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A Novel Approach for the analysis of OCT image in Diabetic Maculopathy using DWT and CNN

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ABSTRACT: As the current graph of diabetes patients count is increasing day by day. It has become a clear platform of research. The latest study has cleared the role of Diabetes Mellitus (DM) in this increasing diabetic macular edema (DME). And also it proved that is effects on the vision of the patients. It is mostly studied by the position of macula. Bu the traditional way of doing this is less effective and slow in the process which is often termed as fundus imaging SO here the research is working to reduce this time of operation and increase the operating efficiency. This is done by operating on clusters of hybrid techniques. So here discrete wavelet transforms and fast Fourier transform has been applied and the classification technique applied here is Covolution neural network (CNN) are used. The improved pictures are subjected to RT to get histograms by using k-mann clustering technique the features are extracted. Lastly, numerous administered classifiers are cast-off to categorise 3 lessons by means of important structures. The planned method produced an organisation correctness of 96.46% using two important topographies for community (kaggle) datasets.

Keywords: Decision support system, Diabetic macular edema, Discrete cosine transform, Discrete wavelet transform, Fundus imaging, Locality sensitive discriminant analysis, Radon transform, CNN”

I. INTRODUCTION

The structural connection of diabetes mellitus often termed as DM, which is functionally effected by the negative effect caused with pancreatic cell. More specifically talking, these cells are β-cells [1, 2, 3].The diabetes is mainly dependent on insulin imbalance in any body. So the diabetes can be categorised in two types namely i.e. type1 and type 2. Type 1 is categorised for the section of deficiency of insulin and second category is resistance diabetes [1, 2, 3]. In the present time era, diabetes is turning more and more common among aged people. According to the research increment in percentage of diabetic patients will increase by nearly 2.3% till 2035 which is currently 8.1% [4].In present state nearly 400 million populations are living with diabetes globally. And this percentage will increase to nearly 500 million with the present increasing rate till 2035[4].DM is mother of many diseases. As is someone gets this condition, DM start to erode rest of the organs. All the major organs like kidney, liver, brain all gets effected by this. Even the minor organs like blood vessels, eyes, pancreas all are completely gets eroded [5].

To check the effects of diabetes on eye. Different types of image modality method are considered for this. One of the technique is Optical coherence tomography (OCT), which is sub category of non-invasive techniques. This is basically concussed regarding the morphological cell of optical nerve. In addition to this technique also give brief information of the major part of the eyes [2, 7]. OCT modelling gives the early indication of infection of disease in the retinal area, which are considered as symptoms on which their treatment can be started [8].Mostly OCT is considered to detect the damage caused by the DME in optical region [9–12]. The optical structure is not plane; it is not homogeneous structural organ. So this technique is preferred yet the method is slow and time consuming. The method give the exact comparison between the healthy and infected person [13]. The effect of diabetes is very slow on retina so for this the person has to go through number of OCT screening so that the effect of DR can be recognised early [14, 15].

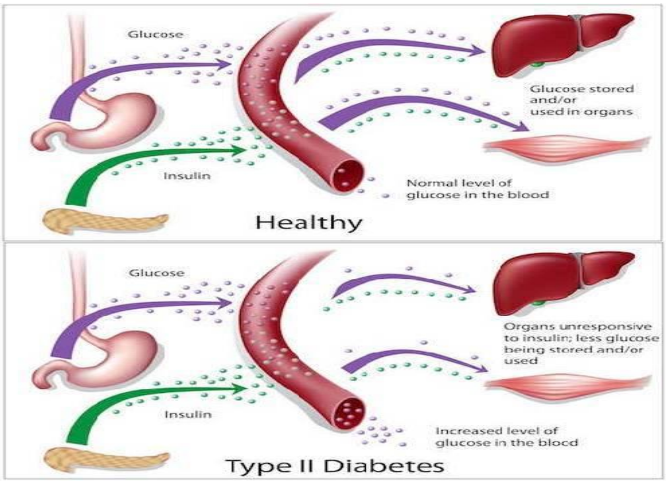

Figure 1 Effect of diabetes mellitus [7]

