

Article

Optimizing EEG-Based Motor Imagery Decoding for Neurorehabilitation: A Deep Learning Framework with Catastrophic Forgetting Mitigation

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Abstract

(1) Background: Motor imagery (MI) analysis via electroencephalography (EEG) is crucial for Brain–Machine Interfaces (BMIs) and neurorehabilitation, though inherent EEG noise challenges robust decoding algorithm development for assistive devices aiding patient recuperation. (2) Methods: This study introduces a deep learning pipeline utilizing the IFNet convolutional neural network with frequency filtering and two scaling methods to decode pedaling MI. To mitigate catastrophic forgetting during transfer learning, a rotative Elastic Weight Consolidation (rEWC)-based weight adjustment procedure was incorporated. The pipeline was validated with 23 non-disabled participants across four sessions each, evaluating four approaches via pseudo-online (open-loop) and real-time online (closed-loop) analyses. (3) Results: The decoding accuracy for MI exceeded 80% (up to 95% individually) in selected pseudo-online approaches, while real-time online classification averaged 70% accuracy with a slight bias towards the relax task, confirming statistical significance for both scenarios. (4) Conclusions: These findings demonstrate that mitigating catastrophic forgetting in transfer learning within deep learning models and applying proper scaling are crucial for optimal performance. Consequently, the proposed deep learning pipeline holds significant promise for effective, adaptive EEG-based neurorehabilitation systems.

Keywords: brain–machine interface (BMI); electroencephalography (EEG); motor imagery (MI); deep learning (DL); convolutional neural network (CNN); catastrophic forgetting; maximum visual threshold (MVT); rotative elastic weight consolidation (rEWC)



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1. Introduction

Neural brain activity encodes a wide spectrum of information, ranging from cognitive processes and emotions to motor commands and muscular intentions [1]. Brain–Machine Interfaces (BMIs) facilitate the acquisition of this neural activity, enabling the extraction of

relevant information [2,3]. These interfaces employ various recording methods, broadly categorized as invasive or non-invasive. Invasive techniques, such as intracranial electroencephalography (iEEG) [4] and electrocorticography (ECoG) [5,6], involve direct brain signal recording, typically requiring surgical procedures that carry inherent risks. Conversely, non-invasive methods, including magnetoencephalography (MEG) [7,8], functional Magnetic Resonance Imaging (fMRI) [9], and electroencephalography (EEG) [10–12], record activity through the scalp, avoiding surgical intervention but often at the cost of signal quality. Due to its ease of implementation and user-friendliness, EEG has emerged as a promising technique in neurorehabilitation, offering a straightforward approach to acquiring neural information [13,14].

Within neurorehabilitation, numerous studies utilize EEG techniques to control clinical devices such as exoskeletons [15,16] and clinical cycle ergometers [17–19], as well as for diagnostic, evaluative, and therapeutic purposes [20,21]. Specifically, EEG-based control of rehabilitation devices offers a significant advantage for stroke patients undergoing motor rehabilitation, since this approach facilitates the use of motor imagery (MI), the neural representation of movement intention without actual physical movement. MI activates the motor cortex, potentially enhancing motor neurorehabilitation outcomes. This enhancement is primarily attributed to the fact that MI-based control elicits deeper activation of the affected motor area in stroke patients, benefiting both muscle function, through device-induced movement (cycle ergometer, exoskeleton, rehabilitation robot, etc.), and neural recovery by stimulating the affected brain regions. MI-based control establishes a closed-loop interaction between the device and the patient's brain, simulating natural movement. This process originates from brain signals (EEG signals) and is translated into physical movement by the rehabilitation device, enabling patients with motor impairments to complete the required movements through the exercise of their motor cortex and the improvement of neuroplasticity [22,23].

Consequently, numerous EEG-based therapies have been developed in recent years [24]. EEG provides a simple and rapid method for establishing a BMI capable of motor imagery decoding, which explains its use in exoskeleton control [12,25]. While exoskeletons facilitate natural gait experiences and represent a valuable tool in these therapies, clinical cycle ergometers offer distinct advantages, including reduced costs, enhanced safety due to limited unbalance risks, and ease of use. Accordingly, several studies have also explored motor imagery-based control for cycle ergometers [26–28]. However, motor imagery decoding presents a significant challenge due to the inherent non-linearity and endogenous nature of EEG signals, compounded by their high signal-to-noise ratio in non-invasive recordings [29]. To address this, various algorithms have been developed to achieve accurate, dynamic, and efficient motor imagery decoding from EEG signals [30]. Typically, these algorithms employ spectro-spatial feature extraction and feature-based classification, preceded by a preprocessing pipeline that often includes frequency filtering and signal standardization. For example, Xu et al. [31] utilized the discrete Wavelet transform for left- and right-hand motor imagery classification. Similarly, the combination of Common Spatial Patterns (CSP) with Linear Discriminant Analysis (LDA) has been extensively explored for motor imagery decoding, demonstrating favorable results [12,32,33]. Nonetheless, the emergence of Deep Learning (DL) techniques and neural network-based classification strategies has shifted the trend, with many studies now focusing on neural network classifiers.

Recent advancements have refined deep learning algorithms for time series analysis [34], including applications in EEG-based motor imagery decoding [35], EEG signal processing [36–38], and specialized motor imagery decoding from EEG [39–41]. These processing methods have demonstrated significant potential and yielded exceptional results,

surpassing traditional classification procedures. Motor imagery classification often incorporates frequency band filter banks, enabling the separate analysis of relevant frequency ranges and the extraction of band-specific features. For example, Wang and colleagues [41] integrated frequency filter banks into their deep learning motor imagery decoding algorithm. However, neural networks present limitations, primarily the substantial training data required for optimal performance. Inter-subject approaches, which utilize data from multiple subjects, offer a potential solution, but are challenging to develop due to significant inter-subject variability in EEG data [42]. EEG signals can exhibit substantial differences for the same task across different individuals, and even within the same individual across different sessions, influenced by factors such as mood, emotional state, hunger, and temperature. Consequently, transfer learning in EEG analysis poses a considerable challenge [28,43]. A common issue encountered when applying transfer learning is catastrophic forgetting, where decoding models lose or “forget” previously learned data distributions while adapting to new training data (e.g., from new subjects). Algorithms based on Elastic Weight Consolidation (EWC) [44], such as rotative Elastic Weight Consolidation (rEWC) [45], address this problem by preserving model weights to prevent the overwriting of functional data distributions. This technique, combined with a fine-tuning strategy (briefly retraining classifiers with recent data before each session to adapt to the user’s current state), may provide an effective solution for EEG-based motor imagery decoding.

This study proposes a deep learning pipeline for processing EEG signals aimed at decoding pedaling motor imagery. The decoding algorithm comprises a preprocessing stage utilizing a frequency filter bank and two distinct scalers, followed by the application of the IFNet deep learning model [41], integrated with the rEWC algorithm [45] and a fine-tuning strategy. The models were trained using data from 23 non-disabled participants, adhering to a transfer learning protocol. In addition, a subset of eight subjects underwent real-time closed-loop testing. Four distinct approaches were evaluated, with some achieving average accuracies exceeding 80%.

2. Materials and Methods

This section details the participant demographics and inclusion criteria, the experimental setup, and the protocol employed during the EEG recording sessions. Furthermore, the pedaling motor imagery decoding algorithm developed in this study is comprehensively described. Finally, the statistical analysis performed on the decoding data is presented.

2.1. Subjects

A total of 23 non-disabled participants took part in this study, comprising ages from 18 to 77 years old (35 ± 18 y.o.). Twelve of them were males (U02, U04, U05, U07, U10, U12, U13, U14, U19, U20, U22 and U23) and the remaining eleven were females (U01, U03, U06, U08, U09, U11, U15, U16, U17, U18 and U21). Every user was free from any type of diagnosed motor or neurological disorder, and all of them met the inclusion criteria, approved by the Comité de Ética de la Investigación con medicamentos (CEIm) del Hospital Universitario Severo Ochoa de Leganés (HUSO) in Leganés, Madrid, Spain. Prior to participation, all participants were provided with clear information about the study, their roles, and the main concerns, as they signed an informed consent form included in the previously mentioned ethics committee, which received the code HLM-CYCLING-EEG.

2.2. Experimental Setup

Three electronic devices were employed in the experimental tests. The first one was an EEG registration system from g.tec medical engineering GmbH, Schiedlberg, Austria, composed of the EEG cap g.NAUTILUSPRO Flexible of 32 channels with g.SCARABEO

channel distribution, including the Wi-Fi HEADSET transmitter and the BASE STATION data receiver. During the user instrumentation prior to each recording session, all electrodes were prepared with EEG-specific conducting gel in order to guarantee an appropriate impedance level under 20 k Ω , ensuring a clean signal quality. As the reference electrode was clipped to the right earlobe, this area was previously cleaned with skin prep gel, enhancing the electrode performance. All the signal recordings were conducted at a 500 Hz sample frequency.

Participants performed the experimental tasks while seated on the second device included in the setup, a clinical cycle ergometer from Fourier Robotics ©, Singapore, Singapore; the CycleMotus™ A4, which was operating in passive mode when moving. To minimize external distractions during the EEG recordings due to reflections and glare, the cycle ergometer screen was covered at all times. Regarding the rotation speed, to ensure a personalized and realistic experimental setting, participants were allowed to select their preferred pedaling speed. This individualized approach aimed to develop a robust MI-decoding system adaptable to diverse user needs and potential clinical scenarios. Following these statements, all users chose rotation speeds within the range of 20–40 revolutions per minute, and they maintained these speeds through all their recording sessions.

During the experimental sessions, the EEG recording system (through the BASE STATION) and the cycle ergometer (through Arduino) were connected via USB to the third device, the registration computer, a PcCom Revolt 4060 from PcCom (Windows x64bit, 13th Gen Intel(R) Core(TM) i7-13700H 2.40 GHz, 16GB RAM, NVIDIA GeForce RTX 4060 Laptop GPU), distributed by PcCom, PcComponentes, Alhama de Murcia, Spain. When undergoing online recordings, all EEG channels were acquired, preprocessed, and processed simultaneously in real time, as the signal was classified and the cycle ergometer commanded depending on the classification outputs, all via the registration computer. Figure 1 shows the experimental setup and all its elements during a recording session.

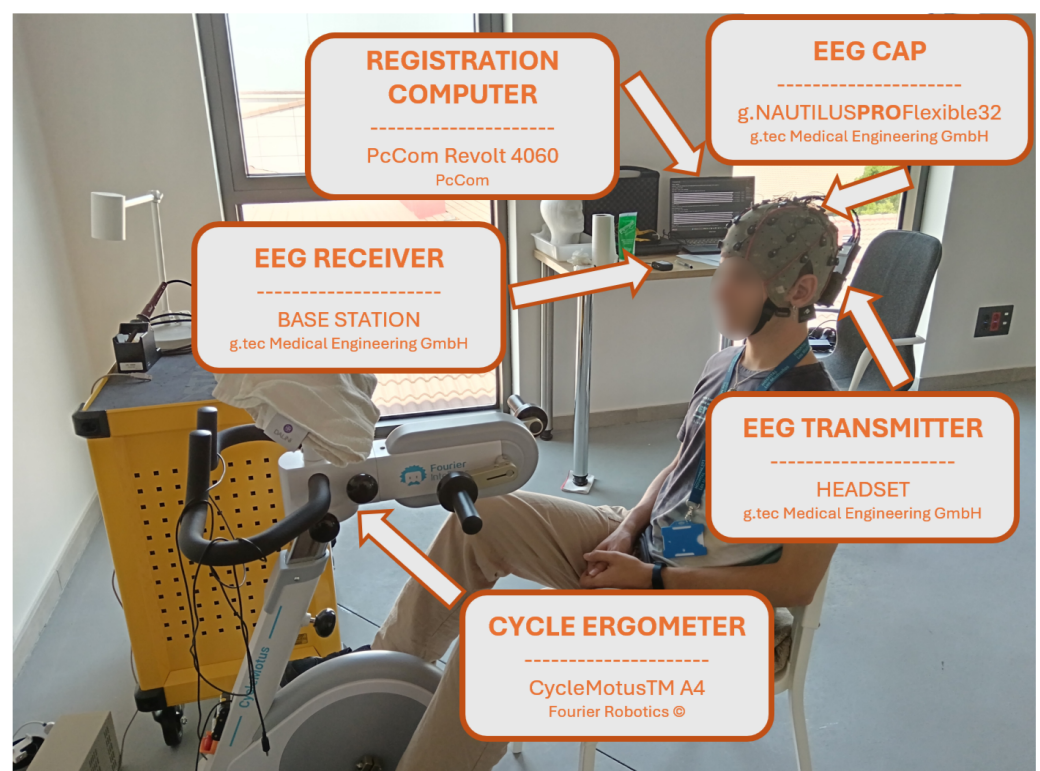


Figure 1. Experimental setup. A participant engaged in an EEG recording session. The image shows the participant seated on the cycle ergometer while his brain activity is being recorded using the EEG system that is described in the picture.

