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An Intelligent Mathematically Modified Fuzzy C-Means Clustering Technique for Fundus Image Segmentation for Diabetic Retinopathy Identification

Anamika Raj [a,b,*], Noor Maizura Mohamad Noor [a], Rosmayati Mohemad [a], Noor Azliza Che Mat[a], Shahid Hussain[b]

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Abstract: Diabetic Retinopathy (DR) is a significant threat to individuals with diabetes, resulting in retinal damage that can lead to vision loss. Early and accurate detection of DR is essential for effective therapy and vision preservation. This study is motivated by a broad range of goals designed to advance the study of diabetic retinopathy (DR) analysis using cutting-edge image processing methods. Firstly, it seeks to enhance pre-processing methods, including techniques like Gabor filtering and Gaussian filtering, with the goal of elevating the quality of fundus images by reducing noise, enhancing features, and preparing them for subsequent analysis. Secondly, the core focus lies in the development and fine-tuning of segmentation algorithms, particularly Mathematically Modified Fuzzy C-Means Clustering (MMFCM), for precise identification of DR-related lesions, such as microaneurysms (MA), haemorrhages (HE), exudates (EX), and Intraretinal haemorrhages (IH) within retinal images. Thirdly, the research aims to establish robust quantitative metrics, including Matthews Correlation Coefficient (MCC), Dice coefficient (DICE), and Intersection-over-Union (IoU), to rigorously assess the accuracy and quality of segmentation results. The incorporation of MMFCM improves the segmentation and analysis of retinal pictures, allowing medical personnel to identify DR early and implement timely therapies, protecting patients' vision and raising their overall quality of life.

Keywords*: *Diabetes, segmentation, diabetic retinopathy, neural network, convolution, feature fusion, lesion, and vessel.

1. Introduction

Medical Imaging is the one of the conventional techniques, which helps to view the interior parts of the body for effective diagnosis. It is considered to be one of the major innovations of the healthcare systems and led to the interdisciplinary field of medical image processing. It includes end to end processes right from data acquisition to clinical interventions and digital communication of medical images [1]. Computer Aided Diagnosis (CAD) helps the specialists on their diagnosis procedure with greater accuracy and efficiency. It enhances the raw medical data with the implementation of problem specific approaches for further analysis [2].

Diabetic Retinopathy is one of the diseases that have created major impacts among diabetic patients. It is a common critical complication of diabetes mellitus which affects the human eye leading to blindness in severe stage [3]. In industrialized countries like US, there are 29 million Americans, in the age group of 25–74 years living with diabetes mellitus (DM) and 33% of them are having the symptoms of diabetic retinopathy. Long Diabetes injures the retinal blood vessels and thereby impairs the visibility of a person, leading to diabetic retinopathy. Diabetic retinopathies move into two main pathological stages such as PDR (Proliferative Diabetic Retinopathy), NPDR (Non-Proliferative Diabetic Retinopathy) and four clinical stages. The early stages of DR, which are divided into mild, moderate and severe phases, are referred to NPDR. Microaneurysm (MA), which denotes the emergence of a tiny red dot in a circular pattern at the end of the blood vessels, is the initial stage, and in the subsequent moderate stage, the microaneurysms progress into deep layers and cause a haemorrhage in the retina [4, 5].

The act of projecting the retina, the semi-transparent, layered tissue lining the inside of the eye, in three dimensions onto an imaging plane is known as fundus imaging. A DR screening test should have sensitivity and specificity of at least 80% and 95%, respectively, with a technical failure rate of less than 5%, according to the UK's National Institute for Clinical Excellence (NICE) standards. DME (Diabetic Macular Edema) and mild retinal neovascularization can both be detected with it. The vital characteristics that are utilized to identify and classify DR may be used to categorize the different stages

[a]*Faculty of Ocean Engineering Technology and Informatics, University Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia*
[b]*Department of Computer Science, Applied College Al Mahala, 61421, King Khalid University, Saudi Arabia*
P5301@pps.umt.edu.my, maizura@umt.edu.my , rosmayati@umt.edu.my , azliza@umt.edu.my , shosain@kku.edu.sa

of DR. Based on the evidence of the existence of lesions in terms of retinal anomalies; it is categorized into four stages: mild, moderate, severe, and proliferative DR. Identification of DR characteristics is therefore a key study area since successful DR categorization depends on precise identification [6].

