CNN-based Approaches For Cross-Subject Classification in Motor Imagery: From The State-of-The-Art to DynamicNet

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Abstract—Motor imagery (MI)-based brain-computer interface (BCI) systems are being increasingly employed to provide alternative means of communication and control for people suffering from neuro-motor impairments, with a special effort to bring these systems out of the controlled lab environments. Hence, accurately classifying MI from brain signals, e.g., from electroencephalography (EEG), is essential to obtain reliable BCI systems. However, MI classification is still a challenging task, because the signals are characterized by poor signal-to-noise-ratio, high intra-subject and cross-subject variability. Deep learning approaches have started to emerge as valid alternatives to standard machine learning techniques, e.g., filter bank common spatial pattern (FBCSP), to extract subject-independent features and to increase the cross-subject classification performance of MI BCI systems. In this paper, we first present a review of the most recent studies using deep learning for MI classification, with particular attention to their cross-subject performance. Second, we propose DynamicNet, a Python-based tool for quick and flexible implementations of deep learning models based on convolutional neural networks. We show-case the potentiality of DynamicNet by implementing EEGNet, a well-established architecture for effective EEG classification. Finally, we compare its performance with FBCSP in a 4-class MI classification over public datasets. To explore its cross-subject classification ability, we applied three different cross-validation schemes. From our results, we demonstrate that DynamicNet-implemented EEGNet outperforms FBCSP by about 25%, with a statistically significant difference when cross-subject validation schemes are applied. We conclude that deep learning approaches might be particularly helpful to provide higher cross-subject classification performance in multi-class MI classification problems with respect to FBCSP. Moreover, in the future DynamicNet could be useful to implement new architectures to further investigate cross-subject classification for MI BCI in real-world scenarios.

I. INTRODUCTION

Brain–computer interfaces (BCI) provide a direct communication channel between the brain and external devices [1], [2]. One of the most common BCIs is based on motor imagery (MI), i.e. the imagination of movements (e.g., of hands, feet, tongue). MI-related EEG has been extensively studied in the context of communication [3], robotic control [4], gaming [5] and rehabilitation [6]. Despite of extensive research, MI-based BCIs still face many challenges. EEG signals have a low signal-to-noise ratio (SNR), can be easily corrupted by various artifacts (like eye movement or other muscular activity), have a poor spatial resolution leading to channel correlation, and the features extracted from the signals are very subject-dependent. This last point remains one of the biggest challenges in the BCI field, making it almost mandatory to collect data and calibrate the BCI for each subject. The search for approaches that allow an efficient cross-subject capability is therefore an attractive area of research in the BCI field. Traditional machine learning approaches for MI classification have been mainly based on common spatial patterns (CSP) [7] and its variants, such as the filter bank CSP (FBCSP) [8], combined with classifiers such as support vector machines (SVM) or linear discriminant analysis (LDA). These approaches have been quite successful in classifying MI data for the within-subject case [8], [9], but have poor performance in the cross-subject scenario [10]. Due to this fact, recently, researchers started to study deep learning (DL) techniques to analyze and classify EEG data [10]–[13]. DL research is also motivated by the success of these techniques in other fields, e.g., image classification, speech recognition and text analysis. Compared with traditional machine learning, DL offers a unique end-to-end solution that can automatically extract features that best classify raw EEG data. However, the design of DL-based architectures can be cumbersome. The need to select and combine different layers in a network, along with the training and validation of the best design is still time-consuming and requires some expertise. This emphasizes the importance of providing flexible tools that allow a systematic implementation of different DL architectures to easily achieve classification models. The main contributions of this work are: (1) to survey the most recent works that used DL to classify MI data, with particular attention to cross-subject classification; (2) to introduce DynamicNet, a new open-source Python-based
The CNN architecture. Their model could robustly learn time-based architecture with feature fusion at different layers of depthwise convolutions.

Another activation function for the last layers and the lack of similar architecture, with the main difference being the use of purposes, as shown in Table I.

ShallowNet attention and have been employed for different classification [17] and the EEGNet well as several variants, have been recently applied to MI vertical convolution to simulate frequency and spatial filtering. CNN inspired by the FBCSP approach that uses horizontal and vertical convolutions, respectively. Then, exploiting the fusion of different abstract representations (i.e., from different CNN layers), it could outperform the state-of-art. Besides, fusion was alternatively obtained via feed-forward network (namely, in the MCNN model) or via autoencoder (namely, in the CCNN model).

