Glaucoma Detection using Deep Learning Techniques

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Abstract

Glaucoma, a progressive neurodegenerative disease, presents a formidable challenge as it affects the optic nerve due to increased pressure within the eye. This impairment results in abnormalities in the visual field called as the "silent thief of sight", because it frequently eludes early detection. This makes regular screenings crucial for timely intervention. In this research, an innovative approach for automating the glaucoma detection is introduced. Leveraging advanced deep learning techniques, including DenseNet201 and NASNet, the research focusses on developing a system capable of detecting glaucoma from fundus images. This novel method shows promise in improving the efficiency and precision of glaucoma diagnosis, potentially transforming patient care in this field.

Keywords: Fundus Images, DenseNet201, NASNet, Image classification, Glaucoma Detection.

1. Introduction

Glaucoma, a prevalent eye disease, leads to optic nerve damage from elevated intraocular pressure, potentially resulting in partial or permanent blindness if not identified early. This emphasizes the critical need for timely detection to improve treatment outcomes [2]. An incurable neurodegenerative condition, develops due to elevated pressure within the eye,

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leading damage to the optic disc and subsequent visual field loss.[6]. Consequently, clinical manifestations of glaucoma primarily manifest in the optic nerve areas. Recent research [13] indicates that approximately 64.3 million individuals aged 40 to 80 were afflicted with glaucoma in 2013, with projections estimating an increase to 113 million by 2040 due to population expansion and aging. In 2013, an estimated 64.3 million people aged 40 to 80 were living with glaucoma, a number anticipated to rise to 113 million by 2040, largely due to demographic shifts and aging populations.Timely detection and diagnosis of glaucoma can potentially avert the majority of vision loss associated with the disease. However, because early-stage symptoms are not noticeable, many individuals remain unaware of their diagnosis [12]. Regular eye check-ups are essential to catch glaucoma early and plan effective treatments to prevent blindness. Various methods exist for detecting and diagnosing glaucoma, catering to the unique ocular characteristics of each patient.

Traditional methods for diagnosing glaucoma are developed by validating six essential factors:

i. **Tonometry:** This procedure, often referred to simply as eye pressure testing, is a common method for assessing the pressure within the eye. [13].Normal eye pressure typically falls from 12 to 22 mmHg. While elevated eye pressure increases the risk of glaucoma, it's not a definitive indicator. However, glaucoma can manifest in individuals with decreased eye pressure as well.

ii. **Ophthalmoscopy:** This plays a crucial role in identifying glaucoma damage by assessing the optic nerve's structure and color. Further tests may be necessary if intraocular pressure deviates from the norm or if the optic nerve exhibits abnormalities.

iii. **Field of Vision Assessment:** This examination assist in determining whether vision has been impacted glaucoma.

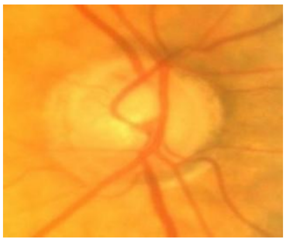
iv. **Angle Assessment:** This procedure involves gently touching the eye's surface with a specialized tool to examine the corneal-iris angle [14]. The specialist determines the type and severity of glaucoma based on the openness or closure of this angle.

v. **Corneal Thickness Measurement:** This procedure is used to measure the thickness of the corneal.When tonometry is performed, the corneal thickness seems to assess corneal edema.

vi. **Optic Nerve Fiber Assessment:** optic nerve fibre assessment is a modern assessment method that evaluates the breadth of the nerve fiber surface [15].Smaller regions may suggest damage associated with glaucoma.

Glaucoma detection methods that prioritize medical image analysis are becoming more widely adopted compared to traditional methods. In such cases, it is essential to examine different characteristics of the ocular retinal structure, such as the optic disc, cup, retinal nerve fiber layer, peripapillary thinning, and so on. The glaucoma or non-glaucoma image is shown as Figure 1 Source: (ACRIMA Dataset)[16].

a) Glaucoma Affected Retinal Image



b) Glaucoma Unaffected Retinal Image

Figure 1. a) Glaucoma Affected Retinal Image and b) Glaucoma Unaffected Retinal Image

In our study, we seek to address the challenges linked with manual glaucoma diagnosis by introducing automated detection techniques. Leveraging the deep learning and medical image processing, the model offers a more efficient and precise approach to diagnosing glaucoma.

