Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 9s (2025)

Glaucoma Detection using Machine Learning with Fundus Images

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Article History:

Received: 12-01-2025

Revised: 15-02-2025

Accepted: 01-03-2025

Abstract: Glaucoma is a leading global cause of the irreversible blindness, presents significant challenges due to its asymptomatic nature in the early stages, which often delays diagnosis until substantial vision loss has occurred. Addressing this critical health issue, the study develops and evaluates an automated glaucoma detection system leveraging the EfficientNetV2 convolutional neural network (CNN) architecture. By utilizing fundus images, a non-invasive diagnostic tool, the system identifies essential structural indicators of the glaucoma, such as optic nerve cupping and retinal nerve fiber layer (RNFL) thinning. The methodology follows a three-phase approach: image preprocessing for normalization and resizing to ensure data consistency, feature extraction using a fine-tuned EfficientNetV2 model to detect glaucomatous changes, and classification into glaucomatous and non-glaucomatous categories. To further enhance detection accuracy, feature selection techniques such as cup-to-disc ratio (CDR) calculation and RNFL thickness measurement were integrated into the process. Experimental results demonstrate the model's exceptional performance, achieving a 93.7% overall accuracy, with a precision of 93.5%, recall of 92.5% for glaucomatous cases, reflecting its ability to identify true positives effectively. Comparative analysis against other architectures, including Inception-ResNet-V2 and traditional CNNs, confirmed EfficientNetV2's superior accuracy, precision, and computational efficiency. Metrics such as precision, recall, and the confusion matrix validated the model's reliability and scalability in real-world diagnostic scenarios. This study underscores the potential of advanced machine learning techniques in revolutionizing glaucoma detection, enabling early intervention to prevent irreversible vision loss. Despite challenges such as dependency on high-quality imaging, false classifications, and the need for regular updates to accommodate diverse populations and advancements in imaging technologies, the system offers a scalable, cost-effective solution. It supports the standardization of diagnostic protocols, facilitates interdisciplinary collaboration, and emphasizes the importance of integrating automated tools in clinical practices. This approach represents a significant step forward in addressing the global burden of glaucoma and improving patient outcomes.

Keywords: Glaucoma Detection, Artificial Intelligence, Machine Learning, Imaging Modalities, Optic Nerve Imaging, Tonometry.

1. Introduction

The Glaucoma is a series of progressive optical neuropathies, constituting an important global health burden with irreversible vision loss if untreated. It damages the optic nerve over time, causing progressive damage that results in poor vision or blindness. Indeed, glaucoma is so often asymptomatic in its early phases that it has been dubbed the "silent thief of sight," because a patient can lose a substantial proportion of their vision before they suspect that they have it. Given that about 80 million persons are expected to experience glaucoma by the year 2040, early detection and treatment are necessary for most patients to maintain vision and to provide better patient outcomes [1].

In this study, we aim to create and evaluate a consistent computational model for automated classification of glaucoma with fundus images, which are captured by non-invasive approaches for instance fundus photography, deliver valuable data concerning the structure of retina, optic nerve head, and nearby vasculature. Powered by recent developments in machine learning, image processing and other artificial intelligence methods, this analysis aims to investigate how fundus images can help in early diagnosis [3] of glaucoma.

Moreover, this work highlights the existing knowledge gaps and possible future research directions related to glaucoma diagnosis. This study aids in standardizing protocols, and diagnostic algorithms, and improves clinical practice for early detection and treatment of glaucoma. This research seeks to improve the future of glaucoma detection by utilizing existing knowledge and promoting interdisciplinary changes that will allow healthcare practitioners and researchers to make well-versed decisions leading to improved glaucoma-related vision loss outcomes.

2. Related Works

Since the development of today's eye sector, many studies have used machine learning and the deep learning methods to progress diagnostic precision and speed of Glaucoma analysis built on fundus images. Li et al. And we all know also that All et al. (2019) applied deep learning to train three different neural networks classifiers on a huge fundus image dataset detecting signs of glaucoma (i.e., optic disc cupping and neuroretinas rim thinning). This method facilitates automated glaucoma diagnosis which is significant for the early discovery of the disease [19].

In another study, Kim et al. Existing work (2022) performed classification of fundus images using traditional machine learning algorithms (XGBoost, random forest and gradient boosting) based on features for instance optic disc morphology and cup-to-disc relation. The objective of their work is to differentiate between healthy eyes and glaucoma eyes, thereby offering possibility for better screening [20].

