The Development of a Tool for the Detection of Cotton Wool Spots, Haemorrhage, and Exudates Using Multi-resolution Analysis

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1 Introduction

The World Health Organization (WHO) estimates that there are 347 million people living with diabetes around the globe, and that more than 80% of diabetes-related fatalities take place in various nations. According to projections made by the WHO, diabetes would rank as the seventh greatest cause of death in the year 2030. Diabetes can induce a condition called diabetic retinopathy, which damages the retina by causing blood or fluid to flow from blood vessels in the retina. The diabetic retinopathy may be broken down into two stages: early and advanced. The first kind of diabetic retinopathy is called non-proliferative diabetic retinopathy (NPDR), while the second type is called proliferative diabetic retinopathy (PDR). Cotton wool spots are the name given to the yellow and white dots. They are brought on by microinfarcts that occur in the retinal nerve fibre layer. The axoplasm of exploded retinal ganglion cell axons is extruded like toothpaste from the cell. You should be on the lookout for Patches that look like cotton wool scattered over the optic disc and along the temporal vascular arcades. Exudates is the term that's used to describe those golden specks. These lipid remnants are the result of serous fluid leaking out of capillaries that have been damaged. And retinal haemorrhage is a condition of the eye in which bleeding occurs into the tissue that is located on the back wall of the eye and is responsible for retentive vision. A retinal haemorrhage can be caused by hypertension, retinal

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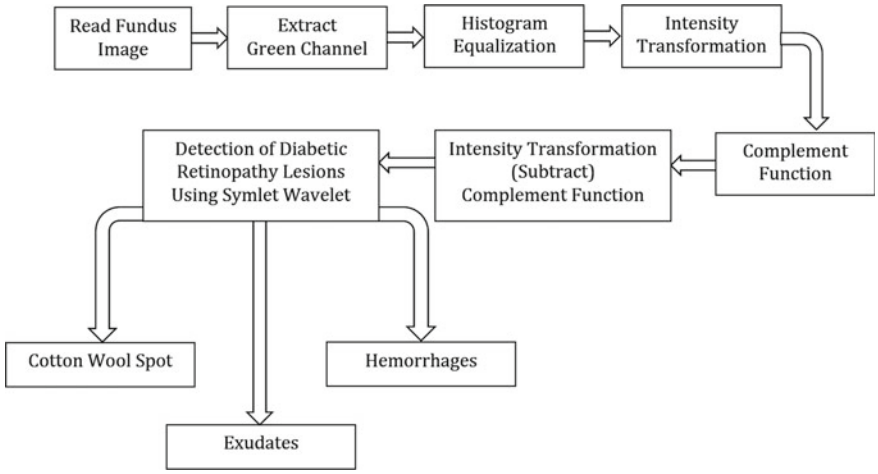

Fig. 1 Workflow for detection of cotton wool spot, exudates and haemorrhages

vein occlusion, which refers to the blocking of a retinal vein, or diabetes mellitus, which causes the formation of tiny blood vessels in the retina that are fragile and easily destroyed. Shaking the head, especially in very young newborns, or receiving a significant blow to the head can also cause retinal haemorrhages [1]. Shaking can also cause retinal haemorrhages. Blood vessels are enhanced and segmented by utilising Gabor wavelet and multilayered thresholding, respectively. This computer-aided technique for the early diagnosis of DR was proposed by Usman M. Akram and others. After that, they localised the optic disc by using a thresholding and an average filter, and then determined the border of the optic disc by using a Hough transform and edge detection. After the blood vessels and optic disc (OD) have been separated from one another, a hybrid fuzzy classifier is used to identify dark and bright lesions [2] (Fig. 1).

