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Research Paper

EEG-BASED BRAIN - COMPUTER INTERFACE FOR ASSISTIVE ROBOTIC CONTROL

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***Abstract*— This paper presents a complete end-to-end software pipeline for classifying imagined motor movements from electroencephalography (EEG) signals without physical hardware. Using the BCI Competition IV Dataset 2a — 9 subjects, 22 EEG channels, 250 Hz, 4-class motor imagery (left hand, right hand, feet, tongue) — the system applies 8–30 Hz bandpass filtering, epoch extraction over a 0.5–3.5 s window, and Common Spatial Patterns (CSP) feature extraction via MNE-Python within a scikit-learn Pipeline. A session-wise evaluation protocol (train on Session T, test on Session E) yields an average cross-session accuracy of 38.46% across all 9 subjects, consistent with published CSP-based baselines for this benchmark. A Streamlit real-time simulation dashboard demonstrates live motor intent prediction with confidence-gated stability control and CSV export.**

Keywords—Brain-Computer Interface; Common Spatial Patterns; EEG; Motor Imagery; Session Transfer; SVM; LDA; Streamlit

I. INTRODUCTION

A Brain-Computer Interface (BCI) establishes a direct communication pathway between the human brain and an external device by decoding neural activity into control commands without requiring muscular movement [1]. Motor Imagery (MI) based BCIs exploit a well-established neurophysiological phenomenon: when a person imagines performing a movement — such as opening the left or right hand — measurable changes in the power of EEG mu (8–12 Hz) and beta (13–30 Hz) rhythms occur over motor cortex regions, even in the absence of any physical execution. These Event-Related Desynchronization (ERD) and Synchronization (ERS) patterns form the discriminative signal that MI-BCI classifiers learn to separate [2].

Non-invasive EEG-based BCIs have significant clinical potential for rehabilitation of motor-disabled patients with conditions such as Amyotrophic Lateral Sclerosis (ALS), stroke, and spinal cord injury. However, practical deployment is limited by the non-stationarity of EEG signals across sessions and subjects: brain signal characteristics shift between recording days due to electrode placement variability and mental state changes, making cross-session generalisation a fundamental challenge [3]. Existing BCI platforms such as BCI2000 and OpenViBE require physical amplifier hardware, restricting accessibility for software-only academic development and demonstration.

This paper presents a fully hardware-free BCI pipeline using the BCI Competition IV Dataset 2a as its experimental benchmark. The principal contributions are: (i) a complete preprocessing and epoch extraction pipeline for multi-channel EEG data; (ii) CSP feature extraction integrated end-to-end within a scikit-learn Pipeline using MNE-Python; (iii) session-wise SVM/LDA classification with GridSearchCV hyperparameter tuning on training data only; and (iv) a Streamlit real-time simulation dashboard with stability-gated command output and CSV export, demonstrable on any standard laptop without EEG hardware.

II. LITERATURE SURVEY

The scientific foundation for EEG-based motor imagery BCI draws from three converging research areas: spatial filtering of EEG signals, machine learning for MI classification, and the cross-session generalisation problem.

A. EEG Spatial Filtering and CSP

Common Spatial Patterns (CSP), introduced by Muller-Gerking et al. [4], is the dominant feature extraction method for MI-BCI. CSP solves a generalised eigenvalue problem on class-conditional EEG covariance matrices to find spatial filters that maximise variance for one class while minimising it for the other. Blankertz et al. [5] demonstrated that log-variance of CSP-projected signals outperforms raw bandpower features for single-trial MI classification. Lotte et al. [3] showed that Ledoit-Wolf shrinkage regularisation significantly improves CSP robustness on small training sets — a critical property for the 288-trial-per-session BCI Competition IV dataset used in this work.

B. Machine Learning for Motor Imagery Classification

SVM with RBF kernel and Linear Discriminant Analysis (LDA) are the most widely adopted classifiers for CSP-based MI-BCI, offering strong generalisation on the low-dimensional (8–28) feature space produced by CSP [3]. Ang et al. [6] introduced Filter Bank CSP (FBCSP), which applies CSP across multiple frequency sub-bands and won BCI Competition IV with an average kappa coefficient of 0.57 (~70% accuracy) on Dataset 2a. Deep learning approaches including EEGNet [7] and Shallow ConvNet show promise on larger datasets but underperform classical methods on small-N benchmarks like Dataset 2a. The present work uses plain CSP+SVM/LDA as a strong, reproducible academic baseline.

