional feature space nonlinearly related to the input space and determine a separating hyper plane with maximum margin between the two classes in the feature space. The SVM is a maximal margin hyper plane in feature space built by using a kernel function. This results in a nonlinear boundary in the data space. The optimal separating hyper plane can be determined without any computations in the higher dimensional feature space by using kernel functions in the input space. There are some commonly used kernels include:-

a) Linear Kernel

K(x, y) = x, y

b) Polynomial Kernel

K(x, y) = (x. y+1) d

2.2.1 SVM Algorithm:

i. Define an optimal hyper plane.
ii. Extend the above definition for non linear separable problems.
iii. Map information to high dimensional space where it is simpler to classify with linear decision surfaces.

3. PROPOSED WORK

The following lists of the phases to be carried out in the proposed work so as to achieve desired objectives. The phases are:

Phase 1: Take an Input Image by using uiget file command in MATLAB.

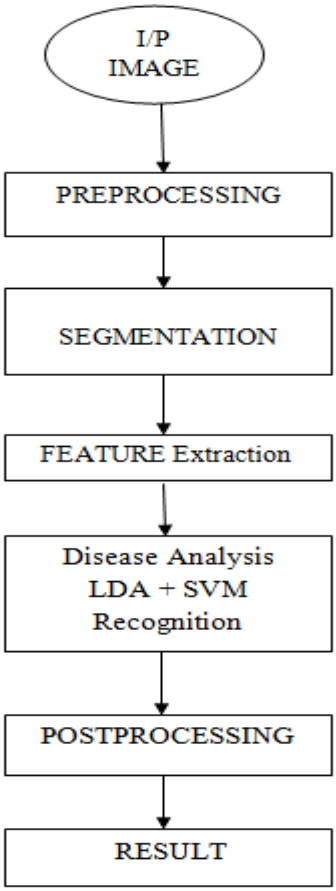


Figure 2: Flow chart of proposed work

Phase 2: Develop a code for the **Pre-processing** where we will perform few steps:

- Conversion from colored image to three components (red, green and blue),
- Resize of image
- Intensity of image is Equalized using HISTEQ
- Filtration using Median Filter.

Phase 3: After the pre-processing process we will perform **Segmentation** process for dividing the image into segments using Blood Vessel tracking segmentation.

Phase 4: After the segmentation process we will perform **Feature Extraction** process for extracting features using SURF.

Phase 5: After the feature extraction process we will apply LDA and SVM Techniques which will perform **Disease Analysis** process where the images of the database will be matched with the input image.

Phase 6: Code will be developed to implement various parameters like: Sensitivity, Specificity, AUC, SSIM, PSNR and MSE. And at last our technique results will be compared with previous techniques on the basis of parameters.

4. PARAMETERS USED

There are many parameters given which are used in previous research papers.

4.1 MSE: Mean Squared Error is essentially an image fidelity measure where compare two images which provide a quantitative score that describes the degree of difference and errors between them and MSE between two images is given by the following formula:

$$MSE = (1/N)\Sigma i|x(i)- e(i)|^2$$

Where x and e are the input and compressed image respectively and N is the size of image.

4.2 PSNR: Embedding this extra data must not degrade human perception about the object. Evaluation of imperceptibility is usually based on an objective measure of quality; called peak signal to noise ratio and PSNR between input and compressed image can be obtained by using following formula:

$$PSNR=20\log10\ (PIXEL\_VALUE/MSE)$$

4.3 SSIM: The **structural similarity** (SSIM) index is a method for measuring the similarity between two images. The SSIM index is a full reference metric; in other words, the measuring of image quality based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human eye perception.

The difference with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate perceived errors; on the other hand, SSIM considers image degradation as perceived change in structural information. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important

information about the structure of the objects in the visual scene.

The SSIM metric is calculated on various windows of an image. The measure between two windows x and y of common size *N*×*N* is:

$$SSIM\ (x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

with

- μx the average of x;
- μy the average of y;
- σ_x^2 the variance of x;
- σ_y^2 the variance of y;
- σ_{xy} the covariance of x and y;
- $c_1=(k_1 L)^2$, $c_2=(k_2 L)^2$ two variables to stabilize the division with weak denominator;
- L the dynamic range of the pixel-values (typically this is $2^{\#bits\ per\ pixel}-1$);
- $k_1=0.01$ and $k_2=0.03$ by default.

In order to evaluate the image quality this formula is applied only on luma. The resultant SSIM index is a decimal value between -1 and 1, and value 1 is only reachable in the case of two identical sets of data. Typically it is calculated on window sizes of 8×8. The window can be displaced pixel-by-pixel on the image but the authors propose to use only a subgroup of the possible windows to reduce the complexity of the calculation.

