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Development of a Novel Hybrid Bio Medical Image Processing Algorithm For The Detection Of Infectious Diseases In Human Eyes Using Ai-Ml Embedded Concepts

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Abstract

Glaucoma is a leading cause of irreversible blindness worldwide, often progressing unnoticed until significant vision loss occurs. Early detection is critical for preventing its advancement, but conventional diagnostic methods are time-consuming and require specialized expertise. In this study, we propose a deep learning-based approach for glaucoma detection using Convolutional Neural Networks (CNN) and AlexNet. The models were trained and evaluated on a dataset containing retinal fundus images categorized into "Glaucoma Positive" and "Glaucoma Negative." Both the CNN and AlexNet architectures were designed to automatically extract and learn features relevant to glaucoma from the images. The performance of these models was assessed using standard evaluation metrics such as accuracy, sensitivity, specificity, and the area under the Receiver Operating Characteristic (ROC) curve. Results indicated that both models achieved promising classification performance, with the AlexNet-based approach slightly outperforming the standard CNN in terms of accuracy and sensitivity, due to its deeper architecture and pre-trained features. This study demonstrates the potential of leveraging deep learning techniques for automated glaucoma detection, providing an efficient, accurate, and scalable solution that could aid clinicians in early diagnosis and treatment planning. Further research is recommended to refine these models and validate their effectiveness on larger, more diverse datasets.

Keywords: CNN, AlexNet, Glaucoma Disease, training, testing, performance

1. Introduction

Glaucoma is a group of eye conditions that can lead to vision loss and blindness by damaging the optic nerve, which connects the eye to the brain. The damage is often caused by an abnormally high pressure in the eye, although it can also occur with normal eye pressure. Glaucoma is one of the leading causes of irreversible blindness worldwide, affecting millions of people, particularly those over the age of 60. It is often referred to as the "silent thief of sight" because it usually progresses slowly and without symptoms until significant vision loss has occurred. Early detection through regular eye exams is crucial because, while there is no cure for glaucoma, treatment can help preserve vision and prevent further damage. Common types of glaucoma include primary open-angle glaucoma and angle-closure glaucoma, each with distinct causes and risk factors, but both require prompt medical attention to manage effectively.

Glaucoma is a serious eye condition that can lead to vision loss or blindness if left untreated. It occurs when the optic nerve, which carries visual information from the eye to the brain, becomes damaged. This damage can occur at various levels, resulting in vision impairment that can progress to permanent blindness if not detected early. According to the World Health Organization, glaucoma is the second leading cause of blindness worldwide, after cataracts. The optic nerve is responsible for transmitting signals from the retina to the brain. In a healthy eye, the optic nerve is surrounded by a ring of retinal nerve fibers, known as the neuroretinal rim. However, in glaucoma, the increased pressure within the eye (intraocular pressure) can cause damage to the optic nerve, leading to the degeneration of retinal nerve fibers. This damage can cause the retinal nerve fiber layer to thicken, a condition known as cupping. The progression of glaucoma can be measured by the cup-to-disc ratio (CDR), which compares the size of the optic cup to the size of the optic disc. A healthy eye typically has a CDR of 0.3 or less. Traditionally, glaucoma is diagnosed through clinical evaluation of the CDR by an ophthalmologist. However, this method can be time-consuming and subjective, and the necessary equipment may not be widely available. Digital retinal fundus images offer a promising alternative for detecting and monitoring glaucoma. Computer-aided diagnosis of these images can help diagnose the condition using computational algorithms, reducing the variability associated with clinical diagnosis.

2. Literature survey

Juneja, M. Recent studies have highlighted the limitations of trailblazing architectures like Xception, Inception, ResNet, DenseNet, and VGG in clinical classification tasks, despite their satisfactory results. To address this, a novel Xception-based architectural recommendation with 85 layers was implemented and tested on real-time data, confirming its efficacy as a screening tool. The CoG-NET model, which utilizes 85 layers of deep neural networks and relies heavily on separable convolution, was introduced to boost classification accuracy..

