Segmentation of Optic Disc and Exudates through Hybrid Model by Utilizing Genetic Algorithm and Root Guided Decision Tree

Malpe Kalpana Devidas
Research Scholar, Department of Computer Science Engineering, of Sri Satya Sai University of Technology & Medical Sciences, Sehore, M.P., India.
Dr. Sudhir W. Mohod
Research Supervisor, Associate Professor, Department of Computer Science Engineering, B. D. College of Engineering, Sevagram Wardha.
Corresponding Author- kmalpe@gmail.com

Abstract:
A crucial step in the diagnosis and treatment of retinal illnesses is the segmentation of the optic disc and exudates in retinal fundus. For precise and effective segmentation of these structures, a hybrid model using a genetic algorithm and a root-guided decision tree is presented in this paper. In retinal imaging, the optic disc is a crucial structural marker, and exudates are important biomarkers for conditions like diabetic retinopathy. The segmentation accuracy is improved by the suggested hybrid model's use of the evolutionary algorithm to optimize decision tree characteristics. Beginning with picture preprocessing, the framework includes color transformation to perceptually uniform color spaces and cropping to establish the field of view. To enhance picture contrast, contrast limited adaptive histogram equalization (CLAHE) is used.
Gabor filters are used to improve blood arteries because they successfully capture the Gaussian approximation of these structures. The suggested technique retrieves features for optic disc segmentation include intensity characteristics, neighborhoods statistics, and picture modifications. These characteristics are used to forecast if a pixel is a part of the optic disc-containing area of interest (ROI). The ability to distinguish exudates from the optical disc is aided by post-processing methods and domain expertise. On benchmark datasets like DRIVE and DIARETDB1, the performance of the suggested technique is assessed. The outcomes show excellent performance in both the segmentation of the optic disc and the exudates tests. The competitiveness of the suggested hybrid paradigm is demonstrated through comparison with alternative approaches. The efficacy of the suggested paradigm has important clinical implications. Exudates and the optic disc can be accurately segmented to enable the early identification and monitoring of retinal disorders, facilitating prompt treatment and intervention. Automation of segmentation activities lightens the load on physicians and improves diagnostic effectiveness. In the segmentation of the optic disc and exudates, the hybrid model using a genetic algorithm and root-guided decision tree shows encouraging results. Retinal image analysis is made easier with the help of the suggested method, which also makes it easier to diagnose and treat retinal illnesses.

Keywords: *Optic disc, exudates, retinal images, segmentation, hybrid model, genetic algorithm, root guided decision tree, retinal diseases, diabetic retino pathy, glaucoma, image preprocessing*.
DOI Number: 10.48047/NQ.2022.20.12.NQ77724 **NeuroQuantology2022;20(12): 3998-4011**

I. Introduction:

A critical stage in the diagnosis and follow-up of many retinal illnesses, including diabetic retinopathy, is the segmentation of the optic disc and exudates in retinal pictures. The early diagnosis and treatment of such disorders depend on the accurate and effective segmentation of these structures. In recent years, the creation of hybrid models incorporating various algorithms and methodologies has shown encouraging results in the segmentation of medical images [1]. One This approach combines a genetic algorithm (GA) and a root guided decision tree (RGDT) to segment the optic disc and exudates. The purpose of this article is to provide a summary of this mixed approach and some of its applications. Genetic algorithms are a type of optimization technique that takes their cues from the principles of natural evolution. They employ a pool of candidates, represented by chromosomes, to find the optimal solution. In order to improve the population as a whole, the genetic algorithm employs processes including crossover, mutation, and selection [2]. The genetic algorithm may be used to the optic disc and exudates segmentation context to optimize parameters or traits that are necessary for precisely distinguishing these structures. In machine learning, decision trees are frequently used for classification and regression problems [3]. Based on feature testing, they create a hierarchical structure that divides the data. A decision tree version known as a root led decision tree works by selecting features starting at the root node and working its way down. In order to obtain the best possible discrimination across classes, the decision tree algorithm iteratively chooses the most discriminative feature at each node. In the hybrid model, the decision tree performs the segmentation of the optic disc and exudates using the genetic algorithm's optimized characteristics [4].

The hybrid model integrating the genetic algorithm and root guided decision tree intends to take advantage of both approaches' advantages to improve the precision and effectiveness of segmenting the optic disc and exudate. The decision tree's performance is improved by using the genetic algorithm as an optimizer to find the ideal collection of parameters or features [5]. The evolutionary algorithm examines the solution space by iteratively evolving the population of potential solutions, improving the segmentation quality. In a feedback loop, the decision tree uses the characteristics that the genetic algorithm has optimized to execute segmentation while the genetic algorithm optimizes the features of the decision tree. The hybrid model is able to converge towards an ideal solution through this iterative method, successfully segmenting the optic disc and exudates from the retinal pictures. The hybrid model using a genetic algorithm and a root-guided decision tree has a lot of potential for use in a variety of medical image analysis applications [6]. As early identification and monitoring of retinal illnesses are made possible by accurate segmentation of the optic disc and exudates, ophthalmologists are better equipped to treat patients on time. By using the evolutionary algorithm to optimize parameters and features, the hybrid model can increase segmentation accuracy while lowering false positives and false negatives. The root guided decision tree's hierarchical structure also yields findings that are comprehensible, enabling doctors to comprehend the segmentation procedure and take wise judgments. In order to diagnose and treat retinal disorders, it is crucial to segment the optic disc and exudates [7]. A promising method for precise and effective segmentation is the hybrid model that combines a genetic algorithm and a root guided decision tree. The genetic algorithm enhances the features of the decision tree, allowing the segmentation process to adjust to the unique properties of retinal images. The improvement of ophthalmology as well as enhanced patient care and diagnostic skills may result from more research and development in this domain.

