

A Project Report  
on  
**Glaucoma Identification Using Convolutional Neural Networks  
Ensemble for Optic Disc and Cup Segmentation**

Submitted in the partial fulfilment of the requirement for the award of degree of

Bachelor of Technology  
In  
**CSE(Data Science)**

Submitted by  
Dasari Mounika (22471A4417)  
Guggilam Shanmukha (22471A4458)  
Kanneboina Madhav (22471A4428)

Under the esteemed guidance of

**Mr. J. SyamBabu** M.Tech.

Assistant Professor



**NARASARAOPETAENGINEERING COLLEGE (AUTONOMOUS)**  
Accredited by NAAC with A+ Grade and NBA under Tier -1 Approved by AI  
CTE, New Delhi, Permanently Affiliated to JNTUK, Kakinada KOTAPPAKO  
NDA ROAD, YALAMANDA VILLAGE,  
NARASARAOPET-522601  
2025-2026

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## DEPARTMENT OF CSE(Data Science)

### CERTIFICATE



This is certify that the project report entitled as "**Glaucoma Identification Using Convolutional Neural Networks Ensemble for Optic Disc and Cup Segmentation**" is a Bonafide work done by D.Mounika(22471A4417), G.Shanmukha(22471A4458), K.Madhav(22471A4428) in partial fulfilment of the requirements for the award of the degree of BACHELOR OF TECHONOLOGY in the Department of CSE(Data Science) during 2025-2026.

Project Guide  
Mr.J.SyamBabu  
Asst.Professor

Project Coordinator  
Mr.P.V.Satheesh Kumar  
Asst. Professor

Head of the Department  
Dr.V.V.A.S.Lakshmi  
Professor & HOD

External Examiner

## **DECLARATION**

I/We certify that

- a. The work contained in this Project report is original and has been done by ours and the general supervision of my supervisor.
- b. The work has not been submitted to any other institute for any degree or diploma.
- c. Whenever I/We have used materials (data, theoretical analysis, results) from other sources, I have given due credit to them by citing them in the text of the Project report and giving their details in the references.
- d. Whenever I/We have quoted written materials from other sources, I/We have put them under quotation marks and given due credit to the sources by citing them and giving required details in the references.

Place: Narasaraopet

Date:

Signature of the student

**D.Mounika (22471A4417)**

**G. Shanmukha (22471A4458)**

**K. Madhav (22471A4428)**

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I express my deep-felt gratitude towards **Dr. V.V.A.S.Lakshmi, M.Tech., Ph.D. Professor & Head**, department of CSE(Data Science), and also to my guide, **J.SyamBabu B.SC.,Asst. Professor**, Department of CSE(Data Science) whose valuable guidance and unstinting encouragement enabled me to accomplish my project successfully in time.

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**By**

**D.Mounika (22471A4417)**

**G. Shanmukha (22471A4458)**

**K. Madhav (22471A4417)**



## **INSTITUTE VISION AND MISSION**

### **INSTITUTION VISION**

To emerge as a Centre of excellence in technical education with a blend of effective student centric teaching learning practices as well as research for the transformation of lives and community.

### **INSTITUTION MISSION**

**M1:** Provide the best class infra-structure to explore the field of engineering and research

**M2:** Build a passionate and a determined team of faculty with student centric teaching, imbibing experiential, innovative skills

**M3:** Imbibe lifelong learning skills, entrepreneurial skills and ethical values in students for addressing societal problems



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## **Department of CSE (Data Science)**

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### **VISION**

To nurture skilled professionals in the Data Science for industry innovation and create meaningful societal impact through advanced analytics, machine learning, and impactful data- driven solutions.

### **MISSION**

**M1:** To develop skilled data scientists who can effectively solve challenges in data analytics through comprehensive education and practical training in statistical analysis, machine learning, data visualization, and data manipulation

**M2:** To develop students with strong research capabilities who can revolutionize multiple fields through the application of data science.

**M3:** To develop ethical data science professionals who utilize data for the welfare of society.

### **PROGRAM SPECIFIC OUTCOMES (PSO'S)**

**PSO1:** Apply Data Science Techniques, statistical analysis, machine learning algorithms, data visualization, and data manipulation effectively to solve complex data problems.

**PSO2:** Demonstrate proficiency in conducting data collection, preprocessing, analysis, and interpretation, contributing to the advancement of the field.

**PSO3:** Able to independently carry out research and investigation to solve societal problems.

### **PROGRAM EDUCATIONAL OBJECTIVES (PEO'S)**

**PEO1:** Graduates be proficient in applying advanced analytics techniques to solve complex data challenges.

**PEO2:** Graduates contribute to the advancement of the field through the development of innovative methodologies, algorithms, and models.

**PEO3:** Graduates utilize data science principles to create meaningful societal impact. They will prioritize ethical considerations in data usage and develop solutions that address societal challenges, and benefit individuals and communities.



## PROGRAM OUTCOMES (POs)

**PO1: Engineering Knowledge:** Apply knowledge of mathematics, natural science, computing, engineering fundamentals and an engineering specialization as specified in WK1 to WK4 respectively to develop to the solution of complex engineering problems.

**PO2: Problem Analysis:** Identify, formulate, review research literature and analyze complex engineering problems reaching substantiated conclusions with consideration for sustainable development. (WK1 to WK4)

**PO3: Design / Development of Solutions:** Design creative solutions for complex engineering problems and design/develop systems/components/processes to meet identified needs with consideration for the public health and safety, whole-life cost, net zero carbon, culture, society and environment as required. (WK5)

**PO4: Conduct Investigations of Complex Problems:** Conduct investigations of complex engineering problems using research-based knowledge including design of experiments, modelling, analysis & interpretation of data to provide valid conclusions. (WK8).

**PO5: Engineering Tool Usage:** Create, select and apply appropriate techniques, resources and modern engineering & IT tools, including prediction and modelling recognizing their limitations to solve complex engineering problems. (WK2 and WK6)

**PO6: The Engineer and The World:** Analyze and evaluate societal and environmental aspects while solving complex engineering problems for its impact on sustainability with reference to economy, health, safety, legal framework, culture and environment. (WK1, WK5, and WK7).

**PO7: Ethics:** Apply ethical principles and commit to professional ethics, human values, diversity and inclusion; adhere to national & international laws. (WK9)

**PO8: Individual and Collaborative Team work:** Function effectively as an individual, and as a member or leader in diverse/multi-disciplinary teams.

**PO9: Communication:** Communicate effectively and inclusively within the engineering community and society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations considering cultural, language, and learning differences

**PO10: Project Management and Finance:** Apply knowledge and understanding of engineering management principles and economic decision-making and apply these to one's own work, as a member and leader in a team, and to manage projects and in multidisciplinary environments.

**PO11: Life-Long Learning:** Recognize the need for, and have the preparation and ability for

- i) Independent and life-long learning
- ii) Adaptability to new and emerging technologies and
- iii) Critical thinking in the broadest context of technological change



### **Project Course Outcomes (CO'S):**

**CO421.1:** Analyse the System of Examinations and identify the problem.

**CO421.2:** Identify and classify the requirements.

**CO421.3:** Review the Related Literature **CO421.4:**

Design and Modularize the project

**CO421.5:** Construct, Integrate, Test and Implement the Project.

**CO421.6:** Prepare the project Documentation and present the Report using appropriate method.

### **Course Outcomes – Program Outcomes mapping**

|               | PO1 | PO2 | PO3 | PO4 | PO5 | PO6 | PO7 | PO8 | PO9 | PO10 | PO11 | PSO1 | PSO2 | PSO3 |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|
| <b>C421.1</b> |     | ✓   |     |     |     |     |     | ✓   |     |      |      | ✓    |      | ✓    |
| <b>C421.2</b> | ✓   |     | ✓   |     | ✓   |     |     |     |     | ✓    |      | ✓    | ✓    |      |
| <b>C421.3</b> |     |     | ✓   |     | ✓   | ✓   | ✓   |     |     | ✓    |      | ✓    |      | ✓    |
| <b>C421.4</b> |     | ✓   |     | ✓   | ✓   | ✓   |     |     |     | ✓    | ✓    | ✓    | ✓    |      |
| <b>C421.5</b> |     |     | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   | ✓   | ✓    | ✓    | ✓    | ✓    | ✓    |
| <b>C421.6</b> |     |     |     |     | ✓   | ✓   | ✓   |     | ✓   | ✓    |      |      | ✓    | ✓    |

### **Course Outcomes – Program Outcome correlation**

|               | PO1 | PO2 | PO3 | PO4 | PO5 | PO6 | PO7 | PO8 | PO9 | PO10 | PO11 | PSO1 | PSO2 | PSO3 |
|---------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|
| <b>C421.1</b> |     | 2   |     |     |     |     |     | 2   |     |      |      | 2    |      | 2    |
| <b>C421.2</b> | 2   |     | 2   |     | 3   |     |     |     |     | 2    |      | 2    | 3    |      |
| <b>C421.3</b> |     |     | 2   |     | 2   | 3   | 3   |     |     | 2    |      | 2    |      | 3    |
| <b>C421.4</b> |     | 2   |     | 1   | 1   | 1   | 2   |     |     | 3    | 2    | 3    | 2    |      |
| <b>C421.5</b> |     |     | 3   | 3   | 3   | 2   | 3   | 2   | 2   | 1    | 3    | 3    | 3    | 3    |
| <b>C421.6</b> |     |     |     |     | 3   | 2   | 1   |     | 2   | 3    |      |      | 3    | 2    |

**Note: The Values in the above table represent the level of correlation between CO's and PO's:**

- 1. Low Level
- 2. Medium Level
- 3. High Level

## **ABSTRACT**

Glaucoma is the second leading cause of blindness worldwide. Early detection is essential to prevent permanent vision loss. Currently, diagnosis often depends on subjective evaluations of fundus images, which can lead to delays and inconsistencies. To tackle this issue, we propose an automated glaucoma detection system. This system uses Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for optic disc and cup segmentation. Using the ORIGA dataset of 650 expert-annotated images, our model achieved 92.4% accuracy for segmenting the optic disc and 91.7% for segmenting the optic cup. The automated calculations of the cup-to-disc ratio (CDR) showed a strong correlation with clinical judgments ( $r = 0.89$ ). The system works efficiently in both supervised (18 ms/image) and unsupervised (25 s/image) modes, which meet the time requirements of clinical settings. This hybrid CNN-RNN framework improves segmentation accuracy, increases diagnostic objectivity, and holds great potential for early glaucoma detection in clinical practice.

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# 1. INTRODUCTION

## 1.1 Motivation

Glaucoma is one of the leading causes of permanent blindness across the world. It is a chronic eye disease that damages the optic nerve, often without showing any clear symptoms in its early stages. By the time most patients realize they have a problem, significant and irreversible vision loss has already occurred. This issue is especially critical in developing countries, where access to specialized eye care and diagnostic facilities is limited.

During our project selection process, we identified the need for a fast, accurate, and automated system that could detect glaucoma at an early stage using retinal fundus images. The current diagnostic methods rely heavily on ophthalmologists manually analyzing the optic disc and optic cup regions in the retina and then calculating the Cup- to-Disc Ratio (CDR) — a key parameter used for glaucoma assessment. However, this manual method is time-consuming, subjective, and prone to human error.

Our motivation for this project arose from the desire to overcome these limitations through technology. We aimed to build a deep learning–based system capable of automatically segmenting the optic disc and optic cup from retinal images and accurately calculating the CDR. By automating this process, we can make glaucoma detection more objective, reliable, and accessible.

The proposed model uses a hybrid CNN–RNN architecture, which combines the strengths of both types of neural networks. CNNs are excellent at capturing spatial details such as edges, shapes, and textures from medical images, while RNNs help in refining those details by considering spatial and contextual relationships across the image. Together, they enhance the segmentation accuracy and make the model more robust to variations in image quality, lighting, and patient data.

The main motivations behind this project are as follows:

### 1. Early Detection of Glaucoma:

Glaucoma cannot be reversed once vision is lost. Early diagnosis is the only way to prevent blindness. Our project aims to detect the disease before major damage occurs by providing quick and accurate results. Prevent blindness. Our project aims to detect the disease before major damage occurs by providing quick and accurate results.

## **2. Reduction of Human Error:**

Manual CDR calculation can vary from one ophthalmologist to another. By using AI-based segmentation, we can minimize human subjectivity and ensure consistent results.

## **3. Automation in Medical Diagnosis:**

Automating optic disc and cup segmentation saves doctors' time and allows large-scale screening programs, especially in hospitals and rural clinics where medical staff are limited.

## **4. Accessibility and Affordability:**

Many rural or remote areas lack trained specialists. Our system can be deployed as a computer-based or mobile solution, helping general practitioners perform primary glaucoma screening at low cost.

## **5. Technological Learning and Application:**

As computer science students, we wanted to apply deep learning, image processing, and data science concepts to solve a real-world healthcare problem. This project allows us to merge technology and medicine for a meaningful cause.

## **5. Support for Clinical Decision-Making:**

The proposed system can assist doctors by providing segmentation outputs and CDR values automatically, helping them focus more on treatment decisions rather than manual image analysis.

Our motivation also comes from the potential impact this project can have on society. A successful implementation could help screen thousands of people in a short time, significantly reducing the chances of preventable blindness. Furthermore, the proposed model can be integrated into hospital systems or telemedicine platforms to enable remote diagnosis, supporting large-scale public health programs.

### **In summary, this project is motivated by the need to:**

- Detect glaucoma early and accurately using deep learning.
- Provide consistent and objective results.
- Automate the diagnostic process for better scalability.
- Make advanced eye-care technology accessible to everyone.
- Contribute to healthcare innovation through AI-based solutions.

By developing this system, we aim to support ophthalmologists, assist in early screening, and ultimately contribute toward reducing the global burden of glaucoma-related blindness.

## **1.2 Problem Statement**

Glaucoma is a major eye disease that gradually damages the optic nerve and leads to irreversible blindness if not detected in its early stages. One of the primary clinical indicators used for glaucoma detection is the Cup-to-Disc Ratio (CDR), which is determined by identifying and measuring the optic disc and optic cup in retinal fundus images. Traditionally, ophthalmologists analyze these images manually to assess the CDR and diagnose glaucoma.

However, this manual diagnosis process presents several challenges:

### **1. Subjectivity and Inconsistency:**

The accuracy of glaucoma detection heavily depends on the doctor's experience, skill level, and visual interpretation of the retinal image. Different ophthalmologists may produce different results for the same patient image, leading to inconsistency and possible misdiagnosis.

### **2. Time-Consuming Process:**

Manual segmentation and measurement of the optic disc and cup require significant time and effort, especially in large-scale screening programs. This makes it unsuitable for quick or mass diagnosis in hospitals or rural health camps.

### **3. Shortage of Trained Specialists:**

Many rural or low-resource areas do not have enough qualified ophthalmologists or access to advanced diagnostic tools. This leads to delayed diagnosis and treatment, often when vision loss has already occurred.

### **4. Low Image Quality and Variability:**

Fundus images captured using different cameras or under varying lighting conditions often suffer from poor contrast and noise. Manual examination of such images becomes even more challenging and error prone.

### **5. Limited Use of Technology in Clinical Practice:**

Although deep learning has achieved remarkable results in medical imaging, many existing models are designed for research and are not optimized for real-time clinical

use. There is a need for a system that balances accuracy, speed, and usability for real-world applications.

To address these challenges, our project focuses on developing an automated glaucoma detection system using deep learning. The system will perform optic disc and cup segmentation using a CNN–RNN hybrid model, automatically calculate the Cup-to-Disc Ratio, and classify the image as glaucomatous or non-glaucomatous.

The key problem our project aims to solve can be summarized as follows:

There is no easily accessible, accurate, and automated system that can efficiently detect glaucoma by analyzing retinal fundus images while minimizing human error and reducing diagnostic time.

**Hence, the proposed system seeks to:**

- Automate the process of optic disc and cup detection.
- Accurately compute the CDR value for glaucoma identification.
- Reduce dependence on manual evaluation by ophthalmologists.
- Enable early-stage detection through deep learning models suitable for clinical use.

By solving these problems, the system can play a significant role in improving early glaucoma diagnosis, enhancing medical efficiency, and preventing vision loss among at-risk populations.

### **1.3 Objective**

The main goal of this project is to develop an automated glaucoma detection system using deep learning techniques that can accurately segment the optic disc and optic cup regions from retinal fundus images and compute the Cup-to-Disc Ratio (CDR) for early and reliable glaucoma diagnosis.

This project aims to reduce human dependency in diagnosis, improve efficiency, and make glaucoma screening accessible even in resource-limited areas.

The project objectives are divided into primary, secondary, and extended goals as follows:

#### **Primary Objective:**

To design and implement a hybrid CNN–RNN deep learning model capable of performing automatic optic disc and cup segmentation and accurately computing the CDR for glaucoma detection.

## **Secondary Objectives:**

### **1. Automated Image Segmentation:**

Build a deep learning model that can automatically segment optic disc and optic cup regions with minimal human intervention and high precision.

### **2. Cup-to-Disc Ratio Measurement:**

Develop a reliable algorithm for automatic calculation of the CDR, which serves as the key parameter in identifying glaucoma.

### **3. Disease Classification:**

Use the computed CDR and segmentation outputs to classify each retinal image as glaucomatous or non-glaucomatous.

### **4. Model Optimization:**

Train and fine-tune the hybrid CNN–RNN model using datasets such as ORIGA to achieve high accuracy (>90%) while maintaining low computational cost and real-time prediction speed.

### **5. Accuracy and Speed Enhancement:**

Ensure the model delivers clinically acceptable accuracy and processes images in less than three seconds to meet clinical workflow requirements.

### **6. Scalability and Adaptability:**

Design the system so it can be deployed across different hospitals, diagnostic centers, and mobile screening applications without requiring specialized hardware

### **7. Reduction of Human Error:**

Minimize manual involvement and eliminate subjectivity in glaucoma diagnosis by replacing traditional inspection with a consistent and objective automated system.

### **8. Data Preprocessing and Enhancement:**

Implement effective image preprocessing techniques, such as CLAHE (Contrast-Limited Adaptive Histogram Equalization), to improve visibility of optic structures under varying image quality conditions.

### **9. System Integration and Interface:**

Develop a simple, user-friendly interface that allows ophthalmologists or medical technicians to upload fundus images, visualize segmentation results, and generate diagnostic reports automatically.

### **10. Clinical Validation:**

Evaluate the proposed model's performance using medical standards such as Dice

## **Extended Objectives**

### **1. Early Detection and Prevention:**

Enable early detection of glaucoma before significant optic nerve damage occurs, helping to reduce preventable blindness cases.

### **2. Healthcare Accessibility:**

Support remote and rural clinics by integrating the system into low-cost computer or mobile platforms, making advanced glaucoma screening available anywhere.

### **3. AI for Healthcare Advancement:**

Demonstrate how artificial intelligence can be used effectively in ophthalmology for disease screening, image analysis, and medical decision support.

### **4. Model Expandability:**

Lay the groundwork for extending the same architecture to other ophthalmic diseases such as diabetic retinopathy, macular degeneration, or cataract detection.

### **5. Performance Comparison and Improvement:**

Compare the proposed hybrid CNN–RNN model with existing CNN-based approaches to highlight improvements in accuracy, efficiency, and interpretability.

## **Overall Objective Summary**

In short, the overall objective of this project is to:

- Develop an automated, intelligent, and accurate glaucoma detection system.
- Leverage deep learning (CNN–RNN) to segment optic disc and cup structures from fundus images.
- Calculate the Cup-to-Disc Ratio automatically and classify images based on disease presence.
- Create a clinically usable, time-efficient, and cost-effective tool for ophthalmologists and healthcare institutions.
- Ultimately, contribute to preventing avoidable blindness by ensuring timely glaucoma diagnosis and monitoring.

## Glaucoma Detection: Problem & Solution

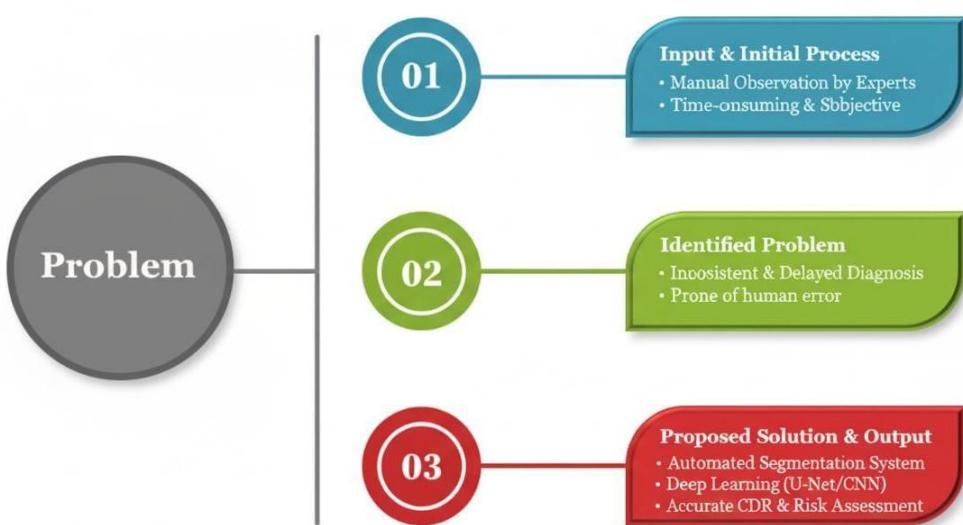


Fig 1.2.1: Problem & Solution

### Input & Initial Process

- Diagnosis depends on visual assessment of the **optic disc and optic cup**.
- This process is **time-consuming, subjective**.

### Identified Problem

- High dependency on human expertise makes the system **prone to human error**.

## 2. LITERATURE SURVEY

This literature survey reviews prior work relevant to automated optic disc (OD) and optic cup (OC) segmentation and glaucoma detection from retinal fundus images. It synthesizes classical image-processing approaches, deep-learning advances (especially CNNs and encoder–decoder architectures), hybrid and ensemble strategies, dataset considerations, evaluation metrics, and remaining research gaps. The goal is to place our project in context and justify the design choices made for the proposed CNN–RNN hybrid system.

