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A CAD Method for Early Detection of Glaucoma Employing CNN from Fundus Photographs

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Abstract: Early detection and diagnosis of glaucoma, a crippling eye illness that causes irreversible vision loss, are essential for effective care. In this study, convolutional neural networks are used to diagnose glaucoma in a novel way (CNNs). The methodology incorporates local binary pattern (LBP) for image preprocessing using a rigorously curated dataset of Fundus Photos, which includes 1450 images with 899 cases of glaucoma and 551 non-glaucomatous images. Ten layers make up the proposed CNN architecture, including a Conv2D layer for feature extraction, a MaxPooling2D layer for down sampling, a Flatten layer for vectorization, and seven Dense levels for classification. By detecting glaucoma with an accuracy of 99% during training and a loss of 4%, this CNN model has demonstrated outstanding performance. On the test dataset, the model achieves a test loss of 30% and an accuracy of 94%. Confusion matrix, precision, recall, F1-score, support, Matthew's correlation coefficient (MCC), and Area Under the Receiver Operating Characteristic Curve are just a few of the metrics used to assess this model (AUC). The model's strong performance in evaluation measures, along with its high accuracy and low loss, point to its potential for early glaucoma detection and, consequently, its critical role in maintaining vision and improving patient treatment. In order to achieve the goal of prompt diagnosis and treatment, this research advances automated glaucoma detection systems.

Keywords: *Glaucoma, CNN, Precision, F1 Score, Recall, Matthews correlation, Local binary pattern*

1. Introduction

If undiagnosed and untreated, glaucoma is a dangerous eye ailment that can cause irreversible vision loss. Convolutional Neural Networks are one of the cutting-edge techniques for glaucoma early detection [1-7]. Early detection of glaucoma is essential for preventing additional damage (CNNs). Convolutional Neural Networks are a family of deep learning models that were created primarily for image-related tasks [8]. Since glaucoma detection requires the processing of retinal pictures and scans of the optic nerve head, these models are excellent for this task. An overview of glaucoma detection with CNNs is provided below: The Importance of Glaucoma Detection. A collection of eye conditions known as glaucoma generally result from elevated intraocular pressure and damage the optic nerve. It is one of the main causes of permanent blindness in the world. Vision loss can be avoided with early detection and prompt treatment. Retinal imaging in glaucoma detection: Ophthalmologists use a variety of diagnostic procedures, such as retinal imaging, to identify glaucoma. OCT and fundus photography, which take high-resolution pictures of the retina and the optic nerve head, are two typical methods [9-13]. CNNs in Medical Image Analysis: CNNs have completely changed the way that medical image analysis is done. They work effectively for jobs like spotting anomalies and diseases in medical imaging because they excel at automatically learning pertinent aspects from photos. CNNs' benefits in glaucoma detection: Traditional image processing methods may find it difficult to automatically learn and extract complex features from retinal pictures using CNNs. They offer a data-driven methodology that enables the model to evolve and enhance its performance over time. CNN-based systems' rapid picture processing speed makes it possible to efficiently screen lots of patients [14]. Increased intraocular pressure and eventual vision loss are typical symptoms of glaucoma, a chronic and progressive eye condition that affects the optic nerve. It is the main contributor to permanent blindness globally. Early identification is critical for optimal care and the preservation of vision because glaucoma frequently develops gradually and without obvious symptoms in its early stages. Individuals with glaucoma suffer from damage to the optic nerve, which is in charge of carrying visual information from the eye to the brain. This leads to a progressive loss of peripheral vision and, eventually, central vision. Glaucoma can cause serious vision loss or perhaps total blindness if ignored. Therefore, early glaucoma diagnosis is essential to start the right therapy and stop future vision loss. Convolutional Neural Networks (CNNs) have demonstrated astounding efficiency in a range of medical imaging applications, including the identification of glaucoma. CNNs are a class of deep learning models that are especially made for processing visual data, making them perfect for examining medical images like retinal scans, which are essential for glaucoma

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diagnosis. We can automate the process of analyzing these photos and help medical practitioners identify glaucoma in early stages by utilizing CNN [7]. In this paper, we explore the use of CNNs for retinal imaging-based glaucoma identification. We investigate how these sophisticated neural networks can extract complex pat- terns and information from retinal pictures to assist in the detection of glaucoma-related symptoms. We want to use CNNs to build a reliable and effective automated system that could revolutionise glaucoma screening and help with early detection and proactive management of this illness that could cause blindness. The remaining sections are given as. In Section 2, we described literature review. Problem formulation given in Section 3. Methodology provided in Section 4. Results are discussed in Section 5. Conclusion given in Section 6.

