Diabetic Retinopathy Detection Using Automated Segmentation Techniques

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***Abstract*— This paper contains a brief discussion about Diabetic Retinopathy. As the name indicates, it's a medical complication present in diabetic patients which affects the retina, which is an essential part of the eye. Diabetic Retinopathy acronymed as DR is a medical circumstance where the high glucose levels in the blood start affecting the blood vessels in the retina. This in turn can lead to blockage, or leakage in the vessels or even initiate the growth of new blood vessels. It is a medical condition that cannot be easily identified at the early stages. To detect the DR there are two types of methods Invasive and Non-invasive Methods. The paper discusses the non-invasive technical method to detect diabetic retinopathy involving various algorithms in every phase of the process. The input fundus images are taken from STARE Database. The methodology conveyed in this paper involves contrast-limited adaptive histogram equalization for noise cancellation purposes and enhancing the base contrast of the image. By consistent distribution of gray values, it will improve the image and aids in bringing out the hidden components. The optimization stage consists of 2 steps and the first step consists of the Fuzzy C-Means clustering primarily to find the coarse vessels present in the retina. Additionally, the Region-based active contour is used to select the region of interest which is to highlight the blood vessels. As a result, The output image would convey the segmented retinal blood vessels with high accuracy as compared to any other algorithms due to the combination of both the algorithms (Fuzzy-C and Region based active contour). Our proposed segmentation method extracts the blood vessels accurately, resulting in the similarity measure value of 85%. Furthermore, these segmented retinal blood vessels are given as the input to CNN classifiers in order to detect Diabetic Retinopathy. For our proposed method, an overall accuracy to detect DR was 92%. This methodology can be used for mass screening processes in the field of ophthalmology.**

***Index Terms*—Diabetic Retinopathy, CLAHE, Segmentation, Fuzzy C Means, Region based active contour, retinal images.**

1. INTRODUCTION

Human eyes are commonly known as the organ of vision. It's the organ that initially detects light and transfers the signals through the optic nerves to the brain in order to perceive the visionary image**.** Eyes are an essential part of the human body as a common fact. It's also a highly sensitive organ, with 23 neurons that transform light into electrochemical impulses. Sclera, Iris, Cornea, Pupil, Lens, Ciliary Body and Muscle, Conjunctiva, Retina, Vitreous Body, Optic Nerve, Macula, and Retinal Blood Vessels are the components of the eyes. These are the essential and common parts of the eyes and can be further segmented if each organ is studied specifically. As it is known that the human body is an interconnected system that is connected and functions by relying on other organs, the same it's an exclusive feature that the nerves in the eyes are to other organs of the body as well. The retina is a fragile portion of the eye that is located in the base of the eye and is the innermost, light-sensitive layer. The retina's job is to give the sharp, center vision needed for tasks like reading, driving, and anything else that requires minute concentration.

The world is evolving towards something new on a daily basis, leading to advancements in every sector be it technical, business or even the overall life style of human beings. Along with these advancements, an essential sector with regular advancements is the medical sector. There are researches, inventions and discoveries of new medical circumstances often. As a result, the medical world and advanced technology work hand-in-hand to resolve problems in an effective manner. The same way diabetes is a medical condition wherein the sugar levels present in the blood are higher than required. It is a disease that can be found in human beings of all ages certainly, including new born babies.

Diabetes is further 48 divided into Prediabetes, Type 1 Diabetes, and Type 2 Diabetes. Prediabetes is a phase wherein the glucose present in the blood is slightly higher than the amount needed. Classification of Type 1 diabetes is as production of minute or nill amount of insulin by pancreas. When the body's ability to metabolize, blood sugar is hampered by excessive amounts of glucose, Type 2 Diabetes develops. Patients with diabetes commonly face other problems like foot ulcers, cardiovascular complications, gum diseases, fatigue, stroke, nerve damage, chest pain, vision complications. DiabeticRetinopathy is a familiar stage of diabetes. It is a medical disorder in which excessive blood sugar levels impact the eyes in a number of ways. And one such And one such condition is Diabetic Retinopathy also known as DR. It is a medical condition wherein high blood sugar levels begin to harm the blood vessels in the eyes, creating serious problems. The most prevalent concerns that individuals with Diabetic Retinopathy may have include vessel obstruction or leakage, as well as the initiation of new blood vessel growth in the Retina. When one end of a blood vessel becomes clogged due to excessive sugar levels, a blockage occurs. And this further tends to lead to the next complication of leakages of the blood vessels when there is continuous supply of blood to the vessel and when there is a blockage, the blood cannot be present within the closed space, hence leading to the leakage of blood as a result of the pressure. Sometimes there can even be new blood vessels formed. In the short or long run, these conditions may result in various issues like blurred vision, impaired color vision, eye floaters, etc., which restricts vision, poor night vision, dark or empty spots in vision.

