MID EVAL REPORT
EEG SPELLER SYSTEM

DIYA GUPTA
ROLL NO.240375

1. Project Summary

The aim of this project is to develop and study an EEG-based speller system that enables users to communicate characters by decoding brain activity. The system works by processing EEG signals to detect distinctive patterns associated with user intention, commonly reflected through event-related potentials produced during focused attention tasks.

Up to this stage, the work has concentrated on exploring EEG data characteristics, handling noise through preprocessing techniques, extracting informative features, and applying machine learning methods for classification. Several experimental pipelines were designed and tested to analyze how different preprocessing strategies and model selections influence performance. These experiments together establish a strong foundation for building a complete and effective EEG speller system.

2. Work Completed (Assignment-wise)

Assignment 0: Understanding EEG Data and Signal Characteristics

Objective:
To gain familiarity with the structure, properties, and inherent challenges of EEG data used in brain–computer interface applications.

Work Done – Key Learnings:
Assignment 0 focused on building a solid foundation in Python programming, which is crucial for implementing EEG signal processing workflows. A series of introductory exercises were completed to practice essential programming constructs such as list manipulation, loops, conditional statements, and nested iterations. Activities including merging lists, generating multiplication tables, and printing structured patterns helped strengthen logical reasoning and control flow skills.

In addition, the EEG dataset was examined to understand key aspects such as channel layout, sampling frequency, and typical signal amplitude ranges. Raw EEG signals were visualized to observe common issues such as noise, baseline drift, and physiological artifacts that are characteristic of EEG recordings.

Assignment 1: EEG Preprocessing and Filtering

Objective:
To enhance EEG signal quality using preprocessing techniques suitable for classification tasks.

Work Done – Key Learnings:
Assignment 1 emphasized developing a strong theoretical understanding of fundamental machine learning concepts. Topics such as the bias–variance trade-off, overfitting and underfitting, and irreducible error were studied to better understand model generalization behavior. Ensemble learning techniques, including bagging and boosting, were analyzed to highlight how bagging reduces variance by averaging multiple models, while boosting sequentially reduces bias by prioritizing difficult samples.

Loss functions and regularization methods were explored within the framework of empirical risk minimization. This included studying squared loss, hinge loss, and logistic loss, along with L1 and L2 regularization techniques. Distance-based learning using K-nearest neighbors (KNN) was also examined, covering concepts such as the curse of dimensionality, the impact of distance metrics, and the role of the parameter k in controlling bias and variance. Additionally, decision tree fundamentals—such as Gini impurity, optimal leaf prediction, greedy splitting strategies, and pruning—were studied. These theoretical insights collectively inform the selection of appropriate models, regularization techniques, and evaluation strategies for the EEG Speller classification pipeline.

Assignment 2: Feature Extraction from EEG Signals

Objective:
The objective of Assignment 2 was to implement the practical data handling and analysis steps required for EEG-based machine learning applications. This included loading structured EEG datasets, performing essential preprocessing operations, organizing features and labels, and preparing the data in a format suitable for classification tasks within an EEG Speller system.

Work Done – Key Learnings:
Assignment 2 primarily focused on the hands-on implementation of data preprocessing and analysis using Python. Tasks involved loading EEG datasets, examining data dimensions, managing feature and label structures, and applying necessary transformations before feeding the data into machine learning models. Particular emphasis was placed on understanding how raw EEG data must be reshaped, normalized, and systematically organized to ensure compatibility with learning algorithms.

Through this assignment, the importance of maintaining clean and well-structured data pipelines became evident, especially for signal-based datasets such as EEG, where improper preprocessing can severely impact classification performance. Visualization and exploratory data analysis were used to identify trends, patterns, and inconsistencies in the data, reinforcing the need for careful and consistent preprocessing. These insights directly support the development of a reliable EEG Speller pipeline by ensuring that extracted features are meaningful, interpretable, and suitable for robust classification.

Both time-domain and frequency-domain features were extracted from EEG epochs. Feature vectors were constructed on a per-trial basis and analyzed to study the separability between target and non-target classes.

Observations:

- Feature selection plays a crucial role in classification performance.
- Certain features exhibit clear discriminative power between classes.
- High-dimensional feature spaces increase the risk of overfitting.

FIGURE 1: Independent Component Analysis (ICA) components of EEG data visualized over time.