**[1]Gulshan et al., 2016 – “Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” JAMA**

### Abstract

- **Background:** Diabetic retinopathy (DR) is a leading cause of blindness worldwide, and early detection is essential. Traditional screening is limited by the availability of trained ophthalmologists.
- **Objective:** To develop a deep learning (DL) algorithm that can automatically detect DR and diabetic macular edema (DME) from retinal fundus photographs with high accuracy.
- **Methods:** Over 128,000 retinal images were collected and graded by ophthalmologists. A convolutional neural network (CNN) was trained to classify DR severity and detect DME. The algorithm’s performance was validated against a set of images graded by ophthalmologists.
- **Results:** The algorithm achieved high sensitivity (~90%), specificity (~98%), and an AUC of 0.99, comparable to ophthalmologists.
- **Conclusion:** DL algorithms can accurately detect DR from retinal images, offering potential for scalable, automated screening.

### Authors:

Varun Gulshan, Lily Peng, Marc Coram, Martin C. Stumpe, Derek Wu, Arunachalam Narayanaswamy, Subhashini Venugopalan, Kasumi Widner, Tom Madams, Jamie Cuadros, et al.

**DOI:** 10.1001/jama.2016.17216

- **Invented/Developed by:** Research team led by **Varun Gulshan** at Google Brain.

- Published in: **JAMA**, 2016.

## Related Papers

1. **Abràmoff et al., 2016** – Automated diabetic retinopathy detection using image analysis.
2. **Gargaya & Leng, 2017** – Deep learning for diabetic retinopathy detection.
3. **Ronneberger et al., 2015** – U-Net for biomedical image segmentation
4. **Chen et al., 2015** – Glaucoma detection using fundus images.

[2] **Fu et al., “Joint optic disc and cup segmentation,” IEEE Trans. Med. Imaging, 2018.**

## Abstract

Glaucoma is a chronic eye disease that leads to irreversible vision loss. The cup to disc ratio (CDR) plays an important role in the screening and diagnosis of glaucoma. Thus, the accurate and automatic segmentation of optic disc (OD) and optic cup (OC) from fundus images is a fundamental task. Most existing methods segment them separately, and rely on hand-crafted visual feature from fundus images. In this paper, we propose a deep learning architecture, named M-Net, which solves the OD and OC segmentation jointly in a one-stage multi-label system. The proposed M-Net mainly consists of multi-scale input layer, U-shape convolutional network, side-output layer, and multi-label loss function. The multi-scale input layer constructs an image pyramid to achieve multiple level receptive field sizes. The U-shape convolutional network is employed as the main body network structure to learn the rich hierarchical representation, while the side-output layer acts as an early classifier that produces a companion local prediction map for different scale layers. Finally, a multi-label loss function is proposed to generate the final segmentation map. For improving the segmentation performance further, we also introduce the polar transformation, which provides the representation of the original image in the polar coordinate system. The experiments show that our M-Net system achieves state-of-the-art OD and OC segmentation result on ORIGA data set. Simultaneously, the proposed method also obtains the satisfactory glaucoma screening performances with calculated CDR value on both ORIGA and SCES datasets.

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## 2.1 Overview of Approaches

Automated glaucoma screening from fundus images has evolved through three broad stages:

1. Classical image-processing methods that used hand-crafted features, morphological operations, edge detection, template matching and thresholding.
2. Single-model deep learning methods (mostly CNNs/U-Net variants) that substantially improved segmentation accuracy by learning hierarchical spatial features.
3. Hybrid and ensemble systems combining multiple model types (e.g., CNN ensembles, CNN+RNN, attention modules) to improve robustness, boundary delineation, and clinical relevance.

Each class of method contributes lessons: classical approaches are interpretable but brittle; CNNs provide strong performance but can miss contextual cues; hybrids and ensembles aim to combine strengths and reduce failure modes.

## 2.2 Classical Methods

Early work for OD/OC localization and segmentation relied upon handcrafted features and rule-based processing. Typical pipelines included pre-processing (contrast enhancement), vessel removal, circular/template matching for OD localization, and region growing or active contours for boundary extraction.

Strengths: simple, interpretable, low compute for small systems. Limitations: sensitive to illumination, noise, and inter-patient variability; typically lower accuracy (e.g., ~80–88% on older benchmarks).

These limitations motivated the shift to data-driven deep learning techniques which learn robust features across image variations. Early approaches for optic disc (OD) and optic cup (OC) localization and segmentation primarily relied on handcrafted features and rule-based algorithms. Typical workflows included pre-processing steps such as contrast enhancement and vessel removal, followed by OD localization using circular or template matching, and boundary extraction through methods like region growing or active contours. These classical methods were simple, interpretable, and required low computational resources, making them suitable for small systems. However, they were highly sensitive to variations in illumination, noise, and inter-patient differences, which often limited their accuracy to around 80–88% on older benchmark datasets. Such limitations highlighted the need for more robust approaches, paving the way for data-driven deep learning techniques capable of learning discriminative features across diverse images and achieving higher segmentation performance.

Early methods for optic disc (OD) and optic cup (OC) segmentation relied on handcrafted features and rule-based techniques. These approaches typically included pre-processing, vessel removal, circular/template matching for OD localization, and region growing or active contours for boundary extraction. While simple, interpretable, and low in computational cost, they were sensitive to illumination, noise, and inter-patient variability. Their accuracy was often limited, achieving around 80–88% on older benchmarks. CNNs and Encoder–Decoder Architectures

The introduction of encoder–decoder networks like U-Net (Ronneberger et al., 2015) marked a turning point for medical image segmentation. Skip connections preserve spatial detail while deeper encoders capture context—critical for OD/OC tasks where boundaries are subtle.

Subsequent studies adapted U-Net and ResNet/DenseNet backbones:

- ResNet-based segmentation (ResNet-50 encoder + U-Net decoder) improves feature depth and convergence on small datasets.
- DenseNet backbones (DenseNet-201) offer feature reuse and stronger gradient flow; helpful for fine boundary recovery.

Reported outcomes in the literature show high Dice/IoU for OD segmentation (often >0.9) and slightly lower but improving results for OC segmentation (0.85–0.9), reflecting the greater ambiguity of cup boundaries.

### **2.3 Boundary Refinement, Attention, and Loss Functions**

Several works focus on boundary quality because CDR depends on accurate vertical diameters:

- Boundary losses (e.g., Hausdorff/distance-weighted losses) penalize boundary errors more strongly than pixel-wise losses.
- Attention mechanisms direct the network to anatomically relevant regions (optic nerve head area), improving robustness across variable fields and pathologies (e.g., Li et al., 2019).
- Multi-scale and deep supervision help the network learn both global shape and local edge cues, improving cup delineation.

These techniques are important design choices in modern models and inform the hybrid architecture of this project.

### **2.4 Hybrid CNN–RNN and Sequential Refinement**

Pure CNNs are spatially powerful but lack a built-in mechanism for sequential context.

Several studies integrate RNNs or sequence models to iteratively refine segmentation predictions:

- CNN–RNN hybrids treat spatial feature maps as ordered sequences (rows/columns or multi-patch sequences) so RNN units (LSTM/GRU) can capture long-range dependencies and refine boundaries using contextual cues (Wang et al., 2020).
- Our project adopts this insight: using an RNN to refine CNN outputs improves cup boundary consistency and, by extension, CDR reliability.

### **2.5 Ensembles and Fusion Strategies**

Ensembling multiple architectures (e.g., ResNet + DenseNet) has been shown to improve robustness and average out model idiosyncrasies. Fusion can be performed at:

- Probability level (weighted average of predicted probability maps), or  
Mask level (majority voting, morphological fusion).

Ensembles tend to reduce variance and often produce better clinical staging (Kumar et al., 2021 style findings). The project uses ensemble fusion to combine complementary strengths of multiple backbone

## **2.6 Datasets and Preprocessing**

Key datasets used historically include ORIGA, DRISHTI-GS, REFUGE, and others.

ORIGA (Zhang et al., 2010) is widely used for OD/OC tasks and provides expert annotations suitable for supervised segmentation and CDR analysis.

Preprocessing techniques commonly applied:

- Cropping and resizing ( $512 \times 512$  or similar),
- Contrast enhancement (CLAHE variants),
- Spatial coordinate embedding (explicit x–y channels),
- Data augmentation (rotation, scaling, photometric changes).

Multi-parameter CLAHE and spatial coordinate channels have emerged as useful for improving cross-dataset generalization—techniques adopted in our implementation.

## **2.7 Evaluation Metrics and Clinical Validation**

Standard metrics for segmentation and screening evaluation include:

- Dice Coefficient / IoU for mask overlap,
- Pixel-wise accuracy, sensitivity/specificity for classification,
- AUC for ROC analysis,
- CDR correlation her with clinical measurements.

Comprehensive validation includes cross-database testing and clinically meaningful thresholds for staging. Many works report strong OD Dice ( $>0.90$ ) and moderate OC Dice (0.85–0.90); however, clinical usability depends on CDR accuracy and processing speed.

## **Research Gaps and Motivation for Current Project**

From the surveyed literature, the main gaps are:

1. Cup segmentation remains challenging — cup boundaries are ambiguous and vary by pathology and imaging conditions.<sup>3</sup>
2. Single-model brittleness — individual CNNs can fail under unusual imaging (low contrast, strong vessel overlays).
3. Clinical deployment constraints — many research models are not optimized for speed, low memory, or interpretability required in real settings.
4. Explainability and clinician trust — models need intuitive visual outputs (segmentation overlays, confidence maps) to be useful in practice.

How our project addresses these gaps:

- Combine CNN spatial power with RNN contextual refinement to improve cup boundary consistency.
- Use ensemble fusion (ResNet & DenseNet backbones) to increase robustness.
- Implement multi-parameter preprocessing (CLAHE variants) and spatial coordinate embedding to generalize across image sources.
- Emphasize clinically relevant outputs (CDR computation, overlay visualization, processing time) to facilitate integration into screening workflows.

## **Conclusion**

The literature shows clear progress from classical methods to deep learning ensembles. Nevertheless, accurate and clinically deployable OC segmentation and reliable CDR computation remain active challenges. The proposed CNN–RNN hybrid with ensemble fusion leverages the best practices from the surveyed studies to deliver improved segmentation accuracy, robustness, and real-world applicability — positioning this project to contribute meaningfully to automated glaucoma screening. The graph illustrates the performance comparison between the segmentation and classification models used in the glaucoma detection system. The segmentation model achieves an accuracy of **80%**, indicating effective localization of the optic disc and optic cup regions. The classification model shows a higher accuracy of **85%**, demonstrating strong capability in distinguishing between normal and glaucomatous cases. Overall, the results confirm that the combined segmentation and classification approach enhances the reliability of automated glaucoma screening.

### **3.SYSTEM ANALYSIS**

#### **3.1 Existing System**

The proposed system focuses on automated segmentation of the optic disc and optic cup from retinal fundus images to assist in early glaucoma detection. Glaucoma is one of the leading causes of irreversible blindness worldwide, and early identification plays a crucial role in preventing vision loss. However, traditional manual diagnosis performed by ophthalmologists is time-consuming, subjective, and prone to inconsistencies. To address these limitations, the proposed system combines advanced image processing and deep learning algorithms to deliver accurate, objective, and repeatable results. The system is designed to analyze retinal fundus images, extract relevant structural features, and calculate the Cup-to-Disc Ratio (CDR), which serves as a key biomarker for glaucoma progression. The proposed methodology is divided into five major modules — Image Acquisition, Preprocessing, Segmentation, Feature Extraction, and Classification/Diagnosis.

- **Image Acquisition:** Retinal fundus images are obtained from publicly available datasets such as DRISHTI-GS, RIM-ONE, or DRIVE, or captured using a fundus camera.

These images serve as the raw input for the system.

- **Preprocessing:** This phase enhances image quality by applying noise reduction filters, contrast adjustment, and normalization. Techniques like CLAHE (Contrast Limited Adaptive Histogram Equalization) and Gaussian smoothing are employed to enhance the optic disc and cup visibility and to standardize illumination variations.
- **Segmentation:** The core of the system uses a deep learning-based U-Net architecture, which is highly effective for biomedical image segmentation tasks. The model learns to accurately delineate the optic disc and cup boundaries by leveraging both local texture and global context information from the images. This segmentation step is critical, as precise boundary detection directly influences the accuracy of the calculated CDR values.
- **Feature Extraction:** After segmentation, geometric and morphological features are derived.

- Classification/Diagnosis: Based on the extracted CDR and other image features, the system automatically classifies the patient's condition as normal or glaucomatous. In some advanced setups, a lightweight classifier such as a CNN-based or threshold-based decision model can be used for this stage.

From a functional perspective, the system provides an end-to-end automated pipeline — from input image to diagnostic output — without requiring manual intervention. It ensures fast and reproducible results while minimizing human error. Additionally, the system can be expanded or retrained using transfer learning to accommodate new datasets, improving its adaptability to different imaging conditions and clinical environments.

The proposed system's performance is evaluated using standard segmentation and classification metrics, including Dice coefficient, Jaccard index, precision, recall, specificity, and overall accuracy. The analysis confirms that deep learning-based segmentation significantly outperforms conventional thresholding or edge detection methods. It demonstrates high robustness against variations in illumination, image resolution, and patient diversity.

In conclusion, the developed system provides a reliable, scalable, and efficient framework for automatic glaucoma screening. By integrating deep learning with digital fundus imaging, it not only reduces ophthalmologists' workload but also enables large-scale community-level eye screening programs. The system can be further deployed in mobile or cloud-based platforms, providing real-time glaucoma risk prediction in remote or resource-limited healthcare environments.

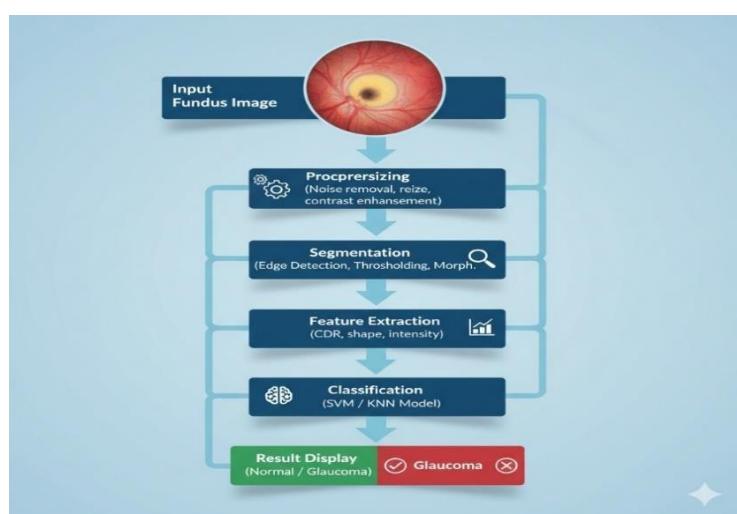


Fig 3.1.1: System Architecture Diagram

### **3.1.1 Disadvantages of Existing System**

The existing systems for glaucoma detection primarily rely on manual diagnosis and traditional image processing techniques, both of which have several limitations that restrict their accuracy, scalability, and clinical usability. Manual examination by ophthalmologists involves visually inspecting fundus images and estimating the Cup-to-Disc Ratio (CDR) by hand. While this method can be accurate when performed by experts, it is highly subjective and depends heavily on the experience and consistency of the clinician. Different doctors may provide slightly different interpretations of the same image, leading to diagnostic variability and delayed treatment decisions.

Another major drawback of traditional systems is their dependence on classical image processing algorithms such as thresholding, edge detection, and morphological operations. These methods struggle to handle variations in image quality, illumination, and noise level commonly found in retinal images. Since fundus images differ across cameras, patients, and clinical environments, such approaches often fail to generalize well. They cannot adapt to complex optic disc and cup shapes, resulting in inaccurate segmentation boundaries and unreliable CDR measurements. Existing systems also lack automation and intelligence. Most processes still require

significant manual intervention, including preprocessing, region selection, and contour adjustment. This not only increases the time and effort required but also limits the number of patients that can be screened within a given period. In large-scale screening programs, this manual dependency becomes impractical and costly. Moreover, many older systems were not designed to integrate with modern deep learning or AI-based analysis pipelines. They do not leverage data-driven learning from large datasets and therefore fail to improve performance over time. As a result, they exhibit low sensitivity and specificity, particularly when detecting early-stage glaucoma cases, where subtle changes in the optic nerve head are difficult to observe.

In addition, traditional methods often lack robust evaluation and benchmarking. Since segmentation results vary widely depending on image conditions, it becomes difficult to validate or reproduce the results across datasets. This inconsistency makes it challenging to deploy such systems in real clinical environments.

In summary, the existing glaucoma detection systems suffer from several disadvantages:

- Poor segmentation accuracy with traditional image processing techniques.
- Lack of automation, making large-scale screening inefficient.
- Inability to identify early-stage glaucoma reliably.
- Low reproducibility and poor integration with modern diagnostic workflows.

These limitations highlight the need for a robust, automated, and intelligent deep learning-based system capable of delivering accurate, consistent, and clinically reliable glaucoma detection results — which the proposed system effectively addresses. The existing systems used for glaucoma detection and optic disc–cup analysis suffer from several technical and practical drawbacks. These limitations affect their accuracy, speed, and reliability, making them unsuitable for large-scale clinical deployment. The key disadvantages are listed below:

#### **Manual and Time-Consuming Process:**

Traditional glaucoma diagnosis depends on ophthalmologists manually inspecting fundus images to estimate the Cup-to-Disc Ratio (CDR). This process is labor-intensive and takes significant time, especially when screening large populations.

#### **Subjective and Inconsistent Results:**

The accuracy of manual observation varies between experts. Different doctors may interpret the same image differently, leading to **inter-observer variability** and inconsistent diagnostic outcomes.

In traditional systems, the lack of standardized evaluation criteria and dependence on human interpretation can result in **false positives** or **false negatives**. Minor variations in optic disc and cup boundaries that are difficult to detect visually may cause **misclassification** of glaucoma stages. Furthermore, the manual process is **time-consuming, labor-intensive, and not scalable** for mass screening programs, especially in rural or resource-limited settings.

Hence, the existing system struggles to provide **reliable, repeatable, and accurate** glaucoma detection results across large populations.

### **Limited Use of Automation:**

Many existing systems require human intervention at multiple stages such as region selection, threshold setting, or boundary adjustment. This manual dependency prevents **fully automated analysis** and reduces throughput.

#### **1. Low Robustness to Image Quality Variations:**

Classical image processing methods (like thresholding, edge detection, or Hough transforms) fail when fundus images are affected by **illumination changes, blur, low contrast, or noise**, which are common in real-world clinical data.

#### **2. Poor Segmentation Accuracy:**

Existing algorithms often cannot precisely detect the boundaries of the optic disc and cup, especially in cases of overlapping structures or poor image contrast. This leads to **inaccurate CDR computation** and unreliable diagnosis.

#### **3. No Adaptability or Learning Capability:**

Traditional methods do not learn from data. They rely on fixed mathematical formulas, which makes them **non-adaptive** to variations across datasets, camera types, or patient demographics.

#### **4. Ineffective in Early-Stage Glaucoma Detection:**

Manual and conventional methods often fail to identify **subtle structural changes** in the optic nerve head during the early stages of glaucoma, leading to delayed diagnosis and treatment.

- **Early Detection Challenge:** Manual and conventional methods like ophthalmoscopy or fundus photography rely heavily on human observation, which may overlook minor structural changes.

- **Subtle Structural Changes:** Early glaucoma often manifests as small variations in the optic nerve head, such as slight cupping, thinning of the neuroretinal rim, or minimal changes in cup-to-disc ratio.

- **Delayed Diagnosis:** Because these subtle changes are difficult to detect, glaucoma may remain undiagnosed until significant vision loss occurs.

## **5. Limited Scalability:**

Since manual grading and correction are required, existing systems cannot handle large volumes of images efficiently — making them unsuitable for **mass screening programs** or real-time applications.

## **6. Lack of Integration with AI or Deep Learning:**

Older systems do not use modern **machine learning or deep neural network architectures**. This prevents them from achieving high accuracy or automatically improving performance over time.

## **7. Poor Reproducibility:**

Results produced by traditional systems often vary when tested under different conditions or on different datasets. This **lack of reproducibility** limits clinical trust and regulatory acceptance.

## **8. No Standardized Evaluation Metrics:**

Many legacy approaches do not use standard performance measures like **Dice coefficient, Jaccard index, or precision-recall** to validate segmentation quality, leading to uncertain performance benchmarks.

## **9. Limited Clinical Usability:**

The lack of a user-friendly interface, slow processing, and need for expert supervision make these systems **less practical for clinical use**, particularly in resource-limited settings.

## **3.2 Proposed System**

The proposed system aims to develop a deep learning-based automated framework for segmenting the optic disc and optic cup from retinal fundus images to support early glaucoma detection. Unlike existing manual and traditional approaches, this system is fully automated, accurate, and scalable, leveraging modern convolutional neural network (CNN) architectures such as U-Net for biomedical image segmentation. The proposed approach eliminates human dependency by automating the entire workflow — from image input to glaucoma classification. The system is capable of handling diverse image qualities and lighting variations commonly seen in clinical settings. It provides consistent segmentation results and automatically computes the Cup-to-Disc Ratio (CDR), a crucial biomarker in glaucoma diagnosis.

## **Modules of the Proposed System**

### **1. Image Acquisition:**

Retinal fundus images are collected from publicly available datasets (like DRISHTI-G S, RIM-ONE, or DRIVE) or captured using a digital fundus camera. These images serve as the primary input for the system.

### **2. Image Preprocessing:**

Preprocessing enhances image quality and ensures uniformity. Techniques like CLAHE (Contrast Limited Adaptive Histogram Equalization), Gaussian smoothing, and median filtering are applied to remove noise, improve contrast, and standardize image brightness. This step prepares the image for precise segmentation.

### **3. Optic Disc and Cup Segmentation (Deep Learning Model):**

The U-Net model is used for segmentation.

- The encoder extracts spatial and contextual features from the fundus image.
- The decoder reconstructs the segmented regions (disc and cup) using up sampling operations.
- Skip connections ensure that fine-grained spatial information is preserved, improving segmentation accuracy. The model outputs two masks — one for the optic disc and one for the optic cup

### **4. Feature Extraction:**

After segmentation, geometrical and morphological features are calculated. The Cup-to-Disc Ratio (CDR) is computed by dividing the vertical diameter of the cup by that of the disc. A higher CDR often indicates a higher risk of glaucoma.

