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GLAUCOMA STAGES DETECTION USING FUNDUS IMAGES THROUGH DEEP LEARNING

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Abstract: A chronic eye condition called glaucoma has a deleterious effect on the optical nerve, which links the brain and eye to transmit visual information. Early detection is essential for stopping the condition's progression. Glaucoma is one of the most prevalent eye conditions, and it's important to catch it early because it can cause blindness and neurological issues. In this study, a Deep Learning system is proposed for the early detection of glaucoma. The eye image undergoes pre-processing to eliminate any noise and prepare them for further analysis. The system utilizes enlarged images of the eyes as input data for the deep learning method. The suggested system classifies new eye images as No_glaucoma Glaucoma_early, Glaucoma_moderate, and Glaucoma_advanced and also provides respective preventive measures based on the features it learned during training.

***Index Terms* -** Glaucoma, Deep Learning, pre-processed, Fundus Images.

I. INTRODUCTION

Glaucoma, One of the leading causes of blindness worldwide is glaucoma, a long-term neurodegenerative eye disease. According to the WHO, an average of 65 million people around the world are affected by glaucoma. Given that the primary symptom of glaucoma, the loss of optic nerve fibers, may be asymptomatic, early diagnosis and treatment are crucial in preventing vision loss. This loss is caused by increased intracranial pressure or decreased blood flow into the optic nerve. Visual data is transmitted via the optic nerve from the brain to the eye. Pathologically high intraocular pressure, which can suddenly rise to 60-70 mmHg is a symptom of glaucoma. Prolonged pressure of less than 25-30 mmHg can result from 2 in visual loss. High pressure in glaucoma is caused by increased reluctance to fluid expulsion into the drainage system of the eye. The fluids generated within the eye and those released are in equilibrium in healthy eyes. A common method used in ophthalmology to examine the human eye is taking a photo of the eye's fundus using a fundus camera. The medical professional takes the picture through the pupil to capture the eye's background. The photos are then analyzed, which can take several hours on a computer, but the results are not always accurate. Diagnosing glaucoma at home is a challenging task that requires determination and patience. We employed a supervised learning method classifier to distinguish between a healthy eye fundus and one affected by glaucoma. SVM aims to build a model, based on training and test data, which predicts the key features of the test data. SVM

is a popular supervised learning technique used for classification or regression problems. For classification issues, the SVM algorithm is a popular choice in machine learning. Its purpose is to create a boundary line or decision point that can divide high-dimensional spaces into classes, making it easier to categorize new data points in the future. This boundary line is referred to as a hyperplane[4]. The objective is to detect the abnormalities automatically and conditions with the least amount of error.
However, when used with SVM algorithms for images obtained with fast-rising spatial resolution, conventional image processing methods that were created and tested on low-resolution images have limits.
A new set of methods must be devised for this purpose. Because Convolutional Neural Networks (CNNs) can handle high-resolution images with minimal processing expense, we use them. CNNs are one kind of neural network that is frequently employed for image recognition applications.
The network's convolutional layer lowers the high dimensionality of the images while retaining crucial data. Another similar model that extracts features through convolutional filters is the Convolutional Neural Network (CNN). In large datasets, CNNs have become the preferred method for efficient and accurate image classification.

II. LITERATURE SURVEY:

Glaucoma, a condition characterized by the loss of retinal cells and astrocytes, can be assessed through specific measurements related to the eye cup and the neuro-retinal rim. Researchers have extensively explored this topic using fundus images, with a primary focus on quantifying the size of the retinal ganglion cell head.
One study proposed a system for measuring the Cup-to-Disc Ratio (CDR) using position-set methods and optic cup masks. Their evaluation involved 104 images, aiming for a CDR difference of less than 0.2 points from ground truth. Another approach, based on anatomical features, identified the optic cup using blood vessel curvature at the cup boundary. Using a container shape and circular Hough transform, this method achieved a CDR error of 0.12 to 0.10 in locating the eye cup.

In a separate study, researchers Yin et al. employed the Circular Wavelet transform to segment the optic disc or cup in 325 fundus images, achieving average correlation measures of 0.92 and 0.81. Cheng and colleagues proposed an alternative method that utilized superpixels for retinal image and cup segmentation. Their system, tested on 650 images, yielded average Jaccard scores of 0.800 and 0.822 across two datasets.

