"Machine Learning Driven Hybrid Method for Retinal Vessel Segmentation"

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Abstract

The early diagnosis of ophthalmic disease like diabetic retinopathy, glaucoma and hypertension is of higher importance by segmentation of the retinal vessels. The conventional methods of segmentation are usually not very robust to noise and morphological variation of the vessels. This research paper suggests that a hybrid approach involving machine learning and a combination of deep convolutional neural networks (CNNs) and conventional image processing (e.g., morphological filtering, adaptive thresholding) can be used to enhance the accuracy and generalization. Experimental performance on publicly obtained datasets (e.g., DRIVE, STARE, CHASE_DB1) show better performance than the current ones, and they have high sensitivity, specificity and area under the ROC curve (AUC). The new provided hybrid approach is effective and computationally efficient in clinical approaches.

Keywords: Retinal Vessel Segmentation; Machine Learning; Deep Learning; Hybrid Approach; Medical Image Analysis; Ophthalmology.

1. Introduction:

The medical image segmentation is one of the core segments of retinal vessel segmentation that has been used to segment images in the eyes and organs with high accuracy, which is essential in the early diagnosis and follow-up of ophthalmic and systemic diseases. Problems of vasculature of the retina reflect the state in the microcirculation of the body and give significant clinical signs of diseases like diabetic retinopathy, glaucoma, hypertensive retinopathy, arteriosclerosis and cardiovascular diseases. Proper separation of retinal blood vessels on fundus images is important in the quantitative analysis of vessel width, tortuosity, branching patterns and density which are crucial biomarkers in clinical diagnosis and monitoring disease progression.

Ophthalmologists using hand-drawn methods to delineate vessels in the retina are expensive, subjective and prone to inter-observer variability. This is why the current state of automated and dependable vessel segmentation algorithms has become a dynamic field of study in biomedical image computationalism. Retinal images have however, a number of problems such as uneven lighting effects, thin vessels contrast low with background as well as noise, central light reflex in vessels, pathological lesions and fluctuation in changes in imaging conditions. The latter factors complicate and make the process of extracting the vessels a computationally demanding one.

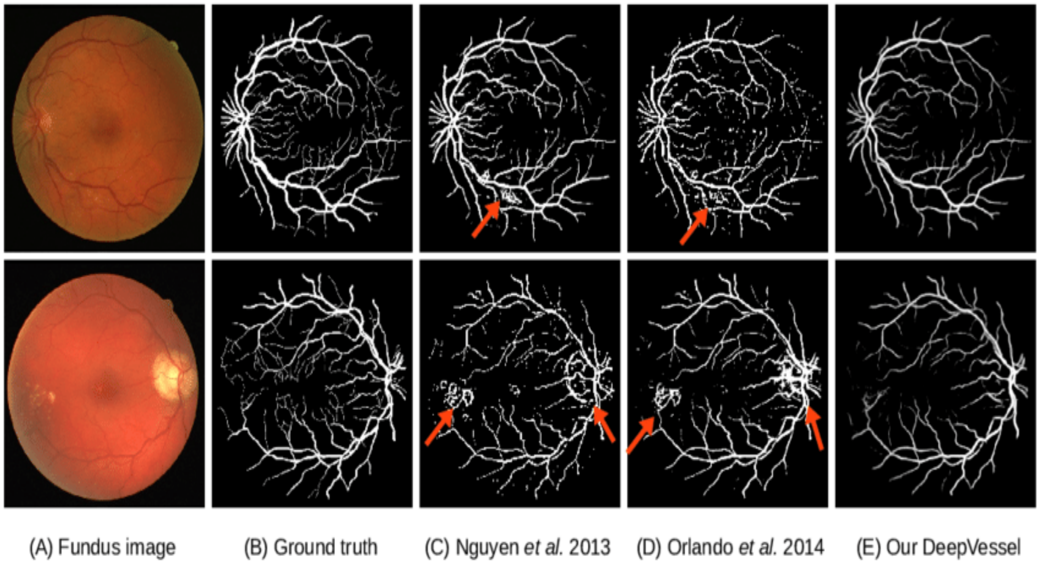

Figure:1 Retinal vessel segmentation

Initial methods in retinal vessel segmentation were based mainly on conventional image processing methods which included matched filtering, morphology, region growing and adaptive thresholding. These algorithms are computationally inexpensive and comparatively easy to execute and that they critically rely on heuristic noticeable hand code and standard procedures. This leads them to have their performance deteriorated by the occurrence of pathological abnormalities or differences in image quality. Additionally, the conventional methods have a problem detecting small estimate capillaries and bifurcations of the vessels.