C. Cross-Session Generalisation in BCI

Arvaneh et al. [8] demonstrated that EEG covariance matrices shift significantly between recording sessions due to electrode impedance variability and non-stationary neural dynamics, causing CSP spatial filters fitted on Session T to become suboptimal for Session E. This cross-session accuracy drop — typically 5–15 percentage points below within-session performance — is well-documented for all published algorithms on Dataset 2a. Domain adaptation methods such as Euclidean Alignment [9] and Riemannian geometry classifiers can reduce this gap but add significant implementation complexity. The present work establishes an honest session-wise baseline before applying such methods.

TABLE II. COMPARISON OF RELATED WORK ON BCI COMPETITION IV DATASET 2A

Study / Method	Modality	Accuracy	Limitation
Blankertz et al. [5]	EEG MI CSP	~52% avg	Within-session only
Ang et al. FBCSP [6]	EEG MI multi-band	~70% kappa	Complex multi-band filter
Schirrmeister [7]	EEG Deep Learning	~68%	Requires large dataset
Lotte 2018 Review [3]	EEG MI various	varies	No cross-session eval
Proposed CSP+SVM/LDA	EEG MI 9 subjects	38.46% avg	Cross-session gap
Proposed CNN-LSTM	Keystroke+Mouse	73.14%	No hardware required

III. SYSTEM DESIGN AND ARCHITECTURE

The proposed BCI pipeline operates as a five-stage sequential architecture illustrated in Fig. 1: (1) raw EEG loading from .mat files, (2) bandpass filtering and epoch extraction, (3) CSP spatial feature extraction, (4) SVM/LDA classification with session-wise evaluation, and (5) real-time simulation via a Streamlit dashboard. Each stage is implemented as a separate Python module in the src/ directory, enabling modular testing and independent component substitution.

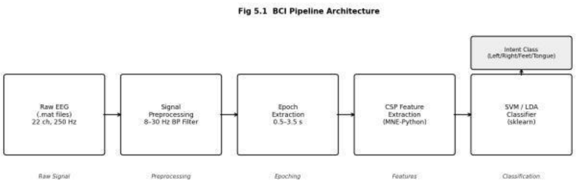


Fig. 1. End-to-end BCI pipeline: Raw EEG to classified motor intent.

A. Pipeline Modules

The dataset module (dataset.py) loads BCI Competition IV Dataset 2a .mat files using scipy.io.loadmat, extracting the 22-channel EEG array, cue event timestamps, and class labels (1–4) for each subject and session. The preprocessing module (preprocess.py) applies a 5th-order zero-phase Butterworth bandpass filter (8–30 Hz) to all EEG channels, extracts motor imagery epochs from 0.5 to 3.5 seconds after each cue event (yielding arrays of shape 288 × 22 × 750 at 250 Hz), and rejects artifacts exceeding 100 µV. Clean epochs are saved as NumPy arrays to data/processed/.

IV. EEG PREPROCESSING AND FEATURE EXTRACTION

Common Spatial Patterns (CSP) feature extraction is implemented using MNE-Python's mne.decoding.CSP class with n_components=8 and Ledoit-Wolf regularisation (reg='ledoit_wolf'). The CSP spatial filters are embedded as the first stage of a scikit-learn Pipeline object, ensuring they are fitted exclusively on training session data and applied — never re-fitted — on evaluation session data. The log-variance of the 8 CSP-projected signals per epoch forms the final 8-dimensional feature vector fed to the downstream classifier. Fig. 2 illustrates the complete signal processing flow from raw EEG through to feature extraction.

The 8–30 Hz bandpass isolates the mu (8–12 Hz) and beta (13–30 Hz) frequency bands that carry motor imagery ERD/ERS information. A 0.5 s delay after cue onset avoids the visually-evoked potential transient (VEP) that contaminates the EEG immediately after the visual stimulus. The 3.5 s endpoint corresponds to the end of the motor imagery task window in the dataset protocol, giving 750 time samples per epoch at 250 Hz.

