ROBUST GLAUCOMA PREDICTION FROM FUNDUS IMAGES USING DENSENET201 AND NASNETMOBILE

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ABSTRACT

Glaucoma is a progressive eye disease affecting approximately 64 million people globally, leading to damage of the optic nerve head (ONH) and potential irreversible blindness. Early detection is critical to prevent vision loss; however, traditional clinical approaches, such as manual segmentation of the optic cup and disc for cup-to-disc ratio (CDR) calculation, are often time-consuming, subjective, and dependent on expert evaluation. To overcome these limitations, this study proposes an automated glaucoma detection system based on deep learning, utilizing retinal fundus images for binary classification of healthy and glaucomatous eyes. The system employs two advanced convolutional neural networks, DenseNet201 and NASNetMobile, both trained using transfer learning techniques and fine-tuned for optimal performance. Preprocessing techniques such as histogram equalization are applied to enhance image contrast, and class imbalance is managed using computed class weights. The model focuses on extracting key features from the optic disc (OD) and optic cup (OC) areas, emphasizing crucial indicators like the cup-to-disc ratio (CDR) and the neuro retinal rim (NRR) structure. Performance evaluation is conducted by comparing the classification accuracy, precision, and recall of both models to identify the more effective solution for practical glaucoma screening. DenseNet201, recognized for its deep feature extraction capabilities, and NASNetMobile, optimized for lightweight deployment, offer valuable insights into achieving a balance between accuracy and computational efficiency. This research highlights the promising role of deep learning in supporting clinicians with faster, more objective, and reliable glaucoma diagnosis.

Keywords : *cup-to-disc ratio (CDR), optic nerve head (ONH), optic disc (OD), optic cup (OC),neuro retinal rim(NRR)*

1. INTRODUCTION:

1.1. GENERAL SYSTEM:

The general system developed for glaucoma detection focuses on the automated analysis of fundus images using deep learning techniques. Fundus photography is a non-invasive and easily available imaging method that captures the back surface of the eye, including the optic disc and optic cup. Since glaucoma mainly affects the optic nerve head (ONH), analyzing these images helps in early identification of the disease. The goal of the system is to create an accurate, affordable, and fast diagnosis tool that reduces the dependence on manual screening by specialists.The system begins by collecting a large number of fundus images from various datasets. These images may vary in quality due to lighting conditions, camera differences, or patient movements. Therefore, preprocessing techniques such as histogram equalization and adaptive histogram equalization are applied to standardize image quality. These steps help in enhancing the visibility of important structures like the optic disc and optic cup, making it easier for the deep learning models to detect abnormalities.

After preprocessing, the system performs segmentation of key regions in the fundus images. Specifically, it segments the optic disc and optic cup using Convolutional Neural Networks (CNNs). Accurate segmentation is important because it allows the system to calculate clinical indicators such as the Cup-to-Disc Ratio (CDR). An increase in the CDR is a major biomarker for glaucoma. Both the vertical CDR (V-CDR) and area-based CDR (A-CDR) are computed to provide a more reliable assessment of glaucoma risk.Once the optic disc and cup are segmented, feature extraction is carried out. Features such as the size, shape, and texture of the optic disc and cup are analyzed. These features are then passed to a classification model, which predicts whether the eye is glaucomatous or healthy. Models like DenseNet201 and NASNetMobile are employed because of their efficiency in feature extraction and classification, even from limited training data.

The system is trained using labeled fundus image datasets where the presence or absence of glaucoma is known. Training involves optimizing the model weights to minimize classification errors. During the evaluation phase, metrics such as accuracy, sensitivity, specificity, and Area Under the Curve (AUC) are calculated to assess the system's performance. High sensitivity ensures that most glaucoma cases are detected, while high specificity ensures that healthy cases are not wrongly classified as glaucoma.Another important aspect of the general system is the inclusion of explainability methods such as Grad-CAM. These methods generate heatmaps that highlight which regions of the image contributed most to the model's decision. This increases the trust of medical professionals in the system, making it more acceptable for clinical use.

Overall, this general system provides a robust, scalable, and effective solution for glaucoma screening. It supports mass screening programs, especially in rural and underdeveloped areas where access to ophthalmologists is limited. With further improvements and clinical validations, such systems have the potential to become a standard tool for early glaucoma detection and management.

