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Modeling of Brain Cortical Activity during Relaxation and Mental Workload Tasks Based on EEG Signal Collection

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Abstract: Coronavirus disease 2019 (COVID-19) has caused everything from daily hassles, relationship issues, and work pressures to health concerns and debilitating phobias. Relaxation techniques are one example of the many methods used to address stress, and they have been investigated for decades. In this study, we aimed to check whether there are differences in the brain cortical activity of participants during relaxation or mental workload tasks, as observed using dense array electroencephalography, and whether these differences can be modeled and then classified using a machine learning classifier. In this study, guided imagery as a relaxation technique was used in a randomized trial design. Two groups of thirty randomly selected participants underwent a guided imagery session; other randomly selected participants performed a mental task. Participants were recruited among male computer science students. During the guided imagery session, the electroencephalographic activity of each student's brain was recorded using a dense array amplifier. This activity was compared with that of a group of another 30 computer science students who performed a mental task. Power activity maps were generated for each participant, and examples are presented and discussed to some extent. These types of maps cannot be easily interpreted by therapists due to their complexity and the fact that they vary over time. However, the recorded signal can be classified using general linear models. The classification results as well as a discussion of prospective applications are presented.

Keywords: guided imagery; relaxation; EEG; GLM

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1. Introduction

A handful of relaxation techniques are used to reduce stress, and they have been the subject of scientific investigation for decades [1–3]. Relaxation techniques can be widely used for stress reduction in the post-COVID-19 reality and may become one of the most often used psychological or pharmacological therapies. Although the COVID-19 pandemic has been associated with physical conditions, social, psychological, and economic consequences are also being observed globally; changes to normal life may lead people to suffer from a higher degree of mental health problems, including fear of infection, uncertainty, stress, anxiety disorders, sleep problems, mood disorders, and suicidal ideation [4–6].

Many methods, including relaxation training [7–9], biofeedback [9], hypnosis [10,11], and various forms of yoga meditation [12,13], have been successfully used to reduce tension and anxiety. Guided imagery is one of the world's oldest healing resources [14]. Interest in the practice of mental imagery and the role of imagination in health and well-being has dramatically increased, as mental imagery has become a popular approach for treating a wide variety of psychiatric and medical concerns and for enhancing sports performance [15]. In medical and scientific research, guided imagery has been defined by some researchers "as the internal experience of a perceptual event in the absence of the actual external stimuli", where imagery refers to the awareness of sensory (physical) and perceptual (cognitive) experiences [16]. Some guided imagery is also referred to as guided visualization [17,18]. Guided imagery (GI) is a cognitive, behavioral, mind–body, evidence-based technique that is employed to manage pain, including cancer pain, which affects and/or modifies the psychophysiological state of patients [19]. GI affects a variety of systems, including the respiratory, cardiovascular, metabolic, and gastrointestinal systems, and immune responsiveness. Psychoneuroendocrinoimmunology (PNEI) research has demonstrated that the psychological response to GI can modulate the activity of the hypothalamic–pituitary–adrenal axis, reducing the stress response and increasing the feeling of well-being. Central and immune nervous system modulation through the release of enkephalins, endorphins, cholecystokinin, and cortisol may be among the mechanisms mediating these effects [20].

Meditation practices are associated with enhanced executive function and working memory together with improvements in mental health condition severity (e.g., anxiety, depression, and eating disorders [21–25]. Hudetz's finding is that relaxation from 16 min of guided imagery significantly increased post-test working memory performance in healthy volunteers, and this improvement paralleled a significant reduction in the state–anxiety scores as a result of relaxation training and EEG activity [26].

No findings other than Hudetz's on guided imagery and brainwave activity have been published, even though this is one of the oldest relaxation techniques, and many studies have proven its positive impact during life-threatening disease treatment [27,28]. This research is novel in this field as our main objective was to revise if quantitative modeling can predict if and when participants enter a relaxation state, meaning alpha power increases and beta power decreases, when exposed to guided imagery. Our original prediction was that the pattern of brainwave activity reverses in comparison with that reported the existing research on brainwave activity during stress response regulation [29,30]. Changes in the EEG brainwave activity, specifically alpha power (8–13 Hz), are thought to decrease because of the association of alpha power with relaxation, with an inverse relationship with cognitive activity [31], whereas beta power (13–30 Hz) is thought to increase in response to stress [32] due to its association with information processing and anxiety [33]. A number of studies have confirmed this hypothesis: oscillatory changes in frontal alpha (decrease) and beta (increase) power during or after applying stressors such as exam stress [34] and during cognitive stressors such as the Stroop task [35]. In contrast, studies on relaxation techniques such as meditation techniques have noted increased alpha power with the use of these techniques [36–39]), which has been linked to improved cognitive performance [40,41].

