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An Enhanced Deep Learning Approach for Detection and Classification of Retinal Diseases using OCT Images

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Abstract-Ophthalmologists can make diagnoses based on the layers of the retina using optical coherence tomography (OCT), a non-invasive procedure produces cross section images of retina layer of the eye. As a result, it is a crucial modality for the identification and measurement of retinal disorders and illnesses. Ophthalmologists must spend a lot of time analysing the pictures since OCT produces many images for each patient. The OCT pictures of patients are divided into four groups in this work using deep learning models: Normal, Drusen, Diabetic Macular Edoema (DME), and Choroidal neo-vascularization (CNV). There are two distinct models suggested. Normal, Drusen, Diabetic macular edoema (DME), and Choroidal neo-vascularization are the four groups that may be classified utilising segmentation using curvature-based ROI and classification using the Folded RESNET101 algorithm (CNV). The proposed approach has the highest accuracy, sensitivity, and specificity of 0.99. The accuracy of binary classifier for the Normal is 0.99. These outcomes demonstrate their capability to function as a primary approach for ophthalmologists.

Keywords— Deep Learning, Convolution Neural Network, Optical Coherent Tomography, Retinal Diseases, Curvature based RoI.

I. INTRODUCTION

A non-invasive imaging method called OCT creates cross sectional pictures of the retina layer. It makes use of near-infrared light pulses, which may penetrate the retinal layer as deep as several hundred microns. Because of this, it is crucial for ophthalmologists to identify and measure retinal diseases and abnormalities as well as to offer treatment recommendations for conditions like glaucoma, Diabetic Retinopathy (DR), age-related macular degeneration (AMD), diabetic macular edoema (DME) and choroidal neo-vascularization (CNV) [1, 2]. Wet AMD and Dry AMD are the two subtypes of AMD. Wet AMD patients mostly have Choroidal Neovascularization (CNV) and related symptoms in the retina, whereas most Dry AMD patients have Drusen [3][4][5]. The development of aberrant blood vessels in choroid layer of the retina is known as CNV [6]. DME is a fluid buildup in the macula region brought on by blood vessel leaking. DME occurs in 30% of individuals with DR [7, 8]. Ophthalmologists must spend a lot of time in analyzing the OCT since each patient receives many images from the procedure. Recently, deep learning techniques have been modified to classify OCT pictures. The categorization of OCT into 4 classes is performed using DenseNet201 [9] [10]. OCT pictures are categorized into four classifications using Inception V3 [11], including Normal, Drusen, DME and CNV [12][18]. In order to categorize OCT pictures into the four groups, ensemble based learning on ResNet152 [13] is utilized [14]. The grouping of images into 4 classes using

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ensemble learning and modified ResNet50 [13] [15][17]]. OCT images are trained for the four-class classification using image normalization and VGG16 [16][19].

In the investigations mentioned above, two different deep learning (DL) models were applied. One uses multiple binary classifiers, while the other uses multi-class classifiers. Since only one classifier needs to be trained, the DL model using a multi-class classifier (DLM) seems to be more practicable than the DL model employing binary classifiers (DLB) for resolving multi-class classification issues.

For each class, the DLB must train several classifiers. There is a benefit to using the DLB when we update or improve the model to categorize one or much more categories in the same data after building the model. For new classes, the DLB just has to train more binary classifiers. The DLM must, however, retrain the model from scratch. When compared to the DLM, the DLB is more extensible. In the case of picture segmentation, several binary classifiers outperform a single multi-class classifier [20]. In order to categorize patients OCT images into four groups—Normal, DME, CNV, and Drusen—this research suggests two DL models. The architectures of the proposed models are designed using four binary CNN classifiers.

Noise is eliminated from the images, and the retina layers are cropped using a preprocessing method. The remaining of this paper is explained as follows. Section II goes into great depth on the data and our classification techniques for OCT images. In Section III it describes the findings of the experiments, and Section IV is the conclusion.

II. Proposed method

The stages of the suggested technique are pre-processing, image segmentation, Feature extraction and classification, The following figure 1 shows the detail about the steps involved in the proposed method.