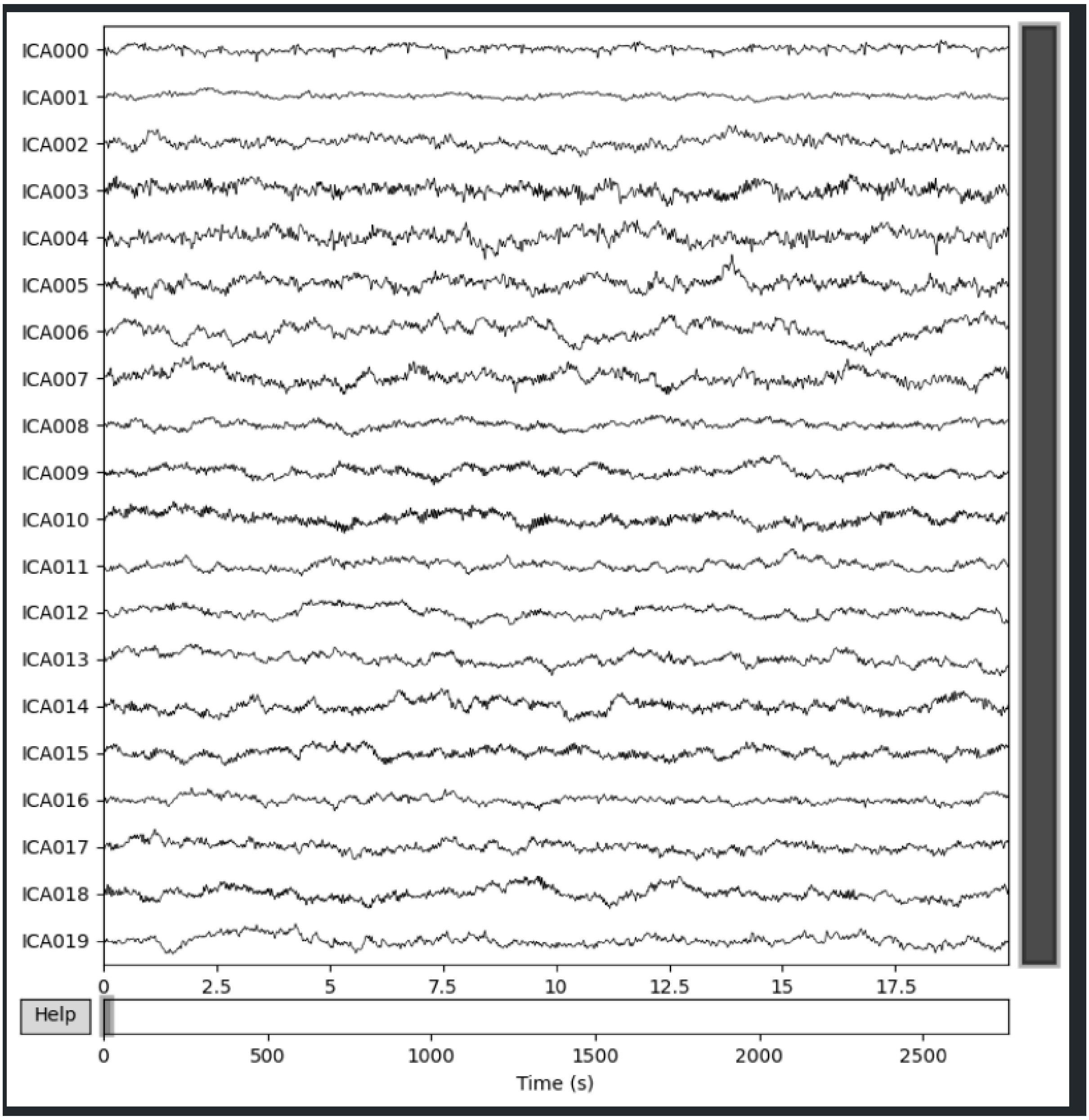
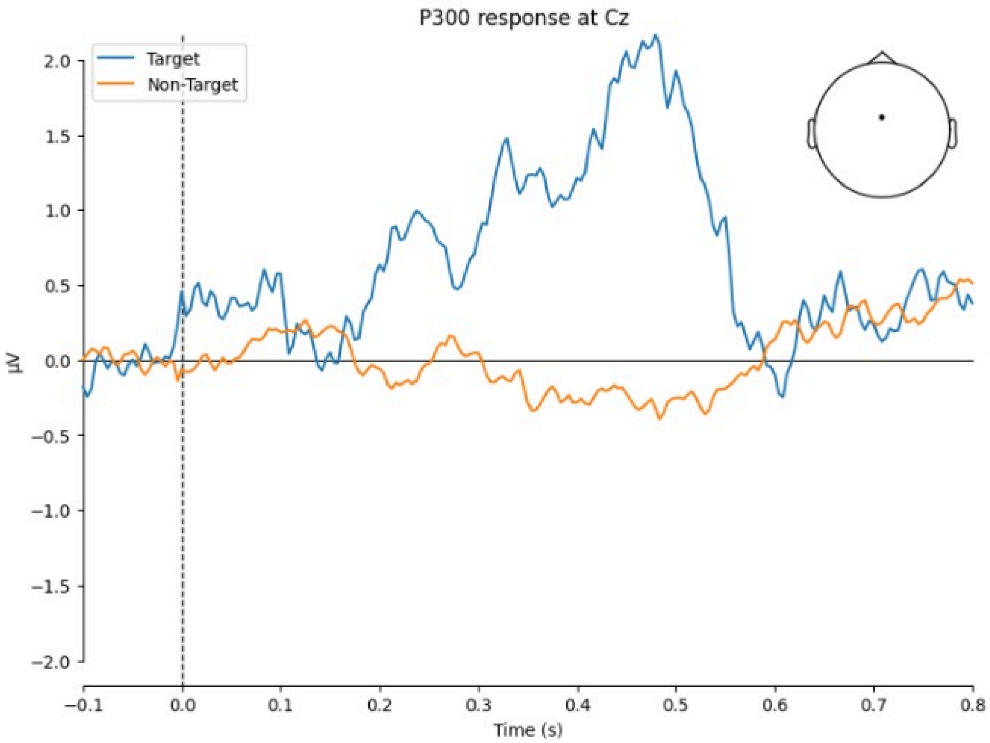
