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MODELING AND ENHANCING LOW-QUALITY RETINAL FUNDUS IMAGES

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Abstract - Retinal Fundus images are widely used for the clinical screening and diagnosis of eye diseases. However, fundus images captured by operators with various levels of experience have a large variation in quality. Low-quality fundus images increase uncertainty in clinical observation and lead to the risk of misdiagnosis. However, due to the special optical beam of fundus imaging and structure of the retina, natural image enhancement methods cannot be utilized directly to address this. The proposed system analyzed the main contribution is a new set of shape features, called Dynamic Shape Features, which do not require precise segmentation of the regions to be classified. Then, based on the degradation model, a clinically oriented fundus enhancement network (cofe-Net) is proposed to suppress global degradation factors, while simultaneously preserving anatomical retinal structures and pathological characteristics for clinical observation and analysis. Moreover, the system show that the fundus correction method can benefit medical image analysis applications, e.g., retinal vessel segmentation and optic disc/cup detection.

Key Words: retinal fundus, retinal vessel segmentation, dynamic shape features, optic disc/cup detection

1.INTRODUCTION

Due to their safety and cost-effectiveness in acquiring, retinal fundus images are widely used by both ophthalmologists and computer-aided diagnosis systems for the clinical screening and diagnosis of ocular diseases. However, fundus images tend to experience large variations in quality. A screening study of 5,575 patients found that about 12% of fundus images are not of adequate quality to be readable by ophthalmologists. In some cases, when the degradation is caused by the images being obtained through internal cataractous turbid media, enhancement methods, such as, can be used to restore 'high quality'. Then, the corrected images can be used to support the observation of other diseases (e.g., age-related maculopathy, diabetic retinopathy, and glaucoma).

Diabetes is a disorder of metabolism. The energy required by the body is obtained from glucose which is produced as a result of food digestion. Digested food enters the body stream with the aid of a hormone called insulin which is produced by the pancreas, an organ that lies near the stomach. During eating, the pancreas automatically produces the correct amount of insulin needed for allowing glucose absorption from the blood into the cells. In individuals with diabetes, the pancreas either produces too little or no insulin or the cells do not react properly to the insulin that is produced. The buildup of glucose in the blood, overflows into the urine and then passes out of the body. Therefore, the body loses its main source of fuel even though the blood contains large amounts of glucose.

A. The Eye Structure

Eye is an organ associated with vision. It is housed in socket of bone called orbit and is protected from the external air by the eyelids. The cross section of the eye is as shown in Fig -1 while that of retina is as shown in Fig -2.

Light enters the eye through the pupil and is focused on the retina. The lens assists in focusing images from different distance. The amount of light entering the eye is controlled by the iris, by closing when light is bright and opens when light is dim. To the outside of the eye is a transparent white sheet called conjunctiva.

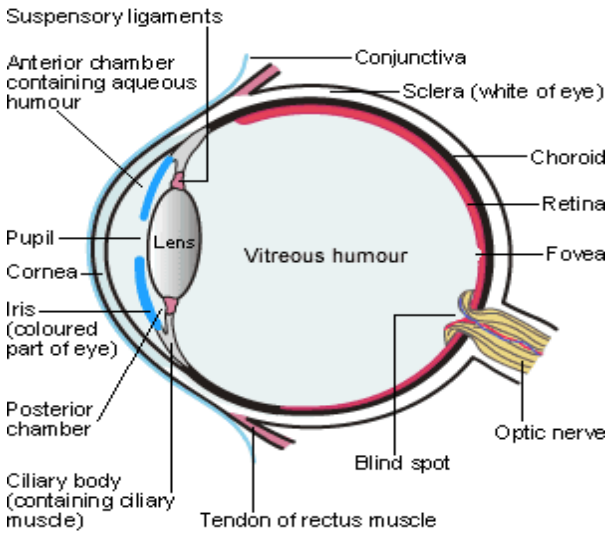

Fig -1: Structure of eye

The retina is a multi-layered sensory tissue that lines the back of the eye. It contains millions of photoreceptor that capture light rays and convert them into electrical impulses.

These impulses travel along the optic nerve to the brain where they are turned into images. There are two types of photoreceptor in the retina: rods and cones. The retina contains approximately 6 million cones. The cones are contained in the macula, the portion of the retina responsible for central vision. They are most densely packed within the fovea, the very center

portion of the macula. Cones function best in bright light and allow us to appreciate color.

