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A Multiclass Age-Related Macular Degeneration Classification

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Abstract

Implementing artificial intelligence in the image classification process can accelerate the diagnosis and monitoring of eye diseases, lowering the cost and time burdens on both the patient and the treatment staff.

This paper focuses on distinguishing three eye conditions including normal eyes, and two eye-related diseases; Dry Age-Related Macular Degeneration (AMD) and Wet AMD. To reach this goal, Optical Coherence Tomography images of these conditions will be used based on the data collected from Negah Hospital. Features of the images are extracted after preprocessing as sequences and then classified by Recurrent Neural Networks. Pre-trained convolutional neural networks including VGG19, InceptionV3, and Xception have been used for modeling. The trained models in this project achieved 92 percent accuracy. The results present a clear look at the challenging nature of diagnosing certain conditions from each other. Challenges of medical data collection and integration of artificial intelligence in the diagnosis process will also be discussed.

Keywords: Transfer Learning, Medical image classification, Age-Related Macular Degeneration, Optical Coherence Tomography, Convolutional Neural Networks

Introduction

Age-related macular degeneration (AMD) is the leading cause of blindness in people over 55. [1]

AMD is categorized as Dry AMD and Wet AMD. Dry AMD is currently not curable [2, 3] but Wet AMD can be managed and is fairly treatable [4, 5]. The main distinguishing difference between the two diseases is the growth of new blood vessels and retinal leakage in wet AMD. Using fundus color images or optical coherence tomography (OCT) is one of the most important methods for diagnosing and classifying AMD [6, 7]. Early detection of patients lowers the risk of vision impairments and blindness [8].

In recent years, a lot of research has been done in the field of artificial intelligence to diagnose eye diseases and vision disorders [9-15]. The majority of the research done on AMD, pursue prediction of changes in eye condition from Dry to Wet AMD [16, 17] or different stages of the disease [18]; In most cases, available datasets are used.

Clinical classification of AMD is accompanied by problems such as time burdens and opinion differences of examiners [19]. Reducing human errors, mitigating the burdens on the patient and the treatment staff, and enabling early diagnosis are among the most important reasons to implement artificial intelligence in the diagnosis process [20-22].

We are aiming to distinguish between 3 different eye conditions, exploring a variety of machine learning models. We will also use a self-conducted dataset from the OCT images of Negah Hospital; Discussing possible approaches for limited data and its challenges.

The VGG19 architecture achieved 93 percent accuracy giving the best result among the pre-trained models. Accuracy of normal eye classification had a clear advantage over Dry AMD and Wet AMD, consistently above 95 percent; showcasing the difficulty of distinction between the two diseases. It also suggests that adding more Dry and Wet AMD samples and improving our data will grant us a balanced performance in each class and a better overall model.

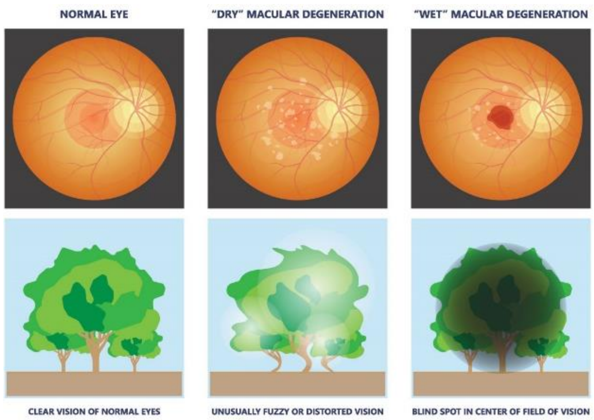


Figure 1: Comparison of normal eye, dry and wet AMD vision, from https://oliviaread.co.za/general-eye-conditions/age-related-macular-degeneration/

Background

This section briefly discusses the main concepts related to artificial neural networks, including the structure of convolutional neural networks and transfer learning for image classification.

Convolutional Neural Networks (CNN):
Convolutional neural networks are a branch of deep neural networks, widely used for image recognition tasks. Their ability to take an image as input, decompose it into perspective features, and then classify the images makes them a compelling choice for image

classification. Convolutional neural networks use less pre-processing than other image classification approaches. CNNs usually consist of three layers: convolutional layers, pooling layers, and fully connected layers [23, 24].

