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RESEARCH ARTICLE

Glaucoma Identification in Digital Fundus Images using Deep Learning Enhanced Auto Encoder Networks (DL-EAEN) for Accurate Diagnosis

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Abstract

Objectives: To propose a novel method to enhance glaucoma identification by leveraging Digital Fundus Images (DFI). The deep learning-based approach, along with feature detection techniques, is utilized to discover the built-in features of the DFI in an unsupervised manner to enable robust detection with high accuracy. **Methods:** The Enhanced Auto Encoder Networks (DL-EAEN) approach is used to evaluate the latent representations from DFI and identify the morphological changes associated with glaucoma for prompt identification and classification. The fundus images are utilized for optic disc localization and glaucoma detection, and the Scale-Invariant Feature Transform (SIFT) approach is used to identify the local features as well as significant spots in the images. The PAPILA retinal dataset is used for this study with a record of 244 patients, which includes 488 fundus images of the left and right eye of all the patients in the M & F category with clinical results of healthy, glaucoma, suspect, and eye with crystalline and with IOL. In order to construct pixel-level masks and define the outer edges of the optic cup, U-Net and Mask-R-CNN techniques are employed as an image segmentation process. To measure the performance of DL-EAEN, MATLAB software is used and compared against existing models such as SVM, Adaboost, and CNN-Softmax classifiers. **Findings:** The proposed deep learning based enhanced AEN method outperforms the prevailing methods of SVM, Adaboost, and CNN-Softmax classifiers with promising results of 95.6% accuracy, 0.8 dice-score, 96.2% sensitivity, 97.01% specificity, 97.08% F-score, 97.41% precision, 98.02% recall, and AUC-ROC with 0.89 TPR & 0.16 FPR. **Novelty:** The evident results of DL-EAEN shows accurate and consistent rate in glaucoma detection and classification, which helps ophthalmologists, make easy diagnosis. In terms of accuracy, dice score, AUC-ROC, sensitivity, specificity, precision and F-score, the DL-EAEN overcomes the limitations of existing models SVM, Adaboost, and CNN-Softmax classifiers.

Keywords: Auto Encoder Networks; Deep Learning; Glaucoma Identification; Classification; Machine Learning; Data Mining; Image Segmentation

1 Introduction

Glaucoma is a common degenerative eye disease caused by increased pressure inside the eye that predominantly damages the optic nerve and ultimately leads to blindness. Millions of people worldwide have been affected by glaucoma, primarily elderly patients. Early glaucoma identification is essential to avoid vision damage. Various automated ML based computational methods are prevailing to identify and classify the glaucoma disease by utilizing fundus images with minimal drawbacks like less accuracy in detection, refraction, inaccurate identification morphology changes, false positive rates, etc. In order to overcome the limitations of the prevailing approach, the new deep learning-based enhanced auto-encoder networks (DL-EAEN) are proposed for glaucoma detection and classification dynamically to boost accuracy and minimize false rates by employing various methods to achieve this. Here, the main focus of the suggested method is to overcome the limitations of existing methods in terms of effective image segmentation, pixel masking, automatic identification of significant spots, and evaluation of latent representations of fundus images to achieve the objective. To enhance the feature representations, additional layers are built into auto-encoder networks to reconstruct the input features while capturing significant variations in glaucoma detection. The encoding and decoding processes take place in DL-EAEN to improve efficiency.

Early detection of glaucoma [(1)] by employing the style transfer method to identify the thickness of retinal fiber on the fundus images by mapping and translation in the spectral retinal domain (SD) An AI detection tool was developed using AEN. Signal strength is measured to identify the similarity between the trained and test images. This approach extracts the thickness of retinal fundus images for reconstruction. The only drawback of this method is that the system won't extract the local features and identify the key points in the DFI, which leads to low accuracy in detection. A CNN based SURF tool [(2)] was introduced to boost accuracy in glaucoma detection. It works on a rank-based feature selection technique by using hybrid feature descriptors for pre-processing. This method benchmarked the detection accuracy rate with minimal drawbacks, such as edge marking and a two-layer learning process. DCNNM [(3)] was introduced for effective segmentation and classification by utilizing the U-Net DL model. The ORIGA dataset was used for feature selection and extraction. Optic cup measurement was done in 2 layers, where layer 1 was used for pixel marking and layer 2 was used for edge masking to measure CDR accurately to minimize false positive rates. The outcome was measured with a detection and classification of 90% and above. But the model has a few drawbacks, such as disc localization, significant spot identification, etc. Computational model with CNN [(4)] was proposed to identify the glaucoma at an early stage with three attention U-Net CNN layers, such as V3, VGG-19, and Res-Net50. The deep segmentation was carried out to classify the glaucoma in a dynamic way. Various data augmentation methods were applied for pre-processing to enhance the quality of the image and achieve accuracy in detection. The drawback here is that the model works only with minimal datasets, and it gets down to complex data training and testing. QoS-IWARP [(5)] model was introduced as an optimization technique in ML, where the model is trained to handle complex data and detect dynamic link failures in real time. This helps the auto-encoder networks optimize the two-layer process for image enhancement. AE-ROI model & AI in detection [(6,7)] were used for annulus thickness detection, where 44 progressing and 176 non-progressing samples were tested. The ALS method was employed for deep analysis to detect optic nerve head damage, maximize the TPR, and minimize the FPR. The model tunes and works well

