Progress Report

EEG-Based Motor Imagery Classification using Deep Learning

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1 Introduction

Brain computer interfaces (BCIs) provide a direct communication pathway between the brain and external devices. Electroencephalography (EEG)-based BCIs, in particular, have gained significant traction due to their non-invasive nature and applicability in motor rehabilitation, assistive technologies, and neuro prosthetics. Among EEG-based tasks, motor imagery (MI) classification, which decodes imagined movements such as movements of the left hand, right hand, or foot, is one of the most studied problems.

Traditional approaches to EEG decoding relied on feature extraction methods such as Common Spatial Patterns (CSP) and classification techniques such as Linear Discriminant Analysis (LDA) or Support Vector Machines (SVM). However, in recent years, artificial intelligence (AI), particularly deep learning, has achieved state-of-the-art (SOTA) results in motor imagery classification. Deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid CNN-RNN architectures have proven effective in capturing both spatial and temporal dynamics of EEG signals.

This report documents the initial findings, literature review, methodology, and future plan for replicating and evaluating CNN-RNN hybrid approaches on publicly available EEG datasets. The ultimate objective is to reproduce recent results reported in the literature using open-source datasets while contributing to reproducibility and benchmarking efforts in the BCI community.

2 Literature Review

2.1 Classical Machine Learning Approaches

Classical methods for EEG decoding have involved manual feature engineering. Techniques such as CSP have been effective for enhancing discriminability between classes, while classifiers such as LDA and SVM has provided relatively high accuracy for small-scale datasets. Despite these successes, classical approaches can face challenges such as non-stationarity of EEG signals, high sensitivity to noise, and poor generalization between subjects. Moreover, handcrafted feature extraction requires domain expertise and may overlook latent patterns in high dimensional EEG data. Other feature extraction methods such as Filter Bank Common Spatial Patterns (FBCSP) and Riemannian geometry based techniques has attempted to improved robustness, but they still depends heavily on preprocessing choices and is limited in scaling to large datasets.

2.2 Deep Learning Approaches

The advent of deep learning has transformed EEG decoding by enabling end to end feature learning.

CNNs: CNNs capture spatial patterns across EEG channels. Schirrmeister et al. [3] developed both deep and shallow CNN architectures, showing that CNNs can decode motor imagery task with high accuracy while providing interpretable spatial features. EEGNet [1] is a compact CNN specifically tailored for EEG, incorporating depthwise and separable convolutions to maintain performance on small datasets.

RNNs (LSTMs, GRUs): EEG signals are inherently temporal. RNNs, particularly LSTMs and GRUs, model sequential dependencies, improving classification of time-series EEG data. They are especially valuable for capturing event related dynamics and temporal correlations in motor imagery tasks.

Hybrid CNN-RNNs: Combining CNNs for spatial feature extraction with RNNs for temporal modeling has proven effective. Muhammad et al. [2] reported that CNN-RNN hybrid outperformed standalone CNNs or RNNs, achieving more robust performance across subjects and sessions. These hybrids leverage the strengths of both architectures, reducing overfitting and improving generalization.

Transformers and Attention Mechanisms: Recent studies employ transformer architecture to model long range temporal and spatial dependencies. Temporal-Spatial-Transformers [4] capture complex interactions between EEG transformers and frequency bands, demonstrating the highest reported accuracy on certain MI benchmarks. Attention mechanisms also enhance interpretability by highlighting the most informative time segments and channels.

2.3 Accuracy and Performance Comparison

The performance of the key models on benchmark datasets in summarized below: These com-

Model	Dataset	Accuracy
Schirrmeister et al. (2017) Deep CNN [3]	BCI Competition IV 2a	$\sim$80%
Lawhern et al. (2018) EEGNet [1]	Multiple EEG datasets	$\sim$76%
Muhammad et al. (2020) CNN-RNN Hybrid [2]	BCI Competition IV 2a	83–85%
Zhang et al. (2021) Transformer [4]	MI datasets	$\sim$86%

Table 1: Comparison of models for EEG-based BCI tasks.

parisons indicate that CNN-RNN hybrids provide a strong balance between interpretability, reproducibility, and high accuracy, making them suitable candidates for replication in this project. In addition, the literature emphasizes the importance of preprocessing steps, data augmentation, and cross subject evaluation to ensure robust performance.

2.4 Additional Insights from Literature

Several recurring themes in recent studies inform the methodology:

- Effective preprocessing significantly impacts model accuracy; common techniques include bandpass filtering (8-30 Hz), normalization, and artifact rejection.
- Data augmentation strategies such as sliding windows and synthetic signal generation can mitigate overfitting, particularly for small EEG datasets.
- Hybrid architectures are consistently more robust across subjects and datasets, suggesting that future work might explore combining CNN-RNN models with attention mechanisms or transformer components to push performance further.

3 Methodology

3.1 Dataset Acquisition

To ensure reproducibility and comparability with prior work, this study will rely on publicly available EEG datasets commonly used for motor imagery (MI) classification:

- **BCI Competition IV (2a and 2b):** These datasets provide multi channel EEG recordings from subjects performing left hand, right hand, foot and tongue motor imagery tasks. Dataset 2a consists of 22 EEG channels and four classes, whereas dataset 2b provides three classes with fewer subjects. Both are widely considered benchmark datasets in the BCI community.

