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A Low-Cost Single-Channel EEG Brain–Computer Interface for Decoding Binary Commands from Self-Generated Emotional States

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Abstract

Brain–computer interface (BCI) systems aim to establish direct communication pathways between neural activity and external devices, enabling interaction without relying on conventional neuromuscular mechanisms. This study investigates the feasibility of decoding binary decisions (“Yes”/“No”) from self-generated cognitive–emotional modulation patterns using a single-channel low-cost EEG device. The proposed approach evaluates whether internally generated modulation strategies can produce distinguishable neural activity suitable for BCI applications under constrained acquisition conditions. EEG signals were recorded from two participants using a consumer-grade headset while they responded to questions through intentional internal modulation associated with affirmative and negative responses. The recorded signals were preprocessed, and multiple feature representations were extracted, including raw temporal data, cepstral coefficients, spectral power, and continuous wavelet transform (CWT) features. Several machine learning and deep learning models, including convolutional neural networks (CNN), long short-term memory networks (LSTM), and support vector machines (SVM), were trained and evaluated using hold-out and stratified k-fold validation strategies. The best performance was achieved by a CWT-based CNN model, reaching an average accuracy of 80.5%, significantly above chance level. Additional models, including CEP-CNN and RAW-LSTM, achieved competitive results, highlighting the relevance of feature representation in EEG-based classification tasks. The results demonstrate that internally generated modulation patterns can produce distinguishable EEG responses, even when using low-cost single-channel hardware. Although the limited number of participants constrains statistical generalization, this work serves as a proof-of-concept and provides a reproducible experimental pipeline for future studies. Overall, the findings support the development of accessible, scalable, and user-centered BCI systems based on internally generated neural modulation strategies, contributing to more natural interaction paradigms in EEG-based communication systems.



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Keywords: brain–computer interface; EEG signal processing; low-cost EEG; single-channel EEG; cognitive and affective state monitoring; deep learning; continuous wavelet transform; binary classification; assistive neurotechnology; human–machine interaction

1. Introduction

Brain–computer interfaces (BCIs) enable direct communication between the human brain and external devices by translating neural activity into control commands without relying on conventional neuromuscular pathways [1,2]. Over the past two decades, BCIs have evolved from experimental laboratory systems to practical tools with applications in neurorehabilitation, assistive technologies, human–computer interaction, and cognitive monitoring. Among the different neuroimaging techniques available, electroencephalography (EEG) has become the most widely used signal acquisition modality for BCI systems due to its non-invasive nature, high temporal resolution, portability, and relatively low cost compared with techniques such as functional magnetic resonance imaging or magnetoencephalography [3,4]. Recent advances in EEG-based emotion recognition have been driven by deep learning models capable of capturing complex spatial–temporal patterns in neural signals [3,4]. Convolutional neural networks, recurrent architectures, and hybrid models have demonstrated strong performance when applied to high-density EEG datasets [5–7]. More recently, transformer-based architectures and graph neural networks have further improved classification performance by modeling long-range dependencies and channel relationships [8–10]. Additional studies based on contrastive learning and capsule-based representations have also demonstrated promising performance in EEG-based affective computing scenarios [11–13]. However, most of these approaches rely on multi-channel EEG systems and externally induced stimuli, limiting their applicability in real-world scenarios. Additionally, many existing studies assume that externally induced emotional stimuli directly correspond to stable affective EEG patterns, while fewer works investigate internally generated modulation strategies under user-driven conditions. In contrast, the use of self-generated cognitive–emotional modulation combined with low-cost EEG devices remains underexplored, particularly for binary decision decoding tasks in practical BCI applications. Advances in signal processing and machine learning have significantly improved the capacity to extract meaningful information from EEG signals. Traditional EEG-based BCI systems relied on handcrafted features derived from spectral power, band energy, or statistical descriptors, which were subsequently classified using algorithms such as support vector machines, linear discriminant analysis, or k-nearest neighbors [2,14]. Although these approaches demonstrated the feasibility of decoding cognitive states from neural activity, their performance often depended heavily on feature engineering and subject-specific calibration procedures [14]. As a result, recent research has increasingly explored data-driven approaches capable of learning hierarchical representations directly from EEG signals. In particular, deep learning techniques have significantly transformed EEG signal analysis by enabling automatic feature extraction from complex neural patterns. Convolutional neural networks (CNNs) have demonstrated strong capabilities for learning spatial and time–frequency representations from EEG signals, while recurrent neural networks and long short-term memory (LSTM) architectures can model temporal dependencies in neural sequences [5,6]. These models have shown promising results across several BCI tasks, including motor imagery decoding, cognitive workload estimation, and emotion recognition [3,4]. By learning representations directly from raw or minimally processed signals, deep neural networks can capture subtle neural dynamics that are difficult to model using traditional feature engineering approaches [15,16]. Emotion recognition from EEG signals has emerged as a particularly relevant research area within affective computing and adaptive human–computer interaction. Emotional states influence neural activity across multiple frequency bands, including alpha, beta, and theta rhythms, allowing the identification of affective responses through EEG analysis [17,18]. Several studies have demonstrated that machine learning models can successfully classify emotional states by exploiting spectral, statistical, or time–frequency features extracted from EEG signals [19].

In this context, publicly available datasets such as DEAP have played an important role in advancing research by providing standardized benchmarks for evaluating emotion recognition algorithms [20,21]. These datasets typically involve emotionally evocative stimuli such as videos or music, enabling the investigation of neural responses to externally induced emotional experiences. More recently, the availability of consumer-grade EEG devices has opened new possibilities for developing accessible and low-cost BCI systems. Devices such as portable or wearable EEG headsets allow researchers to conduct experiments outside specialized laboratory environments while significantly reducing hardware costs. Although these devices generally provide fewer channels and lower signal quality compared with clinical EEG systems, several studies have demonstrated that they can still support meaningful EEG-based research and experimental BCI applications [22–24]. The development of reliable analysis methods for low-cost EEG signals is therefore essential for expanding the accessibility of neurotechnology and enabling real-world BCI applications [19]. Beyond conventional handcrafted approaches, several studies have explored alternative machine learning and deep learning strategies for EEG-based emotion recognition. Survey work has emphasized the importance of robust signal processing, calibration procedures, and user adaptation in BCI systems [25,26]. Other studies have investigated recurrent and hybrid neural architectures for learning latent EEG representations, showing that sequential and hybrid models can improve the discrimination of affective states under controlled conditions [7,15,27]. Additional studies using deep recurrent and convolutional approaches have also reported improved performance in EEG-based emotion classification tasks [28–30]. At the same time, recent studies have investigated advanced deep learning architectures for EEG-based emotion recognition and cognitive state classification. Approaches combining convolutional networks with transformer-based architectures, graph neural networks, and contrastive learning frameworks have demonstrated promising performance improvements by capturing complex spatial–temporal dependencies in neural signals [9,10]. Related studies based on deep belief models, attention mechanisms, hybrid deep structures, and transformer-like frameworks also report improvements in feature discrimination and generalization [8,31]. Despite these advances, most existing studies rely on high-density EEG systems with multiple electrodes and large-scale datasets collected under controlled experimental conditions. Consequently, the feasibility of decoding meaningful emotional patterns using low-cost EEG devices with limited spatial resolution remains an open research question. Furthermore, many emotion recognition studies focus on externally induced emotional responses triggered by multimedia stimuli such as images, videos, or music. While this paradigm is useful for understanding affective processing, it does not necessarily reflect scenarios in which users intentionally generate internal modulation strategies to control BCI systems. In practical BCI applications, the ability to voluntarily modulate internal cognitive–emotional states could provide an alternative mechanism for generating control commands, particularly in systems designed for individuals with limited motor capabilities [1,26]. However, internally generated cognitive strategies may involve overlapping attentional, cognitive, and affective processes, making their interpretation more complex in low-density EEG acquisition settings. Despite the progress achieved in EEG-based emotion recognition, an important gap remains in the literature. Most existing studies rely on externally induced emotions, high-density multi-channel EEG systems, and benchmark datasets collected under controlled laboratory conditions. As a result, current evidence is still limited regarding whether voluntarily self-generated cognitive–emotional modulation patterns can be used to encode binary decisions using accessible low-cost single-channel EEG devices. This unresolved question is especially relevant for practical brain–computer interface applications that require affordable hardware and user-driven interaction paradigms. To address this gap, the present study investigates

