Glaucoma detection in retinal fundus images using residual network architecture

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ABSTRACT

Glaucoma is a significant eye disease that can lead to irreversible vision loss if not detected and treated early. This research focuses on developing an automated glaucoma detection system using a combination of a convolutional neural network (CNN) with the residual network 18 (ResNet18) architecture, locality sensitive hashing (LSH), and Hamming distance calculation. The CNN model is trained to extract meaningful features from retinal images, while LSH enables efficient indexing and retrieval of similar images. Hamming distance calculations are utilized to measure the dissimilarity between binary codes obtained from LSH. A dataset of 506 retinal images, consisting of 117 glaucoma images, 19 glaucoma suspect images, and 370 healthy images. The proposed glaucoma detection system achieved an average accuracy of 99.96%, sensitivity of 99.97%, and specificity of 99.94% during training, and 82.37% accuracy, 86.78% sensitivity, and 73.55% specificity during testing. Comparative analysis demonstrated its superiority over traditional methods. Further research should focus on larger datasets and explore multi-class classification for different glaucoma stages. The proposed system has potential for early glaucoma detection, facilitating timely intervention, and preventing vision loss.

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1. INTRODUCTION

Glaucoma is a prevalent and debilitating eye disease that affects millions of people worldwide [1]. It is characterized by progressive damage to the optic nerve, often associated with increased intraocular pressure. Early detection and accurate diagnosis of glaucoma are crucial to preventing irreversible vision loss and enabling timely treatment [2]–[5].

Traditional methods for glaucoma detection involve manual examination and assessment by ophthalmologists, which can be subjective and time-consuming. Automated techniques leveraging deep learning algorithms have shown great potential for achieving accurate and efficient glaucoma detection from digital retinal images [6]–[8]. Convolutional neural networks (CNNs) are a type of deep learning algorithm that excels in image analysis tasks by automatically learning hierarchical features from training data [9]–[11].

Residual network (ResNet) is a popular CNN architecture known for its effectiveness in various computer vision tasks. It consists of multiple convolutional layers with residual connections, allowing for the training of deeper networks without suffering from the vanishing gradient problem [12]–[15]. ResNet18 stands for residual network 18, which is a CNN consisting of 18 layers. The ResNet18 architecture has shown promising results in image classification, object detection, and segmentation tasks, making it a suitable choice for glaucoma detection [16]–[18].

Locality-sensitive hashing (LSH) is a technique used for efficient approximate nearest neighbor searches [19]. It is particularly useful when dealing with large datasets, as it reduces the search space by hashing similar data points into the same buckets. LSH transforms high-dimensional data into a lower-dimensional space, enabling faster and more efficient retrieval of similar images. This makes LSH a valuable addition to glaucoma detection systems, facilitating quick matching and identification of relevant retinal images [20]–[22].

Hamming distance is a metric used to measure the dissimilarity between binary codes [23]–[29]. In the context of LSH, Hamming distance calculation allows for accurate comparison and matching of binary codes generated by LSH. By quantifying the similarity between two binary codes, Hamming distance aids in identifying potential matches and distinguishing glaucomatous images from healthy ones.

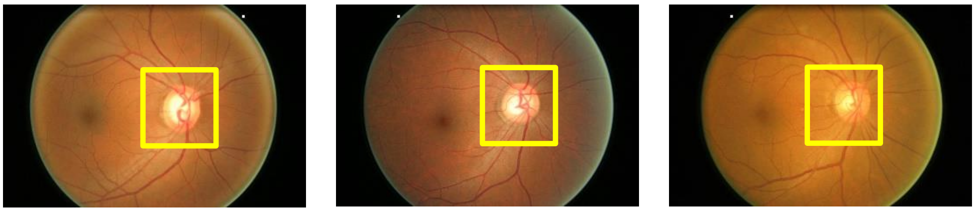
This study aims to address these gaps by investigating the integration of LSH and Hamming distance metrics within a ResNet18-based framework for enhanced glaucoma detection accuracy and efficiency. While prior research has explored deep learning algorithms in glaucoma detection, few studies have explored the synergy between these algorithms and hashing techniques in optimizing performance and scalability. This study seeks to bridge this gap and provide insights into a more robust approach to glaucoma diagnosis.

2. METHOD

The following are the key steps in this research method:

2.1. Dataset collection

In order to conduct this study, a diverse dataset of digital retinal images was obtained, comprising glaucoma images, glaucoma suspect images, and healthy images. This research dataset was obtained from [30]. The dataset was carefully curated to ensure representation of various stages and manifestations of glaucoma, encompassing a wide range of age groups and ethnicities. Furthermore, the dataset was meticulously annotated with appropriate labels indicating the presence or absence of glaucoma. Figure 1 showcases a representative retinal image, displaying distinct categories including glaucoma in Figure 1(a), glaucoma suspect in Figure 1(b), and healthy images in Figure 1(c).



