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RESEARCH ARTICLE

Classification of glaucoma in retinal fundus images using integrated YOLO-V8 and deep CNN

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Abstract

To propose a new system to identify glaucoma at an early stage with the help of deep learning-based AI method by utilizing retinal fundus images (RFI). The method detects intrinsic key structures in the fundus images to predict retinal nerve layer thickness in order to improve the accuracy of glaucoma detection and classification. To learn complex and hierarchical image representations, the CNN model is used to identify the continuous value of retinal nerve layer thickness from RFI. The binary cross entropy (BCE) loss function is used to perform multi-classification tasks to discover classes such as healthy eye, eye with glaucoma, and glaucoma suspect. In order to identify the local and global features in RFI, the YOLO-V8 object detection method is employed, which also helps to perform image localization, which includes image segmentation, deep optic disc analysis, and the extraction of ROIs. The main focus is given, especially for RNL thickness around OD regions and CDR measurement to perform glaucoma identification tasks. The PAPILA dataset is utilized with the ophthalmology records from 244 patients and includes 488 digital retinal fundus images, covering both left and right eyes for both male and female categories. The CNN model is trained on the PAPILA dataset with labeled RNL thickness values. The performance of CNN-BCE with YOLO-V8 is evaluated using MATLAB and compared against the prevailing approaches such as SVM, ADABOOST, and CNN-Softmax classifiers. The new model outperforms the existing methods with proven results of 98.88% accuracy rate, 0.9 dice-score, 97.74 and 98.03% sensitivity & specificity, 98.6 and 98.78% precision & recall, 98.06% f-score, and 0.92 true positive rates and 0.10 false positive rates under AUC-ROC. This clearly shows that the newly proposed CNN-BCE with YOLO-V8 detects and classifies glaucoma, which helps ophthalmologists perform potential screening and predict better treatments.

Keywords: Convolutional neural networks, Deep learning, Glaucoma classification, YOLO-V8, Machine learning, Image processing, Image localization.

Introduction

Glaucoma is a type of eye disease associated with elevated intraocular pressure, which leads to optic nerve damage. Worldwide, millions of people are affected by glaucoma, especially those older than 50. Regular eye examinations and early detection of glaucoma signs are very important to avoid nerve damage and vision loss. Many computer-aided systems have been identified to detect and classify glaucoma signs by using computational methods with the help of retinal fundus images. The shortcomings of the prevailing approaches are less accuracy, high FPR, masking errors, etc., which affect the system in terms of performance and diagnostic results. To overcome the shortcomings of the existing approaches, the AI-based new deep learning CAD model CNN-BCE with YOLO-V8 is introduced to maximize the discrimination power and minimize false rates by employing relevant methods using the PAPILA dataset. The main focus of this new model is to predict the retinal nerve thickness layer (RTNL) and localize the high-order key elements from fundus images and ROIs to achieve the objectives. Three-level layers are processed during CNN implementation to spot the glaucoma signs in a robust manner. The BCE loss function is applied to minimize the loss and classify it into healthy, glaucoma, and suspect. The system helps ophthalmologists predict the glaucoma at an early stage during the candidate screening to treat it better,

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which helps to improve the new CAD system. The real-time object detection in a traffic environment which helps the model to identify the depth ratio to maximize the accuracy (A. Afdhal *et al*., 2023). Deep learning models help to learn the intrinsic patterns and morphological changes in the retinal fundus images to identify signs of glaucoma with more accuracy. This model works on any raw medical data to process the mapping and feature translation digitally. It is very easy for the clinical experts to do candidate screening and produce accurate results (Ajitha S *et al*., 2021). The primary objective of the current CAD model is to identify the robust object detection method by spotting RTNL to help the ophthalmologists to produce better diagnosis. PAPILA RFI dataset is used for the experimental purpose which consists of RFI with clinically proven records (O. Kovalyak *et al*., 2022). A through findings and reports are produced with promising results under various epochs.

Problem Statement

To develop a robust CAD framework for automated glaucoma detection and classification by employing you only look once (YOLO-V8) combined with AI-based deep learning methods, the CNN model and BCE function. The primary goal of this CNN-BCE with YOLO-V8 is to boost the object detection accuracy rate in terms of detecting the RNTL and detect the signs of glaucoma from the RFI using the PAPILA dataset. The CNN model is used to identify the RNTL by extracting the relevant features from fundus images. YOLO-V8 will localize and extract the ROIs, such as OD, OC, and nerve fiber layers, which will serve as input to CNN layers to boost the accuracy of RNTL identification. The binary cross-entropy function is carried out to perform the multi classification task into various categories. This new CAD framework will address the critical need for glaucoma screening tests for early identification and classification of disease in a robust manner, which will contribute to the medical field in terms of improved diagnosis and vision preservation.

Objectives of the Proposed Work

The main objectives of CNN-BCE with YOLO-V8 are: i) early and fast detection of glaucoma; ii) classification; iii) detection of intrinsic key structures in RFI; iv) prediction of RNTL from fundus images using the PAPILA dataset; v) localization of fundus images and extracting ROIs; vi) enhancement of the accuracy rate, etc. To attain the objectives, the major steps are followed:

Localize relevant structures

Key structures are localized, such as the optic disc, the optic cup, and other areas in fundus images with a higher depth ratio.

