iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: VI Month of publication: June 2026

DOI: https://doi.org/10.22214/ijraset.2026.83298

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

An AI-Based Framework for Glaucoma Diagnosis Using Deep Learning and Machine Learning Classifiers

Pedapalli Sobhitha[1], K. Santhi Sree[2]
[1]Post Graduate Student, M. Tech (Data Science), Department of Computer Science and Engineering, Jawaharlal Nehru Technological University, Hyderabad, India
[2]Professor, Department of Computer Science and Engineering, Jawaharlal Nehru Technological University, Hyderabad, India

***Abstract:** Glaucoma is an ocular neuropathy that progresses over time and causes blindness worldwide. Early and accurate identification is crucial to preventing vision loss, but manually evaluating retinal fundus images takes a lot of time and is unreliable. This work uses retinal fundus images to automatically identify and assess the risk of glaucoma using deep learning and machine learning techniques. The suggested approach incorporates a hybrid convolutional neural network that combines DenseNet121 and EfficientNetB3 for reliable feature extraction and preliminary classification, followed by LightGBM for precise and final classification. The optic disc and optic cup are segmented using a U-Net-based segmentation algorithm to improve clinical relevance. This allows for the calculation of the Cup-to-Disc Ratio (CDR), which is essential for glaucoma diagnosis. To create an enhanced feature representation, the deep learning features are combined with the calculated CDR value. A LightGBM classifier is then used to process the representation in order to make the final choice. Standard performance indicators such as Accuracy, Precision, Recall, F1-Score, AUC-ROC, Specificity, and Cohen's Kappa coefficient are used to assess the model. According to experimental findings, the suggested hybrid architecture improves classification robustness and diagnostic reliability compared to standalone approaches. The created system offers an automated glaucoma screening and decision support solution that is both scalable and clinically interpretable.*
***Keywords:** Deep Learning, Machine Learning, U-Net Segmentation, Cup-to-Disc Ratio (CDR), EfficientNetB3, DenseNet121, LightGBM, Retinal Fundus Imaging, and Glaucoma Detection.*

I. INTRODUCTION

A degenerative eye condition called glaucoma gradually harms the optic nerve and, if not treated, may eventually result in severe blindness. Because of its quick rise and lack of obvious signs in the early stages, many patients remain undiagnosed until significant visual impairment occurs. Consequently, timely screening and accurate diagnostic support systems are essential to reduce the global burden of glaucoma-related blindness. Retinal fundus imaging is widely used in ophthalmology to assess structural abnormalities between the optic disc and optic cup. Changes in the appearance of these regions are strong indicators of glaucoma progression. In particular, the Cup-to-Disc Ratio (CDR) is a crucial clinical parameter in evaluating optic nerve damage. However, manual examination of fundus images requires experienced ophthalmologists and may be influenced by subjective interpretation.

As artificial intelligence has developed, computerised image processing methods have become increasingly effective instruments for medical diagnosis. The ability of deep learning models, particularly convolutional neural networks, to extract significant features from intricate medical images has proven to be very strong. Nevertheless, relying solely on deep learning predictions may limit interpretability and overlook clinically significant anatomical indicators. This research introduces a multi-stage hybrid framework that integrates deep feature extraction, anatomical segmentation, clinical biomarker computation, and machine learning-based refinement into a unified diagnostic system. By combining semantic image features with structural measurements such as CDR, the proposed approach aims to enhance both diagnostic accuracy and clinical relevance in automated glaucoma screening.

A. Motivation of the study

The progressive optic neuropathy known as glaucoma is a leading cause of irreversible blindness, especially in its early stages when it is unnoticed. Although prompt detection is essential, traditional diagnosis mostly depends on skilled interpretation of retinal fundus images and structural measurements, which can be subjective and resource-intensive. Limited access to specialized ophthalmic care further restricts large-scale screening, especially in rural and underserved regions.

While deep learning approaches have demonstrated encouraging outcomes in the processing of medical images, many existing models focus solely on classification or segmentation without integrating clinically meaningful biomarkers. This project is motivated by the need to develop a robust, interpretable, and automated glaucoma detection framework that combines deep feature extraction with anatomical assessment. The proposed hybrid approach aims to enhance diagnostic accuracy while supporting scalable and practical screening solutions.

