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Research Paper
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A Deep Learning-Based Technique for Diagnosing Retinal Disease by Using Optical Coherence Tomography (OCT) Images

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Abstract: The retina layer is the most complex and sensitive part of the eye, and disorders that affect it have a big impact on people's lives. The Optical Coherence Tomography (OCT) imaging technology can be used to diagnose diseases that are caused by pathological alterations in the retina. The importance of early diagnosis in the management of these illnesses cannot be overstated. In this article, an approach based on convolutional neural networks (CNN), a deep learning method, is presented for the detection of retinal disorders from OCT images. A new CNN architecture has been developed for disease diagnosis and classification. The proposed method has been found to have an accuracy rate of 94% in the detection of retinal disorders. The results are obtained by comparing the proposed CNN network model in a deep learning application used in classification with the MobileNet50 network model in the literature. The evaluation parameter values for models trained using the 5-fold cross validation approach for each type of disease in the retinal OCT image dataset are also submitted. The proposed method can clearly be utilized as a decision-making tool to assist clinicians in diagnosing retinal illnesses in a clinical context based on its effectiveness thus far.

Key words: Classification, CNN, Deep Learning, OCT, Retina

Optik koherens tomografi (OCT) görüntülerini kullanarak retina hastalığını teşhis etmek için derin öğrenmeye dayalı bir teknik

Öz: Retina tabakası, gözün en karmaşık ve hassas kısmıdır ve onu etkileyen rahatsızlıkların insanların yaşamları üzerinde büyük etkisi vardır. Optik Koherens Tomografi (OCT) görüntüleme teknolojisi, retinadaki patolojik değişiklikler nedeniyle ortaya çıkan hastalıkları teşhis etmek için kullanılabilir. Bu hastalıkların tedavisinde erken teşhisin önemi yadsınamaz.
Bu makalede, OCT görüntülerinden retina bozukluklarının tespiti için bir derin öğrenme yöntemi olan konvolüsyonel sinir ağlarına (CNN) dayalı bir yaklaşım sunulmaktadır. Hastalık tespiti ve sınıflandırması için yeni bir CNN mimarisi geliştirilmiştir. Önerilen yöntemin retina bozukluklarının belirlenmesinde %94 doğruluk oranına sahip olduğu bulunmuştur. Sınıflandırma için bir derin öğrenme uygulamasında, önerilen CNN ağ modeli literatürde mevcut olan MobileNet50 ağ modeli ile karşılaştırılmakta ve sonuçlar verilmektedir. Retinal OCT görüntüleri veri setindeki her hastalık türü için 5 katlı çapraz doğrulama yaklaşımı kullanılarak eğitilen modeller için değerlendirme parametresi değerleri de sunulur. Önerilen yöntem, şimdiye kadarki etkinliğine dayalı olarak, klinik bağlamda retina hastalıklarını teşhis etmede klinisyenlere yardımcı olacak bir karar verme aracı olarak açıkça kullanılabilir.

Anahtar kelimeler: CNN, Derin Öğrenme, OCT, Retina, Sınıflandırma

1. Introduction

The eye layer, which includes nerve fibers that are directly attached to the brain and give vision, is made up of light and color-sensitive cells and is referred to as the retina. Vision loss and blindness can result from defects in the retina. At the same time, it is known that retinal diseases cause diseases such as heart diseases and hypertension, as well as their effect on the sense of sight [1]. The importance of early identification and treatment in preventing or minimizing such adverse outcomes cannot be overstated. Age related macular degeneration (AMD), drusen, diabetic retinopathy (DR), diabetic macular edema (DME) and myopic choroidal neovascularization (CNV) can be given as examples of important retinal diseases.

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According to studies, the number of people living with macular degeneration is expected to reach 288 million worldwide by 2040 [2]. Soft drusen, which is a deposit of granular or amorphous material, is considered a precursor to AMD [3]. The severity of the disease in dry AMD depends on the number, size, and density of drusen lesions. Dry AMD has progressed to wet AMD, which is a more advanced form of the disease. Another kind of retinal illness is diabetic retinopathy, which is described as damage to the blood vessels in the retina caused by diabetes or high blood pressure. It is a progressive eye disease that affects a large proportion of working-age adults [4]. Lastly, CNV is caused by insufficient growth of blood vessels at the back of the eye. It is a very common disease that causes vision loss and threatens vision. Through a rupture in Bruch's membrane, new blood vessels emerge from the choroid and develop into the subretinal pigment epithelium, or subretinal space [2]. Over time, these vessels may burst, causing bleeding and fluid leakage into the retina [5].

