Gaussian Kernel Prompted Fuzzy C Means Algorithm with Multi-Object Contouring Method for Segmenting NPDR Features in Diabetic Retinopathy Fundus Images

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Keywords: non-proliferative diabetic retinopathy, minima transform technique, gaussian kernel, fuzzy c means, multi-class contour tracking algorithm.

I. Introduction

Diabetes mellitus ordinarily referred as diabetes is a protracted disease that occurs when the pancreas is no longer able to create insulin, so the glucose in the blood is not properly transferred into cells which leads to high blood glucose. The prolonged high blood glucose levels in human body causes several complications such as blindness, kidney failure, amputations, heart failure, stroke etc. But among these conditions blindness due to diabetes is considered as a major issue as the eyes are the most essential organs of our body. The health of the human eye is as important as any other...
body organ but the care taken for this organ is emphasized very less in healthcare. There is no common awareness among people about the related complications like blindness caused due to diabetes. For instance, if people get blurry vision, they go for computerized eye test and wear specs considering it as normal eye sight problem but not aware of the fact that it is caused due to any internal disease like diabetes.

According to the Global statistics countersigned by World Health Organization (WHO) [1] among 7.9 Billion of current population about 285.3 million people are visually impaired, out of which 246 million have low vision and 39.3 million are blind. The reasons of blindness include glaucoma (12.3 percent), age-related macular degeneration (8.7 percent), diabetic retinopathy (4.8 percent), childhood blindness (3.9 percent) and trachoma (3.6 percent). Among these eye problems the one which harms the retina part of eyes due to diabetes is referred as Diabetic Retinopathy (DR) [2]. There are numerous eye retinal disorders but the most serious causes which doctors see in retina are hypertension (High blood pressure level) and diabetes (high blood sugar level).

To be more precise, complication in retina due to high blood glucose level is more critical since they are symptomless. As per the review given by ophthalmology studies, the clinical and experimental evidence suggests that diabetic retinopathy and associated vision loss have several debilitating effects, including disruption of family functioning, relationships and roles; and deterioration of work prospects resulting in increased financial strain [3].

The retinal disorder due to tenacious high blood glucose levels famishes the small blood vessels within the retina due to improper supply of oxygen. Hence this distortion to the retinal part of human eyes due to diabetes is called as “Diabetic Retinopathy” which results in cloudy or blurred vision, and it is caused possibly among people with all types of diabetes such as type 1, type 2 and gestational. This complication results in visual impairment and even leads to blindness if undiagnosed and untreated.

There are two types of Diabetic Retinopathy [4] namely Non-proliferative Diabetic retinopathy (NPDR) and proliferative Diabetic retinopathy (PDR). The first type of DR disease is called as Non-Proliferative Diabetic Retinopathy [5] which is the earlier stage that weakens the walls of the blood vessels in retina consequently the frail retinal blood vessels begins to dilate and become irregular in diameter that leads to partial retinal mutilation. And this type can progress from mild to severe stage, as more blood vessels become leaky then retina begin to deteriorate which leads to the advanced stage of Diabetic Retinopathy known as the second type of DR namely Proliferative Diabetic Retinopathy. It refers to the formation of new, abnormal blood vessels in the retina and these fragile new vessels often bleed, if it bleeds a little, a few dark floaters are seen and if it bleeds a lot, it might block all vision, at a point it can spoil both the central and peripheral (side) vision of the eyes.

Detection of the disease in its earlier stage can reduce the risk of disease severity by 100%. This study detects the earlier stage of DR called Non-Proliferative Diabetic Retinopathy that causes different types of illness in the eye such as Microaneurysms (MA), Intraretinal Haemorrhages (IHM) and Hard Exudates (HEXU). The microaneurysm are tiny swellings that protrude from the blood vessel which is the first sign of the NPDR type that appear as small red dots and it is a localized capillary dilatations which are usually saccular (round)[6].

The intra retinal haemorrhages leaks blood into the retina which is the second sign of the NPDR type, it is a ‘dot’ or ‘blot’ or ‘flame’ shaped depending upon their depth within the retina. There are two layers of capillary network in the posterior
retina called nerve fibre layer and inner nuclear layer. Haemorrhage that occurs in the nerve fibre layer tends to be flame shaped. In the inner layer, haemorrhages appear dot or blot shaped, aligned at right angles to the retinal surface which is consequently viewed using an ophthalmoscope; these. The clinical differentiation between dot haemorrhages and microaneurysms is difficult and of little consequence since both are occurrences of background retinopathy[7].

