A Type of EEG-ITNet for Motor Imagery EEG Signal Classification

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Abstract: The brain-computer interface (BCI) is an emerging technology that has the potential to revolutionize the world, with numerous applications ranging from healthcare to human augmentation. Electroencephalogram (EEG) motor imagery (MI) is among the most common BCI paradigms used extensively in healthcare applications such as rehabilitation. Recently, neural networks, particularly deep architectures, have received substantial attention for analyzing EEG signals (BCI applications). EEG-ITNet is a classification algorithm proposed to improve the classification accuracy of motor imagery EEG signals in a noninvasive brain-computer interface. The resulting EEG-ITNet classification accuracy and precision were 75.45% and 76.43%, using a motor imagery dataset of 29 healthy subjects, including males aged 21-26 and females aged 18-23. Three different methods have also been implemented to augment this dataset.

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 application of BCI systems has gone in two main directions. The first direction is studying brain activity to explore a feedforward pathway that controls the external devices without the rehabilitation intention. The other main direction is using closed-loop BCI systems during neurorehabilitation, with the feedback loop playing an essential role in recovering the neural plasticity training or controlling brain activities (Lebedev & Nicolelis, 2017). 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 (Wolpaw et al., 2002). EEG signals have been used to control assistive and rehabilitation devices (Meng et al., 2016).

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) (Mu Li & Bao-Liang Lu, 2009) 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 (Liu et al., 2019). 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.

Deep neural networks, which can extract complex

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features from raw data automatically, have received significant attention in motor imagery signal classification (LeCun et al., 2015) (Altaheri et al., 2023). Convolutional neural networks have proposed neural network models with various architectures to classify motor imagery signals. For example, Schirrmeiste et al. (Schirrmeister et al., 2017) studied deep and shallow convolutional neural networks called DeepConvNet and ShallowConvNet, among the first models used to decode motor imagery tasks from raw EEG signals. Later, Lawhern et al. (Lawhern et al., 2018) introduced EEGNet, a more compact and efficient CNN architecture with fewer parameters than ShallowNet and DeepConvNet. Dai et al. (Dai et al., 2020) proposed a hybrid-scale CNN architecture with a data augmentation method to improve the accuracy of EEG motor imagery classification. Borra et al. (Borra et al., 2020) proposed a lightweight and interpretable shallow CNN (Sinc-ShallowNet) architecture for EEG motor decoding. Santamaría-Vázquez et al. (Santamaria-Vazquez et al., 2020) studied a novel CNN, called EEG-Inception, that improves the accuracy and calibration time of assistive ERP-based BCIs, but the network lacked interpretability. Mirzabagherian et al. (Mirzabagherian et al., 2023), based on convolutional layers with temporal-spatial, Separable and Depthwise structures, developed (Temporal-Spatial Convolutional Residual Network)TSCR-Net and (Temporal-Spatial Convolutional Iterative Residual Network)TSCIR-Net models which decoded distinctive characteristics of different movement efforts and obtained higher classification accuracy than previous deep neural networks. Amin et al. (Amin et al., 2022) introduced an attention inception approach that combines CNN and LSTM networks for motor imagery task classification, which extracts spatial features by CNN and temporal features by LSTM and then merges all features into a fully connected layer. However, because of their exploding/vanishing gradient or lack of memory issues, RNNs (e.g., LSTM) are less common in this field. By including TCN in their structure, Ingolfsson et al. (Ingolfsson et al., 2020) and Musallam et al. (Altuwaijri & Muhammad, 2022) have reported better results for the classification of motor imagery signals in response to the slow training essence of RNNs. TCNs have been shown promising outcomes for temporal analysis of EEG time series with faster computation. In this paper, we introduce EEG-ITNet (Salami et al., 2022), 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.

The subsequent sections of this paper are arranged as follows. Section 2 provides the material and methods used in this research. Following that, our result is presented in section 3. In section 4, we finally conclude and provide some suggestions for the future.