2.3. Experimental Protocol

Each participant completed four experimental sessions on separate days, within the same week, with no exceptions. The protocol was strategically composed of relax phases and MI phases, both at rest and during pedaling in assistive mode, maintaining the rotation speed chosen by the user throughout the experimental sessions. These paradigms allowed for the search of two types of control: cessation of device movement (rest control) and initiation of device movement (motion control) based on EEG signals.

Every experimental session comprised 12 to 20 trials of the open-loop protocol (always an even number). In turn, this protocol was formed by 15 s of the relax task, followed by 30 s of MI, and finishing with another 15 s of the mental relax protocol. Odd-numbered trials were conducted at rest (no motion), while the even-numbered ones were performed during passive pedaling. As trials are class-balanced (30 s of relaxing + 30 s of MI) and the experimental sessions were composed of an even number of trials (the same number of rest and motion trials), this design ensured equal representation of four conditions: rest–relax, rest–MI, pedaling–relax, and pedaling–MI.

Participants U16 to U23, both included, underwent some closed-loop trials during their participation in the study. These participants completed from two to eight closed-loop control trials, which consisted of the same periods of 15 s of the mental relax protocol, surrounding one 30 s MI period. However, in this case, the cycle ergometer was still at the beginning of every trial, and it could be activated or deactivated at any time, depending on the BMI decoding. Since during the closed-loop trials EEG signals were processed in real-time, the system continuously monitored the classification output (MI/relax). If the mean classification output of the last five seconds of recordings indicated motor imagery, the cycle ergometer remained active. Conversely, if the mean classification output indicated relaxation, the cycle ergometer stopped. To prevent rapid and potentially disruptive state transitions, the cycle ergometer state was held constant for five seconds following each state change. Most of these participants began performing closed-loop trials in the second session, as initial training data from at least one session were required for fine-tuning the motor imagery decoding models. As two decoding models were applied to the EEG data (a static model and a pedaling model, see Section 2.4.2), the appropriate model was selected based on the current cycle ergometer state following a state machine concept (similar to the case described in [46]), with the pedaling model used during cycling to determine when it should stop and the static model to determine when it should start.

Figure 2 shows a scheme of the experimental protocol. To cue participants, during the whole study an auditory signal was provided in each task transition, where extra periods of two seconds were added; these auditory cues were subsequently discarded during signal preprocessing to minimize external stimuli.

Regarding the participants' mental task performance, all of them completed the MIQ-3 questionnaire [47] in its Spanish version [48] (given that all participants were native Spanish speakers) before the first experimental session. The participants were instructed in how to effectively perform the motor imagery tasks, teaching them how to distinguish internal and external visual motor imagery from kinesthetic motor imagery, and guiding all participants to focus on a kinesthetic movement imagination. This included trying to avoid visual stimuli since kinesthetic MI stimulates the motor cortex, whereas visual imagination stimulates the visual cortex [49], and, in real therapy with a motor-disabled stroke patient, the motor cortex stimulation is a critical target [50]. Table 1 contains the results obtained by every participant in the MIQ-3 questionnaire. Before every experimental session, participants were reminded about the use of kinesthetic motor imagery, highlighting the importance of using it in a consistent way, as similar as possible to the previous recording days. Furthermore, the participants were also told to initiate motor imagery always with the same limb, and to

avoid extraneous movements during the recordings, especially in the arms or neck, and to maintain a fixed gaze and avoid gulping. Also, participants were instructed to avoid the consumption of caffeine, energy drinks, or other central nervous system stimulants for at least 2 h prior to each session. To replicate the conditions of a prospective therapeutic session, participants were instructed and reminded daily to maintain visual fixation on a designated point throughout the testing procedures. They were allowed to blink, as blinks can be filtered afterwards (since this can impede the participants, causing them to lose concentration). Blink-related metrics were not explicitly quantified. Throughout the experimental sessions, participants were periodically visually monitored and assessed to verify the absence of acute cognitive fatigue.

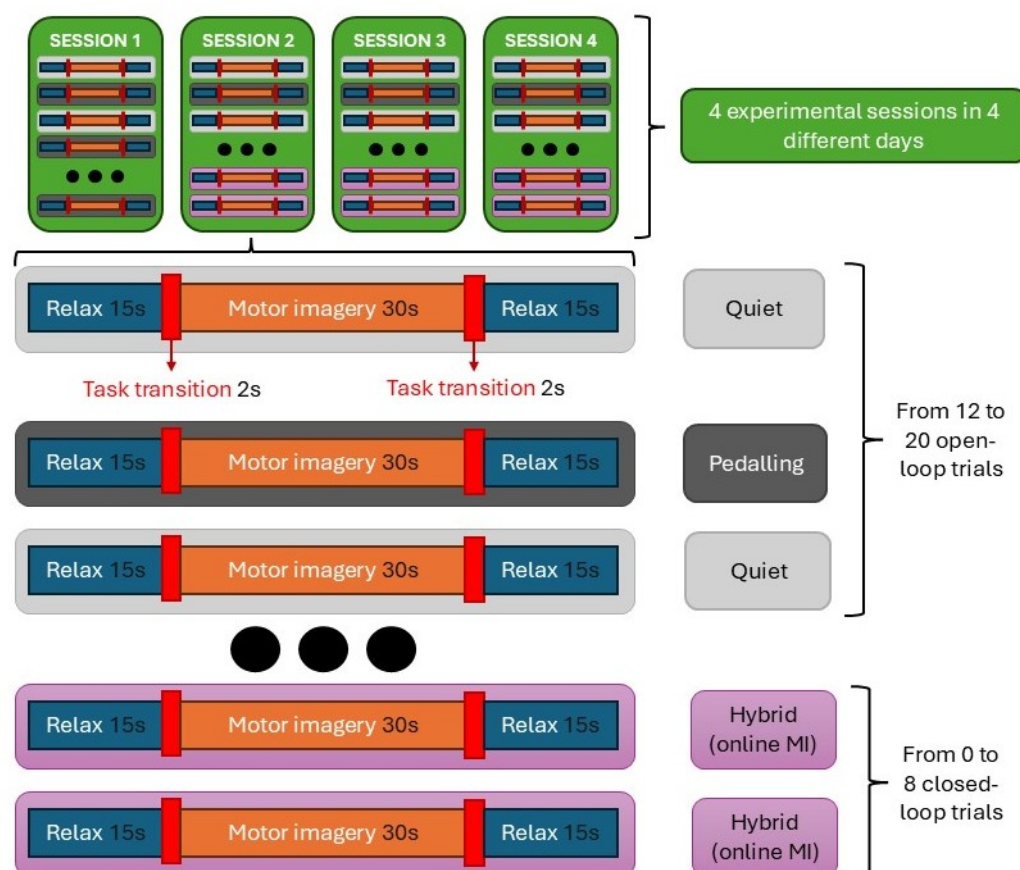


Figure 2. Experimental protocol. The experimental protocol followed by each participant is synthesized in this diagram. Each participant completed four sessions of 20 relax-MI-relax trials, including hybrid trials in some of the sessions, where the cycle ergometer becomes activated depending on the MI real-time decoding levels.

Table 1. MIQ-3 results. Results obtained in the MIQ-3 questionnaire [47] by each participant, comprising internal visual motor imagery index, external visual motor imagery index, and kinesthetic motor imagery index.

Participant	Internal Visual MI Index	External Visual MI Index	Kinesthetic MI Index
U01	6	5.5	7
U02	5.75	6.25	4.75
U03	5.75	6	6
U04	5.5	1.5	2
U05	4	5	3.25

Table 1. *Cont.*

Participant	Internal Visual MI Index	External Visual MI Index	Kinesthetic MI Index
U06	5	5.5	4.5
U07	5.25	5.5	6.75
U08	6.5	6.75	3
U09	5.25	5.5	6.75
U10	5.25	7	6.5
U11	5.75	6.75	5.5
U12	2.75	3.25	2.75
U13	7	7	6.75
U14	7	6.75	6.75
U15	4.75	5.75	5.75
U16	5	5	4.75
U17	5.25	6	4
U18	6	6	5.75
U19	6	6	5
U20	5.5	6.5	5.75
U21	5.75	6	4.75
U22	5	5.25	5.5
U23	5.25	5.5	5.75

2.4. Motor Imagery Decoding Algorithm

The same decoding algorithm was employed for the characterization of training and validation data. The signal processing architecture builds upon the framework presented in [28], incorporating several layers. As mentioned before, all EEG data were recorded at 500 Hz. This complete algorithm, including preprocessing, modeling, and classification, is summarized in Figure 3. Please notice that, as validation must be executed online for closed-loop control, the architecture pipeline works epoch by epoch, with processing times under 0.5 s, shifting processing training registers with a pseudo-online analysis.

2.4.1. Preprocessing

The first preprocessing layer is the one formed by the hardware filters offered by the EEG system manufacturer, g.tec Medical Engineering GmbH. These filters are especially adequate for real-time analysis as they are applied to the signal as a part of the recording pipeline, reducing the processing times and therefore the possibility of excessive delays in the system operation. Concretely, in this study, data have been hardware-filtered by means of a fourth-order Notch filter of 50 Hz (48–52 Hz) to eliminate the power supply component in the signal, as well as an eighth-order band-pass filter between 0.5 Hz and 100 Hz, erasing undesired frequency ranges. A noise reduction algorithm was also applied, integrated in the EEG device.

Next, a channel selection step was implemented for two primary reasons: decreasing the number of channels in the analysis also lessens the processing times, a key aspect for online tests, as well as it minimizes the number of electrodes required, potentially simplifying the setup and making the system more practical for real-world clinical use. The channels selected are distributed over the motor area (fronto-central, central, and centro-parietal) in order to focus on the motor cortex. These 19 channels are according to the 10/10 standard [51]: FZ, F4, F3, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P3, PZ, and P4. Figure 4 depicts the channel selection distribution over the head.

