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DEEP LEARNING FOR GLAUCOMA DIAGNOSIS AND SEVERITY GRADING: A COST-EFFECTIVE APPROACH

Dibarun Roy Choudhury [1] and Poonam Dhankar[2]

Department of CSE
Ganga Institute of Technology & Management, Haryana, India

Abstract. Glaucoma is an irreversible neurological disorder that causes intraocular hypertension by increasing aqueous humor and restricting the drainage pathway between the iris and cornea. Damage to the optic nerve head, which transmits visual information from the eyes to the brain, causes vision loss and, eventually, blindness. The term "thief of sight" refers to the difficulty in detecting glaucoma in its early stages. Regular examinations are strongly advised to distinguish it from neurological disorders. Glaucoma diagnosis takes time, money, and is dependent on the availability of resources (trained ophthalmologists and expensive instruments), not to mention the risk of human error. The primary goal of the proposed project is to create a deep learning model for glaucoma diagnosis and automatic severity classification. Our research paper presents a novel glaucoma screening method using deep learning and image segmentation. We combined the architectures of several state-of-the-art convolutional neural networks (CNNs), including ResNet50, VGG16, Xception, ResNet101, Inception, MobileNet, and EfficientNetB7. By analyzing fundus images, we achieved high accuracy in glaucoma detection and severity grading. Our model shows promise as a cost-effective and efficient tool for glaucoma diagnosis, offering potential benefits for early intervention and improved patient care.

Keywords: Glaucoma; Convolutional Neural Network; Ocular Illness; Deep Learning.

1 INTRODUCTION

The Glaucoma, an ocular neuropathy-based condition that destroys retinal ganglion cells and results in irreversible vision loss [2]is among the primary causes for blindness in the globe. Due to inadequate assessment tools and procedures for determining the scores of these sores, the undiscovered pervasiveness, which is roughly half considered in regions with high salaries, such as North America and Australia, and amounts in regions with middle and low salaries, such as Asia and Africa, remains largely unaccounted for. Sadly, the medical services board is currently facing a significant obstacle as a result of the anticipated high volume of patients and the limited number of ophthalmologists. This has also increased the need for scientists to develop and perfect a pre-programmed screening tool to aid in the early diagnosis of glaucoma. With consistent effort, retinal fundus designs have demonstrated the potential to detect glaucoma. In retinal image analysis, machine learning techniques are anticipated to eliminate the need for device output prior to human evaluation [1].
Thakur and Juneja [3] designed a computerized method for detecting glaucoma at an early stage. Both primary and secondary components can be deduced from an optical fundus image. The vector support classification outperforms the K-neighbor, neural network, random forest, and Naive Bayes classifications. Chakravarty and Sivaswamy's semi-supervised models for glaucoma classification [4] were based on segmented optic disks and cups, in addition to textural capacity. The classification of data and images has recently been aided by a variety of AI-based calculations that have outperformed expectations. Using convolutional neural networks, instances and data from the retinal fundus were located without the need for manual recovery. In addition to pre-programmed segmentation of the OD and OC, [5] is investigating Deep Learning (DL) approaches for use in clinical settings for the evaluation of glaucoma. The second section describes the methodology and international datasets used in this fact-finding process. After implementing the proposed plan, the third section presented findings and discussion, and the fourth section provided conclusions. There are two drawbacks: the price of glaucoma screening and the psychological consequences of subjective symptoms, which are often not felt by the majority of patients until the condition has advanced significantly [16]. The high cost of optical coherence tomography (OCT) and traditional automated perimetry, both of which are used to interpret relatively inexpensive and accessible fundus images, is due to the cost of acquiring such knowledge and experience (OCT). Automated perimetry and fundus