II. Literature Review

Retinal angiography confirms lesion activity in diabetes and malarial retinopathy. The Y. recommends automated retinal image analysis for leak detection. Few automated leakage identification or quantification methods exist, unlike those for identifying retinal lesions in colored fundus photographs [8]. The suggested method identifies three leakage types in MR-imaged eyes. This method counts leaking spots and measures their sizes with 05 MR images. However, it only uses intensity data to construct the saliency map for detection, which might lead to false positives if non-leaking sites have high intensities. leaking in diabetic FA images [9]. A dynamic contour segmentation approach helps employees find leaks. 24 photos identify fovea-centered circular leaks. utilized this criterion to identify retinal layer blockage-induced macula leaking and suggested identifying any FA sequence pixels with a statistically significant rise in grey level around the fovea centre as leakage. This method involves manual fovea centering [10]. DR images were thresholded for leaking areas. Hand-annotated training datasets limit supervised algorithms. The classifier relies on precise annotation. For saliency-based sore identification, WCE photos were advised. A multi-level super pixel representation preprocesses saliency detection, and the saliency map is created by combining all produced maps by color and texture. Image feature encoding and recognition accurately locates areas' contours. This approach is unproven because to the tiny validation dataset. Markov random field saliency and gradient-based dynamic MR image registration [11]. Most strict registration methods fail when intensity changes. Noise can impair inclination information in contrast-enhanced photographs. Digital medical images are abundant. IR helps clinicians evaluate medical pictures by detecting comparable occurrences. These photos are easily accessible in large databases [12]. Sending compressed images. Research sought tiny images. Image compression and content-based photo retrieval minimize bandwidth utilisation. The daubechie wavelet compresses images without compromising quality. Sobel and Gabor transformations remove edge and texture from compressed medical images. Information gain condenses features, and Nave Bayes, Support Vector Machine, IBL, CART, and Random Forest evaluate retrieval classification accuracy. Medical personnel are taking more digital photos as technology progresses. Picture Retrieval (IR) finds comparable medical photographs in vast databases for clinicians to study [13]. Picture storage and transmission employ compression. Studying compressed image retrieval. Image compression and content-based picture retrieval of diagnostic instances like the query medical image minimise bandwidth. The daubechie wavelet compresses pictures losslessly. Gabor and Sobel edge detectors recover edge and texture from compressed medical images. Information gain condenses features, and Nave Bayes, Support Vector Machine, IBL, CART, and Random Forest evaluate retrieval classification accuracy. Diagnostics and treatment today include X-rays, MRIs, ECGs, and CTs. Large databases store medical images [14]. CBIR discovers diagnostic images comparable to the medical image sought. Since databases include plenty of data and picture content is more flexible than semantics, indexing or semantics cannot retrieve photos. CBIR extracts important information from query images and pulls photos from the database using several algorithms [15]. CBIR systems automatically extract picture color , texture, and form. Similarity metrics compare database and query image properties. Found pictures. Medical imaging studies many CBIR systems. Preserve medical images and employ bandwidth to provide huge diagnostic data. Images are compressed. Removing unnecessary elements compresses the image. Lossless compression exists. Lossless compression recovers the image, but lossy compression loses minor information. Lossy compression yields high ratios. Medical image compression cannot lose any characteristics during picture recovery since it may lose vital disease-identifying information [16]. Lossless medical image compression ratios are quite low. The medical picture is often divided into regions of interest (ROI) and compressed using lossless compression in the ROI and lossy compression in the non-ROI. Thus, the diagnostically crucial region may be preserved while compressing more. This study finds compression-optimized diagnostic instances matching the m [17]edical image. One decomposition Daubechie wavelet improves image compression. Gabor and Sobel edge detectors recover edge and texture from compressed medical images. Nave Bayes, SVM, CART, IBL, and Random Forest algorithms assess retrieval classification accuracy. Focus and field-of-view. Wavelet-, Chebyshev-, and statistical-based metrics predicting focus and noise mask quality that separated areas of non-uniform light near to the macula classified pictures as terrible or normal [18]. The Fuzzy Inference System used these features to attain accuracy and AuC of 98 percent and 0.9946 on the MESSIDOR dataset and 97.76 percent and 0.9943 on the complete collection of 1200 MESSIDOR images plus 254 proprietary shots. Few methods without retinal component segmentation are mentioned here. To see the macula in the fundus picture, relative subtraction was proposed. The grayscale image with better contrast was removed from the complementary red channel picture. The improved Grayscale image got iterative and single-pass contrast enhancement. The threshold binary image selected the macula with 90.57 percent accuracy [19]. The approach worked perfectly with 35 DRIVE dataset macula photos. Stochastic hill climbing found maculas. This study found the optimal filtering window size using stochastic annealing. Simulated annealing chose a window size before median filtering the green channel. Subtracting the median filtered image from the green channel image yielded the macula. 68, 86, and 92% of photos in the DRIVE, DIARETDB0, and DIARETDB1 datasets contain the fovea within 0.5 DD of the manually estimated macula centre [20].

III. Segmentation

Exudates correspond to the illness pattern, whereas Optic Disc (OD) belongs to the structural pattern. In terms of intensity levels, both of these topologies are equivalent. In the retinal fundus picture, they both seem brilliant (Patton et al 2006). Figure 1, shows a retinal image exposing the OD and exudates, as well as a binary image disclosing the segmented OD and exudates.