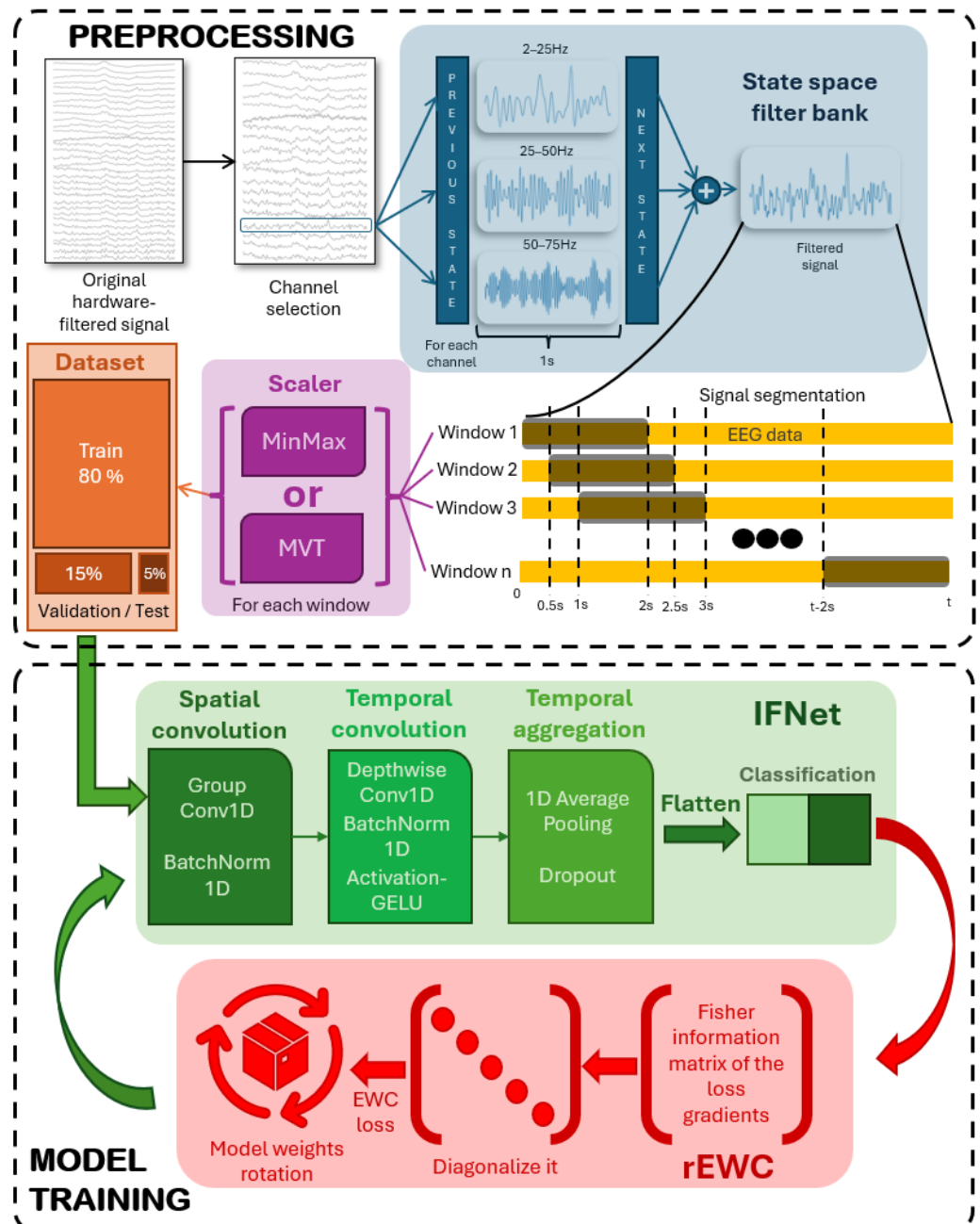


Figure 3. MI decoding algorithm. Complete process for the motor imagery decoding algorithm. In this study, three variants of the algorithm were implemented and evaluated: MinMax scaling without rEWC, MinMax scaling with rEWC, and MVT with rEWC. For the MinMax variant without rEWC, the additional retraining process was applied immediately after the initial training phase.

Following hardware filtering, the selected EEG channels underwent further processing using a software-based online state-space filter bank. This filter bank consisted of three parallel eighth-order Butterworth zero-phase bandpass filters with second-order sections, designed to isolate frequency bands of 2–25 Hz, 25–50 Hz, and 50–75 Hz. The EEG signal was segmented into one-second epochs, which were then processed in parallel by the three bandpass filters. Each epoch was filtered simultaneously through the three bandpass filters. The outputs of these filters were then summed to produce the final filtered signal, as this procedure presumably maximizes the subsequent classification outputs accuracy [41]. The filter states were updated at the end of each epoch. A 10 s warm-up period was used to initialize the filter bank and allow it to converge to a stable state, employing

zero-input conditions to determine an appropriate first state for each filter. The selection of a state space filter was driven by its suitability for processing acquired temporal windows rather than the entire recorded signal, which would not be possible in an online scenario such as real clinical use in neurorehabilitation. To mitigate the potential contamination of ocular movements (such as blinks and saccades) without the need for physical EOG channels, the preprocessing pipeline leverages the spectral differences between EOG artifacts and motor-related EEG signals. Since ocular artifacts are predominantly concentrated in the low-frequency range (typically below 4 Hz), the subsequent implementation of the filter bank—which targets the higher frequency bands associated with sensorimotor rhythms—naturally attenuates this low-frequency EOG energy, ensuring that the features extracted for the deep learning model are not corrupted by eye movements. Figure 3 illustrates a schematic approach of the filter.

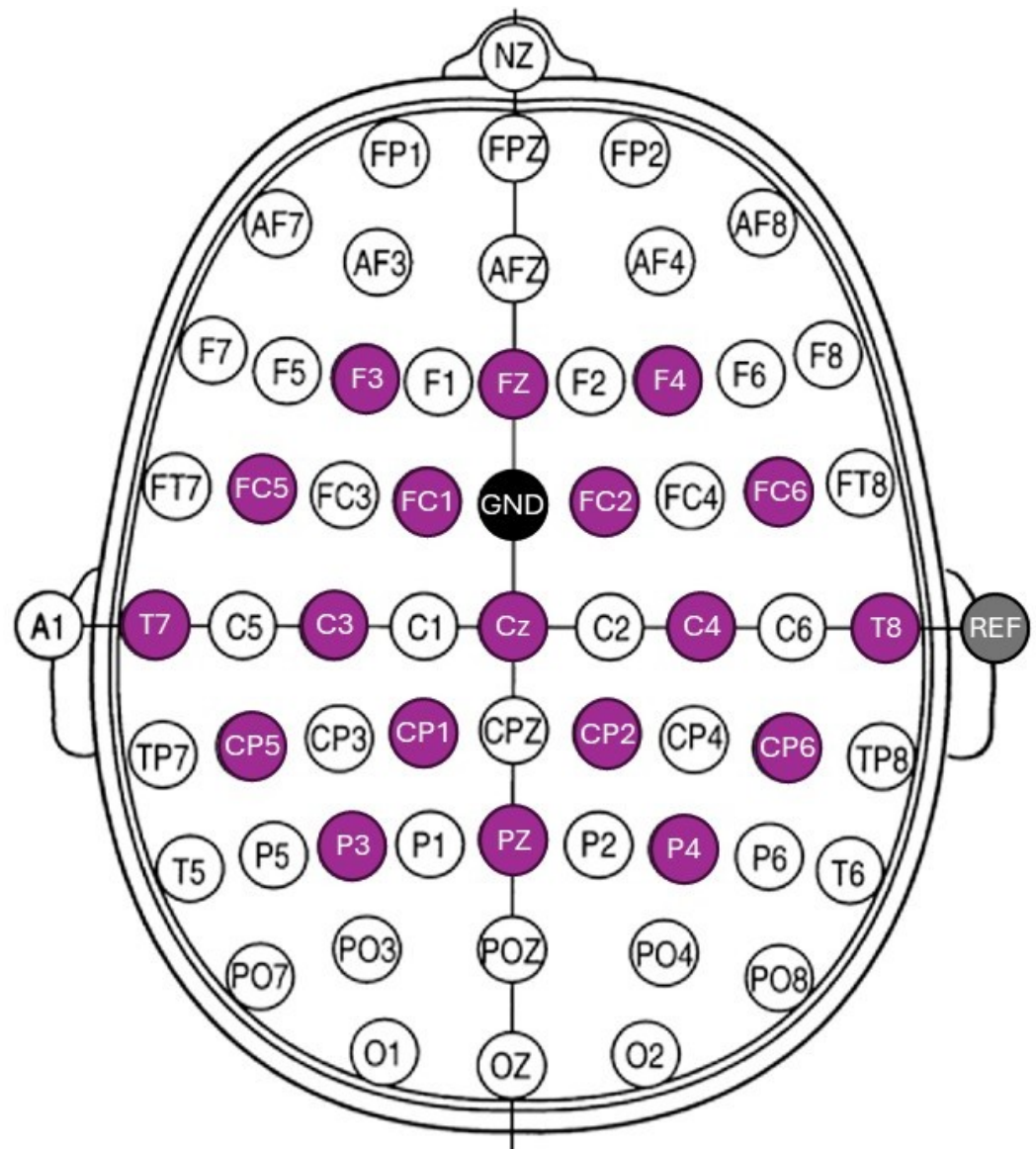


Figure 4. Channel selection. The channels selected for the analysis are highlighted in violet. The ground electrode, depicted as GND, was placed in FCZ (manufacturer criteria); the reference electrode (REF) was attached to the right earlobe (A2).

The next preprocessing step was segmenting the filtered EEG signal into time windows of 2 s shifted at a 0.5 s pace, which produces a data overlap of 1.5 s. This approach resulted in a classification output every half-second, where each classification decision was based on the preceding two seconds of EEG data, as shown in Figure 3. Every window containing task transition data was discarded.

Following signal windowing, a scaler was applied to the EEG data to prepare it for input to the neural network and avoid inter-user discrepancies. Two scaling approaches were investigated in this study:

- **MinMax scaler:** This approach is based on the maximum and minimum values registered in each channel (after all preprocessing processes before this point). These values were used to scale each sample to a range of zero to one and were stored during the model training phase for real-time use afterwards. Every sample was scaled according to Equation (1):

$$X_{\text{scaled}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where X_{scaled} is the scaled sample, X is the sample value prior to scaling, $X_{\min}$ is the minimum value registered in that channel prior to scaling, and $X_{\max}$ is the maximum value registered in that channel prior to scaling.

- **Maximum Visual Threshold (MVT):** Proposed by Costa et al. [52], this algorithm computes the average maximum value across a predefined set of epochs for each channel. These values are then used to normalize the signal. Similar to the MinMax approach, the normalization parameters were calculated during model training and stored for subsequent real-time application.

Once the data were filtered, segmented into time windows, and scaled/normalized, the data windows were pseudo-randomly divided into training (80%), validation (15%), and test (5%) sets (see Figure 3). The only constraint applied to the randomization process, aside from the previous percentages, was ensuring class balance (MI/relax) across all data subsets. Finally, the data were prepared for model training and implementation.

2.4.2. Model Training

To classify signal epochs as either motor imagery or relaxation, a convolutional neural network (CNN) was designed. This classification approach was based on the IFNet architecture proposed by Wang and colleagues in [41]. The preprocessed EEG epochs underwent depth-wise and spatial filtering, followed by temporal aggregation using a single-layer average pooling and dropout. Finally, the processed features were flattened and classified through a fully connected layer. A diagram of the CNN is shown in Figure 3. Two models were developed: one for static data and another one for pedaling data. After a short hyperparameter tuning phase, both models were set with the following parameters: a batch size of 32, repeated trial augmentation (RTA) with a factor of 5, no resampling (factor of 1), a patch size of 125, an embedding dimension of 64, and a kernel size of 63.

Initially, both models were trained using data from the first session of participant U01. Subsequently, data from each new session were incorporated into the models through retraining. This process involved adding the newly acquired recordings (after preprocessing) to the existing training data and retraining the models, following a continual learning strategy. The complete training procedure consisted of an initial training phase followed by a brief retraining adjustment. For pseudo-online classification, the initial training phase comprised 1000 epochs, while the subsequent retraining phase consisted of 500 epochs. In online classification, a fine-tuning strategy was employed. The model, pre-trained with data from previous sessions, was briefly retrained using data from the current recording session.

To minimize the processing and subject waiting times, the training and retraining sets were reduced to 500 and 250 epochs, respectively. Following each session, the preprocessed data were also added to the models.

A fine-tuning phase is particularly useful in EEG applications since these neurological signals are deeply endogenous and strongly non-linear, which results in notable variability in the EEG response between sessions, even for the same participant. Factors such as temperature, mood, hunger, and energy may affect the signals despite the participant's stable mental performance during the recording sessions. Therefore, fine-tuning is essential for maintaining correct model performance, as it adapts the models to the current EEG state.

Catastrophic forgetting is another source of decoding bias and failures in EEG analysis when applying transfer learning techniques; for example, training the models with data from different subjects. This phenomenon occurs when a deep learning model discards or “forgets” previously learned data distributions when the model is retrained with new data (new recording sessions in this work) as the model learns new data distributions. To tackle the impact of catastrophic forgetting, a weight inurement algorithm was tested. This algorithm was applied between training sets. The procedure, called rotative Elastic Weight Consolidation (rEWC) [45], mitigates catastrophic forgetting by a rotation of the model's weight matrix based on the diagonalization of the Fisher information matrix of the loss function gradients and the EWC loss [44]. This adaptation aims to prevent model weight degradation during retraining with new recorded data.