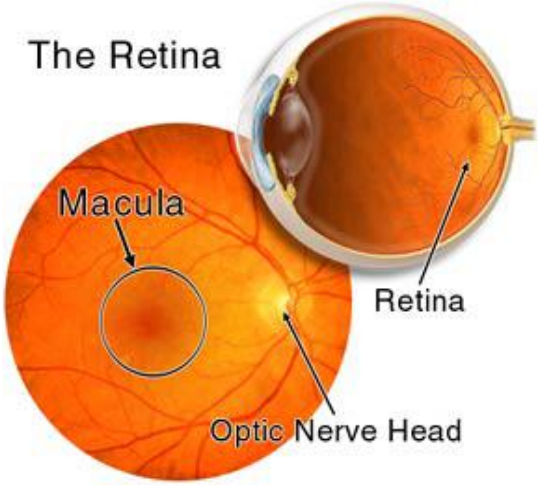

Fig -2: Retina Image

B. Retinal Image Processing

Retinal image Processing is relatively inexpensive, easily accessible study that is suitable for screening of eye diseases, such as glaucoma, diabetic retinopathy, and hypertensive retinopathy. However, ophthalmologists have limited time to look for a variety of abnormal signs on these fundus photographs in a large number of cases. In order to improve diagnostic efficiency, the computerized retinal fundus image analyzer has been developed now days.

The input fundus image is analyzed by the system and the output contains the grading and the result with the co-ordinates of the detected abnormality shown on the GUI.

The input image to the Pre-Processing stage can be a color or a grey level image. The Pre-Processing stage corrects the problem of Illumination variation that occurred when taken the pictures. Other problems corrected by this process include the enhancement of the contrast to aid in segmentation and detection of the abnormalities. Process involves in this stage include Color Space Conversion, Grey level transformation, Walter-Klein Contrast Enhancement, Contrast Limited Adaptive Histogram Equalization (CLAHE), Vessel Removal and extrapolation and Illumination equalization.

The input test image is preprocessed and then the image is segmented to three regions namely optic disk, blood vessels and Exudates. To segment these regions, it requires three region of interest extraction which further helps to segment all three regions. After segmenting the regions, disease detection algorithm can be implemented for further processing.

2. METHODS

This paper utilizes a hybrid of rule-based and machine learning techniques, where the adaptive local fuzzy thresholding represents the hard segmentation phase of proposed methodology, while morphological operations represent the soft segmentation. To our best knowledge, only a very limited number of existing systems have focused on extracting multiple anatomical structures with high achievable performance. Furthermore, there is no record in the literature of the use of hybrid combinations of adaptive fuzzy and morphology to solve this kind of problem. In summary, in the current paper, we develop a stand-alone compact segmentation system that can identify, localize and extract multiple retinal anatomical structures that have highly distinct features in a single segmentation session, while maintaining comparably high segmentation accuracy.

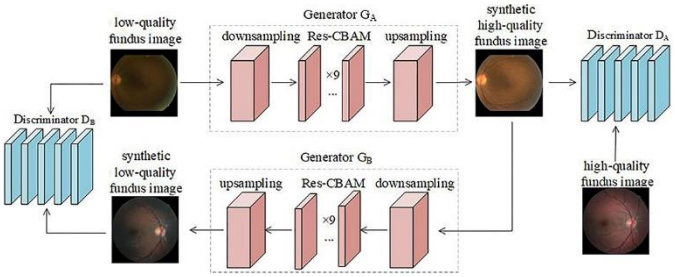

Fig -3: Retinal Image Enhancement Algorithm

An efficient methodology is proposed a system that involves new hybrid thresholding algorithm combines two powerful techniques: adaptive local fuzzy thresholding (coarse segmentation) and mathematical morphology (soft segmentation). The general flowchart of the proposed system, without regarding the acquired anatomical retinal structure, is illustrated in Fig -3.

Morphological operators are used in the pre- and post-processing phases of system algorithm, whereas adaptive local fuzzy thresholding is used in the processing phase, which means that it represents the core of the segmentation algorithm, even though morphological operators are considered more than complement steps.

