International Journal of Scientific Research and Engineering Development-– Volume 9 Issue 1, Jan-Feb 2026
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

An Advanced Deep Neural Network Model for Early Glaucoma Screening through Optic Nerve Head Segmentation and Quantitative CDR Analysis

P.Revathy [1], Dr. R. Jayaprakash[2]
[1]Research Scholar, Department of Computer Science, NGM College, Tamil Nadu, India
E-mail: reva7187@gmail.com
[2]Assistant Professor, Department of Computer Science, NGM College, Tamil Nadu, India.
E-mail:jayaprakash@ngmc.org

--************************--

Abstract:

Glaucoma is a progressive ocular disease and a major cause of irreversible blindness worldwide. Early detection is essential, as vision loss from glaucoma cannot be restored. Clinical diagnosis often relies on analyzing the optic nerve head, particularly the optic disc (OD) and optic cup (OC), and calculating the cup-to-disc ratio (CDR), a key biomarker for disease progression. Manual assessment of retinal fundus images is time-intensive, subjective, and dependent on expert availability, limiting its scalability for large-scale screening. This study proposes a deep learning-based automatic glaucoma detection framework using EfficientDet-D0 with an EfficientNet-B0 backbone. The model is designed to localize OD and OC boundaries with high precision, enabling accurate CDR estimation and subsequent glaucoma classification. EfficientDet's compound scaling ensures a balance between accuracy and computational efficiency, making the system suitable for real-world deployment, including telemedicine and portable diagnostic devices. Evaluations on publicly available fundus datasets demonstrate strong localization accuracy and competitive classification performance, with high sensitivity and specificity. The framework reduces reliance on manual interpretation, offering a scalable, objective, and efficient solution for glaucoma screening. By automating OD and OC detection and CDR computation, this approach contributes to timely diagnosis, improved accessibility, and the global effort to prevent glaucoma-related blindness.

Keywords: Optic disc (OD), Optic cup (OC), Cup-to-disc ratio (CDR), EfficientDet-D0 ,Object detection , Lesion localization, Computer-aided screening, Medical image analysis.

--************************--

I. Introduction

Glaucoma is a progressive eye disease that damages the optic nerve, primarily due to elevated intraocular pressure. This damage manifests as an enlargement of the optic cup relative to the optic disc, leading to an increased cup-to-disc ratio (CDR), which is a critical biomarker for early detection[4]. Identifying subtle changes in the optic nerve head is essential for timely screening, as untreated glaucoma results in irreversible vision loss. Traditional manual assessment of retinal fundus images is labor-intensive, subjective, and unsuitable for large-scale screening programs. To overcome these limitations, automated frameworks powered by deep learning have emerged, offering objective, scalable, and efficient detection of optic disc and cup boundaries. These systems enable accurate CDR estimation and glaucoma classification, reducing reliance on expert interpretation and improving accessibility to early diagnosis. By leveraging advanced neural architectures, automated detection not only enhances precision but also supports widespread screening initiatives, particularly in resource-constrained settings.[5] This technological shift represents a significant step toward combating glaucoma-related blindness by enabling timely, reliable, and cost-effective diagnostic solutions. Fig: 1 compares a normal eye with healthy pressure and optic nerve to an eye where fluid buildup increases internal pressure. Elevated pressure from blocked drainage (trabecular meshwork) can damage the optic nerve, leading to glaucoma. Fig:2 illustrates the anatomy of the human retina with a focus on the **optic disc** and **optic cup**, two key structures used in evaluating eye health. The **optic disc** is the circular region where the optic nerve connects to the retina, and the **optic cup** is the central depression within the disc. These features are clearly labeled and outlined, emphasizing their relevance in calculating the **cup-to-disc ratio (CDR)** a critical metric in diagnosing glaucoma. An enlarged optic cup relative to the disc often signals glaucomatous damage, making this visual representation valuable for clinical assessment and educational purposes.

