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Deep Learning-Based Glaucoma Identification From Retinal Images

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Abstract — Glaucoma is a chronic optic neuropathy that is one of the leading causes of irreversible blindness worldwide [1], [2]. Hence, it is extremely important to detect it at an early stage with maximum accuracy. The paper presents an innovative approach to an automatic binary classification system based on deep learning for glaucoma detection using the ACRIMA dataset images [3]. The system is based on the transfer learning approach with DenseNet-121 architecture for glaucoma detection. It utilizes contrast enhancement techniques and the extraction of the green channel with optic disc localization for better feature representation. The fine-tuning of the pre-trained DenseNet-121 model is done for binary classification of glaucoma images and normal images. The data was split based on stratified data splitting techniques, resulting in better predictive capabilities for the system with an accuracy of 94.0%, precision of 92.98%, recall of 96.36%, and AUC-ROC of 0.961. The model is better compared to the baseline convolutional neural networks for feature propagation and generalization. Hence, the proposed system can be considered reliable for the diagnosis of glaucoma by ophthalmologists.

KEYWORDS: *Glaucoma Detection, Deep Learning, DenseNet121, Fundus Images, Transfer Learning, Optic Disc Localization*

1. INTRODUCTION

Glaucoma leads to gradual visual field loss and, ultimately, permanent blindness if left untreated. It is considered as one of the leading causes of irreversible blindness worldwide. The disease is often asymptomatic in its early stages, earning it the name ―the silent thief of sight.‖ To prevent severe visual impairment, early detection and timely intervention are critical as vision loss caused by glaucoma cannot be restored [1], [2].

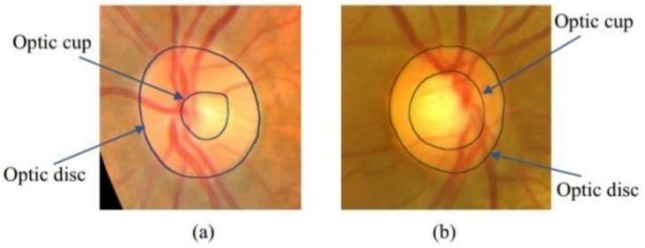

Fig 1: (a) healthy, and (b) glaucomatous optic nerve head.

However, effective screening remains challenging due to limited accessibility to specialized ophthalmic care, particularly in rural and under-resourced regions. Clinically,

glaucoma is associated with structural changes in the optic nerve head. One of the most significant indicators to identify glaucoma is the Cup-to-Disc Ratio (CDR), which measures the proportion of the optic cup relative to the optic disc [4]. An increased CDR often indicates glaucomatous damage. Diagnosis typically involves comprehensive eye examinations like tonometry for intraocular pressure measurement, visual field testing, optical coherence tomography (OCT), and fundus photography [5]. These methods are reliable but time-consuming, require expensive equipment, and depend heavily on clinical expertise. Moreover, subjective interpretation of fundus images may lead to inter-observer variability, which can affect diagnostic consistency.

In recent years, advancements in medical imaging and artificial intelligence have provided promising alternatives for automated disease detection [6]. In particular, retinal fundus

imaging has gained significant attention as a non-invasive and cost-effective diagnostic modality. Fundus images capture detailed structural information about the retina, including the optic disc, optic cup, blood vessels, and surrounding tissues[7]. Automated analysis of these images can assist clinicians by providing objective and reproducible assessments. The integration of artificial intelligence into ophthalmology has the potential to improve early screening, reduce workload on specialists, and expand access to diagnostic services.

Deep learning techniques have recently shown remarkable success in the analysis of medical images. Among these techniques, Convolutional Neural Networks (CNNs) are widely used because they can automatically learn relevant patterns directly from image data [8]. Unlike conventional machine learning methods that depend on manually designed features, CNN models extract meaningful representations through multiple layers of convolution and nonlinear transformations. Initial layers usually capture simple visual patterns such as edges and textures, whereas deeper layers learn more complex structures that are useful for disease classification [9].

Several deep learning architectures have been successfully applied to glaucoma detection, including VGG, ResNet, EfficientNet, and Inception networks [10], [11]. While these architectures have achieved promising results, challenges remain. Medical datasets are often limited in size, leading to overfitting and reduced generalization [12]. Furthermore, glaucoma-related structural changes can be subtle, particularly in early stages, requiring models capable of capturing fine-grained variations in the optic nerve head region. Additionally, interpretability remains a significant concern, as clinicians require transparency to trust AI-based diagnostic systems [13]. To address these challenges, this study proposes a glaucoma identification framework based on the DenseNet121 architecture with transfer learning. DenseNet (Densely Connected Convolutional Network) introduces a novel connectivity pattern in which each layer receives feature maps from all preceding layers [14]. This dense connectivity encourages feature reuse, strengthens gradient flow, and reduces the number of parameters compared to traditional CNN architectures. As a result, DenseNet121 is particularly effective for medical imaging tasks where datasets are relatively small but high-feature.

