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Detecting Eye Diseases from Oct Images Through Deep Learning

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ABSTRACT: *About 23% Indians suffer from eye disorders. The main risk causing loss of vision includes Choroidal Neovascularization (CNV), Diabetic macular edema (DME), Multiple drusen , Normal retina . Diagnosis of the above eye conditions can be done with the imaging technique Optical Coherence Tomography (OCT). It allows the retina specialist to visualize the retina and take different slices early. Manual diagnosis of different diseases by ophthalmologists is very time-consuming and prone to errors due to ocular anomalies. Early detection of eye diseases will prevent severe complications such as total blindness.*

Though the current technique for eye diseases uses fundus photographs to train deep learning models, the method seems ambiguous from the perspective of understanding data since its final results do not inspire confidence. A way out would be the extraction of relevant information from medical Ocular Coherence Tomography (OCT) images through a deep learning model. This requires the use of OCT images followed by a convolutional neural network (CNN), and feature extraction for the early identification of diseases. The proposed work shows the efficiency of VGG16 and RESNET-50 MODELS in predicting various eye disorders at an early stage using OCT images. The expected results showed higher accuracy of the proposed model compared to other existing systems. The proposed model classifies retinal OCT images into four categories: NORMAL RETINA, DME, CNV, and DRUSEN.

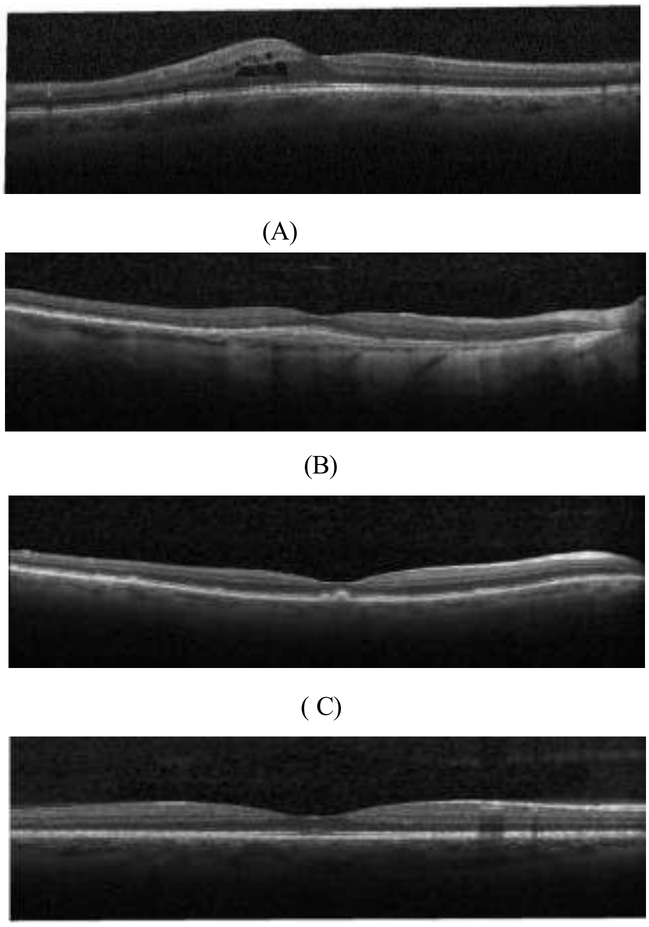
KEY WORDS: *Deep learning,Optical Coherence Tomography, Convolutional neural network ,DME, CNV, DRUSEN.*

1. INTRODUCTION

Optical coherence tomography (OCT) is noninvasive imaging and the branch of ophthalmology was turned upside down with its use in diagnosis and treatment. It provides a comprehensive description of the retinal structure and layers by providing en face or cross-sectional images of the retina created by recoiling reflective waves. The first studies using this technique were done in the early 1990 by a group at MIT led by Dr. James Fujimoto[1].