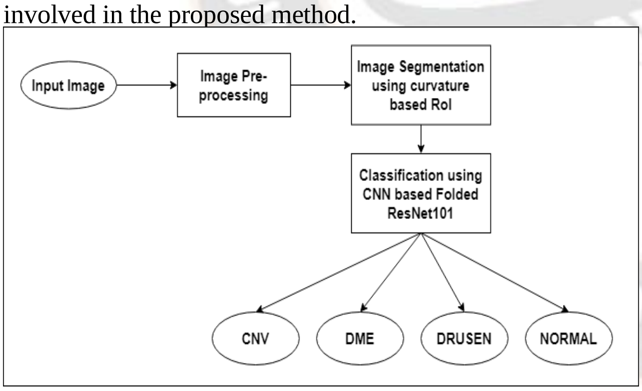

Figure 1. Architecture Diagram for Proposed method

III. Image Pre-Processing

Throughout this study, Gaussian Filter and Pre- RoI methods are used to increase contrast and picture features by highlighting anomalies, since it is more useful in reducing noise distortion and has a more realistic appearance amongst the visualization-based family.

A. Apply Gaussian filter to reduce the noise

A Gaussian filter is a low pass filter that used to blur firm parts of a picture and diminish noise (high frequency components). The filter is built as a simple array of symmetrical kernels of odd sizes, which are then processed through every pixel in the area of interest to achieve the desired result. Since its inner pixels provide significantly more to the final value than any of its outer ones do, the kernel is not responsive to abrupt changes in colour (edges). One may think of a Gaussian Filter as an approximate representation of the Gaussian Function.

$$\mathbf{g(x,y) = 1/2\pi\sigma^2[e^{-(x2+y2)/(2\sigma2)}]}$$

Where x-row and y-column

B. Pre- ROI(Region of Interest)

Pre-ROI is used to remove top(1 to 50) and bottom row (450 to end).

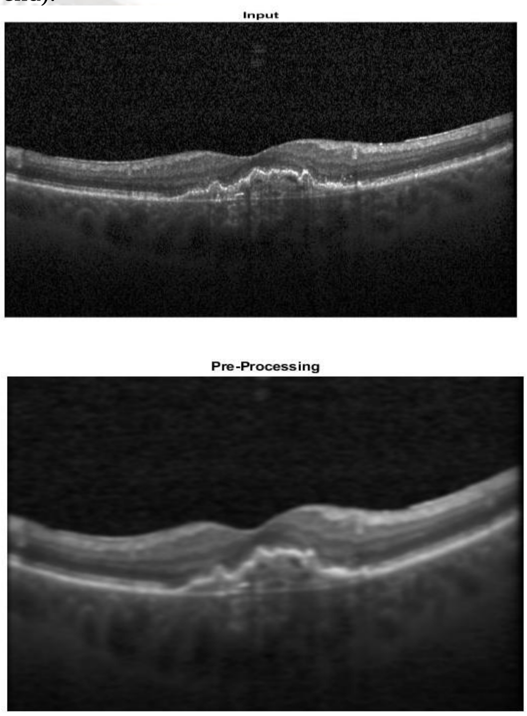

Figure 2 (a). Input Image (b) : Preprocessed Image

IV. Proposed segmentation algorithm – curvature based ROI

The proposed method uses curvature based RoI segmentation algorithm is used to extract the features with the following steps.

A. Region_Idendify

Step1: create mask based on given input size of image

Step2: find the interior and exterior points
Step3: find the curvature points
Step4: apply gradient on the points
Step5: check the curve condition (0.45/gradient point)>0.09
Step6 : apply step 1 to 5 till full image

