Identifying Retinal Diseases on OCT Image Based on Deep Learning

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Abstract—Computer-aided diagnosis has the potential to replace or at least support medical personnel in their everyday responsibilities, such as diagnosis, therapy, and surgery. In the area of ophthalmology, artificial intelligence approaches have been incorporated in the diagnosis of the most frequent ocular disorders, namely choroidal neovascularization (CNV), diabetic macular edema (DMO), and DRUSEN; these illnesses pose a significant risk of vision loss. Optical coherence tomography (OCT) is an imaging technology used to diagnose the aforementioned eye disorders. It enables ophthalmologists to see the back of the eye and take various slices of the retina. The present research seeks to automate the diagnosis of retinopathy, which includes CNV, DME, and DRUSEN. The approach employed is a deep learning-based, and transfer learning technique, applying to a public dataset of OCT pictures and two pertained neural network models VGG16 and InceptionV3, which are trained on the big database "ImageNET." That allows them to be able to extract the main features of millions of images. Furthermore, fine-tuning approaches are applied to outperform the feature extraction method, by modifying the hyperparameters. The findings showed that the VGG16 model performed better in classification than the InceptionV3 architecture, with a 0.93 accuracy.

Keywords—artificial intelligence, deep learning, convolutional neural network, transfer learning, optical coherence tomography, DRUSEN, choroidal neovascularization, diabetic macular edema

1 Introduction

Optical Coherence Tomography (OCT) is considered a technique of imaging based on low coherence lights source to produce high resolution used to generate in vivo optical section images of the retina. The picture is made by detection of optical scattering from the tissue tocode the spatial information of tissue microstructures. This method has become a crucial component of retinal practice for detecting macular abnormalities like diabetic macular edema (DME), choroidal neovascularization (CNV), and Multiple DRUSEN present in early AMD. By displaying the three-dimension image of the retina, It enables the ophthalmologist to track the progression of macular diseases and allows for the measurement of the thickness of various retinal layers.

Diabetic macular edema is known as a rupture of the blood-retinal barrier, which is the primary structural alteration responsible for the disease [1]. The diabetic environment damages many tight junction proteins, resulting in hyper-permeability and vascular leakage as shown in Figure 1. It is the common diabetic retinopathy leading to loss of vision and vision impairment in adults.

