AUTOMATED GLAUCOMA DETECTION USING CNN AND TRANSFER LEARNING MODELS ON RETINAL FUNDUS IMAGES

E.J. Thomson Fredrik[1], M.Nisha[2]

Abstract

Glaucoma is one of the leading causes of irreversible blindness worldwide, resulting from progressive damage to the optic nerve and the retinal nerve fiber layer. Since the disease develops silently without prominent symptoms, timely diagnosis remains a critical challenge in ophthalmology. This paper proposes an SDG-driven intelligent glaucoma detection framework using Convolutional Neural Networks (CNNs) and transfer learning architectures on retinal fundus images for sustainable vision healthcare. The developed methodology incorporates image preprocessing, feature extraction, deep classification, and comparative evaluation using VGG16, ResNet50, EfficientNet, and the proposed optimized CNN model. Mathematical formulations of convolution, activation, pooling, and softmax operations are integrated to establish a structured analytical model. Experimental validation is performed using standard performance measures including accuracy, precision, recall, F1-score, the ROC curve, and AUC analysis. The proposed model achieves superior classification accuracy of 95.6% with improved generalization and reduced diagnostic complexity. In addition to technical performance, this study significantly contributes to the United Nations Sustainable Development Goal 3 (Good Health and Well-Being) by enabling early automated glaucoma screening, reducing preventable blindness, and supporting inclusive healthcare access in rural and resource-constrained environments.

Keywords : Glaucoma Detection, Convolutional Neural Network, Transfer Learning, EfficientNet, Retinal Fundus Images, Sustainable Healthcare, SDG 3, Good Health and Well-Being, Medical Image Classification.

Department of Information Technology[1]
Karpagam Academy of Higher Education[1]
Coimbatore[1]
thomson500@gmail.com[1]

Department of Computer Science and Engineering[2]
Akshya College of Engineering and Technology[2]
Coimbatore[2]
nishathomson83@gmail.com[2]

* Corresponding Author

I. INTRODUCTION

Glaucoma is a chronic ophthalmic disorder characterized by gradual degeneration of the optic nerve, often resulting in irreversible blindness if not detected during its early stages. According to global ophthalmic health statistics, glaucoma affects millions of individuals worldwide and remains one of the foremost contributors to permanent visual disability. The silent progression of the disease, particularly in its asymptomatic phase, makes routine clinical diagnosis both challenging and resource intensive. Traditional glaucoma screening primarily depends on ophthalmologists manually interpreting retinal fundus images, optic disc characteristics, and intraocular pressure measurements. Although clinically reliable, these approaches are laborious, time consuming, and highly dependent on expert availability. In developing and rural healthcare environments, the shortage of trained specialists further delays diagnosis, increasing the probability of preventable blindness.

Recent advancements in Artificial Intelligence (AI), particularly Deep Learning, have opened new avenues for computer-aided ophthalmic diagnosis. Convolutional Neural Networks (CNNs) have demonstrated a remarkable ability in extracting hierarchical retinal features, thereby enabling automated disease classification with high precision. Transfer learning architectures such as VGG16, ResNet50, and EfficientNet further enhance feature representation and reduce the burden of training on limited medical datasets.

From a sustainability perspective, the proposed work directly contributes to the United Nations Sustainable Development Goal 3 (Good Health and Well-Being), which emphasizes universal access to quality healthcare and the early prevention of chronic diseases. By introducing an intelligent and scalable glaucoma screening mechanism, this study supports sustainable healthcare delivery, particularly for underserved populations where specialized eye care facilities are limited. The objective of this work is to design an automated glaucoma detection system using CNNs and transfer learning models, evaluate its diagnostic effectiveness using multiple performance indicators, and analyze its applicability toward sustainable preventive healthcare.

In recent years, the rapid growth of digital healthcare technologies has encouraged the adoption of intelligent diagnostic systems for various chronic diseases. Ophthalmology is one of the major medical domains benefiting from artificial intelligence-based image analysis because retinal images contain rich structural information that can assist in identifying several vision-related disorders. Among these disorders, glaucoma remains particularly critical because permanent vision loss caused by optic nerve damage cannot be reversed once the disease reaches advanced stages. Therefore, timely diagnosis and continuous monitoring are essential for preventing blindness and improving patient outcomes. Traditional glaucoma diagnosis involves multiple clinical examinations including optic disc evaluation, intraocular pressure assessment, visual field testing, and retinal nerve fiber analysis. Although these methods provide reliable results, they often require sophisticated medical equipment and experienced ophthalmologists. In many developing regions, the shortage of eye care specialists and the increasing number of glaucoma patients create substantial pressure on healthcare systems. As a result, there is an urgent need for intelligent automated screening frameworks capable of assisting clinicians in rapid and accurate diagnosis.