B. Datasets and Preprocessing

The most commonly used datasets for motor-related EEG classification are the dataset 2a proposed at the BCI Competition IV [20] (see section IV-A for more details), and the High Gamma Dataset (HGD) [11]. While the former includes MI data from 9 healthy subjects, the latter is a collection of motor execution (ME) EEG data from 20 healthy individuals. The wide use of these two datasets in the BCI community allows us to provide a fair comparison among different DL models used to classify them. Additionally, the dataset 2b from the BCI competition IV (D2b, 2 classes [20]), and the Physionet eegmmidb (109 subjects, 4 classes, both MI and ME task [21]) were used in a few works.

Finally, similar preprocessing has been applied across the surveyed papers: band-pass filtering (with variable choice of the cut-off frequencies) and normalization (e.g., the exponential moving [11]) were mostly used.

C. Classification Accuracy

Table I reports the results for both intra-subject and cross-subject classification.

Intra-subject classification performance was mostly obtained from the dataset 2a with 4 classes. In this scenario, FBCSP reaches an accuracy of 67% [10], while DL models achieve 67% with EEGNet [10] up to 75.7% with MCNN [14]. In the 4-class HGD, FBCSP reaches an accuracy around 91% [11], while DL models vary between 91.2% with Sinc-ShallowNet [15] up to 95.4% with MCNN [14]. Thus, we can conclude that DL models outperform FBCSP in the 4-class problem. It is worth to note that better results have been obtained for HGD because it contains ME data, making the classification easier compared to MI data.

On the other hand, in the cross-subject classification, the results are strongly influenced by the number of classes (2 or 4 classes) and the cross-subject training and validation strategy. For the 4-class problem, Lawhern et al. [10] obtained a cross-subject accuracy around 40% using the dataset 2a. Despite such low accuracy, it still outperformed FBCSP (accuracy around 32%). With the same dataset, Amin et al. [14] reached a better accuracy (55.3%) with the CCNN model. With the HGD, including ME data, the cross-subject classification increased up to 79.2% (obtained with the CCNN model). When only 2 classes are considered, we observe a general increase in the accuracy values, as expected, given the simplification of the classification task. Xu et al. [16] presented an extensive study on cross-subject with 2 different architectures (ShallowNet and the EEGNet) over 8 datasets.
Overall, despite the relatively good results of the binary cross-subject classification, the accuracy values in the 4-class remain generally low, with ample room for improvement. Interestingly, to the best of our knowledge, [16] and [18] are the only works that provide results for cross-dataset classification (i.e., the models were trained on one dataset and tested on another one). For example, in [18], the authors trained a model on D2b and tested it on the data of D2a.

### D. Cross-Subject Training Strategy

We investigated cross-subject classification by analyzing the cross-validation strategy used in the surveyed papers. We can observe that the main cross-validation strategy was the "leave-one-subject-out": given a dataset with \( n \) subjects, then \( n - 1 \) subjects were used as the training set, while the remaining one represented the test set. Alternatively, a training-validation-test strategy was found: in this case, one subject was kept for the test, while the \( n - 1 \) subjects were split into the training set and the validation set. This was the scheme used by Lawhern et al. [10], who considered 5 subjects to train their model, 3 of them for the validation, and 1 subject for testing (they used the dataset 2a, including 9 subjects). Differently, Roots et al. [17], who considered 5 subjects to train their model, 3 of them for the validation, and 1 subject for testing (they used the dataset 2a, including 9 subjects). Differently, Roots et al. [17] mixed the data from all subjects together (this approach is rarely seen in the literature) and a 70%–20%–10% split was implemented for training, validation and test sets, respectively.

### III. MOTOR IMAGERY CLASSIFICATION

#### A. DynamicNet

DynamicNet is a novel open-source toolbox based on PyTorch that allows to quickly implement a variety of DL...
models. As sketched in Fig. 1, **DynamicNet** allows to create a model by simply defining a Python dictionary containing general parameters of a CNN architecture, e.g., the number of convolutional layers, the list of activation functions, and the list of pooling layers. The dictionary of parameters is given as an input to the class. **DynamicNet** allows a rapid construction and debugging of the DL model with the design of on-the-fly configurations for entire layers.

The design of a DL model can be divided into three phases:

1. **The design of the convolutional section.** In this phase, the **DynamicNet** iterates through the parameters of the convolutional section and, at each iteration, a convolutional layer is built. Each convolutional layer has the same structure and consists of the sequence of a convolution, a normalization, an activation, a pooling and a dropout. For each of them, the parameters are included in the corresponding list (e.g., `activation_list`, `dropout_list` etc). At the \( i \)-th iteration, **DynamicNet** takes the \( i \)-th parameters from each list and uses them to build the \( i \)-th layer.

