**Introduction**

Glaucoma is one of the leading causes of irreversible blindness worldwide, affecting an estimated 76 million people as of 2020, with projections reaching 112 million by 2040 [1], [2]. The condition poses a significant burden on public health systems, particularly in low-resource settings where access to specialized care is limited. Early detection and timely intervention are critical for effective glaucoma management, as they can prevent or slow the progression of vision loss [3]. However, traditional diagnostic techniques, such as clinical evaluation, optical coherence tomography (OCT), and visual field testing, are often time-consuming, expensive, and reliant on trained professionals, which limits their scalability and accessibility [4]. These challenges underscore the urgent need for automated, accurate, and efficient diagnostic tools that can assist clinicians in identifying glaucoma early.

Classical machine learning models, such as Support Vector Machines (SVM) and Decision Trees, have been explored for glaucoma detection by leveraging handcrafted features like the cup-to-disc ratio (CDR) and retinal nerve fiber layer thickness [5], [6]. While these methods demonstrated promise, they required extensive feature engineering and were highly dependent on the quality of the extracted features, limiting their generalizability across diverse datasets [7]. Furthermore, traditional machine learning approaches often struggled with robustness when applied to real-world conditions, such as variations in image quality and patient demographics [8].

Deep learning models, particularly Convolutional Neural Networks (CNNs), have revolutionized medical image analysis by eliminating the need for manual feature extraction and demonstrating superior performance in tasks like diabetic retinopathy and age-related macular degeneration detection [9], [10]. However, their application to glaucoma detection has faced several challenges. Existing CNN-based models are often computationally intensive, requiring substantial hardware resources, which restricts their deployment on mobile and resource-constrained devices [11]. Additionally, the lack of lightweight architectures that balance diagnostic accuracy and efficiency has hindered their adoption in real-time clinical settings, especially in remote or underserved areas [12].

This study aims to address the limitations of traditional methods and existing deep learning approaches in glaucoma detection by developing a robust CNN-based framework. A key objective is to design a model that can accurately classify eye images by analyzing critical features such as the cup-to-disc ratio, enabling precise identification of glaucoma presence. To enhance diagnostic performance and generalizability, the study incorporates advanced techniques like data augmentation, transfer learning, and hyperparameter optimization. Additionally, achieving computational efficiency is a central focus, with efforts directed toward designing a lightweight model architecture that minimizes resource demands while maintaining high accuracy, making it suitable for deployment on mobile and edge devices. Ultimately, this research seeks to advance the application of AI in ophthalmology by demonstrating the practicality of CNN-based models in addressing real-world diagnostic challenges, contributing to scalable and accessible solutions for glaucoma detection.

The primary contribution of this research is the development of a CNN-based glaucoma detection framework that is both accurate and computationally efficient. By optimizing the model architecture and leveraging advanced deep learning techniques, this study aims to overcome the trade-offs between accuracy and efficiency observed in existing approaches. Additionally, the proposed solution addresses real-world challenges such as variability in datasets and the need for deployment in resource-limited settings. This work contributes to the broader field of AI-driven ophthalmology by offering a scalable and accessible diagnostic tool, ultimately supporting efforts to reduce the global burden of blindness caused by glaucoma.

**Methodology**

This section outlines the methodology for developing and evaluating a convolutional neural network (CNN)-based model for glaucoma detection using OCT images. The workflow involves multiple stages, including data acquisition, preprocessing, model design, training, and evaluation, ensuring high diagnostic accuracy.

The dataset used for this study was sourced from Kaggle's Glaucoma OCT Images dataset [13]. It contains labeled images representing normal and advanced glaucoma conditions. The dataset was downloaded and extracted programmatically to enable seamless integration with the preprocessing pipeline.

**1. Data Preprocessing**

To enhance the quality of the images and prepare them for model training, the following preprocessing steps were applied:

**a.** Image Loading and Resizing

Images were loaded using OpenCV [14] and resized to a uniform dimension of 224×224 pixels to ensure compatibility with the CNN model [15].

**b.** Image Enhancement

* Noise reduction was applied using Gaussian blur [16].
* Edge detection was performed using the Canny method [17].
* Sharpening was applied using unsharp masking techniques to enhance the key features of glaucoma-related patterns [18].

**c.** Image Normalization

Pixel intensity values were normalized to a range of [0, 1], improving convergence during training [19].

**d.** Label Encoding

Labels were encoded into binary values: 0 for normal glaucoma and 1 for advanced glaucoma, enabling binary classification [20].

**2. Model Development**

The model was implemented using TensorFlow and Keras [21], focusing on extracting hierarchical features through convolutional operations.

**a.** Architecture Design

A custom CNN architecture was developed with:

* **Convolutional Layers:** Extracting hierarchical features using 3×3 kernels and ReLU activation [22].
* **Pooling Layers:** Reducing spatial dimensions using 2×2 and 3×3 max pooling [23].
* **Dropout Layers:** Mitigating overfitting with dropout rates of 20%, 25%, and 50% [24].
* **Fully Connected Layers:** Integrating features with a dense layer of 128 neurons and L2-regularization, followed by a softmax output layer for classification [25].

**b.** Hyperparameter Selection

Key hyperparameters such as learning rate, batch size (60), and number of epochs (60) were empirically tuned. The Adam optimizer [26] and sparse categorical cross-entropy loss [27] were used for optimal performance.

**c.** Early Stopping

Early stopping was applied to terminate training when validation loss failed to improve for three consecutive epochs, ensuring model generalization [28].

**3. Training and Validation**

The dataset was split into training (70%) and validation (30%) subsets using stratified sampling to ensure balanced class representation [29]. The model was trained using the Adam optimizer and a sparse categorical cross-entropy loss function. The validation subset was used for monitoring performance during training [30].

**4. Evaluation**

**a.** Performance Metrics

* Validation accuracy and loss were computed to assess the model's ability to generalize to unseen data [31].
* A confusion matrix was generated to calculate precision, recall, F1-score, and AUC-ROC for a detailed evaluation [32].

**5. Workflow Diagram**

**A black background with white and orange squares

Description automatically generated**

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