

Enhanced Effective Baseline Model for Glaucoma Prediction Using U-Net and Hyperparameter-Tuned CNN with CLAHE

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Abstract: Glaucoma is a progressive eye disease that can lead to permanent vision loss when diagnosis is delayed. Our study proposes an enhanced effective baseline framework for automated glaucoma prediction from retinal fundus images by integrating image enhancement, segmentation, deep feature extraction, and machine learning classification respectively. The methods Contrast limited adaptive histogram equalization is applied to improve image contrast and reveal important retinal structures. The U-Net architecture is then employed to segment the optic disc region and reduce the influence of irrelevant retinal areas respectively. The segmented regions are subsequently processed using a hyper parameter-tuned Convolutional Neural Network to learn discriminative deep features efficiently. The optimized features are provided to an enhanced support vector machine classifier for glaucoma prediction. The hyper parameters of the CNN are systematically optimized to obtain more representative features and improve classification performance effectively. The incorporation of contrast enhancement, U-Net segmentation, optimized deep feature learning, and Enhanced Support Vector Machine provides an effective framework for automated glaucoma screening and early identification of glaucomatous changes respectively.

Keywords: Glaucoma prediction, retinal fundus images, Contrast Limited Adaptive Histogram Equalization, U-Net, Convolutional Neural Network, hyperparameter tuning, Enhanced Support Vector Machine, optic disc segmentation.

I. INTRODUCTION

Glaucoma is a progressive eye disorder that damages the optic nerve and may cause irreversible vision loss when it is not detected at an early stage. Retinal fundus images provide important information about the optic disc, optic cup, and surrounding retinal structures for glaucoma assessment. Variations in illumination, contrast, and image quality can affect the visibility of these important features and influence prediction performance. Contrast Limited Adaptive Histogram Equalization is used to improve local contrast and enhance relevant retinal structures before further analysis. U-Net is incorporated to accurately segment the optic disc region and reduce irrelevant image information. The segmented images are processed using a hyperparameter-tuned Convolutional neural network to obtain meaningful deep features. These features are subsequently classified using an Enhanced Support Vector Machine. The proposed framework combines image enhancement, segmentation, optimized feature learning, and machine learning classification to support effective and automated glaucoma prediction respectively.

II. LITERATURE REVIEW

The framework preparation has increasingly explored deep learning and image-processing techniques for automated glaucoma detection from retinal fundus images respectively. Convolutional Neural Network-based approaches have demonstrated strong capability in learning discriminative retinal features directly from fundus images, reducing the dependence on manually designed features [1]. Deep learning-based glaucoma identification has also been investigated using different network architectures and classification strategies, demonstrating the potential of automated retinal image analysis [2]. Accurate localization and segmentation of the optic disc and optic cup remain important because their structural characteristics provide useful information for glaucoma assessment [4]. U-Net-based segmentation approaches have therefore gained attention for extracting clinically relevant retinal regions and improving subsequent analysis [8]. Multi-task learning has further combined segmentation and classification tasks within a unified framework, showing that related retinal tasks can support glaucoma prediction [5]. Comparative investigations of different Convolutional Neural Network architectures have also demonstrated the effectiveness of deep

feature extraction for fundus-based glaucoma detection [6]. Ensemble deep learning methods have been explored to improve the representation of complex retinal patterns [7]. These developments indicate the importance of combining image enhancement, accurate segmentation, optimized deep feature extraction, and machine learning classification.

The proposed study extends these directions by integrating Contrast Limited Adaptive Histogram Equalization, U-Net segmentation, hyperparameter-tuned Convolutional Neural Network, and Enhanced Support Vector Machine for glaucoma prediction respectively.

III. PROBLEM STATEMENT

- Inaccurate region identification: Irrelevant retinal regions may affect the analysis, creating a need for effective U-Net-based optic disc segmentation to isolate the region associated with glaucoma assessment.
- Limited feature representation: Conventional image analysis may not adequately capture complex glaucoma-related patterns, requiring a hyperparameter-tuned Convolutional Neural Network for improved deep feature learning.
- Classification limitations: Standard classification approaches may not effectively distinguish glaucomatous and normal retinal images, creating a need for an Enhanced Support Vector Machine classifier.
- A unified approach combining Contrast Limited Adaptive Histogram Equalization, U-Net segmentation, hyperparameter-tuned Convolutional Neural Network, and Enhanced Support Vector Machine is required to develop an effective baseline model for automated glaucoma prediction efficiently.

