# On-line Recognition of Emotions Via Electroencephalography

K. A. A. Weiss, F. Concatto, R. G. C.Teive, and A. R. G. Ramirez

***Abstract*—Automated pattern recognition of brain signals can bring about new experiences, enhancing applications in a wide array of areas. One of its fields of study is the recognition of emotions via electroencephalography (EEG), which shows exclusive advantages compared to other methods. However, research with brain-computer interfaces (BCI) is usually structured in two sequential stages: data collection and data analysis. These stages leave a gap in the perspective of a functional system in a production environment since the practitioner needs to wait a considerable length of time until they can see the results of the current activity. An online classification system of emotions (positive, neutral, and negative) was developed using open resources in this work. Five machine learning models were trained with the SEED IV dataset, which is labeled with different emotions. The models were trained and tested using nested cross-validation and grid search to obtain the best hyperparameters. The algorithm implementation in Python was integrated with the OpenBCI software to capture the EEG signals, process them, and command the simulations. The best average accuracy obtained for a single subject was 76.19%, and the average accuracy for all subjects was 57.07%. The average execution time for signal processing and prediction, combined, was around one millisecond, which demonstrates the potential for applications with real-time characteristics.**

***Index Terms*—Emotion Recognition, Brain-Computer Interface, Electroencephalography, Online Processing.**

## I. Introduction

The amount of research in applications of brain-computer interfacing (BCI) is constantly growing. Although originally studied within a limited scope in the medical field, such as sensory and motor rehabilitation, it has recently expanded to other areas, such as entertainment and education. BCI systems consist, in essence, of the acquisition and processing of electrical signals from the brain's neural activity, aiming to fulfill a specific goal [1] by using invasive or non-invasive techniques. Invasive approaches involve the insertion of electrodes directly on the brain, thereby demanding surgical procedures that carry a specific risk. Due to being in direct contact with the brain, the device can acquire signals with much more precision – down to a single neuron – but may cause skin scars [2]. On the other hand, non-invasive methods are safer, but the obtained signals are less specific, since they acquire the collective activation of a group of neurons.

One of the new applications of BCI systems is the recognition of emotions. The recognition of emotions is part of the branch of affective computing, which aims to process, recognize, and simulate the affective nature of human beings. Emotions are a deep and complex phenomenon, and systems that can recognize them reliably and authentically have the potential to be applied in a diverse range of situations. A large portion of the proposed approaches for this task are based on the analysis of images or sounds, which are subject to deception and manipulation. Therefore, in this study, we aim at using a BCI-based methodology, which enables the monitoring of involuntary emotional reactions, acquiring them directly from neural activity.

Most research on applications in BCI systems is based on an analysis performed on data obtained manually or even data processing in an offline manner. In this case, the processing and data acquisition are not executed in a synchronized way. Although this research strategy is necessary for data exploration and the achievement of discoveries, it is also essential to develop practical BCI systems that work online or in real-time and present open source solutions.

To the best of our knowledge the number of works involving practical BCI systems that work in real-time and present open source solutions is scarce. For instance, Oldoni et al. in [3] developed a BCI system to aid in the rehabilitation of aphasia, but since the research results were analyzed offline, professionals had to wait a considerable amount of time to access the acquired results. Another example can be seen in [4], where the authors developed a BCI system for the assessment of users' quality of experience when using an application; in the study, the results are also processed offline, slowing the process of improvement of the software. In this context, this work aims to explore an implementation of a BCI system in an online application involving emotion recognition. Three labels were used to classify emotions: positive, neutral, and negative emotions. The implementation described in this work uses open source technologies to facilitate academic reproduction and reuse and a publicly available dataset, called SEED-IV [5].

This paper is structured as follows: Section II briefly discusses related works. In Section III, the emotion recognition problem is contextualized. Section IV-A presents details of the dataset used. Section IV-B gives the details of the system implementation. It is also presenting the pre-processing, feature calculation, and model training. Section IV-C describes the development of the integration of the simulation system and analysis of the system execution in real-time. In Section VI, some results are reported, and in Section VI-B the limitations of the system are discussed. Finally, in Section VII the conclusions and perspectives for future work are presented.

