Optic Nerve Head Info Injected K-Means Method for Segmentation of OD

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Abstract—Segmenting the Optic Disc (OD) is an important step in the automated detecting of certain serious ocular illnesses. An innovative strategy for segmenting the OD is critical since it faces challenges such as vascular obstruction, low contrast, and poor accuracy. This paper proposes a new method for OD segmentation, namely 'OD segmentation using Optic Nerve Head info injected K-Means method (ONHKM)'. By adding Optic Nerve Head (ONH) structural information through an iterative procedure, the proposed method improves upon the standard K-means segmentation algorithm. Through this integration, the membership matrix is updated gradually based on the ONH structure information that improves the segmentation and identification of the OD region. The contributions through the exclusive membership update and objective function update, make up the ONH structure-specific OD enhancement. The ONH structure-specific membership modification enhances the efficiency of OD segmentation, while the modified OD structure-specific objective function leverages the execution speed of the convergence process. The proposed ONHKM method exhibited an impressive average segmentation accuracy of 97.52% compared to existing methods. The efficacy of the method is shown by this major enhancement, which can be effortlessly incorporated into fundus scanners, offering a useful and dependable tool for medical use. According to the results, the ONHKM method improves automated OD segmentation, which will hopefully assist with ocular disease early diagnosis and treatment.

Keywords: Medical image processing, K-means, Fundus image, OD segmentation, Optic nerve head

INTRODUCTION

The ability to observe the world around us is made possible by the amazing human eye. Its intricate structure and functions enable the reception, transmission, and processing of visual information, that contributes to our perception and understanding of the environment. The inner lining of the eye, more precisely the portion of the eye that is visible via the ophthalmoscope at the back, is referred to as the 'fundus' [1] in medical terminology. It contains the OD, Blood Vessels (BV), retina, and other tissues that can be looked at during an eye exam. The OD [2], often referred to as the optic nerve head, is a crucial component located at the back of the eye where the optic nerve exits the eye and enters the brain. In the center of the retina, it appears as an oval or circular region. It is a crucial part of the fundus, which is the surface of the eye's interior seen through an ophthalmoscope [3]. Identifying the borders of the optic disc in retinal images is a technique known as OD segmentation [4], which can be done either automatically or manually. It is an important

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stage in the analysis of retinal images for the diagnosis and monitoring of different eye diseases and conditions. Accurate OD segmentation enables additional examination of the OD, including measurements of its shape, size, and other parameters. It helps in the detection and monitoring of retinal diseases such as glaucoma, Diabetic Retinopathy (DR), and disorders of the optic nerve because it allows the detection and tracking of changes over time.

A medical imaging technique called fundus photography [5] is used to capture complete images of the retina, OD, macula, and BV that make up the fundus, which is the inner surface of the eye. It is a useful tool for ophthalmologists to diagnose and monitor different eye diseases and disorders.

Ahmed *et al.* [6] discovered a method to identify the midpoint of the OD by using the mean intensity value of the retinal image. This method can be applied to improve the detection of retinal OD or to diagnose retinal disorders. An RGB fundus image's green channel is used to inform a candidate-based method that locates the OD center. This method's excessive computational cost makes it inappropriate. Carmona *et al.* [7] predicted a technique for simultaneously segmenting medical image anatomical characteristics. Similarly, this method is applied in a way that segments the fovea and OD of retinal images simultaneously. Identifying the OD and fovea as crucial anatomical structures is required for any image-based computer-aided diagnosis system designed to diagnose retinal diseases that cause vision loss. The simultaneous segmentation technique makes use of the evolutionary algorithm and the OD Fovea model. It only segmenting a smaller amount of anatomical structure is its inferiority.

Gonzalez *et al.* [8] created the retinal fundus image segmentation method using OD and BV. Herein, segmenting the OD can be done in two different ways namely, Markov Random Field (MRF) and Compensation Factor Method (CFM). It fails in the segmentation of retinal diseases. Miri *et al.* [9] evaluated a multimodal method to utilize the interrelated information from Spectral Domain Optical Coherence Tomography (SD-OCT) and fundus images. OD and OC segmentation is done automatically using this multimodal machine learning graph-based method. The unworthiness of this method is that the blood vessel removal is not included.

Zhang *et al.* [10] provided an OD detection method based on the directional and vessel distribution properties. Herein, three-vessel distribution properties local vessel density, compactness, and uniformity are combined into one feature design to identify an accurate horizontal coordinate of OD. The vertical coordinate of OD is calculated using a General Hough Transformation (GHT). Due to the processing of small-sized images, the range of accuracy in the OD border is quite low. Wu *et al.* [11] offered a method based on directional models for automatically localizing ODs in retinal fundus images. The method uses three different directional models: the hybrid directional model, the local Directional Model (DDM), and the global directional model (R-BPDM). The disfavor of this work is that the performance side is low.