5. RESULTS AND DISCUSSION

The result of proposed work is highlighted in the following figures are:

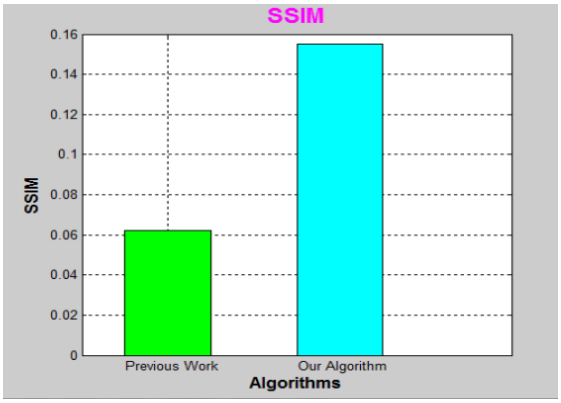
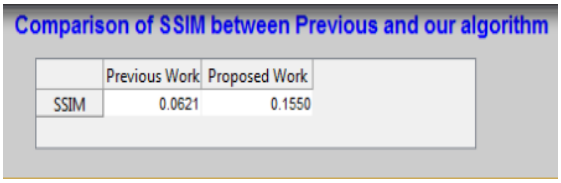


Figure 3: Process of calculating SSIM

Table 1: Values of SSIM



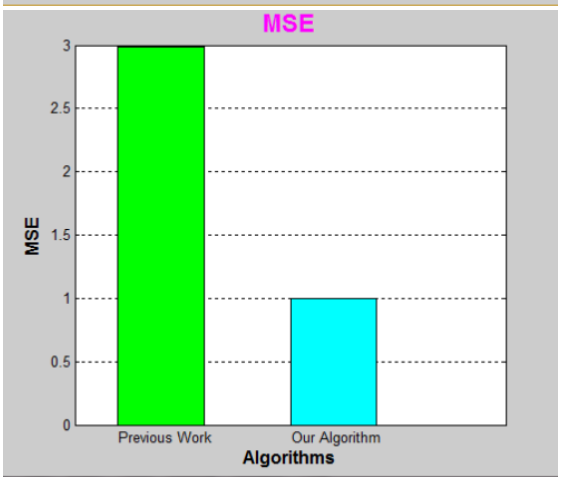
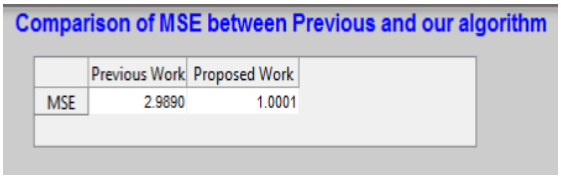


Figure 4: Process of calculating MSE

Table 2: Values of MSE



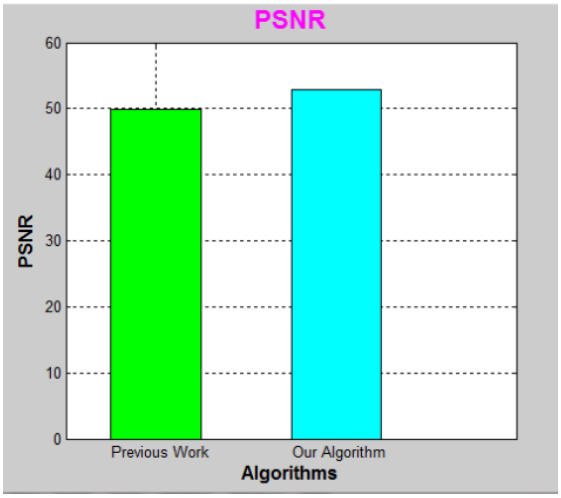


Figure 5: Process of calculating PSNR

Table 3: Values of PSNR

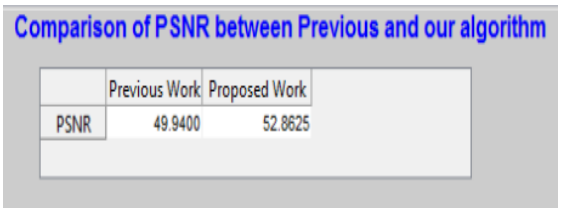


Table 4: Comparison between previous and proposed work

	Sensitivity(%)	Specificity(%)	AUC
Proposed method	99.9948	98.5109	1.4393
DREAM	100	53.1600	0.9040
BARRIGA	98	67	0.8600
Esnaashari	95	89.2900	0.8400

6. CONCLUSION

In this paper using feature based Linear Discriminant Analysis (LDA) technique with combination of SVM techniques and pre-processing is to improve robustness of blood vessel and optic disk detection. LDA used for detecting blood vessels in eye images by grouping the blood vessels into one category as on pixels and remaining part of the eye where another category like off pixels. The detection accuracy calculated with comparison to expert ophthalmologist hand drawn ground truths and results are comparatively analyzed where the implementation of this proposed work use the Image Processing Toolbox under Matlab Software.

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