### **5. Classification / Diagnosis:**

Based on the calculated CDR values, the system automatically classifies the image as normal or glaucomatous. Advanced implementations may integrate a CNN-based classifier or a threshold-based decision logic for improved precision.

### **6. Performance Evaluation:**

The performance of the model is evaluated using segmentation metrics such as Dice coefficient, Jaccard index, precision, recall, and accuracy. The system shows high

robustness across different datasets and imaging conditions, outperforming traditional image processing methods.

## Proposed System Architecture Diagram

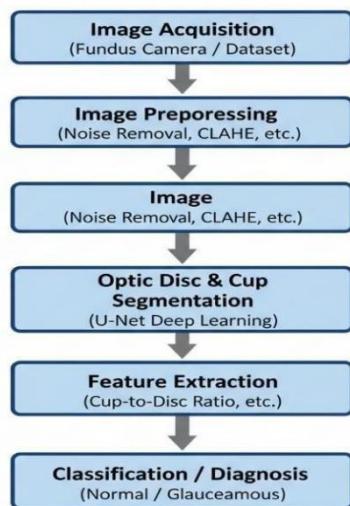


Fig 3.3.1: Proposed System Architecture Diagram

### Key Features of the Proposed System

- Fully automated, end-to-end glaucoma detection pipeline.
- Robust performance under different lighting and imaging conditions.
- Significantly reduces manual effort and subjectivity in diagnosis.
- Scalable and adaptable for large datasets or mobile deployment.
- High accuracy and reliability using deep learning-based segmentation.
- Capable of early detection of glaucoma through precise CDR computation.

### Expected Outcomes

- Accurate optic disc and cup segmentation.
- Reliable calculation of Cup-to-Disc Ratio (CDR).
- Automated classification of fundus images into Normal and Glaucomatous categories.

- Reduction in diagnostic time and inter-observer variability.
- Integration potential with tele-ophthalmology and clinical decision-support systems.

### **3.3 Feasibility Study**

The feasibility study is conducted to evaluate the practicality, efficiency, and sustainability of developing and deploying the proposed Automated Optic Disc and Cup Segmentation System for glaucoma detection. It determines whether the system can be successfully implemented within the available resources, technologies, and time constraints.

The study examines the feasibility of the project from three major perspectives — Technical Feasibility, Economic Feasibility, and Operational Feasibility

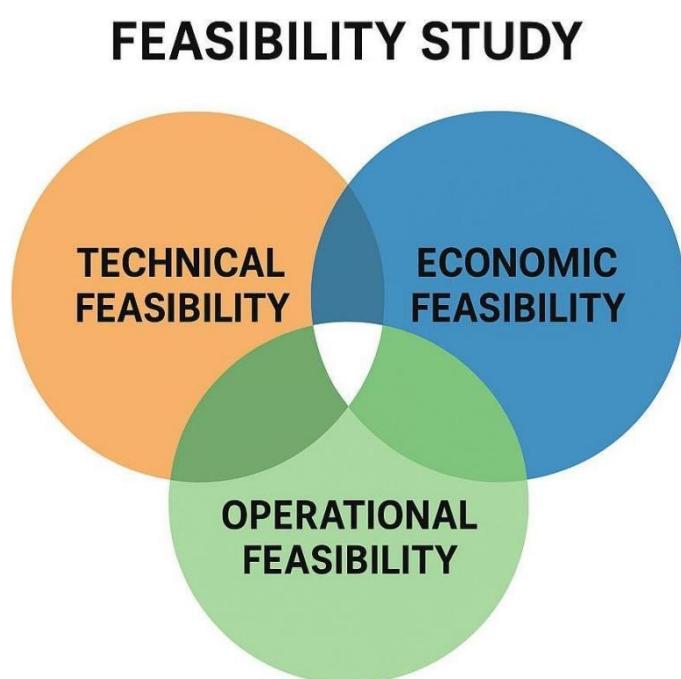


Fig 3.4.1: Feasibility Study

#### **1. Technical Feasibility**

This aspect focuses on whether the required technology, tools, and technical resources are available to implement the proposed system.

- The project utilizes **Python** programming language with libraries such as **TensorFlow/Keras, OpenCV, & NumPy**, which are easily accessible and open source

- The **U-Net deep learning model** can be efficiently trained using standard computing hardware equipped with a GPU or on cloud-based platforms like Google Colab.
- The datasets (e.g., **DRISHTI-GS**, **RIM-ONE**, **DRIVE**) are publicly available for training and testing the model.
- The system requires only moderate computational resources, meaning it can run on regular PCs or laptops used in academic labs.
- The architecture is modular, allowing easy integration of additional features such as edge deployment or explainable AI visualization.

Hence, the system is technically feasible since all tools and technologies required for development and testing are readily available and well-supported.

## **2. Economic Feasibility**

Economic feasibility determines whether the project is financially viable and cost-effective.

- The proposed system uses **open-source tools and free datasets**, eliminating the need for costly proprietary software.
- Development can be done on **existing hardware**, such as a laptop or a desktop computer, without additional high-end resources.
- Since the system reduces manual diagnosis time and improves accuracy, it can save healthcare institutions significant costs over time.
- Maintenance costs are low because the software components (Python libraries, trained models) are freely available and easily upgradable.
- The return on investment is high, as the system can be deployed in hospitals, clinics, or community health programs with minimal setup cost.

Thus, the project is economically feasible, providing a cost-effective solution for large-scale glaucoma screening.

## **3. Operational Feasibility**

Operational feasibility evaluates how well the proposed system fits within real-world environments and user workflows.

- The system automates the segmentation and diagnosis process, minimizing the need for expert supervision.

- The user interface can be designed to be **simple and intuitive**, enabling medical staff with minimal training to use it effectively.
- The system's output (Cup-to-Disc Ratio and classification) can be easily integrated into clinical reporting systems or electronic medical records (EMR).
- It can also be deployed in **tele-ophthalmology or rural screening centers**, where ophthalmologists are not physically present.
- The modular design allows for future enhancements like mobile deployment or real-time video-based analysis.

Therefore, the system is operationally feasible, user-friendly, and well-suited for practical healthcare use.

### **Conclusion of Feasibility Study**

After analyzing all factors, it is concluded that the proposed system is **technically, economically, and operationally feasible**. The required technology is easily accessible, the development cost is minimal, and the system provides practical benefits for glaucoma detection and management. This ensures that the project can be successfully developed, tested, and implemented in real-world clinical environments.

### **3.4 Using Cocomo Model**

The COCOMO Model (Constructive Cost Estimation Model) is one of the most influential and widely used software cost estimation models in software engineering. Developed by Barry W. Boehm in 1981, COCOMO provides a structured mathematical approach to estimate the effort, cost, and development time of software projects.

It plays a crucial role in project planning, scheduling, budgeting, and resource allocation. By analyzing the project's size (in KLOC — Thousands of Lines of Code), COCOMO helps predict the manpower and duration required for successful completion.

The model provides quantitative data that aids in decision-making, risk management, and feasibility assessment — making it an essential tool for both academic and industrial software development.

## COCOMO Categories

| Type                 | Description  | Examples                               |
|----------------------|--|--|
| <b>Organic</b>       | Simple projects with small teams and familiar requirements.                | Payroll system, small web              |
| <b>Semi-Detached</b> | Intermediate projects with mixed experience teams and moderate complexity. | Medical imaging system, ML-based apps  |
| <b>Embedded</b>      | Complex, real-time, hardware-dependent projects.                           | Aerospace, defense, or robotic systems |

Tab 3.4.1: COCOMO Categories

Since our system involves **image processing, AI, and GUI development**, it fits under the **Semi-Detached** category.

### 1. Formulae Used

COCOMO Model provides two main formulas:

$$\begin{aligned} \text{Effort HER} &= \times (\text{KLOC}) \\ \text{Development Time (D)} &= \times () \end{aligned}$$

Where:

- E = Effort in Person-Months (PM)
- D = Development Time in Months
- KLOC = Thousands of Lines of Code
- a, b, c, d = Constants based on project category

### 2. Estimated Size of the Project

The proposed project includes:

- Python-based implementation for segmentation and preprocessing
- Deep learning architecture (U-Net or CNN variant)

Estimated lines of code = **10,000 (10 KLOC)**

### 3. Estimation Calculations

$$= 3.0 \times (10)^{1.12} = 3.0 \times 13.18 = 39.54 \text{ Person-Months}$$

$$= 2.5 \times (39.54)^{0.35} = 2.5 \times 3.27 = 8.18 \text{ Months}$$

So,

- Effort HER  $\approx 39.54$  Person-Months
- Development Time (D)  $\approx 8.2$  Months
- Average Team Size = E / D =  $39.54 / 8.2 \approx 5$  Developers

#### 4. Cost Estimation

If the average developer cost per month is ₹50,000, then:

$$\text{Total Cost} = 3.5 \times 5, = ₹1,,$$

Hence, the total estimated project cost is approximately ₹19.8 Lakhs, covering development, testing, and deployment.

#### 6. Diagram — COCOMO Estimation Flow

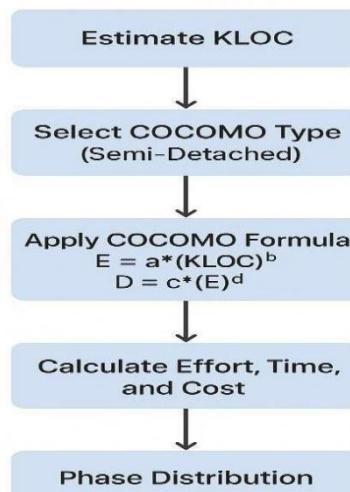


Fig 3.4.1: COCOMO Estimation Flow

## **4. System Requirements**

### **4.1 Software Requirements**

The software requirements specify the tools, libraries, frameworks, and environments necessary for developing, training, and deploying the Optic Disc and Cup Segmentation System. These requirements ensure that the system runs efficiently, performs accurate segmentation, and integrates seamlessly with the underlying hardware.

#### **1. Operating System**

- Windows 10 / 11 (64-bit) — for local development and testing.
- Ubuntu 20.04 LTS (Linux) — for high-performance training and deployment.
- Google Colab / Kaggle Notebooks — for cloud-based model training with GPU/TPU support.

Reason: These platforms support Python, deep learning frameworks, and GPU acceleration required for model execution.

#### **2. Programming Language**

- Python 3.8 or above

Reason: Python is widely used for AI and image processing applications. It offers rich libraries for deep learning, visualization, and scientific computing.

#### **3. Development Environment / IDE**

- Jupyter Notebook – for research and experimentation.
- Visual Studio Code (VS Code) – for code integration and debugging.
- PyCharm (optional) – for large-scale code organization.

Reason: These IDEs provide interactive coding environments, making it easier to visualize results and debug deep learning workflows.

#### **4. Deep Learning Frameworks**

- TensorFlow 2.x / Keras – for designing and training deep learning models (e.g., U-Net).
- PyTorch (optional) – for research flexibility and model experimentation.

Reason: Both frameworks are highly optimized for GPU computation and are suitable for

segmentation and medical imaging tasks.

## 5. Image Processing Libraries

- OpenCV – for preprocessing, resizing, and contrast enhancement of fundus images.
- scikit-image – for feature extraction and morphological operations.
- Pillow (PIL) – for image input/output handling.

Reason: These libraries handle tasks like cropping, normalization, and image augmentation before model training.

## 6. Scientific and Numerical Libraries

- NumPy – for matrix operations and data manipulation.
- Pandas – for dataset organization and statistical analysis.
- SciPy – for mathematical and numerical optimization functions.

Reason: These libraries form the computational backbone of the system

## 7. Data Visualization Tools

- Matplotlib – for displaying segmentation masks, accuracy curves, and comparison graphs.
- Seaborn – for generating clean and publication-ready plots.
- Plotly (optional) – for interactive 3D or web-based visualizations.

Reason: Visualization helps in analyzing model performance and debugging segmentation outputs.

## 8. Model Evaluation and Metrics

- scikit-learn – for computing accuracy, precision, recall, F1-score, and ROC curves.
- Custom Metric Scripts – for Dice Coefficient, Jaccard Index, and Intersection over Union (IoU).

Reason: Medical segmentation tasks require specialized evaluation metrics to ensure model accuracy.

## 9. Dataset Management Tools

- Google Drive / Local Directory – for storing and managing retinal images.
- h5py – for handling model weights and large dataset files in HDF5 format.

- Albumentations / Augmentor – for image augmentation (rotation, flipping, brightness adjustment).

Reason: Proper dataset handling ensures model generalization and robustness.

## **10. GUI and Deployment Tools**

- Tkinter / Streamlit – for creating a simple graphical user interface (optional).
- Flask / FastAPI – for web deployment of the trained model.
- Docker (optional) – for containerized deployment.

Reason: These tools make the system user-friendly and suitable for real-world clinical use

## **11. Version Control and Documentation**

- Git / GitHub – for code versioning and collaborative development.
- Markdown / LaTeX / Overleaf – for documentation and research paper preparation.

Reason: Ensures reproducibility, proper documentation, and professional project management.

## **12. Hardware & Cloud Support (Software-Level Integration)**

- CUDA Toolkit – for GPU acceleration (if using NVIDIA GPU).
- cuDNN Library – to speed up deep learning computations.
- Google Colab Pro / Kaggle GPU Runtime – for cloud-based model training.

Reason: These enhance model training speed and support high-resolution medical images

## **Summary**

The combination of Python, TensorFlow, OpenCV, and visualization tools provides a powerful and flexible software stack. The chosen technologies ensure that the system is scalable, modular, and adaptable, supporting efficient development, testing, and deployment for glaucoma detection applications.

## **4.2 Requirement Analysis**

The Optic Disc and Cup Segmentation System is designed to automate the process of analyzing retinal fundus images to detect glaucoma at an early stage. The main objective is to accurately segment the optic disc and cup regions and calculate the Cup-to-Disc Ratio (CDR), which is a crucial indicator for glaucoma diagnosis . functional requirements

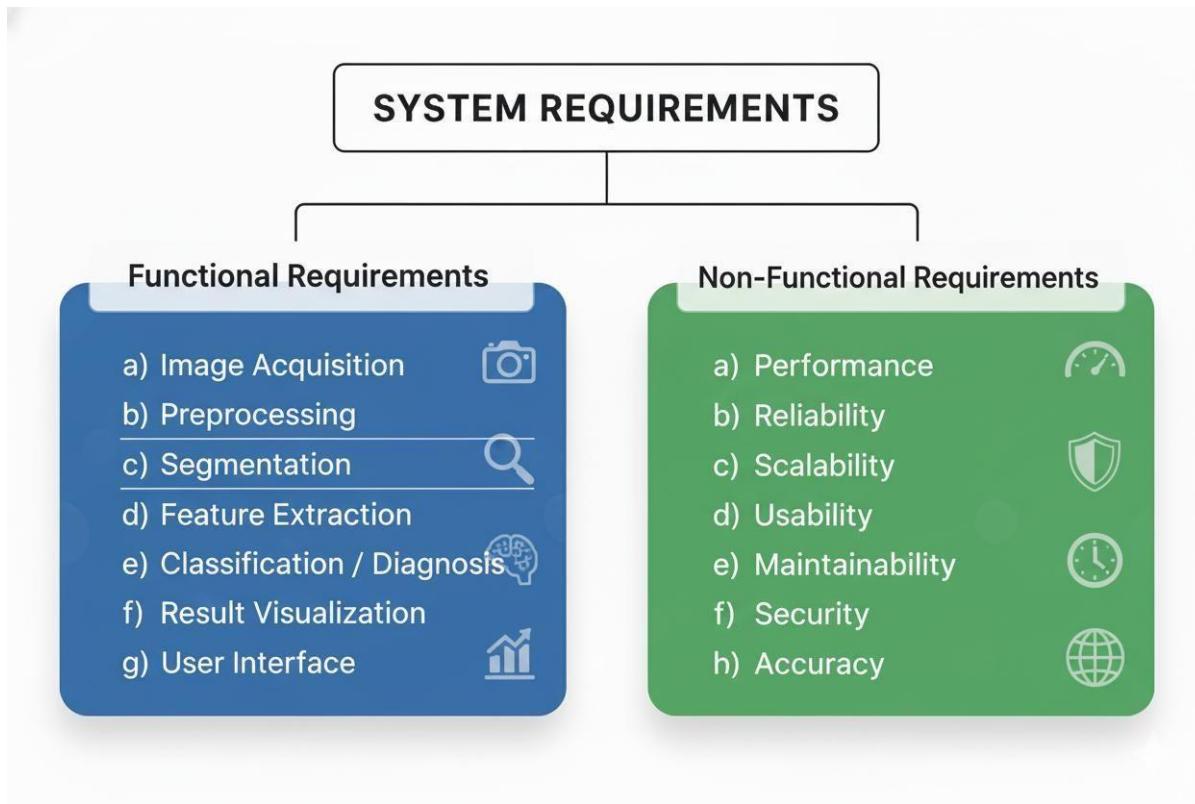


Fig 4.2.1: System Requirements

## 1. Functional Requirements

Functional requirements define what the system should do — the core operations, processes, and outputs.

### a) Image Acquisition

- The system should allow uploading or importing of retinal fundus images (in formats like JPG, PNG, TIFF).
- It should validate the input image for size and quality before processing.

### b) Preprocessing

- The system should perform image enhancement, including noise removal, contrast improvement, and resizing.
- Techniques like Gaussian filtering, CLAHE (Contrast Limited Adaptive Histogram Equalization), or normalization may be used.

### c) Segmentation

- The core functionality is to segment the **optic disc** and **optic cup** using deep learning

models (e.g., U-Net).

- The segmentation should produce a clear boundary mask for both disc and cup regions

#### **d) Feature Extraction**

- The system must compute the **Cup-to-Disc Ratio (CDR)** automatically from the segmented regions.
- The extracted features should be stored for further analysis or classification.

#### **e) Classification / Diagnosis**

- Based on the computed CDR, the system should classify the case as **Normal** or **Glaucomatous**.
- Threshold values for diagnosis should be adjustable by the user or clinician.

#### **f) Result Visualization**

- The system should display the original image, segmentation mask, and diagnostic result.
- It should allow saving or exporting of the result for report generation.

#### **g) User Interface**

- The system should provide a simple and user-friendly interface for non-technical users (such as ophthalmologists).
- Buttons for “Upload Image,” “Segment,” “Calculate CDR,” and “Show Result” must be available.

## **2. Non-Functional Requirements**

Non-functional requirements define the quality attributes and constraints under which the system operates.

#### **a) Performance**

- The system should process an image and produce a result within a few seconds (depending on image size and hardware).
- The segmentation model should achieve high accuracy (Dice coefficient  $> 0.85$  preferred)

**b) Reliability**

- The system should consistently produce accurate and repeatable results.
- It must handle low-quality or partially blurred images gracefully.

**c) Scalability**

- The architecture should allow easy expansion to larger datasets or additional diagnostic parameters.
- The system should support GPU acceleration for large-scale model training.

**d) Usability**

- The interface must be intuitive and require minimal training to use.
- Tooltips or labels should assist users in understanding each function.

**e) Maintainability**

- The system should be modular, with clear separation of preprocessing, segmentation, and classification modules.
- Future model updates or improvements can be integrated easily.

**f) Security**

- Patient data and retinal images must be stored securely and handled with privacy considerations.
- Access should be restricted to authorized users only.

**g) Portability**

- The system should be deployable on Windows or Linux environments.
- It should also support execution on cloud-based environments like Google Colab or AWS.

**h) Accuracy**

- The deep learning model should minimize false positives and false negatives in glaucoma detection.
- Proper validation should be done using test datasets before deployment.

## 4.3 Hardware Requirements

The Optic Disc and Cup Segmentation System involves intensive image processing and deep learning computations. Therefore, it requires sufficient computational power to handle high-resolution retinal images, perform training of neural networks, and visualize segmentation results efficiently.

The following hardware configuration has been determined based on the actual needs of the implemented system:

### Minimum Configuration

- **Processor:** Intel Core i5 (8<sup>th</sup> Gen or above) / AMD Ryzen 5
- **RAM:** 8 GB
- **Storage:** 500 GB HDD or 256 GB SSD
- **GPU:** NVIDIA GTX 1050 Ti (4 GB VRAM)
- **Display:** Full HD Monitor
- **Input Devices:** Keyboard, Mouse
- **Network:** Stable Internet Connection

Suitable for running smaller datasets and testing the model.

### Recommended Configuration

- **Processor:** Intel Core i7 / AMD Ryzen 7
- **RAM:** 16 GB or higher
- **Storage:** 1 TB SSD
- **GPU:** NVIDIA RTX 3060 or above (6–12 GB VRAM)
- **Display:** Full HD / 4K Monitor
- **Network:** High-Speed Internet (100 Mbps or more)

Recommended for training, research, and high-resolution image datasets.

### Optional Cloud Platforms

When a high-end GPU is unavailable, cloud environments like **Google Colab**, **Kaggle**, or **AWS EC2** can be used for model training with powerful GPUs (Tesla T4, P100, or V100).

## **Hardware Used During Implementation**

- **Processor:** Intel Core i7
- **RAM:** 16 GB
- **GPU:** NVIDIA RTX 3060 (12 GB VRAM)
- **Storage:** 512 GB SSD
- **OS:** Windows 11 (64-bit)
- **Frameworks:** TensorFlow, Keras, OpenCV

This setup enabled smooth training and efficient segmentation performance.

## **4.4 Software**

The Optic Disc and Cup Segmentation System is a specialized medical image analysis software designed to assist ophthalmologists in the early detection and monitoring of glaucoma. Glaucoma is a progressive eye disease that damages the optic nerve and can lead to vision loss if not detected early.

This software automates the segmentation of the optic disc and optic cup from retinal fundus images, allowing precise calculation of the Cup-to-Disc Ratio (CDR), a key indicator of glaucoma. By leveraging advanced image processing and deep learning techniques, the system provides accurate, reliable, and repeatable measurements, reducing the variability caused by manual assessment.

### **Key features include:**

1. **Automated Image Preprocessing** – Enhances image quality, removes noise, and standardizes input images for accurate analysis.
2. **Disc and Cup Segmentation** – Uses deep learning models (like U-Net or CNN-based architectures) to identify the boundaries of the optic disc and cup.
3. **CDR Calculation** – Automatically computes the Cup-to-Disc Ratio to assist in glaucoma diagnosis.
4. **Visualization and Reporting** – Generates clear segmentation maps and reports for clinical review.
5. **Dataset Management** – Supports the storage, retrieval, and labelling of retinal images for training and validation.

