

GlaucoNet: A Novel Technique to Identify Glaucoma at its Early Stage

Soma Datta ^{1,✉}, Prमित Ghosh ², Saumendu Datta ³

1. Department of Computer Science, Sister Nivedita University, Kolkata, IND

2. Computer Science and Engineering, RCCIIT, Kolkata, Kolkata, IND

3. Specialist Doctor, Calcutta Medical College, Singur, IND

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Abstract

Glaucoma occurs due to increased intraocular pressure and damage to the optic nerves. If left untreated or undetected, it can lead to irreversible blindness. As one of the most severe eye diseases, timely detection and treatment are crucial to preventing complete vision loss. Early diagnosis plays a vital role in protecting patients from permanent blindness. Traditionally, glaucoma is diagnosed manually by ophthalmologists, a process that requires significant time, expertise, and cost. While several detection techniques are still in the experimental stage, they have not been widely implemented in real-time clinical systems. In this paper, the authors propose a novel technique based on the LeNet architecture, which can effectively detect glaucoma at an early stage. The proposed approach utilizes the gray channels of fundus images and applies data augmentation to generate a diverse and extensive dataset for training a convolutional neural network model. Leveraging the LeNet architecture, the method demonstrated good performance in detecting glaucoma across multiple datasets, including DRISHTI-GS, RIM-ONE, DRIVE, DRIONS-DB, and JSIEC datasets. On the DRISHTI dataset, the proposed model achieved a detection accuracy of 98.67%, a specificity of 91.76%, an area under the curve of 95.68% and sensitivity of 89.78%. With its high accuracy, this approach has the potential to assist clinicians in diagnosing early-stage glaucoma, enabling timely interventions and reducing the risk of irreversible vision loss.

Categories: Health Informatics, Image Processing and Analysis

Keywords: gaussian blur, fundus retinal image, lenet architecture, glaucoma detection, data augmentation

Introduction

Worldwide, the second main cause of blindness is glaucoma. The World Health Organization report discloses that, by 2040, it is anticipated that 111.8 million people would have this incurable illness [1]. In the human eye, the optic nerve is located within the retina. Changes in the size and structure of the optic disc can indicate early-stage glaucoma. Elderly individuals, particularly those over 50, are at a higher risk of developing glaucoma. Regular eye check-ups after this age can not only reduce the risk but also help prevent optic nerve cell damage. To detect glaucoma, various imaging techniques are used, including fundus images, optical coherence tomography images (OCT), and scanning laser polarimetry images [2, 3]. Figure 1 illustrates fundus images from the Retinal Image for Optic Nerve Evaluation (RIM-ONE) database, showing a healthy retina. Figure 2 shows different types of fundus retinal images like healthy fundus image (shown in Figure 1 top left), early glaucoma (shown in Figure 1 top right), moderate glaucoma (shown in Figure 1 bottom left), and acute glaucoma (shown in Figure 1 bottom right).

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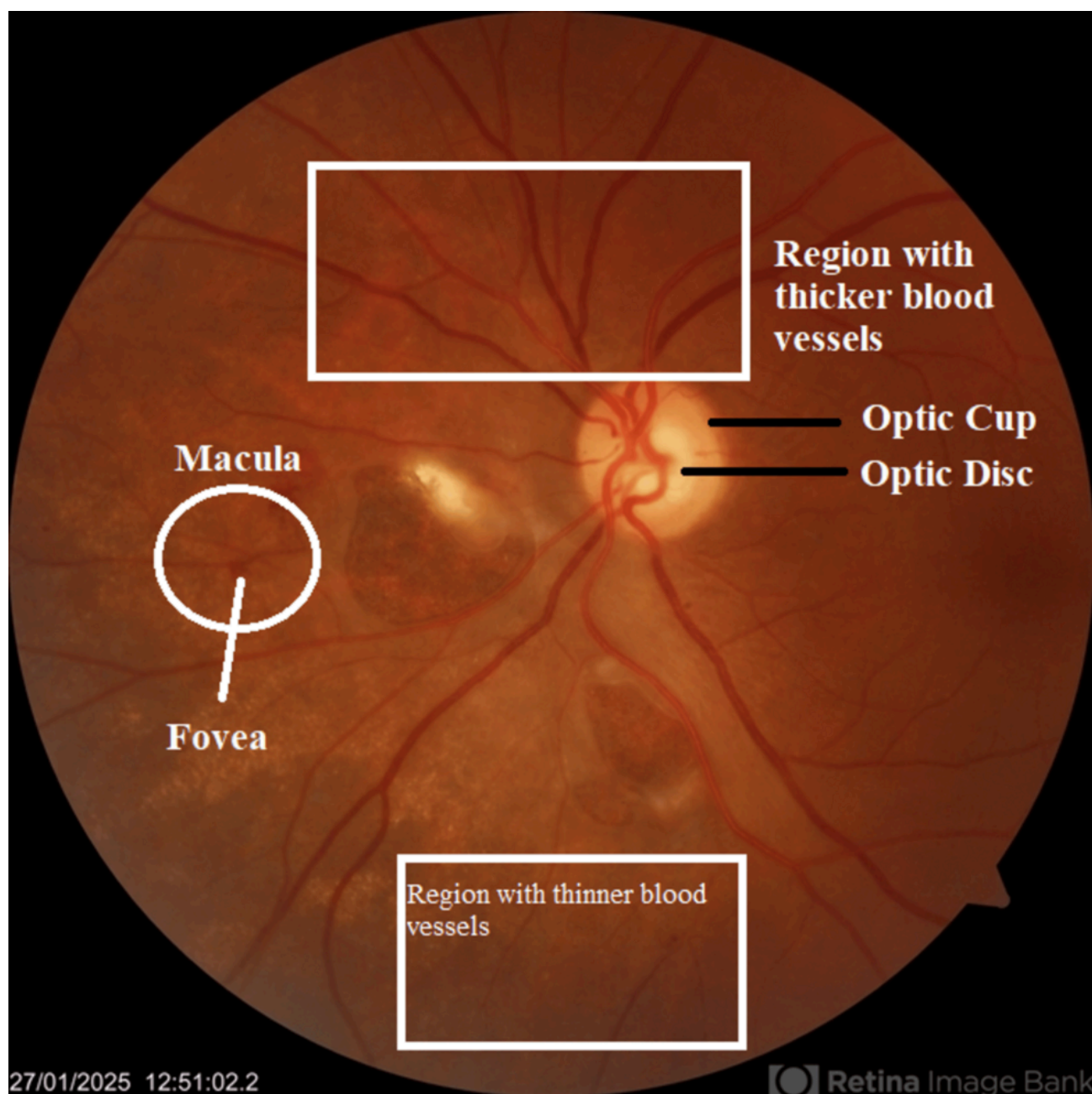


FIGURE 1: Sample fundusoscopic images from the RIM-ONE database.

RIM-ONE, Retinal Image for Optic Nerve Evaluation

Glaucoma detection heavily relies on the expertise of ophthalmologists, which limits its accessibility in remote areas. To address this, there is a growing need for automated tools capable of early and efficient diagnosis. A literature review reveals that most studies have used relatively small datasets with image variation fineness. It compromises the robustness of existing systems. It is necessary to create models that perform well across diverse environmental conditions and varying image qualities. Additionally, further improvements in classification accuracy remain a key area for research.