Irrespective of the target anatomical structure, the proposed system involves three major phases: Region of Interest (ROI) extraction, coarse segmentation and soft segmentation. In the first phase, the target region of interest is extracted out of the raw retina image Iretina in order to enhance the segmentation accuracy of the target retinal anatomical structure (vessels, optic disc or Exudates lesions) and lower the computational cost, then IROI image undergoes a set of pre-processing steps involving major morphological operations that lead to initial identification of the target area. Although this phase is a preliminary one, it has a dramatic effect on the final segmentation accuracy of the fuzzy processing phase. The I_{ROI} forms the input for local adaptive fuzzy thresholding, which yields the I'_{ROI} hard-segmented image. Another set of morphological operations are applied on I'_{ROI} in the soft segmentation stage followed by binarization and convex-hull transform smoothing steps produced the final segmented image: I_{vessel}, $I_{Optic\ Disc}$, or $I_{exudates}$, depending on the target retinal anatomical structure.

The common phases involved in our proposed system are graphically illustrated in Fig -4 and detailed in the following subsections in this paper.

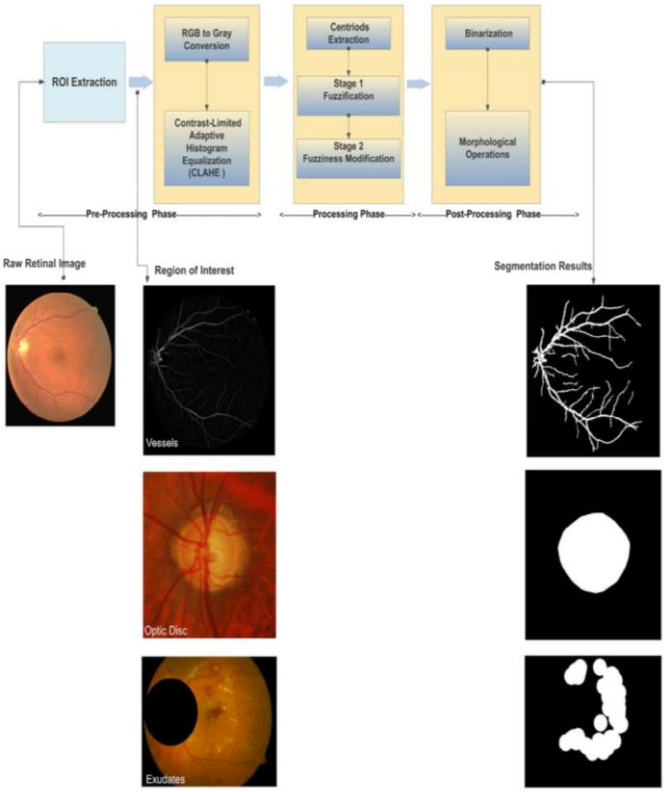

Fig -4: Phases of Retinal Image Enhancement Algorithm

A. Retinal Fundus Image Data set

The training set of the retinal vessel segmentation network consists of three public datasets: DRIVE, STARE, and CHASEDB1. All these three datasets contain multiple color retinal images and their corresponding retinal vessel segmentation images. The DRIVE data set contains 40 pairs of images with a resolution of 565 × 584, 30 pairs for training and 10 pairs for validation. The STARE data set contains 20 pairs of images with a resolution of 700 × 605, 15 pairs for training and 5 pairs for validation. The CHASEDB1 data set contains 28 pairs of images with a resolution of 999 × 960, 21 pairs for training and 7 pairs for validation. The 100 low-quality retinal images and their corresponding enhanced images with the CLAHE, fusion-based, MSRCP, LIME, CycleGAN, and Cycle-CBAM methods were used as the test set.

B. Image Pre-Processing

The major goal of this phase as it called ROI extraction is to extract the retinal anatomical structure of interest in order to reduce the computational cost and to enhance the overall performance; where a window around the target anatomical structure region of the raw retinal image is extracted, then the pre-processing steps are applied on it. Each anatomical structure has its own characteristics and features, thus, some of pre-processing steps may be different. However, the pre- processing general framework keeps unchanged. Since the pre-processing steps are quite dependent on the challenges created by the nature of target anatomical structure, a brief description of each anatomical structure is presented, followed by the corresponding required pre-processing steps.

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C. Retinal Vessels ROI Extraction

Vessel segmentation in retinal images involves a tension between accurate vascular structure extraction and false responses near sites of pathology or other non-vascular structures such as optic disc or macula. In one hand, this tension arises from the low contrast nature of retinal vessels in comparison to the fundus image background.