In this study, three distinct approaches were employed to train the decoding models, each based on the methodologies outlined in the preceding section. The third approach was further divided into two variations, differentiated by the volume of data used in the training datasets. These three approaches are contingent on the scaler selected during the preprocessing stage and the implementation of the rEWC algorithm, as detailed in Table 2. All participants were included across the three approaches. However, to address the impact of ‘outlier users’ (those whose decoding models exhibited lower accuracy), a modified version of the third approach was also evaluated. This variation excluded participants whose EEG signals deviated significantly from average response patterns, aiming to determine if such exclusions could enhance overall model performance. Specifically, participants U02, U09, U10, and U19 were excluded, as their motor imagery decoding models yielded an inter-subject average accuracy below 70% in the third approach (mean of the global accuracy results from all subjects). The closed-loop online tests were only conducted with Approach 2 for participants from U16 to U20, both included, and with Approach 3.1 for participants U21, U22, and U23.

Table 2. MI decoding approaches. Differences between the motor imagery decoding algorithms used in this study, depending on the selected scaler, the use of the rEWC algorithm, and the amount of data employed for training the models.

Approach	Scaler	rEWC	Subjects Included	Closed-Loop Tests
Approach 1	MinMax	No	All	No
Approach 2	MinMax	Yes	All	U16, U17, U18, U19 & U20
Approach 3.1	MVT	Yes	All	U20, U21 & U22
Approach 3.2	MVT	Yes	All except U02, U09, U10 & U19	No

2.5. Evaluation Metrics

The metrics employed for evaluating the open-loop trials are the average classification accuracy (percentage of outputs classified correctly across trials) and standard deviation (STD). However, when applying a closed-loop control, distinguishing solely between the relax and motor imagery accuracy may lead to erroneous conclusions. These metrics do not adequately describe the device's behavior, as a clearer distinction should be made between static and pedaling relaxation and static and pedaling motor imagery. Furthermore, since each model (static and pedaling) activates and deactivates depending on the online classification, variations in task times may occur, and task balance is not guaranteed.

Instead, a set of alternative metrics is provided. These include the False Activations Rate (FAR), as defined by Equation (2), and the average unintended cycle ergometer activations per minute of protocol recording. Additionally, the False Stops Rate (FSR), defined in Equation (3), and the average unintended cycle ergometer deactivations per minute are introduced. Furthermore, the True Activations Rate (TAR), presented in Equation (4), and the True Stops Rate (TSR), described in Equation (5), are utilized. In the context of this study, a false activation is defined as an unintended cycle ergometer activation occurring during a relax period, whereas a true activation is recorded when the cycle ergometer initiates movement during a motor imagery period. Similarly, a false stop is registered when pedaling movement ceases during a motor imagery period, while a true stop occurs when movement ends during a relax period. It is important to note that after every cycle ergometer state transition (i.e., each activation and stop), the cycle ergometer state is maintained for at least five seconds to prevent unstable behavior.

$$FAR = \frac{FA}{FA + TA} \cdot 100 \quad (2)$$

where *FAR* represents the False Activations Rate, *FA* is the total number of false activations across all trials, and *TA* is the total number of true activations. A false activation occurs when the cycle ergometer initiates movement during a relax period, whereas a true activation takes place when the device begins movement during a motor imagery period.

$$FSR = \frac{FS}{FS + TS} \cdot 100 \quad (3)$$

where *FSR* represents the False Stops Rate, *FS* is the total number of false stops along all trials, and *TS* is the total number of true stops. A false stop occurs when the cycle ergometer ceases movement during a relax period, whereas a true stop takes place when the device ends movement during a motor imagery period.

$$TAR = \frac{TA}{FA + TA} \cdot 100 \quad (4)$$

where *TAR* represents the True Activations Rate, *FA* is the total number of false activations across all trials, and *TA* is the total number of true activations. A false activation occurs when the cycle ergometer initiates movement during a relax period, whereas a true activation takes place when the device begins movement during a motor imagery period.

$$TSR = \frac{TS}{FS + TS} \cdot 100 \quad (5)$$

where *TSR* represents the False Stop Rate, *FS* is the total number of false stops along all trials, and *TS* the total number of true stops. A false stop occurs when the cycle ergometer

ceases movement during a relax period, whereas a true stop takes place when the device ends movement during a motor imagery period.

Since the number of closed-loop trials conducted by each participant varied due to their time limitations, the provided average values are weighted by the number of trials per participant.

2.6. Statistical Study

To determine the statistical significance of the classification results, a pairwise Wilcoxon signed-rank test was performed. To mitigate the risk of inflated Type I error rates due to multiple comparisons across the various datasets and approaches, the Benjamini–Hochberg correction was applied, setting the significance level at 0.05. Specifically, this study evaluated the six possible pairwise comparisons of the approaches (1 vs. 2, 1 vs. 3.1, 1 vs. 3.2, 2 vs. 3.1, 2 vs. 3.2, and 3.1 vs. 3.2), comparing relax performance with relax performance and motor imagery with motor imagery. This resulted in a total of twelve corrected p -values.

For the open-loop analysis, six pairwise comparisons were performed, one for each of the six decoding models (static and cycling for Approaches 1, 2, and 3), resulting in six p -values. Due to the limited sample size for closed-loop data (eight participants) and the absence of Approach 1 data, a single, generalized p -value was calculated to represent the overall significance of the classification results, renouncing the Benjamini–Hochberg correction.

3. Results

This section presents the classification accuracy results obtained from Approaches 1, 2, and 3 using both open-loop and closed-loop tests. Both analyses were performed in real time following a pseudo-online or online classification, respectively, to ensure a similar methodology and comparison of the results. The statistical analysis results are also reported.

3.1. Pseudo-Online Classification (Opened-Loop Control)

The pseudo-online classification outcomes are divided into three groups, corresponding to the three approaches evaluated in this study.

3.1.1. Approach 1: MinMax and No rEWC

Table 3 presents the pseudo-online classification results for Approach 1 (MinMax scaling without rEWC). The overall average accuracy across models was 65.5%, indicating a moderate performance. No significant differences were observed between the static and cycling model performance. While the static model showed similar accuracy for both relax and motor imagery classes, the cycling model exhibited an 11% difference in average accuracy between these classes.

Inter-subject variability in average accuracy was relatively low, with a standard deviation (STD) of less than 8.5%, which is normal in EEG applications as there are important physiological differences among subjects. However, substantial class imbalance was observed in some participants (e.g., U01, U05, U10, U20), resulting in highly polarized models. Such polarization could lead to elevated false activation rates in a rehabilitation setting. This polarization appeared less pronounced when comparing static and cycling models. U14 exhibits the best average accuracy, achieving more than 87%, whereas U20 has the worst accuracy indices, resulting in a random classification with only 50% of average model performance.

Table 3. Approach 1 pseudo-online classification results. This table comprises the classification accuracy results obtained with the motor imagery decoding Approach 1 (hinged in MinMax scaler and no rEWC application) for pseudo-online data. The average results (TOTAL) and the standard deviation obtained across trials within each paradigm are also included.

USER	STATIC ACC. [%]			CYCLING ACC. [%]			AVERAGE ACC. [%]		
	Relax	MI	Total	Relax	MI	Total	Relax	MI	Total
U01	100.0	0.0	50.0	62.5	90.2	76.3	81.3	45.1	63.2
U02	76.2	55.2	65.7	60.2	67.1	63.7	68.2	61.2	64.7
U03	61.6	63.0	62.3	67.1	62.7	60.0	64.4	62.9	63.6
U04	58.7	80.4	69.5	27.7	60.7	44.2	43.2	70.5	56.9
U05	18.8	96.4	54.6	72.3	76.8	74.6	45.5	86.6	66.1
U06	54.5	65.2	58.9	79.5	55.4	67.4	67.0	60.3	63.6
U07	64.3	53.6	54.6	62.5	82.1	72.3	63.4	67.9	65.6
U08	95.5	64.3	79.9	53.6	92.9	73.2	74.6	78.6	76.6
U09	26.7	85.7	56.2	71.4	75.9	73.7	49.1	80.8	64.9
U10	100.0	0.0	50.0	57.1	58.9	58.0	78.6	29.5	54.0
U11	85.0	61.2	73.1	33.9	49.1	41.5	59.5	55.2	57.3
U12	77.1	47.3	59.7	60.9	65.2	61.0	69.0	53.8	61.4
U13	42.2	79.0	60.6	87.5	30.4	58.9	64.9	54.7	59.8
U14	68.8	100.0	84.4	92.9	87.5	90.2	80.8	93.8	87.3
U15	32.7	98.1	65.4	57.1	97.9	77.5	44.9	98.0	71.5
U16	33.9	83.0	58.5	61.7	78.5	70.1	47.8	80.8	64.3
U17	60.2	60.2	60.2	68.8	53.6	61.2	64.5	56.9	60.7
U18	90.0	37.6	63.8	61.6	69.4	65.6	75.8	53.5	64.6
U19	60.0	88.6	74.3	28.6	88.6	53.6	44.3	88.6	66.4
U20	100.0	0.0	50.0	0.0	100.0	50.0	50.0	50.0	50.0
U21	85.3	62.2	73.8	100.0	67.2	83.6	92.7	64.7	78.7
U22	62.1	75.1	68.6	60.3	71.4	65.8	61.2	73.3	67.2
U23	72.1	70.2	71.2	89.7	80.2	85.0	80.9	75.2	78.1
TOTAL	66.3	61.8	63.9	61.6	72.2	66.7	64.0	67.0	65.5
STD	24.0	29.5	9.3	22.8	17.0	12.2	14.2	16.8	8.5

ACC., classification accuracy; MI, motor imagery; STD, standard deviation. **Bold values** represent the average results (Total) obtained across conditions or trials.

3.1.2. Approach 2: MinMax and rEWC

The results obtained for pseudo-online classification employing the second approach (Approach 1 adding rEWC before retraining) are summarized in Table 4. The addition of the rEWC model weights readjustment increases the consistency of the results, elevating the average accuracy to nearly 69%. While this represents a remarkable improvement, it remains insufficient for real-world applications due to the non-negligible deficiencies in accuracy, which could cause high false activation ratios. In this case, the cycling model slightly outperformed the static model, achieving an accuracy exceeding 70% (see Section 3.1.5). The balance between classes also improved.

Inter-subject variability remained low, with the standard deviation of each participant's average accuracy below 9%. However, substantial class imbalance persisted in some participants (e.g., U01, U02, U12, and U18). While some of these participants, like U01, exhibited this imbalance in Approach 1 as well, others, such as U02 and U12, showed increased imbalance after the incorporation of rEWC. Conversely, some participants (for example, U10 and U20) exhibited improved class balance after applying rEWC. Performance consistency between models was maintained. Participant U13 achieved the highest average accuracy (over 86%), while participant U02 exhibited the lowest (nearly 52%).

Table 4. Approach 2 pseudo-online classification results. This table comprises the classification accuracy results obtained with the motor imagery decoding Approach 2 (hinged in MinMax scaler and rEWC application) for pseudo-online data. The average results (TOTAL) and the standard deviation obtained across trials within each paradigm are also included.

USER	STATIC ACC. [%]			CYCLING ACC. [%]			AVERAGE ACC. [%]		
	Relax	MI	Total	Relax	MI	Total	Relax	MI	Total
U01	100.0	0.0	50.0	61.6	90.2	75.9	80.8	45.1	63.0
U02	100.0	0.0	50.0	46.4	60.7	53.6	73.2	30.4	51.8
U03	58.9	68.8	63.8	79.5	46.6	63.0	69.2	57.7	63.4
U04	30.7	95.5	63.0	62.1	71.8	67.5	46.4	83.7	65.2
U05	62.3	86.6	74.4	67.9	87.5	77.7	65.0	87.1	76.0
U06	27.7	73.2	50.5	83.0	56.4	69.7	55.4	64.8	60.1
U07	99.1	52.7	75.9	87.5	60.0	73.8	93.3	56.3	74.8
U08	77.7	51.8	64.7	76.8	74.1	75.4	77.2	63.0	70.1
U09	51.8	77.7	64.7	63.8	67.3	65.5	57.8	72.5	65.1
U10	73.2	80.4	76.8	67.4	59.5	63.4	70.3	69.9	70.1
U11	49.3	100.0	74.6	45.7	77.7	61.7	47.5	88.8	68.2
U12	0.0	100.0	50.0	58.2	71.4	64.8	29.1	85.7	57.4
U13	100.0	66.2	83.1	92.9	88.4	90.6	96.4	77.3	86.9
U14	72.3	100.0	86.2	63.8	95.8	79.8	68.0	97.9	83.0
U15	90.6	46.5	68.7	62.6	89.7	76.2	76.6	68.1	72.4
U16	76.8	66.1	71.4	75.8	68.4	72.1	76.3	67.2	71.8
U17	61.3	54.8	58.1	64.4	66.2	65.3	62.9	60.5	61.7
U18	100.0	0.0	50.0	69.8	66.1	68.0	84.9	33.0	59.0
U19	100.0	52.1	76.1	60.5	79.0	69.8	80.2	65.6	72.9
U20	59.8	74.1	67.0	87.7	83.1	85.4	73.8	78.6	76.2
U21	82.2	90.2	86.2	74.2	60.2	67.2	78.2	75.2	76.7
U22	50.2	95.3	72.8	100.0	27.6	63.8	75.1	61.5	68.3
U23	72.2	62.0	67.1	56.0	88.0	72.0	64.1	75.0	69.5
TOTAL	69.4	65.0	67.2	69.9	71.1	70.5	69.6	68.0	68.9
STD	26.8	30.8	11.6	13.9	16.1	8.2	15.3	16.7	8.3

ACC., classification accuracy; MI, motor imagery; STD, standard deviation. **Bold values** represent the average results (Total) obtained across conditions or trials.

