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Comparison of VGG-16 and Few-shot Learning Using a Small-Sized Dataset of OCT Images for Neurodegeneration in Epilepsy

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ABSTRACT

Due mostly to significant improvements in efficacy, deep learning has recently gained a lot of interest. Although there has been progress, there is still much potential for development, particularly when dealing with use cases that have low data availability, as is frequently the case in the field of medical image analysis. In this study, we present a method for detecting neurodegeneration in epilepsy early on in OCT images using a minimal amount of training data. In particular, we developed a predictive model based on convolutional neural network architecture, leveraging few shots learning. Our experimental results show that our predictive model has an accuracy of 88.1% and can obtain higher levels of effectiveness than VGG-16 with an accuracy of 65.4%.

Key words: Deep learning, Neurodegeneration, Epilepsy, Medical image analysis, Few-shot learning

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INTRODUCTION

Deep learning approaches [1] have recently proven to perform better than other computer vision techniques for a variety of applications, including disease detection and video analysis [2,3]. Modern deep learning models are currently more efficient than humans at detecting objects and classifying images, as demonstrated by the Image Net benchmark [4].

However, in practice, over fitting, which is frequently brought on by a lack of data, makes it difficult or impossible to apply deep learning techniques, which are data hungry in nature. As a result, an increasing amount of research is being done to adapt deep learning methods so that they can be used to analyse sets with fewer data points.

In the field of medical image analysis, where the images in issue often have a high resolution to permit easy diagnosis by human professionals, the occurrence of small-sized image datasets is widespread. As a result, we concentrate on using deep learning methods to analyse tiny datasets of medical images in our research. Additionally, since the combination of deep learning with few-shot learning has recently shown to have a high potential, we use few-shot learning to get beyond the limited availability of medical images [5]. We choose to focus our study on early diagnosis of neurodegeneration in epilepsy, one of several issues in the field of medical image analysis.

Global concern is raised by the increasing incidences of epilepsy and neurological diseases. While neurodegenerative disorders like Parkinson's disease (PD) and especially Alzheimer's disease (AD) are on the rise in tandem with the aging of the population in affluent countries, epilepsy is a severe brain disorder that affects about 50 million individuals worldwide.

OCT allows for a quick, non-invasive three-dimensional analysis of the retinal vasculature from the vitreoretinal interface to the choriocapillaris. The outcomes can be assessed separately in automated or user-defined retinal layers. OCT has also been used in patients with neurological diseases since its inception to identify and characterize retinal biomarkers. Many neurological diseases have retinal manifestations, which frequently precede the neurological disease's main symptoms.

The retina is anatomically and developmentally a part of the brain. Also, because retina is an extension of the

central nervous system, neurodegenerative diseases affect the eye as well as the brain and spinal cord. As a result, examination of the eye can be used to diagnose CNS diseases [6]. Unlike the brain, the retina is easily accessible for imaging methods; additionally, retinal imaging is less expensive than brain imaging. The current state of knowledge about OCT findings and potential OCT biomarkers in neurological diseases is summarized and discussed in this review, as is the value of OCT as a diagnostic tool in neurological diseases (Figure 1). Our paper is organized as follows. In Section 2, we review related work. Next, in Section 3, we provide details about our network architecture. We subsequently discuss our experimental setup and results in Section 4. Finally, we conclude our paper in Section 5.

Related work

In this section, we review several machine learning techniques, paying particular attention to learning with limited data, few-shot learning, and convolutional neural networks (CNNs).

Learning with limited data

Deep learning models can contain well into tens of millions of trainable parameters. As an example, EfficientNet-B7 [7], which achieves state-of-the-art performance on ImageNet [8], contains about 66M trainable parameters. Generally, the more parameters a model has, the greater its capacity to learn intricate patterns present in the data and achieve higher accuracy performance [2].

Deep learning models can have hundreds of millions of trainable parameters. EfficientNet-B7 [7], for example, has approximately 66M trainable parameters and achieves state-of-the-art performance on ImageNet [8]. In general, the more parameters a model has, the better it is at learning intricate patterns in data and achieving higher accuracy performance [2].

Large models, on the other hand, tend to over fit on small training datasets because they are unable to learn a correct data distribution due to the low variance of the training set, resulting in critical low classification performance in the validation set.

