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Glaucoma Detection Using CNN ML and DL

Mrs. Smitha P[1], Yashwanth M C[2], A V Prajwal[3], Manvith V[4], Sandeep G[5]

[1]Smitha P, Asst. Prof, Dept. of AD, East West Institute of Technology, Bengaluru

[2]Yashwanth M C, Dept. of AD, East West Institute of Technology, Bengaluru

[3]A V Prajwal, Dept. of AD, East West Institute of Technology, Bengaluru

[4]Manvuth V, Dept. of AD, East West Institute of Technology, Bengaluru

[5]Sandeep G. of AD, East West Institute of Technology, Bengaluru

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Abstract-Glaucoma is a progressive eye condition that causes irreversible vision loss due to damage to the optic nerve. Recent developments in deep learning and the accessibility of computing resources have provided tool support for automated glaucoma diagnosis. Despite deep learning's advances in disease diagnosis using medical images, generic convolutional neural networks are still not widely used in medical practices due to the limited trustworthiness of these models. This study presents state-of-the-art deep learning techniques to segment and classify fundus images to predict glaucoma conditions and applies visualization techniques to explain the results to ease understandability.

Key words: Glaucoma detection, CNN, Image Processing, Deep Learning, Preventive Measures

1.INTRODUCTION

Early detection of glaucoma is vital for preserving vision and preventing irreversible blindness in patients. Manual screening methods, such as ophthalmoscopy or tonometry, suffer from high time demands, subjective variability, and limited accessibility in remote areas. This has spurred demand for automated solutions using image preprocessing techniques alongside CNN-based classification for effective glaucoma detection.

2.RELATED WORK

Previous methods for glaucoma detection relied on hand-crafted features like color histograms from retinal images or texture metrics from optic disc analysis, which often missed subtle disease signs. Deep learning, especially CNNs, steps in to boost accuracy by automatically learning complex patterns straight from raw fundus or OCT scans—no manual feature tweaking needed. It's like teaching a computer to spot the earliest whispers of nerve damage that a human eye might overlook.

3.METHODOLOGY

3.1 System Architecture

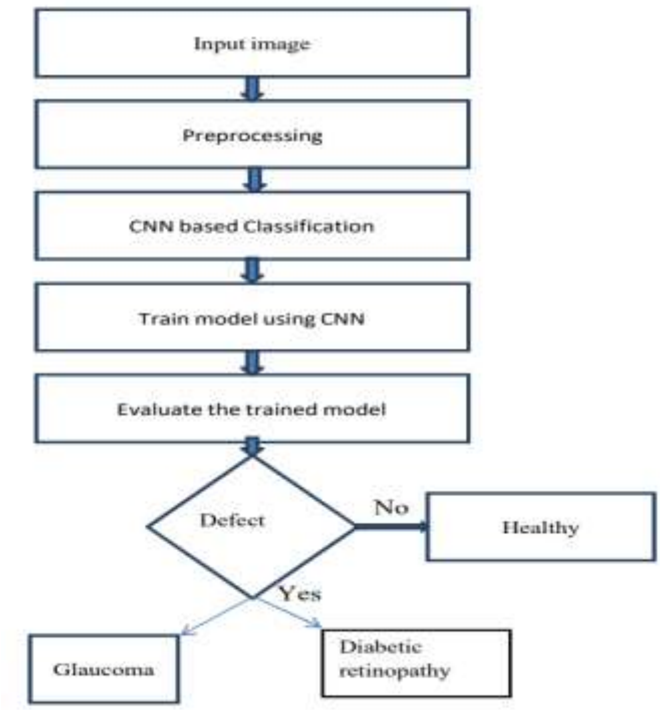

Fig 3.1: System architecture

The system proposed is designed to process eye images, extract disease-relevant features, classify the condition, and recommend preventive actions. The workflow includes the following steps:

- Image Acquisition: This step deals with acquiring the eye images, either from various datasets or other environments.
- Preprocessing: Noise filtering is performed by using Gaussian Blur, resizing of the image, enhancing contrast, conversion of the color space from RGB to HSV, and image segmentation for background removal.
- Feature Extraction: CNN layers automatically learn patterns describing lesion shapes, color variations, and texture irregularities.
- Classification: the SoftMax layer predicts the disease class.