2. RELATED WORK

Early automated glaucoma detection systems were primarily based on traditional machine learning techniques. In these approaches, researchers manually extracted structural features from retinal images, such as optic disc area, cup-to-disc ratio, vessel density, and texture descriptors. These handcrafted features were then used to train classifiers including Support Vector Machines, k-Nearest Neighbors, and Random Forest models. Although these methods provided moderate performance, they were highly dependent on the quality of feature extraction and often struggled to generalize across datasets obtained from different imaging conditions.

Traditional Machine Learning Models: The early attempts at automated glaucoma detection were based on hand crafted feature extraction and traditional machine learning classifiers [15]. Structural and textural features were extracted from retinal fundus images, including blood vessel density, optic disc area, optic cup area, neuro-retinal rim thickness, and color histogram features [16]. These features were then used as inputs to classifiers such as SVM, k-NN, Random Forests, and ANN [10].

Although they demonstrate some success, their performance was highly susceptible to the quality of hand-engineered features. Manual feature extraction was domain expert-dependent and generally lacked generalizability across datasets due to differences in image acquisition conditions. Moreover, conventional models had difficulty modelling the complex nonlinear relationships underlying retinal images [17]. As a result, accuracy rates generally remained in the range of 80-88% [18], especially for early glaucoma detection, where the changes are less prominent.

To overcome these drawbacks, the community started investigating deep learning models that can perform automatic feature extraction directly from raw images.

The Emergence of CNN for Glaucoma Detection: The advent of CNNs has profoundly transformed medical image classification. CNNs remove the necessity for manual feature extraction by automatically learning hierarchical feature representations through convolutional and pooling layers. In glaucoma research, early CNN-based models were derived from those designed for tasks in natural image classification.

VGG-based architectures were among the first deep learning models utilized for analysing retinal fundus images. These architectures feature a sequence of convolutional layers with small receptive fields and have demonstrated better performance compared to conventional machine learning methods. Research utilizing VGG16 and VGG19 models has indicated classification accuracy rates exceeding 90% on limited glaucoma datasets [19]. However, these models have a huge number of parameters, resulting in higher computational complexity and has the possibility of overfitting when trained on small datasets.

ResNet architectures use residual connections to solve the vanishing gradient problem in deep learning models [20] . By adding these shortcut paths, gradients can flow more easily through the layers, making it possible to train much deeper models like ResNet50 and ResNet101 effectively. Several studies have utilized ResNet50 for glaucoma diagnosis,

demonstrating enhanced generalization performance. The concept of residual learning has enhanced feature representation, particularly regarding the optic disc representation. Nonetheless, while residual learning enhances training stability, it may still lead to redundancy in feature maps when trained on smaller datasets.

Dense Connectivity and Feature Reuse: DenseNet architectures represent another significant development in deep learning frameworks. In contrast to traditional CNN models, where each layer is linked solely to the next, DenseNet architectures feature dense connectivity, allowing each layer to connect to all previous layers. This promotes feature reuse and improves the gradient flow throughout the network [14].

DenseNet121 is commonly utilized in medical image analysis due to its lower parameter count and improved information transfer across the network. Studies using DenseNet models to classify retinal diseases have shown good results in detecting conditions like diabetic retinopathy, age-related macular degeneration, and glaucoma. The model design helps in keeping both low-level texture features and high-level meaningful patterns, which are important for identifying small changes in the optic nerve head.

Comparative studies of DenseNet against other architectures like VGG and ResNet indicate that DenseNet can frequently achieve similar or superior results while utilizing fewer parameters. Additionally, the feature reuse mechanism in DenseNet helps mitigate overfitting when working with limited datasets.

Optic Disc Segmentation-Based Methods: Optic disc and cup segmentation is another significant area of research. Recognizing that identifying glaucoma depends largely on examining the structure of the optic nerve head, many researchers have used clear segmentation processes before classifying the images.

Early segmentation methods relied on edge detection, thresholding, morphological processing, and Hough transform techniques to find the circular edges of the disc [21], [22]. While these methods offered decent localization accuracy, they were highly affected by changes in lighting and image flaws.

Segmentation models like U-Net and Fully Convolutional Networks (FCNs), have greatly improved the accuracy of segmenting the optic disc and cup [23]. These models use encoder-decoder frameworks to create segmentation maps at the pixel level. Precise segmentation allows for the accurate calculation of the CDR, which is an important measure for glaucoma.

However, these segmentation-focused workflows add extra complexity to the calculations and can potentially introduce errors if the segmentation is not accurate.

