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Optic Disc Localization using Fuzzy C Mean and DB Scan Clustering - A Comparative Analysis

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Abstract

In the diagnosis and early detection of Glaucoma and diabetic retinopathy, when delicate vasculature grows in the retina, precise identification and localization of the border optic disc are highly significant. This research provides an automated method to localize and detect the optic disc. The proposed method uses the clustering methodology to locate the optic disc region. Fuzzy C Mean and Density Based Scan (DB Scan) clustering approach is evaluated on the publicly accessible DRIVE, diaretdb1, diaretdb0, and databases, which were created to aid comparative investigations on optic disc localization and detection in retinal images. With Diaretdb0 and Drive DB, the DB Scan clustering approach obtained an accuracy of 94.11% and 81.18%, respectively, which is better than the Fuzzy C mean, and it performs DB scan better for the DiaretDB1 dataset.

Keywords: Optic Disc, Clustering, Fuzzy C Mean, DB Scan, Fundus image

1. Introduction

The retina, a translucent structure at the back of the eye, the blood vessels, and optic nerve disc make up the eye fundus, which aids in the detection of many eye illnesses. Glaucoma is a severe condition in the human eye that can be managed but not cured. If the condition of Glaucoma is left untreated, loss of vision progresses progressively, with the possibility of blindness. Glaucoma is detected and diagnosed by tracking changes in the optic cup part of the Optic Disc (OD). The segmentation method shall be used to separate the optical disc area from the retinal images by an automated system. Finding the optic disc, however, is essential for simplifying this segmentation. Therefore, various approaches for locating OD have been the major area of research [1-8] [37-38].

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Glaucoma is often diagnosed by considering a patient's condition, doing a physical examination, completing a visual field loss test, and monitoring the OD Intra Ocular Pressure (IOP) using ophthalmoscopy to check the optic nerve’s shape and color. The OD is a cross-sectional image of the optic nerve that connects each eye's retina. In a retinal fundus image, it appears to be a brilliant circular spot. However, the IOP destroys the nerve fibers that make up the optic nerve in Glaucoma. As a result, OD develops the Optic Cup, a hollow and crater-like depression at the front of the nerve head. The OD’s edge also dilates, and the hue changes from a healthy pink to a faint pink [9].

The possibility of using technologies in ophthalmic analysis and computer vision approaches grows as digital images, and processing power improves. Based on qualities used in image analysis, such as a yellowish disc, brightness, and high contrast through which the blood vessels and optic nerves flow, the technical technique has successfully found the optic disc. As a result, the optic disc has more specific information that may be used to identify it [10].

The OD's edge and center must be identified to distinguish it from other retinal structures and serve as a mark. Techniques for optic disc localization published in the literature often try to determine the approximate center of the disc or place it inside a defined area such as a circle or square [11].

The clustering approach, which distributes data points to numerous groups created on joint correlations and then seeks to uncover parallels and linkages within each grouping, is the best criterion for finding the optimal solution for these challenges. Least-squares solutions are used to discover the optimum place for each data point in a probability space constrained by two or more clusters [12].

The most important objective of this work is to determine and localize the optic disc regions using the clustering techniques on the publicly available dataset, with many variants of clustering techniques available in the literature, Fuzzy C Mean (FCM) and Density Based Scan (DBScan) techniques are considered, and the performance measure of those algorithms are measured, and the comparative analysis is made.

The article is organized as: Section 2 introduces the associated fieldworks that have been done. It also explains why the recommended method is being considered. The approach for optic disc localization and its execution are discussed in Section 3. The results are analyzed in Section 4, and the research is concluded in Section 5.

2. Related Works

Recursive region growth was employed by Sinthunayothin et al.,[13] which resulted in detecting hard exudates and an optic disc. The OD was eliminated by locating the area with the most intensity fluctuation between consecutive pixels. Akara and Uyyanonvara [14] used low-contrast images with FCM and morphological-based segmentation to find exudates. FCM was used for coarse segmentation, whereas morphological reconstruction was used for finer segmentation. Akara [15] conducted a series of tests and compared FCM clustering, Naive Bayesian (NB) classifier, Support Vector Machine (SVM), Nearest Neighbour (NN) Classifier, and identified exudates to hand-drawn ground-truths by ophthalmologists. As a result, FCM obtained the highest sensitivity of 97.29 percent.

