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Deep learning methods for Motor Imagery EEG Signal Classification

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1 Introduction

A brain-computer interface system (BCI) is a control pathway created through a form of communication between the neural activity of the human brain and the outside world via brain signal recording and decoding techniques. The methods for recording brain activity are categorized into invasive and noninvasive groups. While some noninvasive technologies offer superior spatial resolution, such as fMRI, EEG has proved to be the most popular method for its ability to directly measure neural activity, cost effectiveness, and portability for clinical applications. EEG signals have been used to control assistive and rehabilitation devices. Motor imagery involves the brain's imagination without actual physical movement. The contralateral sensorimotor cortical EEG signals in the alpha band (8–12 Hz) and beta band (13–30 Hz) exhibit a decrease in amplitude during unimanual preparation and execution of a movement. This phenomenon is known as event related desynchronization (ERD), which represents a decrease in the amplitude of the activated cortical EEG signals. Simultaneously, there is an increase in the amplitude of the ipsilateral sensorimotor cortical EEG signals in the alpha and beta frequency bands, which is called event-related synchronization (ERS) and represents an increase in the amplitude of the corresponding cortical signals in the resting state. The ERD/ERS observed in the μ and β frequency bands of the brain motor-sensory cortices indicates the activation or deactivation state of the central region of the brain (Khoshkhooy Titkanlou et al., 2024). Deep neural networks, which can extract complex features from raw data automatically, have received significant attention in motor imagery signal classification. Convolutional neural networks have proposed neural network models with various architectures to classify motor imagery signals. We proposed EEG-ITNet and EEG-ITT, which can extract rich spectral, spatial, and temporal information from multi-channel EEG signals with less complexity by using inception modules and causal convolutions with dilation. Also, we proposed hybrid models like CNN-LSTM and CNN-Transformer.

2 Material and Methods

Four cycles in the entire EEG scenario are used for measurement, with a resting and a stimulating phase in each cycle. Every cycle begins with the subject resting for one minute, during which they are required to sit motionless and at complete rest. Following the resting phase, the participant moves their wrists with either their left or right hand for two minutes during the stimulation phase. Following a five-second break, the subject completes the assigned task during the stimulation phase. A green LED positioned in front of the subject alerts them to the phase shift. Each cycle lasts exactly 9 minutes. The cycles differ from each other by the task performed by the subject in the stimulation phase, which is optionally combined with alternating open or closed eyes. The dataset was gathered at the University of West Bohemia in the Czech Republic. 29 healthy people were measured (men aged 21-26 and women aged 18-

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23) (Kodera et al., 2023). The nurse placed an EEG cap with Ag/AgCl electrodes on the subject's head using a 10–20 system. Afterward, she attached two electrodes to the subject's hand and one ground electrode below the elbow because the distance to the bone is smallest there. Lastly, a reference electrode of the EEG cap was attached to the earlobe. Fz, Cz, Pz, F3, F4, P3, P4, C3 and C4 were used for the measurement.

We used EEG-ITNet, CNN-LSTM, CNN-Transformer and EEG-ITT methods to improve the classification accuracy of motor imagery EEG signals. We first used 10-fold (for EEG-ITNet, CNN-LSTM, CNN-Transformer) and 5-fold (for EEG-ITT) cross-validation with 100 epochs. Before classification, 20% of the samples were separated for testing purposes, and the remaining 80% was utilized for training. The learning rate value was 0.001. The models were implemented in Keras.

3 Results

Table 1 contains the resulting metrics (Accuracy, Precision, Recall and F1 Score) which compare binary classification performance of our proposed methods (CNN-LSTM, CNN-Transformer, EEG-ITNet and EEG-ITT) and combination of these models with NI augmentation method, with (Mouček et al., 2024) which used this dataset. It is worth mentioning that our papers which used CNN-LSTM, CNN-Transformer and EEG-ITT methods submitted. Based on the table 1, EEG-ITT model has best results compared to other models.

Method	Accuracy	Precision	Recall	F1 Score
CNN (Mouček et al., 2024)	76.00±0.80	76.73±0.75	76.05±0.79	75.86±0.90
NI CNN (Mouček et al., 2024)	75.34±1.09	76.69±0.67	75.41±1.07	75.05±1.30
EEG-ITNet (Khoshkhooy Titkanlou et al., 2024)	75.45±1.43	76.43±0.96	75.50±1.40	75.23±1.58
NI EEG-ITNet (Khoshkhooy Titkanlou et al., 2024)	75.86±1.21	76.31±1.06	75.89±1.21	75.77±1.27
CNN-LSTM	79.06±1.47	79.13±1.41	79.07±1.47	79.05±1.48
NI CNN-LSTM	79.03±0.89	79.04±0.89	79.03±0.89	79.03±0.89
CNN-Transformer	77.93±0.68	77.96±0.69	77.93±0.68	77.92±0.68
NI CNN-Transformer	78.64±0.98	78.66±0.97	78.65±0.97	78.64±0.98
EEG-ITT	**79.53±1.19**	**79.78±1.13**	**79.56±1.18**	**79.50±1.20**
NI EEG-ITT	78.40±0.75	78.50±0.78	78.41±0.76	78.38±0.75

Table 1: Classification results.

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