Microaneurysms (MAs) are characterized as isolated capillary dilations, red in color, and saccular in form in the mild stage. They can show up either in groups or alone, and their diameter ranges from 10 to 100 m. The initial sign of DR, caused by the focused enlargement of thin blood vessels, is the occurrence of minor blood leakage in the retina in the early stages of MAs. Blood vessel structures are being impacted by haemorrhages (HEs), and there is an increasing chance that the blood will seep out of the vessels and take on a typical form. They typically range in diameter from 3 to 10 pixels [7]. The size of HEs is smaller than MAs and as large as the optic disc. Sometimes, HEs and MAs combine to produce red lesions [8].

Exudates (Ex) are isolated, yellowish-white intraretinal deposits typically seen by MAs that are caused by aberrant retinal capillaries leaking blood and include extracellular lipids and proteins. When compared to large patches, which have clear borders and brilliant structures known as hard EXs, small specks and large patches appear with soft boundaries and foggy structures known as soft EXs. Intraretinal haemorrhages (IH) crop up in the severe stage which produces the blood leakage namely venous bleeding in two or more quadrants of an eye [9].

Motivation

This research is proposed by the escalating global health challenge of Diabetic Retinopathy (DR), a vision-threatening complication of diabetes. The incidence of DR is increasing along with the global prevalence of diabetes, highlighting the urgent need for cutting-edge diagnostic techniques. The drive is to provide precise tools and methodologies for the early diagnosis of DR and its associated disorders by utilising cutting-edge technology like computer vision, artificial intelligence (AI), and medical imaging. This endeavor aims to optimize healthcare resource allocation, particularly in underserved regions, and ultimately enhance patient outcomes by offering accessible and automated DR diagnosis and interventions.

Objective of the Research

The research objectives based on pre-processing and segmentation in the context of diabetic retinopathy (DR) analysis are as follows:

- Optimize Pre-processing Techniques: Develop and refine pre-processing methods, including but not limited to Gabor filtering and Gaussian filtering, to enhance the quality and clarity of fundus images. The primary objective is to reduce noise, enhance relevant features, and prepare the images for subsequent analysis.
- Accurate Lesion Detection: Implement segmentation algorithms, particularly Mathematically Modified Fuzzy C-Means Clustering (MMFCM), to accurately detect and delineate specific DR-related lesions, such as microaneurysms (MA), hemorrhages (HE), exudates (EX), and Intraretinal hemorrhages (IH), within retinal images. This involves optimizing segmentation parameters and techniques for precise lesion identification.
- Quantify Segmentation Performance: Define quantitative metrics such as Matthews Correlation Coefficient (MCC), Dice coefficient (DICE), and Intersection-over-Union (IoU) to assess the accuracy and quality of the segmentation results. The objective is to establish rigorous evaluation criteria for segmentation performance.

The research work is structured as follows: Section 1 provides an introduction to diabetic retinopathy, emphasizing the significance of segmentation and presenting an overview of the research contributions. In Section 2, a comprehensive analysis of DR segmentation is presented, including a gap analysis. Section 3 covers dataset preparation, pre-processing methodology, and a description of the operational principles of the proposed MMFCM. Section 4 illustrates the outcomes of the DR analysis, along with comparative discussions. Finally, Section 5 serves as the conclusion of the article and outlines potential future research directions.

2. Related Works

Diabetic Retinopathy is defined as micro vascular disease which creates the blockage in our retinal blood vessels when diabetic patients have high blood sugar value. It also blocks the main nutrition content from the retina tissues. Several automated techniques and models have been developed in recent decades to identify and grade different stages of DR from eye fundus images. This section summarizes the well – known research contributions on DR identification techniques based on Machine Learning and Deep Learning.

Eswar et al. (2022) [10] developed an optimal feature-based system for the prediction of retinal disease. The ensemble random forest was selected as an ultimate model to predict features-based diabetic retinal system based on its performance. It yields an accuracy of 0.975.

Prathyush gluria et al. (2022) [11] offered a smart healthcare data-centric framework was constructed

utilizing supervised machine learning techniques. The dataset containing 520 instances of diabetic patients and 17 characteristics is applied to an ensemble of several ML algorithms based on boosting and bagging. This ensemble model achieved better performance with F-Score values of 97.8% and 97.6 % respectively for boosted tree and bagged tree.

Skouta et al. (2022) [12] performed semantic segmentation to detect the haemorrhages in fundus images. Modified CNN U Net architecture is implemented for identifying retinal hemorrhages in fundus images. Preprocessing is used to improve the image quality for complex feature extraction and effective segmentation of affected part of an fundus images. This method achieved the best sensitivity, specificity and accuracy of 80.49%, 99.68%, and 98.68%, respectively.