OCT mechanisms initially carried out by time-domain (TD) were rendered obsolete by the rise and mass adoption of so-called spectral-domain (SD) and sweeping-source (SS) OCT that provide higher image acquisition speeds and better resolution. The basis of the OCT working principle is low-coherence interferometry. It measures the delay of the backscattered light in tissue microstructure, since the time of its scattering and reflection. Using this information, very-high resolution cross-sectional images of the retina are made. Optical coherence tomography (OCT), a longitudinal imaging technique for live patients, obtains transverse multilayered images of the retina[2]. Every year, around 30 million OCT scans are performed, which take time to analyze and interpret.

Four types of diseases are shown in the below Figure 1 that are choroidal neovascularization (CNV), Diabetic macular edema (DME), Multiple drusen, and Normal Retina.



(A)

(B)

(C)

(D)

Figure 1 *:* Types of disease

A) Choroidal neovascularization (CNV) with neovascular membrane
(B) Diabetic macular edema (DME) with retinal thickening
(C) Multiple druse
(D) Normal retina with preserved foveal contour and absence of any retinal

Vision loss due to CNV is caused because of the abnormal growth of blood vessels in the back of the retina.It is frequently associated with ocular histoplasmosis and pathologic myopia and ARMD [3].Impaired central vision and distorted and blurry vision are the signs.Intravitreal injections of anti-VEGF agents, photodynamic therapy, and laser photocoagulation are the available treatments. Early detection is key for both of these diseases[4].

Diabetic macular edema (DME) means the disturbance caused by diabetes due to the deposit of fluoride in the macular area of the retina. This occurs due to leaking fluid from damaged blood vessels. Symptoms include dark patches and loss of vision [5].Treatment may include injections of anti-VEGF along with corticosteroids, and laser application.Early detection is essential[6].

Drusens are protein and lipid deposits that form underneath the retina. Drusens are usually associated with age-related macular degeneration (AMD)[7]. Generally, small drusens are benign, but large and multiple drusens are important in the process of causing AMD. Distortion or blurring could be one symptom or many symptoms. Regular check-ups should be done to keep an eye on and manage the future development[8].

The retinal diseases in any way RPE65, RTVD, IFERGV, continue to impair vision and create blindness across the globe [9]. It allows a doctor to detect this problem early enough to prevent it, while some cannot afford it since they might not have medical care available or may be so afraid of going under a knife. Nonetheless, the fundus photos should be checked by a certified ophthalmologist, who may make an error or have a completely different set of opinion[10]. Data mining algorithms are presently being employed to forecast and predict patterns from data sets. These include unsupervised learning techniques, such as cluster analysis and associative, and supervised learning algorithms, such as decision trees or linear regression.Decision trees, support vector machines (SVMs), and deep learning are being applied in many different areas to diagnose diseases and optimize treatments, including sales, banking, engineering, and health care.

Deep learning is part of machine learning which is an ensemble of algorithms inspired by the structure of the human brain [11]. I have seen it being used for things like sound recognition and image identification; natural language processing; medical diagnostics where it performs really well. Convolutional networks and recurrent neurons.

2. LITERATURE SURVEY

Li F, Chen H, Liu Z, Zhang XD, Jiang MS, Wu ZZ, and Zhou KQ to perform important work in computer aided diagnostics (CAD) for medical applications [13]. This study presents retinal disease classification for automatic detection of four classes in optical coherence tomography (OCT) images: choroidal neovascularization (CNV), diabetic macular edema (DME), DRUSEN, NORMAL and proposed classification method retina based advanced residual neural network (ResNet50)). -uses four observations in a classification model to classify OCT images Stacked retinal OCT images were used in the experiments, with a 10-fold patient-level cross- validation procedure. The classification accuracy of the proposed method at the B-scan level was 0.973 (95% CI, 0.971–0.975), sensitivity 0.963 (95% CI, 0.960–0.966), 0.985 (95% CI, 0.983–0.987) and specificity were obtained), which is equal to or better than the results obtained by ophthalmologists with extensive clinical experience. The analysis used the kappa value and area under the customer performance characteristic curve (AUC) as measures of performance. Analysis of the survey showed that integrating multiple ResNet50s is a helpful approach where available medical images are not available. Occlusion testing and qualitative analyzes of the model predictions were performed to better understand the decision-making process of the model Exploratory testing of disease areas and abnormal classification detected by occlusion testing is also included in the text. Lastly, we combine patient history data with retinal OCT images to investigate their effect on model performance.