## II. Related Works

Considering the systematic review presented in [6], the authors conclude that the emotion classification is generally

K. A. A. Weiss, F. Concatto, R. G. C. Teive, and A. R. G. Ramirez are from the Department of Computing, Universidade do Vale do Itajaí, Brazil.
*Corresponding author: F. Concatto (fernandoconcatto@gmail.com)*

either performed offline, or the adopted methodology is not portable. These aspects, according to [6] pose serious limitations to the possibility to transfer BCI-based affective state recognition to real-life situations at the current stage. Thus, it is important the development of online systems, which are able to classify emotion in real-time classification. In this section we explore some studies that are closely related to ours.

According to [7], emotions can be represented using different general models. The most used are the discrete model and the dimensional models. The discrete model identifies basic, innate and, universal emotions from which all other emotions can derived. Some authors state that these primary emotions are happiness, sadness, anger, surprise, disgust, and fear. On the other side, dimensional models can express complex emotions in a two-dimensional continuous space; Valence-arousal (VA), or in three dimensions: Valence, arousal and dominance (VAD). Valence is used to rate positive and negative emotions and ranges from happy to unhappy. Arousal measures emotions from calm to excited. Three-dimensional models add a dominance axis to evaluate from submissive to empowered emotions.

As presented in [7], most systems use the VA or VAD spaces and classify each as a bi-class (for instance, valence positive and negative; arousal low-value and high-value) or tri-class problem (for example, valence positive, neutral and negative). In relation to datasets, DEAP and SEED are publicly available databases, and are the most frequently used.

Lan et al. in [8] used four Circumplex levels to represent the types of emotions classified by the system. The DEAP dataset was used, where fractal dimension was calculated and used as features. An average accuracy of 49.40% was obtained with a threshold of fractal values and max voting. Due to the simplicity of the processing model used, the authors comment on the feasibility of real-time execution.

Hou et al. in [9] classified positive and negative emotions. From the statistical and fractal features, they obtained an accuracy of 91.07% with an SVM classifier. They used a dataset created by themselves. A simulation interface was developed to validate the execution of the system, using a rendered 3D avatar to display the simulated emotions.

Liu et al. in [10] classified positive and negative emotions based on time-frequency features with LDA. An accuracy of 86.63% was obtained with an SVM classifier using a proprietary dataset. A prototype developed for the system simulation allowed the recognition of emotions in real-time. Graphs of valence levels were displayed during the simulation.

Iacoviello et al. [11] proposed an automatic real time classification method of EEG signals from self-induced emotions. In this case, only two kind of emotions were classified: disgust and relax. The signals were classified by a two stage algorithm: the first one was an off-line stage, aiming at the training of a suitable classifier whose input were the selected features; the second stage was the application of the classifier to new data. The specific considered signal required the use and adaptation of mathematical tools like Wavelet Signal Decomposition Theory, which was used in the first stage for calibration and filtering, Principal Components Analysis, which was used to select the features and Support Vector Machine.

In [12] the authors search for the recognition of happy, fear, sad and relax emotion EEG signals, by using a two-stage filtering method. At the first stage, a correlation-criterion is suggested for removal of noisy intrinsic mode functions (IMF) by applying the empirical mode decomposition on the raw EEG signal. The noise-free IMFs are used to reconstructed the denoised EEG signal with improved stationary characteristics. The denoised EEG signal is further decomposed into modes using the Variational Mode Decomposition (VMD). At the second stage, the instantaneous-frequency based filtering of VMD modes is performed and filtered modes are retained for the reconstruction of denoised EEG signal with the desired frequency range. After two-stage filtering, the non-linear measures of filtered EEG signals are used as input features to multi-class least squares support Vector Machine classifier, for emotion recognition.