Roychowdhury *et al.* [12] devised a classification method that identifies both the Vessel Origin (VO) pixel and the OD boundary using an OD segmentation method. The bright regions are divided into bright probable OD regions and non-OD regions using six region-based features and a Gaussian Mixture Model (GMM) classifier. It fails to identify the disease severity, which is the fault of this method. Zahoor *et al.* [13] illustrated an image processing pipeline for automatically detecting glaucoma in retinal images. The Region Of Interest (ROI) used for OC segmentation is the segmented OD. Multi-layer perceptrons (MLP) are utilized for the supervised categorization of OC pixels. A decision tree-based ensemble classifier is used to categorize the glaucomatous images. The mistake of this paper is that it marks the OD region using a standard elliptic model.

Khalil *et al.* [14] portrayed a method to increase the accuracy of the extraction of the Inner Limiting Membrane (ILM) layer. It utilized a method to enhance the shape of the ILM layer. The method applied Bezier curve fitting and interpolation in terms of surface refinement and outlier removal. The downside of this method is that the degeneration of ganglion cells has not been examined while retinal layers are taken into consideration.

Huazhu Fu *et al.* [15] suggested a deep learning method to test for glaucoma directly from the fundus image and obtain extra image-relevant information. The Disc-aware Ensemble Network (DENet) method is used for glaucoma screening. There are four deep streams with different levels and modules: local disc area stream, disc polar transformation stream, segmentation-guided network, and global image stream. The time consumption is high, which is the failure of this method. Huazhu Fu *et al.* [16] depicted M-Net, a deep learning architecture that integrates OD and OC segmentation in a one-stage multi-label system. The major components of M-Net are the multi-label loss function, side-output layer, U-shaped convolutional network, and multi-scale input layer. The failure of this work is that the time consumption is high.

Lei *et al.* [17] revealed an unsupervised domain adaption-based image synthesis and feature matching for OD and OC segmentation. Using boundary data from the OD and OC, the GAN-based Image Synthesis (IS) method is used. Here, the methods of Output-Level Feature Alignment (OLFA) and Content and Style Feature Alignment (CSFA) are applied. The insignificance of this method is the high time and computational complexity of the training network. Veena *et al.* [25] established the segmentation of OD and OC for the automated identification of glaucoma. Accurate segmentation is achieved by the deep learning architecture method using an enhanced version of each of the two CNN models for OD and OC separately. The imperfection is quite time-consuming.

Chen *et al.* [27] presented a Reconstruction-driven Dynamic Refinement Network (RDR-Net), a unique Unsupervised Domain Adaptation (UDA) technique, in which it developed three modules namely, the Reconstruction Alignment (RA) module, Low-level Feature Refinement (LFR) module, and Prediction-Map Alignment (PMA) module to reduce the domain gap and use a due-path segmentation backbone for simultaneous edge detection and region prediction. The flaw of this method is poor region prediction. Meng *et al.* [28] exposed OD and OC segmentation from retinal fundus images. It exhibits a weakly and semi-supervised graph-based network that explores three features of geometric relationships and domain knowledge between segmentation Probability Maps (PM), modified Signed Distance Function representations (mSDF), and Boundary Region Of Interest characteristics (B-ROI). The imperfection of this work is that its algorithm performance is low.

Liu *et al.* [29] devised an adversarial network-based combined segmentation method for the OD and OC, which includes additional monitoring features to direct the network optimization process. This framework was evaluated with two publicly available performance datasets of retinal fundus images. The inadequacy of this work is that the image quality is low. Virbukaite *et al.* [30] portrayed a Convolutional Neural Networks (CNNs) based ensemble for joint optic disc and optic cup segmentation. It used a modified Attention U-Net architecture with pre-trained ResNet34, ResNet50, MobileNet, Inceptionv3, and DenseNet121 as backbones. The minus of this work is that it provided less accuracy.

Multiple methods of OD segmentation have been published in the literature, but they have a few difficulties, like high time consumption, suffering from less accuracy, and OD regions having various appearances due to size, shape, color, and texture across different retinal images. The boundary of the OD is often indistinct because of the blend with the surrounding retina, blood vessels, and other structures, which makes it difficult to precisely determine the disc's boundary. This paper concentrates on the development of an OD segmentation method using fundus images. As a result, this study proposed a segmentation technique called the 'Optic nerve head info injected k-mean method'. The main contributions of the proposed method for OD segmentation using the Optic Nerve Head info injected K-Means method (ONHKM) are as follows:

The proposed ONHKM method's main contribution is the ONH structure-specific membership computation that is injected K-means clustering method.