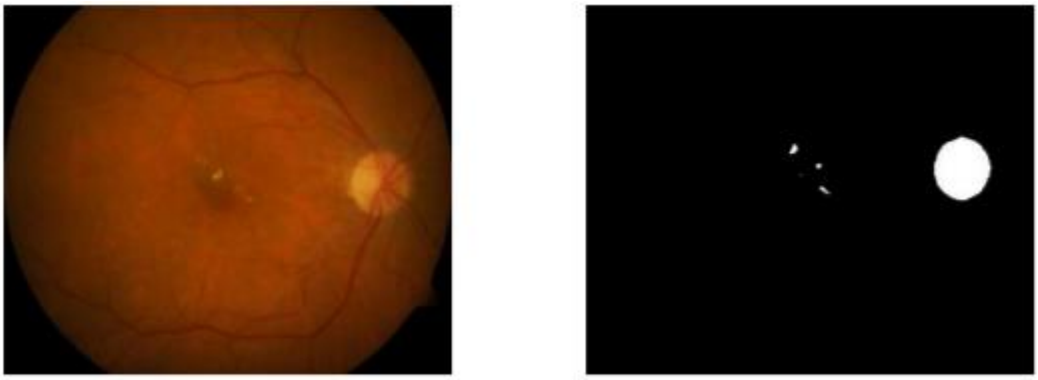


Figure 1.Image of the retinal fundus with segmented optic disc and exudates.

The extraction of OD and exudates is crucial in the diagnosis of retinal disease. The importance of extracting OD and exudates, as well as the proposed approach for extracting them, are discussed in the following sections.

A. Optic disc and Exudates segmentation

The primary blood arteries enter and exit the retina through the optic disc (OD), which is a brilliant oval structure. The optic disc comprises of an optic cup and optic rim. The optic cup, the bright core portion of the OD, is white or yellow, and the rim, the surrounding section, is orange-pink .Differen+ces in the

OD's qualities, such as color , form, border, and vasculature, suggest pathogenic alterations. As a result, OD segmentation aids in the detection of vision-threatening disorders such as Diabetic Retinopathy (DR) and Glaucoma. Extraction of OD has benefited in lowering false positives during exudate detection in the case of DR detection, as both structures seem comparable. In the case of other retinal illnesses, such as glaucoma, OD features such as the cup to disc ratio (CDR) and ISNT ratio serve as important biomarkers for disease detection. The placement of the OD also provides information about the macula, fovea, and blood vessels in the retina. As a result, automated OD segmentation is an important part of an automated retinal image analysis system. The features of exudates (a structure similar to OD) and the relevance of segmentation are discussed in the next section.

IV. Dataset

Table 1.DRIVE Dataset

Feature	Description
Dataset Name	DRIVE (Digital Retinal Images for Vessel Extraction)
Image Acquisition	High-resolution digital color fundus images
	(Retinal images)
Patients	40 (each contributing left and right eye images)
Image Resolution	565 x 584 pixels
Image Format	RGB color format
Ground Truth	Manual segmentation maps provided for each retinal image
Annotations	Pixel-level annotations of blood vessels (foreground vs.
	background)
Dataset Split	Training set: 20 retinal images
	Test set: 20 retinal images
Evaluation Metrics	Sensitivity (recall), specificity, accuracy, F1 score,
	AUC-ROC
Challenges	Varying illumination, vessel width variations, presence of
	pathologies, image noise
Usage	Benchmark dataset for blood vessel segmentation algorithms