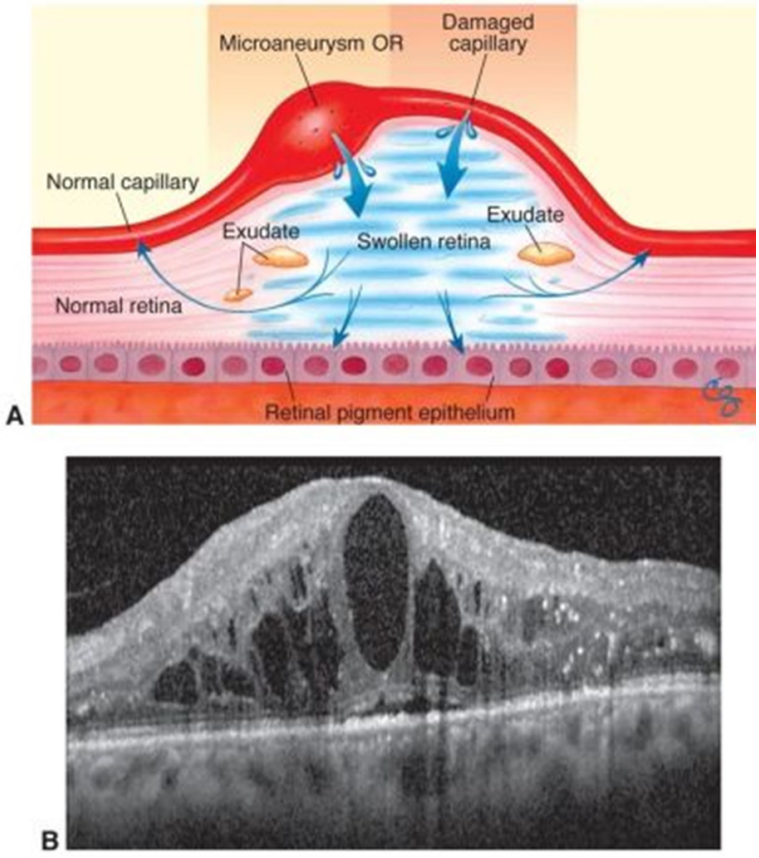

Fig. 1. Schematic diagram of DME disease

The Wisconsin Epidemiologic Study of Diabetic Retinopathy (WESDR) discovered that DME occurred at a rate of 29% among patients who suffer from type 1 diabetes (T1DM) for 25 years [2]. According to the Diabetes Control and Complications Trial (DCCT), 27% of persons with T1DM had DME within nine years after initiation of diabetes [3]. The WESDR showed that DME occurred in 25.4% of Type 2 diabetes (T2DM) patients who used insulin and 13.9% of those who did not [2]. According to Yau et al., [4] DME affects 6.8% of persons with diabetes worldwide. In the United States, estimates range from 2.7 percent to 3.8 percent, with non-Hispanic whites being less likely than non-Hispanic blacks to have DME.

Choroidal neovascularization (CNV) is known for the development of new abnormal blood vessels [6]; they allow fluids and red blood cells to enter the retina, which will distort vision by forming a "blister," which is normally flat. According to the findings, choroidal neovascularization associated with macular degeneration dur to age is the most widespread reason behind old people's losing vision in the Weste [5]. Figure 2 is a schematic representation of CNV, showing the "layered" structure of the macula, the center portion of the retina. A healthy macula relies on the microstructure of the several layers of this tissue (choroid, the retinal-pigmented epithelium (RPE), Bruch's membrane, and the neural retina, which contains the photoreceptors).

Optic nerve DURSEN is the abnormal accumulation of proteinaceous [7] material located between the inner collagenous layer of the Bruch membrane and the basal lamina of the retinal pigment epithelium (RPE). It represents the early stage of macular degeneration caused by age.

Although the OCT technique has been choicest abnormalities in the microstructures of the retina, several scientific studies have been conducted to try to automate the diagnosis of certain ophthalmological pathologies based on artificial intelligence.