Zangeneh et al. [13] proposed a method to classify emotion into four groups, considering the database DEAP. In this proposal, the EEG phase space is reconstructed for each channel and then transformed into a new state space called angle space (AS). Nonlinear features are extracted from AS and fed to classification step. Statistically significant and independent features are fed into two classification models including MLP and Naïves Bayes. Classifiers are combined through Dempster-Shafer Theory and final decision is made.

Recently, a study involving the SEED dataset was carried out by Hwang et al. [14], tackling the problem of subject-independent classification. The authors used an adversarial learning approach, where one neural network learns to classify emotions independent of the subject and the other adversarially attempts to confuse the first by making it incapable of distinguishing between different subjects. By comparing their approach with similar methodologies, the authors concluded that it offered noticeably better results – their best model achieved an accuracy of 75.3%, while a simpler model based on support vector machines (SVM) achieved only 58.2%.

In a paper by Lew et al. [15], an experiment involving both the DEAP dataset and SEED-IV was conducted, where the researchers compared the model they developed, called RODAN, with other competing approaches. They partitioned the experiment into three categories: subject-dependent, subject-independent and subject-biased. In all experiments, their proposed approach offered either better or very similar results when compared to similar techniques; furthermore, accuracies were consistently higher in the SEED-IV dataset, achieving values as high as 98.1% in the subject-biased experiment.

Another study that explored the SEED dataset was reported by Zhong et al. [16], where the authors developed a deep learning approach based on the spatial characteristics of the EEG signals. The model proposed by the authors (called RGNN), by using a graph-oriented neural network, can capitalize on both local and global relationships among different electrodes, offering better inferential capacities. In comparison with other state-of-the-art models, the authors identified that even though the RGNN fell slightly behind on a band-based analysis in the SEED dataset, it achieved better results than the alternatives on both the SEED SEED-IV datasets when analyzing the full spectrum.

These recent studies demonstrate the scientific community's interest in developing statistical models capable of relating electrical signals from an EEG to human-understandable emotional states. Moreover, they show that the SEED-IV dataset, which was selected for this work, is in widespread use by researchers in the field, further justifying the choice of dataset. There is a considerable focus on improving accuracy in these studies, but not much attention is given to deployment aspects such as the algorithm's execution time.

## III. Problem Statement

There are currently several approaches for automated emotion recognition. In [17], facial expressions were recognized to identify seven emotions: joy, sadness, anger, fear, disgust, surprise and neutral. In [18], the recognition of emotions in the valence and arousal axis of the Circumplex model were performed via the classification of patterns found in speech. Both studies present valid techniques for the recognition of emotions but suffer from the limitation of possible simulation or authenticity of the expressed emotion. For example, applications that require a smooth user experience and involve usability tests can easily be compromised if the subjects in trial do not respond with an authentic emotion, which effectively counteracts the experiment [19]. In contrast, the recognition of emotions by means of BCI devices does not suffer from this limitation, since the signals are involuntary and cannot be simulated by the user.

Most research on applications in BCI systems tends to be restricted to manual results of data analysis or processing data in an offline manner, that is, distantly in time from which the data was collected. Although this research strategy is necessary for data exploration and the achievement of discoveries, the number of research papers on BCI systems for the roblem of emotion recognition that work online (or in real-time), using open source solutions, are scarce.

In this context, research on BCI systems carried out at UNIVALI, and in partner institutions, highlighted the need for an online response. Oldoni et al. in [3] developed a BCI system to measure working memory, aiming to assist professionals in the treatment of patients with aphasia. As the results of the research were analyzed offline, there was a latency for professionals to have access to the data and act from the analysis of the acquired results. Ramirez et al. in [4], developed a BCI system to assess user experience when using software. As the results were processed offline, the system took a long time to give feedback to the researchers, hindering the dynamics of the experiments and, consequently, generating a latency that prevented contributing in an agile way in improving the usability of the software.

Therefore, in this work, we aim at answering the following research question: is it possible to monitor the emotional reactions of an individual in an online manner using a BCI device?