IV. ABOUT THE DATASET

The proposed research work utilizes two dataset named as retinal fundus image datasets, DRIVE and REFUGE, to develop and evaluate the glaucoma prediction framework. The DRIVE dataset contains 40 color fundus images, divided equally into 20 training and 20 test images, collected through a diabetic retinopathy screening program in the Netherlands; the images were acquired using a Canon CR5 non-mydratic 3CCD camera with a 45° field of view and a resolution of 768 × 584 pixels with 8-bit color representation. The REFUGE dataset contains 1,200 color fundus photographs, divided into 400 training, 400 off-site validation, and 400 on-site test images, with glaucoma reference labels and manual optic disc and cup annotations. The glaucoma

reference standard was established using clinical information including health records, OCT, and visual-field examination, while optic disc and cup annotations were generated by glaucoma specialists. The two datasets provide complementary retinal image characteristics for evaluating the proposed pre-processing, segmentation, feature extraction, and classification framework. Since DRIVE was originally developed for retinal vessel segmentation and does not provide official glaucoma labels, the article should clearly specify the labelling strategy and dataset partitioning used when incorporating DRIVE images into the glaucoma prediction experiments efficiently.

V. PROPOSED METHODOLOGY

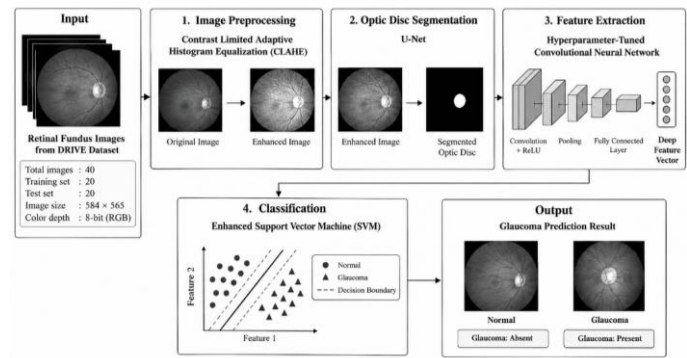


Figure 1: Proposed methodology for glaucoma prediction using CLAHE, U-Net, hyperparameter-tuned CNN and enhanced SVM

Steps involved in this research

Input : Retinal fundus image $I(x, y)$ Output : Glaucoma prediction Y	
Step 1: Image Representation Obtain retinal fundus images from the DRIVE dataset. $I(x, y, c), c \in \{R, G, B\}$ where x, y represent spatial coordinates and c represents the color channel.	(1)
Step 2: Image Enhancement Using Contrast Limited Adaptive Histogram Equalization Normalize the pixel intensity: $I_N(x, y) = \frac{I(x, y) - I_{min}}{I_{max} - I_{min}}$ Apply local histogram equalization: $I_E(x, y) = (L - 1) \text{CDF}(I_N(x, y))$ where L denotes the number of intensity levels.	(2) (3)
Step 3: Optic Disc Segmentation Using U-Net Segment the optic disc from the enhanced image: $S(x, y) = U(I_E(x, y))$ Generate the binary segmentation mask: $S(x, y) = \begin{cases} 1, & P(x, y) \geq \tau \\ 0, & P(x, y) < \tau \end{cases}$	(4) (5)
Step 4: Deep Feature Extraction Using Convolutional Neural Network Convolution operation: $F_k(i, j) = \sigma \left(\sum_m \sum_n W_k(m, n) X(i + m, j + n) + b_k \right)$ Activation function (ReLU): $\text{ReLU}(x) = \max(0, x)$ Deep feature vector: $F = \text{CNN}(S; \theta)$	(6) (7) (8)
Step 5: Hyperparameter Optimization Define the CNN hyperparameters: $\theta = \{\eta, B, K, D, E\}$ Optimal configuration: $\theta^* = \arg \min_{\theta} L_{val}(\theta)$	(9) (10)
Step 6: Enhanced Support Vector Machine Classification Decision function: $f(F^*) = w^T F^* + b$ Classification output: $Y = \begin{cases} 1, & f(F^*) \geq 0 \\ 0, & f(F^*) < 0 \end{cases}$ where $Y = 1$ represents glaucoma and $Y = 0$ represents normal.	(11) (12)