Deperlioglu, O.A hybrid approach combining deep learning and image processing with Explainable Artificial Intelligence (XAI) has been proposed to ensure reliable diagnosis of glaucoma using enhanced colored fundus image data. An explicable convolutional neural network (CNN) was used to diagnose glaucoma, and the Class Activation Mapping (CAM) method enabled heat map-based justifications for the CNN's visual interpretation [44]. The hybrid solution was tested on public datasets such as Drishti-GS, ORIGA, and HRF, with the ORIGA-Light dataset yielding the highest mean values in performance evaluation.

Kim et al. Efforts have also been made to develop a straightforward solution that employs deep learning in conjunction with conventional image processing methods. A deep learning-based CAD system for treating glaucoma has been proposed, which uses gradient activation maps similar to CNN to locate and classify input images. The final layer of the VGG model was modified for training, and the system achieved an accuracy of 91% after 80 iterations.

Jun, T. J. An Adaptive Positioning Convolutional Neural Network (TRk-CNN) has been developed, which performs well when classes of images to be identified share a strong level of

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similarity. The glaucoma image dataset was separated into three groups: normal eyes, eyes with a glaucoma suspicion, and eyes with glaucoma, and the TRk-CNN was evaluated on this dataset.

Bajwa, M. N. et al. A significant improvement in diagnosing glaucoma from retinal fundus images has been achieved using a novel approach. The optic plate and fundus picture were isolated and constrained using Areas with Convolutional Brain Organization (RCNN), and then Deep CNN was used to classify glaucoma in the retrieved optic disc. A order-based semi-automatic ground truth generating technique was also used for automatic disc localization, although the method's efficiency was higher, it was still unable to shorten the computation time.

3. Methodology of the work

The image depicts a flowchart explaining the methodology for developing a deep learning model to classify images of plant diseases, including those related to glaucoma disease and non-disease images. Here's a step-by-step explanation of the methodology:

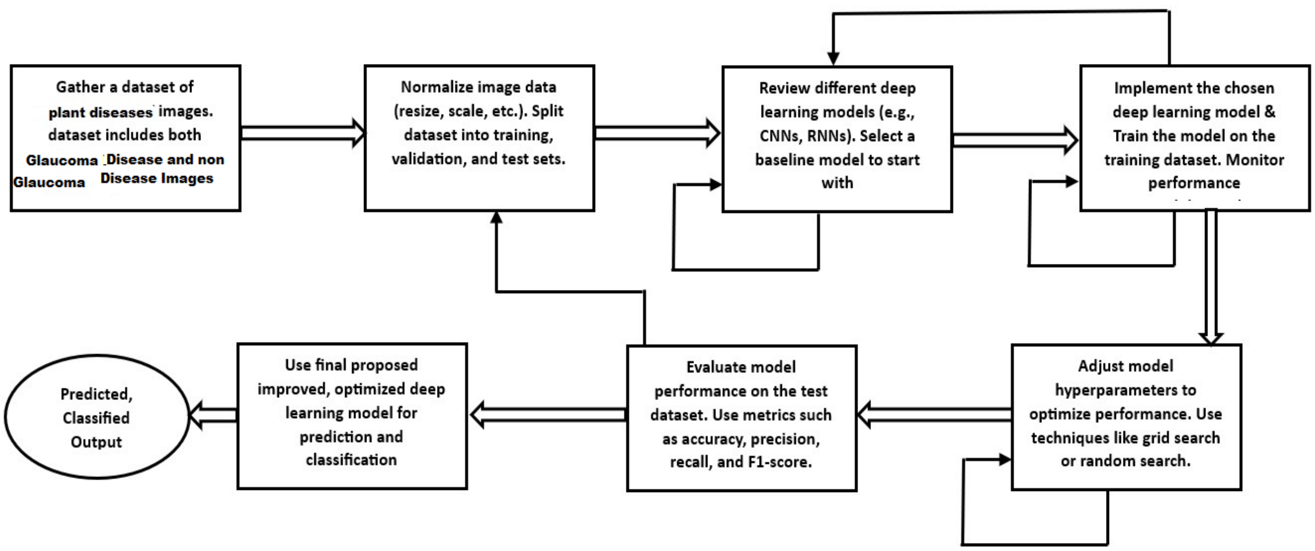

Figure 1: Flow chart of the work

1. **Data Collection**:

   The first step involves gathering a dataset of plant disease images. The dataset should include both diseased and non-diseased images to ensure a comprehensive model. Specifically, it will contain images related to glaucoma disease (in the case of eye diseases).