At the core of our study lies the ACRIMA dataset, a pivotal component introduced in this research. Comprising 705 meticulously labelled high-resolution colour fundus images, the dataset plays a vital role in training and evaluating our glaucoma detection model. Expert ophthalmologists have classified these images as either glaucomatous or non-glaucomatous, ensuring a diverse representation of ocular conditions for robust model training and evaluation.

The methodology centers on leveraging deep learning techniques for glaucoma detection. Specifically, we propose utilizing Deep Neural Network (DNN) architectures, including DenseNet201 and NASNet trained to classify retinal fundus images as indicative of glaucoma or non-glaucoma as shown in Figure 1. These models undergo detailed insights into the training process, encompassing data preprocessing, model architecture selection, and optimization techniques.

The effectiveness of our proposed model undergoes rigorous evaluation uutilizing conventional metrics like as accuracy, precision, recall, and F1-score. Though glaucoma lacks a cure, early detection can avert substantial visual impairment. Automated glaucoma detection stands to revolutionize healthcare by enabling doctors to identify the condition sooner and initiate treatment promptly. These techniques have the potential to streamline glaucoma screening, making it faster and more accurate, leading to improved outcomes for patients and reducing the incidence of vision loss attributable to glaucoma.

2. Related Work

The traditional method of diagnosing glaucoma, involving visual examination of fundus images, necessitates highly experienced and skilled professionals and is largely dependent based on their personal evaluation. Therefore, diagnostic method is expensive, time-consuming, and susceptible to human inaccuracies, relying heavily on resource availability for its efficacy. Over the past few years, there has been significant concern in exploring automated glaucoma analysis using medical imaging and artificial intelligence to overcome these limitations [10]. A consecutive Deep Neural Network (DNN) model, incorporating Rectified Linear Units (ReLU) and sigmoid functions, effectively learns from training and testing data. Implemented on Drishti-GS1 and ACRIMA datasets utilizing 10-fold cross-validation and split ratio methodologies, the model's performance is evaluated using metrics and convergence curves [1]. The research examines colour retinal fundus images and categorizes the retinal images indicative of glaucoma. Deep neural networks are employed to generative features from retinal images, and these features are then classified and processed with various machine learning algorithms. Evaluation outcomes indicate that the fusion of a deep neural network with a logistic regression-based classifier surpasses all current glaucoma assessment systems, enhancing classification accuracy, sensitivity, and specificity [3]. Convolutional neural networks (CNNs) in early disease detection is useful for identifying eye conditions like glaucoma. The research presents a novel methodology utilizing densely connected neural networks (DenseNet), pretrained on ImageNet, and applied to the ACRIMA dataset. This achieved an approximate accuracy of 97% and an F1-score of 0.929. These results offer promising prospects for the efficient classification of glaucoma, facilitating its prompt discovery. [9].

This research utilizes a proprietary dataset consisting 463 non-glaucoma and 171 glaucoma colour fundus images obtained from Bangladesh Eye Hospital (BEH), Dhaka. Trimmed retinal images containing the optic disc and cup portion are created from both proprietary and open-access ACRIMA datasets. Notably, trimmed and segmention of blood vessel fundus images are generated utilizing a U-net trained model with the High-Resolution Fundus (HRF) Image Database. Lastly, various CNN techniques such as MobileNet, EfficientNet, DenseNet, and GoogLeNet are employed as the glaucoma classification Model.[6]. DenseNet-121 with CAM outperforms other state-of-the-art CNN models, with an accuracy of 85.34% on the Harvard Dataverse V1 and 83.85% on the LMG dataset. It is clear that DenseNet-121 with CAM provides a superior AUC score compared to DenseNet-121 without CAM. This enhanced model is referred to as CA-Net [2].

This study explores the probable of deep learning systems, like as deep convolutional neural networks (CNNs), to discern with the glaucoma and normal patterns for diagnostic purposes. The proposed deep learning model comprises six layers, encompassing four convolutional layers and two fully-connected layers. To bolster the accuracy of glaucoma diagnosis, techniques such as dropout and data augmentation are integrated. Through thorough experimentation on the ORIGA and SCES datasets, the model demonstrates encouraging outcomes. It achieves an area under the curve (AUC) of 0.831 and 0.887 in the respective databases, surpassing the existing algorithms [4].

