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EEG-Based Cognitive Response Classification Using Machine Learning for Communication Support in Amyotrophic Lateral Sclerosis

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Abstract

Amyotrophic lateral sclerosis (ALS) is a progressive neurodegenerative disorder characterized by the loss of voluntary motor function, eventually leading to severe communication impairment. In advanced stages, patients may lose the ability to speak, write, or use conventional assistive technologies. Brain–computer interface (BCI) systems provide a promising alternative by enabling communication through direct interpretation of neural activity.

The present study focuses on the acquisition, preprocessing, and classification of electroencephalographic (EEG) signals corresponding to binary cognitive responses (“Yes” and “No”). EEG data were collected using a CleaveLab - BioRadio system in a controlled laboratory environment. The signals were processed and transformed into informative features, including statistical time-domain characteristics.

Machine learning methods were applied to classify cognitive states based on extracted features. The study emphasizes the importance of data-driven approaches in handling non-stationary EEG signals and improving classification performance. The results demonstrate the feasibility of using simple yet effective features combined with machine learning algorithms for communication-oriented BCI applications in ALS.

Keywords: Amyotrophic Lateral Sclerosis (ALS), Electroencephalography (EEG), Brain–computer interface (BCI), Machine Learning, Naive Bayes.

Introduction

Amyotrophic lateral sclerosis (ALS) is a severe neurodegenerative disease that affects both upper and lower motor neurons, leading to progressive muscle weakness and paralysis. As the disease advances, patients gradually lose the ability to communicate, which significantly impacts their autonomy and quality of life.

Traditional communication methods, including speech and motor-based assistive technologies, become ineffective in advanced stages of ALS. Even eye-tracking systems may fail due to fatigue and oculomotor impairments. However, cognitive functions such as attention and decision-making often remain preserved.

This dissociation between intact cognitive processes and impaired motor output provides the foundation for brain–computer interface (BCI) systems. BCI technologies enable communication by translating neural signals into control commands without relying on muscular activity.

Electroencephalography (EEG) is one of the most widely used methods for recording brain activity in BCI applications due to its non-invasive nature and relatively low cost. However, EEG signals are highly complex, noisy, and non-stationary, which makes their analysis challenging.

To address these challenges, machine learning techniques are increasingly applied to EEG signal processing. These methods allow automatic extraction of meaningful patterns and enable classification of cognitive states.

The aim of this study is to develop a framework for classifying binary cognitive responses (“Yes” and “No”) using EEG signals, with the ultimate goal of supporting communication in patients with ALS.

Experimental Environment

The experiment was conducted at the Biomedical Engineering Laboratory of Georgian Technical University. The study was performed in a controlled indoor environment in order to reduce external noise and improve signal quality during EEG acquisition.

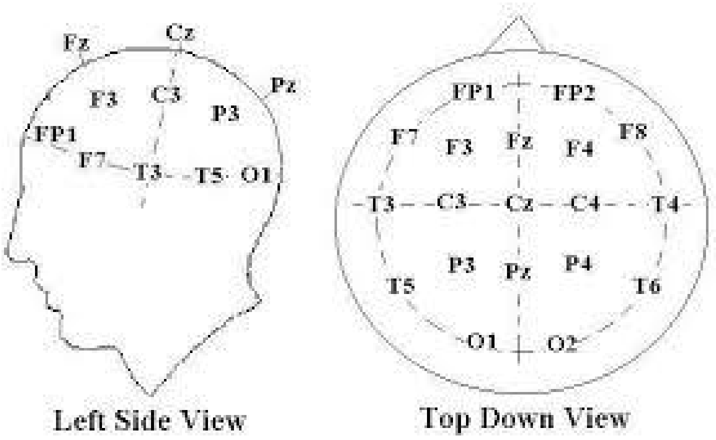
Participants

Two healthy male participants aged 25 and 40 were involved in the experiment. At this stage, healthy individuals were used to test the technical feasibility of the method before considering future application to ALS patients. This is a common initial step in the development of brain–computer interface systems.

EEG Recording System

EEG signals were recorded using a CleaveLab - BioRadio wireless system. The use of a wireless device improved participant comfort and simplified data acquisition. Signal recording was monitored in real time through Capture Lite software.

