 DOI: 10.3217/978-3-99161-050-2-220

An Assessment of the Impact of Feature Preprocessing on Deep Learning Models for P300 Classification

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Introduction: Feature preprocessing is a standard step when using traditional machine learning (ML) models for brain-computer interface (BCI) applications. In contrast, the full channel set and minimally processed data are typically used for deep learning models that automatically learn feature representations from the raw data. The high feature dimensionality of electroencephalography (EEG) signals has implications on BCI classifier performance given the typical amounts of available user-specific training data relative to the number of trainable parameters of a classifier model. The number of parameters is typically in the order of 10^2 for traditional ML models vs. 10^3 to $10^6$for deep learning models, while the amount of user-specific data ranges from 1×10^3 to 6×10^3observations to train a P300 classifier. We investigate the impact of various feature preprocessing techniques on deep learning models for P300 classification.

Material, Methods and Results: We analysed data from the bigP3BCI dataset, which has data from online P300 speller studies with participants with and without amyotrophic lateral sclerosis (ALS) [1]. Participants without ALS in the bigP3BCI dataset have a broader range of online spelling accuracies when compared to participants with ALS in the dataset. Feature extraction techniques applied include channel subset, downsampling and xDAWN filtering [2]. Classifier models include linear discriminant analysis, convolutional neural network and long short-term memory (CNN-LSTM) network [3] and EEGNet [4]. User-specific P300 classifiers were trained on data from the calibration phase and data from the test phase were used to evaluate the performance of the trained classifiers.

Results grouped by participants with and without ALS are shown in Figure 1. The effect conferred by a combination of preprocessing techniques was classifier model and population dependent: all interaction effects of feature preprocessing were statistically significant ($p < 0.05$), except for CNN-LSTM with a downsampling decimation factor (DF) of 8 and xDAWN filtering.

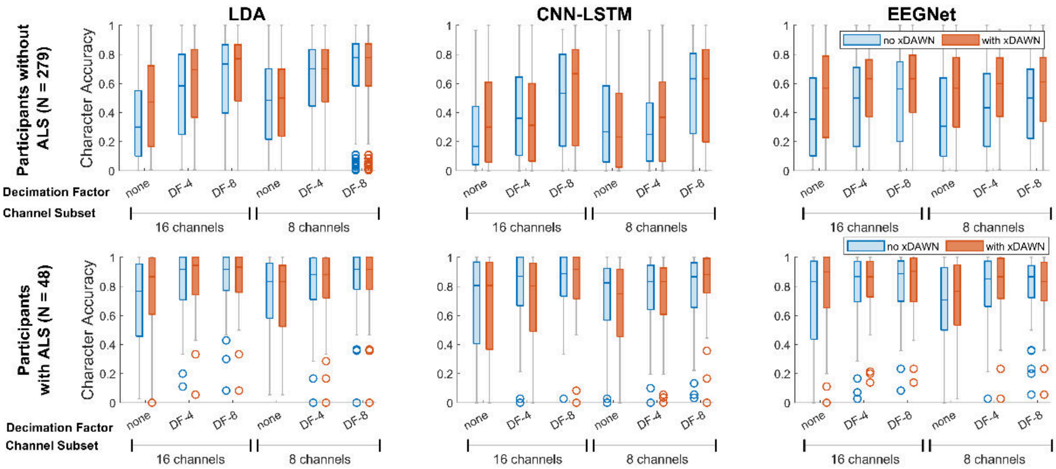

Figure 1: Box plots of P300 speller character accuracy with various signal preprocessing methods and classifier models (linear discriminant analysis (LDA); convolutional neural network long short-term memory (CNN-LSTM) network; and EEGNet).

Conclusion: Overall, deep learning models for P300 classification can derive benefit from feature preprocessing over minimally processed features.

Acknowledgments: This work was funded by the National Institutes of Health (R21DC018347-02S1).

References:

[1] B. O. Mainsah, C. Fleeting, T. Balmat, E. W. Sellers, and L. M. Collins, "bigP3BCI: An Open, Diverse and Machine Learning Ready P300-based Brain-Computer Interface Dataset," ed. PhysioNet.
[2] B. Rivet, A. Souloumiac, V. Attina, and G. Gibert, "xDAWN algorithm to enhance evoked potentials: application to brain–computer interface," *IEEE Transactions on Biomedical Engineering,* vol. 56, no. 8, pp. 2035-2043, 2009.
[3] O. Tal and D. Friedman, "Recurrent Neural Networks for P300-based BCI," in *7th Graz Brain-Computer Interface Conference*, 2017.
[4] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces," *Journal of Neural Engineering,* vol. 15, no. 5, p. 056013, 2018.

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