In this research, we aimed to check if guided imagery (in comparison with a mental workload task) could produce the predicted and observed changes in brainwave activities (mainly an increase in alpha power and, to some extent, a reduction in beta power) as observed using dense array electroencephalography, and whether such differences could be modeled and then classified using a machine learning classifier. This study is innovative because such pattern was found using a guided meditation technique but not (with the exception of [42]) applying the relaxing technique of guided imagery.

With technological advances, new tools can provide computer-generated audio–visual displays and produce immersion in digital 3D environments. The literature in this field is expanding. In a study [43], the authors verified whether a VR-guided meditation experience for patients with cancer would produce significant changes in EEG waveforms and whether any changes would occur in the pain experienced during VR-guided mediation. This study demonstrated the feasibility of using EEG recordings in exploring neurophysiological changes in brain activity during VR-guided meditation and its effect on pain reduction. Such modern brain imaging techniques are valuable as they provide data for the verification of the computational models focusing on understanding the relationship between cognition and the brain [44]. Eduardo Perez-Valero created a stress level classification via electroencephalography (EEG) and machine learning on twenty-three volunteers [45]. Participants were subjected to stressful interactions alternating with phases where they were able to relax. After quantitative assessment of the stress level through individualized regression algorithms, the researchers developed stress classifiers that indicated that regression models could quantitatively predict stress levels with noteworthy performance.

In this study, we wanted to verify whether obtaining such quantitative prediction but on relaxation level is possible. Therefore, the two main objectives of the study were: to record and visualize the brain cortical activity of subcohorts exposed to guided imagery relaxation and mental tasks and to train a general linearized model (GLM) classifier to classify the recorded signal into one of the two classes: relaxation or mental workload. Such a classifier might allow high-probability identification of when a patient is in a state of relaxation, which will provide the opportunity to create computer-based devices that can help with anxiety and stress reduction.

For this study, 60 computer science students at Maria Curie-Sklodowska University in Lublin, were recruited for a randomized trial. Half of the randomly selected students were exposed to relaxation, as recorded by an experienced trainee in guided imagery, whereas the remaining students solved mental tasks.

In this paper, we show that it is possible to build a general linear model that can be used to accurately distinguish the state of a participant's brain. Although the GLM is a commonly known classifier, its application to EEG signal analysis is uncommon. The novelty of this study is the evidence of the possibility of classifying two mental states using EEG signal classification and a GLM, which, in the future, may lead to the construction of new therapy-oriented brain–computer interfaces.

2. Materials and Methods

2.1. Cohort Recruitment

We recruited 60 participants from among computer science students at Maria Curie-Sklodowska University in Lublin.

They were 60 right-handed men aged from 17 to 24 years; the average age was 20.38 with a standard deviation of 1.52.

The experimental cohort consisted of two subcohorts:

- A: 30 subjects who were exposed to relaxation.
- B: 30 subjects who were asked to perform a mental task.

2.2. Inclusion and Exclusion Criteria

To ensure the repeatability of the study, we defined the inclusion and exclusion criteria as follows.

2.2.1. Inclusion Criteria

The age of participants should be in the range of 17–24, as this was the typical age of the computer science students at the university where the experiment was conducted. They should be short-haired, right-handed men, because long hair hinders the recording of signals without noise. The number of women studying computer science was still low, so building a balanced cohort including an equal number of left-handed and right-handed men and women for the experiment would have been difficult. In addition, most of the women studying computer science had long hair. Notably, differences have been reported in electroencephalograms between men and women [46,47], and we wanted to have a relatively equal cohort response.

We also assumed that, due to lateralization, handedness may play a significant role in classification. All students selected for the cohort were white men of Polish nationality or citizenship, fluently speaking Polish.

Another inclusion criterion was being healthy; not using prescribed medication, soft drugs, or hard drugs; with no medical treatment history in the one year following the study; and with no chronic diseases, including chronic fatigue syndrome, cancer, or any other diseases or mental disorders. Participants had to have the ability to attend study appointments with no technological requirements.

The participants were nonsmokers and asked not to consume alcohol or any medications at least 72 h before participation in the experiment.

2.2.2. Exclusion Criteria

Mean younger than 17 or older than 24 years, left-handed, or with long-hair and all women were automatically excluded from the cohort recruitment process due to the reasons explained above.

