Glaucoma Detection with Explainable AI

A MINOR PROJECT SYNOPSIS

Submitted to

ASSAM DON BOSCO UNIVERSITY

by

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in partial fulfilment for completion of Assignment

of

THIRD SEMESTER

OF

MASTER OF COMPUTER APPLICATIONS

DEPARTMENT OF COMPUTER APPLICATIONS

SCHOOL OF TECHNOLOGY

ASSAM DON BOSCO UNIVERSITY

AZARA, GUWAHATI 781017, ASSAM,

INDIA.

BATCH (2024-2026)

ANNEXURE II

CERTIFICATE

This is to certify that the Project Report entitled "Glaucoma Detection With Explainable AI" submitted by **Niresh Singha (DC2024MCA0009), Ruhul Barbhuiya (DC2024MCA0016) and Sandrup Maibangsa (DC2024MCA0017)** to the Assam Don Bosco University, Guwahati, Assam, in partial fulfilment of the requirement for Minor project of 3rd of Master of Computer Applications. It is a bonafide record of the project work carried out by them under my supervision during the Autumn Semester of the academic year 2025–2026.

Sonia Sarmah
13/12/25

Internal Guide:

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Assistant Professor
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ANNEXURE III

CERTIFICATE

This is to certify that the Project Report entitled "**Glaucoma Detection With Explainable AI**" submitted by **Niresh Singha (DC2024MCA0009), Ruhul Barbhuiya (DC2024MCA0016) and Sandrup Maibangsa (DC2024MCA0017)** to the Assam Don Bosco University, Guwahati, Assam, in partial fulfilment of the requirement for Minor project of 3rd of Master of Computer Applications. It is a bonafide record of the project work carried out by them under my supervision during the Autumn Semester of the academic year 2025–2026.

Dr. Gypsy Nandi
Head of the Department
Department of Computer Applications
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Prof. Manoranjan Kalita
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ANNEXURE IV

EXAMINATION CERTIFICATE

This is to certify that **Niresh Singha, Ruhul Barbhuiya and Sandrup Maibangsa** bearing Roll Numbers **DC2024MCA0009, DC2024MCA0016 and DC2024MCA0017** respectively of the Department of Computer Applications has carried out the project work in a manner satisfactory to warrant its acceptance and also defended it successfully.

I wish them all the success in their future endeavours.

Examiners:

1. Internal Examiner:

2. Internal Examiner:

ANNEXURE V

DECLARATION

We hereby declare that the project work entitled “**Glaucoma Detection with Explainable AI**” submitted to the Assam Don Bosco University, Guwahati, Assam, in partial fulfilment of the requirement for minor project of 3rd Semester of Master of Computer Applications, is an original work done by us under the guidance of **Dr. Sonia Sarmah** and has not been submitted for the award of any degree.

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We extend our heartfelt thanks to our **friends and family** for their constant encouragement, patience, and understanding, which kept us motivated throughout this journey. Finally, we express our sincere gratitude to the **Almighty** for providing us with the strength, wisdom, and perseverance needed to complete this project successfully.

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ABSTRACT

Glaucoma is a leading cause of irreversible blindness worldwide, and early detection is crucial to prevent permanent vision loss. Conventional screening methods are often time-consuming, expensive, and highly dependent on expert interpretation, which restricts their accessibility, particularly in rural and resource-limited regions. This project presents a web-based glaucoma detection system using deep learning integrated with Explainable Artificial Intelligence (XAI) techniques. Convolutional Neural Networks (CNNs) are employed to automatically classify retinal fundus images as glaucomatous or normal. To enhance model transparency and user trust, explainability methods such as Gradient-weighted Class Activation Mapping (Grad-CAM). The system is trained and evaluated on publicly available datasets, including REFUGE and ACRIMA, ensuring robustness and generalizability. The proposed platform delivers accurate predictions along with intuitive visual explanations through an interactive web interface, making it suitable for clinical decision support and early glaucoma screening. Experimental results demonstrate that integrating XAI with deep learning improves interpretability while maintaining high diagnostic performance, thereby enabling reliable, transparent, and accessible glaucoma screening.

Keywords: *Glaucoma Detection, Deep Learning, Convolutional Neural Networks, Explainable Artificial Intelligence, Grad-CAM, LIME, SHAP, Retinal Fundus Images, Medical Image Classification, Web-based Screening System*

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ABBREVIATIONS

Abbreviation	Full Form
XAI	Explainable Artificial Intelligence
CNN	Convolutional Neural Network
Grad-CAM	Gradient-weighted Class Activation Mapping
ACRIMA	Acquired Color Retinal Images for the Analysis of Glaucoma
REFUGE	Retinal Fundus Glaucoma Challenge Dataset
AI	Artificial Intelligence
DL	Deep Learning
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
ROI	Region of Interest
UI	User Interface

NOMENCLATURE

Term	Description
Retinal Fundus Image	Image of the inner surface of the eye used for diagnosing eye diseases
Optic Disc	Circular region where the optic nerve exits the retina
Optic Cup	Central depression within the optic disc
Cup-to-Disc Ratio (CDR)	Ratio of optic cup size to optic disc size used to assess glaucoma
Epoch	One complete training cycle of the model
Overfitting	Condition where a model performs well on training data but poorly on unseen data
Transfer Learning	Technique of using a pre-trained model for a new task
Binary Classification	Classification task with two output classes
Heatmap	Visual representation highlighting important regions
ROC-AUC	Measure of a model's ability to distinguish between classes

CHAPTER 1
INTRODUCTION

1.1 Project Title

Glaucoma Detection with Explainable AI

1.2 Introduction

Glaucoma is a group of eye disorders characterized by damage to the optic nerve, which is essential for transmitting visual information from the eye to the brain, leading to vision loss. It often progresses quietly without symptoms until significant vision loss occurs. Individuals at risk, such as elderly patients, people with a family history, or those in rural areas, find it hard to get timely and reliable eye screening.

Common symptoms may include:

i. Gradual loss of peripheral (side) vision, usually in both eyes
ii. Blurred vision or halos around lights
iii. Eye pain, redness, or headaches (in some types of glaucoma)
iv. In advanced cases, tunnel vision and eventual loss of central vision

Consequences if untreated:

i. Permanent optic nerve damage
ii. Irreversible blindness, often starting with peripheral vision and progressing to total vision loss
iii. Reduced quality of life due to difficulty in reading, driving, or recognizing faces.

1.3 Objective

- To Develop a web-based platform that allows users to upload retinal fundus images.
- Implement deep learning models to classify images as *Glaucoma* or *Normal*.
- Integrate Explainable AI techniques to provide visual and feature-based explanations.
- Display diagnostic results and explanations through an interactive web interface

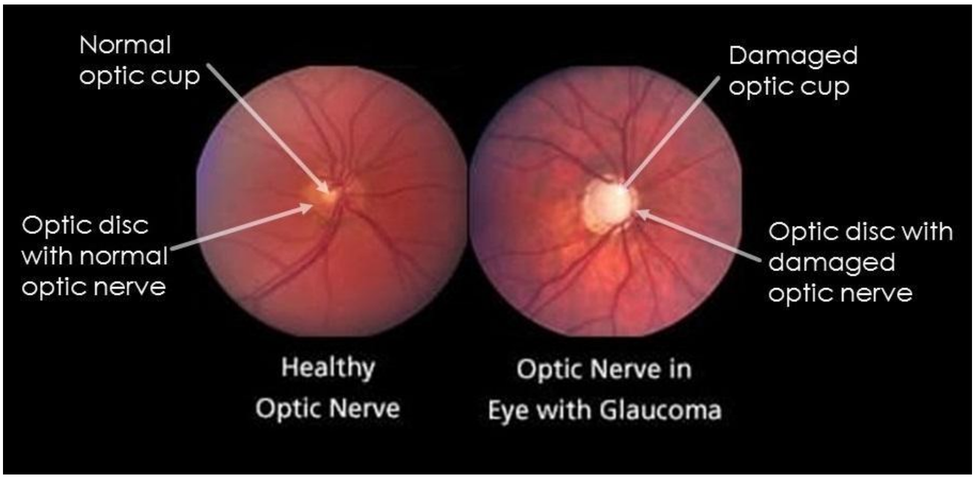

Figure 1.1: Healthy Vs Glaucoma

Left Side: Healthy Optic Nerve

- **Optic Disc with Normal Optic Nerve**:
  The optic disc is the bright circular area where the optic nerve fibers exit the eye. In a healthy eye, this structure appears well-defined.
- **Normal Optic Cup**:
  The optic cup is the small central depression in the optic disc. In a healthy optic nerve, the cup is small compared to the overall disc (low cup-to-disc ratio).