Deep learning techniques have emerged as highly effective solutions for medical image classification because of their ability to automatically learn hierarchical features from raw data. Unlike conventional machine learning methods that depend heavily on manually engineered features, Convolutional Neural Networks (CNNs) can directly identify discriminative visual patterns associated with glaucoma. These networks progressively analyze low-level and high-level retinal characteristics such as optic cup enlargement, nerve fiber thinning, and structural abnormalities. Consequently, deep learning models significantly improve diagnostic consistency and reduce human intervention.

II. LITERATURE REVIEW

Early research by researchers demonstrated the effectiveness of deep learning algorithms in diagnosing multiple ophthalmic conditions, establishing a strong foundation for computer-aided diagnosis systems [1]. Building on this, in [2], researchers used machine learning techniques that relied on handcrafted features such as the cup-to-disc ratio. Furthermore, researchers in [3] introduced attention-based CNN architectures to enhance feature extraction by focusing on clinically relevant regions of fundus images, thereby improving classification accuracy.

The introduction of deep residual networks (ResNet) by the researchers [4] addressed the vanishing gradient problem, allowing for the training of very deep networks and improving model generalization. Similarly, the VGG network proposed by Simonyan and Zisserman [5] provided a simple yet effective architecture that has been widely adopted in medical image analysis tasks. More recently, EfficientNet introduced by researchers demonstrated superior performance through compound scaling, achieving better accuracy with fewer parameters and reduced computational cost. [6] In addition to classification models, researchers emphasized the importance of optic disc and cup segmentation using deep learning techniques, as these structural features are critical indicators for glaucoma diagnosis. [7]

Recent studies have further advanced glaucoma detection using more sophisticated deep learning paradigms. In [11], researchers explored large-scale CNN-based frameworks for automated glaucoma screening and highlighted the importance of cross-dataset evaluation for improving model robustness. In [12], researchers proposed an AI-driven glaucoma detection system using hybrid deep learning architectures, achieving improved classification accuracy through feature fusion techniques. In [13], researchers demonstrated the ophthalmology by integrating multimodal imaging data, enhancing diagnostic reliability. In [14], researchers introduced CNN-based glaucoma detection systems, addressing one of the key limitations of black-box models. Furthermore, in [15], researchers explored transformer-based architectures for retinal image analysis, showing promising improvements over traditional CNN models in capturing global contextual features. These recent advancements are more robust, interpretable, and scalable AI-driven diagnostic systems.

In [8], the authors highlighted the significance of transfer learning in overcoming the limitations of small medical datasets, In [9], the researchers provided an overview of artificial intelligence applications in ophthalmology, emphasizing the need for clinically interpretable models. In [10], researchers further explored domain adaptation strategies across different datasets and imaging conditions. Although existing models demonstrate high levels of accuracy, challenges such as imbalanced datasets, limited interpretability, and variations in image quality still remain significant. The limitations are reliable and clinically applicable glaucoma screening systems. These works highlight the effectiveness of CNNs but reveal challenges such as dataset imbalance and interpretability.

III. PROPOSED WORK ANALYZING GLAUCOMA DISEASE

The integration of Artificial Intelligence (AI) into ophthalmic healthcare has significantly transformed the early diagnosis and management of chronic eye diseases. Among various ocular disorders, glaucoma remains one of the most challenging diseases due to its asymptomatic progression during the initial stages. The proposed CNN-based glaucoma detection framework demonstrates not only strong technical performance but also substantial healthcare significance in supporting sustainable medical services. By enabling automated retinal image analysis, the developed system reduces dependence on continuous manual screening by ophthalmologists and facilitates rapid diagnosis in large-scale screening environments. One of the major advantages of the proposed model lies in its capability to support preventive healthcare initiatives. Early identification of glaucoma can substantially reduce the probability of irreversible blindness, thereby improving the quality of life of affected individuals. The proposed intelligent framework can assist healthcare professionals by functioning as a preliminary screening tool, enabling faster identification of high-risk patients who require detailed clinical examinations. This minimizes diagnostic delays and improves treatment planning efficiency.