Zhang, Li & Tang (2021) developed an ensemble learning approach, which integrates several classifiers,

e.g., random forest, gradient boosting, to enhance the robustness and reproducibility of automated glaucoma screening from fundus photographs. This approach relies on various learning algorithms and produces a robust classifier [21].

Using these strategies as a foundation, others have developed similar techniques to examine machine learning applicability here. This opens the door for more complicated and scalable diagnostics (Burlina et al. In a paper from 2017, Abdul Salam & Al-Hinai studied the potential of convolutional neural networks (CNNs) to learn hierarchical functions from fundus images to perform automatic glaucoma identification [22].

Hammouche et al. (2020) classified glaucoma stages based on fundus images, with machine learning models being used to classify the severity levels of the disease. This study lays the groundwork for modifying treatment plans grounded on the harshness of the disease, which in-turn can translate into management success for the patient [23].

Mookiah et al. Teleophthalmology systems for Remote Fundus Images Teleophthalmology system integrated with machine learning for preliminary glaucoma valuation using remote fundus imaging have been developed by Xu T et al. (2017). The EYE-i system is made for high volume population based screening, which is an example of the role of technology in increasing access to eye health [24].

An important work led by Phan et al. In (2020) an ensemble learning approach remained explored by combining multiple base classifiers (decision tree, support vector machine, neural networks) to enhance the accuracy and robustness of diagnosing glaucoma since fundus images [25].

Additionally, Varghese et al. The authors [26], also used feature fusion to aggregate (merge) features based on texture, shape and intensity-based from fundus images using machine learning procedures to help in early discovery of glaucomatous changes resulting in a better characterization of the incipient stages of the disease.

An alternative and creative strategy is evidenced by the work of Cheung et al. transfer learning for a pretrained deep convolutional neural networks (2020) This approach allowed the re-using of models previously trained with huge datasets to be adapted for long-range efficient glaucoma classification tasks, especially in circumstances where few labelled data are available [27].

Extending the claim of machine learning to the discovery of glaucoma, Rao et al. Q: longitudinal fundus image to predict disease Progression [9] This method used algorithms to monitor longitudinal changes in optic disc characteristics and retinal nerve fibre layer thickness to help clinicians in earlier detection and the initiation of tailored treatments [28].

Ting et al. (2019) provides a full overview of the disruptive role of artificial intelligence (AI) and deep learning in the delivery of ophthalmic care. Highlighting the progress seen in the field of deep learning, particularly convolutional neural networks (CNNs), classification of disease with an emphasis on ocular illnesses such as age-related macular degeneration, diabetic retinopathy, and glaucoma using medical imaging data [29].

Christopher et al. (2018) Reviews deep learning approaches for noticing glaucomatous optic neuropathy (GON) in fundus images. It compares various CNN architectures and the advantages of using transfer learning in nature. Transfer learning can improve the performance of deep learning models used for GON detection by utilizing learned features from previously developed datasets. It stresses the need to choose suitable GON detection specific deep learning approaches for precise detection which would contribute towards improving the value of patient upkeep and outcome in glaucoma detection. [30].

the study by Liu et al. (2019) The researchers sought to fill the gap of needing precise and accurate methods for detecting glaucomatous optic neuropathy, a vital feature of glaucoma, in fundus photographs. The deep learning algorithm was trained on this large dataset of fundus photographs which included both normal and glaucomatous eyes, enabling the model to identify complex shapes and features related with the disease. After thorough validation, the researchers have proven that the deep learning system was able to achieve a promising performance in detecting glaucomatous optic neuropathy with an automated tool that showed potential for glaucoma diagnosis [31].

Gómez-Valverde et al offer an example of this in their study. They had work (2019) to improve the diagnosis of glaucoma by targeted convolutional neural networks (CNNs) and transfer learning on color fundus images. In their approach, the CNN was trained on a hefty data-set that included both ordinary and glaucomatous cases, letting the model learn complex patterns and characteristics indicative of the illness. After severe authentication, these authors demonstrated ability of their deep learning technique to accurately classify glaucoma, representing a novel application of automated glaucoma diagnosis and enabling timely screening and intervention for this important condition[39].