The hard exudates are the protein fluid that oozed out from the blood vessel which is the third sign of the NPDR type and it forms a distinct yellow-white intraretinal deposit which varies from small specks to larger patches and that may evolve into rings known as circinates. Ultimately large confluent plaques can form. Hard exudates are extracellular lipid which leaks from abnormal retinal capillaries and the underlying problem is that it is formed as a ring pattern around the leaking vessels. Hard exudates are primarily found in the macular region and as the lipids coalesce and extend into the central macula, vision can be severely affected[8].

So there is a necessity of an efficient system to discriminate and detect the affected regions with higher accuracy in order to assist the experts for diagnosing the disease severity earlier. In associate to detect the NPDR features from the fundus image, certain Non - Diabetic Retinopathy (Non-DR) features in the retinal fundus images has to be detected and removed for betterment of lesion identification. The Non-DR features are Blood vessels (BV), Optic disc (OD) and Fovea (FV) to be removed because the blood vessels and fovea features appears dark in color so it falls in mismatch with the NPDR features like microaneurysms and haemorrhages and the optic disc is the bright feature which falls in mismatch with the bright feature called exudates.

The retinal blood vessels are the central retinal artery and vein, and their branches which provide and drain blood to and from the eye[9]. The optic disc is the entry point for the major blood vessels that are supplied to the retina. It is a vertical oval, with average dimensions of 1.76mm horizontally by 1.92mm vertically and placed at 3 to 4 mm to the nasal side of the fovea part of the eye[10]. The fovea is a tiny pit located in the macula of the retina that provides the clearest vision of all and it is literally a small depression in the retina. The fovea is a dark region in the eye that normally lies in a fixed orientation and location relative to the optic disc. In fovea, the layers of the retina spread aside to allow the light fall directly on the cones that give the sharpest vision. So it is also called as the central fovea or fovea centralis[11].

In general, DR is assessed with single-field non-mydriatic fundus photography and graded according to the International Clinical Diabetic Retinopathy Disease Severity Scale ‘HbA1c’[12]. HbA1c is glycated hemoglobin measured by standardized test using high performance liquid chromatography. If higher the HbA1c value then greater the risk of diabetes-related complications. The optimal HbA1c cutoff for detecting diabetic retinopathy is 49mmol/mol (6.6%) for mild and is 52mmol/mol ((6.9%) for moderate or severe. This grading is done twice in a year to detect the disease severity. And this conventional eye exam is done manually which becomes a huge and complicated task as the number of patients suffering with the disease is increasing rapidly. Hence considering the importance of the disease severity and the complexity of manual grading method, an emphasized screening system has to be developed with integrated and hybrid methods for accomplishing efficient and accurate diagnosis of the disease.

This paper work detects the first type of Diabetic Retinopathy (DR) disease called Non Proliferative Diabetic Retinopathy (NPDR) with its features from retinal
fundus images. The task is very challenging because detecting the disease signs in the image includes major issues like noise (illumination or contrast) present in the image and also the variability in size, color, texture and shape of the ROIs. Prior to NPDR feature detection certain unwanted background features has to be removed to make the detection process more accurate. The aim of this study is to identify an appropriate segmentation method with better performance and to overcome the limitations mentioned earlier. The PCI, PEI, DSC measures of the proposed method were compared with the existing works on two online databases namely DIARETDB0 and DIARETDB1 [13]. The novelty of this work is that it is compared with the performance of different kernel induced fuzzy algorithms for segmenting the NPDR features in the Diabetic Retinopathy fundus images.

The GK_FCM algorithm incorporates Gaussian Kernel function in conventional FCM to achieve the objective of this work. Initially the input image undergoes preprocessing with green channel extraction and median filtering then background subtraction using extended minima transform technique, mathematical arithmetic operation, pixel replacement method to eliminate the outlier called Fovea. Further it is segmented for extracting NPDR features such as Microaneurysms (MAs), Intraretinal Haemorrhages (IHMs) and Hard Exudates (HEXUs) by integrating Gaussian kernel with FCM on applying multiple parameters. The segmented features are super imposed in the original input image using multi-class contour tracking algorithm with different contouring measures as a post processing operation.