There are 4 stages in Diabetic Retinopathy, and they are:
Stage 1- Mild Nonproliferative Retinopathy: In this stage, microaneurysms start to show up. Microaneurysm is the swelling of blood vessels located in the retina. The blood vessels are in the initial stage of bulging at this point of time.
Stage 2- Moderate Nonproliferative Retinopathy: The swelling of the blood vessels starts to increase. This further starts to severely affect the blood flow in the retina. And this also prevents the proper nourishment required in the eyes.
Stage 3- Severe Non-proliferative Retinopathy: In this stage the blockages in the blood vessels start taking place in large amounts. This significantly reduces the amount of blood flow in the thin areas.
Stage 4- Proliferative Retinopathy: This is the critical stage where the birth of new blood vessels occur, causing severe complications in the delicate areas.

These four stages of DR have their own complications and treatments for cure but this can be done only if the problem can be detected accurately. In order to prevent all these complications, it is advised for all the patients with diabetes Type 1 and Type 2 to take a DR test. Nevertheless, not every patient agrees to do so as there are various factors involved in taking the DR test medically. The medical DR tests are extremely time consuming, they require the physical contact in the eyes which is a method prone to infections if done without proper sanitization, and they are also high in cost. That is why there are various technical methods proposed and carried out with computational algorithms to detect DR. The engineers' methods so far are extremely time effective so that treatment can be started out in an early stage. They are non-invasive, meaning there is no physical contact required so safety is always insured. And finally, they are also cost effective. Another added advantage of the engineer's methods is that the stages of DR can also be configured so that the diagnosis can be done accordingly.

The process of detecting DR will first be started out by first acquiring the retinal fundus image from the STARE Database. STARE stands for Structural Analysis of the Retina. The pre-processing will be done through the CLAHE algorithm. This algorithm is utilized to improve the image's contrast level and for noise cancellation characteristics. As a result, the image is additionally enhanced so that the unseen features are also visible. Then the optimization stage takes place in two steps. The first stage of optimization includes the involvement of Fuzzy-C Means clustering to specifically spot the coarse vessels present in the retina. Later the region of interest is selected utilizing the region based active contour algorithm for better quality and higher accuracy levels of the blood vessels that exist in the particular image. Now the output image will show the segmented retinal blood vessels which will be sent as an input image through the CNN classifier and this is where the presence of diabetic retinopathy is observed, reviewed and confirmed.

2. RELATED WORKS

Using robust hybrid features Aslani [1] demonstrated a new supervised retinal vessel segmentation method They took the hybrid feature vector to merge the supporting complementary local data. There are thirteen Gabor filter responses that make up the 17D feature vector used. It is also noteworthy that as the numbers are reduced, the accuracy also decreases. The proposed method tends to be designed and executed to achieve the highest average accuracy in the DRIVE and STARE datasets. Furthermore, the progress and scope of the development were discussed (Aslani, Haldun 1-12).

Azzopardi [2] discusses trainable COSFIRE filters for vascular description with attributes of retinal imaging. The dominant feature here is that the COSFIRE filter has been structured. B in this case means bar, which is a construction for a container. The implementation of the filter named COSFIRE depends on the approximate values of required parameters. Three records are used in this procedure, namely STARE, DRIVE and CHASE. It has been shown that the proposed methodology achieves significantly lower time efficiency compared to various methods used for segmentation. In addition to vessel segmentation, the expressed method can also be used to detect hidden features such as vessel branches and junctions (Azzopardi 46-57).

Christodoulidis[3] Multiscale Tensor Voting Framework (MTVF) is the reference for the methodology proposed in this paper. It is added up with multi-scale line detection to get rid of line detection limitations when managing smaller vessels. Although the proposed methodology has produced excellent results, there were some issues that needed to be explored and addressed. If the MTVF is attached to the false positive (FP) vessel-like structure of the main vasculature, the main vessel may be lost (Christodoulidis 28-43) .

Zhu[4] The document ultimately aims to improvise the standards of the segmented image. Using State-of-the-art technology they enhanced 39 discriminating feature vectors for fundus imaging. The binary retinal vessel segmentation is the acquired output by the classifier. As a result, the diagnosis of retinal diseases is difficult. Therefore, it is crucial to use the right image segmentation algorithms to accurately find all retinal blood vessels (Zhu 68-77).