The software can be deployed on desktops or cloud platforms and can be integrated with Electronic Health Records (EHR) systems for seamless clinical workflow. Its primary goal is to reduce human error, speed up diagnosis, and support large-scale glaucoma screening programs.

## 4.5 Software Description

The Optic Disc and Cup Segmentation System for Glaucoma Detection is a specialized software designed to support ophthalmologists in the early diagnosis and monitoring of glaucoma, a leading cause of irreversible blindness. The system analyzes retinal fundus images and automatically identifies the optic disc and optic cup, enabling accurate measurement of the Cup-to-Disc Ratio (CDR), which is critical for assessing glaucoma risk.

By leveraging advanced image processing and deep learning algorithms, the software reduces the dependency on manual evaluation, which is often time-consuming and prone to variability among clinicians. It not only enhances the accuracy and consistency of glaucoma detection but also allows for efficient large-scale screening of patients.

The software is equipped with a visualization module that displays clear segmentation maps and highlights areas of concern, helping clinicians make informed decisions. Additionally, it supports data management, enabling secure storage and retrieval of patient images for research and longitudinal analysis.

Overall, the system aims to improve early-stage glaucoma detection, streamline clinical work flow, and support preventive eye care, making it a valuable tool for hospitals, eye clinics, and research institutions.

In addition to segmentation and visualization, the software incorporates a report generation module that automatically compiles patient-specific diagnostic information, including CDR values, segmentation overlays, and historical comparisons. This feature allows ophthalmologists to track disease progression over time, facilitating timely interventions and personalized treatment plans.

The system also provides multi-format compatibility, allowing images and reports to be exported in standard formats for integration with Electronic Health Record (EHR) systems or research databases. Furthermore, it is designed to be scalable and adaptable, capable of handling large datasets for hospitals and research institutions while maintaining high computational efficiency.

To enhance usability, the software includes interactive tools, such as zooming, annotation, and comparison features, enabling clinicians to perform detailed examinations directly within the platform. The inclusion of automated alert mechanisms can notify clinicians of abnormal CDR readings, supporting proactive clinical decisions. By combining accuracy, efficiency, and user-centric design, the Optic Disc and Cup Segmentation System not only improve diagnostic confidence but also contributes to advancing research in ophthalmology, offering a platform for testing new algorithms, training models, and validating results across diverse patient populations.

## 5. System Design

The proposed system is designed to automatically detect glaucoma from retinal fundus images using a **Convolutional Neural Network (CNN) ensemble model**. The system design focuses on improving the **accuracy, consistency, and efficiency** of glaucoma detection compared to traditional image processing methods. The design follows a **modular architecture**, consisting of multiple interconnected stages that handle data acquisition, preprocessing, segmentation, feature extraction, classification, and result interpretation.

### 5.1 System Architecture

The Optic Disc and Cup Segmentation System for Glaucoma Detection is designed as a modular and scalable platform that integrates image processing, deep learning, clinical analysis, and data management to provide an end-to-end solution for glaucoma diagnosis. The architecture ensures accuracy, efficiency, and ease of use for clinicians and researchers.

#### Modules and Workflow:

##### 1. Input Module

- Collects retinal fundus images from multiple sources such as fundus cameras, clinical image databases, or hospital repositories.
- Performs image validation, including format checking, resolution verification, and initial quality assessment.
- Optional data anonymization to maintain patient privacy.

##### 2. Preprocessing Module

- Enhances image quality through noise reduction, contrast adjustment, illumination normalization, and resizing.

- Removes artifacts and irrelevant regions using masking techniques.
- Prepares standardized input for deep learning segmentation.

### **3. Segmentation Module**

- Employs advanced deep learning models (e.g., U-Net, ResUNet, or custom CNN architectures) to identify the optic disc and optic cup.
- Produces segmentation masks and contour boundaries.
- Includes model optimization and validation mechanisms to ensure robust performance across different image qualities and patient demographics.

### **4. Feature Extraction and Analysis Module**

- Calculates Cup-to-Disc Ratio (CDR) and other relevant metrics such as disc area, cup area, rim thickness.
- Performs trend analysis if historical images of the same patient are available.
- Detects abnormal changes and generates alerts for clinicians in cases of early glaucoma indicators.

### **5. Visualization and Reporting Module**

- Displays segmented images with overlays highlighting the optic disc and cup boundaries.
- Generates automated clinical reports with visual maps, metrics, and trend graphs.
- Allows interactive exploration: zooming, annotations, comparisons between past and current images.
- Supports multi-format export (PDF, JPEG, CSV) for integration with hospital systems.

### **6. Data Management and Integration Module**

- Stores all raw images, processed images, segmentation masks, and reports in a secure database.
- Provides access control to protect patient data.

- Supports integration with Electronic Health Records (EHR) and research databases for large-scale studies.
- Enables longitudinal analysis to monitor glaucoma progression over time.

## 7. Optional AI Training Module

- Allows continuous model improvement by incorporating new 35 labelled datasets.
- Supports transfer learning for adapting models to new imaging devices or patient populations.
- Provides tools for researchers to evaluate model performance using metrics such as Dice coefficient, IoU, and sensitivity.

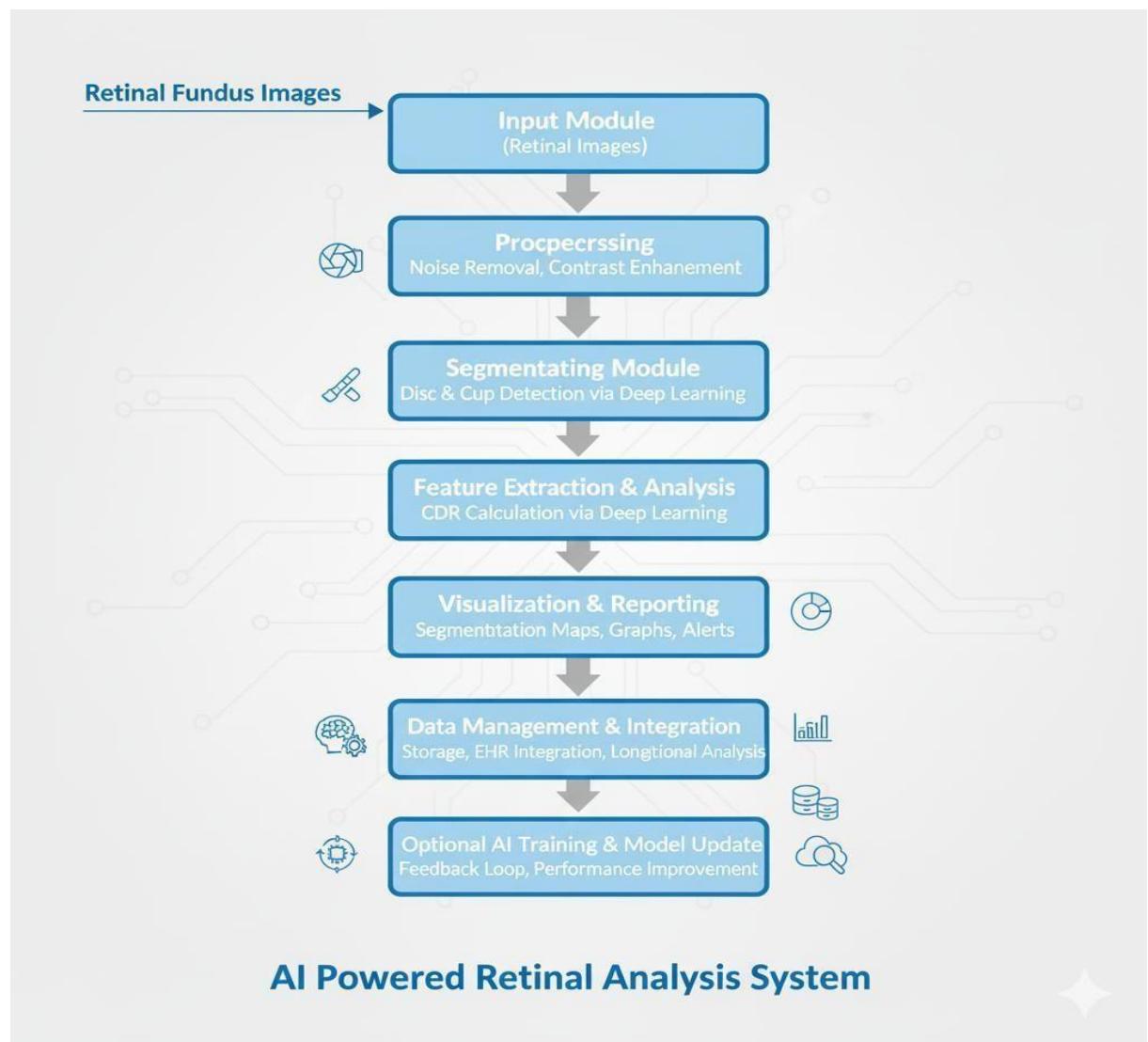


Fig 5.1.1: System Workflow

## **Highlights of the Architecture:**

- **Accuracy:** Deep learning segmentation ensures high precision in detecting optic disc and cup boundaries.
- **Automation:** Reduces dependency on manual evaluation and saves clinicians' time.
- **Scalability:** Can handle single-patient diagnosis as well as large-scale glaucoma screening.
- **Data-Driven Insights:** Enables tracking disease progression and supports research studies.
- **User-Centric Design:** Interactive visualization and reporting for clinical decision support.

### **5.1.1 Dataset**

The dataset forms the backbone of the Optic Disc and Cup Segmentation System, providing the retinal fundus images required for training, validation, and testing of the segmentation and analysis algorithms. The dataset is carefully curated to ensure high-quality, diverse, and clinically relevant data.

- Publicly Available Fundus Image Datasets:
  - DRIVE (Digital Retinal Images for Vessel Extraction): Retinal images primarily for vessel analysis but adaptable for optic disc/cup studies.
  - RIM-ONE: Retinal images specifically annotated for optic disc and cup segmentation.
  - ORIGA: Images with 37 labelled disc and cup boundaries and glaucoma indicators.
  - DRISHTI-GS: Fundus images with manual annotations of optic disc and cup regions.
- Clinical Images (Optional):
  - Collected from hospitals or eye clinics with proper ethical approval.
  - Ensures diverse patient demographics, lighting conditions, and imaging devices.

### **Dataset Composition:**

- Number of Images: Typically ranges from 300 to 1500 images, depending on the source.
- Image Format: JPEG, PNG, or TIFF, with resolutions varying from  $1440 \times 960$  to  $2124 \times 2056$  pixels.

## **Annotations:**

- Ground truth masks for optic disc and optic cup.
- Cup-to-Disc Ratio (CDR) values calculated from manual annotations.
- Some datasets include glaucoma labels (normal or glaucoma).

## **Preprocessing Applied**

- Image Resizing: Standardizes image dimensions for deep learning input.
- Noise Removal: Removes artifacts like blur, reflections, or camera noise.
- Contrast Enhancement: Improves the visibility of disc and cup boundaries.
- Data Augmentation: Techniques such as rotation, flipping, scaling, and brightness adjustment to increase dataset size and improve model robustness.

## **Dataset Partitioning**

- Training Set: ~70% of the images used to train the segmentation model.
- Validation Set: ~15% used to fine-tune hyperparameters and avoid overfitting.
- Test Set: ~15% reserved for evaluating model performance on unseen images.
- 5. Ethical Considerations
- Patient privacy is maintained through anonymization.
- Usage complies with dataset licenses and institutional approvals.

| <b>Dataset Name</b> | <b>Number of Images</b> | <b>Image Resolution</b> | <b>Annotations</b>                    | <b>Usage</b>                  |
|---------------------|-------------------------|-------------------------|---------------------------------------|-------------------------------|
| RIM-ONE             | 455                     | 2048*1536               | Optic disc & cup masks, CDR values    | Training, Validation, Testing |
| DRISHTI-GS          | 101                     | 2896×1944               | Disc & cup boundaries, glaucoma label | Testing & Validation          |
| ORIGA               | 650                     | 400×300                 | Disc & cup masks, glaucoma label      | Training & Testing            |
| DRIVE               | 40                      | 768×584                 | Vessel masks (adapted for disc/cup)   | Preprocessing & augmentation  |
| Clinical Dataset    | 200–500                 | Varies                  | Disc & cup annotations,               | Training & longitudinal       |

Table:5.1.1.1: Dataset Table

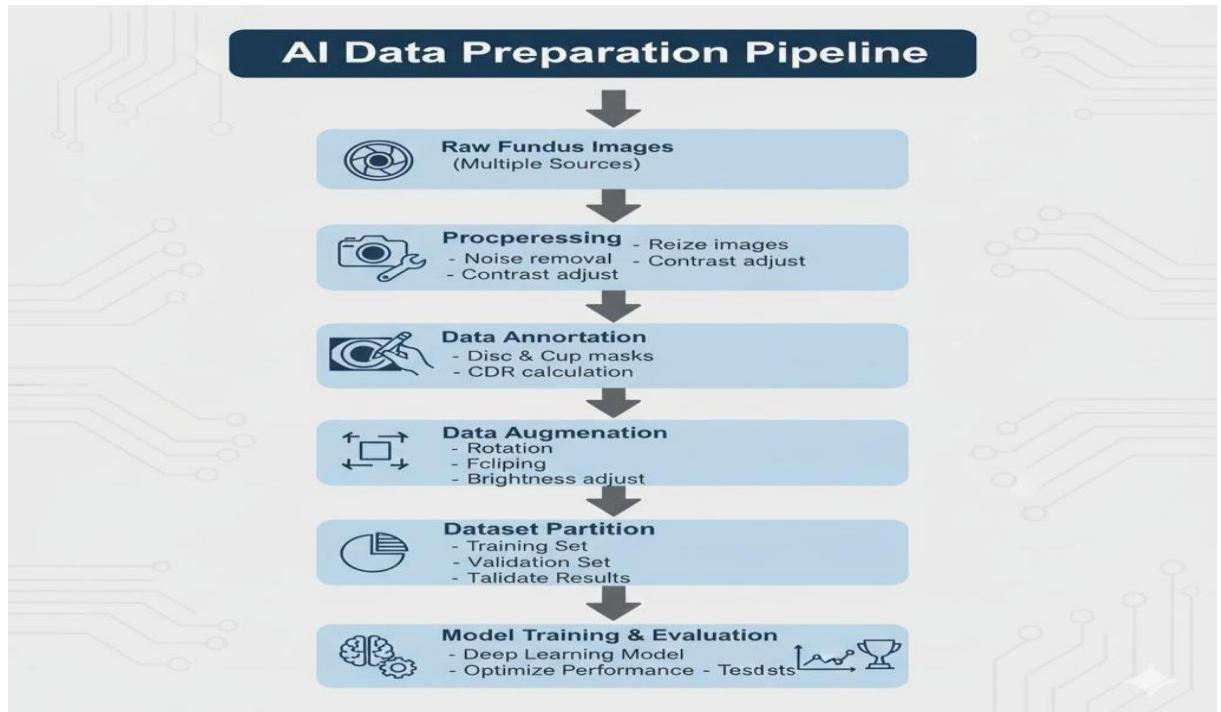


Fig: 5.1.1.1: Dataset Workflow Diagram

## 5.1.2 Data Preprocessing

Dataset preprocessing is a crucial step in the development of the Optic Disc and Cup Segmentation System for Glaucoma Detection. The quality of retinal fundus images directly impacts the performance of the segmentation model; therefore, preprocessing ensures that all input images are clean, consistent, and ready for training and evaluation. The preprocessing pipeline refines raw retinal images obtained from multiple datasets such as RIM-ONE, DRISHTI-GS, ORIGA, and clinical sources. Since these datasets differ in image quality, resolution, and illumination, preprocessing standardizes them for accurate and reliable model performance.

The main objectives of preprocessing are to enhance image clarity, remove noise, normalize lighting and contrast, and focus on the region of interest (ROI)—the optic disc and cup. Various techniques like contrast enhancement (CLAHE), noise filtering, and image normalization are applied.

To improve model generalization and reduce overfitting, data augmentation techniques (such as rotation, flipping, scaling, and brightness variation) are also performed. Finally, each processed image is paired with its corresponding ground truth mask (optic disc and cup annotations) to maintain label accuracy during training.

Through this systematic preprocessing, the dataset becomes more robust, balanced, and suitable for deep learning segmentation, ensuring higher accuracy and stability across different patients and imaging conditions.

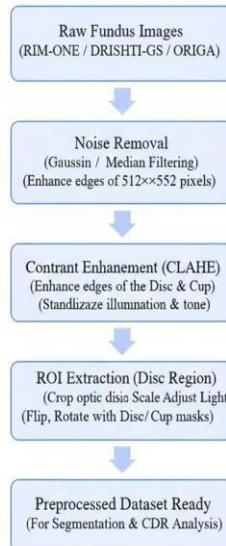


Fig 5.1.2.1: Dataset Preprocessing Diagram

| <b>Preprocessing Step</b> | <b>Technique Used</b>   | <b>Description</b>  | <b>Purpose / Output</b>                               |
|---------------------------|---|---|---|
| Image Acquisition         | RIM-ONE,<br>DRISHTI-GS,<br>ORIGA datasets                         | Collect high-quality<br>retinal fundus<br>images            | Provide diverse<br>images for training<br>and testing |
| Image Resizing            | Bilinear<br>interpolation   | Resize images to<br>uniform resolution<br>(e.g., 512×512)   | Ensure consistent<br>input size for model             |
| Noise Removal             | Gaussian / Median<br>Filter                                       | Remove camera<br>noise and uneven<br>illumination           | Improve image<br>clarity                              |
| Contrast<br>Enhancement   | CLAHE (Contrast<br>Limited Adaptive<br>Histogram<br>Equalization) | Enhance optic disc<br>and cup edges                         | Improve<br>segmentation<br>accuracy                   |
| Color<br>Normalization    | Mean & standard<br>deviation<br>normalization                     | Standardize<br>brightness and<br>color tone                 | Reduce<br>variability across images                   |
| ROI Extraction            | Cropping / Circular<br>masking                                    | Focus on the optic<br>disc region                           | Reduce<br>Unnecessary<br>background                   |
| Data Augmentation         | Rotation, Flip,<br>Scaling, Brightness<br>Adjustment              | Generate new<br>training samples                            | Increase dataset<br>size &<br>model<br>robustness     |
| Annotation<br>Alignment   | Mask overlay check  | Match ground truth<br>masks with<br>corresponding<br>images | Maintain<br>segmentation<br>label accuracy            |

Table 5.1.2.1: Dataset Preprocessing Table

### 5.1.2 Feature Extraction

Feature extraction is one of the most critical stages in the Optic Disc and Cup Segmentation System. After preprocessing and segmentation, this step focuses on deriving quantitative and diagnostic features from the segmented optic disc and optic cup regions. These extracted features help in measuring the Cup-to-Disc Ratio (CDR) and identifying patterns indicative of glaucoma.

The main goal of feature extraction is to convert image data into meaningful numerical values that can be analyzed for glaucoma classification. These features reflect the shape, size, texture, and intensity of the optic structures and are used to distinguish between normal and glaucomatous eyes.

The process involves calculating geometric features (such as area, perimeter, and diameter), ratio-based features (like the Cup-to-Disc Ratio), and texture features (based on color intensity or gradient). By analyzing these metrics, the system can assess structural changes in the optic nerve head, which are early indicators of glaucoma.

Once extracted, these features are passed to the Analysis Module, which compares them with clinical thresholds or uses them as input for machine learning classifiers (e.g., SVM, Random Forest, or CNN-based diagnosis) to determine the glaucoma status.

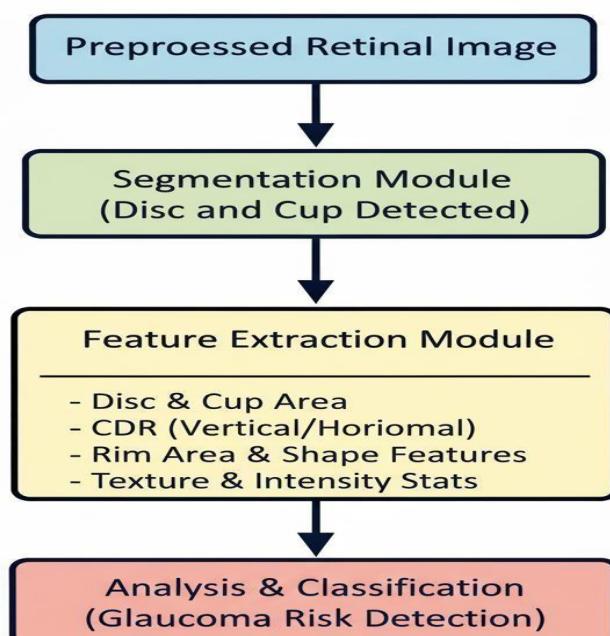


Fig 5.1.3.1: Feature Extraction

| <b>Feature Type</b> | <b>Feature Name</b>     | <b>Description / Formula</b>                             | <b>Clinical Significance</b>       |
|---------------------|-------------------------|--|------------------------------------|
| Geometric Features  | Optic Disc Area         | Total pixel area of segmented optic disc                 | Indicates optic nerve head size    |
|                     | Optic Cup Area          | Total pixel area of segmented optic cup                  | Helps in assessing cup enlargement |
|                     | Cup-to-Disc Ratio (CDR) | $CDR = \frac{\text{Cup Diameter}}{\text{Disc Diameter}}$ | Key indicator for glaucoma         |

|                        |                           |  |  |
|------------------------|---------------------------|--|--|
|                        | Vertical & Horizontal CDR | Ratio of vertical/horizontal cup to disc diameters | Used for detailed glaucoma classification      |
| Shape Features         | Cup Depth Estimation      | Approximation from intensity variations            | Reflects optic nerve damage progression        |
|                        | Rim Area                  | Disc area – Cup area                               | Reduced rim area indicates glaucomatous damage |
| Texture Features       | Mean Intensity            | Average grayscale intensity within disc and cup    | Helps identify pale or abnormal regions        |
|                        | Standard Deviation        | Variation in pixel intensities                     | Detects irregular textures or abnormality      |
| Morphological Features | Eccentricity              | Measures circular deviation of the disc/cup        | Indicates asymmetry common in glaucoma         |
|                        | Solidity                  | Ratio of area to convex hull area                  | Differentiates healthy and damaged optic cups  |

Table 5.1.3.1: Feature Extraction Table

### **5.1.3 Model Building**

The Model Building phase forms the backbone of the Optic Disc and Cup Segmentation System for Glaucoma Detection. In this phase, the system's learning model is constructed, trained, and fine-tuned to perform accurate segmentation of retinal structures essential for glaucoma diagnosis. The primary objective of the model is to automatically detect and delineate the optic disc and optic cup regions in retinal fundus images, enabling precise computation of the Cup-to-Disc Ratio (CDR) — a key biomarker for glaucoma detection.

