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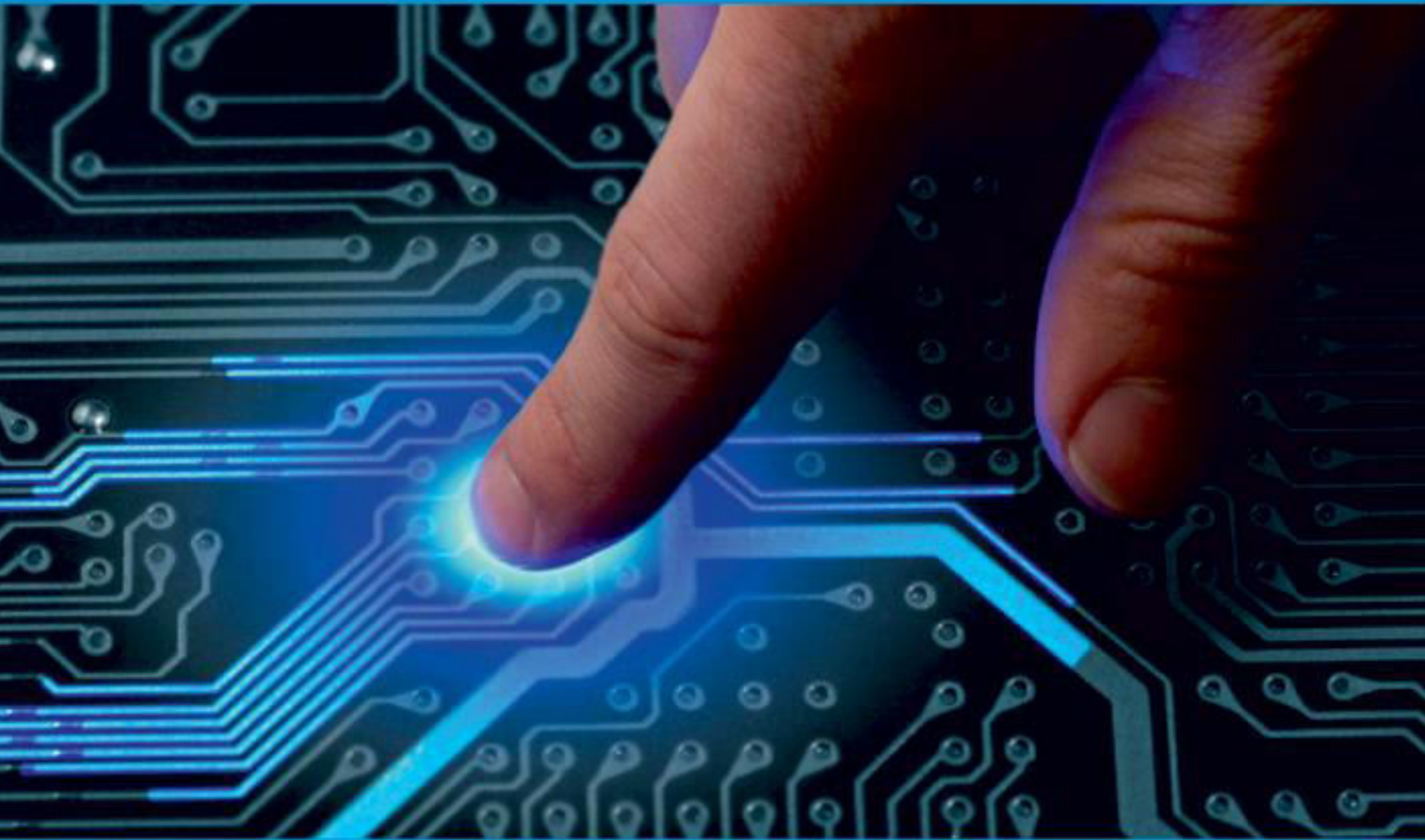

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Glaucoma Disease Detection Using CNN