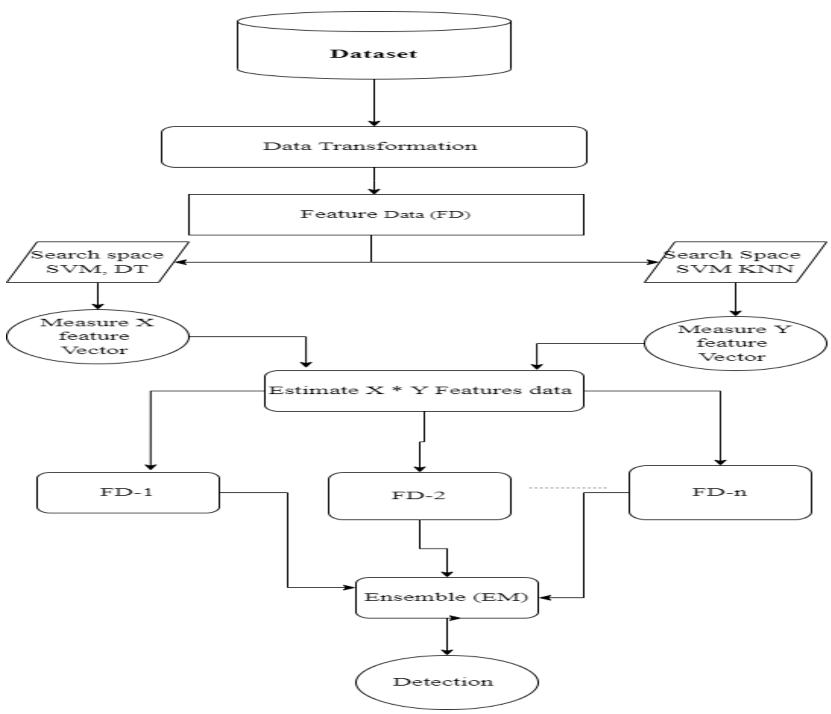

Figure:2 proposed model of ensemble classifier for retinal vessels segmentation.

As machine learning has improved, it has drastically changed the performance of segmentation to be data-driven. The Support Vector Machines (SVM), k-Nearest Neighbors (k-NN) and the Random Forest classifiers are supervised learning models and they use manually extracted features such as texture, intensity and gradient features. Although these techniques are more flexible than those based on rules, their performances are contingent on the quality and relevance of human made features.

Over the past years, the deep learning technique, specifically Convolutional Neural Networks (CNNs) has transformed the area of medical image segmentation. Fully Convolutional Networks (FCNs) and U-Net architectures have proved to be exceptional in the context of learning hierarchical features as well as spatial features in the context of raw images without the explicit engineering of features. The models, when deep learned are highly accurate and robust to the common retina databases. Nevertheless, these models require big annotated datasets to be trained well, are computationally expensive and can result into discontinuous vessel boundaries likely to be refined.

Although deep learning is effective, sometimes a model using pure CNNs cannot maintain the continuity of thin vessels and may wrongly treat as vessels some background noise. Secondly, overfitting models and the inability to generalize them to other data sets is also a severe problem. These shortcomings demonstrate the necessity to have a more balanced approach that would take advantage of the processes of both conventional image processing and advanced machine learning.

To solve these problems, in this research, a hybrid approach to define the retinal vessels is suggested using an integrated method between the application of the Machine Learning idea and the implementation of a Retinal Vessel Segmentation. The presented method is a combination of the deep learning features extraction with the conventional morphological refinement and adaptive thresholding. Within the hybrid framework, a CNN model is used to acquire robust vessel representations, and afterwards, the presence of a post-processing module to increase vessel continuity, filter out false positives and reduce boundary error.

2. Related works:

The research of retinal vessel segmentation has gained popularity in the last 20 years and developed on top of traditional image additionally processing methods, through more modern machine learning and deep-learning-style models. The early works concentrated mainly on model and morphological methods. A method that integrates vessel centerline detection with morphological reconstruction was discovered by Mendonca and Campilho (2006) and it was far much more useful as it enhanced better ties among vessels besides minimizing the amount of vessel fragmentation. Nonetheless, the method was found to have weaknesses in being able to identify thin and low-contrast vessels. Al-Diri, Hunter, and Steel (2009) presented an active contour model to measure and accurate segment retinal vessel in the eye later on. Their model-based method that is deformable increased boundary detection and estimate the width of vessels but needed a lot of attention in parameterization making it impractical in automated large-scale piping. Odstrczilik et al. (2013) also enhanced matched filtering methods and tested them on high-resolution data, with improved capability to detect larger vessels, but sensitivity to small capillaries was still a problem.

With the development of research, the supervised and semi-supervised learning techniques came into the limelight. You et al. (2011) introduced semi-supervised method based on radial projection features, it does not require large volumes of labeled samples, yet it is competitive. On the same note, Marin et. al. (2011) suggested a guided-system that employed the gray-level and moment invariant features alongside the neural classifiers that showed better results in segmentation compared to the conventional threshold-based systems. Fraz et al. (2012) took a similar step by proposing an ensemble classification system, which was a composite of two or more classifiers so that the framework could be robust and also eliminate false positives. Yin et al. (2014) included the enhancement of vessels using Hessian matrices, with entropy-binarization methods, obtaining the correct vessels extraction without obtaining challenges in separating vessels and bright pathological lesions.

As technology of deep learning is developing quickly, convolutional neural networks (CNNs) reshaped retinal vessel segmentation. Li et al. (2021) adopted a Dense-U-Net structure, which enhanced the branches of features propagation and