3. Dataset

For glaucoma analysis, several specialized datasets have played a pivotal role in advancing research. Notably, the RIM-ONE dataset evaluates the optic nerve using annotated retinal images essential for glaucoma diagnosis [11]. Additionally, the DRISHTI dataset focuses on vessel extraction, segmentation, and topological indexing of digital retinal images, significantly expanding the breadth of available retinal imagery for study [5]. Moreover, the DRISHTI_GS (Glaucoma assessment) dataset is particularly designed to advance glaucoma assessment efforts, offering a targeted set of images for developing precise detection tools [7].

This paper employs the ORIGA [17] and ACRIMA [16] datasets which is shown in Table 1, both of which are publicly available.

The ACRIMA dataset, which consists of labeled retinal fundus images categorized as either glaucomatous or healthy (nonglaucomatous), has been used in this study. The dataset consists of 705 color fundus images, including 309 normal/non-glaucomatous and 396 glaucomatous images. Two different deep learning algorithms, DenseNet201 and NASNet, have been employed to diagnose glaucoma and non-glaucoma fundus images. A collection of retinal fundus images, known as ORIGA, comprising labelled glaucoma and non-glaucoma fundus images, has been utilized. The dataset consists of 650 color fundus images, including 482 normal/non-glaucomatous and 168 glaucoma images. Two different deep learning algorithms, DenseNet201 and NASNet, have been employed to diagnose glaucoma and non-glaucoma fundus images.

Table 1. Dataset Samples

Dataset	Glaucoma	Normal	Total
ORIGA	168	482	650
ACRIMA	309	396	705

4. Proposed Methodology

In our paper, we propose a a deep learning method for glaucoma detection within a deep neural network framework, employing models such as NASNet and DenseNet20 1 as shown in Figure 2.

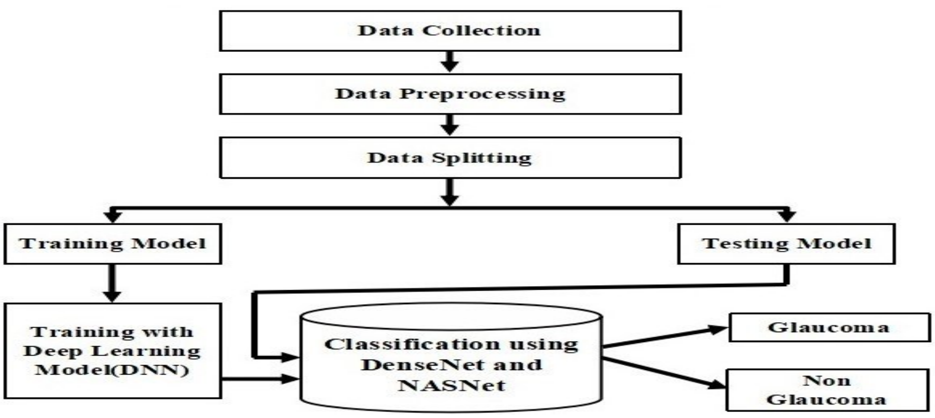


Figure 2. Architecture Diagram for Glaucoma Detection using Deep Learning Techniques

4.1 DNN

A Deep Neural Network (DNN) is an advanced type of neural network that features multiple layers between the input and output. These networks are designed to model complex relationships in data by processing inputs through several interconnected layers of neurons.

We are using four types of layers. They are, Input layer, two hidden layers, and an output layer.

- We use one input layer, followed by two hidden layers, and then an output layer.
- The input layer is utilized to set the input shape.
- In the initial hidden layer, we apply the ReLU activation function across 128 neurons and second layer across 64 neurons.
- Finally, the output layer uses the sigmoid activation function.

4.2 NASNET

Our study focuses on utilizing the NASNet model for glaucoma detection as shown in Figure 2, leveraging its advanced capabilities in deep learning and image analysis. NASNet, renowned for its efficiency and accuracy in handling complex image classification tasks, offers a promising approach to improving glaucoma diagnosis. By automatically searching for the optimal neural network architecture, NASNet optimizes both accuracy and computational efficiency, surpassing manually designed networks. We employ NASNet to classify retinal fundus images as indicative of glaucoma or non-glaucoma, training it on a meticulously labelled dataset curated by expert ophthalmologists. The NASNet architecture can be explained in Figure 3 and Table 2.

Preprocessing: Preprocessing involves preparing the input data before it is fed into the neural network. This includes tasks like resizing images, normalizing pixel values, and augmenting the dataset for better training.

