An Enhanced Pre-Processing Technique For Glaucoma Detection

1st Satrughan Kumar
Computer Science and Engineering
Sharda University
Greater Noida, U.P, India

2nd Arun Kumar
Computer Science and Engineering
Sharda University
Greater Noida, U.P, India

3rd Deepti Sahu
Computer Science and Engineering
Sharda University
Greater Noida, U.P, India

***Abstract*— Early diagnosis is critical in the case of glaucoma, a chronic disease that can lead to irreversible loss of vision. In the last few decades, retinal fundus imaging has been one of the key diagnostic tools for the examination of retinal conditions, including glaucoma. Due to the complex vascular pattern and structure of the retina, precise examination of such images is challenging. Application of image segmentation techniques to locate regions of interest in fundus images is often difficult. This research discusses a range of segmentation methods, focuses the ResNet, VGGNet and Inception V3 which are pre-trained model to evaluate accuracy. Evaluation metrics utilized to identify how effectively segmentation algorithms detect subtle structural changes related to glaucoma are also discussed. It also considers the use of deep learning techniques in optic disc and cup segmentation. Deep learning models usually work poorly on larger datasets, even though they work very accurately on small datasets. The study emphasizes the necessity for more advanced deep learning techniques and effective segmentation processes since it reveals that accurate segmentation of the optic disc (OD) and cup (OC) is still very difficult, particularly for large and complicated datasets.**

Keywords*— Deep learning, Segmentation, Preprocessing, Cup to disc ratio (CDR), fundus images, ResNet, VGGNet.

I. INTRODUCTION

Glaucoma is the second most common cause of visual loss after cataracts, and it constitutes a significant contributing factor to irreversible blindness worldwide. Progressive optic nerve injury is a hallmark of chronic eye conditions, which cause vision loss over time. The optic disc is altered by elevated intraocular pressure (IOP), which is frequently linked to glaucoma. These changes include weakening of the retinal nerve fiber layer and changes in the CDR. Glaucoma is expected to impact approximately 111.8 million individuals by 2040, highlighting the critical need for early detection and efficient management techniques [1].

POAG and PACG are the two primary categories into which glaucoma can be generally divided. Although the pathophysiological causes of the two kinds are different, they both harm the optic nerve. Whereas PACG is defined by an abrupt and severe increase in IOP because of the closing of the drainage angle in the eye, POAG is characterized by a progressive increase in IOP without any noticeable symptoms. If not identified and treated right away, either form can result in irreversible blindness [2].

As seen in Figure 1, the number of cases with glaucoma is expected to reach 243.4 million, based on statistics from 2016 to the present. In order to overcome these obstacles, scientists have created a number of automated techniques that increase early detection and boost diagnostic precision. To address the shortcomings of conventional glaucoma detection techniques, for example, J. Zhong and colleagues presented an Adaptive Feature-fusion Neural Network (AFNN) [3]. With an accuracy of 93.8% on a dataset of 1,120 fundus images, their AFNN combines domain adaptation, self-supervised, and feature-fusion multi-task learning to improve glaucoma segmentation. By using cutting-edge deep learning algorithms, this method addresses problems like domain gaps and feature inaccuracies and better manages the variability in the fundus images and feature extraction challenges [4].

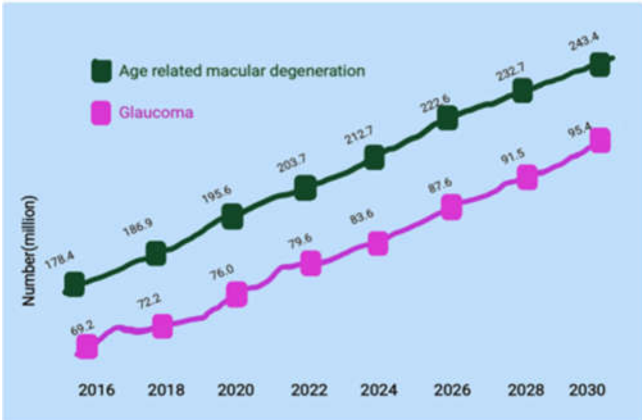

Fig. 1. Estimated global population affected by age-related macular degeneration and glaucoma

In the field of medical image analysis, deep learning has made tremendous strides in recent years. Guangmin et al. created ResFPN-Net, a CNN designed specifically for segmenting joint optic discs and cups. The multi-scale feature extraction and attention pyramid structure are used in their model to improve segmentation performance, and it obtained an outstanding 99% accuracy with a dataset of 260 images [5]. ResFPN-Net successfully collects detailed features and maintains edge information by integrating multi-scale loss supervision and attention processes. This overcomes the shortcomings of previous approaches that had trouble with correct segmentation because of single-scale processing and hand-crafted features. Table 1 shows the relationship between IOP and the drainage system of the eye [6].