The membership function of the K-mean algorithm is framed as an upgraded version of membership calculation through the ONH structure-specific modification.

The intermediate segmented result of the OD region is further enhanced by the horizontal directional filling, which is also considered an innovative approach.

A new objective function for K-mean clustering is designed by concentrating the successive modifications in the structure of the OD region to achieve faster convergence.

This paper presents a novel method that uses Optic Nerve Head (ONH) data to calibrate the K-means segmentation algorithm. The membership matrix can be updated gradually through this iterative method, improving the accuracy of OD segmentation. A two-part ONH structure-specific enhancement is integrated into the study. This consists of an exclusive membership update and an OD enhancement phase, both of which greatly increase the segmentation accuracy. The proposed ONHKM method outperforms previous techniques and demonstrates the method's effectiveness with an astounding average segmentation accuracy of 97.52%. Combining these efforts, a method to OD segmentation becomes more precise and dependable by addressing issues like low contrast and vascular blockage.

The proposed ONHKM method for OD segmentation is explained in Section 2 along with its working process. An explanation of the proposed ONHKM method based on standard measures, the analytical results, and discussions are covered in Section 3. The efficiency of the proposed method in comparison to existing methods is concluded in Section 4.

PROPOSED METHOD

The OD area is segmented from the input fundus image by the proposed ONHKM method. Figure 1 depicts the process of this method's workflow. There are three color channels Red, Green, and Blue in the input color fundus image. Among these three channels, the Red channel points out the OD region much clearer than the other two; hence, the proposed method uses the Red channel as the source for the improved K-means algorithm that is supported by the ONH structure of the fundus image. Figure 1, shows the block diagram of the proposed ONHKM method for OD.

In Figure 1, the process begins with the input of a fundus image, which is a retinal image captured using a fundus camera. The red channel from these images is extracted, which is often used because it provides better contrast for retinal features. The red channel data undergoes an improved K-means initialization process. This is likely used to initialize cluster centroids more effectively, leading to better segmentation results. As part of the K-means algorithm, the central head (centroid) of clusters is computed. The distance between data points and cluster centroids is calculated to assign each point to the nearest cluster. Based on the distance, the membership of each data point to a particular cluster is determined. After several iterations, three clusters are formed, which likely correspond to different regions or structures within the retina. The process further refines the clusters based on specific characteristics of the optic nerve head (ONH). Enhancing the OD to ensure it is correctly identified and segmented. Herein, it updates the cluster memberships to improve the accuracy of segmentation. An objective function is used to optimize the segmentation process, ensuring that the biggest object detected within the image corresponds to the OD region. The segmented regions are analyzed to identify the largest object, which is assumed to be the OD. Finally, the segmented OD region is identified and extracted as the final output. The process aims to accurately segment the OD from retinal images using a combination of image processing techniques and clustering algorithms