Additionally, Liu et al. incorporated patient-specific and genetic information into their study. The loss of eye nerve fibers and astrocytes remains a key symptom of glaucoma, emphasizing the importance of accurate measurements of the eye cup length and neuroretinal rim viscosity. Overall, various techniques, including position-set methods, anatomical verification, and Circular Hough transform, have been explored for computing the CDR, yielding diverse results across different datasets.

III. PROPOSED SYSTEM:

3.1 INTRODUCTION:

The proposed system aims to detect stages of glaucoma using fundus images sourced from Roboflow. Leveraging deep learning models such as MobileNet and InceptionV3, the system seeks to achieve high accuracy in glaucoma stage classification. The system's architecture encompasses data preprocessing, model training, evaluation, and deployment, ensuring a comprehensive approach to glaucoma detection.

3.2 SYSTEM OVERVIEW:

1. Data Acquisition: Utilize Roboflow to acquire a diverse dataset of fundus images, annotated with glaucoma stage labels. Ensure sufficient representation of various stages of glaucoma for robust model training.
2. Preprocessing: Apply preprocessing techniques to standardize image quality and enhance relevant features. These may include resizing, normalization, and augmentation to improve model generalization.

3. Model Selection: Choose MobileNet and InceptionV3 as deep learning architectures for glaucoma stage detection. These models are well-suited for image classification tasks and offer a balance between accuracy and computational efficiency

4. Training: Train MobileNet and InceptionV3 on the preprocessed dataset using transfer learning. Fine-tune the models on fundus images to adapt them to the task of glaucoma stage detection.

5. Evaluation: Evaluate the trained models using validation and test datasets to assess their performance in glaucoma stage classification. Measure metrics such as accuracy, sensitivity, specificity, and AUC-ROC to gauge model effectiveness.

6. Deployment: Deploy the trained models in a production environment for real-time glaucoma stage detection. Integrate the models into a user-friendly interface, allowing healthcare professionals to input fundus images and receive predicted glaucoma stages promptly.

3.3 ADVANTAGES OF PROPOSED SYSTEM:

1. Utilization of Roboflow Dataset: Leveraging a diverse dataset from Roboflow ensures comprehensive coverage of glaucoma stages, enhancing model generalization and robustness.
2. Efficient Model Architectures: MobileNet and InceptionV3 offer a balance between accuracy and computational efficiency, making them suitable for deployment in resource-constrained environments.
3. Transfer Learning: By employing transfer learning, the proposed system can leverage pre-trained models' knowledge, accelerating training and improving performance on the glaucoma detection task.
4. Real-time Deployment: The system enables real-time glaucoma stage detection, facilitating prompt intervention and treatment decisions by healthcare professionals.
5. User-friendly Interface: The integration of the models into a user-friendly interface simplifies the process of inputting fundus images and accessing predicted glaucoma stages, enhancing usability for healthcare practitioners.

3.4 PROPOSED SYSTEM WORKFLOW:

1. Data Collection: The system begins by sourcing a diverse dataset of fundus images annotated with glaucoma stage labels. These images are obtained from Roboflow, ensuring a varied representation of glaucoma stages for robust model training.

2. Data Preprocessing: Prior to model training, the fundus images undergo preprocessing steps to standardize image quality and enhance relevant features. Techniques such as resizing, normalization, and augmentation are applied to optimize image representation and improve model performance.

3. Model Selection: The system selects MobileVNet and InceptionV3 as deep learning architectures for glaucoma stage detection. These models are chosen for their ability to balance computational efficiency with high performance, making them suitable for deployment in resource-constrained environments.

4. Model Training: Utilizing transfer learning techniques, the selected models are trained on the preprocessed dataset. Transfer learning allows the models to adapt quickly to the nuances of glaucoma detection, thereby accelerating training and enhancing overall accuracy.

5. Model Evaluation: Trained models undergo thorough evaluation using validation and test datasets to assess their performance in glaucoma stage classification. Metrics such as accuracy, sensitivity, specificity, and area under the ROC curve are computed to evaluate model effectiveness and generalization.

6. System Deployment: Upon successful training and evaluation, the trained models are deployed in a production environment for real-time glaucoma stage detection. The system interface facilitates seamless interaction, enabling healthcare professionals to input fundus images and promptly obtain predicted glaucoma stages.