TABLE 1. RELATION BETWEEN IOP AND EYE FLUID DRAINAGE SYSTEM

Luis Zhinin-Vera and Marlene S. Puchaicela-Lozano suggested a hybrid method for early glaucoma diagnosis that combines a region proposal network with ResNet-50. Using a dataset of 1,255 photos, their approach addressed issues like image quality and dataset imbalance, achieving 87% accuracy. Their method makes glaucoma detection more accessible and effective by utilizing deep learning techniques and sophisticated picture segmentation algorithms to increase diagnostic precision and automate the process [7].

Image segmentation algorithms are used to identify and emphasize areas of interest in these images in order to address this. Segmentation entails separating particular focus points or structures, including the OC and OP, which are essential for glaucoma diagnosis [8]. Through an analysis of numerous datasets and procedures, this paper offers a thorough evaluation of the different segmentation techniques used on fundus pictures. The following are the main contributions of this study:

1. The literature on image segmentation for glaucoma detection has been thoroughly examined, with an overview of the datasets, techniques, and assessment metrics employed in this are provided.

2. A broad comparison of different image segmentation techniques on a single dataset—an approach that hasn't been thoroughly examined in other studies.

The basic concepts discussed in this section include a summary of several image segmentation techniques and key terms related to fundus images and segmentation. Understanding these ideas is essential to understanding the rest of the work.

The optical disc (OD): The optic disc is the point where the retina and optic nerve converge. The visual information is transmitted from the eye to the brain through around 1.2 million tightly spaced nerve cells. As a result, there is a center depression and a little elevated area. The optic disc in a healthy eye is orange to pink in color and has a diameter of about 1.5 mm.

The optic cup (OC) is a depression in the centre of the optic disc that is formed by closely spaced nerve fibres entering the eye through a tiny aperture. The OC and OD in a normal eye are about one-third the size of each other. The OC appears small because the nerve cells surrounding the optic cup of a healthy eye are thick and closely packed; diseases like glaucoma damage these nerve cells, which causes the OC to enlarge.

Using equation (1) [9], the CDR is the ratio of the OC to OD sizes. An important diagnostic technique for glaucoma identification is a high CDR, which usually implies optic nerve damage. Figure 3 shows the OD and OC of humans.

The vessels in the retina: Retinal vessels are made up of the retina's closely spaced arteries and veins. In fundus imaging, these vessels are crucial for detecting glaucoma because they can display structural abnormalities like blood flow pattern changes, blockages, and vessel weakening.

II. Related Woks

A retinal fundus image shows many physiological components, but only a few are necessary for glaucoma diagnosis. Identification of these crucial areas is aided by retinal-fundus image segmentation. Segmentation for glaucoma diagnosis has historically employed methods such as region-based techniques, edge detection, and thresholding [10]. Despite their effectiveness, these techniques usually require adjustment and might not be able to cope with variations in lighting and image quality. In recent years, segmentation based on deep learning has gained popularity. CNN has proven to be remarkably accurate in distinguishing between the OD and OC in complex retinal images [11]. These algorithms significantly outperform traditional methods in spotting subtle patterns in large datasets. Additionally, hybrid approaches that combine the benefits of deep learning and traditional techniques have surfaced to increase segmentation accuracy [12].

Drainage	**Aqueous Humor production**		
		High	low
	High	No IOP	No IOP
	Low	IOP	No IOP

CNNs can accurately detect significant features once they have been trained on large datasets of annotated images. These networks use many convolutional layers to capture complex spatial correlations and visual changes, resulting in precise and reliable segmentation [13].

Using the DRISHTHI-GS dataset, Figure 5 shows the accuracy percentages of several segmentation methods used to divide the optic disc from 2018 to 2024 [14]. Because this dataset has a good mix of both benign and malignant data, researchers find it appealing [15]. Even while segmentation techniques are commonly utilized, they differ significantly in their performance. This study focuses on the distinct benefits of each method and how they could be applied to clinical and research settings for glaucoma diagnosis and monitoring [16-17].

