STM JOURNALS

Recent Trends in
Sensor Research & Technology

ISSN: 2393-8765
Volume 8, Issue 3, 2021
DOI (Journal): 10.37591/RTSRT

http://engineeringjournals.stmjournals.in/index.php/RTSRT/index

Research RTSRT

Image Preprocessing and Analysis on Eye Fundus Images Segmentation by Using Density Clustering Methods

Snehalatha Katha[1,*], Mohan Das Talari[2]

Abstract

In order to do an automated evaluation of various retinal illnesses such as Diabetic retinopathy, Glaucoma, and Macular Edema, fundus images must be pre-processed first. For many reasons, it's difficult to accurately detect the optic disc. Many blood vessels cross the optic disc, making it difficult to discern the disc's boundaries in fundus images. Lesion regions in diabetic retinopathy look very much like an optic disc's colour and texture, so an automated retinal image analysis system must identify and remove these areas. DR is diagnosed early in this study using machine learning (ML) approaches. For example: Bayesian Classification; K-Means Clustering; PNN; SVM; and Bayesian Classification In order to determine the most effective strategy, these options will be weighed against one another and evaluated. For training and testing, a total of 300 fundus images are processed. Using image processing techniques, these raw photos are processed to extract the features. The results of an experiment show that PNN, Bayes Classifications, SVM, and K-Means Clustering are all more accurate than 94% of the time. It appears that SVM is the best method for detecting early signs of degenerative disease.

Keywords: Segmentation, edge detection, diabetic retinipathy, image enhancement, eye fundus

INTRODUCTION

Impulse signals are transmitted from the retina to the brain by means of an optic nerve (ON). The ON is located near the macula in the eye's anterior region. The distal end of ON, next to the eyeball, is known as the optic disc (OD). Images of the eyeball's anatomical structure and retinal images showing OD and macular locations are depicted in Figure 1 (a) and (b), respectively. The position of the OD in an image of the eye's inner plexus is critical to the diagnosis of retinal abnormalities. There are a number of disorders that can be seen in retinal pictures that are related to ocular disease (OD), such as glaucoma, optic atrophy, and disc drusen. The OD region is aberrant on retinal imaging. Previously, researchers have pinpointed the position of the OD on a retinal image. They proposed a new algorithm based on Hoover and Goldbaum's "fuzzy convergence" algorithm. They pinpointed the retinal blood vessels network's focal point to be the ON positions. Figure 1(b) shows the convergence of several retinal blood vessels, which is where the main point is located. After adjusting the brightness of the images, they were able to pinpoint the exact location of OD. On the retinal image, OD was found in the brightest spot.

The brightness of the image media was improved in an effort to minimise the differences between the input and the improved image media. Each subframe's median is used as a starting point

***Author for Correspondence**
Snehalatha Katha

[1]Assistant Professor, Department of Electronics & Communication Engineering, Jawaharlal Nehru Technological University Hyderabad University College of Engineering Sultanpur, Telangana, India.
[2]Assistant Professor, Department of Electronics & Communication Engineering, Jawaharlal Nehru Technological University Hyderabad University College of Engineering Sultanpur, Telangana

Received Date: February 15, 2022
Accepted Date: February 25, 2022
Published Date: February 28, 2022

Citation: Snehalatha Katha, Mohan Das Talari. Image Preprocessing and Analysis on Eye Fundus Images Segmentation by Using Density Clustering Methods. Recent Trends in Sensor Research & Technology. 2021; 8(3): 11–18p.