Transfer Learning in Medical Imaging: One of the main challenges in glaucoma research is the limited availability of datasets. Medical imaging datasets are usually small because of privacy concerns and the complexities of annotation. Models with such limited datasets can cause overfitting.

Transfer learning has become a popular way to tackle this issue. Pretrained models trained on large-scale datasets such as ImageNet, deep learning models can learn more robust feature representations for medical imaging tasks [24].

Studies on transfer learning with architectures like ResNet, DenseNet, and EfficientNet have shown significant improvements in both convergence speed and accuracy [25]. In glaucoma detection, transfer learning is particularly effective when working with datasets like ACRIMA, RIM-ONE, DRISHTI-GS, and REFUGE.

Explainable Artificial Intelligence in Glaucoma Detection: Although deep learning models have been able to achieve high accuracy in classification, they are often considered ―black-box‖ models [26]. In medical research, interpretability is a major concern for clinical acceptance. To overcome this problem, researchers have used Explainable Artificial Intelligence (XAI).

Grad-CAM (Gradient-weighted Class Activation Mapping) is one of the most popular visualization tools. It produces heatmaps to indicate the regions that contribute most to the model's prediction. It ensures that the model concentrates on the optic disc and cup areas rather than irrelevant regions.

Several studies have proved that the combination of visualization tools can enhance the confidence of clinicians in AI-assisted diagnostic models. Explainability can also help in detecting potential biases and enhancing the reliability of models.

3. METHODOLOGIES

The proposed system is designed to automatically detect glaucoma from retinal fundus images using a deep learning framework. The approach comprises five main components: data organization, preprocessing, feature enhancement focused on specific regions, model development utilizing transfer learning, and evaluation of performance.

The retinal fundus images obtained from the ACRIMA dataset are separated into training and testing subsets for model development. The preprocessing component standardizes the size of images, improves contrast, and normalizes pixel values

to guarantee consistent input quality. To improve robustness and lower the risk of overfitting, we use data augmentation methods during training [27].

A region-of-interest (ROI) refinement module is applied to isolate the optic disc region, which holds key structural indicators of glaucoma. The refined images are then sent to the model development module, where a pre-trained DenseNet121 architecture is used with transfer learning [14]. The final classification layer is adjusted for binary prediction, allowing for distinction between glaucomatous and normal images.Model optimization uses an adaptive learning strategy with regularization techniques. Performance of the model is evaluated using standard metrics including accuracy, precision, recall, F1-score, and ROC-AUC curve [28].

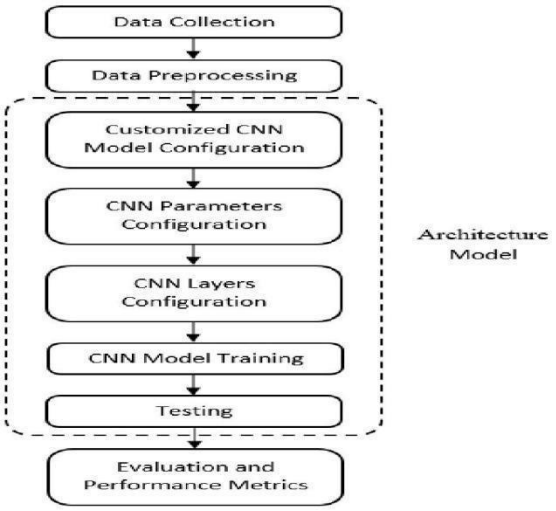

Fig 2: Flow Chart

This modular approach provides a balanced mix of preprocessing improvement, deep feature learning, and clear classification.

5. SYSTEM ARCHITECTURE

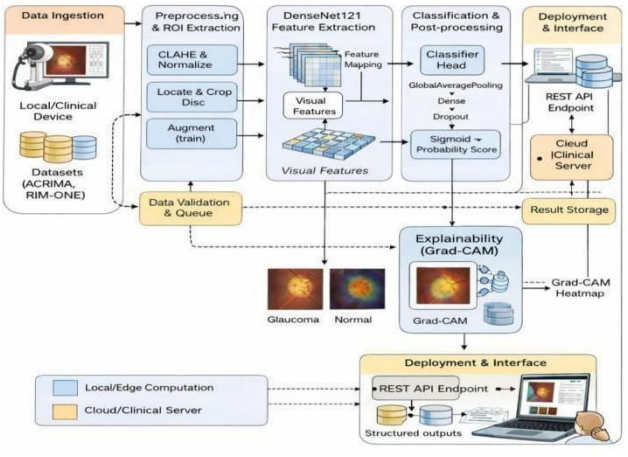

Fig 3: Overview of DenseNet-121 system architecture

Figure 3 illustrates the design framework of the proposed deep learning system developed for automated glaucoma detection using retinal fundus images. The architecture represents the complete processing pipeline, beginning with image acquisition and preprocessing, followed by feature learning, classification, and result validation. Each component of the system is designed to enhance diagnostic performance while ensuring reliable and clinically meaningful outputs.