Pugazhendi A, Hubal M, Jayaram P, Ambati B. Exudative or wet AMD, also known as neovascular age-related macular degeneration, is a common progressive retinal degenerative disease that mainly affects the elderly and obviously choroid It is is gradually blurred new implants. says that it caused it. Overview Anti-VEGF drugs are the cornerstone of treatment for AMD, risk variables such as age, race, heredity, iris color, smoking, alcohol consumption, BMI, and diet all play important roles in disease progression[14] .

Gehrs KM, Anderson DH, Johnson LV, Hageman GS. Optical coherence tomography, or OCT, is the current gold standard for early detection of AMD. Here we describe how OCT imaging can be used to diagnose AMD. Our main goal is to study and distinguish between AMD diagnosis and computer aided classification (CAD) techniques. As a result, we provide an outline of important factors in performance evaluation and lay the groundwork for future research on AMD diagnosis. Thus, treatment of AMD is necessary to avoid this devastating ocular disease and unintended vision loss[15]. Quantification of AMD in the subject is very important for early diagnosis of AMD and prevention of progressive AMD in patients. In this context, we explore the remaining challenges of automated AMD detection systems based on OCT images and possible directions for OCT image-based diagnostic and monitoring systems and telemedicine applicat

Gheorghe, Labib M, Cernat C, and Musat O say, diabetic macular edema (DME) continues to be a very common cause of the loss of vision in individuals having diabetes. [16] As the article suggests, there is a growing interest in the specific pharmacological treatments that may benefit, such as eye steroid therapy, anti-vascular endothelial growth factor (VEGF), and the inhibition of protein Kinase C-beta, of which the understanding of pathophysiology has dramatically grown. According to Early Treatment Diabetic Retinopathy Study, until recently, laser photocoagulation has been the gold standard in most communities OCT (optical coherence tomography) is an effective tool for the monitoring of macular edema[17].

3. METHODOLOGY

The Architecture of eye disease prediction depicted in Figure 2 provides a detailed description of the steps involved in identifying eye disease using the mentioned approach. Below is a comprehensive breakdown of each step within this system architecture

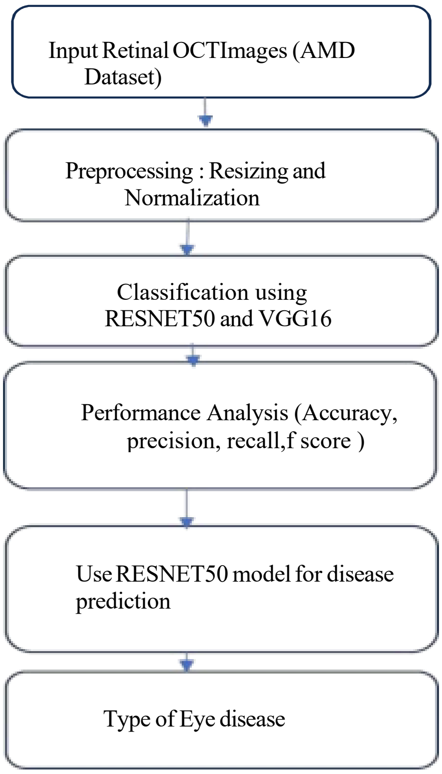


Figure 2 : System Architecture of eye disease prediction

3.1 Data Pre-Processing & Augmentation

For eye disease detection using the Optical Coherence Tomography (OCT) images, the ImageNet dataset includes VGG16 and ResNet50 pre-trained models fine tuning for specific tasks pertaining to blood vessels – CNV, DME, drusen and normal retina[18]. The first step in the process is to compile an extensive range of OCT images that have been annotated. Basic preprocessing steps that need to be performed are taking the images and resizing them to 224 by 224, normalizing the pixel values to be within the range of [0, 1], and augmenting the dataset by rotating and flipping the images.

3.2 Proposed Architecture

In model building, VGG16 was implemented with convolutional layers, while ResNet50 was implemented using residual blocks to solve the vanishing gradient problem. Training involves the division of the entire dataset to into three parts: Training Set, Validation Set and Test Set, adjusting parameters with the ADAM algorithm, and preventing overfitting[19]. New predicted OCT images after training the models are used by the models to classify the images into the new predicted disease class using the class with the highest probability. Lastly, for model performance comparison and evaluation, accuracy and F1 score can be used in order to measure the effectiveness in diagnosing the patient.