the feasibility of decoding binary responses (“Yes”/“No”) from self-generated cognitive–emotional modulation patterns using a low-cost single-channel EEG device. Rather than claiming definitive emotion recognition, the proposed approach evaluates whether internally generated modulation strategies can produce sufficiently separable EEG patterns for binary decision decoding under constrained acquisition conditions. Several machine learning and deep learning models are evaluated using multiple signal representations, including raw EEG, cepstral coefficients, spectral features, and continuous wavelet transform representations, in order to identify configurations that combine decoding performance with accessibility and reproducibility. The main contributions of this work are summarized as follows:

- (1) A novel framework for decoding binary responses from internally generated cognitive–emotional modulation patterns using low-cost EEG signals.
- (2) A comparative evaluation of multiple feature representations and machine learning models under constrained single-channel acquisition conditions.
- (3) A proof-of-concept validation demonstrating the feasibility of binary EEG decoding using consumer-grade hardware.

2. Related Work

Emotion recognition using electroencephalography (EEG) signals has become an important research topic within the fields of affective computing and brain–computer interfaces (BCIs). Emotional processes influence neural activity across several frequency bands, including alpha, beta, and theta rhythms, allowing affective states to be inferred from EEG recordings [17]. Early studies demonstrated that EEG signals contain discriminative information associated with emotional processing [18], establishing the foundations for computational approaches aimed at decoding emotional states from neural activity.

To support the development and evaluation of emotion recognition systems, several benchmark datasets have been introduced. Among them, the DEAP dataset has become one of the most widely used resources for EEG-based emotion recognition research [20]. This dataset provides multimodal physiological recordings collected while participants watch emotionally evocative videos. Similarly, the MAHNOB-HCI dataset integrates EEG recordings with other physiological signals to analyze emotional responses in multimedia interaction scenarios [21]. These datasets have enabled systematic comparisons between machine learning models under standardized experimental conditions.

Traditional approaches to EEG-based emotion recognition rely on handcrafted features derived from signal processing techniques such as spectral power estimation, wavelet transforms, and statistical descriptors [19]. These features are typically classified using machine learning algorithms such as support vector machines or k-nearest neighbors [17]. While these methods demonstrated the feasibility of classifying emotional states from EEG signals, their performance often depends on the quality of manually engineered features and may require significant domain expertise [14,25].

More recently, deep learning approaches have significantly improved EEG signal classification by enabling automatic feature extraction from complex neural patterns. Convolutional neural networks have demonstrated strong performance in learning spatial and time–frequency representations from EEG signals [5,6]. Hybrid architectures combining convolutional layers with recurrent or other deep components have also been proposed to capture temporal dependencies in neural activity and improve classification performance [7,27]. Additional studies have explored recurrent and sequential strategies for affective EEG analysis [15,16]. Related works have also reported improvements using deep models tailored to emotional EEG decoding [28,29].

Recent advances in neural architectures have introduced transformer-based models, graph neural networks, and contrastive learning frameworks for EEG emotion recognition. These approaches aim to capture complex spatial–temporal relationships between EEG channels and improve cross-subject generalization performance [9,10]. Other studies have explored capsule-based, attention-enhanced, and hybrid deep frameworks for richer feature discrimination [11,12]. Additional methodological developments include deep belief models, attention-guided architectures, and transformer-inspired variants [30]. More recent contributions continue to extend this landscape with hybrid, attention-based, and transformer-oriented EEG classifiers [8,13,31]. Although these models achieve high classification accuracy, most studies rely on high-density EEG systems with dozens of electrodes and large publicly available datasets collected under controlled laboratory conditions.

Another important research direction focuses on the use of consumer-grade EEG devices for developing portable and accessible BCI systems. Compared with clinical EEG systems, these devices provide fewer channels and reduced spatial resolution but significantly lower hardware costs and greater portability [24]. Several studies have evaluated the reliability of consumer EEG devices for research applications. For example, Badcock et al. demonstrated that the Emotiv EPOC headset can capture event-related potentials with acceptable research quality [22]. Similarly, Ratti et al. compared consumer and medical EEG systems and reported comparable performance in certain BCI tasks [23]. More recent work has extended this line toward mental-state classification using consumer-grade devices and deep learning frameworks [32]. However, the reduced spatial resolution of consumer EEG devices presents challenges for reliable emotion recognition.

Furthermore, most existing emotion recognition studies rely on externally induced stimuli such as videos, images, or music to elicit affective responses. While this paradigm is useful for analyzing emotional processing, it does not necessarily represent scenarios in which users intentionally generate emotional states to control BCI systems. The ability to voluntarily modulate internal emotional or cognitive states could provide an alternative mechanism for generating commands, particularly in assistive technologies designed for users with limited motor capabilities [26].

This reveals a gap between high-performance EEG emotion recognition systems and accessible BCI implementations, particularly in scenarios requiring intentional and self-generated control signals.

Despite the high performance reported in previous studies, most approaches achieve accuracies above 85% under controlled laboratory conditions using multi-channel EEG systems [18]. These results are not directly transferable to real-world scenarios involving low-cost devices and self-generated emotional responses. Additionally, many studies rely on externally induced stimuli, which may not reflect intentional user-driven control mechanisms required in practical BCI systems [2,25,26].

The present study contributes to this research line by investigating the feasibility of decoding binary responses (“Yes”/“No”) from internally generated cognitive–emotional modulation patterns using EEG signals acquired from a low-cost single-channel device. Unlike previous studies that rely on multi-channel EEG systems and externally induced stimuli, this work explores whether internally generated modulation strategies can produce distinguishable neural patterns suitable for command decoding. Additionally, the study performs a comparative evaluation of several machine learning and deep learning models using different signal representations, including raw EEG signals, cepstral coefficients, spectral features, and continuous wavelet transform representations.

Table 1 summarizes representative studies in EEG-based emotion recognition with emphasis on the experimental stimulus, EEG device configuration, and feature representations.

This overview highlights that most prior studies rely on externally induced stimuli and multi-channel EEG systems, whereas the present study explores self-generated emotional responses using a low-cost single-channel device.

Table 1. Comparison of representative EEG-based emotion recognition studies.