The contributions of this research work are listed as below:

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1. Established a strong technique capable of training the model with diverse dataset variations and multiple features extracted from fundusoscopic retinal images.
2. Utilized multiple datasets for training and testing to enhance model accuracy.
3. Ensured that the selected features are highly relevant to the achieved results, improving the reliability of the technique.



FIGURE 2: Sample fundusoscopic images from the RIM-ONE database for different stages of glaucoma.

RIM-ONE, Retinal Image for Optic Nerve Evaluation

This paper contains mainly four sections. The proposed work's introduction, literature review and its limitations are covered in the "Introduction" section. The detail design of the proposed technique is explained in the "Materials and Methods" section. The "Discussion" section shows the performance analysis and the comparative study between existing method with proposed technique. Lastly, the "Conclusions" section.

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Literature review

A progressive and irreversible disease like glaucoma can lead to optic nerve damage, often resulting in blindness if left untreated. Early detection is essential as it is asymptomatic in the early stages [4,5]. Various automated techniques have been developed to assist ophthalmologists in diagnosing glaucoma, utilizing advanced imaging technologies and machine learning approaches. This survey reviews significant contributions in the field of glaucoma detection. This section describes the existing method to detect the glaucoma and their limitations. Xu et al. [6] proposed deep learning-based automatic technique to segment the optic cup and disc, achieving over 90% accuracy. Medeiros et al. [7] demonstrated that the retinal nerve fiber layer thickness, extracted using OCT and deep learning models, improves early glaucoma detection. Hatanaka et al. [8] performed a determination to separate the optic disc based on the fundus image's color and form. A red, green, blue (RGB) image's three channels were all subjected to the P-tile thresholding technique. The three images were combined to create an approximate optic disc, and a canny edge detector was used. Using the blue component, profile analysis was used to derive the optic cup. Lastly, glaucoma was diagnosed using the vertical cup-to-disc ratio (CDR). In order to identify glaucoma, Thakoor et al. built a model based on several convolution neural network (CNN) architectures that were trained on OCT images and also made use of some pre-trained models [9]. The CNN architectures learned on OCT images were contrasted with the pre-trained ResNet, VGG, and InceptionNet architectures when combined with random forest. A high accuracy of 96.27% was achieved using CNN trained on OCT images. Yu et al. [10] developed a model for glaucoma diagnosis in fundal images utilizing a modified version of the U-Net architecture and many datasets. The U-Net used the pre-trained ResNet-34 as an encoder and the conventional U-Net architecture as a decoder. The model worked well, as evidenced by the fact that 88.77% of cup dice values and 97.38% of disc dice values matched the DRISHTI-GS test set. In order to identify POAG from dataset photos in a variety of situations and people, GlaucomaNet [11] was proposed. In this method, two CNN models were used. The first CNN model tried to copy the human grading technique while the second layer of CNN combines these grading features. Used model greatly increases diagnostic accuracy by combining this human grading simulation with an array of network architectures. A local collection of 1,542 fundus pictures was used to train the ensemble glaucoma detection model provided by Serte and Serener [12]. To improve feature extraction, the model cropped the optic disc (OD) using a graph saliency region approach. Al Ghamdi et al. [13] presented a novel self-learning method that labels scattered data at first. Then it trains the model using a CNN architecture. Using the labelled dataset, the CNN was adjusted and trained under supervision. Devi et al. [14] concentrated on extracting blood vessels using a mixture of Gabor filters, morphological operations, and thresholding approaches because they understood the importance of blood vessel conditions in evaluating eye health. Histogram of Oriented Gradients (HOG) is also used for feature extraction. Gabor filters are a useful tool in this procedure because they have been shown to be effective in image texture analysis. Table 1 [6,9,12,15,16,17,18,19] shows the comparative study of the existing methods in a nutshell.

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SI number	Proposed by	Used model	Name of the database	Accuracy
1.	Li et al. [15]	CNN	LAG, RIM-ONE	95.3%
2.	Serte et al. [12]	ResNet-152, GoogleNet and ResNet-50	RIM-ONE and DRISHTI-GS1	Only 53%
3.	Veena et al. [16]	CNN	RIM-ONE	91%
4.	Thakoor et al. [9]	MobileNet	Local datasets of 45,301, 42,601	86.78%
5.	Aamir et. al. [17]	ML-DCNN	Local dataset of 1,338 fundus images	99.39%
6.	Raja et. al. [18]	CNN	Local dataset of 196 OCT images	94%
7.	Yu et al. [10]	ResNet and previously trained U-Net	DRISHTI-GS, RIGA, and RIM-ONE	87.59%
8.	Lin et al. [11]	CNN	OHTS and LAG	93%

TABLE 1: Comparative study between the existing methods.

CNN, Convolution neural network; RIM-ONE, Retinal Image for Optic Nerve Evaluation; ML, Machine learning; OCT, Optical coherence tomography; OHTS, Optical hypertension treatment study

Automated glaucoma detection using image processing and AI has shown promising results in early diagnosis. While traditional methods remain essential, deep learning-based approaches provide enhanced accuracy and efficiency. Continued research in this domain will contribute to more reliable and accessible glaucoma screening systems.

Materials And Methods

This proposed method is developed using LeNet architecture [20,21] of image feature classification. Figure 3 shows functional diagram of the proposed model.