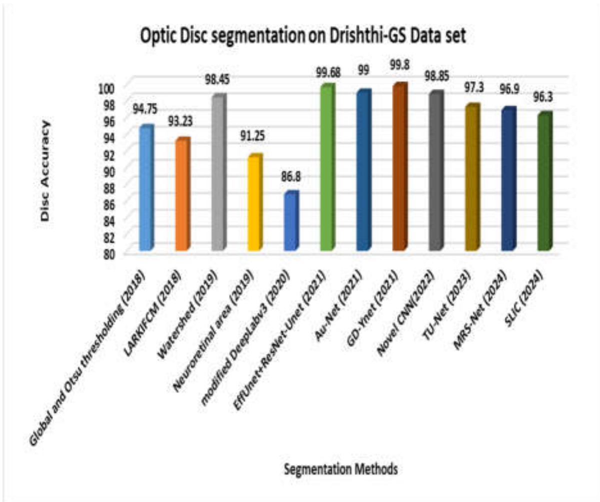

Fig. 2. Performance Analysis of Segmentation Approaches on DRISHTHI-GS Data set

This section discusses the many techniques used by researchers to separate the OD and OC [18]. Suggest for an adaptive feature-fusion Using a dataset of 1,120 fundus photos, a neural network segmented glaucoma with an astounding 93.8% accuracy. The domain gap between natural and medical images is addressed by their method by presenting supervised-learning multi-task learning, a feature-fusion network, and the domain adaptor. By using strategies like weighted-dice-loss and staged optimization, this method enhances segmentation performance, especially on the difficult optic-cup, and guarantees more reliable model generalization in low-data regimes [19]. Provide a study on glaucoma that addresses the disease's effects on vision by utilizing SVM and CNN methodologies. Their method uses a dataset of 400 photos and produces noteworthy results. The "silent thief of sight," glaucoma is characterized by high intraocular pressure (IOP) that destroys the optic nerve, resulting in visual loss [20].

A review of the literature on several segmentation-based methods is shown in Table 2.

TABLE 2. LITERATURE SURVEY OF VARIOUS SEGMENTATION BASED TECHNIQUES

	Title of Paper	**Referred Authors**	**Method used for segmentation**	**performance**	**Datasets**	**Features**	**Drawbacks**
1.	Adaptive feature fusion neural network for glaucoma segmentation on unseen fundus images [17]	J.Zhong, Hu ke, Year: - 2024	Adaptive feature fusion neural network (AFNN), Adaptive learning	93.8%	1120 images	Superior generalization performance	Large data requirement
2.	Diagnosing Glaucoma Using Fundus Images [18]	Mohabbat Ali, Imran Arshad, Muhammad Rehan Faheem. Year:- 2024	Convolution neural network	94.9%	400 images	Precise result compares to other methods	Overfitting issue
3	Machine learning classifiers for detection of glaucoma [19]	R.Verma , L.Shrinivasan , B. Hiremath. Year:- 2023	SVM, k-means classifier, Convolutional neural network	85.39%	100 images	Automatic feature detection	Limited performance on glaucoma images.
4.	Joint optic disc and cup segmentation based on multi-scale feature analysis and attention pyramid architecture for glaucoma screening [20]	G.Sun, Z. Zhang, J. Zhang. Year:- 2021	Deep learning	92.5%	260 images	More accuracy in depicting the edge information	Sometimes risk of misdetection
5.	Deep Learning for Glaucoma Detection: R-CNN ResNet-50 and Image Segmentation. [21]	M. S. Puchaicela-Lozano , Luis Z-Vera , A. J. A-Reyes. Year:- 2023	Convolutional neural network, Region proposal network	87%	1255 images	Deep Architecture	Overfitting
6.	Glaucoma detection, with improved deep learning model trained with optimal features [22]	R. Chandrasekaran, S. Krishna B V Year :- 2023	SVM, Weighted SVM, Reweighted SVM	92%	40 test images	Improved Segmentation Accuracy	Overfitting
7.	Fundus image classification methods for the detection of the glaucoma [23]	T. Saba,S.T.F. B., Muhammad Sharif Year :- 2018	UNet, Transfer Learning, Dense Connection	72.01%	1000 images	Improved Performance, Effective Feature Extraction	Dependency on pre trained model