Predict RNTL

Based on localized ROIs, predict the nerve thickness layer to identify the early signs of glaucoma during screening.

Binary classification

Using features from localized regions, the BCE function is employed to train the classification model to identify glaucoma, healthy or suspect.

Model integration

Combine the output values to perform comprehensive analysis. MATLAB is used to assess the performance of the proposed model with baseline versions.

Related Works

A range of approaches and their respective results are discussed in this section. The SVM and ADABOOST on retinal OCT data were employed where the RNTL is not found and leads to misclassification of glaucoma (Ajitha S *et al*. 2022). The combination of U-Net and Softmax Classifier on multiple datasets including RIM-ONE and DRIVE resulted with 88.5% accuracy (Rutuja Shinde, 2021). ONH scan dataset was used with multi feature analysis with DL approach reached 79% accuracy (Akter N *et al*. (2021). The highest accuracy is reported with 95.6% while using DL based auto encoder

Table 1: Few other literature review with state of art methods

Author and year	*Dataset used*	*Methodology*	*Accuracy* (%)
Henry Shen-Lih N *et al. (2022)*	DST-189	Supervised methods	81
Huang *et al.* (2023)	DRIVE	YOLO-V8 localization with DL	89
Sudhan MB *et al.* (2022)	RNL-SCAN	U-Net with DL	79
Nawaz M *et al*. (2022)	DRIONIS	DL with RFC model	84
Mahum R *et al.* (2022)	DRISHTI	Deep CNN	86
Shyamalee T *et al.* (2022)	RETINAL CSI	Segmentation using NET architecture	89
Talib *et al*. (2023)	D-SCAN REPORTS	YOLO-CAB	92
Divya Jothi *et al*. (2021)	GRAPH-SCAN	Space mapping using OCP	94
Kovalyk O *et al*. (2022)	PAPILA	SVM and RM	80 – 93
Raja P *et al.* (2022)	OCT SCAN	NTKFIBC-IS segmentation	91

networks on the PAPILA dataset (Sathya R *et al*. 2023). In addition to the above few other related works are portrayed as a part of state of art literature methods portrayed in Table 1.

Proposed Methodology

The proposed AI-based deep learning CNN-BCE with YOLO-V8 model mainly focuses on effective object detection with a high accuracy rate in terms of identifying glaucoma signs at an early stage during candidate screening. The main features are commonly extracted, such as: i) optic disc measurement; ii) intensity profiles such as contrast and brightness; iii) texture analysis to categorize surface patterns and microstructures such as homogeneity, entropy, etc. In addition to that boundary detection, vessel analysis such as density and layer health condition, shape analysis, and other global and local significant spots are extracted. To improve the efficiency and reliability of glaucoma detection, this CAD model employs three major techniques: CNN, BCE loss function and YOLO-V8. Image segmentation is done to isolate the RNTL within the ROIs extracted by the new model. This CNN-BCE approach improves glaucoma detection and classification at an early stage, where the results are compared with prevailing CAD models such as SVM, ADABOOST, and CNN-Softmax classifiers.

Materials and Methods for Implementation

The following are the materials and methods for effective implementation of object detection and classification to attain the objective of the research work.

- RFI PAPILA dataset
- Deep learning framework
- Implementation tool
- YOLO-V8 pre-trained optimal values
- Annotated Images to train CNN with BCE loss function

Here, the fundus images are loaded where YOLO-V8 is used to localize and classify objects within the RFI. Assume that bx, by, bw, bh represents the bounding box dimensions and coordinates for localization. $P(Object)$ is the probability of an object presented in the bounding box within the RFI which is called objectness score. Class scores $P(Class_i|\,Object)$ are measured where the probabilities of objects belong to each class in PAPILA RFI. Apply YOLO-V8 to detect OD and nerve fiber layer which provides bounding box and class coordinate probability values. The final object score equation is as follows,

$$Final\ Object\ Score = P(Object)\ x\ P(Class_i|\ Object) \quad (1)$$

Once the final objects core is calculated, input the localized values to CNN to predict the RNTL. The CNN prediction equation is as follows,

$$Predicted\ Probability\ Y = CNN(Fundus\ Image) \quad (2)$$

where, Y is the predicted probability of the RFI belongs to positive cases. Now train with BCE loss function using annotated PAPILA dataset with classification labels. The equation is derived as,

$$BCE\ (Y, y) = -\tfrac{1}{N}\ \ N(i = 1)[y_i.\log(Y_i) + (1 - y_i)\ .\ \log(1 - Y_i) \quad (3)$$

where, y represents ground truth label and$N$ is the number of samples. The optimal value is predicted which shows the classification of glaucoma during initial screening process.

PAPILA Dataset Attainment and Evaluation

The CNN-BCE with YOLO-V8 model uses PAPILA retinal fundus image datasets, which have clinical reports of 244 eye-screened patients and include 488 retinal fundus images of both the left and right eye under male and female categories. The dataset evaluation is presented in Table 2 and Figure 1 which clearly shows the clinical record verifications of 3 classes. The pixel size of the RFI is 2576x1934 for both OD and OS with deep layer segmentations. 75% of the data is used for training and validation, and 25% of the data is used for testing purposes. Table 2 shows the dataset evaluation of PAPILA for model implementation. In addition to dataset evaluation, risk assessment is also done, where sometimes AI models produce unanticipated results or errors. This automation model uses PAPILA clinically proven records to take for further investigation to boost the accuracy level. The AI-based deep learning model is employed in this dataset to predict the early signs of glaucoma in a robust way.