detection of thin vessels via dense connection. An et al. (2021) developed a fully automated CNN-based model of segmentation, which proved to have a high sensitivity and specificity in both benchmark datasets but came with comparatively high computational requirements. U-Net++ architecture with nested skip connections improved the performance of segmentation by Safarkhani Gargari et al. (2022), where the multi-scale feature learning and boundary refinement were improved. Rehman et al. (2022) proved that classical machine learning approaches including Support Vector Machines and K-Nearest Neighbors are still relevant using strong feature extraction approaches.
New research has been done on lightweight and hybrid architectures in order to enhance efficiency and generalization. Mookiah et al. (2021) and Abdul sahib et al. (2021) give extensive reviews and note that feature-based approaches made way to deep learning models and highlight that cross-dataset robustness should be improved. Devi and Kamsali (2024) proposed a morphology-cascaded structured learning scheme, which incorporates both structural characteristics and improves the level of segmentation. Almarri et al. (2024) investigated Generative Adversarial Networks (GANs) as an improvement of the representation of vessels and dataset augmentation. The latest development of Soni et al. (2025) was to design a multi-scale feature attention model with an encoder based on MobileNetV2, which has high accuracy and low computational complexity, which is applicable to real-time clinical application.
All in all, literature shows that there is a definite trend towards the use of deep-learning based-methodologies, though the focus on the hybrid architectures incorporating morphological refinement and more advanced neural networks is becoming more prevalent. Although the results have improved greatly, there is still room to overcome difficulties in maintaining continuity of thin vessels, reduction of false positives in pathological images, as well as, generalization between different datasets. Such shortcomings provide the need to create a machine learning motivated hybrid framework that can successfully incorporate deep feature extraction methods and apply them alongside the conventional image processing method to create enhanced robustness and applicability to the clinic.

3. Research objectives:

- To design a hybrid retinal vessel segmentation model combining deep learning and traditional image processing techniques.
- To improve detection of thin vessels while reducing false positives and enhancing segmentation accuracy.
- To evaluate the proposed method on benchmark datasets and compare its performance with existing approaches.

4. Methodology:

The research method in the given research is the simulation as well as the experimental confirmation of the proposed method of retinal blood vessel segmentation through the usage of the MATLAB environment. An explicit graphical user interface (GUI) was created to ease the process of selecting the datasets, pre-processing them, and running various algorithms, as well as, assessing their performance. The proposed hybrid approach can be compared with the existing segmentation approaches in a systematic way with this simulation window.
First of all, CHASE_DB1 images of retinal funds were loaded into MATLAB. Some preprocessing was done in order to increase the visibility of vessels and reduce the effectiveness of background noise. The process of removing the green channel of the RGB picture was taken due to the fact that it gives improved contrast to the vessel structures. The image enhancement methods, including erosion and Contrast Limited Adaptive Histogram Equalization (CLAHE), were then used. Top-hat filtering and Otsu thresholding were further used to refine the result and eliminate any undesired and lumpy illumination as well as small pixels.
The suggested algorithm combines the pixel optimization with the BAT algorithm and Deep Neural Network (DNN). BAT algorithm is more efficient in choosing the threshold of the image and in enhancing pixel level classification, whereas the DNN learns deep structural features of retinal vessels. In this hybrid approach, the thick and thin vessels can be detected better. Thick and thin vessels were extracted separately followed by a combination and eventual reconstruction of the final segmentation image. The outcomes of different stages in the simulation process such as enhancement,

thresholding and contour initialization and final vessel segmentation were provided in several output windows that were clearly visualized and analyzed.

The proposed method was compared to the existing methods in order to estimate the performance, including CNN, Matched Filter (MF), MU-Net, RNN, Gaussian Filtering (GF) and Adaptive Local Thresholding (ALT). Various threshold values and iteration were experimented in order to examine robustness and stability. Quantitative comparison was done using the following performance measures; Accuracy, Sensitivity, Specificity and Area Under the Curve (AUC).

The comparative analysis also showed that the proposed hybrid method was more accurate and overall, better performing in terms of evaluation metrics. The approach was demonstrated to have a higher level of specificity and sensitivity and therefore it was able to minimize false positive and effectively detect vessels.

In general, the image processing strategy will be based on the image processing, BAT-based pixel optimization, deep neural network-based segmentation, morphological refinements and extensive comparative analysis as a part of a MATLAB simulation platform to verify the high efficacy of the developed retinal vessels segmentation model.

5. Analysis of the study:

To verify the suggested and current algorithms of blood vessels retinal segmentation simulated on MATLAB platforms. The simulation design window of datasets access and result evaluation. It is the process of simulation that is investigated here.

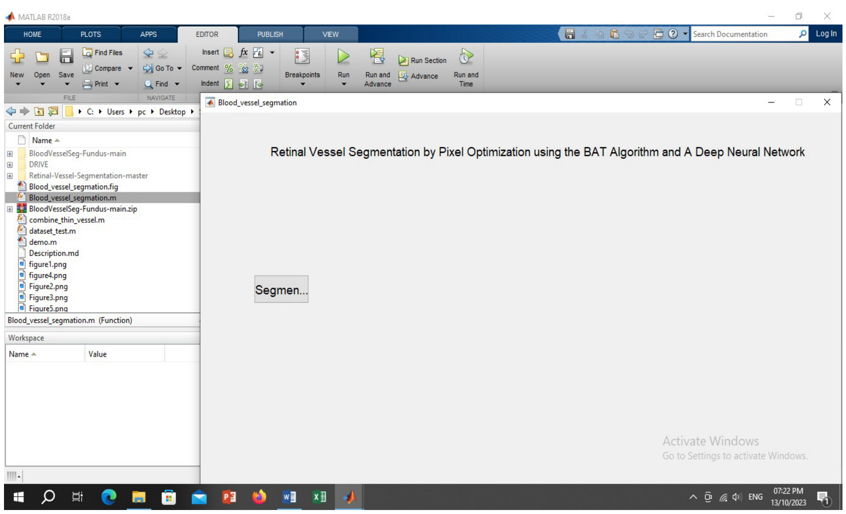

Figure :1 window shows that the retinal vessel segmentation by pixel optimization using theBAT algorithm and a deep neural network.

