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The Distinction of Logical Decision According to the Model of the Analysis of Brain Signals (EEG)

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Keywords

Neuroscience, EEG, Decision making, Feature extraction, Statistical analysis, SVM classification

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RESEARCH PAPER

The Distinction of Logical Decision According to the Model of the Analysis of Brain Signals (EEG)

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Abstract

Recently, brain signal patterns have been recruited by researchers in different life activities. Researchers have studied each life activity and how brain signal patterns appear. These patterns could then be generalised and used in different disciplines. In this paper, we study the brain state during decision making in a lottery experiment. An EEG device is used to capture brain signals during an experiment to extract the optimal state for logical decision making. After collecting data, extracting useful information and then processing it, the proposed method is able to identify rational decisions from irrational ones with a success rate of 67%.

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1. Introduction

Recently, investigation of brain signals has been widely used in various areas such as economics and management, whereas it formerly was used in engineering and medical areas [1,2]. Understanding the methods of Electroencephalogram (EEG) analysis and classification enables researchers to conduct more experiments to make optimal use of these signals [3,4]. When a person performs an activity, he or she produces signals, and recruiting these signals would be beneficial in enhancing any process. By recruiting, we mean studying a signal pattern, which can subsequently be used as a reference for evaluating other people, for example, in robotic hand movement [5,6] and emotion recognition [7,8].

Decision making is an important process in every life activity, be it personal or institutional. In business, decisions are crucial in every step, including planning, staffing, organisation, coordination, and follow-up [9,10]. Decisions can be categorised according to their purpose, structure, complexity, degree of dependence and influence on other decisions, the extent of uncertainties, the circumstances under which decisions are made, and the available timescale [11]. These features constitute any decision.

Free and conscious decision making, if any, is one of the most complex displays of a person's behaviour. The decision-making process is often explored from philosophical and psychological perspectives, yet it remains a poorly studied subject in neuroscience [12].

Neuroscience emerged in the last three decades. The discipline was concerned with consciousness and it is ill-defined by this way [13], with elements of anatomy and physiology uncomfortably mixed with those of medical and psychological research, even coming dangerously close to philosophy. By the end of the 1980s, however, this science had developed into a confident and full-fledged field of knowledge, with its own rights, and could be represented more to the traditional sciences. This

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research (including neuroscience and engineering) has made use of EEG devices in experiments as a major research tool with which to acquire relevant EEG signals [14].

During the twentieth century, development in neuroscience was stimulated by such important discoveries as clinical neuropsychology, brain imaging, Brain–Computer Interface (BCI), cognitive psychology, computational modelling, and electrical and magnetic recording techniques [15]. This process of mixing various approaches led to the creation of a new discipline eventually called cognitive neuroscience.

Today, cognitive neuroscience not only is acknowledged, but also has developed a variety of techniques and methodological approaches that allow contemporary cognitive neuroscientists to investigate which feature of cognitive processing and brain function to select. These techniques represent a variety of recourse tools, ranging from brain absorption and electrical activity indices to injury approaches [16].

In this paper, we study the brain state pattern during lottery decision making. We record the brain signals (EEG) of participants who make decisions in a lottery experiment, and then recognise the pattern model of EEG signals during decision making. According to these signals, we try to discover the state of the decision maker and whether or not he or she is making logical decisions.

2. Literature review

There are a number of researches that have explored the understanding and analysis of EEG signals to employ them in surgery, developing machines to make simulations like brain functions, and in other fields such as the psychological state of a person when making a decision. In previous work, we studied the brain signal patterns related to different emotions [17,18]. We showed the participants different videos that stimulated the brain to react to various situations.

In [19], for example, video clips and musical stimuli were used to determine emotions for five different moods (happy, surprised, frightened, disgusted and neutral). They collected EEG signals from 20 participants by means of high-resolution equipment (62 channels). They extracted the features during pre-processing, and then mapped these features into the corresponding emotions via two classifiers: K-nearest neighbours and probabilistic neural network. They focused on the beta band and achieved a maximum mean classification accuracy of 91.33%.

In [20], the researchers selected specific features that have more of an effect on signals during audio-video stimuli. These features are used as an input to a Multi-Class Least Squares Support Vector Machine (MC-LS-SVM) for classification of human emotions. Although the researchers did not use a specific band from which to obtain the features, they achieved an accuracy of 80.83% regarding the classification of human emotions from EEG signals.