B. *adjacency* matrix:

Step1: get the adjacent matrix index based on interior and exterior points

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C. Get shortest *path:*

Step 1: To compare adjacent matrix based on value with curvature

Step 2: Get border values in each row and columns

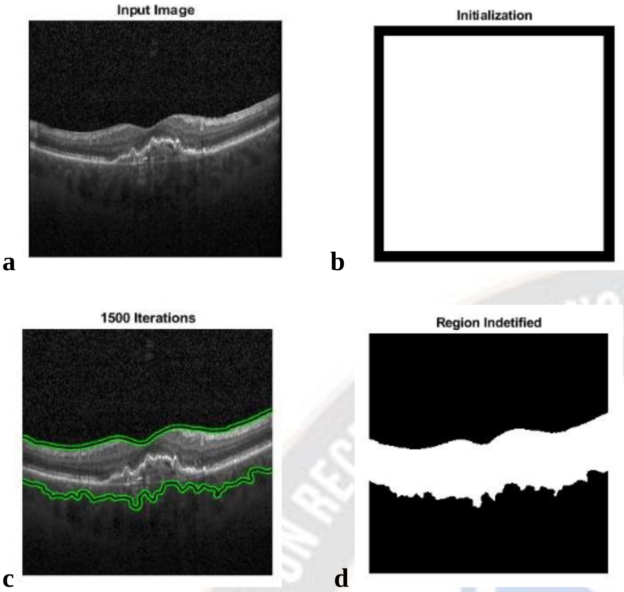

Figure 3. a. Input Image b. Input Image initialization c. Image after 1500 Iterations d. Identified Region

From the figure 3 (1-d) shows the input image, Initialization, and image after 1500 iterations and an identified region. Figure 4 shows the graphical representation of the proposed segmentation method.

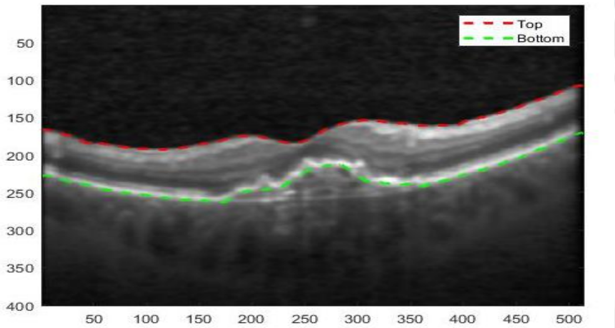

Figure 4. Graphical Representation of Segmented image

V. THE PROPOSED CLASSIFICATION ALGORITHM

The ResNet101 for classification and the Faster CNN were the two deep CNNs employed in this investigation. The Tensor Flow backend was used to build and train the model using the Python programming language and the Keras package. Then used a ResNet101CNN architecture that had already been trained Kaggle database, and retrained it on dataset by means of transfer learning, allows an algorithm to use cumulative information learnt from earlier datasets. Figure 5 (a) shows the typical architecture of the ResNet101.

The CNN was made up of numerous convolutional layers which identified and classified local characteristics in pictures. It included pooling layers (average pool and max pool), which aggregated semantically related features into a single feature, as well as fully linked levels to aggregate these characteristics and generate a final probability value for the class.

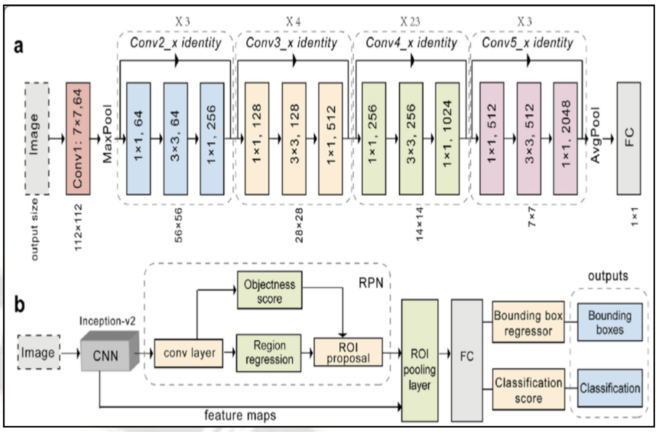

Figure 5. (a) Architecture of Resnet 101 (b) Flow chart of Proposed Model

Shortcut connections are introduced every three convolutional layers across the deep network. Without introducing additional parameters or raising the computational complexity, these shortcut connections execute identity mapping, which makes it simpler to optimise the network during training. ResNet enables deeper networks to attain more accuracy than shallower networks while conducting image classification tasks.

