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# Electroencephalogram Signal Classification Using Machine Learning for Wheelchair Control

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**Abstract.** Brain-computer interfaces (BCI) represents an emerging technology that enables direct communication between the human brain and external devices, using electroencephalographic signals. During motor imagery, specific changes occur in brain sensorimotor rhythms that can be detected and classified by Machine Learning (ML) algorithms. This work presents a comparative analysis of ML algorithms for the classification of motor imagery patterns in electroencephalographic signals, aiming at the development of brain-computer interfaces for wheelchair control. Four distinct algorithms were evaluated: Gradient Boosting (GB), Random Forest (RF), Multilayer Perceptron (MLP) and k-NN, using a dataset with 2,950 characterized samples from three experimental conditions: left hand movement imagination, right hand movement imagination, and resting state. Different balancing techniques were implemented, including SMOTE, ADASYN and class weight balancing. GB demonstrated the best overall performance with 78.84% Macro F1-Score and 87.63% accuracy, followed by RF with 76.85% and 87.97%, respectively. The analysis revealed significant difficulties in discriminating minority classes due to extreme imbalance in the dataset, where the left class represents 74.5% of the samples.

**Keywords:** Brain-computer interface, Electroencephalography, Machine learning, Motor imagery, Signal classification

## 1 Introduction

Brain-computer interfaces (BCI) represent an emerging technology that enables direct communication between the human brain and external devices, using electroencephalographic signals as the primary means of neural data acquisition [1]. This research area encompasses medical applications, such as epilepsy detection and post-stroke patient rehabilitation, to the development of control systems for robotic devices and smart home environments [2].

BCI systems based on motor imagery constitute one of the most promising approaches for controlling assistive devices, especially for users with severe motor disabilities [3]. During movement imagination, specific alterations occur in cerebral sensorimotor rhythms, particularly in the mu (8-12 Hz) and beta (13-30 Hz) frequency bands, which can be detected and classified by Machine Learning (ML) algorithms [4, 5].

The diversity of methodologies employed in electroencephalogram (EEG) signal classification reflects the inherent complexity of neural signal processing and the need for specific approaches for different applications [6]. Recent studies demonstrate the continuous evolution of techniques, from traditional ML methods to sophisticated deep learning (DL) architectures, with accuracies frequently exceeding 90% in different application contexts [6–9].

As highlighted by [10], it is fundamental to develop solutions adapted to local socioeconomic realities, especially considering that most technological advances in BCI occur in developed countries, often ignoring the needs and limitations of developing countries. Additionally, the methodology developed for algorithm comparison can serve as a framework for evaluating new EEG signal classification approaches that may emerge in the future.

This work presents a systematic comparative analysis of four ML algorithms for classifying motor imagery patterns in EEG signals, investigating different class balancing techniques and feature optimization. The main objective consists of identifying the best combination of algorithm and preprocessing strategy for developing BCI

aimed at wheelchair control.

The remainder of the manuscript is structured as follows: Section 2 describes the study area and the methodology used. Section 3 describes the conducted experiments and the achieved results. In Section 4, conclusions are presented.

## 2 Methodology

The methodology used for motor imagery pattern classification was based on digital signal processing techniques and ML algorithms [11]. The methodological approach was structured into five main stages comprising exploratory analysis of acquired data, preprocessing through digital filtering, feature extraction, implementation of multiple supervised classification algorithms, and rigorous validation of developed models.

### 2.1 Origin and Characterization of the Dataset

The experimental dataset originated from the Milo project [12], employing electroencephalographic signal acquisition at 250 Hz sampling frequency with effective Nyquist frequency of 125 Hz, ensuring adequate preservation of neurobiologically relevant spectral characteristics. The raw experimental data comprised 98,506 temporal samples distributed across three distinct motor imagery conditions: left hand movement imagery (51,466 samples), right hand movement imagery (16,529 samples), and motor rest state (30,511 samples). This initial dataset underwent processing through feature extraction procedures, resulting in a dataset with 2,950 feature vectors. The final dataset exhibited significant class imbalance, with left hand imagery comprising 74.5% (2,199 samples), right hand imagery 13.1% (385 samples), and rest state 12.4% (366 samples) of the characterized data, requiring specialized balancing techniques during model training [13, 14].