Study	Device	Ch.	Stimulus	Features
Lin et al. (2010) [17]	Medical EEG	32	External (music)	Spectral power
Zheng & Lu (2015) [18]	EEG system	62	External (videos)	Differential entropy
Tabar & Halici (2017) [33]	EEG system	32	Motor task	Time–frequency (CWT)
Lawhern et al. (2018) [6]	EEG system	32	Task-based	Raw EEG
Li et al. (2016) [27]	EEG system	32	External	CNN-based features
Cheng et al. (2024) [9]	EEG system	32	External	Spectrogram
Hu et al. (2024) [11]	EEG system	62	External (SEED)	Temporal features
This work	MindWave Mobile 2	1	Self-generated	Raw/Cepstral/CWT

The comparison shows a clear methodological distinction between prior work and the present study. Most published approaches employ external stimuli, such as videos or music, and use multi-channel EEG systems to support richer spatial representations. By contrast, this study focuses on internally generated modulation strategies and evaluates whether a minimal hardware configuration can still provide sufficiently informative patterns for binary decision decoding. This difference is central to the practical contribution of the study, as it shifts the discussion from benchmark-driven emotion recognition toward accessible and user-driven BCI communication scenarios.

Because the proposed framework is intentionally designed around affordable neurotechnology, it is important to situate the study within the literature on low-cost EEG devices. Table 2 presents representative works that explore consumer-grade EEG systems for BCI, ERP validation, mobile neurotechnology, and mental-state classification.

Table 2. Representative studies using low-cost EEG devices for BCI and emotion recognition.

Study	Device	Ch.	Application	Key Approach
Badcock et al. (2013) [22]	Emotiv EPOC	14	ERP validation	Event-related potentials
Ratti et al. (2017) [23]	Emotiv headset	14	BCI evaluation	Comparative analysis
Casson (2019) [24]	Wearable EEG	1–8	Mobile BCI	Portable neurotechnology
Dadebayev et al. (2022) [32]	Consumer EEG	Multi	Emotion recognition review	Consumer devices and ML techniques
This work	MindWave Mobile 2	1	Emotion-based commands	Self-generated emotional modulation

The comparison indicates that low-cost EEG devices have already demonstrated value in research contexts, particularly for validation, mobile BCI, and mental-state recognition. However, most reported studies still use multi-channel consumer systems or focus on tasks different from intentional binary command generation. In this context, the present study extends the low-cost EEG literature by evaluating self-generated emotional responses as a direct control mechanism using a single-channel device, which reinforces the study’s practical orientation toward accessible BCI communication.

In summary, although EEG-based emotion recognition has achieved significant advances through the use of deep learning and large-scale datasets, current approaches remain constrained by their reliance on high-density acquisition systems and externally induced stimuli. This limits their applicability in real-world BCI scenarios, particularly those requiring accessible, low-cost, and user-driven interaction paradigms. The present study addresses these limitations by proposing a novel framework for decoding internally generated cognitive–emotional modulation patterns using a single-channel EEG device, contributing to the development of more scalable and practical BCI systems.

3. Materials and Methods

3.1. Experimental Design

The objective of this study is to evaluate the feasibility of decoding binary responses (“Yes”/“No”) from internally generated cognitive–emotional modulation patterns using electroencephalography (EEG) signals acquired with the NeuroSky MindWave Mobile 2 (NeuroSky Inc., San Jose, CA, USA), a low-cost single-channel consumer-grade device. Unlike conventional EEG-based emotion recognition studies that rely on externally induced stimuli, this work focuses on internally generated modulation strategies, exploring whether internally generated affective states can produce distinguishable neural patterns suitable for brain–computer interface applications [1]. This paradigm aligns with foundational BCI frameworks and recent advances in user-centered EEG interaction [2].

The experimental paradigm simulates a decision-making scenario in which participants internally associate emotional states with binary responses. Positive emotional modulation corresponds to affirmative responses (“Yes”), while negative emotional modulation corresponds to negative responses (“No”). This paradigm is particularly relevant for assistive BCI systems, where users may rely on internal cognitive processes for communication [26]. Previous studies have highlighted the importance of user adaptation and cognitive strategies in BCI performance [25].

Participants completed multiple sessions composed of repeated trials. EEG signals were recorded continuously and segmented into temporal windows corresponding to each trial, generating labeled EEG segments associated with binary emotional responses.

3.2. Participants

The study was conducted with two participants as part of an exploratory validation phase. This initial sample size is consistent with early-stage EEG-based BCI research, where the primary objective is to evaluate signal separability and methodological feasibility rather than population-level generalization [1]. Similar pilot configurations have been used to assess user-dependent performance in BCI systems [26].

Both participants performed multiple experimental sessions under controlled conditions. The experimental design ensured consistency in data acquisition and task execution across sessions. Analyses were conducted independently for each participant. Given the small sample size ($N = 2$), results are reported per subject and the study is framed as an exploratory proof-of-concept aimed at establishing feasibility and signal separability under single-channel, consumer-grade acquisition conditions, rather than at supporting population-level inference. Consistency of a given finding across both participants is reported descriptively as a preliminary replication signal, with the explicit caveat that $N = 2$ does not constitute statistical replication and that any observed pattern requires validation in a larger cohort before it can be treated as systematic [2,26].

Both participants were native Spanish speakers, and all experimental questions and task instructions were presented in Spanish. The affirmative response—labeled “Yes” throughout this manuscript for readability—corresponds to the Spanish word “sí” as used during data collection, which appears in the original confusion-matrix figure as “Si”.

3.3. EEG Acquisition

EEG signals were recorded using the NeuroSky MindWave Mobile 2, a single-channel consumer-grade EEG headset that captures frontal neural activity from the FP1 position according to the international 10–20 electrode placement system. The device captures neural activity from a frontal location and transmits the data wirelessly.

The device samples EEG signals at 512 Hz and provides both raw signals and spectral power estimates associated with EEG frequency bands. Signal quality indicators are also included.

Although the device operates with a single EEG channel, its temporal resolution allows capturing neural dynamics associated with cognitive and emotional processes. The use of low-cost hardware enables scalable and accessible BCI solutions [22,23]. Wearable EEG technologies further support the development of mobile neurotechnology applications [24]. More recent approaches have demonstrated the feasibility of deep learning with consumer-grade EEG devices [32].

3.4. Data Understanding

EEG signals are inherently non-stationary and exhibit significant temporal variability. An exploratory analysis was conducted to understand signal behavior and identify relevant characteristics prior to model development.

The dataset includes raw EEG signals, spectral power features, and signal quality indicators. Neural oscillations in frequency bands such as delta, theta, alpha, beta, and gamma are associated with cognitive and emotional processes [17]. Frequency-based analysis has been widely used for emotion recognition tasks [18].

Exploratory analysis included visual inspection of signals, statistical evaluation, and correlation analysis between features.

3.5. Data Preparation and Signal Preprocessing

EEG signals are susceptible to artifacts such as eye movements, muscle activity, and environmental noise. Therefore, preprocessing is essential to improve data quality [14]. Deep learning studies also emphasize the importance of preprocessing for robust EEG classification [4].

Signal quality indicators were used to remove unreliable segments. The continuous EEG recordings were segmented into temporal windows aligned with experimental trials. Each segment represents neural activity during emotional modulation. Signal conditioning relied on the device’s internal preprocessing and on the hardware-provided signal-quality indicator, which was used to reject segments acquired under poor electrode contact. The application of additional software-level bandpass or notch filtering beyond the device’s internal conditioning is not documented in the acquisition pipeline available to the authors.

Signals were normalized to reduce amplitude variability and improve robustness in subsequent analysis. The specific normalization scheme applied in the original acquisition pipeline is not recoverable from the available documentation and is acknowledged as a reproducibility limitation in Section 5.

3.6. Feature Extraction

To capture the complexity of EEG signals, multiple feature representations were considered. EEG signals contain information distributed across time and frequency domains, making it necessary to evaluate different representations.