The link weights from the previously trained model were transferred to the new model throughout the training process, and the model was then retrained for the current task.

The outline box regression model and object classifiers were used to assess prospective containers from the outputs of the region proposal network, which was used to recognise objects in the image. Convolution layers and area of interest pooling were evaluated in the end. Finally, the model generates the bounding box and related category label for each target item. When you combine these two CNN networks as a model, it will finally produce categorization after processing a sizable dataset.

VI. EVALUATION METRICS AND RESULT ANALYSIS

In this experiment, optical coherence tomography (OCT) pictures from a Kaggle dataset are used. It is open to the general public. The dataset consists of 800 test pictures and around 5,000 training photos. There are four courses in it. There are 1000 images in the CNV class, 1000 in the DME class, 1000 in the Drusen class, and 1000 in the Normal class. There are 200 photos in each class in the test dataset.

TABLE I. : DATASET USAGE FOR PROPOSED METHOD FOR TRAINING, TESTING AND VALIDATION.

Type	Training	Model Testing	Validation
CNV	1000	200	100
DME	1000	200	100
Drusen	1000	200	100

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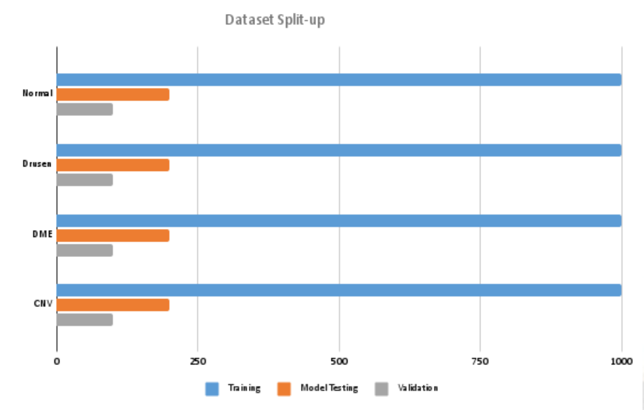
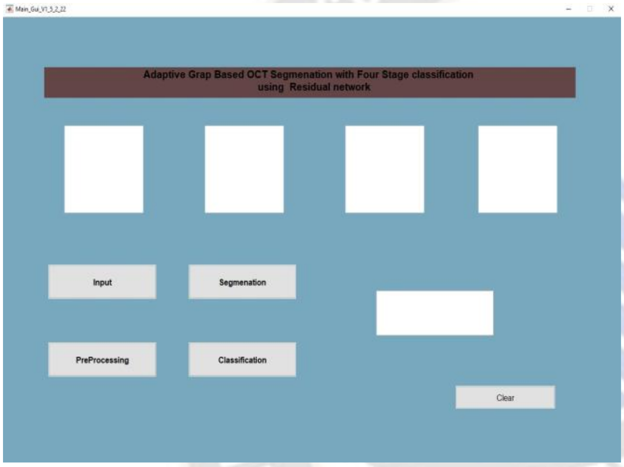
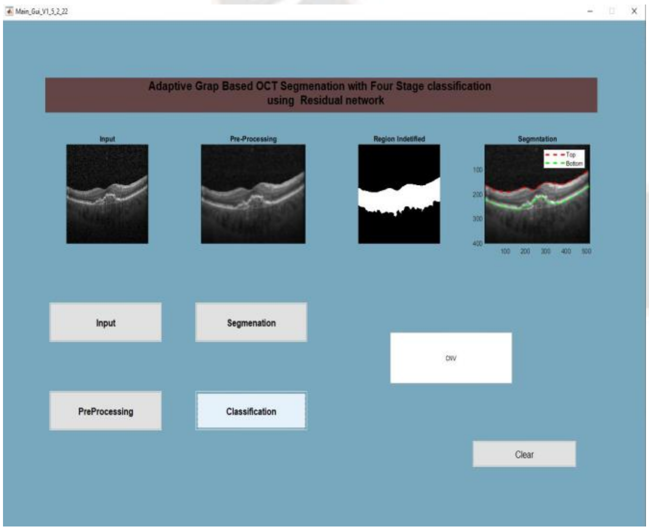


Figure 6. Dataset usage for proposed method

Table I and Figure 6 shows the images used in proposed method clearly and the images used for training, testing and validation.