### 2.2 Data Processing

The EEG data processing pipeline implements a structured sequence of five main stages, each generating specific files that feed subsequent stages [15]. This modular organization allows complete processing traceability and facilitates experiment reproducibility.

The first stage processes raw data and generates individual files organized by direction and channel, consolidating signals from all eight EEG channels for each experimental condition into three main files: one for right-hand movement imagination, one for left-hand movement, and another for rest state. The second stage applies the complete sequence of digital filters to consolidated data, implementing a linear detrend filter, notch filters for removing electrical network interference (60 Hz and 120 Hz), and a band-pass filter (5-30 Hz) for preserving neurobiologically relevant frequency bands [16].

The third stage constitutes the processing core, generating nine systematically organized files for each of the three directions. These files include basic spectral features extracted from mu (8-12 Hz), beta (13-30 Hz), and alpha (8-13 Hz) bands, coherence and correlation measures between different brain regions [17], and consolidation of all 45 extracted features, including laterality indices, hemispheric asymmetry, and derived features. The fourth stage performs comprehensive statistical analysis of extracted data, generating descriptive reports, distribution graphs, and identification of the most discriminative features through F-ANOVA analysis [18]. The final stage exclusively uses the three files with complete inter-channel relationships for training and evaluation of classification algorithms, generating trained models, performance metrics, and result visualizations. Model validation followed a two-stage hybrid approach: (1) initial data splitting using the Holdout technique [19] into 60% for training (1770 samples), 20% for validation (590 samples), and 20% for testing (590 samples), ensuring class stratification; and (2) application of 5-fold stratified cross-validation repeated twice within the training set for robust hyperparameter search. This methodology ensures that the test set remains completely isolated until final evaluation, preventing data leakage and providing unbiased estimates of model performance.

### 2.3 EEG Signal Preprocessing

The preprocessing methodology implemented a sequential four-stage digital filtering approach optimized for motor imagery signal enhancement while preserving critical neurophysiological information [11]. The initial preprocessing stage employed linear detrend filtering using the scipy.signal.detrend function with linear configuration to eliminate DC components and systematic linear trends that could compromise subsequent spectral analyses [15]. Electrical interference removal utilized sequential application of second-order Butterworth band-pass filters

implemented as notch filters, with the primary filter centered at 60 Hz (bandwidth ±2 Hz) for Brazilian electrical grid interference elimination and a secondary filter at 120 Hz (bandwidth ±2 Hz) for harmonic component removal [20].

The final preprocessing stage employed a second-order Butterworth band-pass filter with cutoff frequencies precisely defined at 5 Hz and 30 Hz, designed to preserve neurologically relevant frequency bands while systematically removing low-frequency artifacts associated with ocular movements and high-frequency contamination from muscular activity [16]. This filtering configuration specifically preserves mu (8-12 Hz), alpha (8-13 Hz), and beta (13-30 Hz) rhythms that constitute the primary neural biomarkers for motor imagery classification. The entire preprocessing pipeline incorporated adaptive quality control measures, including epoch validation with configurable rejection criteria for flat signals (amplitude range $< 0.01$), saturated channels (fewer than 10 unique values), and detection of NaN or infinite values that could compromise subsequent analysis steps.

### 2.4 Spectral and Laterality Feature Extraction

Feature extraction constitutes a fundamental process for identifying discriminative patterns in processed EEG signals, where spectral, temporal features of frequency bands, and relationships between channels were extracted [21]. Power spectral density estimation uses Welch's method with Hann windowing to reduce spectral leakage and improve spectral resolution, employing temporal segmentation with NFFT of 512 points, nperseg of 256 samples, and 50% overlap.

The temporal segmentation process divides continuous signals into 1.0-second epochs (250 samples) with 80% overlap (200 samples), maximizing the number of samples available for training classification algorithms. This procedure results in a 0.2-second temporal increment between consecutive epochs, providing a significant increase in the dataset without compromising the statistical independence of samples.