III. METHODOLOGY

The enhanced preprocessing technique for glaucoma detection aims to standardize, enhance, and optimize eye images to make them suitable for machine learning models. This process involves several key stages: noise reduction, contrast enhancement, feature extraction, and normalization. The following steps outline the enhanced preprocessing pipeline are:

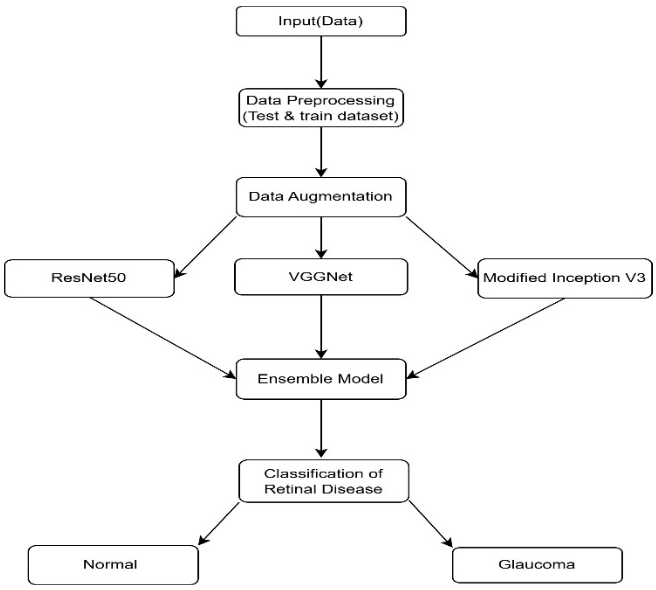

Fig. 3. Architecture of the proposed methodology

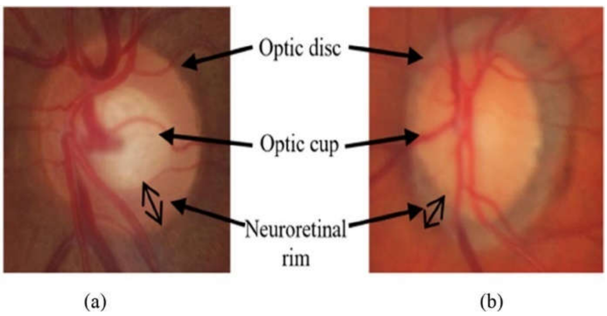

Fig. 4. (a) Normal and (b) Glaucoma eye images

1. Input Datasets:
   - Utilized four publicly available retinal fundus image datasets:
     - RIM-ONE
     - DRIONS-DB
     - DRISHTI-GS
2. Data Preprocessing and augmentation:
   There are several traditional pre-processing methods for medical photos. Contrast Limited Adaptive Histogram Equalization (CLAHE) and dilation were the two methods used in this proposed study. A morphological procedure called dilation is used to increase an image's brightness and size [23]. To improve image contrast and quality in the interim, CLAHE, a popular image processing technique, was used [26]. Deep learning (DL) models typically need a large amount of There are several traditional pre-processing methods for medical photos. Contrast Limited Adaptive Histogram Equalization (CLAHE) and dilation were the two methods used in this proposed study. A morphological procedure called dilation is used to increase an image's brightness and size. A substantial amount of data is typically needed for deep learning (DL) models to yield positive outcomes. Therefore, to address issues like overfitting and data imbalance, a reshaping-based data augmentation was used. Additionally, six data augmentation techniques were used in addition to the previously described methods to solve data imbalance and expand the dataset. Shearing (up to 0.2), zooming (up to 0.1), and rotation (up to 10 degrees) are some of these methods.
3. Model Training:
   - Trained three deep learning architectures with modifications:

Modified ResNet50:
In tasks like image identification and image localization, 50-layer Residual Networks (ResNet) have demonstrated impressive performance [24]. The vanishing gradient problem, which occurs when using a large number of layers, is the main issue that ResNet50 addresses. ResNet50 uses skip connections to address this problem, which allows it to save data from layers located earlier in the architecture. Adjustments were made to the pre-trained ResNet50 model in this study, starting with the final two layers, the dense layer and the softmax layer. A thick layer that is totally connected

