Passive BCI Hackathon: Applying Deep Learning to Estimate Mental Workload

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Introduction

The great potential of passive brain computer interface (pBCI) lies in the fact that one such system can unobtrusively monitor neurophysiological signals to estimate objective, real-time information about a person's cognitive state [1]. This information can further be utilized to improve both safety and performance of workers in a number of industries (e.g., production, transportation, aviation, construction etc.). The advancements in both acquisition equipment and the algorithms for feature extraction, classification, and regression, pave the path for various pBCI applications. However, many challenges remain [2].

Compared to other neurophysiological measurement techniques, when temporal resolution, unobtrusiveness and reliable measurements are at stake, electroencephalography (EEG) proves to be advantageous. On the other hand, advances in the field of machine learning, and deep learning (DL) in particular, and their potential to process non-stationary data, encouraged the investigation of their application to electrophysiological signals. The hope that DL could move the limits posed by classical signal processing techniques, primarily lies in the fact that constructing hand-crafted features can be omitted, and end-to-end learning can be applied. However, there is still no standardized DL-based procedure for EEG processing and feature extraction, but a number of attempts to utilize DL to solve BCI problems can be found in the literature [3].

Keeping in mind all the above, we propose a DL approach based on convolutional neural networks (CNN) as a solution to the problem of estimating mental workload (MWL) using EEG and investigate its capabilities to make reliable decisions about the difficulty of the task at stake.

Experimental Setup

Task:

15 participants (6 female, average 25 years old) performed the NASA Multi-Attribute Task Battery II (MATB-II) in three independent experimental sessions, spaced one week apart from one another. The experimental sessions included three 5-minute blocks of different difficulty level, presented in a pseudorandom manner. The aim of different difficulty levels was to induce different cognitive workload levels in participants.

Data acquisition and Preprocessing:

Acquired and preprocessed dataset for the Passive BCI Hackathon [4] is made available in the following format: 61-channel EEG data, sampled with a frequency of 250 Hz and epoched into 2-second non-overlapping intervals.

Further preprocessing implied standardizing each subject's data to zero mean and unit standard deviation. For standardization, the statistics were calculated from the first session of each subject's data, and then used to standardize all three sessions' data from the corresponding subject. As each subject completed 3 sessions of the task, the first session was always used for training, the second for validation, and the third session was used for testing the classifier.

Method

In order to classify MWL based on EEG for three task difficulty levels, a CNN illustrated in Figure 1 was employed. The model architecture consists of 7 convolutional layers, followed by average pooling and a fully connected (FC) layer with softmax activation function for class prediction. The first three convolutional layers (embedding module of the network) have 256 output channels (i.e., convolutional filters) with kernel sizes (5,3,3) and strides (2,2,1) and the remaining four convolutions (aggregation module) have 128 output channels with kernel sizes (3,4,5,6) and strides (1,2,2,1). The input to the model is 2 seconds of 61-channel raw EEG data, and the model performs 1D convolution across time dimension. Dropout, normalization and GELU activation function are put in between layers. The values of all hyperparameters, including the network depth and size, were chosen based on extensive grid search. Dropout of 0.25 and group normalization (number of groups equal to the number of channels) are applied to the embedding module, and a dropout of 0.37 together with layer normalization to the aggregation module. The models were trained for 100 epochs using AdamW optimizer and Cross Entropy loss function. Learning rate scheduler was applied with 5 epochs linear warmup, followed by cosine decay. Initial learning rate was 0.02, reaching a maximum value of 0.05 after warmup, and decaying to 0.0005 in the last training epoch.

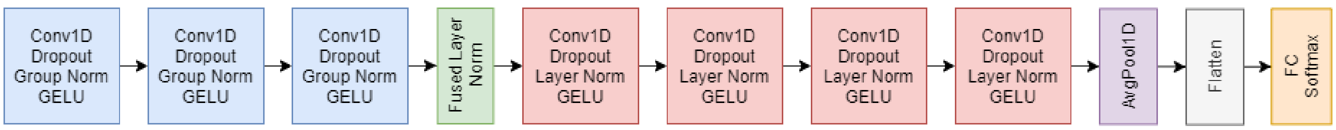

Figure 1. Overview of the model architecture used for MWL classification based on EEG.

By using raw EEG data as an input to the model omits the need for manual feature extraction, therefore protecting the model from any previous hypotheses about which EEG features contain information of interest and allowing it to learn feature extraction in a data-driven way. Furthermore, using 1D convolutions enables the model to perform data processing across time dimension and decide which channels will contribute the most. This approach does not impose any assumptions regarding the channel locations.

The proposed architecture was trained using the transfer learning approach to training. Namely, the model was first trained an all-subjects' data, and then fine-tuned on each subject's data separately. The following section investigates the obtained results and makes a comparison with the models trained from scratch. Performance metric used to report the results is classification accuracy on validation set.

<u>Results and Discussion</u>

The models fine-tuned on each subject's data separately have the average validation accuracy of (58.362 ± 7.404) %. Averaged confusion matrix for these models is shown in Figure 2.

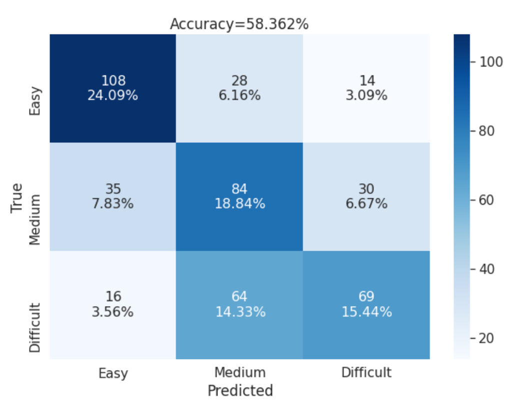

Figure 2. Averaged confusion matrix for fine-tuned models on each subject's data.

The proposed training procedure was compared to training on all subjects' data without fine-tunning and training on each subject's data separately, from scratch. We conclude that, on average, the presented approach has around 7.3% and 5.4% higher validation accuracy, respectively.

The confusion matrix shows that the misclassification most frequently happens between the "Difficult" and "Medium" class. There also seems to be an overlap between "Medium" and "Easy" classes, but very low overlap between the "Easy" and "Difficult" classes. This might be due to short evaluation periods – during those two seconds which are the input to the model, the task might be easier or harder (or perceived that way) than the overall difficulty of the block the data belongs to. Additionally, the difference in cognitive load induced by "Medium" and "Difficult" blocks may be smaller than between the "Medium" and "Easy" blocks.

Conclusion

The results indicate that the proposed architecture has the capacity to extract relevant information from EEG to the extent of generating estimations significantly far from random. Future work will focus on the generalization capabilities of the model and will consider other DL approaches to efficient information extraction.

Considering that only two seconds of the data are used to make a prediction, having more data to learn from and consequently making the model generalize well on different subjects, would lead to reliable real-time use.

Finally, making the measurement technology wearable and mobile, together with the improvement of signal processing using DL, may open the door for larger adoption of EEG technology in industry.

References

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