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Customized Convolutional Neural Network for Glaucoma Detection in Retinal Fundus Images

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Abstract: Glaucoma is one of the leading causes of permanent blindness and remains a current challenge in the field of ophthalmology. This research aims to present a comprehensive investigation into the development and evaluation of new technology for glaucoma detection in retinal fundus images. The development and evaluation are presented on a customized architecture, using the Convolutional Neural Network (CNN) method. The proposed CNN architecture is designed to address the complex characteristics of glaucoma changes in the identification process. The research dataset consists of 506 retinal images categorized into 117 glaucoma images, 19 suspected glaucoma images, and 370 healthy images. Through our in-depth exploration, we conducted a careful analysis to uncover patterns and fundamental trends related to glaucoma-related features. During the training phase, the proposed CNN achieved outstanding average accuracy, sensitivity, and specificity values of 92.88%, 94.66%, and 89.31%, respectively. In the unseen test dataset, the model demonstrated competitive performance with an accuracy of 80.87%, sensitivity of 85.65%, and specificity of 71.26%. These findings emphasize the potential of the model as a reliable tool for glaucoma detection. The results indicate that the proposed method utilizing a customized CNN architecture is designed for glaucoma detection in retinal fundus images. The presented output results also hold promise for clinical relevance and can be considered an improvement in the care of retinal fundus patients.

Keywords: Customized Convolutional Neural Network; Deep Learning; Early Detection; Glaucoma; Retinal Fundus Image

Introduction

Glaucoma, a chronic and progressive eye disease, stands as one of the leading causes of irreversible blindness globally (Shoukat et al., 2023; Kishore & Ananthamoorthy, 2020). Timely detection and accurate diagnosis are pivotal for the effective management and prevention of vision loss among affected individuals. Glaucoma detection poses unique challenges due to the intricate structural changes that occur within the optic nerve head and retinal nerve fiber layer (Lommatzsch & Van Oterendorp, 2024; Shiga et al., 2023). These changes manifest as optic disc cupping, nerve fiber layer thinning, and other distinct morphological alterations. Therefore, an accurate and reliable detection system demands an architecture that can effectively capture and discriminate these nuanced features (He et al., 2016; Russakovsky et al., 2015; Kermany et al., 2018). The emergence of advanced medical imaging technologies has propelled the development of automated detection systems, presenting an opportunity to enhance diagnostic accuracy and efficiency (Shinde, 2021; Elangovan et al., 2020).

Among these technologies, Convolutional Neural Networks (CNNs) have gained prominence due to their ability to learn complex visual patterns and features

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from images (Elangovan et al., 2020; Gómez-Valverde et al., 2019). The primary objective of this research is to introduce a novel Customized Convolutional Neural Network technology designed specifically for the detection of glaucoma in retinal fundus images (Tian et al., 2020; Zhou et al., 2022). Unlike traditional screening methods, which often rely on subjective assessments by medical experts, CNNs offer the potential for objective and standardized assessments, thereby mitigating inter-observer variability and enhancing diagnostic reliability (Geetha & B. Prakash, 2022; Joshi et al., 2022). Convolutional Neural Networks (CNNs) have been extensively applied and further developed for the detection of glaucoma in retinal fundus images (N K et al., 2024). Several studies have reported notable levels of accuracy in this regard (Sudhan et al., 2022; Velpula & Sharma, 2023; Huang et al., 2022). The proposed CNN architecture is tailored to cater to the intricacies of glaucomatous changes within retinal images. It comprises a series of convolutional layers for feature extraction Taye (2023), Atalay et al. (2022), followed by batch normalization and ReLU activation functions to introduce non-linearity. Max pooling layers are incorporated to reduce spatial dimensions while retaining relevant information.

The final layers include a Fully Connected Layer that connects to a Softmax and Classification Layer to provide probabilistic predictions and evaluate the classification performance. The outcomes of this study hold the potential to revolutionize glaucoma detection by offering an accurate, objective, and efficient diagnostic tool for ophthalmologists and healthcare practitioners. Moreover, the insights gained from our exploration of minibatch sizes contribute to the broader understanding of CNN performance optimization strategies in medical imaging applications. In subsequent sections, we delve into the methodology, dataset characteristics, experimental setup, results, and discussions, ultimately emphasizing the significance of our proposed Customized CNN technology for advancing glaucoma detection and patient care.