II. Literature Review

Sasikala et al [14] have proposed a novel medical image segmentation technique using optimal threshold Reaction-Diffusion Active Contour model (RD-ACM) to identify the Attention Deficit Hyperactive Disorder and cervical cancer affected areas. In this method, the acquired input images are segmented using Thresholding, the connected components with label matrix algorithm, Heaviside and Dirac delta function, Level set evolution - Two step splitting method. The proposed method shows very good segmentation results. But the proposed RD-ACM gives better results for brain images when compared to cervical cytology images. So it has been found that RD – ACM method can play a vital role in segmenting the regions of the brain images.

Sasikala et al [15] has presented a review on various segmentation techniques used on haemorrhage images of both MRI and CT of brain and analyzed the classification performance of various existing algorithms. Initially Preprocessing techniques are used to denoise the image and various clustering techniques are applied to clearly portray the existence of haemorrhage Then Machine learning techniques are utilized to focus on issues that manipulate the prediction performance. The methods used for the haemorrhage detection in the input images are Decision Tree classifiers, Support Vector Machine, K-Nearest Neighbours, Thresholding techniques, Fuzzy C Means, Voxel based outlier detection, Multilayer Perceptron. Among these methods, haemorrhage detection done with Fuzzy C Means results suggested that the prospect of using this approach has to be modified in order to process a much larger training sample.

Shyni et al [16] has surveyed on segmentation algorithms for medical images of spinal cord tumor. The analysis carries various algorithms and techniques used on medical image such as Fuzzy C-Means, Structural Similarity Index, Hybrid method (Text-Mining, cross-citation based). Data Mining techniques, Genetic Algorithm, support vector machine (SVM), vertebi object boundaries, learning algorithms
optimization technique, Propagation segmentation (PropSeg), level set (Dice similarity coefficient and Hausdorff distance), minimal path search algorithm, subsequent random-walk methods to identify the similarity and variations on the Spinal cord image analysis.

Shyni et al [17] has proposed a work on spinal cord abnormality detection using the preprocessing techniques like Median, Arithmetic, Gaussian, and Weiner. This preprocessed image is further segmented with kmeans and fuzzy c means clustering algorithm followed by morphological operations and image manipulation are also performed. The performance comparison indices values of two segmentation algorithms witnessed that the proposed FCM method gives improved segmentation results with 84.5% precision.

Aafreen et al [18] has developed an automatic system which is able to segment haemorrhage from brain MRI dataset using Otsu and Watershed segmentation algorithm. The input MRI brain image is preprocessed with median filtering and morphological operations like dilation and erosion are applied. For segmenting the ROI, Otsu and watershed algorithms are used. The proposed system watershed algorithms is validated with measures and resulted with average 0.97 overlap metric, average 0.94 precision and average 0.94 recall respectively.

Shalini et al [19] has presented a survey on detection of diabetic retinopathy which gives a review on different algorithms and techniques that are used for detecting the lesions caused by diabetic retinopathy and also classifying its stages with higher accuracy. From this survey study it is concluded that the DR lesion detection can be done using preprocessing techniques like green channel extraction, median filtering and for the segmentation of DR lesions, FCM algorithm performs better than other segmentation algorithms. To achieve higher accuracy some unwanted features like blood vessels, optic disc need to be removed which produces false results. Finally grading of lesions can be accomplished using classification algorithms like support vector machine, K nearest neighbor etc.

Shalini et al [20] has proposed a comparison work on detection of hard exudates in diabetic retinopathy fundus images using the principles of Fuzzy-C Means and K-means algorithm. The method involves techniques like green channel extraction, median filter, Binary thresholding, K-means, Fuzzy-C-Means. The proposed comparison work shows that segmentation of hard exudates using Fuzzy-C-Means is better with an accuracy of 95.05%.

Alexandre et al [21] has proposed an approach to segment the fovea avascular zone of the retina images. The approach involves methods like gray scale conversion, alternating sequential filtering; H-minima, Regional minima, connected component analysis, distance transform, watershed marker and the final results were expressed in terms of accuracy, specificity and sensitivity respectively of 0.9947, 0.9972 and 0.8442.

Hosanna et al [22] has presented a paper to detect hard exudates feature in diabetic retinopathy affected image. Initially the image is resized, contrast enhanced with contrast limited adaptive histogram equalization and intensity of Clahe image is extracted. Further blood vessels are detected using green channel extraction, adaptive histogram equalization and morphological operations. At the end Fuzzy c means clustering (FCM) method segments the exudates in the preprocessed image. The performance measure results about 97.67% of accuracy, 91.108% of sensitivity, 97.95% of specificity.