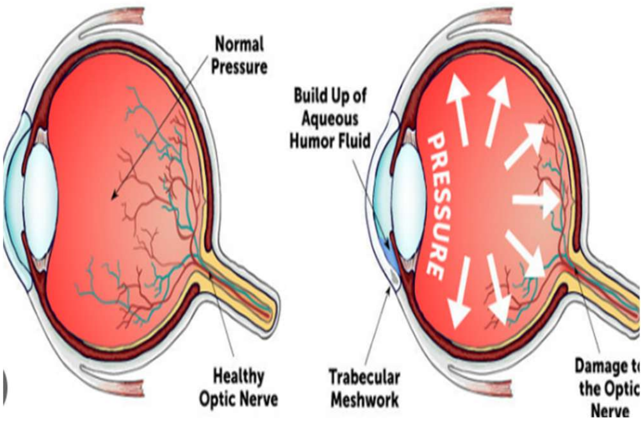

Fig: 1 Normal Eye & Glaucomatous Eye

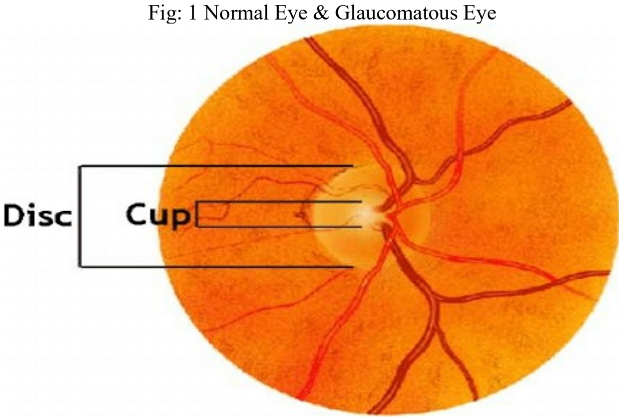

Fig:2 Optic Disc & Optic Cup

1.1 Clinical Significance of CDR

The **cup-to-disc ratio (CDR)** is one of the most critical structural parameters in glaucoma assessment because it reflects the balance between the optic cup (the central depression in the optic disc) and the neuroretinal rim, which contains the retinal ganglion cell axons. A normal CDR varies among individuals, but values above 0.6 or asymmetry greater than 0.2 between the two eyes often raise suspicion of glaucomatous damage. Elevated CDR indicates progressive thinning of the neuroretinal rim due to ganglion cell loss, which precedes measurable visual field defects. Clinically, this makes CDR a sensitive marker for early glaucoma detection, staging disease severity, and monitoring progression over time. Importantly, automated quantification of CDR from fundus images using computer vision and deep learning reduces subjectivity, minimizes inter-observer variability, and enables large-scale screening programs, especially in resource-limited settings[6]. This integration of morphological analysis with AI-driven tools enhances early diagnosis, supports risk stratification, and allows clinicians to intervene before irreversible vision loss occurs. In essence, CDR serves as a bridge between structural imaging and functional outcomes, making it indispensable in modern glaucoma care.

