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Diabetic Retinopathy Diagnosis using Second Order Edge Detection

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Abstract:- When a person has diabetic retinopathy (DR), even after having the condition for a long time, they are highly unlikely to be aware of it. Not everyone is really familiar with this illness. This illness is a little different from others since, depending on the diagnostic syndrome, every diabetes patient has a risk of developing diabetic retinopathy. Various studies have been done in this area, but a good method is still needed. A neural network in machine learning needs to be trained very well because if it isn't, the system won't be able to provide decent results. The rate of false alarms is higher due to poor training. However, there is another method—an edge detection tool—by which DR may be detected more accurately. Edge has the ability to extract the geometry of impairments, and the density of the retrieved region determines whether or not it is diabetic retinopathy. The exudates from the fundus picture are extracted by the proposed method using the Sobel Edge Detection tool. Prior to that approach, a colour mapping tool was used to make exudates from the fundus picture more visible. A colour mapping tool helps improve the visibility of some patches that the illness may cause. The backdrop can also be classified by changing the colours such that exudates are more obvious than in the original image. The suggested system has more accuracy than the existing model and is tested using the Messidor benchmark.

Keywords:- *Diabetic Retinopathy, Fundus Image, Sobel EdgeDetection, Color Mapping, Retina, Optic Cup.*

I. INTRODUCTION

The delicate retinal tissues are directly impacted by diabetic retinopathy, which causes the blood vessels to enlarge and begin to leak fluid. A person may get partial or total vision loss as a result of diabetic retinopathy. A person who has had diabetes for a long period may have the highest risk of developing diabetic retinopathy. This illness can only be healed and made to quit damaging the cells; it cannot be treated [1]. For diabetic individuals, routine testing is crucial for detecting the disease at an early stage. To categorise the blood vessels or backdrop of the exudates, a method must be effective. Because blood vessels can also manifest as deficits and exudates, it might be challenging to recognise the right diagnosis if the system is not skilled. High-precision DR diagnosis is possible by image processing. The number of diabetic people suffering from diabetic retinopathy has increased. One of the most common illnesses, DR is the primary cause of vision loss in people in their middle years.

Little alterations in the retinal vessels are how DR develops. Microaneurysms are the main differentiable aberrations. Theintraregional drain is produced as a result of the twisted microaneurysms. This starts the first stage of diabetic retinopathy (DR), also known as mild non-proliferative diabetic retinopathy. The microinfarcts in the retina obstruct the veins over time as the retinopathy worsens. Delicate exudates are the medical term for these little infarcts. This kind of retinopathy is known as severe non-proliferative diabetic retinopathy when more than three abnormalities are present at the same time.

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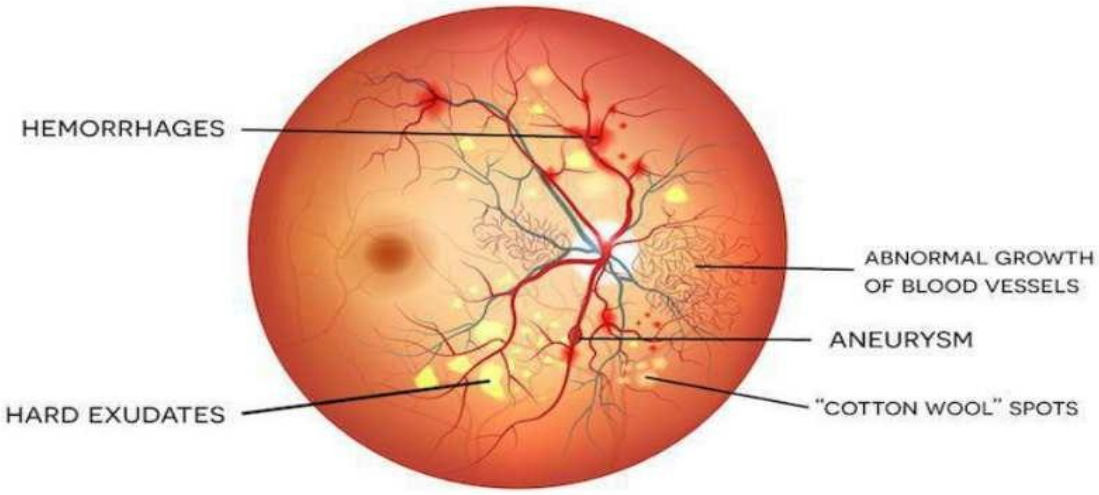