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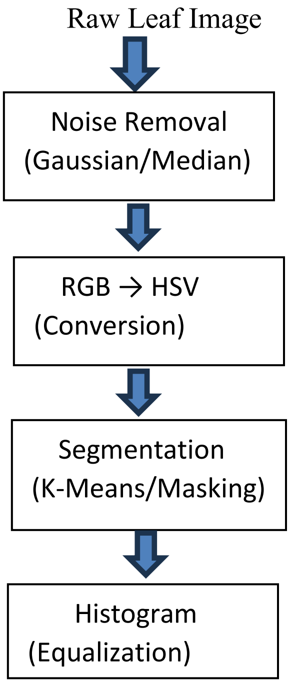
• Preventive Measure Module: It maps the predicted disease to a curated database of preventive steps.

3.2 Image Processing Techniques



Enhanced Image

Fig 3.2: S Preprocessing and Image Enhancement Flow

A. Preprocessing

Image preprocessing prepares retinal fundus or OCT scans for glaucoma detection by removing noise and highlighting critical features like the optic disc. Gaussian or median filters smooth out artifacts from imaging devices, while HSV color space conversion amplifies subtle retinal changes, such as nerve fiber thinning, for clearer visibility. These steps mirror plant disease workflows, ensuring the CNN receives high-quality inputs to spot early glaucoma signs effectively

B. Feature Enhancement and Segmentation

Color thresholding in HSV space or clustering algorithms like K-means segment key retinal regions in fundus images. This step effectively strips away distracting elements such as blood vessels, sclera, or imaging artifacts, letting the CNN focus purely on glaucoma indicators without background interference.

- Enlarged cup-to-disc ratio (CDR
- Nerve fibre layer
- Rim defects and peripapillary atrophy

3.3 CNN Architecture

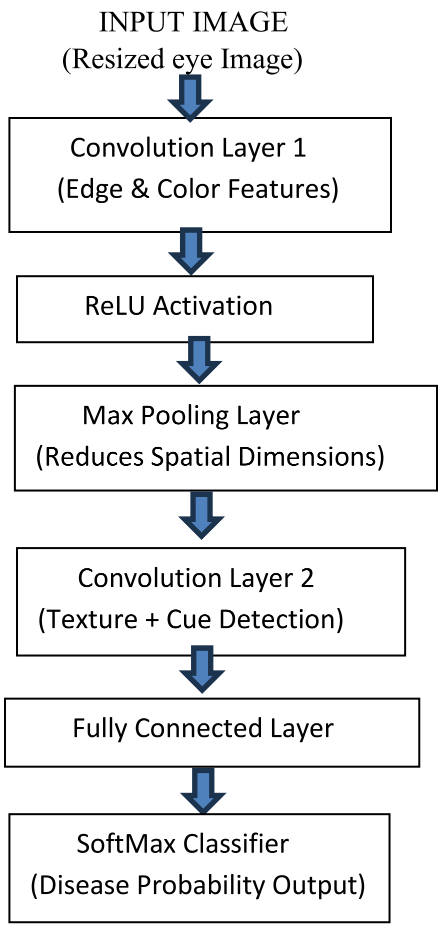


Fig 3.3: CNN Architecture Diagram (Simplified)

The CNN architecture consists of several convolution layers for feature extraction, ReLU activation for nonlinear learning, pooling layers to reduce dimensionality, and fully connected layers for decision-making. The final SoftMax layer gives the probability distribution for each disease class, enabling appropriate classification.