Pelin et al. (2021) [13] designed an application using six different decision tree-based (DTB) classifiers and different ensemble learning methods approaches namely Adaptive Boosting (AdaBoost) and bagging using Naive Bayes classifier. The experimental results achieve the higher accuracy score of 98.65 %.

Zun Shen et al. (2021) [14] explored the methods for the prediction of DR by creating an impact on high-dimensional and small-sample-structured DR Dataset. The proposed SelStacking model was developed with XGB-Stacking model which is the combination of XGBoost and stacking. The proposed prediction model had outperformed existing methods with improved classification accuracy of 83.95 %.

Sambyal et al. (2020) [15] created a modified U-Net architecture for segmenting DR images. Using two publicly accessible datasets (IDRID and E-Optha), this model applied the segmentation method to look for the existence of MA and Hard Exudates (HE). The positive performance indicators are 99.98% (ACC), 99.88% (SE), and 99.89%. (SP).

Keerthiveena et al. (2019) [16] investigated Diabetic Retinopathy diagnosis using the Firefly algorithm. In order to classify normal and pathological fundus images, a screening technique has been devised. Blood vessels were segmented using a match filter and a fuzzy C-means clustering approach. By using directional characteristics that resembled lines, different diameters of blood vessels were obtained from the various filters. A firefly algorithm for the early diagnosis of diabetic retinopathy that selects discriminative features. In order to enhance classification results while utilizing the fewest features possible for the early diagnosis of diabetic retinopathy, the suggested algorithm has been compared to sophisticated methodologies.

Research Gap

In the context of diabetic retinopathy (DR) analysis, there exist specific research gaps that demand attention. These gaps include issues with dataset diversity, computational efficiency, model interpretability, and robustness to image variability. The application of Mathematically Modified Fuzzy C-Means Clustering (MMFCM) holds promise in effectively addressing some of these gaps. MMFCM's prowess in segmentation tasks, critical for precise identification of DR-related features like microaneurysms and hemorrhages, can contribute significantly to enhancing sensitivity and specificity in DR detection, thereby alleviating the segmentation gap. Furthermore, MMFCM's inherent interpretability aligns with the need for models that provide insights into decision-making processes, thus filling the gap in model interpretability. Additionally, its computational efficiency lends itself to real-world deployments, mitigating the computational complexity gap and rendering it more suitable for resource-limited settings. Overall, MMFCM presents a viable solution to these pertinent research gaps in the domain of diabetic retinopathy analysis.

3. Materials and Methods

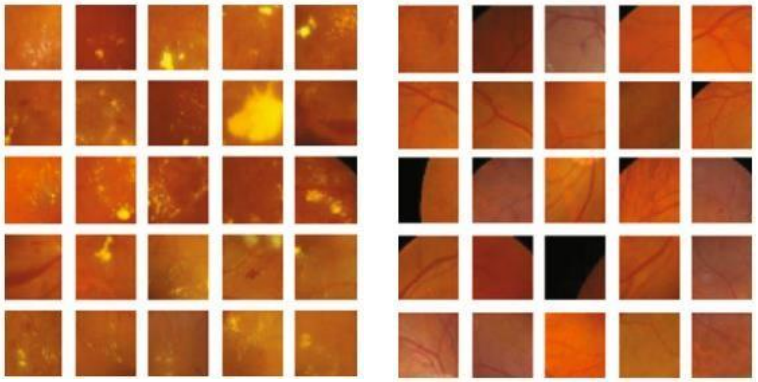
The segmentation is accomplished using Mathematically Modified where the significant regions are highlighted that is detailed in this section.

Data Preparation

The research study employed the Indian Diabetic Retinopathy Image Dataset (IDRID), derived from real clinical examinations conducted at an eye clinic in India. These fundus images were captured using a Kowa VX-10 color fundus camera, offering a 50-degree field of view near the macular region. Each image boasts a resolution of 4288 x 2848 pixels and is stored in JPG format. For the research investigation, a subset of 81 color fundus images with meticulous pixel-level annotations was selected from the larger pool of 516 images. This curated dataset encompasses three common diabetic retinopathy anomalies, as depicted in Figure 2. To facilitate experimentation, the IDRID dataset was partitioned into training and testing sets using various lesion labels, with the distribution results presented empirically in Table 1.