Fig 1 Basic Architecture of Diabetic Retinopathy Image [2]

Figure 1 depicts the retinal architecture in diabetic retinopathy, which includes both soft and hard exudates. An picture of the fundus can be used to identify diabetic retinopathy. The retinal region of the eye called the fundus is visible in black. An picture of the fundus can be used to diagnose any eye diseases. In the domain of automatically identifying diabetic retinopathy, it is essential. Various fundus samples from healthy and DR patient subjects are used to train machine learning models. The machine requires thousands of images in order to train a model that is effective with input photographs. It increases system expenses and processing time, nevertheless. Because it doesn't require any form of machine learning methodology or model, an edge detection technique might be highly useful to substitute the machine learning-based model. Pre-processing helps to make photos or exudates more visible and can process input images directly. Next, edge detection can extract the shape, size, or structural appearance of the DR exudates through which a correct decision can be made that could save lives. A novel strategy for improving the funuds picture for subsequent proceedings is colour correction.

The optical makeup of the veins or blood vessels over the retinal picture might reveal the limitations brought on by disorders of the eye. The most frequent alterations, such as vascular, optic circle, and fova changes, are used to examine particular eye disorders, such as diabetic retinopathy (DR) and other eye illnesses. Physical DR identification has been done using a variety of screening tools. The retinal vessels are photographed using computerized fundus screening devices; as a result, the fundus image securing cycle can significantly degrade the image quality. Therefore, image improvement is always crucial to advancing the optimum image quality. A few methods are suggested by experts to improve the nature of retinal pictures. Image enhancement, discontinuity, highlight extraction, and grouping are some image management techniques that analysts use to examine eye diseases. To spot changes in clinical pictures, image recording is used. For successful recruitment, numerous photos captured from diverse angles are arranged in a single direction framework. Image combining is a technique used to combine different types of data from several photographs into a single image [3].

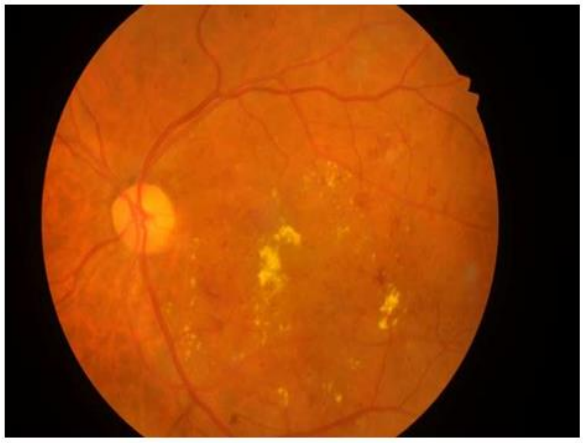

Fig 2 Fundus Image of the Eye with Diabetic Retinopathy Exudates [4]

The fundus picture of the eye with diabetic retinopathy exudates is shown in Fig. 2. The diabetic retinopathy abnormalities that are highlighted in yellow indicate the degree of infection that has developed.

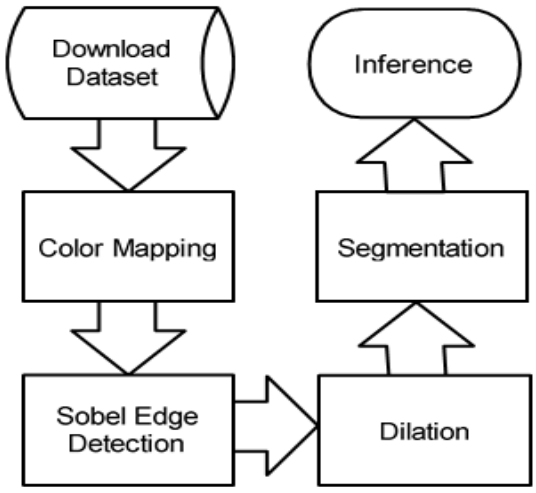

Fig 3 Block Diagram of Proposed System

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The block design of the suggested system is shown in Fig. 3, where a dataset must first be downloaded in order to get testing data for inference. The picture can then be improved using colour mapping, the edges can be retrieved using sobel edge detection, and the broken areas or edges of the image that were missed during edge detection may be filled with morphological dilation. Exudates can then be divided into groups according to their density. Finally, a choice can be made on whether or not the picture is related to diabetic retinopathy.