for early diagnosis and achieved 89% accuracy. The only drawback of this method is the processing of complex data in terms of segmentation and classification. The RNN & CNN [8] combinational method was developed for GD, where fundus videos are used to train the model to boost accuracy. It separates the glaucoma from the healthy and spots the difference in videos with the help of 3-layer video segmentation. 91% F-measure was achieved with 87% accuracy. The shortcomings are that the model works well only with the quality of videos at all levels; if the video has poor quality, there is a slight drop in promising results. Reviews done by the authors on the influence of TPG and IP in glaucoma and how they affect the optic nerve The optic canal, thickness, etc. are measured, and the detection is done with the help of various machine learning models to improve sensitivity and specificity. Glaucoma detection & optimizing bio-inspired EABIFPA DL methods reviews was carried out, where the comparative analysis was done between the traditional and deep learning models [9,10]. QoS-RABCRP, DCNN and DL-GD [11–13] models were introduced to optimize and filter the data in a robust way. These models initially filter the image in the first stage for denoising and then segment it for the identification and classification processes automatically. The ODC measurement was done after filtration and segmentation, where the boundaries are marked and separated in the second layer. The above models have a few shortcomings, like poor edge masking, static selection, and optimization of data, which lead to a low sensitivity ratio. CNN-Softmax [14] with 13 layers was trained by an SVM model where all the significant and vital features are extracted to boost accuracy. Flattering, pooling, and convolution take place in both layers, which helped the AI model identify the glaucoma in a dynamic way. The Softmax classifier was introduced along with CNN to classify glaucoma in all categories and sub-categories. This process works on a large annotated dataset with high-pixel images and optimizes it to achieve the objectives of detection and classification. Three connected layers take the normalized DFI as input and process it by CNN-Softmax for classification. SVM and ADABOOST [15] classifiers were proposed for optic-cup segmentation and input image validation. The classifiers were done using standalone components, which were used for various roles in glaucoma detection. 520 fundus images were used to test and train the model. After image validation, SVM and ADABOOST extracted ROI from the image. The brightest spot algorithm was used for OD and OCS measurements to boost accuracy and minimize the error rate. The PAPILA [16] dataset was uploaded by clinical experts, and the researchers can make use of the DFI with many features for future enhancements. An ensemble DL [17,18] and Automatic detection model for GD was proposed as a problem-solving method for glaucoma identification and classification. Three pre-trained CNN and RF techniques were employed in the Dhristi-GS dataset and created a visual box for segmentation and filtering. All four classifications are spotted by this model where the refraction error was missed, which is considered as limitation. Vanishing gradient problems were addressed by the auto-model, where the system automatically measures OC and finds CDR. The optical coherence feature mapping technique [19] was introduced to perform detection process with the help of fiber optic morphology technique. A 3D imaging technique was applied to spot the significant features and masks to identify AUC-ROC. The results are proven with 87% accuracy, with the shortcoming of identifying morphology changes in the initial stage. The NTK-IS [20] image segmentation method was used in all types of tasks to detect glaucoma with the help of real-time images. Here, the disc is pointed by a specific laser, which measures the nerve thickness, identifies the spot, and records it later, pattern matching was done between the training and testing of images. This model minimizes the false rate, but the consumption of time is very high as it handles complex data. An Automated DL [21] model was proposed to deal with diabetic patients who have glaucoma with the help of deep root sensing and segmentation by AEN. IOT devices were used as a supportive tool to monitor the morphology changes during the glaucoma testing process. A forensic use case for GD using multi-feature analysis TL-based CNN and the automated DL framework [22,23] was proposed by the researchers to analyze the fundus images and convert into layers for filtering, masking, and segmentation to enhance the TPR & TNR to overcome the traditional methods. But the recording of morphological changes was not achieved. Class imbalance [24] is optimized by DL model to boost the accuracy level of detection. All the prevailing methods showed results with limitations. To overcome all those limitations, the Dl-EAEN method is proposed as a problem-solving method for experts to identify and classify glaucoma in a robust way. The objectives of DL-EAEN are: i) glaucoma detection; ii) classification; iii) recording morphology changes; iv) dynamic usage of the PAPILA dataset; v) identification of local features with SIFT; vi) boosting the accuracy rate, etc. The major steps followed in DL-EAEN are,