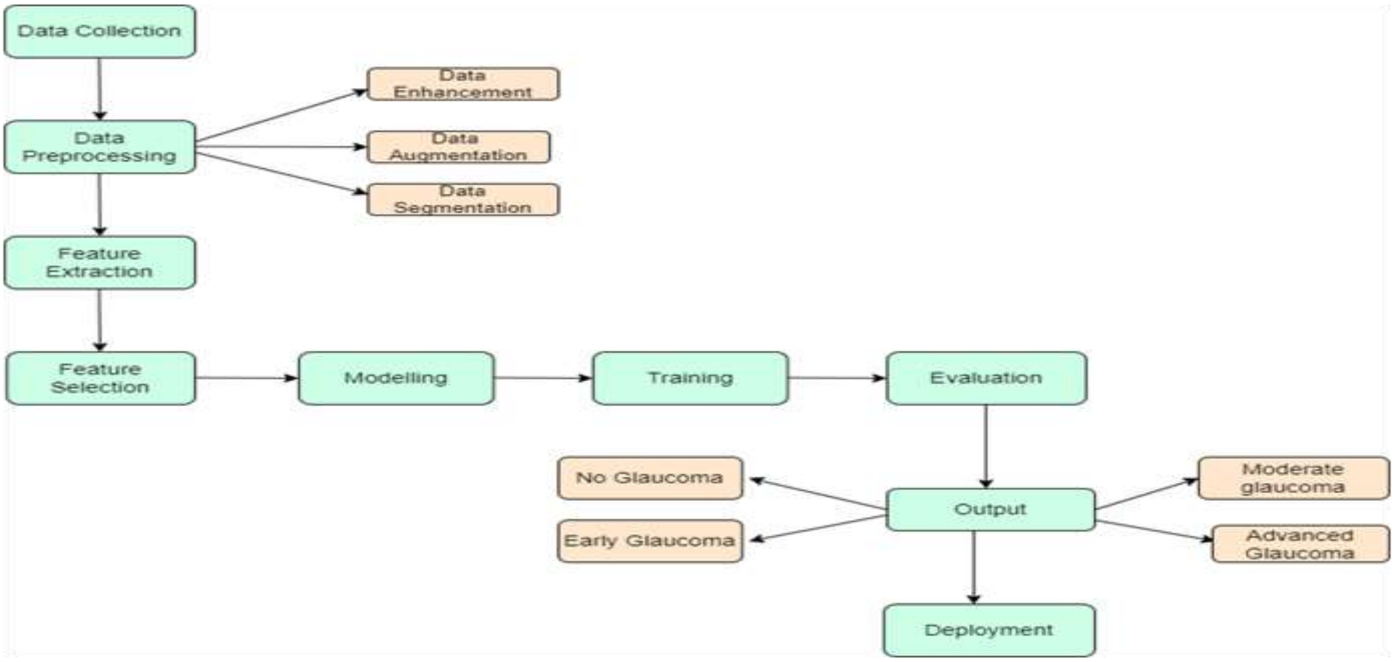


Fig 1: proposed system workflow diagram

3.5 ILLUSTRATIVE WORKFLOW:

1. User Interaction: A healthcare practitioner accesses the system interface and uploads a fundus image of a patient's eye suspected of having glaucoma.

2. Image Processing: The system preprocesses the uploaded image, standardizing its dimensions and enhancing its quality through normalization techniques.

3. Model Inference: The preprocessed image is passed through both MobileVNet and InceptionV3 models for inference. The models analyze the image and provide predictions regarding the likelihood of the patient being in various stages of glaucoma.

4. Result Presentation: The system presents the predicted glaucoma stage(s) along with associated confidence scores or probabilities to the healthcare practitioner. Additionally, it may offer recommendations for proactive measures based on the detected stage(s).

5. Clinical Decision-making: Armed with the system's output, the healthcare practitioner can make informed decisions regarding further diagnostic procedures, treatment modalities, and patient management strategies, thereby enhancing the quality of care provided.

IV. LIBRARIES USED:

1. Deep Learning: Deep learning techniques are employed for training the glaucoma detection models. These techniques involve neural networks with multiple layers that can automatically learn hierarchical representations of fundus images to identify glaucoma stages.

2. Roboflow: Roboflow is employed for managing and preprocessing the fundus image dataset used for training the glaucoma detection models. It offers tools for annotating, augmenting, and organizing image data, streamlining the data preparation process.

3. TensorFlow: TensorFlow serves as the primary deep learning framework for implementing and training the glaucoma detection models. It provides a comprehensive set of tools and APIs for building and optimizing deep neural networks.

4. Keras: Keras, as a high-level neural networks API, is likely utilized in conjunction with TensorFlow for rapid prototyping and experimentation with different model architectures. Keras simplifies the process of designing, training, and evaluating deep learning models.

