3D Multi-Branch CNN for EEG Emotion Classification

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The Electroencephalogram (EEG) is often used in the neuroergonomics field as a means of studying the brain at work, with a relatively low cost and high portability. EEG data offers the capability to investigate a user's brain signals as they interact with their environment in either a work or natural setting, and has been used in applications from attention-based spellers (Li et al., 2010) to robotic system control (Huang et al., 2019). In neuroergonomics, it's important to interpret the user's affective state while they interact with the system/tech/environment, however due to the nature of EEG, data is often noisy and difficult to process. Traditional strategies use machine learning classifiers such as Linear Discriminant Analysis (LDA) or Support Vector Machines (SCM) which require significant pre-processing to prepare the signal before the classifier can make use of it (Lotte et al., 2018). Deep learning models have shown the potential to process raw EEG data, bypassing the significant amounts of preprocessing required to use those traditional strategies (Craik et al., 2019). The EEGNet model has found success as a generalized model capable of performing well in a variety of classification tasks (Lawhern et al., 2018). In previous work, we proposed a modification of the EEGNet model, with two primary changes: a 3D data representation and a multi-branch structure. In the original EEGNet, a 2D input shape (described as Channels x Timesteps) of EEG data was used, however this method lacks the ability to inform the model of the spatial relationship of EEG channels and their positions across the scalp. In the case of 3D EEG data input, a spatially relevant layout of EEG channels is used, allowing the model to better understand the spatial relationship amongst channels. This 3D input method has been found to improve the accuracy of deep learning classifiers (Wei et al., 2018). The second change is to implement a multibranched model structure with varying receptive field sizes. This method allows for each branch to extract different sized features from the model by examining the data through differently sized temporal "eyes" (Liu and Yang, 2021). This combined 3D multibranched model has been tested by Zhao et al. (2019) and our group, and was found to achieve accuracy of 75% on the BCI Competition IV 2a dataset. Notably, all testing of this architecture has been regarding motor imagery, an EEG task paradigm more aimed at disabled persons. We sought to test how the modified version of EEGNet performs in classifying emotional states from EEG data. Ideally, this architecture will inherit some of the reported generalizability across paradigms from the original EEGNet, and function as a decoding tool able to be used in the Neuroergonomics field to better understand the affective state of a user as they perform tasks.

This paper takes a 3D multibranched variation of the EEGNet model and applies it to the SEED IV dataset to classify four possible emotional states from EEG data. The dataset is preprocessed using similar methods described in Zhao et al. (2019). First, we reorganized the data into a 3D representation, with the first 2 dimensions describing a spatial representation of EEG channels according to the international 10-20 system, with the 3rd dimension being time. Next, a cropped strategy is applied to the dataset, a common strategy of data augmentation used when data is insufficient for training purposes. This approach is capable of transforming a dataset containing 72 trials per individual to 3600 data samples per individual. This data is then normalized using a channelwise averaging method, after which it is shuffled. This data is then used to train the model over a course of 100 epochs with a batch size of 50.

In Table 1, the suggested model structure can be observed, with each receptive field labeled as small receptive field (SRF), medium receptive field (MRF), and large receptive field (LRF). In Figure 1, initial findings can be found regarding model accuracy. The figure demonstrates that the model achieves performance on par with the state-of-the-art classification methods used. Each accuracy value is found through a 5-fold cross validation metric. For a comparison of performance, Liu et al. (2021) summarized several methods of emotion classification and reported that their method (DCCA) was able to achieve a mean accuracy of 87.5%. The performance of our approach then is very competitive, achieving a mean accuracy of 83.13%. If we were to exclude subjects 1 and 5, whose classification accuracies across all conditions can be seen as outliers in Figure 1, this mean accuracy increases to 90.30%. Unfortunately, we have not yet been able to determine the cause of these two subjects' outlier statuses, however we find both accuracy values to be very competitive. We believe that this validates our method as an approach to EEG emotion classification using a 3D multibranched EEGNet variation, supporting the use of both 3D input data and the multibranch CNN technique.

Our model offers a high-performance tool for neuroergonomics researchers that allows for them to make more informed decisions throughout studies and have better insight into an individual's state-of-mind throughout a task. The accuracy of the model makes it a valid choice in research settings, given that we can reliably predict an individual's emotional state with 80-90% accuracy, a result better than many current state-of-the-art methods. For example, our model would allow for more accurate understanding of an individual's emotional reaction to a task, assisting with studies like the one performed by Sargent et al. (2020), where they tracked an individual's emotional response throughout the preparation and consumption of coffee. We believe that the documentation and work that has gone into this project will make the use of EEG in neuroergonomics studies more accessible, even to researchers without a significant background in machine learning.

As a final note, all code used in this study can be found in the GitHub repository below, as a significant goal of this project is to allow for others to reproduce these results and apply the model and ideas within to their own projects, without having to recreate all from scratch.

https://github.com/matt-houk/MB3DCNN

Figure 1.