3.1.3. Approach 3: MVT and rEWC

The classification results generated with Approach 3.1 (MVT scaler combined with rEWC application including all participants in the model) for pseudo-online data are presented in Table 5. This approach yielded excellent robustness, achieving an average classification accuracy of 75.7%, a level suitable for real-world clinical applications. The static and cycling models exhibited comparable performance, with minimal differences in classification accuracy between classes overall.

Regarding inter-subject variability, a key concern for the previous approaches, performance remained consistent in general terms, with an STD of 6.7% in average classification accuracy across participants. Furthermore, this approach seems to adequately sort out the model polarization problem that some participants manifested with the first and second approaches, as no substantial differences in inter-class accuracy were noted for any participant. And, once again, both static and cycling models conveyed similar performance results. Participant U21 outperformed all the rest with more than 94% of average classification accuracy, while U02, again exhibiting the lowest performance, achieved nearly 65% accuracy, receding from randomness in classification.

Table 5. Approach 3.1 pseudo-online classification results. This table comprises the classification accuracy results obtained with the motor imagery decoding Approach 3.1 (hinged in MVT scaler and rEWC application including all the participants) for pseudo-online data. The average results (TOTAL) and the standard deviation obtained across trials within each paradigm are also included.

USER	STATIC ACC. [%]			CYCLING ACC. [%]			AVERAGE ACC. [%]		
	Relax	MI	Total	Relax	MI	Total	Relax	MI	Total
U01	88.4	92.9	90.6	61.6	87.5	74.6	75.0	90.2	82.6
U02	75.5	63.6	69.6	58.4	61.6	60.0	67.0	62.6	64.8
U03	69.6	74.6	72.1	73.2	66.4	69.8	71.4	70.5	71.0
U04	78.2	88.4	83.3	68.2	50.2	59.2	73.2	69.3	71.3
U05	73.8	80.4	77.0	67.5	83.0	75.3	70.6	81.7	76.2
U06	73.4	71.6	72.5	87.5	54.8	71.2	80.4	63.2	71.8
U07	97.3	75.0	86.2	66.2	89.3	77.8	81.8	82.1	82.0
U08	67.0	75.5	71.3	72.3	77.7	75.0	69.6	76.6	73.1
U09	65.5	75.2	70.4	71.2	64.1	67.7	68.4	69.6	69.0
U10	79.6	66.1	72.9	57.1	63.4	60.3	68.4	64.7	66.6
U11	74.1	72.7	73.4	93.8	59.5	76.6	83.9	66.1	75.0
U12	77.8	74.1	76.0	88.4	55.7	72.0	83.1	64.9	74.0
U13	71.1	69.3	70.2	93.8	83.0	88.4	82.4	76.2	79.3
U14	89.6	81.3	85.4	70.0	93.8	81.9	79.8	87.5	83.7
U15	65.4	75.7	70.6	73.2	84.1	78.7	69.3	79.9	74.6
U16	70.5	79.5	75.0	79.1	71.3	75.2	74.8	75.4	75.1
U17	75.9	82.8	79.4	72.6	64.5	68.6	74.3	73.6	74.0
U18	84.8	70.9	77.9	73.4	69.8	71.6	79.1	70.4	74.7
U19	62.1	75.0	68.6	47.9	94.0	71.0	55.0	84.5	69.8
U20	95.5	68.0	81.8	100.0	56.9	78.5	97.8	62.5	80.1
U21	93.3	87.1	90.2	97.9	99.3	98.6	95.6	93.2	94.4
U22	48.6	96.4	72.5	66.7	79.5	73.1	57.6	88.0	72.8
U23	80.6	89.3	85.0	100.0	82.1	91.1	80.6	90.2	85.4
TOTAL	76.4	77.6	77.0	75.7	73.6	74.6	75.6	75.8	75.7
STD	11.6	8.6	6.9	14.5	14.4	9.4	10.1	9.9	6.7

ACC., classification accuracy; MI, motor imagery; STD, standard deviation. **Bold values** represent the average results (Total) obtained across conditions or trials.

Figure 5 compares the pseudo-online average results per user for Approach 3.1 models. While both static and cycling models showed improved decoding performance with additional user data, this trend was notably more pronounced for the static model. The correlation between both curves is positive (Pearson correlation coefficient (PCC) of 0.43), indicating a coherent evolution of the models across the participants. Figure 6 also compares the average pseudo-online classification results for MI and relax data using Approach 3.1. Trends were similar, with relax showing a slightly less pronounced improvement. In both cases, the positive trends suggest that model performance benefits from the incorporation of new data. In this case, correlation between curves is slightly negative (PCC of ~ -0.1), reflecting the endogenous and variable nature of EEG signals among users and classes, and hinting that decoding performance between classes may not be related.

As detailed in Table 5, all participants demonstrated satisfactory average performance (above 70% accuracy) for a clinical scenario, with the exception of four individuals: U02, U09, U10, and U19. These participants exhibited average accuracies below 70% using the Approach 3.1 models. Given that their EEG motor imagery distributions could be considered outliers, Approach 3.2 was implemented. This involved retraining the models using the same processing pipeline as Approach 3.1 (MVT scaler with rEWC application), but excluding these four participants. The rationale was that removing these outlier EEG MI

distributions could potentially enhance model performance for the remaining participants. The results of the Approach 3.2 models are presented in Table 6.

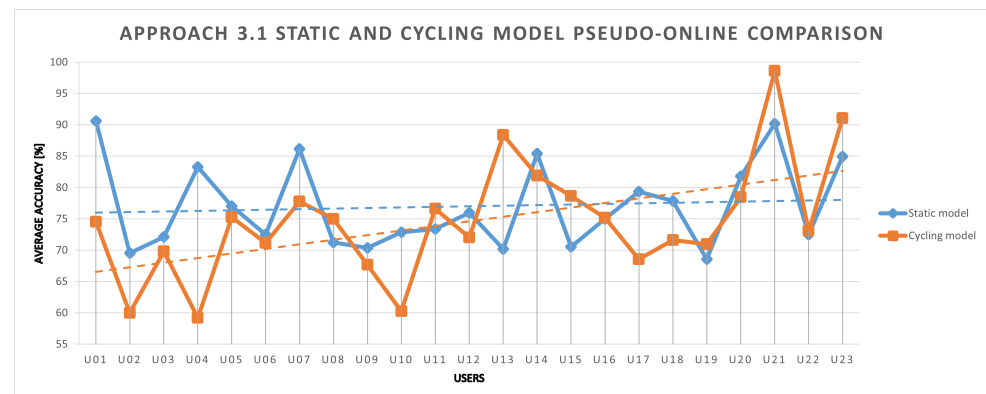


Figure 5. Approach 3.1 static and cycling model pseudo-online comparison. Pseudo-online classification performance with Approach 3.1 comparing a static model (blue) and a cycling model (orange). The graph shows average results for each model, with trend lines (dashed lines) also depicted to highlight overall trends. Statistical analysis and corresponding p -values for these data are detailed in Section 3.1.5.

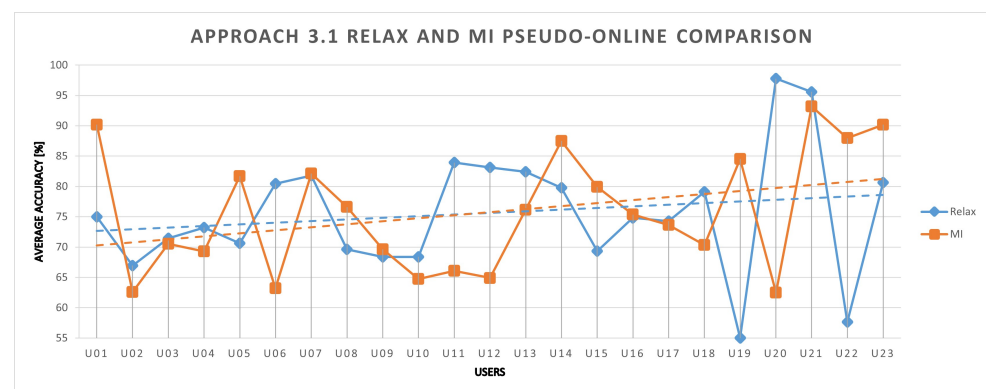


Figure 6. Approach 3.1 relax and MI pseudo-online comparison. Pseudo-online classification performance with Approach 3.1 comparing results from relax task (blue) and from MI task (orange). The graph shows average results for each model, with trend lines (dashed lines) also depicted to highlight overall trends. Statistical analysis and corresponding p -values for these data are detailed in Section 3.1.5.

The Approach 3.2 models demonstrated enhanced performance, achieving an average accuracy exceeding 80%, while preserving the robustness attained with Approach 3.1. The average performance between static and cycling models remained consistent, and the overall classification results for motor imagery and relax classes were virtually identical. Furthermore, inter-participant performance variability was within expected margins for EEG applications, given the endogenous nature of these signals; the average standard deviation (STD) was 6.4%. These results indicate that excluding lower-performing participants did not induce polarization in the models. Participant U21 again achieved the highest performance, with an average accuracy surpassing 95%, whereas participant U22 exhibited the lowest, at 73%. Notably, all participants exceeded the 70% threshold for average classification accuracy.

Similar to the observations with Approach 3.1, both static and cycling models in Approach 3.2 exhibited positive performance trends with the inclusion of new data, which was more pronounced in the cycling model. This trend is clearly illustrated in Figure 7, which compares the pseudo-online performance of both models for each participant, including the

trend lines. When assessing inter-class performance, positive trends were again observed, with minimal differences between classes, as shown in Figure 8. The correlation between the curves was weakly positive, with a Pearson correlation coefficient of 0.27, indicating a coherent performance of the classifiers.

Table 6. Approach 3.2 pseudo-online classification results. This table comprises the classification accuracy results obtained with the motor imagery decoding Approach 3.2 (hinged in MVT scaler and rEWC application excluding participants whose average performance is under 70%) for pseudo-online data. The average results (TOTAL) and the standard deviation obtained across trials within each paradigm are also included. Statistical analyses and corresponding *p*-values for these data are detailed in Section 3.1.5.

USER	STATIC ACC. [%]			CYCLING ACC. [%]			AVERAGE ACC. [%]		
	Relax	MI	Total	Relax	MI	Total	Relax	MI	Total
U01	93.8	95.5	94.6	65.2	87.0	76.1	79.5	91.3	85.4
U03	70.2	80.5	75.4	74.2	68.2	71.3	72.2	74.4	73.3
U04	80.3	90.6	85.4	70.3	55.0	62.6	75.3	72.8	74.0
U05	74.0	81.0	77.5	65.2	85.0	75.1	69.6	83.0	76.3
U06	73.7	71.0	72.4	89.2	58.2	73.7	81.5	64.6	73.0
U07	97.0	89.5	93.3	64.2	84.5	74.4	80.6	87.0	83.8
U08	70.3	73.2	71.7	77.5	77.5	77.5	73.9	75.4	74.6
U11	75.2	76.0	75.6	91.2	64.2	77.8	83.2	70.1	76.7
U12	75.9	74.9	75.4	87.5	59.6	73.6	81.7	67.3	74.5
U13	73.2	70.6	71.9	96.2	85.2	90.7	84.7	77.9	81.3
U14	94.7	87.3	91.0	72.5	91.6	82.0	83.6	89.4	86.5
U15	85.4	86.4	85.9	74.0	84.5	79.3	79.7	85.5	82.6
U16	77.8	79.0	78.4	81.7	70.7	76.2	79.7	74.8	77.3
U17	89.3	70.9	80.1	79.8	83.0	81.4	84.5	76.9	80.7
U18	77.1	78.2	77.7	86.1	89.6	87.9	81.6	83.9	82.8
U20	100.0	77.5	88.8	74.6	95.3	85.0	87.3	86.4	86.9
U21	94.9	88.3	91.6	98.0	99.5	98.8	96.4	93.9	95.2
U22	54.0	95.2	74.6	70.5	72.5	71.5	62.2	83.9	73.0
U23	84.3	88.6	86.4	99.7	87.3	93.5	92.0	88.0	90.0
TOTAL	81.1	81.8	81.5	79.9	78.9	79.4	80.5	80.3	80.4
STD	11.7	8.2	7.8	11.3	13.1	8.7	7.8	8.4	6.4

ACC., classification accuracy; MI, motor imagery; STD, standard deviation. **Bold values** represent the average results (Total) obtained across conditions or trials.

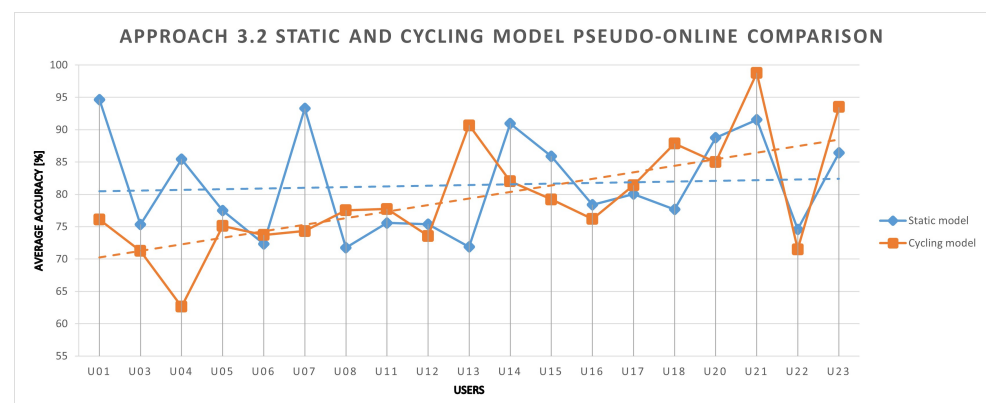


Figure 7. Approach 3.2 static and cycling model pseudo-online comparison. Pseudo-online classification performance with Approach 3.2 comparing a static model (blue) and a cycling model (orange). The graph shows average results for each model, with trend lines (dashed lines) also depicted to highlight overall trends. Statistical analyses and corresponding *p*-values for these data are detailed in Section 3.1.5.

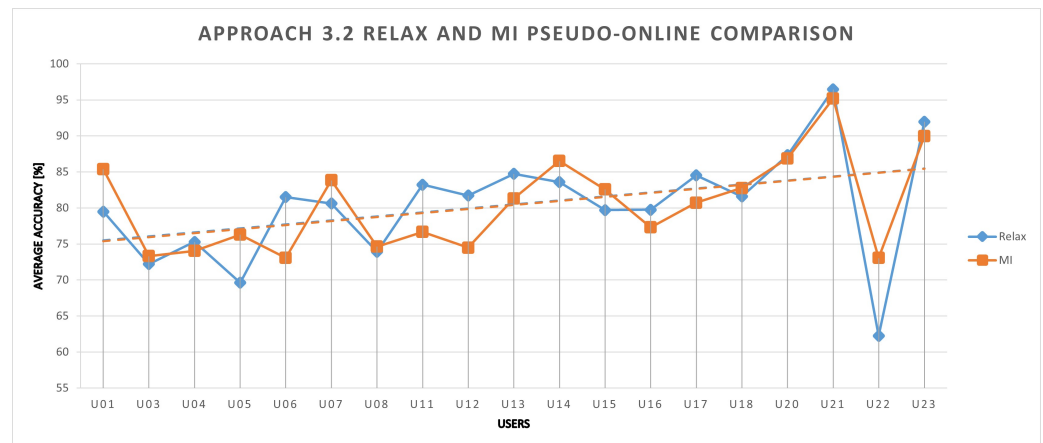


Figure 8. Approach 3.2 relax and MI pseudo-online comparison. Pseudo-online classification performance with Approach 3.2 comparing results from relax task (blue) and from MI task (orange). The graph shows average results for each model, with trend lines (dashed lines) also depicted to highlight overall trends. Statistical analyses and corresponding p -values for these data are detailed in Section 3.1.5.

3.1.4. Comparison of Approaches

The progressive increment in average accuracy across the approaches demonstrates the effectiveness of the algorithm's refinements. While Approaches 1 and 2 exhibited concerning disparities between users, models, and classes, the incorporation of MVT scaling (or the elimination of MinMax scaling) in Approach 3 effectively eliminated these discrepancies, establishing it as the superior decoding option. Figure 9 illustrates the evolution of average accuracy for each approach as a function of the number of users included in the model. Concerning the inclusion of new data, all the approaches show consistently positive trends in the decoding accuracy.

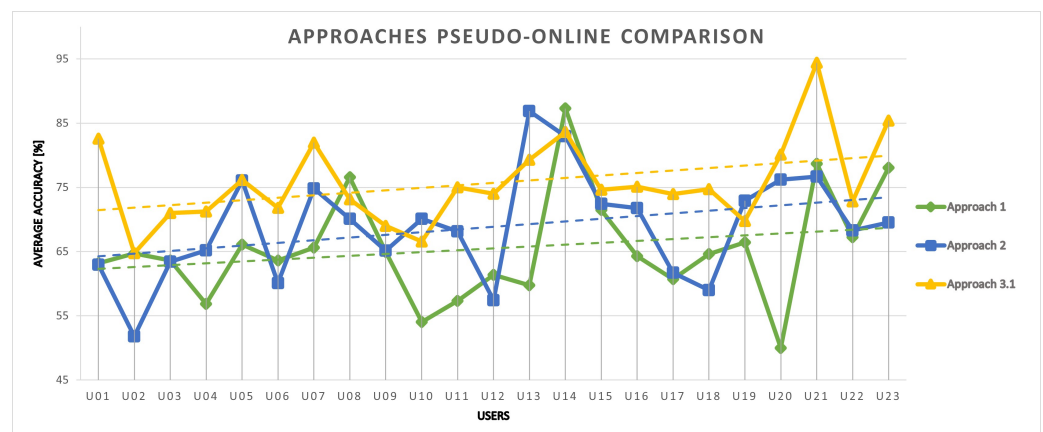


Figure 9. Approaches 1, 2, and 3.1 pseudo-online comparison. Comparison of pseudo-online classification performance across decoding Approaches 1, 2, and 3.1. Approach 1 is represented in green, Approach 2 in blue, and Approach 3.1 in yellow. Trend lines are also represented in the same colors with dashed lines. Statistical analyses and corresponding p -values for these data are detailed in Section 3.1.5.

The overall correlation between the three performance curves is positive (average PCC of ~ 0.34), indicating the influence of inter-subject variability on decoding performance and supporting the consistency of the results presented in this section. For the 23 users, Approach 3.1 outperformed the other two approaches in 17 of the 23 participants, while Approach 2 yielded improvements over Approach 1 in 13 of the 23 participants.

With respect to the third approach, which was divided into Approaches 3.1 and 3.2, the exclusion of the lower-performing outliers significantly enhanced classifier performance. Specifically, 19 out of 19 participants in Approach 3.2 achieved higher classification results compared to Approach 3.1; only participants U13 and U14 obtained superior results with an alternative approach. Figure 10 provides a comprehensive comparison of the average performance between these two decoding approaches, displaying the average classification accuracy for each participant and approach. Trend lines are included, clearly demonstrating the positive accuracy improvement trend in both approaches with the inclusion of new non-bottom outlier participants. Particularly, this trend is more pronounced in Approach 3.2. The curves in the graph exhibit a strong correlation, as both were generated using identical processing methods, with the sole distinction being the volume of data used for training.

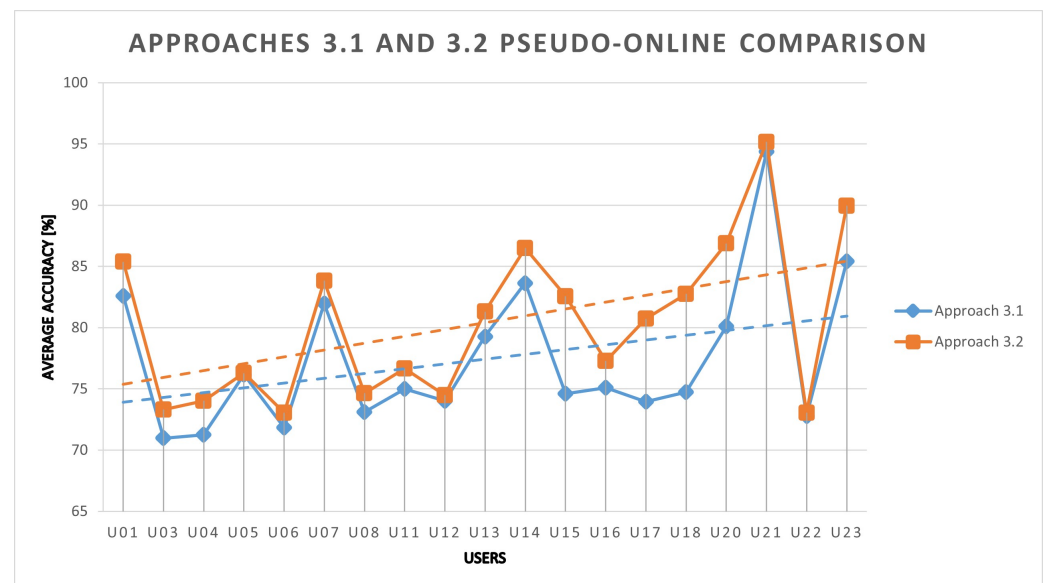


Figure 10. Approaches 3.1 and 3.2 pseudo-online comparison. Comparison of pseudo-online classification performance across decoding Approaches 3.1 and 3.2. Approach 3.1 is represented in blue and Approach 3.2 in orange. Trend lines are also represented in the same colors with dashed lines. Statistical analyses and corresponding *p*-values for these data are detailed in Section 3.1.5.

Finally, it is interesting to remark that there exists a moderately positive correlation between the kinesthetic MI indexes obtained by the participants in the MIQ-3 Questionnaire [47] (Table 1) and the average accuracy results computed with Approach 3.1 (PCC of approximately 0.53); this fact suggests that kinesthetic imagery ability is directly related to correct motor imagery performance. Nevertheless, this correlation is not present when comparing the MIQ-3 kinesthetic results with accuracy data from Approach 1 (PCC ~ -0.01) and Approach 2 (PCC ~ -0.23).

3.1.5. Pseudo-Online Statistical Study

The corrected *p*-values computed in the statistical study (Wilcoxon test with Benjamini–Hochberg correction for multiple tests, Section 2.6) for pseudo-online classification are presented in a color map, contained in Figure 11. The most discordant value is the one corresponding to the static model when comparing the initial two approaches, as it is abnormally high (0.69). This disproportionately high value practically eliminates any chance of endowing these two approaches static models with statistical relevance.

Conversely, the remaining corrected *p*-values are considerably lower and more consistent. Specifically, for Approaches 2 and 3, statistical significance is greater for the static

models. However, for Approach 3.1, the statistical significance of the cycling model (corrected p -value of 0.25 when compared with Approach 2 and 0.24 when compared with Approach 3.2) may be insufficient to draw strong conclusions. Approaches 2 and 3.2 demonstrated the highest statistical significance among all the approaches, asserting that their results are the most reliable, as they reach an adequate statistical relevance level for both the static and the cycling models (corrected p -values below 0.05).

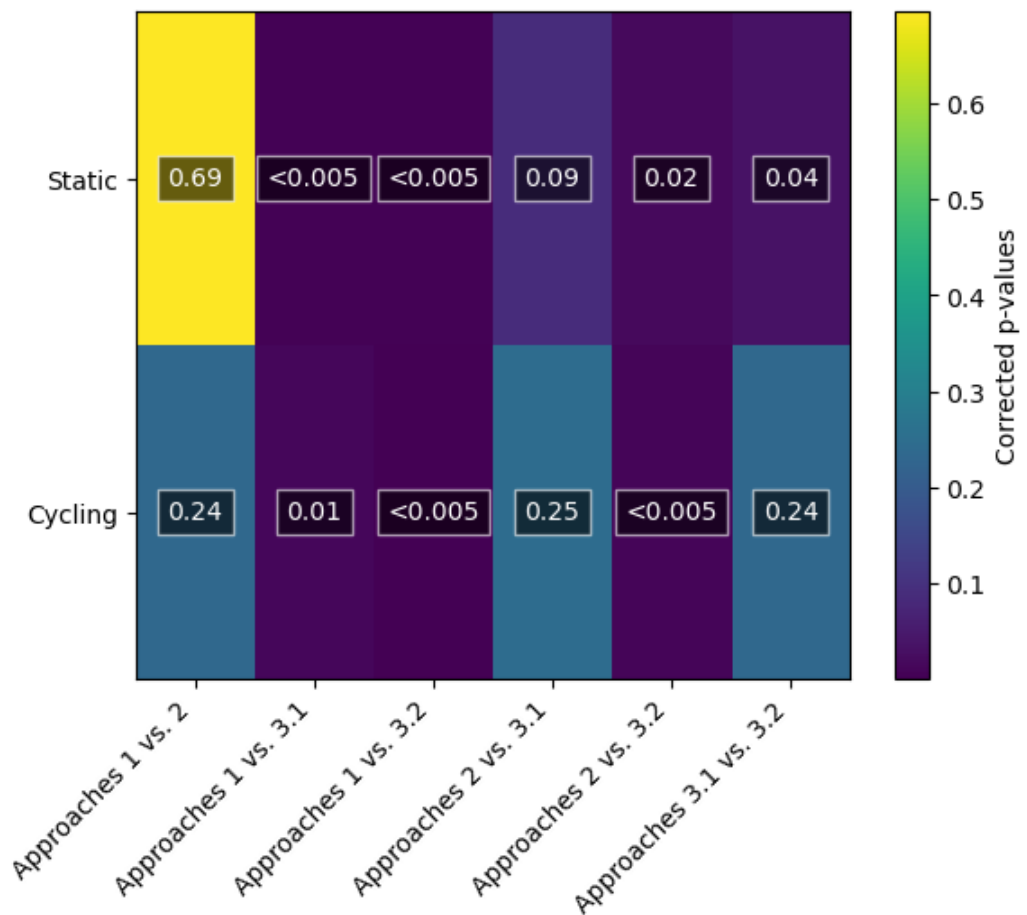


Figure 11. Pseudo-online corrected p -values color map. This figure visualizes the results of the statistical analysis described in Section 2.6, which employed a Wilcoxon signed-rank test with Benjamini–Hochberg correction for multiple comparisons.

3.2. Online Classification (Closed-Loop Control)

This section presents the motor imagery decoding results when closed-loop feedback is provided to the subjects. Only models trained with Approaches 2 (MinMax scaling with rEWC) and 3.1 (MVT with rEWC) were evaluated. Approach 2 was tested with participants U16–U20, while Approach 3 was tested with participants U21–U23 (see Table 2). As the closed-loop control requires an online analysis, specific tests by approach need to be performed.

The metrics employed to evaluate the models during closed-loop control are introduced in Section 2.6. These are the False Activations Ratio, (FAR) (Equation (2)), the average false activations per minute, the False Stops Ratio, (FSR) (Equation (3)), the average number of unintended stops per minute, the True Activations Ratio, (TAR) (Equation (4)), and the True Stops Ratio, (TSR) (Equation (5)).

3.2.1. Approach 2

The average results computed during online classification with Approach 2 models are presented in Table 7. A weighted False Activations Ratio of 26.15 indicates moderate performance, yet some users, such as U18 (47.18) and U17 (45.41), exhibit notably high FAR values. This translates to a high ratio of false activations in some users, with user U18 experiencing an average of two unintended cycle ergometer activations per minute, although the overall weighted average across all users remains below one. In general terms, the False Stops Rate (FSR) values are more balanced than the FAR values, although cases like U18 (47.22) are still a cause for concern. Participant U16 represents an extraordinary case, as no false activation or stop was recorded. Although the online classification accuracy was not 100%, some false positives (MI outputs during the relax time windows) and false negatives (relax outputs during MI periods) were insufficient to provoke false stops and activations. However, it is important to note that only five closed-loop trials were registered for participant U16.

Table 7. This table summarizes the decoding metrics achieved during real-time EEG classification using Approach 2 models. Metrics include the False Activations Rate, average false activations per minute, False Stops Rate, average false stops per minute, True Activations Rate, and True Stops Rate. The number of closed-loop trials conducted by each participant is also provided, alongside the total number of trials. Standard deviation results across all trials have been included as an extra column. All aggregated average results (TOTAL) are weighted by the number of trials per participant. Standard deviation across trials ($\overline{STD}$), weighted by the number of trials, is also included as an extra column. The number of trials' $\overline{STD}$ value is calculated across experimental sessions.

USER	U16	U17	U18	U19	U20	TOTAL	$\overline{STD}$
Number of trials	5	8	6	8	10	7.4	2.4
FAR	0.00	45.41	47.89	21.85	14.22	26.15	7.0
FA/min	0.00	1.52	2.00	0.75	0.50	0.95	0.2
FSR	0.00	21.21	40.22	18.15	27.22	22.39	5.6
FS/min	0.00	0.82	1.60	0.33	0.91	0.76	0.1
TAR	100.00	54.59	52.11	78.15	85.78	73.85	11.5
TSR	100.00	78.79	59.78	81.85	72.78	77.61	6.2

FAR, False Activations Rate; **FA/min**, average false activations per minute; **FSR**, False Stops Rate; **FS/min**, average false stops per minute; **TAR**, True Activations Rate; **TSR**, True Stops Rate; $\overline{STD}$, weighted standard deviation across trials. **Bold values** represent the aggregated average results (TOTAL) weighted by the number of trials per participant.

It is important to note that the classifier produces an output every half second. For a cycle ergometer activation to occur, the mean value of the preceding five classification outputs must indicate motor imagery. Furthermore, to prevent disruptive state transitions, any change in the cycle ergometer's state is held constant for an additional five seconds. Overall, maintaining a false cycle ergometer activation ratio below one per minute is crucial for ensuring the algorithm's safety and consistency, effectively preventing abrupt activations. Figure 12 presents the results of one closed-loop trial, which serves as a representative example of this behavior.

Regarding inter-subject variability, a common issue in EEG applications, the values indicate a moderately high variability. The diverse reactions and individual tempos of users during cycle ergometer activations (or non-activations when expected), combined with the inherent EEG variability, lead to unstable classification model behavior across subjects. This variability results in performances ranging from suboptimal, such as in the case of U18, to excellent, as demonstrated by U16, who exhibited not a single false activation throughout all tests. Weighted values of 73.85 and 77.61 in the True Activations Ratio and True Stops Ratio, respectively, position Approach 2 as an interesting framework for

online classification, but the moderately high variability leads to insufficient performance in some users. Nevertheless, the low standard deviation values across trials suggest a steady performance of the algorithm within each subject. These values were calculated individually for each participant and then aggregated, weighted by the number of trials. Thus, the results provide evidence of minimal inter-trial variability.

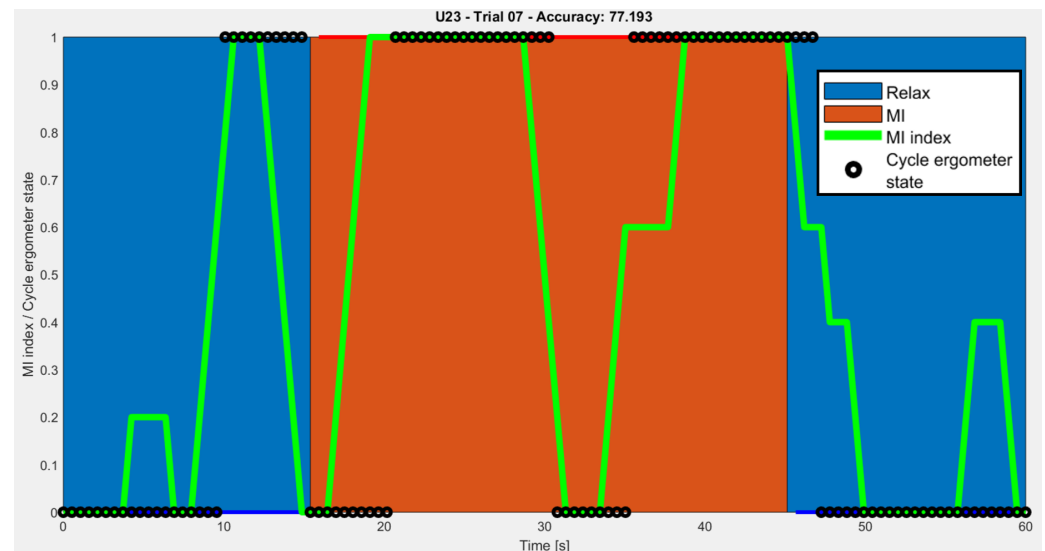


Figure 12. Example of the results obtained during an online classification trial for participant U23 using Approach 3.1. The plot displays the MI index, represented by a solid green line ‘-’, which corresponds to the mean value of the previous five classification outputs (0 for relax, 1 for MI). The cycle ergometer’s state (0 for inactive, 1 for active) is shown with black circles ‘o’. Relax periods are highlighted in blue, and the MI period is marked in orange. To prevent instability, the cycle ergometer’s state is held constant for five seconds following any state transition. Outside of these transition periods, the ergometer activates when the MI index exceeds 0.5 and deactivates when the MI index falls below 0.5 (corresponding to the mode of the last five classification outputs indicating MI or relax, respectively). This trial serves as a clear illustration of the proposed BMI behavior. A false activation occurs during the initial relax period due to a peak in MI classification. This is followed by a true stop before the MI period begins, as the classification quickly returns to the relax classification. Subsequently, a true activation successfully starts movement during the MI period. Later, a false stop takes place during the MI period when the classification shifts back to that of relax. After a new true activation, a final true stop occurs in the last relax period. The trial concludes with a near-false activation, but the MI index peak remains below the 0.5 threshold, and the ergometer persists inactive. The overall accuracy for this online classification trial is provided in the plot’s title.

3.2.2. Approach 3.1

Table 8 presents the online classification results obtained with Approach 3.1 models, which incorporate rEWC and MVT scaling. This approach, tested on only three participants but with eight more trials than the closed-loop tests conducted with Approach 2 models, achieved a reduced weighted FAR of 10.40. This corresponds to fewer than 0.25 average false positives per minute throughout all tests. These values resulted in a robust weighted TAR of 89.60, ensuring consistent and smooth cycle ergometer behavior and positioning Approach 3.1 as an optimal choice for online classification and closed-loop scenarios. Conversely, the weighted FSR of 19.55 is nearly double the FAR value, primarily due to the high ratio of 36.11 observed in U21. Nevertheless, the weighted TSR of 80.45 still represents a strong metric, maintaining the false stops per minute below 0.60.

Regarding the inter-individual imbalanced results in the online classification models, the incorporation of MVT scaling (or the elimination of MinMax scaling) again led to reduced discrepancies among participants. This low variability reinforces the robustness of

the control algorithm, with all users experiencing less than 0.5 average unintended cycle ergometer activations per minute. Conversely, the intra-subject variability remains low, which is reflected by the consistently reduced standard deviation results.