On the other hand, retinal vasculature structure exhibits dynamic change in size and contrast and broad distributed branching on the whole surface of retinal fundus image. For example, the width of retinal vessels ranges widely, from less than one pixel up to more than five pixels in a typical retinal image.

ROI

First, the raw retina image was converted into grayscale through green layer as it presents the higher contrast between vessels and fundus background among other layers as in (1):

$$I_{retina}^{G} = \Im^{G}(I_{retina}^{G}) \qquad (1)$$

where $\Im^{G}(.)$ denotes the green layer extracting operator and I_{retina}^{G} is the green layer of raw RGB fundus image. Then the I_{retina}^{G} image was complemented as a preliminary step for morphological filtering as in (2):

$$I_{retina}^{comp} = \Im^{imcomplement}(I_{retina}^{G}) \qquad (2)$$

where $\Im^{imcomplement}$ denotes the image complementing operator and I_{retina}^{comp} is the complement version of I_{retina}^{G}

The supremum and infimum of morphological openings were performed in aim of generating two images:

(1) Image with emphasized linear structures represents the vessels tissues.

(2) Image with homogenous emphasized flat structures represents fundus background and other tissues.

D. Image Pre-Processing

Edge detection is often applied as preprocessing step to Hough transform. Therefore, the input image fed into Hough transform is an edge map composed of a set of pixels partially describe the boundaries of optic disc. The efficiency and accuracy of Hough transform in finding the center of optic disc

circle can be demonstrated by employing accurate edge detection technique which will give the result as in fig -5.

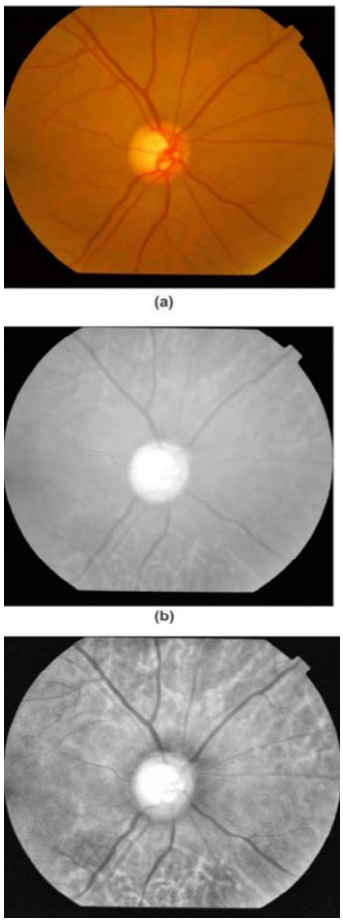

Fig -5: (a) Raw retina image. (b) Corresponding red layer I_{retina}^{R} (c) CLAHE-enhanced image $I_{retina}^{enhanced}$

E. Image Pre-Processing

Fuzzy c-means (FCM) clustering algorithm was applied for this purpose. Before applying FCM algorithm, retina image underwent a set of preprocessing steps in goal of achieving accurate edge map as following:

First, the red layer of retina image was extracted as:

$$I_{retina}^{R} = \Im^{R}(I_{retina}^{RGB}) \quad (3)$$

where $\Im^{R}(.)$ denotes red layer extracting operator. In contrast to vessels extraction, red layer is the layer where optic disc tissues have the higher contrast with other objects on fundus image. Then, I_{retina}^{R} was enhanced as in (8):

$$I_{retina}^{enhanced} = \Im^{CLAHE}(I_{retina}^{R}) \quad (4)$$

where $\Im^{CLAHE}(.)$ denotes the Contrast-Limited Adaptive Histogram Equalization (CLAHE) operator, it locally operates on small data regions of image rather than the entire area yields contrast-enhanced image. For further enhancement, we apply median filtering of 9×9-sized window and fed as input to FCM algorithm as shown in Figure 3.4.

As a first step towards edge map generation is to apply a 25-clusters FCM algorithm on filtered $I_{retina}^{enhanced}$ image with a goal of roughly aggregating OD pixels into one cluster and the other 24 clusters were dedicated for other surrounding tissues.

The binarized version of I_{FCM} was then obtained via simple thresholding as in (9):

$$I_{FCM}^{bw} = \begin{cases} 1, & I_{FCM} = C \\ 0, & Otherwise \end{cases} \quad (5)$$

where I_{FCM}^{bw} represents the binarized version of I_{FCM} image setting c = 25 clusters. Although the binary image I_{FCM}^{bw} forms the seed for our target edge map, some noises (binarization residuals corresponding to non-optic disc tissues) are likely to be introduced into the result during this process. To solve this, we used a morphological opening of size P pixels, which keeps only the connected components (objects) of I_{FCM}^{bw} image whose areas are ≥ P and eliminates the rest.