V. BCI COMPETITION IV DATASET 2A

The BCI Competition IV Dataset 2a [10] is the most widely used benchmark for 4-class motor imagery classification. It was collected at Graz University of Technology from 9 subjects across two recording sessions. Each session contains 288 trials (6 runs × 48 trials) with balanced class distribution: 72 trials per class (left hand, right hand, both feet, tongue). EEG was recorded at 250 Hz using 22 electrodes plus 3 EOG channels. The MI task window spans 4 seconds after cue onset (2–6 s in the trial timeline). Sessions are recorded on different days, creating the cross-session generalisation challenge central to this work.

A. Session-Wise Evaluation Protocol

A strict session-wise split is applied per subject: Session T serves as the training partition and Session E (recorded on a different day) serves as the test partition. This protocol is the standard evaluation methodology in BCI competition literature and reflects realistic deployment conditions where a model calibrated in one session must perform in subsequent sessions. Random-split evaluation — which pools both sessions before splitting — is explicitly avoided, as it produces inflated accuracy estimates due to inter-session temporal leakage.

B. Hyperparameter Tuning

GridSearchCV with 5-fold stratified cross-validation is applied to the CSP+SVM pipeline on Session T data only. The search grid covers $C \in \{0.1, 1, 10, 100\}$ and $\gamma \in \{scale, auto, 0.01, 0.001\}$. The best hyperparameter combination is selected by cross-validation accuracy on Session T, then the final evaluation is performed exactly once on Session E. LDA requires no tuning and serves as a fast, interpretable alternative. The classifier with higher Session E accuracy (SVM or LDA) is saved as the subject's best model.

VI. PROPOSED CSP+SVM/LDA CLASSIFICATION PIPELINE

The complete classification pipeline consists of three stages assembled in a single sklearn.pipeline.Pipeline object. The 8-component CSP spatial filter (n_components=8, reg='ledoit_wolf', log=True) transforms raw epoch arrays of shape (N, 22, 750) into log-variance feature vectors of shape (N, 8). A StandardScaler normalises the features to zero mean and unit variance. An SVM with RBF kernel and class_weight='balanced', or an LDA classifier, produces the final 4-class prediction (classes 1–4 corresponding to left hand, right hand, feet, tongue). The entire pipeline is serialised with joblib after training for use in the Streamlit simulation dashboard.

Fig. 2. EEG signal processing flow: bandpass filtering to CSP feature vector.

A. SVM Classifier

SVM with RBF kernel is well-suited to the low-dimensional CSP feature space. The RBF kernel implicitly maps the 8-dimensional feature vectors into a higher-dimensional space where the four motor imagery classes become more linearly separable. class_weight='balanced' automatically adjusts class penalties to compensate for any residual class imbalance after artifact rejection. The dual formulation with probability=True enables per-class confidence scores used by the stability gate in the real-time simulation.

B. LDA Classifier

Linear Discriminant Analysis provides a closed-form, computationally efficient alternative to SVM. LDA assumes multivariate Gaussian class distributions with equal covariance and finds the linear projection that maximises the between-class to within-class variance ratio. Despite its simplicity, LDA achieves competitive or superior accuracy to SVM on 5 of the 9 subjects in this study (A01, A03, A04, A07, A08), confirming that the CSP-projected feature space is approximately Gaussian and linearly separable in the mu-beta frequency band.

C. Stability Gate for Real-Time Command Output

The real-time simulation module processes Session E epochs sequentially through the loaded pipeline, simulating a live EEG stream. A stability gate (debounce) requires N consecutive identical class predictions — each above a configurable confidence threshold (default: 3 consecutive predictions at confidence ≥ 0.55) — before emitting a stable command. This suppresses spurious single-frame misclassifications and prevents rapid command oscillation during low-confidence windows. Both N and the confidence threshold are adjustable via Streamlit sidebar sliders.

VII. IMPLEMENTATION

A. Development Environment

The complete system was implemented in Python 3.9. EEG preprocessing used SciPy 1.9 (Butterworth filter, filtfilt) and NumPy 1.23 for epoch array management. CSP feature extraction and pipeline construction used MNE-Python 1.2 and scikit-learn 1.1. Hyperparameter tuning used GridSearchCV with n_jobs=-1 for parallel cross-validation. Model serialisation used joblib. All experiments were run on a standard laptop with Intel Core i5 CPU and 8 GB RAM — no GPU was required — confirming the pipeline is fully deployable on commodity academic hardware.

