Study on the Effect of Depth on Convolutional Neural Networks for Brain Tumor Detection

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Abstract
Brain tumors are one of the invasive diseases in children and adults. Due to the complexity involved in brain tumors and their characteristics, manual examination may be error prone. The use of automatic classification technology using machine learning (ML) has always shown higher accuracy than manual classification [1]. Convolutional Neural Network (CNN) is widely used as a deep learning algorithm in detecting brain tumor. However, many people have not paid their attention to how the number of layers affect the accuracy of CNN when applying it in detecting tumor. To find the relationship between the number of layers of CNN model detecting the brain tumor and the accuracy of the model, this study implements three different models with different number of layers. By using a certain data set and preprocessing, the three models' codes are successfully run, and figures and output of the accuracy and loss are showed up. After comparing the graphs and output, a certain relationship is concluded. In this article, it is indicated that the number of layers of model has positive relationship with the accuracy of this model: the more layers the model has, the higher accuracy this model will provide.

Keywords: *Brain tumor detection, convolutional neural network, Influence of depth*

1 INTRODUCTION

With the development of society and science, the medical level has been continuously improved. In today's highly developed medical level, many early "incurable diseases" have cure methods, but people are reluctant to face tumor diseases. Brain tumor refers to a collection of abnormal cells in our brain. A tumor can be cancerous or benign. A cancerous tumor is malignant, which means it can grow and spread to other parts of the body. A benign tumor means the tumor can grow but will not spread.

In this case, diagnosing the tumors precisely becomes very important since it will help people who get tumors not miss the best treatment time and people who do not have tumors not get panic because of wrong diagnosis. In contrast, computer-assisted diagnosis provides a measure of insurance against human error, which can be considered as an effective method to improve the accuracy of diagnosis.

Before artificial intelligence appeared, most people analyzed brain tumor images by traditional image processing algorithms. In recent years, with the emergence and rapid development of artificial intelligence algorithm, convolution neural network has been applied to brain tumor diagnosis as a widely applied algorithm. In this study [6], 218 intensity and texture features were extracted, and principal component analysis (PCA) was used for dimensionality reduction in feature space for the first time. Then the six categories are classified by artificial neural network (ANN) and some results are obtained. In another study [4], two CNN models (SqueezeNet and GoogleNet) were fine-tuned to different levels for specific tumor classification problems. In (Zhao 2016) [10], the author designed a third-rate framework named Multi-Scale CNN, which can automatically detect the first three scales of image size and combine information of different scales in the area around the pixel. According to Zhao Liya's research in 2016, the test accuracy rate was 94.39%, the average accuracy rate was 93.33%, and the average recall rate was 93%. Qiu et al. [5] proposed pretrained neural network based on ResNet [3] for detecting different types of brain tumor and also achieved satisfactory result. However, all mentioned studies mentioned above did not include the impact of different convolutional neural network's depth. This point is very significant since it may influence the efficiency and accuracy of CNN model used for detecting brain tumor. Thus, the impact of depth of CNN model

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should be noticed and considered when investigating CNN model used to detect brain tumor.

Therefore, in order to solve the above problems, this study first employed three convolutional neural networks, namely self-designed CNN, VGGNet (Simonyan) [7] and MobileNet [2], it is found that the more layers the model has, the higher the accuracy of the model will be. If people are looking for greater accuracy when using the CNN model to detect brain tumors, they should choose the models with more layers. The summarization of the contribution is shown below:

1) This study employed different structures to study the effect of depth of convolutional neural network in the accuracy of recognizing brain tumors.

2) Compared to traditional machine learning methods, the chose convolutional neural network can easily achieve better result.

2 METHOD

2.1 Dataset preparation

The dataset used in the study are from the link [9] The dataset contains two folders (yes and no), and each folder contains 1500 images of brain tumors, including both tumorous and non-tumorous.

Since the size of different pictures in the dataset are different, preprocessing is necessary in this study. First, since different size of images is harder for machine learning model to analyze, this study changes the size of all images to 156×156 to efficiently and conveniently to process model analysis. Additionally, normalizing is also done by dividing the pixel of all images by 255 so that the speed of training and normalizing model can be higher than the speed without the preprocessing because machine learning models tend to train smaller images faster than process with larger images. Then, this paper divides the data set into training set and test set according to the ratio of 8:2, which is, 2400 out of 3000 images are used as training dataset and 600 out of 3000 images are used as test dataset.