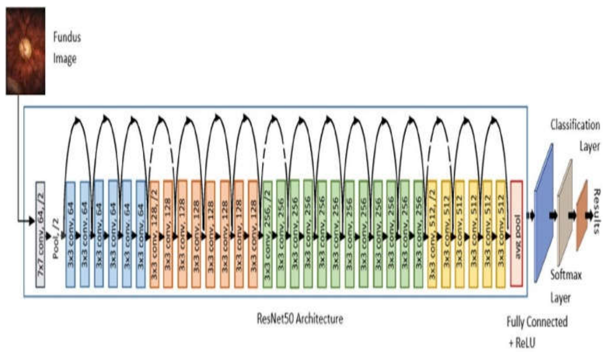

Fig. 5. Modified ResNet50 architecture

was added to the same pre-trained networks after the softmax layer with 256 units, taking the place of the fully linked layer. The outputs from this updated design indicate two classes: normal and glaucoma. The adapted ResNet50 architecture is shown graphically in Figure 5.

VGG-19 architecture:
VGG19, which has 19 layers in total, includes additional convolution layers in its final three blocks. By adding three

more layers following the global average pooling layer, we improved the pre-trained VGG19 model in this study. These extra layers consist of a dense layer with 256 units and a ReLU activation function, a dropout layer with a rate of 0.5, and finally a Softmax layer that generates two outputs. The structure of the updated VGG-19 design is illustrated visually in Figure 6.

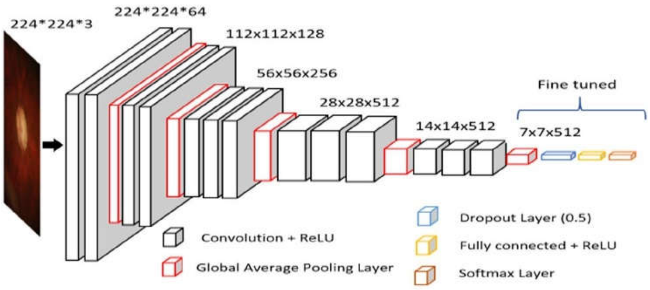

Fig. 6. Modified VGG 19 architecture [25]

Modified Inception V3:

The well-known CNN architecture Inception-v3, which debuted in 2015, has an amazing 48 layers of depth. With an accuracy rating of over 78.1%, this architecture is a well-known image recognition model. The Inception-v3 model used in this study was pre-trained using the Keras API as the fundamental CNN architecture, and it was trained on the ImageNet data-set, which has 1000 classes [26]. In this case, the top dense layers of the model are replaced with new layers. To reduce hyperparameters, a global average max pooling layer was introduced after the Inception-v3 model. The Softmax layer was then included after a dense layer of 512 units was added.
Two neurons, one for normal and one for glaucoma categories, made up the Softax layer. A dropout layer with a dropout rate of 0.7 was added to prevent model overfitting. Additionally, Inception-v3 has an auxiliary classifier designed to address the issue of disappearing gradients. The Adam optimizer, which uses a high learning rate, is used to train this model. Fig. 3 shows a graphic representation of the fine-tuned Inception-v3 architecture.

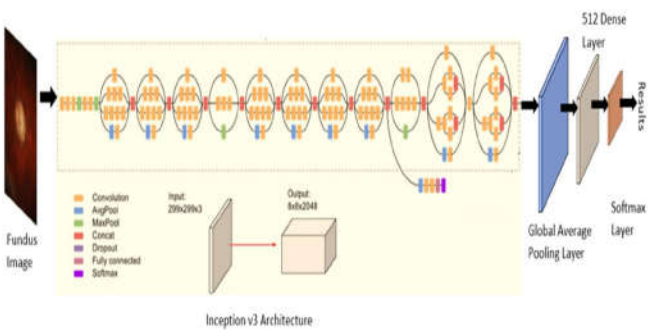

Fig. 7. Modified inception V3 architecture

3. Ensemble deep Learning Model:

The ensemble approach is a powerful and quick method that involves building several separate classification models and then combining their outputs to increase accuracy. Three different ConvNet architectures—ResNet50, InceptionV3, and VGGNet19—are used in this suggested study. They are all based on the Inception-v3 design. Furthermore, transfer learning is used, in which specific ConvNet attributes that have been pre-trained on the ImageNet dataset are transferred. As a result, the Con-vNet architecture can learn general features without requiring further training. Deep feature retrieval is made easier by the trained ConvNet architecture. In order to distinguish between normal and abnormal images, the final method channels ensemble properties through a classifier layer.