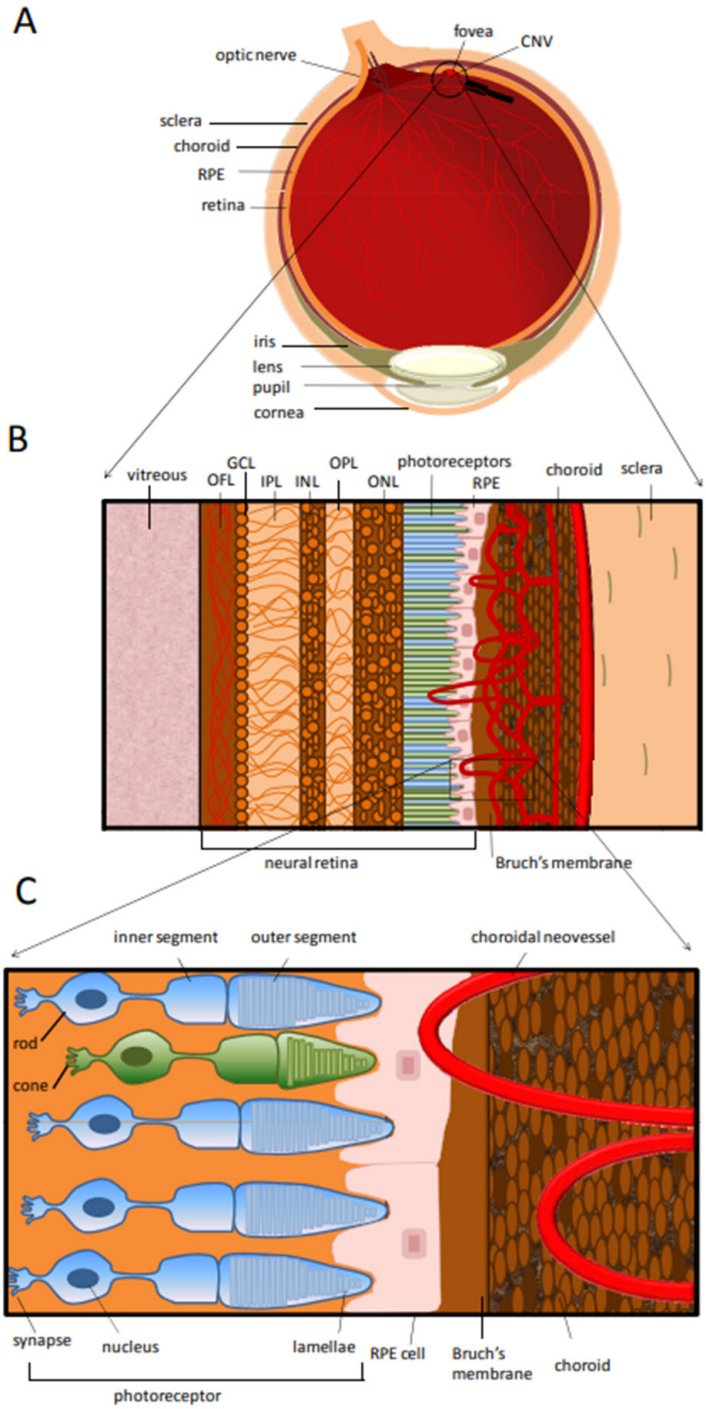

Fig. 2. Schematic representation of choroidal neovascularization

AI refers to technology that can simulate cognitive activities such as learning and problem solving by analyzing and identifying patterns in massive volumes of data. A number of techniques of machine-learning have been used in this context for the sake of automatic classification and segmentation of OCT images [8]. Some studies are using the earning technique that shows a high performance and low cost; in return, it requires using an immense database with the same characteristic. In the present paper, we put forward a method of automatic classification using a pre-trained convolutional neural network model. The following sections of the present article include the literature review, material, and methods, evaluation of results and discussion.

2 Literature review

In Table 1 summarizes some studies that concern our objective in this article.

P. Srinivasan et al. [9] developed in 2014 an automated algorithm to detect the two most common ophthalmic diseases, diabetic macular edema (DME) and Dry-age-related macular degeneration (AMD); by using multi-scale histograms of oriented gradient descriptors and a support vector machine as a classifier, they obtained as an accuracy 100% with AMD, 100% with DME, and 86.67% of normal cases. R. Rasti et al. [10] proposed a multi-scale convolutional mixture of expert (MCME) for AMD and DME OCT images classification, the precision was about 98.86% by employing a dataset presented by P. Srinivasan et al., and also, they created a new public dataset from Noor Eye Hospital in Tehran.

Models pre-trained on large databases have the ability to extract the optimal features needed for classification. With proper tuning, these models can be adapted to similar applications with a relatively small data set. In [11] deep CNN VGG-16 model with transfer learning was successfully applied to categorize brain image. In [12], the VGG-16 deep CNN model with transfer learning was successfully applied for skin cancer image classification. Also, in [13], good results were obtained with Inception 3 transfer learning applied to CT lung image classification. We have also P. Karri et al. [14], their work aimed to create a fine-tuned pre-trained CNN by using pre-trained GoogleNET. Feng Li et al. [15] proposed a new algorithm based on a Residual neural network to automatically detect three anomalies choroidal neovascularization (CNV), DRUSEN, diabetic macular edema (DME), versus healthy retina based on Optical Coherence Tomographyimages.

Table 1. Summary of recent studies

Author	Year	Purpose	Method	Results
P. Srinivasan et al. [9]	2014	Detection of AMD and DME OCT images	Multiscale histograms of oriented gradient descriptors Support vector machine	Acc: 100% AMD 100% DME 86.67% Normal
R. Rasti et al. [10]	2017	Classification of AMD and DME OCT images	A multiscale convolutional mixture of expert	precision: 98.86%
P. Karri et al. [14]	2017	Transfer learning-based classification of OCT images DME and AMD	Fine-tuned pre-trained CNN and GoogleNET	Acc: 94%
M. Hussain et al. [16]	2018	Classification of normal, DME, and AMD based on SD-OCT images	Random Forrest	95% for 3 classes 96% for 2 classes
Feng Li et al. [15]	2019	Multiclassification of DME, DRUSEN and CNV OCT images	Residual Neural Network (ResNET50)	Acc: 0.973 Sen: 0.963 Spe: 0.985
Das et al. [17]	2019	Classification of normal, DME, CNV and DRUSEN on OCT images	Multi-scale deep feature fusion (MDFF) and CNN classification	Acc: 0.996 Sen: 0.996 Spe: 0.998
A. Tayal et al. [18]	2021	Four class classification of macular disease	DL-CNN with three different layers (five, seven, and nine layers)	Acc: 0.965 Sen: 0.960 Spec: 0.986