Method

This study focuses on the development of a Convolutional Neural Network (CNN) with a customized approach involving the configuration of network layers (Tsai et al., 2024). The selection of these layers is based on the system's requirements for detecting glaucoma from retinal fundus images. The steps in developing a glaucoma detection system using Customized CNN are illustrated in Figure 1.

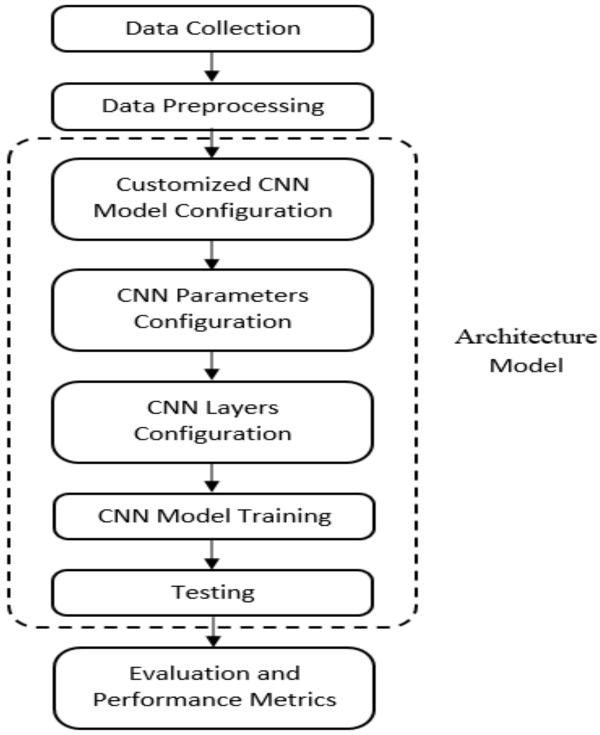


Figure 1. The steps in developing a glaucoma detection system using Customized CNN

The steps involved in developing a glaucoma detection system using Customized CNN include Data Collection to acquire retinal fundus image data, Data Preprocessing to adapt the data to input layer requirements, Building Architecture Model to construct the architecture model for glaucoma detection, and Evaluation and Performance Metrics to assess the system's performance in detecting glaucoma.

Dataset Collection

To conduct this study, we acquired a diverse dataset of digital retinal images that includes glaucoma, glaucoma suspect, and healthy images. This dataset was sourced from https://www.kaggle.com/code/knethsara/glaucomaclassification/input. The research dataset consists of 506 retinal images, comprising 117 glaucoma images, 19 glaucoma suspect images, and 370 healthy images. Our investigation involved a comprehensive analysis of this dataset to unveil underlying patterns and trends associated with glaucoma-related features. The curation of the dataset was meticulous, ensuring the representation of varying stages and manifestations of glaucoma, spanning diverse age groups and ethnic backgrounds. Furthermore, the dataset was meticulously annotated with appropriate labels indicating the presence or absence of glaucoma. An illustrative example of a retinal image used in this study is depicted in Figure 2.

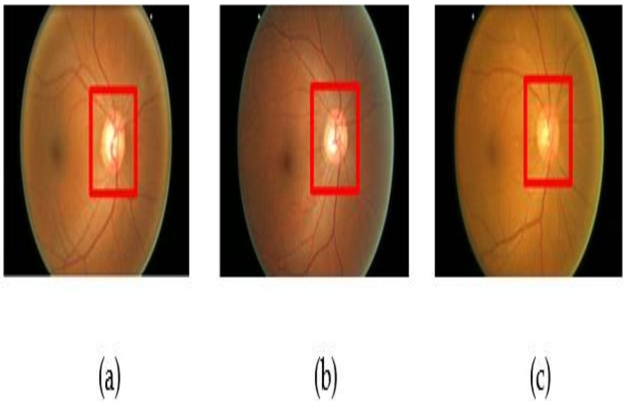


Figure 2. Retinal image; (a) glaucoma image; (b) glaucoma suspect image; (c) non glaucoma image

Glaucoma involves damage to the optic nerve and an increase in the cup-to-disc ratio. Manifestations include swollen or pale optic discs and observable nerve fiber damage. Glaucoma suspects denote individuals displaying potential glaucoma indicators but lacking quantifiable nerve damage. Their fundus images might exhibit subtle changes such as elevated cup-to-disc ratios or optic disc irregularities. Conversely, healthy eyes present normal fundus images characterized by a well-proportioned cup-to-disc ratio, normally colored optic discs, and an absence of apparent nerve damage. However, it's crucial to emphasize that an accurate diagnosis requires a comprehensive eye examination; solely relying on fundus images is insufficient to ascertain glaucoma or glaucoma suspicion.