B. Objective

The primary goal of this research is to use retinal fundus images to create an automated and comprehensible glaucoma detection system.

The specific objectives are:

- To design a hybrid deep learning classification model that integrates EfficientNetB3 and DenseNet121 for enhanced feature extraction.
- To accurately define the regions of the optic disc and optic cup using a segmentation model based on U-Net.
- The Cup-to-Disc Ratio (CDR), a structural biomarker for glaucoma evaluation, is calculated using segmented outputs.
- To combine deep learning features with the computed CDR value through feature fusion.
- To employ a LightGBM-based machine learning classifier for final decision refinement.
- To evaluate system performance using multiple statistical metrics such as Accuracy, Precision, Recall, F1-Score, AUC-ROC, Specificity, and Cohen’s Kappa.
- To develop a deployable interface for automated screening and risk assessment.

C. Problem Statement

Although various automated glaucoma detection methods have been proposed, several challenges remain unresolved. Traditional screening depends heavily on expert evaluation, which is time-consuming and may not be scalable for large populations. Furthermore, standalone deep learning models focus primarily on image-level classification and may not explicitly incorporate clinically meaningful anatomical features. Another limitation lies in the lack of integration between segmentation-based structural analysis and classification-based decision systems. Many existing approaches either perform classification without anatomical interpretation or compute clinical parameters without leveraging deep feature representations.

Therefore, there is a need to design a comprehensive and interpretable framework that:

- Accurately classifies retinal fundus images,
- Extracts structural information from optic disc and cup regions,
- Incorporates clinically relevant measurements into the process of making decisions.

II. LITERATURE REVIEW

The use of artificial intelligence (AI) in the diagnosis of ocular diseases, especially glaucoma and diabetic retinopathy, has grown. A thorough analysis of deep learning (DL) and machine learning (ML) methods for automated retinal disease identification was provided by Grover and Kapoor [1]. Their a structured diagnostic pipeline that includes picture acquisition, preprocessing, augmentation, feature extraction, and classification is highlighted in the paper. Because they can automatically extract complicated information from fundus images, Convolutional Neural Networks (CNNs) were found to be dominating models. Evaluation metrics like accuracy, AUC, F1-score, and dice coefficient for segmentation tasks are also highlighted in the paper. The scientists did, however, note certain difficulties, such as dataset imbalance, imaging instrument variability, and ethical issues with patient data privacy.

Additionally, comparative experimental tests have shown that deep learning is better to conventional machine learning methods. 216 retinal fundus images were used in a controlled experimental investigation by Umashree and Narendran [2], who split the dataset into 80% training and 20% testing samples. With a mean accuracy of 87.37%, their suggested

CNN model outperformed the K-Nearest Neighbour (KNN) classifier, which came in at 72.28%. Despite the fact that the results confirm the efficacy of deep learning architectures, the study is constrained by a small dataset and limited algorithm comparison. Hybrid strategies that combine transfer learning and traditional machine learning models have been investigated in healthcare settings with limited resources. A pre-trained VGG16 model was used by Ba et al. [3] to extract features, and Principal Component Analysis (PCA) was used to reduce dimensionality. Support Vector Machine (SVM), Decision Tree, and KNN classifiers were used to classify the reduced features.

According to their results, SVM performed best, particularly after utilising GridSearchCV for hyperparameter optimisation. Although the paper shows that merging transfer learning with conventional classifiers is feasible, it only briefly discusses anatomical interpretability and does not completely utilise end-to-end deep learning systems.

Barros et al.'s systematic review [4] examined classification-based machine learning techniques for glaucoma detection that were published between 2014 and 2019. The review divides methods into two categories: deep CNN-based techniques and conventional featureengineering-based models. The authors came to the conclusion that deep learning approaches work well but need a lot of processing power and large annotated datasets. The review did not include segmentation-based optic disc approaches, which may have limited its comprehensiveness, even though transfer learning and data augmentation were found to be useful strategies to optimise training. A comprehensive overview of AI-driven glaucoma diagnosis utilising a variety of imaging modalities, such as fundus pictures, OCT, and visual field data, was recently presented by Ashtari-Majlan et al. [5]. CNNs, attention networks, autoencoders, generative adversarial networks, and geometric deep learning models are only a few of the architectural paradigms covered in the survey. The authors highlighted several important issues, such as the variety of datasets, the difficulty of early-stage detection, the interpretability of the model, and real-world clinical integration. Although the survey summarises the latest developments, it draws attention to the lack of consistent experimental validation amongst studies.