Geetha[5] proposed his work based on the Principal component analysis (PCA) that was used to create the feature vector in this paper. Additionally, k-mean clustering is applied to this result to group the pixels into cup or non-cup groups. Vessel group classification improved accuracy but reduced sensitivity in some cases (GeethaRamani, Lakshmi 102-118).

Hassanien[6] In this article, the automated approach to segmentation is based on two-step optimization principles; retinal blood vessels were created. was demonstrated. The suggested method combines artificial bee colony optimization with a fitness function for fuzzy cluster compression with partial membership at first level and approximate vasculature at aggregation (Hassanien, Eid, Hossam 186-196).

Roy Chowdary[7] conducted the research based on blood vessel segmentation from fundus photographs by extracting major vessels and classifying sub-images. In this document, a set of eight features was introduced to distinguish between vascular and nonvascular pixels. The fine pixels of the vessels are found with both Gaussian and GMM classifiers. This technique assists in the automated segmentation of very fine ramifications necessary for the detection of retinal irregularities such as B. intraretinal microvascular anomalies (IRMA) or vascular droplets, are essential. The specified vessel segmentation method not only accurately maintains uniform vessel segmentation, but also confirms the removal of fine vessel branches. In the end, however, the algorithm turns out to be unreliable for the training data (Roychowdhury, Dara, Keshab 1118-1128).

Sil Kar [8] discussed this research study to track the numerous thresholds, they used their understanding of the maximum response of the matched filter and the fuzzy conditional entropy. And differential evolution calculations are used to find the ideal values. The primary goal of this research is extracting canisters by developing a cohesive system design platform by Using a sequential bandpass filter, followed by fuzzy-dependent entropy maximization on the matched filter responses of different ship types. The discussed procedure is also effective in removing the irregular and thin blood vessels in pathological retinal images (Kar, Santi 111-132).

Sreejini [9], this article discusses a PSO-based parameter that was introduced to determine the exact values of the multi-scale coordinated filter parameters. The results generated by the multiscale matching filter take precedence over the single scale matching filter for vessel segmentation. The results prove that the multi-scale combining filter performs better and more efficiently compared to the single-scale combining filter. Finally, vessel morphology can be introduced to improve vessel segmentation results and achieve better performance (Sreejini, Govindan 253-260).

Singh[10] this work analyzes the methodology for this particular experiment consisting of PCA or principal component analysis during the pre-processing phase. In the next stage, CLAHE is employed in order to improve the retinal picture. To obtain the segmented image, after running the proposed combined filter, the post-processing phases include optimal entropy-based threshold and length filtering. The results suggest that this method performs relatively well and efficiently compared to other prominent Gaussian distribution functions (Singh, Rajeev 40-50).

Saranya[11] The Convolution Neural Network (CNN) is the predominant methodology utilized to observe and classify the images according to the four phases of DR as it is capable of managing the pre-processing of images and normalization as well. The concept of filter is used to extract the appropriate features to categorize the DR. It has also been conveyed that the CNN along with the aid of Keras is capable of image handling and processing with higher flexibility. The CNN is a four-step process consisting of Convolution, Non-Linearity, Average Pooling, and Classification. The results have proved that the overall accuracy of the method has been relatively high. The various ways of development have been discussed in the paper along with the implementation of the CNN method in an advanced manner in the medical field of ophthalmology (Saranya, Uma 59-64).

Chaudhary[12] The proposed methodology contains the raw fundus images which are carried out for processing for sound reduction and further changed into gray image. Later the segmentation of the optic disc and the retinal nerves take place. The extracted features will be used for the classification. Post processing consists of erosion and dilation using a structuring element on the pre-processed images. The CNN and the Fuzzy classifier are used to identify the status of the image. This will confirm the presence of DR or a normal eye condition. The results convey that the CNN and Fuzzy classifier have been great algorithms in order to find out the stage of DR. In terms of accuracy, the CNN classifier has shown better results when compared to the Fuzzy Classifier (Chaudhary, Ramya).