In the study, convolutional neural network (CNN) was used to analyze the images. The architecture of employed models can be found in Table 1 and Table 2. Convolution neural network is mainly composed of the input layer, convolution layer, activation function, pooling layer, full connection layer, and loss function. On the surface, it is complex, but its essence is feature extraction and decision inference. To make feature extraction as accurate as possible, combination of these network layer structures otogether is necessary when people try to use CNN to analyze data. The function of convolution layer is to extract features. Because the features that may be extracted by one convolution are relatively rough, multiple convolutions, as well as layer by layer depth convolution are significant in CNN model. The function of activation function is to transform linear distribution into nonlinear distribution, which can be closer to our real scene. In CNN model, Relu is used in most times in activation function instead of sigmoid and tanh. Because when calculating the gradient, it is needed to find the first-order partial derivative of the function, and whether it is sigmoid or tanh, their partial derivative is 0. Therefore, there is problem call vanishing gradient. However, if using Relu as activation function, this problem can be solved efficiently. The pool layer is generally after the convolution layer and Relu. Its function is reducing the size of the input matrix (only width and height, not depth) and extract the main features. It is undeniable that after pooling, there will be a certain loss of features. Therefore, some classical models remove the layer of pooling. Although there will be some loss of features, the purpose of pooling is obvious, that is, it can reduce the operation in subsequent operations. The function of loss function is also obvious: calculate the loss to get the gradient. Also, full connections are also used sometimes. The main role of full connection is like a classifier which maps the features to the sample marker space. And the essence of full connection is matrix transformation. Convolutional neural networks are widely used nowadays, mainly in two categories: data prediction and image processing. For data prediction, Image processing mainly includes image classification, detection, recognition, and segmentation. It also includes the area focused on this study: tumor detection.

In this study, three convolutional neural networks with different number of layers are applied to test how will the different number of layers affect the accuracy and loss of the model to detect brain tumor. One is CNN with low layers, one is MobileNet with medium layers, and the other is VGG-16 with high layers. In the neural network, the number of neurons in the last layer is 1, and the activation function is sigmoid, to facilitate secondary classification. TensorFlow is imported to build neural network structure, matplotlib.pyplot is imported to draw the graphs, os is imported to deal with paths and cv2 is imported as computer vision library. In the study, the data is trained by 30 times for each model with different number of layers and the batch size is set up to 10. Additionally, in the study, the optimizer is Adam, the evaluation index is accuracy, and the loss function is binary _cross entropy.

Table 1: The architecture of the employed mobilenet.

Layer (type)	Output Shape	Param #
mobilenet_1.00_156 (Functional)	(None, 4, 4, 1024)	3228864
flatten	(None, 16384)	0
dense	(None, 1)	16385

Table 2: The architecture of the employed vgg-16.

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 4, 4, 512)	14714688
Flatten	(None, 8192)	0
Dense	(None, 1)	8193

3 RESULTS AND DISCUSSION

3.1 Performance for the proposed model

Table 3 indicates the accuracy and loss for 3 different models. According to the figures above (Figure 1&2), for the proposed CNN model, which have the lowest number of layers, as the times of training increase, both train accuracy and validation accuracy showing an increasing tend with fluctuations. The train accuracy has increased to 0.9646 while the validation accuracy has increased to 0.9067 after 30 epochs. Meanwhile, both train loss and validation loss tend to stay the same after 30 epochs.