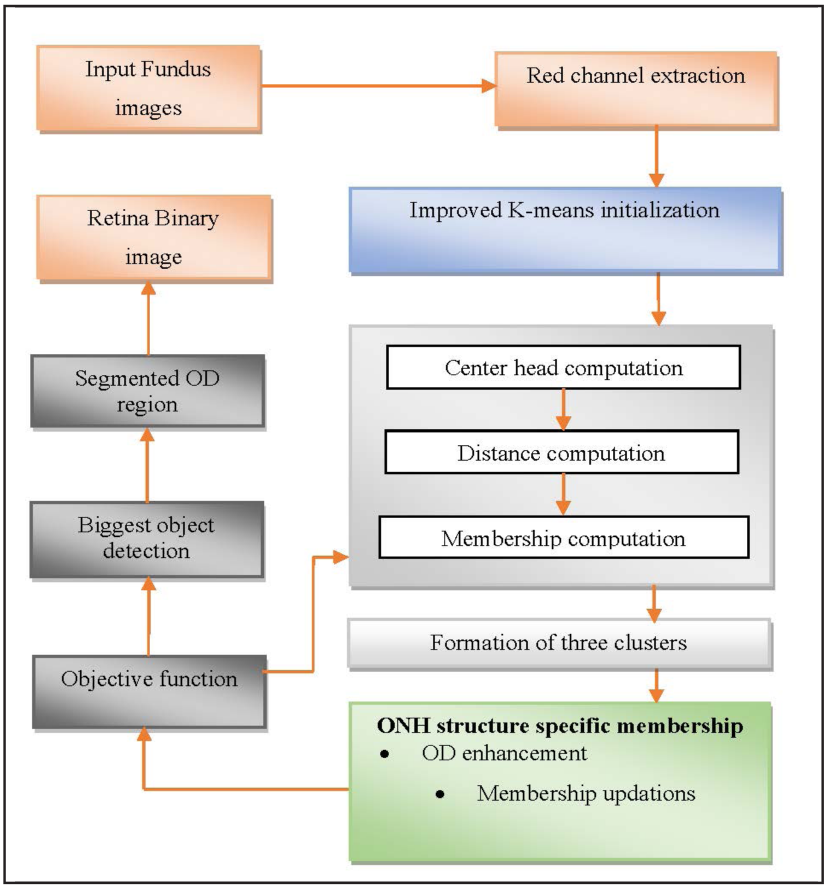

Fig.1: Block Diagram of the Proposed ONHKM Method for OD

The K-means [18] algorithm is used to cluster the meaningful region of an image. It is a famous and effective image segmentation method worldwide. It segments the image into K segments; hence, that name is given to this algorithm. The selection of the K-Means method for OD segmentation in this study is based on several key factors, including computational efficiency, interpretability, and adaptability to fundus imaging constraints. While deep learning-based approaches and adaptive clustering methods have demonstrated high accuracy in medical image segmentation, they often come with significant drawbacks, such as:

- Computational Complexity & Hardware Dependence
- Data Dependency & Generalization Issues:
- Interpretability & Clinical Acceptance
- Performance vs. Complexity Trade-off

Thus, while deep learning and adaptive clustering methods are powerful, the ONHKM method balances accuracy, efficiency, and practicality, making it an optimal choice for real-time and resource-constrained medical applications.

The input fundus image's Red channel is fed as input to the K-means algorithm. The image containing the height 'h' and width 'w' is linearly converted into vector form and named 'x'. It can be expanded as $x = \{x_0, x_1, x_2, \ldots\ldots\ldots, x_{m\times n}\}$. The total element's length is noted as $L = m \times m$. The total cluster P is fixed as 3. The reason for the three clusters is the availability of data such as background, OD region, and another retina region. A membership matrix M, which contains zeros and 1, is constructed in the random format. The dimension of the membership matrix is set to $L \times P$, which obeys Eq. (1).

$$\sum_{j=0}^{p-1} M_{i,j} = 1 \tag{1}$$

There must be only one 1 in any of the three clusters of data of i_{th} element, and other positions should be zeros. The exponent value q is set to 2. The maximum iteration *mitt* is fixed as 50. The cluster head information is noted as C_j where, $j \in [0, p-1]$ and it is computed using Eq. (2).

$$cj = \frac{\sum_{i=0}^{L-1} (M_{i,j})^q \times x_i}{\sum_{i=1}^{n-1} M_{i,j}^q} \tag{2}$$

$$j \in [0.\ p-1]$$

The distance between each pixel and cluster head C_j is computed using Eq. (3).

$$d_{i,j} = ||x_i - c_j|| \tag{3}$$

According to Eq. (3), the minimum distance value providing cluster index is the much more closed cluster index related to the x_i data. This association of a specific cluster is stored in the membership matrix M by specifying 1, and for other locations, it is 0. It can be spelled Eq. (4), Eq. (5) and Eq. (6).

$$M_{i,j} \in [0, p-1] = 0 \tag{4}$$

$$I = Func\_Min\_Index\ (d_{i,0,}\ d,\ d_{i,2}) \tag{5}$$

$$M_{i,j} = 1 \tag{6}$$

where

I - Index of minimum value

In Eq. (4), the entire clusters of i^{th} elements are set to zero. Afterward, the minimum value providing an index of the three clusters is found using Eq. (5). Herein, *Func_Min_Index* refers to the function to compute the minimum index value.