Imran Qureshi[13], demonstrated the computer assisted diagnosis (CAD) systems for treating Diagnosis Retinopathy. It's a combined study on the effectiveness of the different methodologies used to detect DR. The segmentation and the method of extraction using the image combination, pre-processing, improvement and segmentation methods have been briefly explained in the paper. Also, the latest and recent trends in the deep learning methods for diabetic retinopathy have also been detailed in order to comprehend the current scenario better. Later even the survey results of the present DR based screening system has been elaborated and discussed. Furthermore, the articles with major challenges have been explained in terms of the respective methodology along with the possible solutions outlined. It is notable that even a comparison between the hand-crafted methods and deep features have been done. These were the traditional procedures to detect diabetic retinopathy. Overall, this research paper is a comparative study of the various methodologies present in practice to detect Diabetic Retinopathy while outlining the key features and challenges for each methodology (Qureshi, Jun, Qaisar). Solomon A

Akinboro[14] The project is carried out specifically to classify the stage of DR with the proposed approach. The methodology chosen is by first generating the digital fundus image through the convolution neural network CNN and 3662 datasets. The CNN model is built with the Keras infused. There are two independent variants tested in this project. The first independent variable is the separation of the fundus images as binary and categorized data sets. The next independent variable took place in the pre-processing stage where one set of fundus images are pre-processed through CLAHE algorithm web whereas the other set of data is not. The overall results of the comparative experiment have been discussed in detail along with numerical for better clarity. The challenges faced have also been explained in order to understand the drawbacks and work towards accuracy and precision.

S.Prabha[15][16] did the research work on threshold based on an iterative algorithm that has been implemented in the research paper focusing on the accuracy of the segmented images. The proposed methodology is made up of feature extraction, followed by image segmentation, image pre-processing, and finally the classification based on CNN classifier which provides the results of whether DR is present. The proposed methodology is designed in such a way to detect diabetic retinopathy in an earlier stage in order to take appropriate diagnosis. Accuracy, precision, specificity, and the sensitivity rates of this proposed system stays above 85% in all the four aspects. The overall procedure focuses on maintaining the accuracy rates of the results and every algorithm chosen, carefully aids to it.

3. PROPOSED WORK

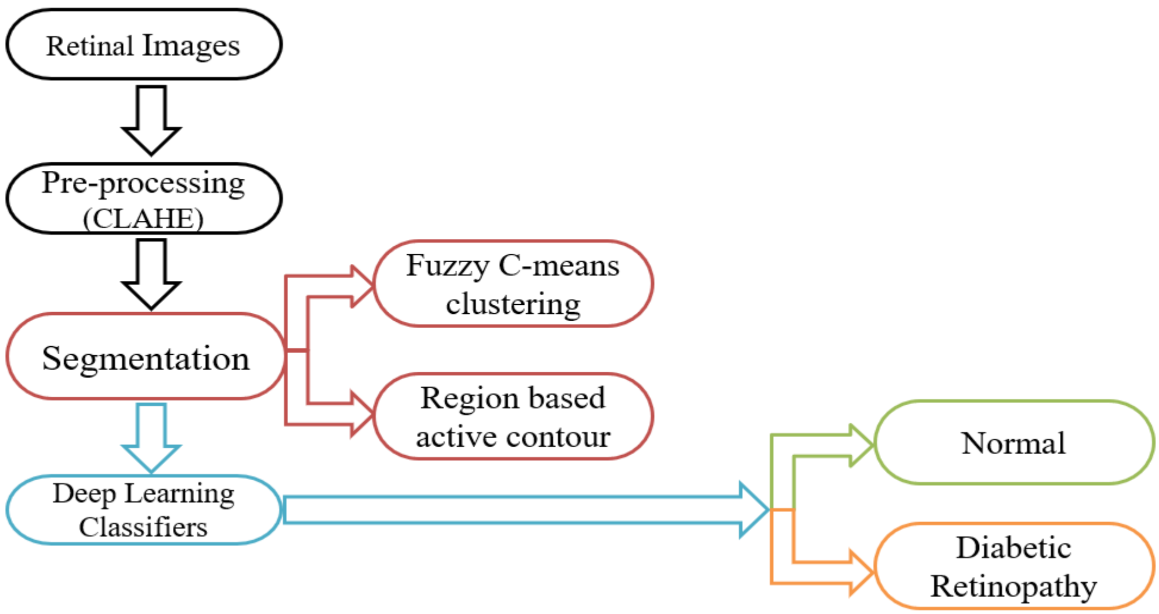


Figure 1

The innovative technique flows through the following six phases.