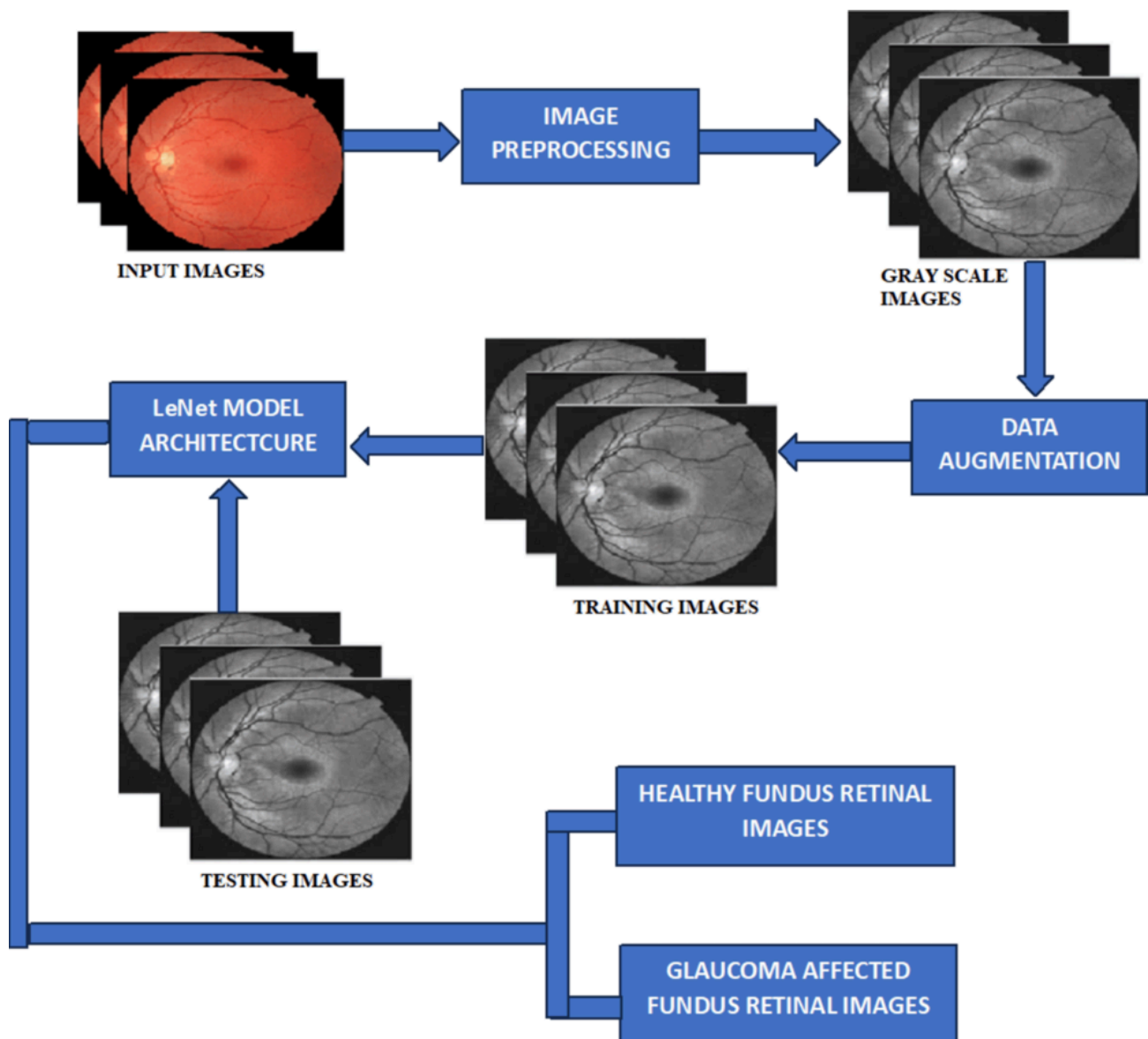


FIGURE 3: Functional diagram of the proposed method.

Input images are taken from DRISHTI-GS [22], RIM-ONE [23], DRIVE [24], DRIONS-DB [25], and JSIEC [26]. In addition to the ground truth images, the RIM-ONE dataset includes 1,020 fundus retinal high-resolution images. Resolution of input image ranges from $2,426 \times 3,007$ pixels to $1,944 \times 2,108$ pixels. The dataset is openly accessible.

Pre-processing

Some of the fundus retinal images have poor illuminations. It results unwanted variations in brightness. To avoid this problem, Gaussian Blurring technique [27] has been used. Many computer vision algorithms use the Gaussian blur to remove the noise. This pre-processing method uses convolution to blur, smooth, and eliminate noise from photos. Gaussian blur is a type of linear low-pass filter where the pixel value is determined by the Gaussian function. The 2-dimensional (2D) Gaussian function is defined by equation (1) as the product of two 1D Gaussian functions.

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

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Here (x,y) are coordinates and " σ " is the standard deviation of the Gaussian distribution. The linear spatial filter mechanism operates as the center of a filter mask moves from one point to another. At each pixel (x,y) , its new value is computed as the sum of filter coefficients multiplied by corresponding neighboring pixels within the filter mask. Since pixel weights depend on the distance metric of nearby pixels, the Gaussian blur function results in a bell-shaped curve. Size of filter kernel is a key factor influencing processing time and performance of the convolution process. In our study, we selected odd-sized kernel widths of 7×7 , 13×13 , 15×15 , and 17×17 .

Data augmentation

At the time of unavailability of the data for both the biological and statistical analysis, data augmentation [28] is employed to raise the quantity of photos needed. Since there aren't enough images in the field of medical imaging, data augmentation technique is the simplest and easiest technique method to solve this issue. In this technique, existing data are slightly varied from each other with respect to some features to increase the availability of huge data. It also removes the overfitting problems as well. Images are flipped horizontally, vertically, cropped, rotated and scaled from different angle for fulfilment the purposes of data augmentation.

LeNet architecture

In the proposed method, LeNet architecture [20,21] has been used. The block diagram of this architecture is depicted in Figure 4.