Table 1. The IDRID Dataset Distribution

Lesion Type	Training Set	Testing Set
Soft exudates	26	14
Hard exudates	54	27
Microaneurysms	54	27
Haemorrhage	53	27



Positive Sample Negative Sample

Fig 2. Colour Fundus Image with Positive and Negative Samples

Pre-processing of Fundus Image

Data preprocessing is a significant stage in the development of robust Machine Learning models used to improve the image's quality and offers computational simplicity. The fundus images used to detect the DR frequently exhibits noise, low contrast, and brightness variations used for detection of DR. To address these issues and make them better suit for training, it is very essential to preprocess the fundus images. The preprocessed fundus images are used further for extraction of the blood vessels, potential lesion channel selection, noise reduction, and contrast amplification. The original RGB color space used for the color fundus image consists of three colors: red, green, and blue. The green channel has the most contrast between the retinal backdrop and blood vessels, while the red channel is quite saturated and the blue channel is dark. The vessels are clearly seen only in the green channel.

In order to do additional research, the green channel with the maximum contrast is chosen. The preprocessing is essential for processing retinal images because noise is introduced during the image acquisition stage or the analogue to digital conversion stage. Due to the noise in the fundus retinal image, the retinal image is considerably affected which may lead to wrong diagnosis and hence, the elimination of noise is therefore crucial. Preprocessing, feature extraction, and classification are all examined in this study. After color space conversion and zero padding, a median filter is used to decrease noise and retain sharp edges.

Gaussian Filter: The Gaussian function functions as an input filter, introducing a high-pass effect within the input's step function while minimizing the initiation and completion times. It transforms the input data into a Weierstrass transform by applying a Gaussian filter. Subsequently, a linear spatial filter is employed to achieve the smoothing of the fundus image, reducing noise levels and frequencies near the edges. The convolution operation involved in the Gaussian function for achieving this smoothing effect is expressed in Equations 1 and 2.

$$G_\sigma(a,b) * I(a,b) \quad (1)$$

$$G_\sigma(a,b) = \frac{1}{2\pi\sigma^2} e^{-\frac{a^2+b^2}{2\sigma^2}} \quad (2)$$

In this context, the input image is represented as $I(x, y)$, and the Gaussian function is denoted as $G\sigma\ (x, y)$, with spatial coordinates σ, x, and y. The convolution operator, *, is used to identify the image edges, and the resulting gradient is applied to the fundus image, as expressed in Equation 3.

$$\nabla(G_\sigma(a,b) * I(a,b)) \quad (3)$$

Here, the gradient operator ∇ is employed to calculate the directional changes in intensity values. The boundary map is defined in Equation 4.

$$M_Y(a,b) = \nabla(-G_\sigma(a,b) * I(a,b)) \quad (4)$$

The equation for the normalized factor of the boundary map is provided in Equation 5.

$$M_{NY}(a,b) = \frac{M_Y(a,b) - \min(M_Y(a,b))}{\max(M_Y(a,b)) - \min(M_Y(a,b))} \quad (5)$$

The threshold value, denoted as T and falling within the range [0, 1], is applied to the boundary map to produce binary values, as defined in Equation 6.

$$M_{YY}(a,b) = \begin{cases} if\ M_{NY}(a,b) & 1 \\ else & 0 \end{cases} \quad (6)$$

The threshold value for the fundus image is determined by its contrast and intensity, which can vary depending on the distribution characteristics. In this case, a threshold value of 0.1 is applied to eliminate the low-intensity region and maintain object continuity within the input fundus image. This extracted border serves as an envelope, ensuring that the final convergence remains within the defined boundaries.

Segmentation of Fundus Image using MMFCM

The modification of the Fuzzy C-Means (FCM) clustering algorithm through the incorporation of differential equations offers significant advantages in diabetic retinopathy segmentation. By integrating spatial information into the algorithm, it enhances segmentation accuracy by considering both pixel intensities and spatial relationships, thereby improving the precision of feature delineation. Furthermore, this approach effectively preserves edges and boundaries, crucial for maintaining structural integrity and accurately segmenting diabetic retinopathy-related lesions, such as microaneurysms and haemorrhages. It also contributes to noise reduction, resulting in more robust segmentation in the presence of image artifacts. Additionally, the modified FCM algorithm yields enhanced contrast within segmented regions, facilitating the identification and analysis of pathological features. Its adaptability to diverse image characteristics and clinical applicability make it a valuable tool for precise diabetic retinopathy diagnosis and intervention planning, potentially leading to improved patient outcomes.