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F. Feature Extraction

The features such as blood vessels, exudates and optic discs are extracted for further analysis. In this extraction process the morphological operations such as opening, closing, erode and dilate are used. This image is converted into a binary image. The logical operations (“AND”, “OR”) and filters like “colpit” are applied and the segmentation is done for exudates and blood vessels.

G. Blood Vessel

Kirsch’s non-linear edge detector is used to search the maximum edge in a few determined directions. Taking a single mask and rotating it to 8 major compass orientations (East, West, North, South, South-East, Southwest, North-West and North-East) helps find the edge direction based on the maximum magnitude produced.

H. Exudates

Small yellow white patches with sharp margins and different shapes. Exudates are one of the early occurring lesions. The method attempts to detect hard exudates using two features of this lesion: its color and its sharp edges. The coloured fundus image is split into number of nonoverlapping blocks. For each block of the image, the coloured histogram is calculated. The threshold value, based on the colour histogram, is used to detect exudates. Hard and soft exudates are separated based on the chosen threshold value. Soft exudates are often called ‘cotton wool spots’ and are more often seen in advanced retinopathy.

3. RESULT AND DISCUSSIONS

The following fig -6 show the input retinal image which is having the three channel input. The image is 400 X 600 with unsigned integer format. The images are collected from the STARE database.

The Retinal images are complex images which is having non uniform intensity distribution and where the green channel is having maximum discrimination in intensity over the spatial domain.

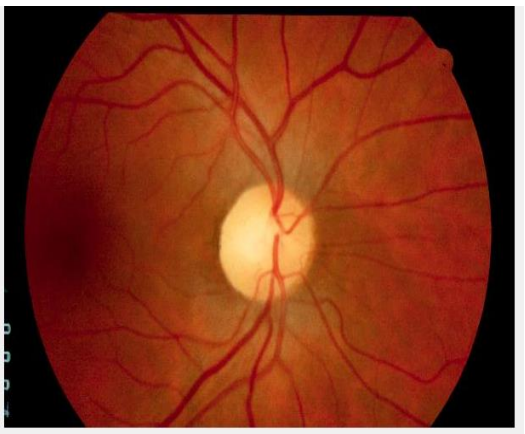

Fig -6: Input Retinal Image

Instead of converting the entire color fundus image to grayscale, this step involves extracting only the green channel from the color image. Green channel images often provide better contrast for blood vessels and other retinal structures compared to grayscale images. In MATLAB, you can achieve this by accessing the individual color channels (red, green, and blue) and selecting the green channel. The following fig -7 displays the green channel image which is extracted from the original color image. The green channel image is clearly showing the vessel and OD location intensities.

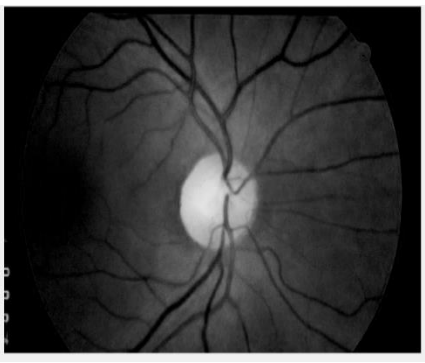

Fig -7: Green Channel Image

The medical images are normally captured with the radiation based imaging system so which are not able to produce high resolution image as well. This is the reason why the preprocessing techniques are exists in every medical image processing algorithms.

CLAHE (Contrast Limited Adaptive Histogram Equalization) is a widely used technique for enhancing the contrast of retinal images. It works by dividing the image into small regions called tiles and then applies histogram equalization to each tile. CLAHE limits the amplification of the contrast in homogeneous areas to avoid over-enhancement and preserves the overall image structure. MATLAB has the function adapthisteq for performing adaptive histogram equalization.

The following fig -8 is showing the contrast adjusted retinal image where the vessel path and the OD is clearly visible and it leads to perform further segmentation algorithm without any lag.