Pallavi et al [23] has proposed a segmentation algorithm using fuzzy based algorithms the input brain image is preprocessed with Gaussian noise, salt and pepper
noise. Then the region of interest is segmented using mercer kernel based fuzzy c means (KFCM) and Generalized Spatial kernel based fuzzy c means (GSKFCM). The proposed methods KFCM and GSKFCM achieved accuracy of 94.92% and 95.38%.

Ravindraiah et al [24] has presented a paper for detection of hard exudates in Diabetic Retinopathy images using Laplacian Kernel Induced Spatial FCM Clustering Algorithm. In this algorithm laplacian kernel metric is induced into the kernel spatial FCM clustering algorithm for the segmentation of retinal fundus images. In existing methods, FCM and KFCM algorithms are very sensitive to noise and other image artifacts because it doesn’t have spatial information. To overcome this problem, the author has presented Laplacian kernel spatial FCM which incorporates spatial information into its objective function and the fuzzy membership function. The performance of this algorithm has been evaluated on different Diabetic Retinopathy images and the methodology is assessed using statistical measures like Sensitivity and Specificity. Thus LKSFCM method achieved greatest Sensitivity of 99% and Specificity 89%.

Surendiran J et al [25] has proposed a method to analyze the abnormal retinal images. In this work, the input images are subjected to hard exudates segmentation using the preprocessing techniques like gray scale conversion, contrast limited adaptive histogram equalization then FCM clustering is applied for segmenting the candidate region. The results obtained are compared with K-Means clustering where FCM outperforms with an accuracy of 91.95%.

Rubya et al [26] has proposed an automatic system that detects and classifies the Diabetic retinopathy lesions using fuzzy logic. Initially the retinal fundus image is preprocessed with green channel extraction, median filter; contrast limited adaptive histogram equalization and contrast stretching. Then linear spatial filtering, morphological filtering, transform operations and binary Thresholding are applied to extract the features like blood vessels, optic disc, hard exudates, microaneurysms and textural features like contrast, homogeneity. The extracted features are classified into respective classes using fuzzy level set algorithm. The proposed system has higher performance with sensitivity, specificity and accuracy up to 95.77%, 94.44% and 95.63% respectively.

Ganesh et al [27] has proposed a new efficient technique for the detection of microaneurysms in the retinal images. The technique uses Fuzzy-C-Means with NLM-ADF algorithm. Initially Fuzzy clustering is done for segmenting the pixels information further NLM in term of anisotropic filter is applied to improve identification of micro aneurysms in retinal images. The results show that the method improves the micro aneurysm detection rate and got ROC score 0.427. The proposed method is tested on various simulated retina data repositories.

Sergio et al [28] has proposed an effective method for detecting Non proliferative diabetic retinopathy features in color eye fundus images. The algorithm carries preprocessing of image using Green channel extraction and contrast limited adaptive histogram equalization, the features like optic disc, blood vessels, fovea are eliminated then the features like microaneurysms and hemorrhages are detected by applying the image processing techniques such as alternative sequential filtering, H-minima transform, region minimum, Sobel and prewitt filters along with morphological operations with the outcome of 87.69% sensitivity and 92.44% specificity.

Ganesh et al [29] has presented a paper on identifying the microaneurysm feature in retinal images using the gray scale conversion, Rotational Cross-Section Analysis and Fuzzy C-Means Clustering algorithm. The proposed approach has scored 0.435 ROC.
Venkatraman et al [30] has proposed a system for detection of Non proliferative Diabetic Retinopathy in Fundus Images by Wavelet Features. The system utilizes histogram equalization, candidate region extraction; wavelet features for detecting the diabetic retinopathy features by applying Mercer kernel, 2nd degree polynomial kernel, 3rd degree polynomial kernel and Gaussian kernel with accuracy of 96.0%, 78.0%, 86.0% and 84.0%.

Lama et al [31] have presented a work on dark lesion detection for Diabetic retinopathy using preprocessing methods like spatial calibration, illumination equalization, Mean Filter, Adaptive Contrast Equalization, color normalization then entropy based Thresholding and multi-scale ring shaped matched filter for optic disc removal. Finally dynamic shape features like Relative area, Elongation, Eccentricity, Circularity, Rectangularity, Solidity are extracted which is classified into lesions using random forest algorithm with AUC of 0.899, 0.916, 0.976, 0.941 by testing four different databases.