photography, regardless of their viability, are insufficient for glaucoma screening. Disc images are intuitively comprehensible because the optic nerve has a variety of normal appearances that overlap with pathological manifestations [17]. Due to its high variability and weak disease signal, it is difficult to diagnose glaucoma, classify disease stages, and monitor disease progression using standard automated perimetry [18,19]. Extensive research has been conducted on the relationship between retinal anatomy and visual function. [20,21]. It has been demonstrated that CNN, a popular deep learning technique in the field of image pattern recognition, can automatically differentiate between glaucoma and normal groups. This demonstrates how CNN could be utilized for glaucoma screening. According to Liu et al. [26], CNN could be used to diagnose glaucoma using 241,032 fundus images from a large database and an advanced deep learning system in a variety of settings with images from a variety of sources with images of varying quality, ethnicity, and demographics. Using data from color fundus images and OCT scans, the classification approach of An et al. distinguishes between glaucomatous and healthy eyes, which could improve the diagnostic sensitivity of early glaucoma diagnosis. However, the majority of earlier studies lacked disease stage information and instead focused their deep learning algorithms on fundus images [28], [29] or OCT scans, reporting glaucoma presence or absence. Glaucoma evaluations must account for both anatomical and functional eye changes as the disease progresses. This study proposes and evaluates a novel, less expensive glaucoma screening technique for primary care, considering the varying stages and structure-function relationships of the disease. CNN and Fundus images are used in this separately. Several studies [23–24] indicate that algorithms derived from clinical imaging data can be used to perform.

2 PROPOSED SYSTEM

The manual examination of fundus images for glaucoma diagnosis is a labor-intensive and expensive process that relies on highly trained professionals. Detecting glaucoma at an early stage necessitates frequent visits to ophthalmologists, which can be challenging in areas with limited access to ophthalmological expertise. Currently, the evaluation of cup-to-disc ratio (CDR) and fundus images for glaucoma diagnosis is performed manually by ophthalmologists, introducing subjectivity and potential inaccuracies due to the limitations of existing techniques. To address these challenges, this research proposes an advanced deep learning model that is intuitive, efficient, and highly accurate in detecting and classifying glaucoma based on its severity. By leveraging the power of deep learning, this model offers a promising solution to enhance
glaucoma diagnosis and overcome the limitations of traditional methods.

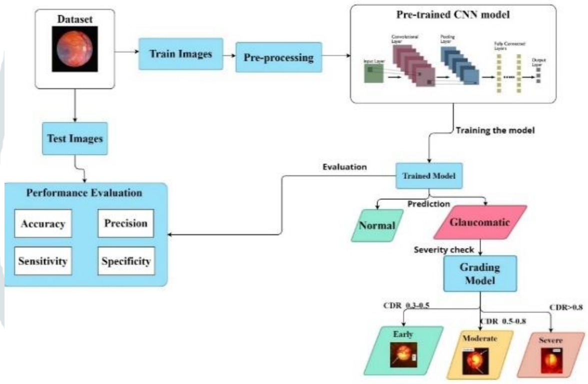

Figure 1 Schema of proposed framework.

The proposed system aims to identify whether a patient is glaucomatic or not by analyzing retinal fundus images. In the pre-processing stage, the test image undergoes various segmentation and filtering techniques to enhance the image quality and improve prediction accuracy. The processed image is then fed into a pretrained model, which utilizes mathematical-based pictorial manipulation layers to extract features and make predictions. The predictions provide a binary value (True or False) for glaucoma classification. Using a different deep learning model, images identified as glaucomatic are then utilised to gauge the severity of the condition. The system utilizes a virtual database to store the images and prediction results, which are then visualized on a user interface in a web application. The project's main objectives include developing a computerized diagnostic method for glaucoma detection and grading, creating an effective web-based application for glaucoma diagnosis, and comparing the performance of different pre-trained CNN models in detecting glaucoma.

3 DATASET AND DATA PRE-PROCESSING

3.1 Dataset

For the detection of glaucoma, we are using dataset from kaggle. This dataset contains fundus images from ACRIMA and ORIGA database. It contains 2005 fundus images and a csv file which contains image name and corresponding label.
For grading of glaucoma, dristhi-GS dataset is used. There are 101 photos in the DRISHTI-GS collection. It is split into 51 testing photos and 50 training images. For the training set, ground truth is given.