3 Material and methods

3.1 Database

In this work, we used a public dataset containing 207 130 collected and validated OCT images, the Figure 3 shows the examples of the 4 types of images. However, only 84483 images from 4686 patients are of good quality and do not require preprocessing [19]. The images are labeled into 4 classes: healthy retina, diabetic macular edema (DME), choroidal neovascularization (CNV), and Multiple DRUSEN present in early AMD. The dataset is collected from patients with different characteristics. Table 2 shows the distribution of patients who were included in this study.

In this work, we randomly took 1000 images from each category to constitute our dataset, of which 80% was used for training and 20% for testing.

Table 2. Characteristics of patients whose OCT images were in the used data set

Diagnosis		Diabetic Macular Edema (DME)	Choroidal Neovascularization (CNV)	DRUSEN	Normal
Number of Patients		709	791	713	3548
Mean Age		57 (Range: 20–90)	83 (Range: 58–97)	82 (Range: 40–95)	60 (Range: 21–86)
Gender	Male	38.3%	54.2%	44.4%	59.2%
	Female	61.7%	45.8%	55.6%	40.8%
Ethnicity	Caucasian	42.6%	83.3%	85.2%	59.9%
	Asian	23.4%	6.3%	8.6%	21.1%
	Hispanic	23.4%	8.3%	4.9%	10.2%
	African American	4.3%	2.1%	1.2%	1.4%
	Mixed or Other	10.6%	0%	0%	7.5%

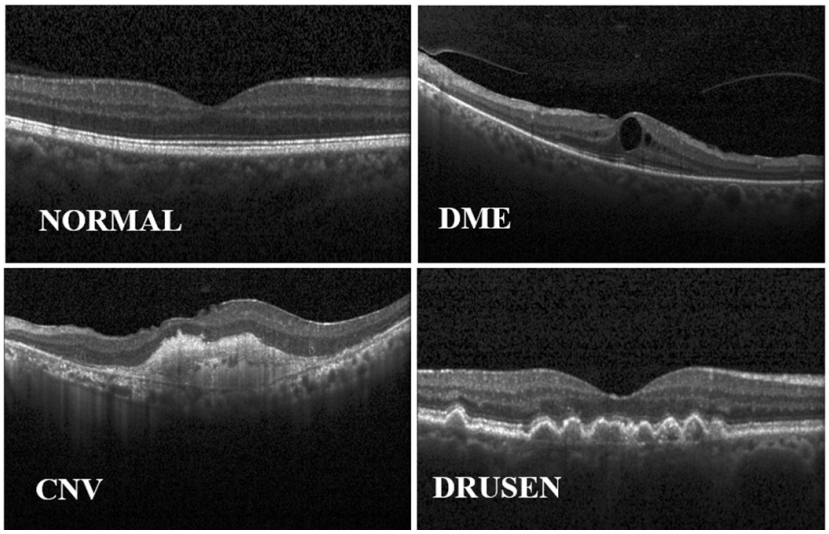

Fig. 3. Overview of OCT Dataset (healthy OCT retina, DME – diabetic macular edema, CNV – choroidal neovascularization and DRUSEN)

3.2 Overall, CNN's architecture

Definition of Convolutional Neural Network. A convolutional neural network is one of the fields in deep learning methods [25]; it is widely used in computer vision. The good point of this deep learning algorithm is the possibility to predict and classify the data without a required pre-processing of the data like machine learning, but it can

learn from large amounts of data [20]. Figure 4 shows the architecture of CNN; the model comprises two principal parts:

- **Feature extraction:** The network will undertake a series of operations in this section. It will detect functions by convolution and pooling.
- **Classification:** Here, the fully connected layers will which are a multilayer perceptron neural network. Which can function as a classifier. This network's inputs are termed feature extraction and come from the previous part.