2. Literature Review

In this section we will go through several published research work based on similar domain. Explainable Machine Learning Model for Glaucoma Diagnosis and Its Interpretation Sejong Oh, Yuli Park, Kyong Jin Cho, and Seong Jae Kim3. The study aims to create a machine learning model for diagnosing glaucoma and provide an explanation for its predictions. Clinical data, including visual field tests, retinal nerve fiber layer optical coherence tomography (RNFL OCT) tests, intraocular pressure measurements, and fundus photography, were used for feature selection. Five features were chosen for the prediction model, which was tested using several algorithms. All models demonstrated high diagnostic performance, with accuracy ranging from 0.903 to 0.947. The XGboost model achieved the highest accuracy at 0.947, along with good sensitivity, specificity, and AUC values. Three statistical charts were employed to explain the XGboost model's predictions. This study represents a pioneering effort in applying explainable artificial intelligence to eye disease diagnosis [15-20].

Glaucoma Diagnosis with Machine Learning Based on Optical Coherence Tomography and Color Fundus Images Guangzhou An, Kazuko Omodaka, Kazuki Hashimoto, Satoru Tsuda, Yukihiro Shiga, Naoko Takada. The study aimed to develop a machine learning algorithm for diagnosing glaucoma in patients with open-angle glaucoma using three-dimensional optical coherence tomography (OCT) data and color fundus images. They enrolled 208 glaucomatous and 149 healthy eyes, capturing OCT data and fundus images. A convolutional neural network (CNN) was trained using different input images, including grayscale fundus images, thickness maps, and deviation maps. Data augmentation and dropout were applied for training the CNN. A random forest (RF) was used to combine the results from each CNN model and classify healthy and glaucomatous eyes. The 10-fold cross-validation area under the receiver operating characteristic curve (AUC) results for the CNNs ranged from 0.940 to 0.952, and the RF com- bining all models achieved an AUC of 0.963. This machine learning system accurately distinguishes between healthy and glaucomatous subjects based on OCT and fundus image data, potentially improving glaucoma diagnostic accuracy [1].

R. N. Weinreb and P. T. Khaw, "Primary open-angle glaucoma, "The Lancet, vol. 363, no. 9422, pp. 1711–1720, 2004. Primary open-angle glaucoma is a common and progressive eye condition that can lead to irreversible vision loss if not detected and treated early. Early diagnosis relies on examining the optic disc, retinal nerve fiber layer, and visual field. Re- cent advancements in imaging and psychophysical tests have enhanced the ability to detect and monitor disease progression. Long-term clinical trials have shown that reducing intraocular pressure can effectively prevent glaucoma progression, with the extent of protection linked to the degree of pressure reduction. Ongoing improvements in treatment include more effective and better-tolerated medications and surgical procedures to lower intraocular pressure. Additionally, there are promising developments in treatments aimed at directly protecting the retinal ganglion cells, which are damaged in glaucoma [21].

M. A. Kass, D. K. Heuer, E. J. Higginbotham et al., "The ocular hypertension treatment study," Archives of Ophthalmology, vol. 120, no. 6, pp. 701–713, 2002 Primary open-angle glaucoma (POAG) is a leading cause of blindness in the United States and globally, affecting millions. Many people in the U.S., estimated at three to six million, are at a heightened risk of developing POAG due to elevated intraocular pressure (IOP) or ocular hypertension. However, there is no consensus on the effectiveness of medical treatment in delaying or preventing the onset of POAG in individuals with elevated IOP. To address this, the Ocular Hypertension Treatment Study was conducted. The study involved 1,636 participants aged 40 to 80 years with no signs of glaucomatous damage but with IOP levels ranging from 24 mm Hg to 32 mm Hg in one eye and between 21 mm Hg and 32 mm Hg in the other eye. These participants were randomly assigned to either an observation group or a group receiving commercially available topical ocular hypotensive medication. The medication group aimed to reduce IOP by 20% or more, with a target IOP of 24 mm Hg or lower [9].