II. RELATED WORKS

Numerous studies have been conducted in the area of diabetic retinopathy, using a variety of approaches to get exact data on the fundus picture. Another method to locate the optic circle was suggested by Ravishankar et al. [5], who had previously identified the important blood veins and used their division to determine the approximate location of the optic plate. Several classifiers were tested by Obscured C-Media Clustering, including SVM, neural network, PCA, and generic Bayesian grouping. refers to the newly developed method of identifying the optic plate, which is home to the important blood arteries and the irregular location of the optic circle caused by their division. Additionally, it is restricted by using shade details. It demonstrates how several components, including blood arteries, exudates, tiny aneurysms, and drainage, may be exactly tied to various changes when they are used appropriately. The victory rate for optical circle limitation is 97.1%, the affectability is 95.7%, 95.2%, and 90.5% microforms individually. These provide a true representation of these frameworks and contrast favourably with existing ones. In this study, dilation and erosion are used to remove blood vessels. Dilation is as follows;

$$A \oplus B = A_1(x,y) = \sup_{i,j \in b} ((x-1, y-1) + B(1,1))$$

Erosion is as follows;

$$A \ominus B = A_2(x,y) = \sup_{i,j \in b1} ((x-i, y-j) + B_1(i,j))$$

Where B and B_1 are structuring elements and b, b1 are grids. The combined morphological operation can be stated as;

$$C' = (A \oplus B_2) \ominus B_2 - (A \oplus B_1) \ominus B_1$$

Another method was put up by KK Palavalasa et al. [6] et al.to identify hard exudates with good accuracy in relation to the severity of the injury. Using foreground and background techniques, the exudates sores were initially differentiated in the current method. After the succeeding steps, the calculation's last progression deleted the loud exudates and adjusted the findings as necessary. The computation has been tested in the publically available DirectDB information base, which provides the crucial data. With an affectability of 0.87, a F7 score of 0.78, and a positive rating of 0.76, it has proven possible to get higher execution outcomes for hard exudates painful level finding as compared to current tactics.

$$TPR = \frac{TP}{TP + FN}$$

$$PPV = \frac{TP}{TP + FP}$$

$$F - Score = \frac{2 * TPR * PPV}{TPR + PPV}$$

A segment based on shading depiction and its fusion with the optimal colour space and Fuse C-Medium (FCM) clustering was proposed by Alireza et al. [7]. They used retina shading data to achieve their goals and demonstrated advances using changes based on a dim scale. An explicitness of 85.4, an affectability worth of 97.2, and an accuracy of 85.6% were provided by the FCM grouping. In this article the center of the pixel can be changed with small window w and stated as p_n. Utilising a back propagation mainstream, GG Gardener et al. The regions of exudates, vascularity, edoema, and microanurism were selected to define the illness phases. It may be completed by examining images from 100 and 47 DR patients as well as thirty regular retinal images with exudates, draining, or microanuria, as well as retinal images with and without blood vessels. The succeeding explicitness and affectability values are, respectively, 88.4 and 83.5. Using the image preprocessing and mass localization technique on retinal images, Meher Madhu Dharmana et al. [9] established an efficient and improved extraction procedure for obtaining fundus characteristics. On a size of 0 to 4.0, the experimentation is carried out in the suggested model, the various characterization calculations are handled with the highlights are removed, and it is discovered that Nave Bayes Classifier is most effective in comparison to other classifiers with a precision of 83%. When compared to the present clustering approaches, the suggested work includes an extraction strategy that has reduced the complexity of the existing situation. By using it on low-cost SOCCs like the Raspberry Pi, this technique may be used to put together an independent, logical critique of machine learning algorithms. Laplacian of the Gaussian function was used for feature extraction. ConvNet-based calculations were proposed by Mamta Arora et al. [10] for the detection of diabetic retinopathy using fundus pictures. This paper demonstrates the applicability of deep learning as a solution to this problem. There is still a lot more study to be done in order to improve this model. It has been discovered that the model can be applied to the best-prepared model scenario, which may significantly improve the results. However, there is much better trial that will apply in the future to further enhance results. A deep learning-based system was proposed by Yash S. Boral et al. [11]. The system's goal is to categorise the fundus picture and identify DR. This research put out a method for improving picture quality in order to boost the system's effectiveness and precision. This deep network, known as V3, is in charge of extracting the characteristics of the fundus picture and attempting to categorise the DR from it. For training purposes, 48 photographs were used, while 90 images were used for