Right Side: Optic Nerve in Eye with Glaucoma

- **Optic Disc with Damaged Optic Nerve**:
  In glaucoma, the optic nerve is progressively damaged, often due to increased intraocular pressure. This damage appears as changes in the optic disc.
- **Damaged Optic Cup**:
  The optic cup becomes much larger compared to the disc (high cup-to-disc ratio). This happens because nerve fibers are lost, creating more hollow space in the center of the disc.

The Glaucoma Detection with Explainable AI (XAI) platform is a web-based tool. It allows users to upload retinal fundus images for automated glaucoma detection using deep learning models. The system uses Explainable AI techniques to give visual explanations of its predictions, such as highlighting the factors that influenced the result. This helps doctors and patients understand the reasoning behind the system's decisions, making the screening process more transparent.

1.4 Significance of the Project

- Supports the healthcare industry by making screening more accessible and scalable.
- Enhances trust in AI systems by providing clear and understandable visual explanations
- Promotes early detection of glaucoma through AI-based automated screening.
- Facilitates research and development of AI models for automated glaucoma detection.

1.5 Expected Contributions

This project is expected to make the following contributions:

- **Improved Healthcare Access:** Enables early detection of glaucoma, especially for patients in rural or underserved areas.
- **Transparency in AI Decisions:** Provides explainable results that build trust among doctors, patients, and healthcare providers.
- **Support for Medical Professionals:** Assists ophthalmologists by reducing manual workload and providing quick second opinions.
- **Scalable Web-Based Platform:** Can be easily deployed in hospitals, clinics, and research institutions.
- **Research Advancement:** Offers a base for future development of AI models in medical imaging and disease detection.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

This literature survey reviews recent research works related to glaucoma detection using artificial intelligence, with a primary focus on deep learning and explainable AI techniques. It examines key approaches such as convolutional neural networks, visualization methods, transfer learning, and hybrid models applied to retinal fundus image analysis. Emphasis is placed on model interpretability, accuracy, and clinical applicability, as these factors are essential for reliable medical decision support systems. The surveyed studies help identify existing research gaps and provide a foundation for the proposed methodology.

2.2 Related Work

Table 2.1-Comparative Summary of Related Work in Glaucoma Detection Using Deep Learning and XAI.

Ref.	Author(s)	Method / Model Used	Key Contribution	Limitation / Remark
[1]	Zhang et al.	CNN + Grad-CAM	Used Grad-CAM to visualize important regions in fundus images, improving explainability and clinician trust	Focused mainly on visualization
[2]	Ali & Chowdhury	Lightweight CNN	Proposed a computationally efficient CNN for real-time glaucoma screening	Limited complexity may affect accuracy
[3]	Kumar & Mehta	CNN + Visualization	Integrated interpretable ML with CNNs to explain predictions using feature maps	Limited dataset size
[4]	Aljohani et al.	CNN + LIME/SHAP	Studied feasibility of XAI methods to improve transparency in glaucoma models	High computational overhead
[5]	Patel & Sharma	Survey	Reviewed XAI techniques and deep learning models in ophthalmology	Survey-based, no implementation
[6]	Velpula et al.	Pre-trained CNN + Grad-CAM	Achieved ~96% accuracy with improved interpretability	Scalability across datasets
[7]	Kumar et al.	CNN + XAI	Combined CNNs with XAI for early glaucoma detection (~95% accuracy)	Need for larger datasets

Ref.	Author(s)	Method / Model Used	Key Contribution	Limitation / Remark
[8]	Nguyen & Lee	Federated Learning + XAI	Improved generalization and privacy using federated learning	Increased system complexity
[9]	Bindu et al.	Transfer Learning (ResNet, EfficientNet)	Showed effectiveness of transfer learning for glaucoma detection	Lack of simple user interfaces
[10]	Aljohani & Aburasain	Hybrid CNN + ML	Combined CNNs with traditional ML classifiers for better accuracy	Complex ensemble design
[11]	Sharma et al.	Traditional Diagnostic Methods	Reviewed manual glaucoma screening techniques	Manual methods are slow and inconsistent
[12]	Li et al.	Attention-based CNN	Improved classification by focusing on optic disc regions	Higher computational cost
[13]	Thompson et al.	Review	Discussed deep learning trends in glaucoma diagnosis	No experimental validation
[14]	Litjens et al.	CNNs in Medical Imaging	Highlighted CNN superiority over traditional methods	Interpretability challenges
[15]	Orlando et al.	CNN + Optic Disc/Cup Segmentation	Learned clinically meaningful features like CDR	Segmentation complexity
[16]	Fu et al.	Disc-aware Ensemble CNN	Focused on optic disc to reduce noise and improve accuracy	Requires ROI annotation
[17]	Al-Bander et al.	Ensemble CNN Models	Improved robustness and reduced misclassification	Higher training cost
[18]	Tjoa & Guan	Survey on XAI	Reviewed visualization-based XAI methods in healthcare	General medical focus
[19]	Diaz-Pinto et al.	Multi-dataset CNN Evaluation	Studied generalization across datasets	Poor cross-dataset performance
[20]	Holzinger et al.	Trustworthy AI	Emphasized explainability and human-centered AI in healthcare	Conceptual study

2.3 Identified Gaps

- Most existing AI-based glaucoma detection systems lack integration of explainability, making it difficult for doctors and patients to trust the results.
- Limited availability of large, labeled glaucoma datasets restricts the generalizability of models.
- Few user-friendly, web-based platforms exist for remote screening and patient accessibility.

CHAPTER 3
FEASIBILITY STUDY

3.1 Scheduled Feasibility

3.1.1 Work Breakdown Structure:

A WBS provides the necessary framework for detailed cost estimating and control along with guiding schedule development and control.

The total development time (in hours) for our project is 210 hrs. To further explain the calculation of hours.

Weekly off (1 per week) = 16 days.

Mid-term break (Sep 28 – Oct 5, 2025) = 8 days.

Class Test 1 (Aug 28 – Aug 30, 2025) = 3 days.

Class Test 2 (Sep 25 – Sep 27, 2025) = 3 days.

Unique non-working days calculation:

16 (Sundays) + (8 − 2 overlap) + 3 (CT1) + 3 (CT2) = 28 days.

Working days = Total days − Unique non-working days = 112 − 28 = 84 days.

Working hours available (before scaling) 84

days × 2.5 hours = 210 hrs.

