Neural Musical Instruments through Brain-Computer Interface and Biofeedback

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Abstract

In the electronic musical instrument scenario, the current paradigm of sound modification during live performance is predominantly based on the use of external control mechanisms to adjust sound configurations predefined by the performer. However, this approach is limited by the introduction of marginal latencies during the transition between sound configurations. To overcome these limitations, this study introduces a novel application of Brain-Computer Interface (BCI) technology in a control system environment for musical instruments during live performances. The proposed system exploits classification between mental states of *activation* and *relaxation*, employing a Machine Learning (ML) system that achieves an average *Accuracy* of 0.92. Using Beta Protocol, the system allows dynamic modulation of sound according to the mental state of the performer. Finally, an explainability analysis was performed to clarify the impact of specific features during the prediction process.

CCS Concepts

• **Information systems → User Modelling Applications, Wearable Devices**.

Keywords

Brain-Machine Interface, Neural Instrument, Artificial Intelligence, Explainable AI.

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1 Introduction

Electroencephalogram (EEG) is an important method to investigate brain electrical activity. Spontaneous activity is recorded using electroencephalographic devices by placing multiple electrodes on the surface of the scalp. Machine Learning (ML) models are able to classify the desired task by observing signal changes associated with external stimuli, such as sound, video, or internal stimuli, like imagining emotional conditions. From this perspective, Brain Computer Interface (BCI)s, which are portable electroencephalograms with a small number of electrodes placed in the area of interest in relation to the task, are very efficient devices for enabling interaction between humans and external devices. Artificial intelligence (AI) plays an important role for a various applications, including BCI [2], information security applications [4], agriculture [18], Unmanned Aerial Vehicle (UAV) detection [11], cyber attack detection [12] and, emotion recognition [6], biofeedback [5], motor imagery [1], steady-state visual evoked potentials (SSVEPs), and device control [7].

An emerging area of EEG research fields is dedicated to the exploration of these interfaces as tools of musical expression. To the best of our knowledge, the scientific literature regarding the control of musical instruments in real time using BCI is lacking. Our research aims to fill this lack by proposing an innovative system that aims to improve the interactive involvement between musicians and their musical instruments. Furthermore, our study explores two critical research questions regarding BCI-based detection of activation and relaxation mental states. Subsequently, an in-depth explainability analysis was conducted to clarify the predominant features among the subjects and the spatial information derived from the electrode positions.

Motivation. Marzabani et al. [16], describes the use of Beta/Theta (Beta protocols) and Alpha/Delta (Alpha protocols) power ratios as a method for real-time control of activation and relaxation. From our perspective, considering only Beta and Alpha protocols is not enough to distinguish between states of focus and relaxation. A more in-depth investigation that considers the different features and spatial information extracted from the EEG is crucially essential to assess individual variability.

In detail, with this study, we aim to answer the following questions:

- Is it possible to observe how different features cooperate to detect the state of activation across a number of subjects?
- Do certain features emerge across the EEG data of the selected subjects?

We used the SHAP algorithm [14] to perform an explainability analysis of the model prediction to answer the above questions.

Contribution. This research proposes the first implementation of a system that allows neural control of musical instruments based on the classification between activation and relaxation mental states.

Roadmap. Section 3 describes materials and methods for preprocessing EEG signal, classifying the user's mental state and procedures for controlling and manipulating a musical instrument's sound. Section 4 details the experimental settings adopted for our experiments, while results are described in Section 5. Section 6 concludes the paper.

2 Background and Related Work

In the current literature, the use of BCI for controlling musical instruments is a relatively unexplored. This section outlines research contributions that have significantly influenced our study.

Knapp *et al.* [9] introduced the BioMuse system, a pioneering advance that integrates physiological biosensing technology with musical instruments. Using electrodes, the system captures EEG, Electrocardiogram (ECG), and Electromyography (EMG) signals, converting them into digital data for computational interaction. A key finding emphasized the correlation between Alpha and Delta waves in regulating relaxation, and the relationship between Beta and Theta waves in improving activation. This research has facilitated the development of EEG-controlled musical instruments, using these physiological parameters to stimulate musical interaction.

Miranda and Brouse in their work, present BCMI-Piano interfaces [17], which details a new music generation system with a EEG signal processing framework. Within the BCMI-Piano system, distinctive features extracted from the raw EEG signals are used to drive music generation algorithms. The system correlates the generation of musical tempo and dynamics with the Hjorth parameters of Activity, Mobility, and Complexity, whereas pitch organization is linked to the frequency band domain. Furthermore, the Midi protocol enables communication between various electronic musical instruments, leveraging these extracted signal features for music creation.