V. Proposed Framework:

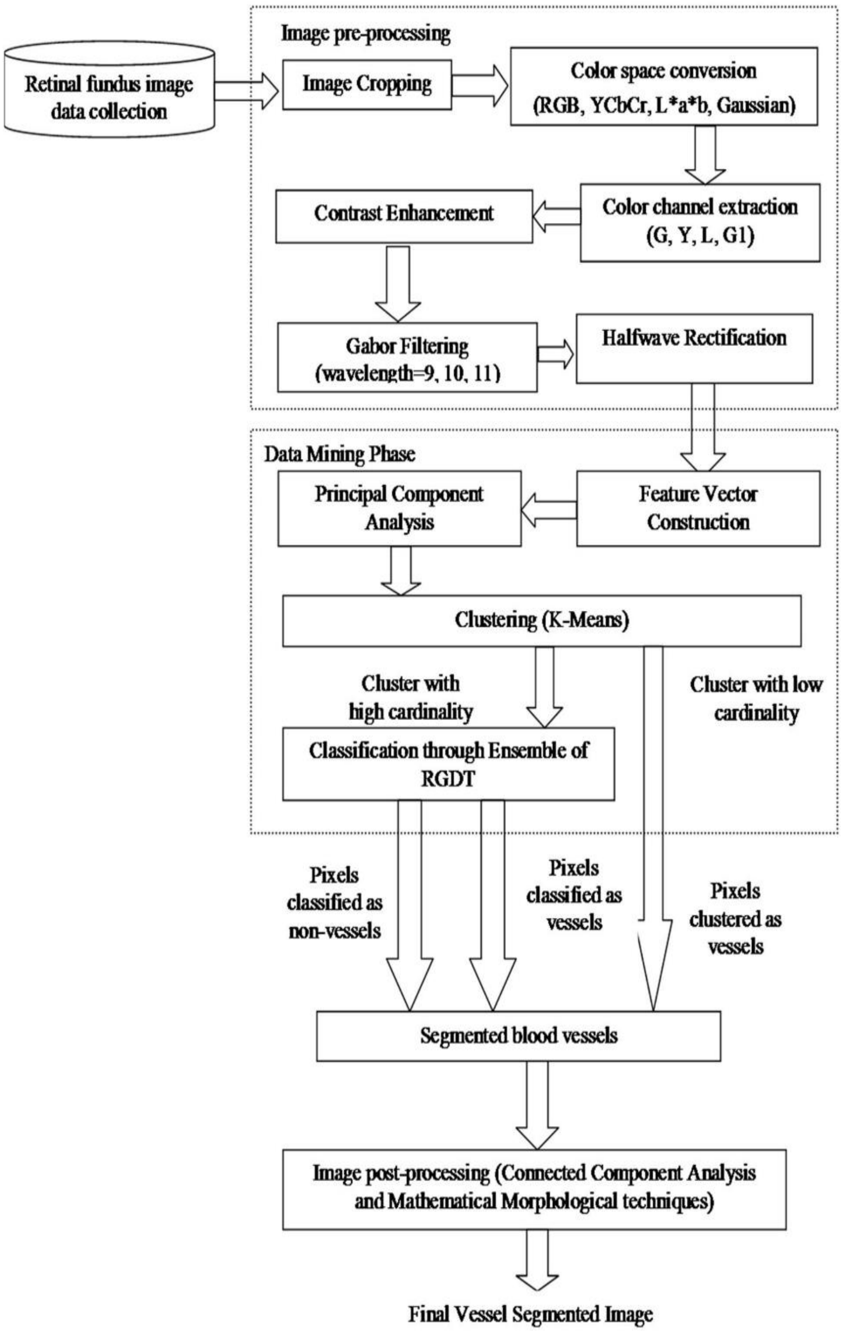


Figure2.Proposedframeworkforretinalvesselsegmentationin imagesofDRIVEdataset

The enhancement of the color fundus picture is the first step in the pre-processing phase of the proposed framework to enable more efficient computations. The DRIVE retinal pictures with a resolution of 584x565 pixels are cropped to eliminate the area beyond the range of vision, which removes around 40,000 pixels (or about 12% of the total pixels). Depending on the extent of the field of view in each image, the precise number of rejected pixels may change. By lowering the image size and consequently the amount of pixels used in future computations, this cropping process lowers the computational complexity in the succeeding steps. After cropping, color modification is implemented.

The three-dimensional RGB space's distances and the perceived uniformity of the RGB color model's representation are both incongruent. In order to remedy this, color fields that provide perceptual consistency are used to extract Gabor features. The Lab, Gaussian, and YCbCr color models are then applied to the RGB image once it has been cropped. The color channels from each color model with the highest contrast are chosen for additional examination. For the purpose of further processing, the R channel from RGB, the Y channel from YCbCr, the L channel from Lab*, and the G1 channel from the Gaussian color model are specifically chosen.

The four contrast-improved pictures are subjected to Contrast Limited Adaptive Histogram Equalisation (CLAHE) in order to increase the visibility of blood vessels. By increasing the contrast, this approach helps the blood vessels stand out against the background. Filters with a gaussian basis are excellent for estimating blood vessel form. In order to improve the blood vessels, two-dimensional Gabor filters—sinusoidally modulated Gaussian functions—are used. Gabor filters' efficiency in discriminating arteries in retinal pictures significantly depends on the parameterization of those filters, which heavily influences how well they operate.

VI. Proposed System

The OD and exudates are essential retinal structures, and their segmentation is critical for automated retinal image processing. It's a component with a low frequency. The suggested framework is divided into three stages, the first of which is an image pre-processing phase in which the picture is appropriately processed and important characteristics are extracted. The collected characteristics are sent into the data mining step, where the hybrid model predicts whether a pixel fits in the ROI or not. In this example, the ROI comprises OD as well as exudates. The OD and exudates are revealed by forming a binary picture from this prediction. After post-processing the binary picture, domain knowledge is used to differentiate the exudates from the OD. Figure 3.depicts the framework presented.

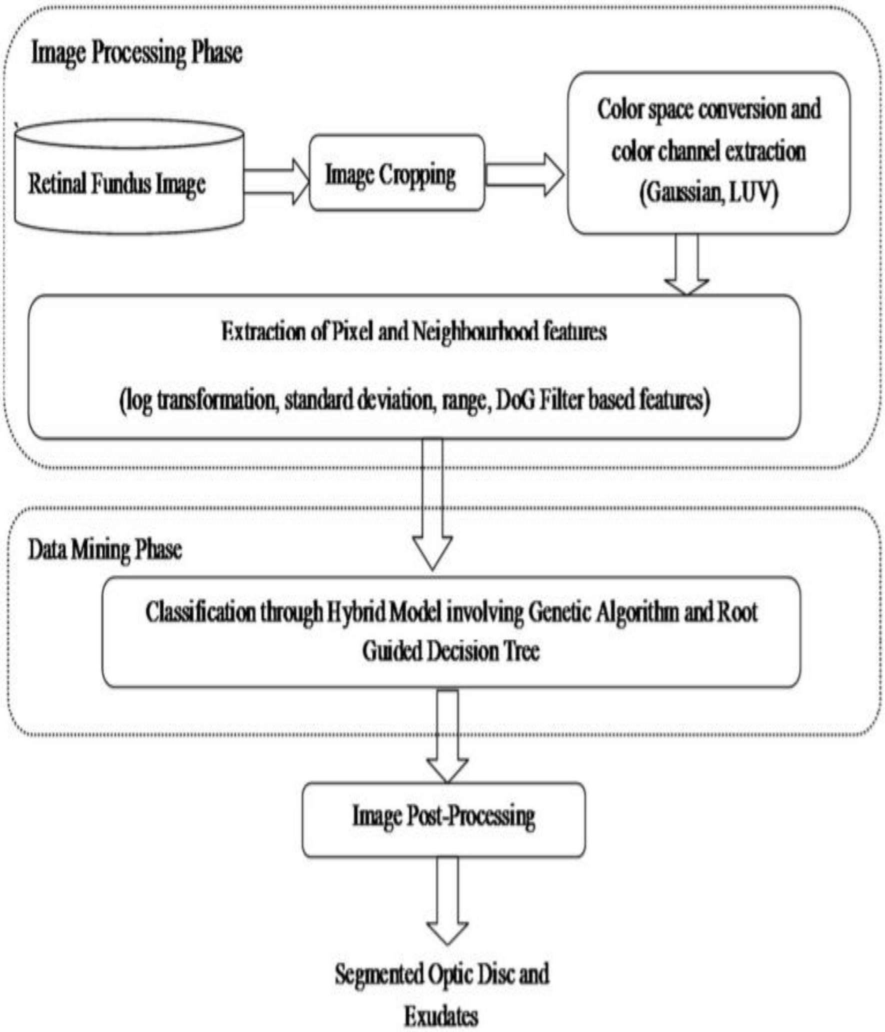
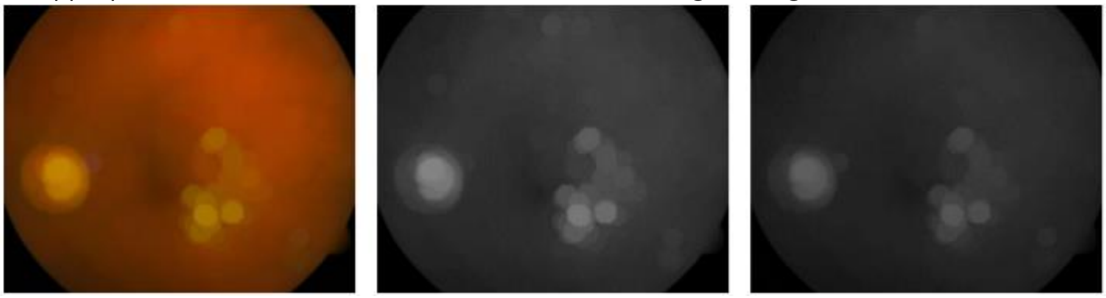