1.2 MOTIVATION

Eye diseases have a major influence on human health, and retinal disorders are rising rapidly across the globe. As a result, there is a strong need for modern diagnostic tools that can provide quick and reliable ophthalmic evaluations. Glaucoma is one of the most common neurodegenerative eye diseases that can lead to irreversible vision loss if not treated early. Thus, early and accurate glaucoma detection is crucial for effective management. Traditionally, ophthalmologists rely on manual techniques and visual assessments for glaucoma diagnosis. However, these methods are often time-consuming, labor-intensive, subjective, and prone to human error. Therefore, automated solutions are increasingly necessary to support clinical practices.

Although numerous methods have been proposed for the automatic detection and classification of glaucoma-related features, there is still significant room for improvement in their performance. Machine learning (ML) techniques have shown promise in handling complex scenarios better than human judgment. Yet, ML methods often struggle with post-processing disturbances and tend to have high computational requirements due to the generation of lengthy codes, leading to slower processing times. Deep learning (DL) models offer alternatives to these challenges but come with increased model complexity and are sometimes less adaptable to variations in disease presentation. Consequently, it remains vital to develop systems that can not only enhance detection accuracy but also reduce computational burden. These needs have motivated the development of the proposed system.

2 . PROPOSED SYSTEM

This project introduces an automated system for glaucoma detection using retinal fundus images, built upon deep learning techniques. The approach begins with acquiring high-quality retinal images from publicly available datasets, which provide detailed views of the eye's internal structures, particularly the optic nerve head and surrounding regions. These images form the foundational input for the detection process.

Before feeding the images into the models, they undergo preprocessing to enhance important visual features. Techniques such as histogram equalization and adaptive histogram equalization are applied. These help to improve both global and local image contrast, making crucial structures like the optic disc and optic cup more visible and distinguishable. Such enhancement is essential for accurately identifying features linked to glaucoma.

The core of the system relies on convolutional neural networks, specifically DenseNet201 and NASNetMobile. DenseNet201 is known for its dense connectivity between layers, which boosts feature reuse and strengthens gradient flow, making it effective in capturing subtle patterns in medical images. NASNetMobile, on the other hand, is a compact and efficient model designed for use in resource-limited or real-time environments. Despite its lightweight architecture, it maintains strong performance through optimized feature extraction. Both models are pre-trained on large datasets and are fine-tuned with glaucoma-specific data to adapt them to this medical classification task.

The models are modified by adding custom layers suited for binary classification of glaucoma. These layers include convolutional blocks that detect increasingly complex features, as well as dense layers that apply non-linear transformations. A final Sigmoid activation function outputs a binary result indicating whether glaucoma is present or not. Dropout layers are used to reduce overfitting during training.

The system places particular importance on features like the Cup-to-Disc Ratio (CDR), a widely accepted clinical measure used to evaluate glaucoma progression. In addition, it focuses on structural markers such as the retinal nerve fiber layer and signs of optic nerve damage, all of which provide critical information for diagnosis.

Both DenseNet201 and NASNetMobile are used independently to analyze the enhanced fundus images. Their outputs are then used to make predictions, and the results are evaluated using accuracy, precision, recall, and F1-score. This dual-model approach improves reliability and confidence in the system's decisions. By testing on unseen validation data, the models' ability to generalize is assessed, ensuring the system remains effective in real-world conditions.

In summary, this system presents a robust and efficient method for early glaucoma detection using deep learning. By combining powerful CNN architectures, contrast-enhancing preprocessing, and clinically significant feature extraction, the system aids ophthalmologists in making faster and more accurate diagnoses, potentially improving patient outcomes.

