Identification of Diabetic Retinopathy Using Deep Learning

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Abstract

The research used deep learning methods to examine the results for Diabetic Retinopathy detection. Two different convolutional neural networks were trained. One was pretrained ResNet50 and the other was custom CNN. Every architecture was trained with and without data augmentation. The accuracy level were at approximately 50%. The low score may be the result of not deep enough network, low training time, poor data augmentation.

Keywords: Deep Learning, Diabetic Retinopathy, Convolutional Neural Network, Image Classification

1 Introduction

1.1 Diabetic Retinopathy

Due to the need to detect diseases at an early stage, machine learning methods are used to create tools to improve the work of doctors. One disease where diagnosis could be improved by machine learning is Diabetic Retinopathy (DR). It is caused by complications from diabetes. High sugar levels damage the retina. Without sufficiently early diagnosis, DR leads to blindness. Regular screening is essential for diabetes patients to diagnose and to prevent DR from spreading. Nowadays, ophthalmologists typically diagnose it visually by direct examination and by evaluation of color photographs. Since the number of people with diabetes is growing, it is harder to examine them by individual professional. Including computers in disease identification process may be a crucial step in diagnostics, because DR is the leading cause of preventable blindness globally and detecting it in early stages could be saving many patients from vision loss. [1] [2]

1.2 Deep Learning

Deep Learning (DL) is a branch of machine learning techniques. DL is a group of algorithms that can be used to learn complex prediction models. One of them is image classification, which was recently used in DR problem because it can successfully learn the features of input data. There are many methods in DL for image recognition such as convolutional neural networks (CNNs), autoencoders or sparse coding. CNNs are one of the most important methods of DL in which several layers are trained to obtain image classification.[3]

In medical image analysis CNNs are more widely used. They are build with 3 main layers [2]:

- Convolution, consist of filters or kernels preforming a scalar product between two matrices and giving tow dimensional representation of an image (activation map).
- Pooling, replace the output by summary statistics of nearby outputs, spatial size reduction and overfitting control.
- Fully connected, responsible for final classification.

For CNNs there are available many pretrained architectures like AlexNet, VGG16, Inception-v3 and ResNet which were previously trained on ImageNet dataset. [2] [4]

1.3 Deep learning in DR detection

In DR detection were many approaches pursued. The methods can be categorized according to the classification method.
Considering binary classification, the study preformed by K. Xu et al. they used 1000 images from Kaggle dataset and divided images into normal and DR images. Resizing to 224x224x3 was preformed with data augmentation including rotation, rescaling, flipping and translation. They achieved accuracy of 94.5 %. [5]
M.T Esfahn et al. used the same dataset and classification method but trained the model on pretrained CNN architecture, which is ResNet34. They also did data augmentation like Gaussian filter and weighed addition to normalized data. They used larger number of images, 35000 in size of 512x512 pixels. Their accuracy was at the level of 85 %. [6]
Multi-level classification was chosen by H. Pratt et al. They divided Kaggle dataset into five DR stages. Image resizing to 512x512 was preformed as well as color normalization. The custom CNN architecture had ten convolutional layers, eight max pooling layers and three fully connected layers. The results have an accuracy of 75%. The architecture was not able to detect lesion. [7]
Issue with lesion detection is one of the drawbacks when it comes to DL models in DR detection. Moreover, most of the researched algorithms used small data sets and struggle to detect DR accurately in larger data sets. Methods which were from the same data set do not generalize to images obtained from

other studies. Those are the main struggles to overcome if we want DL models to be used in practice. [1]

2 Methods and materials

In this project Google Collab with GPU was used.

2.1 Data preprocessing

The predictive algorithm was derived from a Kaggle dataset provided by Eye-PACS (Eye-PACS LLC, Berkley, CA). [8]. The collection includes patients with four different stages of DR. Due to computational limitations, only data train001 was used in training. It consists of 35126 images of left and right eye. Examination of the dataset showed uneven distribution of 5 classes and due to the deep learning model building it was decided to divide the dataset to only two classes, infected and not. Because of the large scale nature of data and different image size, they were downsized to 256x256 pixels. For model training 2000 images were used, 1000 of class 0 (healthy) and 1000 of class 1 (sick).For further image preprocessing, data augmentation were done. This includes: adding Gaussian noise, rotation, resizing, flipping, data distribution normalization and adding Batch normalization.

2.2 Model

Models used in training are one custom CNN architecture and one pretrained CNN architecture, ResNet50 with imagenet weights. The first one consists of six conv layers, three pooling layers and two fully connected . Activation function in the last FC layer was softmax. Both architectures were trained with and without data augmentation.

3 Results

After data processing, the models were trained. Final accuracy score was tested on a test data set which was not taking part in training process. Custom architecture without augmentation appeared to have 51% accuracy and stopped improving just after 5 epochs, there was no sense to train it longer. ResNet without augmentation has 50.5% accuracy in test dataset. It was trained for fifty epochs, but after plotting training history while training accuracy is increasing the validation one is at the same level, which may indicate the start of overfitting. After data augmentations, custom architecture improved its accuracy only to 51 % and ResNet50 has 51.5 % accuracy.

4 Discussion

Presented models were not good, but brought important questions. First of all, it is worth to consider and examine ResNet50 approach in DR detection.

It maybe is parameters fault or this architecture is not the best choice for that kind of problem. Next very important issue is very low accuracy. This may be a number of images used in training, number of epochs and time of training. In this project, it was important to have reusable code independent of computational power available, so time of training was limited by Google Collab due to RAM memory, hard memory and google policy to provide platform for active research. Moreover, more data augmentations can be tested in the future, especially one connected to colors of image. Using cross validation might help to improve the quality of the model. I believe that there are plenty of ideas to be realized later.

References

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