The functionality of the individual modules is described below.

Dataset Acquisition: The Dataset Acquisition Module serves as the entry point of the system and is responsible for collecting and organizing retinal fundus images from standardized ophthalmic datasets. This framework manages image-label associations by categorizing images into glaucomatous and non-glaucomatous classes. It ensures data integrity by validating file formats, removing corrupted or inconsistent samples, and organizing the dataset into structured partitions for training and testing. The output is a clean, labeled, and well-structured image repository ready for subsequent processing.

Retinal Fundus Image Preprocessing: The Retinal Fundus Image Preprocessing Module enhances image quality and standardizes inputs to ensure consistent learning conditions. Fundus images often exhibit uneven illumination, noise, and contrast variations that may affect model performance. Therefore, contrast enhancement techniques are applied to improve structural visibility. The green channel is extracted from the RGB fundus image, as it provides better contrast for optic disc and vascular structures compared to the red and blue channels. Intensity normalization is then performed to maintain uniform pixel distribution across all samples. This outputs enhanced and standardized retinal images suitable for structural analysis and deep feature extraction.

Region of Interest (ROI) Extraction: The ROI Extraction Module isolates clinically significant regions from the preprocessed retinal images. Since glaucoma-related structural changes are primarily observed around the optic disc region, this approach performs localization and cropping of the optic disc area to eliminate irrelevant background information. The extracted region is resized to match the input dimensions required by the convolutional neural network architecture, typically 224×224 pixels. This focused extraction reduces computational redundancy and enables the model to concentrate on anatomically meaningful structures, thereby improving classification efficiency.

Training Phase: The Training Phase Module represents the learning component of the architecture. In this stage, ROI images are fed into a deep convolutional neural network implemented using DenseNet121 as the backbone architecture. The convolutional layers perform hierarchical feature extraction, learning low-level features such as edges and textures in early layers and higher-level structural representations in deeper layers. Pooling operations reduce spatial dimensionality while preserving important information. The extracted feature maps are then forwarded to a fully connected multilayer perceptron layer that transforms them into a compact representation suitable for classification. During training, model weights are iteratively updated using backpropagation and gradient-based optimization until convergence is achieved.

Testing / Inference: After completion of the training process, the system transitions into the Testing or Inference Module. In this stage, unseen retinal images undergo the same preprocessing and ROI extraction pipeline to ensure consistency with the training configuration. However, unlike the training phase, the network parameters remain fixed. The DenseNet121 model performs forward propagation only, generating probability predictions for each input sample. This ensures unbiased evaluation and simulates real-world screening conditions.

DCNN Classification: The DCNN Classification Module serves as the final decision-making stage of the architecture. The high-level features extracted by DenseNet121 are passed through the final dense layer with a sigmoid activation function to generate a probability value between 0 and 1. A predefined threshold converts this probability into a binary label indicating glaucomatous or non-glaucomatous classification. The model outputs both the predicted class and the associated confidence score, enabling reliable and interpretable automated screening.

6. DATASET

Source: Experiments use the publicly available ACRIMA dataset [4], which contains clinician-annotated retinal fundus images specifically curated for glaucoma assessment. The ACRIMA collection contains 705 fundus images (publicly archived) suitable for supervised binary classification. The dataset is composed of 396 glaucomatous images and 309 normal images (approximate class proportions retained for reproducibility).

Partitioning: Images are partitioned using stratified sampling to form training (70%), validation (15%), and test (15%) subsets, ensuring that class ratios remain constant across splits. When reporting final performance, stratified k-fold cross-validation (k=5) is also used to assess generalization stability across different train/test splits.

Annotation quality: Labels in ACRIMA were produced/verified by ophthalmology experts; where possible, clinically ambiguous samples are excluded from training and retained for separate analysis to avoid label noise.

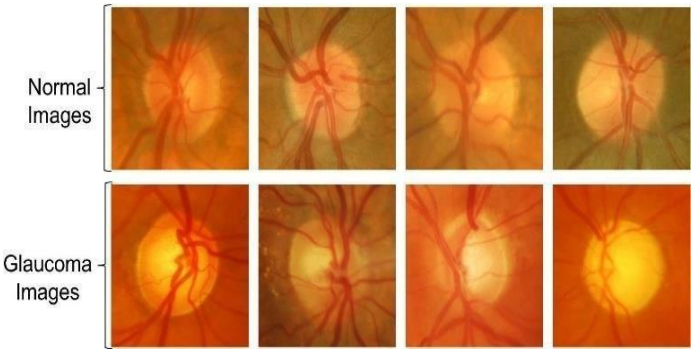

Fig 4: Fundus images from the ACRIMA dataset.