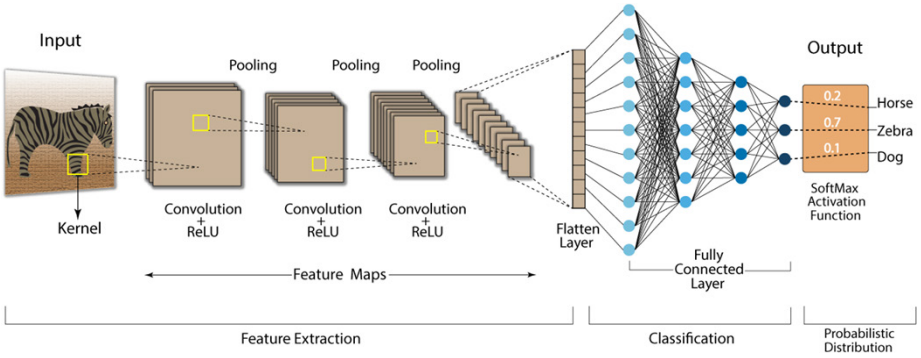

Fig. 4. The architecture of Convolutional Neural Network

Features extraction

- **Convolution:** Convolution in CNN is conducted on an] input picture using a filter or kernel. It is the fundamental operator of linear image processing. Let I will be a digital picture and h be a real-valued [$x1$, $x2$] [$y1$, $y2$] function. The convolution of I by h is defined as

$$(I * h)[x, y] = \sum_{i=x_1}^{x_2} \sum_{j=y_1}^{y_2} h[x, y] \cdot I[x - i, y - j] \tag{1}$$

- **Padding:** In this operation, there are two sorts of results: one in which the result received after convolution is decreased in dimensionality about the input, and one in which the dimensionality is either raised or remains constant. This is accomplished by using a valid padding or the same padding. A CNN adds a Rectified Linear Unit (ReLU) adjustment to the feature map after each convolution operation, imparting nonlinearity to the model.
- **Pooling layers:** We employ function pooling after going through the convolution layer to construct a linear activation set and the non-linear activation layer such as ReLU. It enables gradual representation size reduction to decrease the total weights in the model and, as a result, control overfitting. It enables tiny translations to be invariant. There are several forms of pooling (MAX pooling (extremely common), AVG pooling, etc.).

- **Classification: Fully connected layer:** In the fully connected layer, neurons are directly linked to the next layers. This is similar to how neurons are placed in classic forms of ANN. During this operation, there is a risk of over fitting because all of the parameters in the fully-connected layer are occupied. Thus strategies like dropout are important.
- **Softmax:** SoftMax's concept aims to define a new output layer for our neural networks. It begins similarly to a sigmoid layer by creating the weighted inputs [18]

$$z_j^L = \sum_k w_j^L a_k^{L-1} + b_j^L \tag{2}$$

However, we do not use the sigmoid function to obtain the result. Instead, in a softmax layer, the so-called softmax function is applied to the z_j^L. Equation 3 allows calculating the activation of the output neuron.

$$a_j^L = \frac{e^{x_j^L}}{\sum_k e^{z_k^L}} \tag{3}$$

4 Proposed method

To classify the three common diseases of the retina, based on optical coherence tomography images, we propose two architectures VGG16 and InceptionV3, with the transfer learning technique, these models are pre-trained on over a million images from the ImageNET database, so that they could have learned enough features for a variety of images. They have also been used successfully on medical images, as mentioned in the literature review section.

4.1 VGG 16

Simonyan K. and Zisserman A., introduced 2014 the VGG [21] network; they named it VGG after the Visual Geometry Group department at the University of Oxford to which they belonged. The VGG16 is a convolutional neural network with 16 deep layers. VGG replaced 7×7 and 5×5 filters with a stack of small size filters 3×3. The authors explain that having two successive two 3×3 filters offers an effective receptive field of ×5, while having three 3×3 filters gives a field of 5×5. 7×7 filter receptive field, the number of filters available he after each max-pooling operation, the architecture doubles.

