Convolutional Transformer for EEG Decoding

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Advanced Deep Learning AS2024

Introduction

Objective:

- To classify EEG signals corresponding to different motor imagery tasks (e.g., left-hand, right-hand, foot, and tongue movement).

Importance:

- Brain-Computer Interfaces (BCIs): Helps individuals with physical disabilities control devices using brain activity.
- Motor Imagery: A key component for training BCI systems to interpret imagined movements.

Challenges:

- EEG signals are noisy and non-stationary.
- Small dataset size and potential overfitting in deep learning models.

Dataset

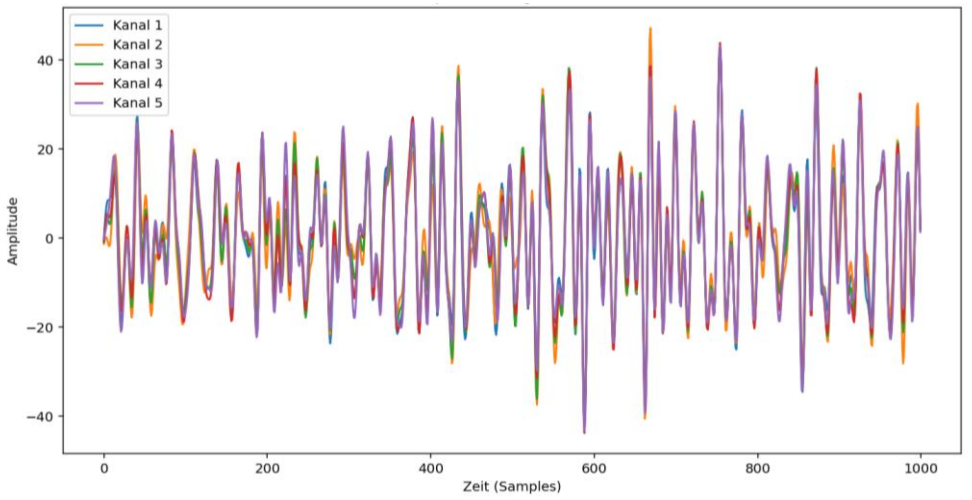
BCI Competition IV - Dataset 2a (Graz University of Technology, Austria)

- **Subjects:** 9 participants
- **Tasks:** 4-class motor imagery: Left hand, right hand, both feet, tongue
- **Trials per Session:** 288 (72 per class, 6 seconds each)
- Includes EGG Data recorded from 22 electrodes and 3 EOG channels (eye movements)
- Two Datasets: Training and Evaluation

```
Label for Trial 10: 769
EEG Data for Trial 10:
[[[ 2.1370866   1.45281202  0.61363009 ... -1.31047775 -1.14948121
   -0.80830721]
  [ 2.15465744  1.43509313  0.77460648 ... -1.40754576 -1.50888581
   -1.39722192]
  [ 2.34687344  1.66140641  0.84218661 ... -1.24684821 -1.26068861
   -1.1289981 ]
  ...
```

Preprocessing

- Bandpass Filtering (4–40 Hz)
- Remapping of Labels & Artifact Removal (EOG, NaN values)
- Z-score normalization



Output

- **Processed Trials:** 3D array (1000 samples (timepoints)× 22 channels × 288 trials)
- **Labels:** Corresponding motor imagery class

https://www.bbci.de/competition/iv/#dataset2a

Model Architecture

Model Architecture:

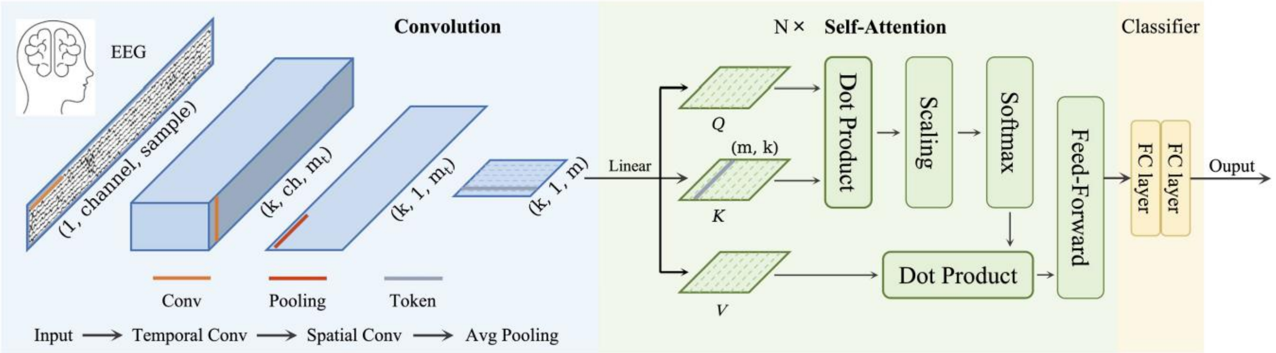
- A hybrid Convolutional-Transformer model.
- Convolution Module: Extracts temporal and spatial features from EEG signals.
- Self-Attention Module: Captures long-range dependencies in the extracted features.
- Classifier: Fully connected layers with dropout for final classification.

Model Details:

- Input Shape: EEG data with shape (288, 1, 22, 1000) (trials, channels, timepoints).
- Attention Heads: 10.
- Layers: 6 Transformer encoder blocks.
- Embedding Size: 40.

Training Setup:

- Loss Function: Cross-Entropy Loss.
- Optimizer: Adam with learning rate 0.0002, betas=(0.5, 0.999).
- Dropout (0.3–0.5) in convolution and classification modules.
- Weight decay (1e-5).



https://ieeexplore.ieee.org/document/9991178

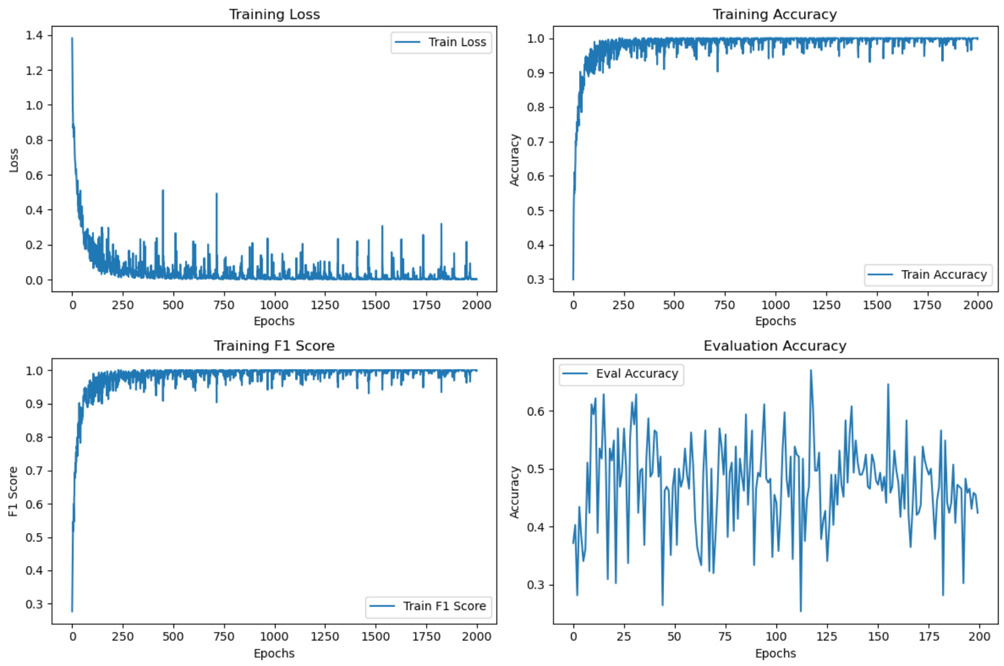
Model Validation

Dataset:

- Training Dataset: A01T, shape (288, 22, 1000) — small EEG dataset.
- Evaluation Dataset: A01E, shape (288, 22, 1000) — used to validate the model.