- **PhysioNet EEG Motor Movement/Imagery Dataset:** This dataset includes EEG recordings of subjects performing both real and imagined motor tasks, covering a broader population and experimental setup. Its diversity makes it particularly suitable for assessing generalization across subjects.

Using more than one dataset ensures that the trained models are not overfitted to a single data distribution and provides a more reliable evaluation of generalization performance.

3.2 Preprocessing

EEG signals are inherently noisy and non stationary which necessitates careful preprocessing:

- **Band pass filtering (8-30 Hz):** This frequency band corresponds to the μ (8-12 Hz) and β (13-30 Hz) rhythms, which are most relevant for motor imagery tasks. Filtering out irrelevant frequencies reduces noise and improves signal to noise ratio.

- **Artifact removal:** Techniques such as Independent Component Analysis (ICA) or thresholding will be used to reduce artifacts caused by eye blinks, muscle activity, and line noise.

- **Normalization and standardization:** EEG channels vary in amplitude across subjects. Normalization ensures consistent feature scaling, which stabilizes training.

- **Epoch segmentation:** Continuous EEG recordings will be segmented into task specific epochs (typically 2-4 seconds per trial), allowing the model to learn discriminative patterns corresponding to motor imagery events.

- **Data augmentation:** To mitigate the issue of limited labeled data, augmentation techniques such as sliding window segmentation, additive Gaussian noise, and random temporal cropping will be explored. These strategies help improve generalization by artificially expanding the dataset.

3.3 Model Architectures

Three deep learning architectures will be implemented to investigate the effectiveness oof spacial, temporal, and hybrid approaches:

- **CNN Model:** Convolutional layers will be used to extract spatial features from EEG electrode topographies. CNNs are particularly effective in modeling spatial correlations between EEG channels and have shown strong performance in previous studies.
- **RNN Model:** Recurrent architectures such as LSTM or GRU layers will be employed to model temporal dynamics. Since EEG is a time series signal, RNNs are well suited to capture dependencies across time, improving classification accuracy in sequential tasks.
- **CNN-RNN Hybrid:** A combined model will be designed where CNN layers first extract spatial features, which are then passed into RNN layers for temporal processing. This hybrid approach leverages the strengths of both models and has been shown in literature [2] to outperform standalone CNNs or RNNs in motor imagery classification.

All models will be trained using the categorical cross-entropy loss function, with optimization handled by the Adam optimizer, chosen for its robustness and adaptive learning rate. Dropout and batch normalization will be applied to reduce overfitting and improve convergence stability.

3.4 Evaluation

Model performance will be systematically assessed using multiple evaluation strategies:

- **Metrics:** Accuracy will serve as the primary metric, while loss curves, confusion matrices, and precision recall values will provide deeper insights into per class performance and potential misclassifications.
- **Cross subject evaluation:** Models will be tested on subjects not included in training to evaluate generalization across individuals, an essential aspect for real world BCI applications.
- **Within subject evaluation:** Performance will also be assessed by training and testing on data from the same subject to measure personalized BCI performance.
- **Benchmarking against literature:** Result will be compared with reported benchmarks (e.g. Schirrmeister et al. [3], Lawhern et al. [1], Muhammad et al. [2]) to determine whether the implemented models achieve competitive accuracy.

This multi faceted evaluation ensures both scientific rigor and practical relevance, highlighting the strengths and weaknesses of each modeling approach.

4 Timeline

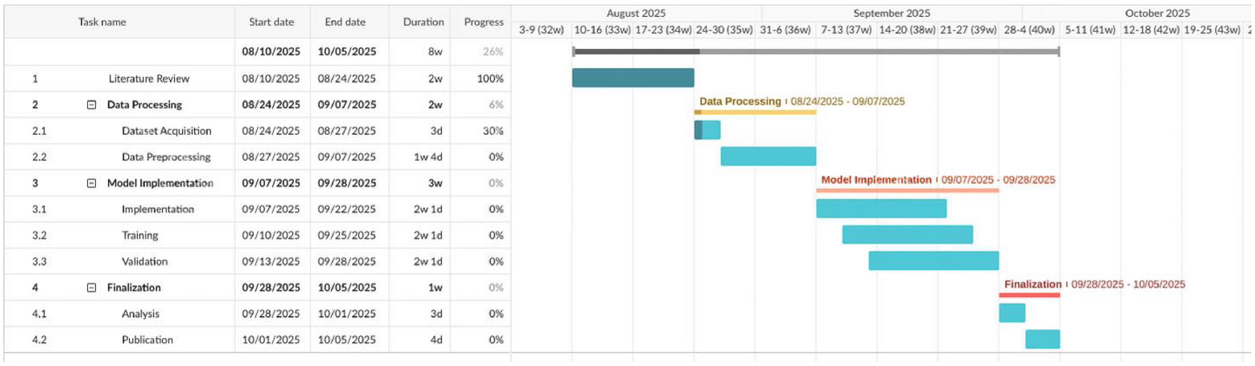

Figure 1: Project Timeline

5 Conclusion

This project aims to replicate and evaluate deep learning methods for EEG-based motor imagery classification, focusing on CNN-RNN hybrid architectures. The literature demonstrates that CNN-RNN hybrids provide a competitive advantage over traditional machine learning approaches and even standalone deep models. By leveraging open-source datasets, this work contributes to reproducibility and benchmarking within the BCI field.

The expected outcome is a reproducible experimental framework that validates the effectiveness of hybrid deep learning models for EEG decoding, paving the way for future exploration into advanced transformer-based models.

References

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