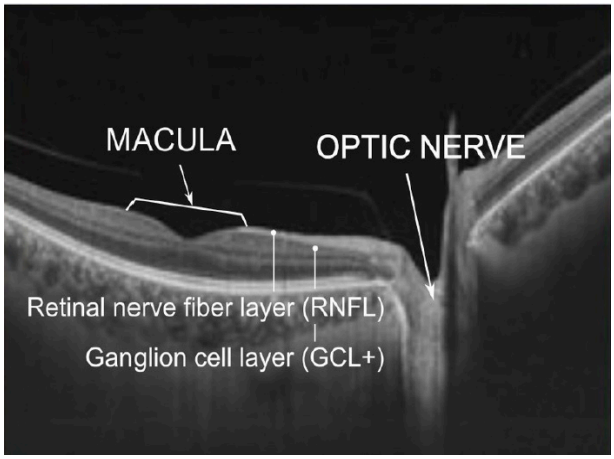

Figure 1: OCT image.

Numerous regularization techniques, such as weight-decay [9], dropout [10,11] data augmentation [12], transfer learning [13], and others, have been developed to address the problem of over fitting. A regularization method can be defined as "any supplementary technique aimed at improving the model's generalization, i.e., producing better results on the test set" [14].

Few-shot learning

Despite the current success of deep neural networks in a variety of application domains, applying these networks to small-sized datasets remains difficult. In order to address this issue, Google Deep Mind introduced a few-shot learning approach in 2016 [5]. The newly introduced approach, which is based on meta-learning [15,16], and Memory-Augmented Neural Networks (MANNs) such as Neural Turing Machines [17] only requires a few samples per class for training purposes (that is, one, five, or ten), outperforming Long Short-Term Memory (LSTM) [18] and humans for the task of Omniglot classification.

With very small datasets, few-shot metric learning with Siamese networks has been used to detect plant diseases 19]. With a few-shot skin disease dataset, a gradient-based meta learning approach was used to improve diagnostic performance [19,20]. Lai, et al. demonstrated the feasibility of classifying fundus photographs using low-shot learning based on automated data augmentation. Few-shot learning with data augmentation has also been used to detect pathological chest images in COVID-19 patients [21]. Previous research has shown that when using small training datasets, few-shot learning techniques can achieve reliable performance and outperform classical machine learning models. To the best of our knowledge, no study on neurodegeneration in epilepsy has been conducted using the concept of FSL and CNN with OCT.

Architecture

Our approach focuses primarily on applying deep learning techniques to small datasets. The FSL model made use of a convolutional neural network made up of convolutional blocks. To aggressively reduce input image dimensionality, each block was composed of a convolutional layer (each with 3 by 3 receptive fields, strides two or three), ReLU activation functions, and max-pooling. ConvNet baseline used the same configuration. Relation Networks employed a relation network composed of two convolutional blocks followed by a linear layer with a single output.

Experiments

In this section, we discuss the results of the experiments, comparing our approach to other cutting-edge neural network architectures. Our primary goal is to investigate the efficacy of binary classification for our small dataset of OCT images. To assess our model, we use accuracy: (#True Positives + #True Negatives) / #Predictions. All approaches have 580 images in the training set, 150 images in the validation set, and 150 images in the test set.

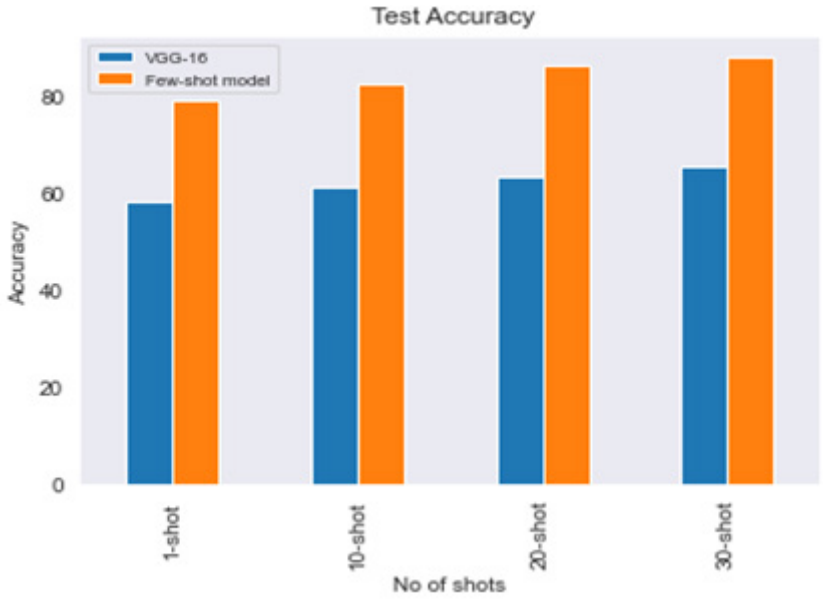

Figure 2: Overall architecture used by our model, showing one-shot learning. One positive and one negative example image are fed into the embedding function (CNN layers). Contrary to the number of example images, only one target image is consistently used for any-shot learning.