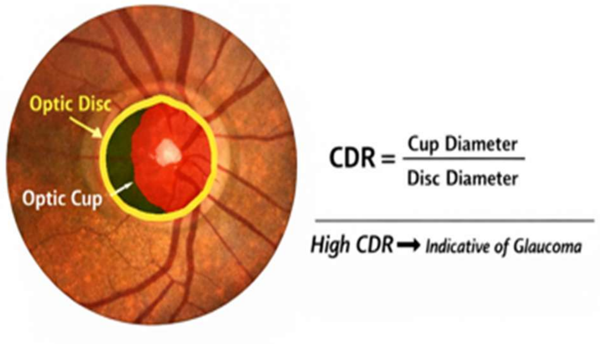

Fig:3 Representation of OD & OC

II. Literature Review

Automated glaucoma detection has evolved from heuristic and feature-based methods to advanced deep learning models. Early approaches relied on handcrafted features or traditional machine learning to segment OD and OC or compute CDR. However, these suffered from limited generalization and robustness across image variations. Recent work leverages convolutional neural networks (CNNs) and transformer-based architectures for joint segmentation and classification, improving both accuracy and robustness. Several deep learning frameworks segment the optic disc and cup to estimate CDR, showing strong potential for clinical screening once fully validated. [1] Nawaz et all in their work , demonstrates OD and OC localization with deep learning for glaucoma detection. [2] F. Li et al in their work highlights Efficient Net-based architectures for glaucoma detection. [3] H. N. Veena Chen, Y et all (2024) in their proposed work, explores segmentation of OD and OC using advanced CNN architectures.

III. Proposed Methodology

The overall system work flow of the proposed system

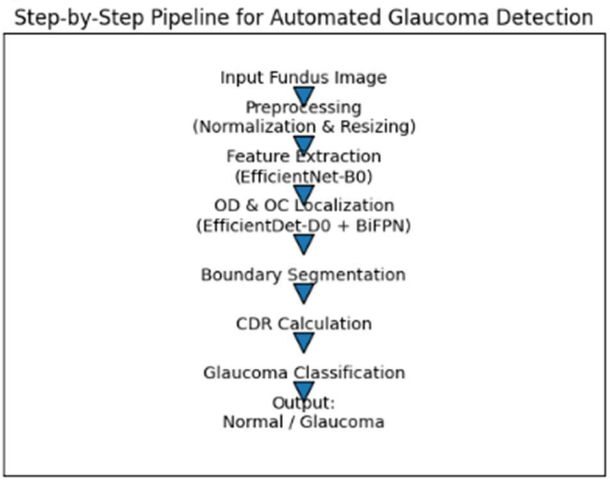

Fig:4 Step-by -step Pipeline

A. Input Fundus Image Acquisition

The process begins with acquiring **retinal fundus images** using fundus cameras. These images capture the posterior segment of the eye, including:

- Optic Disc (OD)
- Optic Cup (OC)
- Blood vessels
- Macula

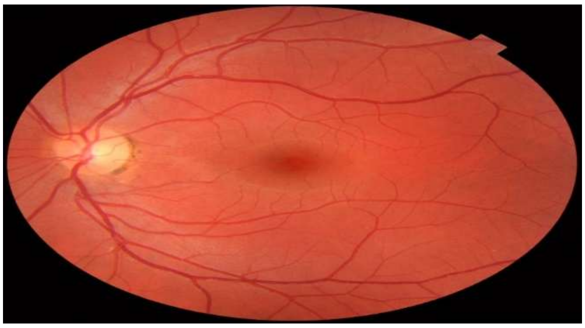

Fig:5 Normal adult Fundus

The system makes use of Public datasets

- DRISHTI-GS
- RIM-ONE
- REFUGE
- ORIGA

High-quality input images are crucial for precise localization and classification.

B. Preprocessing (Normalization & Resizing)

Preprocessing is a crucial stage in automated glaucoma detection, as retinal fundus images often vary in resolution, illumination, contrast, and noise levels. Initially, images are resized to a standardized dimension (e.g., 512×512 or 640×640) to ensure uniform input for deep learning models and reduce computational complexity. Intensity normalization techniques such as min–max scaling or z-score normalization are applied to standardize pixel distributions and stabilize model training[7][8]. To enhance the visibility of optic disc and optic cup boundaries, contrast enhancement methods like Contrast Limited Adaptive Histogram Equalization (CLAHE) are employed, improving local contrast without amplifying noise. Additionally, noise reduction techniques such as Gaussian or median filtering help remove acquisition artifacts while preserving important anatomical structures. Together, these preprocessing steps improve feature extraction, enhance localization accuracy, and ensure robust and reliable glaucoma detection performance.The main purpose is to

- Reduces illumination variations.
- Enhances OD/OC boundaries.
- Improves model convergence.