Performance:

- The model achieved high training accuracy (~100%), low training loss, and high F1 score. Indicates the model is learning to fit the training dataset effectively.
- Evaluation accuracy fluctuates and fails to improve consistently across epochs. Suggests the model is overfitting to the training data and failing to generalize to the evaluation dataset.

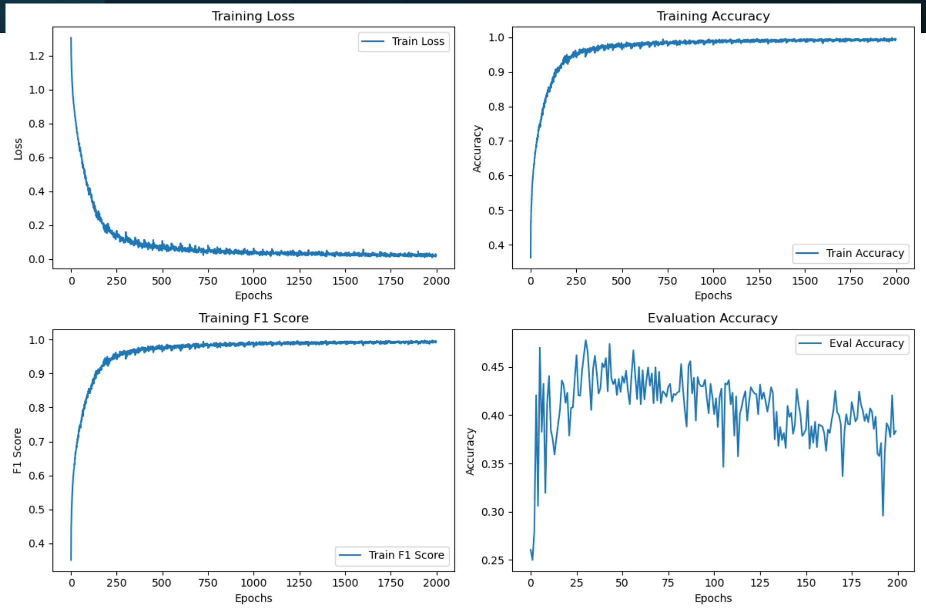


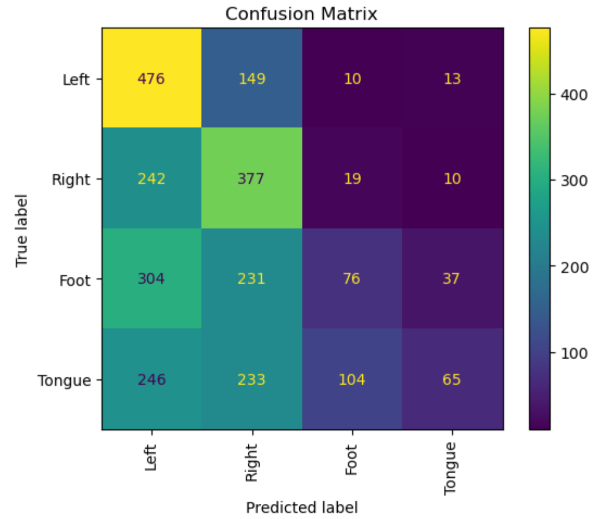
Improving Model Generalization

- **Data Augmentation:** Split EEG signals into smaller segments, shuffle them, and reconstruct to generate augmented data.
- **Full Dataset Training:** Combined all available data: 2592 samples to increase training diversity.
- **Extended Training:** Trained for 2000 epochs to ensure convergence of the model.