- **Image Segmentation:** Segmentation is done using new methods where the system will automatically filter the images.
- **Filtering and Denoising:** Modifying the pixels, such as smoothing, sharpening, edge and boundary detection, etc., and replacing the pixel value for reconstructing the process.
- **Image Segmentation in 2 layers :** Two-layer segmentation is used to identify the ROI based on the threshold value.
- **Masking :** Specific features are masked for robust detection and classification to achieve the optimal value. The abnormalities are identified and recorded for easy diagnosis based on their severity. The OD and OC are measured before masking.

2 Methodology

The proposed deep learning-based enhanced auto-encoder networks focus on glaucoma detection and classification in a robust way by utilizing digital fundus images. Common features like optical disc and cup parameters, color features, optical NH morphology (shape, boundary, and rotation), retinal thickness, and deep layer analysis are extracted in the PAPILA dataset, and features extracted by DL models (ex. CNNs) are utilized for training and testing purposes. The enhanced auto-encoder network method is employed to identify the morphological changes in DFI to prompt glaucoma detection and classification with high accuracy. Additionally, the SIFT method is used to mark the local features and significant spots automatically in DFI. The image segmentation process is done with the help of U-Net and Mask-R-CNN. Normalization, denoising, and resizing are done before feature extraction. This novel approach improves the accuracy of GD, and the performance is compared against the prevailing methods like SVM[15], ADABOOST[15], and CNN-Softmax[14].

2.1 Proposed Methodology

The new DL-EAEN method is specifically trained for glaucoma detection and classification with high accuracy. Data pre-processing is first carried out to normalize the DFI in order to ensure reliable intensity ranges, and then denoising it using Gaussian-Blur is followed by an image resizing process to make the DFI a uniform one for consistency. Train CNN on the selected dataset for FE and FS. Extract features like optical disc and cup parameters, color features, optical NH morphology (shape, boundary, and rotation), retinal thickness, and deep layer analysis by utilizing the trained CNNs. Employ DL-EAEN to encode and decode the data for meaningful representation. Here, the attention mechanism is used for AEN enhancement, where it enables the AEN to focus more on specific input data (DFI) and allows adequate resources for relevant features. This helps the AEN capture significant patterns. Once the DL-AEN is employed, the training process is carried out for the detection and classification of glaucoma in a robust manner. Assume that I represents the sample fundus image and *normalize (I)* is the normalized image and *features = CNN (I_resized)* represents the extracted features in the dataset. The encoded features are *AEN.encode (features)* where it has all the features encoded by the system after SIFT process. The *AEN.decodes (encoded_features)* are the reconstructed or decoded features in the dataset. The equation for GD using DL-EAEN is follows,

$$\begin{aligned}\text{Glaucoma}_{\text{Detection}}\,(I) = \ &\text{Glaucoma}_{\ \text{Classifier}\ (\ \text{encoded}_{\ \text{features}}\ )} + \text{SIFT}_{\text{Features(Iresized}\ )} + \\ &U - \text{Net}_{\ \text{Segmentation(Iresized}\ )} + \text{Mask}_{\ R} - \text{CNN}_{\ \text{Segmentation(Iresized}\ )}\end{aligned} \tag{1}$$

where, $Glaucoma\_Detection(I)$ is the overall outcome of DFI (I). The result of glaucoma classifier is $Glaucoma\_Classifier(encoded\_features)$. The details of the distinctive spots value stored in $SIFT\_Features(I\_resized)$. The DFI segmented regions are marked by the U-NET method and stored in $U-Net\_Segmentation(I\_resized)$. The detailed structure retinal boundaries are measured by Mask-R-CNN segmentation method $Mask\_R-CNN\_Segmentation\ (I\_resized)$. The above equation is solved by using sample values stored in variable. The encoded features are utilized from DL-EAEN for glaucoma detection and classification. In order to reconstruct the input features the loss function, MSE is used while emphasizing the significant details is shown as,

$$\text{loss} = \text{MSE (features, reconstructed\_features)} \tag{2}$$

$$\text{reconstructed\_features} = \text{AEN.decode(encoded\_features)} \tag{3}$$

2.2 Data Attainment, Acquisition and Pre-Processing

This proposed deep learning-based DL-EAEN model uses PAPILA retinal clinical datasets, which consist of the clear retinal report of 244 patients which includes 488 images of the left & right eye under male & female category. It also has the clinically proven values of healthy (0), glaucoma (1), suspect (2), eye with crystalline and eye with lens (IOL). The PAPILA dataset presents 2576x1934 retinal DFI of both OS and OD with clear segmentations. Table 1 shows the PAPILA OS and OD dataset features of 18 patients with sample data of healthy, glaucoma, refractive error, and astigmatism, phakic & pseudopakhic results by ophthalmologists. Here 70% datas are used for training & validation set & 30% are used for testing. Figure 1 shows the DFI of #1 to #3 OS and OD fundus images and contour images with masking.