Rupa V. L. and P. S. Kulkarni details the process of extracting a variety of elements from fundus pictures, including exudates, microaneurysms, optic Disc, macula, blood vessels, and textural attributes such as entropy, amongst other things. In addition, the genetic algorithm and the multilayer feed forward neural network are utilised for the categorization of diabetic retinopathy lesions. The work that is being suggested has a primary emphasis on detecting and classifying [3]. This technique achieves a sensitivity of 80% while also maintaining a specificity of 83%. There are a number of different lesions that manifest themselves, including microaneurysms, haemorrhages, cotton wool patches, and exudates. Exudates have a tendency to gather in a ring around the location of the diseased vessel and seem as yellowish-white deposits with well-defined borders, while cotton wool patches are also present. Since it has a clearly defined border, exudates are simpler to distinguish from the backdrop than cotton wool spots are. This is because of the difference in texture. In order to identify these lesions, the cotton wool patches and exudates need to be separated from the background using the appropriate method. Therefore, the purpose of this research is

to suggest refining the edge in order to ease the segmentation procedure for cotton wool spots and exudates by reducing ramp width [4].

2 Methodology

In the proposed approach, the fundus pictures first undergo preprocessing, which aims to eliminate noise from those images. Remove the optical disc from consideration. In order to get rid of the optical disc, we extract the green channel from the RGB image. This is done since the green channel has a higher intensity than the red and blue channels. After that, perform histogram equalisation so that the image is improved. After that, perform the intensity transformation so that the optic disc is brought to the forefront. After that, perform the function of the complement. The OD may then be removed by deleting the complement image and replacing it with an intensity modified image. In addition to this, remove the mask from the fundus picture. The process of extracting the fundus mask begins with the removal of the red channel from the RGB picture, followed by the use of binarization with a threshold. Following the completion of the preprocessing step, we use the symlet wavelet algorithm to extract diabetic retinopathy lesions. Wavelet analysis is notable for having the critical attribute of flawless reconstruction. This refers to the process of reassembling a deconstructed signal or picture into its original form without any information being lost in the process. In the process of wavelet transformation, there are a few different fundamental functions that might be utilised as the mother wavelet. Because the mother wavelet is responsible for producing all wavelet functions that are utilised in the transformation through translation and scaling, it is the mother wavelet that dictates the properties of the wavelet transform that is produced. In order to make good use of the wavelet transform, it is necessary to take into consideration the specifics of the application (Fig. 2).

Following figure shows the fundus image mask and removal of optic disc (OD) (Figs. 3 and 4).

Under consideration and select an acceptable mother wavelet. The shapes of the wavelets and their capacity to perform signal analysis in a certain context are taken into consideration when selecting the wavelets to use. Orthogonal and biorthogonal wavelet families are the two primary groups that may be identified from one another. The Daubechies, Coiflet, and Symlet wavelet families are all considered to be orthogonal [5]. The extraction of diabetic retinopathy lesions is accomplished with the help of symlet wavelet. Including but not limited to cotton wool spot, exudates, and haemorrhages.