7. PROPOSED METHODOLOGY

The proposed methodology defines a reproducible pipeline for automated glaucoma identification through retinal fundus images. The pipeline is organized into five main subsections: dataset description, preprocessing, model architecture, training strategy, and evaluation. Each subsection below explains the concrete steps, rationale, and parameter choices used in our experiments.

Preprocessing

To reduce inter-image variability and emphasize diagnostically relevant structures, the following preprocessing pipeline is applied:

Green-channel extraction: From the RGB fundus image, the green channel is selected as the primary input because it typically yields higher contrast for blood vessels and optic disc boundaries than red or blue channels.

Contrast enhancement: Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to the green channel to correct uneven illumination and to enhance local contrast, improving visibility of the optic nerve head and cup boundaries.

ROI extraction: Since glaucoma primarily affects the optic nerve head, Region of Interest (ROI) extraction is performed to focus on the optic disc region. Brightness-based thresholding and circular Hough Transform techniques are used to localize the optic disc center. A square region centered on the detected disc is cropped:

$$I_{ROI} = \text{Crop}(I_{CLAHE}, x_c, y_c, L)$$

where (x_c, y_c) represents the optic disc center and L denotes crop size.

Resizing & normalization: All ROI images are resized to pixels to match DenseNet121 input requirements. Pixel

$$I_{norm} = \frac{I_{ROI}}{255}$$

intensities are normalized to the range [0,1] using:

This ensures stable gradient updates during training.

Data augmentation (on-the-fly): During training, real-time augmentation (random rotations ±20°, horizontal flips, small zooms, brightness jitter) increases effective sample diversity, reduces overfitting, and simulates imaging variations.

Model Architecture

Backbone: The core feature extractor is DenseNet121, chosen for its dense connectivity pattern that encourages features to use them again and efficient gradient flow, and reduces the number of parameters compared to traditional deep networks, making it well-suited to medical images with subtle patterns [3]. Lower convolutional blocks are initially frozen to retain general features; higher blocks are fine-tuned to adapt to retina-specific features.

Transfer Learning: Since medical datasets are relatively small, transfer learning is employed. DenseNet121, It is pre-trained on ImageNet and used as a feature extractor. The initial layers capture generic low-level features (edges, textures), while higher layers are fine-tuned for glaucoma-specific representations.

Classification Head: The final classification head consists of:

- Global Average Pooling layer
- Fully connected layer with ReLU function
- Dropout layer (rate = 0.5)
- Output layer with Softmax function

Output Layer: For binary classification, a final softmax layer with two neurons is used, which gives the probability for each class (Glaucoma and Non-Glaucoma). The softmax function is

$$Softmax(z)_i = \frac{e^{z_i}}{\sum_{i=1}^{k} e^{z_j}}$$

given as:

where k=2 is the number of classes.

The model outputs probability values between 0 (normal) and 1 (Glaucomatous), with a threshold (typically 0.5) used for final decision.

Training Strategy:

Optimizer: The Adam optimizer is employed for efficient stochastic gradient-based optimization.

Learning Rate: The Initial learning rate is set to 1 × 10-4 during head training and reduced to 1 × 10-5 during fine-tuning of deeper layers.

Epochs: Training is performed for 25–50 epochs with early stopping (patience = 8) to prevent overfitting.

Loss Function: Binary Cross Entropy (BCE) is used as the loss function. Class weights are incorporated if imbalance is observed.

Evaluation Metrics

Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision

$$Precision = \frac{TP}{TP+FP}$$

Recall (Sensitivity)

$$Recall = \frac{TP}{TP+FN}$$

F1-Score

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

Here, TP, TN, FP and FN means true positive, true negative, false positive and false negative results. Basically, these are used to show how correct or wrong the predictions are.

8. RESULTS

The proposed framework for detecting glaucoma, which is based on DenseNet121, was assessed using the ACRIMA retinal fundus dataset. We employed stratified data splitting to preserve class balance. The model demonstrated a strong capacity to distinguish between glaucomatous and normal images. Following fine-tuning through transfer learning, the network attained an overall classification accuracy of 94.0%, with precision at 92.98%, recall at 96.36%, and F1-score of 94.7%.

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) reached 0.961, with a sensitivity of 96.4%, demonstrating strong discriminative capability for glaucoma detection. Also indicating outstanding separability between the two categories.