Required effective project workload (given) = 210 hr

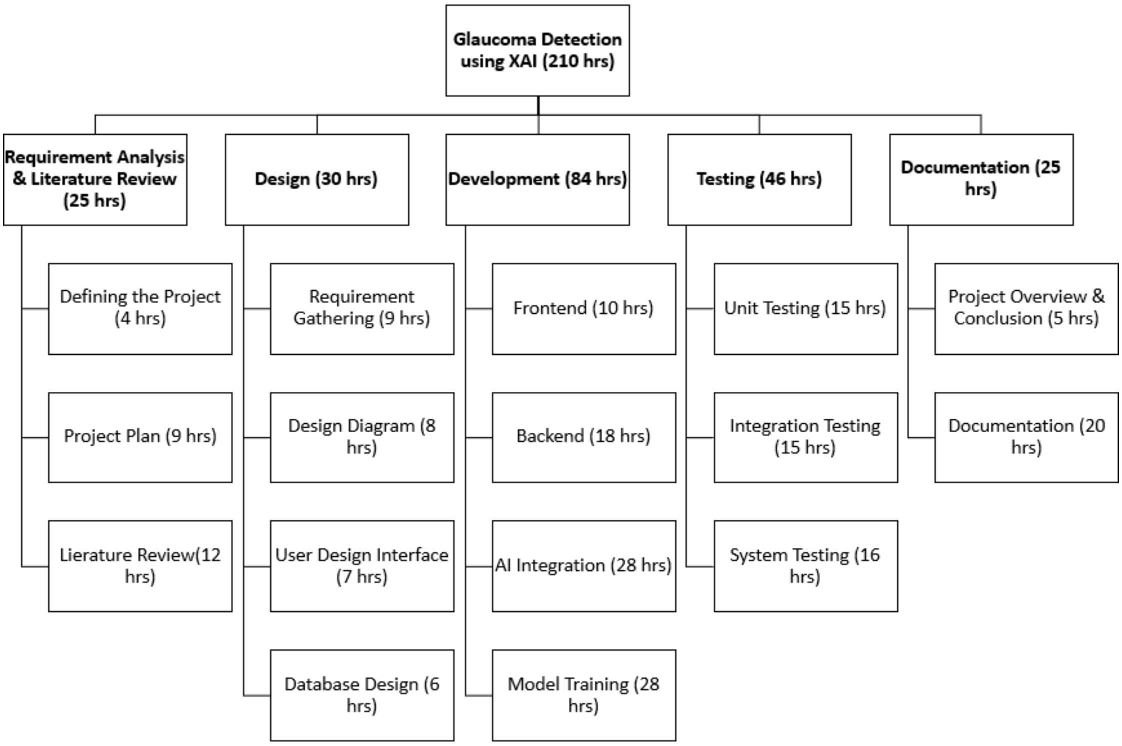

Figure 3.1: Work Breakdown Structure

3.1.2 Gantt Chart

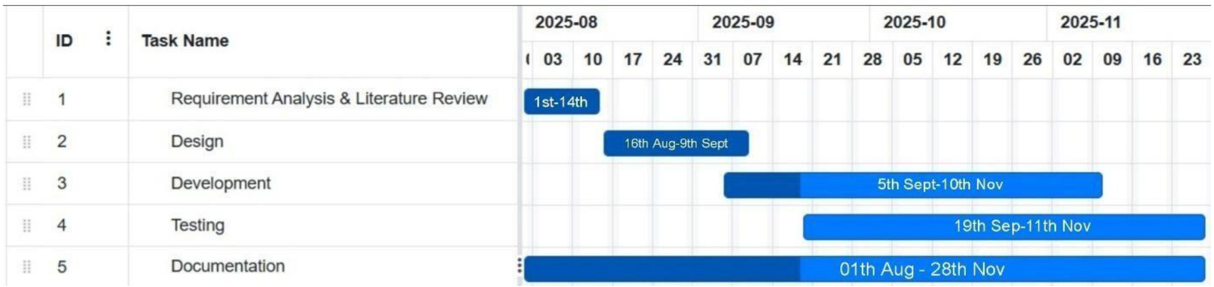

Figure 3.2: Gantt Chart

3.2 Economic Feasibility

- Uses open-source frameworks (Python, ReactJS , Flask/Django, TensorFlow/PyTorch, MongoDB) → minimal licensing cost.
- Main expenses: domain purchase, web hosting, optional cloud GPU services.
- **COCOMO estimation:**
  - Effort: 9.11 person-months
  - Development Time: 5.65 months
  - People Required: ~1.61 (team of 3 shares workload)
- **Benefits:** early glaucoma detection, scalability, reduced healthcare burden, improved patient outcomes.
- **Conclusion:** High cost-effectiveness and positive return on investment.

3.2.1 COCOMO Model

COCOMO (Constructive Cost Model) is a regression-based model that estimates the cost, effort, and development time of a software project based on lines of code.

Table 3.1-COCOMO Model coefficient values.

Software Project	a	b	c	d
Organic	2.4	1.05	2.5	0.38
Semi-Detached	3.0	1.12	2.5	0.35
Embedded	3.6	1.20	2.5	0.32

The basic COCOMO equations are:

Effort(E) = $a \times (KLOC)^b$ [person-months]
Development Time(D) = $c \times (E)^d$ [months] People
Required(P) = E/D

Our Project type: Organic

Estimated Size: 3.5 KLOC
Effort (E):
$E = 2.4 \times (3.5)^{1.05} = 9.11$ person-months

Development Time (D):
D = $2.5 \times (9.1)^{0.38} = 5.65$ months

People Required (P):
P = $9.1/5.65 \approx 1.61$ persons

Since my team has **3 persons**, therefore:

$9.11/3 \approx 3.03$ person-months each

3.3 Operational Feasibility

- Simple and intuitive UI for both patients and medical professionals (creators/doctors.
- Explainable AI Support: Provides clear, results to doctors and patients for better trust and decision-making.
- Can be integrated with hospital/clinic databases for streamlined operations.

CHAPTER 4
SYSTEM DESIGN

4.1 Use Case Diagram

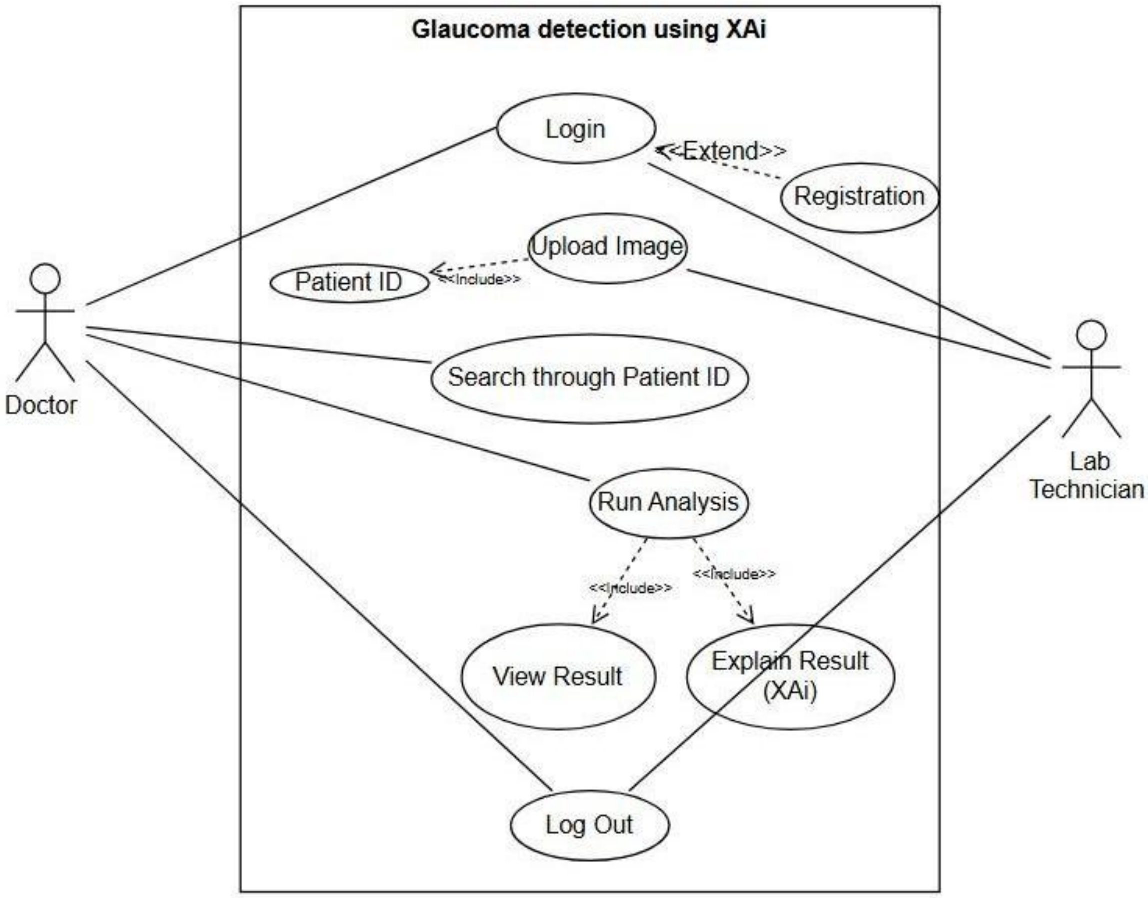

Figure 4.1: Use Case Diagram

The use case diagram illustrates how the Doctor and interact with the Glaucoma Detection system. The system enables image upload, analysis, result viewing, and explainable output generation to support diagnosis.