Data Preprocessing

To enhance the quality and suitability of the retinal images for subsequent analysis, preprocessing steps are performed. The images are resized to a consistent resolution, ensuring compatibility with the chosen CNN architecture. The pixel values are normalized to a standardized range to improve convergence during training. Additionally, image augmentation techniques, such as rotation, scaling, and flipping, are applied to increase dataset variability and prevent overfitting.

Building Architecture Model

The proposed CNN architecture unfolds as follows: First, an Image Input Layer is established to ingest images of size 50x50 pixels, containing three color channels (RGB). This serves as the entry point for the subsequent layers. The Convolution2D Layer (1) initiates the extraction of relevant features by applying eight filters with a 3x3 kernel size. Employing 'same' padding, this layer maintains the input dimensions post-convolution. Batch normalization and a Rectified Linear Unit (ReLU) activation function enhance feature learning. Max Pooling2D Layer (1) follows, facilitating spatial reduction through 2x2 max pooling with a stride of 2. The network's depth increases with Convolution2D Layer (2), which employs 16 filters and mimics the architecture of its predecessor, accompanied by batch normalization and ReLU activation. Max Pooling2D Layer (2) further reduces spatial dimensions. Convolution 2D Layer (3) incorporates 32 filters, maintaining the consistency of architectural elements. Each convolutional layer is followed by batch normalization and ReLU activation to amplify non-linearity.

The model's output layer encompasses a Fully Connected Layer with three neurons corresponding to the distinct classes of glaucoma, glaucoma suspect, and non-glaucoma. A Softmax Layer computes class probabilities based on the previous layer's outputs, while the Classification Layer computes the classification loss and enables accuracy computation during training. The proposed CNN architecture is tailor-made for glaucoma detection in retinal images. The architecture diagram of the customized CNN model is shown in Figure 3.

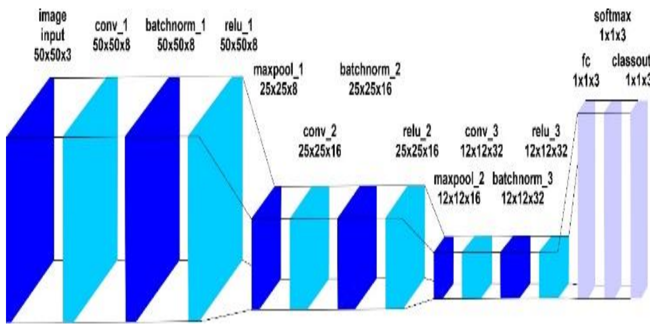


Figure 3. Architecture diagram of the customized CNN model

Minibatches in CNNs enable efficient parallel computation, introduce stochasticity for better convergence, act as a form of regularization, and improve memory efficiency during training. In the course of this research, we investigate the implications of utilizing different minibatch sizes on the performance of the proposed Convolutional Neural Network (CNN). We examine six distinct minibatch sizes: 8, 16, 32, 64, 128, and 256, with the objective of comprehending the trade-offs between computational efficiency and model accuracy.

Evaluation and Performance Metrics

To evaluate the performance of the proposed glaucoma detection system, it is essential to utilize appropriate evaluation metrics, including accuracy, sensitivity, and specificity. These metrics provide valuable insights into the system's effectiveness in correctly identifying glaucomatous cases. Additionally, comparing the obtained results with existing glaucoma detection methods or benchmarks allows for an assessment of the proposed approach's relative efficacy. This comparative analysis helps determine the system's strengths and weaknesses, contributing to the overall evaluation and validation of the proposed glaucoma detection system. The equations used to calculate accuracy, sensitivity, and specificity are as follows:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

True positive (TP) refers to predictions that are correct when the actual value is positive. Conversely, false positive (FP) denotes incorrect predictions when the actual value is positive. True negative (TN) signifies accurate predictions when the actual value is negative, while false negative (FN) indicates incorrect predictions when the actual value is negative. These definitions are crucial for evaluating the performance and accuracy of predictive models in various fields of research and applications.