Hussain F.Jaafar et al. [16] suggested an approach that combines edge detection and region growth with top-down image segmentation and local thresholding. Exudates with firm exudates were graded. For segmentation of potential exudate areas, Maria Garcia et al., [17] employed a blend of global thresholding and local thresholding. RBF networks were trained by using candidate areas. The trained network performed pixel-by-pixel categorization. Vijayamadheswaran et al., [18] employed Contextual Clustering (CC) to extract features, which were then fed into an RBF network. Neera Singh et al., [19] utilized FCM clustering. Then, color, size, edge, and texture were taken from the arising clusters. Finally, using a system-based Backpropagation Neural Network, the pixels were classified into exudates and non-exudates.

SIFT characteristics were recovered from a small ROI region ranging from the site of the optic disc outward toward the center of the retina by Nathan Silberman et al. [20]. The Gaussian SVM was trained to classify particular patches of an image using these attributes. For optic disc identification, Vijayakumari et al., [21] employed template matching. To discover items with sharp edges, the authors employed the Sobel edge detector to find yellowish objects, and used the upgraded MDD classifier. Ivo Soares et al., [22] employed morphological operators in conjunction with adaptive thresholding. The authors claimed that contrast variations, non-uniform lighting, and a changing backdrop do not affect the approach, resulting in accurate identification.

Different strategies for OD and OC extraction for CDR computation are documented in the literature. Huiqi et al., [23] based optical disc detection implemented Active Shape Model (ASM). The parameters for this model were initialized using the Principal Component Analysis approach. Experimental findings demonstrated the technique's quicker convergence rate and resilience. Huajun Ying et al., [24] developed a fractal-based algorithm to autonomous OD localization and segmentation in retinal images. K. Shekar [25] developed an OD segmentation approach based on A.R. Hussain's [26] proposal employing active genetic outlines to segment the optic nerve head.

Liu et al. [27] offered technique to extract the OD and cup ratio. First, the spotted contour was irregular owing to the impact of blood pots and was extracted by variational level set method. Next, the intensity and edge level set technique was used to detect the cup border. For high and low-risk retinal images, thresholding strategies gave improved outcomes. Finally, an elliptical fitting was accomplished for smoothening the boundary.

According to Padmavathi et al. [28], the quality of an underwater image differs from that of an image captured in the air because several elements influence it, including the water media, troposphere, compression, and temperature. This means that image segmentation is required for digital image processing. Image segmentation divides a representation into portions with robust correlations with objects to reflect the unaffected information gathered from this present reality. The simplest method for virtually all robotized image recognition systems is image segmentation.

Naz et al. [29] discovered that image processing researchers are revolutionizing this process because it is the finest and most precise way of spotting medical imaging. A huge amount of work on collecting information from an image and separating it into defined sections has supported numerous approaches that have been put forward to execute enhancements fast. Though, due to the unclear cluster borders revealed in photos, there are complexity, time, and precision restrictions. On the other hand, Fuzzy approaches are mostly unrestricted of issues and produce significantly improved results than other image segmented methods.

In addition, Yambal [30] demonstrated that segmentation is an unsupervised classification approach and a key phase in the advanced image analysis process. Segmentation of Digital Medical Images Detecting anomalies, finding significant features, categorizing data, and compressing data are some original Clustering works. The goal of the image segmentation method, which uses the classic FCMs technique based on a hierarchical self-organized map, is to successfully segment noisy images.

Khalid et al. [31] demonstrated that FCMs could detect various ailments, including Glaucoma, characterized by a rise in intraocular pressure that severely damages the optic nerve.

Glaucoma is the shared origin of vision loss and is irretrievable, but it can be managed for a long time with early detection and appropriate treatment. Norouzi et al. [32] demonstrated the mechanism of clustering algorithms without data training. These methods use an unsupervised learning algorithm and distinct expert to estimate similar features in an image. Also hold things such as keys to distinguish other features with similar characteristics. This process is likeminded with utmost data mining algorithms because unsupervised approaches do not require data training.