The number of diabetic patients is increasing day by day. [16]. To detect diabetic under comprehensive condition is difficult [6, 17]. So researchers are trying to find an effective why, which should be easy and even effective method for its detection. To easy the process OPT image comes handy as this element help doctors to detecting the grade and criticality of DME. This helps in effective decision making regarding the treatment of patients. The system to recognise the treatment in more effective manner. The treatment under the ophthalmologist category. The effective diagnosis and fundamental method of treatment of DME is supported by OCT modelling. [18, 19]. In early 20th century the rapid response of OCT technology was used. But this method was not structured in good condition and the functional values were upgraded and the system was increased to slow response OCT technique. Many more amendments were brought in the structural and the segments for the section with the help of algorithm. These algorithm were namely (GAC) Geodesic active contour and (C-V) Chan-Vese. GAC was categorised for the image identification analysis. GAC algorithm can efficiently handle the noise [20]. On the other hand C-V model is comparatively slow and need to be manually data computation along with the all the iteration of the system [21]. But these both have the limitation of number of input images which ca be considered in it. [22]. If more than the limit, images are uploaded then that will not be considered in the database. Here the paper is presenting the algorithm for DME effect measuring by OCT images. The algorithm is compact version of algorithm including the K-means in addition to the upgraded SBGFRLS algorithm. The resultant algorithm gives an easy hand to work on DME effected regions. Internationally, 21 billion individuals are recognised with DME and its occurrence frequency is 10.2% [7]. Types of DME (See Figure 1) are briefly described in Table 1. Types of DME (See Figure 1) are briefly described in Table 1. Table 1 gives the brief summary of various diabetes features which has been considered in the paper.

Table.1: Categories & medical topographies of DME [12]

DME types	Various diabetic macular edema (DME) features	Location of clinical features
Non-medically important macula deem (NCSME)	Thickening of retina, presence of hard exudates presents of hemorrhages with and without micro aneurysms	>1 and ≤ 2 DD from fovea centre
Medically important macular demi (CSME)	Thickening of retina, presence of hard exudates	≤ 1 DD from fovea centre

The functional outcome by the fluctuating factors, diabetes happen due to mainly misbalance in the hormone namely insulin due to which the glucose generation and absorption is affected. The patients count is increasing day by day. This is also recognised by WHO. Mostly the study was conducted on middle assign regions. The patients are rising from 0.67% in 1980 to 11.6% by 2010 [1].

Many strategies are used in the recognition of damage caused by DME on different organs. One eth e technique is CNN in addition to OCT. This is an artificial dependent on algorithm. Many techniques come in AI like Bayesian organization, fake neural organization, CNN and direct translation and many more. Mostly all are structured to the functional upbringing system for overfitting.

This method use nonlinear section of CNN for classifying the particular part of the structure of organ in the system of the patients [5].

The change might be nonlinear and the changed space high dimensional; in this way however, the classifier is a hyperplane in the high-dimensional element space; it very well might be nonlinear in the first info space.

II. Proposed Methodology

Dataset: the research here is performed under the compliance of tenets for the Helsinki also the approval of all the author's organisation. After the permission of the patient both the optical organ structure is compliance for the inclusion. Hundreds of OCT images is considered. Al the reading were taken from i=single machine for avoiding the fragmentation in the results for the section of accuracy. The operative members were highly trained and were strictly instructed to avoided all kind of error chances in the section evolution was generated by the section of retinal thickening, hard exudates, intra retinal cystoid space formation, and sub retinal fluid.

The procedure is as follows

STEP 1- initial data set images is divided in two different section namely the OCT part of the retinal portion and other backward region, for better observation.

STEP 2- the algorithm working on the SBGFRL principle to study the OCT images for the segmented DME effects.

The structural steps on t=which the algorithm is working is shown in the flow chart below. Here the K-MEANS algorithm preferably used is a steps oriented formulated algorithm [23].Crux to which is to first categorise all the clusters of images for minimizing the mean of the distance between the differences between the images. Here the research if performed after fixing the number of K to the values of 2 so that he dividing OCT images is easy for ROI region. Improved SBGFRLS algorithm is used for DME sensation in OCT image. The level set methods are usually used for medical image segmentation, including the Selective Binary and Gaussian Filtering Regularized Level Set (SBGFRLS) [24], Chan-Vese (C-V) [25], and Geodesic Active Contour (GAC) algorithm [26, 27]. The evolution function of SBGFRLS algorithm is:

(i) Pre-processing is the process in which the images of retina are resized. The data are logged and the parameters which need to be taken are considered and apply selection technique for statistical analysis to remove the non-uniform nature of the image. The colour of the eye and to assign the various histogram to see the number of contrast and pixels of the image.