Figure 3. Proposed design for segmenting the optic disc and exudate

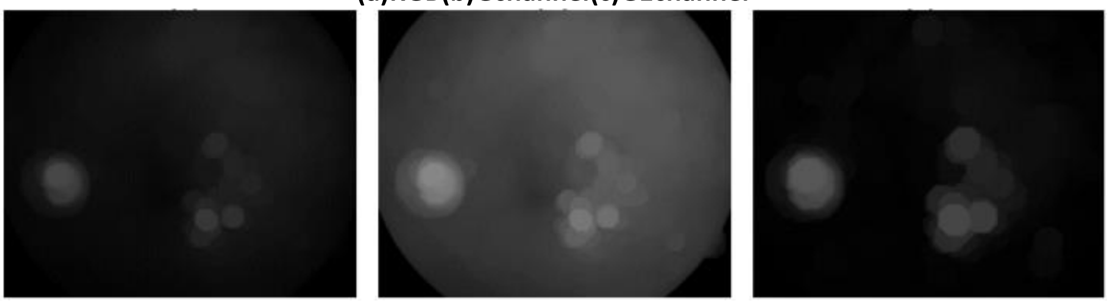
The proposed framework starts with image pre-processing, which involves processing the image to extract the required features. To begin, the photos are cropped in order to define the field of vision. The photos are then transformed to Grayscale and other color spaces, such as LUV and Gaussian, since their channels disclose expressive elements that may be used to identify the OD and exudates from the rest of the image. The conversions from RGB color space to Grayscale and Gaussian, is a color model with three color components: L, U, and V. The processes shown in Figure 4.are followed to convert RGB color space to LUV color space.

The color channels that disclose the OD and exudates are retrieved after conversion to the respective color spaces. On closer inspection, the OD and exudates are clearly visible in the Green channel of the RGB color model, the G1 channel of the Gaussian color space, the L channel of the LUV color model, and the Grayscale picture. The approach then extracts the appropriate characteristics after extracting the color channels required for eliciting the OD and exudates. The feature vector indicates a specific pixel of the picture in this example, because the OD and exudates pertain to structural and illness patterns, respectively. As a result, the intensity characteristics of I color channel pictures, (ii) images operated by neighborhood functions, and (iii) images operated by transforms such Difference of Gaussian (DoG) and Log Transformations are among the features retrieved.

The intensity of the color channel pictures, specifically G, G1, L, and Grayscale, is extracted first. After that, a modification is applied to the image such that the image's boundaries are hidden. The intensities of these boundary suppressed pictures are then triggered for each color channel. Figure 4, illustrates the color channel pictures as well as the border suppressed images. Because the ground truth picture given with the data for comparison is a dilated ground truth image, the images in Figure 4, are dilated.



(a)RGB(b)Gchannel(c)G1channel

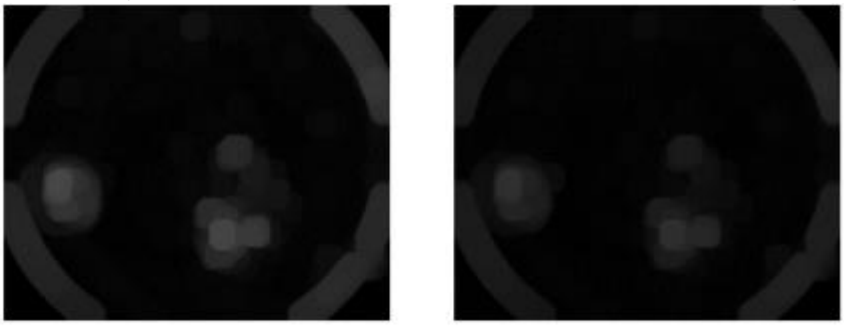


(d)Lchannel(e)Grayscale(f)bordersuppressed

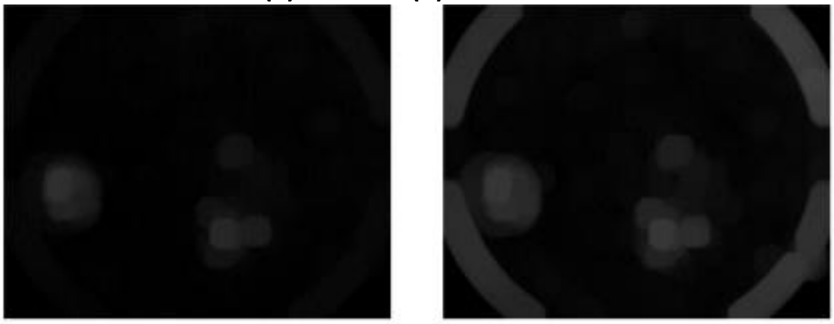
(g)bordersuppressedG1 channel(h)bordersuppressedLchannel (i) bordersuppressedGrayscale