In the literature, researchers in the field of ophthalmology have tried many methods to facilitate the early diagnosis and diagnosis of retinal disorders. From OCT images, AMD proposed a classification method based on linear SVM techniques, including scale-invariant feature transformation, to detect DME diseases and normal status [6]. In another study, OCT images were used to create a computer-aided diagnosis model that could tell the difference between AMD, DME, and a healthy macula [7]. In addition, a computer-aided diagnostic system using a deep learning-based multi-scale convolutional expert mix ensemble model has been presented in the literature. They reported the detection of two common types of AMD and DME pathologies in the retina and the normal state of the retina [8].

Li et al. developed an application based on convolutional neural networks (CNN) to determine CNV, DME and dry type AMD diseases in the retina. OCT images of 5,319 adult patients are used in this study. It was evaluated in their study utilizing the ImageNet database's pre-trained VGG-16 CNN architecture. With the transfer learning method, the weights of the VGG-16 network are retrained with the images taken from the patients. As a result of this study, an estimation accuracy of 98.6% was obtained in the diagnosis of retinal diseases from OCT images [9]. Mishra et al. used OCT images and CNN's ResNet50 architecture to diagnose AMD and DME diseases in the retina. They wanted to apply a technique termed multilevel dual attention mechanism (DAM) to CNN layers in their work. They were able to assess both the unique coarse and fine aspects of the OCT input pictures and display them to the literature using this method. As a result of this experiment, they obtained 99.97% accuracy from the Duke database used [10].

Motozawa and colleagues used two computational deep learning models to investigate the diagnosis of AMD illness and submitted their findings to the literature. Two CNN models are created in this study. As a result of the experiment, the first CNN architecture gave 99.0% accuracy for the diagnosis of AMD disease. The second CNN model is successful in detecting exudative findings with an accuracy of 93.8% [11]. Najeeb et al. focused on the possibility of detecting and classifying retinal diseases through OCT images. Included in the study are CNV, DME and drusen diseases. When the results were examined, it was observed that the proposed system could detect retinal diseases with a sensitivity of 95.66% [12]. Wang et al. studied a dual-trained two-stream CNN model for the investigation of wet AMD and dry AMD. As a result of this study, two single-mode models are superior to single-mode models with an accuracy rate of 94.2% [13]. In the literature review, networks with high computational cost and usually pre-trained are used in deep neural network-based studies.

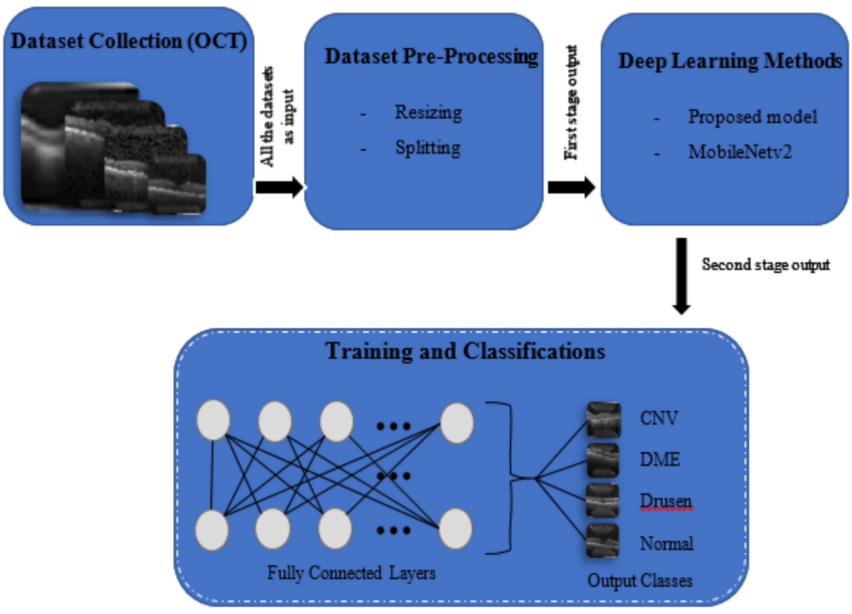


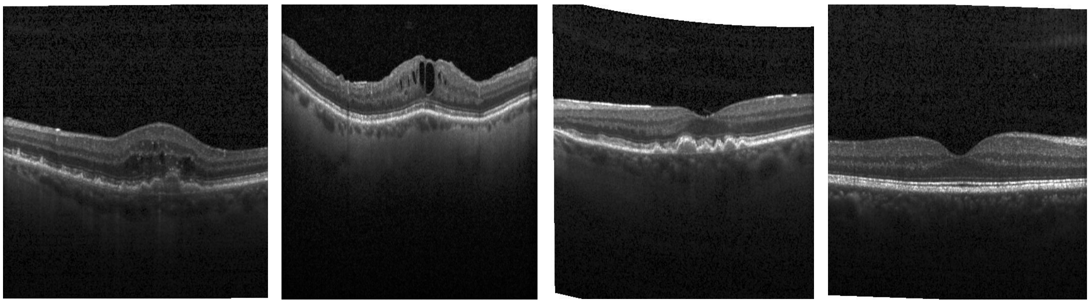
Figure 1. The block diagram of the study