Results:

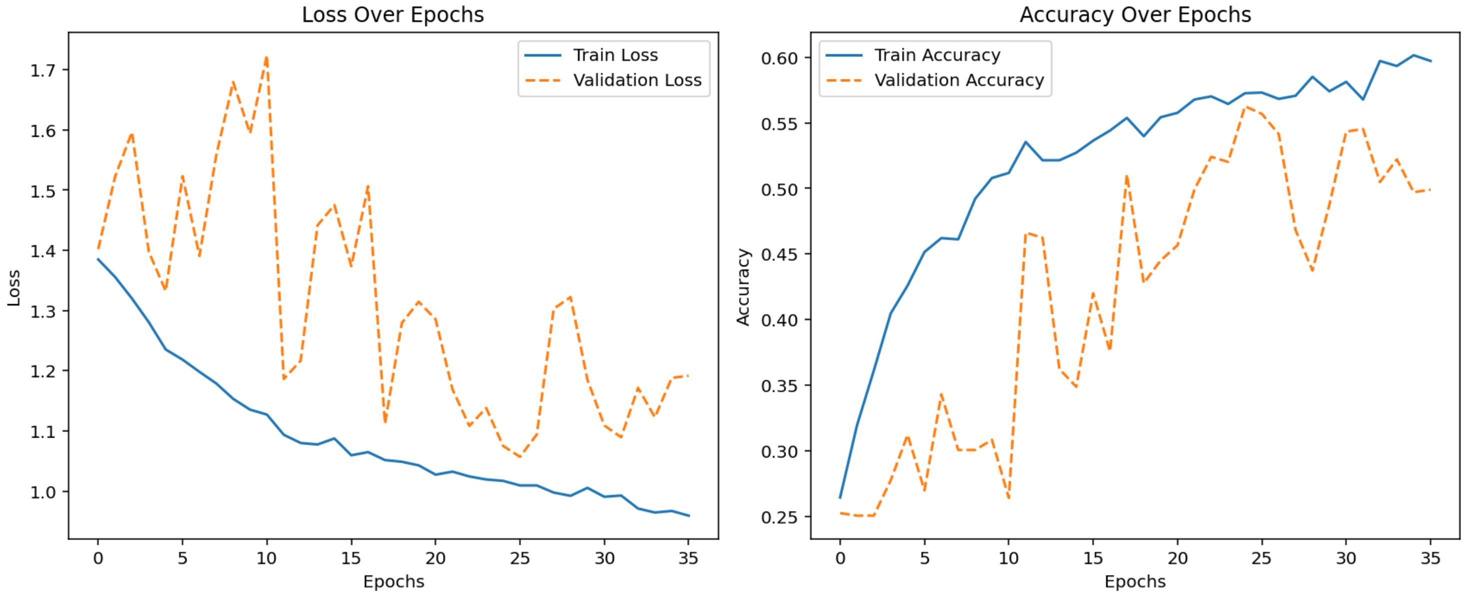
- Training Performance: Training accuracy and F1 score approached ~100%.
- Evaluation Performance: Accuracy remains ~40–45% on the evaluation dataset.
- Model performs well on the "Left" and "Right" classes. Misclassifications remain significant, particularly for the "Foot" and "Tongue" classes.