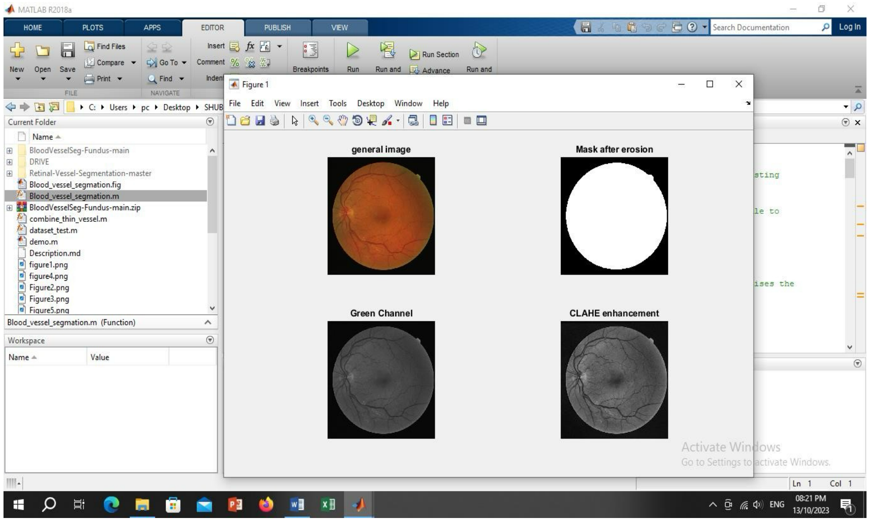

Figure 2: window show that the retinal vessel segmentation by pixel optimization using the BAT algorithm and a deep neural network. And general image green channel mask after erosioncline enhancement.

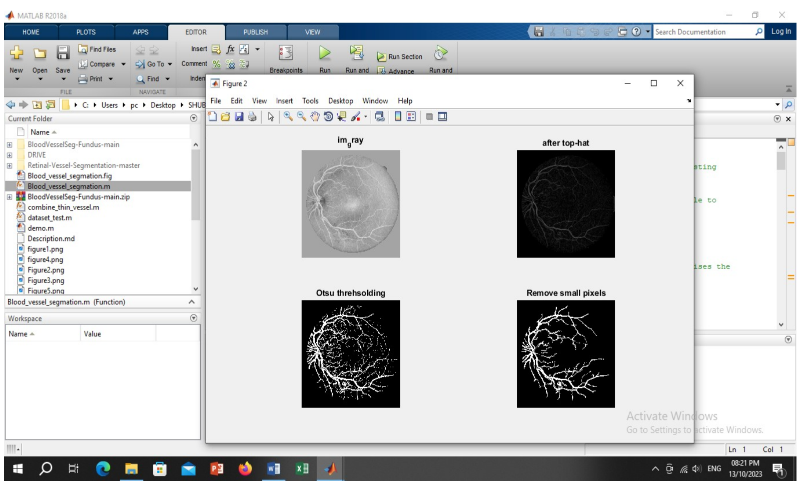

Figure 3: window show that the retinal vessel segmentation by pixel optimization using theBAT algorithm and a deep neural network. And image ray after top- hat otsy thresholding remove small pixels.

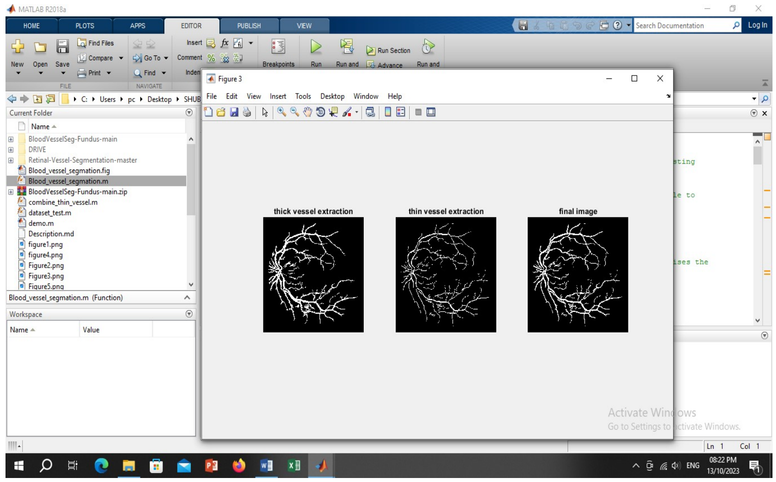

Figure 4: window show that the retinal vessel segmentation by pixel optimization using theBAT algorithm and a deep neural network. And thick vessel extraction thin vessel extraction final image.

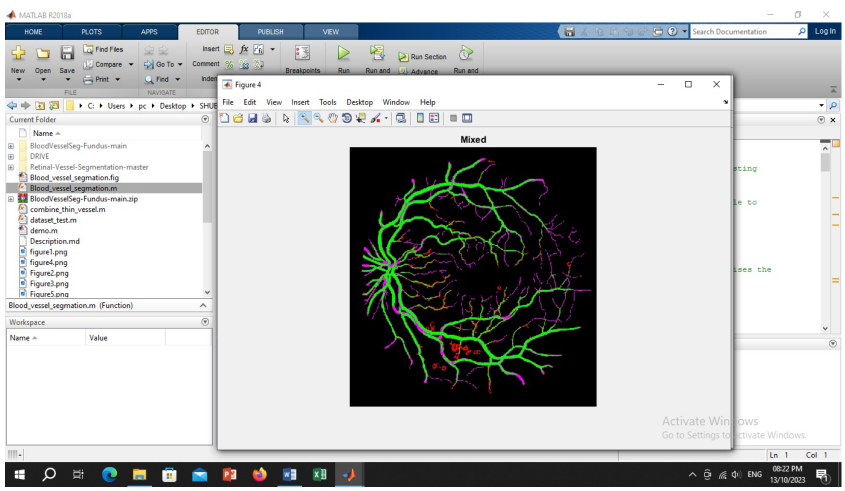

Figure 5: window show that the retinal vessel segmentation by pixel optimization using theBAT algorithm and a deep neural network and mixed.