4.2 Activity Diagram

4.2.1 Doctor Activity Diagram

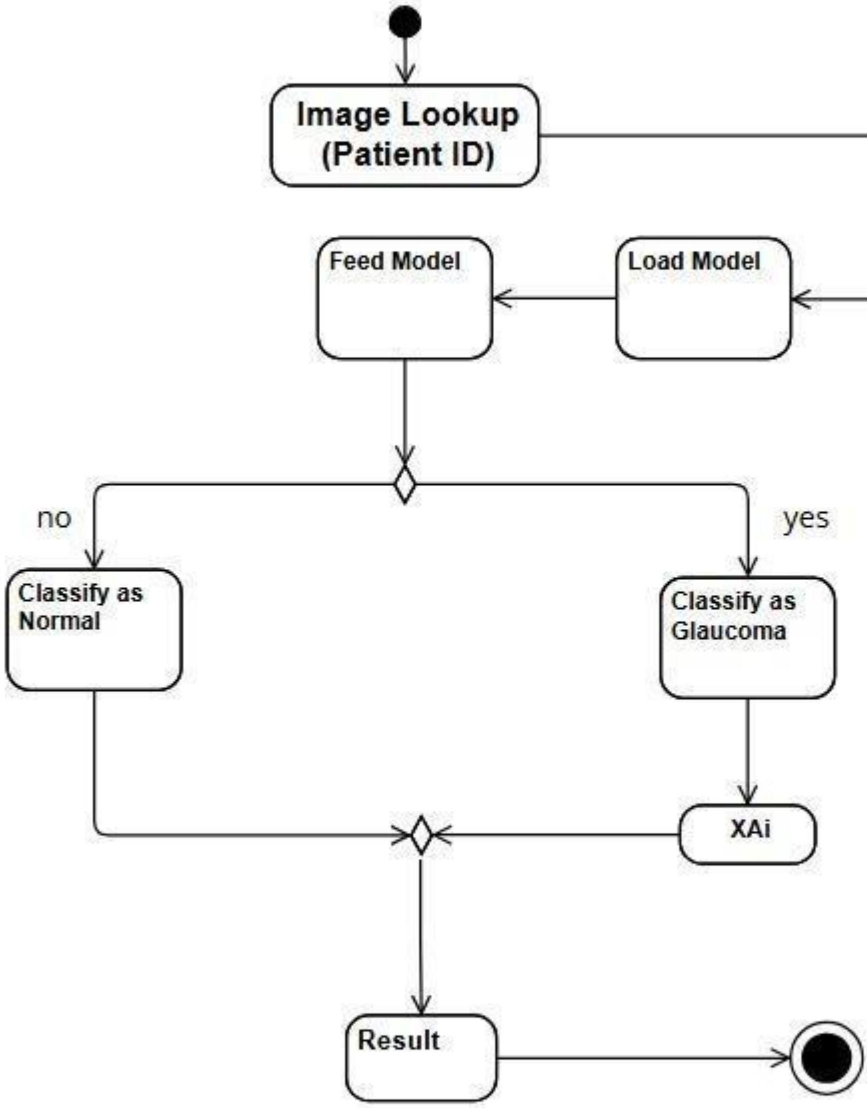

Figure 4.2: Activity Diagram

The activity diagram illustrates the workflow of the glaucoma detection process. The system retrieves the patient image, loads the trained model, and performs classification as normal or glaucoma. For glaucoma cases, XAI is applied before generating the final result.

4.2.2 Lab Technician Activity Diagram

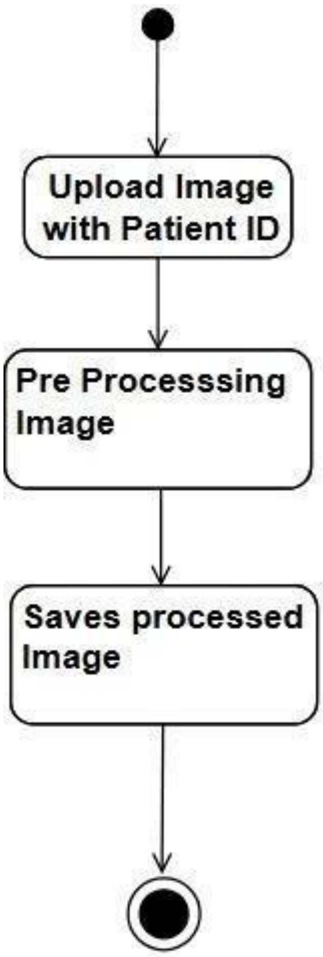

Figure 4.3: Lab Technician Activity Diagram

The activity diagram represents the Lab Technician's workflow in the system. The technician uploads the retinal image with the patient ID, after which the image is preprocessed and securely stored for further analysis.