2. **The design of the flatten layer.** In this phase, **DynamicNet** builds automatically the flatten layer to connect to the first layer of the feed-forward section. The number of neurons in the flatten layer is automatically defined during the design of the convolutional layer (previous step). The user must only specify the dimension of the input. This information is used to create a "dummy input" that is propagated through the convolutional layers. The output of the convolutional layers is then flattened and its dimension is used as the number of input neurons.

3. **The design of the feed-forward section.** This process is similar to the first phase, with the main difference that the parameters are related to the feed-forward section. In the cases where a simple feed-forward architecture is designed (**DynamicNet** allows this simpler case), phases 1 and 2 are skipped.

The current version of **DynamicNet** can only be used to create feed-forward neural networks-based and CNN-based DL models. Future developments will possibly provide more complex modules (e.g., incept module), as well as the integration of explainability tools (e.g., gradCAM [22] and SHAP [23]).

**B. Implementation of EEGNet using DynamicNet**

An example of how **DynamicNet** can be used to implement **EEGNet** is shown in Fig. 2. As mentioned above, the tool works cycling through all parameters and builds a layer at a time. When all the layers are built, they are stacked all together. The complete list of parameters for **EEGNet** can be seen in Table II. The convolutional section consists of 4 layers (\( \text{layers}_\text{cnn} = 4 \)). Also, as it can be seen from the `kernel_list`, the first kernel performs an horizontal convolution (1,32) and the second one implements a vertical convolution (22,1). This step is then followed by another horizontal convolution (1,4) and a point-wise convolution (1,1). The `filters_list` and the `group_list` specify how many input and output channels are in each layer, and how many filters are used in each layer. For example, the (1,8) in the `filters_list` means that an input with a single channel is fed to the model and is convoluted in 8 different channels, such that the output of that layer results in a depth of 8. Depth-wise convolution is achieved by setting the group of each layers equal to the number of input channels. As in [10], the activation, the pooling and the dropout were used only after the spatial convolution (layer 2) and the point-wise convolution (layer 4). The feed-forward section consists of 4 neurons (i.e., the desired number of classes) that are connected to the flattened output of the convolutional section.

The **DynamicNet**-based **EEGNet** model was trained as in its original paper [10]: 500 epochs, ADAM optimizer (default parameters) and negative log likelihood loss (NLLLoss). A RTX 2070 GPU was used.

**C. Cross-validation**

To investigate the performance of the **EEGNet** over different contexts (intra- and cross-subject), we tested the following two different cross-validation schemes:

- **Subject-dependent (intra-subject).** Here, one subject at a time was considered (with his/her data split into a training set and a test set).

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1. [GitHub repository DynamicNet: https://github.com/jesus-333/Dynamic-PyTorch-Net](https://github.com/jesus-333/Dynamic-PyTorch-Net)
Fig. 2: EEGNet implementation with DynamicNet.

- **Cross-subject.** Here, two variants were implemented: (1) leave-one-subject-out cross-validation, where the DL model was trained using data from all subjects except one, whose data were used as test set, and (2) mixed-up training; in this case, first the data from each subject were split into a subject-related training set and subject-related test set; then, all subject-related training sets (from all subjects) were merged together in a mixed-up training set that was used to train the DL model; finally, each subject-related test set was used to test the DL model.

IV. RESULTS AND DISCUSSION

In this section, we report the results of our implementation of the EEGNet through DynamicNet, with the two above-mentioned different cross-validation schemes. Moreover, we emphasize how they can affect the model’s performance and we compare our results with the state-of-the-art. All classification results are reported in Table III. As a baseline comparison, we also reported the results obtained using our implementation of the gold-standard FBCSP.

A. Dataset

We used the dataset 2a from the BCI Competition IV [20]. Particularly, the dataset includes 22-channel EEG recordings from 9 subjects performing the imagination of 4 different movements, i.e., right and left hand, feet and tongue movements. Therefore, the dataset is a 4-class MI EEG dataset. The sampling frequency is 250 Hz. For each subject, 288 training trials and 288 testing trials have been collected (a total of 5184 trials were available in the dataset). The dataset has been preliminarily pre-processed by the authors, applying a band-pass filter in 0.5 – 100Hz and a notch filter around 50 Hz. From each trial of each subject, a 4 s EEG segment is extracted.

B. Classification accuracy

The DL model reached an average accuracy across all subjects of 68% with the subject-dependent training strategy, outperforming the FBCSP method that achieved a 63% accuracy (see Table III). When the mixed-up training strategy was used, the accuracy of the DL model increased to 73%, while the accuracy obtained through FBCSP dropped to 46%. The improvement provided by the DL model can be due to the increase in the amount of data used for the training. EEGNet managed to outperform FBCSP also with the cross-subject training strategy (EEGNet achieved an accuracy of 59% while the FBCSP reached 34%).