5. Streamlit: Streamlit is utilized to create a user-friendly web application for interacting with the trained glaucoma detection models. It enables healthcare professionals to upload fundus images and receive predictions regarding the stages of glaucoma in real time.

V. METHODOLOGY

Introduction: The methodology proposed in this paper aims to leverage deep learning techniques, specifically InceptionV3 and MobileNet architectures, for the accurate detection of glaucoma stages from fundus images. Additionally, the methodology extends to providing personalized proactive measures based on the detected stage. This review outlines the key steps and approaches employed in the proposed methodology.

Data Collection: The methodology begins with the collection of a diverse dataset of fundus images, comprising images from individuals at various stages of glaucoma. Data collection efforts likely involved collaboration with healthcare institutions or utilizing publicly available datasets, ensuring adequate representation of different glaucoma stages for robust model training.

Preprocessing: Fundus images undergo preprocessing steps aimed at standardizing image quality and enhancing relevant features. Common preprocessing techniques include resizing, normalization, denoising, and contrast adjustment. These steps ensure consistency across the dataset and optimize image quality for subsequent analysis.

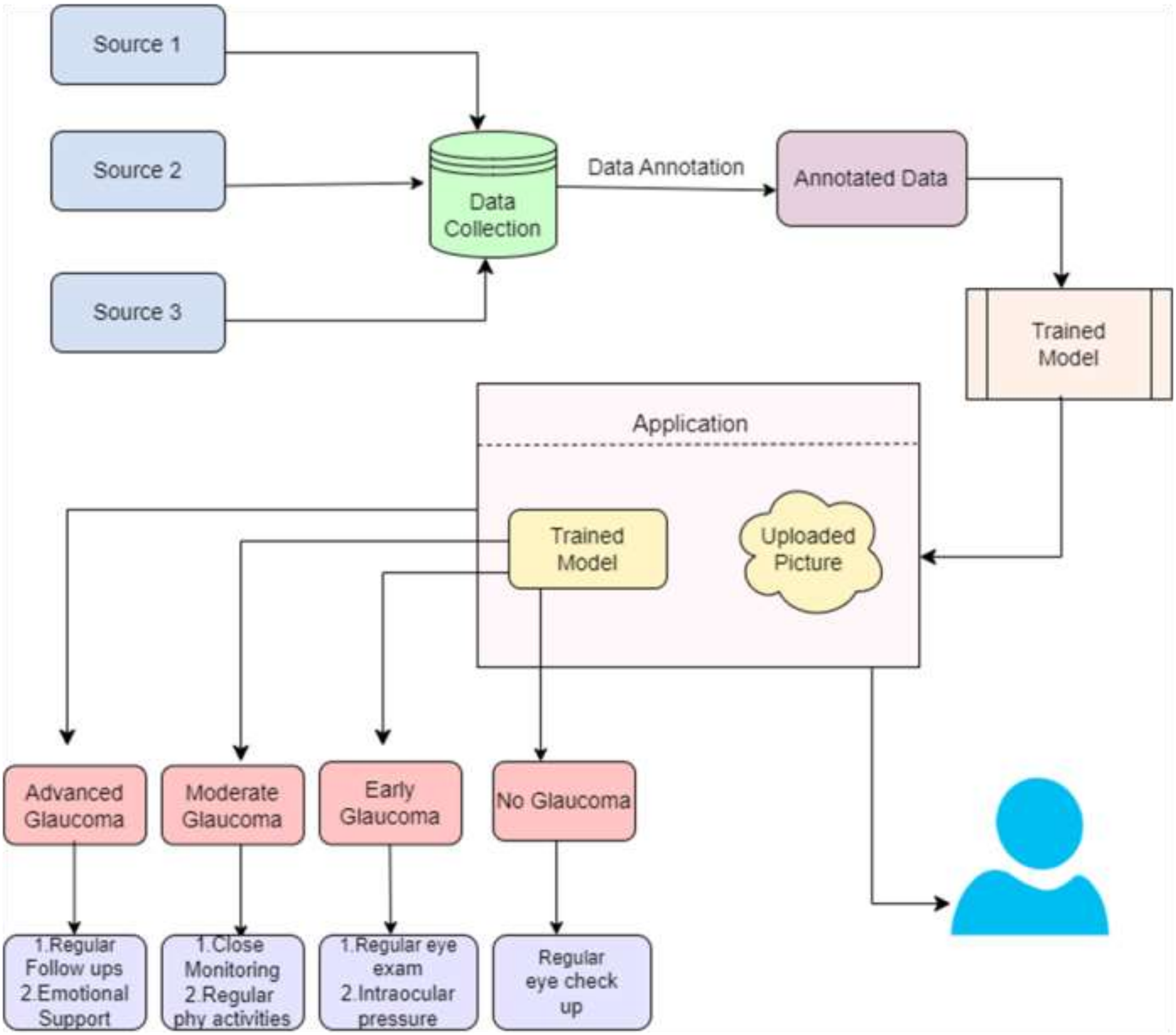
Feature Extraction: Extracting informative features from fundus images is crucial for accurate glaucoma stage detection. The methodology likely involves extracting optic disc parameters (e.g., cup-to-disc ratio, disc area), retinal nerve fiber layer thickness, and vessel morphology, among other relevant features associated with glaucoma progression.