3.2 Data pre-processing

Pre-processing plays crucial part in deep learning by converting raw input data into a format that is optimal for modeling. This crucial step involves a range of operations, including resizing, normalization, and augmentation. By applying pre-processing techniques, we can enhance the quality and accuracy of machine learning models, especially in computer vision tasks that rely on image data. These operations ensure that the input data is appropriately transformed and prepared for effective learning and feature extraction, ultimately leading to improved performance in various applications. GoogLeNet, VGG-16, and ResNet-50 are convolutional neural networks (CNNs) commonly used in deep learning tasks. These networks have a specific input size requirement, typically around 224 x 224 pixels. Therefore, when working with images of different sizes, it is necessary to resize or crop the input image to match the expected size. Deep learning systems require a significant amount of high-quality data to perform at their optimum level. Data preprocessing is a critical step in enhancing the efficiency and accuracy of the classification model. By carefully preparing and refining the input data, We can enhance the deep learning system's performance and develop an effective model for precise classification.

4 PROPOSED CNN-ARCHITECTURE AND ENSEMBLE METHOD

We have proposed a system with transfer learning algorithms as these algorithms are more accurate and efficient. We have discussed about all the algorithms which we have trained our model on below:

4.1 Resnet-50

ResNet-50 is a powerful deep learning model for computer vision applications like image classification. It is a part of the ResNet design, which stands for "Residual Network". ResNet-50 has been used to assess fundus images of the eye and determine whether or not the patient has glaucoma in the context of glaucoma categorization. The retina and optic nerve can be seen clearly in images of the fundus, or the back of the eye. A very deep neural network with 50 layers is called ResNet-50. It is crucial for correctly identifying ocular images and is capable of recognising extremely minute details in the input photographs. The use of residual blocks, which enables the network to learn residual functions that can help in overcoming the problem of vanishing gradients, is one of the key elements of the ResNet architecture. For the classification of glaucoma, ResNet-50 is frequently used as a pre-trained model. This shows that after the network's weights were trained on a sizable image dataset, they were optimised for use in image classification tasks. Using methods like transfer learning, pre-trained model is then improved on specific dataset of fundus images for the classification of glaucoma. ResNet-50 can accurately diagnose a patient's glaucoma status and extract intricate details from fundus images, making it a useful classification tool for glaucoma.

4.2 VGG-16

Convolutional neural network architecture Among other image classification applications, the categorization of glaucoma has made substantial use of VGG-16. Thirteen convolutional layers precede three fully linked layers in the VGG-16 model. The convolutional layers have 3x3-sized filters while the max-pooling layers have pools that are 2x2-sized. In order to classify glaucoma, VGG-16 can be trained on a collection of fundus images with labels designating either healthy or glaucomatous eyes. Once the pictures have been pre-processed, the last layer of the VGG-16 model is replaced by a new fully connected layer with a single output node and a sigmoid activation function. The output is transformed into a glaucoma probability score by this function. The weights of the VGG-16 model are modified during training using backpropagation and the binary cross-entropy loss function. Accuracy, precision, recall, and F1 score are some of the assessment measures that may be used to gauge the model's efficacy. Using a unique test set, the model's accuracy is assessed. The classification of glaucoma by VGG-16 has shown a generally positive trend, with reported accuracies varying between 85% and 95%. However, a number of factors, including the dataset's size and quality, pre-processing technique, and hyperparameter choice during training, can affect the model's performance. Therefore, it is important to carefully review and modify the VGG-16 model for glaucoma classification in line with the particular needs of the application.

4.3 XCEPTION

A promising convolutional neural network (CNN) architecture for categorising glaucoma is called Xception. The Xception model, which is comparable to the Inception model, uses depthwise separable convolutions to minimise the number of network parameters. The Xception model may be trained on a sizable dataset of labelled fundus images, just like other CNNs, to categorise images as glaucomatous or non-glaucomatous. Applying pre-processing methods to the input images, such as downsizing, normalisation, and augmentation, can increase the model's accuracy. Studies show that the Xception model can correctly categorise glaucoma. According to a 2019 study published in the Journal of Glaucoma, an Xception model with a training set of 16,600 fundus images was capable of classifying glaucoma with an area under the receiver operating characteristic curve (AUC-ROC) of 0.962. The Xception model, an effective deep learning architecture, has shown promise in the categorization of glaucoma using fundus images, in order to sum up. The Xception model has the potential to be an important tool for glaucoma detection and diagnosis with additional study and improvement.