Electrodes were placed according to the international 10–20 system (Pic. 1). The selected positions were Fp1, Fp2, O1, and O2, representing frontal and occipital regions. These channels were chosen as a practical configuration for detecting relevant neural activity during internal binary response generation.



Pic. 1 international 10–20 system

Experimental Procedure

During the experiment, participants were asked questions and instructed to think of a binary response, either "yes" or "no," without speaking or making visible movements. The purpose was to capture EEG patterns associated with internal cognitive intention rather than overt motor response.

Each trial lasted approximately 3–4 seconds and was repeated multiple times. More than 800 recordings were collected in total in order to provide sufficient data for machine learning analysis. Repeated trials were necessary because EEG signals are variable and often contain noise, so a larger number of samples improves the reliability of the dataset.

Data Processing

After data acquisition, the recordings were exported to Excel and MATLAB for preprocessing and analysis. Since raw EEG signals are often affected by artifacts and inconsistent trial lengths, several preprocessing steps were carried out before classification.

First, noisy segments and outliers were identified and removed. This step was important to exclude recordings with abnormal values caused by movement, poor electrode contact, or environmental interference.

Second, signal values were normalized to reduce variation in amplitude across different samples. Normalization improves the performance of many machine learning algorithms by making the data more consistent.

Third, all EEG segments were converted into a uniform structure. Because trial durations could vary slightly, the number of signal points per sample was standardized so that all observations had the same data length. This created a consistent dataset suitable for supervised learning.

Finally, each EEG sample was labeled according to the intended response category: "Yes" or "No."

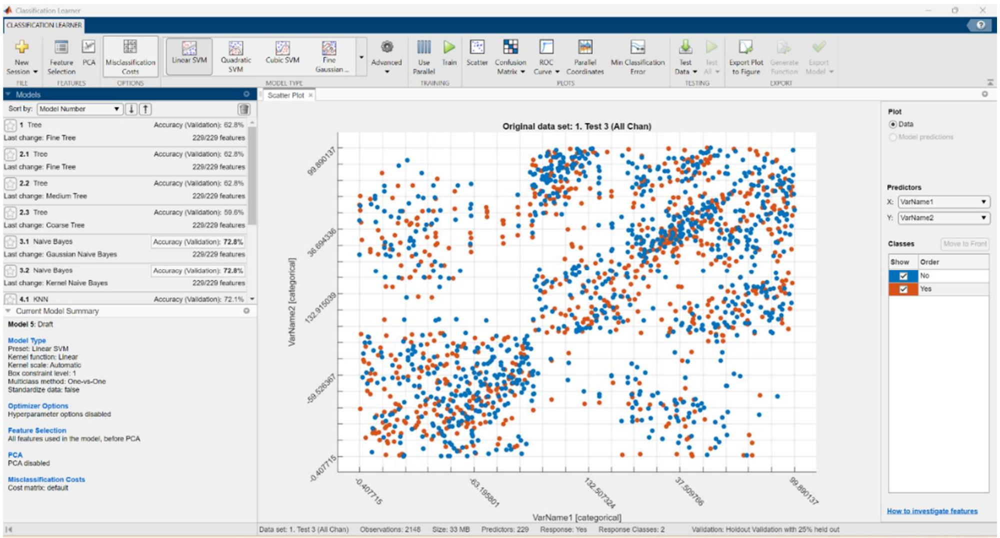
Machine Learning Analysis

Classification was performed using MATLAB's Classification Learner tool. Several machine learning algorithms were tested in order to compare their ability to distinguish between the two cognitive response classes. These included:

- Decision Trees
- Naive Bayes
- Support Vector Machines
- k-Nearest Neighbors
- Ensemble methods
- Neural Networks

Different datasets were evaluated, including single-electrode and multi-electrode configurations. In the MATLAB environment, EEG features were defined as numerical predictor variables, while the target variable ("Yes" or "No") was defined as categorical.

To evaluate model performance, a 25% holdout validation method was used. This means that 75% of the data were used for training and 25% were reserved for validation. This approach allowed estimation of how well each model could classify previously unseen data (Pic 2).