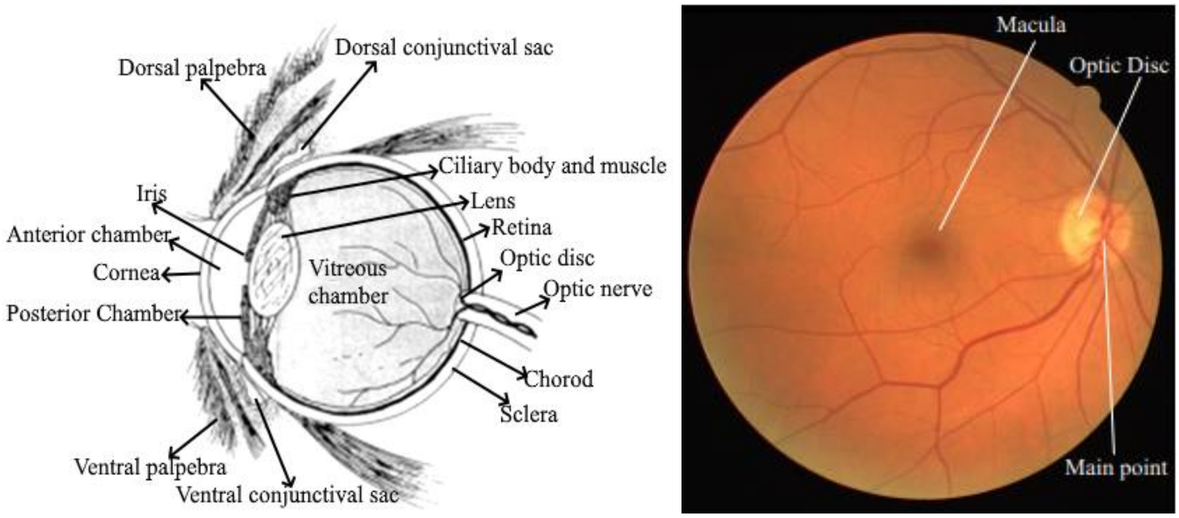

Figure 1. The structure of retina: (a) Sagittal section of the eye, (b) The retinal image showing the optic disc and the macula.

for tinkering with the top of its input histograms. Even while it was possible to lower the standard deviation of the brightness error, there was no apparent logic for adopting the median value as the clipping limit. Consequently, In the future, a method for reducing the project's scope was devised. Instead of emitting a wider range of brightness, a narrower range was used, resulting in a final image whose brightness was as close to the original image's as possible [1–3]. The average brightness problem has an alternative solution: a weighted sum method. The average brightness value was taken into consideration in order to create pixel groups of lower and higher intensity. Tiated group groups were merged with other groups and weighed in order to give a more accurate representation of the data. It was necessary to relax the requirement for the average brightness error to be perfectly minimised in light of the fact that this is not always possible. As a result, the histogram trimming method has been altered. The sum of the histogram, median, and mean values was chosen as the clipping limit. Because of the low cropping size provided by it, pixel functions in the subgroups may be lost when the median is low and provides a small amount of cropping. There was a comparative evaluation of the most common colour space for images based on the available techniques. Color space that approximates image brightness is used to level the histogram when reporting, according to the research.

An effective segmentation approach with two phases, as well as structure extraction filters, are used in this work as preprocessing procedures to identify lesions. Segmentation is difficult because the EFI images themselves are widely varied in luminance, colour, and clarity, sometimes with poor contrast. Aside from that, the colours, sizes, and shapes of the regions and lesions themselves might vary greatly. Segmentation techniques should be used to the fullest extent possible, even in the most challenging situations. We include experimental outcomes that examine the detection phase's runtime, segmentation fraction, and accuracy.

LITERATURE REVIEW

The early identification of DR has been achieved by designing a patch-based localization model. Selecting training patches has helped minimise the model's complexity while increasing its performance. In order to classify the data, a probability map was used. ROC is 0.912, and the sen is 0.940 for the proposed model, which was tested on the DIARET DB1 dataset (Dorizzi et al., 2019) [4].

Detecting characteristics such as blobs and blood vessels has been accomplished using a variety of methods. SVM classifier has been used to classify the images after the green channel was extracted, segmentation using the Otsu technique, and feature extraction using Hough transformation. Implemented in the DIARET Dataset, the suggested algorithm has a sens/spec score of 73/70 in the blob detection and 77/80 in the blood vessel detection (see Table 1). (Sakshi Gunde and Gupta, 2020) [5].