For each eye 12 RNTL segmented values are predicted to each direction (30-degree). The depth evaluation has

Table 2: PAPILA clinical dataset evaluation

S. No.	*Dataset values*	*Proportion*	*Clinical record verifications*
1	Training data	75%	Male: 93 Female: 151 Healthy: 333 GD: 87
2	Testing data	25%	Suspect: 68 Phakic: 318 PseudoPh: 159 Missing: 11

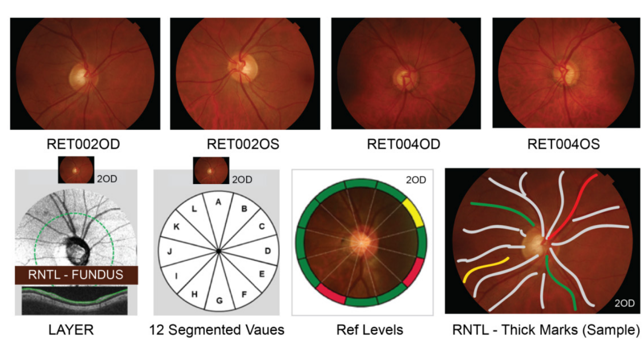

Figure 1: DFI - of 2 Patients with RNTL sample results (Normal: 1st Row / RNTL Detection: 2nd Row)

been carried out in 360-degree. The levels are bifurcated into three categories such as normal (green), border (yellow) and beyond (red) as shown in Figure 1. The predicted thicknesses are calculated and values are recorded to detect and classify the glaucoma by employing the BCE loss function.

Features with Iteration Values

The above values are purely based on the proposed model iterations. The sample iterative values are given in Table 3. As the iteration increases, the values will change, which will improve the results of the model. The feature values are extracted from PAPILA digital fundus images to identify glaucoma based on the retinal nerve thickness layer. As the model carries out a 360-degree depth evaluation, the intrinsic features are extracted to predict the thickness level of the retina. The fundus images are analysed and documented for future use. Table 3 shows the Features Values with YOLO-V8 CNN BCE for 3 iterations as s ample.

Table 3: Features values with YOLO-V8 CNN BCE

Feature Categories	*Iteration 1*	*Iteration 2*	*Iteration 3*
Optic disc measurement			
Diameter (mm)	1.5	1.7	1.6
Cup-to-disc ratio	0.3	0.28	0.29
Vertical cup/disc ratio	0.6	0.55	0.58
Area (mm^2)	2.3	2.5	2.4
Intensity Profiles			
Mean intensity	120	118	122
Contrast	35	33	34
Brightness	80	78	82
Texture analysis			
Homogeneity	0.85	0.87	0.86
Entropy	4.2	4	4.1
Energy	0.78	0.76	0.77
Vessel analysis			
Vessel density	0.12	0.11	0.13
Vessel tortuosity	1.8	1.7	1.9
Artery/vein classification	*60% arteries*	*62% arteries*	*58% arteries*
Shape analysis			
Circularity	0.92	0.91	0.93
Eccentricity	0.4	0.42	0.38
Symmetry	0.88	0.87	0.89
Other features			
Optic nerve head shape	*Oval*	*Round*	*Oval*
Fovea location	3.2 mm temporal to the disc	3.5 mm temporal to the disc	3.3 mm temporal to the disc
Macular pigment density	Moderate	Low	Moderate

YOLO-V8 for Localization

You only look once (YOLO-V8) model is employed in this research study for fundus image localization and efficient object detection with high accuracy. It uses multiple anchor boxes, which are predefined with various shapes and characteristics. The model automatically learns to modify the dimensions and placements for better fitting during the PAPAILA RFI training phase in order to detect the object in the fundus image with a greater accuracy rate. The YOLO-V8 model uses the multi scale prediction (MSP) technique to identify intrinsic features in the retinal fundus image with different sizes, dimensions, and aspect ratios. CNN serves as the foundation for the early identification and categorization of glaucoma symptoms in this research study. CNN will use the YOLO-V8 output values as input, and from the pixel values of the resulting YOLO-V8 image, CNN will extract hierarchical features. The boundaries are calculated from the segmented image to measure CDR. CDR equation is,

$$Cup\ to\ Disc\ Ratio\ (CDR) = CupDiameter\,/\,Disc\ Diameter \tag{4}$$

The glaucoma signs are identified using the computed CDR values. To maintain high accuracy in object detection and localization, deep features such as bounding box coordinates, dimensions, IoU, probability scores, object scores, confidence scores, etc., are required in addition to the standard features such as area, eccentricity, equiv diameter, Euler number, and main axis length. The degree of glaucoma is determined by calculating the damage ratio of the retinal nerve using the given CDR value. With a low false rate and great precision, this value assists CNN model in determining the RNTL values to improve detection and classification accuracy.

CNN for RNTL identification

After preprocessing and extraction of ROIs, CNN is employed to process the localized fundus images captured by YOLO-V8 and identify the retinal nerve thickness by extracting the relevant hierarchical features. CNN extracts both low and high levels from localized ROIs. Images are processed through the C-layer, P-layer, and FC-layer for efficient extraction. In the C-layer, each CNN has a set of filters to perform multiplications and summations to create feature maps. The filters detect the patterns in the fundus image and produce the optimal value. The P-layer reduces or down-samples the duplications and retains the relevant features for RNTL prediction. The FC-layer makes final predictions by learning complex relationships between features. The FC layer integrates the spatial C and P layers. The derived formula is given in equation 2.