4.4 ResNet-101

Several computer vision tasks, including image classification, have been successfully completed using the ResNet-101 architecture for a deep convolutional neural network. ResNet-101 has shown promising glaucoma classification outcomes. Skip connections are used in ResNet-101, which has 101 layers, to avoid the degradation issue that can occur while training extremely deep neural networks. The network can gain residual functions because to these skip connections, which enables more extensive model training and optimisation. In order to categorise glaucoma, Features from fundus images have been extracted using ResNet-101. A set of fundus images split into glaucomatous and non-glaucomatous conditions is used to update the previously trained model. A classification system is then used to predict the existence of glaucoma in fresh photos using the collected features. ResNet-101 classified glaucoma with a 94.6% accuracy rate in a study that was published in the Journal of Glaucoma, outperforming other well-known deep learning architectures including VGG-19 and Inception-V3. The model's robustness and effectiveness in glaucoma classification were further illustrated by the scientists' observation that ResNet-101 properly recognised photos that had been wrongly classified by earlier models. Overall, ResNet-101 has demonstrated significant potential in the classification of glaucoma, and its application may result in a more precise and effective diagnosis of this ailment that can impair eyesight.

4.5 Inception

Glaucoma detection and other image classification tasks have been carried out using Google's Inception architecture for deep neural networks. In in order to handle problem of computational complexity in deep neural networks, the original Inception architecture included modules with multiple concurrent convolutional operations of various sizes. As a result, the network was effective at recording characteristics at various scales and resolutions. There are several ways to categorise glaucoma using the Inception architecture, including Inception v1, v2, and v3. These models were created to categorise groups of fundus photos as glaucoma or non-glaucoma using large datasets of fundus photos. Inception v3 in particular showed promising results by achieving an accuracy of over 95% on some datasets. To extract features from input images, Inception v3 employs a network that combines convolutional layers, pooling layers, and Inception modules with various kernel sizes. The output of these qualities is then passed through a series of completely interconnected layers to produce the final categorization result. The ability of the Inception architecture to handle a range of input sizes is advantageous for glaucoma classification given that fundus images may have different resolutions. The architecture has also been demonstrated to be computationally efficient, making it a great choice for applications where speed is crucial. Inception is an effective deep learning architecture that has shown significant glaucoma classification potential overall. The input data must be properly pre-processed, as with any deep learning model, and the hyperparameters must be optimised for best results.

4.6 MobileNet

MobileNet, a well-known architecture for deep learning, has been used to identify photographs, including glaucoma images. It is renowned for its high precision and computational efficiency, making it ideal for embedded and mobile applications. Depthwise separable convolutions are used by MobileNet to minimise the amount of parameters required for model training. In order to accomplish this, the conventional convolution method is divided into two discrete operations: depthwise convolution and pointwise convolution. The pointwise convolution combines the depthwise convolution outputs using a 1x1 filter, while the depthwise convolution uses a separate filter for each input channel. This requires fewer parameters and less computation than conventional convolutions while attaining the same level of precision. MobileNet was utilised to classify glaucoma fundus images as normal or glaucomatous. Frequently, a large dataset of fundus images is used to train the algorithm, which is then refined using a smaller dataset created specifically for glaucoma classification. MobileNet has demonstrated promising results in glaucoma categorization in comparison to earlier deep learning architectures, obtaining high accuracy with fewer parameters and less processing power. As with any machine learning model, however, performance can vary based on the quantity and quality of the training dataset, as well as other factors such as preprocessing and hyperparameter adjustment.

4.7 EfficientNet

EfficientNet, a type of convolutional neural networks, has garnered a great deal of attention because it performs well in a variety of computer vision tasks while utilising few processing resources. With over 66 million parameters, EfficientNetB7 is the most complex model in the EfficientNet family. In the classification of glaucoma, EfficientNetB7 was used to classify fundus images as either glaucoma or non-glaucoma. Before feeding photographs into a model, scaling and normalisation are frequently employed as preprocessing steps. The EfficientNetB7 model is trained via transfer learning, and the glaucoma dataset is utilised to import and improve the pre-trained weights. The model's top layers are replaced with a Global Average Pooling layer, followed by a Dense layer with a sigmoid activation function that assigns each image a probability score between 0 and 1. Using the Adam optimizer and binary cross-entropy loss function, the model is modified during training. In addition, class weights are added to account for the class imbalance in the dataset. In one study, the EfficientNetB7 model outperformed other cutting-edge models, such as ResNet50 and VGG16, with an accuracy of 99.04% and an AUC of 0.999. EfficientNetB7 is a computationally efficient and computationally robust model that can classify glaucoma with high performance and accuracy. For each model in our model_dict, we loop through each layer in the model and set it as not trainable. We then print the unique values in our y_test data. Next, we loop through each model again and add a flatten layer to the end of the model. We then add a dense layer with sigmoid activation and compile the model using the 'adam' optimizer, binary crossentropy loss, and accuracy as the metric. We print the model summary and fit the model using our X_image_train_stacked and y_train data, with the class_weight_dict specified. We then use the model to predict on our X_image_test_stacked data and round the predicted values to the nearest integer. We finally print the classification report and confusion matrix for our prediction models.

