Glaucoma diagnosis using deep learning and machine learning

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Abstract. —A Glaucoma diagnosis approach based on the combination of Machine Learning and Deep Learning with a CNN (ResNet50, VGG-16 models) classifier has been proposed as a model for diagnosing glaucoma. predictions are aggregated through a set of post-processing rules to assess the overall risk for glaucoma. A group of eye diseases that can cause blindness is called cataracts, which results in damage to the optic nerve. For early diagnosis with advances in machine learning techniques, CNN (Convolutional Neural Networks) with ResNet50, VGG-16 such as the proposed it was possible to significantly improve Glaucoma diagnosis using medical imaging data. The Glaucoma diagnosis model comes with an Accuracy of 96%, Precision of 99.37%, Recall of 88.50%, and F1-Score of 93.60%. Finally, one of the key highlights in this Glaucoma diagnosis is this Framework ensemble method using ResNet50, VGG-16, and Random Forest yields great results concerning correctness, exactness, retrieval, and F1-Score. This model is for better early detection of glaucoma. Thus preventing loss Of sight while using Machine Learning and Deep Learning with neural networks that takes place in the brain's cortex convergence promises an even better future for ophthalmic health care.

Keywords: Classification, Image Processing, Feature Extraction, Machine Learning, Deep Learning, Convolutional Neural Networks.

1 Introduction

Glaucoma is a severe eye disease characterized by irreversible blindness primarily caused by optic nerve damage from elevated intraocular pressure (IOP) levels. According to World Health Organization projections, as many as 79 to 112 million persons may suffer [1]. Examinations are imperative among those at greater eye risk suffering from Glaucoma disease. Several risk factors predispose and it is one of the major disease suffering from glaucoma disease including age, family history of the condition as well Diabetes, hypertension, and prolonged use of corticosteroids. One major consequence of This disease is permanent blindness which has drastic impacts on a person's life quality. Especially since most times, there are no apparent indicators until something goes wrong With them [2]. Regular eye check-ups save on early discovery of such cases whilst making possible prevention measures to the process of diagnosing this disease. In the long run, persistent research on Endeavors will play a vital role in coping with the challenge, who predicts that Vision impairment linked to glaucoma, [1,3]the number of affected people can rise from 79 million in 2020 to 112 million by 2040, hence stating that "an early diagnosis and prompt Therapy is critical".

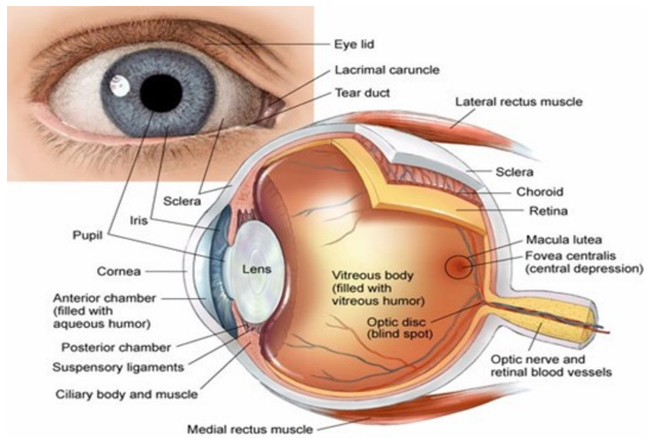


Fig. 1. Internal Eye Parts

Systems that are AI-based have their main aim of imitating human behavior, including reasoning and problem-solving abilities by using Machine learning is simply a branch of AI whereby computers utilize data to learn and predict outcomes with minimal human supervision. Also, deep learning means using neural networks for data processing specifically in the case of image recognition through convolutional neural networks including ResNet50 [1] which enhances retinal image analysis that helps detect vision loss risks increasing its accuracy rate within healthcare lines. In this study, the researchers proposed a hybrid diagnosis system for glaucoma combining machine learning (ML), deep learning[7], and imaging techniques to provide accurate diagnosis. This was achieved by employing models such as ResNet50 and VGG-16 [10] combined with Random Forest resulting in an accuracy level of 96%, recall of 88.50%, and precision of 99.37%. , In this Paper call upon large data sets to make models more robust, four benchmarks are given: ACRIMA, G1020, and ORIGA among them all. It can now easily occur with this type of hybrid system thereby revolutionizing glaucoma diagnosis in remarkable ways.