Two Dense Layers: Dense layers, also known as fully connected layers, establish connections between each neuron in one layer and every neuron in the subsequent layer. Having two dense layers means there are two such layers in the network architecture, allowing for more complex feature learning.

Dropout Layer: The dropout layer randomly drops a subset of input units during training to prevent over fitting. By temporarily removing some neurons, it encourages the network to learn more robust and generalizable features.

Activation Layer: The activation function adds complexity to the network, allowing it to grasp intricate patterns. Common activation functions like ReLU and sigmoid help the network model non-linear relationships in the data.

NASNet Mobile: NASNet Mobile is a variant of the Neural Architecture Search (NAS) algorithm optimized for mobile devices. It's designed to be efficient and computationally lightweight.

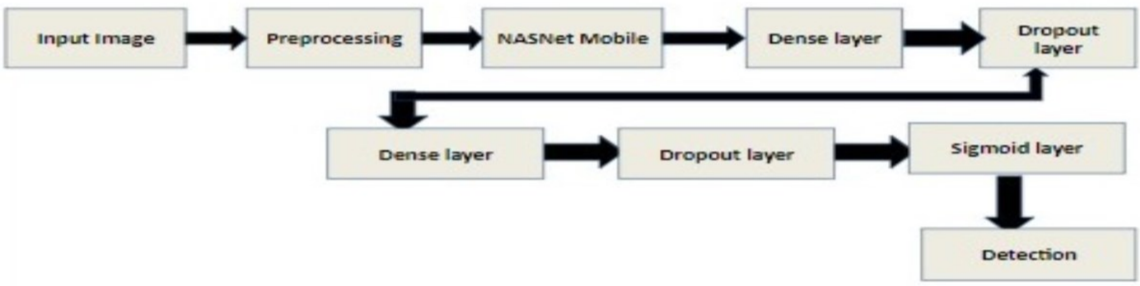


Figure 3. NASNet Model Architecture

Our evaluation encompasses accuracy, sensitivity, specificity, and other relevant metrics to assess the NASNet model's performance rigorously. Through this approach, we intended to enhance the efficiency and accuracy of glaucoma diagnosis, potentially leading to earlier intervention and improved patient outcomes.

Table 2. NASNet Model Layer Architecture

Layer type	Layer size	Layer Explanation
Input layer	224 x 224	Set the input size
Dense layer	128 Neurons	Connected with 128 neurons
Dropout layer	-	Dropout rate in used in 0.2
Dense layer	68 Neuron	Connected with 68 neurons
Dropout layer	-	Dropout rate used in 0.2
Sigmoid layer	-	It produces a probability for the positive class (0 to 1)

4.3 DenseNet 201

DenseNet-201 represents a convolutional neural network architecture renowned for its depth and connectivity. With a total of 201 layers, it boasts a deeper and wider structure compared to its predecessors. A distinguishing feature is its dense connectivity, where each layer directly links to every other layer in a feed-forward manner. This design promotes effective feature reuse and gradient flow throughout the network, facilitating efficient information propagation and optimization Figure 4 illustrate the architecture of DenseNet 201[18] and Table 3. Illustrates its architectural layer.

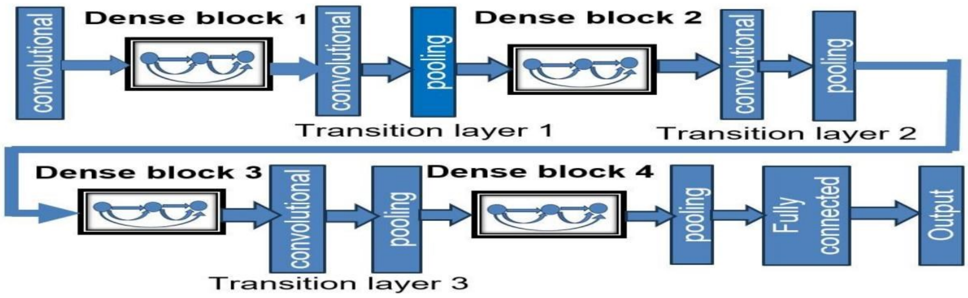


Figure 4. DenseNet Model Architecture.

Convolutional Layer: Neural networks employs filters to extract features from input data through element-wise multiplication and summation operations, forming feature maps.

Transition Layers: situated between convolutional blocks, adjust the dimensions of feature maps. They often combine convolutional and pooling operations to reduce spatial dimensions while adjusting the number of channels.