Manoj et al [32] has implemented a computer aided detection system for segmentation of Non proliferative diabetic retinopathy features and retinal features in color fundus images. The implementation comprises of algorithms like green channel, median filter, contrast limited adaptive histogram equalization, shade correction, Matched Filter-First Order derivative of Gaussian, Mathematical filtering, morphological operations, watershed segmentation, in-painting, h-extended minima algorithm, Selective Binary and Gaussian Filtering Regularized Level Set and Signed Pressure Force algorithm. The proposed methodology for segmentation of microaneurysms feature attained 90% accuracy and exudate feature detection has given 93.41% accuracy.

The review done on detecting and segmenting the NPDR and Non-DR features renders various image processing methods. And these existing works have performed the segmentation process with preprocessed inputs and some works have been done on non-preprocessed inputs and others employed kernels, parameter values to identify the object of interest (OOI) still there are some inability in achieving the accuracy of medical experts’ outcome. There are a number of challenges in distinguishing and categorizing DR features; such as the presence of noise and outliers like the blood vessel, optic disc and fovea that are present in input images, the vacillating location of features, the similarity of shape and texture among some features (the microaneurysms and haemorrhages happen to occur with matching texture), which may direct to extracting redundant or ineffective features and results in low segmentation accuracy. This leads to improper diagnosis of the patient at the time of emergency states by the Physicians, which ultimately causes the severity of the retinal disease. The proposed FCM based segmentation evolves some initiatives to manage the inabilities found in the existing works.

This paper work is organized as follows; section 3 presents theoretical background of the techniques used. Section 4 describes the experiments conducted to compare the different fuzzy algorithms adopted for NPDR features segmentation. The dataset description is given in section 4.1. Then the results are presented in section 4.2 and discussed in section 4.3 followed by conclusions and future work in section 5

III. Theoretical Background

This paper has considered fuzzy based algorithm for detecting the ROIs. This section presents a brief description of the proposed approaches.
a) **Fuzzy clustering algorithm**

The conventional Fuzzy based algorithms are used for partition the data points, where data point assigns memberships to each center as a result of which, for each iteration data point belong to more than one center point. It segments the ROI based on data point which is chosen precisely among many data point, so the segmentation is more accurate.

For a given data set $X=\{x_1, x_2, \ldots, x_n\}$, clustering algorithms partition the n data objects in X into c groups $C=\{C_1, C_2, C_c\}$ based on similarity/dissimilarity metric [33]. The standard Fuzzy C Means algorithm [34] uses the Euclidean distance as an objective function to be minimized and expressed as the following equation:

$$J_{FCM}(U, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^m \| x_j - v_i \|^2$$

(5)

Where $v_i$ is the cluster center of cluster $C_i$, $m$ is the weighting exponent or the degree of fuzzifier in FCM. The fuzzy partition matrix is expressed as

$$U = [\mu_{ij}]_{c \times n}, \quad \mu_{ij} \in [0,1]$$

(6)

It is the membership degree of data object $x_j$ to cluster $v_i$, and

$$\sum_{i=1}^{c} \mu_{ij} = 1, \quad \forall j = 1,2,3,\ldots,n$$

(7)

In the iterations, the membership degree $P_{ij}$ and the cluster centers $v_i$ are updated as

$$\mu_{ij} = \frac{1}{\sum_{i=1}^{c} \left( \frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}}$$

(8)

$$C_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m x_j}{\sum_{j=1}^{n} \mu_{ij}^m}$$

(9)

We iterate (8) and (9) until the changes in the fuzzy partition matrix are very small or some other stopping criterion has met.

**IV. MATERIAL AND PROPOSED METHODOLOGY**

In this section, we present the methodology adopted in the work, dataset and proposed approach.

a) **Material**

i. **Dataset and Tools used**

The Experimentation of Non Proliferative Diabetic Retinopathy features detection is conducted on The Processor AMD A8-7410 APU with AMD Radeon R5 Graphics HP Platform, 64-bit operating system, x64-based processor, 2.20 ghz Processor Speed and 4 GB Memory. The Segmentation Algorithm is developed in Matlab2014b -32 bit version. The dataset taken for this segmentation process were obtained from eye care clinics and online repositories namely DIARETDB0 and DIARETDB1 database, with a resolution of 93 x 71 in 24 bit depth PNG format. The databases contain 200 number of color fundus images for the experiment in which 11 are normal and 189 contain signs of the diabetic retinopathy.

ii. **Data Preparation**

**Resizing:** To standardize the image, resizing is carried out by Bi-Cubic interpolation Area method [35], uses the biased average of four translated pixel values
for each output pixel value then the input image is zero padded and translated in
positive horizontal direction by five tenths of pixels.

\[ p(x, y) = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{ij} x^i y^j \]  \hspace{1cm} (10)

\textit{Fig. 1:} Fundus retinal image \hspace{1cm} \textit{Fig. 2:} Resized image

\textit{b) Methodology}

The image contains the unwanted features such as BV, OD, FV and the NPDR
features MA, IRH, HEXU which are to be segmented and they are shown in Fig 2. The
preprocessing technique improves the image quality and removes the Non-DR
(unwanted) features in the image then segmentation algorithms segments the NPDR
features. The purpose of removing the unwanted features is reducing the false detection
rates in order to achieve more accurate results in NPDR features segmentation.