4.3 System Block Diagram

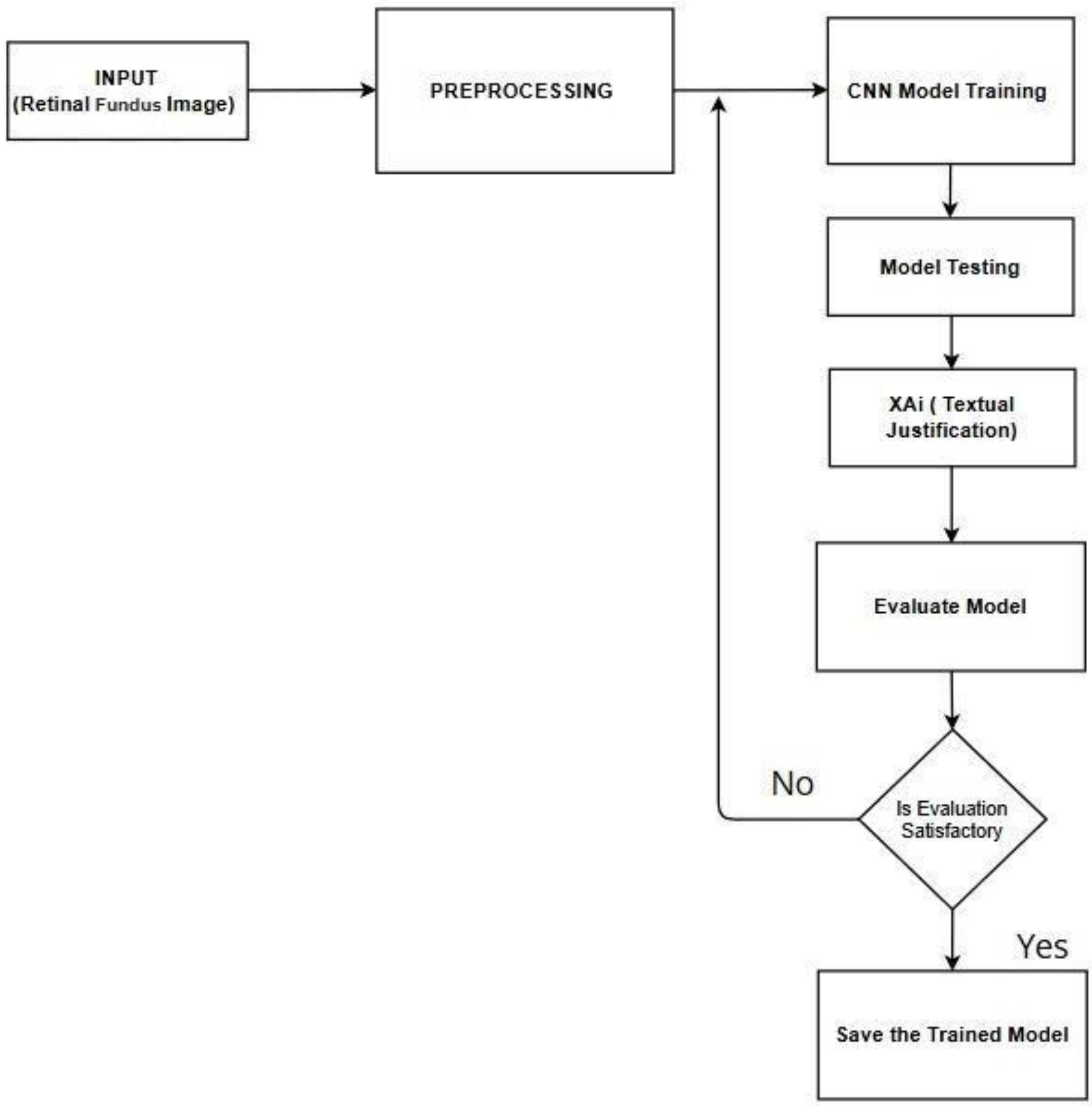

Figure 4.4: System Block Diagram

The block diagram shows the end-to-end glaucoma detection process, including image preprocessing, CNN training and testing, XAI-based explanation, and model evaluation before saving the trained model.

4.4 Class Diagram

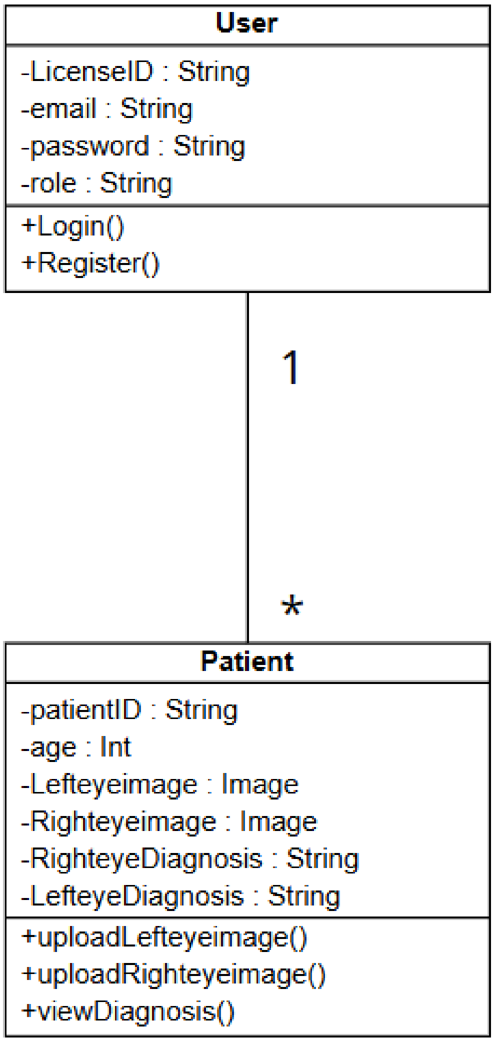

Figure 4.5: Class Diagram

The block diagram shows the end-to-end glaucoma detection process, including image preprocessing, CNN training and testing, XAI-based explanation, and model evaluation before saving the trained model.

CHAPTER 5
METHODOLOGY

5.Proposed Methodology

5.1 Tools and Technologies Used

The following tools and technologies are used to develop the *Glaucoma Detection with Explainable AI (XAI)* platform:

i. Programming Languages:

Table 5.1 – Programming Languages Used for Development

Python	for AI model development and backend processing
JavaScript	for frontend development using ReactJS

ii. Frameworks and Libraries:

Table 5.2 – Frameworks and Libraries Used

Frontend	ReactJS (for building the web interface)
Backend	Python (for handling server-side operations)
AI and Image Processing	TensorFlow, PyTorch, OpenCV
Explainable AI	Grad-CAM, LIME (for generating visual explanations)
Database	MongoDB (for storing user and image data)

5.1.1 Platforms and Tools:

i. Google Colab (for training and testing AI models)

ii. Local Development System (for developing, running, and testing the model and web application)

iii. GitHub (for version control and collaboration)

iv. Web Hosting and Domain (for deploying the application online)

5.2 Algorithms and Techniques

The following algorithms and techniques are used in the Glaucoma Detection with Explainable AI (XAI) project:

i. **Convolutional Neural Networks (CNNs):**

   a. CNNs are a type of deep learning algorithm mainly used for image analysis.

   b. They automatically learn patterns and features from retinal fundus images to detect signs of glaucoma.

ii. **Binary Classification:**

   a. The model classifies each image into one of two categories:

      i. **Glaucoma** (diseased eye)

      ii. **Normal** (healthy eye)

   b. This helps in providing a clear and simple diagnostic result.

iii. **Explainable AI Techniques (Grad-CAM / LIME):**

   a. Used to highlight important regions of the image that influenced the AI's decision.

   b. This makes the model's prediction more transparent and trustworthy for doctors and patients.

5.3 Dataset Description

Table 5.3-Summary of Publicly Available Glaucoma Datasets Used in the Study

Dataset	Classes (Healthy/ Glaucoma)	Total Sample	Link
ACRIMA	Healthy:396 Glaucoma: 309	705 images	Acrima
REFUGE	Healthy:1,080 Glaucoma: 120	1,200 images	Refuge

The project uses two publicly available glaucoma datasets—REFUGE and ACRIMA. Each provides healthy and glaucomatous cases with detailed clinical annotations, making them highly suitable for developing and evaluating glaucoma detection models.

5.3.1 Sample Retinal Fundus Image

Non-Glaucoma Sample:

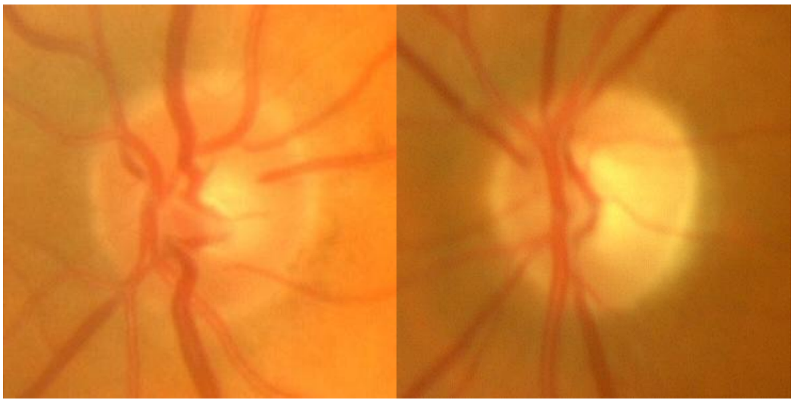

Figure 5.1:Non-Glaucoma Sample

In non-glaucoma images, the optic disc appears healthy with a small optic cup and a normal cup-to-disc ratio.

Glaucoma Sample:

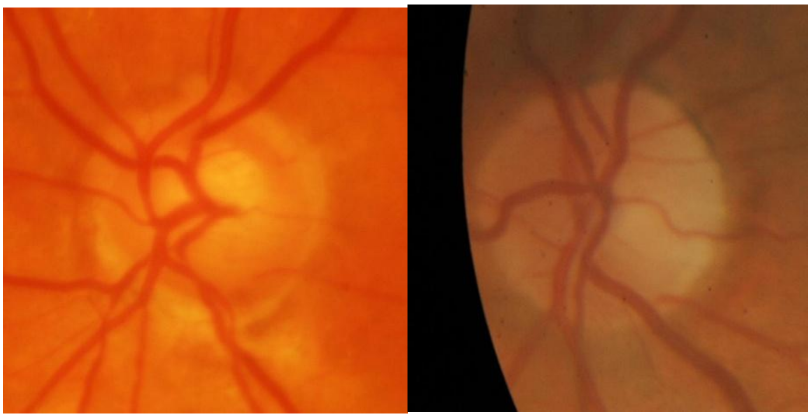

Figure 5.2:Glaucoma Sample

In glaucoma images, the optic disc shows signs of damage, including an enlarged optic cup and an increased cup-to-disc ratio, indicating loss of optic nerve fibers commonly associated with glaucoma.