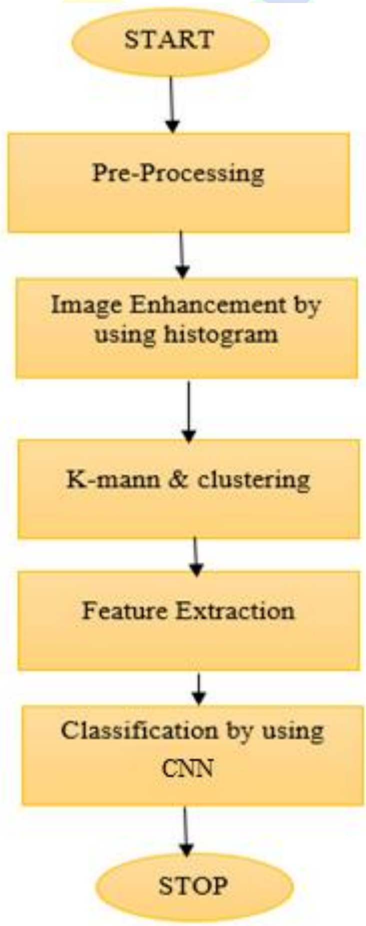

Fig.1 Proposed Flowchart for detection of diabetes in an OCT image

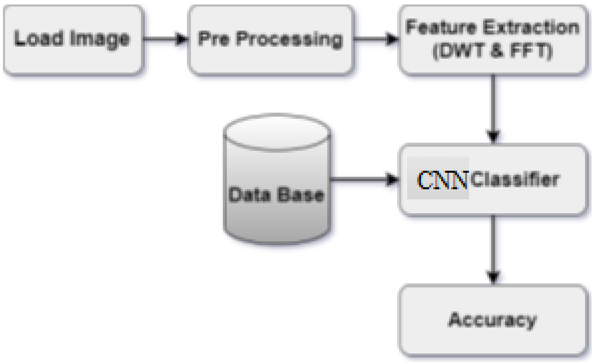

Fig.2 Proposed Methodology for Pre-Processing

(ii) Feature Extraction

The discrete wavelet transform records both types of frequencies that provides information about the signal. It investigates the image by approximation and filtering approach and detail information is provided by high-pass clarifying that constitutes the image and number of iterations. The image is extracted into gray code and the vertical and horizontal components are extracted for different components. The constituent matrix are then traversed into low pass and high pass filtering of size M/2 and N/2 which consists of the information of distinct frequencies of different levels. The horizontal component are named as Dh1, Dh2 and vertical as Dv1, Dv2 and approximate as A1. The energy values are extracted as features. The test for statistical analysis is performed as t-test.

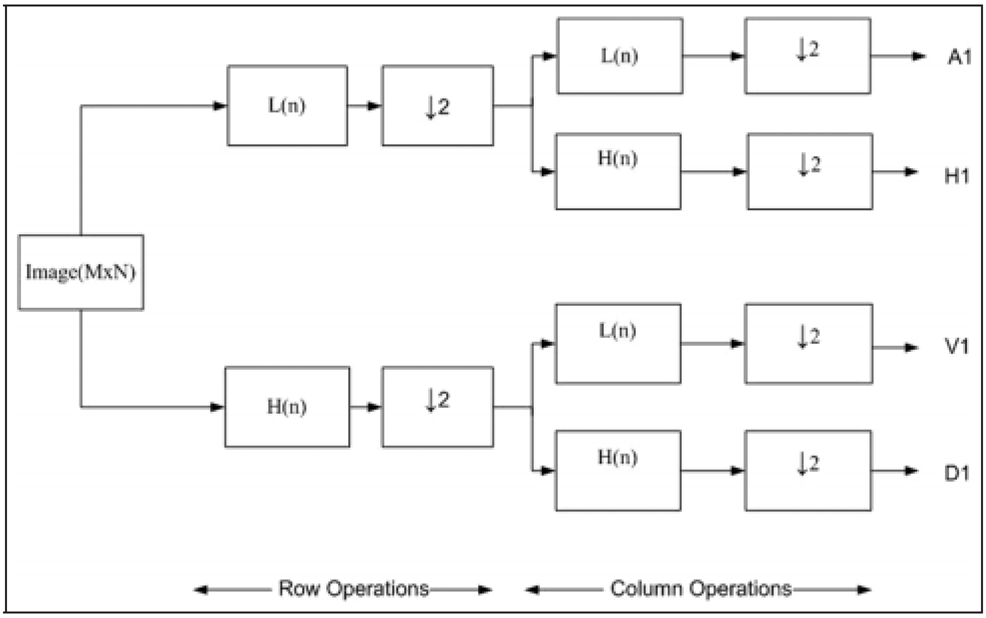

Figure 3. Block diagram of wavelet decomposition

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules [8]. The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere e. g. the dilation equation.