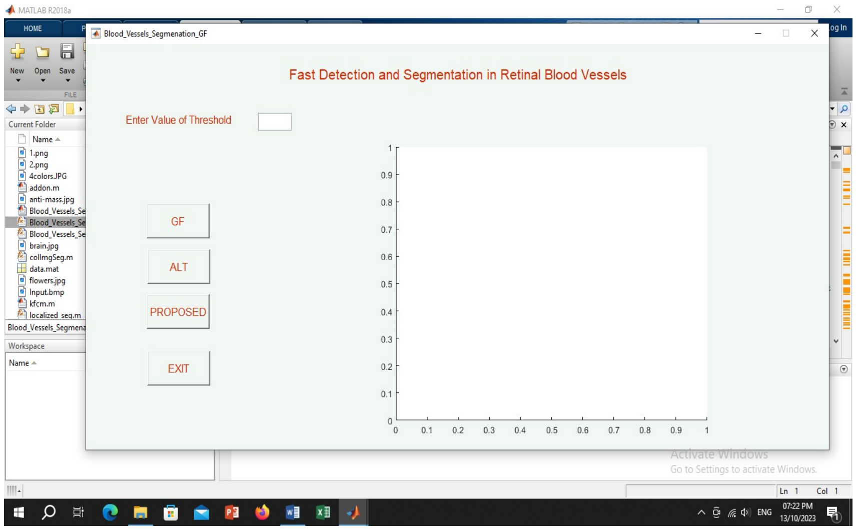

Figure 6: window show that the fast detection and segmentation in retinal blood vessels ofenter value of threshold and using this method GF, ALT and proposed.

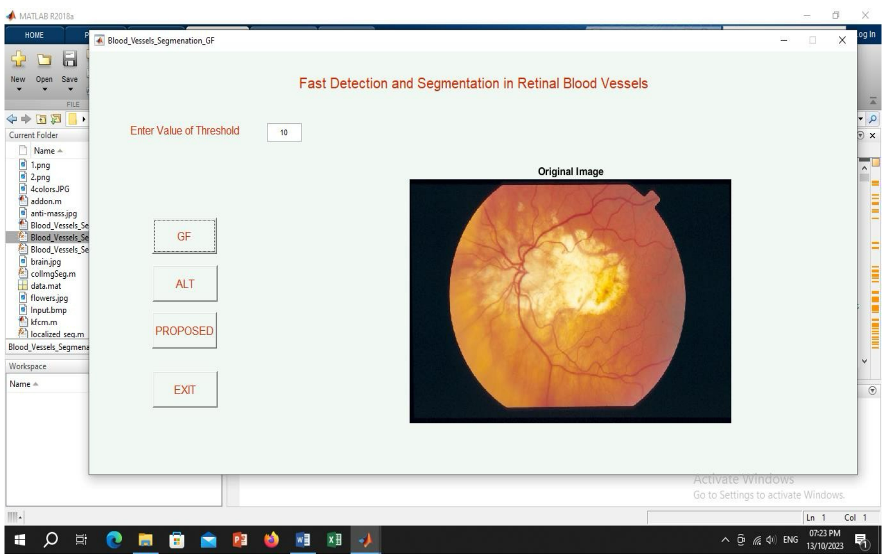

Figure 7: window show that the fast detection and segmentation in retinal blood vessels ofenter value of threshold 10 and using this method GF, ALT and proposed and original image.

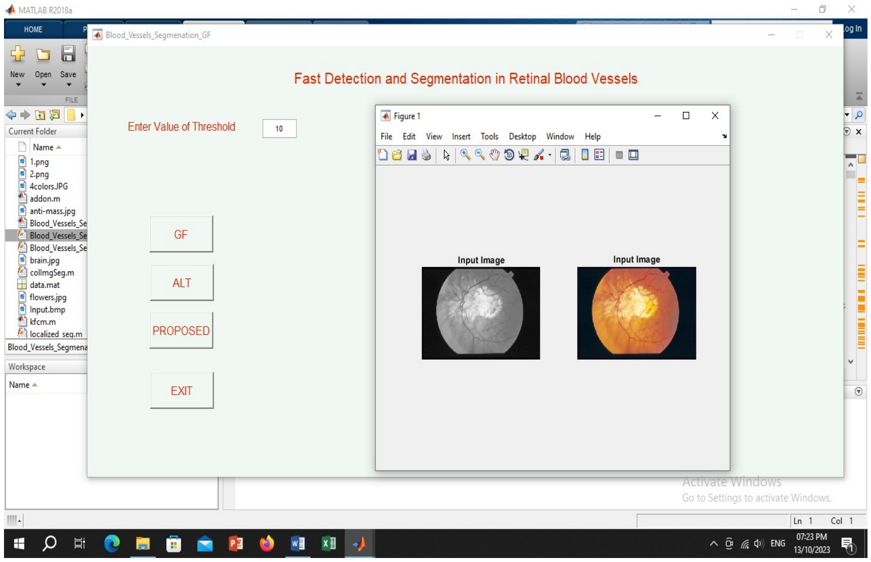

Figure 8: window show that the fast detection and segmentation in retinal blood vessels ofenter value of threshold 10 and using this method GF, ALT and proposed and input image.