Transfer Learning:
Transfer learning is a machine learning method that uses knowledge gained from one model to improve performance on a new task and/or dataset. In other words, we can use pre-trained models and weights to enhance our image classification or any other training task. Complex models such as VGG are trained on large-scale datasets like Imagenet or COCO and used in transfer learning. By using a transfer learning model, you can achieve good performance with less data because these models are already trained on a large dataset. The first layers of a model usually focus on general features while the last layers detect details like edges of an object. Therefore, the main distinguishing features of a dataset are trained through the final layers. Because of this, to finetune a pre-trained model, the initial layers are frozen and a number of final layers are often adjusted to complement the current task and dataset. After feature extraction and removing the original classifier, a classifier layer is added and the training process can be carried out. The pre-trained transfer learning models used in this research are InceptionV3, Xception, and VGG19.[25]

Methods
Data collection and preprocessing:
The collected dataset contains 1240 OCT images in jpg format. This dataset was collected from Negah Hospital. These images were not classified. Therefore, first, it was necessary to determine the class of each photo. The data classification and labeling process was also done in this hospital with the help of Dr. Anoushirvan Rahimi. Also, before modeling, it is necessary to make changes to the data to prepare these photos to enter the network. For this, we crop the required part of the photo. The size of all photos is (596, 1008), which changes to (435, 508) after the pre-processing process. An example of the initial photos and the photos after the pre-processing process are shown in Figure 1.

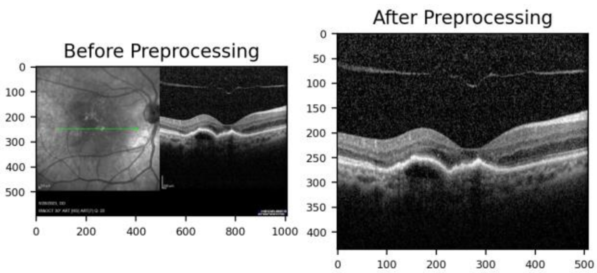


Figure 1: An example of the images before and after the pre-processing process

This dataset contains 3 classes (healthy eye, Dry AMD disease, and Wet AMD patient) that characterize the eye disease state. In order to expand the data set, after the pre-processing process, the images are flipped, and the flipped images are added to the initial dataset. This doubles the number of images in each class. Figure 2 shows an example of images of each class and Table 1 shows the distribution of data in each class in this dataset.

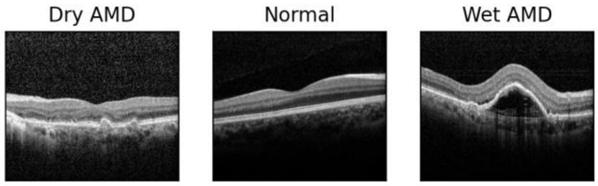


Figure 2: An example of images of each class of the dataset

Table 1: Distribution of data in each class

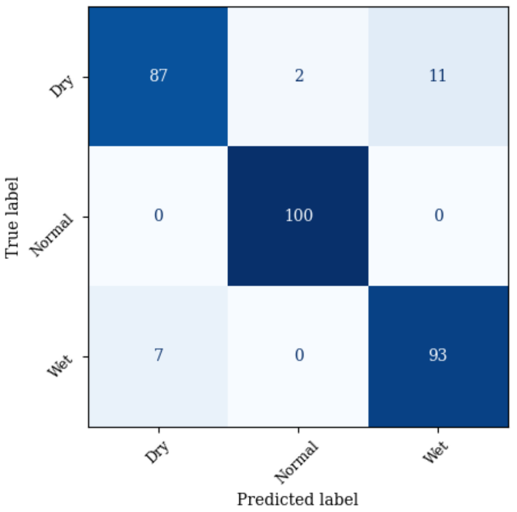
Class name	Name in network	Total number	Train number	Test number
Dry AMD	0	356	256	100
Normal	1	458	358	100
Wet AMD	2	426	326	100
Total	-	1240	940	300

Trained models:
Three pre-trained models, named VGG19, Xception, and InceptionV3, were trained on the used dataset. There are different approaches to implementing transfer learning. We decided to freeze all except the last 5 layers of the pre-trained models and add a three fully connected layers network, referred to as MLP classifier on top of it. Feature extraction is done by the pre-trained models, then the inputs are classified using the structure shown in Table 2. The models were trained on Google Colab's GPU T4, with a gradually decreasing leaning rate starting at 0.0001 using Adam optimizer. The batch size and numbers of epochs were 8 and 20 respectively.