Also in Ref. [21], the researchers used BCI as a pathway, which allows communication between a computer and a human brain. They acquired real-time EEG data through the use of the Neurosky MindWave Mobile device. They further carried out an experiment for the acquisition of data. It was conducted on 40 subjects (33 males and 7 females). Statistical measures such as mean, standard deviation, and maximum and minimum amplitudes do the extraction features of EEG signals. They explore the approach of ensemble learning with the random forest classifier to build a BCI model with which to predict such mental states as concentration and meditation. The analysis and results of the proposed model show that it achieves about 75% consequences accuracy.

In [22], the authors conducted an EEG experiment in which the results of a binary lottery evaluation via certainty equivalents were compared with the results of a bisection method. The bisection method gives money that corresponds to the midpoint of the utilities of two payoffs in a binary lottery. Thereafter, the authors analysed EEG data, focusing on whether or not a probability had been evaluated. The results of the experiment show that the differences between the two methods were related to the attention towards sure monetary payoffs. They, however, do not show the brain activity connected with a devaluation of the probability of 0.5. Finally [23], applied the methodology of EEG analysis through data mining to analyse two different band frequencies of brain signals (full band and beta band) during an experiment in which visually impaired and sighted individuals were to recognise spatial objects through the sense of touch. They presented details of the proposed methodology and a case study using decision trees to analyse EEG signals from visually impaired and sighted individuals during the execution of a spatial ability activity. They conducted an experiment. The hypothesis was that sighted individuals, even if blindfolded, use vision to identify objects and that visually impaired people use the sense of touch to identify the same objects. They achieved an accuracy rate of 90% or above as an output of the decision tree classification algorithm.

3. Research methodology

The adopted methodology is similar to the work conducted in Ref. [20]. Generally, this approach is widely used in engineering and medical areas [24]. In this methodology, we undertake an experiment on a number of participants through stimulating their brains to make decisions by testing them on a lottery problem. The test consists of a number of multiple-choice questions that should be answered within a short time. During the test, we record the brain signals by means of an EEG system. After collecting the data, we follow a procedure to obtain useful information from those data. Firstly, we remove the interfering and noise signals via high- and low-pass filters. Secondly, the artefacts are filtered out, as these will contaminate the original signal. Thirdly, the collected signals are partitioned into segments. Each segment contains the brain signals during decision making for each question. The length of segments depends on the period of question answering. Fourthly, features are extracted from the clean segment. These features represent the signal information. Fifthly, we select the features with the highest number of iterations. The selected features will represent the decision pattern element [25]. Sixthly, we use supervised classification methods to recognise those patterns that are close to logical decisions.

In this work, we focus on the frontal lobe of the brain, which is responsible for making decisions and solving problems. We extract the signals from electrodes that are distributed in the standard 10−20 system, which are placed in scalp positions (AF3, AF4, F7, F8, F3, F4, FC5, FC6), as illustrated in Fig. 1. We used the EMOTIV EPOC+ [26]. The frequency of the device is 128-sample per second, which is the maximum bandwidth supported by this device.

4. Data collection and preparation

The proposed methodology is applied to 12 healthy participants. We conduct the experiment in an EEG lab by explaining the general idea behind the research to the participants. We use the EMOTIV EPOC + device to register the EEG data while the device is connected to the testing PC. The connection between the testing PC and the EEG device will capture the exact EEG raw data regarding the answer to a question. The EMOTIV EPOC + has 14 channels for recording signals. We use only eight channels (which are defined in the methodology section).

The test consists of 10 multiple-choice questions, with two choices each. The participant should answer all questions within two minutes, as, firstly, a longer time means more data, and, secondly, because the questions do not require a long time to answer. The nature of the lottery questions depends on the person's intuition and the mechanism of his or her thinking with regard to solving any problem or making a decision. Basically, the questions will measure a risk-averse person, because a risky person has illogical thinking, as in Ref. [27]. The test consists of three sections, the first and third of which are our concern. The questions in these sections will decide whether or not a person is rational (has logical thinking).

After finishing the test, the collected data require pre-processing. The data are recorded as a