The ONH structure-specific modification is set into the membership matrix through some processes. First, the membership matrix is utilized to get the partially segmented image, which contains the three labels such as 0, 1, and 2. This intermediate process is performed at 20^{th} iterations to confirm the formation of the three clusters. The partially segmented image is converted into three binary images, and the mean of their foreground data is computed. The mean values of the three clusters are noted as μ_o, μ_1, and μ_2. Generally, the OD region is formed with high-intensity data; hence, the cluster info related to high intensity is fixed as the mean intensity of the OD region. This process is given in Eq. (7).

$$\mu = Func\_Max\ (\mu_0, \mu_1, \mu_2) \tag{7}$$

where

μ – Mean of OD area

The minimum providing clusters index value is noted as OD_{IND}, and it can be expressed using Eq. (8).

$$OD_{IND} = Func\_Max\_Index\ (\mu_0, \mu_1, \mu_2) \tag{8}$$

The OD region-oriented binary image is enhanced by filling the gaps in between the OD surface in the horizontal direction. Herein, the OD region is sliced row by row and the gaps are filled by 1s, hence the structure of the OD region is enhanced. The binary segmentation contains multiple bounded regions, and they can be eliminated to get the OD region only by using the biggest object detection method.

The OD region-specific pixels updated their membership matrix info by setting 1 for their O_{DIND} cluster index, and 0 for other cluster indexes. The linear vector x is altered by the OD mean intensity value. This phenomenon is shown in Eq. (9), Eq. (10), Eq. (11) and Eq. (12).

$$\alpha = OD_{IND} \tag{9}$$

$$M_{r*w+c,}\ j \in [0, p-1] = 0 \tag{10}$$

$$M_{r*w+c}, \alpha = 1 \quad (11)$$

$$x_{r*w+c} = \mu \quad (12)$$

where

γ – Current pixels row

C – Current pixels column

Now, the membership matrix M and the linear vector x are altered based on the ONH structure. This process enhances the OD region through the iterations of K-means segmentation that perform in a specific interval of 4.

After the formation of three clusters, the objective function is implemented using Eq. (13).

$$k = OD_{IND}$$
$$fn\_obj\,(itt) = \sum_{i=0}^{n-1} D_{i,k}^2 \times MM_{i,k} \quad (13)$$

In Eq. (13), the convergence property computation is performed only for the OD-oriented cluster index, which is OD_{IND}. In other words, the OD_{IND} based modification quantity calculation is progressed instead of the entire cluster, which is much enough for an intelligent convergence determination system because in this work the target is only the OD region. The term *itt* refers to the current iteration progressed in the K-means clustering process. If the difference between the continuous values of the objective function is very small, then the iterative process is terminated; otherwise, it loops up to the maximum iteration *mitt*. The segmented image is drawn out using the membership matrix. The OD_{IND} index-oriented binary image is extracted, and the biggest object is found to extract the OD region. The real intensity information from the input image is projected in the OD region to show the segmented output. In this way, the proposed ONHKM method effectively segments the OD region from the fundus image.

Algorithm for Optic Nerve Head Info Injected K-Means (ONHKM)

Input:

- Dataset X with n data points (image pixels/features)
- Number of clusters K
- Optic Nerve Head (ONH) information (e.g., region mask, center coordinates)
- Maximum iterations (optional)

Output:

- K cluster centroids
- Cluster assignments for each data point

Step 1: Initialize

1. Extract ONH-related information from the image
2. Assign higher weight or priority to data points near the ONH region
3. Select K initial centroids, ensuring at least one centroid is near the ONH region

Step 2: Iterate until convergence or max iterations

4. Assign each data point to the nearest centroid
   - For each data point xi in X:
   - Compute weighted distance based on ONH influence
   - Assign xi to the cluster with the closest centroid
5. Update cluster centroids
   - For each cluster j (1 to K):
   - Compute the weighted mean of all points assigned to cluster j
   - Update the centroid accordingly
6. Check for convergence
   - If centroids do not change significantly, stop iteration

Step 3: Return final cluster centroids and data assignments

DISCUSSION AND ANALYSIS

The effectiveness of the novel method is illustrated in this section by evalu[a]ting the proposed ONHKM method with alternative methods for segmentation. This analysis contains three existing methods to aid in the evaluation of the proposed method. Those three existing segmentation techniques are known as:

- OD Segmentation using Morphological Adaptive Fuzzy Thresholding based OD segmentation (ODSMAFT) [19]
- OD Segmentation using Region-based Convolutional Neural network-oriented OD segmentation (ODSRCNN) [20]
- OD Segmentation using Fuzzy Broad Learning System based OD segmentation (ODSFBLS) [21].

Different benchmark datasets are used to analyze the proposed OD segmentation method ONHKM. These four fundus image datasets are used for this analytic component. They are:

- Kaggle Fundus Image DataSet (KFI) [22]

- Retinal Fundus Multi-disease Image Dataset (RFMI) [23]
- ChaseDB1 database (CHASEDB1) [24]
- STructured Analysis of the REtina DataSet (STARE-DS) [31].