4. Classification

For deep learning models, the data images have to be resized the images to a common size, scaled to a range of [0, 1], and enhanced by other methods, such as flipping and rotating the images[20]. The dataset is further partitioned into training, validation, and test sets. The following architectures as shown in figure 3 and figure 4 which examples are selected based on requirements and resources are VGG16 and ResNet50. The aims of the study were to test the potential use of ADAM optimization algorithms to adjust the weights and test/validate using preprocessed OCT images.

VGG16 network was provided by the Visual Geometry Group which consists of 16 layers and employs small 3x3 convolutional filters, a ReLU function, and 2x2 max pooling. Three final layers are added, with twith the last one being for softmax.

Figure 3 : VGG16 Architecture

ResNet50, a member of the Residual Network family, uses residual learning and 50 layers to solve the vanishing gradient problem. A fully connected layer and softmax activation are used for classification, together with a combination of 1x1 and 3x3 filters and batch normalization

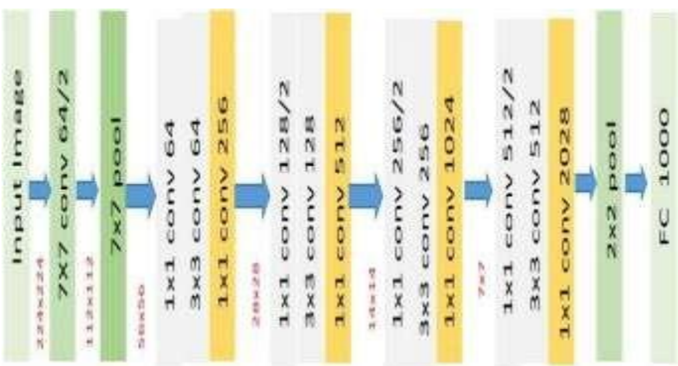


Figure 4 : RESNET-50 Architecture

5. RESULTS

5.1 Performance Measures

The performance is crucial part while detecting the disease by using different models . Several important metrics measure and provide a comprehensive assessment regarding strengths and weaknesses of the models:

Accuracy: Accuracy: This measures by what method many pixels are right recognized across the whole dataset, bestowing a general sense of the model's overall act

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision:Precision shows the dimension of valid a still plan of how trustworthy the model's beneficial classifications .

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall (Sensitivity): Assesses the model's ability to capture all true positive instances, such as identifying river pixels accurately.

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

F1 Score: The F1 Score balances accuracy and recall, contributing a more uniform measure of the model's capability to correctly categorize .

$$F1 \ Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (4)$$

There are different metrics that can be used to evaluate the performance of the segmentation model for eye disease detection. Accuracy is a general measure of correct classification. Precision and Recall are particular measures of the model's ability to identify disease regions without false positives or negatives. The F1 Score has practical importance in avoiding misdiagnosis. These put together constitute a high understanding of model performance for a basis of improved accuracy and reliability in eye disease detection from medical images.

5.2 Performance Comparison

The Comparison of RESNET 50 has accuracy of 97% ,While VGG16 is giving 88% accuracy. So it is predict that Resenet algorithm is giving highest accuracy as compared to VGG16. the plotting graph of both algorithms Resenet And VGG16 to analyse the performance of both algorithms.The below Figure 5 shows the bar graph of Accuracy,Precision,recall,F1score for both Vgg16 and Resnet50