Dataset	Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
ACRIMA	CNN (Baseline)	87.4%	85.2%	83.1%	84.1%	0.91
	ResNet50	90.1%	89.3%	86.7%	88.0%	0.93
	VGG16	89.5%	88.1%	85.4%	86.7%	0.92
	EfficientNetB0	91.2%	90.0%	88.2%	89.1%	0.94
	EfficientNetB0	91.2%	90.0%	88.2%	89.1%	0.94
	Proposed DenseNet121	94.0%	92.98%	96.36%	94.64%	0.961

Table I: Performance measure of Accuracy, Precision, Recall, F1-score, and ROC-AUC of different models

The training and validation curves displayed stable convergence with minimal divergence, suggesting effective generalization and controlled overfitting. The use of early stopping and dropout regularization contributed to maintaining training stability. Comparative experiments with other pre-trained models such as ResNet50 and VGG16 indicated that DenseNet121 provided superior performance.

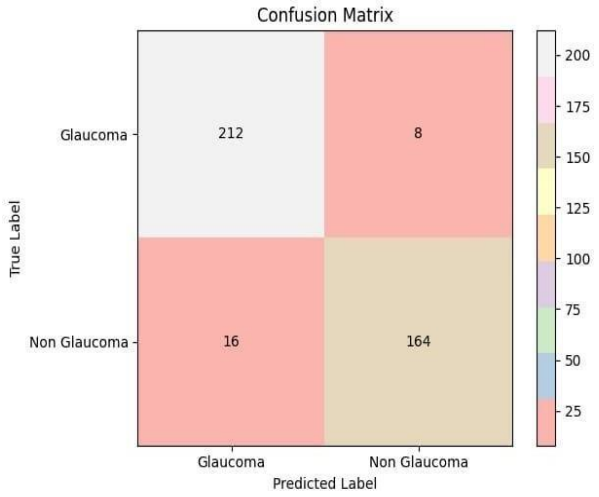

Fig 5: Confusion Matrix of the model

The confusion matrix showed very few false negatives, which is vital for medical screenings where missing a glaucoma diagnosis can lead to irreversible damage. These results validate the effectiveness and applicability of the suggested approach for automated glaucoma screening systems.

Also, eceiver Operating Characteristic (ROC) curves and Area Under Curve (AUC) values are calculated to check how well the model can tell between classes at different thresholds.

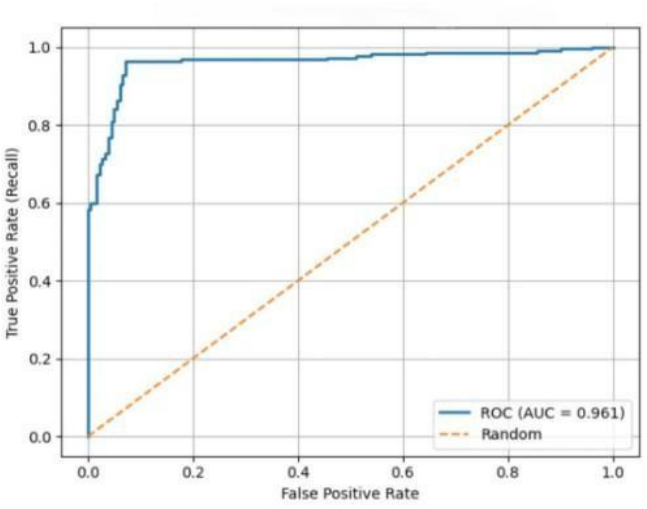

Fig 6: ROC-AUC Curve for the proposed model.

9. Conclusion

This work demonstrates that a transfer-learning approach built on DenseNet121 can reliably identify glaucoma from retinal fundus images with strong classification performance. The model's architecture — which encourages extensive feature sharing across layers — proved effective at capturing subtle optic-nerve head variations, yielding high accuracy and favorable precision/recall trade-offs on the ACRIMA dataset. The addition of contrast enhancement, refinement of regions of interest, data augmentation, and regularization also helped in obtaining stable training of the model, considering that data is limited in this domain.

Beyond numeric performance, visualization via class-activation mapping showed that the network's attention aligns with clinically meaningful regions (primarily the optic disc), supporting the method's interpretability and potential clinician trust. Low false-negative rates further indicate the approach's suitability for screening contexts, where missing positive cases carries serious consequences. The pipeline is computationally efficient enough for practical use (with GPU acceleration) and can be integrated into telemedicine or mass-

screening workflows to expand access to early glaucoma detection.

However, some limitations of the results obtained need to be considered. The results are based on the dataset used for training the network. Therefore, the results need to be validated based on alternative datasets. The deployability of the results is an advantage of the study. The results obtained reveal that the DenseNet121-based framework is an advancement towards the automated screening of glaucoma.

10. FUTURE WORK

The proposed system for detection of glaucoma can be further improved by expanding the dataset and including a diverse set of images from different clinical resources and imaging. The inclusion of a greater and more diverse set of images at varying stages of disease progression will help in enhancing the robustness and generalization capability of the deep learning model. Future studies will be carried out for extending the proposed system for the detection of other eye diseases such as diabetic retinopathy, cataract, age-related macular degeneration, etc. This will help in the development of a comprehensive eye detection and diagnosis system.