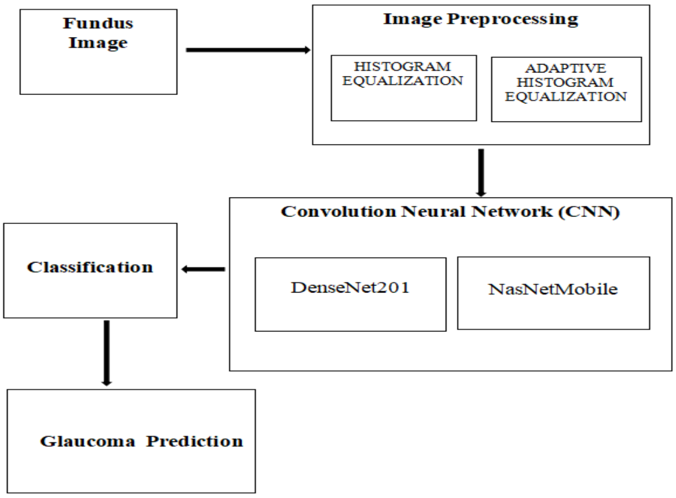

Fig 1: Block Diagram of Glaucoma Detection

3.METHODOLOGY

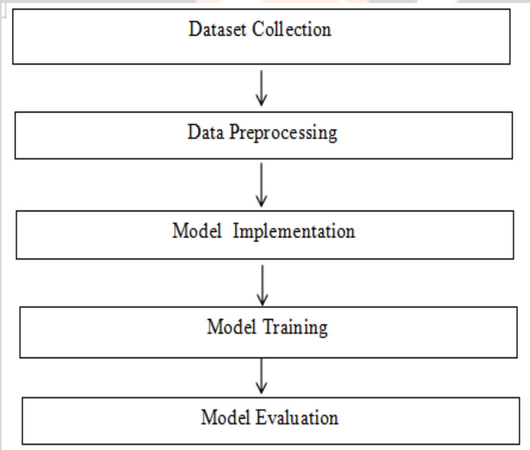

Fig 2: Implementation Workflow

The glaucoma detection system was developed through a structured workflow, beginning with the collection of a comprehensive set of fundus images. These images are essential for identifying glaucoma, as they provide detailed views of the optic disc, cup, and surrounding retinal regions. Care was taken to ensure the dataset included diverse samples across different ages, genders, ethnicities, and health backgrounds. This variety helps the model generalize well to various patient types. After gathering the images, labeling and annotation were done by medical professionals, marking whether glaucoma was present and highlighting critical regions like the optic disc and optic cup. Accurate labeling is essential since the model relies on these annotations to learn distinguishing features effectively.

Next, the collected images underwent preprocessing to improve their quality and prepare them for model input. This involved resizing all images to a uniform size of 224×224 pixels and normalizing the pixel values. Two contrast enhancement techniques were applied—Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE). HE improved global contrast by adjusting the brightness and darkness across the entire image, which is helpful when illumination is uneven. CLAHE, on the other hand, enhanced contrast locally in small regions of the image while limiting noise amplification. This method is especially effective in highlighting subtle structures such as blood vessels and the neuroretinal rim, both of which are important in glaucoma diagnosis.

Following preprocessing, the project implemented two deep learning models: DenseNet201 and NASNetMobile. These convolutional neural network architectures are known for their efficiency and ability to capture complex features in images. Transfer learning was used by importing models pre-trained on the ImageNet dataset and adapting them to the glaucoma detection task. The top layers of the original models were replaced with a custom classification head that included a global average pooling layer, dropout for regularization, and fully connected layers with a sigmoid function to perform binary classification. This structure allowed the models to focus on glaucoma-related patterns while avoiding overfitting.

During model compilation, the Adam optimizer was chosen for its ability to adjust learning rates dynamically, making training faster and more stable. The binary cross-entropy loss function was used since the task involved distinguishing between two classes—glaucomatous and non-glaucomatous. Class weights were also introduced to address the issue of imbalanced data, giving higher importance to correctly identifying the less frequent glaucoma cases. The models were evaluated using metrics like accuracy, precision, and recall to assess their overall performance and sensitivity to detecting glaucoma.

Model training was conducted over 25 epochs using data generators to handle the image batches efficiently. Early in training, the models showed modest performance, but with each epoch, accuracy, precision, and recall steadily improved. By the 10th epoch, the models achieved over 98% accuracy, and performance continued to rise, eventually reaching 100% in accuracy, precision, and recall. These improvements demonstrated the models' ability to learn meaningful patterns from the data and distinguish between healthy and glaucomatous eyes effectively. The consistent drop in loss values indicated strong confidence in predictions and good generalization ability, proving the robustness of the developed system.

4. EXPERIMENTAL RESULTS

The output of this project is a trained deep learning system designed to distinguish between normal and glaucoma-affected eyes using fundus images. It employs two deep convolutional neural network models—DenseNet201 and NASNetMobile—to perform binary classification. When a new fundus image is input, the model predicts whether the eye is healthy or affected by glaucoma. In this system, the label '0' corresponds to a normal eye, while '1' indicates the presence of glaucoma. Throughout the development process, key evaluation metrics such as accuracy, precision, recall, F1-score, and loss were monitored to assess model performance. These metrics are critical in medical imaging as they reflect the system's ability to detect disease accurately while minimizing incorrect predictions. For instance, high recall ensures the system detects most glaucoma cases, while high precision helps avoid flagging healthy eyes unnecessarily.