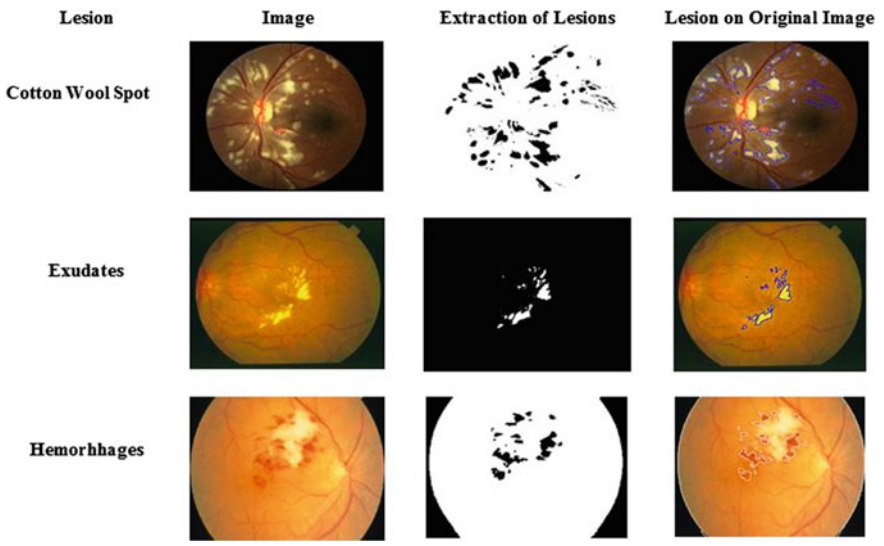

Fig. 2 Extracted diabetic retinopathy lesions

3 Result

Long-term diabetes and fluctuating blood glucose levels can develop diabetic retinopathy, which is now the most prevalent cause of vision loss globally. It has developed into a serious issue among people of working age that requires speedy response to prevent future eyesight loss. Develop a graphical user interface tool for the diagnosis of diabetic retinopathy complications such cotton wool spots, haemorrhages, and exudates (EX). Digital image processing techniques and wavelet decomposition with the help of symlet wavelet are utilised by our team in the process of detecting diabetic retinopathy lesions. The graphical user interface (GUI) tool was designed with MATLAB 2013a. Use certain online databases in addition to the local fundus image database that was created by Dr. Manoj Saswades for the purpose of evaluating this method. The specifics of the databases are shown in the Table 1.

Following the extraction of diabetic retinopathy lesions, statistical analysis is performed by calculating the mean, the variance, the standard deviation, and the correlation. The statistical approach for cotton wool spot is presented in the following Table 2.

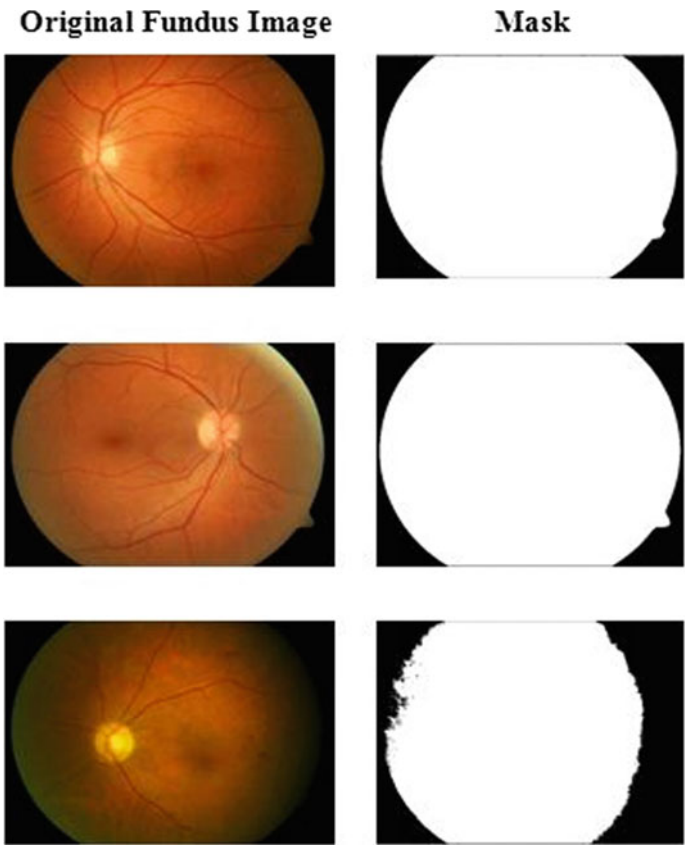

Fig. 3 Fundus mask

3.1 Statistical Operation on Cotton Wool Spots

$$M.(x). = \frac{491.7}{30} = 16.39$$
$$M.(y) = \frac{502.7}{30} = 16.76$$

$$\text{Var.}(x) = \frac{\sum\left(x - \overline{X}\right)}{N} = \frac{475.31}{30} = 15.85$$
$$\text{Var.}(y) = \frac{\sum\left(y - \overline{Y}\right)}{N} = \frac{485.94}{30} = 16.19$$

$$\text{Std.}(x) : \sqrt{\text{Variance}(x)} = \sqrt{15.85} = 3.99$$
$$\text{Std.}(y) : \sqrt{\text{Variance}(y)} = \sqrt{16.19} = 4.03$$