Participants that did not fluently speak the Polish language were excluded from the cohort because the GI session was recorded in Polish and mental tasks were formulated in Polish. To replicate the study, we suggest choosing the same language for GI sessions, mental tasks, and cohort members.

Candidates even nonseriously ill (flew, cold, running nose, etc.) were excluded from the cohort recruitment process.

Candidates taking prescribed medications, soft drugs, or hard drugs were excluded from the cohort recruitment process.

Candidates with a medical treatment history in one year following the study or with chronic diseases, including chronic fatigue syndrome, cancer, or any other diseases or mental disorders diagnosed were excluded from the cohort recruitment process.

Candidates who could not attend study appointments could not be included in the cohort.

2.3. Information for Participants

Before participating in the study, participants received information about EEG research and technology and their role in the project. Then, they signed the agreement for participation.

They also filled and signed the declaration fulfilling the requirements of inclusion and exclusion criteria in an attempt to determine that none of our participants suffered from chronic diseases. The participants were asked to declare serious diseases such as chronic fatigue syndrome, cancer, and all other chronic diseases, including mental disorders. If they declared so, they were automatically excluded from the cohort.

2.4. EEG Recordings

All EEG recordings were obtained using a 256-channel dense-array EEG amplifier with a HydroCel GSN (geodesic sensor net) 130 manufactured by Electrical Geodesic Systems (EGI) (500 East 4th Ave. Suite 100, Eugene, OR 97401, USA), and the sampling frequency was 250 Hz. The amplifier worked with Net Station 4.5.4 and SmartEye 5.9.7 software for gaze calibration and eye-blinking or saccadic artifact removal. The laboratory was also equipped with a geodesic photogrammetry system (GPS), which was operated using Net Local 1.00.00 and GeoSource 2.0. The event-related potential (ERP) experiments were designed in PST e-Prime 2.0.8.90.

2.5. Deep State of Relaxation

During relaxation, each participant sat in a comfortable armchair with earphones on his head, and the relaxation procedure was played through the earphones from the record. The record was prepared by a trained expert, which is the typical method used in guided imagery (GI) [48–50]. Guided imagery is a relaxation technique that involves dwelling on a positive mental image or scene. The length of the record was 21 min and 7 s; however, for this research, the first 21 min were taken into consideration. It was assumed that sooner or later, each member of this subcohort would be relaxed enough to manifest brain cortical activity that could be classified.

2.6. Mental Task

During the mental task, participants were asked to recall facts from memory as much as possible. These facts included the capitals of European countries, zodiac signs, and the states of the United States of America. The participants were told that they would be asked to write these answers down after the experiment and that their reward was dependent on the results. We assumed that such a task would require some mental effort, leading to a high level of mental workload.

2.7. Preprocessing Pipeline

The collected signal was preprocessed using the following procedures and parameters set on Net Station software: filtration with 1 Hz high-pass and 45 Hz low-pass filters. Then, the standards for Net Station interpolation and noisy channel removing algorithms were applied as well as automatic and, in some cases, manual artifact removal. Then, the signal was divided into 1 s epochs, and noisy epochs were removed in Net Station using the AutoReject toolbox. See Figure 1.