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ABSTRACT: Glaucoma is a vision loss disorder caused by a rise in intraocular pressure that destroys the visual nerve fibers. Since there are usually no symptoms until significant vision loss develops, it is challenging to diagnose in the early stages. However, more precise and dependable glaucoma detection and diagnostic systems have been made possible by recent advances in deep learning and machine learning techniques. The objective of this proposed effort is to improve diagnosis accuracy and identify those who are at risk for glaucoma by examining the use of deep learning and the DenseNet algorithm to classify retinal fundus photos as normal or abnormal. This proposed method used a modified version of the DenseNet 121 algorithm, trained on a preprocessed dataset of optic disc pictures classified as either normal or glaucoma. This may make it possible to diagnose and treat glaucoma early on, lowering the chance of blindness. Although these results are promising, more research is required to determine the therapeutic effectiveness of this method in an actual setting. In order to improve the model's generalizability and explore the viability of applying this strategy in a clinical context, it is advised that future study enlarge the dataset. To effectively categorize images, this suggested model is optimized by converting the final output layer to a binary classifier and adding further optimizing layers.A separate set of test photos was used to assess the model's performance. Our findings showed that, with an overall accuracy of 96.28% and a loss of 1%, the modified DenseNet algorithm was highly accurate in classifying retinal fundus images as normal or glaucoma[2]. This model emphasizes how deep learning techniques increase the accuracy of glaucoma diagnosis and detection. The modelclassified pictures as normal or glaucoma with remarkable accuracy using a modified version of the DenseNet algorithm. Lastly, a possible tool for the diagnosis and detection of glaucoma is the DenseNet algorithm, which has been improved by deep learning. Because of its great accuracy and potential for early detection, it is a valuable supplement to the diagnostic techniques

KEYWORDS: Deep Learning, DenseNet, CNN, Glaucoma, Fundus image

I.INTRODUCTION

Glaucoma is a complex eye condition characterized by progressive damage to the optic nerve, often resulting in vision loss and potentially blindness if left untreated. Early detection and timely intervention are crucial in managing this disease effectively. Machine learning (ML) and artificial intelligence (AI) have emerged as powerful tools in medical diagnostics, including glaucoma detection. By leveraging advanced algorithms and large datasets, ML models can analyse various ocular parameters and patterns to aid in the early identification of glaucoma. In the context of glaucoma detection, machine learning algorithms can be trained on diverse datasets comprising clinical data, imaging scans (such as optical coherence tomography or OCT), visual field tests, and other relevant information. These models learn to recognize subtle indicators of glaucoma progression that might not be immediately apparent to human observers. The introduction of ML-based glaucoma detection systems holds immense promise in enhancing diagnostic accuracy, facilitating early intervention, and ultimately improving patient outcomes. By integrating these technologies into clinical practice, healthcare professionals can potentially identify glaucoma at earlier stages, allowing for timely treatment and management strategies to preserve vision and quality of life

World Health Organization (WHO) conducted a survey in 2020 which revealed that glaucoma remains a significant public health issue globally[20].The most recent data also shows that vision impairment is still a significant problem for humanity, with an estimated 285 million individuals worldwide suffering from some kind of visual impairment [24]. According to the WHO study report, 39 million of these people have total and irreversible blindness. Glaucoma continued to rank as the second most prevalent cause of visual loss worldwide in 2022, with an estimated 76 million cases recorded worldwide. According to the report, the number of cases could increase to 112 million by 2040 and 95 million by 2030[34], which would have a major effect on a sizable section of the world's population.Glaucoma is

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an irreversible neuro-degenerative eye disease [18][23]. It first shows no signs before gradually harming the optic nerve and permanently affecting vision.

II. LITERATURE REVIEW

Rutuja Shinde et.al, This literature review describes the creation of an offlinesystem (CAD) for glaucoma diagnosis utilizing retinal fundus pictures[26]. This system validatesinput data, extracts regions of interest, segments the disc and cup of eye, and classifies it usingdeep learning, machine learning and image processing algorithms. For input picturevalidationbest accuracy was obtained using the Le-Net architecture. The accuracy of regionextraction was high and the Dicecoefficients for the segmentation of disc and cup are 0.93and 0.87, respectively, utilizing the U-Net model. Eventually, the system achieved 100%classification rate, specificity, sensitivity, and recall using Neural Network, SVM, and Adaboost classifiers.