1. The proposed method uses a fundus camera as an input image (STARE database).
2. For the first step of preprocessing, the input image is transformed to the green channel. The picture is then subjected to CLAHE to boost the image's local contrast.
3. Fuzzy C-Means(FCM) is utilized to detect the coarse vasculature during the segmentation phase.
4. The region based active contour method is used to select the region of interest & aids in highlighting the blood vessels.
5. The segmented retinal blood vessels are seen in the output image.
6. The segmented image is given as an input image to the deep learning classifier to find whether the respected image is affected with DR or NOT.

Resulted in the creation of the Designed analysis of the Retina database (STARE). The STARE database photos were taken using a 35 degree narrow field view camera and have a resolution of 700*605 pixels. Retinal imaging is a frequent procedure performed during an eye examination. To the posterior inferior surface of the eyeball in order to see the pupil of the eye an optical camera is assisted . The retinal layer, the optic nerve, the fovea, and the surrounding arteries are all imaged. The ophthalmologist can then use this image as a reference point for evaluating any findings or to examine the eye condition.

AHE (adaptive histogram) is a computer image processing approach for enhancing image contrast. Traditional histogram equalization differs from the adaptive technique.It's designed to build a number of histograms, each corresponding to a different portion of the image, and then use them to disperse the image's brightness values. This makes it great for increasing local contrast and sharpening edge sharpness in different areas of a photo. AHE also tends to exaggerate noise in relatively similar areas of an image. By limiting gain, a variant of AHE known as CLAHE was developed to minimize or prevent noise. Microaneurysm pixels were enhanced with the CLAHE filter. The CLAHE filter produces adequate vein enhancement while removing excess noise. Other global enhancement methods such as traditional contrast stretching and universal histogram equalization work less efficiently compared to the CLAHE filter. The use of an independent elemental analysis is the second way to increase the contrast of the veins. Various image enhancement techniques have been added in recent research at the pre-processing stage, including grayscale conversion of image, spectrum normalization, brightness enhancement using CLAHE, and gamma modification to improve overall appearance. The CLAHE histogram has been clipped to a standard clipping value to avoid excessive contrast enhancement that could result in an image with an odd appearance and unwanted detail. Also, incorrect approaches to implementing contrast enhancement could result in poor appearance in missing areas, such as small veins lead. By summing up a global threshold to the fixed point of contrast the above consequence could be solved. Edge detection is a technique for detecting frequent changes in pixel values. The brightness level of neighboring pixels is used to examine the edge information of a given target pixel. Without a clear difference in brightness, there can be no image edge.

The FCM (Fuzzy C-Means) clustering technique allows a single data item to be assigned to two or more clusters. Pattern Recognition also runs on the basis of the above Strategy. This algorithm assigns the link to each data point corresponding to each group center based on the distance between the group and the data point. The closer the data is to the cluster center, the more likely it is to belong to that cluster center. The iterative unsupervised Fuzzy C Means (FCM) method is the most extensively used clustering technique for picture segmentation. Pattern recognition and clustering are used to analyze and segment most medical images. Compared to the k-Means algorithm, fuzzy C-mean clustering is considered a better option. The fuzzy C-means algorithm, unlike the k-means technique, which requires data points to belong to only one group, allows data points to belong to many groups with probability.

The fuzzy C means that the clustering process starts first by outputting the input image first. Then the size of the image is retrieved. The possible range is then calculated. In addition, the possible number of iterations is identified. Then the given dimension of the images is calculated. Then the iteration begins. When the maximum number of iterations is reached, the procedure is repeated, and the picture is submitted for iteration once more until the maximum number of iterations is achieved. This is the complete procedure of the fuzzy pooling process C.

Active Contouring is a Segmentation approach that separates relevant pixels from an image for further processing and analysis using forces and power constraints. An active contour is a model used in the segmentation process. Contours are the lines that define the area of interest in an image. There's a need of converting segmented images into multiple similar images to get represented in the region-based technique. The basic idea behind active contour models, sometimes referred to as snakes, is to generate a curve to group objects in a given image while constrained by these constraints. The curve approaches its interior normal and must end at the edge of the object. In classic active snake and contour models, To come to a halt, an edge detector employs the curve evolution at the boundary of the target element based on the gradient of the image. The following steps are used to evacuate the papilla: i. To capture the retinal image mask, first select the underlying raw, apply the region-based active contour to the segmented image mask. I. The mask from the input picture is removed, resulting in a new mask. ii. The segmented image without a mask is the result of subtracting the new mask from the previous one.