Sidhu and Mansoori (2024) explore the field of glaucoma identification, utilizing AI methods on color fundus images. His team's study, which appeared in the Indian Journal of Ophthalmology, aims to harness the power of AI to improve glaucoma diagnosis. The researchers are using color fundus images together with sophisticated algorithms aiming to develop a reliable method for detecting signs of glaucoma. Such innovative strategies may aid in earlier detection and prevention of the disease, which may improve patient outcomes [40].

CO Publication Review: Kanse and Yadav (2019)–The use of retinal fundus images for recognition of glaucoma – a review and study Satyam Parashar2023-10-12 It represents a thorough review of approaches and approaches used in the area to fine-tune functionalities and faces various challenges to harnessing retinal imaging for glaucoma detection. The authors synthesise the current state of research and subsequently, share their own findings as they relate to how intelligent systems may assist with the detection and management of the disease as early as possible to better the outcome of the patient [42].

On the other hand, when we begin to search about the studies in the discovery of glaucoma after retinal or fundus images, a highly diverse body of literature emerges due to the number of ongoing work to the automate these diagnosis process. The papers executed vary from exploratory studies of new image processing approaches, the utilization of new machine learning methods, and the use of multi-modal imaging information. Each paper although bringing its own advancements and insights to the field emphasizes the collaborative search for improved technologies to detect glaucoma as an inherently interdisciplinary area of research.

3. Proposed Methodology

To achieve the best performance, we are implementing a novel CNN architecture EfficientNetV2 for our glaucoma detection system. EfficientNetV2 uses compound scaling that stabilizes network depth, width, and resolution to attain the strongest accuracy while minimizing computational cost. While regular deep learning models scale only one axis, EfficientNetV2 uniformly scales

all three axes, making it a much more resource-efficient and scalable model for building large medical image datasets. Such keeps it appropriate for subcellular feature extraction for fine level resolution mainly in detecting glaucoma by analyzing retinal images in terms of retinal nerve fibre layer thinning, and optic nerve cupping [10]. Thanks to its efficiency and low computation, EfficientNetV2 optimizes early identification and supervision of glaucoma, and given the depth and demands of common deep learning models, reduces complexity and resources

3.1. Framework of the Proposed Glaucoma Detection System

The approach for detecting glaucoma is based on EfficientNetV2 storage model. It is a 3-stage procedure including image preprocessing, feature extraction and classification. EfficientNetV2 model used in this study detects structural changes associated with glaucoma using retinal images from modalities such as fundus photography.

- Data Preprocessing: The retinal images are normalized and resized to avoid any inconsistency in the data. This helps the model generalize better the local variation of the image quality
- Feature extraction: The EfficientNet is first pretrained on largescale image datasets, then tweaked to perform features extraction from retinal images such as optic nerve cupping, RNFL thickness and other changes which are relevant.
- Classification: The model categorized distinct images under the glaucoma or nonglaucoma labels, based upon the features extracted.

3.2. Feature Selection Methods

- To increase the precision of glaucoma recognition and reduce complexity of the model, feature selection techniques are employed:
- Cup-to-Disc Ratio (CDR) Calculation: The cup-to-disc relation remains automatically computed from segmented optic nerve images using the formula:

$$CDR = \frac{\text{Diameter of the disc}}{\text{Diameter of the cup}} \quad \text{`} \tag{1}$$

- Count relation: this is a seminal parameter in evaluating the development of glaucoma as an increasing ratio indicates optic nerve damage
- Peripapillary RNFL Thickness – Automatic segmentation of peripapillary RNFL thickness, which aids detection of initial glaucomatous changes using the state-of-the-art edge detection of EfficientNetV2 to ensure that the thickness measurement is accurate.