This paper used a dictionary-based strategy to implement the SDDR method for checking the severity of DR disease. This method incorporates a pathological representation of an image into a learning plan. To develop a dictionary, the features are organised according to the point of interest. Finally, histogram-oriented gradients together with coding and pooling methods are used to compress features. The 5-level classification of images has been achieved using radial basis SVM and neural network. Kaggle's National Data Science Bowl dataset is used to test the approach, and it obtains 95.2 percent /98.9% /98.3% accuracy (Leeza and Farooq, 2019) [6].

Tests on a user-generated dataset (Ophthalmic image processing Medical Image and Signal Processing Research Center, 2021) show that the sensitivity and specificity values are both 100%. They plan to implement alternative transforms, such as the contourlet transform and the shearlet transform, instead of the Curvelet transform.

Rahim et al. [7], 2015 have used fuzzy image processing to demonstrate the detection of DR and maculopathy. If you don't have any maculopathy, you could eventually lose your vision. Image acquisition, fuzzy pre-processing and feature extraction, and classification by machine learning algorithms are all part of the proposed system. There are two kinds of classification for this system's dataset. Two-category misclassification error is 0.2539/7461/0.4536/1.0803 for the binary decision tree and 0.2139/0.7861/0.5572/0.8598 for the k-nearest neighbour.

In the future, the focus will be on machine learning research using visual graph extraction. There have been four proposed measures for grading the severity of DR using CNN. A new clinical dataset has been presented with a favourable labelling for clinical use. Using a processing pipeline, we were able to standardise the data across the board. The performance of the Inception V-3 model has been compared to that of other well-known models. A trial diagnostic service has been launched using all of the cloud-based models that have been trained. For DR grading, the method is 88.72 percent accurate (Gao et al., 2019) [8].

METHODOLOGY

Image segmentation can benefit greatly from density-based clustering algorithms. However, the size and variability of individual pixels make it impossible to distinguish macro-regions in such a small image. The first step in the two-step process is to create super-pixels by combining individual pixels. There are no local regions that overlap with each other in a super-pixel because it is a (small) cell in a grid. A superpixelation technique computes and modifies these polygons to represent region homogeneity using the set of all super-pixels. The term "super-pixel" comes from the fact that it combines adjacent pixels into a single, uniformly-sized unit. Local homogeneity zones are identified via super-pixel computations utilising rigorous criteria (a number of super-pixels and a maximum weighted colour and spatial distance threshold). The density clustering process will join regions whose homogeneity exceeds a predetermined threshold [9–11].

Pre-processing of Images

To remove the unwanted distortions from the images, we apply image processing. It is done in two ways: The first is to remove the unnecessary parts, and the second is to enhance the important parts. All 300 images are taken from credential sources (http://webeye.ophth.uiowa.edu/ROC/). They are accredited retinal images, including both healthy and unhealthy images, 600 x 600 pixels, but they were converted into 256 x 256 pixels. The input sample images used in the RGB format as seen in Figure 2 (a) and grayscale conversion in 2 (b).

It is to remove the uneven illumination in the retinal images' gray level shading. To turn the images into grayscale, a special application was created. First, it inputs the image one after another and converts it into greyscale. Then it generates a digital number for each image from 0 to 256 in a matrix form; with this application, the images can be turned into sharpening and blurred format presented in Figure 3 (a) and 3 (b).

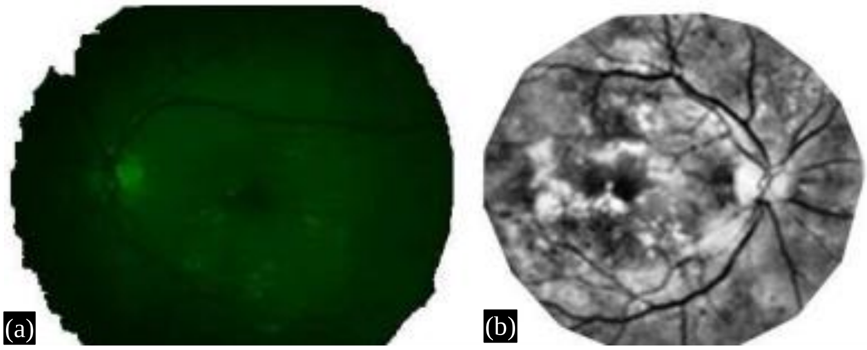

Figure 2. (a) Green channel image, (b) Image contrast.