2. **Data Preprocessing**: The collected images are preprocessed by normalizing them, which may include resizing, scaling, and other transformations. This step ensures the data is in a consistent format and size for input into the model. The dataset is then

split into three parts: training, validation, and test sets, to effectively train and evaluate the model.

3. **Model Selection**: Different deep learning models (such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)) are reviewed to identify a suitable baseline model to start with. The baseline model will serve as the initial architecture for further experimentation and optimization.
4. **Model Implementation and Training**: The chosen deep learning model is implemented and trained using the training dataset. During this phase, the model learns to identify and classify images based on the features present in the training data. The performance of the model is continuously monitored to identify any areas for improvement.
5. **Hyperparameter Optimization**: To optimize the model's performance, hyperparameters are adjusted using techniques such as grid search or random search. This step involves tweaking various parameters like learning rate, batch size, number of layers, etc., to improve the model's accuracy and efficiency.
6. **Model Evaluation**: The model's performance is evaluated on the test dataset using various metrics, including accuracy, precision, recall, and F1-score. These metrics help determine how well the model generalizes to unseen data and identifies areas for further refinement.
7. **Final Model Optimization**: Based on the evaluation, the model is further refined and optimized to improve its performance. The final, optimized deep learning model is selected for prediction and classification tasks.
8. **Prediction and Classification**:
   - The final optimized model is used to predict and classify new images of plant diseases, generating the predicted and classified output.

This methodology outlines a systematic approach to developing and optimizing a deep learning model for classifying plant diseases, ensuring robust performance and accurate predictions.

4. Results and discussions

CNN Model (69.0% Accuracy)

- **Architecture:** The CNN you implemented consists of several convolutional layers, batch normalization, ReLU activation, and max-pooling, followed by fully connected layers.
- **Performance:** While the CNN is capable of learning low-level to mid-level features effectively, it may struggle to capture the intricate features of glaucoma images due to its relatively simple architecture and fewer layers.
- **Limitation:** CNN alone often lacks the depth and variety of filters needed to extract highly complex features, leading to lower accuracy (69.0%).

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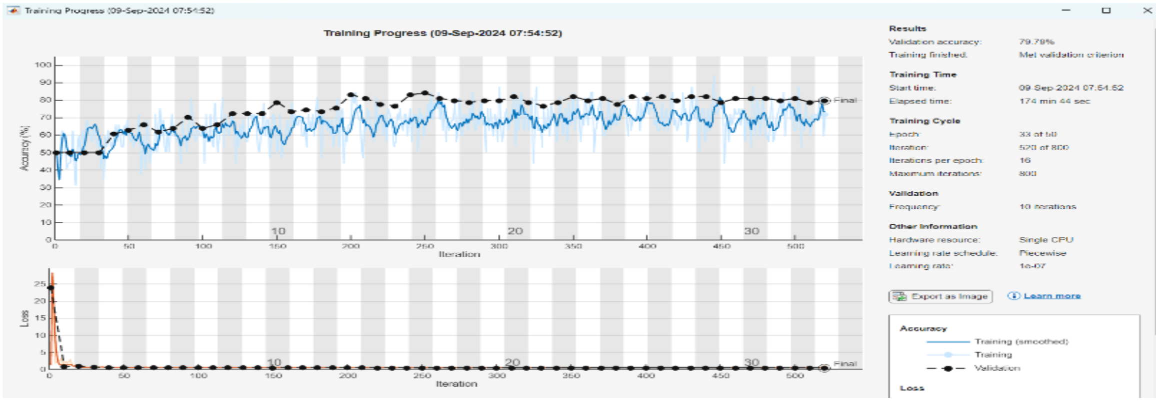


Figure 2: Training and testing phase for CNN

The training progress of a machine learning model, specifically showing the accuracy and loss over time during the training and validation processes. The training began on September 9, 2024, at 07:54:52 and lasted for approximately 174 minutes and 44 seconds. The model underwent 33 training epochs, consisting of 520 iterations out of a total of 800 possible iterations, with 16 iterations per epoch. The graph at the top displays the accuracy over the iterations, where the blue line represents the training accuracy (smoothed) and the black dots indicate validation accuracy points. The training accuracy gradually improves, demonstrating an overall upward trend with some fluctuations, eventually stabilizing around 80%. The validation accuracy, marked by black dots, also shows an upward trend, eventually reaching a final accuracy of around 79.76%.