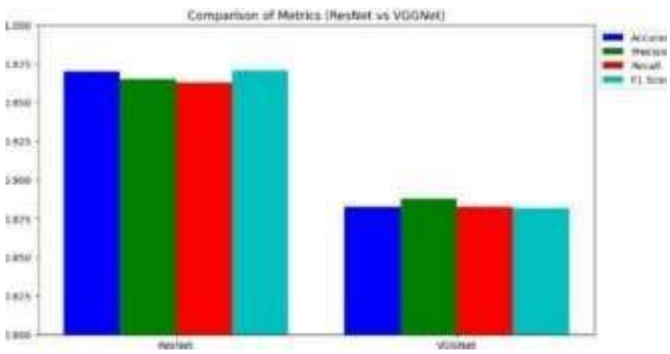


Figure 5 : comparison graph of resnet 50 and vgg16

The Accuracy table 1 below shows the accuracy of both models, where RESNET50 has higher accuracy compared to VGG16. Specifically, VGG16 achieves an accuracy of 88.07%, while RESNET50 achieves an accuracy of 97.2%. This indicates that RESNET50 is more effective for this particular task or dataset

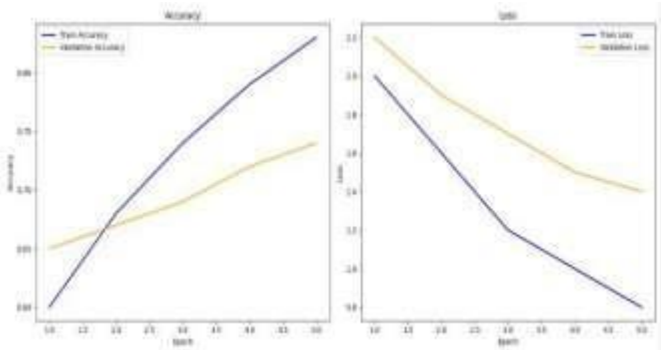
METRICS	VGG16	RESNET50
Precision	0.89	0.9701
Recall	0.88	0.9625
F1Score	0.88	0.9632

Table 1 : Classification of Metrics

RESNET50 performs better than VGG16 for every measured criterion,according to classification metrics table 2 below. VGG16 specifically obtains 0.89 precision, 0.88 recall, and0.88 F1 score. On the other hand, with an F1 score of 0.9632, a recall of 0.9625, and a precision of 0.9701, RESNET50 performs better. According to these findings, VGG16 is not as good at making predictions for the given dataset as RESNET50.

5.3 Comparative analysis of results

The figure 6 (a) and (b) illustrates the model accuracy and loss curve for the vgg16 and resnet50, with the accuracy of 0.89 and loss of 2.2 for vgg16 and accuracy of 0.97 and loss of 1.75 for resnet50. This model shows its



performance for detecting the type of disease. RESNET50 performs better than VGG16.

(A)

(B)

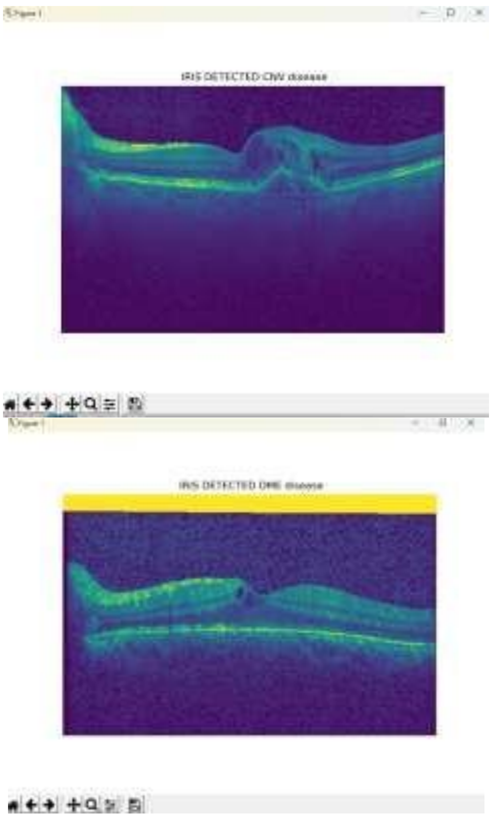
Figure 6 (A) and (B) : It shows the model accuracy and model loss of vgg16 and resnet50