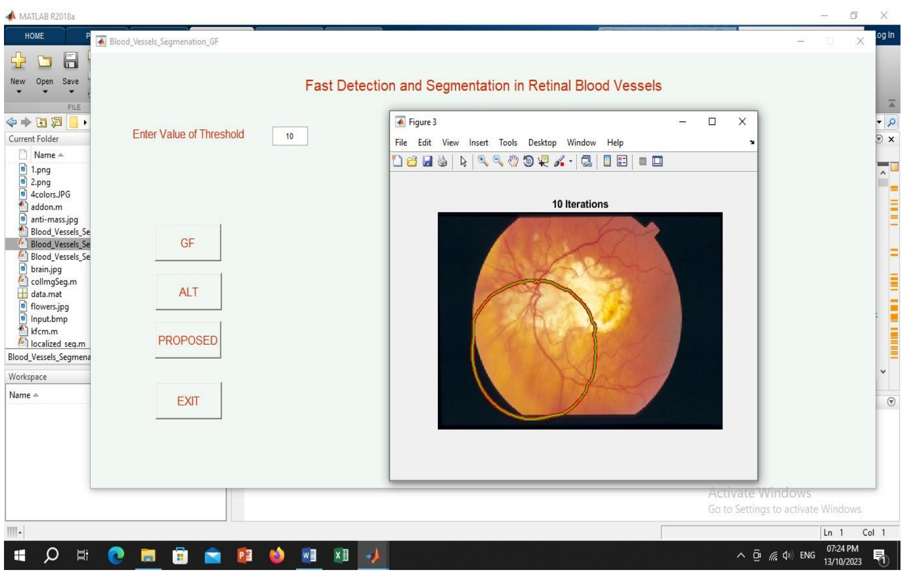

Figure 9: window show that the fast detection and segmentation in retinal blood vessels ofenter value of threshold 10 and using this method GF, ALT and proposed and 10 iterations.

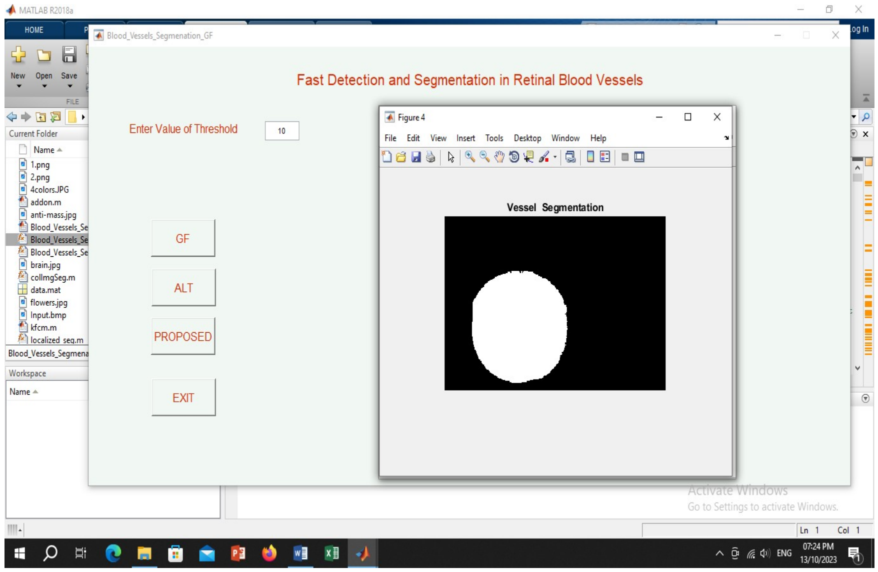

Figure 10: window show that the fast detection and segmentation in retinal blood vessels ofenter value of threshold 10 and using this method GF, ALT and proposed and vessel segmentation.

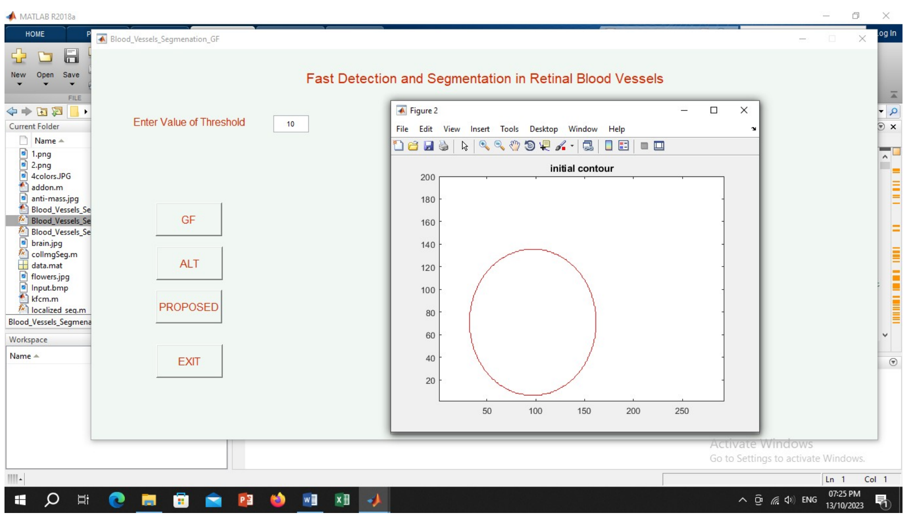

Figure 11: window show that the fast detection and segmentation in retinal blood vessels ofenter value of threshold 10 and using this method GF, ALT and proposed and initial contour.