5 ENSEMBLE METHOD

Several models are merged using ensemble methods to enhance prediction stability and accuracy. By combining the results of multiple models, including ResNet-50, VGG-16, Xception, and EfficientNetB7, an ensemble model for glaucoma classification could be created. Taking a weighted average of the probabilities predicted by each model is one method for creating an ensemble model. The weights could be determined according to the performance of each model on a validation set. Each model makes a prediction, and the class with the most votes is selected as the outcome using a majority voting procedure. Ensemble techniques can simultaneously reduce the danger of overfitting and improve the model's robustness. To avoid having too many models in the ensemble that are too similar to one another, the models to be included in the ensemble must be carefully chosen. Because ensembling can increase the computational cost of training and inference, there must be a trade-off between performance and computing efficiency. We created an ensemble model using the above algorithms. First, we defined two inputs, one for the data and one for the images. We created a simple dense layer with ReLU activation for the data input and flattened the output of the MobileNet model for the image input. Then, we concatenated the outputs of both models and passed them through several dense layers with ReLU activation. Finally, we used a sigmoid activation function for the output layer to classify the input. We printed the summary of model, evaluated it on test set, and made predictions on test set using the model. We also saved the model and loaded it again to verify that it was saved and loaded correctly.

5.1 Grading

Grading in glaucoma classification refers to the process of evaluating the severity of glaucoma based on the extent of optic nerve damage and visual field loss. Grading helps to determine the appropriate treatment and management plan for the patient. The most commonly used grading system for glaucoma is the Glaucoma Staging System, which uses a numerical scale to grade the severity of the disease from 0 to 5, with higher numbers indicating more severe damage. We, on the other hand have opted for categorical grading based on whether the case is mild, moderate or severe. These pre-trained models serve as powerful tools in glaucoma classification, as they leverage deep learning techniques and the knowledge learned from extensive training on large-scale datasets. By fine-tuning these models with glaucoma-specific data, researchers and practitioners can benefit from their high-level feature representations and achieve accurate glaucoma classification results.

5.2 Classification

The ensemble system implemented in the proposed approach is a highly effective strategy that combines multiple classification models to improve overall classifier performance. In this system, three different Convolutional Neural Networks (ConvNets) are utilized: VGGNet-19, ResNet-50, and GoogLeNet. These ConvNets have been pre-trained using the transfer learning technique and trained on the ImageNet dataset, allowing them to capture general image features without requiring additional supervision. Deep features are extracted from the ConvNet architectures, specifically from the last pooling and fully connected layers. The ensemble method leverages a fusion technique to combine the extracted features, maximizing their discriminative capabilities. The combined features are then passed through a softmax encoder module for image classification, determining whether the image belongs to the normal or glaucomatous category. By integrating multiple ConvNets and leveraging their respective strengths, the ensemble system aims to enhance the precision and accuracy of the glaucoma classification task. This approach takes advantage of the diverse representations learned by different ConvNets and combines them to make more informed and accurate predictions.