Result and Discussion

The dataset comprises 506 retinal images, specifically 117 glaucoma images, 19 glaucoma suspect images, and 370 healthy images. These images were collected from multiple medical institutions and standardized to maintain consistency in resolution and format. Expert ophthalmologists carefully labeled each image, indicating whether glaucoma was present or absent. This meticulous labeling ensures the dataset's accuracy and reliability, making it suitable for training and evaluating glaucoma detection models. The CNN training process was conducted using a maximum epoch of 50, a minibatch size of 8, a learning rate of 0.01, and a momentum of 0.9. The training progress is depicted in Figure 4.

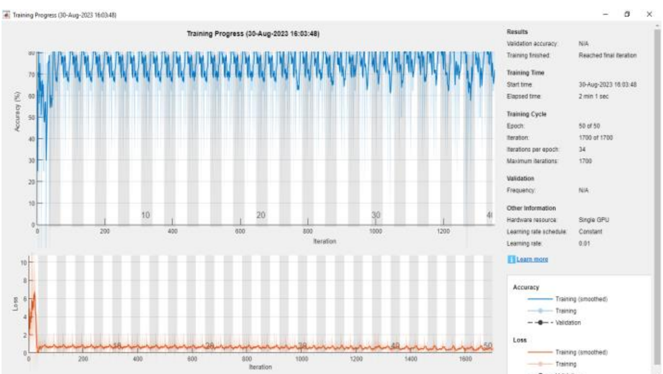


Figure 4. Training Progress of CNN

During training, the CNN processes the training dataset over multiple epochs, with each epoch consisting of multiple iterations, each using a minibatch of size 8. The network's parameters are updated using the computed gradients and the specified learning rate and momentum values. The training progress involves monitoring metrics such as loss, accuracy, and other performance measures to assess how well the network is learning and improving its ability to make accurate predictions. This process continues until the maximum specified number of epochs (in this case, 50) is reached or until a convergence criterion is met. The performance results of CNN development in glaucoma detection can be presented in Figure 5.

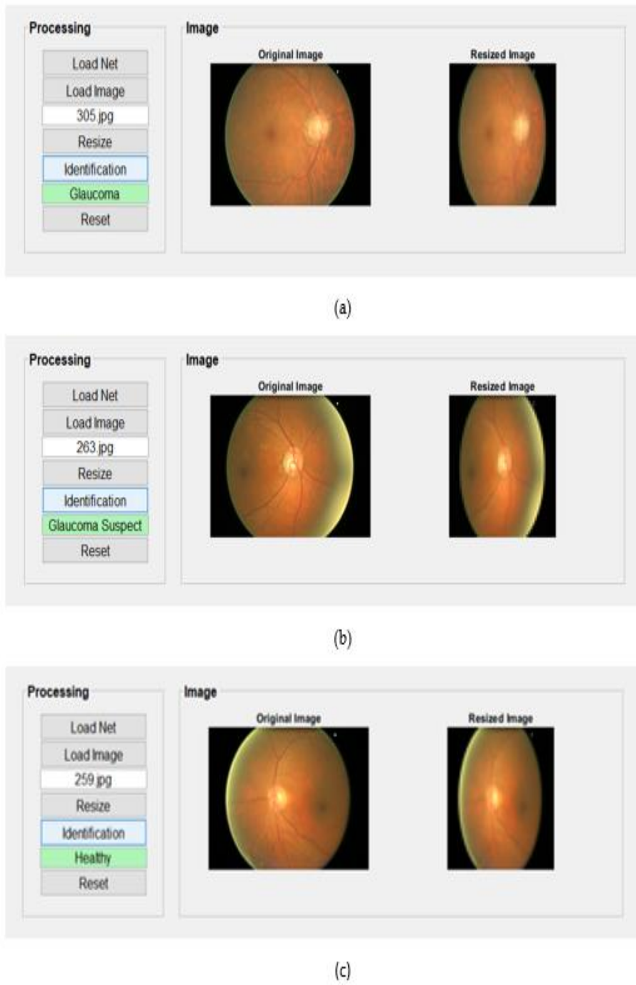
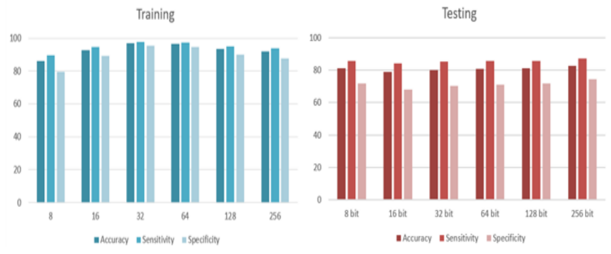