Alvin Lucier is recognized as a pioneering figure in the utilization of electroencephalography EEG for music generation, as evidenced by his seminal work "Music for Solo Performer" [13, 21]. Lucier's method involved the modulation of Alpha wave amplitudes, recorded through two frontal electrodes, to engage with percussion instruments. This approach utilized the fluctuations in Alpha wave amplitudes to control the actuation of percussion instrument surfaces via the transfer of energy from loudspeakers.

Levican *et al.* [10] outlines the development of a brain-computer-music interface (BCMI) utilizing the Enobio-8 EEG device, which is equipped with eight or more electrodes and a 3D accelerometer. The researchers introduced Enobio2OSC, a software that acquires data from the Enobio device via TCP/IP, processes this data according to frequency bands, and subsequently transmits it utilizing the Open Sound Control (OSC). The manuscript elucidates two demonstrative applications of the BCMI: one leveraging alpha wave synchronization, and the other based on mental arithmetic tasks. Furthermore, the authors developed Max/MSP[1] patches that parse raw EEG and accelerometer data and convert these into musical parameters via OSC. This BCMI architecture provides users the capability to interface with and manipulate musical outputs through physical actions, such as the closing and opening of eyes, head movements, or engagement in mental arithmetic exercises.

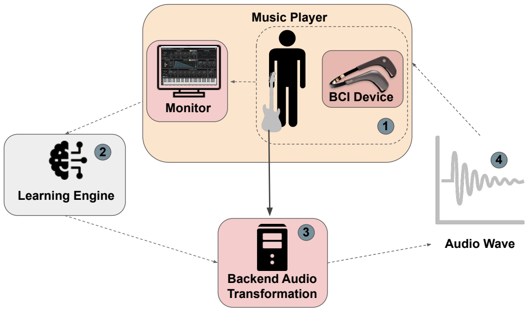

Figure 1: System Architecture.

3 Materials and Methods

In this Section, we describe the architecture and workflow of the system (Section 3.1), the BCI device adopted (Section 3.2), and the Virtual Musical Instrument (VST) paradigm (Section 3.3).

3.1 System Architecture

System architecture, as depicted in Figure 1, is presented into four principal steps. Initially, a musician, equipped with a BCI, engages in playing a musical instrument (in our case, the musician plays a guitar). In *Second Step*, the Learning Engine module receives the EEG signal, preprocesses the signal, and returns the classification value of the pre-trained models. Simultaneously, the Beta protocol, followed by Marzbani *et al.* [16], is employed to compute the coefficient representing the intensity of the Focus mental state. Subsequently, the third step involves an audio transformation backend module, which, based on the classification results, adapts the parameters of the VST. This value is shown on the display monitor and changes the sound produced by the instrument in real time, providing a dynamic and conscious sound modulation experience. In the final stage, the musician, by listening to the modified sound of their instrument, can dynamically control the parameters of the VST based on their real-time mental state. This control mechanism allows for the modification of the selected VST parameter, which can be accomplished by the musician focusing on or ignoring a specific control knob.

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[1] https://cycling74.com/products/max

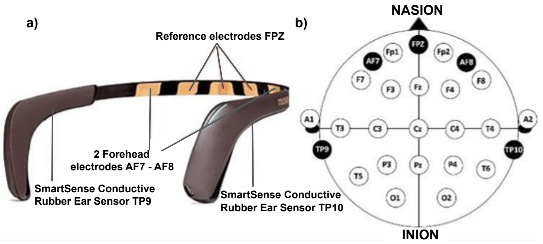


Figure 2: Representation of (a) Muse EEH Headset and (b) international 10-20 **system for the electrode position.**

3.2 Muse Headset

We adopted the *MUSE* 2 device (Figure 2a) in our system. It is an innovative and versatile BCI helmet designed to acquire EEG signals. It incorporates four dry sensors to detect brain activity, ensuring high signal quality while eliminating the need for scalp preparation with conductive gels. Moreover, the helmet is ergonomically designed with an adjustable band to comfortably fit the user's head, ensuring a pleasant experience during operation. Electrical voltages are captured with electrodes located on the user's scalp according to the international 10-20 system (Figure 2b). The electrodes are strategically placed at positions Fpz, $AF7$, $AF8$, $TP9$, and $TP10$ with sampling frequency at 256 Hz.