## IV. Proposed Solution

In this section, we describe in detail our proposed solution to the problems previously posed: a BCI-based system which acquires electroencephalographic signals from an individual, in a non invasive manner (thus avoiding surgical procedures), while simultaneously classifying recently captured windows of data into positive, negative and neutral emotional states. The training and classification processes are applied to a dataset available in the scientific literature, presented in the following subsection. Then, we describe the methodology we used for the generation of features, the construction of the statistical models and the development of the software itself, using an open source platform.

### *A. Analysis and Choice of Dataset*

Three datasets were found for public use and for academic purposes related to the context of recognizing emotions via EEG signals, namely: DEAP [20], MAHNOB HCI [2] and SEED IV [5]. All datasets feature different sessions and different classes of emotion. In this work, the SEED IV dataset was chosen, because it is more compatible with the objectives of this research, which involves differentiating between positive, negative and neutral emotions.

The DEAP dataset follows the PAD (Pleasure, Arousal, Dominance) model of emotions [18], [21], and therefore we considered it unsuitable for the goals of the present study. The MAHNOB HCI dataset, on the other hand, classifies emotions in nine different categories: sadness, joy, disgust, neutral, amusement, anger, fear, surprise and anxiety [2], [17]. Since the aim we established for this work had a more focused and narrow point-of-view, we selected the SEED IV dataset, which has four classes: happiness, sadness, fear and neutral [5]. We discarded instances classified as fear, and considered happiness as positive emotion and sadness as negative emotion, as they are opposites [22].

The datasets, however, are not exclusive; it is possible to also use other two datasets for the purpose of this study , but since they use a different representation of emotion, additional transformations would be required. This approach could be explored in a future work.

The SEED IV dataset features 1080 trials with 15 participants and an average duration of 2 minutes each. In each trial, signals from 62 electrodes positioned according to the 10-20 system were recorded, while participants watched emotionally-inducing film clips [5]. Additional details about the dataset, as well as a link to download it, can be found here: http://bcmi.sjtu.edu.cn/~seed/seed-iv.html.

### *B. Feature Generation and Models*

As the designed system needs to work online, the prediction must be carried out as new signals arrive. This prediction model implies defining parameters for a sliding window, such as size and overlap. The sliding window runs through the entire dataset, in which the features are calculated, as shown in Figure 1.

The window parameters widely vary in related research and there is no definite consensus on which parameters sizes to use. Thus, preliminary tests were performed with a smaller partition of the dataset, with different window parameters. The results are shown in Table I.

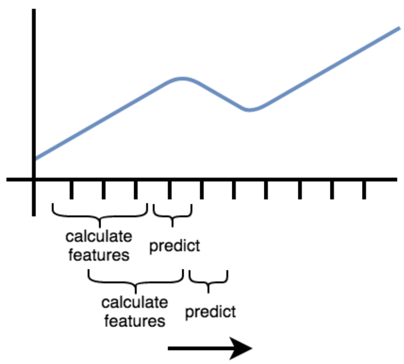


Fig. 1. Sliding window to calculate the features for prediction. Source: adapted from [23].

TABLE I
PRELIMINARY TESTS WITH VARYING WINDOW SIZES AND OVERLAP.

| Size (s) | Overlap (s) | Accuracy |
|---|---|---|
| 1 | 0 | 46.67% |
| 1 | 0.5 | 47.28% |
| 2 | 0 | 47.67% |
| 2 | 1 | 47.53% |
| 4 | 0 | 45.12% |
| **4** | **2** | **47.91%** |

As the preliminary results demonstrate, no significant distinction could be observed between the different parameters. However, the ones that showed the best results were used: a window size of 4 seconds with 2 seconds of overlap.

The incoming signals were discretized in five bands, following the usual nomenclature of the brain signal processing literature. Table II shows the upper and lower bounds of each band.