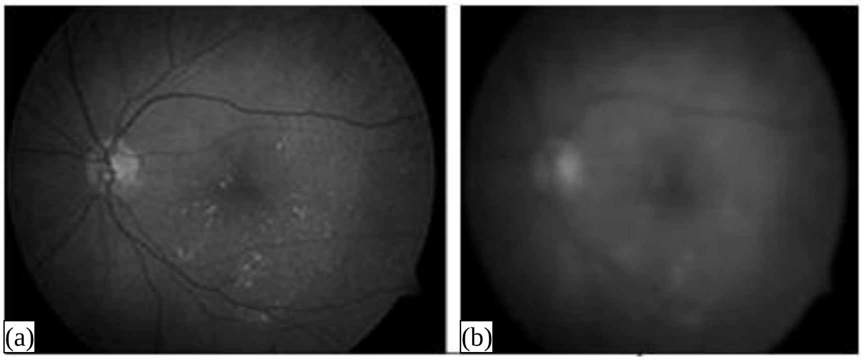

Figure 3. (a) Sharpen images, (b) Blurred images.

The Detection of Optic Disk

Fundus images show it as a bright yellowish or white zone, indicating a healthy eye. Removal of the optic disc (OD) is necessary because exudates have similar values. OD and blood vessels can be located using edge detection methods when a pre-processing step has been completed.

Detection of countermeasures is carried out using Canny edge detection. To improve fuzzy edges, the Canny edge detection algorithm keeps all local maxima of the gradient, which detects the borders of features best. Mask images are created using logical black and white functions, as depicted in Figure 4.

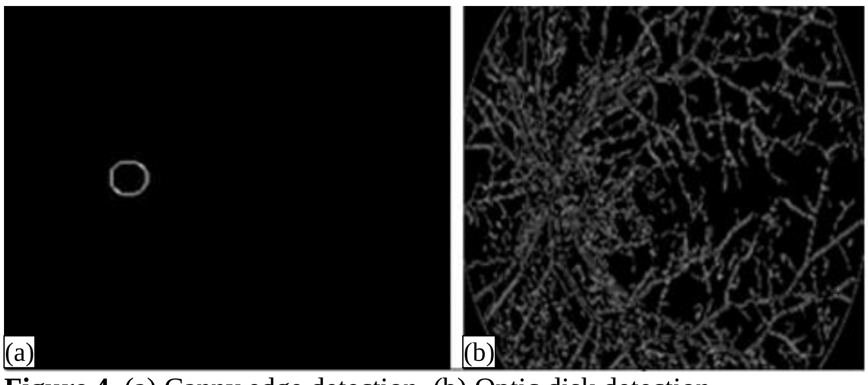

Figure 4. (a) Canny edge detection, (b) Optic disk detection.

Recent Trends in Sensor Research & Technology
Volume 8, Issue 3
ISSN: 2393-8765

Eliminating Blood Vessels in the Fundus Images

It is a process to eliminate the blood vessels. Because blood vessels exist, a major sign of DR [12] may be mistaken for exudates, so it is necessary to remove them. For this process, we are using mathematical morphology, which has opening and closing operations.