C. Cross-subject investigation

Our cross-subject results are higher compared to the work of Lawhern et al. [10] (40%) and also 4% higher than [14] (55.3%). These two works are the most similar to ours and therefore the easiest to compare with, since they are the only ones that used 4 classes.

To understand the difference between our results and the results of Lawhern et al., we conducted further tests using their training strategy (5 subjects for training, 3 for validation set and 1 for testing). The initial hypothesis was that the lower results were due to the smaller training set. Instead, we found out that the discriminant factor was the data preprocessing. We used their same training strategy with both raw data and preprocessed data. For both cases, we repeated the experiment 10 times. We obtained an average accuracy of 53% for the raw data (in line with our previous results) and an average accuracy of 45% with the preprocessed data (in line with [10]). This suggests that MI deep learning models could be very sensitive to subject-to-subject variability in data contamination and amplitude range, and that the filtering and the normalization could remove subject-independent features while leaving only subject-dependent features. This hypothesis is also supported by the fact that, generally, filters and normalization either have no effect or increase the accuracy in intra-subject training.

Another interesting fact is the general increase in accuracy when we used the mixed-up strategy, i.e., we used the training set of all subjects during the training. This approach could still be seen as a cross-subject training because the model is fed with data of multiple subjects and the test set includes data from a single one, only. This suggests that, as the dataset
TABLE III: 4-class classification accuracy and standard deviation for EEGNet and FBCSP for different training strategies on raw data. The measures are reported on a scale from 0 to 100%. * on the AVG row means that t-test between EEGNet and FBCSP corresponding values resulted in a p-value < 0.005.

|            | EEGNet (Single) | EEGNet (mixed-up) | EEGNet (Cross) | FBCSP (single) | FBCSP (mixed-up) | FBCSP (Cross) |
|------------|-----------------|-------------------|----------------|----------------|------------------|---------------|
| 1          | 74.76±6.43      | 81.4±2.13         | 67.22±2.87     | 69.5±1.13      | 57.05±1.17       | 41.7±1.11     |
| 2          | 52.8±4.64       | 60.0±2.24         | 48.82±2.31     | 55.27±0.81     | 42.26±0.68       | 28.8±1.23     |
| 3          | 84.5±3.22       | 89.3±2.24         | 73.4±1.11      | 79.28±1.73     | 53.44±1.81       | 47.74±2.03    |
| 4          | 53.19±4.12      | 69.86±2.56        | 58.82±1.78     | 53.07±0.84     | 38.89±0.82       | 36.72±0.83    |
| 5          | 69.86±2.81      | 60.5±14.54        | 42.78±7.24     | 46.35±0.7      | 31.35±0.71       | 25±0.55      |
| 6          | 53.82±3.31      | 61.7±1.66         | 48.13±1.02     | 40.86±0.88     | 34.06±0.9       | 26.04±1.13    |
| 7          | 74.5±6.63       | 80.7±2.51         | 68.75±3.31     | 76.85±0.66     | 37.22±0.73       | 27.17±0.67    |
| 8          | 73.47±1.17      | 82.3±12.23        | 71.46±1.87     | 69.73±0.88     | 62.92±1.63       | 36.72±0.15    |
| 9          | 73.92±6.89      | 66.4±2.61         | 54.79±2.28     | 71.7±1.41      | 55.49±1.57       | 36.11±1.7     |
| AVG        | 76.88±1.79      | 72.5±1.8*         | 59.35±1.97     | 62.36±1.25     | 45.85±0.23       | 34.01±0.29    |

size increases, provided that also data from multiple subjects are included, EEGNet has the ability to extract more robust features, especially if compared with FBCSP. This increase in accuracy is also in line with the surveyed literature on DL, where the performance of the models increase with the size of the dataset.

V. CONCLUSIONS

In this paper we have surveyed several deep learning models for MI EEG data classification. Deep learning can achieve accuracy between 67% and 76% in 4-class intra-subject classification over the publicly available dataset 2a (the most common dataset for MI classification). Deep learning was able to match and outperform FBCSP in intra-subject classification. In binary cross-subject classification, deep learning models performed well with accuracy of 70% (dataset 2a), 76% (dataset 2b) and 83% (eegmidib). From our survey, we can conclude that room for improvement remains in multi-class cross-subject MI classification, where less studies are available, and the performance are still relatively low (~60%). Moreover, from our results, deep learning outperformed FBCSP in 4-class MI classification with an improvement of about 25%, from our results, deep learning outperformed FBCSP in 4-class MI classification with an improvement of about 25%, but further studies are needed to allow a wider use of this model in real-world scenarios. Finally, DynamicNet showed to be an effective tool for the quick implementation of simple deep learning models, even though it is still in a preliminary version.

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