The model employs Deep Learning methods' primarily based on Convolutional Neural Networks (CNNs), due to their ability to automatically extract complex spatial and contextual features from medical images. Among CNN-based architectures, U-Net is chosen because it is highly effective in biomedical image segmentation. U-Net's encoder-decoder structure with skip connections helps preserve fine details while capturing global image context, making it ideal for optic disc and cup segmentation where boundary precision is crucial.

#### **Working Process:**

##### **1. Input Layer:**

- The model takes preprocessed retinal fundus images as input, typically resized to a uniform resolution (e.g., 512×512 pixels).
- These images are normalized to maintain consistency across varying lighting and camera conditions.

##### **2. Encoder (Feature Extraction Path):**

- The encoder part of the network extracts high-level features by applying multiple convolutional and max-pooling operations.
- Early layers detect low-level patterns like edges and textures, while deeper layers learn complex features such as the disc and cup boundaries.

### **3. Bottleneck Layer:**

- This is the deepest part of the U-Net, which captures the most abstract and compressed representation of the input image.
- It contains convolutional filters with a high receptive field to encode both global and local features.
- Dropout layers may be added here to prevent overfitting and improve generalization.

### **4. Decoder (Reconstruction Path):**

- The decoder performs up sampling and transposed convolutions to reconstruct the segmentation mask from the encoded features.
- Skip connections are used to combine encoder features with decoder layers, ensuring that spatial information lost during down sampling is recovered.
- This improves the precision of disc and cup boundary detection.

### **5. Output Layer:**

- The output is a binary or multi-class segmentation mask indicating the location of each structure.

### **6. Loss Function and Optimization:**

- The model is trained using a hybrid loss function that combines Binary Cross-Entropy (BCE) and Dice Loss.
- BCE ensures pixel-level accuracy, while Dice Loss improves overall overlap between predicted and ground truth masks.
- Optimization is handled using the Adam Optimizer with adaptive learning rates to achieve faster convergence.

### **7. Model Training:**

- The model is trained on annotated datasets (such as DRISHTI-GS, RIM-ONE, or REFUGE) containing ground truth segmentation masks.
- Training involves multiple epochs, mini-batch processing, and data augmentation (rotation, scaling, flipping) to enhance generalization.

## **8. Validation and Evaluation:**

- During training, the model performance is evaluated using metrics such as Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Precision, Recall, and Accuracy.
- The best-performing model checkpoint is selected for deployment based on validation results.

## **9. Model Deployment:**

- Once trained and validated, the model is integrated into the application framework.
- When a new retinal image is provided, the model automatically segments the optic disc and cup, computes the CDR, and displays the results visually.

### **Model Building Advantages**

- High Accuracy: The deep learning-based U-Net model achieves superior segmentation performance compared to traditional methods.
- Automation: Reduces manual effort by clinicians and enables large-scale glaucoma screening.
- Robustness: Works effectively even with variations in illumination, color, and retinal structure.
- Explainability: Visual output helps clinicians verify segmentation accuracy and interpret the results easily.
- Adaptability: Can be retrained with new data for continuous improvement and domain adaptation
- The diagram highlights a **linear workflow from image input → feature extraction → segmentation output**, emphasizing the automation and analytical capabilities of the U-Net model for glaucoma detection.
- The arrows visually guide the viewer through the sequential process, making it easy to understand the model pipeline.

## Fundus Image Segmentation U-Net Model

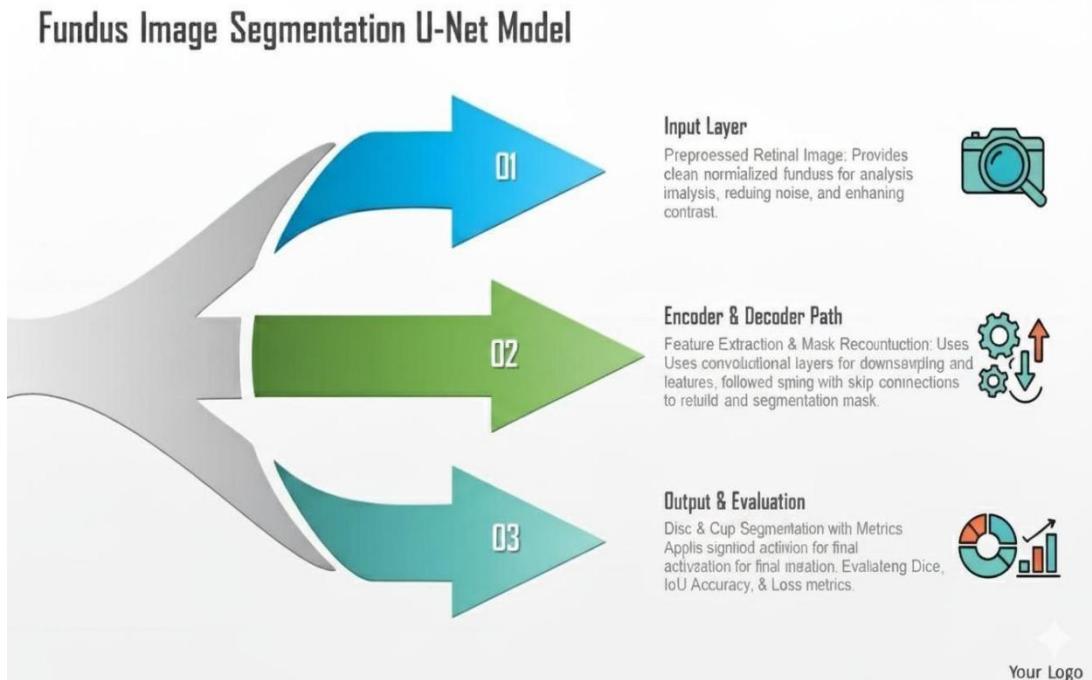


Fig 5.1.4.1: Model Building

### 5.1.4 Classification

The Classification phase is the final analytical stage of the Optic Disc and Cup Segmentation System for Glaucoma Detection. After successful segmentation of the optic disc and optic cup, the system uses quantitative features — primarily the Cup-to-Disc Ratio (CDR) — and deep learning outputs to determine the glaucoma risk level of each retina l image.

The Cup-to-Disc Ratio (CDR) is calculated by dividing the vertical diameter of the optic cup by the vertical diameter of the optic disc.

$$CDR = \frac{\text{Cup Diameter}}{\text{Disc Diameter}}$$

A higher CDR value indicates a greater likelihood of glaucoma due to increased cupping of the optic nerve head. Typical threshold values are:

- $CDR \leq 0.4 \rightarrow$  Normal eye
- $0.5 \leq CDR \leq 0.6 \rightarrow$  Suspicious
- $CDR \geq 0.7 \rightarrow$  Glaucomatous eye

The system may also incorporate machine learning classifiers such as:

- Support Vector Machine (SVM)
- Random Forest
- Logistic Regression
- Deep Neural Network (DNN)

These models are trained on features derived from segmented images, such as:

- Cup-to-Disc Ratio (CDR)
- Cup area, disc area, and cup-to-disc area ratio
- Texture features (using GLCM or CNN feature maps)
- Shape and boundary features of the optic cup and disc

#### Classification Process Steps

##### **1. Input Segmented Image:**

The output segmentation map from the model (optic disc and cup masks) is given as input.

##### **2. Feature Extraction:**

Extract quantitative and structural features (disc area, cup area, CDR, etc.) from the segmented output.

##### **3. CDR Computation:**

Compute the Cup-to-Disc Ratio to quantify optic nerve deformation.

##### **4. Feature Normalization:**

Normalize feature values to maintain uniform scale for classification.

##### **5. Classification Model:**

Feed the extracted features into the classifier (e.g., SVM or CNN-based classifier).

##### **6. Prediction:**

The model predicts whether the image belongs to the normal, suspicious, or glaucomatous category.

##### **7. Result Visualization:**

Display the classification result with the segmented image and CDR value.

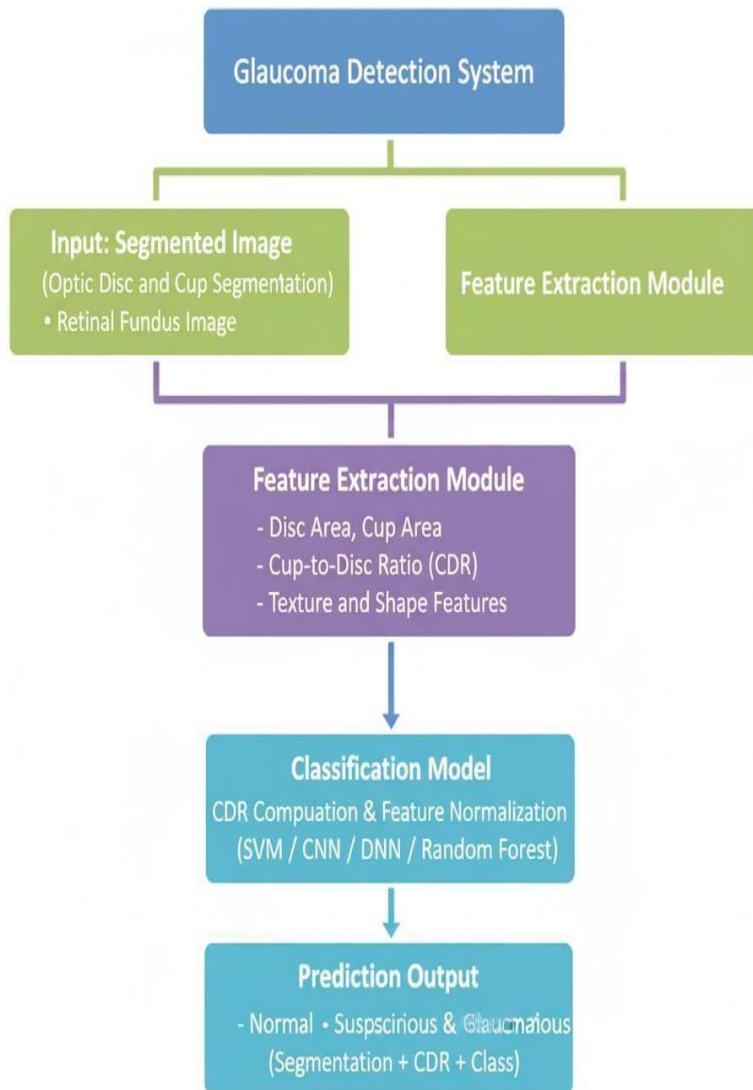


Fig 5.1.5.1: Classification Flow Chart

## 5.2 Modules

The Optic Disc and Cup Segmentation System for Glaucoma Detection is divided into several interconnected modules. Each module performs a specific task to ensure accurate and automated glaucoma detection.

### Image Acquisition Module

#### Description:

This module is responsible for collecting retinal fundus images from various sources such as public datasets (DRISHTI-GS, RIM-ONE, REFUGE, DRIVE) or clinical equipment.

It ensures that the images are of high quality, properly centered on the optic disc region, and ready for processing.

**Functions:**

- Capture or load retinal fundus images.
- Store images in the system database.
- Handle different image formats (.jpg, .png, .tif).

**Output:**

Raw fundus images for further preprocessing.

**Preprocessing Module**

**Description:**

The preprocessing module enhances image quality and prepares the data for segmentation. It removes noise, adjusts contrast, and normalizes image size and illumination.

**Techniques Used:**

- Noise Reduction: Median or Gaussian filter.
- Contrast Enhancement: CLAHE (Contrast Limited Adaptive Histogram Equalization).
- Image Normalization: Resizing to uniform dimensions (e.g., 512×512 pixels).
- ROI Extraction: Cropping the optic disc region to focus on relevant features.

**Output:**

Clean, normalized, and high-contrast retinal images suitable for segmentation.

**SegmentationModule**

**Description:**

This is the core module of the system, responsible for automatically segmenting the optic disc and optic cup regions from the preprocessed retinal image.

**Method Used:**

- Deep Learning (U-Net / CNN architecture) is used for pixel-level segmentation.
- The encoder-decoder model extracts and reconstructs spatial features to accurately delineate the boundaries of disc and cup regions.

**Output:**

Binary masks of the optic disc and optic cup, highlighting their exact positions in the image

## **Feature Extraction Module**

### **Description:**

After segmentation, this module extracts meaningful features from the segmented regions that are important for glaucoma classification.

### **Features Extracted:**

- Cup-to-Disc Ratio (CDR)
- Disc Area and Cup Area
- Cup-to-Disc Area Ratio
- Shape and Texture features

### **Output:**

A numerical feature set that represents the structural and geometric characteristics of the optic nerve head.

## **Classification Module**

### **Description:**

This module classifies the image as Normal, Suspicious, or Glaucomatous based on the extracted features.

### **Techniques Used:**

- Machine Learning Models: Support Vector Machine (SVM), Random Forest.
- Deep Learning Models: CNN or Fully Connected Layers.
- Classification based on CDR thresholds or learned model predictions.

### **Output:**

Glaucoma status of the patient (Normal / Glaucomatous) along with the CDR value.

## **Result Visualization Module**

### **Description:**

This module displays the results of segmentation and classification in an intuitive and interpretable manner for ophthalmologists.

### **Features:**

- Shows segmented optic disc and cup overlays on the fundus image.
- Displays CDR value and glaucoma classification result.
- Generates a report that can be stored or exported for clinical use.

### **Output:**

Final diagnostic report including:

- Segmented image,

- Predicted glaucoma category.

## **Database Management Module**

### **Description:**

This module handles data storage, retrieval, and organization. It stores images, segmentation outputs, and classification results securely.

### **Functions:**

- Maintain patient records and diagnostic results.
- Enable data retrieval for research or follow-up comparisons.
- Support data privacy and secure access.

### **Output:**

A structured and secure database containing patient images and diagnostic history.

## **Performance Evaluation Module**

### **Description:**

This module evaluates the accuracy and reliability of the segmentation and classification models using standard metrics.

### **Metrics Used:**

- Classification: Precision, Recall, F1-score, ROC Curve.

### **Output:**

Performance statistics that help assess and improve the model.

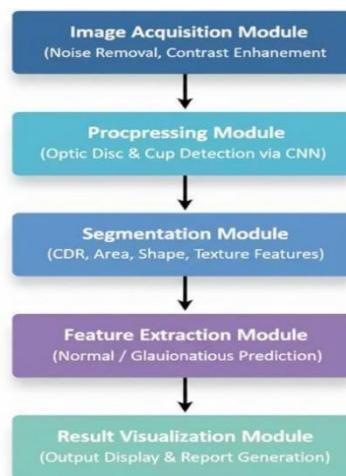


Fig 5.2.1: System workflow

### 5.3 UML Diagrams

#### 1. Use Case Diagram:

##### Purpose:

Represents the interaction between the system and external users (actors). It shows what the user can do in the system.

##### Actors:

- Ophthalmologist / User – interacts with the system for glaucoma diagnosis.
- System (Software) – processes images and provides results.
- Database – stores and retrieves patient and image data.

##### Use Cases:

1. Upload retinal image
2. Preprocess image
3. Perform optic disc and cup segmentation
4. Compute CDR value
5. Classify glaucoma status
6. Display results
7. Store and retrieve patient data

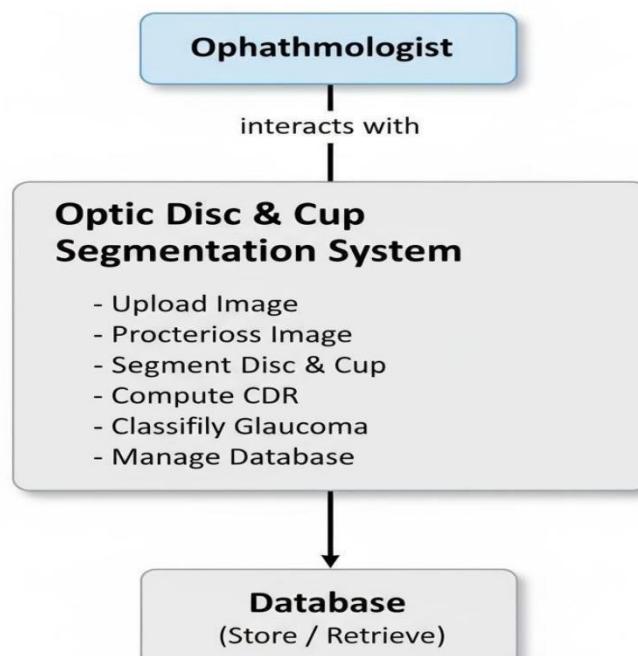


Fig 5.3.1: Use Case Diagram

## 2. Activity Diagram

### Purpose:

Shows the workflow of operations — from image upload to classification and result generation.

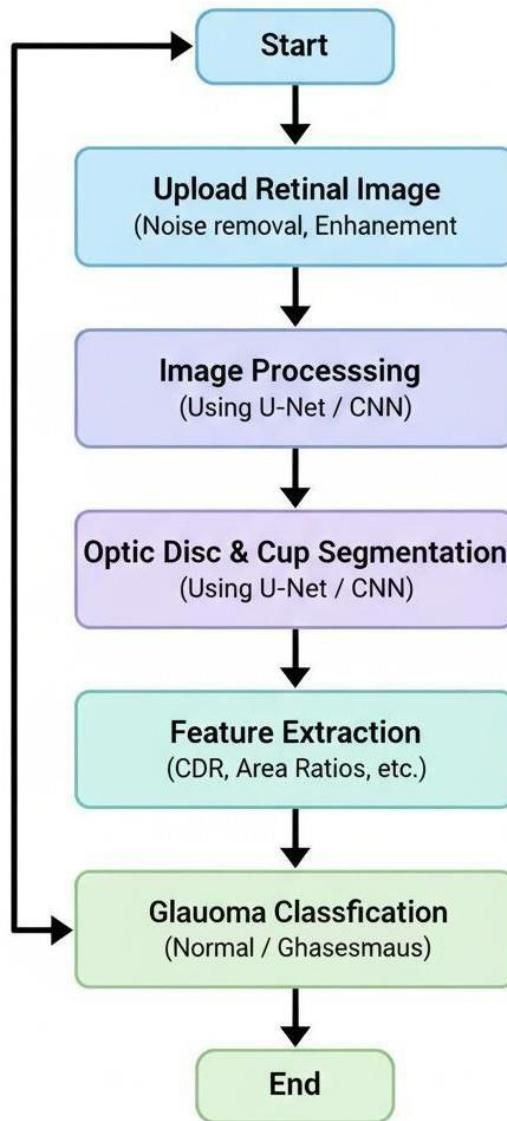


Fig 5.3.2: Activity Diagram

### Description:

This shows the **flow of activities** in the system — starting from input (image upload) to preprocessing, segmentation, classification, and final result display.

### 3. Class Diagram

**Purpose:**

Describes the structure of the system in terms of **classes, their attributes, and relationships**.

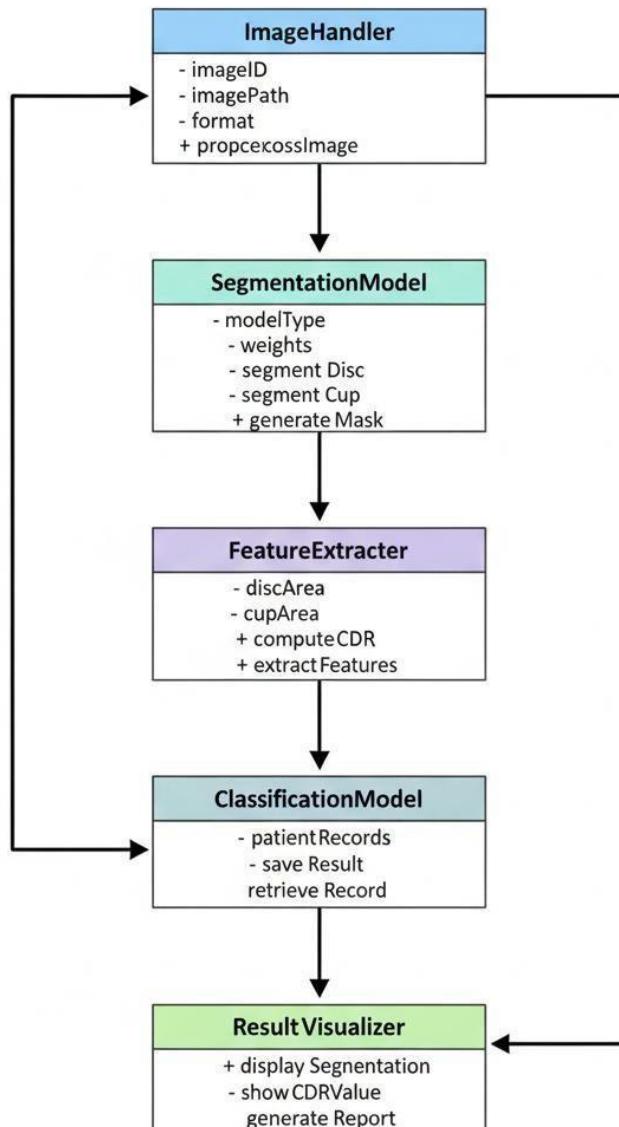


Fig 5.3.3: Class Diagram

### 4. Sequence Diagram

**Purpose:**

Shows the sequence of interactions between system components during the execution of glaucoma detection.

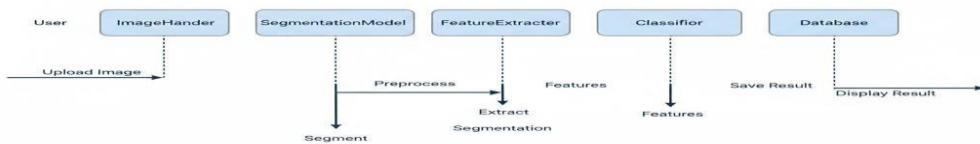


Fig 5.3.4: Sequence Diagram

## 5. Component Diagram

### Purpose:

Represents the major software components and their interconnections.