Therefore, it is necessary to develop innovative methods that can improve accuracy while keeping the mesh size as small as possible. In this study, a system for automatic classification of retinal diseases is proposed using OCT images subjected to CNN architecture. The block diagram of the study is given in Fig.1. The following is a summary of the paper's structure. The dataset and deep learning models are described in Section 2. The created deep learning application models' parameters are presented. In section 3, deep learning classifiers' work and outputs and also assessment measures including accuracy, recall, precision, and F1-scores are discussed K-fold results are also given in that section. Finally, the advantages and success rate of the proposed model, and recommendations for future research are given in section 4.

2. Material and Methods

2.1. Dataset

Retinal optical coherence tomography (OCT) is a method for capturing high-resolution retinal images of the patients.



(a) CNV (b) DME (c) Drusen (d) Normal

Figure 2. Examples of each class from the dataset.

The OCT images used in the project were obtained from adult patients from the Eye Institute database at the University of California San Diego Shiley Eye Institute, California Retinal Research Foundation, and Medical Center Ophthalmology Associates in Shanghai. In this study, training and testing of the model is done by Kermany et al. publicly available optical coherence tomography image dataset is used [14]. Examples of each class from the dataset are shown in Fig. 2.

Table 1. Total and number of images used in the dataset.

No	Case Name	Total Images	Used Images
1	CNV	37455	2500
2	DME	11598	2500
3	Drusen	8916	2500
4	Normal	26615	2500

The dataset is organized into three folders (train, test, and validation) with its own subdirectory for each image type (CNV, DME, Drusen, Normal). It has 84,495 X-Ray images (jpeg) divided into four categories: CNV, DME, Drusen, and Normal. A total of 10,000 data are taken, with 2,500 for each class used in the testing and training process. The sum of images in the dataset and the number of images used are given in Table 1.

2.2. Deep learning

The term "deep learning" refers to a category of machine learning algorithms that are used to program computers to think and act in ways that are analogous to those of humans. In other words, it is a method of learning and decision-making that attempts to emulate the human brain's functioning [15], [16].

Neural networks, progressive probability models, and unsupervised and supervised feature learning algorithms are all part of the deep learning family, and their applications are growing by the day. The research areas of deep learning are at the intersection of artificial intelligence, graph modeling, optimization, pattern recognition and signal processing [15]. The most common deep learning architectures such as Convolutional Neural Networks (CNN), Deep Belief Networks, Deep Auto-Encoders and Reccurent Neural Networks-RNNs are given below with subheadings.

2.2.1. Convolutional neural network models (CNN)

Convolutional Neural Networks (CNNs) are special types of multi-layered neural networks. The visual cortex inspired a convolutional neural network design that is analogous to the connecting structure of neurons in the human brain. Individual neurons here only respond to stimuli in the receptive part, which is a small part of the visual field. CNN is made up of neurons having weights and biases that may be learned. Each neuron in the system gets some input and, if desired, outputs it non-linearly via a dot product. Classification, localization, detection, segmentation, and recording of medical images are all tasks that CNNs excel at. While the earliest research employing CNN was published towards the end of the 1970s, Lo et al. reported one of the first studies based on medical images using CNN in 1995 [17].

2.2.2. Proposed CNN model

In this section, the proposed convolution-based CNN model to detect retinal diseases from OCT images is analysed. The CNN model is designed using the sequential model of the Keras library. In order to reduce the overfitting situations that may occur, dropout layers with different densities have been added to the model. The ReLu activation function, which is frequently used in image processing, is used as the activation function. Fig. 3 depicts the proposed CNN network design.

The network architecture consists of the convolution layer, maximum pooling, dropout, and a classification layer. A set of convolution and max pooling layers act as feature extractors. The network architecture consists of convolution layers and maximum pooling layers, respectively. There are also dropout layers in the model. Proposed CNN model structure parameters are demonstrated in Table 2.

Table 2. Proposed CNN model structure parameters.