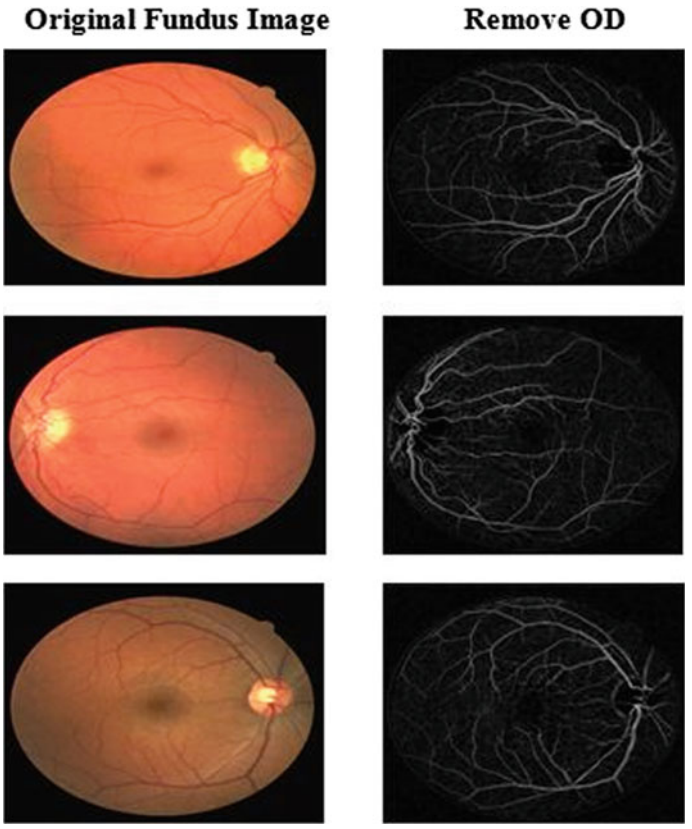

Fig. 4 Optic disc removal from fundus image

Table 1 Fundus image database

Sr. No	Name of fundus database	Total images
1	HRF (Diabetic retinopathy) [21]	15
2	HRF (Glaucoma) [21]	15
3	Diarect DB 1 [22]	89
4	DRIVE [23]	40
5	STARE [23]	402
6	Saswade (Local)	500

Correlation:
Where

$$\sum(x - \overline{X}) = 475.31,$$
$$\sum(y - \overline{Y}) = 485.94$$

Table 2 Statistical techniques on diabetic retinopathy lesions

Sr. No	Manual counting of CWS (x)	CWS by algorithm (y)	Manual counting of haemorrhages (x)	Haemorrhages by algorithm (y)	Manual counting of exudates (x)	Exudates by algorithm (y)
1	612	912	120,070	120,080	35	42
2	984	985	110,070	110,071	47	49
3	932	932	131,600	131,602	102	106
4	889	905	145,410	145,414	31	31
5	204	204	138,320	138,320	68	68
6	795	795	98,868	98,869	18	18
7	891	891	80,622	80,627	41	41
8	138	138	90,982	90,989	96	96
9	137	147	113,110	113,110	89	89
10	688	688	104,120	104,120	48	48
11	474	474	98,650	98,650	21	21
12	100	100	82,427	82,428	48	48
13	136	136	121,290	121,290	302	309
14	143	143	116,040	116,040	37	37
15	149	149	80,753	80,753	66	66
16	31	31	75,480	75,480	65	65
17	88	89	87,198	87,198	39	39
18	320	322	193,540	193,540	154	155
19	734	734	109,350	109,350	8	8
20	817	817	128,770	128,770	37	37