BCE for classification

Binary cross entropy (BCE) is adapted for multi classification tasks to identify the signs of glaucoma in three categories such as healthy, glaucoma and suspect (0, 1, and 2). One vs all classification is involved in BCE for each class. Let's assume, C is the number of classes where the loss function for multi-class is calculated independently by the following equation.

$$BCE_{multiclass} = Summation\ of\ C\ \&\ j = 1\ (x)\ BCE_j \tag{5}$$

where, BCE is the loss function and j is the class (0, 1,2). The positive, negative and suspect class terms are calculated. During the CNN-BCE training the main focus is to minimize the total loss to achieve predicted probabilities of each class with more accuracy. CNN-BCE with YOLO-V8 architecture diagram as shown in Figure 2. The total BCE loss for multi-class classification is calculated by adding the BCE losses for each class. The AUC-ROC levels are measured to identify the TPR and FPR in an effective manner.

CNN-BCE with YOLO-V8 Architecture Diagram

The CNN-BCE with YOLO-V8 is a novel architecture for detecting and classifying glaucoma indications with high accuracy. A complete method to glaucoma detection combines YOLO-V8 for localization, CNN for determining retinal nerve thickness, and a multi classification model for glaucoma detection providing a strong foundation for early detection. Using YOLO-V8 for localization allows for focused analysis and diagnosis based on specific regions of interest within fundus pictures. This strategy not only improves clinical relevance, but also helps to focus diagnostic efforts where they are most required. By automating the analytical process, the suggested approach improves an efficiency and accuracy in glaucoma identification, potentially leading to better diagnosis through early intervention and treatment. Figure 2 show the complete step-by-step method for calculating the RNTL and performing the classification process. The suggested system's key advantages include efficiency, accuracy, resilience, adaptability, scalability, and an end-to-end solution for object location and detection. The major features which include,

- Single pass object detection with high accuracy which helps for real-time applications
- Anchor based detection to predict bounding boxes for multiple objects within an image
- Ability to capture multi-scale objects
- It maintains balance between accuracy and computational efficiency
- This helps as backbone architecture to extract high level ROIs in images

Process of CNN-BCE with YOLO-V8

Input: MATLAB settings with PAPILA Dataset

Begin:

Load the digital retinal fundus images from PAPILA dataset

$data.papila$

Perform pre processing

for image in dataset:

$Localize_{Data} |\ YOLOV8$

get_{Iimage}

$Identify\ ROIs\ (\ YOLO\ V8)$

$return\ get_{image\ from\ YOLOV8}$

Predict ROI object score

$P(Object)\ x\ P(Class_i |\ Object)$

Train CNN

$ROI\ Features\ =\ CNN(PAPILA\ Fundus\_Images)$

Train Classifier using $Binary\ Cross\ Entrophy$

Calculate CDR measurement

Apply multi class method

Mark key structures and compute value

$Optimal\ Value =\ \ Predicted\ Score$

Calculate Multi Class Score and Single Class Score

Compute Glaucoma Assessment Values

Generate output (0,1,2)

Output: Glaucoma detection

Repeat the iterations (48 EPOCHS with 10 Batch Size)

End

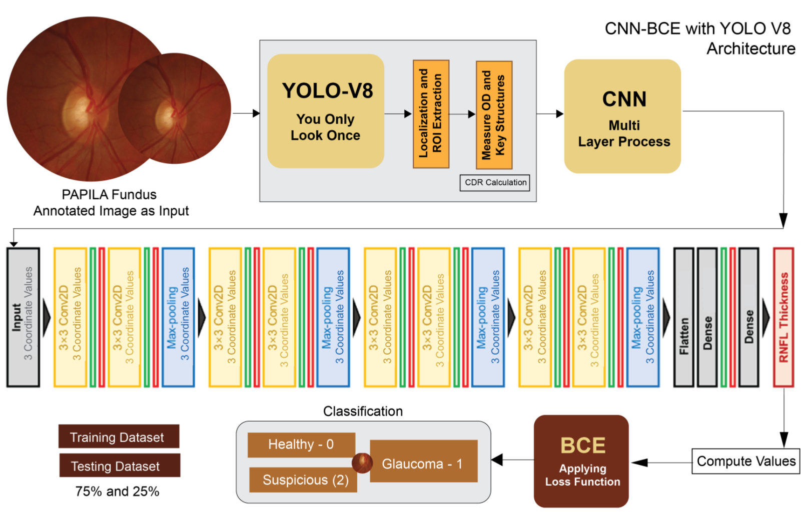

Figure 2: CNN-BCE with YOLO-V8 architecture diagram

Confusion Matrix

After the model is tuned for training, 25% of test data is applied to test the prediction and classification of glaucoma with multi class. It is noteworthy that the new model achieved a 98.88% accuracy rate, 97.74% sensitivity, and 98.03% specificity with 0.10 false positive rates under AUC-ROC which clearly illustrates that with YOLO-V8 CNN multi-layer process can perform better in predicting, categorizing and classifying glaucoma based on DFI with labeled data. Independent runs are performed and in each run the whole PAPILA dataset is bifurcated into training and testing. The explanation of confusion matrix is given below. There is no change in the original data colour intensity. Out of all the healthy instances, the model successfully identified 321 healthy samples, demonstrating its remarkable performance in detecting healthy individuals. This suggests that patients without glaucoma may be identified with high accuracy. The total instances are accurately labeled as suspect by the model is 66, indicating that it successfully detects a significant percentage of suspect cases. This demonstrates the model's ability to separate glaucoma sufferers from healthy instances. These promising results indicate that the YOLO-V8 with CNN-BCE model has a strong ability to correctly classify healthy patients, glaucoma patients and reasonable capability in identifying suspect cases Figure 3.