Layer (type)	Output Shape	Parameters
Conv2D	222 x 222 x 32	896
MaxPooling2D	111 x 111 x 32	0
Dropout	111 x 111 x 32	0
Conv2D	109 x 109 x 64	18496
MaxPooling2D	54 x 54 x 64	0
Dropout	54 x 54 x 64	0
Conv2D	52 x 52 x 64	36928
MaxPooling2D	26 x 26 x 64	0
Dropout	26 x 26 x 64	0
Conv2D	24 x 24 x 128	73856
MaxPooling2D	12 x 12 x 128	0
Dropout	12 x 12 x 128	0
Conv2D	10 x 10 x 256	295168
MaxPooling2D	5 x 5 x 256	0
Dropout	5 x 5 x 256	0
Flatten	6400	0
Dense	4	25604
Total Params: 450.948		
Trainable Params: 450.948		
Non-trainable Params: 0		

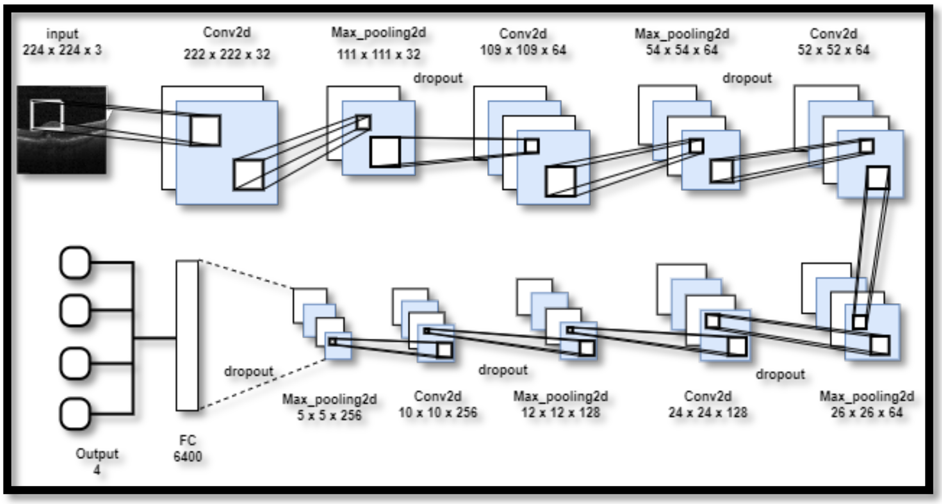
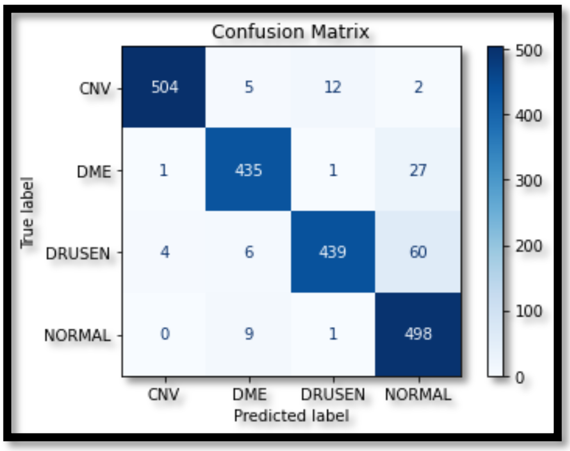


Figure 3. Proposed CNN architecture.

3. Experimental Results

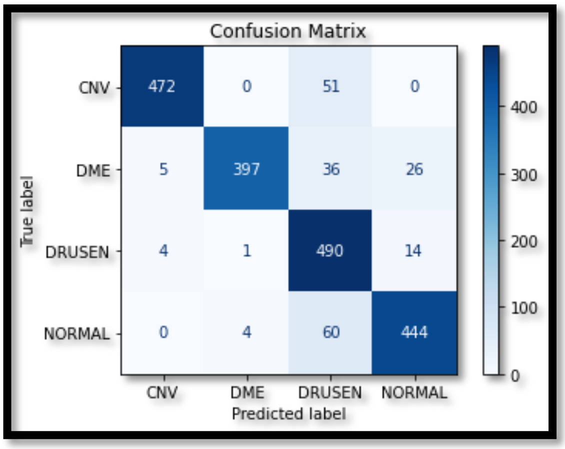
In this study, besides the CNN model, the MobileNetv2 network architecture, which has been pre-trained with the ImageNet dataset and has proven its performance, is used. For these two models, the optimization algorithm is chosen as Adam, and the initial learning rate is 0.0001. The performance metric is accuracy and the loss function is categorical_crosentropy. Training data for each model is trained in 150 epochs in the form of 100 batch sizes. Then, the trained model is tested with the test data. From the testing of CNN and MobileNetv2 models, 94% and 90% accuracy are obtained, respectively.



Classification Report

	precision	recall	f1-score	support
CNV	0.99	0.96	0.98	523
DME	0.96	0.94	0.95	464
DRUSEN	0.97	0.86	0.91	509
NORMAL	0.85	0.98	0.91	508
accuracy			0.94	2004
macro avg	0.94	0.94	0.94	2004
weighted avg	0.94	0.94	0.94	2004

Figure 4. Confusion matrix and classification report of the proposed CNN model.