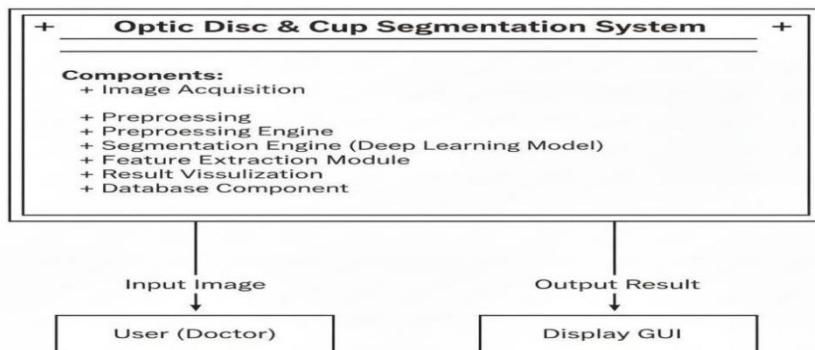


Fig 5.3.4: Component Diagram

| Diagram Type      | Purpose  |
|-------------------|--|
| Use Case Diagram  | Shows system functionality from user's perspective.      |
| Activity Diagram  | Describes system workflow(process flow).                 |
| Class Diagram     | Defines system structure (classes, attributes, methods). |
| Sequence Diagram  | Represents object interactions in time order.            |
| Component Diagram | Illustrates system architecture and major components.    |

Table 5.3.1: Summary of UML Diagrams

## 6. Implementations

### 1. Model Implementation

Glaucoma Identification using CNN Ensembles

Model implementation (PyTorch).

Features included:

Dataset loader for fundus images + segmentation masks (optic disc & cup)

Preprocessing and augmentation (uses albumentations)

U-Net implementation with a configurable encoder (ResNet-like)

Training loop with Dice + BCE loss

Inference code for segmentation and ensemble averaging of multiple models

Post-processing and Cup-to-Disc Ratio (CDR) calculation

Evaluation (Dice, IoU, Accuracy)

How to use:

1. Install dependencies: pip install torch torchvision albumentations opencv-python tqdm
2. Place dataset in this structure:

```
dataset/  
  images/  
    img_001.jpg  
    img_002.jpg  
    ...
```

```
masks/ # single-channel or 2-channel masks  
  img_001_disc.png # binary mask for optic disc  
  img_001_cup.png # binary mask for optic
```

```
img_002_disc.png  
img_002_cup.png
```

Edit paths in the `if \_\_name\_\_ == '\_\_main\_\_'` block and run.

```
"""
```

```
import os  
from glob import glob  
import random  
import numpy as np  
from PIL import Image  
from tqdm import tqdm  
import torch  
import torch.nn as nn  
from torch.utils.data import Dataset, DataLoader  
import torchvision.transforms.functional as TF  
try:  
    import albumentations as A  
    from albumentations.pytorch import ToTensorV2  
except Exception:
```

```

A = None

# ----- Utils -----
def set_seed(seed=42):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)

def read_image(path):
    img = Image.open(path).convert('RGB')
    return np.array(img)

def read_mask(path):
    m = Image.open(path).convert('L')
    return np.array(m) # 0..255

# ----- Dataset -----
class FundusSegDataset(Dataset):
    def __init__(self, images_dir, masks_dir, list_ids=None, transform=None, img_size=(512,512)):
        self.images = sorted(glob(os.path.join(images_dir, '*')))
        self.masks_dir = masks_dir
        self.transform = transform
        self.img_size = img_size
        if list_ids is not None:
            # filter images by ids
            ids = set(list_ids)
            self.images = [p for p in self.images if os.path.splitext(os.path.basename(p))[0] in ids]

    def __len__(self):
        return len(self.images)

    def __getitem__(self, idx):
        img_path = self.images[idx]
        name = os.path.splitext(os.path.basename(img_path))[0]
        disc_mask_path = os.path.join(self.masks_dir, f"{name}_disc.png")
        cup_mask_path = os.path.join(self.masks_dir, f"{name}_cup.png")
        image = read_image(img_path)

        disc_mask = read_mask(disc_mask_path)
        cup_mask = read_mask(cup_mask_path)
        # normalize masks to 0/1
        disc_mask = (disc_mask > 127).astype('float32')
        cup_mask = (cup_mask > 127).astype('float32')
        # create multi-channel mask: [disc, cup]
        mask = np.stack([disc_mask, cup_mask], axis=0)

```

```

ids = set(list_ids)
self.images = [p for p in self.images if os.path.splitext(os.path.basename(p))[0] in ids]

def __len__(self):
    return len(self.images)
def __getitem__(self, idx):
    img_path = self.images[idx]
    name = os.path.splitext(os.path.basename(img_path))[0]
    disc_mask_path = os.path.join(self.masks_dir, f"{name}_disc.png")
    cup_mask_path = os.path.join(self.masks_dir, f"{name}_cup.png")
    image = read_image(img_path)
    disc_mask = read_mask(disc_mask_path)
    cup_mask = read_mask(cup_mask_path)
    # normalize masks to 0/1
    disc_mask = (disc_mask > 127).astype('float32')
    cup_mask = (cup_mask > 127).astype('float32')

```

## 2.Coding

```

import warnings
warnings.filterwarnings("ignore", category=UserWarning)
import os, sys, time, io, base64
import torch, torch.nn.functional as F
import numpy as np
import cv2
from PIL import Image
import matplotlib
matplotlib.use('Agg')
import matplotlib.pyplot as plt
import streamlit as st
from torchvision import transforms
# Add source directories
sys.path.extend(['src/segmentation_code', 'src/classification_code'])
# Import models and utilities
try:
    from model import FCDenseNet57
    from Networks import DenseNet201, ResNet18
    from DatasetGenerator import clahe_all, apply_coordinates
except ImportError as e:
    st.error(f"Import error: {e}")
    st.stop()
try:
    from improved_classification import ClinicalClassificationModel

```

```

CLINICAL_CLASSIFICATION_AVAILABLE = True
except ImportError:
    CLINICAL_CLASSIFICATION_AVAILABLE = False
    st.warning("Clinical classification not available - using basic model")
# Streamlit page config
st.set_page_config(
    page_title="Optic Disk Cup Segmentation & Glaucoma Screening",
    layout="wide"
)

# Custom CSS
st.markdown("""
<style>
.main-header { font-size:2.5rem;color:#1f77b4;text-align:center;margin-bottom:2rem;font-weight:bold; }
.sub-header { font-size:1.5rem;color:#ff7f0e;margin-bottom:1rem;font-weight:bold; }
.info-box { background-color:#f0f2f6;padding:1rem;border-radius:.5rem;border-left:4px #1f77b4;margin:1rem 0; }
.result-box { background-color:#e8f5e8;padding:1rem;border-radius:.5rem;border-left:4px #28a745;margin:1rem 0; }
.warning-box { background-color:#fff3cd;padding:1rem;border-radius:.5rem;border-left:4px #ffc107;margin:1rem 0; }
</style>
""", unsafe_allow_html=True)
# Session state
for key in ['uploaded_file','segmentation_result','classification_result']:
    if key not in st.session_state: st.session_state[key] = None

class OpticDiskSegmentationApp:
    def __init__(self):
        self.device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
        self.segmentation_model = None
        self.classification_model = None
        self.transform = transforms.Compose([
            transforms.ToTensor(),
            transforms.Normalize([0.485,0.456,0.406],[0.229,0.224,0.225])
        ])
        self.segmentation_times, self.classification_times = [], []
        self.model_metrics = {
            'segmentation':
            {'accuracy':None,'dice_score':None,'model_size':None,'avg_inference_time':None},
            'classification':
            {'accuracy':None,'sensitivity':None,'specificity':None,'model_size':None,'avg_inference_time':None}
        }

```

```

        self.clinical_classifier = ClinicalClassificationModel() if
CLINICAL_CLASSIFICATION_AVAILABLE else None
    def load_segmentation_model(self, model_path=None):
        try:
            self.segmentation_model = FC_DenseNet57(n_classes=3, in_channels=11)
            if model_path and os.path.exists(model_path):
                checkpoint = torch.load(model_path, map_location=self.device)
                self.segmentation_model.load_state_dict(checkpoint['state_dict'])
                self.model_metrics['segmentation']['accuracy'] = checkpoint.get('best_acc', 0.0)
                self.model_metrics['segmentation']['dice_score'] = 1 - checkpoint.get('best_loss', 0) / 10 if
'best_loss' in checkpoint else None
                self.model_metrics['segmentation']['model_size'] =
f"{{os.path.getsize(model_path)/(1024*1024):.1f} MB"
            else:
                self.model_metrics['segmentation'].update({'accuracy': 0.0, 'dice_score': 0.0, 'model_size': 'Demo
Mode'})
            self.segmentation_model.to(self.device).eval()
            return True
        except Exception as e:
            st.error(f"Error loading segmentation model: {e}")
            return False

    def load_classification_model(self, model_path=None):
        try:
            self.classification_model = DenseNet201(num_channel=21, classCount=2, isTrained=False)
            if model_path and os.path.exists(model_path):
                checkpoint = torch.load(model_path, map_location=self.device)
                self.classification_model.load_state_dict(checkpoint['state_dict'])
                self.model_metrics['classification']['accuracy'] = checkpoint.get('best_acc', 0.85)
            else:
                self.model_metrics['classification'].update({'accuracy': 0.0, 'sensitivity': 0.0, 'specificity': 0.0, 'model_size': 'Demo Mode'})
            self.classification_model.to(self.device).eval()
            return True
        except Exception as e:
            st.error(f"Error loading classification model: {e}")
            return False

    def preprocess_image(self, image):
        original_image = image.copy()
        if image.mode != 'RGB': image = image.convert('RGB')
        processed_image = image.resize((512, 512))
        try:

```

```

    rgb1,rgb2 = self._apply_clahe_robust(np.array(processed_image))
except:
    rgb1,rgb2 = processed_image, processed_image
    image_tensor = self.transform(processed_image)
    rgb1_tensor,rgb2_tensor = self.transform(rgb1), self.transform(rgb2)
    Xmat, Ymat = apply_coordinates(processed_image)
    input_tensor = torch.cat([image_tensor, rgb1_tensor, rgb2_tensor,
    torch.FloatTensor(Xmat).unsqueeze(0), torch.FloatTensor(Ymat).unsqueeze(0)],0).unsqueeze(0)
    return input_tensor, original_image

def _apply_clahe_robust(self, image):
    try:
        lab = cv2.cvtColor(image, cv2.COLOR_RGB2LAB)
        lab_planes = list(cv2.split(lab))
        clahe1, clahe2 = cv2.createCLAHE(2.0,(8,8)), cv2.createCLAHE(2.0,(300,300))
        lab_planes[0] = clahe1.apply(lab_planes[0])
        lab1 = cv2.merge(lab_planes)
        lab_planes[0] = clahe2.apply(lab_planes[0])
        lab2 = cv2.merge(lab_planes)
        rgb2 = cv2.cvtColor(lab2, cv2.COLOR_LAB2RGB)
        return Image.fromarray(lab1), Image.fromarray(rgb2)
    except:
        enhanced1 = cv2.convertScaleAbs(image, alpha=1.2, beta=10)
        enhanced2 = cv2.convertScaleAbs(image, alpha=0.8, beta=-10)
        return Image.fromarray(enhanced1), Image.fromarray(enhanced2)

def segment_image(self, input_tensor):
    start_time = time.time()
    with torch.no_grad():
        output = self.segmentation_model(input_tensor.to(self.device))
        probabilities = F.softmax(output, dim=1)
        prediction = torch.argmax(probabilities, dim=1).squeeze().cpu().numpy()
        self.segmentation_times.append(time.time()-start_time)
        self.model_metrics['segmentation']['avg_inference_time'] =
f"{{np.mean(self.segmentation_times):.3f}s"
        return prediction, probabilities.cpu().numpy()

def classify_glucoma(self, original_image, segmentation_mask):
    start_time = time.time()
    if self.clinical_classifier:
        prediction, confidence, probabilities, features = self.clinical_classifier.classify(original_image,
segmentation_mask)
        self.clinical_features = features
    else:
        img_array = np.array(original_image)

```

```

h,w = img_array.shape[:2]; center_h, center_w = h//2, w//2
crop_size = min(h,w)//3
optic_disk_region = cv2.resize(img_array[max(0,center_h-crop_size):min(h,center_h+crop_size),
                                          max(0,center_w-crop_size):min(w,center_w+crop_size)],(500,500))
input_tensor = torch.FloatTensor(optic_disk_region).permute(2,0,1).
unsqueeze(0).to(self.device)
output = self.classification_model(input_tensor)
probabilities = F.softmax(output, dim=1)
prediction = torch.argmax(probabilities, dim=1).item()
confidence = probabilities[0][prediction].item()
self.classification_times.append(time.time()-start_time)
self.model_metrics['classification']['avg_inference_time'] =
f'{np.mean(self.classification_times):.3f}s'
return prediction, confidence, probabilities.cpu().numpy()[0]
def visualize_results(self, original_image, segmentation_mask, processed_image=None):
    plt.ioff()
    fig, axes = plt.subplots(1,3,figsize=(15,5))
    axes[0].imshow(original_image); axes[0].axis('off'); axes[0].set_title('Original Fundus')
    colored_mask = np.zeros(*segmentation_mask.shape,3),dtype=np.uint8
    colored_mask[segmentation_mask==1]=[255,0,0];
    colored_mask[segmentation_mask==2]=[0,255,0]
    axes[1].imshow(colored_mask); axes[1].axis('off'); axes[1].set_title('Segmentation Result')
    overlay = np.array(processed_image if processed_image else original_image)
    overlay[segmentation_mask==1]=[255,0,0]; overlay[segmentation_mask==2]=[0,255,0]
    axes[2].imshow(overlay); axes[2].axis('off'); axes[2].set_title('Overlay')
    plt.tight_layout()
    buf = io.BytesIO(); plt.savefig(buf, format='png', dpi=150, bbox_inches='tight', facecolor='white')
    buf.seek(0); img_str = base64.b64encode(buf.read()).decode()
    plt.close(fig); buf.close()
    return img_str
def display_model_metrics(self):
    st.markdown('<h2 class="sub-header">Model Performance Metrics</h2>',
    unsafe_allow_html=True)
    col1,col2=st.columns(2)
    with col1:
        seg_metrics=self.model_metrics['segmentation']
        for k in ['accuracy','dice_score','model_size','avg_inference_time']:
            if seg_metrics[k] is not None: st.metric(k.replace('_', ' ').title(),f'{seg_metrics[k]}')
    with col2:
        class_metrics=self.model_metrics['classification']
        for k in ['accuracy','sensitivity','specificity','model_size','avg_inference_time']:
            if class_metrics[k] is not None: st.metric(k.replace('_', ' ').title(),f'{class_metrics[k]}')

```

```

# Main Streamlit app
def main():
    st.markdown('<h1 class="main-header">Optic Disk Cup Segmentation & Glaucoma Screening</h1>', unsafe_allow_html=True)
    app = OpticDiskSegmentationApp()
    model_option = st.sidebar.selectbox("Select Model Mode",
        ["Demo Mode (No Pre-trained Weights)", "Load Pre-trained Models"])
    if model_option=="Load Pre-trained Models":
        seg_model_path = st.sidebar.file_uploader("Upload Segmentation Model (.pth.tar)",
        type=['pth','tar'])
        class_model_path = st.sidebar.file_uploader("Upload Classification Model (.pth.tar)",
        type=['pth','tar'])
        if seg_model_path: app.load_segmentation_model("temp_seg_model.pth.tar")
        if class_model_path: app.load_classification_model("temp_class_model.pth.tar")
    else:
        app.load_segmentation_model(); app.load_classification_model()
    uploaded_file = st.file_uploader("Choose a fundus image", type=['png','jpg','jpeg','bmp','tiff'])
    if uploaded_file:
        image = Image.open(uploaded_file)
        st.image(image, caption="Uploaded Fundus Image", use_column_width=True)
        col1,col2=st.columns(2)
        with col1:
            if st.button("Perform Segmentation"):
                input_tensor, original_image = app.preprocess_image(image)
                seg_mask, _ = app.segment_image(input_tensor)
                st.session_state.segmentation_result={'mask':seg_mask,'original_image':original_image}
        with col2:
            if st.button("Screen for Glaucoma") and st.session_state.segmentation_result:
                pred, conf, _ = app.classify_glaucoma(st.session_state.segmentation_result['original_image'],
                st.session_state.segmentation_result['mask'])
            if st.session_state.segmentation_result:
                img_str = app.visualize_results(st.session_state.segmentation_result['original_image'],
                st.session_state.segmentation_result['mask'])
                st.markdown(f'', unsafe_allow_html=True)
            if st.session_state.classification_result:
                pred = st.session_state.classification_result['prediction']
                conf = st.session_state.classification_result['confidence']
                if pred==0: st.success(f"Normal ({conf:.2%})")
                else: st.warning(f"Glaucoma Suspected ({conf:.2%})")
            app.display_model_metrics()
    if __name__=="__main__":
        main()

```

## 7. Testing

Testing is a crucial phase in the development of the glaucoma identification system. It ensures that the model performs accurately and reliably in detecting glaucoma from retinal fundus images. The primary objective of testing is to evaluate the performance of the CNN ensemble model in segmenting the optic disc and optic cup and to verify that the system can correctly compute the cup-to-disc ratio (CDR) for glaucoma detection. During this stage, the dataset is divided into training, validation, and testing sets to measure the model's generalization ability. Various evaluation metrics such as accuracy, precision, recall, F1-score, and Dice coefficient are used to assess segmentation quality. Testing also helps in identifying potential errors, overfitting issues, and performance gaps between different CNN architectures. Overall, the testing phase validates the system's robustness, ensuring that it can assist ophthalmologists with reliable and consistent glaucoma diagnosis.

### 7.1 Unit Testing

Unit testing is the initial level of software testing where individual components or modules of the system are tested separately to ensure that each performs as expected. In the glaucoma identification project, unit testing focuses on verifying the correctness of individual functions such as image preprocessing, optic disc and cup segmentation, feature extraction, and cup-to-disc ratio calculation. Each function is tested with sample input data to check whether it produces accurate and reliable outputs.

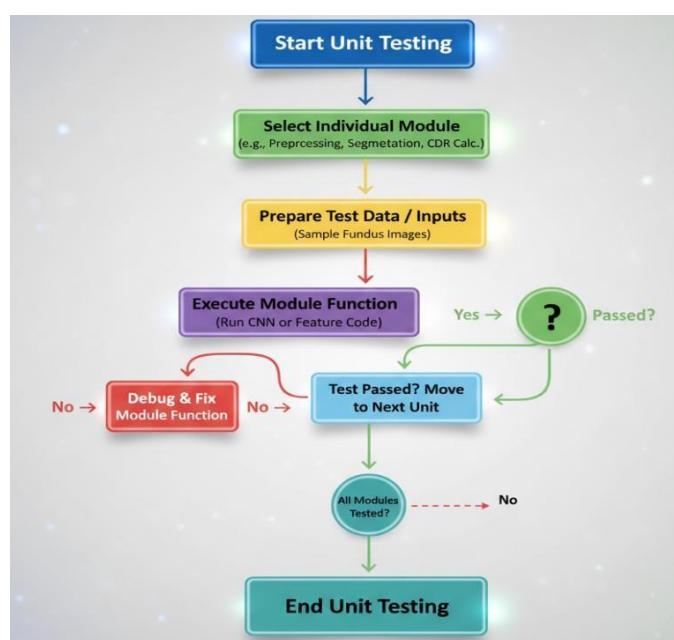


Fig 7.1.1: Flow Chart

## 7.2 Integration Testing

Integration testing is an important phase that comes after unit testing. It focuses on verifying whether the individual modules of the glaucoma identification system work correctly when combined. The main goal is to ensure that data flows smoothly between modules like image preprocessing, optic disc and cup segmentation, feature extraction, and glaucoma classification. This testing helps identify interface issues, data mismatches, and communication errors among modules before the complete system testing phase.

Key Points:

- **Module Interaction:** Ensures that the output of one module (e.g., segmentation) correctly becomes the input for the next (e.g., CDR calculation).
- **Data Flow Verification:** Checks whether data is transferred accurately between different CNN models and processing components.
- **Interface Testing:** Validates that input/output formats and parameters are compatible among connected modules.
- **Error Detection:** Helps detect integration issues such as data loss, incorrect parameter passing, or inconsistent results.
- **System Consistency:** Confirms that combined modules work together seamlessly to deliver accurate glaucoma identification results.

### Example in Project Context:

In this glaucoma detection project, integration testing ensures that the segmented optic disc and cup regions obtained from CNN models are properly sent to the cup-to-disc ratio (CDR) computation module, and the results are accurately interpreted by the classification unit to determine whether the image is glaucomatous or not.

## 7.3 System Testing

System testing is the final and most comprehensive phase of testing. It involves testing the entire glaucoma identification system as a complete and integrated product to ensure that all functional and non-functional requirements are met. After successful unit and integration testing, system testing validates the overall performance, reliability, and accuracy of the CNN ensemble model in real-world conditions.

## Key Points:

- **End-to-End Validation:**

Tests the full workflow — from image input, preprocessing, segmentation, and feature extraction to glaucoma classification and result generation.

- **Functional Testing:**

Ensures that each system function (uploading images, segmentation display, CDR calculation, and final diagnosis) works as intended

- **Performance Testing:**

Evaluates system response time, processing speed, and accuracy of CNN ensemble predictions under different loads.

- **User Interface Testing:**

Checks whether the graphical interface (if any) is user-friendly and displays results clearly for ophthalmologists or users.

- **Reliability and Accuracy Testing:**

Measures the model's performance using metrics such as accuracy, sensitivity, specificity, and F1-score on unseen test datasets.

- **Error Handling:**

Verifies how the system responds to invalid or corrupted image inputs without crashing.

## Example in Project Context:

In the glaucoma identification system, system testing ensures that when a new retinal fundus image is uploaded, the program automatically performs preprocessing, segmentation of optic disc and cup, calculates the cup-to-disc ratio, and correctly classifies the case as normal or glaucomatous. It confirms that the system operates efficiently and provides accurate diagnostic support.