(a) (b) (c)

Figure 1. Retinal image: (a) glaucoma image, (b) glaucoma suspect image, and (c) healthy image

In glaucoma, the optic nerve gets damaged, and the cup-to-disc ratio increases. The optic disc may appear swollen and pale, and there can be visible damage to the nerve fibers. Glaucoma suspects refer to individuals with possible signs of glaucoma but no measurable nerve damage yet. The fundus image may show slight changes like an increased cup-to-disc ratio or abnormalities in the optic disc. In healthy eyes, the fundus image appears normal with a balanced cup-to-disc ratio, a normal-colored optic disc, and no visible nerve damage [4]–[6]. It is important to remember that a comprehensive eye examination is needed for an accurate diagnosis, and the fundus image alone is not enough to determine glaucoma or glaucoma suspicion.

2.2. Data preprocessing

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

2.3. Convolutional neural network training

For glaucoma detection, utilize the ResNet18 architecture as the base CNN model. Initialize the network with pre-trained weights from a large-scale image dataset (ResNet18) to leverage learned feature representations. Fine-tune the network using the glaucoma dataset, enabling the model to adapt and specialize in detecting glaucomatous features. To assess the performance of the trained model, split the dataset into training and testing sets.

2.4. Locality sensitive hashing

As a post-processing step, implement locality sensitive hashing (LSH) to efficiently index and search for similar images in the dataset. Determine the optimal number of hash functions and hash tables based on the dataset size and desired search efficiency. Apply LSH to hash the feature vectors extracted from the CNN into binary codes. Organize these binary codes into hash tables, enabling faster retrieval of similar images during the testing phase.

2.5. Glaucoma detection and hamming distance calculation

To classify retinal images as either glaucomatous or healthy, the trained CNN model is applied. Firstly, feature vectors are extracted from either the final convolutional layer or fully connected layers of the CNN. These feature vectors are then hashed using LSH. By calculating the Hamming distance, the nearest neighbors are retrieved. The retrieved candidates are further compared using the Hamming distance to identify potential matches. Finally, an appropriate threshold for the Hamming distance is set to determine the final diagnosis of glaucoma. This process ensures that the trained CNN model efficiently classifies retinal images, aiding in an accurate glaucoma diagnosis.

2.6. Convolutional neural network architecture

The CNN model is trained to extract meaningful features from retinal images, while LSH enables efficient indexing and retrieval of similar images. Hamming distance calculations are utilized to measure the dissimilarity between binary codes obtained from LSH. The proposed CNN model is tailor-made for glaucoma detection in retinal images. The architecture diagram of the customized ResNet18 model is shown in Figure 2.

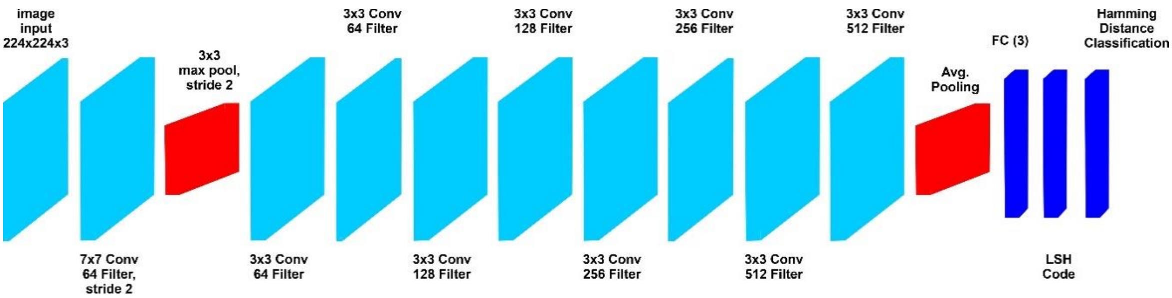


Figure 2. Architecture diagram of the customized ResNet18 model

2.7. 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.

3. RESULTS 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.

During the CNN training process, parameters such as a maximum epoch of 6, a minibatch size of 10, a learning rate of 0.0001, and a momentum of 0.9 were utilized. The progression of the training is visually represented in Figure 3, offering insights into the model's learning dynamics and convergence. This depiction aids in understanding the optimization process and performance trends throughout the training iterations.