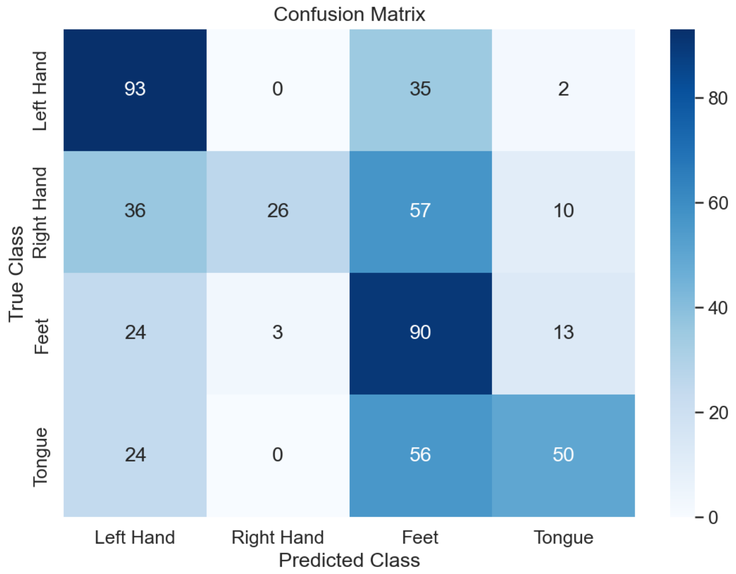
Another approach: Early stopping

- Training loss decreases, validation loss fluctuates
- Did not improve the model significantly:
  - Change of sensitivity for early stopping
  - Basic augmentation of data
  - Combining Training and Evaluation Dataset



Validation and Evaluation Dataset (early stopping)

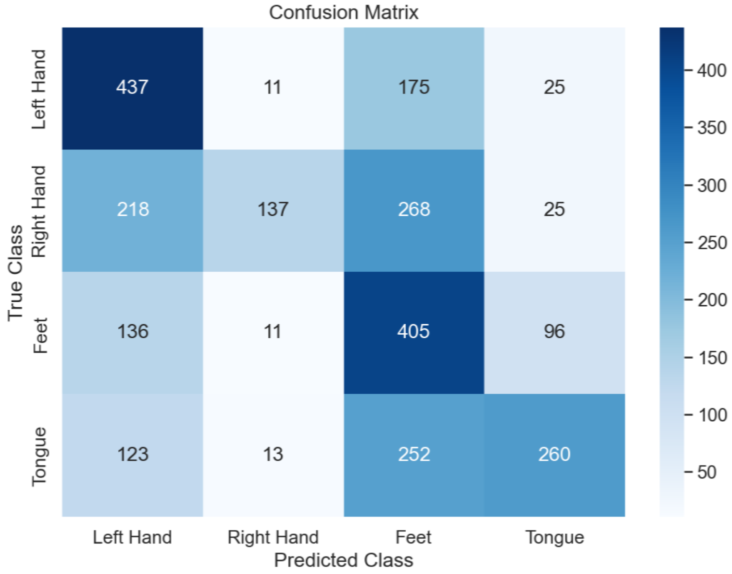
Validation



Class	Precision	Recall	F1 - Score
0	0,53	0,72	0,61
1	0,90	0,20	0,33
2	0,38	0,69	0,49
3	0,67	0,38	0,49
average	**0,62**	**0,50**	**0,50**

Samples per class: 130

Evaluation



Class	Precision	Recall	F1 - Score
0	0,48	0,67	0,56
1	0,80	0,21	0,33
2	0,37	0,62	0,46
3	0,64	0,40	0,49
average	**0,57**	**0,48**	**0,46**

Samples per class: 648

Benchmarks

Modelname	Accuracy
Our model	~50%
FBCSP	67,75%
ConvNet	72,53%
EEGNet	86,81%
EEG Conformer	**78,66%**

Performance on the same dataset.

Source:
Y. Song, Q. Zheng, B. Liu, and X. Gao, "EEG Conformer: Convolutional Transformer for EEG Decoding and Visualization," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 710–719, 2023, doi: 10.1109/TNSRE.2022.3230250.

Next steps

Conclusions:

- Designed and implemented a hybrid Convolutional-Transformer model for EEG-based motor imagery classification.
- Achieved high training accuracy and F1 score. Validation accuracy remains challenging, showing room for improvement.

Overfitting:

- High training accuracy (~100%) but low evaluation accuracy (~50%).
- Indicates the model memorizes training data rather than generalizing to unseen data.

Enhance Data Augmentation:

- Add Gaussian Noise: Mimic real-world noise in EEG signals.
- Temporal Shifting: Shift EEG signals along the time axis.

Expand Dataset:

- Use external publicly available datasets (e.g., BCI Competition datasets).
- Generate synthetic EEG signals using Generative Adversarial Networks (GANs).

Thank you!