Classification Report

	precision	recall	f1-score	support
CNV	0.98	0.90	0.94	523
DME	0.99	0.86	0.92	464
DRUSEN	0.77	0.96	0.86	509
NORMAL	0.92	0.87	0.90	508
accuracy			0.90	2004
macro avg	0.91	0.90	0.90	2004
weighted avg	0.91	0.90	0.90	2004

Figure 5. Confusion matrix and classification report of the MobileNetv2 model.

The classification estimation results for each model are presented in the complexity matrix and classification reports are given in Figs. 4 and 5, respectively. With a confidence interval of 96 percent, accuracy, precision, recall, and Area Under a Curve (AUC) metrics are used to assess the performance of the network models, and a comparison is made between models to select the best model in terms of performance. The number of correctly classified photos divided by the total number of test images provides precision. The model's ability to identify abnormal from normal in retinal OCT images is evaluated using receiver operating characteristic (ROC) curves. AUC is used to summarize the diagnostic accuracy of each parameter. The higher the AUC of the active model ranging from 0.5 to 1, the better its performance is.

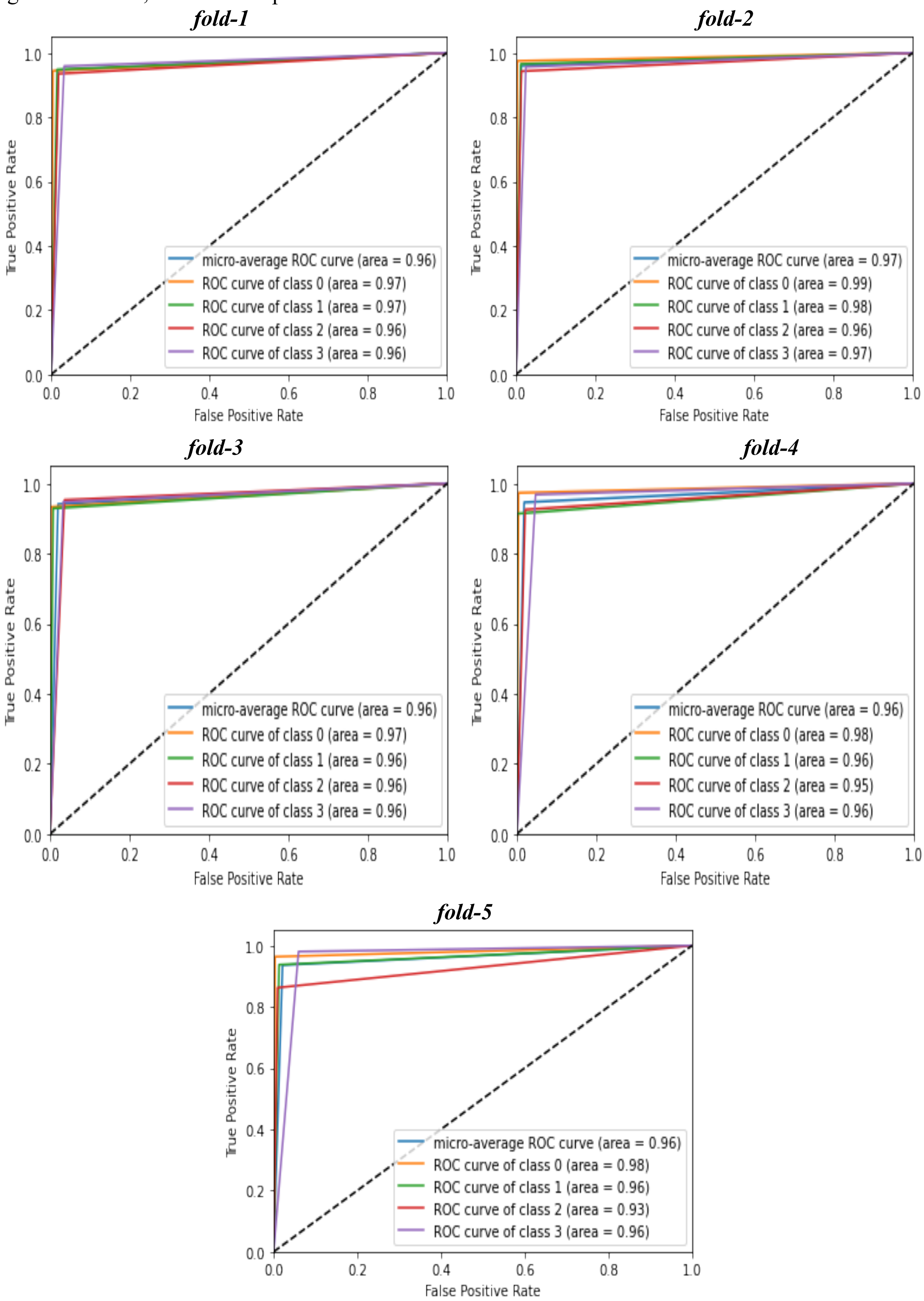


Figure 6. ROC graphs for 5 folds of the proposed CNN model.