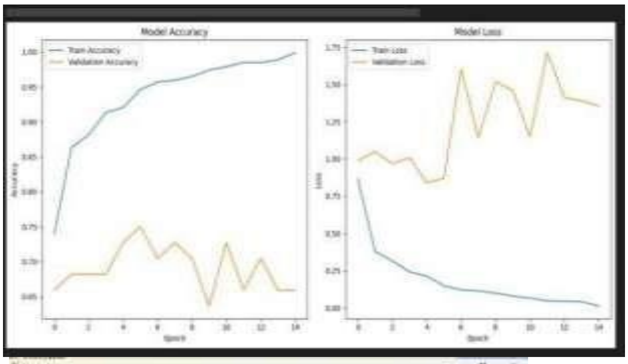
5.4 Eye disease detection

A custom GUI allows the model to be interactively applied for eye disease detection. The GUI designed for the Eye Disease Detection facilitates the user-friendly, interactive analysis of retinal OCT images. With a GUI, it will be possible to effortlessly choose an image to apply processing for the selected deep learning model. Users can easily switch between two models, VGG16 and ResNet-50, from a dropdown menu for rapid model selection in disease prediction.

The GUI further has various evaluation metrics to be applicable for thorough judgment of model performance - precision, recall, F1 score.The Model Performance tab in the GUI is yet another feature allowing the view of different performance graphs. To view how successfully each model is trained to identify eye conditions, it shows plots of accuracy and loss in both models with training and validation loss.

For the predictions results, the GUI displays predicted disease shown in the figure 7 .The users can see and compare the quality of features in each model. The model ResNet-50 typically predicts with higher accuracy and offers more enhanced visualization of the detected eye diseases.





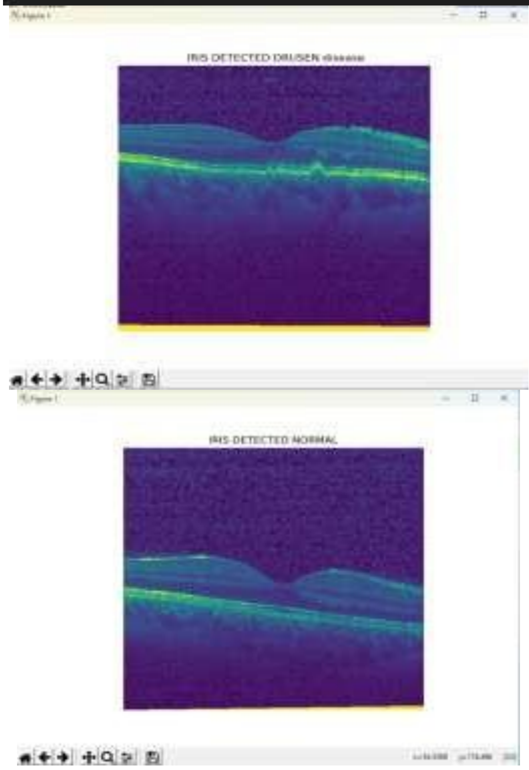


Figure 7 : Shows all types of predicted disease

6. CONCLUSIONS

Patients with retinal pathologies often do not seek medical assistance in a timely manner. Therefore, early detection is of utmost importance to avoid irreversible blindness. The authors of the present study employed sophisticated fully automated techniques based on deep learning to detect retinal pathologies on OCT images. The study is quite extensive since it includes data preprocessing and feature extraction with pre-trained models, which are further used to train classifiers capable of distinguishing between diseases. The obtained results demonstrated great efficacy and efficiency when the proposed strategy was tested on a substantial and varied dataset. Furthermore, direct measurements indicated that ResNet50 was more accurate than VGG16 thanks to the potential application of this approach in aiding practitioners in making timely and accurate diagnoses and better managing patients with eye diseases.

7. FUTURE WORK

The future of eye diagnostics may be revolutionized by OCT machine learning image processing technologies which are still in research stages. OCT image datasets as well as models perform better with enhanced contrast and noise reduction during preprocessing or with generative adversarial networks as a form of data augmentation..Attempts to exceed VGG16 and ResNet-50 include exploring other advanced CNN architectures like denseNet or EfficientNet to capture more features which are important when trying to detect disease in OCT scans. The use of automated hyperparameter tuning tools make the process of model tuning end within a blink as desired metrics are evaluated and models improved per those metrics. Deployment of ready, tuned, and tested models on the edge or in cloud services allows the timely analysis of OCT images and thus the opportunity to connect AI-assisted diagnosis with real clinical practice.

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