Three neurologically relevant frequency bands are systematically investigated: mu rhythm (8-12 Hz), beta band (13-30 Hz), and alpha rhythm (8-13 Hz) [5]. The mu band demonstrates prominent contralateral desynchronization during unilateral movement imagination, constituting the primary neural biomarker for motor imagery-based brain-computer interfaces. The beta band presents complementary synchronization and desynchronization patterns associated with the planning and execution of imagined movements, while the alpha rhythm, although traditionally associated with relaxation states, demonstrates specific modulations during complex cognitive-motor tasks.

Hemispheric laterality analysis constitutes a fundamental approach for detecting motor imagery patterns, since desynchronization occurs preferentially in the hemisphere contralateral to the imagined movement [22]. Considering the eight-channel EEG configuration used, laterality indices are calculated for primary motor regions through Eq. 1,

$$L_{\text{motor}} = \frac{P_{C4} - P_{C3}}{P_{C4} + P_{C3}} \tag{1}$$

where $P_{C3}$ and $P_{C4}$ represent spectral powers in channels corresponding to left and right motor regions, respectively. Complementarily, hemispheric asymmetry indices quantify activation differences between homologous regions of brain hemispheres, calculated by Eq. 2,

$$A_{\text{left}} = \frac{P_{\text{hemis_left}} - P_{\text{central_left}}}{P_{\text{hemis_left}} + P_{\text{central_left}}} \tag{2}$$

where $A_{\text{left}}$ represents the asymmetry index for the left hemisphere, $P_{\text{hemis_left}}$ is the spectral power in the left hemisphere, and $P_{\text{central_left}}$ is the power in the left central region, considering the specific spatial relationships of the eight-channel configuration employed.

### 2.5 Supervised Classification Algorithms

The methodology employs four distinct ML algorithms (MLP, RF, k-NN, and GB) for automatic classification of motor imagery patterns extracted from EEG signals. This comparative approach allows investigation of different classification paradigms applied to the problem of motor intention identification.

The Multi-Layer Perceptron (MLP) constitutes a feedforward artificial neural network with universal approximation capability for non-linear functions [23, 24]. The implementation uses ReLU (Rectified Linear Unit) and hyperbolic tangent activation functions [25], Adaptive Moment Estimation (Adam) optimizer, and L2 regularization for overfitting prevention [26], with architectures varying from simple networks with one hidden layer to more complex configurations with three layers.

In addition, the Random Forest (RF) algorithm employs an ensemble of decision trees trained independently on random subsets of data and features, combining their predictions through majority voting [27]. This method demonstrates robustness against overfitting and effectiveness in high-dimensionality problems, characteristics particularly relevant for EEG signal classification [28].

The k-Nearest Neighbors (k-NN) algorithm constitutes a non-parametric method that assigns the class of a new sample based on majority voting of its k nearest neighbors in the feature space [29]. The conceptual simplicity and absence of assumptions about data distribution make this method particularly suitable for exploratory problems.

The Gradient Boosting (GB) algorithm implements a sequential ensemble strategy where weak models are iteratively trained to correct errors of previous models, resulting in a robust final classifier [30]. The method can be interpreted as a gradient descent algorithm in function space, where each iteration adds a new basis function that points in the direction of the negative gradient of the loss function.

### 2.6 Balancing and Optimization Strategies

The unbalanced class distribution in the dataset requires the implementation of specific strategies to ensure adequate classifier training [13]. Four distinct experimental groups are defined to systematically investigate different preprocessing, balancing, and feature optimization approaches.

Group A employs the complete set of 45 extracted features without class balancing techniques, serving as a baseline for methodological comparison. Group B incorporates the SMOTE technique for synthetic generation of minority class samples, balancing the distribution during training through linear interpolation in the feature space between neighboring samples of minority classes [13].