3.3 Virtual Musical Instrument (VST)

The popularity of musical instruments that interface directly with computers or mobile devices (e.g. iPads and mobile phones) has caused an exponential increase in the use of VST [22]. VST is useful plug-in software for audio and MIDI file editing in specific musical environments such as Digital Audio Work Station (DAW). Indeed, the typical setup adopted by a musician using electronic instruments is to use devices (e.g. USB music keyboards or guitars) interfaced with the computer. The instrument's sound can be obtained by modifying certain parameters of the VST. Based on the previous considerations, our system uses MAX/MSP to develop the graphical user interface of our system. Figure 3 shows the GUI of our system. In particular, three metrics display objects based on the ML models of our systems (described in Section 4) can be seen. Additionally, two buttons were added to preload and display VST. Regarding the chosen open-source VST, the Figure 4 shows the control parameters for sound synthesis.

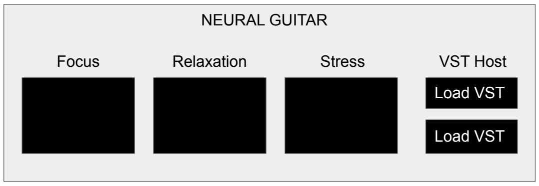


Figure 3: Neural Guitar GUI.

WAVEFORM TX W3
RATE 01.0000
OFFSET (Hz) 0000.13
DETUNE 0 ct
PHASE 0 deg
VEL. SENS. 0
PAN Center
LEVEL 100
FEEDBACK 0
CUTOFF 4713 Hz
RESO 29
ENV AMT 0
VEL. SENS. 0
WAVEFORM Tri
RATE 2/1
DEPTH 18
LEVEL A 0
LEVEL B 0
LEVEL C 0
LEVEL D 17
PITCH 7
CUTOFF 32
GAIN 57

Figure 4: VST GUI.

3.4 Interpretable Model

In the present study, we adopted the SHAP algorithm [14]. The algorithm introduces a variant of Shapley's method. This approach allows a detailed and specific understanding of the influence of the input variables on the model's predictive results.

4 Experimental Settings

The experiments were conducted using the *EEG brainwave dataset: mental state* public dataset [3]. Specifically, the dataset consists of EEG signals from four users (two men and two women), related to the focus, neutral, and relaxation mental states.

The schema of stimuli presented to users during the EEG signal acquisition step is summarized as follows.

- The mental state of relaxation is elicited through listening to relaxing sounds.
- For the neutral condition, no specific stimuli were used. EEG signal was acquired during the normal brain activity.
- For the condition of attention, users performed a task that required them to pay attention to a ball that was hidden under one of the three cups. The test was designed to determine in which cup the ball was hiding.

4.1 EEG Preprocessing Pipeline

EEG signal preprocessing pipeline is crucial for the attenuation of noise components, which are predominantly generated by high-frequency muscle artefacts, head movements, and blinking-eye artefacts.

During the initial step of EEG data analysis, an accurate visual inspection of the dataset was carried out to ensure the signal quality. The $TP9$ and $TP10$ channels were excluded due to high noise levels. Following this preliminary evaluation, data segmentation in a second sub-epoch was performed. Specifically, sub-epochs with amplitude levels above the 150 μV threshold have been systematically excluded from further analysis. Furthermore, the use of the Autoreject [8] facilitated the calculation of a global threshold to identify further noisy epochs. As a result, epochs exceeding this threshold have been omitted.

Table 1: Dataset after whole preprocessing pipeline.

S_{ID}	Fcs	Rx
1	240	698
2	346	418
3	256	610
4	80	506

(a) S_{ID}:Subject$_{ID}$, Fcs:Focus, Rx:Relaxation

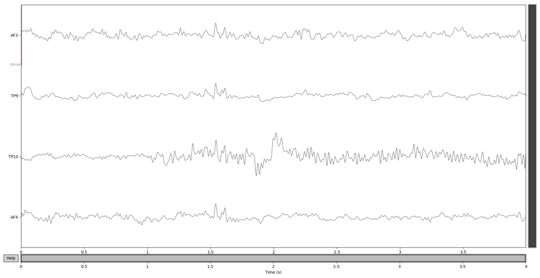


Figure 5: An example of EEG trial (duration 4 *sec.*) post SPA framework.

As can be seen in the pipeline steps listed below, we have applied filtering of signals, eliminating residual noise and extracting relevant features. Therefore, we have applied this process to ensure the integrity and reliability of the EEG data for subsequent analytical efforts.