4.2 Inception V3

Inception-V3 is the third version of Inception model, it was introduced by Szegedy et al. [22] in 2014. The model won the ImageNET Large Scale Visual Recognition Challenge (ILSVRC) contest in the image classification category in 2014. Five fundamental convolutional layers make up Inception-v3, and Batch Normalization and

ReLU activation are applied after each convolutional operation. Then came 11 Inception modules, which ranged in size from mixed 0 to mixed 10 modules. Convolutional kernels 1×1, 3×3, 1×3, 3×1, 5×5, 1×7, and 7×7 are used in the design of the 11 Inceptionv3 module blocks. This model was trained on a large number of photos and can be retrained on a smaller dataset while retaining the trained model's expertise. This leads to very accurate classification with minimal processing resources and without the need for significant training.

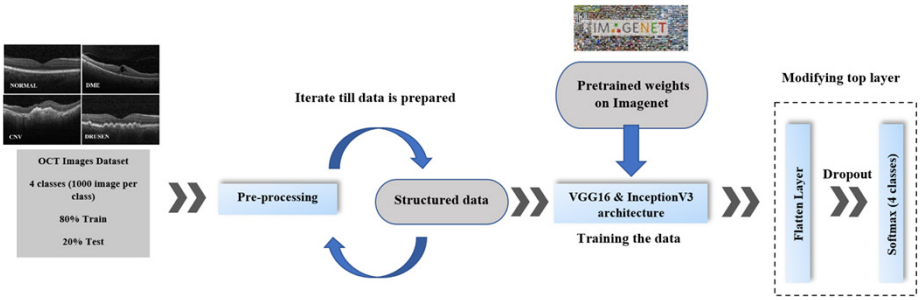

Fig. 5. The plan of the proposed method

4.3 Transfer learning

Transfer learning is how information gained in one network may be utilized in another. It is a popular strategy because it alleviates the difficulty of creating new networks and training them from the ground up. The weights of the pre-trained model are used as an initial parameter for the new model.

4.4 Training method

Figure 5 shows the organigramme of our proposed Neural Network, two different architectures VGG16 and Inception V3 are used to extract deep features for classification; they are based on initial weights obtained from pre-training on the ImageNET dataset. We froze all the layers of based model and we followed each model with a flatten layer, dropout layer with a ratio of 0.75, and Adam optimizer with learning rate 0.0001 is used for updating the weights, we complied the model with 100 epochs to improve the result.

5 Results

Accuracy, recall, and the precision rateis significant indicators that should be taken into consideration in the evaluation, while misdiagnosis or missed diagnosis events can be a major influence on patients.These parameter rates are used as the evaluation criteria for drawing the confusion matrix [23] and they are defined as followed:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

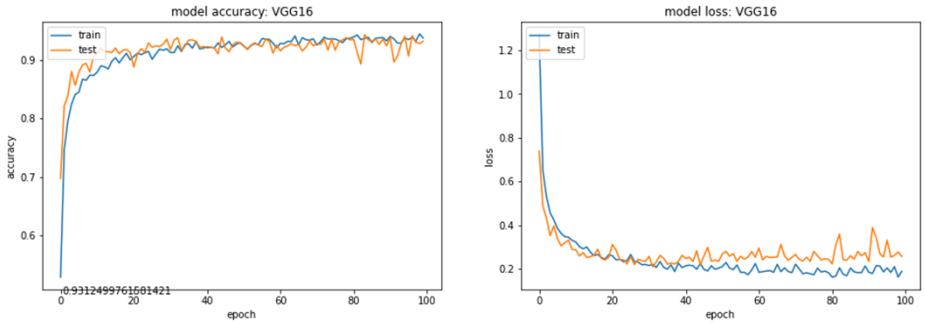

Fig. 6. Accuracy and loss curves during training and validation: model VGG16

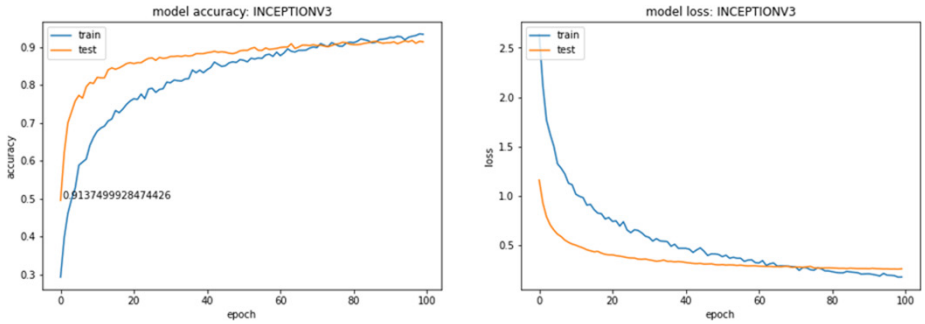

Fig. 7. Accuracy and loss curves during training and validation: model InceptionV3