M.T.Islamet.al[16], This research argues that deep learning models such asGoogLeNet, EfficientNet-b3, DenseNet and MobileNet v3, may be used to doautonomous glaucoma classification[17]. To train these models, a carefully curated 634 dataset ofretinal fundus picturewere used with EfficientNet-b3 which was attaining the max resultswith a test accurate value of 0.9652, 0.9512 of F1 score, and 0.9574 of ROC AUC[3]. A freshdataset of blood vessel segmentation of retinal fundus pictures likewise obtained a reasonabletested accurate levelthat is of 0.8348 and an 0.7957 of F1 score, indicating that it may beutilised as an alternative approach for identifying glaucoma. Because early identification ofglaucoma is critical for averting vision loss and blindness, further study is needed to enhancethese automated glaucoma categorization algorithms.

III. PROPOSED METHODOLOGY

a.WorkOutline

The modified DenseNet algorithm was implemented in the CNN utilizing the Keras deep learning library[14].The dataset employed to train and test the network was the dataset, which included 1237 images from 2 different categories. The dataset was separated into training and testing sets in a 75:25 ratio, , entertaining utilizing Adam as the optimizer, with a learning rate of 0.01. The network was trained for 16 epochs, with abatch size of 32. During training, the validation accuracy was monitored to prevent model overfitting[13]. After training, the model's performance on the testing set was evaluated, which was unseen during training. The developed modified DenseNet algorithm demonstrated a classification accuracy of 96.4%, which is considerably higher than the performance of CNN architectures.

Convolutional Layer: This is the primary building block of a CNN. In this layer, multiple filters (also known as kernels) are applied to the input data through a process called convolution[10].

$Hi,j = f(k = 1\sum Kl = 1\sum LWk,lXi + k - 1, j + l - 1 + b)$ (1)

Where X is the input feature map of size $M \times N, W, is the convolutional kernel (or filter) of size K times L, H is the output feature map of size (M-K+1) \times (N-L+1), b is a bias term, and f is the activation function (e.g., ReLU).

Activation Function: Following the convolutional layer, an activation function is applied to introduce non-linearity into the network. This helps the CNN learn complex patterns and representations. The most commonly used activation function in CNNs is the Rectified Linear Unit (ReLU), which replaces all negative values in the feature maps withzeros.Theactivationfunctions,suchassigmoidisusedforoutput.

$$ReLU(x) = max(0, x) (2)$$

$$Sigmoid(x) = 1 / (1 + exp(-x)) (3)$$

Pooling Layer: The pooling layer serves to reduce the spatial dimensions of the feature maps, thereby reducing the number of parameters and computational complexity of the network. This also helps to make CNN more robust to small variations in the input data.

$\mathrm{GAP(x) = mean(x)}$,where x is the input feature map and mean is the mean operation over all spatial locations.

$$\mathrm{BatchNorm(x) = (x - mean)/sqrt(variance + epsilon) * Gamma + beta} \quad (4)$$

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Where mean and variance are the mean and variance of the input, epsilon is a small constant to avoid division by zero, gamma and beta are learned scaling and shifting parameters.

Dropout: Dropout is a regularization technique used to prevent overfitting in neural networks. It works by randomly dropping out (setting to zero) a certain percentage of the neurons in a layer during each training iteration. This forces the remaining neurons to learn more robust features and prevents the network from relying too much on any particular neuron. Dropout is particularly effective when dealing with large networks with many layers and a high number of parameters.
During training: output = input * mask, where mask is a binary mask that randomly sets some of the input values to zero.
During testing: output = input * (1 - dropout_rate), where dropout_rate is the probability of dropping out a neuron during training.

Flatten layer: The flatten layer is a simple layer that is used to convert multidimensional arrays (such as the output of a convolutional layer) into a single dimension.