C.Feature Extraction (EfficientNet-B0 Backbone)

Feature extraction is a fundamental stage in the proposed glaucoma detection framework, where deep discriminative representations are learned from pre-processed retinal fundus images using the EfficientNet-B0 backbone. Instead of relying on handcrafted features, the convolutional neural network automatically captures hierarchical patterns ranging from low-level features such as edges, colour gradients, and vessel boundaries to high-level structural representations of the optic disc (OD), optic cup (OC), and surrounding neuroretinal rim. EfficientNet-B0 employs compound scaling, which systematically balances network depth, width, and resolution to achieve high accuracy with fewer parameters and reduced computational cost. Through stacked convolutional layers, batch normalization, and non-linear activation functions, the model generates multi-scale feature maps that encode texture variations, cup enlargement characteristics, vessel convergence patterns, and subtle morphological changes associated with glaucoma progression. These rich feature representations are then passed to the EfficientDet detection head, enabling precise localization of OD and OC regions and facilitating accurate cup-to-disc ratio estimation and subsequent classification.

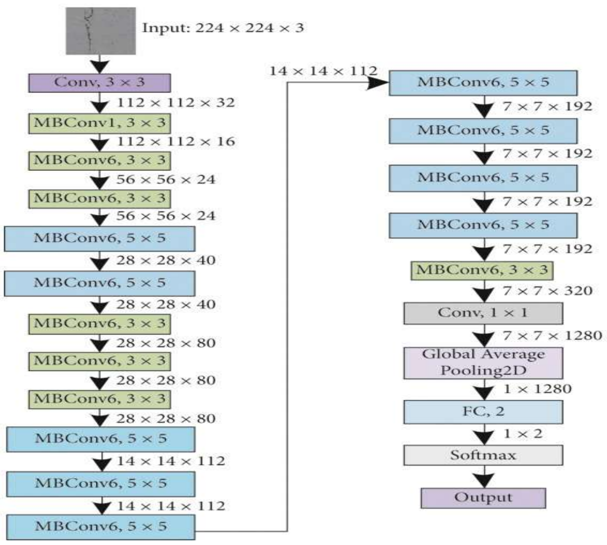

Fig:6 EfficientNet-B0 backbone Architecture Map

EfficientNet-B0 is chosen as the backbone architecture because it provides an optimal balance between accuracy, computational efficiency, and model complexity, making it highly suitable for medical image analysis tasks such as glaucoma detection. Unlike traditional convolutional neural networks that scale depth, width, or resolution independently, EfficientNet-B0 employs a compound scaling strategy that uniformly scales all three dimensions, resulting in better feature representation with fewer parameters. This leads to improved performance while maintaining low memory usage and faster inference speed, which is especially important for real-world deployment in telemedicine systems and portable diagnostic devices. Additionally, EfficientNet-B0 is pretrained on large-scale datasets, enabling effective transfer learning and faster convergence when fine-tuned on retinal fundus images. Its lightweight design ensures that the model can accurately capture subtle structural variations in the optic disc and optic cup without requiring extensive computational resources, making it an ideal backbone for efficient and scalable glaucoma screening systems.**Finally Extracted Features** Edge patterns ,Texture variations ,Structural boundaries of OD and OC, Vessel convergence near optic disc. These deep features are forwarded to the detection head.

D. OD & OC Localization (EfficientDet-D0 + BiFPN)

Optic Disc (OD) and Optic Cup (OC) localization is performed using EfficientDet-D0 integrated with a Bidirectional Feature Pyramid Network (BiFPN) to accurately detect and delineate these critical anatomical structures. EfficientDet-D0 is a lightweight yet powerful object detection model that leverages compound scaling to balance accuracy and computational efficiency, making it suitable for real-time medical applications. The EfficientNet-B0 backbone extracts rich feature maps, which are then refined through the BiFPN layer to enable effective multi-scale feature fusion. This is particularly important because the optic disc is relatively larger while the optic cup is smaller and requires finer detail recognition. The BiFPN enhances the model's ability to capture both high-level semantic information and low-level spatial details, improving detection precision. As a result, the system accurately predicts bounding boxes and confidence scores for OD and OC regions, providing reliable localization necessary for precise cup-to-disc ratio computation and subsequent glaucoma classification. This step ensures accurate spatial localization.