5.4 Model Architecture Used

In this project, EfficientNet-V2-S is used to detect glaucoma from retinal fundus images from the REFUGE and ACRIMA datasets. The model uses pre-trained ImageNet weights to learn important features, and the final layer is modified to classify images as glaucoma or non-glaucoma. EfficientNet-V2-S is chosen due to its balanced trade-off between accuracy and computational efficiency, making it suitable for medical image analysis.

5.5 Model Training and Performance Evaluation

The model is trained for 10 epochs using a stratified train–validation split. To address class imbalance in the dataset, class-weighted loss is applied during training. Model performance is evaluated using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC score.

5.6 Result and Discussion

5.6.1 Confusion Matrix

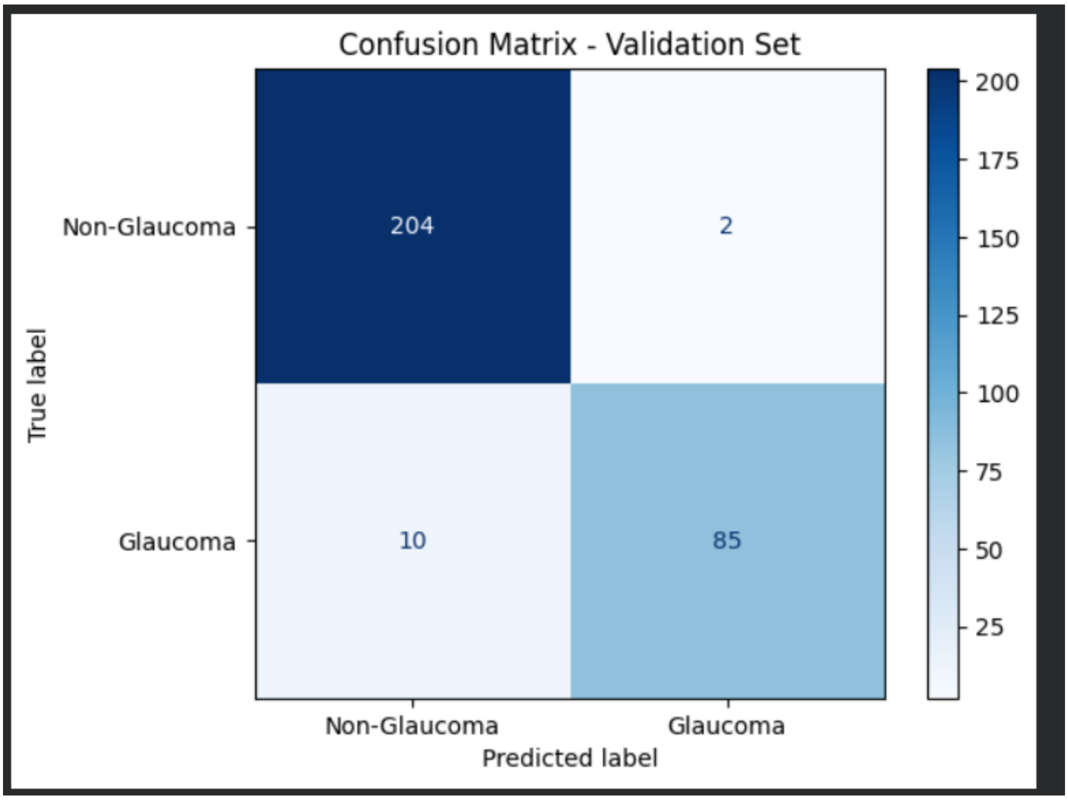

Figure 5.3: Confusion Matrix

The confusion matrix shows the performance of the EfficientNet-V2-S model on the validation dataset. The model correctly classified 204 non-glaucoma and 85 glaucoma images, with only a few misclassifications. Only 2 healthy images were incorrectly labeled as glaucoma, while 10 glaucoma cases were missed, indicating that the model can reliably distinguish between the two classes with good accuracy.

5.6.2 Classification Report

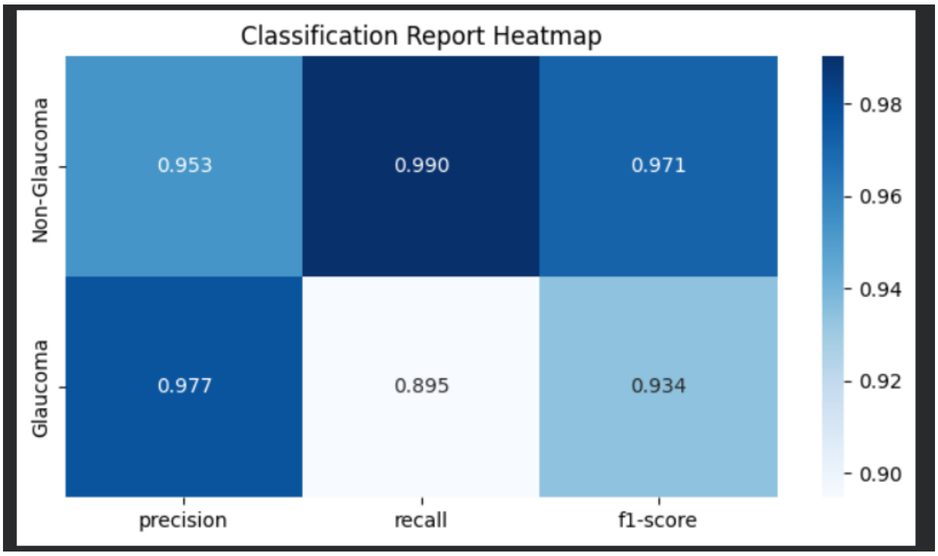

Figure 5.4:Classification

The classification report summarizes the model's performance using precision, recall, and F1-score. A high precision of 0.98 for glaucoma shows that most predicted glaucoma cases are correct, while a recall of 0.89 indicates that the model detects most actual glaucoma cases. The strong F1-scores for both classes reflect a good balance between accuracy and reliability

5.6.3 ROC Curve

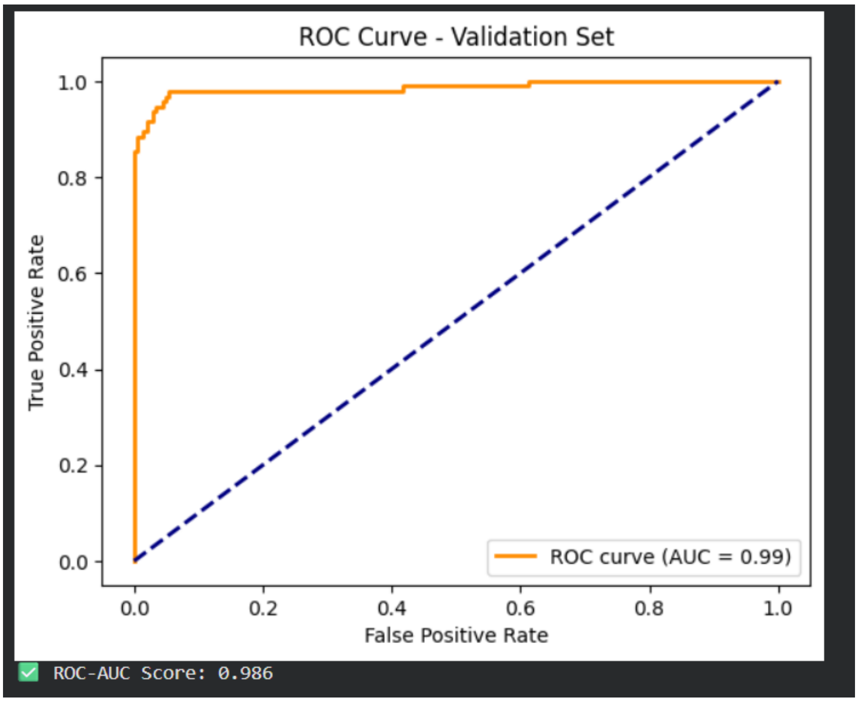

Figure 5.5:ROC curve

The ROC curve shows how well the model distinguishes between glaucoma and non-glaucoma cases at different thresholds. The curve stays close to the top-left corner, and the high ROC-AUC score of about 0.99 indicates excellent performance. This confirms that the model can reliably separate glaucomatous images from normal ones.