M. C. Leske, A. Heijl, L. Hyman et al., "Predictors of long-term progression in the early manifest glaucoma trial," Ophthalmology, vol. 114, no. 11, pp. 1965–1972, 2007. The study found that overall progression of primary open-angle glaucoma (POAG) was 67% by the end of the follow-up period (median of 8 years). Treatment with ocular hypotensive medication reduced the risk of progression by approximately half (hazard ratio [HR] of 0.53 with a 95% confidence interval [CI] of 0.39–0.72). This protective effect of treatment was consistent for patients with both higher and lower baseline intraocular pressure (IOP). Baseline factors associated with a higher risk of progression included higher IOP, presence exfoliation syndrome, having glaucoma in both eyes, and older age. New baseline predictors of progression included lower ocular systolic perfusion pressure (¡=160 mmHg) in all patients, a history of cardiovascular disease in patients with higher baseline IOP, and lower systolic blood pressure (¡=125 mmHg) in patients with lower baseline IOP. Postbaseline factors affecting progression included IOP levels at follow- up, with a 12% to 13% average increase in progression risk for each millimeter of mercury increase in IOP. Disc hemorrhages were also predictive of progression. Additionally, thinner central corneal thickness (CCT) was identified as a new significant factor. Thinner CCT was associated with a higher risk of progression, particularly in patients with higher baseline IOP, and there was a significant interaction between IOP and CCT in affecting progression risk [11]. F. Badala`, K. Nouri-Mahdavi, D. A. Raoof, N. Leep- rechanon, S. K. Law, and J. Caprioli, "Optic disk and nerve fiber layer imaging to detect glaucoma," American Journal of Ophthalmology, vol. 144, no. 5, pp. 724–732, 2007. In a tertiary care academic glaucoma center, a study involved 92 eyes of 92 subjects, which included 46 individuals with early perimetric open-angle glaucoma and 46 controls. The study aimed to assess the diagnostic performance of various diagnostic technologies, including optical coherence tomography (OCT), scanning laser polarimetry, confocal laser ophthalmoscopy, and qualitative assessment of stereoscopic optic disk photographs. The evaluation was based on different outcome measures, including the areas under the receiver operator characteristic curves (AUCs) and sensitivities at specific predefined specificities. The study also employed Classification and Regression Tree (CART) analysis to explore combinations of quantitative parameters for diagnostic purposes. This research sought to compare and assess the effectiveness of these different diagnostic tools in distinguishing between early perimetric open-angle glaucoma and healthy control eyes [3].

R. Lisboa, A. Paranhos Jr, R. N. Weinreb, L. M. Zangwill, M. T. Leite, and F. A. Medeiros, "Comparison of different spectral domain OCT scanning protocols for diagnosing perimetric glaucoma," Investigative Ophthalmology Visual Science, vol. 54, no. 5, pp. 3417–3425, 2013. In this study, 142 eyes from 91 patients were evaluated for glaucoma. Of these, 48 eyes had progressive glaucomatous damage, while 94 eyes were controls with no signs of damage. The study assessed various parameters' diagnostic accuracy using the area under the receiver operating characteristic curves (AUC). The best parameters for diagnosis were average RNFL thickness, inferior hemisphere average thickness, and inferior quadrant average thickness. These outperformed ONH and macular parameters. Notably, the average RNFL thickness performed better than vertical cup-to-disc ratio and GCC average thickness in distinguishing glaucoma [12]. Y. K. Kim, J. W. Jeoung, and K. H. Park, "Inferior macular damage in glaucoma: its relationship to retinal nerve fiber layer defect in macular vulnerability zone," Journal of Glaucoma, vol. 26, pp. 126–132, 2017. The study aimed to investigate the prevalence of abnormally thin regions in the inferior macular ganglion cell-inner plexiform layer (mGCIPL) in glaucoma and to understand its relationship with abnormal areas in the peripapillary retinal nerve fiber layer (pRNFL), specifically the macular vulnerability zone (MVZ). The research involved 186 eyes of individuals with glaucoma. An integrated deviation map was created by overlaying mGCIPL and pRNFL deviation maps, derived from spectral-domain optical coherence tomography, onto retinal nerve fiber layer (RNFL) photography. The alignment was achieved using Photoshop software based on vascular landmarks. The peripapillary region was divided into two areas as per a previously suggested schematic model: (1) the MVZ and (2) the infer inferior portion [10].

D. S. W. Ting, C. Y.-L. Cheung, G. Lim et al., "Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes," JAMA, vol. 318, no. 22, pp. 2211–2223, 2017. In a primary validation dataset with over 71,000 retinal images from nearly 15,000 patients, a Deep Learning System (DLS) demonstrated strong diagnostic performance 90.5% sensitivity and 91.6% specificity for referable diabetic retinopathy. 100% sensitivity and 91.1% specificity for vision-threatening diabetic retinopathy. 96.4% sensitivity and 87.2% specificity for possible glaucoma. 93.2% sensitivity and 88.7% specificity for age-related macular de- generation (AMD). The DLS was trained on a total of 494,661 retinal images for detecting these conditions and validated using a primary dataset from the Singapore National Diabetic Retinopathy Screening Program and multiethnic diabetes cohorts. Training was completed in May 2016, and validation was concluded in May 2017 [18].