The ability of an algorithm to identify and respond to the changes in the input image is referred to as 'Average Sensitivity' (AS), which measures the percentage of actual positive values that are correctly identified in OD segmentation fundus images. Using Eq. (14), the average sensitivity measurement is calculated.

$$AS_{OD} = \frac{TP}{TP + FP} \quad (14)$$

AS_{OD} – Average Sensitivity for OD Segmentation

TN – Pixels count of True Positive for background

FN – Pixels count of False Positive for background

Table 1: AS Analysis for OD Segmentation

Dataset	Average Sensitivity			
	ODSMAFT	ODSRCNN	ODSFBLS	Proposed ONHKM
KFI	0.925	0.932	0.941	**0.946**
RFMI	0.932	0.937	0.944	**0.950**
CHASEDB1	0.928	0.934	0.942	**0.947**
STARE	0.926	0.933	0.942	**0.947**

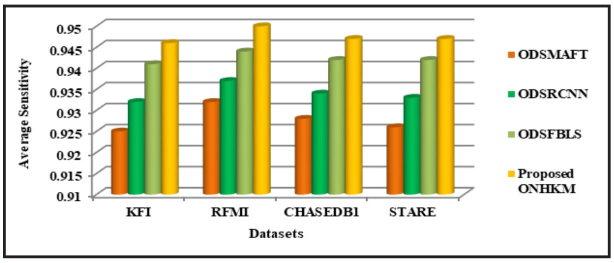

Fig. 2: Chart for Average Sensitivity

Table 1 and Figure 2 expose the average sensitivity [8] on OD segmentation in four databases such as KFI, RFMI, CHASEDB1, and STARE. The proposed ONHKM method achieves the highest average sensitivity value of 0.950 in the RFMI dataset. The ODSMAFT method exposes the least performance in this analysis.

Segmentation Accuracy (SA) measures the quality of segmentation of objects of interest from images, which is a crucial factor in determining their performance. In this work, segmentation accuracy is measured to compare the performance level of the proposed and existing methods in OD segmentation. The Segmentation accuracy is computed using Eq. (15).

$$AS_{OD} = \frac{TP + TN}{TP + FP + TN + FN} \quad (15)$$

where

SA_{OD} – Segmentation Accuracy for OD Segmentation

TN – Pixels count of True Negative for background

FN – Pixels count of False Negative for background

Table 2: Segmentation Accuracy for OD Segmentation

Dataset	Images	Segmentation Accuracy			
		ODSMAFT	ODSRCNN	ODSFBLS	Proposed ONHKM
KFI	KFI-0	95.11	96.06	96.39	**96.77**
	KFI-1	95.32	96.2	96.56	**96.96**
	KFI-2	95.24	96.13	96.49	**96.85**
RFMI	RFMI-0	95.85	96.65	96.92	**97.38**
	RFMI-1	95.7	96.54	96.79	**97.25**
	RFMI-2	95.53	96.42	96.68	**97.15**
CHASEDB1	CHASEDB1-0	95.39	96.33	96.71	**97.16**
	CHASEDB1-1	95.55	96.41	96.84	**97.25**
	CHASEDB1-2	95.26	96.23	96.6	**97.04**
STARE	STARE-0	95.12	96.07	96.40	**96.78**
	STARE-1	95.33	96.03	96.57	**96.97**
	STARE-2	95.25	96.14	96.50	**96.86**