Healthy (True Label) vs. Predicted Labels

Healthy predicted as healthy

YOLO-V8 CNN correctly identified 321 patients as healthy.

Healthy predicted as glaucoma

The model did not incorrectly predict any healthy patients as having glaucoma.

Healthy predicted as suspect

The model significantly identified the suspect patients who has glaucoma and not healthy

Color Intensity

The number of occurrences is indicated by the colour intensity in each cell. Higher numbers are represented by darker cells. The mapping of color's count is displayed in the colour bar on the right, where light blue denotes the lowest count (1) and dark blue, the maximum count (321), shown in Figure 3. The findings are portrayed in the results and discussions section.

Healthy patients (True Label)

Predicted as healthy: 321 (True Positive) & predicted as glaucoma: 4 (False Positive) & predicted as suspect: 5 (False Negative)

Glaucoma patients (True Label)

Predicted as healthy: 3 (False Positive) & predicted as glaucoma: 80 (True Positive) & predicted as suspect: 01 (False Positive)

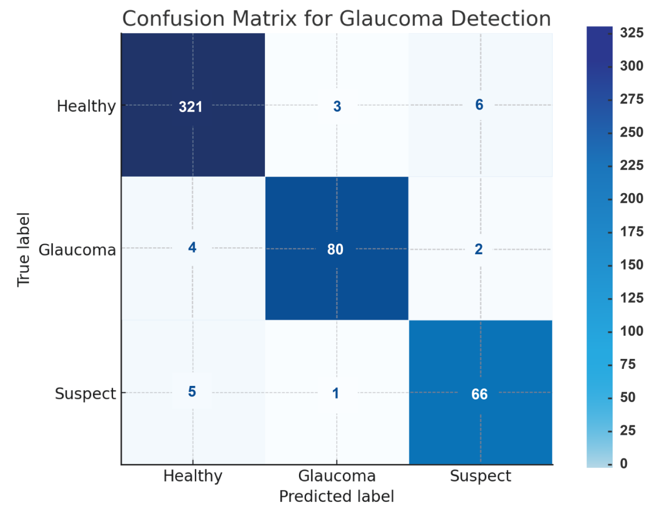

Figure 3: Confusion matrix of 3 class classification results

Suspect patients (True Label)

Predicted as healthy: 6 (False Negative) & predicted as glaucoma: 2 (False Negative) & predicted as suspect: 66 (True Positive)

Performance Evaluation Metrics

The novel CNN-BCE with YOLO-V8 glaucoma RNTL detection and classification model is identified mainly to boost the object detection and learn the intrinsic pattern with more depth ratio and high accuracy rate. The model is compared with baseline approaches such as SVM, ADABOOST, and CNN-Softmax models. MATLAB R2020a tool is used to evaluate the performance of the new model. Initially, import of PAPILA dataset in the MATLAB tool for preprocessing to ensure normalization and resizing and followed by dataset annotation to identify RNTL values. Train YOLO-V8, CNN-BCE and evaluate the performance. Confusion matrix is generated to analyze the performance. Visualize the performance results in the graph plotted. The following are the performance evaluation metrics for CNN-BCE with YOLO-V8. The PEM equations are used to calculate the values for metrics which is given below.

$$GD_{Accuracy} = \frac{(TPR+TNR)}{(TPR+TNR+FPR+FNR)} \times 100 \tag{6}$$

$$GD_{Sensitivity} = \frac{TPR}{(TPR+FNR)} \times 100 \tag{7}$$

$$GD_{Specificity} = \frac{TNR}{(TNR+FPR)} \times 100 \tag{8}$$

$$GD_{Precision} = \frac{TPR}{(TPR+FPR)} \times 100 \tag{9}$$

$$GD_{DiceScore} = (2 * |A \cap B|) / (|A| + |B|) \tag{10}$$

$$GD_{Precision} = \frac{TPR}{(TPR+FPR)} \quad GD_{Recall} = \frac{TPR}{(TPR+FNR)} \tag{11}$$

$$GD_{FScore} = \frac{2*(Precision * Recall)}{(Precision+Recall)} \tag{12}$$

$$MCC = \frac{T_1}{\sqrt{T_2 \times T_3 \times T_4 \times T_5}} \times 100 \tag{13}$$

where, ***GD** denotes glaucoma detection* and the performance metrics equation is combined the multiple PEM into single expressions to provide the comprehensive evaluation of CNN-BCE with YOLO- V8 model. $T_1 = (TPR \times TNR - FPR \times FNR)$, $T_2 = (TPR + FPR)$, $T_3 = (TPR + FNR)$, $T_4 = (TNR + FPR)$, and $T_5 = (TNR + FNR)$.