Pooling Layers: reduce feature map dimensions by summarizing subregions, typically through max pooling (retaining maximum values) or average pooling (computing average values).

Fully Connected Layers: Fully connected layers link each neuron in one layer to every neuron in the subsequent layer. They perform nonlinear transformations on input data, commonly used for classification tasks to map extracted features to class scores.

Overall, DenseNet-201 is renowned for its efficient use of parameters, robust feature extraction abilities, and outstanding performance across numerous computer vision tasks, including image classification, object localization, and scene parsing.

Table 3. DenseNet 201 Model Layer Architecture

Layer Type	Layer size	Layer Explanation
Input layer	224 x 224	Set the input size
Convolution layer	224 x 224 x 64	Connected with 64 neurons
Transition layer	56 x 56 x 128	Connected with 128 neurons and reduce the spatial dimension of the feature maps.
Global average pooling layer	28 x 28 x 128	Connected with 128 neurons and reduce the computational complexity and control overfitting
Fully connected layer	1	It produces a probability for the positive class (0 to 1)

5. Result and Discussion

In this section, the implications of the implemented glaucoma detection system are explored. In our work, we utilise the ACRIMA database and implement the DNN architecture to detect glaucoma or non-glaucoma cases. To finalize, a diverse range of DNN methods, such as NASNet and DenseNet 201, are utilized to categorize the images into two groups.

The subsequent tuning parameters were employed in training the DNN, DenseNet-201, and NASNet models on the dataset, as shown in Table 4. The Adam optimizer, with parameters listed in Table 4, was used along with a specific loss function to train these models.

Table 4. Hyper Parameters Used

Parameter	DenseNet Value	NASNet Value
Batch size	32	18
Learning rate	0.001	0.001
Batch normalization	True	True

Training various neural network models on cropped fundus images demonstrated effective glaucoma diagnosis. To assess the proposed system's efficiency for automated glaucoma diagnosis, diverse evaluation metrics were examined, including the confusion matrix, validation accuracy graph, precision, recall, F1 score, and training and testing accuracy graphs.

5.1 ORIGA Dataset

The input images were scaled, normalized, and segmented into training, validation, and test sets. ORIGA was employed to train DenseNet-201 networks. The validation accuracies across epochs for various models trained on the ORIGA dataset demonstrated 89% accuracy in training and 88% in testing for DenseNet, as shown in Table 5 and Figures 5 and 6. For NASNet, the training accuracy was 83% and testing accuracy was 87%, displayed in Figures 7 and 8.

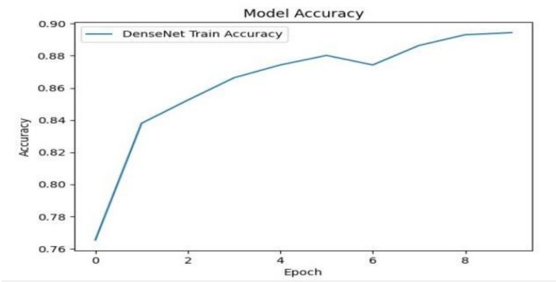


Figure 5. DenseNet 201 Train Accuracy

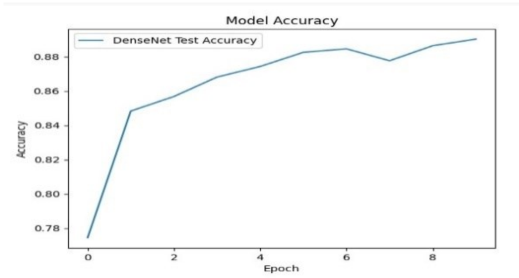


Figure 6. DenseNet Test Accuracy

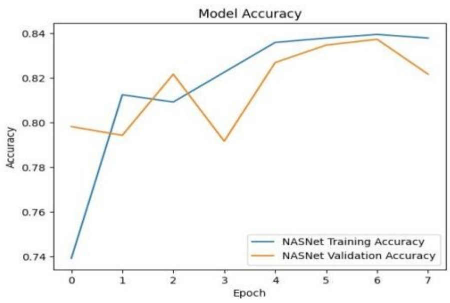


Figure 7. NASNet Train Accuracy

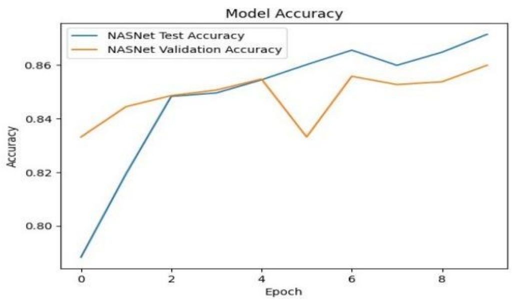


Figure 8. NASNet Test Accuracy

5.2. ACRIMA Dataset

The ACRIMA dataset is analogous to the ORIGA dataset in terms of the sizes of their training, validation, and testing sets. The DenseNet training accuracy can be seen in Figure 9, and the DenseNet test accuracy can be seen in Figure 10. Similarly, the NASNet training accuracy is shown in Figure 11, and the test accuracy is shown in Figure 12.