Kumar et al. [33] investigated correlative distance by employing large starting prototypes and Gaussian weights to construct fuzzy weights after eliminating, grouping, and merging. The geographical information was included in normal FCM spatial FCMs procedures, and every cluster membership weight was altered after considering the cluster distribution in the vicinity. According to Ali et al., [35] segmentation is an important stage in the sensitive study of human tissue lesions to increase the division of various clusters of images based on comparable characteristics. The region is expanding, and thresholding algorithms, among those developed thus far, have trouble calculating the threshold value. Computer algorithms that do pixel-by-pixel categorization are computationally intensive. Edge-based techniques struggle to distinguish between pixels belonging to arteries and pixels belonging to exudate edges. It's tough to determine the no. of clusters in clustering-based systems.

3. Methodology

A. Dataset Description

The whole optic disc localization process is tested and assessed using the Diaretdb0, Diaretdb1, and Drive datasets, the publicly available retinal fundus imaging datasets. The DiaretDB1 dataset has around 89 fundus retinal images acquired at Kuopio University Hospital. 84 photos were deemed to have moderate non-proliferative diabetic retinopathy based on the marks presented, while the remaining five images were healthy [36]. Diaretdb0 contains 130 color fundus photographs, 20 images of normal, and 110 images have diabetic retinopathy symptoms. DRIVE comprises of 40 images obtained from a diabetic retinopathy screening program in the Netherlands.

B. Fuzzy C Mean Clustering:

FCM is a clustering technique that assigns membership to each data point based on its distance from the corresponding cluster center. The likelihood of a data point belonging to a particular cluster center increases with its distance from the center. The initial stage of FCM clustering involves setting the cluster value, selecting a value for m, and initializing the partition matrix U. Next, the centroids are computed, and the partition matrix is updated, followed by repetition of this process until convergence is reached.

C. DB Scan Clustering:

DB Scan Clustering refers to unsupervised learning techniques that aim to identify distinct clusters or groups in data. The method operates on the underlying assumption that a cluster in the data space is a region with a high point density, separated from other clusters by areas with a low point density. It can detect clusters of varying shapes and sizes, including noise and outliers, even in extensive datasets. To initiate the process, DB Scan selects an arbitrary point and checks if there are at least two points within a specified radius. If so, they are considered the part of the same cluster. The clusters are then expanded recursively by computing the neighborhood for each neighboring point.

D. Optic Disc Localization:

Optic disc location is carried out in a series of tasks, with Fig.1 showing the various implementation stages for detecting optic discs from fundus images. Initially, an image of the fundus is collected from publicly available datasets and pre-processed to eliminate noise. Then, the optic disc area is obtained using the Fuzzy C mean, and DB scan clustering approaches.

Figure 1. Methodology of Optic Disc Localization

After completing the pre-processing of the input, the Fuzzy C Mean and DB Scan clustering algorithms are utilized to identify the optic disc region. The input image and the resulting images from the segmented clustering process on the Diaretdb0 dataset are depicted in Fig.2. In contrast, Fig.3 represents the sample input and the Clustering segmented output images of the Diaretdb1 dataset, and Fig.4 represents the sample input and the clustering segmented output images of the Drive dataset.