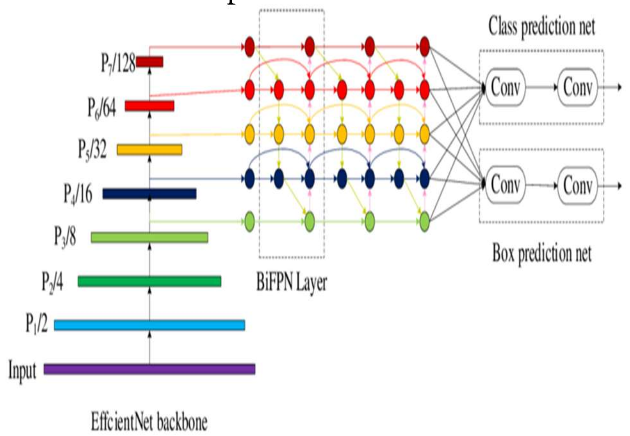

Fig: 7 Efficient net Architecture

E. Boundary Segmentation

After localization, precise segmentation refines the OD and OC boundaries. The following Techniques Used in boundary segmentation

- Mask prediction
- Pixel-wise classification
- Thresholding refinement

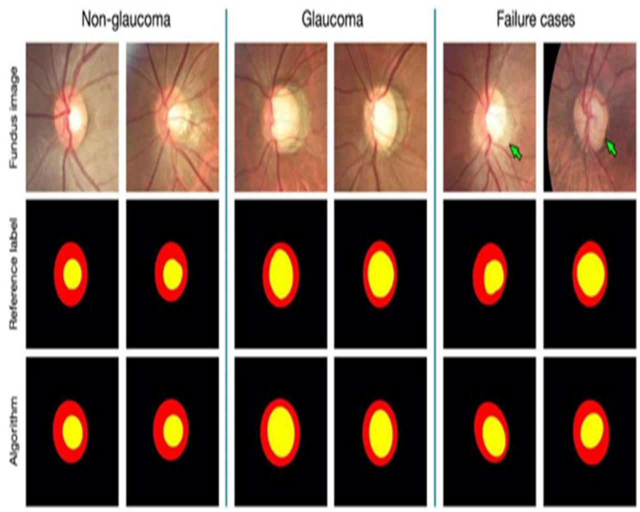

Fig:8 Visual comparison of ground truth and predicted optic disc–cup segmentations for non-glaucoma, glaucoma, and failure cases.

F. Cup-to-Disc Ratio (CDR) Calculation

CDR is calculated as:

CDR=Vertical Diameter of Cup/Vertical Diameter of Disc.

It is interpreted that if

CDR < 0.5 → Normal
CDR 0.5– 0.7 → Suspicious
CDR >0.7 → Glaucoma

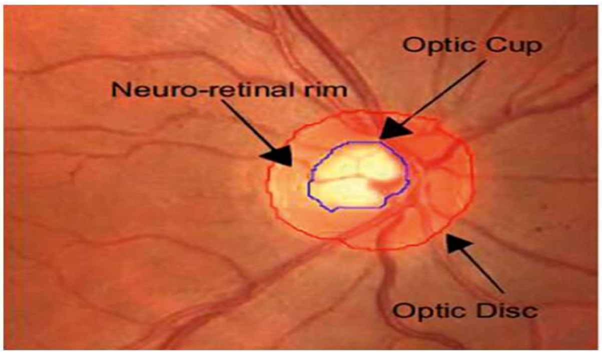

Fig:9 Demonstration of Identification of OC & OD

4. Evaluation and Results

A Datasets and Metrics

The model was evaluated on the *Online Retinal Fundus Image Database for Glaucoma Analysis (ORIGA)* and tested in cross-dataset settings with HRF and RIM-ONE DL datasets. Localization and classification were assessed using standard metrics such as *mean Average Precision (mAP)*, *Intersection over Union (IoU)*, accuracy, precision, and recall.