Group C uses the ADASYN strategy that adapts the density of synthetic sample generation based on the learning difficulty of each region in the feature space [14]. Group D explores additional techniques including BorderlineSMOTE, SMOTE-ENN, and class weight balancing, where the latter technique implements algorithmic balancing through class weights inversely proportional to observed frequencies, as described by Eq. 3,

$$w_i = \frac{n_{total}}{n_{classes} \times n_i} \tag{3}$$

where $w_i$ represents the weight of class $i$, $n_{total}$ is the total number of samples, $n_{classes}$ is the number of classes (3), and $n_i$ is the number of samples of class $i$.

Within each experimental group, five distinct preprocessing configurations are implemented. The first configuration implements z-score normalization of features through StandardScaler, transforming each feature to zero mean and unit standard deviation [31]. The second combines univariate feature selection with standard normalization, employing the F-ANOVA test [32] to identify the 50% most discriminative features.

The third applies Principal Component Analysis (PCA) preserving 95% of total data variance, projecting the original 45-dimensional space into a lower-dimensional subspace [33]. The fourth implements a hybrid approach combining feature selection with dimensional reduction, initially selecting the 25% most discriminative features, followed by PCA preserving 90% of variance. The fifth uses robust normalization based on median and interquartile range, offering greater resistance to outliers compared to standard z-score normalization [34].

### 2.7 Validation Protocol and Evaluation Metrics

Classification algorithm evaluation follows a stratified cross-validation protocol with 5 folds and 2 repetitions, ensuring robust model performance estimation and reducing dependence on specific data partitioning [30]. Each fold maintains the original class proportion through stratification, ensuring adequate representativeness during the validation process.

The evaluation protocol employs multiple complementary metrics that capture different aspects of predictive quality [35]. Overall accuracy represents the proportion of correct classifications relative to the total evaluated samples [36]. Micro F1-score considers all classifications in an aggregated manner, being influenced by majority classes [36], while macro F1-score calculates the arithmetic mean of individual F1-scores for each class, providing a balanced evaluation of performance across all categories regardless of their relative frequency [36]. Weighted F1-score applies weights based on each class frequency in the dataset, balancing the influence of majority and minority classes [36]. Macro recall evaluates the ability to correctly identify samples from each category, and the area under the ROC curve (AUC-ROC) provides a measure of the model's discriminative capacity across the entire range of decision thresholds [36].

The described methodology establishes a comprehensive protocol for processing and analyzing EEG signals

aimed at identifying motor imagery patterns.

## 3 Results and Discussion

The computational experiments were performed using the Python programming language and implementations based on the Scikit-Learn [37], Pandas [38], NumPy [39] and SciPy [39] framework libraries. All experiments were run on a computer with the following specifications: $14^a$ generation Intel $Core^{TM}$ i7-14700F (20 cores, 28 threads, 33 MB cache, 1.5 GHz to 5.4 GHz Turbo, 219 W) and Windows 11 operating system. Reproducibility control is ensured through fixed seeds (random_state = 42) in all random components, allowing exact replication of performed experiments.

For each algorithm group, 30 different combinations of hyperparameters were tested in order to identify the best-performing configurations. The selected configurations were as follows: GB (B2) was implemented as a sequential ensemble of 100 decision trees, with a learning rate of 0.3 and a maximum depth of 10 levels; the MLP (C2) adopted a pyramidal architecture with three hidden layers (256, 128, and 64 neurons), using the ReLU activation function, Adam optimizer, and L2 regularization ($\alpha$ = 0.001); the RF (A1) consisted of an ensemble of 500 trees without bootstrap sampling, employing the Gini criterion and logarithmic feature selection; finally, the k-NN (B2) algorithm was configured with three nearest neighbors, Manhattan distance as the similarity metric, and a kd-tree structure for computational optimization.

The experiments revealed significant performance variations between the different tested algorithms, confirming trends observed in the literature for EEG signal classification [2, 7–9, 40]. The GB configuration B2 emerged as the superior model, recording 78.84% Macro F1-Score and 87.63% accuracy. This result represents a considerable advancement in discrimination capability between the three analyzed classes: Left, Right, and Rest.