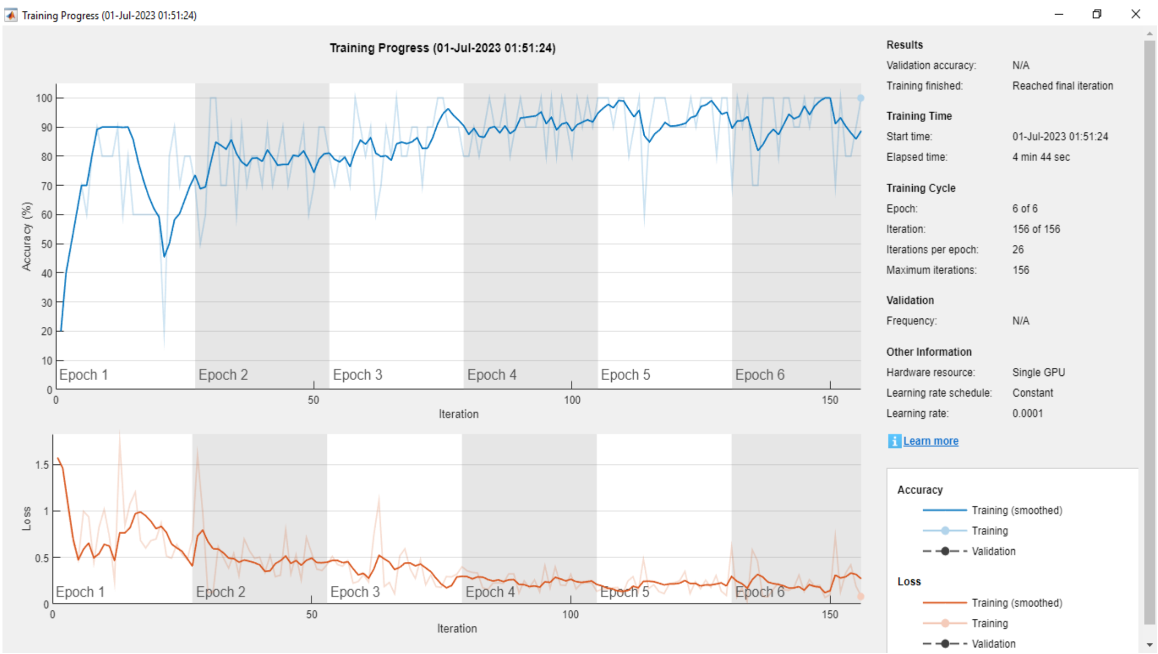
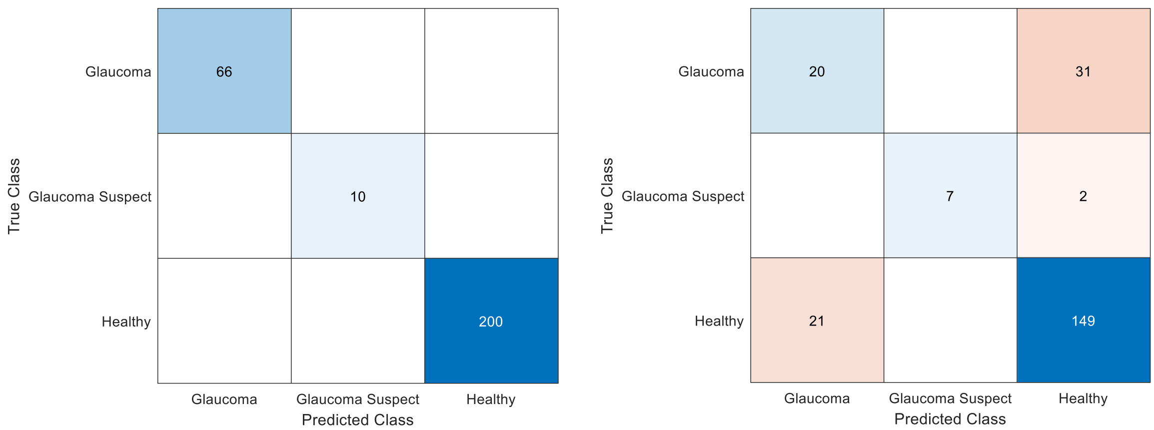