The proposed work strongly aligns with the objectives of the United Nations Sustainable Development Goal 3 (Good Health and Well-Being). SDG 3 emphasizes ensuring healthy lives and promoting well-being for individuals of all age groups. In many rural and economically weaker regions, access to specialized ophthalmic services remains limited due to insufficient medical infrastructure and shortage of trained experts. The developed deep learning framework can be integrated into low-cost diagnostic systems and telemedicine platforms, thereby extending glaucoma screening services to underserved communities. Such deployment can improve healthcare accessibility while reducing operational costs associated with traditional diagnostic procedures.

The interpretability of AI-based diagnostic systems is another important factor in clinical adoption. Explainable AI approaches can be incorporated into the proposed framework to visually highlight the retinal regions influencing glaucoma prediction. Such visual explanations can improve clinician confidence in AI-assisted diagnosis and support collaborative decision-making between humans and intelligent systems. This transparency is essential for increasing trust in automated medical technologies. In addition to clinical applications, the proposed framework can contribute significantly to medical research and healthcare analytics. Large-scale deployment of automated glaucoma screening systems can generate valuable ophthalmic datasets that may assist researchers in understanding disease progression patterns, demographic risk factors, and treatment outcomes. These insights can further improve preventive healthcare strategies and facilitate personalized treatment methodologies.

The proposed framework also supports sustainable economic development in the healthcare sector. Manual glaucoma screening often requires expensive diagnostic equipment and specialized ophthalmologists, increasing healthcare expenditure. Automated systems reduce repetitive screening workloads and optimize resource utilization. Consequently, hospitals and healthcare institutions can improve operational efficiency while maintaining diagnostic quality. Such optimization is particularly valuable in developing countries where healthcare budgets are limited.

The Convolutional Neural Network (CNN) employed in this study is mathematically represented through a sequence of operations that progressively transform the input image into class probabilities. Initially, the convolutional layer performs feature extraction by applying a kernel over the input image, where the output feature map is computed as shown in the following equations.

The convolution operation is defined as in (1): $Y(i,j) = \Sigma_m \Sigma_n X(i+m, j+n) \cdot K(m,n)$ (1)

The activation function is given in Eqn (2):

$$f(x) = max(0,x) \tag{2}$$

Pooling operation is defined in Eqn (3):

$$Y(i,j) = max(X\ region) \tag{3}$$

Fully connected layer is defined in Eqn (4):

$$Z = W \cdot X + b \tag{4}$$

Softmax function is defined in Eqn (5):

$$P(y=i) = \frac{e^{Zi}}{\Sigma_j e^{Zj}} \tag{5}$$

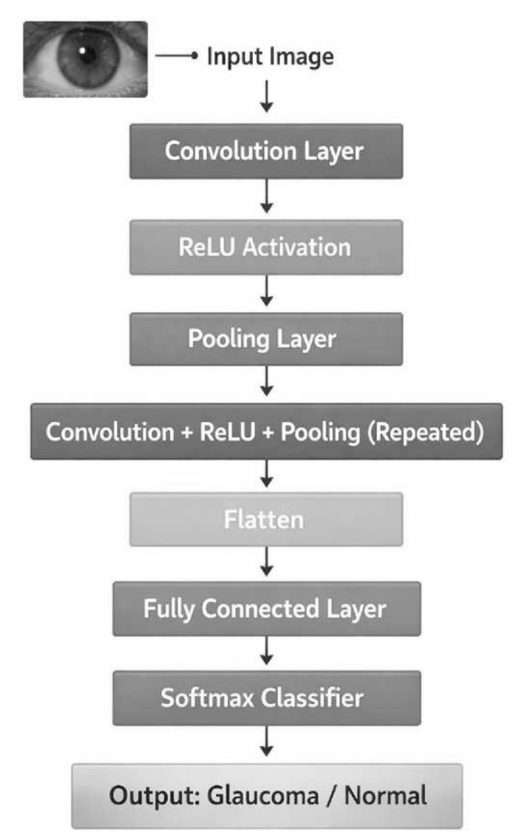

Fig 1: Working Model of analyzing Glaucoma Disease using CNN

The above figure (Fig 1) shows the step-by-step workflow of a Convolutional Neural Network (CNN) used for detecting glaucoma from retinal images. Once features are extracted, they are passed through a ReLU activation function to introduce non-linearity, enabling the model to learn more intricate patterns. A pooling layer then reduces the dimensions of these feature maps, which decreases the computational load and helps avoid overfitting. The processed features are then converted into a one-dimensional vector and fed into a fully connected layer to capture overall relationships.