Model Selection: The methodology selects two deep learning architectures, InceptionV3 and MobileNet, for glaucoma stage detection. These architectures are known for their effectiveness in image classification tasks and are chosen for their ability to handle the complexity of fundus images efficiently. The selection process likely considers factors such as model complexity, computational resources, and performance metrics.

Training and Evaluation: The selected models undergo training using the preprocessed dataset, with appropriate validation and test splits. During training, model parameters are optimized to minimize classification errors and maximize performance metrics such as accuracy, sensitivity. The trained models are then evaluated using separate validation and test sets to assess generalization performance and obtain unbiased estimates of effectiveness in glaucoma stage detection.

Output Generation: Upon successful training and evaluation, the trained models generate predictions for glaucoma stage detection. The output includes predicted stages for each fundus image, accompanied by corresponding confidence scores or probabilities. Visualizations of model predictions and performance metrics aid in interpretation and decision-making for clinicians and healthcare practitioners.

VI. ARCHITECTURE DESIGN:



VII. FUTURE PROSPECTS:

1. Advancements in Imaging Modalities: Anticipate ongoing enhancements in imaging technologies like optical coherence tomography (OCT) and adaptive optics, promising more detailed assessments of glaucoma-related structural changes. These advancements could significantly elevate diagnostic accuracy and refine staging capabilities.

2. Integration of Multifaceted Data: The fusion of various data streams, including fundus images, OCT scans, visual field assessments, and patient demographics, holds immense potential for a comprehensive understanding of glaucoma progression. Innovations in machine learning algorithms capable of synthesizing and interpreting diverse datasets may revolutionize staging precision and individualized treatment strategies.

3. Deep Learning and Artificial Intelligence Innovations: Continued evolution and fine-tuning of deep learning algorithms and artificial intelligence methodologies are projected to streamline and optimize glaucoma staging processes. Models trained on extensive and diverse datasets may exhibit improved adaptability and accuracy in identifying and categorizing distinct glaucoma stages.

4. Longitudinal Tracking and Predictive Analytics: Envision a future where longitudinal monitoring of glaucoma patients, facilitated by remote monitoring devices and wearable technologies, becomes commonplace. Predictive analytics algorithms leveraging longitudinal data could offer insights into future disease trajectories, enabling proactive interventions aimed at mitigating vision loss risks.

5. Telemedicine Integration and Remote Consultation: Expect telemedicine platforms and remote consultation services to increasingly integrate automated staging algorithms. This integration has the potential to revolutionize glaucoma management, particularly in remote or underserved regions, by facilitating prompt diagnosis and personalized treatment planning.

6. Emphasis on Patient-Centered Care and Informed Decision-Making: Foresee a shift towards patient-centric care models emphasizing shared decision-making. Future tools and technologies should empower patients by providing personalized risk assessments, treatment options, and prognostic insights, thereby fostering active engagement in their care journey.

7. Collaborative Research and Clinical Collaboration: Collaboration across research institutions and concerted efforts in large-scale clinical trials will be pivotal for validating and fine-tuning emerging staging technologies. Multicenter studies involving diverse patient cohorts and longitudinal follow-ups will yield invaluable real-world insights into the efficacy and clinical applicability of novel staging methodologies.