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3.4 System Workflow

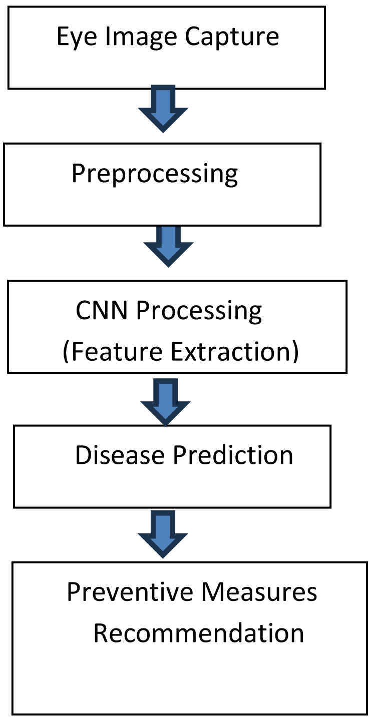


Fig 3.4: System Workflow

The process begins with capturing a retinal fundus or OCT image of the patient's eye, which is then preprocessed to enhance clarity and highlight the optic disc and nerve fiber layer. The CNN analyzes this processed image to detect glaucoma-related patterns and classify the eye as healthy, suspect, or glaucomatous. Based on the detected stage or risk level, the system can present clinical decision-support suggestions such as recommending visual field testing, intraocular pressure measurement, follow-up intervals, or referral to a specialist. This workflow supports continuous screening in clinics or tele-ophthalmology setups and enables timely, data-driven decisions to protect patients from irreversible vision loss.

4. IMPLEMENTATION

- Programming Language: Python
- Libraries: TensorFlow/Keras, OpenCV, NumPy, Matplotlib, Pandas
- Framework: Flask for interfacing
- Environment: Google colab/VS code
- Dataset: Manually collected eye images and publicly available eye image datasets

Python, OpenCV, and TensorFlow/Keras were used to build the detection model. The dataset includes multiple disease classes. A user interface allows eye image uploads and displays predictions along with preventive suggestions. The pipeline converts raw eye images into clean, enhanced inputs suitable for CNN classification. The system automatically handles errors such as blurry images or empty uploads through exception handling. The CNN is trained using thousands of processed images across multiple categories. Techniques such as augmentation, early stopping, and dropout help improve model accuracy and prevent overfitting.

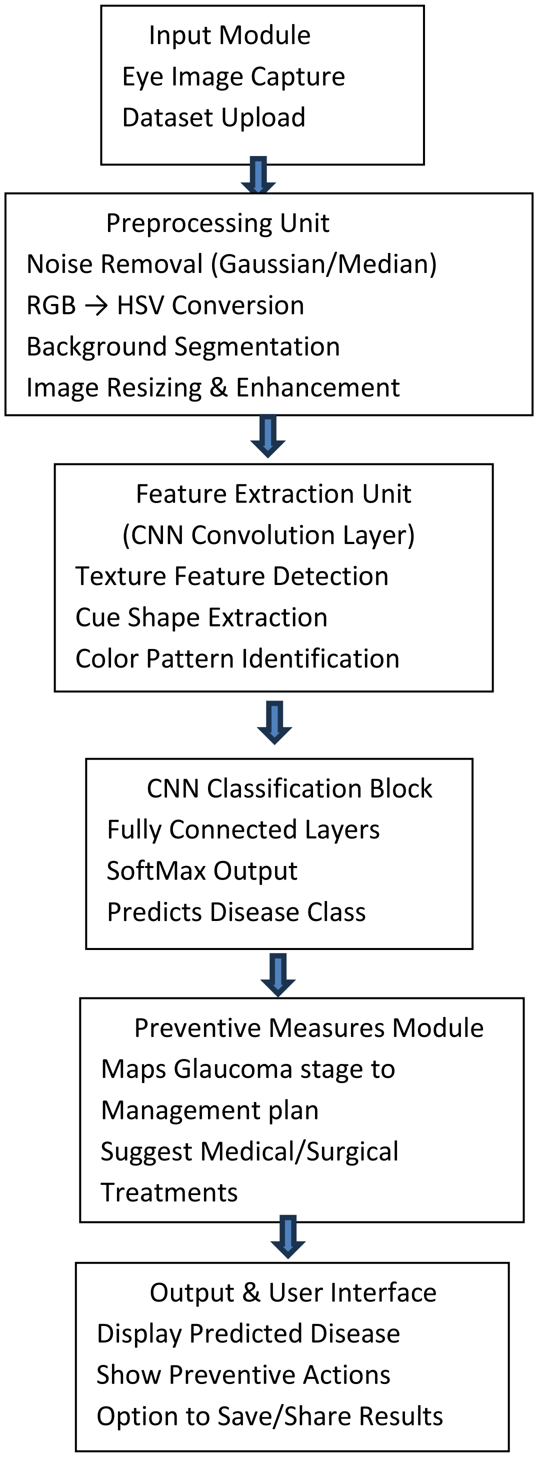
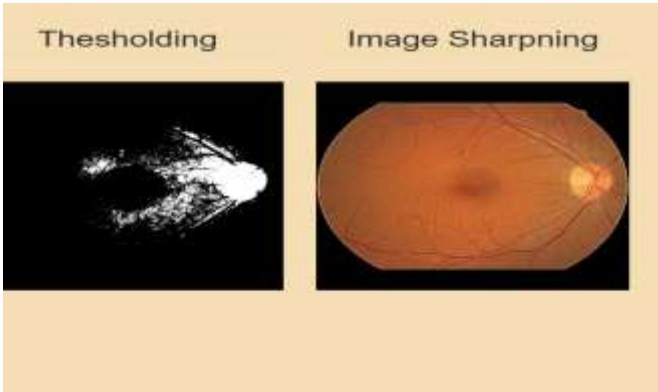