$$\mathrm{Flatten}(x) = \mathrm{reshape}(x, (\mathrm{batch\_size}, -1))$$

Where x is the input tensor and batch_size is the size of the batch

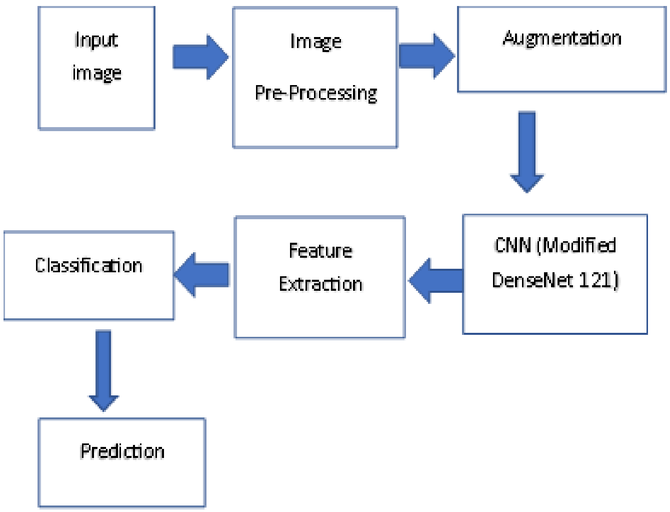

Figure 1 System Architecture

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IV.RESULTS AND DISCUSSION

The model architecture used in this proposed system is a modified version of DenseNet121, which is a popular convolutional neural network architecture. Pre-trained on the dataset, the DenseNet121 model has demonstrated superior performance across a range of computer vision applications[4]. This method starts with loading the DenseNet121 model that has already been trained and setting all of its layers to non-trainable. This implies that just the extra layers added on top of the pre-trained model will be taught; the pre-trained model's weights will not be changed during training.

The DenseNet 121 model was given multiple layers in order to optimize it for the glaucoma classification challenge. To avoid overfitting, a Dropout layer with a rate of 0.5 was added. After that, a Flatten layer is applied to transform the DenseNet121 model's output into a 1D array. The Batch Normalization layer was implemented in order to equalize the Flatten layer's output. Subsequently, two densely connected layers were employed, each consisting of 1024 and 512 neurons. After that, layers for dropout and batch normalization were added in between them. Lastly, a single output neuron with a sigmoid activation function was added in order to create the binary classification output.

In order to optimize the DenseNet121 model architecture for the glaucoma classification problem, it incorporates a few extra layers into a pre-trained model, hence enhancing its strengths. The learnt characteristics in this pre-trained model were gathered from a sizable dataset, which makes it possible to achieve high accuracy with a comparatively minimal amount of data. We can tailor the pre-trained model for a certain task by adding further layers on top of it, which may result in better performance. In order to ensure that the model generalizes adequately to fresh data and to avoid overfitting, batch normalization and dropout layers are used.

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Table4.1Number of image data in the class Glaucoma and Normal

S.No	Class	No.of images
1	Glaucoma	597
2	Normal	650

Figure4.3Resultofnormalfundusimagefromthetrained model

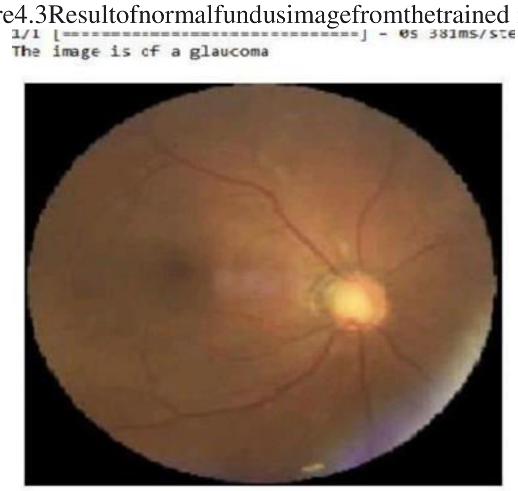

Figure4.4TheresultofGlaucomafundusimage

V.CONCLUSION

In conclusion, the development of a predictive model for glaucoma disease holds significant promise in advancing early detection and intervention strategies, thereby mitigating the risk of irreversible vision loss. Through the integration of machine learning techniques and advanced data analytics, this project has successfully addressed the limitations of traditional diagnostic methods and proposed a novel approach to glaucoma screening and management. By leveraging a comprehensive dataset of eye health parameters and employing sophisticated algorithms, the predictive model demonstrates enhanced accuracy and efficiency in identifying individuals at risk of glaucoma. The scalability, accessibility, and interpretability of the model ensure its practical utility in clinical settings, empowering healthcare professionals to make informed decisions and deliver personalized care to patients. Furthermore, the validation of the model's performance on independent datasets underscores its reliability and robustness in real-world applications. As we continue to refine and optimize the model through ongoing research and collaboration, we remain committed to advancing glaucoma management and improving patient outcomes on a global scale. Through concerted efforts and innovative approaches, we aspire to make meaningful strides in combating the burden of glaucoma-related vision loss

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and promoting eye health for all individuals.

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