Creating a comprehensive mathematical model for the modification of the Fuzzy C-Means (FCM) clustering algorithm using differential equations for diabetic retinopathy segmentation involves complex equations and parameters. Below is a simplified conceptual representation of such a model:

Let X be the input image, U represent the fuzzy membership matrix, C denote the cluster centers, W be the weight matrix, D stand for the distance matrix, λ represent the regularization parameter, α and β be parameters controlling the impact of differential equations.

Differential equations are introduced into the objective function to capture spatial relationships. These equations may include terms that relate data points or cluster centers in the image domain. The objective function to optimize in this modified FCM model can be represented in Equation 7.

$$\min_{U,C} J(U,C) = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^m \|x_i - c_j\|^2 + \lambda \sum_{i=1}^{n}\sum_{j=1}^{c} (1 - \exp(-\alpha \|x_i - c_j\|^2)) u_{ij}^m \quad (7)$$

Subject to the following constraints:

$$\sum_{j=1}^{c} u_{ij} = 1 \ for\ all\ i,$$

$$0 \le u_{ij} \le 1 \ for\ all\ i,j.$$

Here, n represents the number of pixels in the image, c is the number of clusters, and m is the fuzziness parameter. This mathematical model combines the traditional FCM objective function with differential equations, where the regularization term and parameters α and β introduce spatial information and contribute to the segmentation process. Solving this model involves iterative optimization techniques to update U and C until convergence is achieved.

The regularization terms are applied in the objective function to ensure the smoothness of the segmentation and prevent overfitting. Regularization terms may penalize abrupt changes in membership values or cluster centre positions, promoting spatial coherence in the final segmentation. The convergence of the optimization process is observed. Typically, the algorithm iterates until either a specified number of iterations is reached or a convergence criterion is met (e.g., negligible changes in membership values).

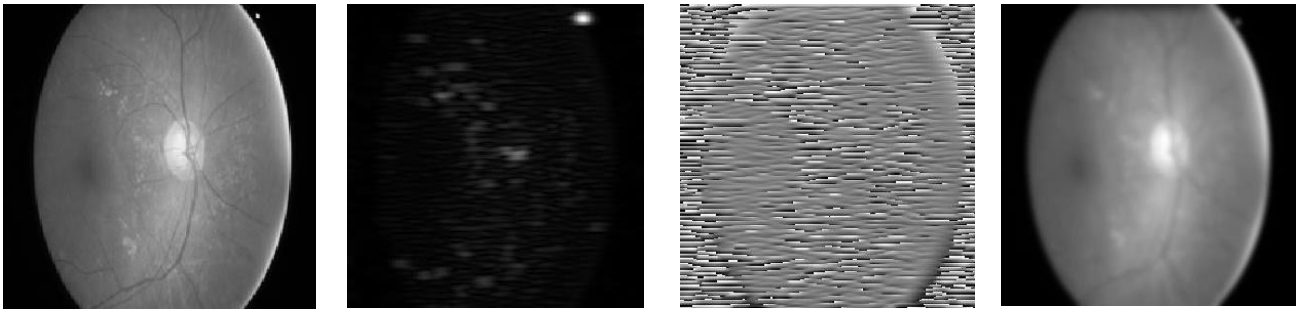
4. Result and Discussion

The proposed MMFCM is executed on an NVIDIA GPU equipped with 24GB of RAM, utilizing PyTorch as the underlying framework. The training process employs a batch size of 16. The initial learning rate is set to 0.001 and gradually decreases, reaching 0.1 times its previous

value after 120 epochs. Each model undergoes training using the SGD optimizer for 250 iterations, with momentum set to 0.9 and weight decay set to 0.0005. The return loss is specified as 0.1. Furthermore, the weights assigned to different components are as follows: L_lesion of MA is weighted at 1.0, HA at 0.001, HE at 0.1, and SE at 0.1. The coefficient for L_vessel is assigned two values: 1.0 and 0.01. This section provides an explanation of the pre-processing and segmentation of fundus images through a comparative analysis.

Pre-Processing of Fundus Image

In the pre-processing of diabetic retinopathy images, various techniques are employed to enhance the quality and extract relevant features. Gabor filters play a pivotal role in this process, offering two critical components: Gabor magnitude and Gabor phase. The Gabor magnitude highlights the strength of texture and edge features in the image, making it particularly useful for emphasizing blood vessels and lesions, essential factors in diabetic retinopathy diagnosis. On the other hand, Gabor phase encodes information about the orientation of local patterns, preserving structural details like the arrangement of blood vessels. Additionally, Gaussian filters are often applied as a pre-processing step to reduce noise, making subsequent feature extraction and analysis more robust. These techniques collectively contribute to improved image quality and aid in the early detection and diagnosis of diabetic retinopathy, a vital step in ensuring timely medical intervention for patients. The pre-processing approach is illustrated in Figure 2.