The contour results shows that the patient #002 has suspicious of glaucoma in both OD & OS whereas patient #004 has glaucoma in both OD & OS.

Table 1. PAPILA Clinical Dataset (OD & OS Samples are given)

P.No	Age	Eye	Gen	Diagnosis	Refractive Defect			Ph/PsedoPh	Proven Results
					D1	D2	AM		
#027	78	OD	1	0	0.25	-1.25	30	1	
#028	26	OD	0	0	-2.25	-0.25	177	1	
#029	41	OD	1	0	-1.25	-0.25	180	1	
#027	26	OS	1	1	-0.5	-2	85	1	
#028	26	OS	0	0	-1.5	-0.5	5	1	**Male: 93**
#029	41	OS	1	0	-1.25	0	0	1	**Female: 151**
#004	79	OD	1	1	1.5	-1.75	85	0	**Healthy: 333**
#005	72	OD	1	1	-0.75	-1.25	101	1	**GD:87**
#010	70	OD	1	1	2.25	-1.5	105	0	**Suspect: 68**
#004	58	OS	1	1	1.5	-2.5	85	1	**Phakic: 318**
#005	89	OS	1	1	-0.5	-2	100	1	**PsedoPh: 159**
#010	72	OS	1	1	2.5	-1	70	0	
#002	47	OD	0	2	0.75	-1.75	90	0	
#006	69	OD	0	2	1	-1.5	95	0	
#007	22	OD	1	2	-0.25	0	0	0	
#002	47	OS	0	2	-0.5	-1.5	88	0	
#006	69	OS	0	2	1	-1.5	85	0	
#007	22	OS	1	2	-0.25	-0.5	0	0	

(Out of 244 patient's samples, 18 are displayed for reading)

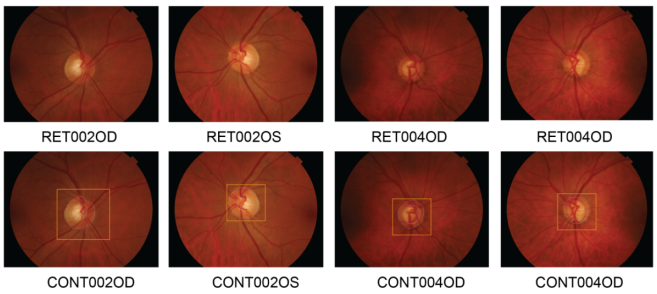

Fig 1. DFI - of 2 Patients with Contour Results (Normal: 1st Row / Detection & Masking: 2nd Row)

2.3 Optic Disc, Optic Cup Segmentation & CDR Measurement

The semantic segmentation of the optic disc is done by employing U-Net and training the U-Net annotated fundus images where the OD region is labeled. Here, the red channel is subtracted from the DFI. The optimal value or vessel image of the U-Net highlights the OD region in the form of a binary mask. Employ Mask-R-CNN for optic cup segmentation where the boundaries and edges of the optic cup are marked. The output of Mask-R-CNN will provide the pixel-level masks of the optic cup. The pixel intensities at the boundaries standard deviation are determined. The critical measure in glaucoma diagnoses is CDR (cup-to-disc-ratio). Initially the diameter of the cup and the disc is measured from the segmented masks obtained from U-Net and Mask-R-CNN and calculate the CDR. The CDR is calculated by using the obtained diameters.

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

Based on the CDR values, the glaucoma categorization is identified. Different CDR thresholds will indicate varying degrees of glaucoma development. The CDR values are compared with the PAPILA clinical OS & OD data to determine the classification stage, which includes early, moderate, or advanced of open and closed angle glaucoma. The following are the features extracted from the segmented image, along with CDR measurements for both the cup area and the segmented area. i) Area (A); ii) Eccentricity (ECC); iii) Equiv Diameter (ED); iv) Euler Number (EN); and v) Main Axis Length (MAL), along with other

features that were shown above. The CDR is relatively small in healthy eyes since the cup only takes up a small fraction of the disc. However, because to the loss of nerve fibers in glaucomatous eyes, the cup may grow, raising the CDR. An elevated CDR is frequently regarded as a key glaucoma signal and may indicate increasing optic nerve damage.