Another aspect that will be considered in further studies is how best to ensure that the model is more interpretable, especially by employing more advanced tools in explaining how the model is making its diagnosis, such as attention visualization and region-based analysis, for better understanding on what features of the retina are being considered by the model in its diagnosis.

Validation of the model on a large scale by ophthalmologists in a real-world environment will be carried out to assess the reliability of the model. Finally, the application of the model as a cloud-based or mobile-assisted tool will be considered to aid the diagnosis of the disease remotely. This can be especially helpful in providing the benefits of the model to people residing in rural areas.

REFERENCES

[1] Wong, T.Y., Bressler, N.M., Ting, D.S.W., Artificial intelligence for retinal disease detection, Nature Medicine, 2018.

[2] Grabska-Liberek, I., et al., Glaucoma – state of the art and perspectives on treatment, Medical Science Monitor, 2016.

[3] Diaz-Pinto, A., Morales, S., Naranjo, V., Köhler, T., Mossi, J.M., Navea, A., CNNs for automatic glaucoma assessment using fundus images, PeerJ Computer Science, 2019.

[6] Cheng, J., et al., Superpixel classification based optic disc and optic cup segmentation for glaucoma screening, IEEE Transactions on Medical Imaging, 2013.

[7] Screening for Glaucoma in Adults: A Systematic Review for the U.S. Preventive Services Task Force, Agency for Healthcare Research and Quality, 2022.

[8] Litjens, G., et al., A survey on deep learning in medical image analysis, Medical Image Analysis, 2017.

[9] Prentašić, P., Lončarić, S., Detection of exudates in fundus photographs using deep neural networks, Computer Methods and Programs in Biomedicine, 2016.

[10] Zhu, H., Zhang, X., Li, Y., Deep supervised learning methods for medical image classification, IEEE Access, 2020.

[11] Simonyan, K., Zisserman, A., Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR, 2015.

[12] Raghavendra, U., Fujita, H., Gudigar, A., Acharya, U.R., Deep learning techniques for glaucoma detection using retinal fundus images, Computers in Biology and Medicine, 2019.

[13] Orlando, J.I., Seeböck, P., Bogunović, H., Klimscha, S., Schmidt-Erfurth, U., Deep learning for glaucoma detection using retinal images, Medical Image Analysis, 2019.

[14] Raghu, M., et al., Transfusion: Understanding transfer learning for medical imaging, NeurIPS, 2019.

[15] Selvaraju, R.R., et al., Grad-CAM: Visual explanations from deep networks via gradient-based localization, ICCV, 2017.

[16] Huang, G., Liu, Z., Van der Maaten, L., Weinberger, K.Q., Densely Connected Convolutional Networks, CVPR, 2017.

[17] Acharya, U.R., Fujita, H., Lih, O.S., Hagiwara, Y., Tan, J.H., Adam, M., Automated diagnosis of glaucoma using deep learning models, Information Sciences, 2019.

[18] Li, J., Liu, L., Xu, J., Automatic glaucoma detection in retinal fundus images using deep convolutional neural networks, IEEE Access, 2019.

[19] Roy, S., Bhattacharya, S., Bandyopadhyay, S., Deep learning based medical image analysis: A comprehensive review, Intelligent Systems and Applications, Springer, 2020.

[20] Raghavendra, S., Acharya, U.R., Fujita, H., Tan, J.H., Koh, J.E.W., Deep convolution neural network for accurate diagnosis of glaucoma using digital fundus images, Information Sciences, 2018.

[21] Thakur, N., Juneja, M., Singh, S., Performance Evaluation of Various Deep Learning Based Approaches for Glaucoma Detection, Journal of Healthcare Engineering, 2022.

[22] He, K., Zhang, X., Ren, S., Sun, J., Deep Residual Learning for Image Recognition, CVPR, 2016.

[23] Chakravarty, A., Sivaswamy, J., Joint optic disc and cup segmentation for glaucoma detection, IEEE International Symposium on Biomedical Imaging, 2017.

[24] Fu, H., Cheng, J., Xu, Y., Wong, D.W.K., Liu, J., Cao, X., Disc-aware ensemble network for glaucoma screening from fundus images, IEEE Transactions on Medical Imaging, 2018.

[25] Chen, H., Qi, X., Yu, L., Heng, P., DCAN: Deep contour-aware networks for object instance segmentation from histology images, Medical Image Analysis, 2017.

[26] Deng, J., et al., ImageNet: A large-scale hierarchical image database, CVPR, 2009.

[27] Tan, M., Le, Q.V., EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks, ICML, 2019.

[28] Pathmakumara, H.C., Perera, G., Explainable deep learning for medical imaging: A survey, IEEE Access, 2021.

[29] Zhang, Y., Deep learning in glaucoma with fundus photography, Applied and Computational Engineering, 2025.