2 MATERIAL AND METHODS

2.1 Data Acquisition

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. If their eyes are open, this includes minimizing their blinking. 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. The subject completes the task and enters the stimulation phase when the LED is on, and the subject is in the resting phase when the LED is off. The phases are then alternated this way, and each of them is repeated three times. This means that 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- 23) (Kodera et al., 2023). Each subject received instructions on completing the measurement before it began, and the procedure for each cycle was specified before it began. In the meantime, 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. Following preparation, the subject was put in a dark, sound-proof chamber to prevent background noise from the surroundings during measurement.

The EEG data were captured using the BrainAmp DC amplifier in conjunction with BrainVision recorder software. For EMG recording, the microcontroller STM324F429I-DISCO board and the EKG/EMG shield from Olimex company were employed to generate synchronization pulses and implement the stimulation scenario, as illustrated in Figure 1.

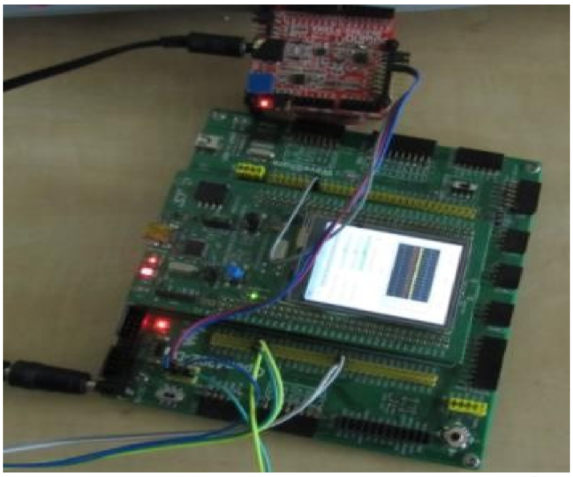

Figure 1: Microcontroller board STM324F429I-DISCO and EKG/EMG shield from company Olimex.

2.2 Our Proposed Method

The four primary blocks that comprise the general architecture of EEG-ITNet are the inception block, temporal convolution (TC) block, dimension reduction (DR) block, and classification block, as shown in Figure 2.

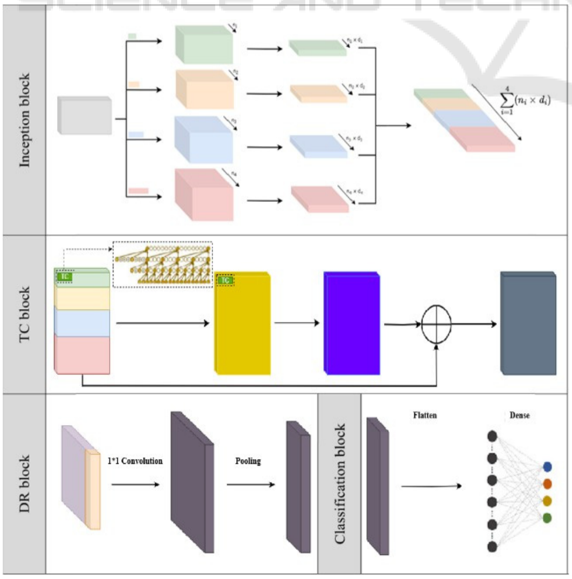

Figure 2: Details of different blocks in EEG-ITNet architecture.

- **Inception Block**

Four parallel sets of layers are used to begin the learning process, each comprising a 2D convolutional layer along the temporal axis serving as frequency filtering, followed by a 2D depthwise convolutional layer functioning as spatial filtering. Adding inception modules with different convolutional kernel sizes eliminates the need for a fixed-length kernel (Santamaria-Vazquez et al., 2020). It allows the network to learn filters that represent various frequency sub-bands. In order to prevent overfitting and enable the network to learn more complex nonlinear spatial information, this block ends with a nonlinear activation function and dropout.