Figure4.IllustrationofvariouscolorchannelsandbordersuppressedimagesGchannel

After the original color channel images (OD and exudates) are acquired, the ROI is exposed using local neighborhoods procedures such as range, standard deviation, and mean. These statistics may be used to characterize an image's texture since they reveal information about the local variability of the intensity values of pixels in the picture. In parts of smooth texture, for instance, there is a narrow band of values around each pixel, but in areas with rough texture, the band is much larger. The degree to which pixel values are unpredictable may be determined, however, by computing the standard deviation of pixels in the area. In this implementation, we analyze a 15 by 15-pixel region to get the image's median, standard deviation, and range. The range is the difference between the highest and lowest values close to the pixel under consideration. The formulae provided in Section 5 are used to determine the standard deviation and mean of the area immediately surrounding the pixel in question. Figures 4-6 depict the average and median intensities across all color channels and the range of intensities.

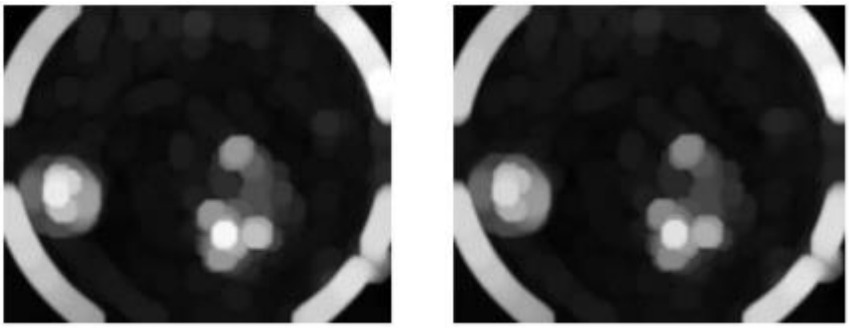


(a)Gchannel(b)G1channel

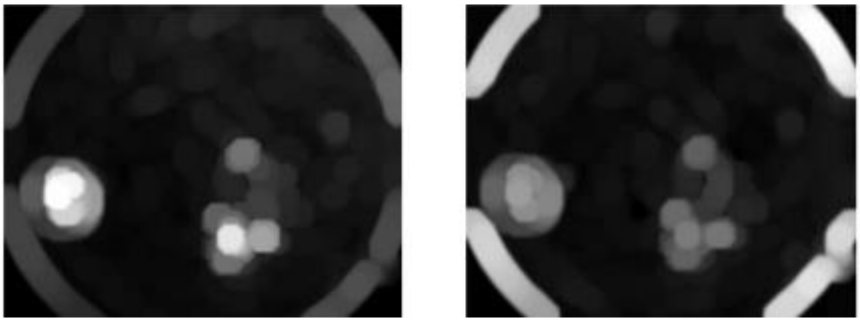


(c)Lchanneland (d)Grayscale

Figure 5. Range filtered pictures of multiple channels



(a)Gchannel(b)G1channel



(c)Lchannel and(d)Grayscale

Figure 6.Standard deviation pictures of multiple channels are depicted.