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testing. SVM has been utilised in the last step of diagnosis to categorise the condition as either diabetic retinopathy or a normal picture. A methodology for detecting diabetic retinopathy using a capsule network was put out by G. Kalyani [12]. Large datasets cannot be used to test the capsule network. The inner loop may cause it to slow down and allow for fewer iterations. Comparing the intricacy of the two networks, the capsule network is more complicated than the CNN. Small filters should be used by the network to make it speedier and take less calculation time.

III. IMPLEMENTATION DETAILS

The proposed method is based on Sobel Edge Detection and Color Mapping techniques. Color mapping is a method for transforming RGB images by pixel intensities, which can be used to draw attention to image flaws. Calibrating a photometric camera is another name for color correction. In the area of image processing, color mapping is a key activity that aids in the classification of objects. The fundamental goal of color mapping is to establish a statistical correlation between an image's color and brightness using the image's mean and variance.

$$H = \{(h(1), v(1)),...,(h(O), v(O))\} \quad (1)$$

Where H is the histogram, w is the width and O is the structure of an image I

$$O = \left[\frac{\max(I)-\min(I)}{w}\right] \quad (2)$$

$$h(i) = \sum_{k=1}^{N} P(I(p), i), i \in [1, O] \quad (3)$$

$$w(i) = min(I) + (i-1)w \quad (4)$$

$$(I(p), i) = \{^{i} = \frac{(p) - \min(I)}{w_0} + 1 \quad (5)$$

where i is the pixel intensities and P is the probability distribution. An method for statistical colour mapping treats pixel intensities as 3D colour spaces and reshapes the data to correspond to the statistical points. Various methods map the colour individually, one channel at a time, depending on the colour chosen. However, the colour mapping method alters many colours at once. The colour mapping of the fundus picture improves the visibility of exudates and makes it simple to identify background vessels by concentrating on damaged cells. The colour mapping of the input fundus picture for the Messidor benchmark is shown in Fig. 4.

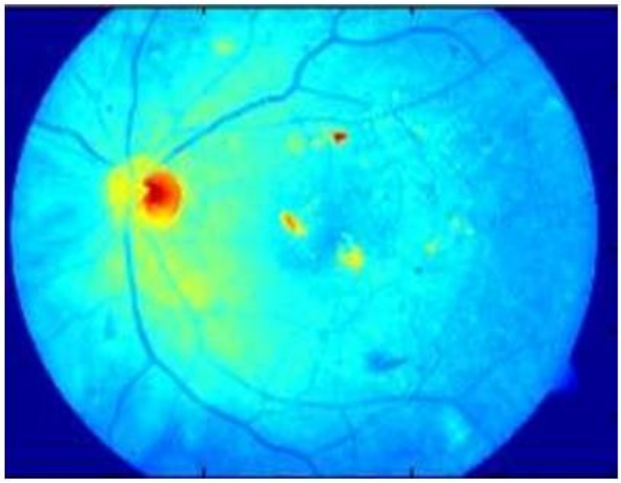

Fig 4 Color Mapping of Input Fundus Image of Messidor Benchmark

A. *Sobel Edge Detection*

The proposed system is based on Sobel Edge Detection, whose goal is to identify the edges of an image—vertically and horizontally—in order to gather data. Because Sobel edge detection plays a significant part in the majority of contemporary systems, it is a highly well-liked edge detection technique. The form and density of exudates may be determined with the use of sobel edge detection. It distinguishes between the main item and background noise. Edge detection is defined as a quick shift in the brightness or pixel value of a picture. Prewitt, Canny, Laplacian, Roberts, and many more edge detection methods exist, but they are all tailored to the needs of the system. Sobel is regarded as the best edge detection tool available for disease diagnosis.