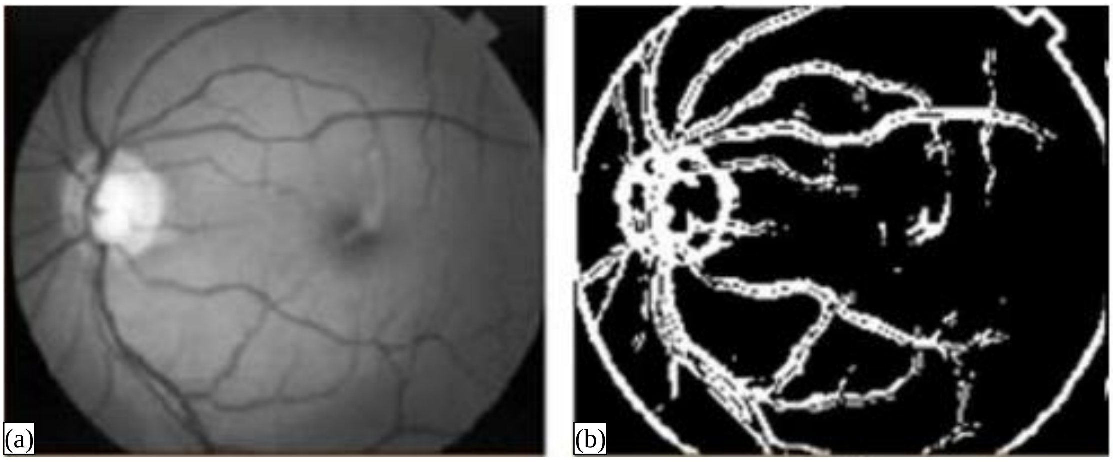

Figure 5. (a) Contrast-enhanced image, (b) Blood vessel detection.

Blood vessels behave as a landmark for optic disc detection, exudates [13]. Therefore, morphological methods have been benefitted from detecting blood vessels. Firstly, the morphological closing operation is applied on the contrast enhanced image (Figure 5 (a)) followed by filling operation then it is ready for blood vessel detection (Figure 5 (b)).

SIMULATION RESULTS [14, 15]

Figure 6 shows that in the fundus image, there are damaged areas and healthy areas. SVM is used to separate these areas at optimal results.

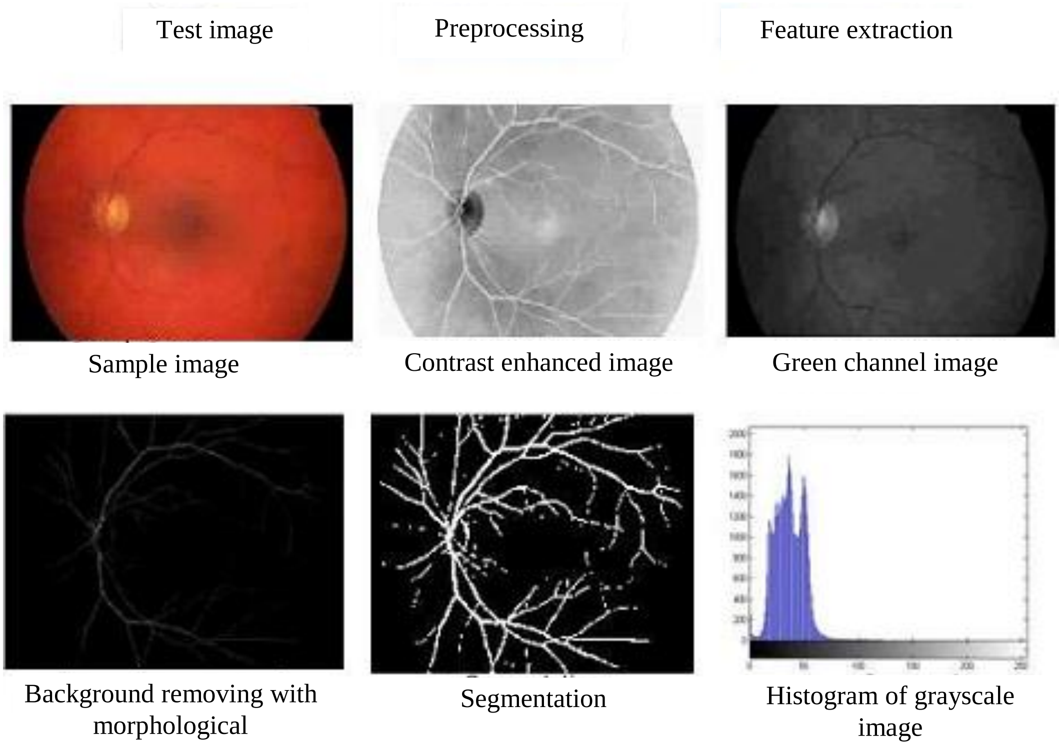

Figure 6. SVM is applied process.