Table 2. MLP network structure

Fully connected layers		
Layer's Number	**Activation function**	**Number of neurons**
1	Relu	300
2	Relu	200
3	Softmax	3

Results and Discussion
In this section, we will talk about the performance of trained models, the challenges of data collection, and the possible uses of artificial intelligence in the process of disease diagnosis. Among the developed models, the VGG19 architecture has the best accuracy, but we are witnessing some overfitting; Which tells us that the model is memorizing the data and not learning it. In contrast, the Xception architecture provided a more standard model with less accuracy and prevented overfitting. Also, implementing training regulators, such as the gradual reduction of Learning Rate and EarlyStopping (which stops training when a monitored metric isn't improving), greatly helped our results; Without them, the models didn't perform as successfully.



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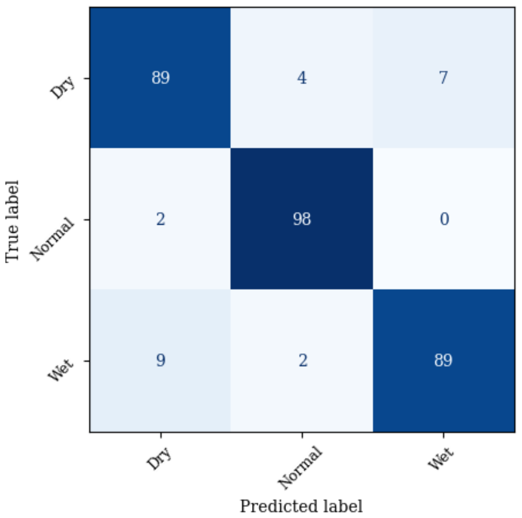

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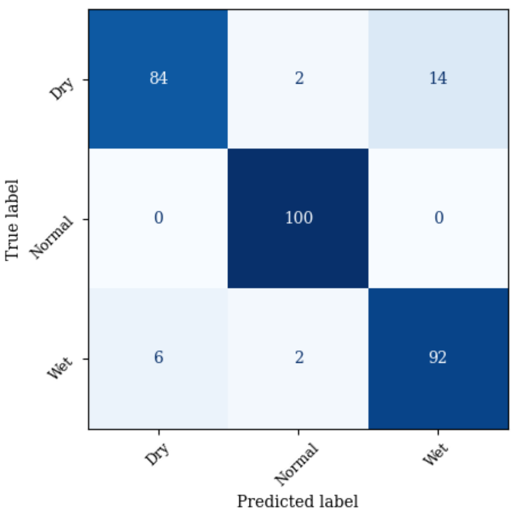
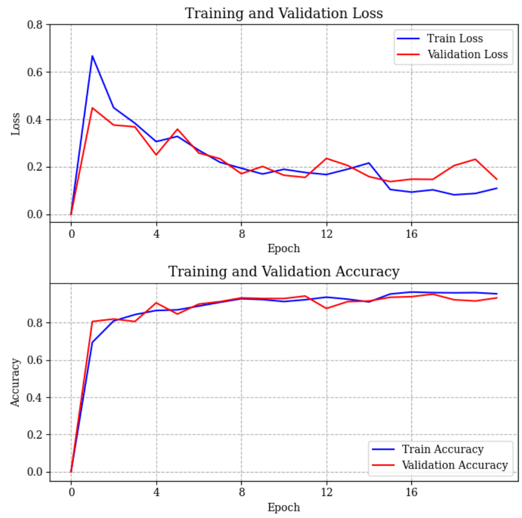


(c)

Figure 6: Confusion Matrices:
a. VGG19 , b. InceptionV3 , c. Xception



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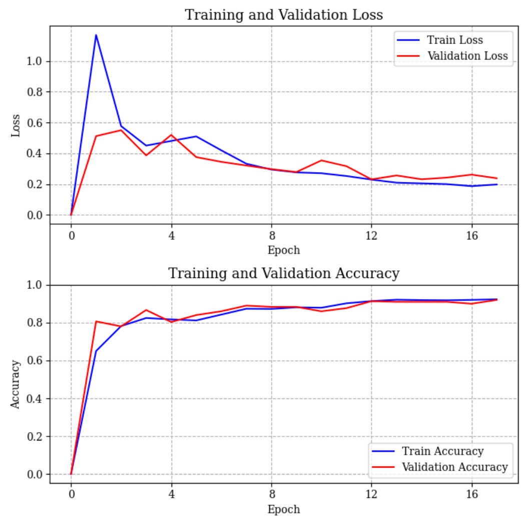