2 Literacy Survey

The previous paper 2023 Year presents an efficient method for diagnosing glaucoma using a 13-layer convolutional neural network (CNN). We analyzed 1113 fundus images (660 healthy, 453 glaucomatous) and used Google Colab for easy implementation. The split of the data included 70 percent training, 20 percent validation, and a testing segment of 10 percent with a total of 12,012 augmented training images [1,2]. Important components in eye anatomy consist of the cornea, iris, pupil, lens, retina, tear film, and optic nerve [6].

In 2022, the retina receives light and converts it into nerve impulses that enter our brain, while the iris controls how much light gets in. The optic nerve consists of about a million nerve cells that connect to ganglia in the retina and carry information about what we see in the occipital cortex of the brain from Figure 2. Also, the presence of aqueous humor in the eye and blockage of the aqueous humor will increase intraocular pressure and damage to the retina and optic nerve [2].

in 2021 the Early signs of glaucoma include degeneration of retinal ganglion cells and changes such as an increased cup-to-disc ratio (CDR) in the optic disc [3] . Figure 1 shows a schematic of the components that make up the body of the human eye. Complete loss of these cells can lead to complete blindness in glaucoma patients. Therefore, changes in visual perception are important in the Glaucoma diagnostic process. [2,3].

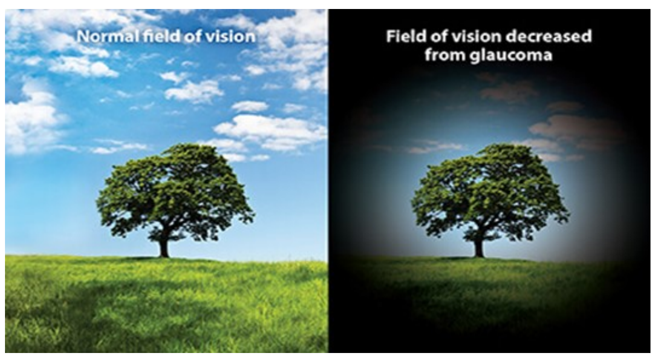
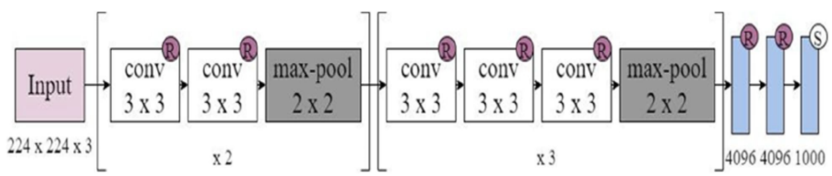


Fig. 2. Comparision of Normal and Glaucoma image

3 Proposed Work

In glaucoma diagnosis algorithm is proposed that combines to prevent visual impairment which may eventually lead to blindness and ensure better accuracy during diagnosis using machine learning (Machine Learning), convolutional neural networks (CNN), and Deep Learning. The framework consists of a collection of datasets, preprocessing steps, training, and classification which uses four standard datasets ACRIMA, G1020, ORIGA, and REFUGE consisting of 2775 retinal fundus images. During this phase, RGB images are first transformed to greyscale before feature extraction followed by training using ResNet50, VVG-16, and Random Forest to find the glaucoma or normal from Figure 3.