- **Temporal Convolution (TC) Block**

The discriminative temporal features are extracted using the TCN architecture, which considers the time series history, following the extraction of sources in various informative frequency sub-bands. The TC block comprises multiple residual blocks, each composed of depthwise causal convolutional layers with leading zero padding, followed by activation function and dropout. Using depthwise causal convolution followed by batch normalization instead of weight normalization made this model more robust and performed better than the conventional TCN. This block is also preceded by an average pooling layer, which reduces the data dimensions and prevents overfitting.

- **Dimension Reduction (DR) Block**

The output of the TC block fundamentally contains temporal information retrieved from sources with various frequency spectrums. To control the number of final features used for the classification task, we combined these temporal features using a 1 × 1 convolutional layer. This block also includes an average pooling layer at the end, an activation function, and a dropout layer to reduce the tensor dimension further.

- **Classification Block**

The last component of the EEG-ITNet has a fully connected layer with a "softmax" activation function that comes after a flattened layer. Even though we call it the classification layer, it is easily adjustable based on the problem set and desired output.

We first used 10-fold 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 model was implemented in Keras.

It is worth mentioning that, since our dataset is not large enough to obtain better results, we try to implement three data augmentation approaches (noise injection (NI), conditional variational autoencoder (cVAE), and conditional GAN with wasserstein price function and gradient penalty (cWGAN-GP)) in order to expand the training set of input data with newly created artificial samples.

3 RESULTS

Table 1 summarises the classification accuracy, precision, recall, F1 score, and AUC for the EEG-ITNet model and the combination of this model with the augmentation methods implemented in this research. The accuracy of EEG-ITNet and NI EEG-ITNet is 75.45 % and 75.86 %, respectively. The accuracy and loss graphs of these two models are shown in figure 3 and Figure 4.

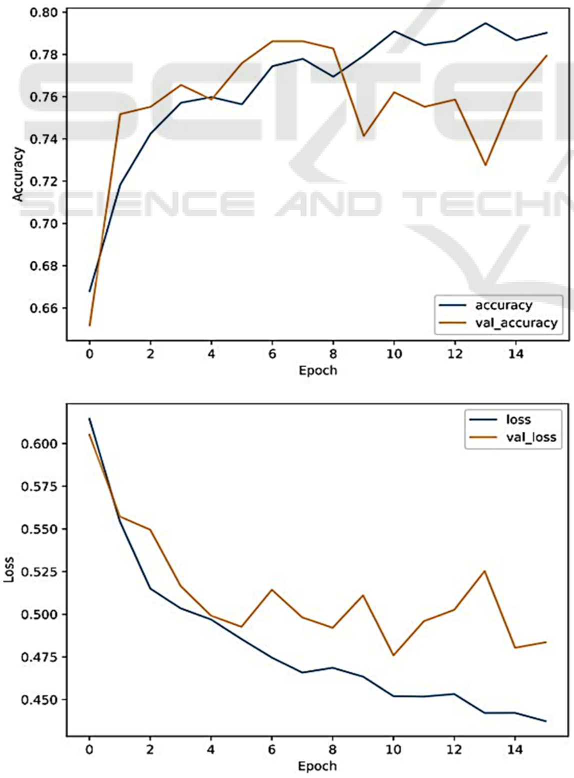

Figure 3: Accuracy and loss curve of EEG-ITNet.