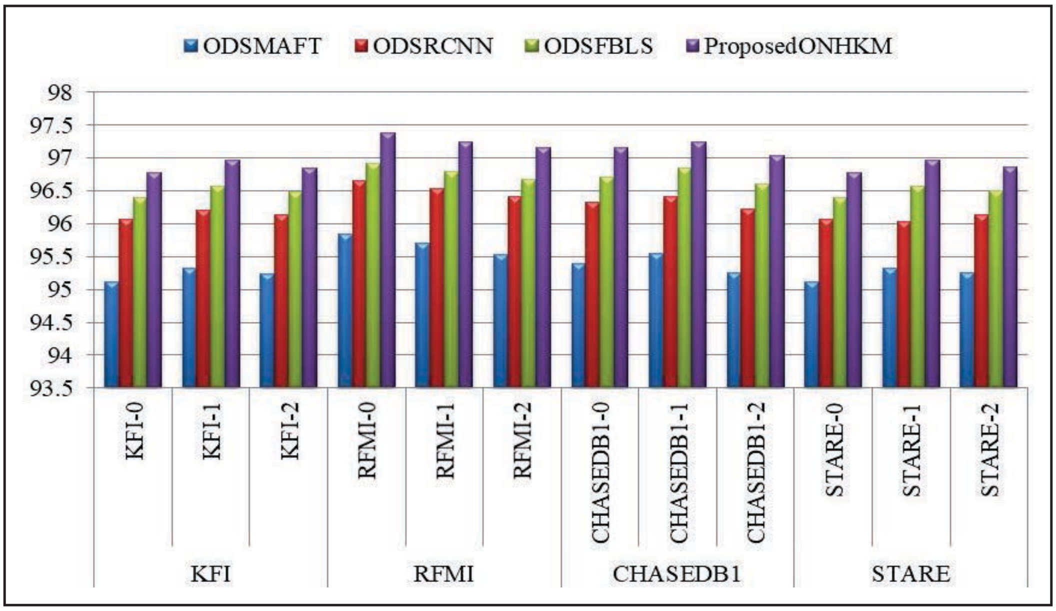

Fig. 3: Chart for Segmentation Accuracy

Table 3: Time-taken Analysis for OD Segmentation

Database	Time Taken (in sec)			
	ODSMAFT	ODSRCNN	ODSFBLS	Proposed ONHKM
KFI	5.52	6.05	6.42	**5.89**
RFMI	5.43	5.83	6.21	**5.71**
CHASEDB1	5.51	6.01	6.34	**5.80**
STARE	5.53	6.06	6.43	**5.90**

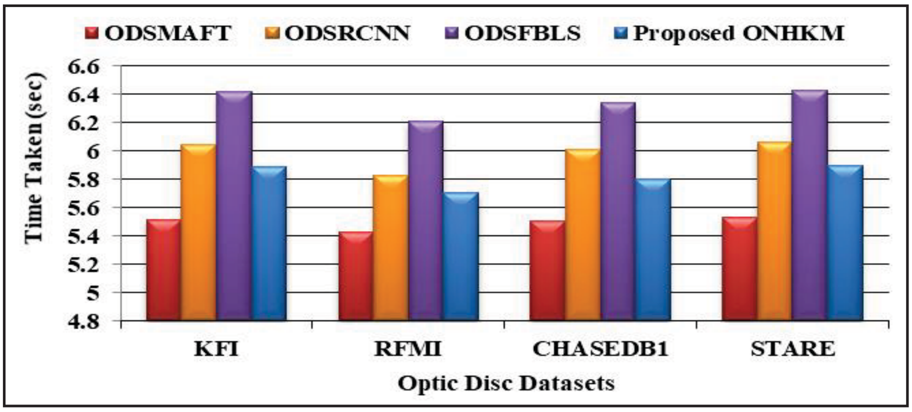

Fig. 4: Average Time taken Analysis for OD Segmentation

The segmentation Accuracy on OD segmentation is revealed in Table 2 and Figure 3. Herein, the three different images of four different databases, i.e., KFI, RFMI, CHASEDB1, and STARE are chosen for this analysis. The proposed ONHKM method provides a high accuracy value of 97.39. The second-best accuracy value is 97.25. The lowest performance accuracy value is 96.77.

The time taken for optic disc segmentation is an important metric of the segmentation algorithm's efficiency and scalability in real-world scenarios. In Figure 4, a chart represents the time occupied in seconds between the 'beginning' and 'end' of the optic disc segmentation process. The resulting values are listed in Table 3.

The time taken for OD segmentation analysis for the four datasets, including KFI, RFMI, CHASEDB1 and STARE, is shown in Table 3 and Figure 4. In this time-taken analysis, the execution time is calculated using 100 photos from each dataset. Comparing the proposed ONHKM method to the other three existing methods, it evaluates all three datasets in a significantly shorter amount of time. The RFMI dataset shows an outstanding average of 5.71 seconds according to the proposed method. The performance of the KFI dataset in the overall technique comparison is awful in the time taken analysis.

A Ranking Index Metric (RIM) could refer to a particular score or measurement that is used to evaluate and contrast ranks. In actual use, it might stand for the effectiveness of various algorithms, the usefulness of search results, or the effectiveness of a recommendation system.