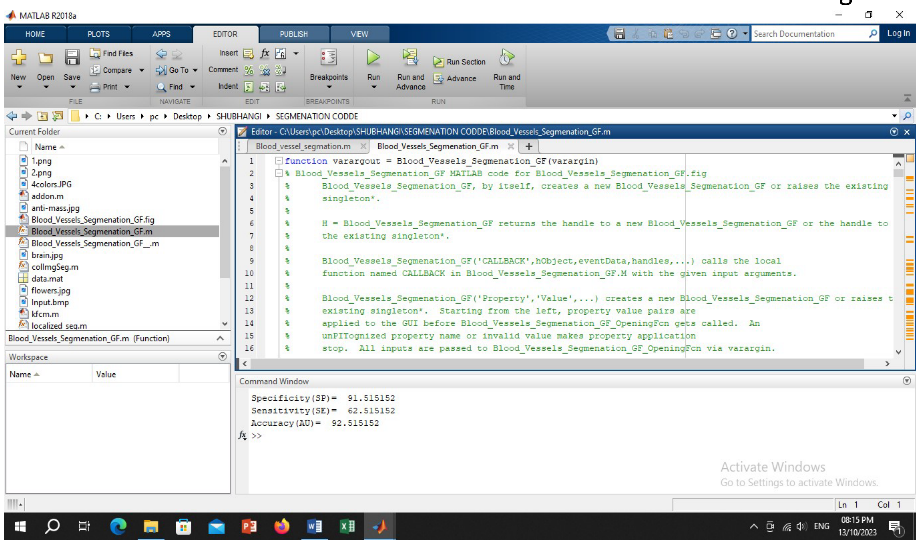

Figure 12: window show that the fast detection and segmentation in retinal blood vessels ofenter value of threshold and using this method GF, ALT and proposed and result.

Table 1: Comparative result of analysis of existing with Proposed-1 CNN, MF, and MU-netusing method for Accuracy, Sensitivity, AUC and Specificity for CHASE – DB1 dataset.

Method	Proposed-1	CNN	MF	MU-net
Accuracy	92.89	91.86	91.85	92.84
Sensitivity	65.87	63.48	65.49	63.89
Specificity	91.81	92.25	90.94	91.56
AUC	91.87	91.79	90.79	90.35

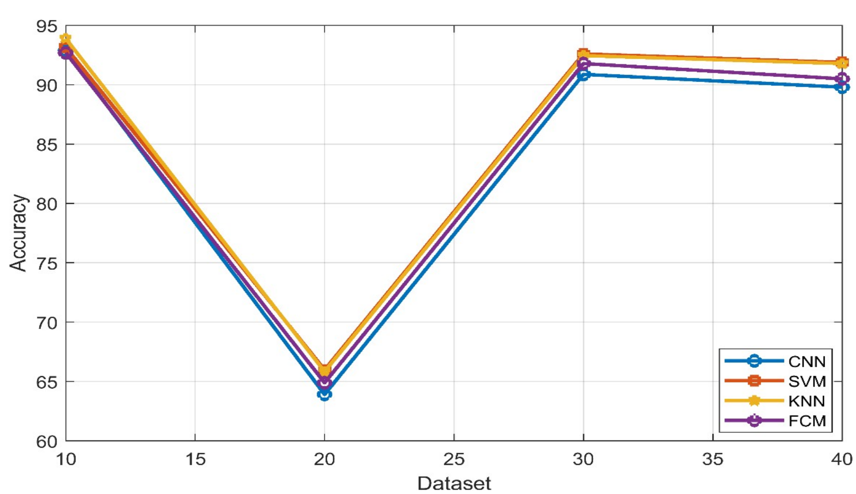

Figure 1 Comparative performance of Accuracy of CNN, SVM, KNN, and FCM methodusing CHASE – DB1 dataset.

We have found the value of KNN is superior to that of the other three methods and is as follows: KNN has a value of 93.89 on dataset 10 which is superior to the other methods. The value of FCM also values 92.69 on dataset 10 and SVM. It is also 93.15 at dataset 10 and CNN has also a value of 92.87 at dataset 10.

Table 2: Comparative result of analysis of existing with GF, ALT, and Proposed using methodfor Accuracy, Sensitivity, AUC and Specificity, for CHASE – DB1 dataset.