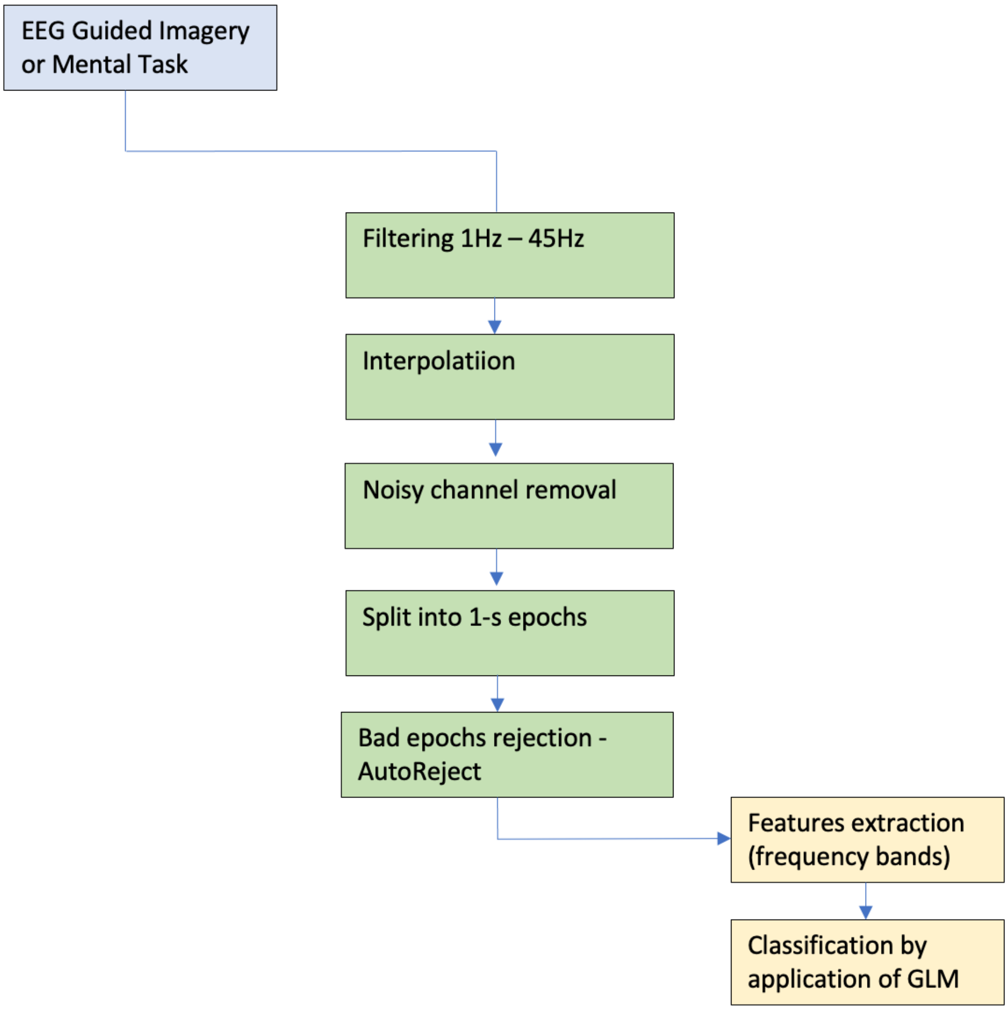

Figure 1. Data analysis pipeline for the experiments. For details, see the text.

3. Results

Examples of 3-min time interval plots are presented in Figure 2 for a selected student in subcohort A, who experienced GI relaxation, and in Figure 3 for a student in subcohort B, who performed the mental workload task. These maps, however, are too similar and cannot be easily interpreted using the naked eye. For example, in Figure 2 (state of relaxation), we can see increased activity in the β band, and in Figure 3, considerably α-band activity can be observed. However, Figures 2 and 3 present particular student cases and a specific 3-min time interval from a 21 min recording of brain cortical activity. As expected, plots such as those in Figures 2 and 3 change over time, and quickly analyzing them would be difficult.

Nevertheless, differences in activity are visible, even though they are not easily interpretable. An appropriately trained machine learning classifier can be used for this task.