Keras CNN - accuracy: 0.9312499761581421

	precision	recall	f1-score	support
Normal	0.88	0.92	0.90	192
CNV	0.96	1.00	0.98	207
DME	0.92	0.89	0.90	176
DRUSEN	0.96	0.92	0.94	225
accuracy			0.93	800
macro avg	0.93	0.93	0.93	800
weighted avg	0.93	0.93	0.93	800

Fig. 8. Parameters of evaluation: VGG16

Keras CNN - accuracy: 0.9137499928474426

	precision	recall	f1-score	support
Normal	0.87	0.91	0.89	203
CNV	0.95	0.96	0.96	185
DME	0.96	0.89	0.93	199
DRUSEN	0.88	0.89	0.89	213
accuracy			0.91	800
macro avg	0.92	0.91	0.92	800
weighted avg	0.92	0.91	0.91	800

Fig. 9. Parameters of evaluation: InceptionV3

TP are the True Positives, i.e., the observations that have been classified as positive and which are really positive. *FP* are the false positives, i.e., the individuals classified as positive and who are actually negatives [24]. In the same way, *FN* are false negatives and *VN* are true negatives.

Accuracy is the ratio ofunmistakably classified samples to total samples in the dataset.

Precision is defined as the number of rightly classified positive samples divided by the total number of positive samples classified (correct or incorrect) [24].

Recall ratio denotes the proportion between total positive samples that were successfully categorized as positive samples and the entire positive samples. In order to perform our model, which is considered a multi-classification problem, we can transform it into a binary classification for each class.

The proposed method of classification of retinal abnormalities is based on using a pre-trained model, "**InceptionV3**" and "**VGG16**", and a transfer-learning technique on 1000 OCT images in each class. Figure 6 points out the accuracy with regard to training and validation as opposed to several epochs of the fine-tuned VGG16 model; it has a convergence value after 20 epochs, as well the loss variation has a convergence value after 40 epochs. We achieved 93.12% accuracy. Figure 8 shows the performance parameters of the VGG16 model, we can easily denote that the best precision is obtained for DRUSEN with 96%. The same parameters and setting were implemented in InceptionV3, Figure 9 makes it clear that we achieved a 91.37% of accuracy, and we have obtained the best accuracy for DME (Diabetic Macular Edema) classes (about 96%). However, we can see from Figure 7 that the training and the loss curves have a convergence value after 80 iterations, and the variance between the validation and training curves is remarkable, contrary to VGG16 model. Figures 10 and 11 show the confusion matrix of both models VGG16 and InceptionV3.

6 Discussion

In the present study, prep-trained convolutional neural network architectures were proposed, based on a publicly available OCT dataset in diagnosing DME, CNV, and DRUSEN from the normal cases are tested and evaluated. Two neural network architectures were tested and evaluated (VGG16 and InceptionV3). We used the evaluation criteria like accuracy, recall, precision, and confusion matrix of each model. The results have shown that VGG16 achieves 93.12% of accuracy rate, and the average recall value of the three categories is above 0.90. Whereas the InceptionV3 still has a result less than VGG16, it achieves 91.3% accuracy and a recall rate of 0.90 as an average due to its complexity. After this analysis, we can say that VGG16 has better effects, although the size of data is very small (1000 images of each class) in comprising with other studies. VGG16 produces a better accuracy than InceptionV3 due to the application of the small filters which makes the model deeper and allows the model to detect the smallest object with a good precision. That's why the VGG16 is considered a good application model in transfer learning technique with this dataset.

There is another point that we can consider as an improvement in our work, which is the time, thanks to the transfer learning technique we can reduce the training time, which has been always a limited condition. So, the pre-trained models and fine-tuning techniques have shown that with small data, we can achieve a considered result. Therefore, transfer technique should be considered a practical operation to help doctors prevent misdiagnosis and missed diagnoses.