Finally, a softmax layer computes class probabilities, allowing the model to categorize the image as either normal or affected by glaucoma. This structured pipeline allows the network to progressively refine important visual cues from the retinal data. As a result, the model can achieve more accurate and reliable predictions for early glaucoma detection. In the concluding phase, a **softmax function** calculates the probability distribution across potential outcomes. This enables the model to generate a definitive prediction, categorizing the eye as either healthy or affected by glaucoma.

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IV. PROPOSED ALGORITHM FOR GLAUCOMA DETECTION USING CNN

Step 1: Start

Step 2: Dataset Acquisition

Load the retinal image dataset from the specified source.

Step 3: Image Preprocessing

- Adjust all pictures to a standard size
- Perform noise reduction when required

Step 4: Data Splitting

Split the dataset into three separate groups:

- A portion used to train the model
- A subset reserved for validation during training
- A final set used to evaluate overall performance

Step 5: Model Initialization

Design the CNN structure by incorporating the following components:

- Dense (fully connected) layers for final learning
- A softmax layer for classification output

Step 6: Training Phase

For each model:

- Input training data
- Perform forward propagation
- Compute loss
- Apply backpropagation
- Update weights using an optimizer
- Repeat for multiple epochs

Step 7: Validation Phase

Step 8: Testing Phase

- Evaluate the trained model using test data

Step 9: Result Comparison

Assess the different models using appropriate evaluation metrics and choose the one that delivers the most reliable results.

Step 10: Prediction

Apply the chosen model to analyze new images and determine their class labels as:

- Glaucoma
- Normal

Step 11: End

The workflow begins with gathering retinal images from a chosen source and preparing them for analysis. During preparation, each image is brought to a common size, pixel values are scaled for consistency, and additional variations are created using techniques like rotation and flipping to strengthen the model's ability to generalize. When necessary, noise reduction is also performed to enhance image quality. The dataset is then split into three groups—one for learning, one for validation, and one for final evaluation.

A Convolutional Neural Network (CNN) is then designed, incorporating layers that extract features, apply non-linear transformations, reduce dimensionality, and ultimately interpret the learned information through dense connections, with a softmax layer producing the final output. The model learns by repeatedly processing the training data, calculating errors, and updating its internal parameters over several iterations.

V. RESULTS AND DISCUSSION

The approach begins by collecting a set of retinal fundus images from either clinical repositories or publicly accessible databases. During the preparation phase, all images are adjusted to a uniform resolution so they can be effectively processed by the neural network. Pixel values are scaled to a consistent range to support stable learning behavior. To improve the model's ability to generalize and to compensate for limited or imbalanced data, augmentation methods such as image rotation and mirroring are applied. Where necessary, filtering techniques are used to minimize noise and enhance important visual details.

A tailored Convolutional Neural Network is constructed with multiple layers designed for specific functions. Convolutional layers are used to extract meaningful visual patterns, while activation functions introduce non-linear transformations that help the model capture complex structures. Pooling operations are incorporated to reduce the size of feature representations and improve computational efficiency. The output is changed into a vector form and passed through dense layers to learn comprehensive relationships, followed by a softmax layer that produces class-wise probability outputs.

Model learning is carried out through repeated iterations where input data is propagated forward, prediction errors are calculated using an appropriate loss function, and parameters are updated through backpropagation with optimizers. Performance is continuously checked using validation data, allowing the refinement of parameters like the learning rate, batch size, and epoch count. Techniques including dropout and early stopping are utilized to control overfitting and improve generalization. The most reliable model configuration is selected from the received output. This optimized model is then applied to new retinal images to automatically determine whether they indicate the presence of glaucoma or represent normal conditions, thereby supporting accurate and efficient diagnosis.