Table 3: Three model's accuracy and loss table after 30 epochs

	Train Accuracy	Validation Accuracy	Train Loss	Validation Loss
Proposed CNN	0.9646	0.9067	0.1174	0.3004
MobileNet	0.9854	0.9500	0.0335	0.1473
VGG-16	0.9917	0.9633	0.0237	0.1592

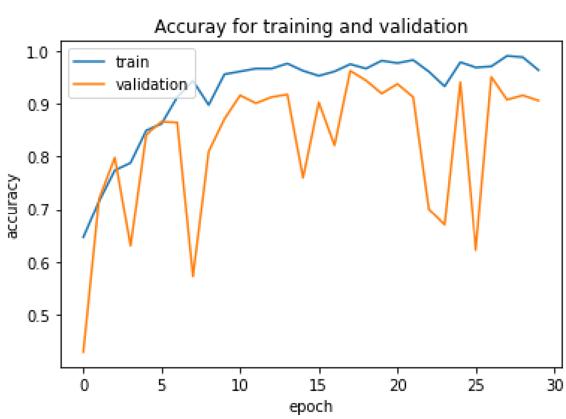

Figure 1: Accuracy for training and validation of proposed CNN.

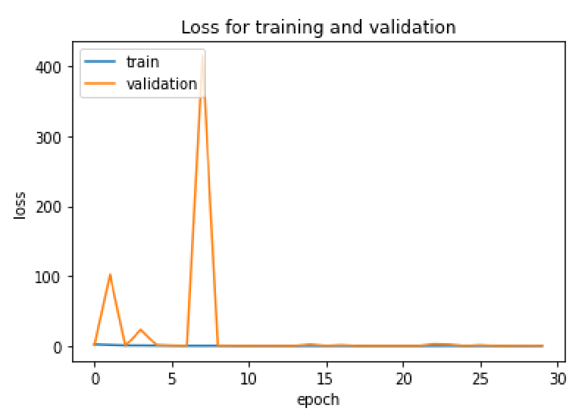

Figure 2: Loss for training and validation of proposed CNN.

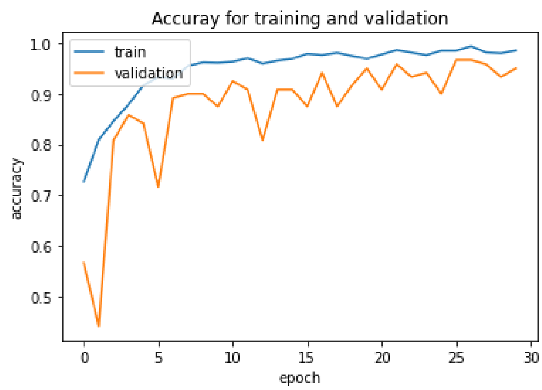

Figure 3. Accuracy for training and validation of MobileNet.

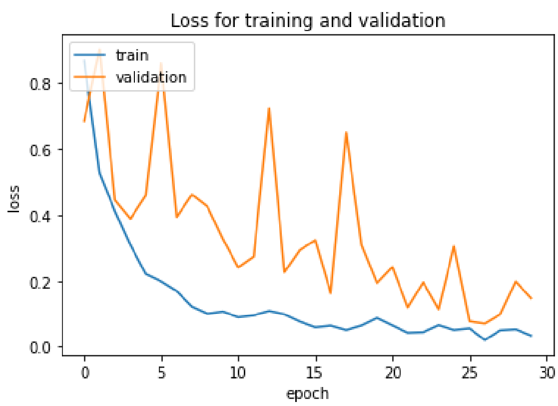

Figure 4. Loss for training and validation of MobileNet.

According to the figures above (Figure 3&4), for the MobileNet model, which have the middle number of layers compared to other two models, as the times of training increase, both train accuracy and validation accuracy showing an increasing tend with fluctuations, too. The train accuracy has increased to 0.9854 while the validation accuracy has increased to 0.9500 after 30 epochs. However, unlike the proposed CNN, the loss tends to decrease from its starting point and the graph of validation loss fluctuates dramatically.

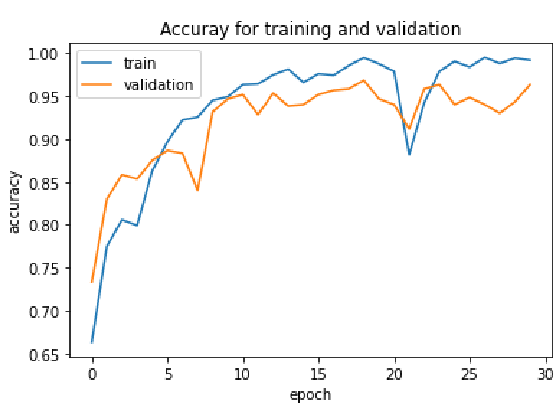

Figure 5: Accuracy for training and validation of VGG-16.