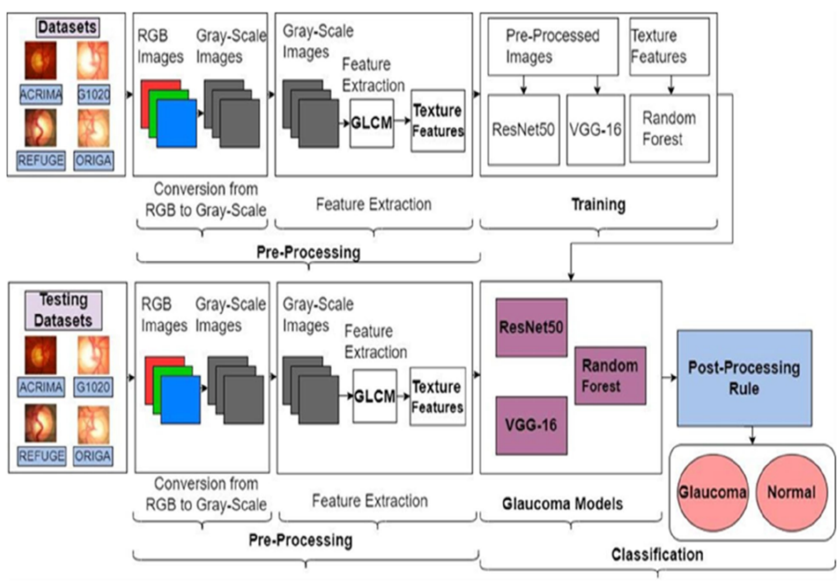


Fig. 3. Proposed Artificial Neural Networks Model Architecture

3.1 DataSet

Glaucoma classification research utilizes four datasets namely ACRIMA, G1020, ORIGA, and REFUGE data including images of the cornea, normal conditions, and glaucoma from Figure 4. To avoid overfitting, spatial modifications are made so that image sizes are 224×224×3 which allows efficient processing of them. The hybrid framework consists of such as ResNet50, VGG-16, and Random Forests.

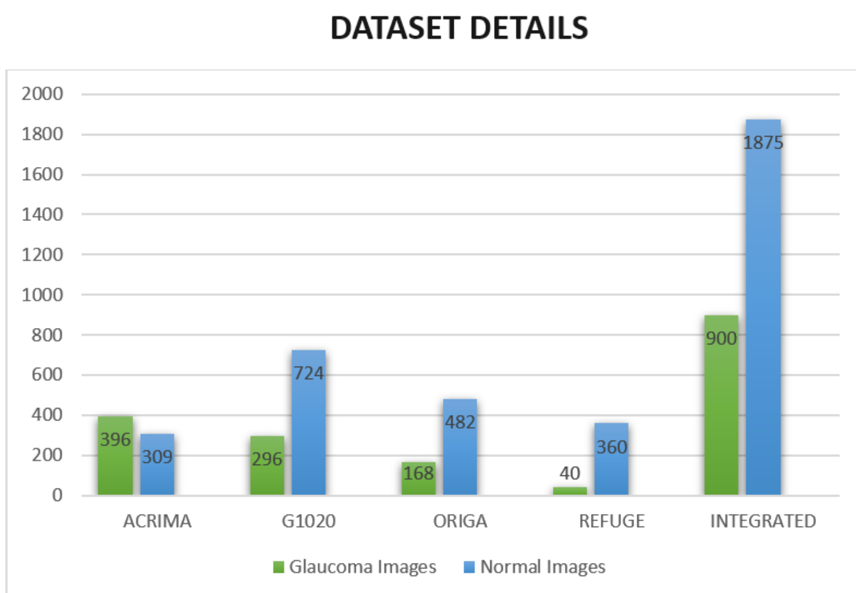


Fig : Dataset Details

Fig. 4. DataSet Details

Dataset Link `https://github.com/skrizwana824/inte.git`

3.2 Preprocessing

For effective analysis of images especially in deep learning and machine learning, retinal fundus images must be changed from RGB to grayscale from Figure 5. The transition is necessary since it is the means of acquiring accurate texture features needed for enhancing classification tasks like glaucoma detection.

3.3 Conversion Process

As per the paper written by the authors, they utilized the function rgb2gray() present in Python to change RGB images into gray-scale. This function follows certain criteria that assign weightings to different colors depending on the intended luminance perception.
The following equation demonstrates the workings of this conversion:
Gray=(wr×R + wg×G +wb×B) It implies that, The RGB channel weights are 0.2989 for Red, 0.5870 for Green, and 0.1140 for Blue.
This means that the following holds. WR = 0.2989
WG =0.5784 + wb0.1140(the second part)
Where: wr(RedWeight): 0.2989.
wg(GreenWeight) : 0.5870.
wb(BlueWeight) : 0.1140.