J. De Fauw, J. R. Ledsam, B. Romera-Paredes et al., "Clinically applicable deep learning for diagnosis and referral in retinal disease," Nature Medicine, vol. 24, no. 9, pp. 1342–1350, 2018 The ever-increasing volume and complexity of diagnostic imaging surpasses the availability of human expertise for interpretation. While AI has shown promise in classifying common diseases from 2D images, applying it to 3D diagnostic scans in real-world clinical pathways has been a challenge. In this study, a novel deep learning architecture was employed to analyze a diverse set of 3D optical coherence tomography scans from an eye hospital. The AI system demonstrated referral recommendations for sight-threatening retinal diseases that met or exceeded expert performance after training on just 14,884 scans. Notably, the tissue segmentations generated by this architecture proved to be device-independent, ensuring referral accuracy even when using segmentations from different devices. This breakthrough removes barriers to broader clinical use, eliminating the need for prohibitively large training datasets across multiple pathologies in a real- world clinical context [4].

3. Problem Statement and Objectives

Millions of people worldwide suffer from glaucoma, a chronic and degenerative eye illness that places a heavy cost on both individuals and healthcare systems. Among its key problems are Lack of Awareness and Late Diagnosis: Many glaucoma cases are not discovered until they are at an advanced stage, partly because there are no outward signs in the early stages. This leads to preventable vision loss or blindness. Limited Access to Screening and Diagnostic Services: Regular eye exams are frequently difficult to obtain, especially in underserved and rural areas, which hinders early diagnosis and intervention. Adherence to prescribed glaucoma treatments can be difficult for some people, even after they have been diagnosed, which makes the condition worse. Research and Innovation Gaps: Although there have been advancements in glaucoma management over time, there is still a need for novel therapies, diagnostic equipment, and a deeper comprehension of the disease's processes. Glaucoma has a significant financial impact on patients and healthcare systems because of the high expenses of diagnosis, treatment, and rehabilitation. The quality of life and economic productivity of persons who have vision loss are also impacted.

Convolutional neural networks (CNNs) are used to detect glaucoma, and their main goals are as follows:

Early Detection and Diagnosis: Finding glaucoma in its earliest stages is the main goal. Early diagnosis is essential for prompt intervention and therapy to stop or delay the disease's progression and, eventually, save the patient's vision.

High Sensitivity and Specificity: CNNs should successfully detect the majority of positive instances of glaucoma and should do so with high sensitivity. In addition, they must retain a high level of specificity, which means minimizing false positives and the need for additional testing on patients who do not have glaucoma. Automated screening: CNNs should make it possible to efficiently screen a lot of patients automatically. This can lessen the workload for medical staff members, making glaucoma detection more practical and affordable. Objective Evaluation: The diagnosis is made more objectively by the use of CNNs. It gets rid of the potential subjectivity that can exist in manual evaluations made by various clinicians. Efficiency and Speed: Retinal pictures can be processed by CNNs quickly, which is necessary for real-time or nearly real-time diagnosis in clinical situations. The shorter wait times for results can have a big influence on patient care. And By adopting CNNs, glaucoma detection may now be carried out not only at specialized clinics but also in rural or underdeveloped areas, enhancing healthcare equity. Scalability: The use of CNNs enables scaling, allowing for the analysis of numerous pictures as needed accommodating population-based screening and follow- up. CNNs can aid in reducing variability in image interpretation, which may be influenced by elements like the clinician's experience or the caliber of the imaging equipment. Real-time Monitoring: For patients with a proven diagnosis of glaucoma, CNN-based systems can be used to track the evolution of the disease in real-time, enabling doctors to modify treatment regimens as necessary.

In summary, glaucoma detection using CNNs aims to revolutionize the screening and diagnosis of this sight-threatening condition by improving accuracy, efficiency, and accessibility while reducing subjectivity and variability in diagnosis. Early detection and timely treatment are key to preserving patients' vision, making this application of CNN technology a critical component of modern ophthalmology.