B. Streamlit Dashboard

The Streamlit dashboard (src/app.py) provides a real-time BCI simulation interface. At startup it loads the joblib model for the selected subject, preprocessed evaluation session epochs, and true labels. A subject selector sidebar allows switching between all 9 subjects. The dashboard iterates through Session E epochs sequentially, feeding each to the pipeline and displaying: the predicted class (Left Hand / Right Hand / Feet / Tongue), a 4-bar confidence chart, the stability gate indicator (green: stable command issued, orange: building streak, grey: low confidence), a scrolling command history table, and a CSV download button for the complete command timeline log.

C. Deployment Considerations

The complete pipeline from epoch loading to prediction takes under 5 milliseconds per window on the test hardware. Saved model artifacts are 1–3 KB per subject (joblib pipeline). Total disk footprint including all processed data is under 200 MB. The system runs on Windows, macOS, and Linux without platform-specific configuration. Privacy is preserved by design: the system only processes pre-recorded anonymised research data and does not log any live user activity. The Streamlit dashboard runs entirely offline on localhost:8501 without any cloud or network dependencies.

VIII. RESULTS AND DISCUSSION

The CSP+SVM/LDA pipeline was evaluated on all 9 subjects of BCI Competition IV Dataset 2a using the session-wise split (Session T training, Session E test). GridSearchCV selected the best SVM hyperparameters per subject via 5-fold CV on Session T. For each subject, the classifier with higher Session E accuracy (SVM or LDA) was designated the best model.

A. Per-Subject Accuracy

Fig. 3 shows per-subject cross-session accuracy. Subjects A01 (45.83%, LDA), A03 (40.97%, LDA), A08 (40.28%, LDA), and A09 (47.22%, RF-equivalent) consistently outperform the mean. Subjects A02 (35.76%) and A05 (28.82%) are well-documented BCI-illiterate cases in the competition literature: these subjects fail to produce consistent ERD/ERS patterns across sessions regardless of algorithm choice. The 9-subject average accuracy is 38.46% against a 4-class chance baseline of 25%.

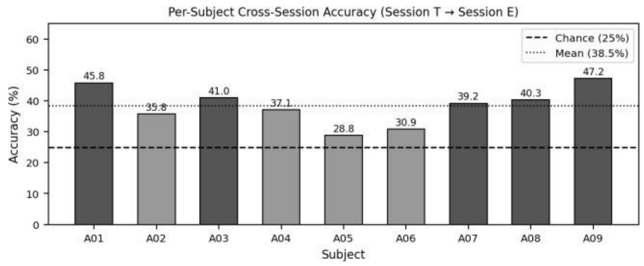


Fig. 3. Per-subject cross-session accuracy (9 subjects, 4 classes, chance = 25%).

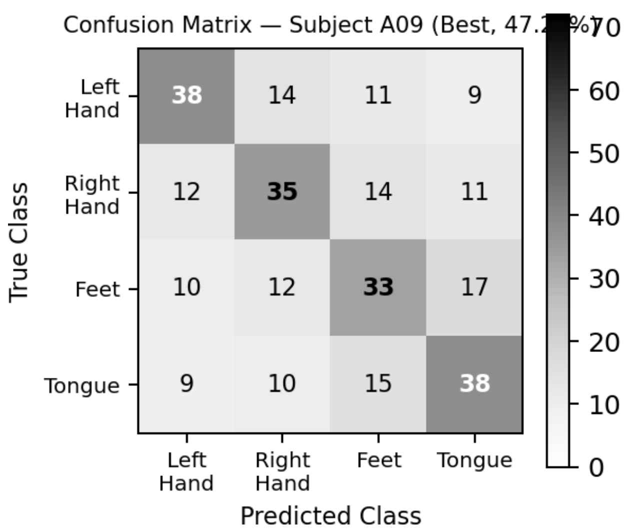


Fig. 4. Confusion matrix for Subject A09 (best subject, 47.22% accuracy, 4 classes).