When the K-Means algorithm is applied to the obtained information about blood vessels, it can benefit grading DR severity. As seen in Figure 7(a, b), the parts are visible. Using K Means Clustering we can select to extract the features in each local in advance before it is used for classification.

The function of selecting the feature extraction (Figure 7a, b) is to select the results having a big difference between class and the unimportant feature extraction results.

Latent information and index calculation are shown on the X-axis of Figure 8 in terms of a Gaussian level clustering.

X-axis: Viscous Circle characteristics; Y-axis: Determined rate. Figure 9 shows the optic disc localization with viscous data.

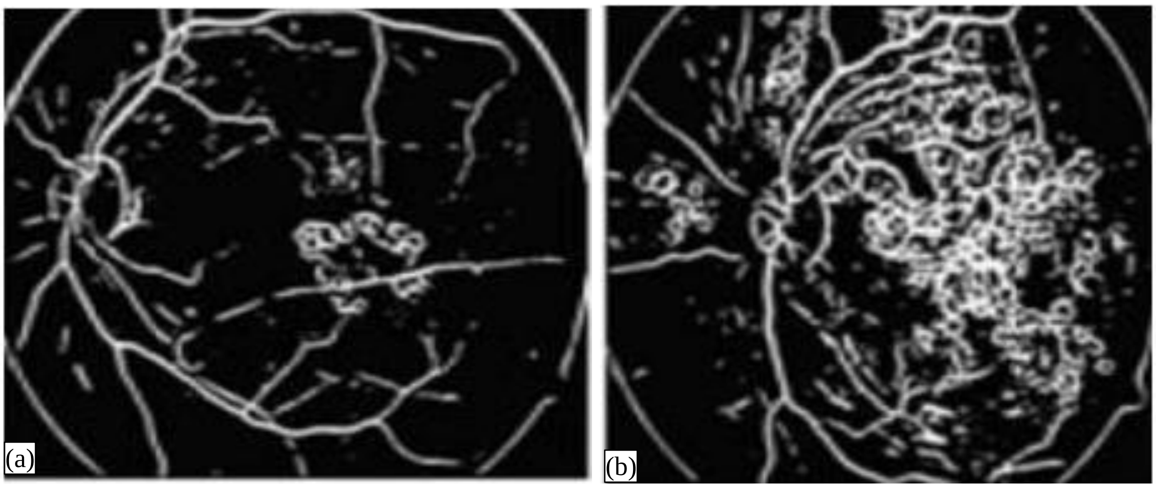

Figure 7. K-means clustering images (a) Before (b) After.