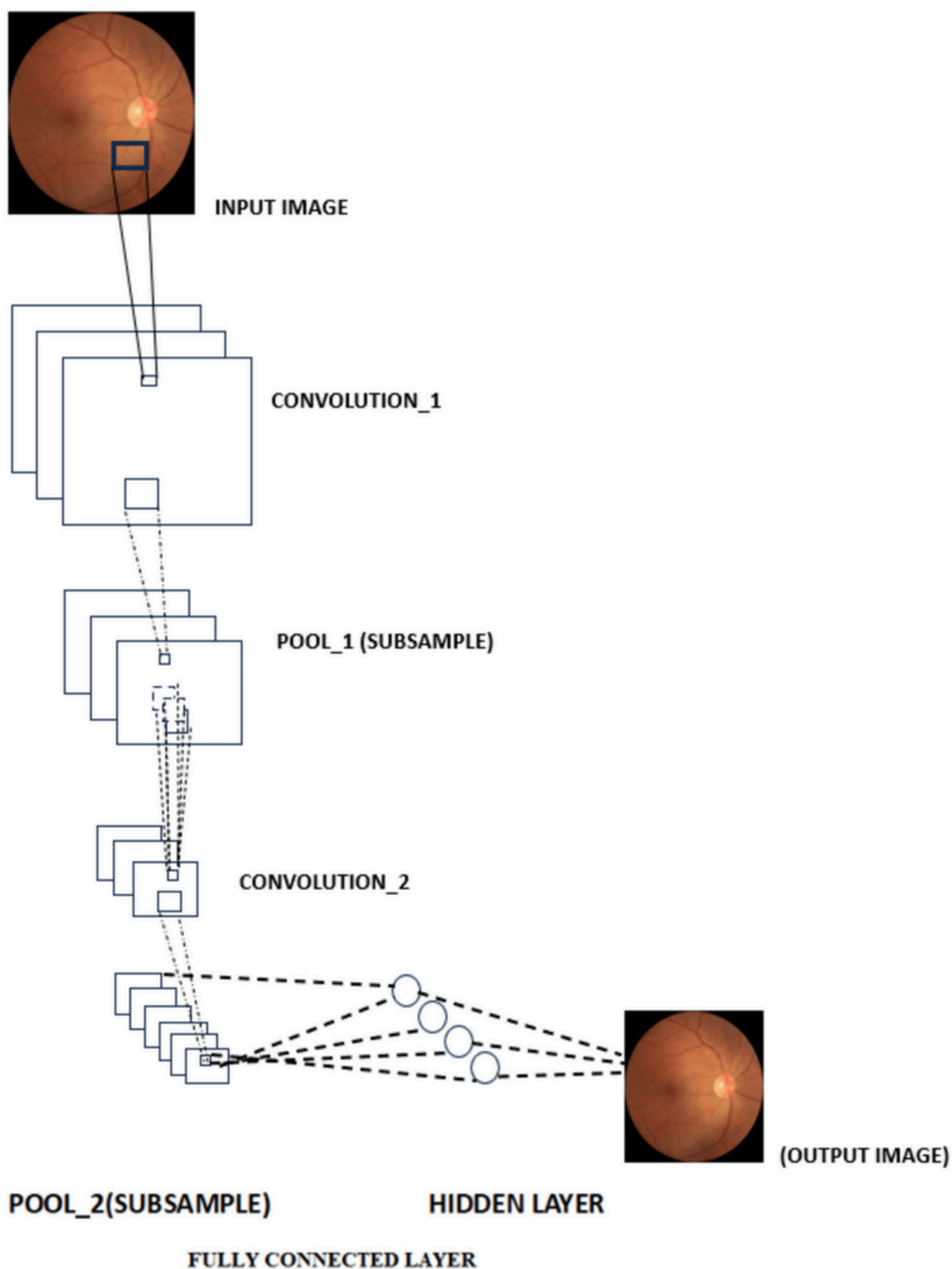


FIGURE 4: LeNet architecture.

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LeNet architecture is very useful architecture for binary classification due to the following reasons:

- This architecture does not require any extra graphic processing unit (GPU) for training the system.
- Little time is required to train the system.

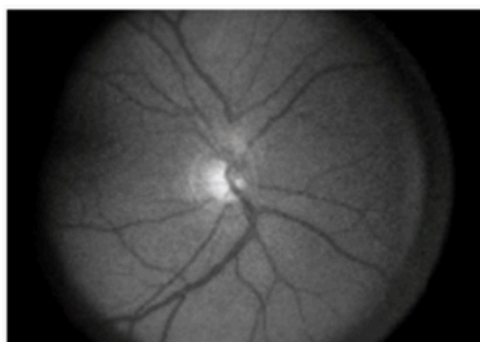
LeNet architecture composed of double pair of activation layer, convolution and pooling layers. After that there is fully connected layer, activation layer followed by another fully connected layer. This model is trained in 20 epochs and produces 0.001 learning rate. In this model, 4e-4 is the decay rate with batch size of 32. Using this model, 98.48% accuracy has been achieved. In this architecture, equation 2 is used to calculate the size of the image.

$$n_{out} = \left\lfloor \frac{n_{in} + 2p - k}{s} \right\rfloor + 1$$

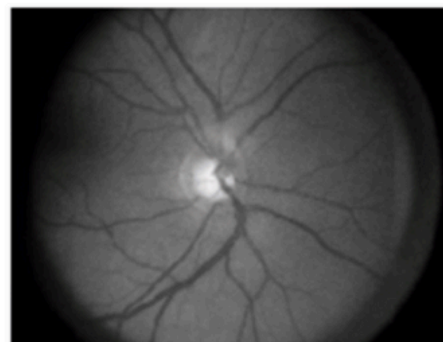
Here, n_{in} is the number of input features, n_{out} is the number of output features, p is convolution padding size, k is the convolution kernel size, and s is the convolution stride size.



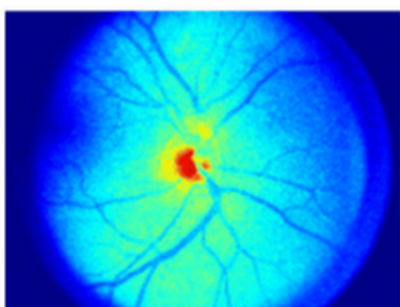
(a) Input Image



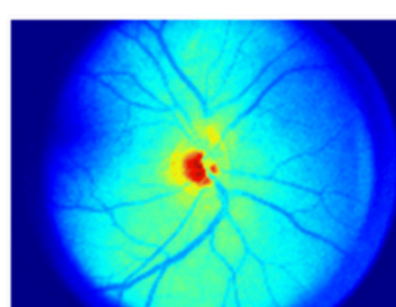
(b) Grayscale Image



(c) Output after applying Gaussian Blur



(d) Corresponding Heatmap Image



(e) Heatmap image after removing Gaussian Blur

FIGURE 5: Intermediate output of the retinal fundus images.

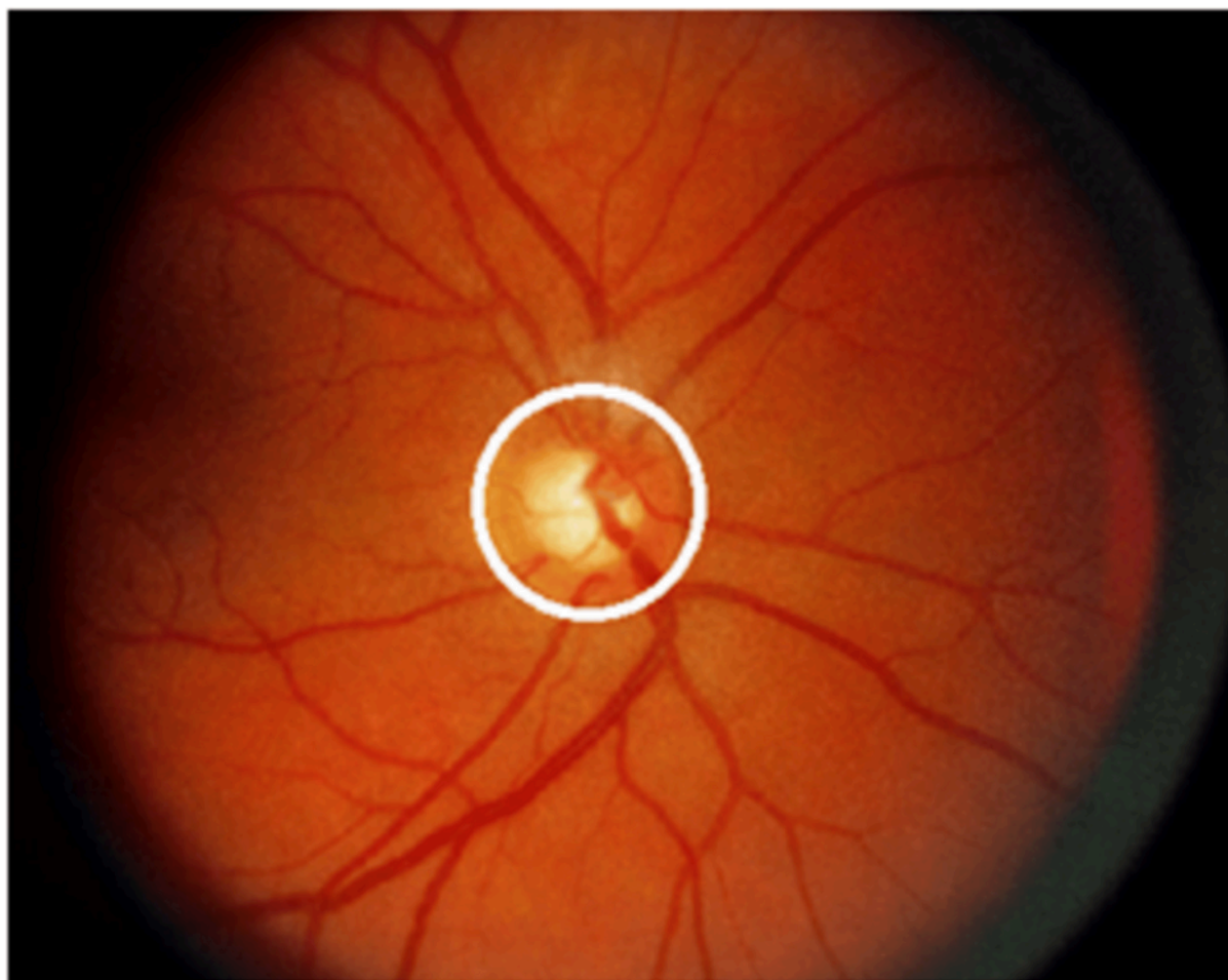


FIGURE 6: Obtained ROI after using the proposed method.