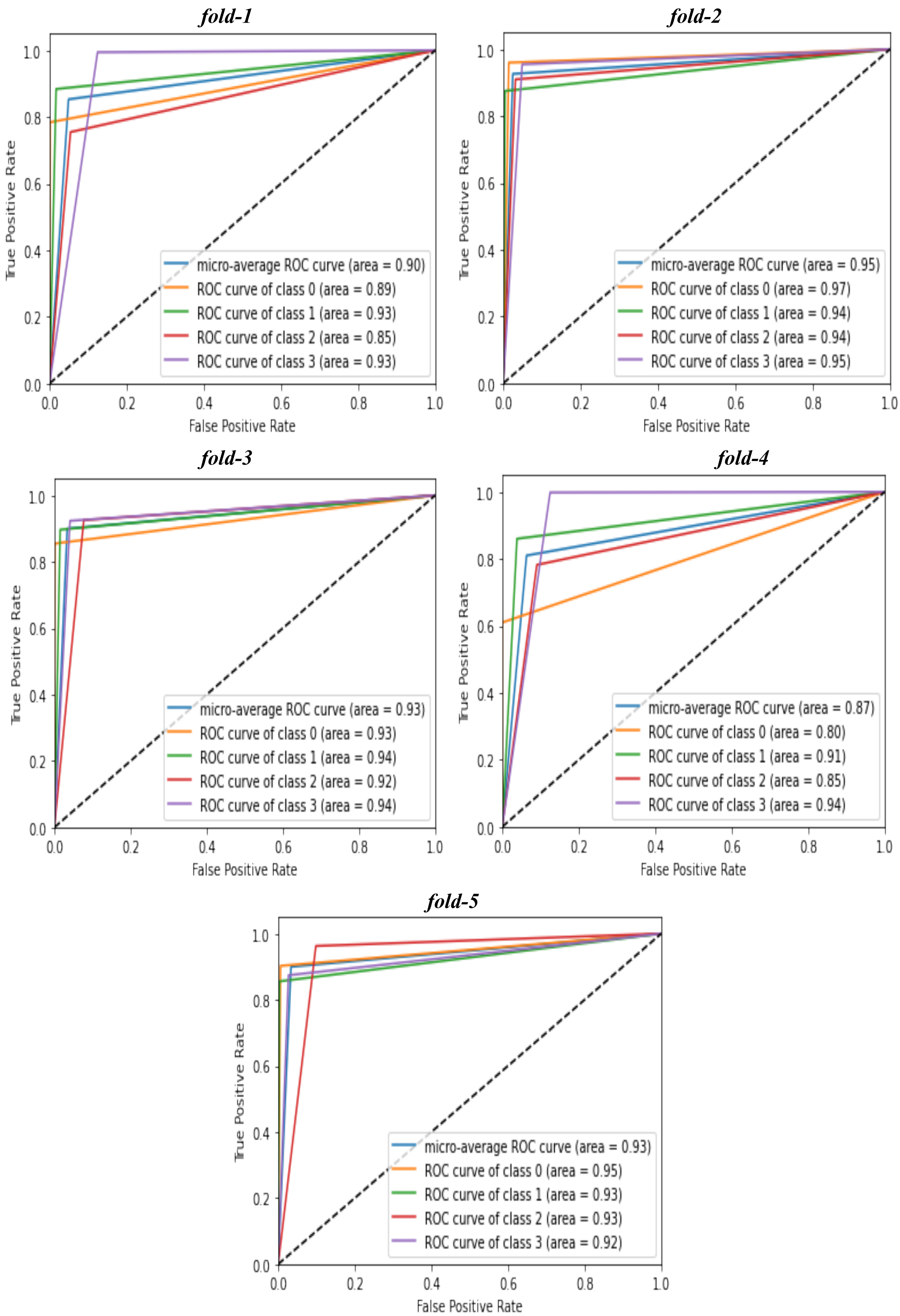


Figure 7. ROC graphs for 5 folds of the MobileNetv2 model.

The test dataset is used to evaluate the model's performance. The CNN model scored 0.94 accuracy, 0.94 precision, and 0.94 recall in a multiclass evaluation of CNV, DME, Drusen, and Normal. A ROC curve is constructed to achieve the capacity to distinguish normal from 3 abnormals. A high AUC of 0.96 is obtained with the results of testing. The MobileNetv2 model, on the other hand, reached 0.90 accuracy, 0.91 precision and 0.90 recall. The AUC of 0.93 is obtained with the results of testing. ROC graphs for 5-folds of CNN and MobileNetv2 models are given in Figs. 6 and 7, respectively.