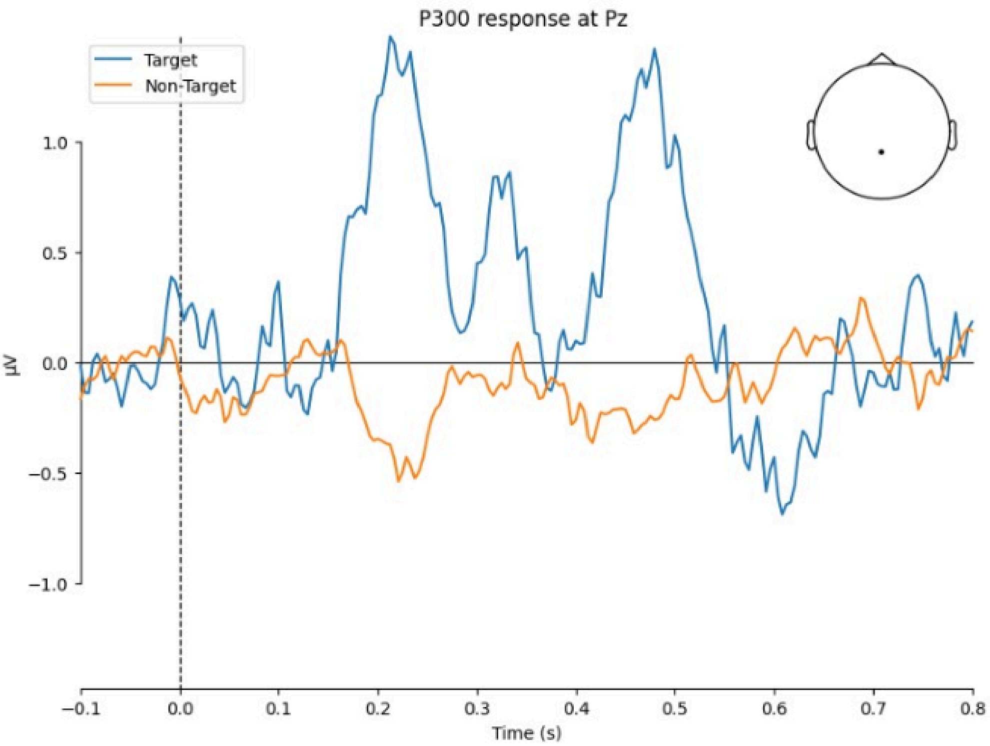