The proposed framework integrates six stages for automated glaucoma prediction. Retinal fundus images are first enhanced using Contrast Limited Adaptive Histogram Equalization to improve local contrast and retinal visibility. U-Net is then employed to segment the optic disc region. The segmented images are processed through a Convolutional Neural Network to extract discriminative deep features. The network hyper parameters are optimized to improve feature representation. Finally, the optimized features are classified using an Enhanced Support Vector Machine into normal and glaucoma categories efficiently.

VI. RESULTS & DISCUSSIONS

Table 1: Precision rate on enhanced glaucoma prediction using U-NET and Hyperparameter-Tuned CNN with CLAHE

No of Images	Precision in %
200	89.50
400	89.10
600	90.20
800	91.30
1000	94.80

The above table represents the precision performance of the proposed approach for different numbers of images. The precision varies across the dataset sizes respectively.

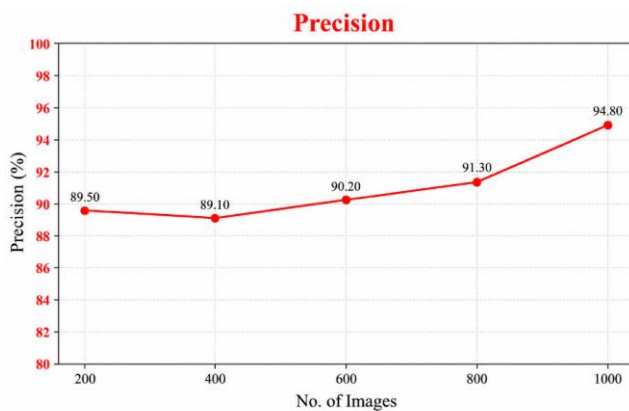


Figure 2: Precision rate on Glaucoma prediction using U-NET and Hyperparameter-Tuned CNN with CLAHE

The above figure represents the performance evaluation of the proposed approach using different numbers of images. The graph illustrates the variation in precision across different dataset sizes respectively.

Table 2: F1-Score on Glaucoma prediction using enhanced U-NET And Hyperparameter-Tuned CNN with CLAHE

No of Images	F1-SCORE in %
200	89.52
400	86.69
600	89.28
800	90.03
1000	91.90

The above table represents the F1-Score performance of the proposed approach for different numbers of images. The F1-Score varies across the dataset sizes respectively.

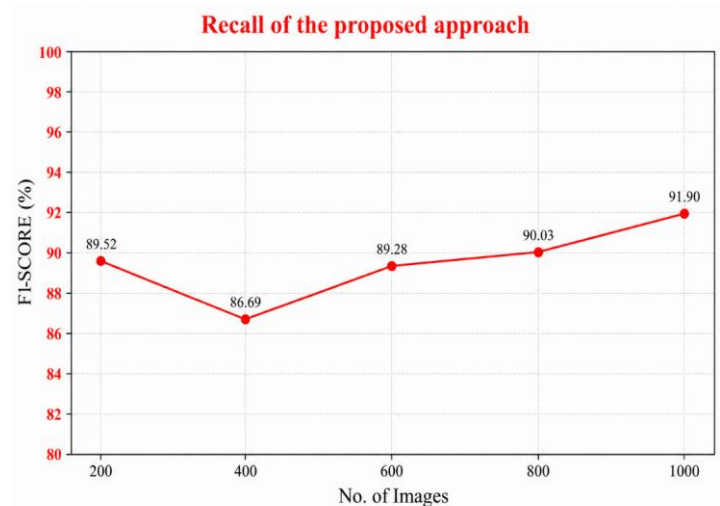


Figure 3: F1-Score on Glaucoma prediction using enhanced U-NET and Hyperparameter-Tuned CNN with CLAHE

The above figure represents the performance evaluation of the proposed approach using different numbers of images. The graph illustrates the variation in F1-Score across different dataset sizes respectively.