1. Calibration buffer is created and divided into 32 sub-epoch lists with 32 samples.
2. All sub-epochs are concatenate and filtered between 1 and 40 Hz and processed with SPA algorithm [19].
3. Band power values Delta, Theta, Alpha, and Beta for $AF3$ and $AF4$ channels are extracted with Neurokit2 framework [15] and saved in a second buffer.
4. When the second buffer reaches a size of 50 trials, all buffered trials are averaged.
5. For each user in the dataset, a data frame is created as a dictionary. User_ID, and the previous average band power for each channel is collected.
6. The first sub-epoch is removed from the calibration buffer, and a new trial with 32 samples is queued.
7. Until the end of the EEG signal for every subject, all cycles are repeated.

Figure 5 shows an EEG signal segment after the whole preprocessing pipeline.

In addition, as a result of a series of previous steps, the final dataset is composed of 4 entries with several *focused* epochs equal to 922 and several *relaxed* epochs equal to 2232. Specifically, Table 1 displays the number of EEG epochs for each subject related to focus and relaxation condition.

4.2 Machine Learning LOSO Pipeline

To reach the best model, we adopted a Grid Search in hyperparameter approach, with Leave One Subject Out (LOSO) strategy. Indeed, this is a cross-validation strategy used in ML and highly recommended in biometric data processing. During the training and testing step of a machine learning model, the LOSO involves excluding an entire set of data related to each subject from the whole dataset. The model is trained using data from the remaining subjects and tested on the excluded subjects. This process is repeated for each subject in the whole dataset. The models explored for this task are (i) Neural Network, (ii) AdaBoost, (iii) LogisticRegression, (iv) RandomForest Classifier, and (v) SVM Classifier. Specifically, through Scikit Learn Framework [20], the following pipeline was executed:

- Unique *IDs* have been assigned for the four users present in the dataset.
- According to the LOSO, a training dataset and an independent test are created for all subjects present in the dataset.
- Grid search method in hyperparameter space is used to find the best model.
- Four machine learning models were obtained related to focus/relaxation tasks.

For performance analysis, accuracy, precision, recall, and F1 score were used. These measurements are based on the analysis of the data in a confusion matrix. Accuracy is defined as the percentage of correctly predicted observations relative to the total number of observations. Recall denotes the proportion of correctly predicted observations to all observations in the true class (those that should be positively predicted). Precision signifies the ratio of correctly predicted observations to all observations in the predicted class (those that were positively predicted). The F1 score is a weighted average of both Recall and Precision, thus considering both false negatives and false positives.

5 Results

Table 3 shows the best models obtained during LOSO. Figures 6a, 6b, 6c, and 6d, show the confusion matrix for all test subjects. The average metrics values of all models are shown in Table 4.

The outcomes produced by the four ML models in Section 4, applied to the entire independent test set, are elucidated by the SHAP algorithm. Furthermore, the beeswax plot representing the SHAP values on the test set for all the models are shown in Figs 7a, 7b, 7c, 7d. The SHAP values, shown on the horizontal axis, quantify the magnitude and direction of the contribution of each function to the model output. The negative values indicate a decrease in the expected result, while the positive values indicate an increase. The plots describe the predominance of the Alpha band power value in the $AF3$ channel as a crucial determinant in the predictive accuracy of the model across all subjects. Additionally, the analysis reveals a collaborative interaction between several feature bands and both the $AF3$ and $AF4$ electrodes that influence the model's predictive capacity. The importance of customized approaches in modelling brain activity is highlighted by variability, as individual differences can significantly impact the predictive accuracy of the model.

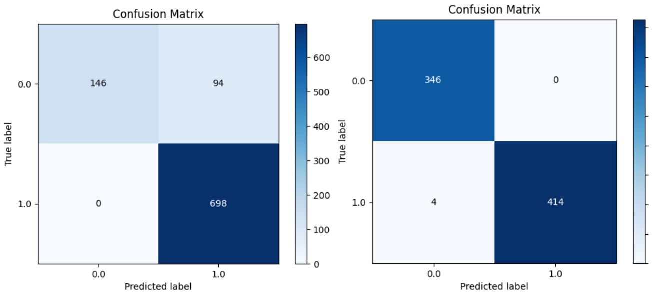
6 Discussion and Conclusion

In this study, a prototype that enhances the expressive potential of musicians during live performances is presented . The developed system is able to classify the states of focus and relaxation of each

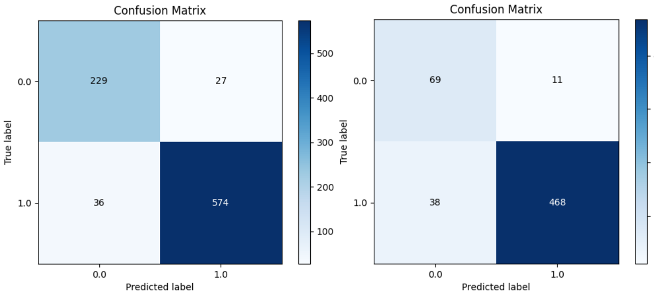
Table 2: Best Models.