\textit{Fig. 3:} DR-Fundus retinal image with NPDR and Non-DR Features

The goal of this work is implemented by following the proposed methodology
represented in Fig 4, which consists of four phase namely standardization,
preprocessing, segmentation and feature recognition. The fundus retinal input image
acquired from DR database is standardized using bi-cubic interpolation area method
[35] for resizing of image. In first phase, the resized image undergoes preprocessing by
using the techniques like Green channel extraction, median filter for image enhancement
then Binarized contour tracing (BCT), hybrid BINI Thresholding [36], extended minima
transform algorithms are applied to detect the Non-DR features like blood vessels, optic
disk and fovea. In the second phase, the detected Non-DR features are removed from
the input image using mathematical arithmetic operation (MAO) and pixel replacement
method (PRM). The third phase carry out the segmentation on the preprocessed image
to isolate the NPDR features like microaneurysms, intraretinal haemorrhages, and hard
exudates on applying Gaussian kernel prompted Fuzzy c means method. The fourth
phase comprises marking of the segmented features in the input image using multi-class
contour tracking (MCT) algorithm to outline multiple region of interests. The detailed
execution of algorithm is explained below.
ii. **Preprocessing**

Conventionally, the image data recorded or obtained through imaging systems like satellites, digital cameras. Though the images captured by high configured fundus camera, there is lack in contrast and brightness because of the illumination conditions. These errors are improved using applicable mathematical models which are either definite or statistical models. This process is termed as image preprocessing and it is performed for enhancing certain image structures for consequent analysis or for image display. Basically image enhancement is the alteration of the pixel brightness values in an image to improve its visible effect which is suited for human or machine interpretation. The enhancement process does not upturn the needed information content in the data but justemphasizes certain specified image features. Hence the preprocessing is done for making the image more suitable for further processing. Enhancement algorithms are usuallycooperative and application reliant, the enhancement techniques chosen for DR feature detection is resizing, channel extraction, noise filtering.

To enhance the fundus image segmentation process, the preprocessing operations are carried out using the green channel [37] of the RGB fundus image which project the DR features (ROI) more prominent than the Blue and Red Channels and unlike the other two channels (red, green), the green channel is neither lower illuminated nor over-saturated.

\[ g = \frac{G}{R+G+B} \]
The equation represents red channel \((R)\), green channel \((G)\) and blue channel \((B)\), respectively. The resulting image for normalized green channel is denoted by \(g\).

The Median Filtering is a non-linear filtering technique [38] which removes noise while preserving the edges to enhance the region of interest.

\[
y[m, n] = \text{median}\{x[i, j], (i, j) \in \mathcal{U}\}
\]

Where \(\mathcal{U}\) represents a neighborhood defined by the user, centered around the location \([m, n]\) in the image.

The extended-minima transform (exMT) is a Thresholding technique which segments the fovea region. It is the regional minima of h-minima transform. The regional transform replaces the pixel values to zero. The h-minima transform subdues all the minima in the intensity image whose depth is less than or equal to a predefined threshold value [39].

\[
EM_{(x,y)} = t(I, T)
\]

Where, \(t\) is minima transform function

\(I\) is image

\(T\) is threshold value

iii. Segmentation

The segmentation process is the significant difficulties in image processing which is performed to dissect the ROIs. It subdivides the preprocessed image into some component parts or objects until the object of interests are isolated e.g., initially, dissection of the background from the image then the foreground is segmented. Segmentation of images involves not only the discrimination between regions of interest and the background, but also separation of more than one region of interests. One method for such separation is known as FCM segmentation algorithm as follows;

**Gaussian Kernel based fuzzy clustering algorithm**

The kernel-based fuzzy clustering [40] introduced kernel method into the FCM algorithm which overcomes FCM’s shortcomings in terms of insufficiency caused by data distribution characteristics to clustering results. Define a nonlinear map as

\[
\phi : x \rightarrow \phi (x) \in F, \text{ where } x \in X, X
\]