Table 3: Recall on Glaucoma prediction using U-NET and Hyperparameter-Tuned CNN with CLAHE

No of Images	Recall in %
200	89.42
400	90.75
600	93.68
800	94.3
1000	97.20

The above table represents the Recall performance of the proposed approach for different numbers of images. The Recall varies across the dataset sizes respectively.

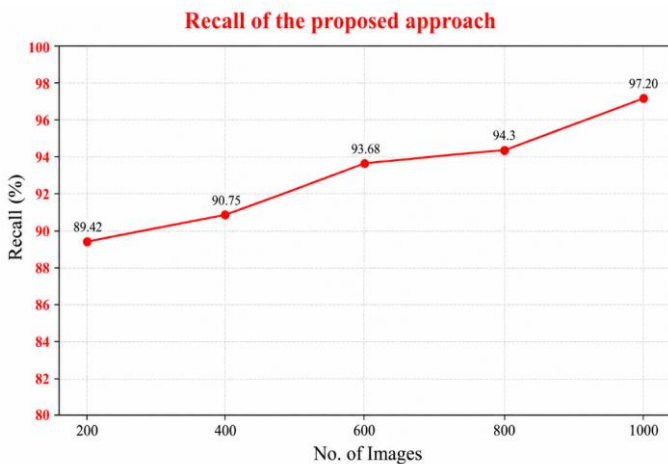


Figure 4: Recall on Glaucoma prediction using U-NET and Hyperparameter-Tuned CNN with CLAHE

The above figure represents the performance evaluation of the proposed approach using different numbers of images. The graph illustrates the variation in Recall across different dataset sizes respectively.

Table 4: Accuracy rate on Glaucoma prediction using U-NET and Hyperparameter-Tuned CNN with CLAHE

No of Images	Accuracy in %
200	91

No of Images	Accuracy in %
400	89.0
600	88.90
800	90.05
1000	93.20

The above table represents the Accuracy performance of the proposed approach for different numbers of images. The Accuracy varies across the dataset sizes respectively.

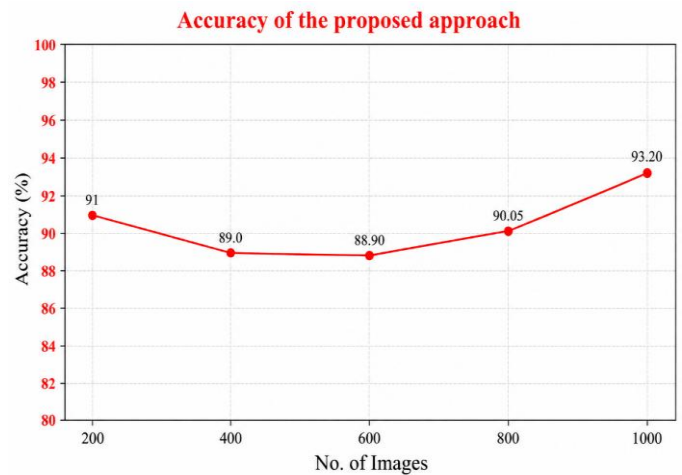


Figure 5: Accuracy rate on Glaucoma prediction using U-NET and Hyperparameter-Tuned CNN with CLAHE

The above figure represents the performance evaluation of the proposed approach using different numbers of images. The graph illustrates the variation in Accuracy across different dataset sizes respectively.

VII. CONCLUSION

The proposed framework presents an integrated approach for automated glaucoma prediction by combining Contrast Limited Adaptive Histogram Equalization, U-Net segmentation, hyperparameter-tuned Convolutional Neural Network, and Enhanced Support Vector Machine. Contrast enhancement improves the visibility of relevant retinal structures, while U-Net focuses the analysis on the optic disc region. The hyperparameter-tuned Convolutional Neural Network extracts optimized deep features, which are subsequently classified using

the Enhanced Support Vector Machine respectively. The experimental results show that the proposed approach achieves a precision of 94.80%, recall of 97.20%, F1-score of 91.90%, and accuracy of 93.20% with 1000 images. The increasing recall and precision values with larger image sets indicate the usefulness of the integrated framework for glaucoma prediction efficiently.

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