Sensitivity and specificity

Measures +ve and -ve instances out of actual +ve and -ve cases by CNN-BCE with the YOLO-V8 model.

Accuracy and F-score

Overall predictions are measured by CNN-BCE with a ratio of total samples in the PAPILA dataset with balanced +ve and -ve instances.

Dice-coefficient

To assess how the CNN-BCE model accurately localizes & segments RNTL in RFI.

AUC-ROC

Calculate AUC-ROC using predicted probabilities by CNN-BCE and truth labels from the testing or validation PAPILA dataset.

Precision and recall

It evaluates the performance of the CAD system, especially where the classes are imbalanced. It shows the accuracy of +ve predictions made by CNN-BCE with TPR and FPR ratios.

Results and Discussions

The proposed CNN-BCE with YOLO-V8 system overcomes the drawbacks of the prevailing deep learning and machine learning object detection methods in the form of RNTL detection for early identification and classification of glaucoma in a robust manner. The CNN-BCE with YOLO-V8 is compared against SVM [2], ADABOOST [2], and CNN-Softmax [12] classifiers to showcase the performance of the new CAD system. This new system collects input from the PAPAILA dataset as a fundus image, extracts the necessary features, and produces promising results. The complete performance metrics report is derived from CNN-BCE method and the findings are portrayed with values and graphs from Figures 4 to 9, where the x-axis shows the PEM and the y-axis shows the percentage value of the new system.

Sensitivity and Specificity

The performance analysis of sensitivity and specificity is measured for the newly identified CNN-BCE with YOLO-V8 system and compared against prevailing models such as SVM, ADABOOST, and CNN-Softmax classifiers. As the new model fine-tunes and optimizes the hyper parameters such as the number of layers, learning rate, etc. The YOLO-V8 identifies the exact ROIs from fundus images such as OD and RNTL, which gives accurate input values to the CNN-BCE model, which leads to an increase in sensitivity and specificity. It is proved that the novel deep learning model overcomes the prevailing methods and achieves 97.74% sensitivity & 98.03% specificity which is shown in Figure 4 and Table 4.

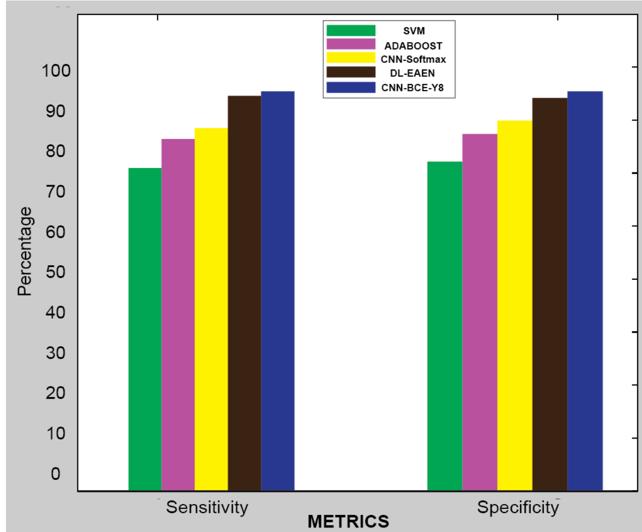

Figure 4: Sensitivity and specificity

Table 4: Sensitivity and specificity analysis (%)

Metrics / Methods	*SVM*	*ADA-BOOST*	*CNN Softmax*	*DL-EAEN*	*CNN-BCE YOLO-V8*
Sensitivity	75.45	84.05	87.76	97.01	97.74
Specificity	78.37	86.30	88.20	97.08	98.03

Table 5: Accuracy analysis (%)

Metrics / Methods	*SVM*	*ADA-BOOST*	*CNN Softmax*	*DL-EAEN*	*CNN-BCE YOLO-V8*
Accuracy (It-1)	75.20	79.87	86.92	96.78	97.12
Accuracy (It-N)	76.40	81.46	88.50	98.60	98.88

Accuracy

Detection and classification accuracy is measured and shown in Figure 5 and Table 5. The classification model uses the BCE loss function by adjusting the decision threshold values, which fully optimizes the performance of the proposed model. The model enhances the ability to discriminate between three types, such as healthy, glaucoma, and suspect. RNTL is accurately measured by YOLO-V8, and thereafter CDR is calculated. Thresholding and classification are done by applying the threshold to the calculated CDR for robust classification using BCE. The accuracy of 98.88% is achieved, which is comparatively higher than existing methods.