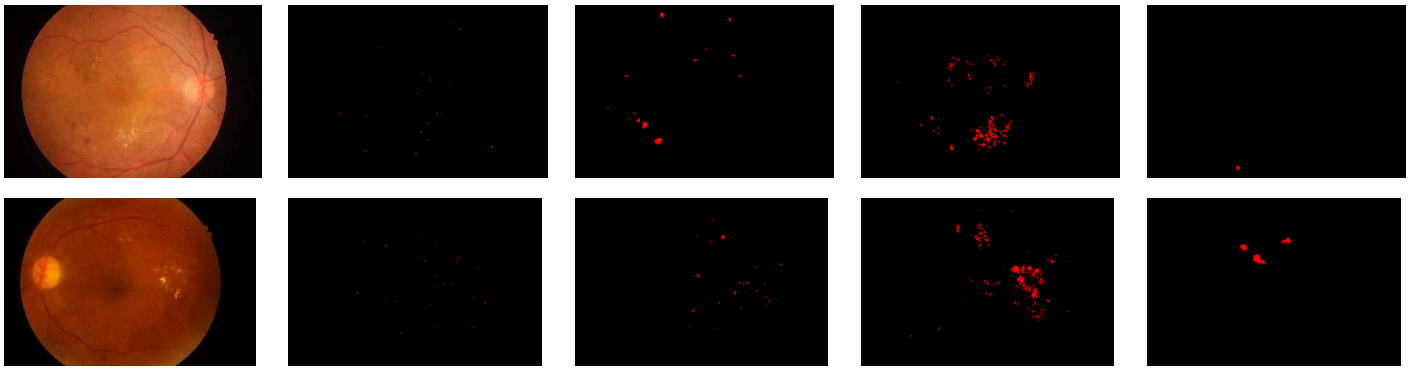
(a) Input Image (b) Gabor Magnitude (c) Gabor Phase (d) Gaussian Filter

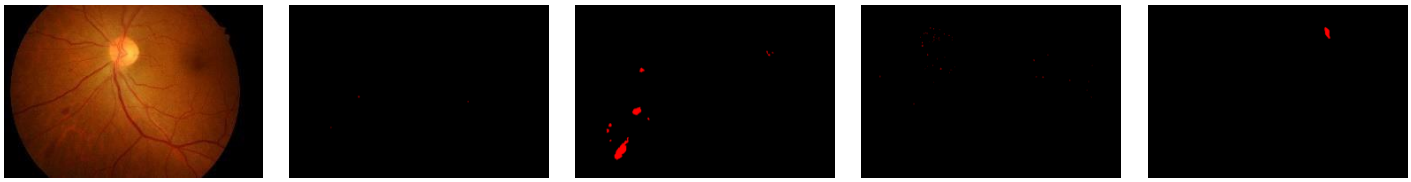
Fig 2. Comparison of Pre-Processing Approaches

Figure 2 depicts the pre-processed images. The significant Pre-Processing Components are (a) Input Image: Original diabetic retinopathy image. (b) Gabor Magnitude: Enhances texture and edge strength. (c) Gabor Phase: Preserves structural orientation. (d) Gaussian Filter: Reduces noise for improved clarity.

Segmentation of Fundus Image

Achieving generalization across diverse domains and imaging conditions is a challenging yet crucial task in the context of medical image analysis. In this study, model evaluations are conducted on the IDRiD dataset [17], which originates from a different source, subsequent to the training process on images from the DDR dataset's training set [18]. Figure 3 illustrates the results of the segmentation analysis, clearly demonstrating that the proposed approach achieves optimal performance when the dissimilarity between images captured under different conditions is minimized.





(a) Input Image (b) MA (c) HA (d) HE (e) SE

Fig 3. Comparison of Segmentation

Fig 3. Segmentation of Fundus Image Vessels using Mathematically Modified Fuzzy C-Means Clustering

This figure provides a visual representation of the segmentation process applied to fundus images for the extraction of blood vessel structures. The technique employed is Mathematically Modified Fuzzy C-Means Clustering, which is a mathematical approach used to partition the image into distinct regions, highlighting the intricate network of blood vessels within the retinal image. This segmentation step is a crucial component of medical image analysis, particularly in the context of diagnosing conditions like diabetic retinopathy.