Table 4: Ranking Index Metric Analysis

METHOD	KFI	RFMI	CHASEDB1	STARE
ODSMAFT	1	1	1	1
ODSRCNN	2	2	2	2
ODSFBLS	3	3	3	3
Proposed ONHKM	**4**	**4**	**4**	**4**

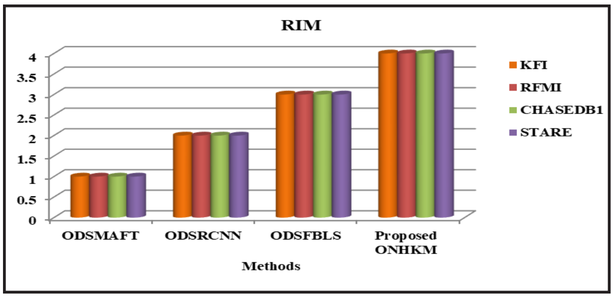

Fig. 5: Chart for Ranking Index Metric

Here, Table 4 and Figure 5 reveal the analysis result using Ranking Index Metric (RIM) in OD segmentation. According to SA, Sensitivity, the proposed ONHKM method gets a high rank of 4. The ODSFBLS method gets the rank of 3. The ODSRCNN method gets a rank value of 2. The ODSMAFT method gets the worst rank value of 1.

Table 5: Statistical Validation Result

Method	Statistical Validation
ODSMAFT	95.28
ODSRCNN	95.69
ODSFBLS	95.12
Proposed ONHKM	94.58

Table 5 portrays the statistical validation analysis result of the proposed ONHKM and chosen existing methods to ensure the reliability of the proposed method.

This research segments the OD region from the fundus image, and it is validated using soft and hard models. This study validates the effectiveness of the proposed OD segmentation method using four comprehensive datasets. This process involves comparing the segmentation results against ground-truth annotations provided by expert radiologists. This research uses the datasets comparing 200 images with varying OD sizes and locations to ensure a thorough evaluation. The performance of the segmentation method is evaluated using standard metrics, including sensitivity, segmentation accuracy, time taken, RIM, and statistical validation analysis result. Comparative analysis is done using benchmarked existing methods such as ODSMAFT, ODSRCNN, and ODSFBLS. The proposed ONHKM method outperformed traditional methods by achieving better sensitivity, segmentation accuracy, time taken, RIM, and statistical validation analysis result across different cases. Visual inspection of the segmentation results confirmed that our method effectively delineates OD boundaries even in cases with complex OD shapes and heterogeneous tissue structure. The validation results indicate that the proposed OD segmentation method is both accurate and reliable, making it a tool for clinical applications such as,

- **Early Disease Detection:** OD segmentation plays a critical role in the early detection of glaucoma, diabetic retinopathy, and other optic neuropathies. By improving segmentation accuracy, ONHKM can enhance the reliability of automated screening systems, aiding ophthalmologists in early diagnosis.
- **Integration with Fundus Imaging Systems:** The method is computationally efficient and can be seamlessly integrated into existing fundus cameras and diagnostic tools, providing real-time assistance without requiring complex deep learning models or extensive datasets.

- **Enhanced Decision Support for Clinicians:** The interpretability of ONHKM makes it clinically practical, allowing doctors to visually verify the segmentation results and make informed decisions. Unlike deep learning methods, which often function as "black-box" models, our approach provides transparent and explainable segmentation results.
- **Potential Limitations & Future Directions:** Handling of Pathological Variations: While ONHKM achieves high accuracy (97.52%), extreme pathological variations (*e.g.*, severe optic disc cupping in glaucoma) might still pose segmentation challenges. Future work will involve fine-tuning ONHKM for pathological cases.
- **Cross-Dataset Generalization:** Clinical fundus images vary significantly in quality, resolution, and illumination. We plan to validate ONHKM on larger, multi-source datasets to ensure generalizability across different clinical environments.

By addressing these aspects, we aim to bridge the gap between research and clinical practice, making ONHKM a practical, efficient, and reliable tool for ophthalmic diagnostics. We appreciate this valuable suggestion and will incorporate a detailed clinical discussion in our revised manuscript.

CONCLUSION

The OD region is segmented from the fundus images by the proposed ONHKM method. The K-mean algorithm is the base of its functioning. The OD region is successfully segmented from the fundus image using the proposed ONHKM method. The KFI, RFMI, CHASEDB1, and STARE. databases are used to demonstrate the strength of OD segmentation of the proposed ONHKM method. This paper offers an analysis of the performance of the proposed ONHKM segmentation method in comparison with the state-of-the-art segmentation methods, including ODSMAFT, ODSRCNN, and ODSFBLS. The average SA values for the KFI, RFMI, CHASEDB1, and STARE databases are 96.96, 97.38, 97.25, and 96.16 respectively, according to the proposed ONHKM method. The ODSFBLS approach achieves the second-best average sensitivity of 0.944, while the proposed ONHKM method reaches a high average sensitivity value of 0.950. The ODSMAFT approach yields the lowest average sensitivity value of 0.932. This paper's future work will be focused on creating a novel OD segmentation method using convolutional neural networks.

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