➢ *Horizontal Kernel*

1	0	-1
2	0	-2
1	0	-1

The horizontal kernel mask's direction is leftward, which suggests that the calculation should be carried out from right to left. And derivative is as follows-

$$\frac{\partial f}{\partial x} = \frac{f(x, y + D_y) - f(x, y)}{-D_y}$$

$$\frac{\partial f}{\partial x} = f(x, y) - f(x, y + 1)$$

$$(y_3 = y_2 + D_y, y_2 = y, x_3 = x, D_y = 1)$$

First order derivation is computed in the specified direction and is sensitive to horizontal edges.

➢ *Vertical Kernel*

1	2	1
0	0	0
-1	-2	-1

When using a vertical kernel mask, the calculation must be done from right to left while facing upward. First order derivation is computed in the specified direction and is sensitive to vertical edges.

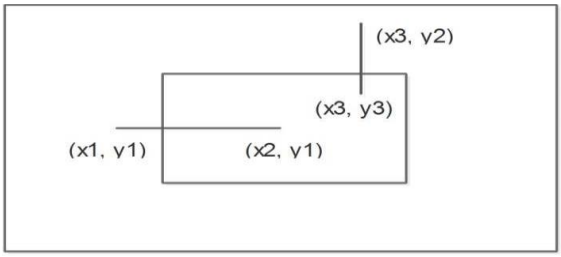

Fig 5 Horizontal & Vertical Coordinates

$$\begin{matrix} a_0 & a_1 & a_2 \\ a_7 & [i, j] & a_3 \\ a_6 & a_5 & a_4 \end{matrix}$$

The partial derivatives $\frac{\delta f}{\delta x}$ $\frac{\delta f}{\delta y}$ can be computed by –

$$M_x = (a_2 + ca_3 + a_4) - (a_0 + ca_7 + a_6)$$

$$M_y = (a_6 + ca_5 + a_4) - (a_0 + ca_1 + a_2)$$

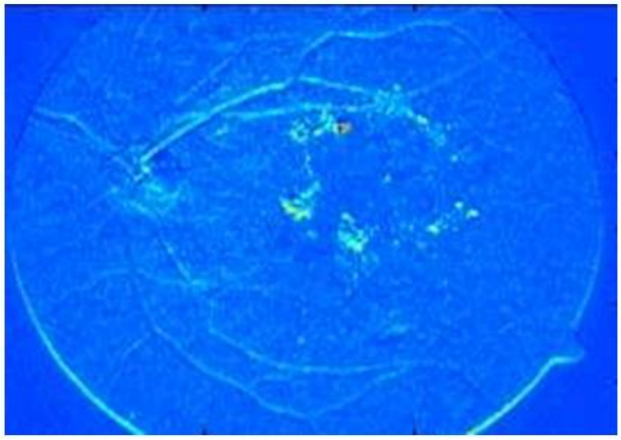

Fig 6 Encoding and Decoding Model

B. Exudates Localization

Exudates are the defects in the picture that indicate the existence of diabetic retinopathy. Exudate differs slightly from normal cells and blood vessels, but it is difficult to distinguish them with unaided vision. It may be detected by medical specialists or by doing a thorough examination of the fundus picture using a specific approach. The segmentation of background noise or blood vessels is shown in Fig. 8, and the system has coloured the exudates in red.