Table 8. This table summarizes the decoding metrics achieved during real-time EEG classification using Approach 3.1 models. Metrics include the False Activations Rate, average false activations per minute, False Stops Rate, average false stops per minute, True Activations Rate, and True Stops Rate. The number of closed-loop trials conducted by each participant is also provided, alongside the total number of trials. All aggregated average results (TOTAL) are weighted by the number of trials per participant. Standard deviation across trials ($\overline{STD}$), weighted by the number of trials, is also included as an extra column. The number of trials' $\overline{STD}$ value is calculated across experimental sessions.

USER	U21	U22	U23	TOTAL	$\overline{STD}$
Trials	6	24	15	45	3.7
FAR	17.11	15.22	0.00	10.40	2.1
FA/min	0.50	0.33	0.00	0.24	0.0
FSR	36.11	20.00	12.21	19.55	6.6
FS/min	1.12	0.53	0.40	0.57	0.2
TAR	82.89	84.78	100.00	89.60	9.5
TSR	63.89	80.00	87.79	80.45	7.0

FAR, False Activations Rate; **FA/min**, average false activations per minute; **FSR**, False Stops Rate; **FS/min**, average false stops per minute; **TAR**, True Activations Rate; **TSR**, True Stops Rate; $\overline{STD}$, weighted standard deviation across trials. **Bold values** represent the aggregated average results (TOTAL) weighted by the number of trials per participant.

3.2.3. Online Statistical Study

The p -value obtained from the Wilcoxon signed-rank test (see Section 2.6) for the online classification data (Approaches 2 and 3) was 0.06. This indicates statistically significant results for the online classification despite the limited number of participants in the real-time evaluation. This p -value supports the assessments and conclusions drawn from these data.

4. Discussion

This section contextualizes and interprets the core neurophysiological and classification findings presented in Section 3, evaluating the performance of the proposed deep learning framework and the comparative dynamics between the static and cycling motor imagery protocols. To provide a structured analysis of these main contributions, the discussion is organized into two main subsections focused on open-loop and closed-loop modalities, respectively, allowing for a comprehensive evaluation of both system validation and real-time operational performance.

4.1. Opened-Loop Results

The results obtained with the pseudo-online classification improved with each successive refinement of the motor imagery decoding approach. Not only did the average accuracy increase across the three approaches, but the model polarization also decreased, effectively eliminating the bias in class classification observed in earlier results. While the static and cycling models demonstrated consistent performance across participants and similar performance, even in the initial approach, the improvements in both accuracy and, especially, class bias make Approach 3 a viable option for clinical therapies, especially Approach 3.2, as malicious outliers for the decoding models are not included. The performance achieved with this approach suggests a safe and accurate method for effective motor imagery decoding.

The incorporation of a model weight adjustment algorithm, such as rEWC in Approaches 2 and 3, significantly increased accuracy for both models and classes. This improvement is consistent with the chosen training strategy, which leverages transfer learning combined with a fine-tuning process before each online test. This approach was selected due to the continuously growing nature of training datasets in real-world therapy settings. Deep learning models typically benefit from additional data making a transfer learning strategy, where data from each participant contributes to an organically growing model, well-suited for this application. However, this strategy carries the risk of catastrophic forgetting, a phenomenon where pre-trained convolutional models lose previously learned representations with the addition of new data. This is particularly pronounced with physiological signals like EEG due to their endogenous and subject-specific variability. Distributions learned from certain recordings may be overwritten when models are re-trained with other recordings, negatively impacting overall performance. EWC techniques aim to mitigate this catastrophic forgetting, and rEWC, a refined version of EWC, employs a weight rotation mechanism that preserves previously learned gradients while accommodating new ones. Therefore, this algorithm is highly appropriate for the challenges posed in this study, and its effectiveness is evident in Figure 9. As the approaches have been improved, the trend lines have become increasingly positively sloped with the inclusion of new data, especially when addressing the catastrophic forgetting problem using the rEWC algorithm (Approaches 2 and 3), demonstrating improved model performance with the inclusion of data from new participants. Thanks to rEWC, the new data are effectively utilized, leading to model improvement, suggesting that performance will increase with each new patient in a clinical environment.

Even so, the addition of rEWC alone was insufficient for achieving viable motor imagery decoding in a real-world patient setting due to the significant model polarization observed in some participants. This bias is attributed to the data scaling method, as it was effectively eliminated in approach three through the substitution of MinMax scaling with MVT scaling. The use of MVT scaling and the resulting equalization of the decoding models led to the highest accuracy scores among the three approaches, reaching an average accuracy exceeding 75% (Approach 3.1). This, combined with the use of rEWC, which ensures a positive tendency in model performance with the addition of new data, establishes Approach 3 as the optimal choice for clinical applications. What is more, erasing erratic distributions from the decoding models has led to an average accuracy over 80% for the rest of the participants (Approach 3.2), demonstrating the potential and clinical usability of the proposed MI decoding algorithm and posing Approach 3.2 as the optimal solution.

In conclusion, the participant cohort provided a sufficient dataset for robust statistical analysis, particularly for Approaches 2 and 3.2. Approach 3.2, identified as the most effective method, demonstrated a high degree of statistical significance, thereby ensuring its reproducibility and robustness. This level of statistical rigor allows for the derivation of consistent and reliable conclusions from the study.

4.2. Closed-Loop Results

While online and pseudo-online data share a similar nature and have undergone identical preprocessing and analyses, the online scenario introduces an inherent uncertainty caused by the activation of the cycle ergometer. Specifically, this uncertain initiation or stopping could induce inconsistencies in participants' motor imagery performance. This unpredictability might lead to surprise when the cycle ergometer starts moving (or even frustration when it should), affecting the consistency of EEG signal patterns. Consequently, these variations in EEG signal behavior within the online context likely contributed to a decrease in classification accuracy, especially in the Approach 2 models. The weighted TAR

and FSR values generated for closed-loop trials with Approach 2 are encouraging; however, the inter-subject variability leads to unstable BMI behavior in some cases. This highlights the need for further refinement of the MI decoding method.

Notwithstanding, the results obtained with Approach 3.1 models are more promising. The low FAR and FSR scores consequently generated few activations and stops, ensuring the algorithm's consistency and safety for use. This, summed with the consistent TAR and TSR values, positions Approach 3.1 as a fully viable option for clinical applications. The rEWC algorithm refined the models, yielding strong performance in well-performing users, mirroring observations in pseudo-online classification and with Approach 2 in online classification. Crucially, the addition of the MVT scaler significantly reduced disparities in model performance across subjects, thereby enhancing the results of lower-performing users, as evidenced in both pseudo-online classification and corroborated in online classification with Approach 3.1. This phenomenon is likely attributed to the EEG-specific nature of the MVT scaler. While general scaling procedures such as MinMax scaling may not fully capture the inherent individual variability in EEG recordings, potentially leading to non-robust results and significant outliers when disruptive patterns or neural rhythms are present, the design of the MVT procedure better accommodates the unique characteristics and idiosyncrasies of EEG signals, thus preventing disparate distributions and unifying classification outcomes. The slightly higher False Stops Rate may be attributed to noise induced by the cycle ergometer's movement, which could also affect the True Stops Rate. It is plausible that MVT scaling, in particular, may be more susceptible to this type of noise than MinMax scaling, as these differences attenuate in the Approach 2 results. In any case, the standard deviation results demonstrate strong consistency of intra-subject performance across both approaches.

The primary limitation of these results, particularly concerning Approach 3.1, is the restricted number of participants, although more closed-loop trials have been completed with Approach 3.1. Relying on data from only three users is insufficient for drawing robust conclusions; thus, further research with a larger cohort is essential to fully validate the findings presented in this section. Nevertheless, in a real-world therapeutic setting, each participant would undergo numerous sessions, generating substantial subject-specific EEG datasets. Despite the limited size of the online datasets used in this study, the statistical evidence provided in Section 3.2.3 strengthens the conclusions reached for the online scenario.

5. Conclusions

Decoding motor imagery from EEG signals presents a complex challenge with significant potential benefits. Although EEG signals are endogenous, subject-specific, and highly non-linear, accurate decoding of motor intention enables the development of effective neurorehabilitation therapies. In this study, four distinct motor imagery decoding approaches were proposed, developed, and evaluated in both pseudo-online and online scenarios. Pseudo-online classification yielded promising results, particularly with Approach 3. Similar results were achieved for the closed-loop scenario, albeit with a limited dataset. Further testing is required to fully ascertain its effectiveness. The statistical evidence supports the conclusions drawn from both scenarios.

This study demonstrates the feasibility of accurately decoding motor imagery using a highly optimized, lightweight EEG framework designed for real-world therapeutic translation. By successfully integrating the rEWC algorithm alongside specific signal scaling techniques, such as MVT scaling, the proposed framework effectively mitigates catastrophic forgetting during continual learning tasks. The empirical and statistical evidence establishes that targeting a reduced, neurophysiologically relevant electrode subset minimizes patient fatigue and computational overhead without sacrificing classification

robustness. While pseudo-online and closed-loop online evaluations validate the high adaptability of these transfer learning models, their stability across extended, large-scale clinical deployments remains a key trajectory for future validation. Ultimately, these findings underscore that precise model weight characterization and localized spatial filtering are pivotal for developing dependable, cost-effective brain-computer interfaces tailored for neurorehabilitation environments.

Limitations and Future Work

Despite the promising classification accuracy and the robust mitigation of catastrophic forgetting achieved by the proposed framework, certain limitations must be acknowledged. First, while the pseudo-online validation was extensive, the fully closed-loop online scenario was evaluated on a more constrained dataset. Although these preliminary online results are highly encouraging, a larger cohort of participants is required to comprehensively validate the real-time stability of the system. Second, the current study focused on healthy subjects performing motor imagery. Transitioning this setup to actual clinical scenarios involving post-stroke or spinal cord injury patients may introduce higher inter-subject variability, lower signal-to-noise ratios, and distinct neuroplastic patterns, which will require further adaptation of the MVT scaling and rEWC algorithms. Future work will focus on expanding online clinical trials and optimizing the lightweight electrode montage for long-term therapeutic sessions.

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Institutional Review Board Statement: All participants fulfilled the inclusion criteria, which were approved by the Ethics Committee for medicinal products Research (CEIm) at University Hospital Severo Ochoa (HUSO) in Leganés, Madrid, Spain. Before their involvement, each participant received comprehensive information regarding the study's objectives, their role in the research, and potential risks and benefits. They then provided their informed consent by signing a form approved by the aforementioned ethics committee, which was assigned the code HLM-CYCLING-EEG. This code specifically references the study involving motor imagery during cycling, recorded via EEG at Los Madroños Hospital.

Informed Consent Statement: Informed consent for the publication of anonymized study results (including images) was obtained from all participants prior to their inclusion in the study. Signed consent forms explicitly addressed the dissemination of findings, ensuring participant awareness and agreement. The consent forms are securely retained and available for review upon request.

Data Availability Statement: The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ACC.	Accuracy
BMI	Brain–Machine Interface
CEIm	Comité de Ética de la Investigación con medicamentos
CNN	Convolutional Neural Network
CSP	Common Spatial Patterns
DL	Deep Learning
ECoG	Electrocorticography
EEG	Electroencephalography
EWC	Elastic Weight Consolidation
fMRI	functional Magnetic Resonance Image
FA	False Activation
FAR	False Activations Ratio
FS	False Stop
FSR	False Stops Ratio
GELU	Gaussian Error Linear Unit
GmbH	Gesellschaft mit beschränkter Haftung
GND	Ground
GPU	Graphics Processing Unit
HLM	Hospital Los Madroños
HUSO	Hospital Universitario Severo Ochoa
I3E	Instituto de Investigación en Ingeniería de Elche
iEEG	intracranial electroencephalography
LDA	Linear Discriminant Analysis
MEG	Magnetoencephalography
MI	Motor imagery
MIQ	Motor imagery questionnaire
MVT	Maximum Visual Threshold
NN	Neural network
PCC	Pearson correlation coefficient
RAM	Random Access Memory
REF	Reference
rEWC	rotative Elastic Weight Consolidation
RTA	Repeated trial augmentation
STD	Standard deviation
TA	True Activation
TAR	True Activations Ratio
TM	Trademark
TN	True Negative
TS	True Stop
TSR	True Stops Ratio
UPV	Universitat Politècnica de València
ValGRAI	Valencian Graduated School and Research Network of Artificial Intelligence

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