$$\sum \left(x - \overline{X}\right)^2 = 225919.60,$$
$$\sum \left(y - \overline{Y}\right)^2 = 236137.69$$

$$r = \frac{475.31 * 485.94}{\sqrt{225919.60 * 236137.69}}$$

$$r = \frac{230972.15}{230971.51} = 1$$

The value of the coefficient, denoted by r, might fall anywhere between $+1$ and -1. If one of the variables has a value of 0, it means that there is no connection between the other two variables. If the value is larger than zero, this shows that there is a positive link between the two variables; this indicates that the value of the other variable will also increase whenever the value of the first variable increases. A number that is less than zero shows an inverse relationship; this means that as

the value of one variable increases, the value of the other variable decreases. This is shown by the fact that an inverse relationship is denoted by a number that is less than zero.

3.2 Statistical Operation on Haemorrhages

$$M.(x) = \frac{110105.37}{30} = 3670.17$$
$$M.(y) = \frac{110106.77}{30} = 3670.2$$

$$\text{Var.}(x) = \frac{\sum\left(x - \overline{X}\right)}{N} = \frac{106435.2}{30} = 3547.84$$
$$\text{Var.}(y) = \frac{\sum\left(y - \overline{Y}\right)}{N} = \frac{106436.57}{30} = 3547.89$$

$$\text{Std.}(x) : \sqrt{\text{Variance}(x)} = \sqrt{3547.84} = 59.57$$
$$\text{Std.}(y) : \sqrt{\text{Variance}(y)} = \sqrt{3547.89} = 59.57$$

Correlation
Where

$$\sum\left(x - \overline{X}\right) = 106435.2,$$
$$\sum\left(y - \overline{Y}\right) = 106436.57,$$
$$\sum\left(x - \overline{X}\right)^2 = 11328451799.1,$$
$$\sum\left(y - \overline{Y}\right)^2 = 11328749819.6.$$

$$r = \frac{106435.2 * 106436.57}{\sqrt{11328451799.1 * 11328749819.6}}$$
$$r = \frac{11328597615.27}{11328597615.22} = 1$$

3.3 Statistical Operation on Exudates

$$M.(x) = \frac{52.86666667}{30} = 1.77$$
$$M.(y) = \frac{54.2}{30} = 1.81$$

$$\text{Var.}(x) = \frac{\sum(x - \overline{X})}{N} = \frac{51.11}{30} = 1.71$$
$$\text{Var.}(y) = \frac{\sum(y - \overline{Y})}{N} = \frac{52.40}{30} = 1.75$$
$$\text{Std.}(x) : \sqrt{\text{Variance}(x)} = \sqrt{1.71} = 1.31$$
$$\text{Std.}(y) : \sqrt{\text{Variance}(y)} = \sqrt{1.75} = 1.33$$

Correlation:

$$r = \frac{\sum(x - \overline{X})\sum(y - \overline{Y})}{\sqrt{\sum(x - \overline{X})^2 \sum(y - \overline{Y})^2}} \tag{1}$$

where

$$\sum(x - \overline{X}) = 51.11,$$
$$\sum(y - \overline{Y}) = 52.40,$$
$$\sum(x - \overline{X})^2 = 2612.24,$$
$$\sum(y - \overline{Y})^2 = 2745.76$$
$$r = \frac{51.11 * 52.40}{\sqrt{2612.24 * 2745.76}}$$

$r = \frac{2678.17}{2678.17} = 1$

3.4 K-Means Clustering

K-means is a clustering technique. Clustering algorithms are unsupervised approaches for dividing a larger dataset into more manageable groups. The moniker that can be used to a priori label unsupervised data indicates that they do not originate from clearly defined categories. In machine learning, the challenge of unsupervised learning is to look for latent structure in unlabelled data. Since there are no error or reward signals to aid in the identification of workable solutions, learners are taught