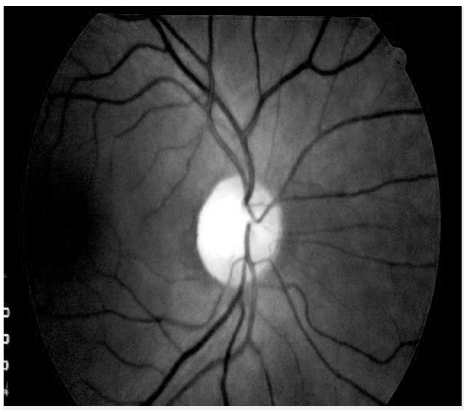

Fig -8: Contrast Adjusted Retinal Image

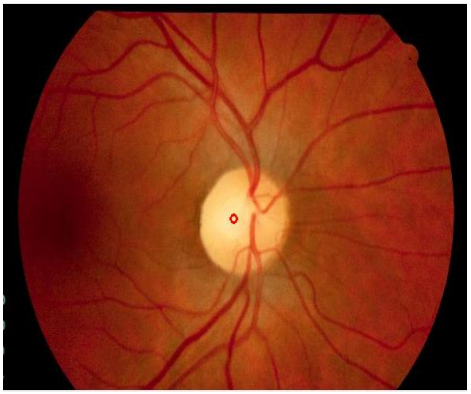

Fig -9: Optic Disc Center

The OD center is an exact bright pixel in a retinal image. So with the help of Kaiser Windowing technique all the rows and all the columns of the contrast adjusted image is filtered. This results in providing the maxima pixel location which is nothing but the OD center. The above fig -9 is showing the OD center.

A binary mask can be used to enhance specific regions of the retinal image. For example, if you are interested in enhancing blood vessels or exudates, you can create a binary mask that highlights these regions. By applying the mask to the original image, you can selectively enhance the desired features. The binary mask can be generated using techniques like thresholding, morphological operations, or machine learning-based segmentation algorithms. The following fig -10 is shows the Enhanced Retinal Image.

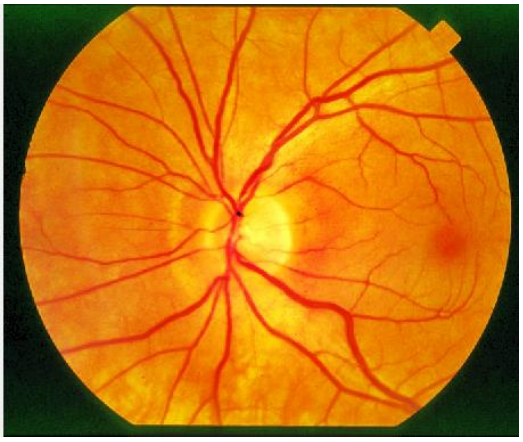

Fig -10: Enhanced Retinal Image

Fuzzy logic-based vessel segmentation is a common technique to identify blood vessels in retinal images. Fuzzy logic allows handling uncertainties and vagueness in the image data, making it suitable for retinal images with varying vessel sizes and intensities. The fuzzy logic-based vessel segmentation process typically involves defining membership functions and applying fuzzy rules to extract vessel pixels. MATLAB provides tools for implementing fuzzy logic-based systems. The following fig -11 is shows the Enhanced Retinal Image.

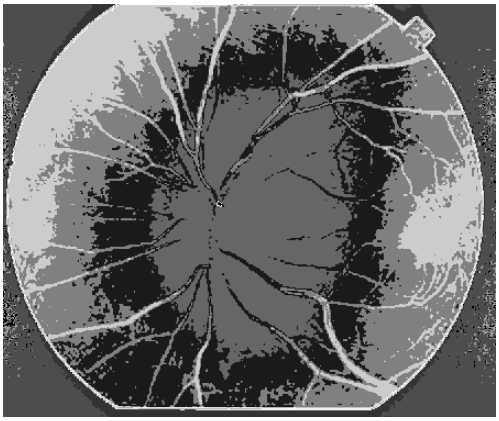

Fig -11: Vessel Segmentation

Morphological operations, such as dilation, erosion, and morphological gradient, can be used for exudate detection. Exudates often have distinct shapes and intensities compared to the background retinal tissue, making them amenable to morphological analysis. By applying appropriate morphological operations, you can highlight and detect exudates in the retinal image. The following fig -12 is shows the Enhanced Retinal Image.