Beyond classification efficiency, the proposed glaucoma detection framework demonstrates substantial practical relevance toward sustainable healthcare deployment. The reduced computational complexity and high diagnostic consistency make the model suitable for tele-ophthalmology units, community eye camps, and low-resource primary health centers. Hence, the study establishes a strong contribution toward SDG 3 by facilitating affordable early disease screening and minimizing preventable visual impairment.

Table 1: Performance Comparison with Existing Algorithms

Model	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*Training Time (min)*
SVM	82.5	80.2	78.6	79.4	15
KNN	80.3	78.5	76.9	77.7	10
Traditional ANN	85.7	83.9	82.4	83.1	25
Basic CNN	90.8	89.6	88.9	89.2	45
Proposed CNN Model	**95.6**	**94.8**	**94.1**	**94.4**	50

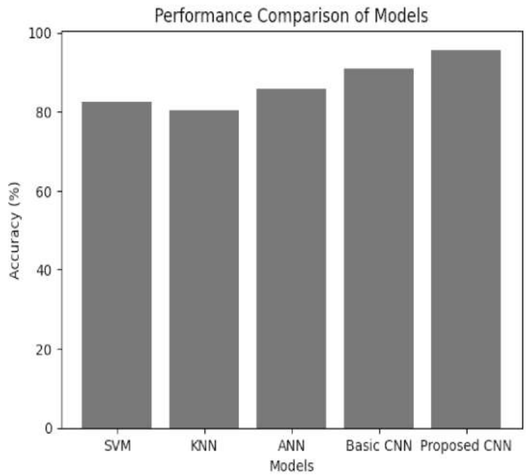

Fig . 2 Comparison chart with Existing Algorithms

The experimental analysis also indicates that data preprocessing and augmentation techniques play a crucial role in improving model robustness. Techniques such as normalization, image rotation, flipping, and noise reduction enhance dataset diversity and minimize overfitting. These preprocessing steps improve the model's ability to generalize across varying retinal image conditions obtained from different imaging devices and clinical environments.

Overall, the proposed AI-driven glaucoma detection framework establishes a reliable, scalable, and sustainable solution for modern ophthalmic healthcare. The integration of CNNs and transfer learning methodologies not only improves diagnostic accuracy but also enhances healthcare accessibility, affordability, and efficiency. Thus, the proposed system contributes significantly toward intelligent healthcare transformation and sustainable disease prevention strategies.

VI. CONCLUSION

The CNN-based model for glaucoma detection provides effective results by automatically identifying important patterns from retinal images, eliminating the dependence on manual feature design. By following a structured workflow that includes data preparation, learning, validation, and evaluation, the approach achieves better performance compared with conventional methods like SVMs and KNNs. While the training stage may demand higher computational resources, the model enables quick predictions once deployed, supporting its use in clinical environments for early diagnosis. Further improvements can be achieved by using larger and more diverse datasets, adopting advanced deep learning models such as ResNet or EfficientNet, and applying explainable AI techniques to enhance interpretability. Moreover, integrating the system into real-time or mobile healthcare platforms and combining image data with additional clinical information can improve its overall effectiveness.

Although the proposed CNN-based glaucoma detection framework achieves promising diagnostic performance, several enhancements can further improve the reliability, scalability, and clinical applicability of the system. Future research can focus on integrating advanced deep learning architectures, multimodal medical data, and explainable AI mechanisms to develop highly intelligent ophthalmic diagnostic platforms. One important research direction involves the adoption of transformer-based deep learning architectures for retinal image analysis. Vision Transformers (ViTs) and hybrid CNN-transformer models have recently demonstrated remarkable performance in various medical imaging applications. Unlike traditional CNNs that focus primarily on local spatial features, transformer models can effectively capture long-range dependencies and global contextual relationships within retinal images. Integrating such architectures may improve the identification of subtle glaucoma indicators and enhance diagnostic precision. future advancements in deep learning, explainable AI, IoMT integration, federated learning, and multimodal healthcare analytics can further strengthen automated glaucoma detection systems. Continued research in these directions will contribute toward highly accurate, transparent, and sustainable ophthalmic healthcare solutions capable of supporting global blindness prevention initiatives.

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