TABLE II
BAND NAMES AND RESPECTIVE LOWER AND UPPER BOUNDS.

| Band name | Lower bound | Upper bound |
|---|---|---|
| Delta | 1 Hz | 4 Hz |
| Theta | 4 Hz | 8 Hz |
| Alpha | 8 Hz | 12 Hz |
| Beta | 12 Hz | 30 Hz |
| Gamma | 30 Hz | 50 Hz |

For each frequency band of EEG signals, the spectral density was calculated using an FFT; the densities were then used as input features to train the machine learning models. According to the experiments carried out by the authors of the SEED IV dataset, Zheng et al. [5], the configuration with only 6 electrodes was used – FT7, FT8, T7, T8, TP7, and TP8. The authors positioned the electrodes in opposite areas of the brain and located them near regions that are responsible for processing emotions. This configuration presented results equivalent to the configuration of 62 electrodes [5]. Thus, a total of 30 features are generated per window instance, originating from the signals of 6 electrodes and features of 5 frequency bands.

Before starting the feature generation process, we applied a 1-50Hz bandpass filter to remove artifacts of unwanted frequencies, using Scipy's *filtfilt()* function, which applies the filter forwards and backwards. Then, before computing the FFT, we applied a Hann window of the same size as the FFT window (4 seconds) to minimize spectral leakage effects.

With regards to the machine learning models utilized in the prediction of emotions, we selected five well-known classifiers for our experiments. Table III specifies the models and hyperparameters used to implement the system in this work.

TABLE III
MODELS AND HYPERPARAMETERS.

| Model | Hyperparameters |
|---|---|
| Neural Network (MLP) | # of layers and neurons, alpha |
| Random Forest (RF) | # of estimators |
| SVM | Kernel, gamma, C |
| LDA | – |
| Logistic Regression (LR) | C |

### C. Software Development

The OpenBCI platform [24] simulated the acquisition of EEG signals. It provides several tools integrated within the acquisition boards developed by the OpenBCI. Since the OpenBCI was developed on the processing platform, it uses Java programming language to create custom graphical interfaces, including custom widgets. In this work, we developed a custom widget to display the current emotion being predicted by the system.

The prototyping and development environment of the prediction system was carried out in Python. Therefore, it was necessary to develop a communication layer between the two execution contexts. In this work, we established a TCP connection between the OpenBCI widget and the Python environment, following a client-server model. The OpenBCI acts as a client, which forwards the EEG data to a Python server, which is constantly waiting for new data. The Python server responds with the classification results. Figure 2 illustrated the exchange of messages between the two contexts.

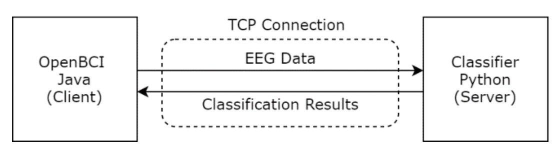


Fig. 2. Communication protocol between the two execution contexts.

Before running the simulation, the EEG data from a trial are transformed into a format accepted by OpenBCI. Then, the data file is selected and imported into the OpenBCI to start the simulation, as depicted in Figure 3.

Figure 4 displays the simulation of an ongoing trial. The emotions widget is displayed in the lower right quadrant, which shows a negative emotion, in this case.

## V. EXPERIMENT SETUP

As we described in Section IV-B, the calculated characteristics have an associated time dependency; therefore, it is impossible to shuffle all the data in the dataset, as is usually

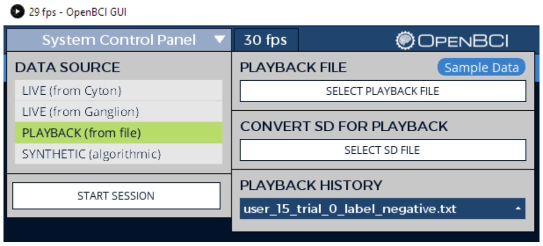


Fig. 3. Simulation setup.