(a) Initial GUI Window



(b) Final GUI with segmentation and Classification

Figure 7. (a) Initial GUI window (b) Final GUI window with Segmentation and Classification

Sensitivity, accuracy, Specificity, F1 Score and precision, which are specified in equations 1 through 3, are among the metrics utilised for evaluation. Four separate parameters—true negative (TN), true positive (TP), false-negative (FN), and false positive—are used to measure these measurements (FP). Accuracy is defined as the proportion of documents from all the data that were correctly classified. Precision is the proportion of the performance that is relevant. On the other hand, recall is the percentage of correctly classified results that the algorithm produced for all functional outcomes. The ratio of anomalous records correctly identified as abnormalities to all anomaly records is known as the detection rate (DR), also known as the true positive rate. (TPR) [19][20]]. Figure 7 (a) and (b) shows the output screenshots of implementation process.

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

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$precision = \frac{TP}{FP + TP} \quad (3)$$

$$SP = \frac{TN}{TN + FP} \quad (4)$$

$$F1-Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (5)$$

The above said quality measures are taken into consideration for measuring and comparing the performance of the proposed work with the existing model.

TABLE II: TRUE POSITIVE, TRUE NEGATIVE, FALSE POSITIVE AND FALSE NEGATIVE COUNT FOR EXISTING AND PROPOSED METHOD

	Existing Method 1 (OCT Net)	Existing Method 2 (VGG16)	Proposed Method (Folded Resnet101)
TP	90	92	97
FP	8	6	4
FN	6	5	3
TN	5	4	3

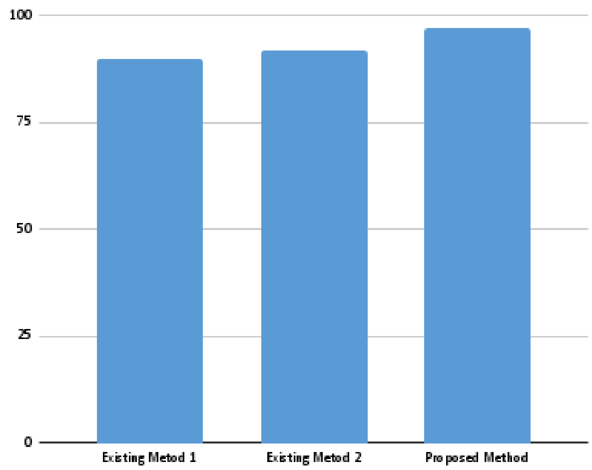


Figure 8. True Positive of Existing and Proposed method.

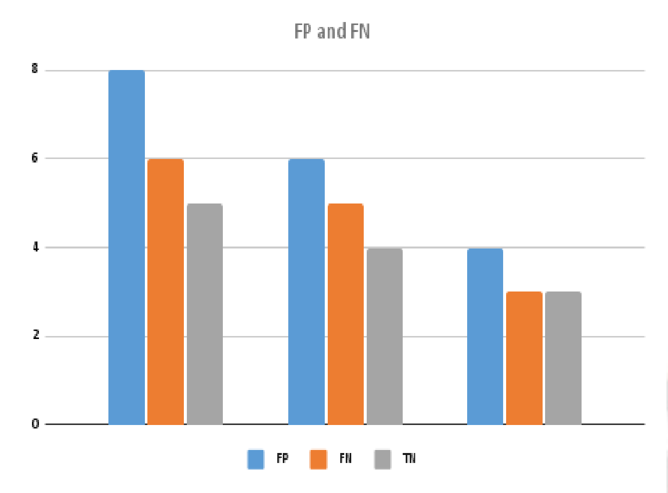


Figure 9. FP,FN, and TN of Existing and Proposed method

Table II, figure 8 and Figure 9 shows the TP, TN, FP and FN count of existing and proposed method. The proposed method achieved better value for ZTrue positive when compared to other existing methods.. FP, FN and TN are lesser in proposed method. This shows the proposed method outperforms when compared to existing methodologies.