During training, both models demonstrated consistent improvement in performance. The training accuracy increased with each epoch, and the loss values decreased gradually. DenseNet201 achieved particularly strong results, with some training runs reaching 100% accuracy, and test accuracy ranging between 70% to 100%, depending on the dataset conditions and preprocessing techniques. NASNetMobile also performed well but typically scored slightly lower than DenseNet201 across most metrics. These results reflect the models' learning capacity and indicate that they are capable of supporting real-time diagnostic decisions.

The preprocessing phase began with loading and resizing fundus images from the dataset. All images were resized to 224x224 pixels, a standard input size required by most deep learning models, which also reduces computational complexity. Additionally, the images were converted to RGB format for compatibility with the model input requirements. To validate preprocessing, a batch of nine images was selected at random and visualized along with their labels—either “Glaucoma - Positive” or “Glaucoma - Negative.” This visualization helped ensure the images were correctly loaded, resized, and labeled.

As part of contrast enhancement, histogram equalization was applied to improve the visibility of important retinal features, especially those that are critical for glaucoma detection such as the optic disc and optic cup. Global histogram equalization redistributed pixel intensity values to enhance image contrast, though in some cases, local details remained insufficiently enhanced. To resolve this, adaptive histogram equalization was used, which operates on smaller regions of the image. This approach significantly improved the clarity of fine structures like blood vessels and boundaries of the optic cup and disc, which are often obscured due to uneven illumination or subtle contrast differences. This enhancement not only improved visual clarity for human review but also helped the models learn from clearer features during training.

To further explore how image channels contributed to learning, the intensity distributions of the red, green, and blue color channels were analyzed. The red channel showed a wide intensity range and highlighted vascular structures effectively. The green channel was found to be the most informative, as it provided better visibility of fine retinal features important for diagnosis. Its histogram showed a well-balanced distribution, which justified its use in further enhancement processes. On the other hand, the blue channel carried less useful diagnostic information, exhibiting a narrow and skewed distribution, often associated with noise and background artifacts.

The performance of two deep learning models, DenseNet201 and NASNetMobile, was thoroughly evaluated for the task of glaucoma detection using fundus images. DenseNet201 demonstrated a progressive learning curve throughout training, beginning with an initial accuracy of 58.65% and improving consistently across epochs. By the 13th epoch, the model achieved perfect accuracy (100%) and maintained it through to the 25th epoch, while the loss steadily decreased to a minimal value of 0.0110. This strong learning trajectory indicates robust feature extraction and convergence. On testing, DenseNet201 delivered exceptional results with an overall accuracy of 100%, and perfect scores for precision, recall, and F1-score across both glaucoma and non-glaucoma classes, confirming its reliable performance.

NASNetMobile, while starting with lower initial accuracy (54.04%) and modest precision and recall values in the first few epochs, showed marked improvement over time. The model learned to distinguish classes more effectively by adapting through class weighting strategies to handle data imbalance. Training precision and recall increased notably over epochs, with significant reduction in loss. When evaluated on the test data, NASNetMobile also achieved a 100% accuracy, along with perfect precision, recall, and F1-score. The results clearly demonstrate the effectiveness of both models, with DenseNet201 showing faster convergence and NASNetMobile demonstrating high generalization capability, making both architectures well-suited for automated glaucoma classification tasks.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	386
1	1.00	1.00	1.00	134
accuracy			1.00	520
macro avg	1.00	1.00	1.00	520
weighted avg	1.00	1.00	1.00	520

Fig 3: Testing Results

5. CONCLUSION

In recent advancements in medical image analysis, deep learning—particularly in computer vision—has become a powerful tool for disease detection and diagnosis. This study introduces an AI-based glaucoma screening model designed to aid ophthalmologists by offering a faster and more economical diagnostic solution. Leveraging the DenseNet201 and NASNetMobile architectures, the system analyzes fundus images to identify signs of glaucoma. The model emphasizes detecting asymmetries between the optic disc and the retinal nerve fiber layer (RNFL) in both eyes. It incorporates key clinical indicators such as optic rim width, Cup-to-Disc Ratio (CDR), Retinal Disc Ratio (RDR), and RNFL thickness obtained from Optical Coherence Tomography (OCT) to extract relevant features. These indicators play a crucial role in distinguishing healthy individuals from those potentially affected by glaucoma. Both models—DenseNet201 and NASNetMobile—exhibited outstanding classification performance, achieving 100% accuracy during evaluation. This highlights the potential of integrating fundus imaging with OCT-derived features to enhance sensitivity and ensure more accurate glaucoma detection, supporting timely clinical decision-making.

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