5.6.4 Grad-CAM Visualization Results

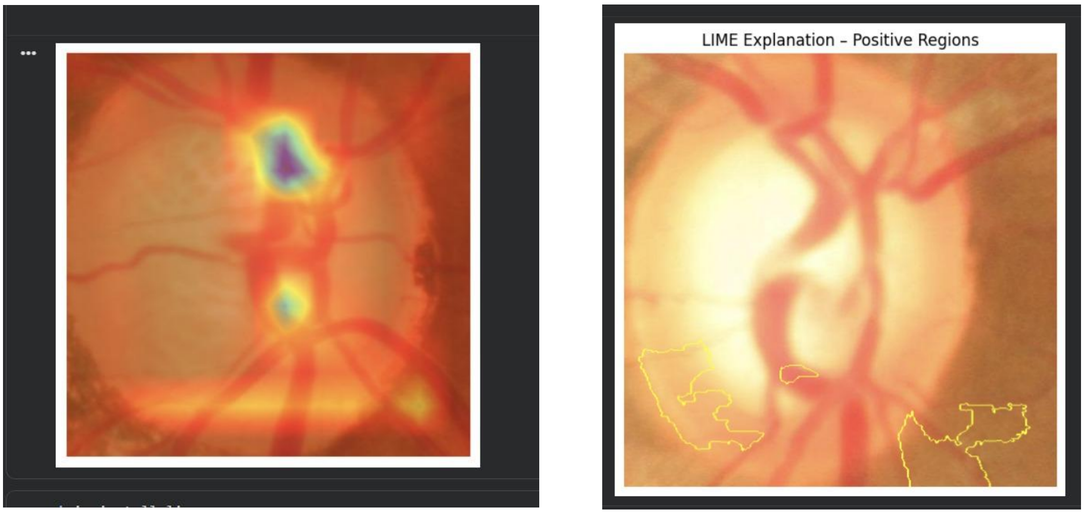

Figure 5.6:Grad CAM Visualization

Grad-CAM visualizations show the image regions that influence the model’s decisions. The heatmaps mainly highlight the optic disc area, which is important for glaucoma diagnosis. This indicates that the model focuses on clinically relevant features, improving transparency and trust in its predictions.

CHAPTER 6

IMPLEMENTATION

6.1 Login Interface

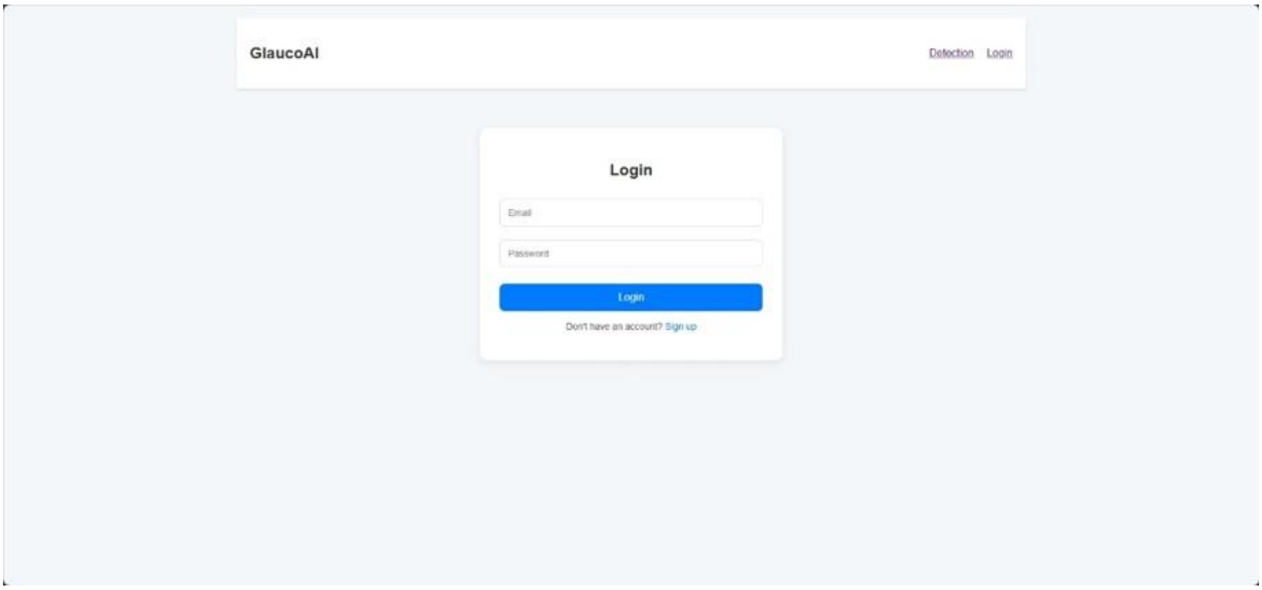

Figure: 6.1 Login interface

The login interface allows registered users to securely access the system by entering their credentials.

6.2 Sign-Up Interface

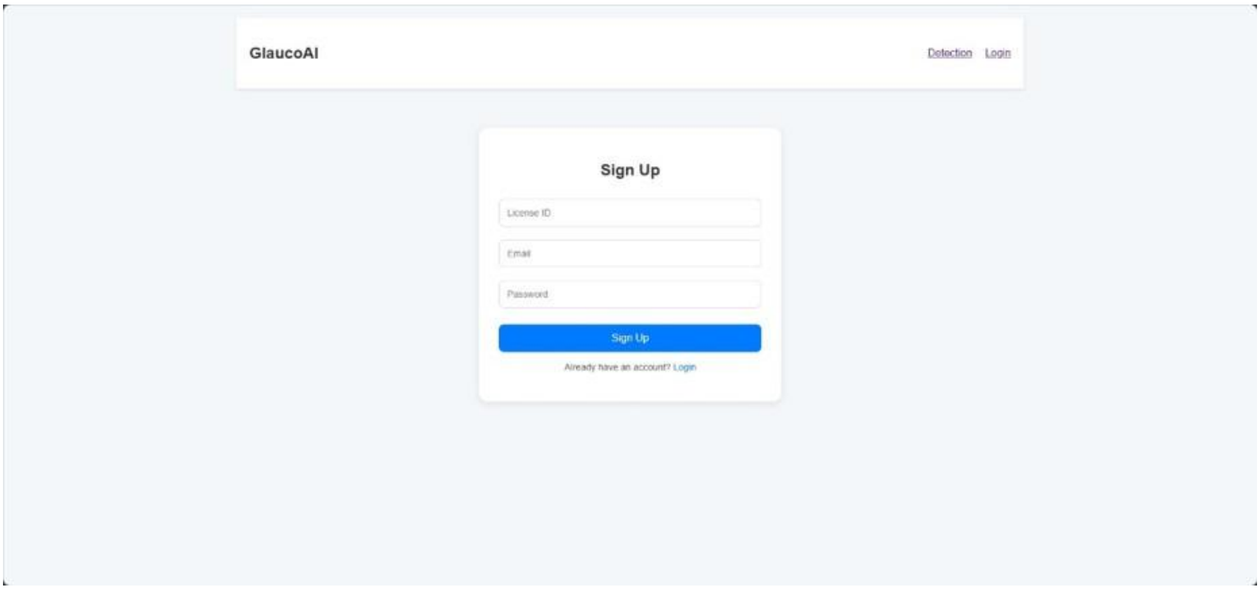

Figure: 6.2 Sign-up interface

The sign-up interface enables new users to create an account by providing basic registration details.