2.4 DL-EAEN Architecture Diagram

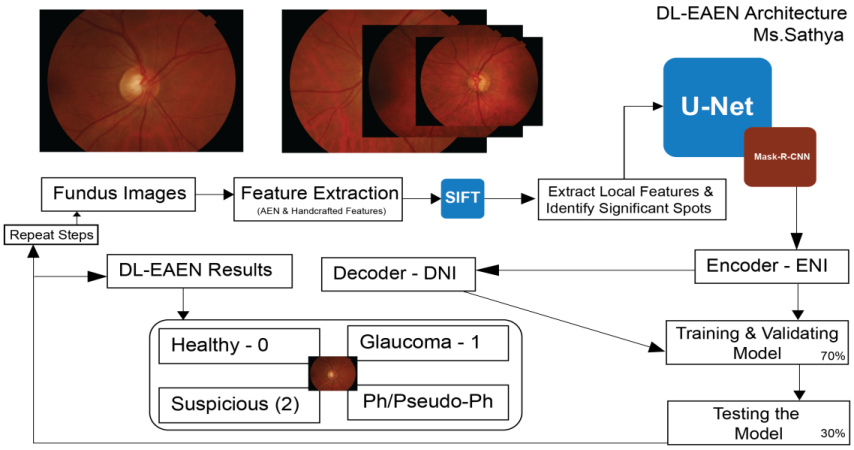

Fig 2. DL-EAEN Architecture Diagram

The DL-EAEN architecture shows the DFI segmentation process, followed by the encoding and decoding processes. Methods like SIFT, U-Net, and Mask-R-CNN are used for efficient glaucoma detection and classification. The counter results clearly showcased healthy, glaucoma, suspicious, or refractive error.

(DL-EAEN) Enhanced Auto Encoder Networks Process

1. Input: MATLAB settings with PAPILA Dataset
2. Begin
3. Load the Digital Retinal Fundus Images from PAPILA dataset data.papila
4. Perform pre processing for image in dataset: normalized_image = normalize(I) denoised_image = denoise(I) resized_image = resize(I) preprocessed_images.append(resized_image) return preprocessed_images

Train DL-EAEN Encoded_Features $= DL -$ **EAEN.Encode(Fundus_Images)**

5. Train Classifier using Encoded_Features
6. Optic Disc Segmentation using U -Net $Segmented_Disc, Segmented_Cup = U - Net_Segmentation(Fundus_Images)$
7. Local Feature selection with SIFT keypoints, descriptors = SIFT (Segmented_Disc)
8. Structure identification /boundaries marking with Mask-RCNN
   Detailed_Structures = MaskRCNN_Segmentation(Fundus_Images)
9. Glaucoma Assessment CDR Measurement
10. Generate **CDR output (0,1,2)**
11. Output: Glaucoma detection

End

2.5 Identification of significant spots in DFI using SIFT

Scale-Invariant Feature Transform method is employed here to spot the critical spots and minor structural changes in fundus images which will help in deep diagnosis of glaucoma. The image transformation happens in order to extract the features. The extraction of local features such as vessel width & density, retinal thickness, grey-level based on pixel, basic geometric morph-metrics, colour moments & histograms from DFI irrespective of scale and orientation, the following steps are used.

- Analyze the regions of PAPILA-DFI & Detect unique key points

- Generate the descriptors such as OD, cup_edges, patterns etc
- Identify the significant spots like minute structural changing (deviations in cup & morphology, layer detects, wool cotton spots, drusen, macular changes, retinal minute tears etc)
- Identify the subtle changes in PAPILA dataset fundus images
- Capture the change and record for results

2.6 Image Segmentation using U-Net and Mask-R-CNN

Detailed instance level identification was achieved with effective image segmentation process using U-Net and Mask-R-CNN. It records the edges of optic disc and cup regions and masks the regions to get clear picture of classification. CDR and structural changes also measured with the help of global & local features extracted from PAPILA. During the detection process, the enhanced auto-encoder collects output data (after masking) consequently with the purpose of reconstructing unique input data after segmentation by U-Net and Mask-R-CNN. The optic disc and optic cup are segmented at the same time in order to calculate the pixel value. The retinal structures and edges are measured and masked to refine the boundaries with an exceptional output. The retinal abnormalities also masked for robust detection and classification of glaucoma.