Pic. 2 Naive Bayes 72.8% Result

Result and Review

The results showed that machine learning algorithms were able to classify binary cognitive responses from EEG data with moderate success. Although all tested models demonstrated some classification capability, their performance differed depending on the algorithm and the channel configuration used.

Among all evaluated classifiers, the Naive Bayes model achieved the highest performance, with an accuracy of 72.8%. This result indicates that the model was able to identify meaningful differences between EEG patterns associated with “yes” and “no” responses. While the accuracy is still below the level required for dependable clinical use, it provides clear evidence that the approach is feasible.

The selected model was further evaluated using several standard validation tools. The confusion matrix showed the distribution of correct and incorrect classifications for both response classes (pic. 3), helping to reveal the balance between true predictions and misclassifications. The ROC curve provided additional information about the model’s ability to separate the two classes across different thresholds. In addition, the parallel coordinates plot illustrated the distribution of features and the degree of overlap between the classes.

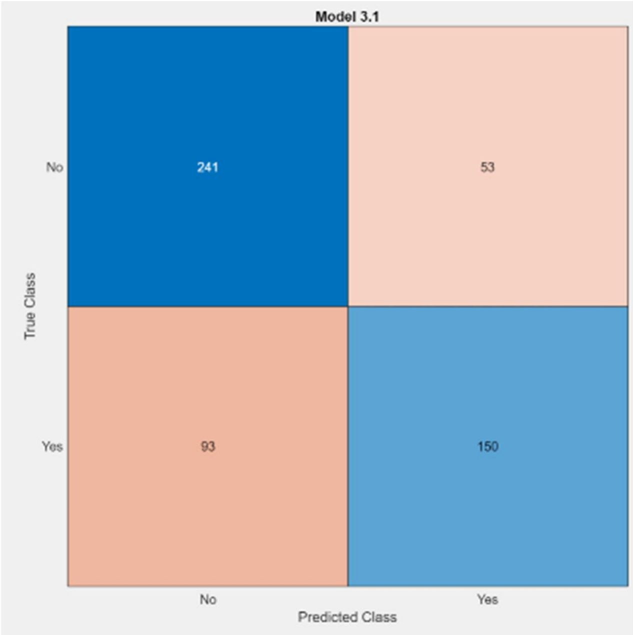
These validation tools confirmed that the classifier captured differences between the two internal response states, although the separation was not perfect. This is expected in EEG-based classification tasks, where signals are often weak, noisy, and highly variable across trials.

The findings of this study are important because they support the concept of using EEG-based artificial intelligence systems for communication assistance. For ALS patients, even a simple binary communication system could be valuable. The ability to answer yes/no questions may help patients express essential needs, make simple choices, and maintain a basic level of interaction with caregivers and family members.

At the same time, the study has several limitations. First, the experiment included only two healthy participants, which limits the generalizability of the results. EEG signals differ significantly across individuals, and performance may vary even more in clinical populations such as ALS patients.

Second, the study used relatively basic preprocessing and direct classification methods. More advanced feature extraction techniques, such as frequency-domain analysis, wavelet transforms, or time-frequency methods, may improve classification performance in future work.

Third, the experiment was conducted under controlled laboratory conditions. Real clinical use would introduce additional factors such as fatigue, reduced concentration, disease progression, and individual neurological differences. Therefore, the present results should be considered preliminary.



Pic. 3 Validation Confusion Matrix

Conclusion

This study examined the feasibility of improving communication in ALS patients through the use of EEG-based artificial intelligence systems. The results showed that machine learning methods can classify binary cognitive responses such as “yes” and “no” from EEG recordings obtained in a controlled environment.

Among the tested algorithms, the Naive Bayes classifier produced the best result, with an accuracy of 72.8%. Although this level of accuracy is not yet sufficient for direct clinical implementation, it demonstrates the potential of EEG-based brain–computer interfaces as assistive communication tools.

The research provides an initial foundation for the development of non-invasive communication systems for individuals who have lost the ability to speak or move. Future studies should focus on expanding the dataset, improving preprocessing and feature extraction methods, and evaluating the system in more realistic and clinically relevant conditions.

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