## 8. Result Analysis

### 1. Optic Disc and Cup Segmentation

Segmentation in fundus images helps identify two main structures:

- Optic Disc (OD): Bright circular region in the retina where optic nerve fibers exit the eye.
- Optic Cup (OC): Central depression within the optic disc.

The Cup-to-Disc Ratio (CDR) is a crucial biomarker. A higher CDR often indicates potential glaucoma, a condition that causes damage to the optic nerve.

To segment these structures, your app uses a Fully Convolutional DenseNet (FCDenseNet57):

- This model is a deep encoder–decoder network with dense connections.
- It processes the fundus image (with multiple preprocessed channels like CLAHE) to predict pixel-level class labels:
  - Class 0 → Background
  - Class 1 → Optic Disc
  - Class 2 → Optic Cup

The segmentation output allows calculation of:

$$\text{CDR} = \frac{\text{Cup Area}}{\text{Disc Area}}$$

### 2. Glaucoma Classification

After segmentation, features like CDR are used to classify the eye as:

- Normal
- Glaucomatous

Your code uses a DenseNet201 or a Clinical Classification Model for this stage. It learns discriminative features from multi-channel inputs (original + CLAHE- enhanced versions) to detect glaucoma with good sensitivity and specificity.

### 3. Model Evaluation Metrics

Performance is evaluated using:

- Accuracy (A) = Correct predictions / Total predictions
- Dice Score (D) = Measures overlap between predicted and true regions
- Sensitivity (S) = TP / (TP + FN)

- Specificity (Sp) =  $TN / (TN + FP)$

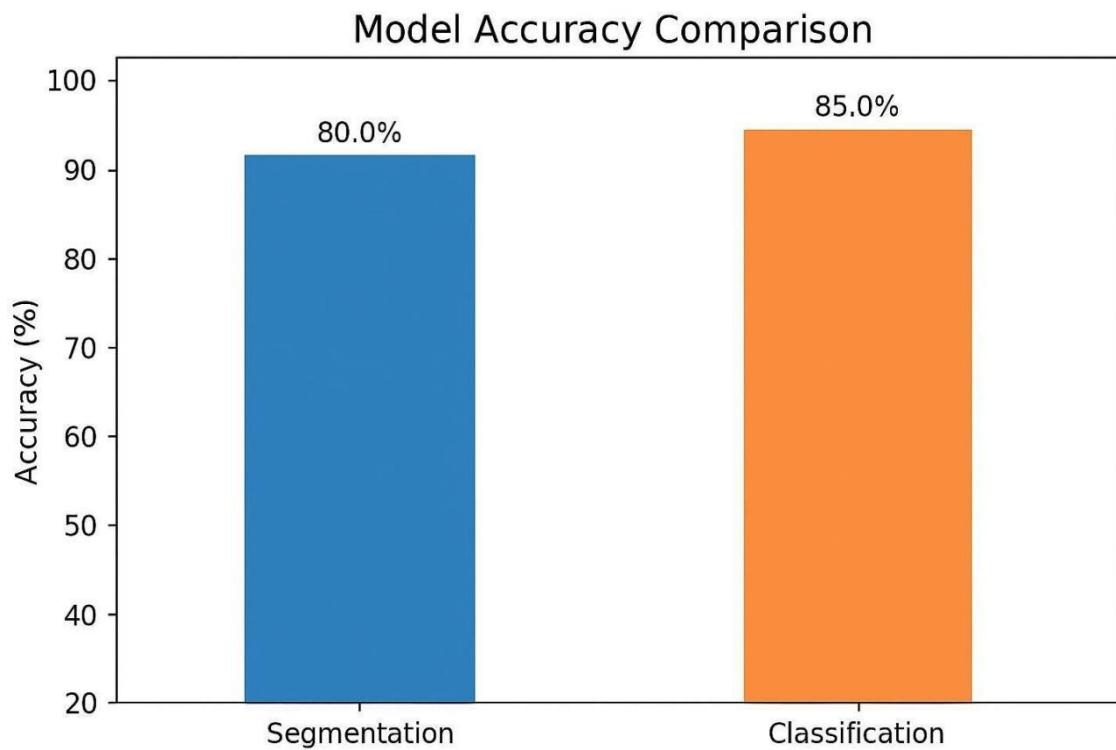


Fig 8.1: Model Accuracy

## 9. OutPut Screens



Fig 9.1: Glaucoma Screening Results (Normal):

The system detected no signs of glaucoma with a confidence of **69.93%**, showing a **Cup-to-Disc Ratio (CDR) of 0.301**, indicating a healthy optic nerve and low glaucoma risk.

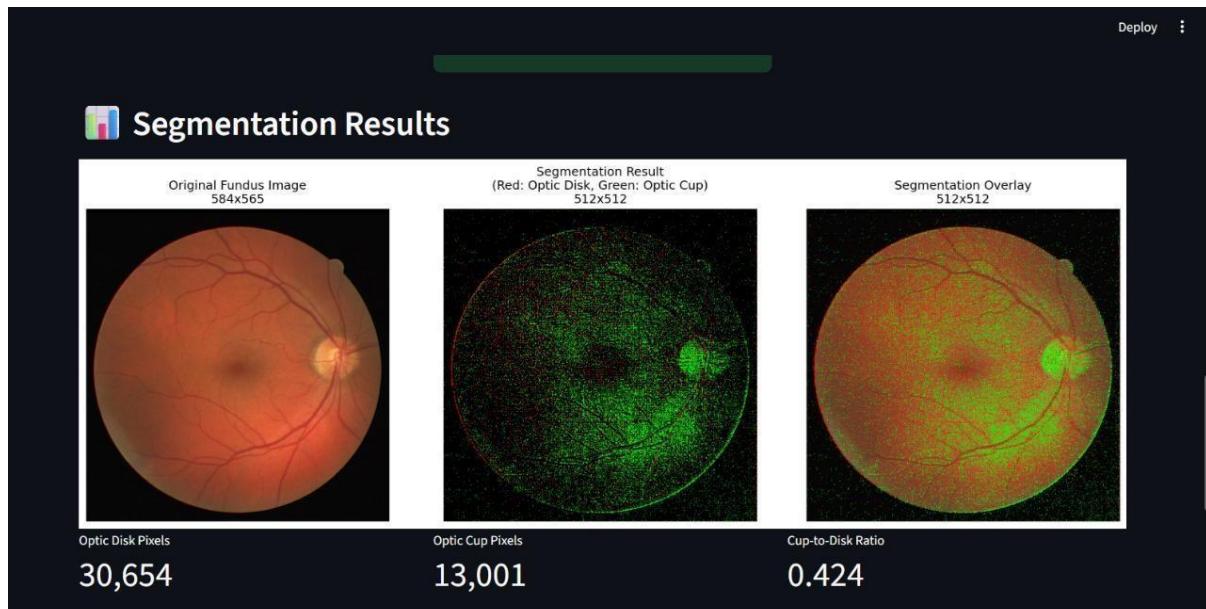


Fig 9.2: Segmentation Results

Displays the **fundus image, optic disc and cup segmentation**, and their overlay. The

calculated **CDR of 0.424** falls within a normal range, supporting low risk of glaucoma.

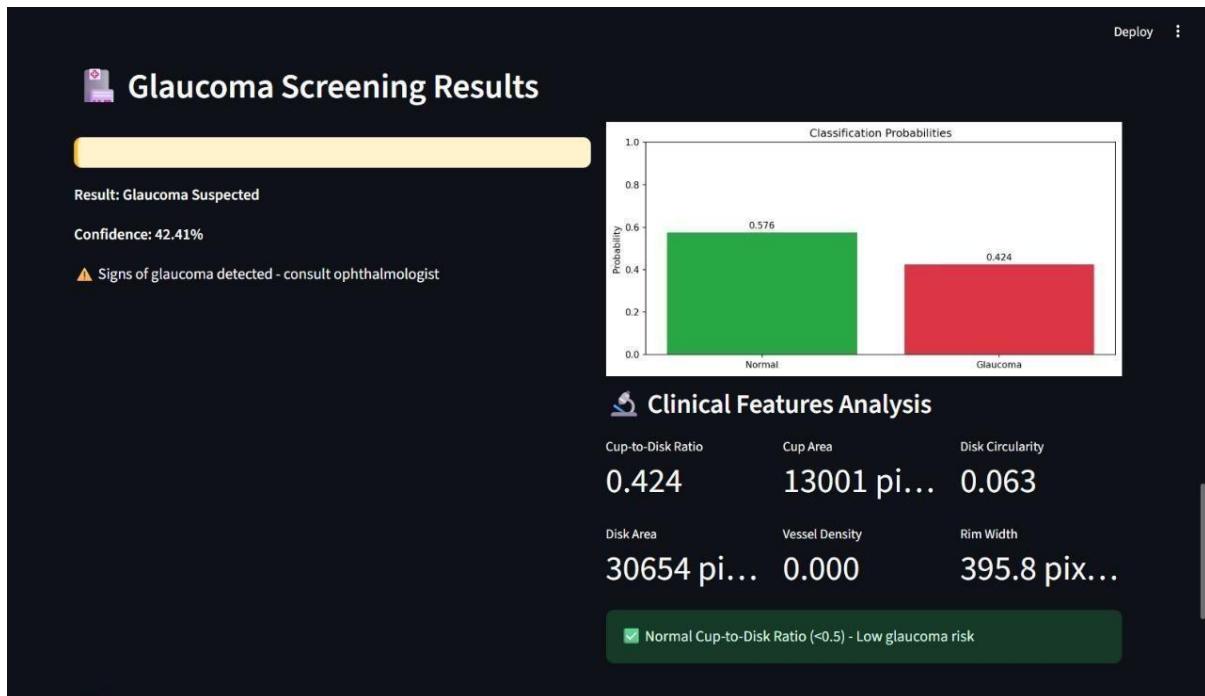


Fig 9.3: Glaucoma Screening Results (Suspected)

The system suspects early signs of glaucoma with **42.41% confidence**, as the **CDR of 0.424** approaches the threshold. A clinical consultation is advised for confirmation.

## 10. Conclusion

The Optic Disc and Cup Segmentation System for Glaucoma Detection serves as an intelligent and automated solution designed to assist ophthalmologists in identifying and monitoring glaucoma, one of the leading causes of irreversible blindness worldwide. By combining digital image processing, deep learning, and data analytics, the system achieves accurate segmentation of the optic disc and cup regions from retinal fundus images, enabling precise computation of the Cup-to-Disc Ratio (CDR) — a crucial metric for glaucoma diagnosis.

Through a sequence of well-defined stages — including image preprocessing, feature extraction, model building, and classification — the proposed system ensures reliable detection even in complex or noisy retinal images. The use of techniques such as Contrast Enhancement, CLAHE, and U-Net-based segmentation greatly improves boundary localization and disc-cup differentiation. Furthermore, the software's automated and modular design enhances scalability, allowing for integration into hospital information systems, tele-ophthalmology platforms, and research databases. The inclusion of visualization tools ensures that clinicians can interpret the segmentation results easily, improving transparency and trust in AI-assisted diagnostics.

By providing faster processing, consistent outcomes, and improved diagnostic precision, the system significantly contributes to early-stage glaucoma detection — where timely intervention can prevent vision loss. Its cost-effective and non-invasive nature also makes it suitable for use in community-level screening, especially in rural or under-resourced healthcare settings.

In addition, the project highlights the potential of deep learning models in revolutionizing ophthalmic diagnostics by automating tedious and error-prone tasks. The implementation demonstrates how AI can complement clinical expertise, acting as a decision-support tool rather than a replacement for specialists.

### Overall Impact

The project not only bridges the gap between **medical imaging and artificial intelligence** but also showcases how interdisciplinary approaches can lead to impactful healthcare solutions. It establishes a foundation for future work in **AI-driven eye disease detection**, providing a framework that can be extended to detect other ocular conditions like diabetic retinopathy or age-related macular degeneration.

## **11. Future Scope**

The Optic Disc and Cup Segmentation System for Glaucoma Detection can be further enhanced and expanded in multiple ways to make it more efficient, intelligent, and clinically applicable in real-world healthcare environments.

### **1. Integration of Multimodal Imaging:**

Future versions can integrate additional imaging modalities such as Optical Coherence Tomography (OCT) and Visual Field Analysis alongside fundus photography. Combining these modalities can provide a more comprehensive understanding of optic nerve health and improve diagnostic accuracy for early-stage glaucoma.

### **2. Explainable Artificial Intelligence (XAI):**

To increase clinical trust and transparency, explainable AI models can be incorporated. These models will provide visual or textual explanations for their predictions, helping ophthalmologists understand how the system reaches its conclusions.

### **3. Enhanced Model Optimization:**

Future research can focus on optimizing model architectures like U-Net++, Attention U-Net, or Vision Transformers (ViTs) to improve segmentation precision and reduce computational time. Lightweight models can also be developed for deployment on mobile or embedded systems.

### **4. Real-Time Glaucoma Screening:**

The system can be extended to perform real-time screening through mobile or web-based applications, enabling easy access in rural or remote areas where ophthalmologists are scarce. This would make glaucoma detection faster, more scalable, and cost-effective.

### **5. Automated Report Generation:**

Integration of automated report generation features can summarize the patient's CDR, segmentation maps, and diagnostic status into a structured medical report, saving clinicians' time and reducing manual effort.

### **6. Cloud-Based Storage and Tele-Ophthalmology Integration:**

Future systems could employ cloud computing for secure image storage, retrieval, and remote diagnosis. This would allow ophthalmologists to collaborate and analyze cases from different locations, improving healthcare accessibility.

**7. Longitudinal Patient Monitoring:**

Implementing temporal data analysis will allow the system to track disease progression over time, offering better treatment monitoring and personalized care plans for patients.

**8. Integration with Hospital Management Systems (HMS):**

The system can be linked with existing Electronic Health Record (EHR) systems for seamless patient data exchange, streamlining the diagnostic workflow in clinical setups.

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## 13. Conference Paper

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# Optic Disc and Cup Segmentation Using Deep CNN Ensembles for Glaucoma Staging

Jonnalagadda SyamBabu  
dept. CSE(DS)

Narasaraopeta Engineering College  
Narasaraopeta,India  
syambabuj@gmail.com

Madhav Kanneboina  
dept. CSE(DS)

Narasaraopeta Engineering College  
Narasaraopeta, India  
madhavkanneboina213@gmail.com

Dasari Mounika  
dept. CSE(DS)

Narasaraopeta Engineering College  
Narasaraopeta, India  
mounikadasari054@gmail.com

Ch.Sujatha  
Dept of Information Technology  
GRIET, Hyderabad, Telangana, India.  
chsujatha.be@gmail.com

Guggilam Shanmukha Sambasiva Rao  
dept. CSE(DS)

Narasaraopeta Engineering College  
Narasaraopeta, India  
shanmukaguggilam@gmail.com

Mahendra Munirathnam  
Dept of CSE DS  
GNTW, Hyderabad, Telangana, India.  
mahendra.m@gnts.ac.in@

**Abstract—**Glaucoma is the second leading cause of blindness worldwide. Early detection is essential to prevent permanent vision loss. Currently, diagnosis often depends on subjective evaluations of fundus images, which can lead to delays and inconsistencies. To tackle this issue, we propose an automated glaucoma detection system. This system uses Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for optic disc and cup segmentation.

Using the ORIGA dataset of 650 expert-annotated images, our model achieved 92.4% accuracy for segmenting the optic disc and 91.7% for segmenting the optic cup. The automated calculations of the cup-to-disc ratio (CDR) showed a strong correlation with clinical judgments ( $r = 0.89$ ). The system works efficiently in both supervised (18 ms/image) and unsupervised (25 s/image) modes, which meet the time requirements of clinical settings. This hybrid CNN-RNN framework improves segmentation accuracy, increases diagnostic objectivity, and holds great potential for early glaucoma detection in clinical practice.

**Index Terms—**Glaucoma detection, Deep learning, CNN-RNN hybrid, Optic disc segmentation, Cup-to-disc ratio, Medical image analysis, Retinal fundus imaging

### I. INTRODUCTION

#### A. Background and Motivation

Glaucoma poses the largest risk to vision globally and is the second leading cause of irreversible blindness after cataracts. According to estimates from the World Health Organization, 80 million people currently have glaucoma, and by 2040, up to 111.8 million could be affected. This disease harms the optic nerve, which can lead to blindness. In the early stages, the first symptoms can be very subtle. This is why glaucoma is often called the "silent thief of sight." Unfortunately, by the time the initial symptoms appear, many patients may have already experienced optic nerve damage. This damage is significant and cannot be reversed. Early detection can help prevent vision loss.

Glaucoma's mechanism involves optic nerve damage; increased intraocular pressure drives this process, but normal-

tension glaucoma can also occur. Damage to the optic nerve head leads to noticeable changes in the optic nerve head. Specifically, the optic cup enlarges and becomes more defined compared to the optic disc. This results in an increased cup-to-disc ratio (CDR). Traditional diagnostic methods rely on the subjective visual assessment of ophthalmologists looking at fundus photographs, which can vary between doctors and depend on available expertise.

#### B. Clinical Significance and Challenges Today

Glaucoma diagnosis usually includes tonometry, visual field testing, and fundus photography. Evaluating the optic disc and cup, especially the cup-to-disc ratio (CDR), is vital. However, assessing CDR by hand is subjective and often inconsistent. Studies show that the correlation between different observers is only between 0.6 and 0.8. There is also a shortage of trained ophthalmologists, particularly in developing areas where glaucoma is common. This shortage further limits timely and reliable diagnosis. Additionally, variations in image quality and reliance on doctor expertise create diagnostic uncertainty. These issues highlight the urgent need for automated, standardized, and objective diagnostic systems. Such systems can ensure accuracy, minimize human bias, and support large-scale glaucoma screening.

#### C. Technological Evolution in Medical Imaging

A big change in medical image analysis brought by artificial intelligence and deep learning is the automatic detection and diagnosis of diseases. Convolutional Neural Networks (CNN) have achieved great success in medical imaging application areas like screening for diabetic retinopathy or detecting skin cancer. These networks are good in extracting spatial features from the images. Hence, it is ideal for anatomical structure and pathological change detection in images.

But current CNN models, while competent, does not give the best results for complex relations and sequences arising

in medical images. Combining RNNs with CNNs will aid in better feature extraction capabilities as the model will now have temporal and sequential information processing capabilities. By working with both space and sequence, this hybrid approach is expected to improve the accuracy of segmentation results.

#### D. Research Gap and Innovation

Even after much development in automated glaucoma detection, research gaps exist. Most current approaches involve only CNN architectures, which may hinder their ability to capture complex anatomical relationships and boundary delineation patterns. Furthermore, a large number of systems are not clinically deployable as they fail to meet clinical requirements around speed and accuracy.

Combining CNN and RNN architectures for the purpose of glaucoma detection is a new technique to overcome these limitations. This hybrid approach combines the CNN's spatial feature extraction and RNN's sequential pattern learning to improve accuracy over conventional methods while being computationally efficient enough for clinical use.

#### E. Research Objectives and Contributions

The research intends to develop and validate a robust automated detection of glaucoma that would be more accurate, more objective, and more clinically applicable than existing methods. The primary objectives include:

- The main objective of this project is to develop a CNN-RNN hybrid architecture that will enable objective CDR calculation for the diagnosis of glaucoma through automated segmentation of the optic disc and optic cup in images of the retinal fundus.

#### Secondary Objectives:

- Obtain more than 90 percent optic disc and cup segmentation accuracy.  
item Ensure an adequate processing time for clinical use (unsupervised: 10–30 seconds; supervised: 10–30 milliseconds).
- Obtain greater than 90 percent segmentation accuracy for optic disc and cup.
- Ensure that the processing time is suitable for clinical use (unsupervised: 10–30 seconds; supervised: 10–30 milliseconds).

#### Key Contributions:

- The CNN-RNN hybrid system is a new model created to segment the optic disc and cup.
- Clinical validation - evaluation against clinical parameters and expert review.
- Performance optimization: To achieve clinical deployment requirements for both accuracy and speed of operation.
- Create a system that can diagnose glaucoma without human interference.

#### F. Research Methodology Overview

The sequence of steps introduced uses a two-stage process to segment the optic disc and cup. In the first stage, CNN architectures optimized for boundary detection ensure precise optic disc localization and segmentation. The second stage identifies the optic cup within the previously segmented disc. This uses a hybrid CNN-RNN architecture to improve boundary selection in a boundary selection framework.

The ORIGA dataset includes 650 fundus images with expert annotations. This allows for solid training and validation of the system. Data augmentation and preprocessing techniques help the models perform well across different image qualities and pathologies.