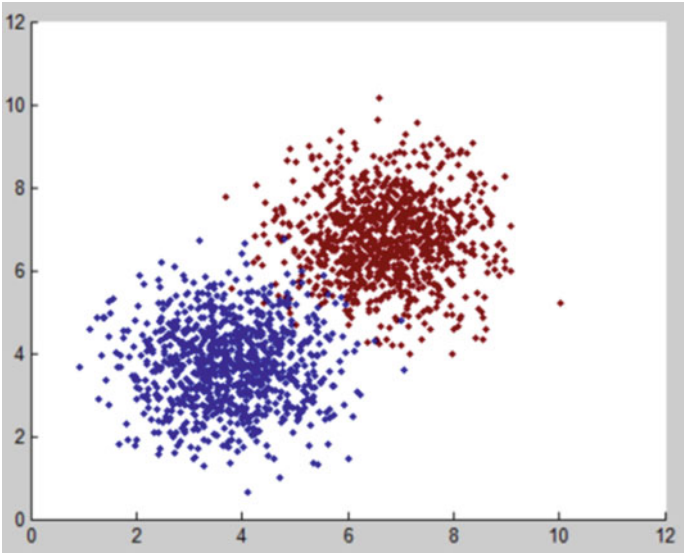

Fig. 5 K-means clustering

using examples without labels. Now, supervised learning and reinforcement learning may be distinguished from unsupervised learning (Fig. 5).

3.5 ROC Curve

The area under the receiver operating characteristic curve (AUC-ROC) is a performance assessment that can be used for classification problems using a variety of threshold settings. The ROC is a probability curve, and the AUC is the degree of separability, sometimes known as a measure of separability. It indicates the degree to which the model is able to differentiate between different classes. The higher the area under the curve (AUC), the more accurately the model can predict that 0 classes will be 0 and 1 classes will be 1. By analogy, a higher AUC indicates that the model is more able to differentiate between patients who have the disease and those who do not have the disease (Fig. 6).

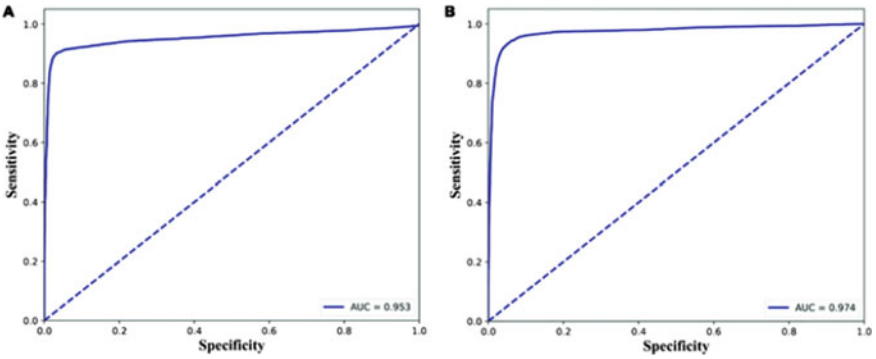

Fig. 6 ROC curve for performance analysis

4 Conclusion

In order to assist in the diagnosis of diabetic retinopathy lesions, we make use of digital image processing techniques as well as symlet wavelet. After the lesions have been removed, we then make use of statistical approaches such as computing the mean, standard deviation, variance, and correlation. Additionally, we have designed a diagnostic tool for diabetic retinopathy that features a graphical user interface (GUI). This tool is used to locate lesions caused by diabetic retinopathy. Which is of great use to the ophthalmologist in reaching a diagnosis of the illnesses when it comes to the matter at hand. When evaluated via the lens of statistical methodology, the proposed algorithm demonstrated a success rate of 94%. Working with a dataset that is both balanced and multimodal could be the focus of work to be done in the future. The second thing is to combine deep neural networks with techniques such as supervised learning and unsupervised learning [6–21].

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