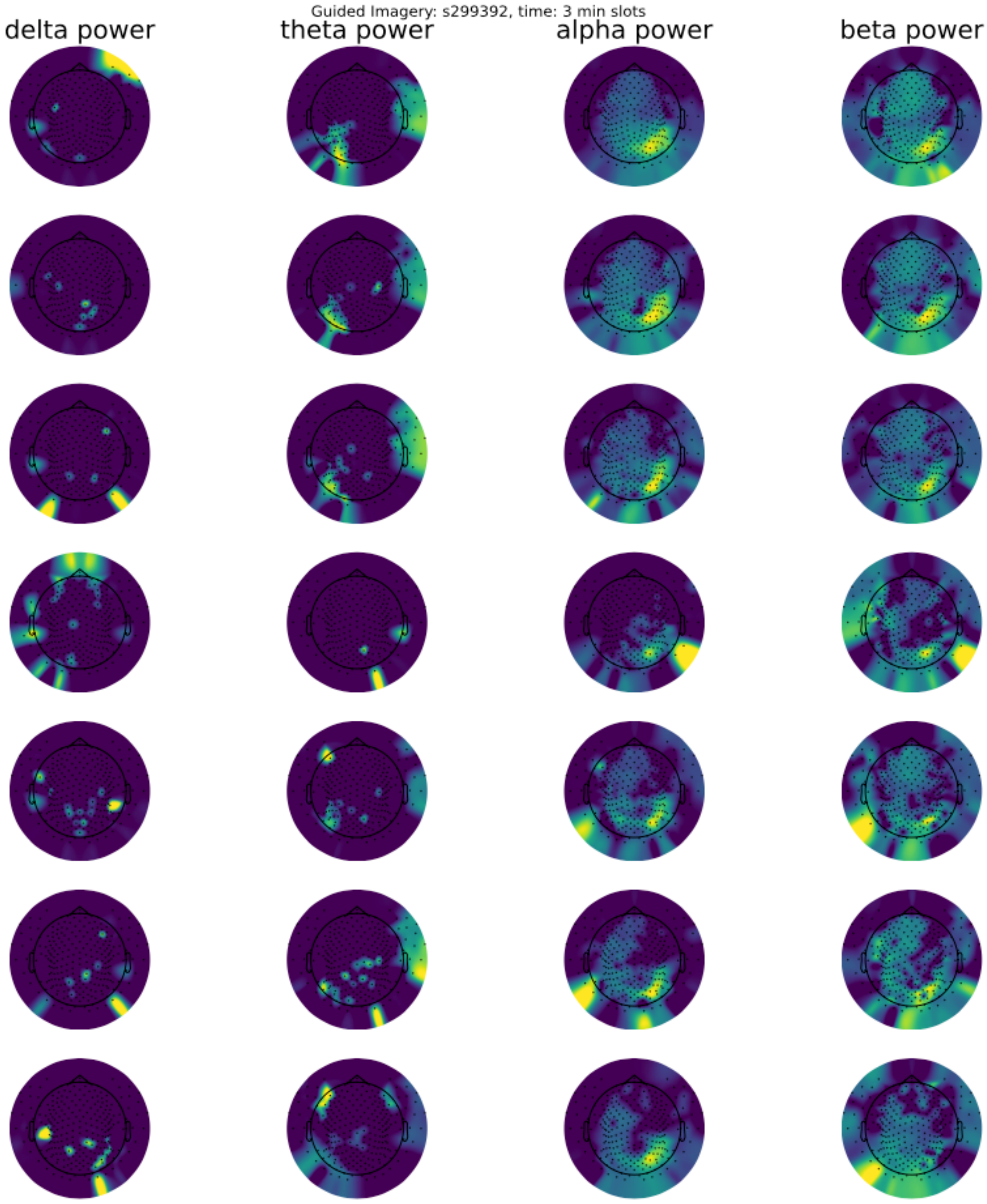

Figure 2. Power activity in the δ, θ, α, and β bands for participant s299392 exposed to guided imagery. Each row, one-by-one, represents a 3-min slot, for 21-min in total. For details, see the text.

Machine Learning Data Analysis

The signal was classified using generalized linear models (GLMs) using the implementation included in the h2o library available for Python. Model tests based on different time windows were conducted in Python version 3.7.5.

The quality of the classification was tested for the same time intervals in the two data groups.

Group A: Signals with less than 10% erroneous epochs; Group B: all signals included in the dataset (60 signals). According to the documentation of the h2o library, using generalized linear models, balanced data were not required.

In the case of Group B, the signals removed due in noisy epochs were interpolated by the library mentioned above.