Method	GF	ALT	Proposed
Accuracy	91.59	92.89	93.45
Sensitivity	65.48	65.54	62.65
Specificity	90.58	91.69	92.84
AUC	91.79	90.74	91.87

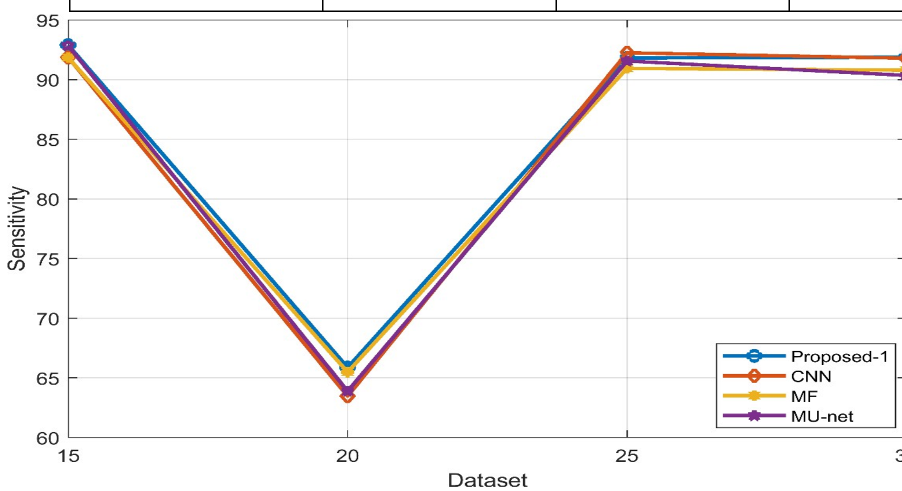

Figure 2 Comparative performance of sensitivity of Proposed-1, CNN, MF, and MU-netmethod using CHASE – DB1 dataset.

We have found that Value of Proposed-1, which is best of the other three methods, is as below: The value of Proposed-1 which is better, is 91.89 on dataset 15 which is more than the other methods. Datasets 15 also have the value of such CNN. Is 91.86 and the MF value equals to 91.85 on 15 th dataset and the value of MU-net equals to 92.88 on 15 th dataset.

Table 3: Comparative result of analysis of existing with RNN, MF, and Proposed-2 usingmethod for Accuracy, Sensitivity, AUC, and Specificity, for CHASE – DB1 dataset.

Method	RNN	MF	Proposed-2
Accuracy	92.64	92.85	93.79

Sensitivity	62.85	61.79	63.45
Specificity	91.89	91.65	92.36
AUC	90.81	90.87	91.85

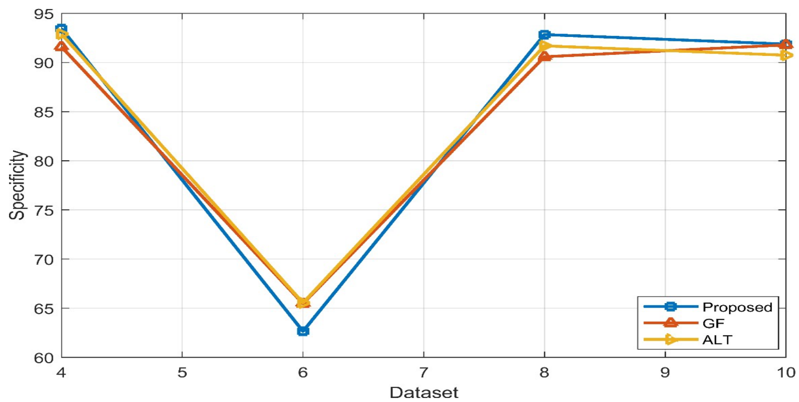

Figure 3 Comparative performance of specificity of Proposed, GF, and ALT method usingCHASE – DB1 dataset.

We have found out the Value of the Proposed Method, being superior to the other two methods is given below: The value of the proposed method, which is superior is 93.45 on Dataset 4, and this is better than any other methods. On ALT and Dataset 4 also, the value of GF is 91.59. Dataset 4 has a value of is of 92.89 as well.

6. Final conclusion:

The study provided a successful and streamlined method to detect the retinal blood vessels in terms of pixel optimization through the BAT algorithm that is incorporated with a Deep Neural Network model. The suggested methodology became implemented and tested in the MATLAB simulation domain on the CHASE database number 1 dataset. Different steps were considered during the simulation process because they consisted of loading the dataset, preprocessing (removal of green channel, enhancement of the CLAHE, erosion, top-hat and Otsu thresholding), vessel extraction (thin and thick vessels), vessel contour initiation and final segmentation output.

As can be seen through the experimental results, the proposed models (Proposed-1 and Proposed-2) outscore several already existing methods such as CNN, MF, MU-net, RNN, GF and ALT in practically all of the evaluation measures such as Accuracy, Specificity and AUC.

In case of CHASE-DB1 dataset, the algorithm proposed attained:

- Accuracy up to 93.79%, which is higher than RNN (92.64%), MF (92.85%), CNN (91.86%), and MU-net (92.84%).
- Specificity up to 92.84%, indicating improved capability in correctly identifying non-vessel pixels.
- AUC up to 91.87%, demonstrating better overall classification performance.

Even though there is a moderate enhancement in the values of sensitivity compared to some models, the proposed framework has a good balance between vessel detection and background rejection. The ability to optimize the BAT algorithm improves the accuracy of pixel-level segmentation, and the deep neural net is effective to improve the degree of feature extraction and classification.

Graphical analysis further proves the fact that the suggested solution works better than traditional segmentation methods like GF and ALT, as well as allows to demonstrate competency with even the more powerful models of deep learning.

On the whole, this research comes to the conclusion that a hybrid framework combining optimization and deep learning can potentially increase the retinal vessel segmentation performance significantly. The algorithm is also efficient in the automated retinal image analysis and computer-aided diagnosis system as the algorithm has quick detection time, excellent vessel extraction and sound segmentation outputs. The given strategy helps to enhance the detection of eye anomalies on the initial stage and can be used as a sound basis to make medical image segmentation studies further advanced.

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