FIGURE 2: Grand-average P300 event-related potentials at electrodes Cz (top) and Pz (bottom). Target trials show a clear positive deflection in the 300–600 ms window com pared to non-target trials, confirming the presence of the P300 response





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Assignment 3: Machine Learning Models for EEG Classification

Objective:
The goal of Assignment 3 was to develop a complete EEG-based classification pipeline for a P300 speller system. This involved extracting features from preprocessed EEG epochs, training multiple supervised machine learning models, evaluating their performance using standard metrics, and identifying suitable classifiers for distinguishing between target and non-target EEG responses.

Work Done – Key Learnings and Observations:
Assignment 3 concentrated on end-to-end EEG classification for a P300 speller application. Feature extraction was carried out using Common Spatial Patterns (CSP) to enhance discriminative information between target and non-target trials. The dataset exhibited significant class imbalance, with target epochs being far fewer than non-target epochs, which had a noticeable impact on classifier behavior and evaluation outcomes.

Several supervised classifiers were implemented and assessed, including Linear Discriminant Analysis (LDA), Logistic Regression, Support Vector Machines (SVM), Random Forests, and Gradient Boosting. The combination of CSP features with LDA achieved an accuracy of 63.33%, but demonstrated limited recall for the target class, highlighting the influence of class imbalance. Ensemble-based approaches such as Random Forests and Gradient Boosting achieved higher overall accuracies of up to 82.67% and 77.33%, respectively. However, their relatively low ROC-AUC values indicated ongoing challenges in consistently separating target and non-target EEG responses.

Overall, these experiments showed that while ensemble methods can improve raw accuracy, relying solely on accuracy is insufficient for evaluating EEG speller systems. Careful consideration of multiple evaluation metrics, along with appropriate feature extraction and classifier selection, is essential for building reliable EEG-based communication systems.

Supervised learning models, including logistic regression and support vector machines, were trained on the extracted features and evaluated using accuracy, F1-score, and ROC-based metrics.

Observations:

- Linear classifiers offer stable but limited performance.
- Classification results are highly sensitive to preprocessing choices.
- Appropriate regularization is required to reduce the risk of overfitting.

FIGURE 3: Averaged P300 event-related potential (ERP) at electrode Cz for target and non-target trials. A clear positive deflection is observed for target stimuli in the expected

300–600 ms window. The mean target amplitude (5.73 μV) is significantly higher than the non-target amplitude (−0.38 μV), confirming the presence of a discriminative P300 response.