2.7 Performance Evaluation Metrics of DL-EAEN

The DL-EAEN for glaucoma identification and classification is compared with machine learning-based approaches such as SVM, ADABOOST, and CNN-Softmax. MATLAB software is used to assess the performance of the proposed deep learning model. The software enables efficient processing and interpretation of the DFI (Digital Fundus Images) and simplifies the image segmentation process. The software program that helps train and evaluates the ML models includes SVMs, RF, CNN, AEN, etc. It is very easy to access with the help of a complete toolbox. The DL-EAEN model is tested in real-time applications with the help of results generated in MATLAB. The PEM of the new deep learning based enhanced auto-encoder networks method (DL-EAEN) is compared against the existing approached such as SVM[15], ADABOOST[15], and CNN-Softmax[14] chosen in the preceding section. The following are the PEM equation is used to measure the performance of DL-EAEN during the execution stage. 400+ images with batch size of 10, 40 iterations are carried out with 4 epochs.

$$GD_{\text{Accuracy}} = \frac{(TPR+TNR)}{(TPR+TNR+FPR+FNR)} \times 100 \tag{5}$$

$$GD_{\text{Sensitivity}} = \frac{TPR}{(TPR+FNR)} \times 100 \tag{6}$$

$$GD_{\text{Specificity}} = \frac{TNR}{(TNR+FPR)} \times 100 \tag{7}$$

$$GD_{\text{Precision}} = \frac{TPR}{(TPR+FPR)} \times 100 \tag{8}$$

$$GD_{\text{Dicescore}} = (2 * |\,\text{A} \cap \text{B}|)/(|\text{A}| + |\text{B}|) \tag{9}$$

$$GD_{\text{Precision}} = \frac{TPR}{(TPR+FPR)} \quad GD_{\text{Recall}} = \frac{TPR}{(TPR+FNR)} \tag{10}$$

$$GD_{\text{FScore}} = \frac{2 * (\text{ Precision } * \text{ Recall })}{(\text{ Precision } + \text{ Recall })} \tag{11}$$

$$MCC = \frac{T_1}{\sqrt{T_2 \times T_3 \times T_{4 \times T_5}}} \times 100 \tag{12}$$

where, *GD denotes Glaucoma Detection* and the PEM equation is derived using, $T_1 = (TPR \times TNR - FPR \times FNR)$, $T_2 = (TPR + FPR)$, $T_3 = (TPR + FNR)$, $T_4 = (TNR + FPR)$, and $T_5 = (TNR + FNR)$.

- **Sensitivity and Specificity:** Sensitivity measures the +ve instances detected by DL-EAEN out of all actual positive cases, and Specificity measures the -ve instances identified by DL-EAEN out of all negative cases.
- **Accuracy and Fscore :** Accuracy measures the overall predictions of DL-EAEN. It is the ratio of correctly classified samples to total samples in the dataset, and Fscore is used to balance the +ve and -ve instances.
- **Dice Score:** Used to assess how the DL-EAEN model accurately segments OC in fundus images**.**
- **AUC-ROC:** Evaluate the performance (TPR & FPR) based on precision and recall when dealing with imbalanced datasets.
- **Precision:** It Estimates the accuracy of +ve predictions made by DL-EAEN and is calculated as the ratio of true positives to the sum of true positives and false positives.

3 Results and Discussion

This chapter shows the outcome of the performance evaluation achieved by the newly proposed deep learning-based enhanced auto-enhanced networks method to improve glaucoma detection and classification in a robust manner. The DL-EAEN was compared against SVM [15], ADABOOST [15], and CNN-Softmax [14] which shows the remarkable output in terms of detection, classification, and image segmentation processes. The DL-EAEN overcomes the drawbacks of existing unsupervised learning methods. The identification of local features in DFI, pixel masking, and outer edge measurements helps boost the accuracy of detection. The findings of the comparative analysis are showcased below in Figures 3, 4, 5, 6, 7 and 8 the form of a graphical representation with the X axis and the Y axis measuring.

3.1 Sensitivity and Specificity Analysis

The performance and comparative analysis of sensitivity and specificity are shown in Figure 3. The proposed DL-EAEN detection method is compared against prevailing machine learning approaches such as SVM [15], ADABOOST [15], and CNN-Softmax [14]. It is observed that the proposed DL-EAEN method effectively bifurcates glaucoma-positive and glaucoma-negative cases by leveraging the SIFT method. Due to the rigorous filtering and segmentation process, the outcome of the DL-EAEN is commendable, with efficient data classification and extraction. 97.01% sensitivity and 97.08% specificity are achieved, which is comparatively higher than other models.