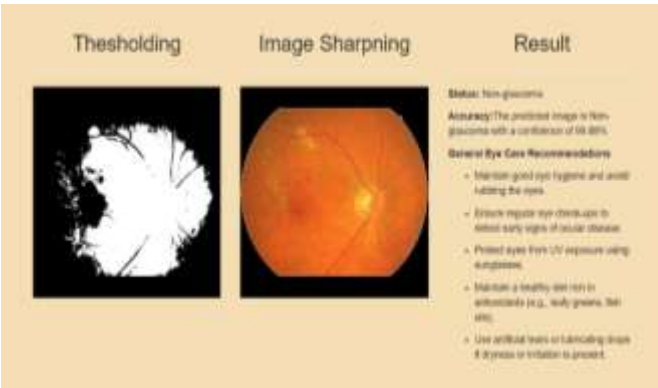
Fig 4.1: Implementation Diagram of the Glaucoma Eye Disease Detection System Using Image Processing and CNN

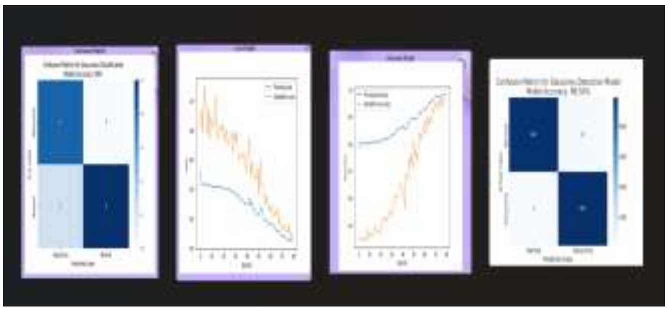
This implementation diagram shows the end-to-end system workflow, beginning with image capture and preprocessing to enhance leaf quality. The CNN performs hierarchical feature extraction and classification, after which the system retrieves preventive measures from a stored database. The user interface displays both the detected disease and recommended actions, enabling person or system users to make immediate decisions.

5. Result and Discussion

The findings from this glaucoma detection method show that combining advanced image analysis with a CNN classifier significantly improves how well it spots early and established glaucoma cases. Instead of simply chaining stages, careful denoising, disc–cup region isolation, and extraction of key structural cues reduce distractions while sharpening optic nerve changes, helping the network focus on clinically meaningful patterns. During evaluation, the tuned model achieved strong performance in separating healthy, suspect, and glaucomatous eyes, even when images varied due to illumination differences, camera type, or media opacities. This demonstrates that CNNs can cope with noisy, real-world retinal data without collapsing when conditions are less than ideal. It is also evident that outcomes depend heavily on sharp, high-resolution, and diverse scans; the richer the dataset in terms of anatomy and disease stage, the more robust the learning.







6. CONCLUSIONS

This research presents a deep-learning-based system for the automated detection of glaucoma using CNN and ophthalmic image-processing techniques. The proposed approach offers an efficient, accurate, and clinician-friendly solution for eye-care centers and screening programs. By integrating risk-based management recommendations, the system moves beyond mere detection to support informed clinical decision-making.

Future work may include handling multiple optic nerve and retinal pathologies, deploying the model on smartphone-based fundus cameras, integrating with tele-ophthalmology and IoT-enabled screening devices, and using larger, more diverse datasets to enhance scalability, fairness, and reliability across populations.

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