Raw EEG signals preserve temporal dynamics and allow deep learning models to learn representations directly from data [5]. Spectral features describe power distribution across frequency bands and are associated with emotional processing [17]. Additional studies highlight the relevance of spectral representations for emotion classification [19]. Cepstral coefficients provide a compact representation of spectral characteristics.

Time–frequency representations were obtained using continuous wavelet transform (CWT), which is particularly suitable for analyzing non-stationary signals such as EEG [33]. Previous research has also demonstrated the effectiveness of time–frequency representations in deep EEG models [4]. Figure 1 presents an example of the time–frequency representation generated using the CWT applied to EEG signals.

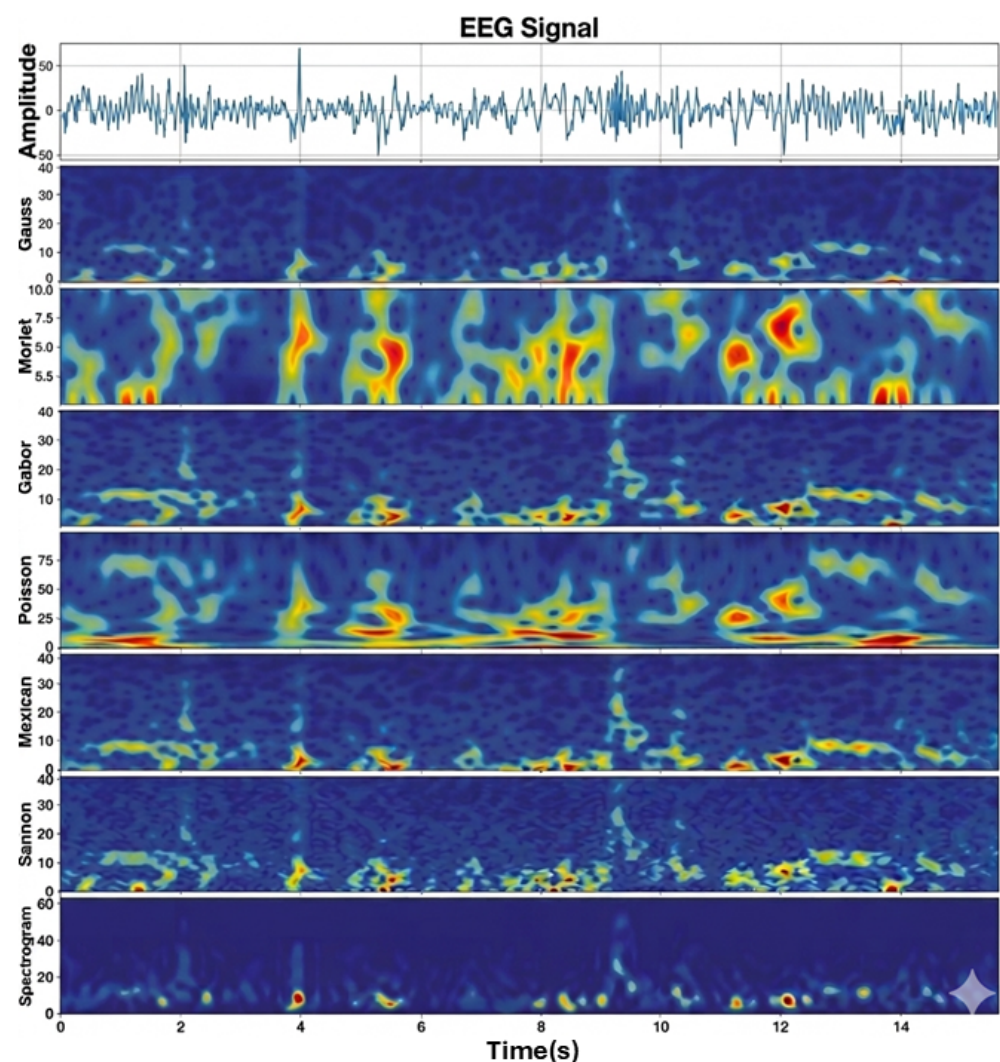


Figure 1. Time–frequency representation of EEG signals using continuous wavelet transform (CWT). Warmer colors (yellow / red) indicate higher signal energy or coefficient magnitude, whereas cooler colors (blue) represent lower energy levels across time–frequency scales.

3.7. Classification Models

Different classification models were evaluated to determine their effectiveness in decoding emotional responses. Both traditional and deep learning approaches were considered.

Support Vector Machines (SVM) were used as a baseline due to their effectiveness in high-dimensional feature spaces. Convolutional Neural Networks (CNN) were employed to learn spatial patterns from time–frequency representations [6]. Long Short-Term Memory (LSTM) networks were used to model temporal dependencies in EEG sequences [7,16].

3.8. Implementation Details

This subsection consolidates the implementation parameters required for reproducibility. The deep learning models were implemented in Python 3.9 using the Keras library, and the support vector machine classifier was implemented using scikit-learn. Continuous wavelet transforms were computed with SciPy, and cepstral coefficients were extracted using the `python_speech_features` library.

3.8.1. Trial Segmentation and Synchronization

Each experimental trial was structured around a generic yes/no question presented to the participant. After reading the question and deciding on the answer, the participant voluntarily generated a positive emotional stimulus for an affirmative response or a negative emotional stimulus for a negative response, sustaining the stimulus for approximately two seconds while EEG activity was recorded. The response window was defined as the final two seconds of each recording, which corresponds to 1024 raw samples at the device's 512 Hz sampling rate. Data captured during the earlier question-reading and decision phase were discarded. For the EEG spectral power stream, which the device outputs at 1 Hz, the last two records per trial were retained and a 5-s synchronization delay was applied to compensate for the buffering delay measured between the device's Bluetooth transmission and the acquisition program.

3.8.2. Feature Extraction Parameters

The four feature representations were extracted with the following parameters. Raw EEG: the 1024-sample response window was used directly as a temporal vector. Cepstral coefficients: 26 coefficients were computed per analysis window of 350 samples with a step size of 100 samples, yielding a matrix of coefficients per trial. Continuous wavelet transform: the Ricker (Mexican hat) mother wavelet was used, selected after preliminary comparison with the Morlet wavelet; scales ranged up to 128, producing a time–frequency scalogram per trial. EEG spectral power: the ten canonical band-power values provided by the device (low/high alpha, low/high beta, low/high gamma, delta, theta, attention, meditation) were read from the last two 1 Hz records per trial and flattened into a 20-dimensional feature vector.

3.8.3. Model Architectures

All deep learning models use a two-neuron sigmoid output layer for binary classification, batch normalization layers to aid convergence, and dropout with rate 0.2 to mitigate overfitting. Architecture-specific details are as follows.

RAW/LSTM. An LSTM-based recurrent architecture that processes the 1024-sample raw EEG sequence directly.

CEP/CNN. A convolutional architecture operating on the cepstral coefficient matrix. Two convolutional layers with 2×2 kernels and ReLU activations (32 and 64 filters respec-

tively), each followed by 2×2 max-pooling. The convolutional block feeds into two fully connected layers with 128 and 64 neurons, also with ReLU activations.

CWT/CNN. A convolutional architecture operating on the CWT scalogram, treating it as a two-dimensional time–frequency representation. Two convolutional layers with 3×3 kernels and LeakyReLU activations (16 and 32 filters respectively), with 2×2 max-pooling. The convolutional block feeds into two fully connected layers with 128 and 64 neurons, also with LeakyReLU activations.