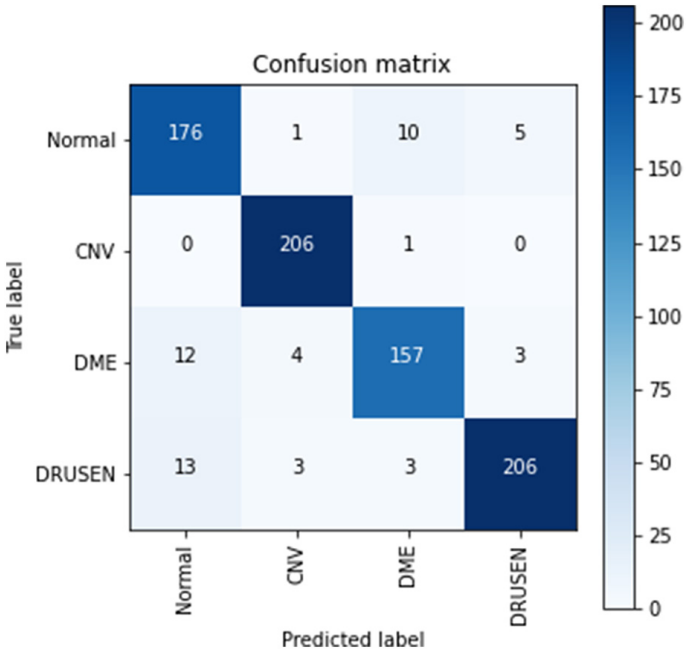

Fig. 10. Confusion matrix obtained using VGG16 model

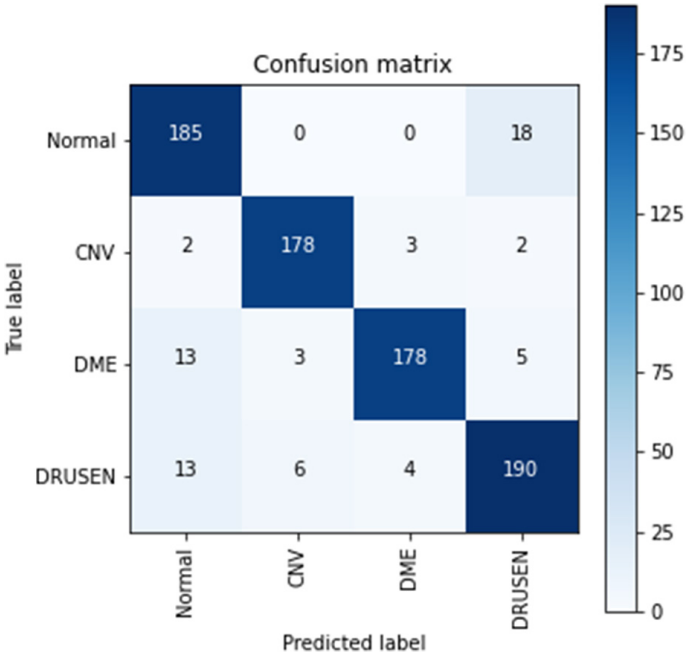

Fig. 11. Confusion matrix obtained using the InceptionV3 model

7 Conclusion

For a variety of reasons, retinal disorders are the leading cause of vision impairment. We attempted to offer a technique that would allow ophthalmologists to profit from automated identification of these disorders, particularly choroidal neovascularization, diabetic macular oedema (DME), and numerous DRUSEN prevalent in early AMD.

This tool is based on a deep learning algorithm that uses convolutional neural networks to classify different OCT images based on their true diagnosis. The implementation of the transfer learning technique also played a significant role in improving the performance of the proposed model and reducing the training time of the program despite the small size of the database used. This strategy also allowed for a comparison study between two models, VGG16 and InceptionV3, that were previously pre-trained on a very big database called "ImageNET". Even though the retinal illness categorization system produced excellent results, there are still many improvements that may be made, such as Adding new retinal disordersCreating an application that includes all the capabilities that an ophthalmologist may use to segment, detect, and categorize diseases based on OCT images.

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