The evaluation parameter values of the models trained using the 5-fold cross-validation strategy for each infection type in the Retinal OCT Images dataset are given in Table 2. While the first model, the CNN model, provided 0.94 accuracy, 0.94 precision, 0.94 recall and 0.94 F1-score, the second model, MobileNetv2, achieved 0.90 accuracy, 0.91 precision, 0.90 recall and 0.90 F1-score. When these results are evaluated, it is observed that the CNN model is the better. In addition, the accuracy, precision, recall and F1-score obtained as a result of 5-fold cross validation for the two models are taken separately for each fold and are reflected in the graphs shown in Figs. 8 and 9. Performance of network models are given in Table 3. The accuracy graph and the loss graph of the system are illustrated in Figs. 10 and 11, respectively.

Table 3. Performances of network models

Number	Network	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
1	CNN	94	94	94	94
2	MobileNetv2	90	91	90	90

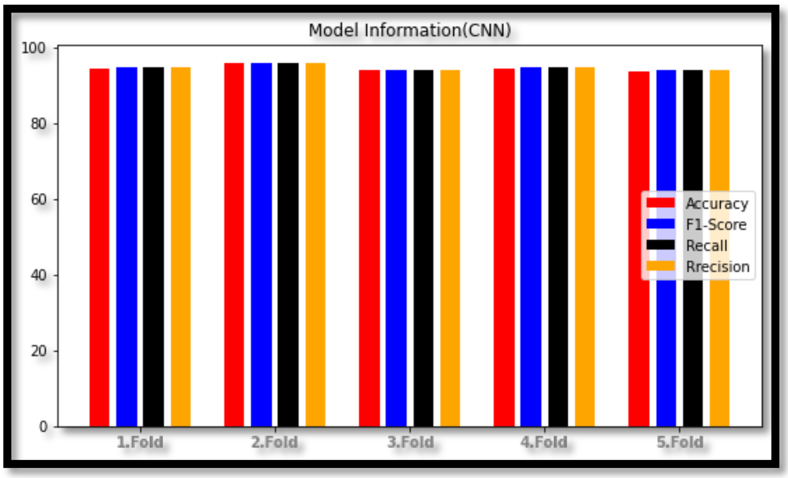


Figure 8. Infographic of proposed CNN model.

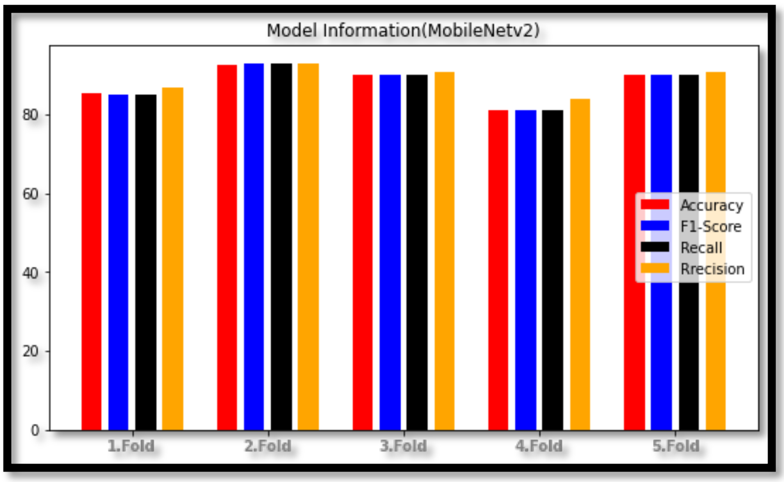


Figure 9. Infographic of the MobileNetv2 model.

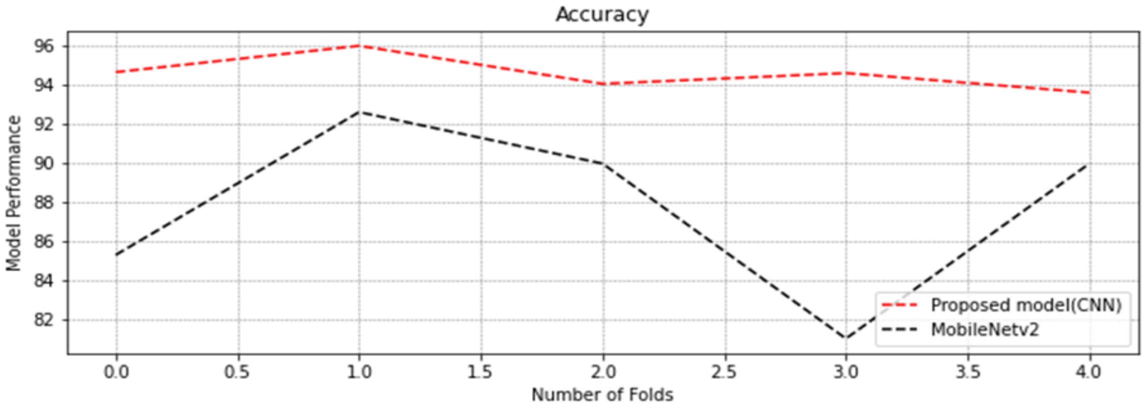


Figure 10. Accuracy graph of the system.