The Structural Similarity Indexing Method (SSIM) is a tool that compares the structural similarity of two photographs. If the second image is of perfect quality, the SSIM index can be regarded as a quality indication for one of the photos under consideration. It is an improved version of the first proposed Global Image Quality Index. The SSIM tool is used in this case to compare the actual terrain image with the segmented image. The relevant output image for the fundus image retrieved from the STARE database is the actual image of the floor. And the segmented image is the starting picture that is received after the CNN after the final processing of the image. The SSIM tool will be used to compare the differences present in the ground truth image and the segmented image which will prove the accuracy and the efficiency of the methodology. Keras was used to build and compile the Convolutional Neural Network (CNN) models. Except for their last layer, both models have the same architecture; the first model, which was used to classify the severity of DR, has 5 outputs, while the other model, which was used to identify DR, has 2. The models are divided into four stages:

i. Input

ii. Feature Learning

iii.Classification

iv. Output

The retinal fundus image is the CNN model's input, which was read by the computer as a matrix of 64 * 64 * 3 pixels, that represents the height, width, and dimension. The RGB values are represented by the three dimensions of the images. The input phase's outcome is subsequently passed on to the feature learning phase. The input image is passed through a series of convolution layers with filters in the feature learning phase, and the model extracts and learns features about the images. The extracted features are then forwarded to the classification phase, in which the image is categorized with probabilistic values 26 between 0 and 1. The pre-processed image is fed into the input layers, which produce an array of pixels as output, which is then transferred to the first convolution layer. The link between/among of the pixels exists by learning visual attributes of minute squares and convolutions. The first convolution layer uses a 64 * 64 * 3 picture as input and produces an output of 62 * 62 * 128 feature map with relu activation.

The output was fed into the second convolution layer as input. The second convolution layer, which likewise uses a (3 * 3) filter matrix with relu activation, produced a (60 * 60 * 128) output that was transferred to the pooling layer. By picking the largest element from the feature map, the max pooling layer minimizes the feature map's dimensionality, producing an output of size (30 * 30 * 128) and passing it to the dropout layer. Over fitting was reduced by using the dropout layer. During the training, it switches off some neurons randomly. The output of the dropout is flattened using a flatten layer, which transforms the entire feature map into a single column of size (115200). The dense layer contains densely linked neurons and gets input from the prior layer's neurons. To reduce overfitting, a dropout layer was added between the two thick layers. The last dense layer employed the SoftMax activation function to assign probabilistic values between 0 and 1 to each class in the image.

4. RESULTS OBTAINED

Normal Images: The normal images refer to the pictures of healthy eyes received from the STARE database. These images do not contain or have the symptoms of DR. The retina will be clear in this image with normal and regular functioning blood vessels without any complications or abnormalities. Images considered to be normal will provide the image of the healthy retina when the image is fully processed.

Abnormal Images: Abnormalities refer to images that contain Diabetic Retinopathy. These images will commonly show up as abnormalities while retrieving from the STARE database. The images classified as abnormalities will contain the image of the affected retina where the blood vessels may have blockages or leakages. In other cases, there might also be new blood vessels formed or growing depending on the severity of the stage.

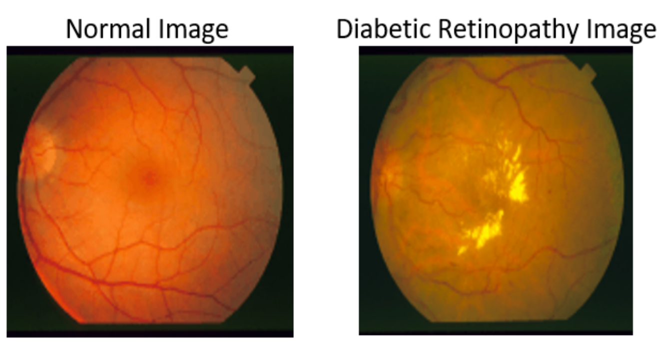


Figure.2 Describes the Normal and the Diabetic Retinopathy Image.

CLAHE Images:
As we know that having the perfect contrast to an image will give the best results. To obtain best results we are using Contrast Limited adaptive histogram equalization, The contrast to an image shouldn't be low meanwhile it shouldn't be high. So, it should be in the limit. To maintain that certain contrast limit to an image we are using CLAHE.

