EEG Transfer Learning for Sleep Diagnostics and BCI Decoding

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1 Introduction

Electroencephalography (EEG) is an electrophysiological measurement method that records the electrical activity of the brain through electrodes attached to the scalp. EEG signals are convenient to use, and also has the advantage of not having to perform surgery and good time resolution [2].

As brain analysis during sleep is essential for humans, many have studied sleep monitoring and stage classification using EEG signals using deep neural networks [1].

Motor imagery (MI) have played a core role in brain-computer interface (BCI), and has been known as having spatial characteristics for each class. However, it has not much high accuracy across the subjects and takes a lot of time and resources to train the subjects. Therefore, it is necessary to reduce the training time for subjects while obtaining higher scores [3].

Transfer learning can improve the performance of the target learner in the target domain by transferring knowledge included in the different but related source domains [5].

2 Methods

2.1 Task1. Sleep Diagnostics

Task1 aims at the automatic sleep stage of EEG data through machine learning-based automatic analysis.

Dataset The dataset is open DB Physionet dataset including various aged subjects. The training set was 80 subjects aged 25-64, and test dataset was 25 subjects aged 80+ given with target data of 5 subjects in same age.

Learning Strategy For the training, I modified ans use DeepSleepNet[4] which is one of the state-of-the-art model for sleep stage classification. The Figure 1a depicts the architecture including two-stream of four convolutional neural networks (CNN) and bi-direct long short-term memory (LSTM) networks. The first parts including two-stream CNN can extract the time-invariant features from the EEG signals. The kernel size consists of two different size related to sampling frequency to extract frequency information as well. The second parts including bi-LSTM can extract sequential residual features from the sequence of EEG signals. The temporal transition information in an epoch can be trained in this part.

I used focal loss as the loss function to reduce the effect of imbalanced data problem among the classes. The proportion of data for each class had large difference in the number of trials, maximally 10 times the difference.

During training session, I experimented the different optimizer such as AdamW and SGD and different learning rate from 1e-2 to 1e-7 to find the optimal strategy. During the transfer learning session, I also experimented the different learning rate and the different number of freezing layers for fine-tuning. We froze the layers which would not optimized during fine-tuning from the first convolutional layer module to the last convolutional layer module in the first part.

2.2 Task2. BCI Decoding

This task aims at training networks with various datasets to solve the limitations of MI and expand practicality.

Dataset The motor imagery dataset consists of four different data. Cho2017, BCICIV2a, and Physionet MI dataset were used for the training dataset, and Cybathlon 2020 dataset were used for the target and test dataset. Training data are provided through MOABB, and had different classes consisting of left hand, right hand, and others (tongue, feet, both hands, or rest). The channels were selected with overlapping among all dataset, consisting of Fz, FC1, FC2, C5, C3, C1, C2, C4, C6, CP3, CP1, CPz, CP2, CP4, P1, Pz, P2.