The formula explains that "Grey" denotes the pixel value in grayscale while RR, GG, and BB represent pixel values corresponding to red, green, and blue channels respectively of an original RGB image. This proportion originates from respective brightness's which are traditionally used in image processing for reproducing authentic grayscale.

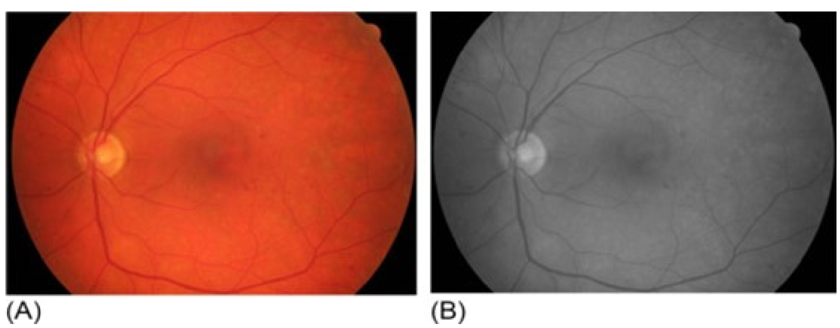


Fig. 5. This is the process of changing color in RGB format into black and white

3.4 Feature Extraction

This captures the meaningful characteristics from raw data, rendering it smaller while maintaining key details, and can thus reduce dimensionality. It gets rid of any unnecessary and irrelevant information hence making it possible for the models to concentrate on only important attributes hence improved accuracy and reliability. In analyzing textures and structures, for example, gray-level co-occurrence matrix (GLCM) is one widely adopted technique in image classification . For instance, in health care where model interpretation is necessary for diagnosis or treatment planning feature extraction is handly. Also, this process helps to improve performance by modulating algorithms to various datasets. Therefore, extracting features is a prerequisite for effective machine learning, especially during visual processing where there is a lot of disordered data to handle.

3.5 Training

The data set is generally split between two parts: 80% allocated for training and 20% for testing. This is done by extracting features like texture from images to train models such as Random Forests. So the whole performance of these models is post evaluation and their evaluation is adjusted accordingly. For example, CNNs like ResNet50 and VGG16 uses grayscale retina images. Therefore, these networks do not need to be autonomous as they extract important features of the image. Gray-scale retinal images are utilized for CNNs such as ResNet50 and VGG-16. Such networks do not need manual feature engineering since they will automatically extract relevant features this model performance through data augmentations is also common practice.

Random Forest Machine learning is a system based on experience that combines aspects of computer science and statistics. Random Forest, SVM, and Decision Tree are among the algorithms used to do classification and regression activities. In texture feature test comparison, Random Forest was found to be the most accurate (90.45%,) and It builds decision trees from slow random data parts which later on depend on them. In addition, Random Forest determines the importance of characteristics in the classification process. This image Features is converted into a text Data format

ResNet50 ResNet50 originates from a deep residual neural network model having several layers equal to 50 having a 7×7 convolution layer and 64 filters located in front of the max pooling layer from Figure 6. Five stages are represented in this structure with convolutional layers assisted by residual blocks that enable learning of complex network features mostly for image classification purposes.