It is clear from the reviewed research that segmentation-based techniques improve anatomical interpretability, while deep learning-based classification models offer good predictive performance. Nevertheless, few research combine gradient-boosting classifiers, hybrid CNN architectures, and optic disc and cup segmentation for CDR computation in a single multi-stage framework. In order to fill this research gap, the suggested work combines clinically relevant anatomical indicators with deep semantic characteristics and uses an ensemble machine learning approach to refine predictions.

III. METHODOLOGY

The proposed framework consists of three major stages:

1) Stage 1: Hybrid CNN-Based Classification

In the first stage, To perform preliminary glaucoma classification and extract high-level information from retinal fundus images, a hybrid convolutional neural network architecture is utilised.

This stage combines two advanced deep learning architectures:

- EfficientNetB3
- DenseNet121

For effective feature learning, EfficientNetB3 is renowned for its optimised scaling technique, which strikes a balance between network depth, width, and resolution. DenseNet121, on the other hand, facilitates improved feature propagation and mitigates vanishing gradient problems through dense connectivity between layers. By combining these two architectures, the system benefits from:

- Complementary feature extraction capabilities
- Enhanced representation diversity
- Improved learning of complex retinal patterns
- Reduced risk of missing subtle pathological indicators

The features extracted from both networks are fused to create a comprehensive deep feature representtation. This step generates a preliminary forecast that indicates if the input image is glaucomatous or not.

2) Stage 2: U-Net Based Segmentation

While classification provides image-level prediction, it does not explicitly analyze anatomical structures. Therefore, the second stage introduces a U-Net-based segmentation module to improve clinical inter- pretability. With its encoder–decoder structure and skip links, the U-Net architecture was created es- pecially for medical picture segmentation. It enables precise localization of anatomical regions while preserving contextual information. In this stage: · The optic disc area is divided into segments. · The optic cup area is divided into segments. · The Cup-to-Disc Ratio (CDR) is calculated automatically. This stage enhances the system by:

- Providing structural understanding of the disease
- Improving transparency of predictions
- Supporting ophthalmologists with interpretable measurements
- Reducing dependence on subjective manual estimation

Thus, segmentation ensures that the system does not operate as a purely black-box classifier but incor- porates clinically meaningful parameters.

3) Stage 3: Hybrid Feature Fusion with Machine Learning Refinement

The third stage integrates through feature fusion and decision refinement, the advantages of both deep learning and conventional machine learning. In this stage: The hybrid CNN is used to extract deep feature vectors.

- The computed CDR value is appended to the deep feature representation.
- The combined feature vector is normalized using a StandardScaler.
- A LightGBM classifier is applied for final prediction.

The gradient boosting framework LightGBM is renowned for its effectiveness, speed, and strong general- ization capability. By applying LightGBM on the fused feature set, the system:

- Reduces classification bias
- Improves robustness
- Enhances generalization to unseen data

This final refinement stage ensures that both semantic image features and anatomical biomarkers con- tribute to the diagnostic decision.

4) Deployment-Ready Framework

The model is implemented using Streamlit, enabling practical deployment through a user interface. This facilitates uploading an image, prediction generation, and risk assessment visualization.

5) System Architecture

The proposed architecture follows a multi-stage hybrid approach where retinal images are processed through deep feature extraction, anatomical segmentation, and machine learning-based refinement. The hybrid CNN models extract semantic features, U-Net performs optic disc and cup segmentation to compute CDR, and LightGBM integrates both semantic and anatomical features to generate the final glau- coma diagnosis and risk assessment.