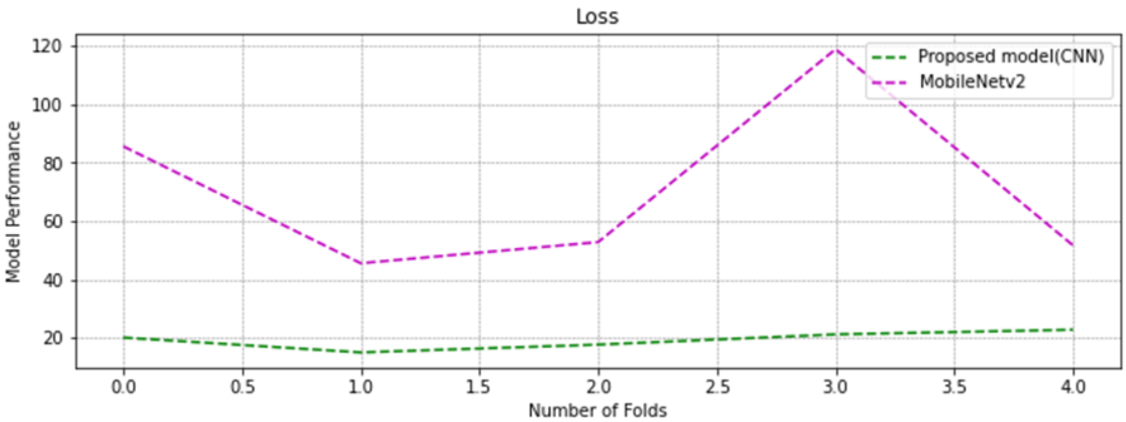


Figure 11. Loss graph of the system.

4. Discussion

Globally, there are more retinal diseases, and technological advancements have made it simpler to identify and treat these diseases. Cost, expert mistakes, timing, technological infrastructure, and other factors can all have a negative effect on the disease's diagnosis and treatment. This study's objective is to suggest a method for accurately identifying retinal diseases while reducing error rates. In this study, the applicability of neural network models based on retinal OCT datasets in the detection of various retinal illnesses is evaluated and examined. The publicly accessible OCT dataset is used to evaluate the performance of the proposed and selected neural networks. Two different neural network topologies (the proposed CNN and the MobileNetv2 model) are tested and appraised. Accuracy, recall, precision, and AUC are used as evaluation criteria to show the ROC curve and confusion matrix of each neural network. The proposed CNN model achieves higher results than MobileNet with an accuracy rate of 94% and an AUC value of 0.96 as a result of k-layer cross-validation methods (5 folds) in the data set used. When examining and comparing the studies conducted for OCT diagnosis and classification in the literature with our proposed model, it becomes clear that the proposed model performs more satisfactorily than some architectures and less accuracy rate than others [17], [18]. Our study has limitations; the fact that OCT datasets are not very common in the literature and especially the lack of labelled data is a significant challenge. In addition, the external generalizability of the system can be demonstrated with the datasets to be trained using images from several academic centers. Future work will include expanding the number of diagnoses using all images from a macular OCT scan, including images from different OCT manufacturers, and validation of OCT scans from other institutions.

5. Conclusions

Retinal diseases are one of the most critical variables affecting human life quality. Degeneration of the retina is the most common cause of retinal diseases. With the advancement of technology, tremendous progress in acquiring images in medicine has recently been made. OCT imaging techniques are commonly utilized in ophthalmology to diagnose retinal disorders. A deep learning-based technique for diagnosing eye problems from OCT images is proposed in this article. A CNN architecture with five convolution layers has been created for this purpose. Deep learning adaptation has been shown to improve image classification with a high accuracy of 94%. The proposed CNN network model is compared to the MobileNet50 network model available in the literature in a deep learning application for classification, and their results are provided. The paper also includes the evaluation parameter values for the models trained using the 5 fold cross-validation approach for each infection type in the retinal OCT Images dataset. In short, it provides ophthalmologists with a new easy and efficient way to diagnose and detect previous stages of the disease.

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