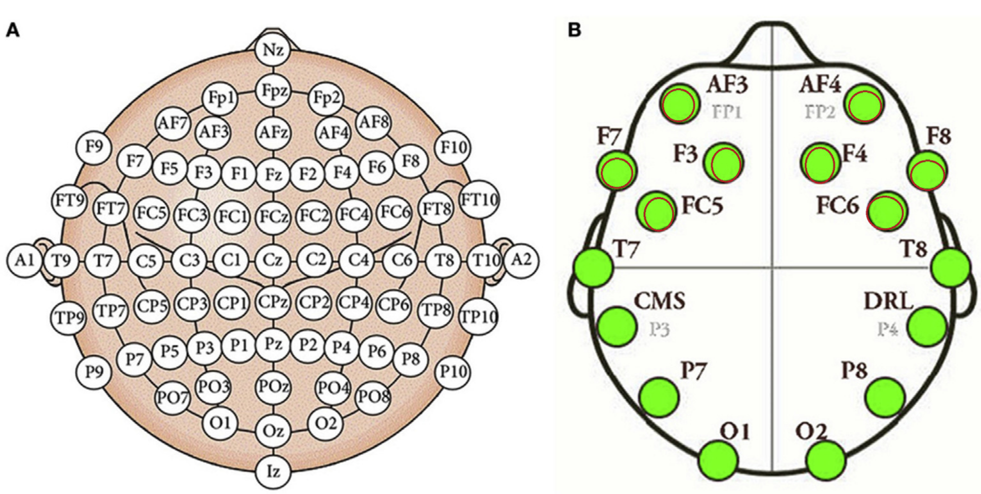

Fig. 1. EMOTIV EPOC + electrode distribution according to the 10−20 system [26].

European Data File (EDF) exported from EMOTIV EPOC + device software. The first stage consists of removing the interfering and noise signals by applying notch filtering to the EEG raw data, using low-pass and high-pass filters for the whole signal. The filters remove noise signals below 0.4 Hz and interfering signals above 50 Hz, such as the signals generated from the surrounding electronic devices [28].

The second stage is that of artefact removal. These artefacts come from muscle movement and eye blinking during the experiment and will contaminate the frequency of signals [29]. We use the Wavelet Independent Component Analysis (wICA) approach to remove artefacts from entire signals for each channel separately. As an example, Fig. 2A shows the EEG raw data with artefacts that affect the first five channels (between 0 and 0.5 s) for this epoch. After applying the wICA approach, the signal shape will look like that of the signals illustrated in Fig. 2B.

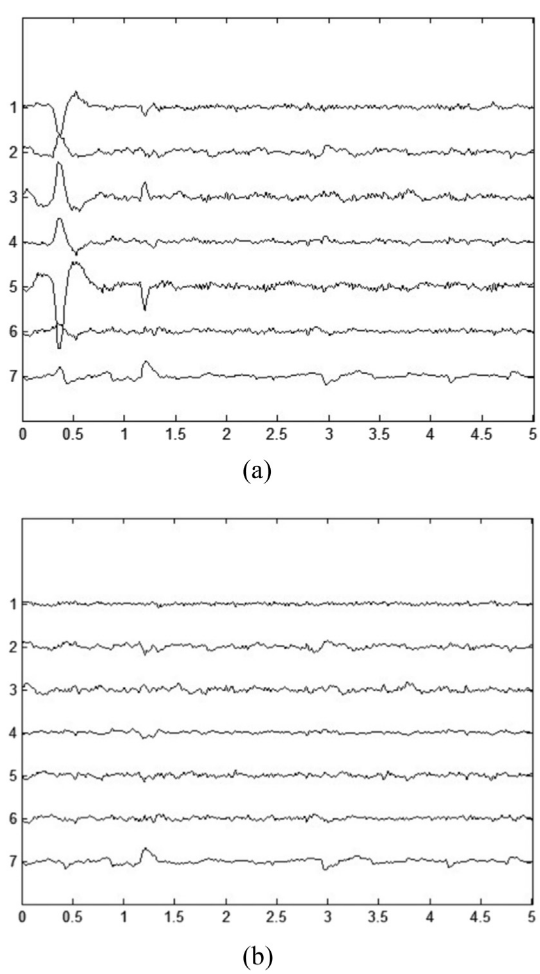

Fig. 2. EEG data (a) signal with artefact and (b) signal after applying wICA.

The third stage is that of data segmentation. Segmentation means finding and cutting out the exact brain signals during decision making when answering a question. Having undertaken the three stages, we now have clean signals ready to be processed.

5. Data processing

Recognising the human state requires understanding EEG raw data. The data-processing stage is required to extract the features of brain signal frequencies from the epochs of the EEG raw data [30]. The diagram in Fig. 3 demonstrates the method of feature extraction.