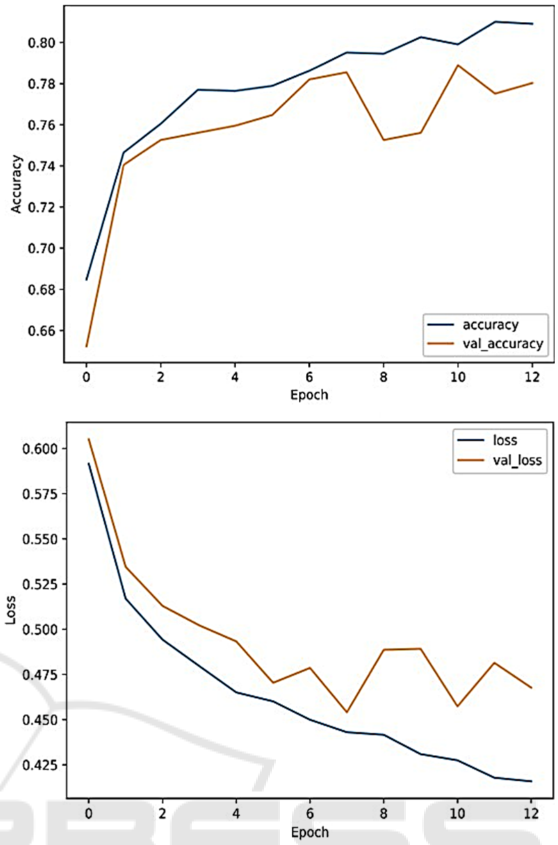

Figure 4: Accuracy and loss curve of NI EEG-ITNet.

Based on the results, only the noise injection augmen-tation method improves the accuracy of motor image-ry classification from 75.45% to 75.86% (0.41%). So, data augmentation does not affect the result for this dataset. Unfortunately, there is no English paper related to this dataset to compare our results.

Table 1: Results of four models used in this study.

Method	Accuracy	Precision	Recall	F1 Score	AUC
EEG-ITNet	**75.45 ±1.43**	**76.43 ±0.96**	**75.50 ±1.40**	**75.23 ±1.58**	**0.755 ±0.01**
NI EEG-ITNet	**75.86 ±1.21**	**76.31 ±1.06**	**75.89 ±1.21**	**75.77 ±1.27**	**0.759 ±0.01**
cVAE EEG-ITNet	74.25 ±1.28	74.54 ±1.29	74.28 ±1.28	74.18 ±1.29	0.743 ±0.01
cWGAN-GP EEG-ITNet	73.18 ±2.04	74.42 ±1.17	73.25 ±2.01	72.84 ±2.43	0.732 ±0.02

4 CONCLUSIONS

The suggested method has proven to be suitable for classifying hand movements in EEG. Our proposed architecture includes four blocks, inception block, temporal convolution (TC) block, dimension reduction (DR) block, and classification block. The dataset used in this paper consists of 29 healthy people who move their hands with open or closed eyes. Alternatively, one of the limitations of this dataset is that it is not large enough for EEG-ITNet to prove its advantages, so data augmentation could be an appropriate technique to solve this problem.

After adjusting the hyperparameters, our model's accuracy and precision were 75.45% and 76.43%. Furthermore, the best result with data augmentation was related to the noise injection method, NI EEG-ITNet, and its accuracy and precision were 75.86% and 76.31%, respectively.

Since few models have been implemented on this dataset, other researchers can try other deep networks or combine our proposed method with other algorithms to improve accuracy. The proposed data is available in (Kodera et al., 2023).

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REFERENCES

Lebedev, M. A., & Nicolelis, M. A. L. (2017). Brain-Machine Interfaces: From Basic Science to Neuro-prostheses and Neurorehabilitation. *Physiological Reviews*, *97*(2), 767–837. https://doi.org/10.1152/physrev.00027.2016.

Wolpaw, J., Birbaumer, N., McFarland, D., Pfurtscheller, G., & Vaughan, T. (2002). *Brain-Computer Interfaces for Communication and Control. Clinocal Neurophysiology, 113, 767-791*.

Meng, J., Zhang, S., Bekyo, A., Olsoe, J., Baxter, B., & He, B. (2016). Noninvasive Electroencephalogram Based Control of a Robotic Arm for Reach and Grasp Tasks. *Scientific Reports*, *6*(1), 38565. https://doi.org/10.1038/srep38565.

Mu Li & Bao-Liang Lu. (2009). Emotion classification based on gamma-band EEG. *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 1223–1226. https://doi.org/10.1109/IEMBS.2009.5334139.