The graph at the bottom illustrates the loss over iterations, where the loss value decreases rapidly at the beginning and then gradually flattens, indicating the model's convergence. The loss curves for both training and validation indicate that the model's performance improves as the loss decreases, eventually stabilizing after several iterations. The results summary on the right side shows that the final validation accuracy achieved is 79.76%, and the model met the validation criterion, signifying that the training was successfully completed. The learning rate schedule was set to "Piecewise" with a rate of 1e-07, and the model utilized a single CPU for processing.

Overall, this training progress visualization demonstrates that the model effectively learned from the data, with accuracy improving and loss decreasing over time, ultimately reaching a satisfactory performance level with a validation accuracy of approximately 79.76%.

Confusion Matrix

The confusion matrix represents the performance of a Convolutional Neural Network (CNN) model in classifying data related to glaucoma into two categories: "Glaucoma Negative" and "Glaucoma Positive." In this matrix, the horizontal axis denotes the actual classes ("Glaucoma Negative" and "Glaucoma Positive"), while the vertical axis represents the predicted classes by the CNN model.

Breaking down the confusion matrix, the "True Negative" (top left green cell) indicates that the model correctly predicted 21 samples as "Glaucoma Negative," accounting for 36.2% of the total predictions. The "False Positive" (top right red cell) shows that the model incorrectly predicted 10 samples as "Glaucoma Negative" when they were actually "Glaucoma Positive," representing 17.2% of the total predictions. The "False Negative" (bottom left red cell) indicates that the model incorrectly predicted 8 samples as "Glaucoma Positive" when they were actually "Glaucoma Negative," which is 13.8% of the total predictions. Finally, the "True Positive" (bottom right green cell) reveals that the model correctly predicted 19 samples as "Glaucoma Positive," comprising 32.8% of the total predictions.