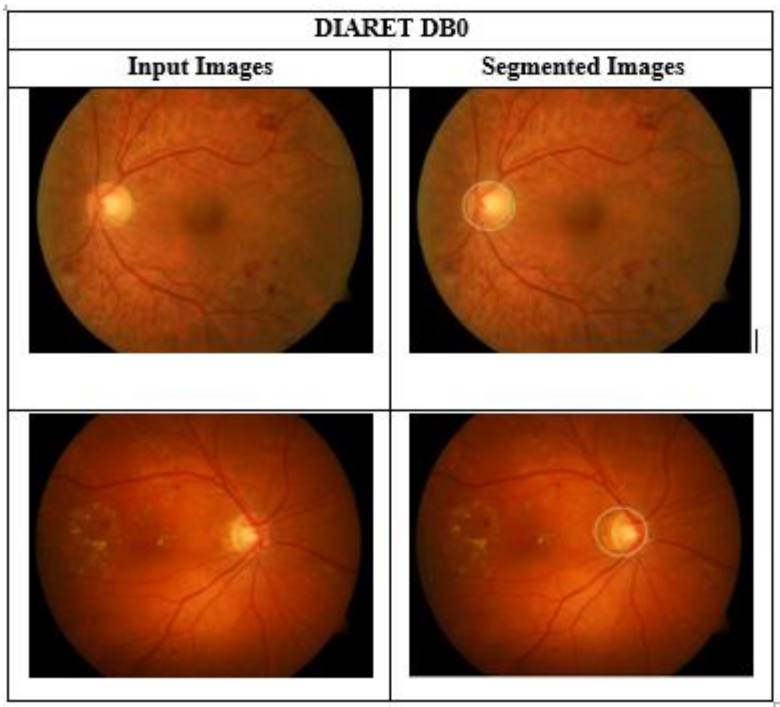


Figure 2. Optic disc Localization in DIARET DB0 dataset

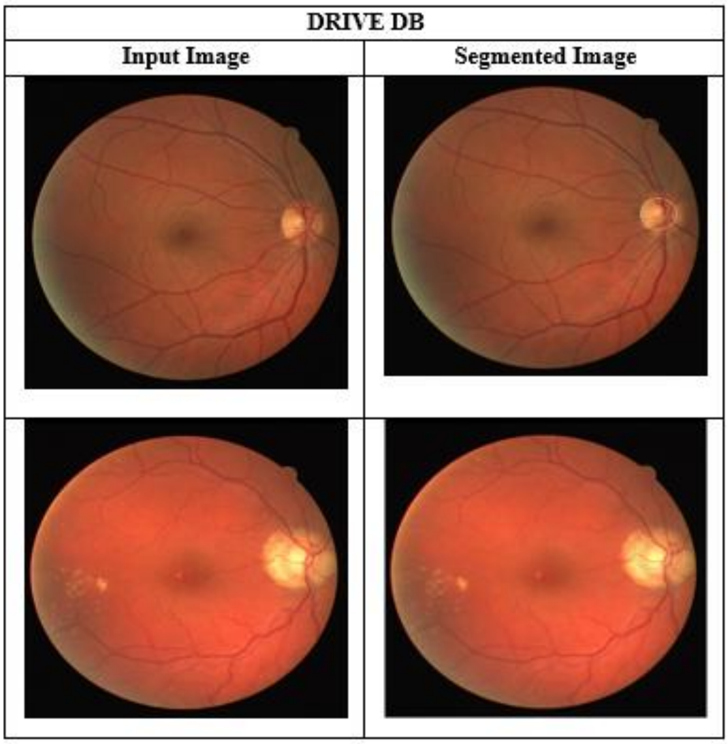


Figure 3. Optic disc Localization in DIARET DB1 dataset

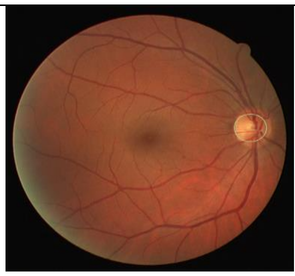
DRIVE DB	
Input Image	Segmented Image
	
	

Figure 4. Optic disc Localization in DRIVE dataset

The clustering techniques used do not work to determine the optic disc of the images. Few images did not determine the optic disc correctly, as those images had many challenges like many bright spots like exudates. Some of the sample improper segmented images are shown in Fig.5.

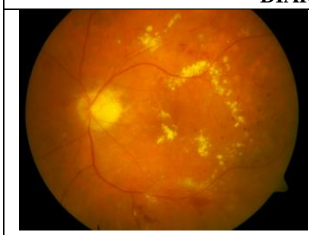
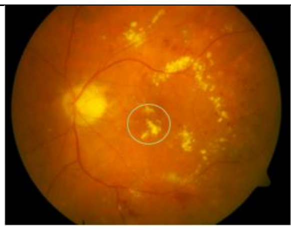
Input Image	Segmented Image
DIARET DB0	
	
DIARET DB1	
	
DRIVE DB	

Figure 5. Sample images of improper optic disc localization

4. Result Analysis

The evaluation of Fuzzy C Mean and DB Scan clustering techniques is based on various metrics such as Accuracy, Precision, Recall, and F1 score. Table 1 and Table 2 present the performance results of these clustering methods on the DIARET DB0, DIARET DB1, and DRIVE datasets. The accuracy of the performance parameters demonstrated in these tables indicates that Fuzzy C Mean clustering is superior to DB Scan clustering for the DIARET DB1 dataset, whereas DB Scan clustering outperforms Fuzzy C Mean clustering for the other datasets, namely Diaretdb0 and Drive dataset.