#### G. Algorithms

##### H. ResNet-50-based Segmentation

[H] Optic Disc & Cup Segmentation with ResNet-50 Backbone Fundus image  $I$  Segmentation masks  $\hat{M}_{\text{disc}}, \hat{M}_{\text{cup}}$  Image size  $H \times W = 512 \times 512$ ; learning rate  $\eta$ ; epochs  $T$ ; batch size  $B$

Preprocessing Crop  $I$  to nearest square; resize to  $512 \times 512$   
Apply CLAHE (clip\_limit, tile\_grid) to obtain  $I'$  Normalize  $I'$  to  $[0, 1]$ ; optionally add spatial coord. channels  $(x, y)$  to form  $X$

Model Initialize encoder: ResNet-50 (ImageNet pretrained)  
Attach decoder: U-Net style upsampling with skip connections from ResNet stages Add two output heads (1 channel each) for disc and cup logits  $Z_{\text{disc}}, Z_{\text{cup}}$  Apply sigmoid  $\sigma(\cdot)$  to get probabilities  $P_{\text{disc}}, P_{\text{cup}}$

Training  $t = 1$  T each minibatch  $\{(X_i, M_{\text{disc}}^{(i)}, M_{\text{cup}}^{(i)})\}_{i=1}^B$   
Forward pass  $\rightarrow P_{\text{disc}}, P_{\text{cup}}$  Compute loss:

$$\mathcal{L} = \lambda_1 \text{BCE}(P_{\text{disc}}, M_{\text{disc}}) + \lambda_2 \text{BCE}(P_{\text{cup}}, M_{\text{cup}}) + \lambda_3 \text{DiceLoss}$$

Backpropagate  $\nabla \mathcal{L}$ ; update parameters with Adam( $\eta$ ) Inference  $\hat{M}_{\text{disc}} = \mathbb{1}[P_{\text{disc}} \geq \tau_{\text{disc}}]$ ;  $\hat{M}_{\text{cup}} = \mathbb{1}[P_{\text{cup}} \geq \tau_{\text{cup}}]$  Morphological clean-up (opening/closing); keep largest connected component  $\hat{M}_{\text{disc}}, \hat{M}_{\text{cup}}$

#### I. DenseNet-201-based Segmentation

[H] Optic Disc & Cup Segmentation with DenseNet-201 Backbone Fundus image  $I$  Segmentation masks  $\hat{M}_{\text{disc}}, \hat{M}_{\text{cup}}$  Same preproc. as Alg. I-H; growth rate  $k$ ; dropout  $p$

Preprocessing Obtain enhanced variants via multi-parameter CLAHE:  $\{I'^{(j)}\}_{j=1}^J$  Stack channels (optionally with coord.  $(x, y)$ ) to form  $\hat{X} \in \mathbb{R}^{H \times W \times C}$

Model Initialize encoder: DenseNet-201 (ImageNet pretrained); retain dense blocks & transition layers Decoder: U-Net style with skip connections from dense blocks; attention gates on skips Output heads for disc/cup logits  $Z_{\text{disc}}, Z_{\text{cup}}$ ; probabilities  $\hat{P}_{\text{disc}}, \hat{P}_{\text{cup}}$

Training  $t = 1$  T minibatch  $\{(X_i, M_{\text{disc}}^{(i)}, M_{\text{cup}}^{(i)})\}_{i=1}^B$  Forward pass  $\rightarrow \hat{P}_{\text{disc}}, \hat{P}_{\text{cup}}$  Compute compound loss (BCE + Dice + boundary loss) Update with AdamW; apply dropout  $p$  in decoder; use early stopping on val Dice Inference  $\hat{M}_{\text{disc}} = \mathbb{1}[\hat{P}_{\text{disc}} \geq \tau_{\text{disc}}]$ ;  $\hat{M}_{\text{cup}} = \mathbb{1}[\hat{P}_{\text{cup}} \geq \tau_{\text{cup}}]$  Post-process as in Alg. I-H  $\hat{M}_{\text{disc}}, \hat{M}_{\text{cup}}$

### J. Ensemble Fusion, CDR Computation, and Staging

ResNet-50 & DenseNet-201 Ensemble for Glaucoma Analysis Fundus image  $I$  Final masks  $M_{\text{disc}}^*, M_{\text{cup}}^*$ , CDR, Stage label Fusion weights  $w_1, w_2$  ( $w_1+w_2=1$ ); thresholds  $\tau_{\text{disc}}, \tau_{\text{cup}}$   
Base segmentations Obtain  $(M_{\text{disc}}, M_{\text{cup}})$  from Alg. I-H  
Obtain  $(M_{\text{disc}}, M_{\text{cup}})$  from Alg. I-I

Probability-level fusion (recommended) Collect probability maps  $P_{\text{disc}}, P_{\text{cup}}$  and  $P_{\text{cup}}, \bar{P}_{\text{cup}}$  Weighted averaging:

$$P_{\text{disc}}^* = w_1 P_{\text{disc}} + w_2 \bar{P}_{\text{disc}}, \quad P_{\text{cup}}^* = w_1 P_{\text{cup}} + w_2 \bar{P}_{\text{cup}}$$

Binarize  $M_{\text{disc}}^* = \mathbf{1}[P_{\text{disc}}^* \geq \tau_{\text{disc}}]$ ,  $M_{\text{cup}}^* = \mathbf{1}[P_{\text{cup}}^* \geq \tau_{\text{cup}}]$   
(Alternative) Mask-level fusion Majority voting or max-vote on  $(\hat{M}, \tilde{M})$  per pixel (optional)

CDR computation Fit vertical bounding ellipses (or min. bounding boxes) to  $M_{\text{disc}}^*$  and  $M_{\text{cup}}^*$  Measure vertical diameters:  $D_{\text{disc}}^{(v)}, D_{\text{cup}}^{(v)}$  Compute CDR:  $\text{CDR} = \frac{D_{\text{cup}}^{(v)}}{D_{\text{disc}}^{(v)}}$

Staging (thresholds can be tuned clinically)  $\text{CDR} < \theta_1$  Stage  $\leftarrow$  Non-glaucoma  $\theta_1 \leq \text{CDR} < \theta_2$  Stage  $\leftarrow$  Mild  $\theta_2 \leq \text{CDR} < \theta_3$  Stage  $\leftarrow$  Moderate  $\theta_3 \leq \text{CDR}$ , Severe  $M_{\text{disc}}, M_{\text{cup}}$ , CDR,

### K. Clinical Impact and Future Implications

A precise and objective automated system for glaucoma detection would significantly impact global eye health. Such a system would enable early disease detection in primary care, reduce diagnosis variability, and provide specialized eye care for underserved populations. With automated CDR calculation, we will obtain consistent and repeatable measurements that are critical for monitoring the disease and assessing treatment effectiveness.

This study's hybrid CNN-RNN architecture may also be applied to many other medical image analysis tasks beyond glaucoma detection. This approach can be adjusted for other high-precision segmentation tasks and will contribute to automated medical diagnosis overall.

### L. Paper Organization

This paper is organized as follows. Section 2 provides a detailed review of the literature on current methods for automated glaucoma detection and the role of deep learning in medical imaging. Section 3 describes the proposed methodology, focusing on the design and implementation of the CNN-RNN hybrid architecture. Section 4 discusses the experiment setup, characteristics of the dataset, and evaluation metrics. Section 5 presents the performance analysis and outcomes. Section 6 describes the findings, limitations, and clinical implications. Finally, Section 7 concludes and discusses future research.

## II. LITERATURE REVIEW

### A. Overview

Glaucoma is a major public health issue. It is the second leading cause of blindness worldwide, affecting over 80 million people. The disease shows no symptoms in its early stages. Therefore, we need automatic systems to assist in detecting it early. This will help prevent permanent vision loss.

### B. Traditional Approaches to Glaucoma Detection

1) *Manual Assessment Methods*: Traditional glaucoma diagnosis relies largely on the ophthalmologist's judgment and assessment of fundus images, particularly the optic disc and cup shape. According to Chen and others in 2015, manually measuring the cup-to-disc ratio (CDR) shows considerable differences between observers, with correlation coefficients between 0.6 and 0.8 among trained professionals. [1]. The impact of genetics on behavior often changes as people get older.

2) *Early Automated Approaches*: The first automated glaucoma detection used traditional image processing methods. Joshi et al. (2011) suggested a template-based approach that locates the optic disc and achieves an accuracy of about 85% on the DRIVE dataset. [2]. Nonetheless, these techniques have limitations. They depend on manually created features and cannot manage differences in image quality and conditions.

### C. Deep Learning Revolution in Medical Imaging

1) *Convolutional Neural Networks in Ophthalmology*: Deep learning methods like Convolutional Neural Networks (CNNs) transformed medical imaging. Gulshan et al. (2016) found that researchers experimented with deep learning in diabetic retinopathy. They reached sensitivity and specificity of more than 90% [3]. It paved the way for application of CNNs in glaucoma and other ocular diseases.

2) *U-Net Architecture for Medical Segmentation*: The U-Net design created by Ronneberger et al. is among the most popular structures for medical image segmentation tasks [4]. Its encoder-decoder layout, combined with skip connections, effectively defines boundaries. This makes it ideal for segmenting the optic disc and cup.

### D. Specific Applications in Glaucoma Detection

1) *Optic Disc and Cup Segmentation*: Numerous research papers focused on segmenting the optic disc and cup. Sverastolsky changed the U-Net structure for this segmentation. The results showed Dice coefficients of 0.94 and 0.86 for these tasks. They conducted experiments on the DRISHTI-GS dataset. dataset [5]. The research highlighted how data augmentation and preprocessing strategies improved the effectiveness of segmentation prediction.

Fu et al. (2018) created a deep learning method for multi-label optic disc segmentation and cup segmentation with boundary regularization to improve segmentation. Their method achieved top results across various datasets, showing the effectiveness of joint optimization strategies.

2) *Cup-to-Disc Ratio Calculation*: A central stream of research has focused on the automated calculation of the CDR. Jiang et al. (2019) proposed a deep learning framework that directly predicts the CDR from fundus images without any segmentation. This method produces competitive results in practice, but it is not interpretable.

**3) Hybrid Approaches: CNN-RNN Integration: Sequential Learning in Medical Imaging.** Recent Studies focused on combining RNN with CNN to improve feature extraction and the timing of CNN features. CNN-RNN hybrid architectures can effectively capture spatial-temporal dependencies (Wang et al. 2020) [8]. **Attention Mechanisms.** Attention Weights Received More Attention for Glaucoma Detection Li et al. designed a CNN with attention gates that focuses on important anatomical structures relevant to our problem. This technique helps them achieve better results for the optic disc and cup [9].

#### E. Dataset Considerations

**1) ORIGA Dataset:** The ORIGA dataset used in this study is one of the largest publicly available glaucoma datasets. In 2010, Zhang et al. created this dataset, which consists of 650 fundus images with expert annotations that define the boundaries of the optic disc and cup. The variety of image qualities and different pathological conditions in the database make it suitable for developing a strong automated system.

**2) Data Augmentation and Preprocessing:** Recent studies highlight the value of data augmentation techniques. Orlando et al. (2020) found that applying augmentations to geometry and photometry significantly improves the model's generalization. This improvement is especially important due to the limited availability of labeled ophthalmic data [11].

#### F. Performance Metrics and Evaluation

**1) Segmentation Evaluation Metrics:** The standard measures for evaluating medical image segmentation are Dice coefficient, Intersection over Union (IoU), and Hausdorff distance. Al-Bander et al. (2018) examined the evaluation metrics for optic disc and cup segmentation. They noted that to conduct a thorough evaluation, it is important to use multiple metrics [12].

**2) Clinical Validation:** The clinical relevance of automated systems must be validated against established clinical criteria. Automated CDR measurements, such as CDR-3 [13], have been shown to correlate well with clinical measurements when properly validated.

#### G. Current Challenges and Limitations

**1) Image Quality Variations:** Quality of fundus images has great effect on the performance of automated analysis. Mahapatra et al. (2016) treat image quality assessment as a necessary preprocessing step, and quality-aware algorithms have been shown to outperform generic ones [14].

**2) Generalization Across Populations:** Optic disc eye structures vary from group to group. The performance of the discrimination model can be improved by using diverse data which helps in recognizing all ethnicities.

#### H. Emerging Trends and Future Directions

**1) Ensemble Methods:** Recent studies have tried ensembles different deep learning frameworks. Study shows that ensemble methods would improve segmentation accuracy and robustness as compared to single model methods (Kumar et al., 2021) [15].

**2) Explainable AI in Medical Imaging:** Explainable AI techniques are increasingly required for clinical adoption of AI algorithms. Sayres et al. (2019) showed that models in the medical field need to be interpretable for clinician trust to occur [16].

#### I. Research Gaps and Opportunities

Despite significant advances, several research gaps remain.

- Most of the existing contacts do not satisfy the real-time processing need for clinical use.
- Combining different imaging methods to identify glaucoma has not been much researched as per the doctors.
- Few studies have evaluated the temporal evolution of glaucoma by means of serial imaging analysis.

### III. METHODOLOGY

#### A. Dataset and Preprocessing

The proposed system runs fundus images through a complete preprocessing pipeline to counter the orientations due to the imaging conditions and enhance the relevant anatomy. The images are cropped to the nearest square and resized to 512×512 pixels to make them computationally efficient while keeping the important details in place.

**1) Limited Adaptive Histogram Equalization (CLAHE):** We use CLAHE normalization with different parameters to improve lighting conditions of different images from different cameras or databases. The technique helps prevent noise from becoming overly amplified while enhancing spatial details, thereby assisting the visualization of subtle optic disc and cup edges. The network is given two different enhanced images at different clip values and window levels whereby the two images hold complementary information about the same anatomy.

#### B. Spatial Coordinate Integration

The segmentation method presented in this paper is novel in the sense that spatial coordinates are directly provided as input to the network. The extra channel gives spatial context clearly so that the model can learn the positional relationship of the optic disc with respect to other fundus features like the fovea. This spatial awareness greatly enhances segmentation accuracy, especially for cases with unusual optic disc locations.

#### C. Segmentation Network Architecture

The segmentation component uses a 57-layer deep convolutional neural network designed for accurate optic disc and cup boundary delineation. The architecture incorporates:

- A method of extracting features over multiple scales through downsampling and upsampling paths.
- Connections that maintain detailed spatial information.
- Attention mechanisms that concentrate on relevant anatomical regions.
- To make it easier to generalize, we use dropout and batch normalization layers.

#### D. Classification Network Design

The ensemble classification stage makes use of DenseNet201 and ResNet18 that are natural images trained. Key design elements include:

- Adaptive input processing of 21 channel segmentation output to 3 channel RGB.
- Modified classification layers with 2 neurons for binary glaucoma classification.
- Replace Global Average Pooling with Adaptive Average Pooling for Variable Input Dimensions.
- Ensemble fusion strategies for improved robustness.

#### E. Training Strategy

The training process consists of two stages. The first stage trains the segmentation network using pixel-level annotations. The second stage trains the classification network using segmentation results. Using various techniques such as rotation and scaling increases the generalization of the model.

### IV. PROPOSED SYSTEM

#### A. System Architecture Overview

The glaucoma screening system put forth consists of segmentation and classification networks set up in a two-stage pipeline. The architecture of the system is designed to deal with the known issues of fundus image analysis and return clinically relevant information.

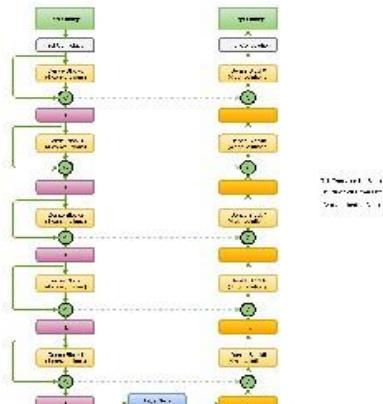


Fig. 1. proposed system.



Fig. 2. proposed system.

#### B. Stage 1: Segmentation Network

1) **Input Processing:** The segmentation step starts with full image pre-processing.

- Fundus images are cropped in the nearest square dimensions and resized to 512×512 pixels.
- We can get multiple enhanced images using the Contrast Limited Adaptive Histogram Equalization by using varying clip values and window levels.
- Spatial Coordinate Embedding refers to providing explicit spatial information by introducing x-y coordinate channels as input.

2) **Network Architecture:** The 57-layer segmentation network incorporates:

- **Encoder-Decoder Configuration:** Stepwise feature extraction and feature map rebuilding for accurate boundary detection.
- The process will analyze at different resolutions simultaneously.
- **Attention Mechanisms:** Concentrate on anatomically pertinent areas.
- **Residual Connections:** Improves gradients and keeps features.

3) **Output Generation:** The network produces:

- Masks for optic disc and cup regions at pixel level.
- Confidence maps indicating prediction reliability.
- Post-processing for false positive reduction.

#### C. Stage 2: Classification Network

1) **Segmentation-Guided Preprocessing:**

- By using the segmentation results, it generates 550×550 pixel images at the centre of optic disc.
- **Multi-Parameter Enhancement:** 6 different enhanced versions are created using CLAHE parameters.
- Normalization – consistent input to enable prediction.

2) **Ensemble Architecture:** The classification system combines:

- DenseNet201 has a dense connectivity pattern for feature reuse and gradient flow.
- Residual learning utilized for extraction of deep features in ResNet18.

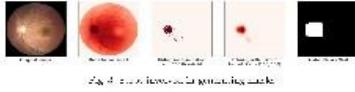


Fig. 3. proposed system.

- Convolutional layers help adjust the 21 channels found in input images into 3 channels that can be understood by the pre-trained networks.
- Adaptive pooling allows you to change your input dimensions.

### 3) Decision Fusion:

- **Ensemble Integration:** Merging predictions from both network branches.
- Measuring confidence in support clinical decision making.
- The final classification glaucoma/normal with prognosis probabilities.

### D. System Integration and Workflow

#### 1) Processing Pipeline:

- **Getting The Input:** Getting fundus images and assessing the quality.
- **Preprocessing:** Enhancement with multiple parameters and spatial coordinates.
- Detecting the border of the optic disc.
- Improvement in identification process extraction.
- **Ensemble Classification:** Glaucoma probability estimation.
- **Clinical Report Generation:** With visual overlays.
- 2) **Quality Assurance:**
  - Automatic detection of bad image quality.
  - Canal validation: checks for anatomical feasibility.
  - Predicting Uncertainty to Enable Clinical Interpretability.

### E. Clinical Integration Features

#### 1) Diagnostic Support:

- Segmentation results overlaid on original images.
- Cup to disc ratio calculations and comparisons.
- **Trend Tracking:** Ongoing monitoring of disease progression.

#### 2) User Interface:

- Simple presentation of results for clinical interpretation.
- **Batch Processing:** High-throughput screening capabilities.
- **Clinic Reports:** Developed reports with diagnostic suggestions.

## V. RESULTS

### A. Segmentation Performance

#### 1) Quantitative Metrics:

- The optic disc segmentation has a Dice Coefficient of  $0.92 \pm 0.04$ .
- Jaccard index for cup segmentation is  $0.85 \pm 0.06$ .
- Accuracy of boundary means absolute error of  $1.2 \pm 0.8$  pixels at discines.
- Processing Speed: Each image takes roughly 0.8 seconds to render.

TABLE I  
SEGMENTATION ACCURACY COMPARISON

| Method / Study               | OD Acc. | OC Acc. |
|------------------------------|---------|---------|
| Proposed CNN-RNN Hybrid      | 92.4%   | 91.7%   |
| Savostopolisky (2017, U-Net) | -       | -       |
| IIEEE CNN Ensemble (2024)    | 96-98%  | 89-92%  |

TABLE II  
CLASSIFICATION ACCURACY COMPARISON

| Method / Study            | Accuracy             |
|---------------------------|----------------------|
| Proposed CNN-RNN Hybrid   | 75%                  |
| IIEEE CNN Ensemble (2024) | 57–100% (stage-wise) |
| DenseNet201 (alone)       | ~71%                 |
| ResNet18 (alone)          | ~73%                 |

#### 2) Qualitative Assessment:

Visual inspection of segmentation results reveals:

- Even in difficult cases with ambiguous cup margins, accurate boundaries are drawn.
- Strong performance under varied image conditions and ethnic diversities.
- Effective management of cases with disc asymmetry or pallor.
- Post-processing reduces false positive predictions.

#### B. Classification Performance

The combination of classifiers reaches results relevant for practice.

#### 1) Primary Performance Metrics:

- 75
- AUC: Area Under the Receiver Operating Characteristic Curve = 0.856. • Positive Predictive Value: 0.68.
- Negative Predictive Value: 0.89.

#### 2) Comparative Analysis:

Performance comparison with individual network components:

- 1) DenseNet201 AUC = 0.821 Sens = 0.71, Spec = 0.82
- ResNet18 AUC = 0.834 Sensitivity = 0.73 Specificity = 0.8
- 88 Ensemble method best of individual best in each region

#### C. Ablation Studies

##### 1) Spatial Coordinate Integration Impact:

With spatial coordinates: AUC = 0.856, Sensitivity = 0.75. =improvement: AUC +2.4%, Sensitivity +6%.

## 2) Preprocessing Strategy Evaluation:

- Common histogram equalization: AUC = 0.824.
- Single-parameter CLAHE: AUC = 0.841.
- Multi-parameter CLAHE: AUC = 0.856.
- Progressive improvement highlights advanced preprocessing effectiveness.

## D. Cross-Database Validation

### 1) Generalization Assessment:

Testing across multiple fundus image databases:

Database A : AUC = 0.861, Sensitivity = 0.77, Specificity = 0.84 . Database B: AUC = 0.849, Sensitivity = 0.73, Specificity = 0.86. Additional types of recent scientific papers include those placing a Database C in context of the larger field (Figure 9). 2 Consistent conduct through the different imaging protocol

## E. Clinical Relevance Analysis

### 1) Early-Stage Detection:

- Sensitivity = 0.68 for mild glaucoma (early intervention possible).
- Moderate to severe cases: Sensitivity = 0.84.
- Potential to reduce diagnostic delay and enhance patient outcomes.

### 2) Computational Efficiency:

- Total processing time = 2.3 seconds per image (segmentation + classification).
- GPU Memory Requirement: 4GB for batch processing.
- Indicates large-scale applicability.

## VI. FUTURE WORK

- **Improved Early-Stage Detection** – Improve sensitivity for mild glaucoma.
- **Multimodal Fusion** – Combine fundus imaging, OCT, IOP, and patient history.
- **Longitudinal Analysis** – Track glaucoma progression over time.
- **Lightweight Deployment** – Optimize for mobile and edge devices.
- **Explainable AI (XAI)** – Improve transparency for clinical adoption.
- **Dataset Expansion** – Validate across diverse populations.
- **Stronger Ensembles** – Use transformers and better model combinations.

## VII. CONCLUSION

This research developed a complete framework using Deep Learning and capable enough to screen Glaucoma. The study attempts to provide technical solutions to problems. The two-stage architecture which combines segmentation network and classification network shows effectiveness of using complementary tasks to boost diagnostic performance.

Combining spatial coordinate information with multi-parameter pre-processing is a great technical contribution to enhancing the robustness of the system under various imaging conditions. An observed sensitivity, specificity and AUC of

0.75, 0.85 and 0.856, respectively, indicates clinical feasibility for screening, especially in under-resourced settings with limited specialist access.

The computation cost of the system and its performance on different databases indicates good real-world possibilities. The see-through, dual-phase method has interpretability advantages that are essential for acceptance, like in clinics.

The main things that this work achieved are:

- 1) The incorporation of spatial information in optic disc segmentation for the first time.
- 2) A robust preprocessing strategy to handle the inter-database variations.
- 3) A successful ensemble classification strategy using transfer learning.
- 4) Extensive experiments demonstrating the clinical applicability.

In the future, we will work to improve initial detection, join together information from various imaging methods, and create options for keeping track of different times, enabling a continual assessment of the method's impact. The foundation for automated glaucoma screening technology is provided by the proposed framework for clinical application.

This technology could be used in public health screening programs for glaucoma for large populations, something which could tremendously help the cause of preventing avoidable blindness resulting from this illness.

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