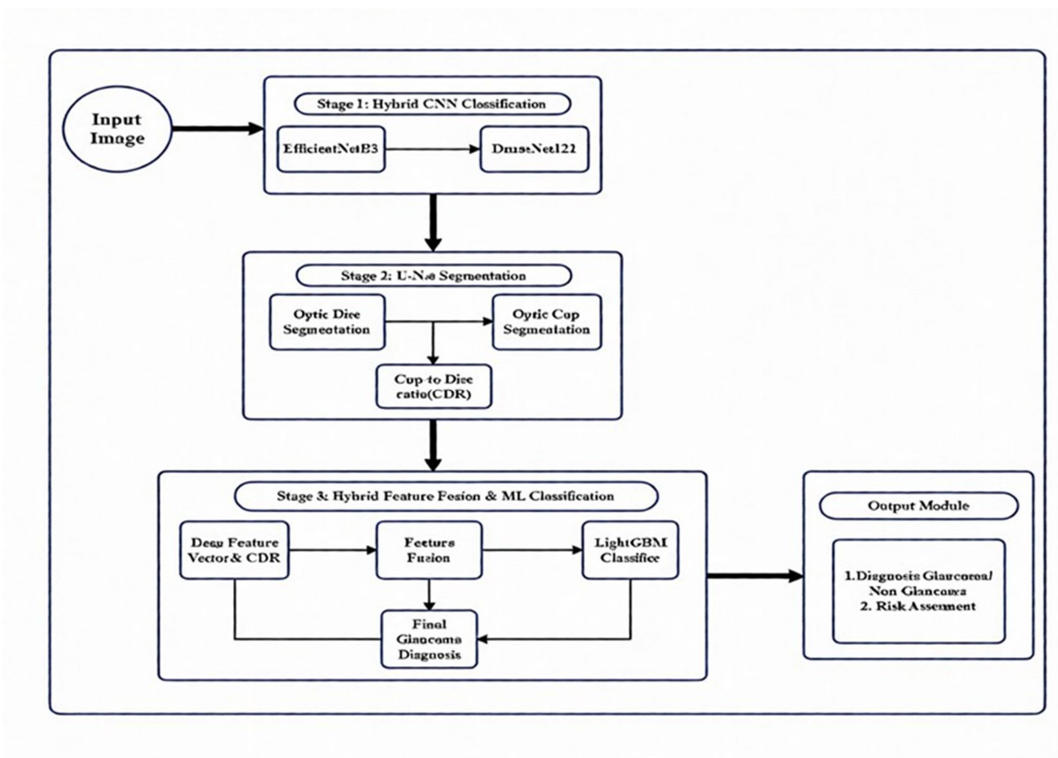


Figure 1: Architecture of Glaucoma Diagnosis

IV. RESULTS AND DISCUSSION

A. *Evaluation and Interpretation of System Interfaces*

Figure 2: The AI-Powered Glaucoma Detection System's User Interface

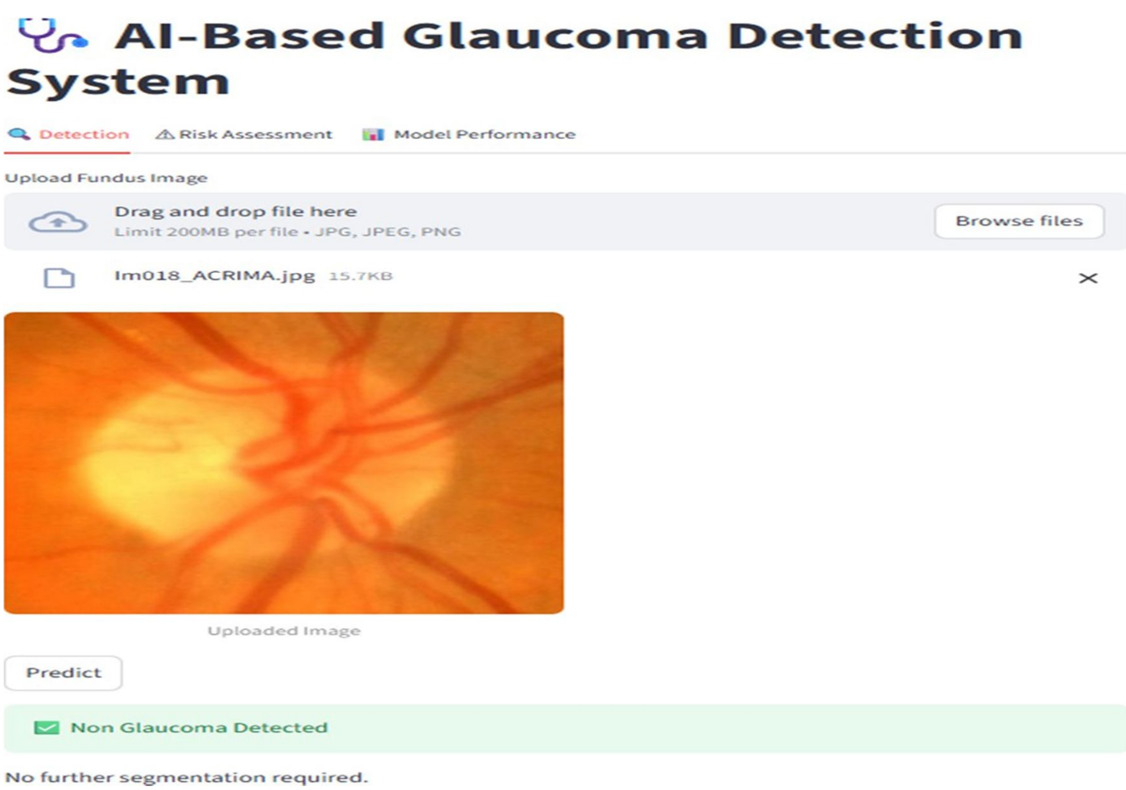


Figure 3: The AI-Based System's Non-Glaucoma Detection Output Screen

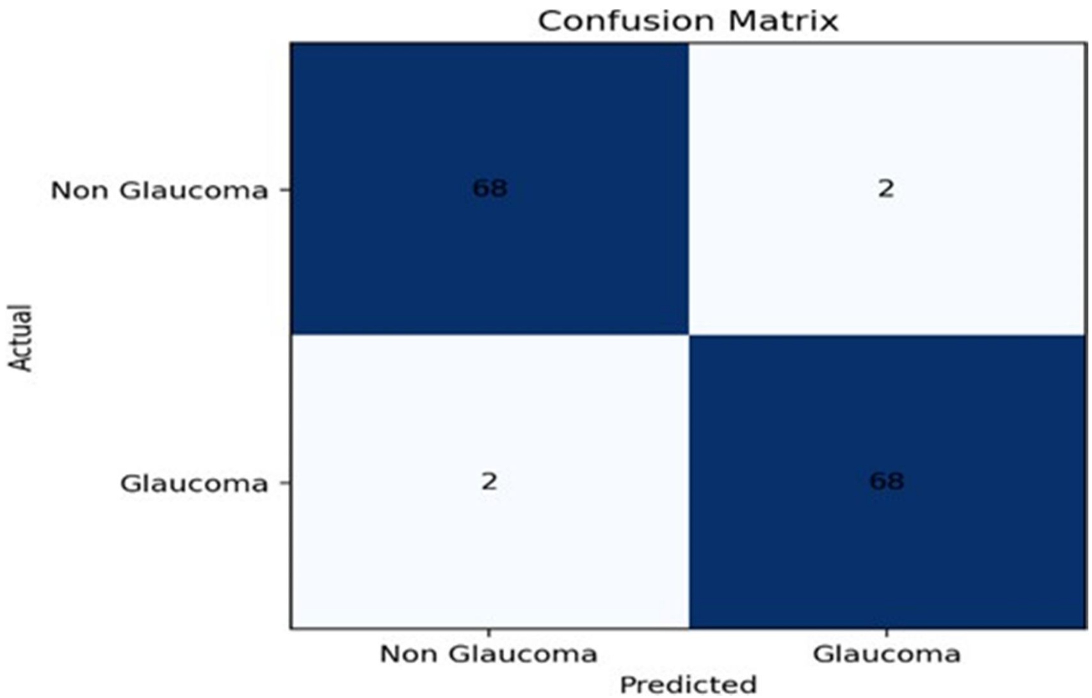


Figure 4: Confusion Matrix

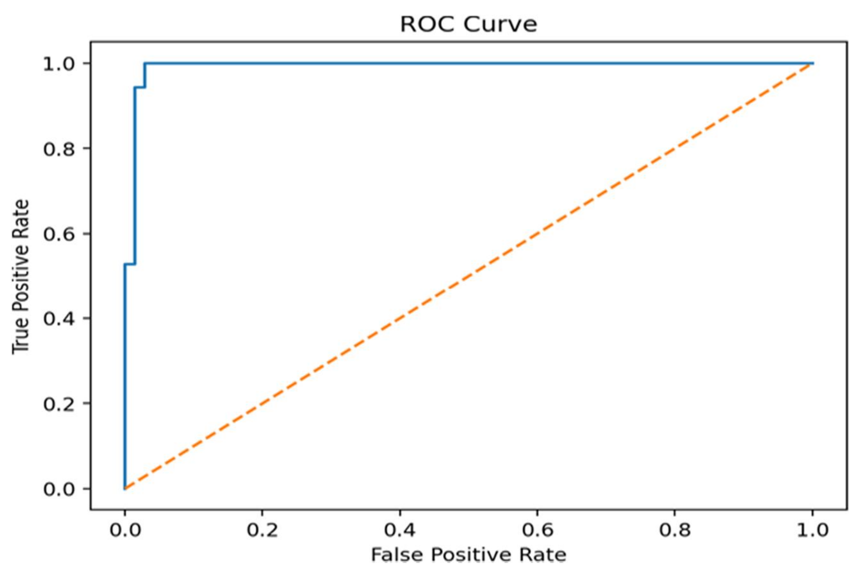


Figure 5: ROC Curve

B. Metrics for Evaluation

The suggested AI-Based Glaucoma Detection System's performance is assessed using common classification metrics including ROC-AUC, F1-Score, Accuracy, Precision, and Recall. These parameters aid in gauging the model's ability to differentiate between fundus images of glaucoma and those that are not.

Let's:

TP = True Positives (accurately detected glaucoma)

TN = True Negatives (accurately detected non-glaucoma)

FP = False Positives (healthy cases that are mistakenly diagnosed as glaucoma) FN= False Negatives (cases of glaucoma that are mislabeled as non-glaucoma)

Accuracy:
The ratio of accurately predicted instances (true positives and true negatives) to all forecasts is known as accuracy. Accuracy in glaucoma identification refers to the model's overall efficacy in correctly recognising both healthy and glaucomatous retinal fundus images. When the accuracy is high, the system works effectively in both classes.

$$\textbf{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

1) Precision

Relative to the total number of expected positive observations (True Positives + False Positives), precision is the proportion of correctly predicted positive observations (True Positives). It shows the proportion of photos that are indeed glaucoma cases out of those who were predicted to have the condition.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

In order to prevent unneeded stress and further medical treatments, glaucoma identification requires precision. If it is not, healthy persons may be mistakenly classified as having glaucoma. Fewer false alarms are ensured by high precision.

2) Recall (Sensitivity)

The ratio of accurately predicted positive observations (True Positives) to all actual positive observations (True Positives + False Negatives) is called recall, sometimes referred to as sensitivity or true positive rate.

$$\textbf{Recall} = \frac{TP}{TP + FN} \tag{3}$$

Because it gauges the model's capacity to identify real glaucoma cases, recall is crucial to this endeavour. In medical diagnosis, a high recall guarantees that very few glaucoma patients are overlooked.

3) F1-Score

Precision and Recall's harmonic mean is the F1-Score. False positives and false negatives are balanced by a single performance metric.

$$\textbf{F1Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

In medical picture classification, where it's crucial to strike a balance between identifying glaucoma patients and reducing false alarms, F1-Score is especially helpful.

4) Receiver Operating Characteristic-Area Under Curve (ROC-AUC)

Plotting the True Positive Rate (Recall) against the False Positive Rate at different threshold values, the ROC-AUC calculates the area under the ROC curve.

The likelihood that a randomly selected glaucoma image will be ranked higher by the model than a randomly selected non-glaucoma image is shown by the AUC.

$$\mathbf{AUC} = \int TPR(FPR)d(FPR) \tag{5}$$

ROC-AUC is a comprehensive performance metric that spans all classification thresholds in this glaucoma detection system. Reliability for clinical screening applications is demonstrated by a high AUC value (around 1), which shows that the model successfully separates cases of glaucoma from non-glaucoma.