Table 2. Sensitivity and Specificity Comparative analysis

Metrics / Schemes	SVM [15]	ADABOOST [15]	CNN-Softmax [14]	DL-EAEN
Sensitivity	75.45	84.05	87.76	97.01
Specificity	78.37	86.30	88.20	97.08

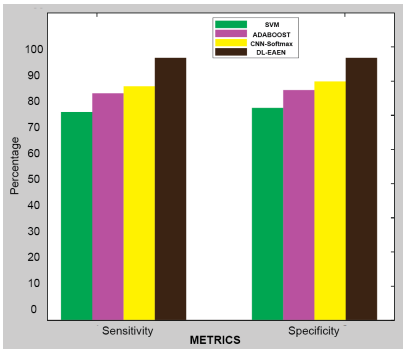

Fig 3. Sensitivity and Specificity

3.2 Accuracy Analysis

Accuracy in the +ve and -ve predictions with the classification of glaucoma is portrayed in the Figure 4 . The novel deep learning-based technique DL-EAEN is compared against baseline methods such SVM [15], ADABOOST [15], and CNN-Softmax [14]. Robust methods such as effective segmentation, pixel masking, and OCM yield promising results in accuracy in detection and

classification. It shows the potential and superior capability of the DL-EAEN method in distinguishing positive and negative cases of glaucoma. The accuracy is achieved up to 98.6%, which is relatively higher than all other existing approaches.

Table 3. AccuracyComparative analysis

Metrics / Schemes	SVM [15]	ADABOOST [15]	CNN-Softmax [14]	DL-EAEN
Accuracy (It-1)	75.20	79.87	86.92	96.78
Accuracy (It-N)	76.40	81.46	88.50	98.60

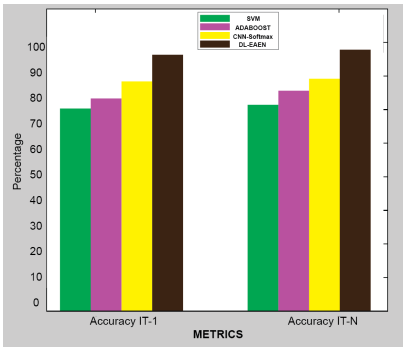

Fig 4. Accuracy

3.3 Dice Score Analysis

Figure 5 presents the Dice Score analysis of the proposed DL-EAEN method for image segmentation between the predicted and ground truth segmentation masks. The suggested model is compared with the baseline versions of SVM [15], ADABOOST [15], and CNN-Softmax [14]. On the selected PAPILA dataset with the target attributes 0, 1, and 2; the DL-EAEN outperforms the existing approaches in terms of quality of segmentation results in terms of measuring OC and ODR in DFI. The perfect overlap is measured between 0 and 1, where the DL-EAEN method outperforms with a value of 0.8, whereas other baseline algorithms have not shown the expected results during the comprehensive evaluation.

Table 4. Dice Coefficient Comparative Analysis

Metrics / Schemes	SVM [15]	ADABOOST [15]	CNN-Softmax [14]	DL-EAEN
Dice Score (It-1)	0.51	0.62	0.64	0.78
Dice Score (It-N)	0.56	0.64	0.71	0.80

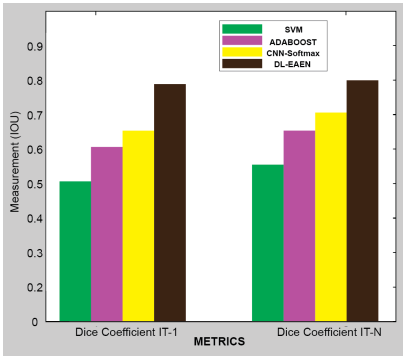

Fig 5. Dice Coefficient

3.4 AUC-ROC Analysis

Figure 6 demonstrates the AUC-ROC in terms of TPR and FPR under various threshold settings. The comparative analysis is done to evaluate the true positive and false positive against the existing models such as SVM [15], ADABOOST [15], and CNN-Softmax [14]. The threshold value is set for balance sensitivity and specificity, where it provides a reasonable trade-off between glaucoma detection in +ve cases while minimizing false positives to prove the significant diagnosis. The PAPILA data is trained and tested with repeated iterations for better accuracy in all iterations. The result of the AOC-RUC is 0.89 TPR & 0.16 FPR, indicating the DL-EAEN has a strong ability to discriminate between +ve and -ve cases.

Table 5. AUC-ROC Comparative Analysis

Metrics / Schemes	SVM [15]	ADABOOST [15]	CNN-Softmax [14]	DL-EAEN
TPR	0.70	0.74	0.80	0.89
FPR	0.31	0.28	0.21	0.16