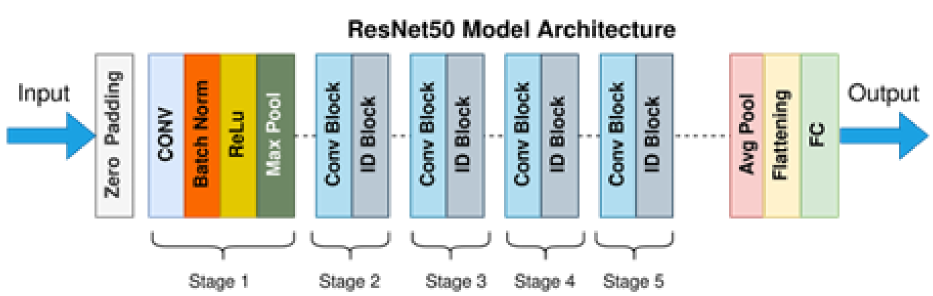


Fig. 6. ResNet50 Process

VGG-16 VGG16 is a powerful 16-layer convolutional neural network developed by the Visual Geometry group at the University of Oxford and known for its excellent performance capabilities. It is a convoluted neural net kind of architecture that is mostly applied in medical imaging with small samples to attain a higher accuracy rate. To define this model, it has a series of convolutional layers of 3×3 size that is followed by max pooling, an increase in the number of filters such as 64, 128, 256, and 512, and the final level has three thick layers from figure 7.

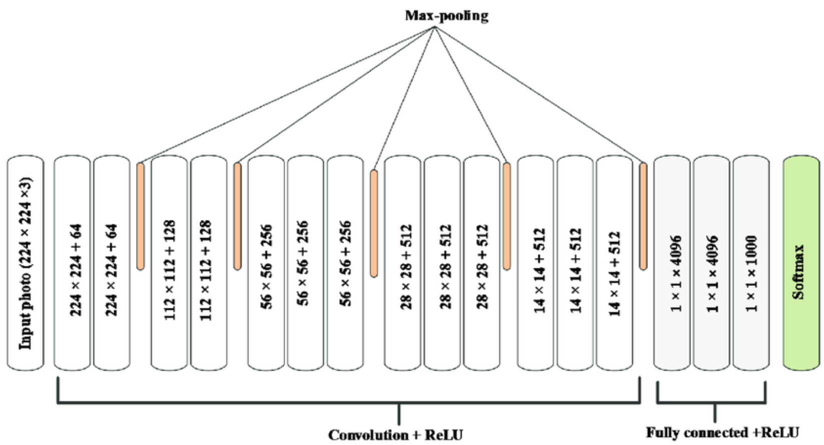


Fig. 7. vgg architecture

4 Result and Discussion

The formula used to compute accuracy is:
Accuracy = (TP + TN) /(TP + FP + TN + FN)
Precision: TP / (TP + FP)
Recall: TP / (TP + FN)
True Positive (TP): Cases of glaucoma that are correctly identified by the model.
True Negative (TN): Cases of people who do not have glaucoma that are rightly classified by the model.
False Positive (FP): Individuals who do not have it but are wrongfully predicted to be suffering from glaucoma by the model.
False Negative (FN): Occurs when a person has glaucoma but it is not detected by the model.

By using the above formulas we got an Accuracy of 96%, a precision of 99.35%, Recall of 88.50%. The use of a classifier has an 89.50% true positive rate,99.68% true negative rate, 4.90% false discovery rate, and 96 percent positive predictive values among other metrics. These metrics assess its performance hence very important for evaluating the effectiveness of any glaucoma diagnosis detection by using models of Random Forest comes with results of 90.45% and ResNet50 comes with results of 90.81%, VGG-16 comes with results of 91.05% and Glaucoma Detection

Framework comes with results of 96% .

Random Forest This method has an accuracy rate of 90.45% and other remarkable measures, its success might be influenced by the associations between trees. Several ensemble techniques have included Convolutional Neural Networks (CNNs) like ResNet50 and VGG16 in Random Forest models to improve accuracy. This way, when each model makes its prediction independently, more accurate forecasts are possible because their collective response usually converges towards a common and better outcome.