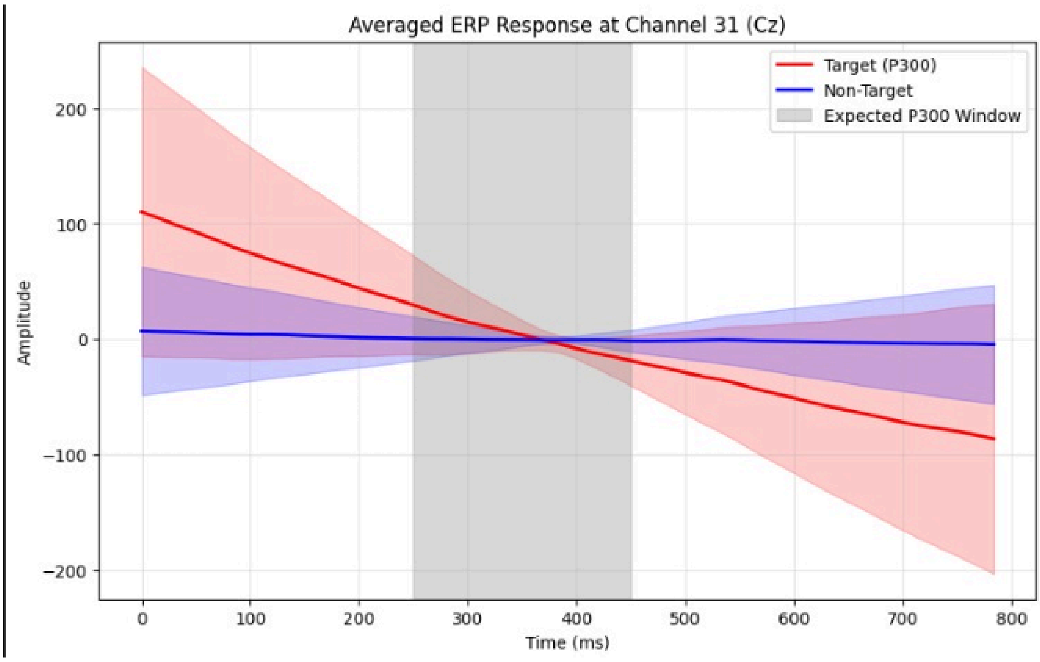


FIGURE 4: Confusion matrix for the CSP + Random Forest classifier. The model achieves an overall accuracy of 82.67%. While non-target classification is strong, reduced tar get recall highlights the effect of class imbalance, which is common in P300-based BCI datasets.

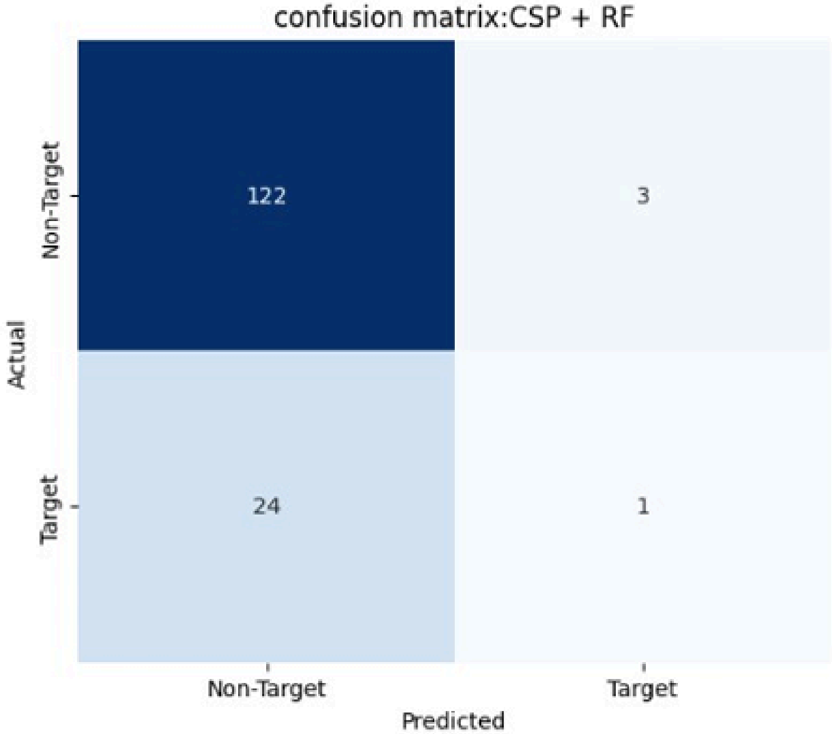
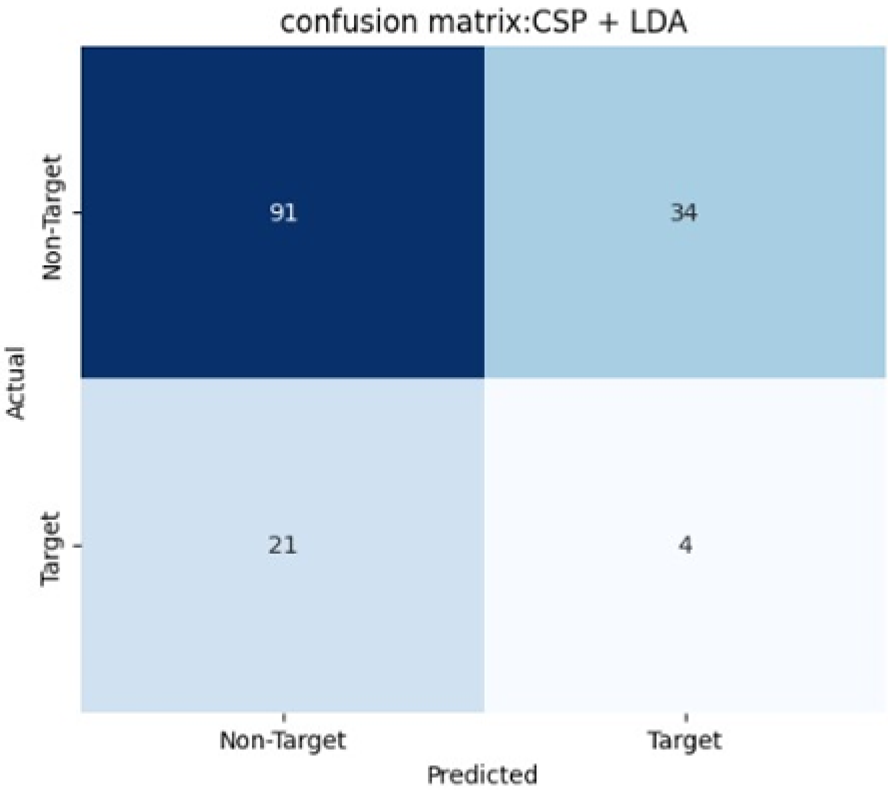