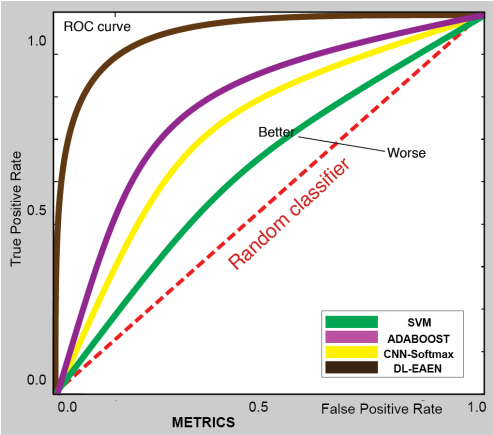

Fig 6. AUC-ROC

3.5 Precision and Recall Analysis

Figure 6 displays the comparative analysis of precision and recall of the proposed DL-EAEN technique for effective glaucoma detection. DL-EAEN is evaluated and compared against baseline methods such as SVM [15], ADABOOST [15], and CNN-Softmax [14]. In DL-EAEN, the incorporation of effective FS and FE techniques yielded remarkable outcomes. The use of DL-EAEN, when combined with the modified feature extraction approach, reveals promising results to enhance glaucoma diagnostic accuracy. 97.41% precision and 98.02% recall were achieved.

Table 6. Precision and RecallComparative Analysis

Metrics / Schemes	SVM [15]	ADABOOST [15]	CNN-Softmax [14]	DL-EAEN
Precision	78.75	83.60	88.75	97.41
Recall	76.50	84.61	89.05	98.02

3.6 F-Score Analysis

Figure 8 showcases the comparative and performance analysis of the F-score of the novel DL-EAEN glaucoma detection method to overcome the shortcomings of the existing methods, SVM [15], ADABOOST [15], and CNN-Softmax [14]. Pixel-wise, effective segmentation is done to boost the accuracy by measuring the OD and OC by employing the U-Net and Mask-R-CNN methods. It is noted that the proposed new deep learning approach gives substantial results up to 97.08%.

Table 7. F-Score Comparative analysis

Metrics / Schemes	SVM [15]	ADABOOST [15]	CNN-Softmax [14]	DL-EAEN
F-Score (It- 1)	76.15	80.55	86.56	95.65
F-Score (It-N)	78.60	82.68	90.06	97.08

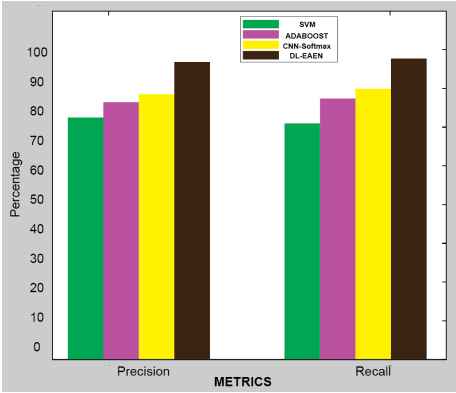

Fig 7. Precision and Recall

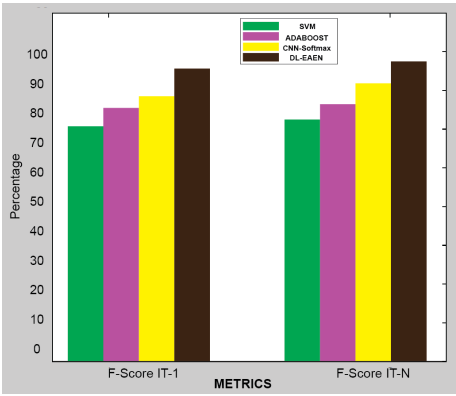

Fig 8. F-Score

4 Conclusion

The novel deep learning-based enhanced auto-encoder networks (DL-EAEN) approach is utilized for glaucoma identification and classification. The automatic identification of significant spots and extracting the local & histogram features are the unique method of Dl-AEN. The PAPILA retinal dataset is used in this study with various features. 244 patient samples were taken and bifurcated for training & validation set (70%) and testing set (30%). The SIFT approach is employed along with DL-EAEN to extract the local features and spots in the fundus images. Anatomical features like CDR, OC values, and data points are measured to detect glaucoma for easy diagnosis. Fundus images are used to quantify these features. Based on these anatomical characteristics, the DL-EAEN makes accurate and timely predictions. Image segmentation methods like U-Net and Mask-R-CNN are employed for pixel masking and to measure the outer edges of OC. 95.6% detection accuracy is achieved with a high classification rate. The DL-EAEN also shows remarkable results in terms of a 0.8 dice score, 96.2% sensitivity, 97.1% specificity, 97.08% F-score, and 0.89 TPR & 0.16 FPR measured under AUC-ROC. The significant results show that the new method outperforms the prevailing approaches such as SVM, Adaboost, and CNN-Softmax classifiers. Some of the noted limitations are that data accuracy will be affected when there is noise in fundus images. Complex task in preprocessing the fundus images, which includes image registration, normalization, enhancements, etc. Clinical validation is highly required for every model to measure its performance in a real-time scenario. This method may be enhanced further and recommended to researchers to incorporate multi-model data such as OCT, conduct visual field tests, etc. Batch normalizations also can be employed to focus

more on critical regions in fundus images.

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