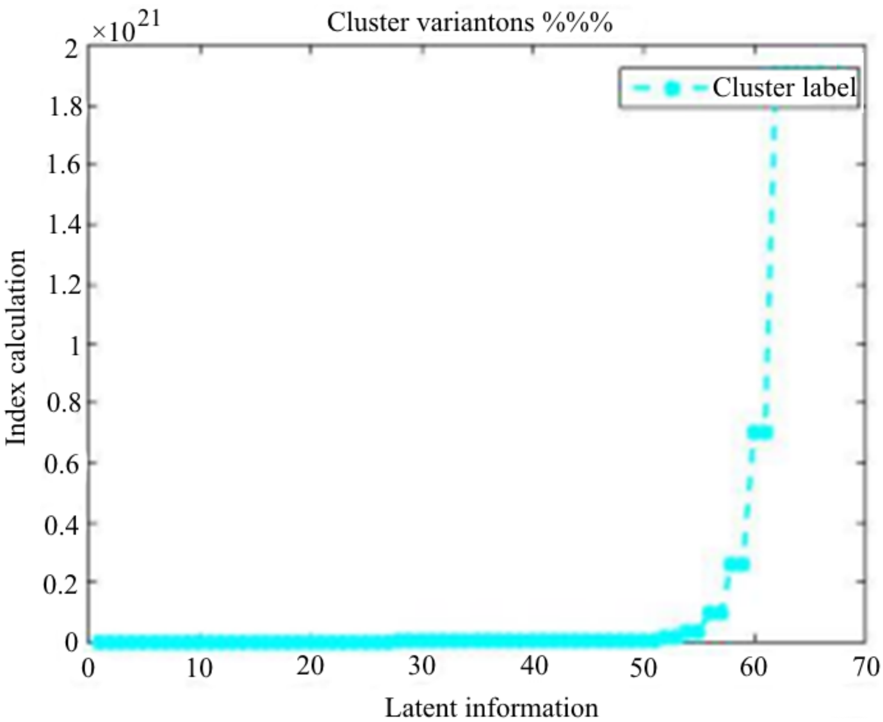

Figure 8. Cluster variations percentage.

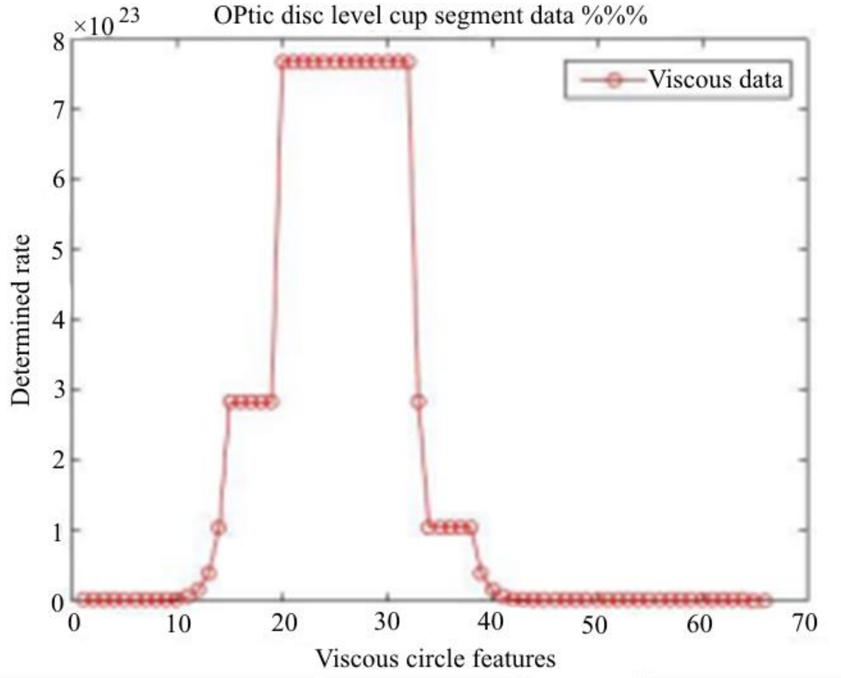

Figure 9. Optic disc level segmentation.

CONCLUSION

Segmenting and removing the optic disc can identify diabetic retinopathy, glaucoma, and diabetic maculopathy, to name a few common eye conditions. Rather than being bound by the optic disc's location on the retina, a new method for segmenting it is provided in this work. We start by pinpointing an approximate location for the optic disc before performing morphological operations such as repeated thresholding and connecting component methods to pinpoint its exact location. As a result, the proposed algorithm can locate the optic disc's centre regardless of where it is located on the optical disc. Graphical User Interface (GUI) for the ophthalmologist to mark fundus images. The images that have been marked will be used to create a DR grading and database system for use in the current and future projects. Several machine learning (ML) methods for DR detection are the subject of this investigation. It has been reported that detecting DR early can lower the chance of vision loss by up to 76%. Additionally, this study proposes a new method for diagnosing DR using ML approaches. SVM, Naive Bayes Classification, PNN, and K-Means Clustering are the top three methods, respectively, with a combined percentage of 97.3 percent, 86.4 percent, and 78 percent.