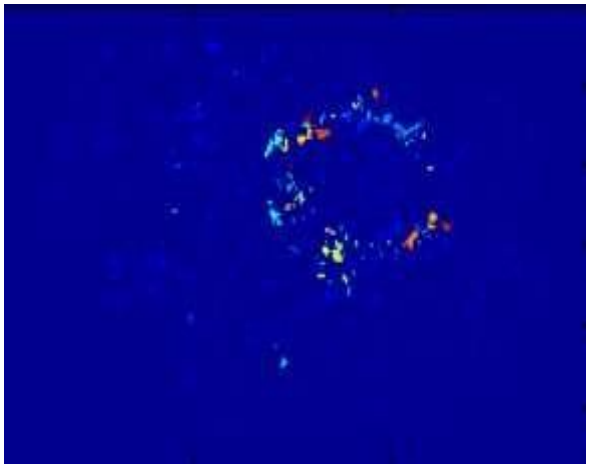

Fig 7 Exudates Extraction

Diagnoses based on Sobel edge detection are superior to those based on machine learning because they can handle fresh patient data or data that does not pertain to the original variant. The samples for which a machine learning-based model has been trained are its only bounds. Therefore, it is preferable to employ edge detection methods that are applicable to all data.

Table 1 Proposed Algorithm

Sobel Operator & Color Mapping Algorithm

Initialization
Input: Set of Image $X=(x_1, x_2, x_3, \ldots\ldots x_N)$
Output: Exudates
Step 1: Input image
Step 2: Normalize image by color mapping

$$H = \{(h(1), v(1)), \ldots, (h(O), v(O))\}$$

Where H is the histogram, w is the width and O is the structure
Step 3: Apply sobel edge detection by multiplying with kernel operator K;

$$G_x = \begin{bmatrix} +1 & 0 & -1 \\ +1 & 0 & -1 \\ +1 & 0 & -1 \end{bmatrix} * I, \quad G_y = \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} * I$$

Step 4: Compute gradient magnitude

$$G = \sqrt{G_x^2 + G_y^2}$$

Step 5: Dilate Matrix

$$(A \oplus B) = U_{b \in B}\ A_b$$

Where A is the gradient magnitude affected matrix and B is the dilated matrix.
Step 6: Compute Entropy

$$H = -\sum_{i=0}^{255} p_i log_2 p_i$$

p_i is the probability associated with the graylevel i

Step 7: **if** $H > T_r$ **then**
Diabetic Retinopathy;
else
Normal Fundus Image;
end else
end if
Step 8: End

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IV. EXPERIMENTAL RESULT

The four parameters True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) are used to base the results of the experiment. If a system correctly identified a condition as having either hard or soft exudates on an image, the designation will be TP; otherwise, it will be TN. When a system diagnoses diabetic retinopathy in an image with a grade level of 0, it is referred to as a false positive (FP). When a system diagnoses normal vision in an image with DR, it is referred to as a false negative (FN). In the Messidor benchmark, there are a total of 1212 testing photos, 655 of which include soft and hard exudates, and 557 of which have none. This indicates that 557 photos are from healthy eyes and 655 images are from the class of diabetic retinopathy. System identified 550 photos as having healthy symptoms and 642 images as having soft and hard exudate.

