Application of Transfer Learning to 3-Dimensional Medical Imaging

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1 Introduction

3-Dimensional medical imaging especially magnetic resonance imaging (MRI) is widely used in routine clinical diagnosis and treatments. In Japan, brain-dock MRI is being conducted for medical checkup, then we propose an application of the transfer learning strategy of VGG16 to the brain dock MRI gender estimation. We conduct the experiment to clarify the performance of transfer learning and optimize the model to obtain better results.

The result shows that transfer learning is better than training from scratch and the VGG16 optimized model is best of all. The proposed method and idea of the transfer learning to 3-Dimensional medical imaging can be extended for other medical imaging tasks and also can be useful to make a development in medical diagnosis domain.

2 Methods

We use the data augmentation method to oversample the positive samples by random 3 times and oversample the negative samples by random 4 times to make class balance and more data samples. Now, there are 1249 samples including 628 negative (Female) samples and 621 positive (Male) samples so that we have a good balance and more samples data collection to train the model in the next step.

There is a difference between natural image and medical image especially MRI image in NIFTI format which is used to train CNN model as input. Natural image is 3-channel colorful image which has RGB channels, but NIFTI image is a series of 1-channel grayscale image slices. VGG16 model is used for natural image so the model needs 3-channel colorful image input.

Then we propose a new multi-channel fusion method to adjust images to VGG16 input. We choose the middle 3 slices of the image to represent 3 channels like RGB, and concatenate with each other so that we can get a fake 2.5D image with 3 channels available for VGG16 input. By trial and error experiments and several references, we find that choosing middle 3 slices from all slices derives the best accuracy. The figure 1 shows the result.

In our experiment, we choose VGG16 to train from scratch directly with brain dock MRI labeled data. We only retain all the convolutional layers and remove the top-level full connection layer. We add a new three-layer full connection layer at the top layer to form a new network model architecture. Because we do not have a large amount of data such as ImageNet and we just need to do binary classification of gender, we choose a little smaller layer with just a few weight parameters and the final layer is just with 2 neurons to avoid overfitting problem. This experiment uses this architecture as a prototype to compare the two training methods, i.e., training from scratch and parameters knowledge transfer learning.

Transfer learning has 2 steps (figure 2). First, we use a large image database like ImageNet to train the network to learn the features, output labels and update weight parameters. Then, we transfer the pretrained weight parameters and train the model with our medical domain images to learn the features in the low layer and output labels in the top layers to avoid overfitting problem. It is not only for reuse of the pretrained model and for faster training speed, but also for converging earlier and higher recognition accu-

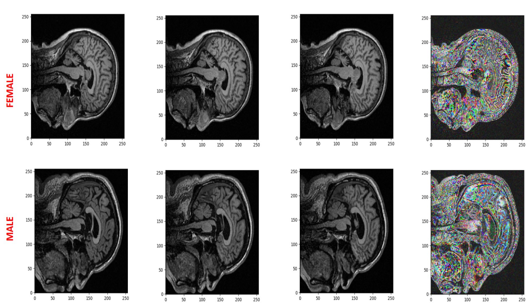

Figure 1 Multi-Channel Fusion Sample.

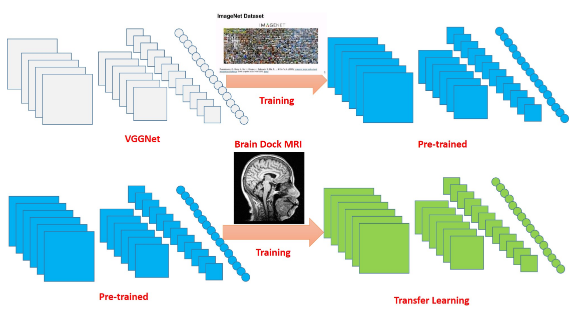

Figure 2 Transfer Learning Steps.

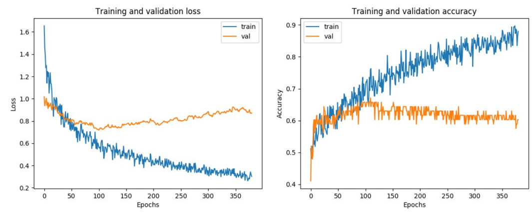

Figure 3 Train from Scratch Results.

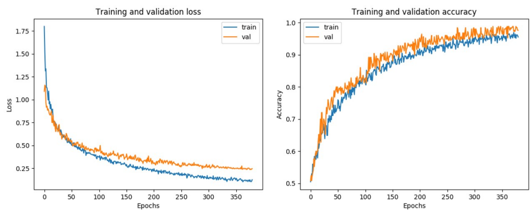

Figure 4 Transfer Learning Results.

racy. For example, the transfer learning for brain dock MRI diagnosis process is shown in image. We use parameters knowledge transfer learning method to share the weight parameters. We use the VGG16 pretrained weight parameters because lots of experiments show that we can obtain same features in low layers such as color, edge, but obtain different features in high layers. The network architecture and the initialization parameters are the same as training from scratch.

We also optimize model by using fine-tune (called "Optimized model"), fully-convolution methods, and using a new method of training learning rate to reduce more weight parameters to obtain a good model convergence and to improve both the model classification accuracy and training speed to reduce training time.

3 Results

We conduct experiments and compare all methods above to get better results. The transfer learning is better than training from scratch both in loss and accuracy. The figure 3 shows that the training loss is decreasing with the increasing epochs but validation loss is decreasing first and increasing later which shows that the model is overfitting to the train set so that it gets worse in validation set.

The figure 4 shows that the training loss is decreasing with the increasing epochs together with validation loss so that it can certifies that the shared weight parameters transfer learning can avoid over fitting problem and it works well both on training set and validation set.

We optimize the model and compare with the optimized VGG19. VGG16 optimized model is best in all in loss, accuracy and time as the table shows. The training time is calculated by one epoch.

Table 1 Loss, accuracy, and training time

Models	Val loss	Val acc	Time
Train from scratch	0.8695	0.6027	325ms
Transfer learning	0.2465	0.9760	268ms
VGG16 Optimized	0.0686	0.9923	186ms
VGG19 Optimized	0.1267	0.9662	190ms

4 Conclusions

We proposed a new Multi-channel fusion method that choose and combine the MRI middle 3 slices into 3 channels to represent a 2.5D fake colorful image with RGB as input like natural images to make VGG16 available. We compare two methods, training from scratch and transfer learning, and do experiments to certify that transfer learning is better than learning from scratch both in speed and accuracy. We optimize the pretrained VGG16 model by using fine-tune and fully-convolution methods to improve the experiment results both in speed and accuracy. We compare 2 different model architecture models: VGG16 and VGG19 to analyze and certify that transfer learning method does not need many layers and parameters, which may cause overfitting problems, analyze the successful reason and condition of transfer learning.

However, there are still many shortcomings in the experiment. We have not tested more complex network architectures such as GoogLeNet, ResNet, and it is not known whether transfer learning is equally valid in these networks due to our experimental conditions. For the problem concerning the data, because it is difficult to obtain public medical image datasets, we can't compare our models with others, and we can only verify our experiment results in a small area.

References

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