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Enhanced SSVEP Classification with Pre-trained Models: The SSVEP-CAT Approach for Calibration-Free BCI

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Introduction: This study addresses the challenge of developing calibration-free Steady-State Visual Evoked Potential (SSVEP) classification models for Brain-Computer Interface (BCI) systems. Inter-user generalization may reduce the user burden of calibration sessions and improve user experience. However, deep learning technique requirements for large datasets hinder practical deployment. To address this limitation, we introduce the SSVEP-CAT (Convolution, Attention, and Transformer) model. We adopted a transfer learning approach that utilizes a pre-trained model including a Convolutional Neural Network (CNN) for feature extraction and a transformer-based classification module, leveraging self-attention to maintain high accuracy. This project aims to evaluate the impact of using a small number of users on SSVEP-CAT classification accuracy.

Material, Methods, and Results: We evaluated the SSVEP-CAT model on two open access datasets to verify if its use reduces data dependence. Dataset I [2] contained 12-class frequency-phase modulated SSVEPs from 10 users, and dataset II [3] included 64-channel EEG data from 35 users. From both datasets, data corresponding to 12 target stimuli and 8 occipital lobe channels were employed for analysis. The data underwent a 4th-order Butterworth band-pass filter, sliding window technique, and complex Fast Fourier Transform (FFT). The model used 2D CNNs for feature extraction, an attention layer for feature recognition, and a transformer encoder for complex temporal representation analysis (Figure 1). When trained on dataset I, SSVEP-CAT achieved an accuracy of 89%, outperforming the CCNN (CNN based on complex features) [1], which reached 81% (Table 1). An advantage of SSVEP-CAT lies in its ability to leverage pre-training on another dataset with a sufficiently large number of users and trials, such as Dataset II. When training was conducted on 3 users without pre-training, the accuracy achieved was 19% (CCNN) and 36% (SSVEP-CAT). However, this accuracy increased to 82% when pre-training was performed prior to fine-tuning on the same 3 users.

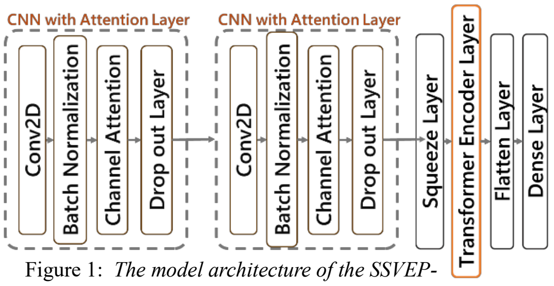

Figure 1: *The model architecture of the SSVEP-CAT model*

Table 1: *Impact of Increasing Number of Users on Model Performance: Mean Accuracy ± Standard Deviation*

	Number of users for training/fine-tuning from Dataset I		
Model	**3**	**5**	**9**
CCNN [1]	19±11	54±17	81±15
SSVEP-CAT without pre-training	36±7	68±9	89±8
SSVEP-CAT with pre-training on Dataset II	82±12	86±10	91±7

Conclusion: The proposed SSVEP-CAT model outperformed the CCNN without pre-training, highlighting its robustness as it generalized better with increasing fine-tuning data. Transfer learning enabled better performance of the SSVEP-CAT model on limited users, but its reliance on large datasets remains a limitation. The SSVEP-CAT improved classification accuracy demonstrating a potential strategy for addressing BCI calibration and improving BCI system user experience.

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