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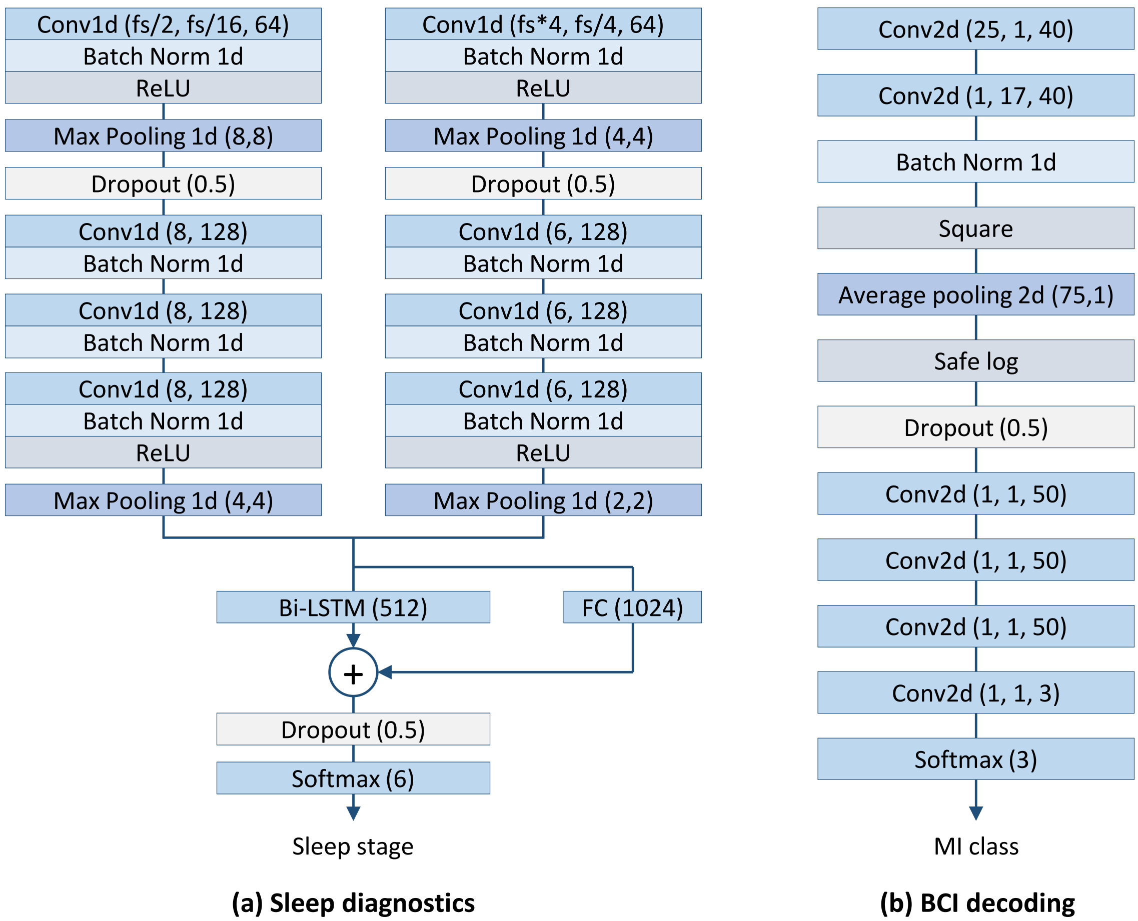

Figure 1: Training architecture for sleep diagnostics and BCI decoding

Learning Strategy The network architecture is demonstrated in Figure 1b. The networks consist of six convolutional layers, extracting optimal features from MI. The first convolutional layer can extract the time-variant features from the EEG signals, having the kernel with sampling frequency-related size. The second convolutional layer can extract the spatial feature with the kernel in size of the number of channels.

To solve the data imbalanced problem having twice number of the data of 'others' class, I reduced the number of 'others' data and also used focal loss.

During training session, I experimented the different optimizer such as AdamW and SGD and different learning rate from 1e-2 to 1e-7. During the transfer learning session, I also experimented the different learning rate and the different number of freezing layers for fine-tuning.

Moreover, since the target dataset has large difference between trials but small number, I split it into three-fold cross-validated sets, consisting the same number of trial for each class. Then, the final results came out with voting algorithm with the most chosen results among the three cross-validated models.

3 Results

The Table 1 depicts the results of classification of sleep stage and MI. Based on the validation set, the accuracy of sleep diagnostics was 73.52% with transfer learning. This result improved the models without transfer learning as 2.3%. As the difference between transfer and non-transfer is not huge, it can refer that the difference between the datasets of different ages is acceptably similar.

The accuracy of MI classification based on the validation set was 60.39% with transfer learning. The model was improved during transfer learning as around 10%. It refers that MI datasets have large difference among the datasets and also subjects even though they performed the same imagery tasks.

4 Conclusion

In this competition, transfer learning was conducted to sleep diagnostics and BCI decoding. As the results, transfer learning was effective on both tasks. While the monitoring our brain can be acceptably similar to different data, endogenous BCI decoding had large different among the datasets and subjects.

Table 1: The results of classification of sleep stage and MI

	Sleep state classificaion	MI classification
without Transfer	71.23%	50.83%
with Transfer	73.52%	60.39%

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