Experiment setup

This section outlines the procedures to set up the experiment and analyze the data thoroughly in order to reach the suggested solution. All statistical analyses were computed using the Python (version 3.7) and Scikit_ learn modules (Anaconda, version 1.9.12, Continuum Analytics) with personal computer which has 8 GB RAM and 2.5 GHz Core i7 processor.

Dataset

Our dataset consists of 880 OCT images, gotten from a public database. 880 OCT pictures, obtained from a public database, make up our collection. This database contains labeling information that has been verified by knowledgeable ophthalmologists and was compiled from numerous eye hospitals. We also pulled additional retinal image datasets from Google Images and Google Search. The photos in the dataset were manually categorized into two evenly matched classes: positive, which represents epileptic patients, and negative, which represents healthy controls. Each class contains 440 OCT images in total. We center-cropped each image to a zone of interest with a size of 1024X1024, considering that the size of the photographs varies. Because all the crucial elements for identifying neurodegeneration are situated between the optic nerve and the macula, it should be noted that we chose to center-crop.

Training

For comparison purposes, we made use of several state-of-the-art deep neural networks, as also included in Table 1. In general, we have used the default settings for the different neural networks [22]. We have then run VGG16 and Inception ResNet V2 with their default settings, as described in the respective papers. Furthermore, to alleviate the problem of over fitting, we applied data augmentation. We centre-cropped and eventually resized the input images to three different resolutions (that is, 256X256, 512X512, and 1024X1024). We make use of a 1-shot, 10-shot, 20-shot, and 30-shot approach per class, thus feeding 1, 10, 20, or 30 positive example images per class and 1, 10, 20, or 30 negative example images per class, vector for both the positive and the negative images. The vectors are then used for the prediction of label for an unseen target image.

In summary, all inputs go through the CNN layers and then through the attention mechanism for classification. Next, the loss, which is calculated based on the last output, is optimized.

EXPERIMENTAL RESULTS

A recent study emphasized the large amount of OCT data required to train a DL model but did not investigate the feasibility of FSL in OCT imaging [23]. To address the limitations of traditional DL models, we first performed an experiment to explore the feasibility of FSL in the OCT imaging domain. While highlighting the substantial amount of OCT data needed to train a DL model, a recent study did not look at the viability of FSL in OCT imaging [23]. We first ran an experiment to test the viability of FSL in the OCT imaging domain in order to solve the constraints of conventional DL models (Figure 3and Figure 4).

VGG-16 did not perform well for the provided dataset, as shown in Table 1. Given the dataset's balance, VGG-16 performed very similarly to random guessing. Among all studies, our model achieved the higher accuracy. We used a 1-shot, 10-shot, 20-shot, and 30-shot strategy.

We found that the more samples we had for each class, the more accurate the results were, which is consistent with [24].

Table 1 only shows the accuracy results; 30-shot learning outperformed 1-, 10-, and 20-shot learning

Table 1: Results obtained by the different predictive models.

Model	1-shot	10-shot	20-shot	30-shot
VGG-16	58.2%	61.1%	63.3%	65.4%
Our model	79.1%	82.7%	86.3%	88.1%

Figure 3: Accuracy graph for VGG-16.

Figure 4: Accuracy graph for our model.

by a significant margin. Given that human experts have a diagnosis accuracy of around 80%, the proposed approach is more effective.

CONCLUSIONS

In this paper, we presented a method for detecting neurodegeneration in medical images using a few-shot learning technique that makes use of CNN. Our experimental results show that the effectiveness of our approach is promising than VGG-16, even when training with a small dataset. In future research, we intend to evaluate our approach for various types of diseases and images. Finally, we will investigate whether additional data augmentation techniques can be used to achieve further improvements.

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