4. Proposed Methodology

This approach seeks to build a CNN that accurately identifies glaucoma from pictures of the eyes using layers an

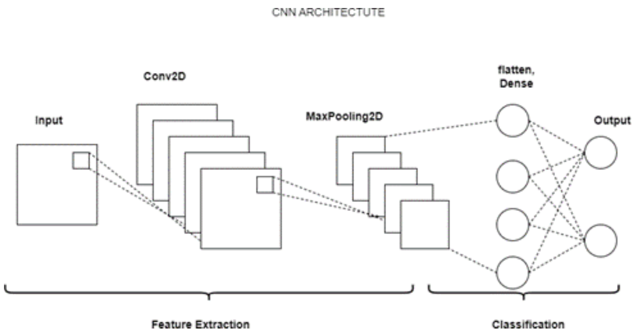

Fig. 1. CNN System Architecture

hyperparameters. It's crucial to adjust the design and parameters depending on testing and performance analysis on a relevant dataset [2] Following is the process that was used is broken down in full below: Data gathering: Compile a database of retinal photos showing both glaucoma and non-glaucoma instances. Make sure the dataset has accurate labels. Data pre-processing with Local Binary Pattern (LBP): To extract texture features from retinal images, pre-process the images using the Local Binary Pattern (LBP) method. LBP converts each pixel into a binary pattern based on the immediate area, which aids in capturing texture data. Splitting the pre-processed dataset into two subsets: A training set and a test set—is known as data splitting. Usually, a split of 80/20 is employed. Model Architecture: Add the following layers to a CNN model: One Conv2D layer with a suitable kernel size, activation function, and filter count. To down sample the features, use one MaxPooling2D layer. One Flatten layer to create a 1D vector from the 2D feature maps. Seven dense layers with the proper activation mechanisms. You can experiment with various neuronal densities in each layer. A single neuron with a sigmoid activation function in the final dense layer should be used to output the likelihood of glaucoma.

Model Training: Build the model using an optimizer and a suit- able loss function, like binary cross-entropy (e.g., Adam). Establish the number of epochs, batch size, and validation data before training the model on the training dataset. Model Evaluation: Use the following metrics to assess the model on the training and test datasets: Calculate the accuracy to assess the overall success of the categorization process. Build a confusion matrix to determine the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Precision: It evaluates how accurately favourable predictions come true. It is calculated in equation 1 and represents the proportion of correctly predicted glaucoma cases.

$$Precision = \frac{TP}{FP+TP} \tag{1}$$

Recall: The model's capacity to recognise all pertinent events is measured by recall (also known as sensitivity). The percentage of actual glaucoma cases that were accurately predicted is computed in equation 2.

$$Recall = \frac{TP}{FN+TP} \tag{2}$$

F1-Score: The harmonic mean of memory and precision is the F1-score, which balances the trade-off between recall and precision. In equation 3 it is calculated.

$$F1\ Score = \frac{Precision*Recall}{FN+TPrecision+Recall} \tag{3}$$

Support: The number of instances of each class in the actual dataset is known as support. It gives precision and recall values context.

Matthews Correlation Coefficient: A metric for evaluating the effectiveness of binary classification models is the Matthews Correlation Coefficient (MCC). It generates a value between -1 and 1, considering the four values from the confusion matrix (TP, TN, FP, and FN). Even with unbalanced courses, MCC offers a balanced solution. Area AUC (Under the ROC Curve): The model's capacity to differentiate between glaucoma and non-glaucoma cases is assessed using AUC. The area under the ROC curve, or AUC the false positive rate. Better discrimination is indicated by an increased AUC. Iterative Model Improvement: To enhance performance, modify the model's architecture, hyperparameters, or data preparation based on the evaluation findings.

Reporting and archiving: Record all aspects of the methodology, such as the dataset's specifications, the LBP preprocessing, the model's architecture, the hyperparameters, and the evaluation metrics. Give a concise description of the findings that includes the evaluation metrics, accuracy, and AUC (confusion matrix, precision, recall, F1-score, sup- port, MCC). Discuss the model's capabilities and potential ap- plications for glaucoma detection in real-world settings. By using this approach, you may methodically create and test a CNN-based glaucoma detection model with LBP pre-processing making sure it achieves the required goals of early detection and high accuracy while utilizing texture information collected by LBP. In the following Fig. 1 we have made System architecture of our CNN model which represents how layers are connected with each other. In this we can clearly see that first we have input layer which is connected to Convolutional layer i.e. Conv2D layer which is further connected to Pooling layer i.e. MaxPooling2D layer. Using convolutional and pooling layers we can extract the features and after pooling layer all other layers are connected i.e. flatten layer and remaining 7 dense layers. At last we have our output as 0 or 1.