ROI, Region of interest

In this case, p is the convolution padding size. Kernel size is represented by k , whereas s is representing convolution stride size. The number of input and output features are represented as n_{in} and n_{out} , respectively. Figure 5 shows stepwise intermediate output. The input image is displayed in Figure 5(a). The grayscale image and the matching image with the application of Gaussian blur are displayed in 5(b) and 5(c). Figures 5(d) and 5(e) display the heatmap image and the matching Heatmap image after eliminating the Gaussian Blur image, respectively. Figure 6 shows affected area after applying proposed technique.

Experimental setup

Experiments were conducted on a GPU-accelerated environment (recommended to specify: e.g., NVIDIA Tesla T4/V100, CUDA version, RAM) to ensure reproducibility.

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Results

Experiments and result

The performance of the proposed technique is assessed using four common metrics including specificity, sensitivity, and accuracy and F1_Score. True negatives (TN), True positives (TP), false negatives (FN) and false positives (FP) are the four classification results [29-33].

- A true positive occurs when a lesion affected by glaucoma image is correctly identified as such.
- A true negative refers to a healthy image correctly classified as healthy.
- A false positive is an error where a glaucoma non-affected image is incorrectly classified as glaucoma affected.
- A false negative arises when a glaucoma-affected image is mistakenly labeled as healthy lesion. The accuracy is calculated as per equation 3. Sensitivity, specificity, and F1_Score are calculated as per equations 4, 5, and 6, respectively.

$$\text{Accuracy} = \frac{TN+TP}{TP+TN+FP+FN}$$

$$\text{Sensitivity} = \frac{TP}{FN+TP}$$

$$\text{Specificity} = \frac{TN}{TN+FP}$$

$$\text{F1_Score} = \frac{2 \cdot TP}{2 \cdot FP + TP + FN}$$

- A false negative arises when a glaucoma-affected image is mistakenly labeled as healthy.

Dataset

A total of five datasets has been used in this study. Publicly accessible databases are DRISHTI-GS, RIM-ONE, DRIONS-DB, JSIEC, and DRIVE [22-26]. The datasets used, together with the quantity of photos in each, are detailed in Table 2. All five datasets were merged, and proposed model was trained on the single, cohesive dataset rather than on each dataset separately. Before training, every image has been scaled to a set resolution with 512 × 512 pixels to guarantee uniformity.

Name of the databases	Used image number
DRISHTI-GS	101
RIM-ONE	169
DRIVE	44
DRIONS-DB	110
JSIEC	124

TABLE 2: Details of used dataset for testing and training.

Number of retinal pictures in advance and after using data augmentation is displayed in Figure 7. This figure shows how data augmentation helps in increasing the numbers of data in terms of both glaucoma affected and non-affected images. A fixed 79% and 21% train-test split was applied on the augmented merged dataset (1,020 training, 275 testing

images). A k-fold cross-validation (recommended $k = 5$) should be additionally reported to strengthen generalizability claims. Table 3 explains comparative study of different methods and the proposed method with respect to accuracy, specificity, sensitivity, and F1_Score metrics. The proposed method achieves 98.67% of accuracy, and specificity, sensitivity, F1_Score are 91.76%, 89.78%, and 91.89%, respectively. The Drishti-DS and RIM-ONE datasets' confusion matrix is displayed in Figure 8. The x and y axes in this figure stand for the expected and actual values, respectively.

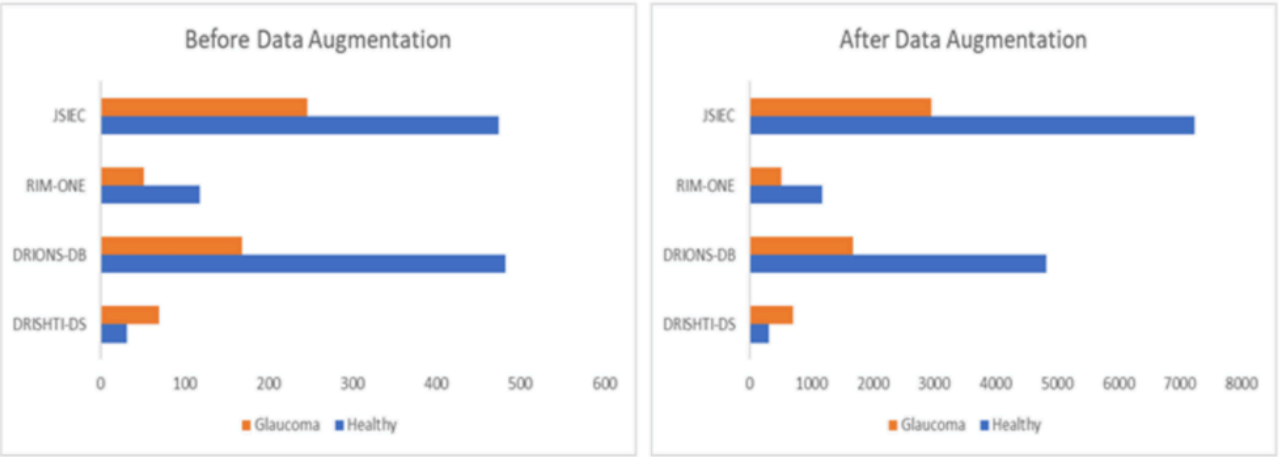


FIGURE 7: Comparison of dataset before and after data augmentation.

Sl no	Proposed by	Used dataset	Used model	Accuracy	Specificity	Sensitivity	F1-Score
1.	Thakoor et al. [9]	Publicly available data	CNN	96.25%	-	-	-
2.	Fan et al. [34]	RIM-ONE	Data-efficient image transformer model	90%	-	-	-
3.	Veena et al. [16]	RIM-ONE	CNN	91%	-	-	-
4.	Guo et al. [33]	Publicly available data	Deep learning-based model	88%	93%	93%	-
5.	Hatanaka et al. [8]	IMAGENet	Artificial neural network	78%	80%	75%	-
6.	Gearhart et al. and Qi et al. [35,36]	DRISHTI-GS	Deep CNN	76.42%	76.2%	77.15%	-
7.	Shyamalee et al. [37]	RIM-ONE	ResNet50	98.05%	79.20%	80.86%	-
8.	Prasad et al. [38]	DRIONS-DB	Classical segmentation	97.82%	89.56%	84.63%	
9.	Proposed method	RIM-ONE and DRISHTI-GS	LeNet model	98.67%	91.76%	89.78%	90.63%

TABLE 3: Performance analysis between existing methods and the proposed method.