B. Performance Outcomes

- The framework achieved high localization accuracy with an average mAP of *0.971* and IoU of *0.981* on OD and OC detection.
- Classification accuracy reached *≈97.2%* on ORIGA.
- Cross-dataset evaluations demonstrated strong generalization.

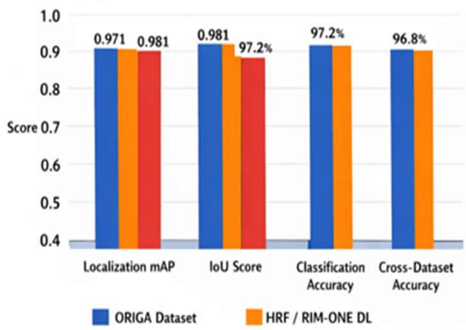

Fig:10 Performance outcome of Proposed system

These results underscore the model's capacity to reliably locate OD and OC regions — foundational to calculating measures like CDR.

5. Discussion

A. Advantages of the Deep Learning Approach

- **Robust Detection**: EfficientDet-D0 effectively handles variations in lesion size, color, and imaging artifacts.
- **Computational Efficiency**: Its one-stage design enhances speed without sacrificing accuracy.
- **Generalizability**: Cross-dataset performance indicates potential for real-world deployment.

B. Limitations and Future Work

While localization and classification are accurate, future work may integrate explicit CDR estimation and segmentation refinement. Real-world clinical validation and integration with screening workflows remain key next steps.

6. Conclusion

This study demonstrates a reliable deep learning framework for automatic glaucoma detection via OD and OC localization in retinal fundus images. The strong performance in identifying key optic nerve head structures underscores its utility for early glaucoma screening, with CDR estimation as a valuable extension.

References

[1]Nawaz, M. et al. *An Efficient Deep Learning Approach to Automatic Glaucoma Detection Using Optic Disc and Optic Cup Localization*, *Sensors*, 2022, 22(2):434. DOI:10.3390/s22020434.

[2]F Li et al., "Joint optic disc and cup segmentation based on multi-label deep network and polar transformation," *IEEE Transactions on Medical Imaging*, vol. 37, no. 7, pp. 1597–1605, Jul. 2018, doi: 10.1109/TMI.2018.2791488.

[3] H. N. Veena, A. Muruganandham, and T. Senthil Kumaran, *"A novel optic disc and optic cup segmentation technique to diagnose glaucoma using deep learning convolutional neural network over retinal fundus images," J. King Saud Univ. – Comput. Inf. Sci.*, vol. 34, no. 8, pp. 6187–6198, 2021.

[4]Automated vertical cup-to-disc ratio determination using deep learning, *PubMed*

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, 2016, doi: 10.1109/CVPR.2016.90.

[6] J. Orlando, E. Prokofyeva, and M. Blaschko, "A discriminatively trained fully connected conditional random field model for blood vessel segmentation in fundus images," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 1, pp. 16–27, Jan. 2017.

[7] H. R. Roth et al., "Deep learning and its application to medical image segmentation," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.

[8] Z. Chen et al., "Automatic optic disc and cup segmentation using deep learning for glaucoma detection," *Biomedical Signal Processing and Control*, vol. 55, p. 101566, 2020.

[9] M. Tan and Q. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," in *Proc. International Conference on Machine Learning (ICML)*, 2019, pp. 6105–6114.

[10]M. Tan, R. Pang, and Q. Le, "EfficientDet: Scalable and efficient object detection," in *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 10781–10790.

[11] J. Cheng et al., "Superpixel classification based optic disc and optic cup segmentation for glaucoma screening," *IEEE Transactions on Medical Imaging*, vol. 32, no. 6, pp. 1019–1032, Jun. 2013, doi: 10.1109/TMI.2013.2247770.