VIII. OUTPUT SCREENS:

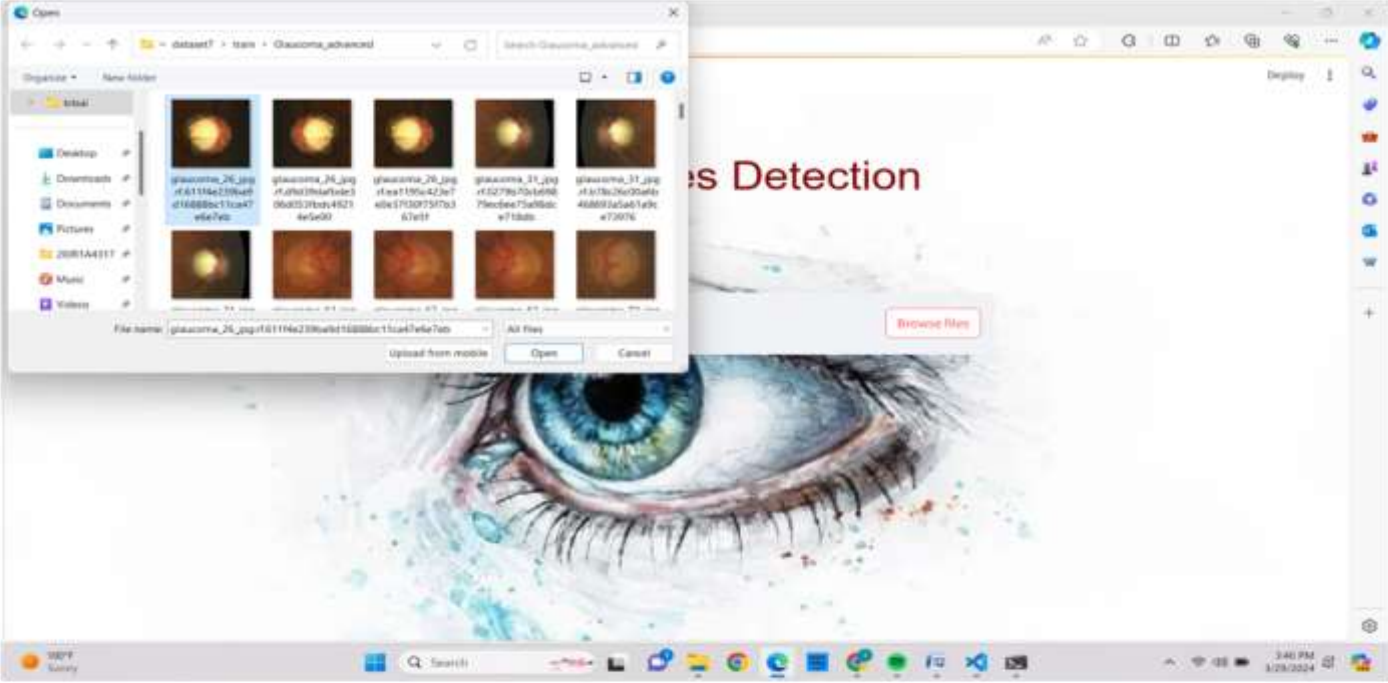
The output of the proposed system is given in 4 ways.There are as follows