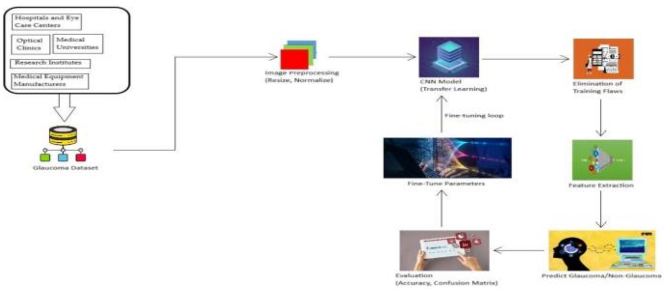

Figure 1. Proposed Framework

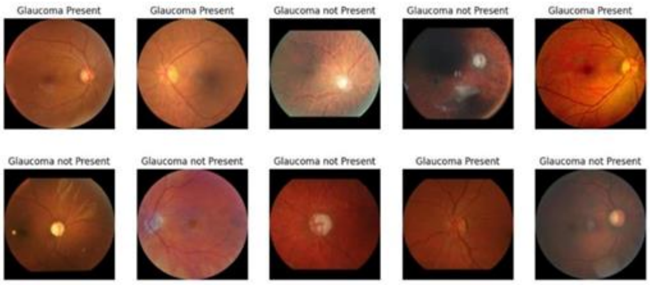

Figure 2. Dataset

3.3. Dataset

Retinal images publicly available were used. The dataset includes images of both glaucoma and non-glaucoma. The database includes images together with clinical data such as a Retinal Nerve Fiber Layer (RNFL) Thickness.

Dataset Parameters and Features:

•Images—fundus high-definition images where the structural variations of optic nerve and retina can be observed.

•Labels: Each image is annotated to be of a glaucomatous or a non-glaucomatous eye.

•Cup-to-Disc Ratio (CDR): An important measure of the optical nerve damage that is calculated from images of the optic nerve automatically.

•RNFL Thickness: Used to evaluate early glaucomatous changes.

•It steps involved data preprocessing, normalization and splitting of data into train, validation and test set to ensure balanced representation during EfficientNetV2 model and other classifier trained.

3.3.1 Distribution of Glaucoma Presence in the Dataset

Bar plot showing the distribution of glaucoma cases in a dataset (Left: Normal, Right: Glaucoma) The x-axis denotes the two classes that our target variable can take: "Glaucoma Present" or "Glaucoma Not Present," and y, counts of observations per class. This plot shows the relative frequency of occurrences of Glaucoma against all other diagnoses in the dataset.

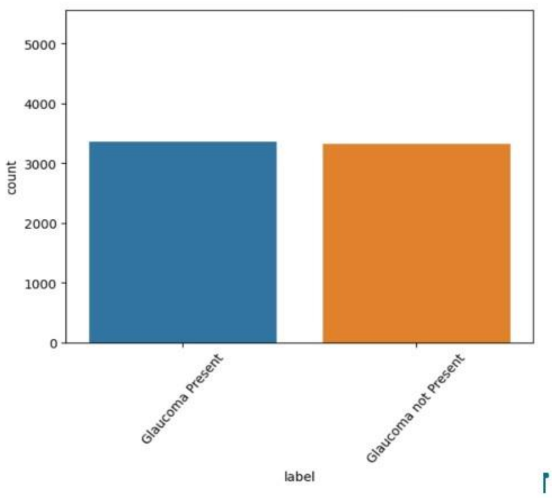

Figure 3. Dataset Distribution

3.3.2 Evaluation Measures

We employ multiple standard evaluation metrics commonly used for evaluating the performance of medical image analysis methods, for glaucoma detection system performance evaluation. Such metrics give us a complete picture of how well the model remained able to distinguish between glaucomatous and non-glaucomatous cases.

- Accuracy: This refers how many cases were correctly classified against the total sum of case.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Population}}$$

- Recall: Also called as true positive frequency, recall gives us an indication of how well the model is able to build all the appropriate cases.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- Precision: Precision is a measure of the accurateness of positive guesses.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- F1 Score: the F1 score is the harmonic mean of precision and recall, it is a well-adjusted average of both. This is especially helpful if the classes are skewed, taking false positives and false negatives in-to deliberation.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} + \text{Recall}}{\text{Precision} \times \text{Recall}}$$

- FNR: Fraction of positive cases where the model incorrectly predicted a negative class. It measures how frequently the model fails to correctly identify true positive instances.
- FPR: Rate of actual negatives which are falsely predicted by the model as positive. It calculates the false positives rate that is, how frequently the model calculates negatives as positives

3.3.3 Confusion Matrix

The next image shows a confusion matrix for our model predicting whether glaucoma is present or not. The confusion matrix gives a clear view of the true and predicted classifications:

- Top-left (True Positive, Glaucoma Present): 1687 cases where the model correctly predicted glaucoma as present

- Top-right (False Positive, Glaucoma Present): 67 cases where the model incorrectly predicted glaucoma as present when it was not.

- Bottom-left (False Negative, Glaucoma not Present): 121 cases where the model incorrectly predicted glaucoma as not present when it actually was.