EEGPOWER/LSTM. An LSTM-based architecture that processes the 20-dimensional flattened spectral power vector as a short temporal sequence.

EEGPOWER/SVM. A support vector machine classifier trained on the 20-dimensional spectral power vector. Kernel and regularization were tuned per subject: a linear kernel with $C = 500$ for Subject 1, and a sigmoid kernel with $C = 2$ for Subject 2.

3.8.4. Training Configuration

Training hyperparameters were selected per model. RAW/LSTM was trained for up to 100 epochs with the Adam optimizer and batch size 32, with an early stopping criterion triggered when training accuracy exceeded 0.72. CEP/CNN was trained for up to 200 epochs with the SGD optimizer and batch size 16, stopping when training accuracy exceeded 0.75 and validation accuracy exceeded 0.60. CWT/CNN was trained for up to 200 epochs with the Adam optimizer and batch size 32, stopping when training accuracy exceeded 0.80 and validation accuracy exceeded 0.60. EEGPOWER/LSTM was trained for up to 200 epochs with the Adam optimizer and batch size 16, stopping when training accuracy exceeded 0.80. No class-balancing technique (class-weighted loss, oversampling, or undersampling) was applied during training; the implications of this choice are discussed in Section 5.

3.8.5. Dataset Partitioning

For each participant, the complete set of labeled trials was partitioned randomly into training (70%), validation (10%), and test (20%) subsets. With the full datasets of 225 trials for Subject 1 and 142 trials for Subject 2, this produced test partitions of 45 and 29 segments respectively. The test partition was used exclusively for the final evaluation reported in Section 4, with no exposure during training or hyperparameter tuning. The split was performed using the default pseudo-random number generator of the training program. No explicit random seed was recorded, which means the exact partition used in the original experiments cannot be reproduced bit-for-bit; however, the class proportions, the total counts per subset, and the evaluation metrics reported in Section 4 are fully documented.

3.9. Model Training and Evaluation

Each model was evaluated using a subject-dependent hold-out protocol: for each participant, the full set of labeled EEG segments was split into a training partition (used for model fitting) and a held-out test partition (used exclusively for final evaluation). The resulting test partitions contained 45 segments for Subject 1 and 29 segments for Subject 2. This protocol reflects the single-case, subject-dependent design described in Section 3 and prevents test-set leakage across training epochs. Because no cross-validation was used, performance estimates should be interpreted as single-split evaluations rather than cross-validated averages.

Performance was evaluated using accuracy, precision, recall, F1-score, and per-class confusion matrices. The majority-class baseline—the accuracy that would be obtained by always predicting the more frequent class—is 54.2% for Subject 1 and 53.5% for Subject 2, and serves as the reference against which the reported accuracies should be compared.

3.10. Experimental Workflow

The complete experimental process is summarized in Figure 2. The workflow integrates all stages from data acquisition to model evaluation.

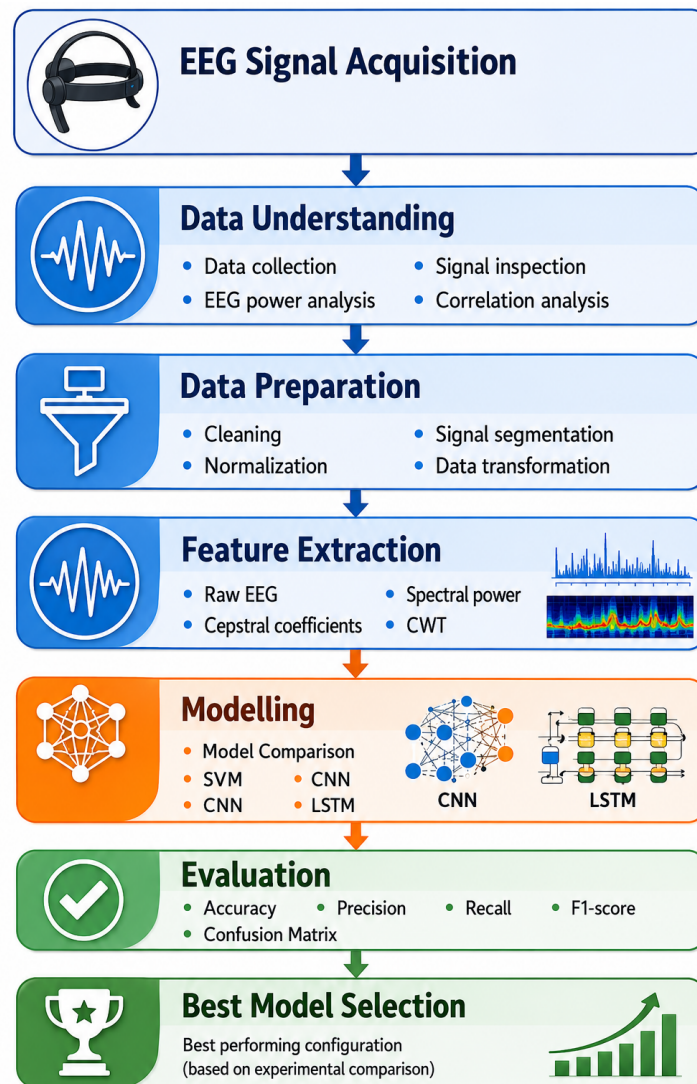


Figure 2. Experimental pipeline of the EEG-based emotion decoding framework. Blue blocks represent the EEG data acquisition, preprocessing, and feature extraction stages. Orange blocks correspond to the application and training of artificial intelligence models. Light green blocks indicate the extraction and evaluation of performance metrics, while dark green blocks represent the final model selection stage based on the obtained metrics.

The proposed workflow follows a structured pipeline that integrates EEG signal acquisition, data inspection, preprocessing, feature extraction, and model development. This structured approach is consistent with established EEG processing frameworks [2]. Deep learning pipelines for EEG classification also follow similar stages of transformation and evaluation [3,4].

The proposed methodology integrates EEG signal acquisition, data understanding, preprocessing, feature extraction, model training, and performance evaluation into a coherent pipeline. EEG signals were collected using a low-cost single-channel device, and preprocessing steps were applied to reduce noise and artifacts. Feature extraction included raw signal analysis, cepstral coefficients, spectral features, and continuous wavelet transform (CWT), which has been widely used for time–frequency representation of EEG signals [3,19].

The extracted features were used to train and evaluate multiple machine learning and deep learning models, including convolutional neural networks, which are known for their ability to learn hierarchical representations from EEG data [5,6]. This structured pipeline ensures methodological consistency, enhances reproducibility, and provides a solid foundation for the interpretation of results.

This study was designed as a proof-of-concept under subject-dependent conditions. Although the number of participants was limited to two, the objective was not statistical generalization but the evaluation of methodological feasibility and signal separability. This design is consistent with exploratory BCI research, where pilot experiments are used to validate control paradigms [1]. Similar approaches emphasize user-dependent evaluation in early BCI stages [25,26].

4. Results

4.1. Dataset Characteristics

The dataset used in this study was generated from EEG recordings collected during the experimental sessions described in the previous section. Each experimental trial produced a labeled EEG segment corresponding to one of the two emotional responses associated with the binary decision task (“Yes” or “No”).

Two subject-dependent datasets were collected. For User 1, the final corpus comprised 225 responses, including 122 labeled as “No” and 103 labeled as “Yes”. For User 2, the dataset comprised 142 responses, including 76 “No” responses and 66 “Yes” responses. This distribution indicates a relatively balanced binary classification setting, although a slight predominance of the “No” class was observed in both cases.