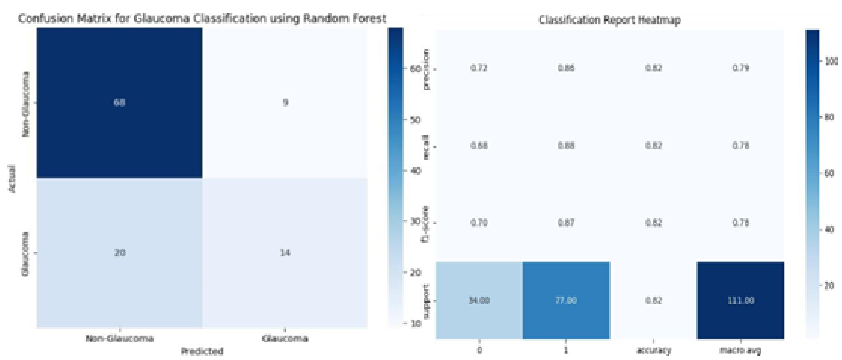


Fig. 8. Confusion Matrix for Glaucoma Classification using Random Forest and Classification report heatmap

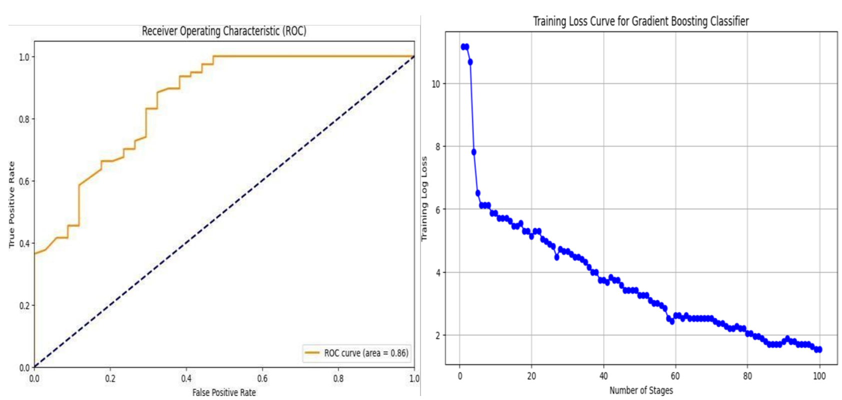


Fig. 9. Receiver Operating Characteristicand Loss Curve by using Random Forest

ResNet50 ResNet50, having 50 layers is ultimately utilized to solve classification and regression problems. For this purpose, some retinal grayscale fundus images were utilized to train the model 50 epochs were used for training with a batch size of 32, and the Adam optimizer was used to increase the speed of classification during training. To cope with the vanishing gradient problem, the ReLU activation function was implemented, while no data shuffling was done during training. For the confusion matrix in glaucoma detection with an impressive 91.81% accuracy rate, the ResNet50 model has a precision of 90.50%, a recall value of 86.04%, and an F1-score standing at about 89.45%.

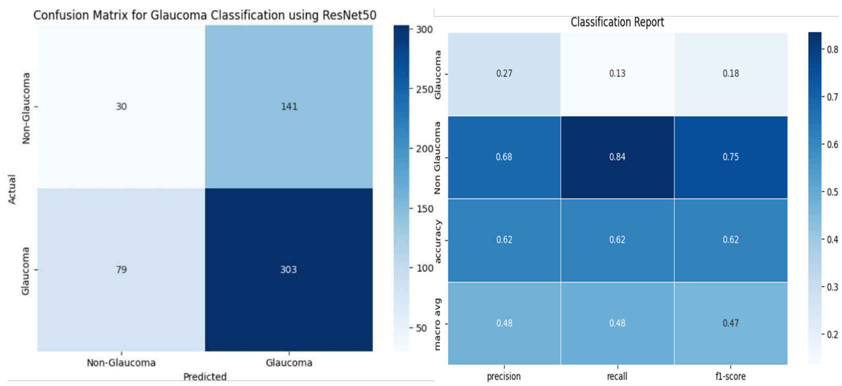


Fig. 10. Confusion Matrix for Glaucoma Classification using ResNet50 and Classification Report heatmap