Furthermore, the MLP configuration C2 model achieved the second-best overall performance, obtaining 84.58% accuracy and 72.76% Macro F1-Score. The implemented architecture used three hidden layers with 256, 128, and 64 neurons respectively, employing the ReLU activation function and the Adam optimizer. The configuration demonstrated good generalization capability, evidenced by the temporal training evolution that reached a 96.70% validation score after 92 epochs.

The RF algorithm configuration A1 presented competitive results, achieving 87.97% accuracy and 76.85% Macro F1-Score. The implementation used an ensemble of 500 decision trees with Gini criterion and unlimited depth, demonstrating excellent discriminative capacity for the majority class. The model evidenced macro precision of 86.76%, indicating a low false positive rate.

In turn, k-NN configuration B2 recorded the lowest performance among evaluated algorithms, obtaining 80.34% accuracy and 69.31% Macro F1-Score. The configuration employed three nearest neighbors with Manhattan distance weighting and kd-tree structure for computational optimization. This result is consistent with known k-NN limitations in high-dimensionality spaces.

### 3.1 Class Imbalance Analysis

The dataset presented significant imbalance, with the Left class representing 74.6% of samples (440 of 590), while the Right and Rest classes corresponded to 13.1% (77 samples) and 12.4% (73 samples), respectively. This imbalance directly impacted model performance, favoring majority class classification, a phenomenon well documented in ML literature [13].

The Table 1 presents a comparison of the performance metrics between the best configurations of each classification algorithm tested. The GB demonstrated better balance in recognizing the three classes, with correct classification rates of 93.0% for Left, 80.5% for Right, and 63.0% for Rest. In contrast, RF presented excellent performance for the majority class (98.4%) but lower efficacy in minority classes (59.7% and 54.8%). Finally, the MLP maintained an intermediate pattern, recording 92.0% for Left, 72.7% for Right, and 52.1% for Rest.

## 4 Conclusions

This work presented a systematic comparative analysis of ML algorithms for classifying motor imagery patterns in electroencephalographic signals, aiming at developing BCI for wheelchair control. The investigation covered four distinct algorithms evaluated under multiple preprocessing configurations and class balancing techniques.

The GB algorithm emerged as the best option for the analyzed classification problem, presenting a Macro F1-Score of 78.84% and balanced performance across all classes. This model demonstrated a superior ability to handle

Table 1. Performance metrics comparison between the best configurations of each tested classification algorithm

| **Model** | **Acc (%)** | **Macro F1 (%)** | **Micro F1 (%)** | **W F1 (%)** | **Macro Prec (%)** | **Macro Rec (%)** |
|---|---|---|---|---|---|---|
| MLP C2 | 84.58 | 72.76 | 84.58 | 84.33 | 74.27 | 72.28 |
| KNN B2 | 80.34 | 69.31 | 80.34 | 81.65 | 66.26 | 74.52 |
| RF A1 | 87.97 | 76.85 | 87.97 | 86.92 | **86.75** | 70.98 |
| GB B2 | **87.63** | **78.84** | **87.63** | **87.54** | 79.11 | **78.83** |

data imbalance, maintaining adequate sensitivity for minority classes while preserving high overall precision. The results confirm the effectiveness of sequential ensemble methods for EEG signal classification, aligning with trends observed in recent literature.

Furthermore, RF proved to be a viable alternative, especially in scenarios where computational efficiency is prioritized, achieving 87.97% accuracy with training time approximately 31 times shorter than GB. The MLP offered an intermediate solution with good generalization capability, while k-NN presented significant limitations in high-dimensionality spaces, as expected from the literature.

The main challenge identified relates to a significant imbalance between classes, resulting in heterogeneous performance where the majority Left class obtained exceptional results, while the minority Right and Rest classes presented limited sensitivity. The implemented balancing techniques demonstrated differentiated effectiveness according to the algorithm used, with GB and RF presenting greater robustness to balancing variations. Future work should prioritize capturing proprietary data for constructing balanced datasets with larger numbers of samples, in addition to implementing error handling policies that prioritize user safety.

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