After preprocessing and signal quality filtering, the resulting dataset consisted of segmented EEG signals representing neural activity generated during internally generated modulation strategies. These segments were then transformed into multiple input representations for the classification experiments.

The final experimental data include raw EEG time series, spectral power features derived from canonical EEG frequency bands, cepstral coefficients describing spectral characteristics, and time–frequency representations obtained through continuous wavelet transform (CWT). These representations have been widely used in EEG-based classification tasks due to their ability to capture complementary signal properties [3,19].

The data were divided into training, validation, and testing subsets to assess model generalization and reduce the risk of overfitting under subject-dependent experimental conditions.

4.2. Feature Representation and Model Performance

To investigate the discriminative capacity of EEG signals generated through internally generated modulation strategies, multiple feature representations were evaluated in combination with different classification models. These representations capture complementary characteristics of EEG signals in both temporal and spectral domains.

Raw EEG signals preserve the temporal dynamics of neural activity and allow deep learning models to learn hierarchical representations directly from the signal [5]. Spectral features describe the distribution of signal power across canonical EEG frequency bands associated with cognitive and emotional processes [17]. Cepstral coefficients provide a compact representation of spectral characteristics. Time–frequency representations obtained using continuous wavelet transform provide a detailed description of signal energy evolution across time and frequency, which is particularly suitable for EEG analysis due to its ability to capture transient patterns in non-stationary signals [4,33].

Table 3 summarizes the classification accuracy obtained by each feature-representation and model combination across both participants, ordered by descending average accuracy.

Table 3. Comparative performance of feature-representation and model configurations across users, ordered by descending average accuracy. CWT: continuous wavelet transform; CEP: cepstral coefficients; CNN: convolutional neural network; LSTM: long short-term memory; SVM: support vector machine.

Model/Features	User 1	User 2	Average Accuracy
CWT/CNN	82.0%	79.0%	80.5%
CEP/CNN	78.0%	69.0%	73.5%
EEGPOWER/LSTM	67.0%	79.0%	73.0%
RAW/LSTM	64.0%	76.0%	70.0%
EEGPOWER/SVM	60.0%	69.0%	64.5%

The CWT/CNN configuration achieved the highest overall performance (average 80.5%), with consistent results across both users (82.0% for User 1 and 79.0% for User 2). The CEP/CNN model showed competitive performance at 73.5%, followed by EEGPOWER/LSTM (73.0%) and RAW/LSTM (70.0%). The lowest performance was observed for EEGPOWER/SVM (64.5%), confirming that linear classifiers operating on spectral features are insufficient to capture the non-linear structure of self-generated emotional EEG patterns.

Two patterns emerge from the combined analysis of feature representation and model architecture. First, time–frequency representations provide the strongest discriminative capacity: the CWT-based representation paired with a CNN achieved the highest accuracy for both participants, suggesting that joint time–frequency encoding captures richer discriminative patterns in EEG signals than either raw temporal dynamics or spectral summaries alone. This is consistent with prior EEG deep learning studies that highlight the advantages of structured time–frequency inputs [4,33]. Second, among the spectral approaches, cepstral coefficients (CEP/CNN) outperformed raw spectral power (EEGPOWER/LSTM and EEGPOWER/SVM), suggesting that compact spectral representations preserve relevant emotional information more effectively than direct band-power features under single-channel constraints. Raw EEG (RAW/LSTM) achieved intermediate performance, indicating that temporal dynamics alone contain some discriminative information but are insufficient without a structured frequency decomposition.

These results highlight the advantage of deep learning approaches over traditional machine learning methods. CNN models trained on CWT representations achieved the strongest results, confirming that structured time–frequency inputs are especially suitable for EEG classification under constrained single-channel conditions [5,6]. The inter-subject variability observed—particularly for RAW/LSTM (64% vs. 76%) and CEP/CNN (78% vs. 69%)—is consistent with the known subject-dependent nature of EEG-based emotion recognition [2].

Table 4 presents a detailed breakdown of Precision, Recall, and F1-score per class for the four models whose confusion matrices were available for verification. The EEGPOWER/LSTM model is omitted from this table because its per-class confusion data could not be recovered from the acquisition pipeline available to the authors; its overall accuracy is reported in Table 3.

Table 4. Per-class evaluation metrics for the four models with recoverable confusion matrix data. Class 0 = “No” (Spanish “no”); Class 1 = “Yes” (Spanish “sí”). EEGPOWER/LSTM is omitted because per-class confusion data could not be recovered; its overall accuracy is reported in Table 3.

Model	Subject	Class	Precision	Recall	F1-Score	Accuracy
CWT/CNN	User 1	No	79.3%	92.0%	85.2%	82.2%
		Yes	87.5%	70.0%	77.8%	
	User 2	No	75.0%	93.8%	83.3%	79.3%
		Yes	88.9%	61.5%	72.7%	
CEP/CNN	User 1	No	81.8%	75.0%	78.3%	77.8%
		Yes	73.9%	81.0%	77.3%	
	User 2	No	53.3%	80.0%	64.0%	69.0%
		Yes	85.7%	63.2%	72.7%	
RAW/LSTM	User 1	No	69.2%	42.9%	53.0%	64.4%
		Yes	62.5%	83.3%	71.4%	
	User 2	No	93.3%	82.4%	87.5%	75.9%
		Yes	88.9%	57.1%	69.6%	
EEGPOWER/SVM	User 1	No	50.0%	66.7%	57.1%	60.0%
		Yes	71.4%	55.6%	62.5%	
	User 2	No	73.3%	68.8%	71.0%	69.0%
		Yes	64.3%	69.2%	66.7%	

The metric-level analysis confirms that deep learning configurations achieve a better balance between precision and recall across both classes. The EEGPOWER/SVM configuration shows the weakest per-class balance, with Precision for the “No” class in User 1 dropping to 50.0%, further confirming that linear models are inadequate for this task. Inter-subject variability in recall patterns is consistent with the known challenges of single-channel EEG classification [2].

4.3. Best Model Evaluation

Based on the comparative results, the CWT/CNN configuration was identified as the best-performing model. In addition to its highest average accuracy (80.5%), this model achieved the best F1-scores across both classes and both participants (Table 4), reinforcing the effectiveness of time–frequency representations for decoding internally generated cognitive–emotional modulation patterns.

Figure 3 presents the confusion matrices of the CWT/CNN model across both subjects.

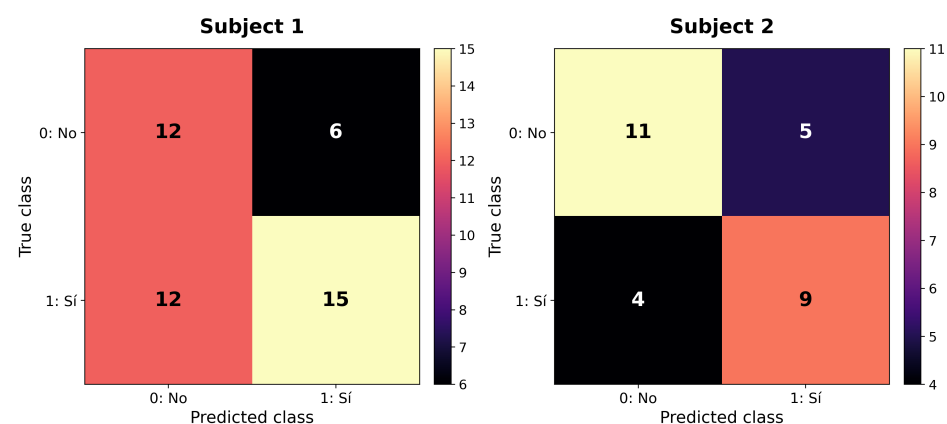


Figure 3. Confusion matrices of the best-performing CWT/CNN model for both participants. Subject 1 (left): TN = 23, FP = 2, FN = 6, TP = 14; accuracy = 82.2%. Subject 2 (right): TN = 15, FP = 1, FN = 5, TP = 8; accuracy = 79.3%. Class 0 = “No” (Spanish “No”); Class 1 = “Yes” (Spanish “sí”, shown in the figure as “Si”).