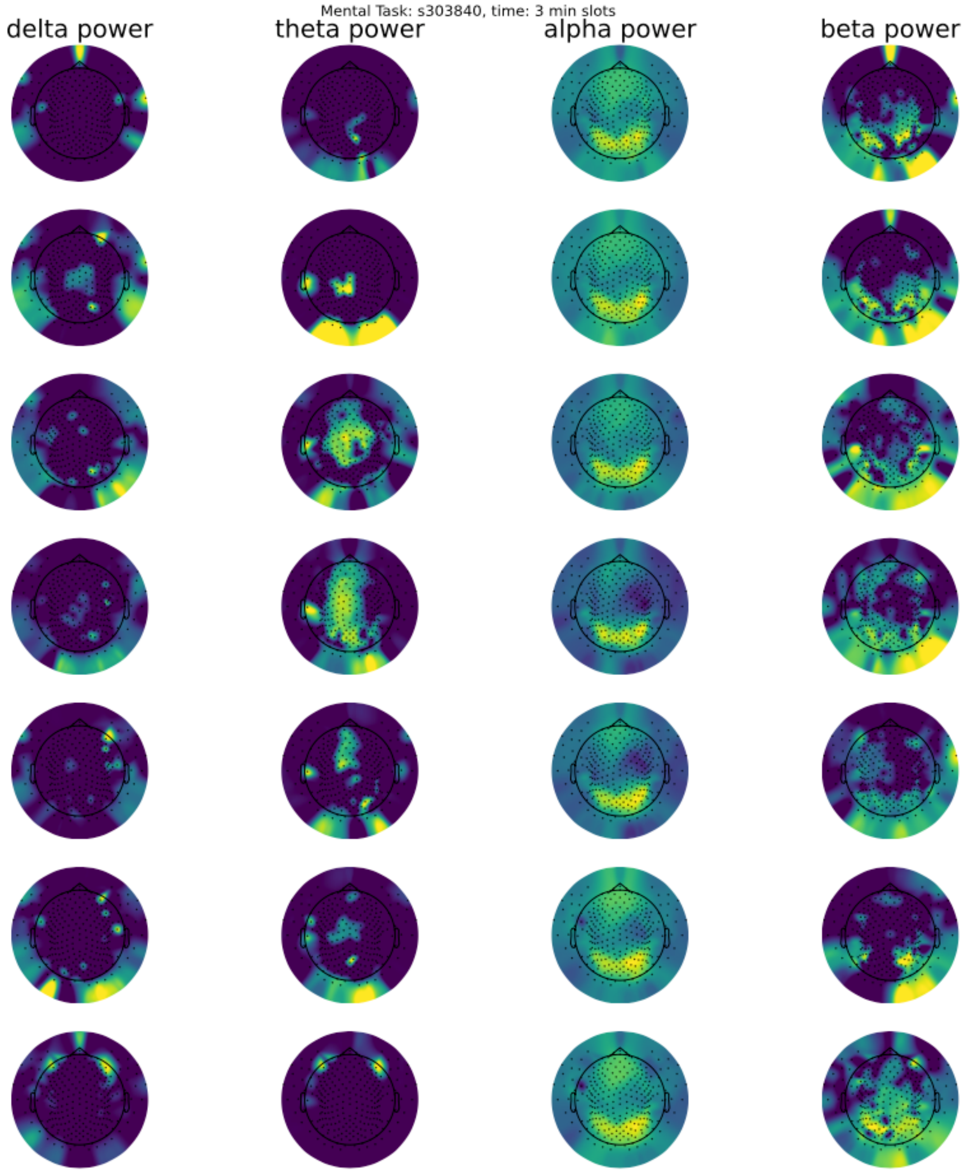

Figure 3. Power activity in the δ, θ, α, and β bands for participant s303840 exposed to mental task. Each row, one-by-one, represents a 3-min slot, for 21-min in total. For details, see the text.

The training and validating sets were divided into proportions of 80% and 20%, respectively.

Table 1 shows the results of the GLM classifier for Group A. The 3 s long time intervals were investigated around the 5th, 10th, 13th, 14th, and 15th minutes. The choice of these probing times was arbitrary based on the experience of the GI relaxation therapist.

The results of the GLM classifier for Group B are shown in Table 2, where a 60 s time interval was chosen because we suspected that the signals were of worse quality in this group. The probing was investigated around the 5th, 10th, 13th, 14th, and 15th minutes and the following 1 min after each probe.

Table 3 shows the results of the GLM classifier for Group B, and the whole 20-min signal recordings were classified without any signal probing.

In Figure 4, the ROC curve for the GLM applied to Group B using the full-length 20-min signal recordings is presented. The set of statistical characteristics for this case are presented as follows: For the training set: MSE: 0.0634, RMSE: 0.2518, LogLoss: 0.2021, AUC: 0.9748, AUCPR: 0.9834; For validation set: MSE: 0.05227, RMSE: 0.2286, LogLoss: 0.1676, AUC: 0.9823, and AUCPR: 0.9877.

Table 1. GLM classifier results for Group A: all signals and 3 s time intervals.

Group	dT (s)	ACC Train	F1 Train	AUC Train	ACC Valid	F1 Valid	AUC Valid
A	299–301	0.6559	0.7165	0.7255	0.6252	0.7027	0.6808
A	599–601	0.6578	0.7156	0.7291	0.6401	0.7051	0.7006
A	779–781	0.6853	0.7326	0.7672	0.6693	0.7279	0.7451
A	839–841	0.6842	0.7336	0.7663	0.6629	0.7221	0.7355
A	899–901	0.6660	0.7177	0.7441	0.6506	0.7167	0.7252

Table 2. GLM classifier results for Group B: all signals and 60 s time intervals.

Group	dT (s)	ACC Train	F1 Train	AUC Train	ACC Valid	F1 Valid	AUC Valid
B	299–359	0.7785	0.8337	0.8620	0.7804	0.8360	0.8602
B	599–659	0.7884	0.8407	0.8678	0.7955	0.8478	0.8727
B	779–839	0.8097	0.8532	0.8926	0.8113	0.8578	0.8929
B	839–899	0.7830	0.8367	0.8628	0.7827	0.8409	0.8631
B	899–959	0.7812	0.8345	0.8634	0.7839	0.8410	0.8625

Table 3. GLM classifier results for Group B: all signals and full signal length.