REFERENCES

1. Parashuram Bannigidad and Asmita Deshpande, "A Hybrid Approach for Digital Fundus Images using Image Enhancement Techniques", International Journal of Computer Engineering and Applications, Vol. XII, Issue I, 2017, pp.122-131.
2. Parashuram Bannigidad and Asmita Deshpande, "A Multistage Approach for exudates detection in fundus images using texture features with k-NN classifier", International Journal of Advanced Research in Computer Science, Vol. 9, No. 1, 2018, pp.1-5.
3. Parashuram Bannigidad and Asmita Deshpande, "Exudates Detection in Digital Fundus Images using GLCM features with SVM classifier", International Journal of Modern Electronic and Communication Engineering, Vol. 6, Issue. 6, 2018, pp.184-189.
4. B. Dorizzi, G. Tozatto, R. Varej, E. Ottoni, and T. Salles, ''Diabetic retinopathy detection using red lesion localization and convolutional neural networks ~ o Andre a," vol. 116, no. November 2019, 2020, 10.1016/ j. compbiomed.2019.103537.
5. Sakshi Gunde, A.A., Gupta, S.D., 2020. Diabetic retinopathy detection using nonmydriatic fundus images. Our Herit 1, 141–145.

6. Leeza, M., Farooq, H., 2019. Detection of severity level of diabetic retinopathy using Bag of features model. IET Comput. Vis. 13 (5), 523–530. https://doi.org/ 10.1049/cvi2.v13.510.1049/iet-cvi.2018.5263
7. S. S. Rahim, V. Palade, C. Jayne, A. Holzinger, and J. Shuttleworth, ‘‘Detection of Diabetic Retinopathy and Maculopathy in EYe Fundus images using Fundus image processing,” vol. 9250, pp. 275–284, 2015, 10.1007/978-3-319-23344-4.
8. Soomro, T.A., Gao, J., Khan, T., Hani, A.F.M., Khan, M.A.U., Paul, M., 2017. Computerised approaches for the detection of diabetic retinopathy using retinal fundus images: A survey. Pattern Anal. Appl. 20 (4), 927–961. https:// doi.org/10.1007/s10044-017-0630-y.
9. J. Hemanth and J. Anitha, "Hybrid clustering method for optic disc segmentation and feature extraction in retinal images", World Congress on Information and Communication Technologies, Trivandrum, 2012, pp. 320-325.
10. Juan Xua, Opas Chutatapeb, Eric Sungc, Ce Zhengd, Paul ChewTec Kuand, “Optic disk feature extraction via modified deformable model technique for glaucoma analysis”, Pattern Recognition, Vol. 40, Issue 7, 2007, pp. 2063-2076.
11. Arturo Aquino, Manuel Emilio Gegúndez-Arias, and Diego Marí, “Detecting the Optic Disc Boundary in Digital Fundus Images Using Morphological, Edge Detection, and Feature Extraction Techniques”, IEEE transactions on medical imaging, Volume. 29, no. 11, 2010, pp. 1860-1869.
12. Muhammad Abdullah, Muhammad Moazam Fraz, and Sarah A. Barman, “Localization and segmentation of optic disc in retinal images using circular Hough transform and grow-cut algorithm”, PeerJ4: e2003; DOI10.7717/peerj.2003
13. J. Sivaswamy, S. R. Krishnadas, G. Datt Joshi, M. Jain and A. U. Syed Tabish, "Drishti-GS: Retinal image dataset for optic nerve head (ONH) segmentation", 2014, IEEE 11th International Symposium on Biomedical Imaging (ISBI), Beijing, 2014, pp. 53-56.
14. Image Database. (2007). DIARETDB1-Standard Diabetic Retinopathy Database Calibration level 1 [online]. Available from http://www.it.lut.fi/project/imageret/diaretdb1/
15. Wikipedia. (2022). Sensitivity and specificity. [online]. Available from https://en.wikipedia.org/wiki/Sensitivity_and_specificity