5) Specificity

The capacity of the model to accurately identify negative cases is measured by specificity, also known as true negative rate.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{6}$$

Specificity in glaucoma detection refers to the model's ability to accurately identify non-glaucoma (healthy) fundus images.

6) Cohen's Kappa

A statistical metric called Cohen's Kappa () assesses the degree of agreement between expected and actual classifications while accounting for chance agreement.

$$\kappa = \frac{2 \times (TP \times TN - FN \times FP)}{(TP + FP) \times (FP + TN) \times (TP + FN) \times (FN + TN)} \tag{7}$$

It gauges the model's ability to outperform arbitrary guesswork.

Model	Accuracy	Precision	Recall	ROC	F1 Score	Cohen's Kappa
Hybrid Model	0.9714	0.9721	0.9714	0.9924	0.9735	0.9429

Table 1: Comparision Table for Evaluation Metrics

V. CONCLUSION

To improve diagnostic precision and clinical interpretability, a multi-stage hybrid architecture combining deep feature extraction, anatomical segmentation, and machine learning-based classification was devel- oped for automated glaucoma detection using retinal fundus pictures. In order to precisely calculate the Cup-to-Disc Ratio (CDR), the system integrates hybrid convolutional neural networks for semantic feature learning with U-Net-based optic disc and cup segmentation. This captures both structural biomarkers and pathological visual patterns linked to glaucoma. In comparison to solo methods, a Gradient Boosting classifier applied to the fused feature representation increases robustness and decreases misclassification, resulting in an overall classification accuracy of 97.14%.

VI. ACKNOWLEDGMENT

I express my sincere gratitude to my guide, Dr. K. Santhi Sree, Professor and Head, Department of Computer Science and Engineering, Jawaharlal Nehru Technological University Hyderabad, for her valuable guidance, continuous support, and constructive suggestions throughout the development of this research work. Her encouragement and technical insights greatly contributed to the successful completion of this project.

I also extend my heartfelt thanks to the faculty members of the Department of Computer Science and Engineering for their support and motivation during the course of this study.

REFERENCES

[1] Karanbir Singh Grover ,Nitika Kapoor ," Artificial Intelligence for Glaucoma and Diabetic Retinopathy:A Review" , Lecture Notes in Networks and Systems ((LNNS,volume1181),pp:217–227,February2025,https://doi.org/10.1007/978-981-97-8861-3_19.

[2] Thukkaram Umashree and S. Narendran," Convolutional Neural Network Analysis for Glaucoma Detection in Retinal Image Analysis Compared with the K-Nearest Neighbors Algorithm's Accuracy", Lecture Notes in Networks and Systems ((LNNS,volume 1038), pp 651–658 ,September 2024,https://doi.org/10.1007/978-981-97-4149-6_45.