S_{ID}	BM	BS	BMP
1	Logistic Regression	Standard Scaler	C=2.3
2	Logistic Regression	Standard Scaler	C=0.1
3	SVM Classifier	MinMax Scaler	C=14
4	Random Forest	Standard Scaler	Max_depth=3 n_estimator=62

(a) S_{ID}:Subject$_{ID}$, BM:Best Model, BS:Best Scaler, BMP:Best Model Parameter.



(a) Confusion Matrix for Subject 1 **(b) Confusion Matrix for Subject 2**



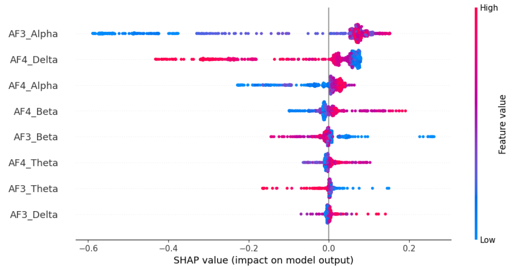
(c) Confusion Matrix for Subject 3 **(d) Confusion Matrix for Subject 4**

Figure 6: Confusion Matrices for Different Subjects

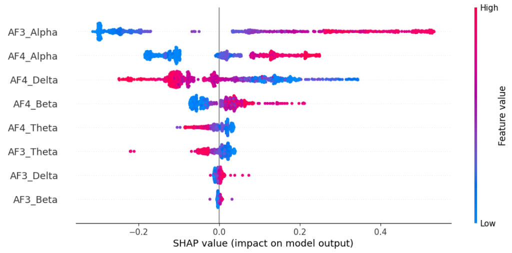
Table 3: Best metrics for all subjects in LOSO.

S_{ID}	MS	Precision	Recall	F1-score	Accuracy
1	Focus	1	0.61	0.76	0.90
	Relaxation	0.88	1.00	0.94	
2	Focus	0.99	1.00	0.99	0.99
	Relaxation	1.00	0.99	1.00	
3	Focus	0.86	0.89	0.88	0.93
	Relaxation	0.96	0.94	0.95	
4	Focus	0.64	0.86	0.74	0.92
	Relaxation	0.98	0.92	0.95	

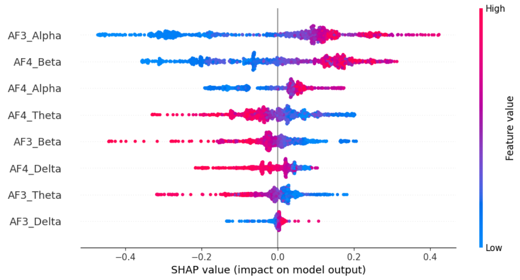
(a) Subject$_{ID}$:S_{ID}, MS: Mental States.



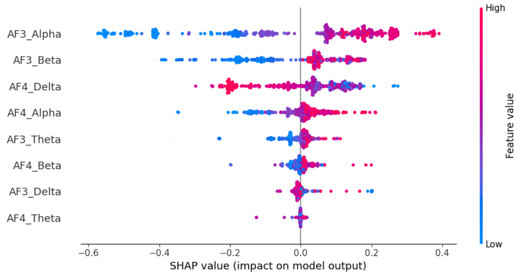
(a) Subject 1 features beeswarm plot.



(b) Subject 2 features beeswarm plot.



(c) Subject 3 features beeswarm plot.



(d) Subject 4 features beeswarm plot.

Figure 7: Subfigures with beeswarm plots for different subjects.

user. Afterwards, through the beta protocol, the parameters of sound in virtual and acoustic instruments are changed in real-time.

The investigation aimed to address two principal research questions. The findings indicate that Alpha band power features associated with the AF3 electrode are consistently relevant across all participants. Notably, the models' predictive accuracy is modulated by the power of various frequency bands across different electrodes. For precise classification of a user's focused mental state, using a minimum of two electrodes is advocated to preserve spatial information alongside the relevant features. Future work will focus on

Table 4: Mean Metrics Values.

MS	MP	MR	M F1	MA
Focus	0.87	0.84	0.98	0.92
Relaxation	0.95	1.00	0.96	

(A) MS: Mental States, MP: Mean Precision, MR: Mean Recall, MF1: Mean F1-score and, MA: Mean Accuracy.

the implementation of further metrics and models able to control multiple sound parameters simultaneously.

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