\(X\) denotes the data space, and \(F\) is the transformed feature space with higher or even infinite dimension [41]. The objective function of KFCM is defined as

\[
J_{KFCM} = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^{m} \| \phi(x_{j}) - \phi(v_{i}) \|^{2}
\]

Where

\[
\| \phi(x_{j}) - \phi(v_{i}) \|^{2} = K(x_{j}, x_{j}) + K(v_{i}, v_{i}) - 2K(x_{j}, v_{i})
\]

We adopt the Gaussian function [42] as a kernel function, i.e.

\[
K(x, v) = \exp \left[ -(x - v)^{2}/\sigma^{2} \right], K(x, x) = 1
\]

Where \(\sigma\) is Gaussian kernel with multiple parameters, according to Eq.(12), Eq.(11) can be rewritten as:

\[
J_{GK,FCM}(U, V) = 2\sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^{m} \left[ 1 - K(x_{j}, v_{i}) \right]
\]
Minimizing Eq. (14) under the constraint of \( \mu_{ij} \).

\[
\mu_{ij} = \frac{(1-K(x_j, v_i))^{-1/(m-1)}}{\sum_{i=1}^{n} (1-K(x_j, v_i))^{-1/(m-1)}} \tag{15}
\]

\[
v_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m \kappa(x_j, v_i) x_j}{\sum_{j=1}^{n} \mu_{ij}^m \kappa(x_j, v_i)} \tag{16}
\]

iv. Post processing

The post process is performed for super imposing the segmented ROI in the input image. The segmented NPDR features are marked in the original input image using Contour base Object tracking algorithms [43]. Object tracking is considered to be an essential task in the computer vision field. The state of the contour which shows the position of the segmented object is defined using co-ordinates of its centroid. In the proposed work six different features are segmented and super imposed so the multi-class contour tracking algorithm is applied to mark the multiple features in the fundus input image.

V. Results

a) Evaluation Metrics

For internal and external evaluation of the proposed segmentation techniques, certain validation measures like Partition Coefficient Index (PCI), Partition Entropy Index (PEI) and Disc similarity Coefficient (DSC) are calculated.

Partition Coefficient is the index value that determines the cluster partitions of two different techniques. The index value ranges between 0.894–0.9160.

\[
PCI = \frac{1}{N} \sum_{p=1}^{M} \sum_{i=1}^{N} \mu_{iM}^2 \tag{17}
\]

Partition Entropy is the index value that determines the entropy of cluster partitions of two different techniques. The index value ranges between 0.1989–0.2703.

\[
PEI = \frac{1}{N} \sum_{p=1}^{M} \sum_{i=1}^{N} \mu_{iM}^2 \log_2(\mu_{iM}) \tag{18}
\]

Dice Similarity Coefficient is a performance analysis method based on the spatial overlap between two different segmentations process of the same image. It is same as f-score, considered as an accuracy measure which counts all the true positives, false positives and true negatives.

\[
DSC = \frac{2TP}{2TP + FP + FN} \tag{19}
\]

Where TP, FP, TN, FN are true positive, false positive, true negative and false negative which are defined as the number of pixels classified correctly and incorrectly in abnormal existence and normal image by the proposed method.

| Methods     | PCI  | PEI  | DSC  |
|-------------|------|------|------|
| MK FCM      | 0.90 | 0.23 | 0.78%|
| LK FCM      | 0.91 | 0.48 | 0.89%|
| Proposed GK FCM | 0.94 | 0.79 | 0.98%|
### b) Implementation Outcome

| S. no | Resize Image | Preprocess | Segmentation | Post process |
|-------|--------------|------------|--------------|--------------|
|       |              |            |              |              |
|       |              |            |              |              |
|       |              |            |              |              |

**Non-DR Detection**
- **Non-DR removal**
- **NPDR Features Detection**

- **BCT**: BV
- **BINI**: OD
- **exMT**: FV
- **MAO & PRM**: MA, IRH, HEXU

**Fig. 5**: NPDR features Segmentation

### c) Discussions

NPDR stage is the sign of leaking blood vessels which drop out blood, fatty deposits and fluids on the retina. Segmentation of NPDR features is a necessary process in order to support the expert in analysis of disease to obstruct its severity as earlier as possible. At first, the acquired inputs are standardized by resizing it to 512 X 512 dimensions as portrayed in fig.3, column 2. The purpose of resizing is to make images more receptive for accomplishing further processing and for complete visibility on screens of different devices. Then the resized images undergo the preprocessing operation using green scale conversion as it enhances the fundus image, it is done by extracting the green channel of the color fundus image which projects the DR features more noticeable than the Blue and Red Channels. Then median filtering is performed on the green scale image to suppress the noise present in the image that are represented in fig.2, column 3.1 and column 3.2.