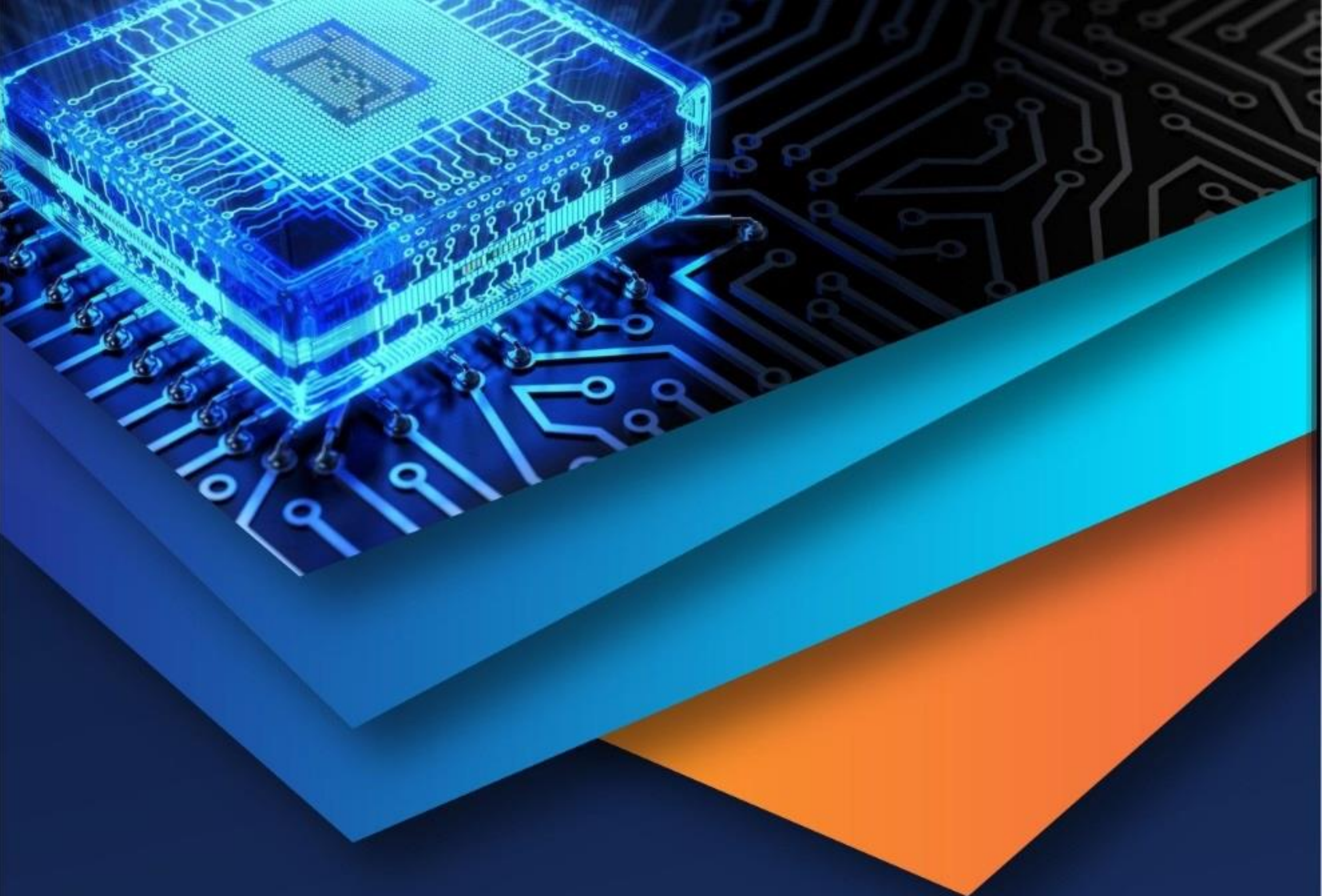
[3] Mandicou Ba(B), Amadou Mbaye, Idy Diop, and Alassane Bah, "Comparative Study of Machine Learning Models for Glaucoma Detection Based on Retinal Images ", Lecture Notes in Networks and Systems ((LNNS,volume 1421), pp 372–385, June 2025, https://doi.org/10.1007/978-3-031-92545-0_34.

[4] Wisal Hashim Abdulsalam, Rasha H. Ali, Sawsan H. Jadooa, Samera Shams Hussein, "Automated Glaucoma Detection Techniques: A Literature Review", Pages:19891-19897,Volume:15,Issue:1,February2025,doi: https://doi.org/10.48084./etasr.9316

[5] Geetha, M. Carmel Sobia, D. Santhi, A. Ahilan, "DEEP GD: Deep learning based snapshot ensemble CNN with EfficientNet for glaucoma detection", Biomedical Signal Processing and Control, Elsevier, Volume 100,Part B, February 2025,doi: https://doi.org/10.1016/j.bspc.2024.106989

[6] Jie Xu, Erkang Jing & Yidong Chai, "A deep learning model integrating domain-specific features for enhanced glaucoma diagnosis", BMC Medical Informatics and Decision Making, Volume :25, Article no:195, May 2025, https://doi.org/10.1186/s12911-025-02925-9

[7] Hubert Swierczynski, Juliusz Pukacki, Szymon Szczesny,Cezary Mazurek, Robert Wasilewicz, "Application of machine learning techniques in GlaucomAI system for glaucoma diagnosis and collaborative research support", Scientific Reports, Article No:7940, March 2025, https://doi.org/10.1038/s41598-025-89893-2



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY