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Original Article

Study of an Optimization Tool Avoided Bias for Brain-Computer Interfaces Using a Hybrid Deep Learning Model

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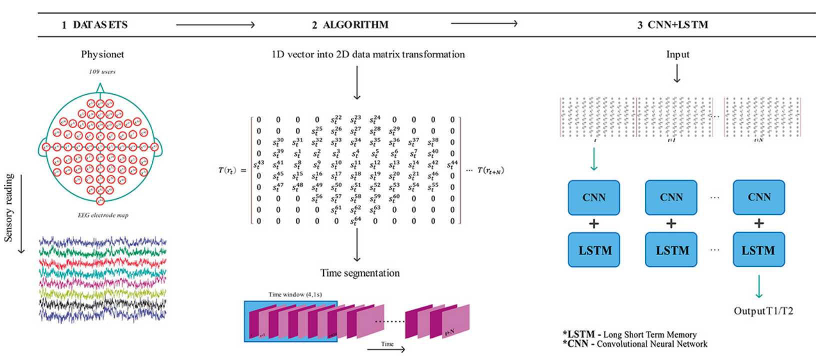
HIGHLIGHTS

- Hybrid model that tackles bias in user-specific Brain Computer Interfaces training.
- Combined 2D CNN and LSTM for EEG mental task classification.
- Classification rates of up to 90% with an average of 74.54% for EEG tasks.
- Set thresholds increase accuracy by 21.34%, remove low affinity.
- Methodology enhances BCI systems, improves accuracy and reliability avoiding bias.

GRAPHICAL ABSTRACT



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ABSTRACT

Objective: This study addresses the challenge of user-specific bias in Brain-Computer Interfaces (BCIs) by proposing a novel methodology. The primary objective is to employ a hybrid deep learning model, combining 2D Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) layers, to analyze EEG signals and classify imagined tasks. The overarching goal is to create a generalized model that is applicable to a broader population and mitigates user-specific biases.
Materials and Methods: EEG signals from imagined motor tasks in the public dataset Physionet form the basis of the study. This is due to the need to use other databases in addition to the BCI competition. A model of arrays emulating the electrode arrangement in the head is proposed to capture spatial information using CNN, and LSTM algorithms are used to capture temporal information, followed by signal classification.
Results: The hybrid model is implemented to achieve a high classification rate, reaching up to 90% for specific users and averaging 74.54%. Error detection thresholds are set to eliminate subjects with low task affinity, resulting in a significant improvement in classification accuracy of up to 21.34%.
Conclusion: The proposed methodology makes a significant contribution to the BCI field by providing a generalized system trained on diverse user data that effectively captures spatial and temporal EEG signal features. This study emphasizes the value of the hybrid model in advancing BCIs, highlighting its potential for improved reliability and accuracy in human-computer interaction. It also suggests the exploration of additional advanced layers, such as transformers, to further enhance the proposed methodology.

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Nomenclature

AI	Artificial intelligence	GRU	Gate Recurrent Unit
BCI	Brain-Computer Interface	JCR	Citation Reports
BiLSTM	Bidirectional Long short-term memory	LSTM	Long short-term memory
CNN	Convolutional Neural Networks	ML	Machine Learning
DL	Deep Learning	PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
EEG	Electroencephalogram		
MI	Motor Imagery	RMSProp	Root Mean Square Propagation

1. Introduction

Brain-Computer Interface (BCI) establishes a direct pathway between the brain and the computer. This type of technology, which is being widely researched, can capture and transmit the neural signals of an individual at different mental stages to a computer or external device [1]. Subsequently, after being processed, these signals are treated by these computers or devices using artificial intelligence algorithms (Deep Learning (DL), Machine Learning (ML)). This can be used for making predictions of imagined movements or to diagnose mental illnesses such as Parkinson's disease or sleep disorders among other applications [2–7].

Therefore, BCIs are very useful for people with motor problems, physical dependence, or neurodegenerative diseases, as they provide a direct link between the brain and the device to be controlled (without passing nerves, muscles, or tendons) and consequently improve life quality of the subjects [8]. Moreover, the signals captured by the BCI are electrochemical signals derived from brain synapses [4,9,10]. This signal is an effect of the neuronal activity of thoughts or imaginary tasks and is captured by recording brain signals using the electroencephalogram (EEG) [6,7]. The brain signal, according to several authors, is structured depending on its frequencies into five bands: delta, theta, alpha, beta, and gamma [5,11]. These frequencies vary between different ranges, consider Table 1.

According to Roc et al. [13], these types of readings require a high level of concentration and vary depending on the subject. In addition, in the tasks performed, it should be taken into account for factors such as breathing, heartbeat, or even eye movement, that can produce noise in the signal as they are movements associated with low frequencies, that can mask the frequencies of the brain signal.

1.1. Literature review

There are several works in which Deep Learning (DL) is used to classify mental tasks such as spelling words, emotions recognition, or even the movement of an arm with the mind [14,15].

One of the most difficult problems associated with BCI and brain signals is the poor signal-to-noise ratio, and a long list of tools, filters, and methods have been developed over the years to solve this problem. There are also various optimization techniques to improve the collection of this type of data and thus obtain better results. One example is the technique developed by Jin et al. [16], where the BCI-based steady-state visual evoked potential (SSVEP) was studied. Specifically, the task-related component analysis (TRCA)-based method and its variant, the ensemble TRCA (eTRCA)-based method. In order to solve the noise problems in these methods, they successfully designed a novel time filter that introduces the temporal local weighting into the objective function of the TRCA-based method and uses singular value decomposition. Thus, a tool with promising potential for SSVEP detection was established.

Table 1
Classification of brain signals according to Miller et al. [12].

Type	Frequency (Hz)
Delta(Δ)	1-4
Theta(θ)	4-8
Alpha(α)	8-13
Beta(β)	13-35
Gamma(γ)	>35

Another method developed by Jin et al.[17] to improve EEG signal processing was related to common spatial pattern (CSP) algorithms. This is a well-known spatial filtering method for feature extraction in motor imagery (MI)-based BCIs. In their work, they address the problem of EEG non-stationarity and its derived features in the context of CSPs. To this end, they design a new feature selection method based on an improved objective function. In particular, improvements are made in outlier suppression and feature discovery with larger inter-class distances. Furthermore, a fusion algorithm based on the Dempster-Shafer theory is proposed, which takes into account the feature distribution. As a result, less additional computational cost and a significant increase in the performance of MI-based BCI systems are achieved.

There are also other methods that mix different techniques and devices to complement the EEG, such as the one developed by Yang Yu et al. [18]. In this paper, they use an electrooculogram (EOG) to complement spelling tasks with EEG. Specifically, they use a classic P-300 speller (where the peak of brain intensity marks the desired letter), and through the EOG they create an asynchronous method that assists and improves spelling. This allows for a speller that works as long as the subject wants to spell and increases the speed of this type of procedure.

Finally, a very famous way to address the noise signal problem is the one developed by Sun, B et al. [19], which deals with how to make an optimal subset of channel selection without seriously affecting the classification performance. In this article, they propose an end-to-end deep learning framework called EEG Channel Active Inference Neural Network (EEG-ARNN), which is based on Graph Convolutional Neural Networks (GCN) to fully exploit the correlation of signals in the temporal and spatial domains. They use the BCI IV 2a competition and the Pysionet dataset to evaluate performance. Their results show that the proposed method outperforms state-of-the-art methods in terms of both classification accuracy and robustness.

In this work, although the selection of channels is taken into account, an approach based on the demonstration of the hypothesis for the simplest case has been preferred, specifically on the binary classification of the imagined movement of the right hand versus the left hand, using the complete set of channels.

Previous work has shown a 60-95% success rate for such classification [20–23]. This success rate depends on the database, the method, and even the predisposition of the subjects. Therefore, each study must be analyzed according to its characteristics, being difficult to compare two studies based on different databases and conditions. There are generalized classification models (less suc-

Table 2
Summary of the databases used in 89 studies selected from Scopus and PubMed using PRISMA criterion.

Dataset	Channels	Users	Percentage of use in studies
BCI competition III-3a [26]	64	3	17/89 (19%)
BCI competition III-4a [26]	118	5	27/89 (30%)
BCI competition IV-1 [27]	59	7	14/89 (15%)
BCI competition IV-2a [28]	22	9	52/89 (58%)
BCI competition IV-2b [29]	3	9	36/89 (40%)
Dataset from GigaScience [30]	64	52	3/89 (3%)
High-Gamma Dataset [31]	128	14	3/89 (3%)
PhysioNet EEG [32]	64	109	2/89 (2%)
MAMEN Phase I [33]	61	34	2/89 (2%)
Other datasets [34–36]	15-62	5-15	3/89 (3%)
Private datasets	2-64	1-12	9/89 (10%)

cessful) and very specific ones (more successful). Jiao et al. [20] propose a new representation model group to improve the efficiency of MI-based BCI by exploiting the information between subjects, obtaining a success rate of 78.2% with BCI by exploiting the information between subjects, obtaining a success rate of 78.2% with BCI Competition IV dataset IIb. Lee and Choi [21] with a success rate of 78.93%, present a new convolution neural network (CNN) approach to classify motor imagery EEG. Ha and Jeong [22] offers a capsule network (CapsNet) to learn about the properties of EEG signals, increasing and improving performance over previous CNN methods, such that they achieved a 78.44% success rate. On the other hand, Luo and Chao [23] offer a new method of constructing and modeling highly accurate and robust ICMs based on limited trials of EEG signals, obtaining a success rate of 82.75 ±3.84. Finally, Biao Sun et al. [24] propose an adaptive spatio-temporal graph convolutional network (ASTGCN) that exploits the characteristics of EEG signals in the time domain and channel correlations in the spatial domain simultaneously. They use their own data set in which twenty-five healthy subjects performed MI movements of the right hand and feet to generate motor commands. Their experimental results show that the proposed method outperforms state-of-the-art methods both in terms of classification quality and robustness.

1.2. Bias with different datasets

In the studies previously mentioned, it is observed that BCI competition IIa, IIIa, and IV databases are used. These data sets are widely used, as they achieve high success rates due to the use of small groups of people, between 3 and 9 users. This implies that the system trains with a very specific number of data, resulting in a system that is not very generalized or with a certain bias, even in certain cases with the overtraining problem.

According to Arpaia et al. [25] it is important to carry out studies with different databases, such as Physionet, High-Gamma Dataset, or GigaScience, as more than 75% of the studies are carried out with BCI competition databases. The use of these databases with more users would imply a drop in the success rate, as the system is more generalized, but, on the other hand, a higher reliability rate is achieved by using groups with a greater number and variety of people and a greater amount of data to train and test the system. Table 2 shows the most famous databases and their percentage of use in a total of 89 studies indicated in JCR and selected with the PRISMA criterion, together with the number of users they have. Table 2 is summarized in Fig. 1, it can be seen how the works focused on the use of BCI competition databases occupy most of the state of the art, since they allow a much higher percentage of success in the studies as explained before, being of interest the use of other databases with a greater number of users.

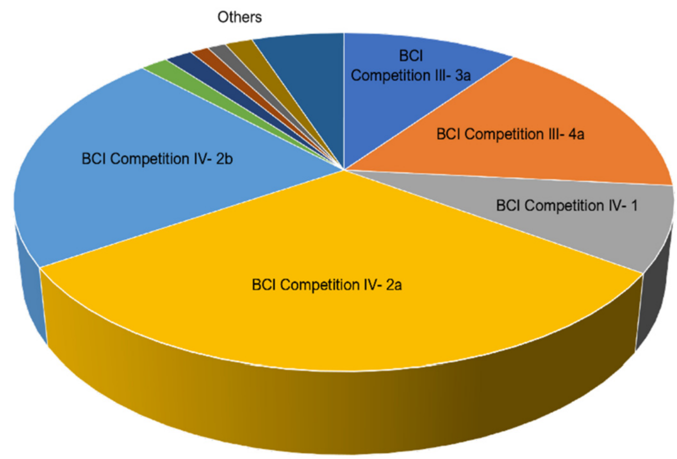

Fig. 1. Percentage of use of databases in the state of the art by Arpaia et al. [25].

1.3. Our proposal

This study presents a novelty over previous research by employing a unique data processing approach using event-specific low-resolution time windows and unconventional spatial shaping of the data. This approach allows our algorithm to extract and specifically package the EEG signal from the Physionet database to obtain useful spatio-temporal information.

By combining this algorithm with a CNN-LSTM network, a success rate of over 90% for some users and an average of 74.54% was achieved, with improvement potential. The network was then tested and trained user by user. To minimize bias and avoid data cross-contamination, each user is k-fold trained on 2/3 of their experiments and tested on 1/3 of their experiments. Thus, the final analysis is user and session independent, but the classifier relies on data from the entire set. This avoids the generalized training of other studies [20–23].

A secondary analysis was performed to identify users with low EEG responsiveness. This led to the development of a novel validation tool that includes setting different thresholds of success for subjects, testing, or data collection. Overall, this study makes several significant contributions to the field, including the use of a larger dataset, a unique approach to data processing, a novel validation tool, and a more generalized system that can be applied to a diverse range of users and data.

By way of outline, the paper is structured as follows:

After an introduction and contextualization of previous work and an explanation of the existing bias in the use of the database, the materials and methods are explained. A presentation of the database used and the parts of the network, such as the CNN and LSTM networks, is given as well as the network architecture and conditions. Finally, the results obtained in both the user-to-user classification and the use of detection thresholds are explained. All this is accompanied by a comparison of existing works to obtain a contextualization and to frame the precision of the work concerning others of a similar nature. It ends with some conclusions summarizing the work and explaining the most important results.

Furthermore, the proposed methodology for brain-computer interfaces has several potential connections to the United Nations' Sustainable Development Goals (SDGs), including [37]:

- **SDG 3.8:** Universal Health Coverage - By developing a more generalized system for brain-computer interfaces that can be trained on a large amount of data from different types of users, this work has the potential to improve access to healthcare for people with disabilities, such as those who may benefit from brain-computer interfaces.

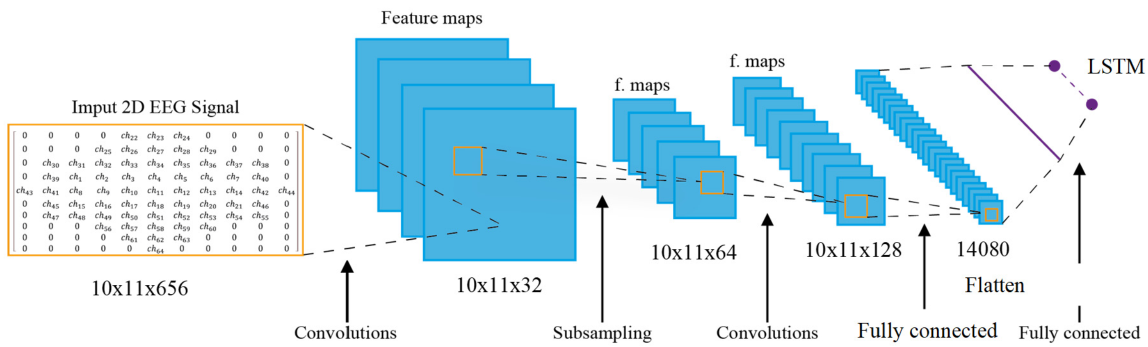

Fig. 2. General outline of an image recognition through a CNN. It can be seen how the different convolutions are performed to extract the feature map that will later define the output.

Table 3
Task used in PhysioNet.

Task 1	Open and close left or right fist
Task 2	Imagine opening and closing left or right fist
Task 3	Open and close both fists or both feet
Task 4	Imagine Opening and closing both fists or both feet

- **SDG 3.d:** Strengthen the capacity of all countries, in particular developing countries, for early warning, risk reduction, and management of national and global health risks - By improving the accuracy and reliability of brain-computer interfaces, this work may contribute to more effective management of neurological disorders and other health risks related to the brain.
- **SDG 10.2:** Social, economic, and political inclusion of all, irrespective of age, sex, disability, race, ethnicity, origin, religion, or economic or another status - The proposed methodology seeks to develop a more generalized system that can be applied to a larger population, potentially reducing biases that arise from user-specific models. This may lead to more equitable access to brain-computer interfaces and the benefits they provide.

2. Materials & methods

2.1. Dataset

This work was conducted using the PhysioNet public database [32,38], which consists of a series of two-minute EEG recordings from 109 individuals provided by the developers of the BCI2000 instrumentation system. A number of tasks are performed on this database. First, a baseline EEG is obtained from users with their eyes closed and then with their eyes open in the relaxation phase. Subsequently, users are asked to perform various real and thought motor tasks, which are recorded by the 64-channel EEG.

In total, subjects perform 14 experimental tasks divided into five runs: the first two, as mentioned above, are baseline runs with a duration of one minute. The remaining 12 trials are divided into 4 task types, each of which is performed 3 times, see Table 3. The first type of task consists of opening and closing the right or left fist (denoted T2/T1), depending on which side a symbol appears on a screen. Task type 2 is the same as task 1, but the movement of opening and closing the left or right fist is imagined. Tasks 3 and 4, which consist of moving both fists and both legs (task 3) and imagining this movement (task 4), are not considered in this study because we focus on the development of the tool in a binary way.

Therefore, keeping task 1 and task 2, both repeated 3 times, we have a set of 6 experiments. Each experiment lasted 2 minutes and was recorded with 64 electrodes using the 20-10 system. EEG channels Nz, F9, F10, FT10, A1, A2, TP9, TP10, P9 and P10 were excluded. The sampling rate was 160 Hz. In each two-minute experiment, movements or thoughts T1 and T2 (lasting 4.1 s) are alternated with rest periods recorded as T0 (lasting 4.2 s). That is, there is always a T1 or T2 event lasting 4.1 s followed by a T0 rest period lasting 4.2 s. T0 events are eliminated for data uniformity and to treat all trials in the same way.

These data, provided in European Data Format (EDF+) files, are converted from EDF+ format to numerical format and from there to matrices that, after passing through the algorithm, are in the correct format to enter the classifier.

2.2. CNN

CNN is a type of artificial neural network (ANN) designed to process pixel data, which is commonly applied for visual image analysis and processing, using a mathematical operation called convolution in at least one of its layers [39,40]. These types of networks usually consist of three layers: the input layer, the output layer, and one or more hidden layers where the convolutions are performed. These layers alternate with grouping layers, fully connected layers, and normalization layers to group the feature maps that are obtained to arrive at a layer that connects them all in one or several outputs.

This network is suitable for image analysis due to its grid-like typology since during convolution and clustering it takes into account the different spatial relationships existing between its separate features [41,42]. The general scheme of the CNN architecture is shown in Fig. 2. In this work, 2D convolutional layers are used to process the EEG signal data. These data are presented in the form of 2D matrices after being treated. These matrices are the result of arranging the EEG channels by copying the structure of the EEG cap. In other words, the conformation of the array is the same as the conformation of the electrodes in the cap.

With this, the CNN will have the advantage of taking into account the spatial conformation of each moment of the experiment. Three convolutional layers are used in series with 128, 64, and 32 feature maps. The mathematical expression for a 2D CNN layer is given by [43]:

$$O_{i,j,k} = f\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\sum_{c=0}^{C-1} I_{i+m,j+n,c} * K_{m,n,c,k} + b_k\right) \tag{1}$$

Where, O is the output tensor of dimensions $(I_o,\ J_o,\ K)$ I, is the input tensor of dimensions (I_{i}, J_{i}, C), K is the kernel (or filter) tensor of convolution of dimensions (M, N, C, K), f is the activation function (for example, ReLU), b is the bias tensor (scalar). The summation is over the indices m, n, and c to traverse the input tensor and the kernel tensor.

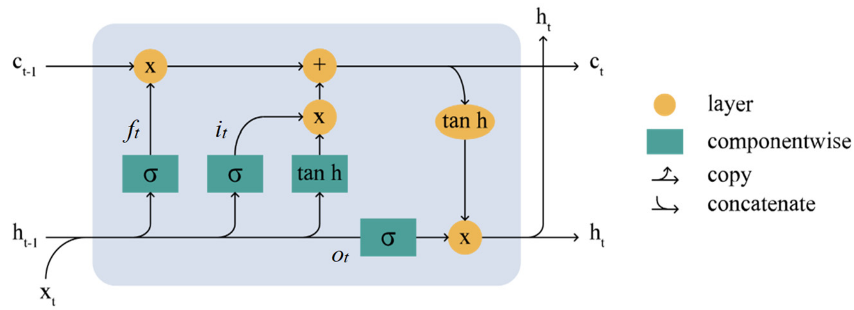

Fig. 3. LSTM architecture.

2.3. LSTM

LSTMs are one of the most widely used neural networks in the field of DL for time series processing or prediction. They use a memory cell (c_k), which can store and transmit information from previous and present states for future use. Along with this, LSTMs use a series of algorithmic gates capable of retaining useful information from previous or current stages and acting according to the target.

There are variants such as Bidirectional LSTM (BiLSTMs) or Gate Recurrent Units (GRUs) with slightly different functions. LSTMs apply to tasks such as handwriting recognition, speech recognition, healthcare, video games, and weather prediction, among others. It can also be combined with other techniques to improve the overall network architecture, as in this case.

LSTM is essential for our model as it takes into account the temporal features of the system (sequences) and analyzes the CNN spatial windows over time. It extracts useful temporal information and improves performance significantly.

The LSTM is mainly composed of three parts and a memory cell, their mathematical expressions are as follows [44,45]:

Input gate: this layer, is responsible for updating the status of the network. In the next step, decide the values to be updated through the sigmoidal function.

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{2}$$

W_i represents the weight for input, b_i represents the corresponding bias, x_t is the current time-step, and (h_{t-1}) is the output from the previous time-step. The output of the sigmoid function (σ) will be a value $\in$ [01], representing fully discard or fully save data, respectively [45,46].

Forget gate: the decision to save or discard information is made by this layer which is the first step of LSTM. Inputs to the gate are output from the previous time-step (h_{t-1}) and input at the current time-step (x_t) [46].

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{3}$$

W_f and b_f represent the weight and the bias for the forget gate respectively.

Output gate: determines what information is eventually outputted. The output is based on the filtered version of the cell state. The sigmoid layer decides on output values and then it is multiplied by the cell state [46].

$$\mathrm{o_t} = \sigma\left(\mathrm{W_o} \cdot [\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_o}\right) \tag{4}$$

$$h_t = o_t \cdot tanh(C_t) \tag{5}$$

W_i and b_o are the weight and bias for the output gate, respectively. h_t is the output of the LSTM layer at the current time step.

The final step is to update the previous cell state (c_{t-1}), which, as can be seen from Fig. 3 is calculated through forget and input gates.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot g_t \tag{6}$$

Where g_t is the *tanh* layer.

In this study, the CNN layers' output is fed into a two-layer LSTM network with 64 hidden neurons, which are analyzed to incorporate temporal information about the events. This approach enables the study to consider time-series data and reduce the data's resolution while increasing the quality of information. The time series is the size of a complete event, which ensures that the data contain sufficient quality information. Using shorter fragments would increase the resolution but would result in the loss of useful information. More details about this approach can be found in Section 2.4.

2.4. Pre-processing

Our study introduces a novel CNN-LSTM architecture for T1 or T2 event classification (previously explained in Section 1.3) of EEG signal data related to imaginary right and left fist movements.

The preprocessing consists of a series of arrays in which the extractable features are sought to be maximized. Specifically, this preprocessing seeks to establish an optimal spatial and temporal conformation to feed the algorithm and make it as efficient as possible in performing the classification.

After acquiring the signal from the database (with 64 channels) and performing the separation by subjects and sessions, the session data are treated to eliminate the rest events (T0), leaving only events of type T1 and T2. At this point, we have vectors of each user and session containing only events of type T1/T2 (corresponding to left/right). Each of these events, as explained in section "2.1. Dataset" has a duration of 4.1 seconds and a sampling frequency of 160Hz, so there are 656 samples per event. This results in a 64x656 vector per event.

The next preprocessing step is to restructure this data into 10x11 matrices. Here, the 64 channels used to measure the brain signal are restructured to have a matrix conformation similar to that of the EEG helmet, mimicking the physical configuration of the electrodes in the helmet and resulting in a 10x11 2D matrix (where the gaps with no signal are filled to 0), see Fig. 4.

This 2D matrix is then labeled and sorted into 10x11x656 vectors. Where 656 is the number of samples contained in a full T1 or T2 event. We note that using the full event provides higher accuracy than using shorter time windows (e.g., 328 or 164 samples) This could be due to the fact that by using much higher resolutions (shorter time windows), useful information is lost from the full events of each subject, as they have different response capabilities. With this event grouping step, we are able to capture spatial information, which will be crucial for classification later on.

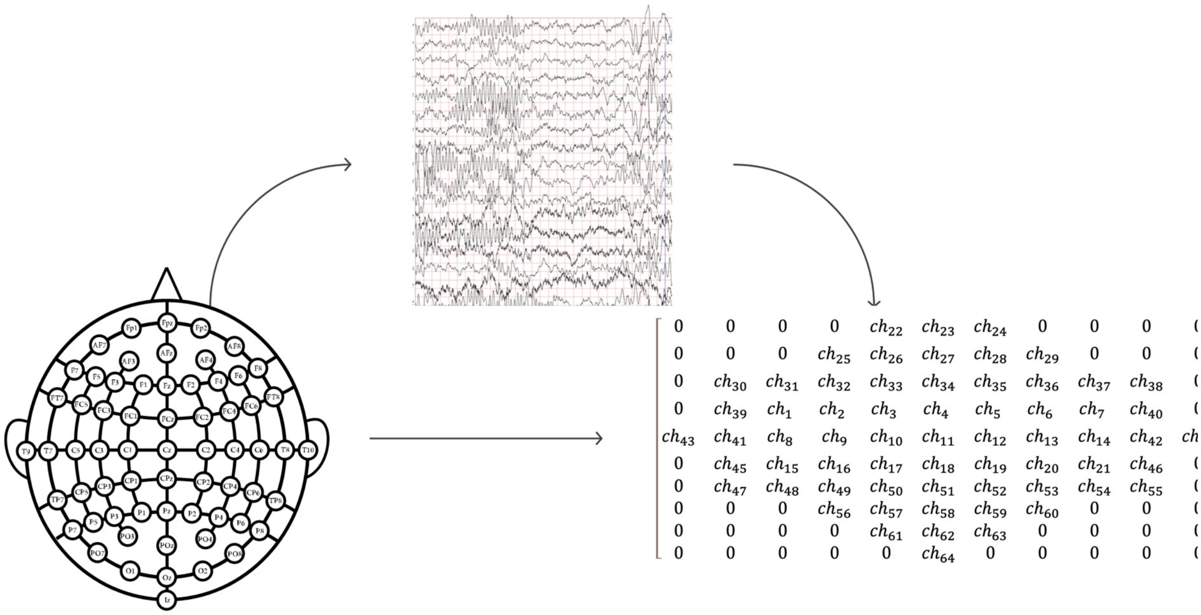

Fig. 4. Conversion of the EEG data into 2D arrays with the same layout as the EEG helmet.

These two preprocessing methods work synergistically in classification, providing better performance than if they were used separately.

2.5. Architecture of the network

After this pre-processing of the data using our own algorithm, the data is passed to the classifier architecture. This was developed and implemented using Matlab and DL Toolbox software and has the following structure:

- First, the architecture consists of a sequential input layer "sequenceInputLayer", where the 3D matrices (10x11x656) are treated as 2D matrices (10x11), with the remaining 3 dimension taken as a temporary variable (656), since they correspond to the event to be classified. In this layer, a normalization of the type "Zscore", which normalizes the data to "zero" is carried out. This is done to try to equalize the different microvolt values that exist between different users and have a standard.
- After the output of this layer, the folding layer "sequenceFoldingLayer" is added, which is used to make the use of CNN and LSTM layers compatible in Matlab and have the correct format. Within this layer, 3 CNN layers are added sequentially. These have 32, 64, and 128 feature maps as parameters, respectively. The first two convolutional layers use a "same" type and a "replicated" value padding as parameters of the CNNs, while the last layer uses a "symmetric-includes-edge" padding value. The goal of these layers is to capture the spatial information contained in the event matrices through convolutions.
- After the output of the CNNs, a fully connected layer is used followed by a dropout layer. These two layers, based on the bibliography, have a good perform in these types of classifications [47]. On one hand, what is sought with the fully connected layer is to establish multiple connections between the output neurons, improving the relationships between neurons [43]. And on the other hand, with the dropout layer it seeks to reduce the randomness of the classification by randomly deactivating neurons. This results in less bias and more reinforced and less random learning [48].
- The folding is then closed using the "sequenceUnfoldingLayer" layer so that the output of the dropout is in the correct input format to the next layer. This layer is the Flatten layer which seeks to flatten and convert the output matrix into a 1-dimensional vector. This is done in order to allow entry into the next 2 layers.
- These are 2 LSTMs layers placed in series that will iterate. Hence, the sequences are treated as a set of vectors from which the LSTM algorithms are capable of extracting temporal characteristics. These 2 LSTM layers have 64 neurons in the hidden layer each. The first LSTM layer has the parameter set to iterate only with the "last" value while the second LSTM returns the entire "sequence" value. This allows feedback in these layers that provide information about the previous event or sequence and that subsequently result in the complete sequence with the temporal information being output.
- As was done in the output of the CNN layers, a Fully connected layer and another dropout layer are added with the same objective.
- Finally, a softmax layer is placed, which is responsible for performing a statistical distribution of the output and finally the binary classification layer that will perform a comparison with the labels to give a final output response.

Fig. 5 shows the Matlab DL toolbox diagram where it can be seen the sequence of steps described above. On the other hand, Fig. 6 shows a flowchart of the process where it can be seen the steps that were followed.

1- Dataset, where data were collected from the Physionet database, showing the nature of the signal in different channels and the formation of an EEG helmet in data collection according to the 20-10 system.
2- Example of the formation of a 2D matrix after applying the preprocessing algorithm. It is observed how the 64 channels form a matrix representing the helmet, and below what the 3D matrix would look like.
3- Simplified diagram of an example where 2D matrices are fed into the classification algorithms and a T1 or T2 response is obtained at the output.

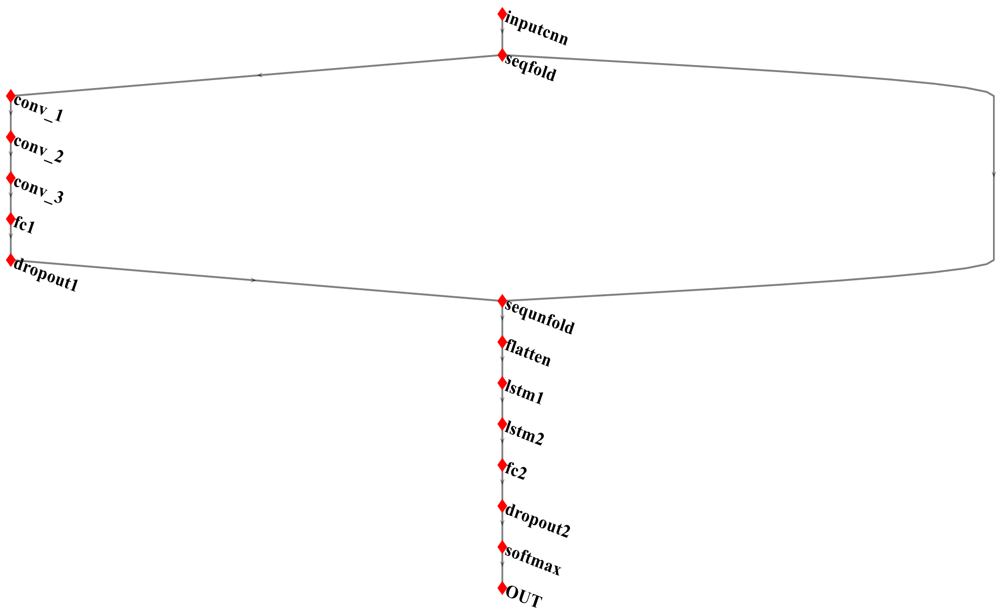

Fig. 5. Scheme of classifier architecture in DL toolbox.

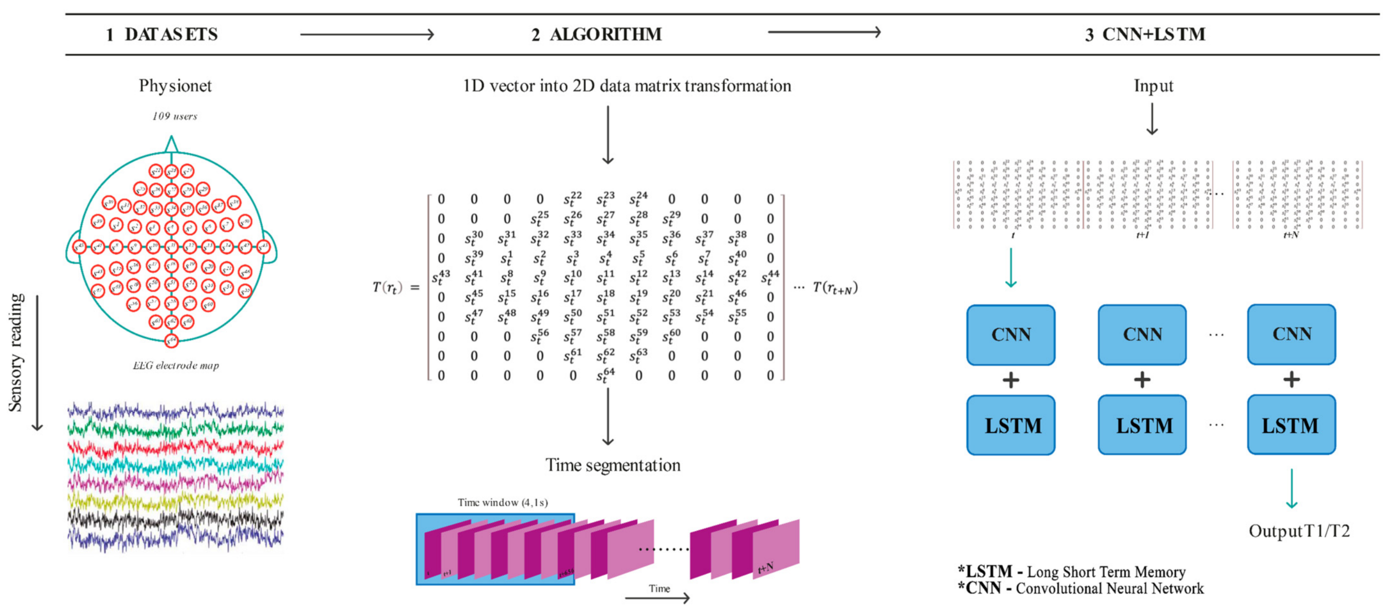

Fig. 6. Outline of the process carried out in the study.

The proposed architecture represents a significant contribution to the field due to its unique combination of CNN and LSTM layers and its synergy for EEG signal data classification.

2.5.1. Network training options

The model used in the classification was trained in Matlab using the Adaptive Moment Estimation or Adam method, which consists of a Root Mean Square Propagation (*RMSProp*) with momentum [49]. The values of the hyperparameters in the classifier were:

- "*Epsilon*" value of 1-10-9.
- *Initial Learn Rate* value of 0.0001
- *Mini Batch Size* of 128
- *Max Epochs* of 90 and "*Shuffle*" in each epoch
- *Gradient Threshold Method* is set to "*l2norm*"
- *Gradient Decay Factor* is set to 0.8.

Training and testing are performed using the k-fold method with n = 10, with multiple iterations for each user. In each iteration, 8 of the folders are used for training and the remaining 2 are used for a blind test. This gives a percentage of accuracy for each user and the associated standard deviation.

2.6. Metrics

The metric that has been used to evaluate the performance of the models is accuracy, which has been derived from the confusion matrices for each experiment. To ensure the reliability of our findings, we have also included the standard deviation, and the experiments were conducted using the k-fold 10 method to achieve a more homogeneous representation.

The results have been analyzed and we have taken into consideration the p-value to ensure that the findings are statistically significant, being this a key factor in determining the significance of

Table 4
Results of the user-by-user prediction with standard deviation and total mean.

User	Success	STD	USer	Success	STD	User	Success	STD
1	66,25	2,25	36	65,38	2,77	71	78,57	1,98
2	66,47	1,28	37	78,88	1,49	72	81,56	1,60
3	74,07	1,62	38	57,04	3,15	73	74,93	1,61
4	86,28	2,05	39	85,71	1,16	74	76,56	1,56
5	61,01	1,28	40	77,77	2,04	75	63,52	3,03
6	58,92	2,49	41	85,48	1,27	76	78,52	1,64
7	64,32	2,31	42	80,51	2,80	77	87,17	1,59
8	75,46	1,86	43	72,84	2,36	78	71,76	2,85
9	86,50	2,08	44	76,08	1,95	79	64,38	1,16
10	77,40	1,80	45	62,78	1,64	80	60,82	2,00
11	87,58	1,53	46	76,79	1,91	81	83,92	1,40
12	77,11	2,05	47	78,74	2,62	82	77,07	1,56
13	62,22	2,34	48	82,88	1,42	83	71,94	1,20
14	68,95	1,41	49	67,22	1,69	84	85,07	0,73
15	66,43	2,35	50	78,21	1,65	85	66,65	1,64
16	85,42	1,93	51	83,04	1,08	86	70,29	1,89
17	85,19	1,80	52	72,03	2,04	87	58,30	1,78
18	79,78	1,85	53	64,84	1,96	88	70,59	1,60
19	60,55	0,95	54	83,11	1,62	89	72,88	2,43
20	78,06	2,01	55	76,56	1,14	90	77,80	1,38
21	74,46	1,06	56	64,08	1,52	91	63,21	1,21
22	76,08	1,88	57	78,00	1,50	92	71,23	1,98
23	63,74	1,78	58	74,18	1,15	93	76,97	3,11
24	64,25	2,27	59	83,30	2,67	94	65,44	1,84
25	73,30	0,96	60	84,78	2,08	95	76,54	1,34
26	85,44	1,95	61	69,56	1,49	96	65,24	2,10
27	81,97	1,90	62	85,36	1,85	97	75,90	2,51
28	86,70	2,05	63	58,97	2,15	98	83,15	2,05
29	80,76	1,73	64	79,16	1,70	99	72,13	2,16
30	76,83	1,77	65	73,06	1,75	100	83,55	1,21
31	76,40	3,93	66	60,29	3,08	101	90,37	2,11
32	74,81	1,90	67	77,80	2,08	102	79,36	1,94
33	72,54	1,88	68	90,54	1,22	103	71,28	1,61
34	75,57	1,28	69	69,47	1,80	104	73,68	2,07
35	58,22	2,38	70	81,52	2,57	105	81,73	2,47
						Average	74,54	1,86

the findings. The most advanced study in binary classification with Physionet has been used. This study by Kim et al. [50] achieves a hit rate of 80.05%, so our hypothesis will be based on a confidence level of $\alpha = 0.05$ where users either exceed or fail to exceed this value for the different thresholds. The use of accuracy, standard deviation, k-fold 10, and p-value analysis has allowed us to gain valuable insights into the effectiveness of the proposed model and tool.

3. Results & discussion

In this section, the results of a user-by-user classification have been shown and discussed. Consequently, a threshold was applied to create a tool to discern which users are valid to use EEG or if there were any problems in the EEG samples or the experiment when it was carried out.

The hardware used to obtain the results is a computer with an I7-9600-K processor, 16 GB of RAM, and a Gigabyte GeForce RTX-2060 Windforce OC-6GB-GDDR6 graphic card with a 7.03 TFLOPS. The computation time ranges from 25 to 35 ms.

3.1. Classification user-by-user

Table 4 shows the results of the user-by-user classification of the 105 users in the database (described in Section 2.1). For each user, we use the k-fold method with n = 10, where each user is trained on its data and tested on a blind sample of it at each iteration. Thus, we are looking for specificity and a model that is trained on data from the whole set, but separately, unlike previous work that trains on data from the whole set at the same time.

The results show an average accuracy of 74.54%. Some subjects exceed 90% accuracy, while other subjects stay around 60% accuracy, see Fig. 7. As can also be analyzed in these results, 56 of the 105 database users show a classification success rate above 75%, while 49 of the 105 of the subjects did not exceed 75% classification success.

This indicates that in the generic classification experiments, when training with the whole ensemble at once, it is not possible to distinguish which subjects contribute value to the network and which ones contribute noise by being inappropriate. This, together with reviewed studies such as Roc et al. [13], suggests that there is a limit to the success due to the nature of the subjects, who have different predispositions and must be trained correctly to respond to the stimuli.

For this reason, a secondary analysis is proposed in which a decision threshold is established above which the test is valid. The objective is to create a tool capable of detecting subjects whose test is invalid and who are burdening the system. This will make it possible to analyze the reason (distractions in the test, bad predisposition, need for specific training, or even instrumentation errors in the acquisition of the signal) and to increase the accuracy of the whole set.

3.2. Threshold

As mentioned above, a series of pass thresholds were then established for the subject's test to be considered valid. These thresholds are set at 75%, 80%, 85%, and 90% success. 75% is chosen because it is the average of the experiment. 80% because it is the average of other experiments using the same methodology and database [50]. The 85% threshold is used because it is an objective

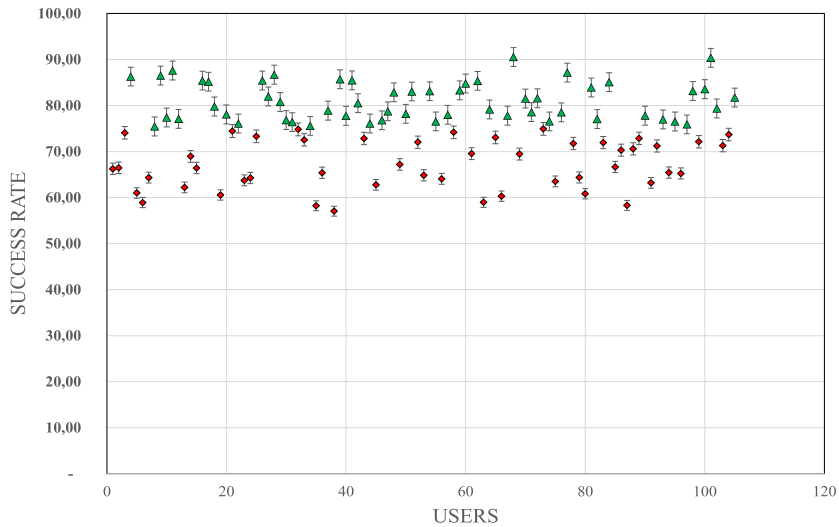

Fig. 7. Representation of the classification accuracy of the 105 users. In green, those that exceed 75% of accuracy (golden users). In red those that do not.

Table 5
Classification results applying the different thresholds. The percentage change in success and in the number of users with respect to.

Threshold	Users	Success	Increase of success (%)	p-value ($\alpha = 0.05$)
none	105	74,54	none	$P > 0.05$
75	56	81,01	8,68	$P > 0.05$
80	28	84,59	13,48	$P < 0.01$
85	14	86,63	16,22	$P < 0.01$
90	2	90,45	21,34	$P \cong 0.25$

value that would exceed that of other user-to-user training studies, such as that of Luo et al. [23] (82.75%). No study using user-to-user training and the Physionet database has managed to exceed this threshold. Finally, the 90% threshold is set because there is no study with a similar methodology (user-to-user) that reaches this percentage.

It should be noted that there are certain subjects who have a better predisposition to obtain a good EEG and, on the contrary, there are others who do not reach sufficient concentration to obtain an optimal signal-to-noise ratio. Some studies have referred to these as “golden users”, i.e. subjects with a good EEG predisposition, while they also use the term “EEG illiterates” for users with a bad predisposition [51]. The latter can improve their signal in a new attempt by various methods, such as a short meditation before the tests [52]. Thus, by establishing this threshold, a tool is created that allows us to distinguish between valid users and those who should repeat the test. Establish an improvement in the system. The results are shown in Table 5.

These show that only by applying a threshold of 75% success, the success rate increased from an average of 74.54% to 81.01%. The success concerning the initial experiment is 8.68% higher while the users go from 105 to 56. This would guarantee a success rate higher than that of most studies with this number of subjects.

When the threshold is set at 80%, the number of users drops to 28 (a drop of 73.33% respect the first experiment), while the average success rate increases to 84.59%. For the 85% threshold, the number of users is 14, which is still a higher number than databases like the BCI competition. With this threshold, an average percentage of success of 86.63% is reached. This is a 16.22% improvement over the full set.

Finally, if the threshold is set at 90, only 2 users manage to exceed this limit, being too demanding for the rest of the users and obtaining an average of 90.45% in the classification success.

This implies that the use of this threshold in the classification works, allowing tests to be discarded so that the set reaches a higher success rate and the subjects that fall below know that they must repeat the test. With this, a system is achieved that is capable of working with a large number of users and responds correctly.

Furthermore, the p-value indicates that the probability that the data you have observed (in this case, the classification successes) were obtained randomly or by chance is practically zero in the cases where the threshold was 80 and 85%. In the case of 90% having a small population, the statistics do not apply well. And in the case of 75% and no threshold, the p-values indicate that there is not enough evidence to guarantee that some classifications have not arisen from chance or the nature of the data.

3.3. *Comparison of applied threshold method with other studies*

Below, in Table 6, a comparison of some existing jobs taking into account the number of users, channels, and success rate is shown. They are not included in the table of works with their own database because they have not been studied enough to be compared.

If we use the number of users as a reference, when applying the 85% threshold we have 14 users (5 more than in the BCI IV contest). With a higher number of users, we obtain an average success rate of 86.63%. This percentage is higher than the 85.04% of Olivas-Padilla and Chacon-Murguia [53] using 9 users with the BCI database. On the other hand, using a threshold of 90%, a success rate of 90.45% was obtained, surpassing the 3 users of the BCI III competition whose ranking gave 89.2% in Miao et al. [55].

4. Conclusions

In conclusion, the results of this study demonstrate the potential of the proposed methodology to address a major challenge in the development of BCIs, that is the bias that arises from user-by-user training models and the bias associated with small datasets used in most studies.

Two tasks from the four possible ones suggested in the database were chosen because we gave priority to proving the hypothesis. We wanted to apply it to a simple case where subjects open and close their fist and then imagine themselves doing these movements. On the other hand, the reason for doing an intra-subject analysis is that in the existing bibliography, many works propose a system where training is done with a set, where the

Table 6
Comparison of applied threshold method with other studies.

Article	Dataset	Channels	Users	Success rate
Yong et al. [20]	BCI competition IV-2b	3	9	78.2%
Lee and Choi [21]	BCI competition IV-2b	3	9	78.93%
Ha and Jeong [22]	BCI competition IV-2b	4	9	78.44%
Luo and Chao [23]	BCI competition IV-2b	3	9	82.75%
Olivas-Padilla and Chacon-Murguia [53]	BCI competition IV 2a	8	9	85.04%
Ai et al. [54]	BCI competition IV 2a	3	9	79,70%
Miao et al. [55]	BCI competition III 4a	118	3	89,2%
This study (complete set)	PhysioNet dataset	64	105	74.54%
Kim et al. [50]	PhysioNet dataset	64	105	80.05%
This study (threshold 75%)	**PhysioNet dataset**	**64**	**56**	**81.01%**
This study (threshold 80%)	**PhysioNet dataset**	**64**	**28**	**84.59%**
This study (threshold 85%)	**PhysioNet dataset**	**64**	**14**	**86.63%**
This study (threshold 90%)	**PhysioNet dataset**	**64**	**2**	**90.45%**

data of some subjects are mixed with those of others. Here we wanted to develop a classification tool based on the subject, which allows us a generalization when it comes to know if any new user is valid or not and, if so, to have a system that allows a good classification of its imaginary signal of movement.

By using a hybrid deep learning model consisting of a CNN and LSTM network to analyze the spatial and temporal characteristics of EEG signals from the Physionet public dataset, a high classification accuracy of up to 90% for some users and a global average of 74.54% is achieved.

In addition, a second analysis using different test acceptance thresholds is performed, resulting in a significant improvement in classification accuracy of up to 21.34%. The proposed methodology represents a significant contribution to the field of BCIs, providing a more generalized system that can be trained on a large amount of data from different users, thus avoiding biases arising from user-specific models. Additionally, the proposed model effectively captures spatial and temporal features of EEG signals, improving classification performance and providing a discriminative tool to detect inefficient EEG recordings. The potential impact of this research extends beyond the field of BCIs and has implications for the broader area of human-computer interaction. We believe that this work represents a promising step towards developing more reliable and accurate BCIs, and can serve as a valuable tool for analyzing users who present worse results on their EEG recordings. Future research could explore the addition of more advanced layers, such as transformers, to further improve the performance of the system, as well as the addition of multitasking classification, which adds another level of complexity to the process. Also, technics as the developed by Sun, B et al. [18] could allow us to improve the proposed system.

Human and animal rights

The authors declare that the work described has not involved experimentation on humans or animals.

Informed consent and patient details

The authors declare that the work described does not involve patients or volunteers.

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Author contributions

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Declaration of competing interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

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