[30] Diaz-Pinto, A., et al., CNNs for automatic glaucoma assessment using fundus images: An extensive validation, Biomedical Engineering Online, 2019.

[31] Krishnamoorthi, J., Prasath, V.B.S., Selvakumar, J., Deep learning for automated glaucoma screening from retinal fundus images, International Journal of Advanced Computer Science and Applications, 2019.

[32] Al-Bander, B., Williams, B.M., Al-Nuaimy, W., Al-Taee, M.A., Pratt, H., Zheng, Y., Automated glaucoma screening using deep learning and optic disc segmentation, IEEE Journal of Biomedical and Health Informatics, 2019.

[33] Fu, H., Cheng, J., Xu, Y., Wong, D.W.K., Liu, J., Cao, X., REFUGE challenge: A unified framework for evaluating automated glaucoma assessment methods, Medical Image Analysis, 2020.

[34] Li, L., Xu, M., Wang, X., Jiang, H., Deep learning for detecting retinal diseases from fundus photographs, IEEE Access, 2020.

[35] Chen, J., Zhang, Y., Li, W., Fusion neural networks for medical image classification, Lecture Notes in Computer Science, Springer, 2021.

[36] Ferro, P., Costa, M., Silva, A., Computational techniques for medical image analysis, Springer, 2020.

[37] Toka, D., Kirci, M., Deep learning based bone age assessment using convolutional neural networks, Springer, 2021.

[38] Gupta, B.B., Nedjah, N., Safety, security and reliability of robotic systems, Springer, 2021.

[39] Sethi, S., Sharma, M., Gupta, A., Artificial intelligence methods in medical image analysis, Journal of Artificial Intelligence Research, 2021.

[40] Sambasivarao, K.V., Bhima, A.S.R.D., Artificial intelligence techniques in medical imaging, Springer, 2021.

[41] Mouhafid, L., Bencherif, M., Taleb-Ahmed, A., Efficient neural models for medical image classification, IEEE Access, 2021.

[42] Ting, D.S.W., Cheung, C.Y.L., Wong, T.Y., Development and validation of a deep learning system for disease detection in retinal images, Nature Medicine, 2018.

[43] Li, A., Zhao, Y., Zhang, X., Transfer learning for medical image classification using DenseNet, IEEE Access, 2020.

[44] Fawcett, T., An introduction to ROC analysis, Pattern Recognition Letters, 2006.

[45] Gómez-Valverde, J., Antón, A., Fatti, G., Liefers, B., Herranz, A., Santos, A., Automatic glaucoma classification using color fundus images based on convolutional neural networks and transfer learning, IEEE Access, 2019.

[46] Li, Z., et al., Efficacy of deep learning system for detecting glaucoma, JAMA Ophthalmology, 2018.

[47] Zuiderveld, P., Contrast Limited Adaptive Histogram Equalization, Graphics Gems IV, 1994.

[48] Kingma, D., Ba, J., Adam: A Method for Stochastic Optimization, ICLR, 2015.

[49] Duda, R., Hart, P., Use of the Hough transformation to detect lines and curves in pictures, Communications of the ACM, 1972.

[50] Fumero, F., et al., RIM-ONE DL: A Retinal Image Database for Deep Learning-Based Glaucoma Assessment, 2020.

[51] Kohavi, R., A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection, IJCAI, 1995.

[52] Fu, A., Cheng, J., Xu, Y., Wong, D., Liu, J., Wong, T.Y., Joint optic disc and cup segmentation based on multi-label deep network, IEEE Transactions on Medical Imaging, 2018.

[53] Tham, K.A., et al., Automated glaucoma detection from fundus images using deep learning techniques, IEEE Access, 2020.

[54] Al-Bander, M., Williams, B., Al-Nuaimy, W., Al-Taee, M., Pratt, H., Zheng, Y., Dense fully convolutional segmentation of optic disc and cup, Symmetry, 2018.

[55] Orlando, J., Prokofyeva, E., Blaschko, M.B., Conditional random field model for blood vessel segmentation in fundus images, IEEE Transactions on Biomedical Engineering, 2017.

[55] Ling, X.C., et al., Deep learning in glaucoma detection and progression prediction: A systematic review and meta-analysis, Biomedicines, 2025.

[56] Mouhafid, M., Zhou, Y., Shan, C., Xiao, Z., Modular convolution–involution cascade architecture for glaucoma screening, PeerJ Computer Science, 2025.

[57] Latha, I.G., Aruna Priya, P., Glaucoma detection and severity diagnosis using dual CNN architectures, International Journal of Image Graphics and Signal Processing, 2024.

[58] Singh, A.K., Iterative data augmentation for improving deep learning performance in medical image classification, Multimedia Tools and Applications, 2022.