This green Channel image is applied with background subtraction process using numerous image processing techniques to detect and remove the unwanted Non-DR features like Blood Vessel, Optic Disc and Fovea so that the NPDR features becomes more projective. The first feature Blood Vessel is detected using the binarized contour tracing (BCT) method and the second feature Optic disc is detected using BINI Thresholding are shown in column 3.3 and 3.4 which is already done and that is described in the existing work [36]. The proposed work: detected the third feature called Fovea feature using extended minima transform method as shown in column 3.5.

Then these three detected features are removed from the input image using the mathematical arithmetic operation (MAO) and pixel replacement method (PRM) in column 4. Further this image is given as input for the segmentation process for segmenting the NPDR features like MA, IRH and HEXU using Gaussian kernel based fuzzy c means algorithm which is showed in column 5.1, 5.2, 5.3. Finally, the segmented features are plotted in the fundus input image using multi-class contour tracking (MCT) algorithm and the result is shown in column 6.
The first algorithm [30] in table 1 called Mercer-Kernel induced Fuzzy C Means where clustering is done by FCM integrating with Mercer function to cluster the data points. The mercer function is the basic kernel method used in the segmentation algorithms to segment the ROI that are unlabeled and it is suitable for cluster with spherical, ring shape by default, also the function needs prior information of the cluster shape. If the shape of the ROI is not exactly fixed with default cluster shape and the cluster shape is not specified prior then grouping of data points in segmentation process flops. The second algorithm [24] in table 1 is Laplacian-kernel based Fuzzy C Means which uses the kernel with Cauchy distribution to deploy more frequency components which overlooks the noises present in the image. But this distribution is not time adaptive in handling the large dataset since it uses single parameter. The fourth algorithm in table 1 is the proposed Gaussian-kernel based Fuzzy C Means and this algorithm carries normal distribution of pixels to handle the noise present in the image that makes grouping of identical pixels more contented. Here the kernel is employed with multi-parameters which is suitable for handling large dataset with less time and also performs better in multiple ROI segmentation. Hence, the proposed GK_FCM method has given better results than the existing fuzzy C means algorithms for segmenting multiple ROI and achieved accuracy of 98.21%.

The validation measures of the proposed segmentation algorithms are evaluated in terms of PCI and PEI. The values are 0.89 and 0.51 for FCM, 0.90 and 0.23 for MKFCM, 0.91 and 0.48 for LKFCM, 0.98 and 0.79 for GK_FCM. The performance analysis of NPDR feature segmentation using FCM gives 91.95% accuracy, MKFCM gives 78.0% accuracy, LKFCM gives 90.88% accuracy and GK_FCM algorithm gives 98.21% accuracy. The evaluation results are shown in table 1 and the graph for the resulted values is given in Fig 4. This shows that the proposed method GK_FCM gives the better result.

Fig. 6: Comparison of accuracy of NPDR feature segmentation algorithms

VI. Conclusion and Future Work

The earlier identification of the diabetic retinopathy and its features is more necessary to avoid the precarious condition. So, the segmentation of NPDR features using Fuzzy based algorithm in the fundus images has been implemented by resizing the input image using bi-cubic interpolation method. Then preprocessing techniques like green channel extraction and median filter are used for highlighting the image features for subsequent exploration. Further background subtraction is done which applies algorithms like binary contour tracing, BINI Thresholding, extended minima transform, mathematical arithmetic operation and pixel replacement for detecting and removing
the unwanted features like blood vessels, optic disc which ignores the false positives and enhances the area of interest to be segmented. For segmenting the ROI so called NPDR features like microaneurysms, intraretinalhaemorrhages and hard exudates, Gaussian kernel based Fuzzy C means algorithm has been applied. In this segmentation algorithm, the Gaussian function identifies all the pixels with equal distribution also kernel has been set which improves the features detection process more efficient and accurate. The proposed work has achieved 98.21% accuracy. Future work focus on feature extraction of Diabetic retinopathy fundus images with a greater accuracy.

Conflict of Interest
The authors declare that there is no conflict of interests regarding the publication of this paper.

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