- Bottom-right (True Negative, Glaucoma not Present): 999 cases where the model correctly predicted glaucoma as not present.

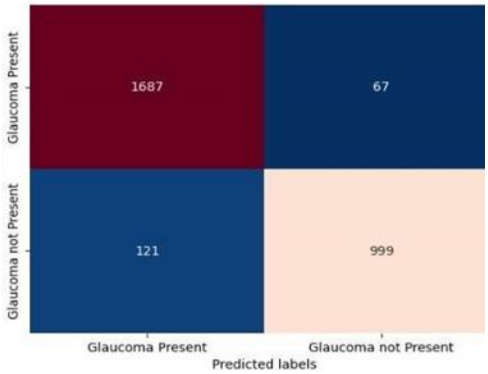

Figure 4. Confusion Matrix

This matrix shows the model performs well, with relatively low false positives and false negatives, meaning it is accurate in identifying glaucoma

3.4. Performance Evaluation

The classification report attached below shows the performance of our model predicting glaucoma. Key metrics include:

- Glaucoma Present: Precision (0.93·), Recall (0.96·), F1-score (0.95·) per 1754 cases.
- Glaucoma not Present: Precision (0.94·), Recall (0.89·), F1-score (0.91·) per 1120 cases.
- Accuracy: 93% overall.
- Macro average: 0.94· precision, 0.93· recall, 0.93· F1-score.
- Weighted average: 0.93 for all system of measurement.

(The above metrics are calculated on the basis of model testing over the test set.)
The model performs well, especially at detecting glaucoma, with balanced precision and recall.

3.5. Model Comparisons

The table summarizes performance metrics for various models in glaucoma detection, including precision, recall, average precision, and accuracy. EfficientNetV2 achieved the highest precision (93.5) and recall (92.5), demonstrating robust performance in accurately identifying glaucoma cases. Inception-ResNet-V2 followed closely, with a precision of 87.74 and recall of 88.89, indicating strong effectiveness. The DCNN and CNN showed moderate results, with DCNN attaining a precision of 82.27 and recall of 80.34, while CNN had a precision of 85.3 but a inferior recall of 69.23. Inception-V2 performed slightly lower with a precision of 81.43 and recall of 80.71. These verdicts highlight the varying effectiveness of each model, emphasizing the importance of choosing the right approach for glaucoma detection.

Table 1. Model Comparison

METHOD	Accuracy	Error rate	FPR	FNR	Precision	Recall
CNN	85.2	0.148	0.0325	0.0325	85.3	69.23

INCEPTION-V2	81.59	0.184	0.1203	0.2839	81.43	80.71
DCNN	84.94	0.151	0.1203	0.2984	82.27	80.71
INCEPTION-RESNET-V2	86.52	0.135	0.0764	0.0764	87.74	88.89
PROPOSED EFFICIENTNET V2-S	93.7	0.063	0.108	0.0382	93.5	92.5

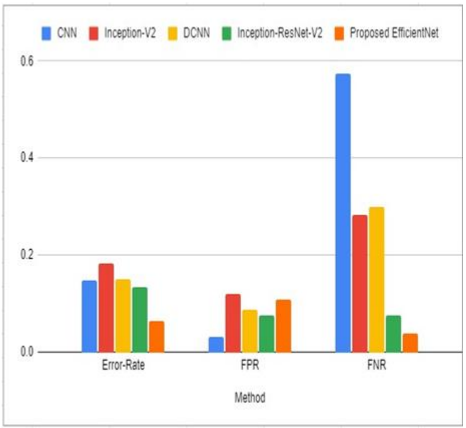

Figure 5.1 Model Comparison Measure

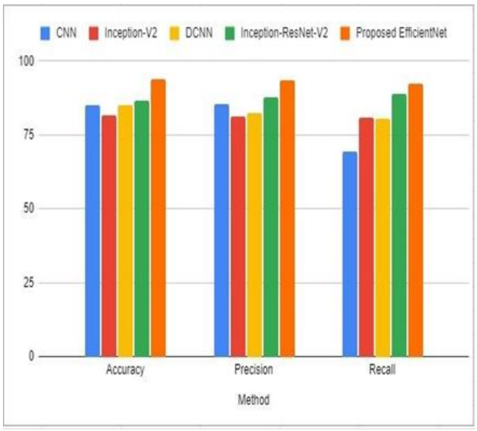

Figure 5.2 Model Comparison Measures

3.6. Learning Curve

This image shows two graphs: one for Train & Validation Loss and another for Train & Validation Accuracy over 25 epochs.