Dice coefficient

Figure 6 and Table 6 portrays the comparative analysis of dice coefficient of the proposed deep learning CNN-BCE with the YOLO-V8 model. Here, the CNN is trained using BCE

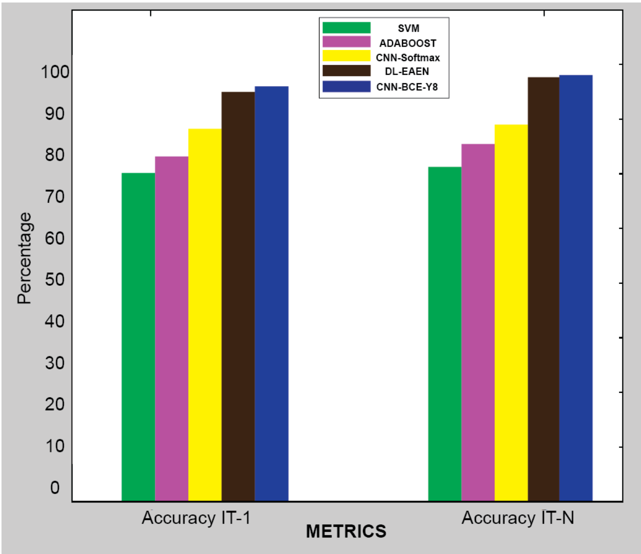

Figure 5: Accuracy

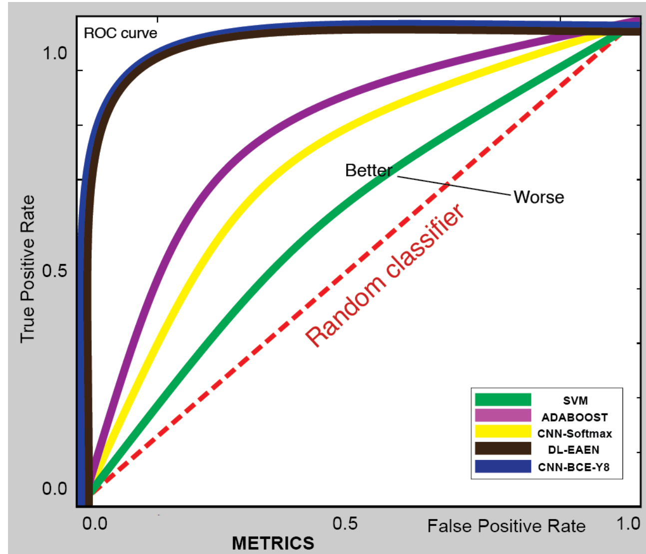

Figure 7: AUC-ROC

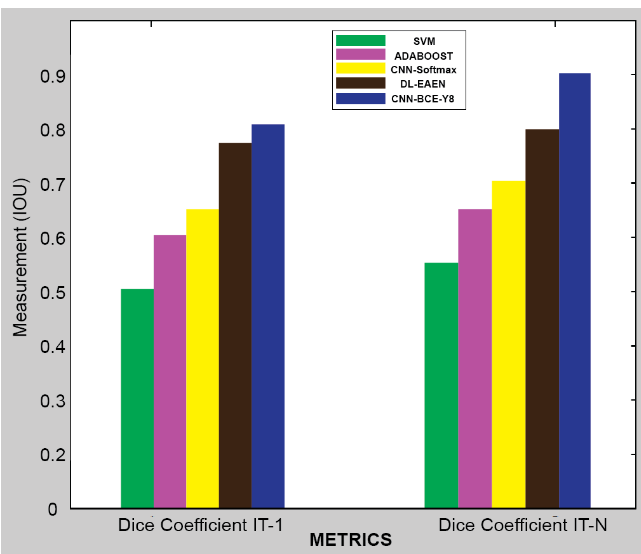

Figure 6: Dice coefficient

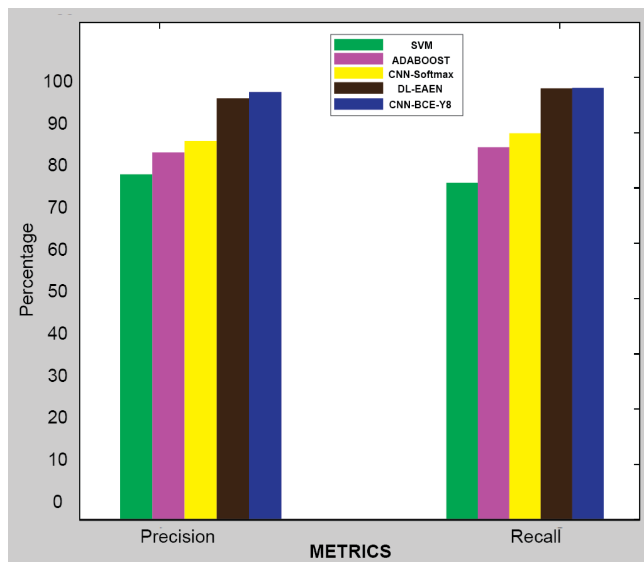

Figure 8: Precision and recall

to optimize the deep image segmentation to enhance the accuracy of the ROIs extracted from PAPILA. The calculated DC values measures the overlap between the anticipated and ground truth RFI annotations (ranging from 0 and 1). All the annotated values are taken as input in different batches to increase the performance of the CNN-BCE model. After reasonable epochs, the dice coefficient results increased to 0.9 once the training data was augmented, which is higher than the prevailing models such as SVM, ADABOOST, and CNN-Softmax classifiers. The model precisely delineates the boundaries of the optic disc and cup within the extracted ROIs.