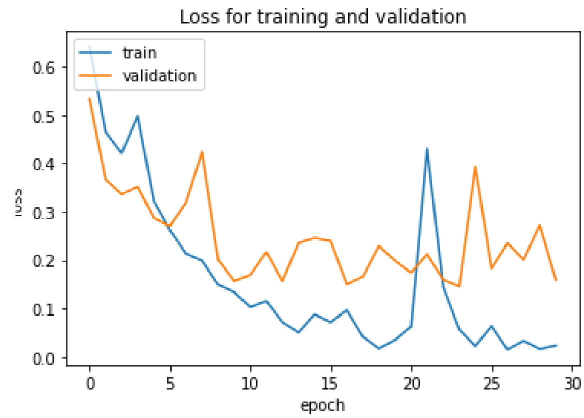

Figure 6. Loss for training and validation of VGG-16

According to the figures above (Figure 6&7), for the VGG-16 model, which have the largest number of layers compared to other two models, as the times of training increase, both train accuracy and validation accuracy showing an increasing tend with fluctuations, like the other two. The train accuracy has increased to 0.9917 while the validation accuracy has increased to 0.9633 after 30 epochs. Like the MobieNet model, the loss tends to decrease from its starting point. Both graphs of validation loss and train loss fluctuate during the 30 epochs.

After comparing and analyzing the figures and chart of the three different CNN model with different number of layers, a relationship of the number of layers of CNN model to detect brain tumor and the accuracy of the model (the evaluation index set in the study) can be concluded. The three models: proposed CNN, Mobilenet, and VGG-16 (ordered with the number of layers from the lowest to highest) have corresponding train accuracy: 0.9646, 0.9854, and 0.9917 and corresponding validation accuracy: 0.9067, 0.9500 and 0,9633. Both train accuracy and validation accuracy increase with the number of layers of model increases. Therefore, the result indicates that when implement CNN in brain tumor detection model, the model with larger number of layers tends to have a higher accuracy than the model with a smaller number of layers does. To implement this result in deep learning field, when people choose the model to detect brain tumor, if they consider the accuracy as the most significant, models with more layers will perform better then models having fewer layers.

3.1 Visualization for brain tumor classification

Gradient-weighted Class Activation Mapping (Grad-CAM) [8] was employed to visualize which regions of the original image data were helpful for final classification as shown in Figure 7. Heat maps are generated based on the class fraction gradient associated with each activation map. The results indicated that the employed model can effectively detect the position of the tumor and give it higher weight.

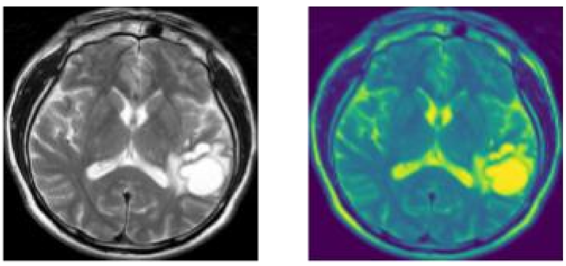

Figure 7. Visualization results for brain tumor detection based on MobileNet.

4 CONCLUSIONS

CNN is widely used in medical field to detect brain tumor since due to the tumors' complexity, manual diagnosis of tumor has low accuracy. In this study, the main goal is testing how the number of layers of CNN model detecting brain tumor will affect the final accuracy of the model, which is a part can be easily ignored when people research the use of CNN in tumor detection. The three models: proposed CNN, Mobilenet, and VGG-16 (ordered with the number of layers from the lowest to highest) are implemented and table and graphs of accuracy and loss are displayed. After comparing the results, it is indicated that the more layers the model has, the higher accuracy the model will has. If people seek for higher accuracy when apply CNN model to detect brain tumor, they should choose the models with more layers. However, in the study, the number of samples used are limited. More models should be implemented to support the study's result.

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