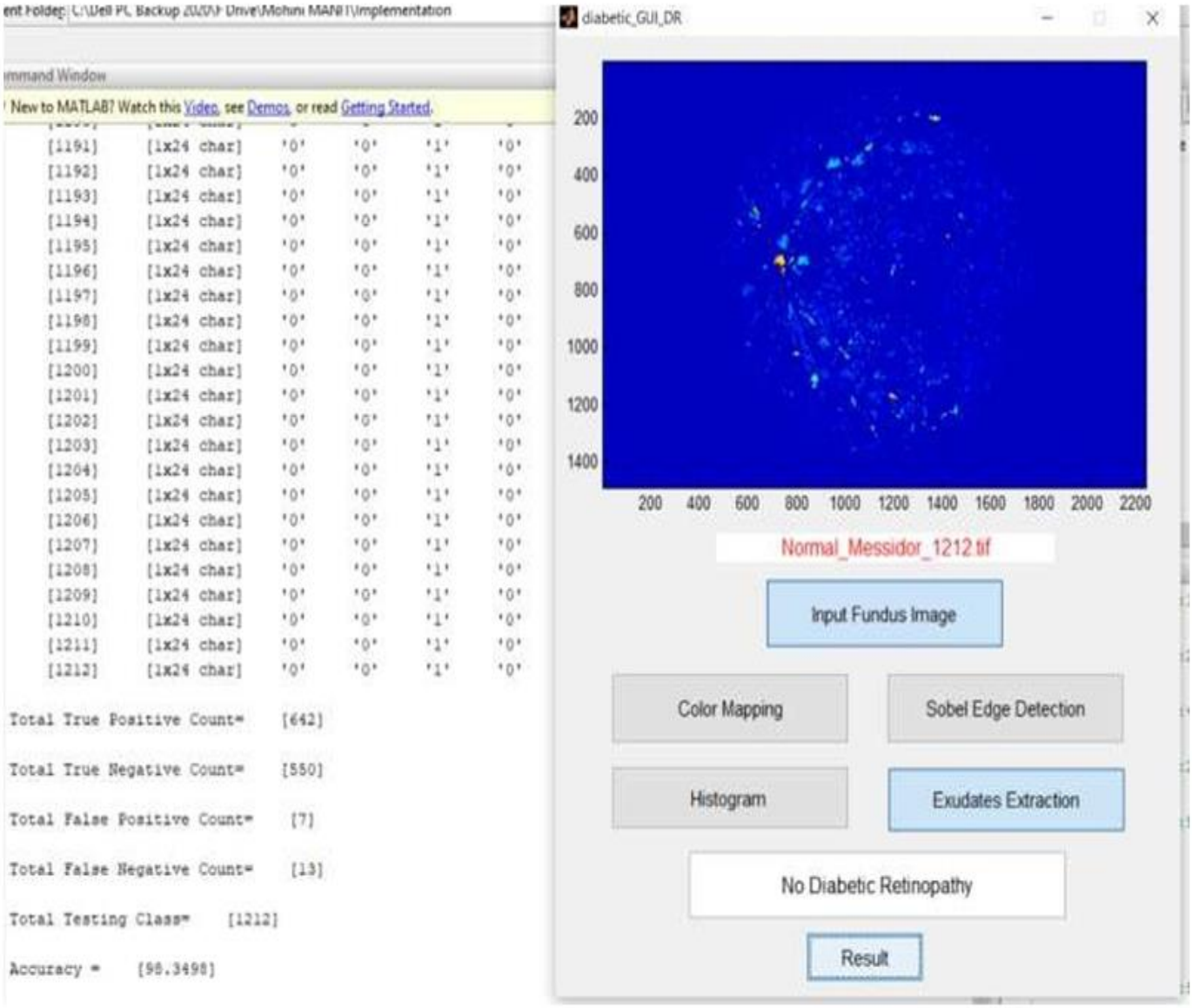

Fig 8 Console Result & GUI

Fig 8 shows the MATLAB console result and Graphical User Interface of proposed system.

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Table 2 Experimental Results

Terms & Parameters	Proposed
Total Testing Class	1212
True Positive	642
True Negative	550
False Positive	7
False Negative	13
Sensitivity in %	98.02
Specificity in %	98.74
Precision in %	98.92
Negative Predictive Value in %	97.69
False Positive Rate in %	1.26
False Negative Rate in %	1.98
Accuracy in %	98.35
F1 Score in %	98.47
Recall in %	98.02

Table 2 shows the result of the proposed system for Messidor benchmark. As per the confusion matrix, the calculations are as follows;

Table 3 Results Comparison

Terms & Parameters	G. Kalyani [12]	Proposed
Precision in %	95.62	98.92
Accuracy in %	97.98	98.35
F1 Score in %	95.82	98.47
Recall in %	96.11	98.02

Table 2 represents the result obtained for all metrics and table III shows the result comparison with capsule network.

V. CONCLUSION & FUTURE SCOPE

It is difficult for artificial intelligence to diagnose any ailment from a picture. There are several models that may be used to perform autonomous diabetic retinopathy diagnosis, however it is necessary to have greater precision and faster processing. The proposed approach is based on Sobel edge detection and colour mapping. In comparison to the machine learning technique, Sysetm can diagnose the DR more quickly. Exudates may be seen more clearly thanks to colour mapping, and Sobel can extract the exudate's structure and entropy. Comparing the system to prior proposed models like the capsule method, it showed remarkable accuracy. Messidor benchmark was held by the system while it reviewed the test results. The accuracy of the system is 98.35%, somewhat better than the prior method. Future research can examine various datasets and improve accuracy. Future system improvements might increase efficiency and accuracy.

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