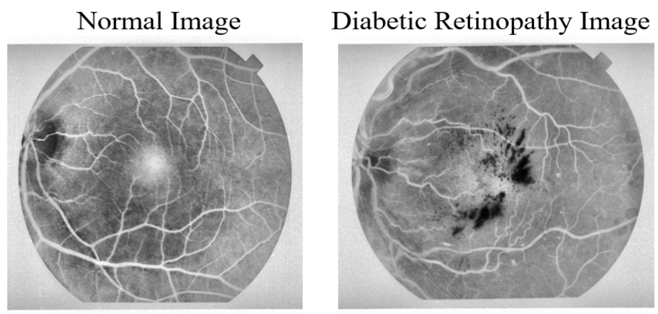


Figure 3 Describes the Normal and the Diabetic Retinopathy Image after preprocessing.

Here, by using the CLAHE we can clearly observe the Blood vessels in the image compared to the input image.

Segmented images:

Segmented images are the images received after the raw fundus image goes through the whole segmentation process. This is the image that will be received from the Segmentation process. The image of the blood vessels present in the retina can be seen in this image. The segmented image can also be considered as the proof for the presence of Diabetic Retinopathy for the particular processed image.

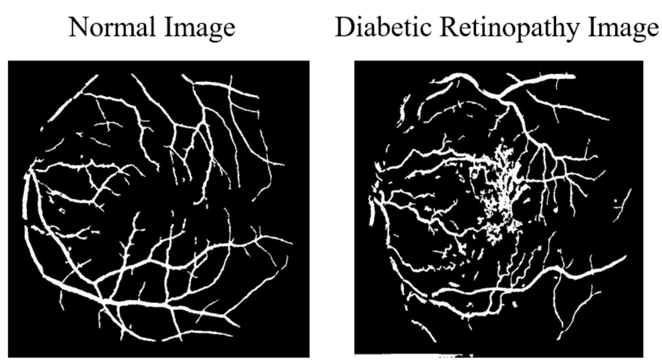


Figure 4 Describes the Normal and the Diabetic Retinopathy Image after segmentation.

Ground truth Image:

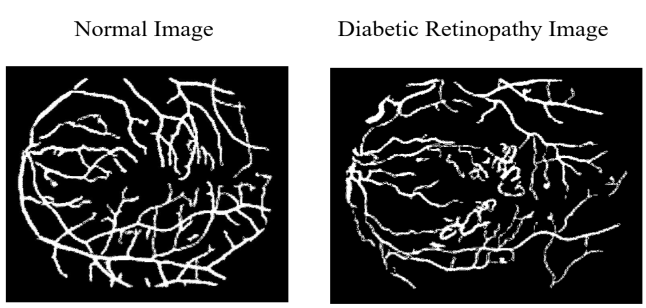


Figure 5 Describes the Normal and the Diabetic Retinopathy Image of ground truth images.

These images are the segmented Outputs of the STARE project. Ground truth is data that’s famed to be real or true, provided by direct observation and measurement.

SSIM:

SSIM stands for structural similarity index measure. The Structural Similarities Indexing Method (SSIM) is a technique for assessing structural similarity between two photographs. If one of the photos being compared is of perfect quality, the SSIM index can be considered as a quality indicator for that image. It's an improved version of the global picture quality index that was first suggested. In the present scenario the SSIM tool will be used to compare the ground truth image and the segmented image. The ground truth image is the respective output image for the fundus image that is retrieved from the STARE Database. And the segmented image is the output image received from the CNN after the final processing of the image. The SSIM tool will be used to compare the differences present in the ground truth image and the segmented image which will prove the accuracy and the efficiency of the methodology.

Our proposed segmentation method extracts the blood vessels of each image accurately, resulting in the similarity measure value of 85%. The primary reason for the high accuracy rates is the combination of the Fuzzy C-means clustering and the Region based active contour algorithms.

Classification:

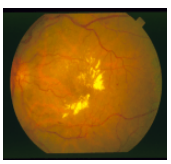
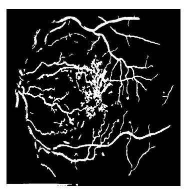
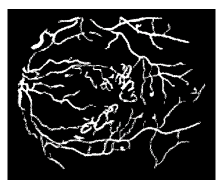
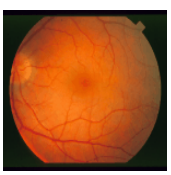
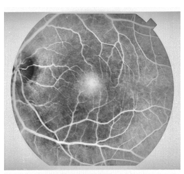
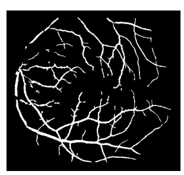
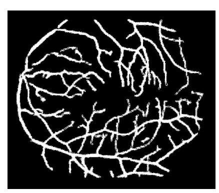
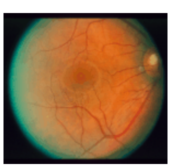
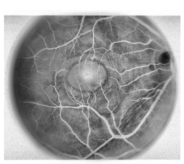
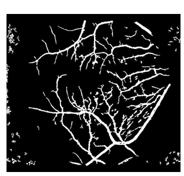
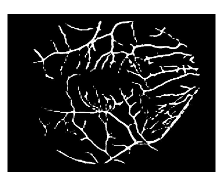
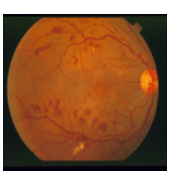
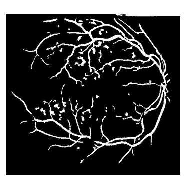
S.No	**Input Image**	**CLAHE Image**	**Segmented Image**	**Groundtruth Image**	**Accuracy**	**Classification**
1					0.96	Affecting with Diabetic Retinopathy
2					0.93	Not Affecting with Diabetic Retinopathy
3					0.92	Not Affecting with Diabetic Retinopathy
4					0.95	Affecting with Diabetic Retinopathy

Table 1

The output images are the segmented images. Those segmented images are given as the input images to the CNN classifier to classify whether the image is affected with diabetic retinopathy or not.
Total we have 88 segmented images. All these 88 images are divided into two stages, one is training dataset and another stage is testing dataset. In that 88 images, 67 images are given to train the classifier and the remaining 21 images are given to test the classifier. Each stage is divided into 2 classes, class0 and class1. Class0 represents the normal segmented images which are not affected with Diabetic retinopathy. Class1 represents the segmented images affected with diabetic retinopathy.

The classifier will undergo the classification process with the help of training dataset and testing dataset to provide the accurate result. For our proposed method, an overall accuracy to detect DR was 92%.

Performance Measure

The performance measure of our proposed method includes sensitivity, specificity and accuracy are shown in the figure.6. The primary reason for the high accuracy rates is the combination of the Fuzzy C-means clustering and the Region based active contour algorithms along with CNN classifier. The visual representation of the performance measure has been provided in figure 6.

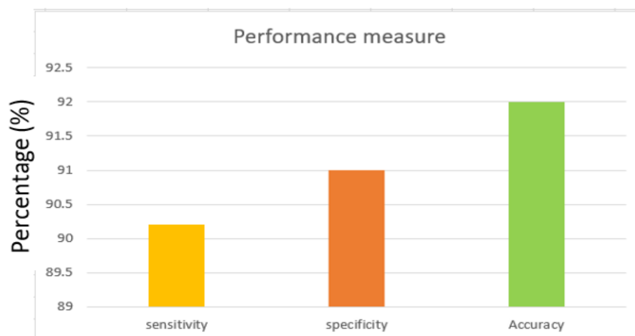


Figure.6 Shows the Performance Measure

5. CONCLUSION

In order to determine the severity level of DR, it is critical to accurately identify the retinal blood vessels during the ophthalmological examination. Many algorithms aren't capable of differentiating the depigmented abnormal retinal images from the retinal blood vessels. The research findings have emerged from each of the STARE database's 88 photos. The results indicate that the proposed methodology consisting of FCM clustering along with Region based active contour accurately identifies all the blood vessels. Both these algorithms aid in increasing the accuracy rate of the segmented blood vessels. There are no discontinuities between the minor vessels and they are also identified in this process.

CLAHE minimizes the level of noise in depigmented retinal images. By examining the segmented vessel structure through the proposed method, it is evident that it is capable of minimizing the ophthalmologists' effort in analyzing the diabetic retinopathy affected blood vessels. The proposed retinal blood vessels segmentation approaches can be used for datasets with similar attributes. Our proposed segmentation method extracts the blood vessels of each image accurately, resulting in the similarity measure value of 85%. For our proposed method, an overall accuracy to detect DR was 92%.

6. FUTURE SCOPE

In the long-run, the proposed methodology can be implemented in the field of ophthalmology for retinal screening if it is further developed. There is still room for advancements in the present procedure wherein there can be progressive algorithms designed to be involved in order to classify the stage of Diabetic Retinopathy. If this advancement is added in this methodology, it will be a procedure that will specifically convey the stage of DR the patient is currently in so that appropriate diagnosis or treatment can be started at the earliest. Once the methodology is developed with the classification, the procedure can be implemented for ophthalmological campaigns carried out especially in rural areas. As the method discussed is time efficient, it can be introduced in campaigns and other screening areas as the retinal examination can be done in a short span of time and the results can also be retrieved soon.

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