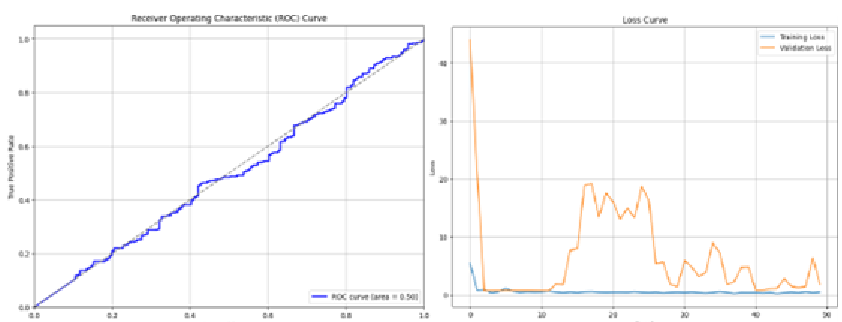


Fig. 11. Receiver Operating Characteristicand Loss curve by using ResNet50

VGG-16 Designed exclusively for glaucoma diagnosis utilizing retinal grayscale fundus images, the structure attained performance indicators are as follows Accuracy of 91.05%, precision of 93.05%, recall of 83.02%, F1 score of 87.30%. Such a degree of competence is crucial when it comes to ophthalmologists scrutinizing minuscule aspects in remotely taken pictures. Also, adding models such as ResNet50 and Random Forest greatly improved performance enabling an amazing precision rate of 96%.

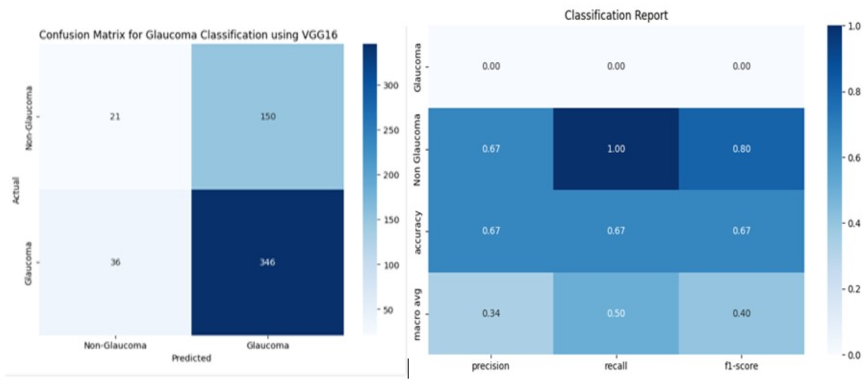


Fig. 12. Confusion Matrix for Glaucoma Classification using VGG-16 and Classification Report heatmap

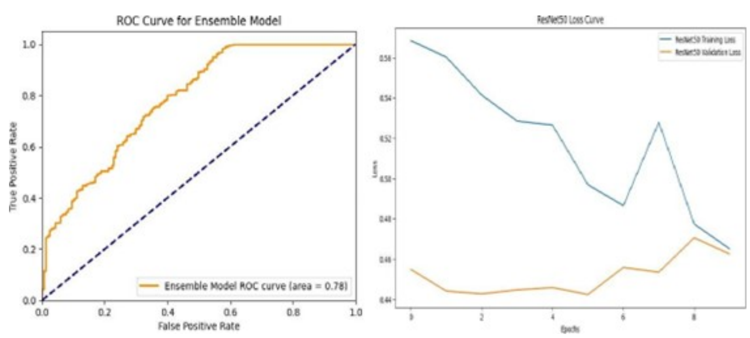


Fig. 13. Receiver Operating Characteristicand Loss curve by using VGG-16

Glaucoma Detection Framework The ensemble method combining machine learning and convolutional neural networks for glaucoma detection is yielding remarkable results. In the beginning, Random Forest with texture properties attained an overall accuracy rate of 90.45%, but that was not appropriate enough for clinical application. Each of the CNN architectures is Random Forest, ResNet50, and VGG16 accuracy of 91.05% however, each had its limitations due to being used in isolation.

Integrating Random Forest, ResNet50, and VGG16 into one combined architecture resulted in increased accuracy rates of up to 96% from Figure 14. This framework passes input data through each algorithm separately before applying post-processing rules, which helps in refining the final classification. Four benchmarks were used here (ACRIMA, G1020, ORIGA, REFUGE) with RGB images converted into grayscale to enhance feature extraction. According to the calculation results, the score (F1) is 95.40%, the score (Precision) is 99.38%, and the score (For) is 88.90%. This sophisticated scheme improves early detection of glaucoma and decreases the chances of losing eyesight hence better patient outcomes, especially during the initial stages of the disease.