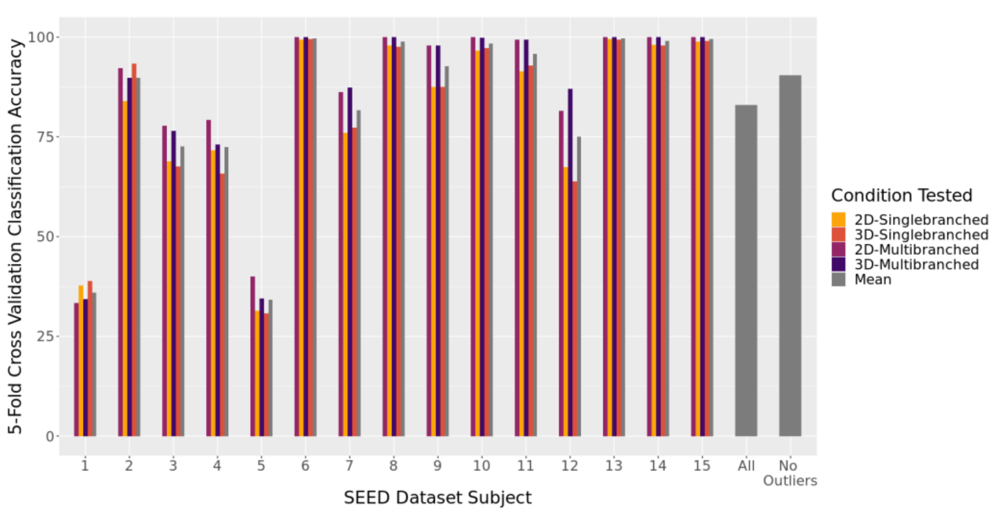

Figure 1. The results of a 5-fold cross validation analysis of each subject's data. Subjects 1 and 5 are clear outliers, with consistently lower performance, so average model accuracy has been presented with and without these subjects.

Table 1.

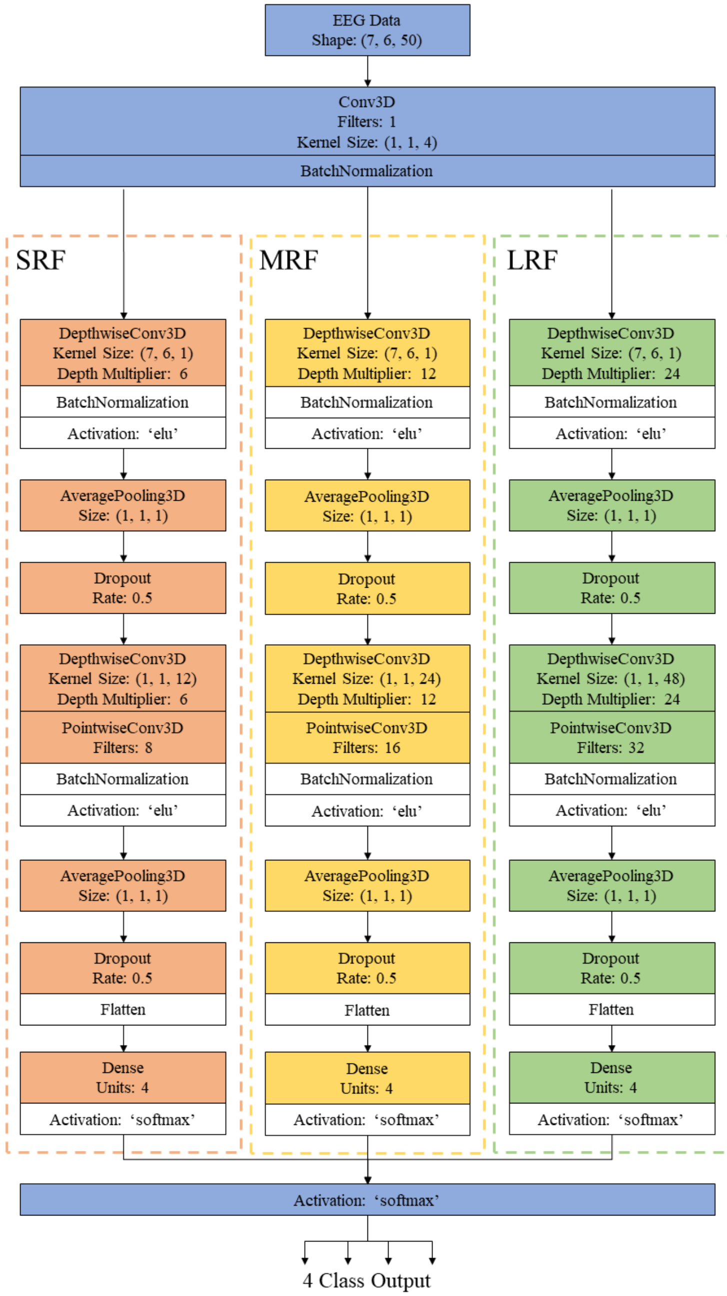

Table 1. The 3D Multibranched Model structure, based on the EEGNet architecture.

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