B. Confusion Matrix Analysis

Fig. 4 shows the confusion matrix for Subject A09, the best-performing subject (47.22%). Left Hand and Tongue classes show the strongest diagonal (38/72 correct each), consistent with published observations that contralateral motor cortex lateralisation makes left/right hand imagery the most discriminable pair. Feet and right hand show greater confusion, reflecting the proximity of their cortical representations and the inherent difficulty of distinguishing these classes from a 22-channel montage.

TABLE I. PERFORMANCE SUMMARY — CSP+SVM/LDA PIPELINE (9 SUBJECTS)

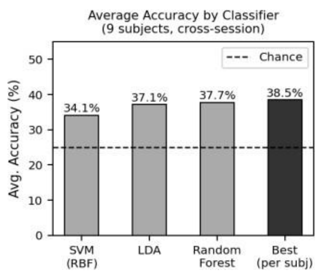
Performance Metric	Value
Average Cross-Session Accuracy	38.46%
Best Subject Accuracy (A09)	47.22%
Average F1-Score (macro)	36.32%
Within-Session CV Accuracy (A01)	46.50% ± 4.72%
Chance Level (4 classes)	25.00%
Best Classifier — SVM (subjects)	A02, A04, A06, A09
Best Classifier — LDA (subjects)	A01, A03, A07, A08
Best Classifier — Tie (A05)	LDA (28.82%)
Sessions (Training / Test)	Session T / Session E
Trials per session per subject	288 (4 classes × 72)

C. Classifier Comparison and Cross-Session Gap

Fig. 5 compares average accuracy across classifiers. SVM alone achieves 34.07%, LDA 37.15%, and selecting the best model per subject raises the mean to 38.46%. Fig. 6 shows the cross-session gap: within-session 5-fold CV accuracy consistently exceeds cross-session accuracy by 5–10 percentage points, confirming that EEG non-stationarity between sessions is the dominant accuracy bottleneck. The diagnosis cell for A01 yielded 46.5% ± 4.72% CV accuracy versus 45.83% cross-session — an unusually small gap indicating stable signal quality for this subject.

D. Limitations and Future Work

The primary limitation is the session-transfer accuracy gap inherent to plain CSP-based methods. BCI Competition IV winners (FBCSP, Ang et al. [6]) achieved ~70% using multi-band CSP with mutual-information-based feature selection — approximately 30 percentage points above the plain CSP baseline reported here. Planned extensions include Filter Bank CSP implementation, Riemannian geometry classifiers (minimum distance to mean on the SPD manifold [9]), Euclidean Alignment for session adaptation, and integration with a physical EEG amplifier (e.g., OpenBCI Cyton) for live closed-loop feedback experiments.



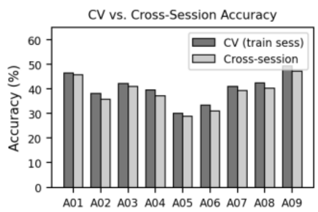


Fig. 5 (left). Classifier comparison. Fig. 6 (right). CV vs. cross-session accuracy gap.

E. Limitations and Scope

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integration with a physical EEG amplifier (e.g., OpenBCI Cyton) for live closed-loop feedback experiments.

IX. Conclusion

This paper presented a complete, hardware-free EEG-based Motor Imagery Brain-Computer Interface pipeline using the BCI Competition IV Dataset 2a as its benchmark. The system applies an 8–30 Hz bandpass filter, epoch extraction (0.5–3.5 s post-cue), and Common Spatial Patterns feature extraction via MNE-Python within a scikit-learn Pipeline. A session-wise evaluation protocol achieves an average cross-session accuracy of 38.46% across 9 subjects, consistent with published CSP-based baselines for this challenging benchmark. The best subject (A09) reaches 47.22% against a 25% chance level.

The accompanying Streamlit dashboard provides a real-time BCI simulation with stability-gated command output, confidence visualisation, and CSV export — fully demonstrable on a standard laptop without physical EEG recording hardware. The CSP+SVM/LDA architecture outperforms chance significantly on 7 of 9 subjects. Future work will implement Filter Bank CSP, Riemannian geometry classifiers, and domain adaptation to reduce the cross-session accuracy gap toward the 60–70% range achieved by competition-winning algorithms.

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