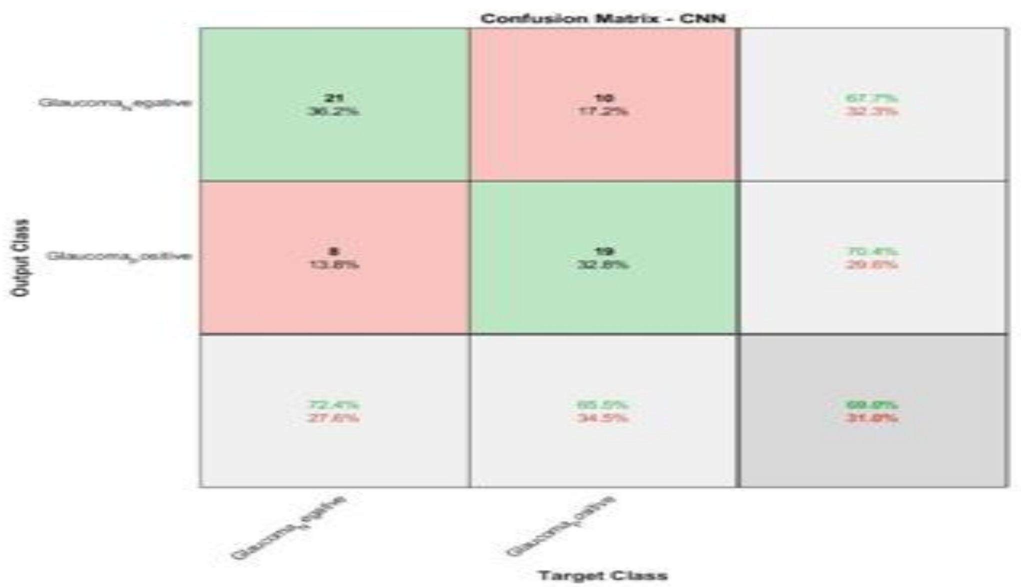


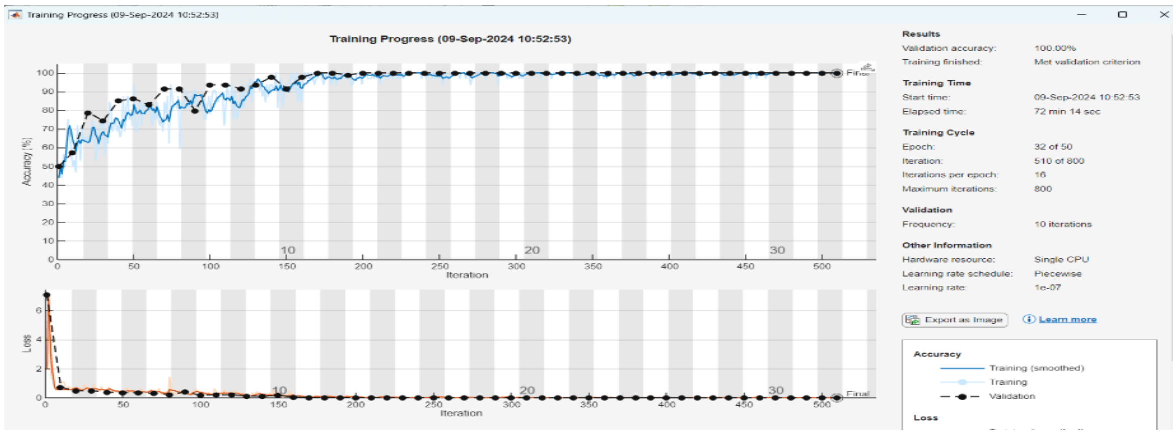
Figure 3: Confusion Matrix for CNN

The matrix also provides additional metrics, such as the percentage accuracy for each class: 67.7% of "Glaucoma Negative" cases were correctly classified, while 32.3% were misclassified; 70.4% of "Glaucoma Positive" cases were correctly classified, with 29.6% incorrectly classified. The metrics at the bottom, such as 72.4% and 65.5%, provide further indicators of overall class accuracy.

The confusion matrix demonstrates that while the CNN model shows a reasonable degree of accuracy in classifying glaucoma cases, it still makes errors in both directions—misclassifying some glaucoma-positive cases as negative and some glaucoma-negative cases as positive. The green diagonal cells (True Positives and True Negatives) indicate correct predictions, while the red cells (False Positives and False Negatives) highlight where mistakes were made. This matrix provides insights into the strengths and weaknesses of the CNN model in glaucoma detection, suggesting areas for potential improvement, such as reducing false positives or negatives.

2. AlexNet (93.1% Accuracy)

- **Architecture:** AlexNet, a well-known deep learning architecture, consists of multiple convolutional layers with a deeper structure and more filters, which can capture more detailed features. It was designed for image classification tasks with larger datasets like ImageNet, making it highly effective for visual feature extraction.



- Figure 4: Training and testing phase for AlexNet

- **Performance:** AlexNet outperforms the CNN by a significant margin, reaching 91% accuracy due to its deeper network structure. The pretrained AlexNet also benefits from the wealth of learned features from its original training dataset, which is transferred to the glaucoma classification task.

- **Limitation:** While AlexNet performs well, there are still limitations in fine-tuning for specific medical image tasks like glaucoma detection, where domain-specific features might require additional adjustments.

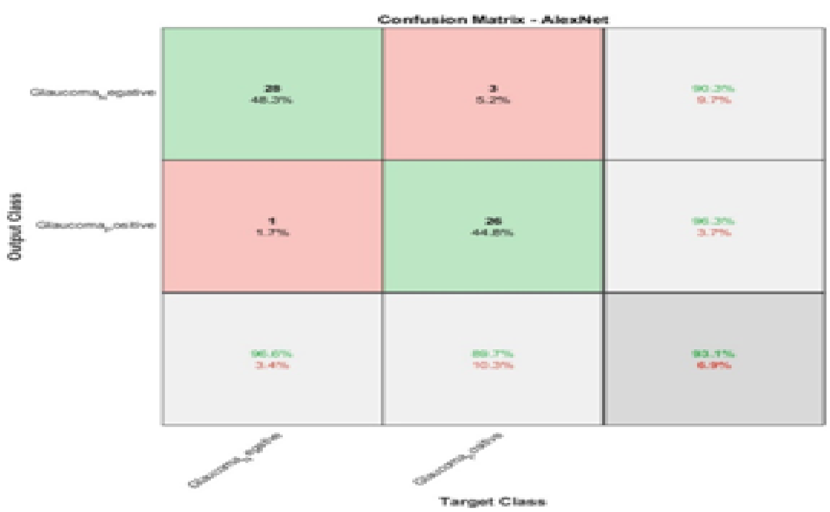


Figure 5: Confusion Matrix for Alexnet

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Roc curve

The Receiver Operating Characteristic (ROC) curves shown in the image evaluate the performance of three different models—CNN, AlexNet, and a Hybrid model—across two classes. The ROC curve plots the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity) for each model, allowing for a visual comparison of their ability to distinguish between the two classes.