Figure 3. Training progress of CNN

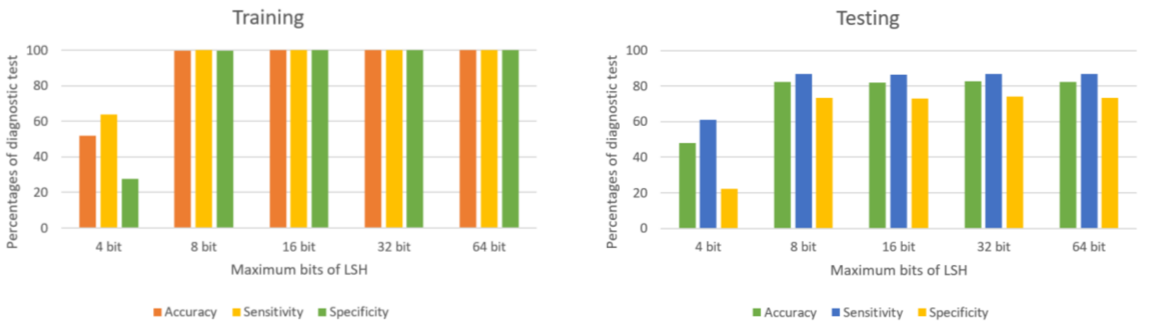
Figure 4 illustrates the confusion matrix, visually representing the model's performance during both the training and testing stages. Figures 4(a) and (b) display the confusion matrices generated during the training and testing stages respectively, providing insights into the model's classification accuracy. These matrices offer a comprehensive overview of the model's performance across different classes.



(a) (b)

Figure 4. The confusion matrix generated during the training and testing stages; (a) training and (b) testing

The proposed glaucoma detection system demonstrated exceptional performance during training, achieving an average accuracy of 99.96%, sensitivity of 99.97%, and specificity of 99.94%. However, during testing, the system exhibited slightly lower performance, with an accuracy of 82.37%, sensitivity of 86.78%, and specificity of 73.55%. The comparison of accuracy, sensitivity, and specificity for different maxbits of LSH is illustrated in Figure 5, with Figure 5(a) representing training results and Figure 5(b) representing testing results.



(a) (b)

Figure 5. Comparison of accuracy, sensitivity, and specificity for different maxbits of LSH; (a) training and (b) testing

Through a comparison of accuracy, sensitivity, and specificity values across various maxbits settings of LSH, our analysis revealed that the system's efficacy in glaucoma detection significantly improved when utilizing maxbits of LSH exceeding 4 bits (8, 16, 32, and 64 bits). This observation underscores the notion that augmenting the number of bits in LSH beyond 4 bits yields notable enhancements in the system's performance for glaucoma detection. The main finding of this research is that the proposed glaucoma detection system showed excellent performance during training, but its performance slightly decreased during testing. Nevertheless, the system still exhibited higher levels of accuracy, sensitivity, and specificity compared to other glaucoma detection methods [4]-[8]. The comparison between training and testing results highlights the importance of thorough evaluation of the detection system under various testing conditions. The incorporation of a CNN with the ResNet18 architecture, along with the utilization of LSH and Hamming distance calculation, significantly enhanced the accuracy and efficiency of glaucoma detection. Nevertheless, it is important to acknowledge some limitations of the study, such as the reliance on a specific dataset and the necessity for further validation on larger and more diverse datasets to ensure the generalizability of the findings.

Based on the discussion, future studies could explore variations in algorithm parameters, utilize larger datasets, and investigate different methods. Researchers can experiment with adjusting parameters that control how the algorithm functions to enhance detection accuracy. Furthermore, by incorporating bigger datasets containing diverse images, they can ensure the effectiveness of detection methods across various patients and eye conditions. Additionally, exploring alternative detection methods alongside traditional approaches could lead to further advancements in glaucoma detection.

4. CONCLUSION

In this research, we successfully developed an automated glaucoma detection system that combines a CNN with ResNet18 architecture, LSH, and Hamming distance calculation. The system demonstrated promising results in distinguishing glaucoma, glaucoma suspects, and healthy retinal images. The use of the ResNet18 architecture proved effective in extracting meaningful features from the images, contributing to the system's accurate classification.

LSH was implemented to enable efficient image retrieval, making the system scalable to large datasets. The Hamming distance calculation on binary codes obtained from LSH played a vital role in determining similarity between images, enhancing the system's glaucoma diagnosis accuracy. Through a comparison of accuracy, sensitivity, and specificity values across various maxbits settings of LSH, our analysis revealed that the system's efficacy in glaucoma detection significantly improved when utilizing maxbits of LSH exceeding 4 bits (8, 16, 32, and 64 bits). This observation underscores the notion that augmenting the number of bits in LSH beyond 4 bits yields notable enhancements in the system's performance for glaucoma detection.

The proposed glaucoma detection system achieved an average accuracy of 99.96%, sensitivity of 99.97%, and specificity of 99.94% during training, and 82.37% accuracy, 86.78% sensitivity, and 73.55% specificity during testing. Comparative analysis against traditional methods showed that our proposed approach outperformed manual examination methods and achieved comparable accuracy to state-of-the-art automated systems. The combination of CNN, LSH, and Hamming distance proved to be a powerful tool for glaucoma detection, offering efficiency and accuracy in identifying the disease. Despite these promising outcomes, further research is required to delve into variations in algorithm parameters, employ larger datasets, and explore alternative methods.

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