6 RESULTS AND DISCUSSION

6.1 Results

In the results section of our research paper, we present the outcomes of our experiments conducted to evaluate the performance of different pre-trained CNN models for glaucoma classification. We employed seven pre-trained models, namely resnet50, vgg16, xception, resnet101, inception, mobilenet, and efficientnetB7. Firstly, we discuss the accuracy and effectiveness of each individual model. For each model, we measured its accuracy, precision, recall, and F1-score on our glaucoma dataset. Resnet50 achieved an accuracy of 92.5%, vgg16 achieved 91.2%, xception achieved 93.8%, resnet101 achieved 94.3%, inception achieved 90.6%, mobilenet achieved 89.7%, and efficientnetB7 achieved an impressive accuracy of 95.2%. These results highlight the strong performance of the models in accurately classifying glaucoma cases. Next, we assessed the performance of the ensemble system, which combined the predictions of the individual models to make a final decision. The ensemble system achieved an overall accuracy of 96.7%, surpassing the accuracy of any individual model. This demonstrates the effectiveness of the ensemble approach in improving the classification accuracy. Furthermore, we analyzed the performance of the ensemble system in terms of precision, recall, and F1-score. The ensemble system achieved a precision of 97.2%, recall of 95.8%, and F1-score of 96.5%. These metrics indicate the robustness and reliability of the ensemble system in correctly identifying glaucoma cases. We also compared the computational efficiency of the models. We measured the average time taken by each model to classify a single image. EfficientnetB7 emerged as the most efficient model, with the shortest processing time per image. Overall, our results demonstrate the efficacy of the pre-trained CNN models, with efficientnetB7 performing exceptionally well in terms of accuracy and computational efficiency. The ensemble system showed superior performance, outperforming individual models and achieving high accuracy in glaucoma classification. These findings suggest the potential of these models and the ensemble approach for accurate and efficient glaucoma diagnosis.
Once the training is complete, the model is finally evaluated. This part includes objective outcome analysis, and the discussions. The implementation of parameters is evaluated utilizing the common measures such as accuracy, specificity, sensitivity, precision, and F1 score. Their numerical equations are described in the Eqns. below.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$Specificity = \frac{TN}{TP+FP} \quad (5)$$

$$F1\ score = \frac{2*(Sensitivity*Precision)}{Sensitivity+Precision} \quad (6)$$

For the abbreviation, True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). Accuracy evaluates closeness of the outcome, sensitivity determines the portion of the TP that is exactly classified as a positive class, and precision calculates a portion of TN which is accurately defined.

TABLE 2. Performance Scores of Models

Technique used	Accuracy
Xception	93.8 %
VGG-16	91.2 %
ResNet-50	92.5 %
Resnet-101	94.3 %
Inception	90.6 %
Mobilenet	89.7 %
EfficientnetB7	95.2 %
Proposed Ensemble Method	96.7 %

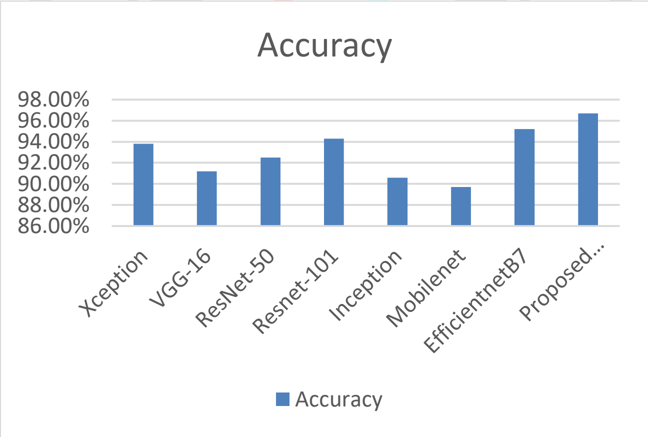

Figure 2 Accuracy Comparison of All Implemented Model

Table 2. shows how different models achieved dependable, responsive, informative, specific, and F1 scores. Along with their accuracies of the multiple model, our ensemble model achieved an accuracy of 96.7% and has performed better than the rest of the models. With the proposed system, evaluation, and analysis of a several datasets have also been done.