Table 1. Result analysis of DB Scan Clustering

	DIARETDB0	**DIARETDB1**	**DRIVE DB**
PRECISION	**94.11**	**96.45**	**98.68**
RECALL	**97.45**	**85.28**	**81.81**
ACCURACY	**94.11**	**80.19**	**81.18**
F1 SCORE	**95.75**	**90.52**	**89.46**

Table 2. Result analysis of Fuzzy CMean Clustering

	DIARETDB0	**DIARETDB1**	**DRIVE DB**
PRECISION	**92.19**	**89.76**	**91.24**
RECALL	**87.71**	**86.75**	**87.07**
ACCURACY	**83**	**89.29**	**80.42**
F1 SCORE	**89.89**	**88.23**	**89.11**

Figures 6-8 represent the performance of the Fuzzy C Mean and DB Scan clustering technique on DIARET DB0, DIARET DB1, and DRIVE datasets, respectively.

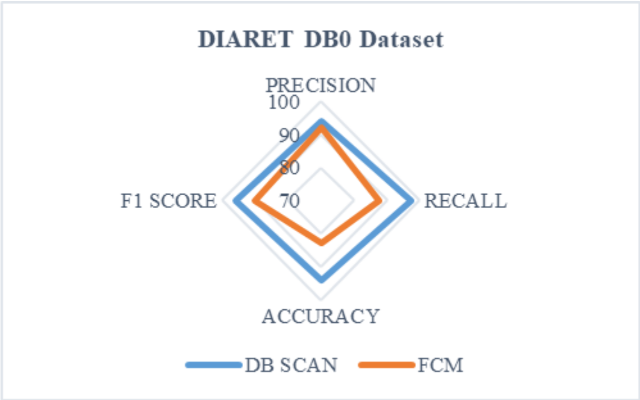


Figure 6. Accuracy, Precision, Recall, and F1-Score of DIARETDB0 dataset

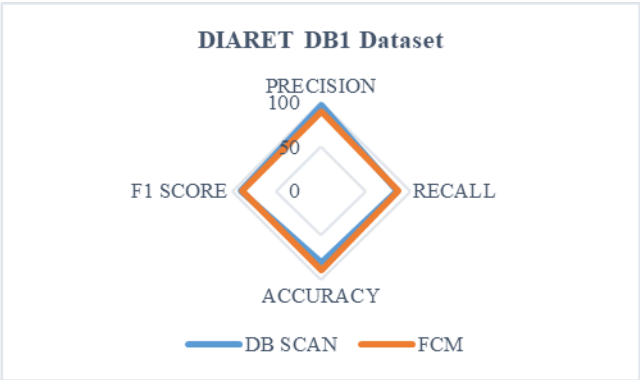


Figure 7. Accuracy, Precision, Recall, and F1-Score of DIARETDB1 dataset

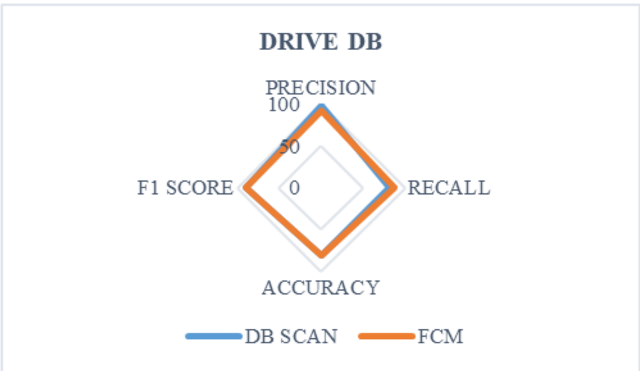


Figure 8. Accuracy, Precision, Recall, and F1-Score of DRIVE dataset

5. Conclusion

This research has proposed an automated method for diagnosing Glaucoma and diabetic retinopathy, which relies on optic disc segmentation utilizing the Fuzzy C Mean and DB Scan clustering techniques. The evaluation of this approach's performance is based on metrics such as Precision, Recall, F1-Score, and Accuracy. The results indicate that DB Scan performs better than Fuzzy C Means on the Diaretdb0 and Drive datasets, while Fuzzy C Means outperforms DB Scan for the Diaretdb1 dataset. To further improve the optic disc localization, future research could explore enhancing the pre-processing stage and leveraging learning and optimization techniques.

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