$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(S_x - k)$$

Where, S is a scaling factor (usually chosen as 2). Moreover, the area between the function must be normalized and scaling function must be orthogonal to its integer translates e.g.

$$\int_{-\infty}^{\infty} \phi(x)\phi(x+1)dx = \delta_{0,l}$$

After introducing some more conditions (as the restrictions above do not produce unique solution) we can obtain results of all these equations, e. g. finite set of coefficients which define the scaling function and also the wavelet. The wavelet is obtained from the scaling function as

$$\psi(x) = \sum_{k=-\infty}^{\infty} (-1)^k a_{N-1-k} \psi(2x-k)$$

Where, N is an even integer. The set of wavelets than forms an orthonormal basis which we use to decompose signal. Note that usually only few of the coefficients ask is nonzero which simplifies the calculations.

(iii) CNN classifier

A convolutional neural network convolves an input image with a defined weight matrix image features extraction without losing information spatial arrangement. The performance of the CNN is determined by evaluating the different architectures and different performance levels are achieved. The multiclass models are trained for enhancing the sensitivities which includes the data processing methods for improving accuracy and efficient dataset sample size increment.

The multi-class models are trained for sensitivity enhancement for early stage classes. Various data processing methods improve test accuracy and increase efficient dataset sample size. The insufficient sample size issue is also addressed by this technique utilizing the CNN with transfer learning for recognition task. The CNN architecture is performed for recognition task on color space. CNN is trained and tuned and optimally performed on the dataset utilizing the several techniques. Different experimental studies were conducted utilizing the primary data sources.

Here in table 2 the features to be taken for classification have been mentioned for applying various optimization techniques. The features are normal, diabetic, P-value and approximated values.

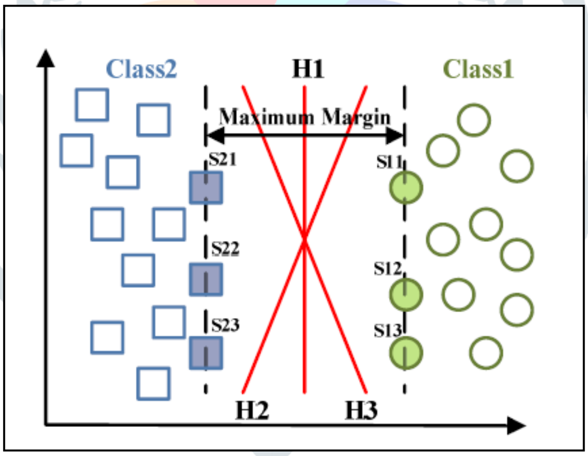

Fig. 4 The geometric Interpolation of Linear CNN

Table 2. Range of the wavelet-based features (DWT energies) extracted from the retinal images [4]

Features	Normal	DR	P value
A2	5.828+03±1.475E+03	9.93E+03± 2.346E+03	< 0.0001
A1	5.663E +03± 1.437E+03	9.647E +03 ± 2.272E+03	< 0.0001
Dh2	8.29 ± 10.3	3.50 ± 5.08	< 0.0001
Dh1	0.593± 0.682	0.258 ± 7.738E-02	< 0.0001
Dv2	12 ± 11.5	8.88 ± 4.56	< 0.0001
Dv1	1.26 ± 1.55	0.661 ± 0.329	< 0.0001
Dd2	1.69 ± 1.97	0.774 ± 0.472	< 0.0001
Dd1	7.253E-02 ± 6.524E-02	4.553E-02 ± 6.54E-03	< 0.0001