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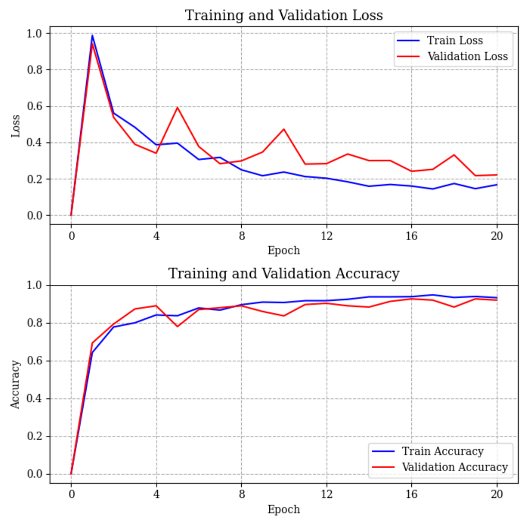

(c)

Figure 7: Performance charts:
a. VGG19 , b. InceptionV3 , c. Xception

The prediction accuracy of Dry AMD in all models is lower than the rest of the classes, and according to the Confusion Matrix, it's clear this disease is confused with Wet AMD samples. One of the reasons for this is the variation seen in Wet and Dry AMD compared to the normal samples. In contrast, Normal has given us benchmarks above 95%.

One of the common problems in collecting medical data is the difference in the quantity of data available for different diseases [26]. In the topic of AMD, we see that patients with Wet AMD need to do imaging tests in less time intervals due to the need for surgery or frequent injections and overall worse vision. On the other hand, Dry AMD cannot be treated; Imaging is done to remove the concern of worsening the disease or changing it to Wet AMD. As a result, it’s common to see in many pre-prepared datasets that the number of Wet AMD images is more than Dry or even normal [27]. It will also be more challenging and time-consuming to collect data for Dry AMD or similar data-poor diseases due to less imaging.

We faced many challenges in collecting the OCT images. None of the local hospitals we visited to collect images had an online or systematic patient archive based on disease. Since the doctor does not personally participate in the imaging process or the person's disease is determined in advance and by clinical observation, it is not customary to include the disease in the patient's file. In some diseases, like some cases of Dry AMD, we see a change in the condition of one eye from Dry to Wet AMD [28], which makes the process of observing and storing a patient's disease history and data quite difficult. One of the biggest contributions that can be made to hospitals by using artificial intelligence in research topics is helping to archive images categorically. Apart from the model (in this case for eye patients) making a preliminary prediction, it can also place images next to similar cases. This is not at all unattainable and in this case, it can be done by building a local server for hospital systems. Of course, the unification of the process of imaging and the recognition of the artificial intelligence model will be quite challenging. For example, in Negah Hospital, two main devices are used for eye imaging, each from a different company that has its own software. If we want simultaneous and seamless diagnosis with imaging, it is necessary to integrate third-party apps with the hospital's local server.

Apart from archiving, these models can act as an educational aid tool for residents and be used for disease diagnosis practice in the learning or teaching process. If the number of data is sufficiently increased, the models can also help doctors as an auxiliary tool to recognize challenging disease samples and clear doubts.

Table 3. Number of trainable parameters

Architecture	Train params
VGG19	17,026,735
InceptionV3	39,382,703
Xception	64,667,823

Table 4. Classification report table

Architecture	Precision	Recall	F1 Score
VGG19	0.93	0.93	0.93
InceptionV3	0.92	0.92	0.92
Xception	0.92	0.92	0.92

Conclusions

Artificial intelligence can be a decisive tool in helping and advancing the healthcare system. This article examined the identification of normal, Dry AMD, and Wet AMD eyes using Transfer Learning. The results showed that despite limited and self-conducted data, desired accuracy can be achieved with the help of pre-trained models. These neural network models can solve the problems we had in data collection and labeling, as well as archiving patient information, especially disease classification.

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