The input data for this step are the clean segmented EEG signals. The first step is that of frequency decomposition. It involves decomposing a frequency into magnitude and phase information for each frequency present in an EEG. Decomposition is implemented for each channel (i.e. electrode), since a channel contains a number of frequency bands. We use the Discrete Wavelet Transformation (DWT) method, specifically the Daubechies-8 (db8) method, to decompose the frequency bands through the use of four levels of extraction, with the remaining frequencies corresponding to the fifth level. In level one, we extract the gamma waves ranging from 31 to 50 Hz. Level two extracts the beta waves ranging from 14 to 31 Hz. Level three extracts the alpha waves ranging from 8 to 14 Hz. Level four extracts the theta waves ranging from 4 to 8 Hz. The remaining signal is a delta wave ranging from 0.4 to 4 Hz. Values below 0.4 Hz are already suppressed in a previous stage by means of low-pass filters [31].

The next step is to find the High Peak Order (HPO) frequencies that represent the features of a specific band of wave signals through the use of Fast Fourier Transformation (FFT). In the previous step, we obtain five frequency bands (delta, theta, alpha, beta and gamma) for each channel, constituting a huge amount of data. For illustration, suppose that a decision takes 30 s. This means that we have 30 s of multiplying 128 frequency samples per second for each of the eight channels. Multiplying these values gives us 30,720 for each decision, which is a very complicated number to analyse. A large number of EEG raw data tend to utilise this technology because of its reliability, consistency and scalability [32]. Therefore, we select the values with high iteration to

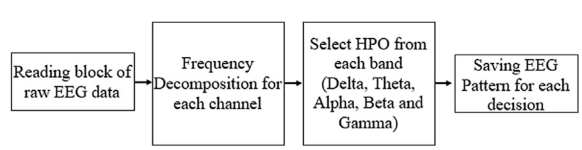

Fig. 3. Data-processing model.

reduce the complexity of the analysis [33]. To obtain these values, we apply FFT to the five frequency bands. The result is the HPO, which is a single value for each band in each decision.

At the end of this step, we have a table that contains (delta, theta, alpha, beta and gamma) values for each channel in each question. These values represent the brain state pattern for a person when making a decision.

6. Results and data analysis

The objective of the experiment is to understand and recognise the brain state pattern during decision making, and find out when a participant has made a logical or illogical decision. To analyse the captured data, we use two approaches: a statistical approach and the supervised classification algorithm [34].

Before using the classification algorithm, we manually analyse the sample participants to determine the correlation between the brain signal pattern and the logicality of the answers. As mentioned previously, there are four questions of our concern that reflect rationality. We choose two participants with a mix of correct and wrong answers for these four questions. We calculate the standard deviation for each frequency band in all channels' values. Thereafter, we plot the standard deviation for each decision in each frequency band, as shown in Fig. 4 (a and b).

From these charts, we observe that the gamma bands with high standard deviation values have