Train Loss & Validation Loss

- Train Loss (blue): loss declines as the number of epochs rises, meaning the model is improving its performance on the training figures.
- Validation Loss (orange): validation loss also decreases but more steadily, indicating the model simplifies fine to unnoticed data without overfitting.
- Both losses stabilize towards the end, showing that further training is unlikely to improve performance significantly

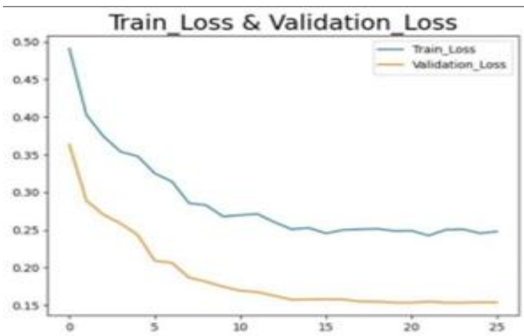

Figure 6.1 Train Loss & Validation Loss

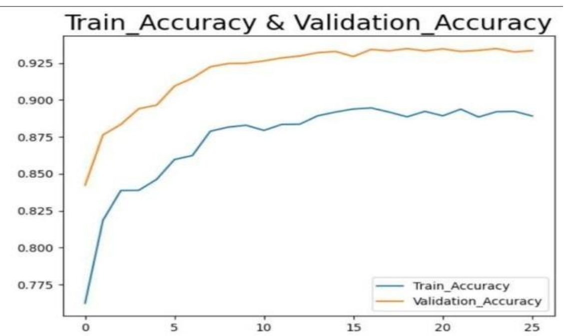

Figure 6.2 Train Accuracy & Validation Accuracy

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Train Accuracy & Validation Accuracy

- Train Accuracy (blue): accuracy on training data increases sharply in the early epochs and then gradually improves, reaching around 92%.
- Validation Accuracy (orange): Validation accuracy improves quickly then remains consistently higher than training accuracy, stabilizing at approximately 93%.

Overall, both graphs suggest the model is learning well, showing a good balance between training and validation performance.

4. Results

The proposed glaucoma detection system, utilizing the EfficientNetV2 CNN architecture, demonstrated outstanding performance in distinguishing between glaucomatous and non-glaucomatous retinal images. The system achieved an overall accuracy of **93.7%**, highlighting its ability to correctly classify the majority of cases. For glaucomatous cases, the model exhibited a precision of **93.5%**, indicating a high level of accuracy in predicting true positives while minimizing false positives. The recall rate of **92.5%** underscores the system's capability to identify nearly all glaucomatous cases, ensuring minimal false negatives. To assess the overall model performance, a confusion matrix was analysed. Out of the test samples, **1,687 true positives** were correctly classified as glaucomatous, while **999 true negatives** were accurately labelled as non-glaucomatous. Misclassifications included **67 false positives** and **121 false negatives**, indicating relatively low error rates.

The model was benchmarked against other architectures, such as Inception-ResNet-V2, traditional CNNs, and DCNNs. Among these, EfficientNetV2 consistently outperformed others, achieving the highest precision (**93.5%**) and recall (**92.5%**) scores. In contrast, Inception-ResNet-V2 followed with a precision of **87.74%** and recall of **88.89%**, while traditional CNNs and DCNNs lagged with moderate performances.

Learning curves showed that both training and validation losses decreased steadily over epochs, stabilizing towards the end, which indicated the model's effective generalization to unseen data without overfitting. The validation accuracy stabilized at around **93%**, demonstrating consistent performance across training and validation sets.

Overall, the results underscore the effectiveness of the EfficientNetV2-based system in accurately detecting glaucoma, offering a reliable tool for early diagnosis. Its superior performance metrics and computational efficiency make it a promising candidate for real-world clinical deployment, potentially reducing the burden of irreversible vision loss caused by delayed glaucoma detection.