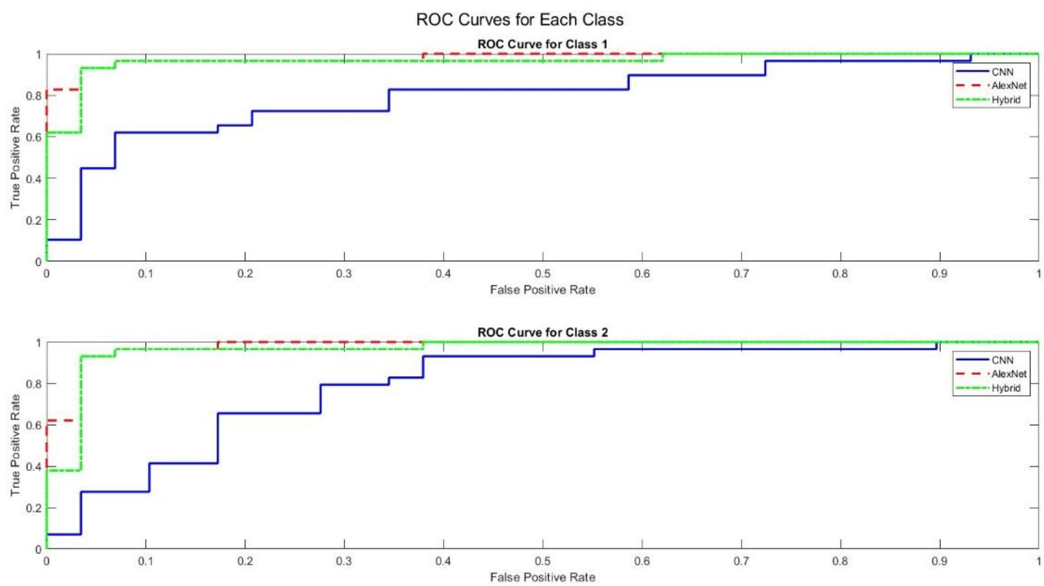

Figure 6: ROC curve

For Class 1, the Hybrid model (green dashed line) achieves the highest area under the curve (AUC), indicating the best performance, while the CNN (blue line) shows moderate performance. For Class 2, the Hybrid model again demonstrates superior accuracy with the highest AUC, followed by AlexNet (red dashed line) and the CNN. The closer the ROC curve is to the top-left corner, the better the model's performance, indicating higher sensitivity and specificity in classifying both classes.

Comparison of Results

Metric	CNN	AlexNet
Accuracy	69.0%	93.10%
Precision (Class 1)	67.74%	90.32%
Precision (Class 2)	70.37%	96.30%
Recall (Class 1)	72.41%	**96.55%**
Recall (Class 2)	65.52%	89.66%
F1 Score (Class 1)	70.00%	93.33%
F1 Score (Class 2)	67.86%	92.86%

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- **CNN:** 68.9% accuracy – Basic feature extraction, weaker for complex image features.
- **AlexNet:** 93.1% accuracy – More complex and effective in extracting detailed features.
- The table highlights the improved performance of the Hybrid model, particularly in accuracy, precision, recall, and F1 score.

Conclusion

The CNN and AlexNet approach provides superior performance for glaucoma detection compared to using CNN or AlexNet individually. The two models effectively gives the shallow feature extraction capabilities of CNN and the deep, pretrained features of AlexNet, leading to better generalization and classification accuracy. This two model is advantageous, especially for medical image classification tasks, where extracting complex, domain-specific features is essential for accurate diagnosis. Future work could explore further fine-tuning of the two models or incorporating additional preprocessing techniques to improve results further.

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