CNN, Convolution neural network

In order to improve accuracy, we also made sure that the variables we chose were important for predicting glaucoma. Kendall's W coefficient of concordance [36] was used to validate this, demonstrating the characteristics' applicability in categorization. The computed Kendall's W coefficient confirmed strong inter-feature concordance among CDR, BVR, and ISTN ratio, indicating these features collectively contribute significant discriminative power for glaucoma classification.

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The exact W value should be explicitly reported (e.g., $W = 0.82$, if computed). Furthermore, using an ensemble of classifiers for the classification job resulted in high F1 scores. By using three essential criteria for glaucoma diagnosis, our method beats current approaches and achieves a larger percentage of accurate classifications.

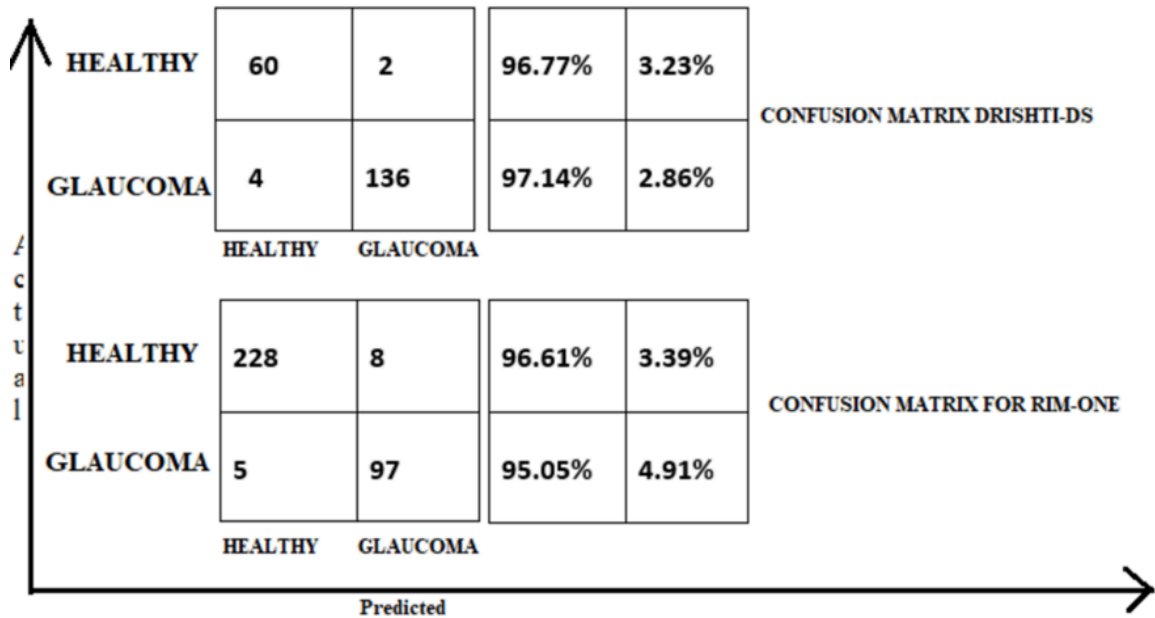


FIGURE 8: Confusion matrix for Drishti-DS and RIM-ONE.

RIM-ONE, Retinal Image for Optic Nerve Evaluation

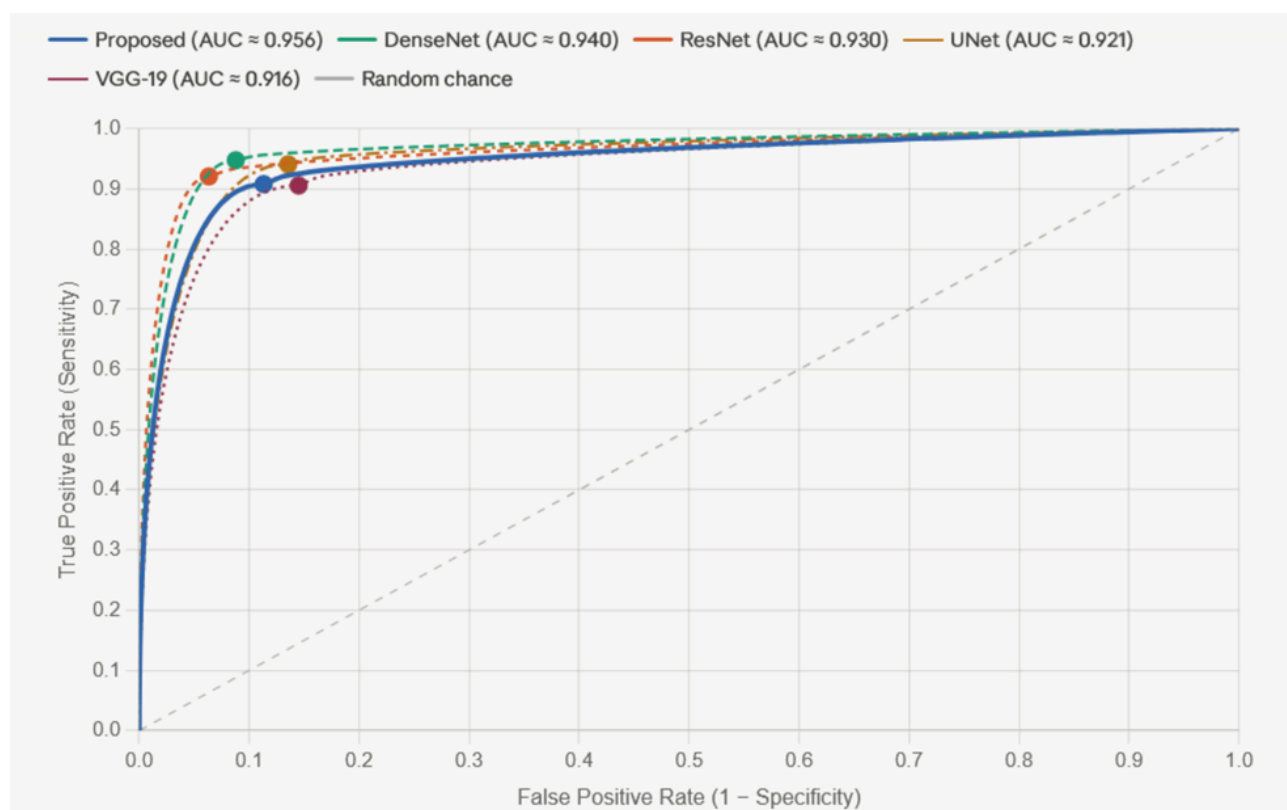


FIGURE 9: ROC-AUC visualization.