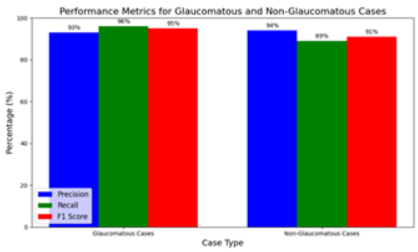

Figure 7. Performance Metrics

5. Discussion

The findings of this study demonstrate the potential of leveraging machine learning, particularly the EfficientNetV2 architecture, for automated glaucoma detection using fundus images. The model's high accuracy of **93.7%**, coupled with strong precision and recall metrics, validates its efficacy in identifying both glaucomatous and non-glaucomatous cases. These results are consistent with existing literature emphasizing the role of deep learning in improving diagnostic precision in ophthalmology. By effectively analysing structural features such as optic nerve cupping and RNFL thinning, the system bridges a significant gap in early glaucoma detection, a critical factor in preventing irreversible vision loss.

The superior performance of EfficientNetV2 over other architectures, such as Inception-ResNet-V2 and traditional CNNs, highlights the advantages of compound scaling in optimizing model depth, width, and resolution. This ensures a balance between accuracy and computational efficiency, making the system scalable and suitable for deployment in clinical settings. Furthermore, feature selection techniques like cup-to-disc ratio (CDR) calculation and RNFL thickness measurement enhance the interpretability of the results, offering clinicians actionable insights.

Despite its promising performance, the system faces certain limitations. The dependency on high-quality retinal images poses a challenge, as poor image quality can adversely impact model predictions. This underscores the need for standardized imaging protocols to ensure consistent inputs across diverse clinical environments. Additionally, the potential for false negatives or positives, while low, cannot be eliminated, necessitating the system's use as an assistive tool rather than a standalone diagnostic solution.

Another concern is the system's generalizability. While the dataset used for training and testing included diverse cases, it may not fully capture the variability in real-world populations, such as differences in imaging equipment, ethnic backgrounds, or disease progression stages. Expanding the dataset to include such variations can further enhance the robustness of the model.

The broader implications of this research are significant for both clinical practice and public health. Automated glaucoma detection systems like the one proposed in this study can alleviate the burden on healthcare professionals by enabling early and efficient screening in resource-limited settings. Moreover, they hold promise for integration into teleophthalmology frameworks, facilitating remote diagnostics and improving access to care for underserved populations.

Looking forward, this study opens avenues for further research. Combining fundus imaging with other diagnostic modalities, such as optical coherence tomography (OCT) or visual field analysis, could enhance diagnostic accuracy. Additionally, incorporating longitudinal data to monitor disease progression may offer predictive insights, enabling tailored treatment plans. Regular updates to the system, reflecting advancements in medical imaging and machine learning techniques, will ensure its continued relevance and effectiveness.

6. Conclusion

The findings of this study underscore the potential of automated approaches to revolutionize glaucoma detection and management. Automated systems, particularly those leveraging advanced machine learning techniques, have emerged as pivotal tools in early recognition and intervention, significantly reducing the risk of irreversible vision loss associated with glaucoma. This study focused on utilizing non-invasive fundus imaging as the primary diagnostic input, emphasizing advancements in optical nerve head (ONH) processing and segmentation of optic disc and optic cup. These techniques enable the precise identification of structural changes indicative of glaucomatous damage, such as optic nerve cupping and Retinal Nerve Fiber Layer (RNFL) thinning.

EfficientNetV2, a state-of-the-art convolutional neural network (CNN) architecture, was employed as the backbone of the proposed glaucoma detection system. The model was fine-tuned and trained on an augmented dataset to classify the presence of glaucoma effectively. Training was conducted for 50 epochs with the Adam optimizer and a learning rate scheduler, ensuring efficient convergence and reduced overfitting. Early stopping was implemented as a precaution to prevent overtraining and maintain the model's generalizability to unseen data.

The experimental results highlight the model's robust performance. For glaucomatous cases, the system achieved an impressive accuracy of 93.7%, with a precision of 93.5%, indicating a high likelihood of correctly identifying true positive cases while minimizing false positives. The recall rate of 92.5% reflects the model's ability to capture nearly all true glaucomatous cases, ensuring minimal false negatives.

The study's findings reinforce the practicality and scalability of integrating automated systems in clinical settings. The EfficientNetV2-based approach offers a reliable, efficient, and scalable solution for early glaucoma screening, capable of addressing the limitations of manual diagnostics and resource constraints. However, the results also emphasize the importance of further refining the model to improve recall for non-glaucomatous cases and addressing challenges such as dependency on image quality and dataset diversity. Overall, this work provides a significant step forward in leveraging artificial intelligence to mitigate the global burden of glaucoma and improve patient outcomes through early intervention.

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