Examination of the per-class performance across all four configurations with recoverable confusion matrices (Table 4) shows that the asymmetric pattern (higher recall for “No” than for “Yes”) is robust only under the CWT/CNN configuration, where “No” recall exceeds “Yes” recall by 22 percentage points for Subject 1 (92.0% vs. 70.0%) and by 32 percentage points for Subject 2 (93.8% vs. 61.5%). The other configurations show either an inverted direction in one of the two subjects (RAW/LSTM shows Yes > No recall for Subject 1 and No > Yes for Subject 2) or near-balanced per-class recall (CEP/CNN, EEGPOWER/SVM). This cross-model variability is methodologically informative. If the asymmetry were a simple consequence of the mild class imbalance in the training data (54.2% and 53.5% “No” for Subject 1 and Subject 2 respectively), it would be expected to manifest consistently across all models trained on the same data, because the class prior is identical. The fact that it does not argues against a generic prior-inheritance explanation and suggests that the asymmetry reflects discriminative properties specific to the time–frequency representation extracted by the CWT. A definitive separation between signal-based and prior-based contributions would require re-training under class-balanced protocols and is a primary target for follow-up work. Similar class-level asymmetries have been reported in emotion recognition studies using frontal EEG [17,18].

Despite this asymmetry, the model maintains strong overall performance, demonstrating that internally generated modulation strategies can generate sufficiently separable neural signatures for practical binary decoding under minimal hardware constraints [24,32].

Given the exploratory nature of this study and the limited number of participants, formal inferential statistical testing across subjects was not applied. Performance differences are therefore reported descriptively. The CWT/CNN configuration consistently achieved the highest accuracy for both participants (82.0% and 79.0% respectively), providing preliminary within-subject evidence of its superiority over the evaluated baselines. The subject-dependent nature of EEG-based emotion recognition [2] further supports treating each participant’s results as an independent evaluation, consistent with single-subject BCI research designs [26].

5. Discussion

The results of this study demonstrate the feasibility of decoding binary responses (“Yes”/“No”) from internally generated cognitive–emotional modulation patterns using EEG signals acquired from a low-cost single-channel device. The evaluated models achieved consistent performance across subjects, indicating that even minimal EEG configurations can capture discriminative neural patterns when appropriate feature representations are employed. Although the achieved performance levels are lower than those commonly reported for multi-channel EEG systems, they remain substantially above chance level, supporting the viability of the proposed approach under constrained acquisition conditions.

A detailed analysis of subject-specific results (see Tables 3 and 4) reveals variability in model performance, which is consistent with the subject-dependent nature of EEG-based affective and cognitive state classification. Some models achieved higher accuracy for specific individuals, whereas others demonstrated more stable behavior across participants. These findings suggest that personalization plays a critical role in optimizing classification performance in low-density EEG scenarios [26]. This observation is consistent with previous evidence indicating that inter-subject variability remains one of the principal challenges in EEG-based BCI systems and affective computing applications [25].

The comparison between feature representations indicates that time–frequency approaches, such as the continuous wavelet transform, provide richer representations of EEG signals than raw temporal or cepstral features. This finding is consistent with previous studies emphasizing the importance of simultaneously capturing temporal and spectral

dynamics in non-stationary EEG signals [4,33]. Additional reviews further support the relevance of time–frequency representations for improving EEG classification performance [19]. The superior performance achieved by the CWT/CNN configuration suggests that transient time–frequency patterns contain relevant information for distinguishing internally generated modulation states.

From a machine learning perspective, the results confirm that classification performance is influenced not only by model architecture but also by the quality and representation of input features. Although deep learning models have demonstrated strong performance in previous EEG classification studies, their advantages become less pronounced under constrained experimental conditions involving limited data and low-channel acquisition systems. These findings reinforce the importance of selecting appropriate signal representations and avoiding excessive model complexity in low-resource EEG environments [5,6]. Systematic reviews further indicate that preprocessing quality and feature representation strongly influence EEG model performance [3]. Consequently, increased model complexity alone does not necessarily guarantee improved performance in constrained EEG scenarios.

Importantly, this study differs from most previous EEG-based affective classification approaches in that it does not rely on externally induced stimuli such as videos, music, or images. Instead, the proposed paradigm focuses on internally generated modulation strategies associated with binary decision responses. This distinction is especially relevant for practical BCI applications, where users may need to generate commands without dependence on external stimulation [17,18]. Previous work has also highlighted the importance of user-driven paradigms for improving interaction usability in BCI systems [26]. In contrast to conventional paradigms, the proposed approach emphasizes internally generated interaction strategies that may be more suitable for assistive communication scenarios.

The findings indicate that internally generated cognitive–emotional modulation patterns can serve as a viable input modality for binary command decoding, opening new possibilities for accessible and user-driven BCI systems. However, the observed variability across subjects suggests that further research is needed to improve robustness and generalization. Compared with high-density EEG systems reported in the literature, the proposed framework introduces an explicit trade-off between classification accuracy and hardware simplicity, which is an important consideration for real-world deployment.

The observed asymmetry between the “Yes” and “No” classes should also be interpreted cautiously. Although the CWT/CNN configuration achieved higher recognition rates for the “No” class, this behavior may be influenced by multiple factors, including inter-subject variability, class distribution, stopping criteria, or differences in internally generated modulation strategies. Therefore, the results should not be interpreted as evidence of a stable neurophysiological distinction between affirmative and negative emotional responses, but rather as an exploratory observation requiring additional validation under larger experimental settings.

Overall, the results support the hypothesis that low-cost single-channel EEG devices can be used for practical binary decoding tasks when combined with appropriate signal processing and machine learning techniques. This work contributes toward bridging the gap between high-performance laboratory BCI systems and accessible real-world neurotechnology solutions [22,23]. Wearable EEG technologies further reinforce the feasibility of portable and scalable neurotechnology systems [24]. Recent studies have additionally demonstrated the applicability of deep learning approaches in consumer-grade EEG hardware environments [32]. From a practical perspective, the proposed approach may facilitate the development of affordable assistive communication systems for users with severe motor impairments.

Compared with multi-channel EEG systems reported in the literature, which frequently achieve higher accuracy levels under controlled laboratory conditions [18], the proposed framework demonstrates competitive proof-of-concept performance while operating with substantially reduced hardware complexity and acquisition cost. Similar compact neural architectures have also shown effectiveness in EEG classification tasks [6].

Although the proposed framework does not achieve the performance levels commonly reported for high-density laboratory EEG systems, it prioritizes ecological validity, portability, accessibility, and reduced acquisition complexity. These characteristics are essential for the practical adoption of BCI technologies outside controlled laboratory environments, particularly in assistive communication scenarios where low-cost and easy-to-use systems are required.