VII. Results:

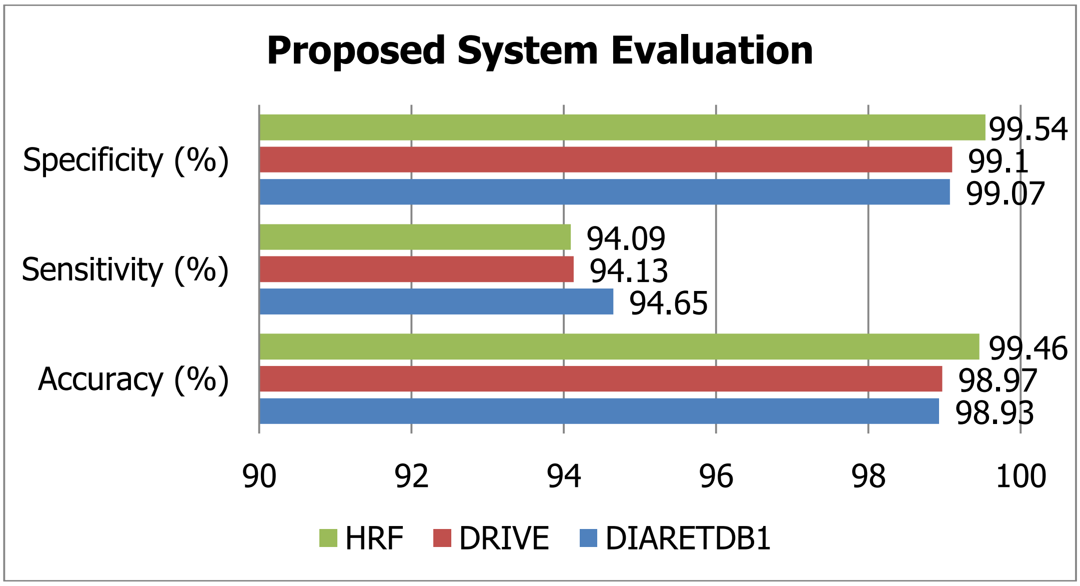


Figure 7.Optic Disc Segmentation Performance of the Proposed Methodology

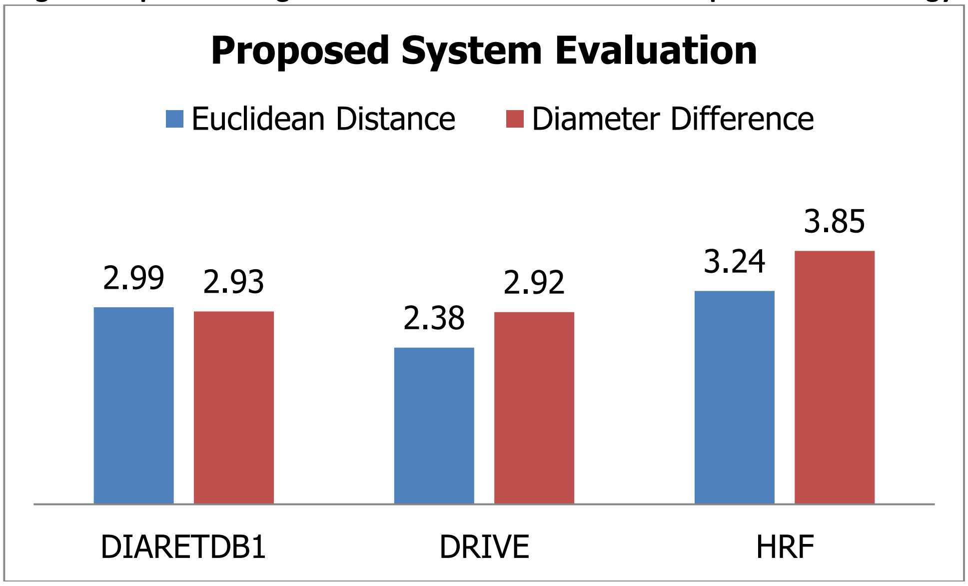


Figure 8. Optic Disc Segmentation Distance and Difference of the Proposed Methodology

The reported findings in Figure 7 and 8, show that the suggested technique performs admirably in the setting of OD segmentation. An average accuracy, sensitivity, specificity, Euclidean distance and diameter difference of 99.12%, 94.28%, 99.24%, 2.87 and 3.23 is accomplished. Following that, a comparison of the proposed method is offered. The performance of OD segmentation on the DRIVE dataset is compared in Table 2.

Methodology	Accuracy (%)	Sensitivity (%)	Specificity (%)	Euclidean Distance	Diameter Difference
Proposed	98.97	94.13	99.10	2.38	8.92
(Esmaeili et al 2012)	94.51	-	-	-	-
(Eswaran et al 2008)	-	94.00	-	-	-
(Lupascu et al 2008)	70.00	-	-	8.99	11.22
(Wang et al 2015)	-	92.58	99.26	2.46	-
(Welfer et al 2013)	-	83.54	99.81	7.48	-

The findings shown in Table 2, suggested technique performs as well in segmenting OD from the DRIVE dataset. With relation to the DIARETDB1 dataset, Table 3, compares the performance of the proposed technique with similar research on OD segmentation.

Table 3.Comparison of the suggested approach's performance on the DIARETDB1 dataset for optic disc segmentation

Methodology	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Euclidean Distance**	**Diameter Difference**
Proposed	98.93	94.65	99.07	2.99	2.93
(Esmaeili et al2012)	93.42	-	-	-	-
(Wanget al 2015)	-	93.24	98.94	3.11	-
(Welferetal 2013)	-	92.51	99.76	4.95	-

The exudates are a key biomarker for Diabetic Retinopathy diagnosis (DR). The appearance of exudates is a sure sign that DR is starting. As a result, detecting the presence of exudates aids the ophthalmology society tremendously in DR identification. This section examines how well the suggested approach performs when it comes to detecting exudates in a retinal fundus picture. During this examination, the exact boundaries, position, and number of exudates are not taken into account. The approach is tested on an image-by-image basis to see if it can identify an exudate in a picture containing exudate. The results are confirmed using DIARETDB1 , a dataset that offers exudates detection ground truth. There are 48 photos with exudates and 41 images without exudates in the collection. Table 4, shows the results of the suggested methodology's performance in terms of accuracy, sensitivity, and specificity, as well as a comparison to previous work.

Table 4. Performance of the suggested approach in identifying the presence or absence of exudates

Methodology	Accuracy (%)	Sensitivity (%)	Specificity (%)
Proposed	100	100	100
(Harangi&Hajdu 2014)	-	90.00	-
(Kauri & Kaur 2015)	88.76	91.33	86.04
(Karegowda et al 2011)	-	96.97	100

VIII. Conclusion

In conclusion, the diagnosis and treatment of several retinal illnesses, including diabetic retinopathy and glaucoma, depend greatly on the segmentation of the optic disc and exudates in retinal fundus pictures. Early identification, monitoring, and treatment planning are made possible by the accurate and effective segmentation of these structures, which improves patient outcomes. For the segmentation of the optic disc and exudate, a hybrid strategy combining a genetic algorithm and a root-guided decision tree was developed in this work. The segmentation of the optic disc and exudates using the suggested framework showed encouraging results. An essential structural marker that sheds light on a number of retinal disorders is the optic disc. By examining its color , shape, border, and vasculature, automated segmentation of the optic disc assists in the diagnosis of conditions that might compromise vision, such as glaucoma and diabetic retinopathy. During exudate detection, the hybrid model's capacity to use a genetic approach to optimize decision tree characteristics led to increased accuracy and decreased false positives. On the other hand, exudates are an important indicator for detecting diabetic retinopathy. For successful care, their emergence is a sign that diabetic retinopathy is developing. The suggested method effectively determined whether exudates were present or not, exhibiting a high degree of accuracy, sensitivity, and specificity. The efficiency of the suggested technique was evaluated using benchmark datasets like the DRIVE dataset. The hybrid model's efficacy in effectively segmenting the optic disc and exudates was demonstrated by the performance measures accuracy, sensitivity, specificity, Euclidean distance, and diameter difference. The findings were contrasted with those of other techniques already in use, demonstrating the competitive performance of the suggested strategy. The DRIVE dataset, with its high-resolution retinal pictures and hand-annotated manual segmentation, provides an appropriate platform for assessing and testing the suggested hybrid model, it is vital to remark. The dataset's variety of difficulties, including diseases, different vessel widths, varied lighting, and picture noise, further highlighted the resilience and applicability of the suggested technique. The segmentation of the optic disc and exudates by the proposed hybrid model has important clinical consequences. It can help medical personnel identify and monitor retinal problems early, allowing for prompt treatment measures. In addition, by automating these segmentation processes, physicians are freed up to concentrate more on interpretation and diagnosis. The hybrid model may be improved and optimized by more study and development in this area. The accuracy and robustness of the segmentation method may be improved by the inclusion of other characteristics like texture analysis and vascular segmentation. Additionally, using cutting-edge deep learning methods like convolutional neural networks may enhance segmentation performance. In segmenting the optic disc and exudates, the hybrid model using a genetic algorithm and a root-guided decision tree showed encouraging results. This method has a great deal of potential for helping medical professionals diagnose and treat retinal problems. The development of automated retinal image processing systems, which will improve patient outcomes and revolutionize the discipline of ophthalmology, will be facilitated by further developments in this area.