6.3 Dashboard

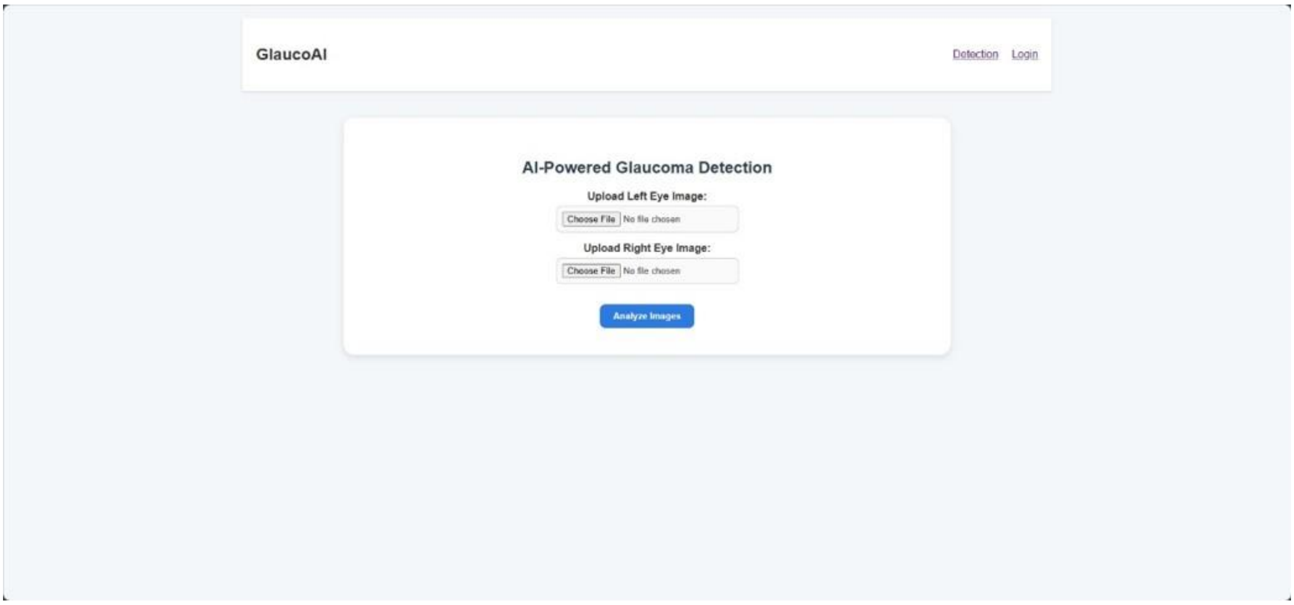

Figure: 6.3 Dashboard

The dashboard displays the main functionalities of the system, including image upload, prediction results, and explainable AI visualizations.

Conclusion

This project successfully demonstrates the application of deep learning and Explainable Artificial Intelligence (XAI) for automated glaucoma detection using retinal fundus images. By utilizing a convolutional neural network with transfer learning, the proposed system is able to accurately classify images as glaucomatous or non-glaucomatous while maintaining reliable performance on publicly available datasets such as REFUGE and ACRIMA. The integration of explainability techniques, particularly Grad-CAM, enhances transparency by visually highlighting important regions that influence the model's predictions, thereby improving trust and interpretability.

The developed web-based platform provides a user-friendly interface that allows users to upload images, view diagnostic results, and understand the reasoning behind the predictions. This makes the system suitable for clinical support, remote screening, and educational purposes. Overall, the project highlights the potential of combining deep learning with explainable AI to create accessible, accurate, and trustworthy medical diagnostic tools, contributing toward early glaucoma detection and improved eye-care outcomes.

Future Scope

- Integration with mobile applications for on-the-go screening and reporting.
- Incorporation of advanced AI models for higher accuracy and multi-disease detection.
- Adding patient history tracking and predictive analytics for risk assessment.

References

[1] Y. Zhang et al.,
"Visualization with Grad-CAM in glaucoma classification,"IEEE Access, 2020.

[2] M. Ali and T. Chowdhury,
"Lightweight CNN models for real-time glaucoma screening" Computers in Biology and Medicine, 2021.

[3] R. Kumar and S. Mehta,
"Interpretable machine learning approaches for glaucoma detection,"Biomedical Signal Processing and Control, 2022.

[4] A. Aljohani et al.,
"Feasibility of explainable AI in medical imaging: Application of LIME and SHAP in glaucoma detection," in Proc. IEEE Int. Conf. Medical Imaging, pp. 45–50, 2023.

[5] S. Patel and R. Sharma,
"A survey of explainable AI techniques in ophthalmology," Artificial Intelligence in Medicine, 2023.

[6] S. Velpula et al.,
"Explainable glaucoma detection using pretrained CNNs and Grad-CAM," Journal of Ophthalmic AI Research, vol. 5, no. 2, pp. 115–130, 2024.

[7] S. Kumar et al.,
"Explainable artificial intelligence (XAI) in glaucoma detection: Integrating CNNs with LIME and SHAP," Journal of Medical Imaging and Health Informatics, vol. 14, no. 2, pp. 123–135, 2024.

[8] T. Nguyen and J. Lee,
"Federated learning with explainable AI for glaucoma detection," IEEE Journal of Biomedical and Health Informatics, 2024.

[9] R. Bindu et al.,
"Transfer learning approaches for glaucoma detection using ResNet-50 and EfficientNet," Journal of Ophthalmic Research, vol. 12, no. 4, pp. 200–210, 2024.

[10] A. Aljohani and A. Aburasain,
"Hybrid ensemble approaches for glaucoma detection integrating CNNs and machine learning," International Journal of Medical Imaging Systems, vol. 9, no. 1, pp. 44–58, 2024.

[11] P. Sharma, P. A. Sample, L. M. Zangwill, and J. S. Schuman,
"Diagnostic tools for glaucoma detection and management," Survey of Ophthalmology, vol. 53, no. 6, pp. S17–S32, 2008.

[12] L. Li, M. Xu, X. Wang, L. Jiang, and H. Liu,
"Attention-based glaucoma detection: A large-scale database and CNN model,"in Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR),
pp. 10571–10580, 2019.

[13] A. C. Thompson, A. A. Jammal, and F. A. Medeiros,
"A review of deep learning for screening, diagnosis, and detection of glaucoma progression," Translational Vision Science & Technology, vol. 9, no. 2, p. 42, 2020.

[14] G. Litjens et al.,
"A survey on deep learning in medical image analysis," Medical Image Analysis, vol. 42, pp. 60–88, 2017.

[15] J. I. Orlando et al.,
"Glaucoma detection from fundus images using deep learning," Medical Image Analysis, vol. 35, pp. 70–82, 2017.

[16] H. Fu et al.,
"Disc-aware ensemble network for glaucoma screening," IEEE Transactions on Medical Imaging, vol. 37, no. 11, pp. 2493–2504, 2018.

[17] B. Al-Bander et al.,
"A deep learning framework for glaucoma detection," IEEE Access, vol. 6, pp. 68400–68410, 2018.

[18] E. Tjoa and C. Guan,
"A survey on explainable artificial intelligence (XAI): Toward medical XAI," IEEE Access, vol. 8, pp. 52138–52160, 2020.

[19] A. Diaz-Pinto et al.,
"CNN-based glaucoma detection across multiple datasets," IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 6, pp. 1–10, 2019.

[20] A. Holzinger et al.,
"What do we need to build explainable AI systems for the medical domain?" Artificial Intelligence in Medicine, vol. 100, p. 101, 2019.