In the context of segmenting fundus images using the Mathematically Modified Fuzzy C-Means Clustering (MMFCM) method, several key evaluation metrics play a vital role in assessing the accuracy and quality of the segmentation outcomes. Matthews Coefficient Correlation (MCC) is employed to gauge the correlation between predicted and ground truth binary masks, offering insights into the overall quality and agreement of the segmentation. The Dice coefficient (DICE) quantifies the similarity between these binary masks, with higher values indicating better overlap and alignment. Intersection-over-Union (IoU), also known as the Jaccard Index, measures the spatial accuracy of the segmentation by calculating the ratio of intersection to union between predicted and ground truth regions. These metrics, including MCC, DICE, and IoU, are pivotal for providing a quantitative assessment of the MMFCM-based segmentation's precision and spatial accuracy in fundus image analysis, supporting the critical tasks of medical diagnosis and decision-making. The performance evaluation is illustrated in Table 2 and Table 3. The performance measure is Estimated using Equation 8-10.

$$MCC = \frac{(TP*TN)-(FP*FN)}{\sqrt{(TP+FP)*(TP+FN)*(TN*FP)*(TN+FN))}} \quad (8)$$

$$DICE = \frac{2TP}{2TP+FP+FN} \quad (9)$$

$$IOU = \frac{TP}{TP+FP+FN} \quad (10)$$

Table 2. Comparison of Performance of Segmentation of MA and HA

Feature	MA			HA		
Segmentation Method	MCC	DICE	IOU	MCC	DICE	IOU
FCM	0.5234	0.5432	0.4867	0.6754	0.7972	0.6638
U-NET	0.5612	0.5915	0.5453	0.7023	0.8659	0.7021
Modified CNN	0.5987	0.5456	0.5689	0.7412	0.8702	0.7523
MMFCM	0.6703	0.6239	0.6932	0.7542	0.8813	0.7679

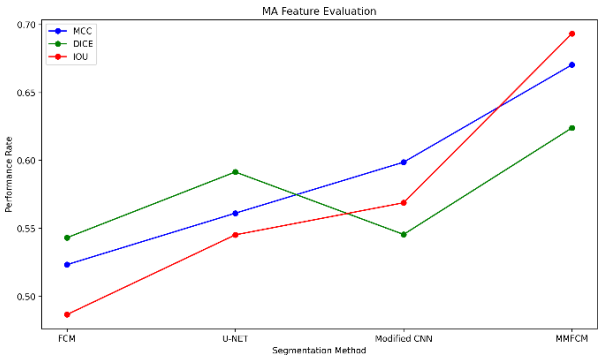


Figure 4(a). Comparison of MA Segmentation

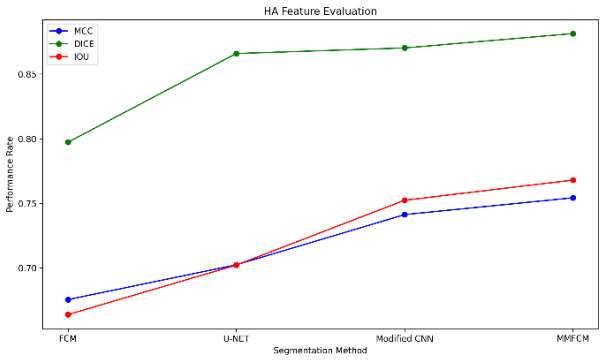


Figure 4(b). Comparison of MA Segmentation

Fig 4. Comparison of Performance of Segmentation of MA and HA

In the comparative analysis of diabetic retinopathy segmentation methods for "MA" and "HA" features, numerical results underscore notable performance distinctions. The Matthews Correlation Coefficient (MCC) reveals MMFCM as the top-performing method, boasting MCC scores of 0.6703 for "MA" and 0.7542 for "HA." U-NET follows closely with MCC values of 0.5612 and 0.7023 for "MA" and "HA," respectively. These scores signify MMFCM's superior ability to capture true positive and true negative predictions. Similarly, the DICE coefficient emphasizes MMFCM's exceptional performance, yielding DICE scores of 0.6239 for "MA" and 0.8813 for "HA." U-NET excels as well, particularly for "HA." In terms of Intersection-over-Union (IOU), MMFCM consistently leads with IOU scores of 0.6932 for "MA" and 0.7679 for "HA." Overall, MMFCM and U-NET emerge as robust contenders, with MMFCM exhibiting exceptional segmentation accuracy and region overlap. However, further refinements may enhance the performance of FCM and Modified CNN, which achieved relatively lower scores in this evaluation.