5. Results and Discussions

In this section we will discuss about what are the scores we obtained during our experimentation. Our CNN model was tested on the ”test” dataset after being trained on images from the ”train” dataset. The accuracy graph generated by CNN model is in Table 2. We can see that CNN performed very well as we achieved accuracy of 99% with 4% loss on train dataset and similarly on test dataset we obtained 94% accuracy with 30% loss. Other than accuracies we also calculated some other evaluation parameters that are shown in Table 1. In the following table II we have compared four similar papers and describing how our paper is different from them. As we can see our proposed solution has given the most reliable results with the accuracy of 94% on test dataset and 99% on train dataset using Convolutional Neural Network (CNN) only which differs it from others. The accuracy for training dataset in shown in Fig. 2. The validation accuracy for testing dataset is provided in Fig. 3.

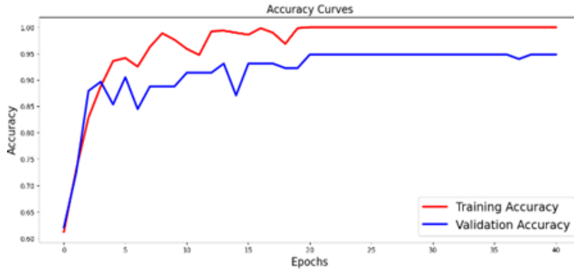

Fig. 2. Accuracy table for training dataset

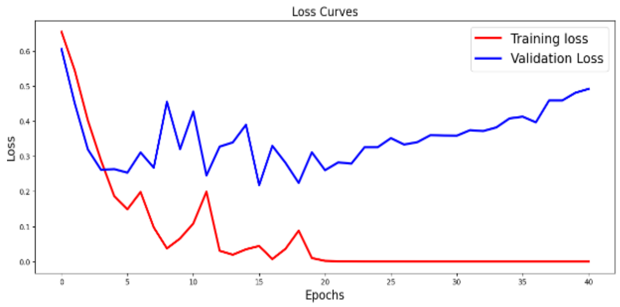

Fig. 3. Validation accuracy table for testing dataset

Table. 1. Evaluation Parameters for CNN

Evaluation Parameters	**Value**
Train Accuracy	99%
Train Loss	4%
Test Accuracy	94%
Test Loss	30%
Precison	0.95
Recall	0.94
F1 Score	0.95
Support	290
MCC	88%
AUC	98%

Table. 2. Comparative Analysis with other available method

Dataset	Ref No	Method	Accuracy
LAG	[15]	ResNet152	86.7%
RIM-ONE	[16]	GoogLeNet	83%
HVD	[19]	Fusion (ResNet50, VGG19, AlexNet, Dns201 & IncRes)	85.43%
Private Dataset	[5]	VGG19	92%
Fundus Image Glaucoma Normal Dataset	Proposed Solution	CNN	**94%**

6. Conclusion

In conclusion, the use of Convolutional Neural Networks (CNNs) in the identification of glaucoma has shown tremendous promise as a potent weapon in the battle against this condition that threatens vision. A stunning CNN architecture with 10 layers, including Conv2D, MaxPooling2D, Flatten, and seven Dense Layers has been produced using the methods described in this paper, which uses a carefully selected dataset of Fundus Images and makes use of the local binary pattern (LBP) for preprocessing. With a training accuracy of 99 percent and an astonishingly low loss of 4 percent, the CNN model excelled. The model maintained its high accuracy of 94 percent with a test loss of 30 percent even on the test dataset. These findings demonstrate the model's potential to aid in early diagnosis and prompt intervention by demonstrating its high degree of accuracy in differentiating between glaucoma and non-glaucoma cases. Additionally, the confusion matrix, precision, recall, F1- score, support, Matthews correlation coefficient (MCC), and Area Under the Receiver Operating Characteristic Curve (AUC) evaluation metrics used in this work highlight the model's robustness and efficiency in detecting glaucoma. These measures provide a comprehensive picture of the model's performance, demonstrating its capacity to reduce false positives and false negatives (essential for early diagnosis) (crucial for reducing unnecessary treatments). The potential for automated glaucoma detection in a clinical scenario is demonstrated by the coupling of an accurate and effective CNN model with LBP preprocessing. This technology has the potential to improve healthcare by lessening the workload for doctors, enhancing access to early diagnoses, and eventually saving countless patients' eyes.

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