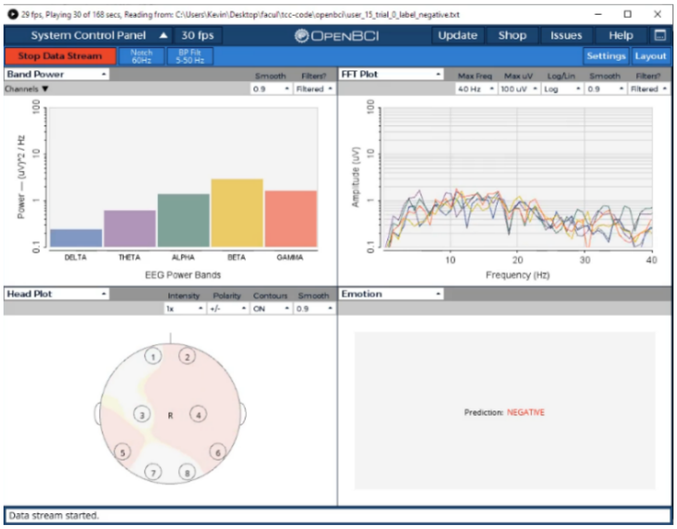


Fig. 4. Simulation in progress.

done before training machine learning models. This restriction exists because the trained model must be tested in trials never seen before, and the shuffling of the dataset will mix samples from different trials causing a data leak between the training and test datasets. Therefore, shuffling the dataset needs to be performed at the trial level and not at the sample level. The 5-fold cross-validation was used to alleviate over-fitting problems when training the models.

A grid search was used to determine the best model hyperparameter combinations. A second 5-fold cross-validation layer is performed during the grid search execution to avoid over-fitting issues when finding the best hyperparameters. This training strategy is called nested cross validation and was applied to all trained models.

The implementation of the classifier system was performed in the Python language, using the Scikit-Learn library. The pre-processing of the six data channels was carried out with the libraries of Scipy and Numpy. The implementation takes advantage of the vectorized operations available in the libraries, to efficiently process multiple data channels.

## VI. Results

This section reports the results obtained in our work, describing the accuracies achieved for each model and their computational performance, closing with a discussion about the limitations of the proposed platform.

### A. *Accuracies on the SEED Dataset*

Table IV presents the average accuracy of the models used for the different sessions for each subject of the SEED-IV dataset. Training was done in a subject-dependent manner; that is, for each individual, a different model was trained. To do this analysis, each chunk of electroencephalographic data was processed according to the description in Section IV-B: first partitioning into bands, then filtering and then extracting the spectral features using an FFT. The models are trained using these features as inputs, with the expected outputs (happiness, sadness, neutral) coming from the SEED-IV dataset. Accuracy is measured by comparing the output of the trained model with the actual emotion. Details about the participants are available in a paper by Zheng et al. (2019), which describes how the dataset was constructed [5].

TABLE IV
Average Accuracies of the Models for Each Subject.

| Subject | MLP | RF | SVM | LDA | LR |
|---|---|---|---|---|---|
| 1 | 39.19 | 44.41 | 41.31 | 40.03 | 40.49 |
| 2 | 60.62 | 65.92 | 63.78 | 64.36 | 62.83 |
| 3 | 42.24 | 44.6 | 44.9 | 46.22 | 43.47 |
| 4 | 61.31 | 67.28 | 64.49 | 59.56 | 61.42 |
| 5 | 50.02 | 56.09 | 50.85 | 52.86 | 50.41 |
| 6 | 66.18 | 68.92 | 67.56 | 64.58 | 67.97 |
| 7 | 54.74 | 61.71 | 60.84 | 58.53 | 59.93 |
| 8 | 60.01 | 62.07 | 61.66 | 60.31 | 62.39 |
| 9 | 53.66 | 52.82 | 52.56 | 55.17 | 45.17 |
| 10 | 52.97 | 56.93 | 52.88 | 52.22 | 54.39 |
| 11 | 43.4 | 45.09 | 49.8 | 49.71 | 48.2 |
| 12 | 42.33 | 46.5 | 44.29 | 42.11 | 41.32 |
| 13 | 49.17 | 52.16 | 54.03 | 54.97 | 52.03 |
| 14 | 52.44 | 55.69 | 53.95 | 52.68 | 54.55 |
| 15 | 71.23 | 75.93 | 76.18 | 73.67 | **76.19** |
| Avg. | 53.3 | 57.07 | 55.94 | 55.13 | 54.72 |

Analyzing the results of Table IV it is possible to verify that there is no significant variability across the different models tested. For example, accuracy for subject 3 shows similar results across the different models. In contrast, the accuracy among participants varies widely. For example, the models have an accuracy of around 40% for subject 1, and around 75% for subject 15. Therefore, the models show a correlation that is highly subject-dependent.

The execution time of the processes of filtering, feature extraction and prediction (using an SVM model), was, on average, close to 1 millisecond for each 4-second window of data. This was measured with Python's *time.perf_counter()* function. It shows the capacity for developing BCI applications in real-time. The results were obtained with an Intel Core i5-7400 @ 3.00 GHz processor.

### B. *Limitations*

One of the challenges of processing EEG signals is the precise removal of artifacts. EEG signals are subject to several and different types of artifacts that arise from internal physiological occurrences and external sources. Despite the existence of several algorithms detecting and removing artifacts, most of them are not suitable for an online application, since they have unsupervised nature or high processing complexity [25]. In this work, we did not implement an artifact removal algorithm due to time restrictions. We applied a bandpass filter to remove unnecessary frequencies, but there are still unwanted artifacts in the frequencies used. The artifacts and their removal will be addressed in future works, thereby further improving the results reported here.

The spectrograms of two subjects with different performance results from the trained models were compared to illustrate this issue. Figure 5 shows the spectrogram of a trial from subject 1, with visible artifacts delimited by rectangles in red.

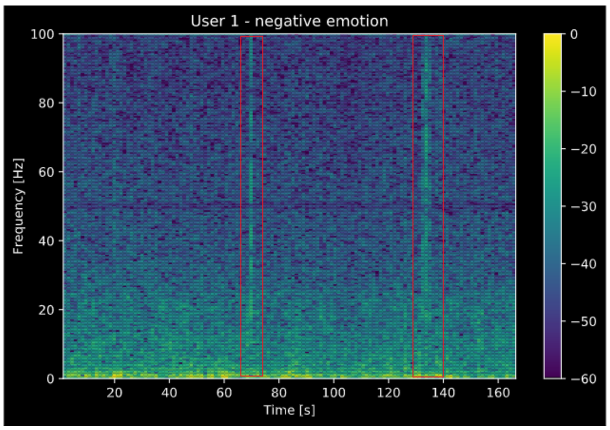


Fig. 5. Normalized spectrogram of the FT7 electrode with spectral density in dB of subject 1. In this trial, a negative emotion is stimulated.

The artifacts have the characteristic shape of the frequency domain transformation of the Dirac Delta function, which represents an impulse in the time domain. The artifact was probably due to a sudden reaction from the subject. The effect of this type of artifact produces outliers in the dataset, which can negatively affect the performance of trained models. As shown in Table IV, subject 1 exhibits low performance in all models.

In contrast, the trial with subject 15 (who presented the best performance among all subjects, according to Table IV), shown in Figure 6, does not show the discussed artifact illustrated in Figure 5. However, it contains non-easily perceptible artifacts that cannot be detected from the spectrogram.

## VII. Conclusions

In this work, open-source technologies were explored to develop an online BCI system to recognize emotions. The OpenBCI platform was used to develop the application via simulation, and five machine learning models were used to search for the best classification results.