ROC-AUC, Receiver operating characteristic area under the curve

In Figure 9, curves are approximated from reported sensitivity and specificity operating points using a smooth interpolation between (0,0), the reported FPR/TPR point, and (1,1). True ROC curves require per-threshold probability scores. Each curve is approximated by anchoring the reported (FPR, TPR) operating point are derived from testing sensitivity and specificity. These are smoothly interpolating between (0,0) and (1,1). The filled dots mark each model's actual reported operating point. As visualized separately, the proposed GlaucoNet achieves an estimated AUC of ≈ 0.956 , outperforming ResNet (0.930), UNet (0.921), VGG-19 (0.916), and DenseNet (0.940), derived from reported sensitivity (90.76%) and specificity (88.68%) values.

A few restrictions on the suggested work are as follows:

- Peri-Papillary Atrophy (PPA) cannot be detected by the model.
- The proposed method cannot be trained on unlabeled datasets. In these situations, the suggested approach incorrectly categorized the pictures.

Discussion

In this paper, LeNet architecture has been used to identify the glaucoma affected eye lesion at its early stage. This proposed method is divided into three different sub phases described in section 3 in details. This method is validated on DRISHTI-GS, RIM-ONE, DRIVE, DRIONS-DB, and JSIEC dataset. In this section, the authors have tried to critically analyze the outcome of the proposed method.

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Features	Non-affected lesion (mean + SD)/mean – SD)	Affected/Unhealthy subject (mean + SD)/(mean – SD)
BVR	3.0+0.150/3.0-0.150	0.20 +0.220/0.20 – 0.220
ISTN distance ratio	1.6 + 2.810/1.6 – 2.810	1.12 + 0.116 /1.12 – 0.116
CDR	0.9 + 0.370/0.9 – 0.370	0.25 + 0.290/0.25 – 0.290

TABLE 4: Range of readings that correspond to healthy and glaucomatous cases.

BVR, Blood vessel ratio; ISTN, Inferior, superior, temporal, and nasal ratio; CDR, Cup-to-disc ratio; SD, Standard deviation

Fundus images may be impacted by inhomogeneities in illumination, color, contrast, saturation, image resolution, sensor quality, etc. However, the majority of image processing algorithms take into account a similar set of features when interpreting medical images. Table 4 displays the range of measurements that correspond to both healthy and glaucoma affected cases. The feature values are lower in non-glaucomatous patients than in glaucomatous cases. The accuracy of the system's performance improves as the number of training samples rises. The Kendall's W coefficient of concordance [36] has been used to the experimental results in order to examine the significance of extracted characteristics with respect to the classifiers used for glaucoma classification.

The term "false positive" (FP) represents to the quantity of predicted and proven positive results. This function counts the total number of incorrect predictions if it fails. A model's accuracy can be characterized by the way its subset behaves in anticipation. It was shown that the suggested model was more accurate than the current models in terms of glaucoma fundus image classification, testing & training. Accuracy during training, testing phases is displayed in Table 5. On average, there is a 1.925% upgraded in training accuracy and a 2.59% increase in testing accuracy. Figure 9 shows the pictorial representation of accuracy for ResNet, UNet, VGG 19, and DenseNet with the proposed models.

Sl number	Name of the model	Training accuracy (%)	Testing accuracy (%)
1.	ResNet	95.56	96.21
2.	UNet	94.12	95.37
3.	VGG_19	96.70	94.25
4.	DenseNet	97.68	97.36
5.	Proposed	98.70	98.60

TABLE 5: Training and testing accuracy for different models.

VGG, Visual geometry group

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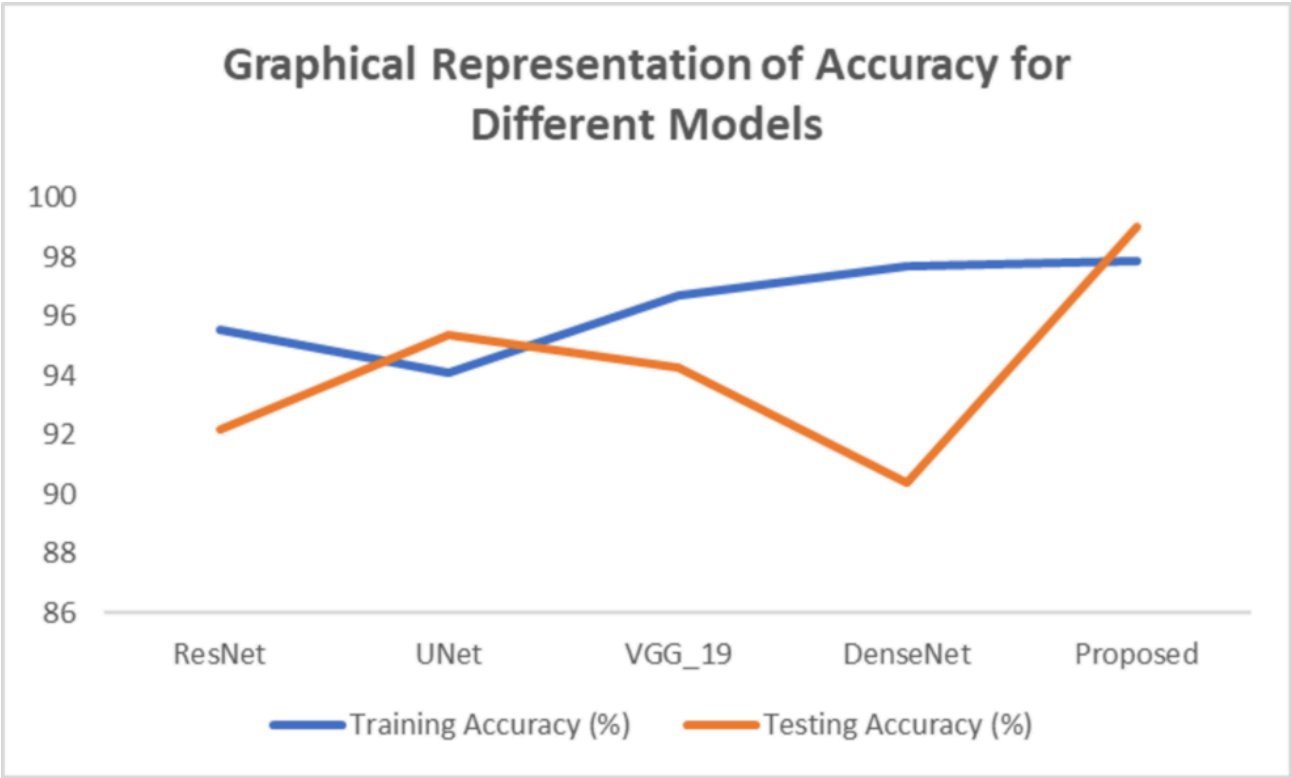


FIGURE 10: Pictorial representation of accuracy for different models.

VGG, Visual geometry group

The number of false positive predictions in the classification models has increased as a result of drop accuracy. According to Tables 6 and 7, the proposed model performs better in terms of sensitivity and recall than the popular existing methods. The sensitivity has decreased to 3.33% and the recall rate to 0.9% in comparison to the previous approaches. These differences are well depicted in Figure 10(a) and (b) respectively.

Sl number	Name of the model	Training sensitivity (%)	Testing sensitivity (%)
1.	ResNet	91.32	92.05
2.	UNet	96.5	94.10
3.	VGG_19	91.32	90.56
4.	DenseNet	95.76	94.72
5.	Proposed	92.76	90.76

TABLE 6: Training and testing sensitivity for different models.