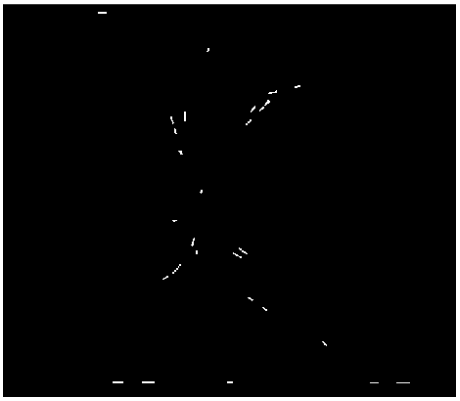

Fig -12: **Exudates**

A. Discussion

The mentioned image processing techniques are commonly used in the analysis of retinal fundus images for various applications, including diabetic retinopathy screening, glaucoma detection, and retinal vessel analysis.

Converting the image to grayscale simplifies further processing steps and reduces computational overhead.

CLAHE helps improve the visibility of subtle details and structures in the retinal image, which is crucial for accurate analysis and diagnosis.

The use of binary masks allows targeted enhancement or segmentation of specific features of interest, such as blood vessels and exudates.

Fuzzy logic-based vessel segmentation is beneficial in handling the variations in vessel appearance and reducing false positives.

Morphological operations for exudate detection can help identify regions of interest for further analysis and potential medical intervention.

It's essential to evaluate the performance of each processing step and fine-tune the parameters to achieve optimal results. Additionally, validation against ground-truth annotations by experts is necessary to ensure the accuracy and reliability of the algorithms. Retinal image processing is an active research area, and advancements in machine learning and deep learning have also led to promising results in automated analysis and diagnosis.

4. CONCLUSION

The proposed system is implementing the retinal image processing technique where the fundus image is indulged with the process of Segmentation of Vessels, OD and Exudates. The Retinal fundus image is undergone with the preprocessing technique and the Green channel image is enhanced in terms of intensity. The complex structure of fundus image is identified and segmented with the help of fuzzy based work where the OD center point is detected with the help of Kaiser Window technique.

It is demonstrated that the combination of these image processing techniques can effectively improve the quality of low-quality retinal fundus images. The conversion to the green channel image proved beneficial in enhancing the visibility of blood vessels, enabling more accurate vessel segmentation. The CLAHE contrast enhancement helped reveal finer details and structures, which are crucial for reliable diagnostic interpretations. The use of binary masks allowed us to focus on specific regions of interest, enhancing the visualization of important features like blood vessels and exudates. The fuzzy logic-based vessel segmentation exhibited better adaptability to variations in vessel appearance, enhancing the precision of vessel identification. Lastly, the morphological operations for exudate detection successfully highlighted potential abnormalities, aiding in the early detection and monitoring of retinal diseases.

Overall, the results of our study indicate that the proposed image processing pipeline can significantly improve the quality of low-quality retinal fundus images, potentially leading to more accurate and reliable diagnoses.

5. FUTURE WORK

Despite the promising outcomes of this research, there are still avenues for further improvement and exploration. Some potential directions for future work include:

Deep Learning Approaches: Investigate the use of convolutional neural networks (CNNs) and other deep learning

architectures for retinal image enhancement, vessel segmentation, and exudate detection. Deep learning models have shown impressive performance in various medical imaging tasks and may offer more robust and automated solutions.

Large-scale Evaluation: Validate the proposed pipeline on a larger and more diverse dataset to assess its generalizability and performance across different retinal pathologies and image qualities.

Multi-Modal Fusion: Explore the integration of data from different imaging modalities, such as optical coherence tomography (OCT) or fluorescein angiography, to improve the overall retinal analysis and enhance disease detection capabilities.

Real-Time Implementation: Focus on optimizing the processing pipeline for real-time or near-real-time applications to support clinical decision-making and telemedicine.

Clinical Validation: Collaborate with ophthalmologists and other medical experts to perform a thorough clinical validation of the proposed pipeline's effectiveness in diagnosing and monitoring retinal diseases.

User-Friendly Interface: Develop a user-friendly interface that allows clinicians to interact with and adjust parameters in the processing pipeline based on specific patient needs and pathologies.

Automated Lesion Quantification: Investigate methods for automatically quantifying the severity and extent of retinal lesions, providing valuable information for disease progression monitoring.

By addressing these areas of future work, we can further enhance the efficiency and accuracy of retinal image processing, making a positive impact on patient care and the early detection of sight-threatening conditions.

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