1. No_Glaucoma

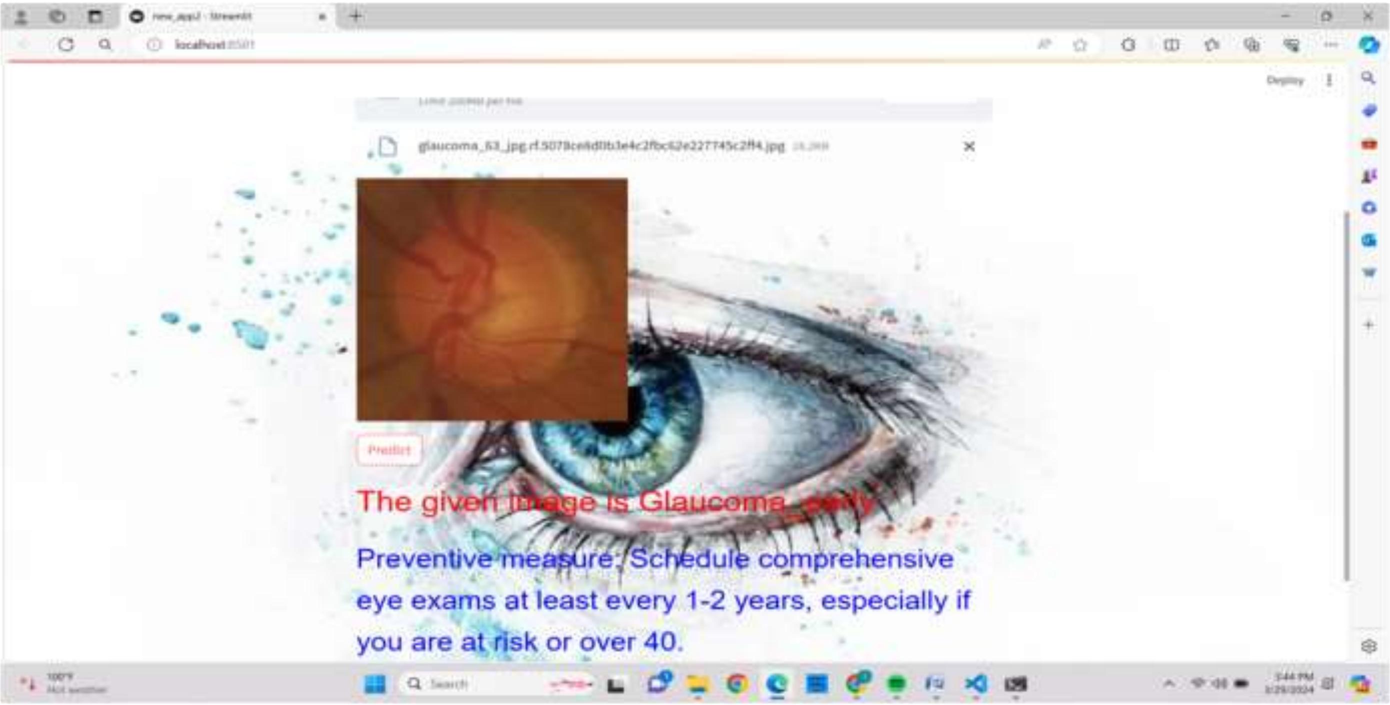
2.Glaucoma_early

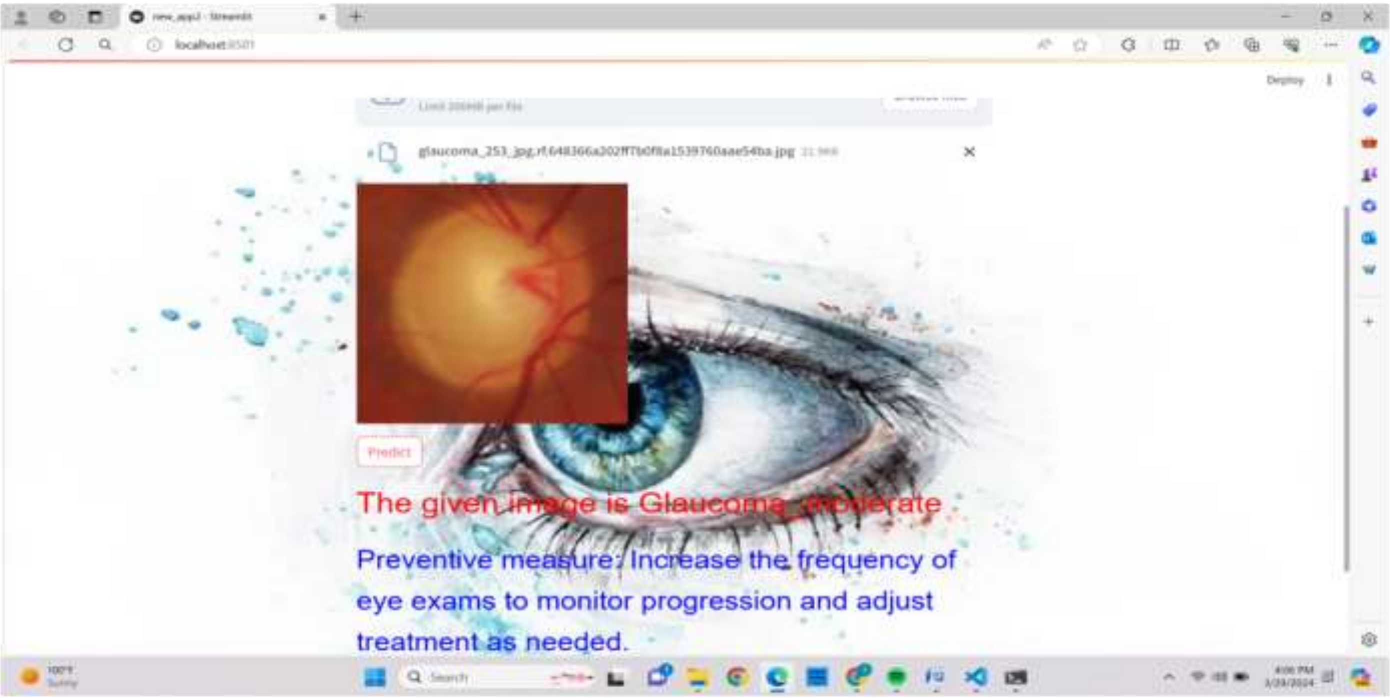
3.Glaucoma_moderate

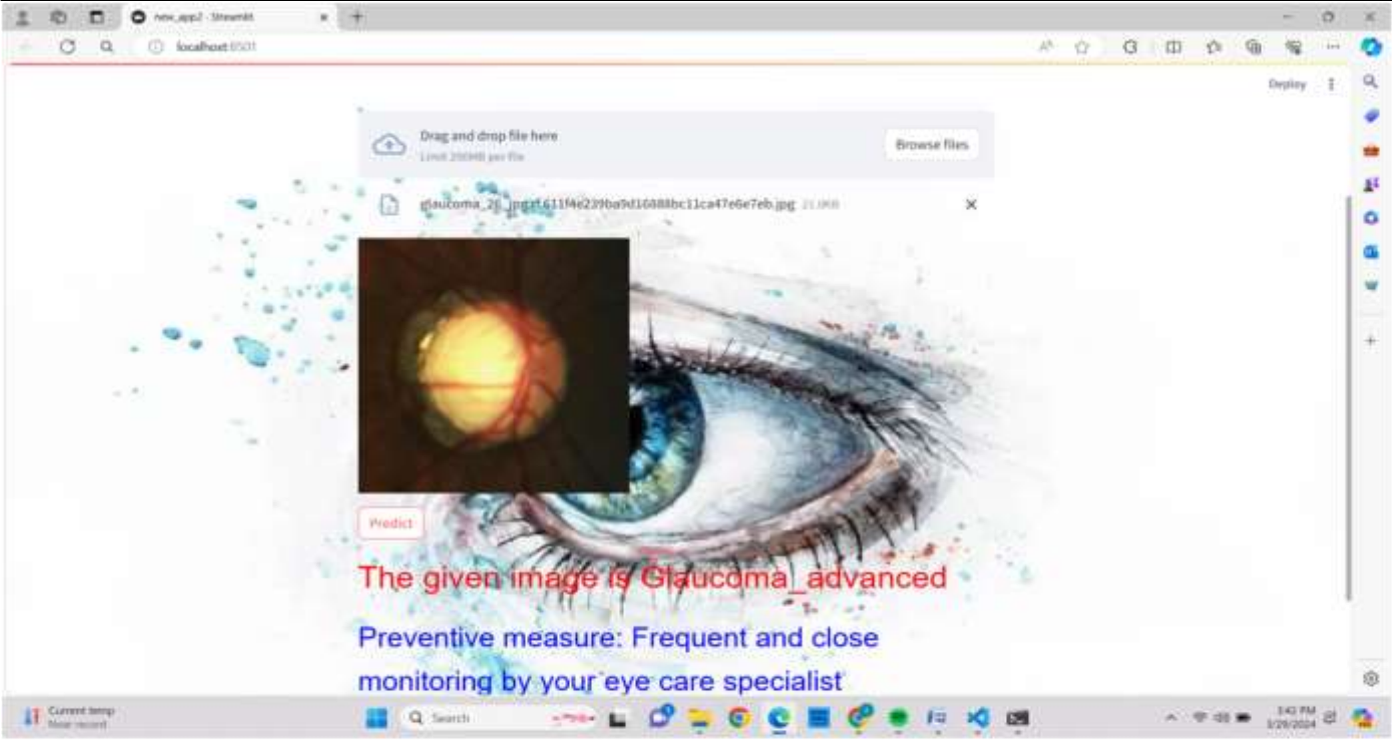
4.Glaucoma_advanced


es Detection
Browse files


Drag and drop file here
Browse files
Predict
The given image is No_Glaucoma
Preventive measure: Frequently check your eyes so that you are not effected by glaucoma.


Predict
The given image is Glaucoma_early
Preventive measure: Schedule comprehensive eye exams at least every 1-2 years, especially if you are at risk or over 40.


Predict
The given image is Glaucoma_moderate
Preventive measure: Increase the frequency of eye exams to monitor progression and adjust treatment as needed.



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