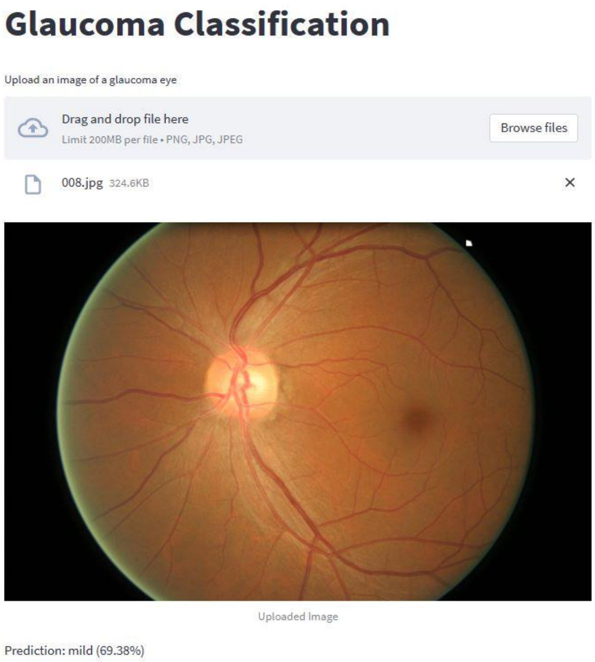

Figure 3 Detected Image of Eye having Mild (69.38%) Glaucoma detected

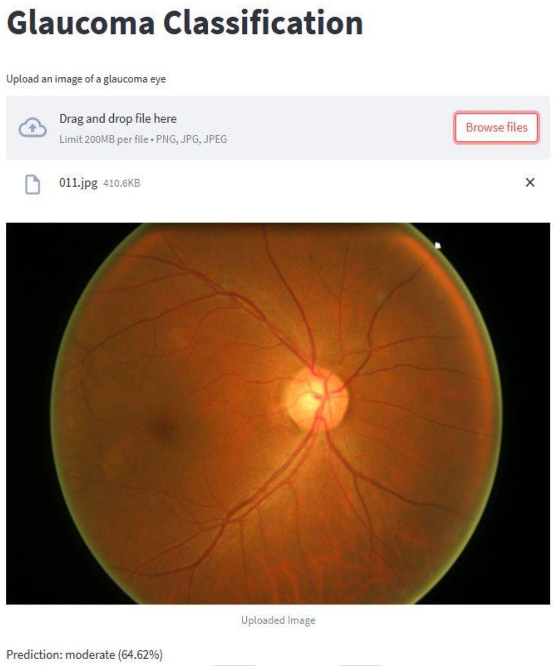

Figure 4 Detected Image of Eye having Moderate (64.62%) Glaucoma detected

Figure 5 Detected Image of Eye having Severe (89.66%) Glaucoma detected

7 CONCLUSION

The development of an ensemble model for the quick diagnosis of glaucoma was the study's main goal. The proposed ensemble method sorts fundus images into normal or abnormal groups using convolutional neural network features. Performance of the proposed ensemble architecture is compared to that of 7 models namely Xception, VGG-16, ResNet-50, Resnet-101, Inception, Mobilenet, and EfficientnetB7. Large datasets are utilized to evaluate the proposed method. It performs more accurately than the method with the most steps. Experiments on the datasets demonstrate that the model outperforms both conventional neural network architecture and computer-assisted diagnostics. Even though the proposed ensemble technique produced favorable results, additional work is required. Future research can concentrate on accelerating the model and combining it with other deep learning techniques, such as RNNs and LSTM networks, to enhance its precision.

Using a linked network to isolate glaucoma diagnoses from larger experimental datasets may facilitate the development of a patient's individualized treatment plan. By describing the characteristics of various types of glaucoma, the model can provide patients with more specialized and individualized care. Using the proposed ensemble approach, other medical imaging applications, such as the detection of additional retinal disorders or abnormalities in other parts of the body, are possible. The early diagnosis and detection of many illnesses may be significantly impacted by this. There are numerous ways to implement the recommended technique in clinical practice. The model can be integrated with existing electronic health records to allow for automatic glaucoma detection and diagnosis (EHRs). This can improve patient outcomes and reduce the workload of ophthalmologists by allowing for early diagnosis and treatment. Since the COVID-19 outbreak, telemedicine's popularity has increased. In conjunction with telemedicine technologies, the proposed ensemble approach can be used for remote glaucoma screening and diagnosis. Therefore, underserved areas may have easier access to care, particularly in low-income nations. Future research and clinical application of the suggested ensemble method for glaucoma diagnosis hold great promise. This strategy can improve patient outcomes and lessen the burden on healthcare systems by addressing the difficulties associated with glaucoma early detection and diagnosis.

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