Liu, Y.-H., Lin, L.-F., Chou, C.-W., Chang, Y., Hsiao, Y.-T., & Hsu, W.-C. (2019). Analysis of Electroencephalography Event-Related Desynchronisation and Synchronisation Induced by Lower-Limb Stepping Motor Imagery. *Journal of Medical and Biological Engineering*, *39*(1), 54–69. https://doi.org/10.1007/s40846-018-0379-9.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539.

Altaheri, H., Muhammad, G., Alsulaiman, M., Amin, S. U., Altuwaijri, G. A., Abdul, W., Bencherif, M. A., & Faisal, M. (2023). Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: A review. *Neural Computing and Applications*, *35*(20), 14681–14722. https://doi.org/10.1007/s00521-021-06352-5.

Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., & Ball, T. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. *Human Brain Mapping*, *38*(11), 5391–5420. https://doi.org/10.1002/hbm.23730.

Lawhern, V. J., Solon, A. J., Waytowich, N. R., Gordon, S. M., Hung, C. P., & Lance, B. J. (2018). EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces. *Journal of Neural Engineering*, *15*(5), 056013.

Dai, G., Zhou, J., Huang, J., & Wang, N. (2020). HS- CNN: A CNN with hybrid convolution scale for EEG motor imagery classification. *Journal of Neural Engineering*, *17*(1), 016025. https://doi.org/10.1088/1741-2552/ab405f.

Borra, D., Fantozzi, S., & Magosso, E. (2020). Interpretable and lightweight convolutional neural network for EEG decoding: Application to movement execution and imagination. *Neural Networks*, *129*, 55–74. https://doi.org/10.1016/j.neunet.2020.05.032.

Santamaria-Vazquez, E., Martinez-Cagigal, V., Vaquerizo-Villar, F., & Hornero, R. (2020). EEG- Inception: A Novel Deep Convolutional Neural Network for Assistive ERP-Based Brain-Computer Interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *28*(12), 2773–2782. https://doi.org/10.1109/TNSRE.2020.3048106.

Mirzabagherian, H., Menhaj, M. B., Suratgar, A. A., Talebi, N., Abbasi Sardari, M. R., & Sajedin, A. (2023). Temporal-spatial convolutional residual network for decoding attempted movement related EEG signals of subjects with spinal cord injury. *Computers in Biology and Medicine*, *164*, 107159. https://doi.org/10.1016/j.compbiomed.2023.107159.

Amin, S. U., Altaheri, H., Muhammad, G., Abdul, W., & Alsulaiman, M. (2022). Attention-Inception and Long-Short-Term Memory-Based Electroencephalography Classification for Motor Imagery Tasks in Rehabilitation. *IEEE Transactions on Industrial Informatics*, *18*(8), 5412– 5421. https://doi.org/10.1109/TII.2021.3132340.

Ingolfsson, T. M., Hersche, M., Wang, X., Kobayashi, N., Cavigelli, L., & Benini, L. (2020). *EEG-TCNet: An Accurate Temporal Convolutional Network for Embedded Motor-Imagery Brain-Machine Interfaces*. https://doi.org/10.48550/ARXIV.2006.00622.

Altuwaijri, G. A., & Muhammad, G. (2022). Electroencephalogram-Based Motor Imagery Signals Classification Using a Multi-Branch Convolutional Neural Network Model with Attention Blocks. *Bioengineering*, *9*(7), 323. https://doi.org/10.3390/bioengineering9070323.

Salami, A., Andreu-Perez, J., & Gillmeister, H. (2022). EEG-ITNet: An Explainable Inception Temporal Convolutional Network for Motor Imagery Classification. *IEEE Access*, *10*, 36672–36685. https://doi.org/10.1109/ACCESS.2022.3161489.

Kodera, J., Mouček, R., Moutner, P., Mochura, P., & Saleh, J. Y. (2023). *EEG motor imagery* [dataset]. Zenodo. https://doi.org/10.5281/ZENODO.7893847.