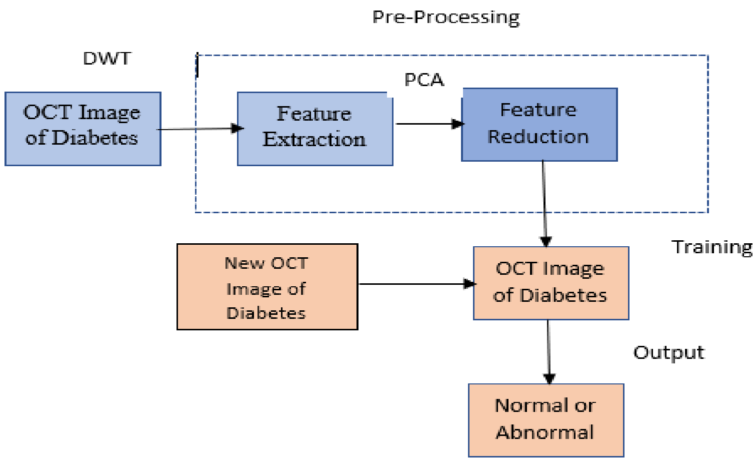

Figure 4 Working image classification model [5]

Figure 2 demonstrate the workflow model of the proposed model in which the model loads the image for the initial pre-processing step where the cleaning of the image take place for the next step. After the cleaning of the image feature extraction takes place using combination of two model DWT and FFT after that CNN model comes into picture which collects the data from existing data base and using that knowledge it processes the input data from feature extraction step. At last, the accuracy is measured to determine the correctness of the proposed model.

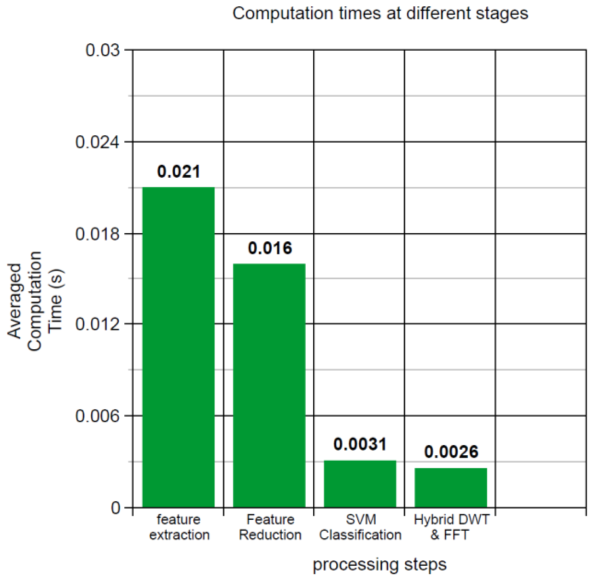

Fig.5 Graphical Representation between computation and Average computation [6]

VII. Proposed Algorithm

Step-I. Firstly Image is Extracted.

Step-II. Image Enhancement using histogram

Step-III K-mann & Clustering has been performed

Step-IV Feature Extraction through DWT+FFT

Step-V CNN classifier for classification

Step-VI Training, Testing and Validation has been done with the help of formulas

VIII. Results & discussion

The following figure gives deep analysis of the images which gives the representation of the size of the retina which is normal and that of suffering from diabetes. The first image gives the original size then the resized image has been given with segmentation and enhancement techniques which give the pictorial understanding about the effect of diabetes on the eye of a patient that is on retina. The deformity can be easily seen by the picture in the first, second and third section of the row of an image. The first row especially gives the abnormal images which are showing the abnormality of the patient and the following one gives the analysis for normal imaging. Fig.5 gives the graphical representation by applying the algorithm of CNN classifier between computation rate and average computation. Table 3, 4, 5 gives the analysis for the computation used in different algorithm with the optimization techniques. In table 3 the detailing of the data taken for diabetes patients has been explained whereas in the table 4 the method has been validated with the previous literature and accuracy has been compared with the data given. Table 5 gives the comparative analysis between the number of system and the passive system.