Figure 5. The performance results of CNN development in glaucoma detection; (a) glaucoma; (b) glaucoma suspect; (c) healthy

The trained architecture model is used to predict output classes during both the training and testing stages. Subsequently, an evaluation is conducted, and performance metrics are calculated for each stage. The comparison of accuracy, sensitivity, and specificity for different minibatch is shown in Figure 6.



(a) (b)

Figure 6. Comparison of accuracy, sensitivity, and specificity for different minibatch; (a) training; (b) testing

By averaging the accuracy, sensitivity, and specificity values during both the training and testing phases, the proposed glaucoma detection system achieved an average accuracy of 92.88%, sensitivity of 94.66%, and specificity of 89.31% during training, and an average accuracy of 80.87%, sensitivity of 85.65%, and specificity of 71.26% during testing. The detailed architecture of the Convolutional Neural Network (CNN) utilized in the study further illustrates the complexity of the model's design (Chen & Tsou, 2022; Alzubaidi et al., 2021; Yamashita et al., 2018; Ghosh et al., 2022). The network consists of multiple layers, including convolutional layers, batch normalization layers Amin et al. (2020), Krichen (2023), ReLU activation functions, and pooling layers. The architecture enables the system to extract intricate features from the retinal images Das et al. (2021), Közkurt et al., (2024) Haider et al. (2022), Saha et al. (2023), contributing to its robust performance in glaucoma detection (Ganokratanaa et al., 2023; Barros et al., 2020; Singh et al., 2022).

The study highlights the potential of customized CNNs for accurate glaucoma detection, with significant accuracy, sensitivity, and specificity metrics (Vijayan et al., 2024; Wang et al., 2024; Chiang et al., 2024). Challenges, such as occasional misclassification of non-glaucoma cases, may be addressed through data refinement and model parameter optimization (Li et al., 2018). The proposed Customized Convolutional Neural Networks show promise in glaucoma detection, emphasizing their diagnostic value, and ongoing research could further improve their performance (Alayón et al., 2023). This study contributes to medical image analysis in ophthalmology, potentially revolutionizing glaucoma diagnosis and patient care.

Conclusion

In this study, we proposed a Customized Convolutional Neural Networks (CNN) for the detection of glaucoma in retinal fundus images, addressing three distinct classes: glaucoma, glaucoma suspect, and non-glaucoma. The designed Convolutional Neural Network architecture played a pivotal role in achieving these results. Comprising image input layers, multiple convolutional layers, batch normalization, ReLU activation functions, and pooling layers, the architecture exhibited a depth of complexity suited for intricate feature extraction from retinal images. This architecture facilitated the system's capacity to recognize subtle patterns and features indicative of glaucoma-related conditions. The achieved accuracy, sensitivity, and specificity metrics suggest its valuable role in aiding medical practitioners in early diagnosis. However, addressing challenges like non-glaucoma misclassifications remains an ongoing endeavor. The findings contribute to the advancement of medical image analysis through deep learning, specifically in the realm of ophthalmology, offering the prospect of transforming glaucoma diagnosis and patient care. As we continue to refine and optimize the technology, it holds the potential to significantly impact glaucoma detection and improve visual health outcomes.

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Author Contributions

Conceptualization, F. I.; methodology, S.; validation, S. D.; formal analysis, F. I; investigation, S.; resources, S. D.; data curation, F. I.: writing—original draft preparation, S.; writing—review and editing, S. D.: visualization, F. I. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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