TABLE III: PERFORMANCE ANALYSIS WITH RESPECT TO EXISTING METHOD

Quality Measures	**Existing Method 1 (OCTNet)**	**Existing Method 2 (VGG16)**	**Proposed Method (Folded Resnet101)**
Accuracy	87.2	89.7	93.5
Precision	91.8	93.9	96.0
Recall/Sensitivity	93.8	94.8	97.0
Specificity	38.5	40.0	42.9
F1 Score	92.8	94.4	96.5

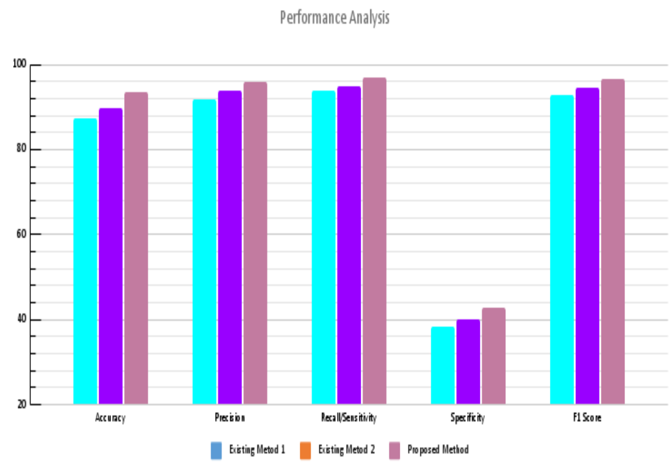


Figure 10. Performance Analysis of Existing and Proposed Method

Table III and Figure 10 shows the performance analysis of existing and proposed methodologies with various quality measures, Accuracy, Precision, Sensitivity, Specificity and F1-Score. The proposed approach has the highest accuracy, sensitivity, Precision, Specificity and F1-Score. The accuracy of the binary classifier for the Normal class is 93.5%. Table IV provides the confusion matrix of the evaluation of the proposed and the existing models.

TABLE IV: CONFUSION MATRIX COMPARISON

A) PROPOSED MODEL (FOLDED RESNET101) CONFUSION MATRIX

CNV	291	4	5	0
DME	5	290	2	3
Drusen	2	5	287	4
Normal	0	0	3	292
	CNV	DME	Drusen	Normal

B) EXITING MODEL 1 (OCTNET) CONFUSION MATRIX

CNV	268	8	13	0
DME	6	263	12	10
Drusen	14	5	265	10
Normal	2	10	1	279
	CNV	DME	Drusen	Normal

C) EXISTING MODEL 2 (VGG16) CONFUSION MATRIX

CNV	270	10	15	2
DME	17	265	14	0
Drusen	8	7	267	16
Normal	3	12	3	281
	CNV	DME	Drusen	Normal

The precision of the class is 96%. Recall, Specificity and F1 Score are 97%, $7.9% and 96.5% respectively. These results shows that the proposed method outperforms in all quality measures when compared to other existing technologies taken into considerations.S These outcomes demonstrate their capability to function as a primary approach for ophthalmologists.

VII. CONCLUSION

Overall, our DL-based approach demonstrated the potential for very accurate and precise automatic recognition of four-level categorization OCT images. The system's performance was on par with or better than that of retinal specialists, indicating that it may be utilized to help with clinical judgments. This is the first stage in the method's clinical translation. As it is understood throughout this paper, a methodology to instinctively classify the retinal disease is essential in the present scenario. The proposed method is fully capable of real-time discovery of retinal diseases. The outcomes validate that the proposed model can perceive the general types of diseases in Kaggle database with 93.5% of very high accuracy in real time and provide possible solutions for the retinal diseases. In future this work can be extended with high performance deep learning model to classify the diseases more accurately by experts in ophthalmology.

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