The steps in the suggested framework are as follows:

Step 1: Separate the input samples into training and testing data to start the model.
Step 2: The fundus picture undergoes image preprocessing. Enhancing particular characteristics, reducing distortions, and improving the overall image data are the goals of this procedure.
Step 3: After preprocessing, three distinct deep learning algorithms—VGGNet, ResNet50, and InceptionV3—are used to train the ImageNet.
Step 4: Extracting deep features from the three ConvNet architectures is the next step.
Step 5: A single prediction vector is created by combining the features that were retrieved from the three pretrained networks. For each input image, a majority vote system is used to determine the final class label. This ensemble approach may enhance overall classification performance by utilizing the diversity of the various models.
Step 6: The last stage involves classifying digital fundus images into two groups: normal and pathological (glaucoma).

Consequently, after applying the preset 70:15:15 split ratio and doing data augmentation, the RIM-ONE dataset's training set was enlarged to include 2034 fundus images, of which 720 were of glaucoma and 1314 were of normal fundus. Similarly, the training set of the DRION-DB dataset was expanded to 402 fundus images, which included 192 glaucoma images and 210 normal fundus images; the training set of the HRF dataset was expanded to 120 fundus images, which included 60 glaucoma images and 60 normal fundus images; and the training set of the DRISHTI-GS dataset was expanded to 480 fundus images, which included 228 glaucoma images and 252 normal fundus images. A total of 3036 fundus photos makes up the combined training dataset from all four datasets, which includes 1836 post-augmentation normal fundus images and 1200 glaucoma images.

IV. Results and Discussion

A machine with an i5-8th Gen processor, 64 GB of RAM, and an NVIDIA GeForce MX110 3 GB graphics card is used to create the suggested model using Python 3.10. Additionally, the Scikit-Image library's CLAHE implementation was utilized. Metrics such as accuracy, specificity, precision, sensitivity, and F1 score are analysed in order to assess each deep learning architecture's performance [29, 30, 31]. Equations (2) through (6) provide a mathematical expression for the performance measurements.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + F + FN} \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Specificity} = \frac{TN}{TN + FN} \quad (5)$$

$$\text{F1 Score} = \frac{2 * (Sensitivity * Precision)}{(Sensitivity + Precision)} \quad (6)$$

The number of correctly predicted glaucoma images is known as True Positive (TP), the number of correctly predicted normal images is known as True Negative (TN), and the number of glaucoma images that are wrongly predicted as normal images is known as False Negative (FN), and the number of normal images that are wrongly predicted as glaucoma images is known as False Positive (FP). With the ResNet-50, VGGNet-19, and InceptionV3 architectures, the resulting accuracy, precision, sensitivity, specificity, and F1 score are shown in Table 3. The RIM-ONE, DRISHTI-GS, DRIONS-DB, HRF, and combined datasets are the five distinct datasets used to analyze the results.
According to Table 3, the suggested ensemble model has a lower testing loss and a greater accuracy across all datasets. With careful hyper-parameter adjustment, this study's primary achievement is the classification of fundus images utilizing a range of deep learning architectures across five datasets. This work is unique in that it makes use of the dilation approach, which was frequently disregarded in earlier glaucoma classification studies. Furthermore, augmentation techniques, such as reshaping, were used to address class imbalance issues in the original datasets and prevent the model from overfitting. Figure 8 shows how the ensemble architecture's F1 score is represented across different datasets. With a higher value in terms of accuracy, specificity, sensitivity, precision, and F1 score, the data in Fig. 75.00 clearly show how well the suggested ensemble architecture performs when compared to ResNet-50, VGGNet-19, and Inception-v3.