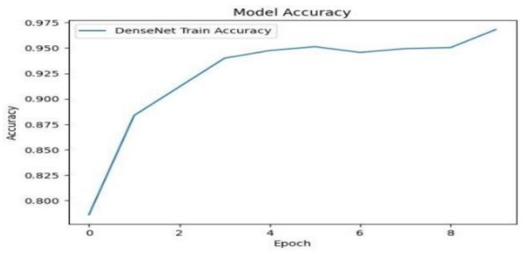


Figure 9. DenseNet 201Train Accuracy

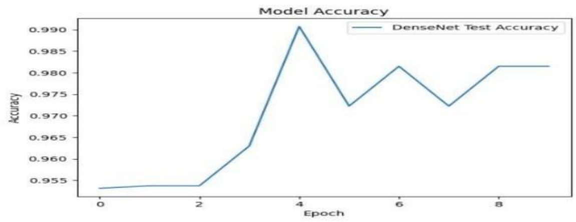


Figure 10. DenseNet Test Accuracy

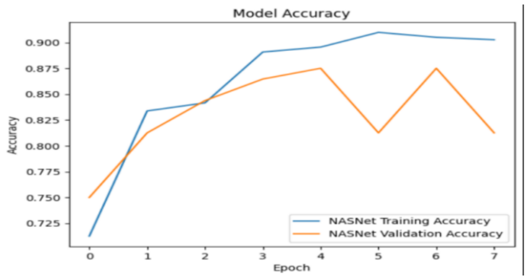


Figure 11. NASNet Train Accuracy

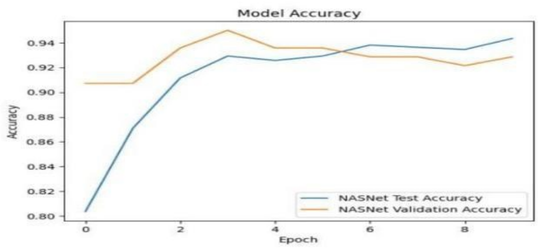


Figure 12. NASNet Test Accuracy

Table 5. Comparison for the Performance Metrics of Proposed Model and other Existing Model

Author	Datasets	Backbone	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
[2]	Harvard Dataverse v1	VGG-19	79.09	78.09	79.09	78.48
		Inception	80.60	80.25	80.60	80.42
		DenseNet-121	85.34	85.15	85.34	84.92
	LMG	VGG-19	79.03	77.95	79.03	78.10
		Inception V3	80.08	79.61	80.08	79.57

		DenseNet-121	83.85	83.69	83.85	83.48
Proposed work	ACRIMA	DenseNet 201	93.52	86.46	87.63	89.23
		NASNet	90.45	85.63	86.36	82.36
	ORIGA	DenseNet 201	89.03	84.52	85.03	88.10
		NASNet	87.15	82.89	83.08	85.57

6. Conclusion

Glaucoma is a disease that damages the second cranial nerve and can lead to visual impairment. Detecting it manually can sometimes result in error, but while AI can also make mistakes, it generally does so less frequently than human. This study aims to develop an automatic system to diagnose glaucoma using deep learning. We use a public dataset from ACRIMA, which includes normal and glaucoma color fundus images, to test different deep neural networks (DNNs) such as DenseNet-201 and NASNet for classification. DenseNet-201 performs the best, achieving a training accuracy of 0.965 and a testing accuracy of 0.9532, while NASNet yields similar results. These promising results could help doctors diagnose and assess glaucoma more quickly and easily. In the future, the system could be improved by training it with a larger dataset that includes both public and synthetic eye fundus images. Additionally, this system could be adapted to diagnose other intricate eye conditions like diabetic retinopathy and amblyopia, making it more useful for early and accurate detection of various ocular diseases.

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