Table 3. Comparison of Performance of Segmentation of HE and SE

Feature	HE			SE		
Segmentation Method	MCC	DICE	IOU	MCC	DICE	IOU
FCM	0.5598	0.7914	0.5241	0.7995	0.8328	0.7990
U-NET	0.4997	0.7577	0.4732	0.7518	0.7910	0.7407
Modified CNN	0.4932	0.7474	0.4777	0.7944	0.8078	0.7771
MMFCM	0.5954	0.8348	0.5701	0.8542	0.8450	0.8375

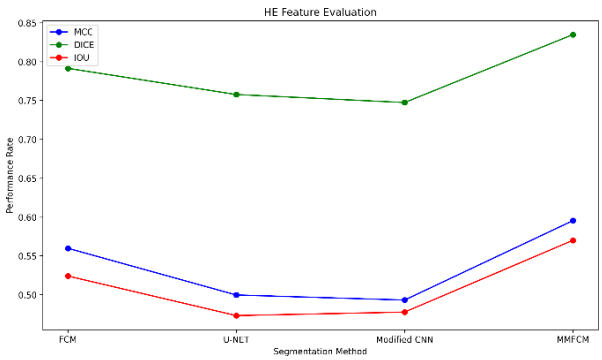


Fig 5(a). Comparison of HE Segmentation

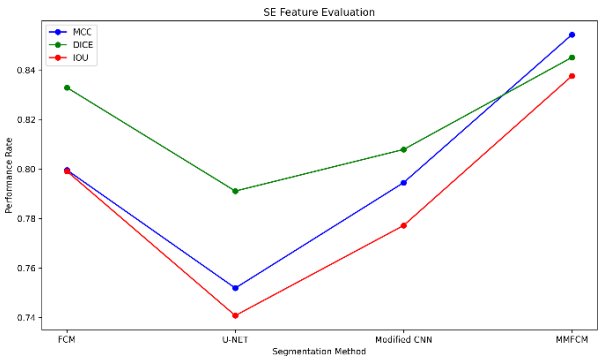


Fig 5(b). Comparison of SE Segmentation

Fig 5. Comparison of Performance of Segmentation of HE and SE

In the comparative analysis of diabetic retinopathy segmentation methods for "HE" and "SE" features, numerical evaluations reveal distinct performance disparities. Matthews Correlation Coefficient (MCC) assessments underscore MMFCM's excellence, achieving an MCC score of 0.5954 for "HE" and 0.8542 for "SE," signifying its robust classification precision. Additionally, MMFCM excels in terms of the DICE coefficient, securing the highest scores of 0.8348 for "HE" and 0.8450 for "SE," indicative of substantial overlap with the ground truth. This trend persists in Intersection-over-Union (IOU) scores, where MMFCM consistently records superior results, scoring 0.5701 for "HE" and 0.8375 for "SE." Overall, MMFCM demonstrates remarkable segmentation proficiency, closely followed by FCM, while U-NET and Modified CNN exhibit room for enhancement in their segmentation precision and region overlap with the ground truth.

5. Conclusion and Future Work

Diabetic Retinopathy is the leading cause of blindness worldwide, although it is generally asymptomatic until severe. When DR is treated at an early stage, vision loss can be prevented. If left untreated, it can progress to a severe stage. Therefore, a regular screening of the patient is required for early identification and treatment. The proposed study was concerned with the automated identification of DR to help ophthalmologists improve the visual appearance of the retina. the comparative analysis of diabetic retinopathy segmentation methods highlights notable variations in their performance across different features. Matthews Correlation Coefficient (MCC), DICE coefficient, and Intersection-over-Union (IOU) scores were used as evaluation metrics, and the results demonstrate distinct strengths among the methods. MMFCM consistently emerges as a strong contender, achieving high MCC, DICE, and IOU scores for various features, including "MA," "HA," "HE," and "SE." Its robust classification precision and substantial region overlap with the ground truth make it a promising choice for diabetic retinopathy segmentation. The future directions of research would include implementation of various Pre-trained CNN Models for large datasets in order to increase the classification accuracy. Some advanced pre-processing techniques would be applied to remove artifacts such as eyelashes from the images to reduce the number of features to be learned by the CNN Models.

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