Group	dT (s)	ACC Train	F1 Train	AUC Train	ACC Valid	F1 Valid	AUC Valid
B	1–1200	0.9258	0.9370	0.9822	0.9077	0.9238	0.9748

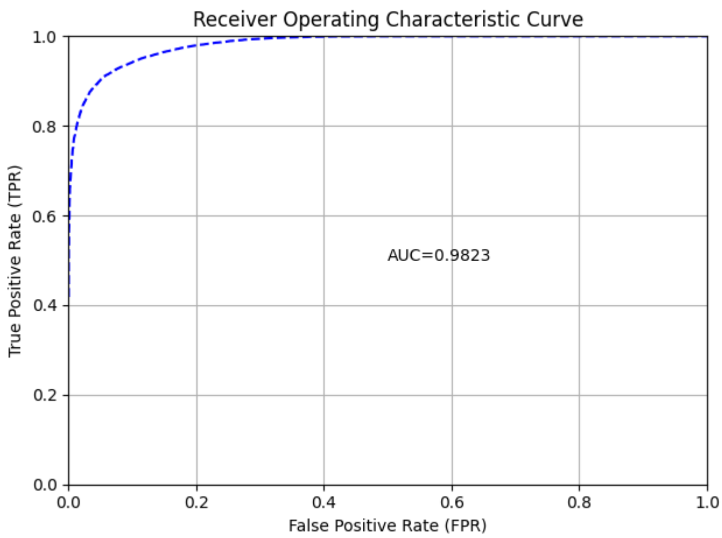

Figure 4. The ROC curve for the results presented in Table 3.

Table 1 shows that the best results, with approximately 68% accuracy, were achieved near the 13th and 14th minutes using the GLM classifier. A 3 s time interval was sufficient for analyzing and estimating the state of the brain during the time in which it was recorded.

Figures 5 and 6 show topographical maps of participants from Figures 2 and 3 for five frequency bands of the time window where the classifier was performing best.

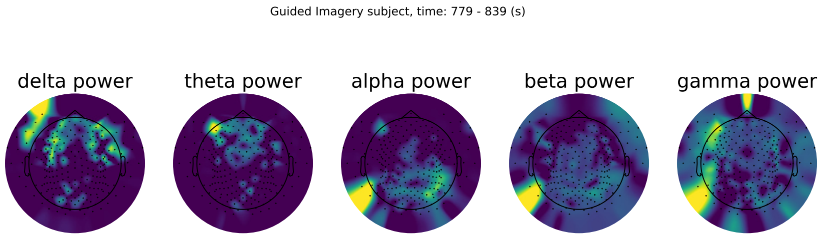

Figure 5. Power activity in the δ, θ, α, and β bands for participant s299392 exposed to guided imagery.

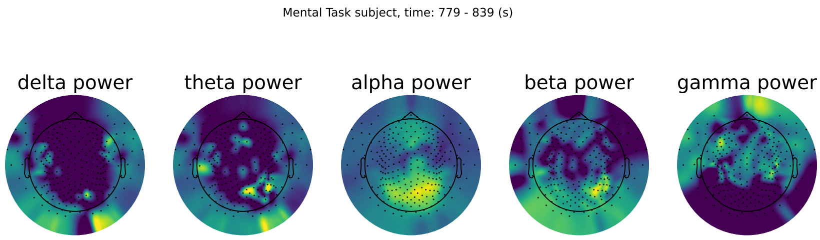

Figure 6. Power activity in the δ, θ, α, and β bands for participant s303840 exposed to the mental task.

4. Discussion

4.1. Signal Classification

According to our experience and expectations, most of the patients were sufficiently relaxed in the 14th minute. The best results of the classifier at this time confirmed our expectations, to some extent. To examine the hypotheses about the substantial increase in alpha power and decrease in beta (to some extent) power in the estimated phase of deepest relaxation, we carried out the two one-way ANOVAs comparing the individual scores in brainwaves between group conditions (guided imagery or mental task) during the time phase of 14 min. We found predicted, significant effect of group (F (1, 53) = 4.01, p = 0.05, p2 = 0.070), indicating that the alpha power in the guided imagery group (M = 0.24, SD = 0.14) was significantly higher than that in the mental task group (M = 0.17, SD = 0.12). However, we found no significant effect of group for beta power scores (F (1, 53) = 0.53, p = 0.47, p2 = 0.010), and beta power in the guided imagery group (M = 0.08, SD = 0.03) was very similar to that in the mental task group (M = 0.07, SD = 0.03). However, only the best signal (with less than 10% excluded epochs) was considered. Table 1 presents the GLM results obtained for both the training set and validation set, and the values of the obtained parameters confirmed the classifier's high level of stability in the considered time range.

As an accuracy of 68% was achieved by the classifier when using a 3 s time interval, we wondered if inputting more signal would increase the efficiency. The answer to this was yes, and in Table 2, the results with respect to classifier efficiency for 1-min-long intervals of time are shown. After 13 min, the efficiency of the GLM increased to 78%, which is a satisfactory result, especially because, in this case, we took all the signals recorded instead of the best ones. Notably, poor epochs were interpolated by the software and used for analysis, as described in the Methods section. Similarly, Table 2 presents the GLM results obtained on both the training and validation sets, and the values of the obtained parameters indicate the classifier's high level of stability in the discussed time range.

Table 3 presents the results obtained for the GLM classifier for all collected signals in the whole 20-min-long time range. An accuracy of approximately 92% with a similar F1 score proved its high efficiency for the whole collection of data, both on the training and validation sets. Th ROC curve presented in Figure 4 confirms its stability.

The software libraries discussed in the Methods section provided us with overtraining and data leakage incidents.

The aim of this study was to check whether machine learning can be used to classify the state of the participant's brain and distinguish engaging in deep GI relaxation from performing a mental task. The results presented herein confirm this possibility.

The other conclusion that can be derived from this study is that the more signal (or the longer signal) the classifier obtains, the higher the accuracy.

4.2. Future Research

This study is part of the initial stage of our project.

Depending on personal characteristics and external influence, each patient has their own ability to enter into relaxation, which varies with respect to time and other conditions.

In the future, the pace at which particular subjects enter a deep state of relaxation. should be investigated. We expected that this could be achieved in approximately 14 min. However, each individual can be characterized by their own pace. Plotting the state as a function of time would be recommended.

The use of machine learning classifiers is expected to be applied in the classification of biomedical signals at therapy support sites [51,52]. Machine learning tools and algorithms have also been used for decades for the diagnosis of many disorders, such as alcoholism or depression [53,54], among others [55], using new measures such as those defined in [56], as well as advanced modeling of biological system behavior [57–60], including diagnostic purposes [61–63].

Our findings are useful for the construction of brain–computer interfaces (BCIs) that have been known for half a century [64,65] and can support therapists in running GI relaxation sessions. In the next step, we can imagine AI-trained robotic therapists that are able to instantaneously treat their patients at an appropriate pace based on EEG recordings and classifiers applied. Although BCIs have been known for such a long time, some ethical dilemmas may arise when using them [66], especially with children [67]. Thus, another interesting aspect is the investigation of the characteristics of the deep state of relaxation inclination as a function of psychological personality predictors.

In the future, patients provided with simple EEG equipment will be able to use it during relaxation to support a trainee during brain monitoring. This type of approach could increase the effectiveness of therapy, and the study presented here can be the first step toward achieving this goal.

Another aspect leading to the possible application of this finding, especially when considering therapist support, is the design of tools that can be used to instantaneously process the collected data. Although the use of 256 electrodes can be too power-consuming, in practical applications, fewer electrodes may be sufficient. The data analysis pipeline may also consist of an Apache Spark Streaming-based engine, such as in [68], which, due to in-memory processing and the Python interface, seems to be a suitable candidate for pipeline implementation.

This will, however, require the analysis of several additional tests. After meditation vs. control manipulation, we examined the effectiveness of attentional processes (accuracy and reaction time) using three classical tests: the antisaccade test, Stroop test, and go/no-go test. They did not affect the EEG recordings, but their analysis was not the goal of this study. This type of approach will broaden our knowledge concerning relaxation interventions and will be reported in future papers.

Author Contributions: K.Z.: meaningful participation in the key phases of research and publication process, research project conceptualization, verification of results and analysis, manuscript writing, responses to reviewers, literature review, and implementing guided imagery relaxation technique; G.M.W.: head of the project, experiment idea and coordination, data science pipeline design, and manuscript writing; K.W.: EEG recordings, work in the laboratory, and data analysis; F.P.: EEG recordings, work in the laboratory, and data analysis; A.K.: classifier construction advise and evaluation; G.S.: research idea, selection of participants to the cohort, and statistical analysis. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: The studies involving human participants were reviewed and approved by the Maria Curie-Sklodowska University Bioethical Commission (MCSU Bioethical Commission permission 9 July 2021). The patients/participants provided their written informed consent to participate in this study. Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The raw data supporting the conclusions of this manuscript will be made available by the authors without undue reservation to any qualified researcher.

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