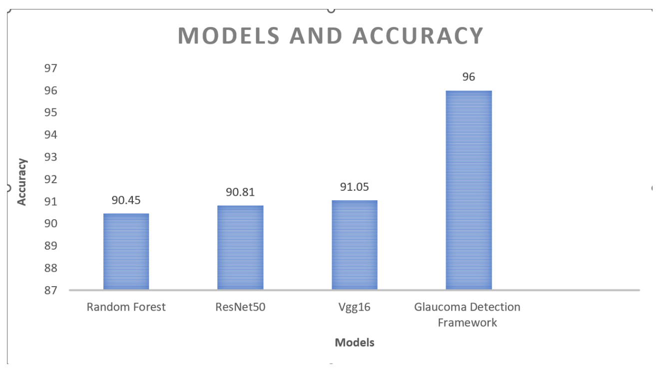


Fig. 14. Comparasion between Models and Accuracy

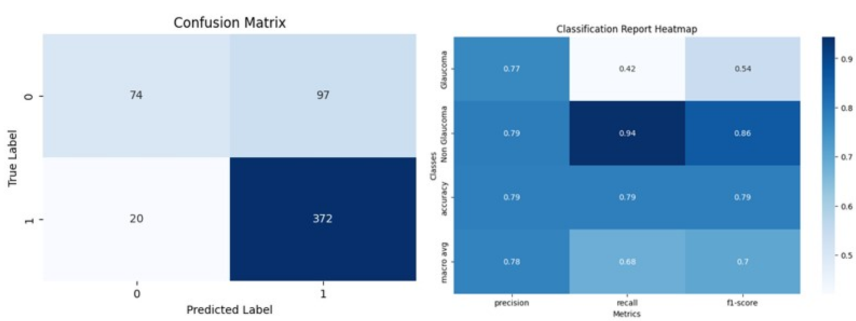


Fig. 15. Confusion Matrix for Glaucoma Classification using FrameWork

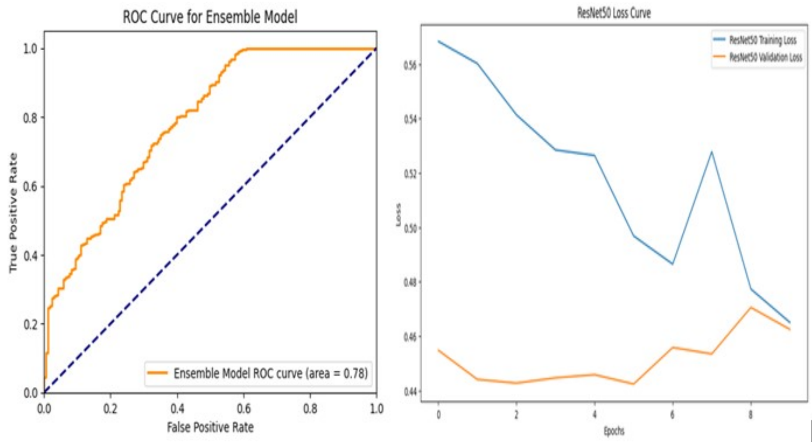


Fig. 16. Receiver Operating Characteristicand Loss curve by using FrameWork

5 Conclusion

Glaucoma is one of the most common eye disorder and may lead to blindness unless diagnosed early. This study's goal was to create a robust system that would detect and classify glaucoma. The post-processing rule defined 'glaucoma' if two or more models were in independent agreement with each other. This research study is based on an integrated data set that has been derived from four publicly accessible data sets ACRIMA, G1020, ORIGA, and REFUGE. whereas Smoothness and roughness of the surface were extracted from capsule retinal images. The remarkable outcomes of this system were 96 percent accuracy, 99.37 percent precision, 88.50 percent recall, and F1 a score of 93.60 percent using Random Forest, ResNet50 and VGG16 combined as three models. Such a combination holds promise for improved early diagnosis thus giving glaucoma patients hope of getting better.

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