The SEED-IV dataset was used to train the models using a spectral density. The best average accuracy obtained for a subject was 76.19%, and the average accuracy among all subjects was 57.07%. The variation observed among the classification results indicates that they are highly subject-dependent. The implemented system is modular, allowing its use in other BCI projects and not only for emotion recognition. In addition, a preliminary analysis of the system's processing time was

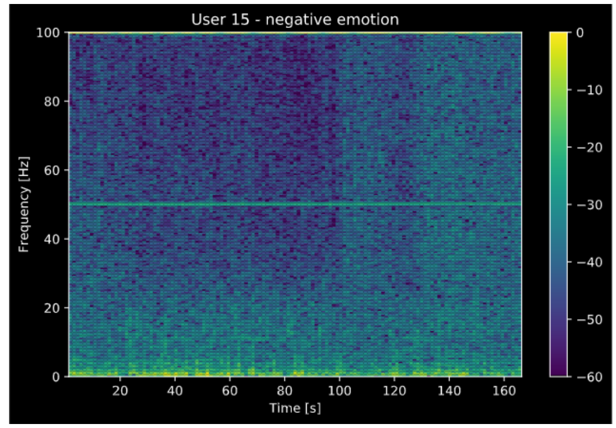


Fig. 6. Normalized spectrogram of the FT7 electrode with spectral density in dB of subject 15.

performed, demonstrating the potential use in applications with real-time processing restrictions.

As the data used in our experiments came from either the simulations with the OpenBCI platform or the SEED-IV dataset, we did not submit our study to be reviewed by an ethics commitee. This will be a necessary step, however, when planning the deployment of the products of this research in an environment where data will be collected from real individuals.

The scripts and algorithms developed in this work have been made available in a repository at GitHub, accessible with the following link: [redacted]. The repository also includes all the results obtained during training and testing procedures of the models, including the best hyperparameters found using a grid search. We hope the publicization of these resources aids in replicating and validating the experiments described in this work.

Future work may investigate the usage of two classes – positive and negative – instead of three, reducing the problem to binary classification. Other studies may also address the emotion recognition or other BCI applications using the algorithms provided by this project, which will allow a faster iteration on the development cycle of new studies. Another future work that we consider important is investigating the viability of subject-independent learning for our platform, which would improve its application in practical contexts, avoiding the necessity to train a new model for each different user.

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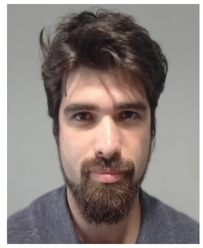

**Kevin A. A. Weiss** was born in São Paulo, Brazil, in 1995. In 2020, he received his bachelor degree in Computer Engineering from the Universidade do Vale de Itajaí, Brazil. Currently, he works as a Software Engineer developing Web-based Enterprise Applications. His research interests include microcontrollers, hardware and software integration, artificial intelligence, and the internet of things.

**Fernando Concatto** graduated in Computer Science with honors at Universidade do Vale do Itajaí, Brazil, in 2020, and is currently a student in the Master’s Program in Applied Compputing, at the same university. He has been actively participating in various research projects since 2016, in the fields of social network analysis, mathematical optimization and brain-computer interfaces. At the moment, he works as a lead software developer and is a Fapesc research fellow, investigating the rehabilitation of neurological disorders.

**Raimundo C. Ghizoni Teive** graduated at Federal University of Santa Catarina (UFSC), Brazil, in Electrical Engineering in 1985. He earned his M.S. and PhD. degrees both at UFSC, in 1991 and 1997, respectively. In 1994, he obtained a split PhD at Queen Mary University of London. He is lecturer in the Master’s Program in Applied Computing at Universidade do Vale de Itajaí. His research interest areas include application of Artificial Intelligence techniques into engineering problems. He has over one hundred published papers. He is a Elsevier and IEEE reviewer.

**Alejandro R. Garcia Ramirez** received the Electronics Engineer degree from the Instituto Superior Politécnico José Antonio Echeverría, Cuba, in 1989, and the Dr. of Electrical Engineering degree from the Universidade do Estado de Santa Catarina, Brasil, in 2003. He is currently Associate Professor at Universidade do Vale do Itajaí and Researcher at Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq). His research interests include Embedded Systems, Robotics and Assistive Technologies.