REFERENCES

[1] *Tewari, A , Gupta, D &Sivaswamy*, J 2014, Bilateral Symmetry basedApproach for Joint Detection of Landmarks in Retinal Images : 2014InternationalConferenceonSignal Processing andCommunications(SPCOM),pp.1-6.

[2] Tu Ying, Xu Liang, Wei Wen-bin, Wang Shuang, Wang Ya-Xing and Jost B

Jonas, 2011, " Progression of diabetic retinopathy: the Beijing Eye Study," Chinese Medical Journal, Vol. 124, No. 22, pp. 3635-3640.

[3] Borkar, P., Wankhede, V.A., Mane, D.T. *et al.* Deep learning and image processing-based early detection of Alzheimer disease in cognitively normal individuals. *Soft Comput* (2023). https://doi.org/10.1007/s00500-023-08615-w.

[4] V. Mareeswari "Prediction of Diabetes Using Data Mining Techniques"2017

[5] Veiga, D , Pereira, C , Ferreira, M , Gonçalves, L &Monteiro, J 2014,'QualityEvaluationofDigitalFundusImagesthroughCombinedMeasures',JournalofMedicalImaging,vol.1,no.1,p.014001.

[6] Verneer, KA , Vos, FM , Lemij, HG &Vossepoel, AM 2004, 'A Model based Method for Retinal Blood Vessel Detection', Computers in Biology and Medicine, vol. 34, no. 3, pp. 209-219.

[7] Wang, C ,Kaba, D & Li, Y 2015, 'Level Set Segmentation of Optic Discs from Retinal Images', Journal of Medical and Bioengineering , vol. 4, no. 3.

[8] Ajani, S.N., Mulla, R.A., Limkar, S. *et al.* DLMBHCO: design of an augmented bioinspired deep learning-based multidomain body parameter analysis via heterogeneous correlative body organ analysis. *Soft Comput* (2023). https://doi.org/10.1007/s00500-023-08613-y.

[9] Welfer, D , Scharcanski, J &Marinho, DR 2013, 'A Morphologic Two-Stage Approach for Automated Optic Disk Detection in Color Eye Fundus Images', Pattern Recognition Letters, vol. 34, no. 5, pp. 476-465.

[10] Wu, X & You, J, ‗Detection of microaneurysms using multiscale correlation coefficients', Pattern ecognition, vol. 43, no. 6, pp. 2237-2248. 2006

[11] Y.Yuan,J.Wang,B.Li,andM.Meng,"Saliencybasedulcerdetectionforwirelesscapsuleendoscopydiagnosis,"IEEETrans. Med.Imag., Apr.2015.

[12] Y.Zhao,I.J.MacCormick,D.Parry,S.Leach,N.Beare,S.P.Harding,andY.Zheng,"Automateddetectionofleakageinfluoresceinangiographyimageswithapplicationto malarialretinopathy,"Sci.Rep.,vol.5,p. e10425,2015.

[13] Yan, X , Yang, G , Meng, X , Han, Z & Yin, Y 2014, 'A Classification-Based Method for Retinal Image Quality Assessment', International Journal of Electrical Engineering, vol. 21, no. 3, pp. 75- 84.

[14] Ajani, S. and Amdani, S.Y., 2020. Dynamic Path Planning Approaches based on Artificial Intelligence and Machine Learning. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *11*(3), pp.2084-2098.

[15] Yanli 2014, 'Automatic Segmentation of Retinal Blood Vessels based on Improved Multiscale Line Detection', Journal of Computing Science and Engineering, vol. 8, no. 2, pp. 119-128

[16] Yao, C & Chen, HJ 2009, 'Automated Retinal Blood Vessels Segmentation based on Simplified PCNN and Fast 2D-Otsu Algorithm', Journal of Central South University of Technology, vol. 16, pp. 640-646.

[17] You, X , Peng, Q , Yuan, Y , Cheung, Y & Lei, J 2011, 'Segmentation of Retinal Blood Vessels using the Radial Projection and SemiSupervised Approach', Pattern Recognition, vol. 44, no. 10, pp. 2314- 2324

[18] Yu, H , Agurto, C , Barriga, S , Nemeth, SC , Soliz, P & Zamora, G 2012, Automated Image Quality Evaluation of Retinal Fundus Photographs in Diabetic Retinopathy Screening : 2012 IEEE Southwest Symposium Image Analysis and Interpretation (SSIAI) , pp. 125-128.

[19] Yuji Hatanaka et al. , 2008, " Improvement of Automatic Hemorrhages Detection Methods

using Brightness Correction on Fundus Images," In Proc of the international society of optics and photonics on medical imaging, Vol. 6915.

[20] Zhang, B , Zhang, L , Zhang, L &Karray, F 2010, 'Retinal Vessel Extraction by Matched Filter with First-Order Derivative of Gaussian', Computers in Biology and Medicine, vol. 40, no. 4, pp. 438-445.