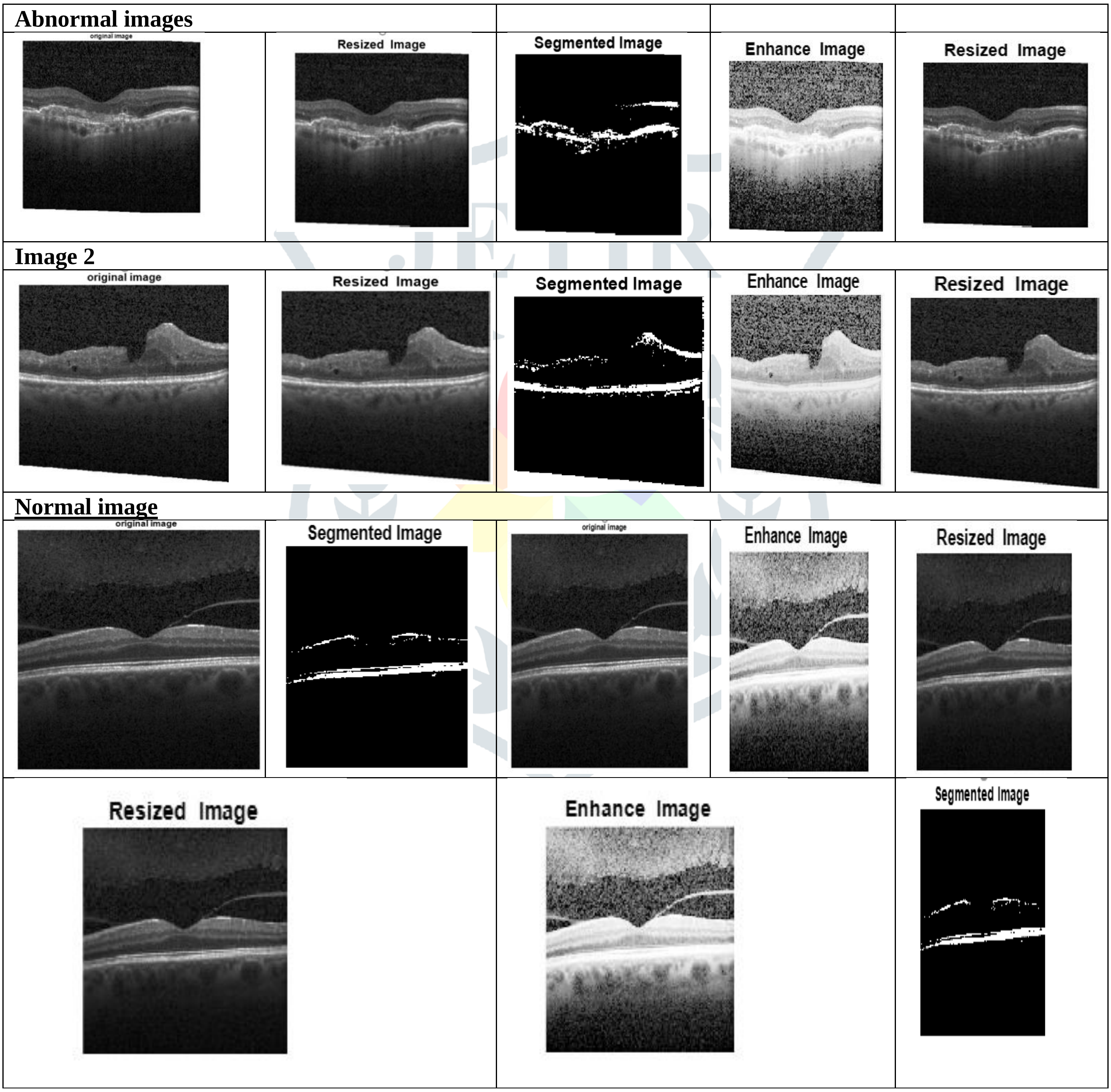

Figure 6 – Deformity in eye retina

Table 3. Detailed data of PCA. [7]

No. of Prin. Comp.	Variance (%)	No. of Prin. Comp.	Variance (%)
1	42.62	11	87.62
2	55.92	12	88.97
3	62.78	13	91.11
4	72.59	14	91.49
5	76.41	15	92.39
6	76.68	16	93.37
7	79.62	17	94.21
8	82.42	18	94.97
9	84.41	19	95.71
10	85.97	20	96.46

Table.4 Classification accuracy comparison [8]

Approach from literatures	Passive systems
DWT+SOM	94%
DWT+CNN with linear kernel	96%
DWT+PCA+CNN	95%
Proposed Method	**96.46%**

Table.5 Classification of accuracy on number of images [9]

Number of images	Passive systems
500	96%
420	95%
400	94%
380	93%

IX. Conclusion

In this manuscript we have given the computer vision analysed model to detect the normal and diabetic images and extracted the features by applying the DWT approach and for classification CNN classifier is used for automatic detection. We have gained an accuracy, sensitivity, specificity of 9.46%, 95% & 96.76% for 10-fold validation. We have also formed the GUI of this scheme. It's a automatic detection system by which the features can be trained and tested. The efficiency is 97% which is far better than any other classifier. In last, we may decrease the scope of the article for future classification & towards get better results. This proposed gives the novelty as compared to the applicable approach used earlier as the proposed method accuracy is far better than the earlier approach used for retina images taken for the impact of diabetes.

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