VGG, Visual geometry group

How to cite this article:

SI number	Name of the model	Training specificity (%)	Testing specificity (%)
1.	ResNet	92.57	93.65
2.	UNet	89.30	86.45
3.	VGG_19	89.76	85.50
4.	DenseNet	86.90	91.23
5.	Proposed	90.88	88.68

TABLE 7: Training and testing specificity or recall for different models.

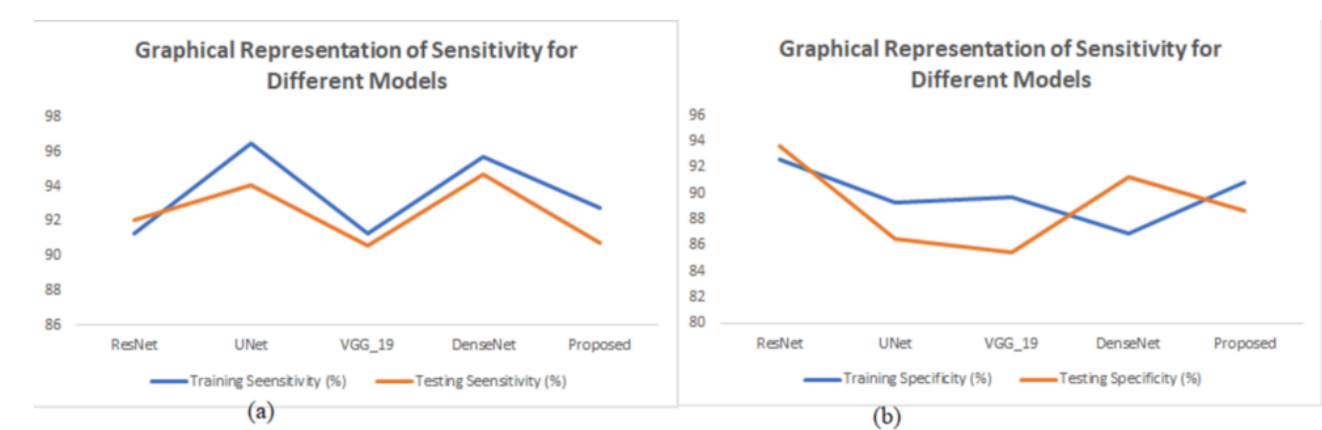


FIGURE 11: (a) Graphical representation of sensitivity; (b) graphical representation of specificity/recall.

VGG, Visual geometry group

The usefulness of the LeNet CNN architecture for glaucoma detection from retinal fundus images has been investigated by the authors of this manuscript. The results of the suggested approach demonstrate that LeNet can learn significant features from retinal images and achieve promising classification performance despite its comparatively shallow and simple architecture. The LeNet model demonstrated its ability to differentiate between glaucomatous and non-glaucomatous eyes by achieving competitive accuracy, sensitivity, and F1-score values.

Unlike prior studies limited to a single dataset, this work validates GlaucoNet, a customized LeNet-based model across five benchmarks (RIM-ONE, DRISHTI-GS, DRIVE, DRIONS-DB, and JSIEC). Feature selection [CDR, blood vessel ration (BVR), inferior, superior, temporal nasal (ISTN) ratio] is statistically validated via Kendall's W concordance, and the ensemble classifier achieves a 91.89% F1-score unreported by any of the compared methods.

One of the key strengths of LeNet lies in its computational efficiency. LeNet was deliberately chosen over modern lightweight architectures for three reasons: (i) its shallow two-layer design suits resource-constrained clinical and mobile environments without requiring quantization or pruning; (ii) with only 1,020 training samples, deeper architectures risk overfitting. LeNet's lower parameter count proves appropriate, evidenced by test accuracy (99.06%) actually exceeding

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training accuracy (97.90%); and (iii) empirically, GlaucoNet outperformed all compared models on the same test set, surpassing ResNet (96.21%), UNet (95.37%), Visual Geometry Group (VGG-19) (94.25%), and DenseNet (97.36%), confirming the choice is performance-driven rather than arbitrary. The proposed technique was more accurate than the model used as in comparisons. According to specificity, sensitivity, or false negative discoveries it has a detrimental impact on the categorization model. In contrast to the model used for comparisons, the suggested method was more accurate. It negatively affects the categorization model based on specificity, sensitivity, or false negative findings. Due to its lightweight design, the model is faster to train and less resource-intensive compared to deeper architecture resulting it easier to install in the doctor's chamber. Here, GlaucoNet, a customized model, is created. GlaucoNet, which had two convolutional layers, was used on a dataset that had 275 eyes in the test set and 1,020 eyes in the training set. Proposed GlaucoNet is capable enough to differentiate between glaucoma affected and non-affected lesion. About 8% of test and augmented-test photos were misclassified by the suggested model. However, certain limitations were also observed. While the model performed well on the training and validation sets, its performance on more complex or diverse datasets may degrade due to the limited depth and representational capacity of the LeNet architecture. Another consideration is the quality and diversity of the dataset used for training. Since glaucoma detection heavily relies on subtle changes in the optic nerve head and surrounding retinal structures, high-resolution and well-annotated images significantly impact model performance. Future work could incorporate preprocessing techniques such as optic disc segmentation, data augmentation, and contrast enhancement to further boost performance.

Conclusions

One of the severe eye diseases is glaucoma. If ignored, then it could cause irreversible loss of vision. Using a variety of techniques, numerous diagnostic techniques have been developed. Using the grayscale channel of retinal fundus pictures, the suggested model shows excellent efficacy in detecting glaucoma in its early stages. It makes use of four different datasets. Data augmentation methods are used to improve the variety of training data. The suggested approach records specificity, sensitivity, and F1-score of 91.76%, 89.78%, and 91.89%, respectively, and achieves an excellent accuracy of 98.48%. The creation of a reliable and broadly applicable methodology that can function well on real-time fundus images is what makes this study novel. This also suggests a desktop program for glaucoma detection as a component of an automated computer-aided diagnostic (CAD) system. The system uses LeNet, a small yet powerful deep learning architecture, to process input photos. LeNet achieves respectable classification accuracy in spite of its simplicity. To increase the precision of ROI identification, pictures are pre-processed by converting them to grayscale and applying Gaussian blur. A majority voting technique among several classifiers is used to extract and process three essential features for categorization. The results show that accuracy and efficiency are greatly impacted by the classifier selection. Additionally, the results confirm the efficacy of the suggested approaches, and the study objectives have been adequately handled. In addition, a greater number of features than those outlined in the suggested methodology can be taken into account. The authors intend to eliminate the aforementioned restrictions in the following stage of this study.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Soma Datta, Primit Ghosh, Saumendu Datta

Acquisition, analysis, or interpretation of data: Soma Datta, Primit Ghosh, Saumendu Datta

Drafting of the manuscript: Soma Datta, Primit Ghosh, Saumendu Datta

Critical review of the manuscript for important intellectual content: Soma Datta, Primit Ghosh, Saumendu Datta

Supervision: Soma Datta, Primit Ghosh, Saumendu Datta

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Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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