AUC-ROC Analysis

The AUC-ROC comparative analysis of the proposed CNN-BCE with YOLO-V8 is shown in Figure 7 and Table 7

Table 6: Dice Coefficient Analysis (%)

Metrics / Methods	*SVM*	*ADA-BOOST*	*CNN Softmax*	*DL-EAEN*	*CNN-BCE YOLO-V8*
Dice Score (It-1)	0.51	0.62	0.64	0.78	0.81
Dice Score (It-N)	0.56	0.64	0.71	0.80	0.90

Table 7: AUC-ROC Analysis (%)

Metrics / Methods	*SVM*	*ADA-BOOST*	*CNN Softmax*	*DL-EAEN*	*CNN-BCE YOLO-V8*
TPR	0.70	0.74	0.80	0.89	0.92
FPR	0.31	0.28	0.21	0.16	0.10

for TP and FP rate predictions. Initially, the PAPILA dataset is divided into training, testing, and validation processes. The

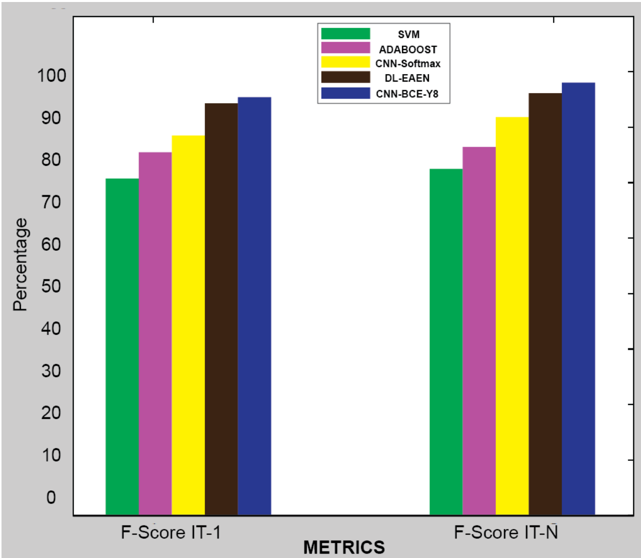

Figure 9: F-score

Table 8: Precision and recall analysis (%)

Metrics / Methods	*SVM*	*ADA-BOOST*	*CNN Softmax*	*DL-EAEN*	*CNN-BCE YOLO-V8*
Precision	78.75	83.60	88.75	97.41	98.6
Recall	76.50	84.61	89.05	98.02	98.78

Table 9: F-Score analysis (%)

Metrics / Methods	*SVM*	*ADA-BOOST*	*CNN Softmax*	*CNN-BCE YOLO-V8*
F-Score (It-1)	76.15	80.55	86.56	96.15
F-Score (It-N)	78.60	82.68	90.06	98.06

CNN-BCE inputs are taken from ROIs extracted by YOLO-V8. AUC-ROC is calculated from the test or validation dataset using predicted values and ground values. The TP and FP are calculated under a minimal range of threshold settings to measure the accurate range of AUC-ROC by applying the cross-validation technique. The 0.92 TP rate and 0.10 FP rate values are plotted, which are remarkably higher than the existing methods such as SVM, ADABOOST, and CNN-Softmax classifiers.

Precision and Recall Analysis

By computing TP, FP, and FN, the precision and recall values are calculated for the proposed CNN-BCE with YOLO-V8, which is portrayed in Figure 8 Table 8. As balanced precision and recall are crucial, the method is keenly trained based on the specific requirements to outperform the existing methods to ensure that no +ve cases are missed and no -ve cases are marked as +ve, which leads to potential patient screening for a better diagnosis. 98.6% precision and 98.78% recall are obtained by CNN-BCE with YOLO-V8, which is higher than the baseline models.

F-score Analysis

The performance analysis of F-score for the proposed CNN-BCE with the YOLO-V8 model is projected in Figure 9 and Table 9. To maximize accuracy and minimize misclassifications, deep object detection is carried out using YOLO-V8, which helps the CNN-BCE train and test in an effective manner. Pixel values are calculated and taken as input to all CNN layers to calculate the optimal value. 98.06% F-score is achieved by the proposed method, which is comparatively higher than SVM, ADABOOST, and CNN-Softmax classifiers in terms of detection and classification of glaucoma cases.

Conclusion

The suggested novel deep learning-based AI method predicts and classifies the glaucoma at an early occurrence, which helps to avoid risky conditions. PAPILA RFI is used for experimental purposes to measure the thickness of the retinal nerve layer. CNN, BCE, and YOLO-V8 are the computational methods employed to attain the objectives. This CAD system enables the ophthalmologists to perform deep eye screening at three levels, such as glaucoma eye, healthy eye, and glaucoma suspect, during the initial level. 75% of the RFI dataset is used for training and validation, and 25% is used for testing purposes. The RFI images are annotated to train YOLO-V8 with bounding boxes around the optic disc (OD) to boost accuracy. This automated system streamlines the eye screening process, which could potentially improve early diagnosis of glaucoma. CNN-BCE with YOLO-V8 shows promising results with a 98.88% accuracy rate, 0.9 dice-score, 97.74 and 98.03% sensitivity and specificity, 98.6 and 98.78% precision and recall, 98.06% f-score, and 0.92 true positive rates and 0.10 false positive rates under AUC-ROC. The new model is compared against the baseline approaches called SVM, ADABOOST, and CNN-Softmax classifiers. Some of the noted limitations are that the system typically requires large amounts of training to learn the intrinsic representation of data in RFI. Insufficient training data leads to overfitting. As CNN is a black-box model, it lacks interpretability. This automated model can be enhanced further by incorporating point cloud processing (PCP), which represents 3D geometry images, and cross-model fusion of 3D data to develop a robust AI-based 3D object detection system.

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