TABLE 3. PERFORMANCE ANALYSIS OF BOTH INDIVIDUAL AS WELL AS COMBINED DATASET

Dataset	Technique used	Accuracy	Sensitivity	Specificity	Precision	F1 Score	AUG
RIM-ONE	Inception V3	95.56	98.31	93.51	97.22	97.76	0.98
	VGGNet	94.95	97.98	94.08	95.37	96.66	0.95
	ResNet	95.49	97.59	95.06	96.50	97.04	0.97
	Proposed Model	96.67	98.86	96.92	99.09	98.97	0.98
DRISHTI-GS	Inception V3	95.38	95.83	92.37	93.18	95.00	0.96
	VGGNet	91.64	94.76	94.83	94.84	95.30	0.93
	ResNet	94.83	96.28	94.13	95.34	95.81	0.95
	Proposed Model	97.71	97.80	98.02	97.37	97.58	0.97
DRIONS-DB(D2)	Inception V3	93.04	85.78	89.02	89.03	87.37	0.93
	VGGNet	91.08	83.37	94.20	87.06	85.69	0.91
	ResNet	93.06	84.03	92.07	91.65	87.67	0.93
	Proposed Model	97.22	94.92	97.44	93.33	94.12	0.95
HRF	Inception V3	96.38	94.76	94.67	95.94	95.35	0.95
	VGGNet	95.33	95.69	95.94	94.76	94.72	0.95
	ResNet	96.04	94.80	97.26	96.33	96.05	0.95
	Proposed Model	97.50	96.72	96.67	98.33	97.52	0.96
COMBINED	Inception V3	95.95	94.56	92.04	97.60	96.06	0.95
	VGGNet	95.75	94.67	92.73	90.38	93.42	0.94
	ResNet	96.40	94.23	92.58	93.13	93.68	0.93
	Proposed Model	98.58	98.80	98.17	98.86	98.83	0.98

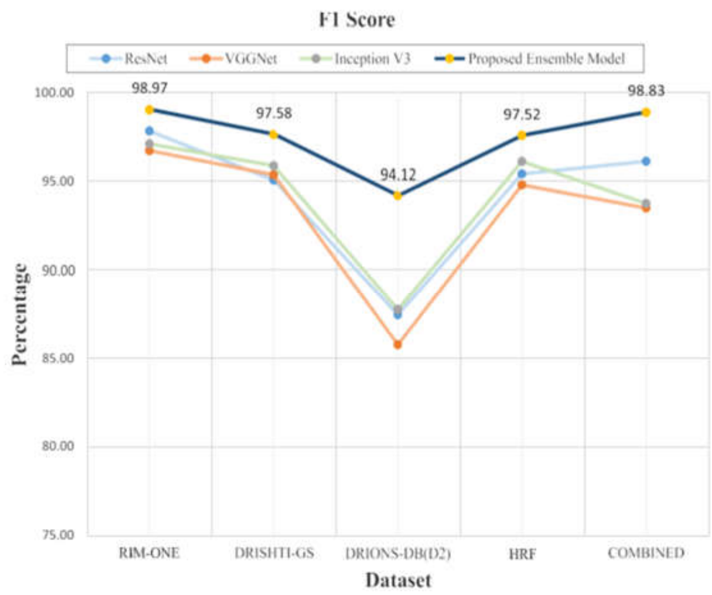

Fig. 8. Representation of F1 score for various deep learning architectures

V. CONCLUSION

In the project, the different segmentation methods for identifying the OD and OC in a retinal fundus image are thoroughly examined. It demonstrates how OS segmentation using the DRISHTHI-GS datasets has been the focus of most of the research, while optic cup segmentation has seen less work. The study highlights the need for more efficient approaches, even though deep learning-based techniques frequently produce amazing accuracy.

Computational methods for OS and OC segmentation, especially when dealing with complex datasets. Conventional deep learning techniques may not be as effective due to factors including uneven dataset sizes, poor illumination, contrast issues, and overall image quality. Data imbalance can potentially lead to problems with either too much or too little segmentation. To solve these issues, new techniques that can handle issues with contrast, size variations, and interference from other structures in retinal images are needed. Future research should focus on using large and complex datasets, improving segmentation techniques, and developing deep learning algorithms that can manage the many conditions found in retinal scans.

VI. FUTURE SCOPE

Future developments in deep learning, artificial intelligence, and multi-modal images bode well for picture segmentation for glaucoma-affected eyes. Synthetic As teleophthalmology permits remote-based diagnosis and real-time monitoring, intelligence-driven segmentation will be improved for early detection, individualized therapy, and progressive tracking. Deep learning methods including self-supervised learning, generative adversarial networks, and transformers will increase the accuracy of annotated datasets.

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