Although statistical significance tests were not extensively applied in this study, future work will incorporate hypothesis testing, confidence interval estimation, and larger participant cohorts to strengthen result validation and reproducibility.

These findings position internally generated EEG modulation patterns as a promising alternative for intuitive, scalable, and accessible human–computer interaction systems.

Limitations

Several limitations must be considered when interpreting these results. First, the participant sample was limited to two individuals, which restricts statistical generalization and precludes the use of robust inferential analysis across subjects. Consequently, the findings should be interpreted within the context of an exploratory proof-of-concept study, where consistency across independent participants serves as the primary evidence rather than population-level inference. Future studies should incorporate larger and more diverse participant cohorts to evaluate the generalizability of the observed patterns.

Second, the subject-dependent nature of the proposed framework requires model calibration for each user, limiting cross-subject applicability. This challenge has been widely documented in EEG-based BCI research and highlights the need for personalized modeling strategies [26].

Third, the use of a single-channel frontal EEG device substantially reduces spatial information compared with multi-channel systems and increases susceptibility to ocular, muscular, and motion-related artifacts [1]. In addition, wearable EEG technologies inherently provide lower signal quality than laboratory-grade acquisition systems [24]. Although signal quality indicators and preprocessing procedures were used to reduce unreliable segments, residual artifacts may still influence classification performance.

Another limitation concerns the interpretation of the observed class-level asymmetry. Although the CWT/CNN configuration achieved higher recall for the “No” class, this behavior was not consistently observed across all evaluated models. Consequently, alternative explanations related to class distribution, participant-specific strategies, or training dynamics cannot be excluded. This observation should therefore be interpreted as a preliminary finding that requires controlled replication studies using larger datasets and standardized emotional modulation protocols.

Methodological reproducibility limitations must also be acknowledged. Certain implementation details of the original acquisition and training pipeline could not be fully recovered from the available documentation, including whether additional software-level filtering was applied beyond the device’s internal signal conditioning, the precise normalization scheme employed prior to feature extraction, and the random seed used during data partitioning. Although these limitations do not invalidate the reported performance metrics, they may affect exact replication of the experiments. Future implementations will explicitly document these parameters to improve reproducibility.

Future work should address these limitations by incorporating larger participant cohorts, evaluating cross-subject generalization, and exploring hybrid configurations that balance accessibility and signal richness. Future studies may also benefit from integrating more advanced transformer- and graph-based EEG architectures [9,10], contrastive learning approaches [11,12], and recent generalizable deep EEG frameworks [8,13].

6. Conclusions

This study investigated the feasibility of decoding binary responses (“Yes”/“No”) from internally generated cognitive–emotional modulation patterns using EEG signals acquired from a low-cost single-channel device. The results demonstrate that discriminative neural patterns can be extracted from minimal EEG configurations, enabling binary classification performance significantly above chance level under constrained acquisition conditions. In particular, the best-performing configuration based on continuous wavelet transform and convolutional neural networks achieved an average accuracy of 80.5%, highlighting the relevance of time–frequency representations for EEG-based classification tasks.

The comparative evaluation of feature representations demonstrated that time–frequency approaches provide more informative signal characteristics than purely temporal or reduced spectral representations. These findings reinforce the importance of capturing non-stationary EEG dynamics when analyzing internally generated modulation patterns. Furthermore, the results confirm that EEG-based classification remains strongly subject-dependent, particularly in low-density acquisition scenarios, emphasizing the relevance of personalized modeling strategies for practical BCI applications.

Unlike conventional EEG emotion recognition approaches that rely on externally induced stimuli and multi-channel EEG systems, the proposed framework focuses on internally generated modulation strategies associated with binary decision responses. This paradigm represents a shift toward more accessible and user-driven BCI interaction models capable of operating under real-world hardware constraints [1]. Previous studies have also emphasized the importance of adaptive and user-centered interaction paradigms in BCI systems [26]. The use of a low-cost single-channel EEG device further reinforces the potential for scalable and affordable neurotechnology solutions.

Although the proposed framework does not achieve the performance levels commonly reported for high-density laboratory EEG systems, it prioritizes accessibility, portability, reduced acquisition complexity, and ecological validity, which are essential characteristics for the practical adoption of BCI technologies outside controlled laboratory environments. From a practical perspective, the proposed approach may contribute to the development of affordable assistive communication systems for users with severe motor impairments while reducing dependence on complex and expensive EEG infrastructures.

However, several limitations should be considered carefully when interpreting the findings. First, the experimental validation was conducted using only two participants under subject-dependent conditions, which limits statistical generalization. Second, the absence of direct emotional-state validation prevents the interpretation of the observed EEG patterns as definitive emotional responses. Instead, the findings should be interpreted as evidence that internally generated cognitive–emotional modulation strategies can produce distinguishable EEG activity suitable for binary decoding tasks. Third, the use of a single frontal EEG channel increases susceptibility to ocular, muscular, and movement-related artifacts, which may partially influence the classification outcomes.

A consistent class-level asymmetry was observed under the best-performing CWT/CNN configuration, where the “No” class achieved higher recall than the “Yes” class across both participants. Although this behavior may suggest differences in the stability of internally generated modulation patterns, alternative explanations related to class distribution,

participant-specific strategies, or training dynamics cannot be excluded. Consequently, this observation should be interpreted as a preliminary finding that requires validation using larger participant cohorts and class-balanced experimental protocols before establishing systematic neurophysiological interpretations.

Despite these limitations, the proposed framework provides a reproducible proof-of-concept for low-cost EEG-based binary decoding using internally generated modulation strategies. The findings demonstrate that meaningful classification performance can be achieved even with substantially reduced hardware complexity, which is especially relevant for scalable and accessible assistive BCI applications.

Future work should incorporate larger and more diverse participant populations, standardized emotional self-assessment procedures, cross-subject evaluation protocols, and more robust statistical validation strategies, including confidence intervals, repeated experimental runs, and hypothesis testing. Additional research should also explore advanced deep learning approaches such as transformer-based models, graph neural networks, contrastive learning strategies, and hybrid architectures in order to improve robustness and generalization in low-resource EEG environments [9–13].

Overall, this work contributes to the development of scalable, low-cost, and user-centered BCI technologies by demonstrating that internally generated modulation strategies can serve as viable control mechanisms in EEG-based communication systems. These findings open new research directions toward more natural, accessible, and internally driven paradigms for human–computer interaction.

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Institutional Review Board Statement: This study was conducted in accordance with the principles of the Declaration of Helsinki. Formal institutional ethics review was not obtained for this exploratory pilot because the study involves non-invasive EEG data collection from consenting adult participants using consumer-grade equipment, without clinical intervention, pharmacological or genetic analysis, or processing of sensitive personal data beyond de-identified neurophysiological signals. The study involved minimal risk, non-invasive EEG acquisition from adult volunteers under informed consent conditions. Under the research regulatory framework applicable to the authors' institutions (including, in the Chilean context, Ley 20.120 on scientific research involving human beings), studies of this scope and design do not mandate formal institutional review board approval. All participants provided informed consent prior to data collection, and the data presented in this work contain no personally identifying information.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
BCI	Brain–computer interface
CNN	Convolutional neural network
CWT	Continuous wavelet transform
DEAP	Database for Emotion Analysis using Physiological Signals
DL	Deep learning
EEG	Electroencephalography
ERP	Event-related potential
LSTM	Long short-term memory
SVM	Support vector machine
SEED	SJTU Emotion EEG Dataset
CEP	Cepstral coefficients

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