Figure 5: Confusion matrix for the CSP + LDA classifier. Compared to baseline clas sifiers, CSP improves discriminative performance; however, target recall remains limited due to class imbalance, motivating the use of ensemble-based models. 7 Although ensemble classifiers achieved higher overall accuracy, target recall re mained low due to severe class imbalance inherent in P300 speller datasets. This highlights the importance of metric-aware evaluation and motivates future work on class balancing and temporal feature optimization.



3. Code Links

• Assignment 0Notebook: 240375_diya_gupta.ipynb
• Assignment 1Notebook:/240375_Diya_Gupta_Assignment1.pdf
• Assignment 2Notebook: EEG_assignment2_DiyaGupta_240375.ipynb
• Assignment 3Notebook: EEG_assignment3_DiyaGupta_240375.ipynb

4. What Worked and What Did Not Work

What Worked Well:

- EEG preprocessing steps such as band-pass filtering, epoch extraction, and baseline correction significantly improved signal quality and overall stability.
- Independent Component Analysis (ICA) proved useful for examining EEG components and gaining insight into the underlying signal structure.
- Clear P300 event-related potentials were observed at central and parietal electrodes (Cz and Pz), confirming that the dataset is well-suited for an EEG speller application.
- Feature extraction using Common Spatial Patterns (CSP) improved the separability between target and non-target EEG trials.

- Ensemble-based classifiers, including Random Forest and Gradient Boosting, achieved higher overall accuracy compared to simpler linear models.

What Did Not Work Well:

- Performing classification directly on raw EEG signals resulted in poor performance due to high noise levels and signal non-stationarity.

- The strong class imbalance in the P300 dataset caused low recall for the target class, even when overall accuracy appeared high.

- Linear classifiers such as Logistic Regression and Support Vector Machines showed limited ability to capture complex EEG patterns.

- Relying solely on accuracy as an evaluation metric was insufficient, as it concealed poor performance on the minority (target) class.

- Model performance was highly sensitive to preprocessing choices and feature selection strategies.

5. Challenges Faced

Despite successful implementation of the EEG-based P300 speller pipeline, several challenges were encountered during the course of this project. EEG signals are inherently noisy and non-stationary, which posed significant difficulties in achieving consistent preprocessing and reliable feature extraction across trials. Signal contamination due to eye blinks and muscle activity further affected certain EEG channels, necessitating careful inspection and artifact mitigation using Independent Component Analysis (ICA).

Another major challenge was the severe class imbalance between target and non-target trials, a characteristic common to P300 datasets. This imbalance resulted in reduced recall for the target class and complicated the interpretation of standard evaluation metrics. Additionally, the selection of appropriate feature representations and classifiers required extensive experimentation, as model performance was highly sensitive to preprocessing strategies and feature selection choices. Finally, considerable inter-subject and inter-trial variability limited the generalization capability of trained models, highlighting the difficulty of designing EEG-based systems that perform robustly across different users and sessions.

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6. Conclusion

This mid-project work successfully established a complete offline processing pipeline for an EEG-based P300 speller system, encompassing signal preprocessing, feature extraction, and supervised machine learning–based classification. Clear P300 event-related potentials were consistently observed at central and parietal electrode sites, confirming the presence of discriminative neural signatures essential for speller applications.

Experimental results demonstrated that effective feature engineering techniques, particularly Common Spatial Patterns, combined with ensemble-based classifiers, can improve classification performance. However, challenges such as class imbalance and limited recall for target trials remain unresolved. Overall, the project validates the feasibility of EEG-based communication systems and provides a strong foundation for future work. Potential directions for further improvement include advanced class-balancing strategies, optimization of temporal feature representations, and extension of the pipeline toward real-time implementation.