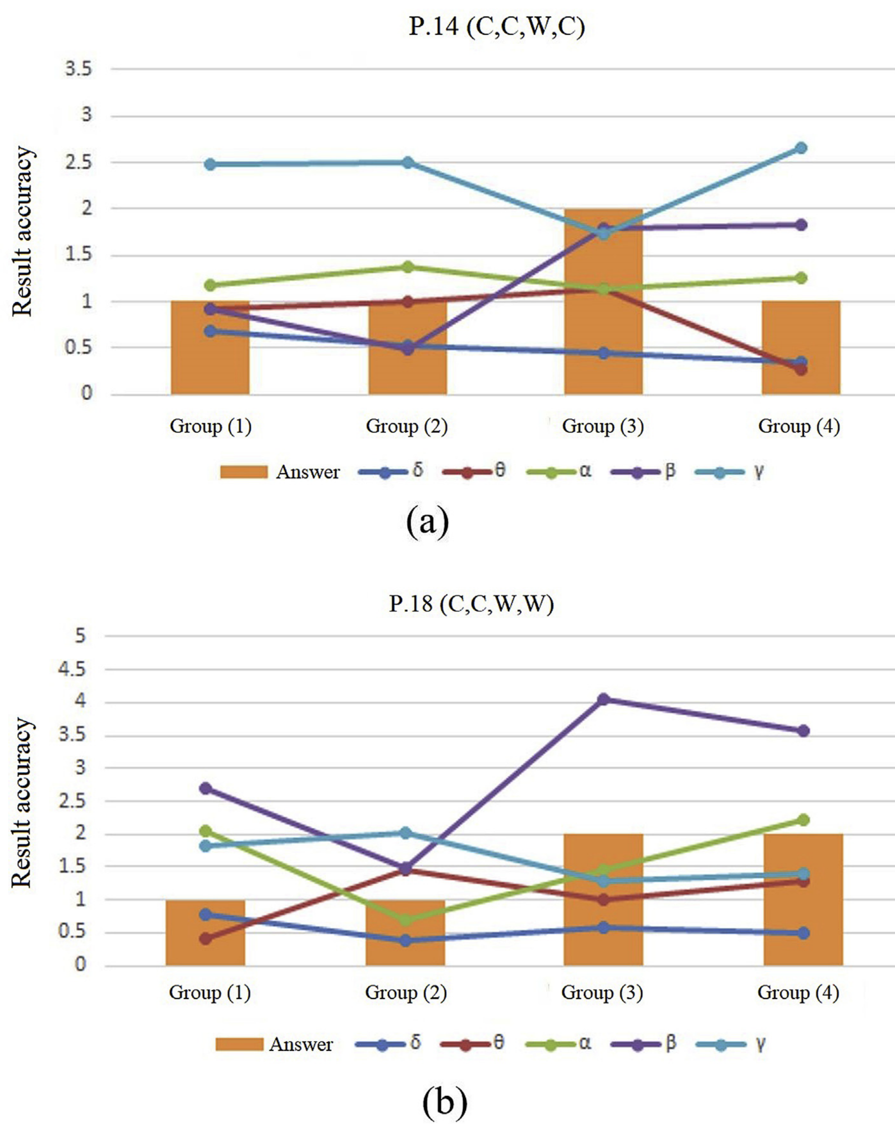

Fig. 4. Frequency band standard deviation.

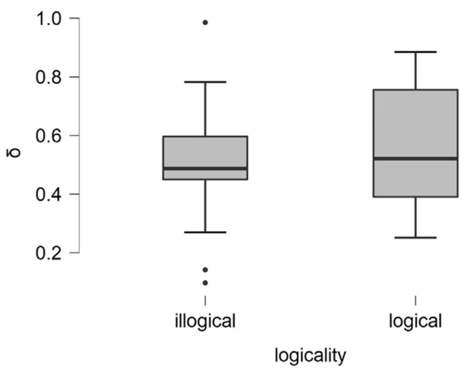

Fig. 5. Boxplot of gamma bandwidth.

correct answers, whereas low values have wrong answers. The process of analysis concentrates on gamma bands of signals for two reasons. Firstly, they have a wider range of data between 31 and 50 Hz. Secondly, making a decision requires high attention and, consequently, high gamma values [35]. These findings are based on our lottery test bed; probably, therefore, these types of decisions with uncertainty results have higher gamma values.

Fig. 4 shows the values (features of extracted signal) of arbitrary decisions. If we follow the first three bands (delta, theta and alpha) for each decision in the two charts, they have close values. Furthermore, it is difficult to recognise the differences in each decision to determine to which side it belongs (correct or wrong). The beta band, however, has fuzzy results, as we can observe that it shows a variation between different decisions. Clearly, the gamma band shows two distinct groups of values. The values above the threshold belong to correct answers, while the values below the threshold belong to wrong answers. This threshold is not a fixed value; rather, it is like a line that splits the data into two groups.

6.1. Statistical analysis

For the rationality of the six questions, the answers have been categorised into ‘logical’ and ‘illogical’. Within all of the bands, brain wave

Table 2. Descriptive statistics.

Coefficients					Wald Test		
	Estimate	Standard Error	Odds Ratio	z	Wald Statistics	df.	p
Intercept	1.938	0.819	6.945	2.366	5.600	1	0.018
γ	−1.212	0.444	0.298	−2.728	7.441	1	0.006

Note: Logicality level ‘logical’ coded as class 1.

fluctuation values of the logical and illogical answers overlap one another. However, the gamma band shows a tendency to have lower fluctuation when the response is logical. This tendency is notable in the box plots shown in Table 1.

Logistic regression was performed to determine the possibility of estimating an answer's ‘logicality’ by measuring the fluctuation of the gamma band in brain waves.

The logistic regression model was statistically significant ($\chi2$ (70) = 8.72, p = .003). The model correctly predicted 62% of the results.

Tables 2 and 3 and Fig. 5 show the logistic regression model. The probability of having a ‘logical’ response decreases when a person shows higher fluctuation in gamma band brain waves.

In Fig. 6, the authors observe that rationality decisions can be elicited from EEG signals because there are clear distinctions between the data.

6.2. Supervised classification algorithm

There are a number of classification algorithms that will obtain the optimum pattern recognition. One of these is the Support Vector Machine (SVM), which can achieve the optimal pattern recognition, according to Ref. [34]. The classification algorithm requires two inputs: training set and testing set.

As mentioned previously, we choose the gamma band to be used as the training and data sets for the classification algorithm. In our experiment, we use 75% of the data sample as the training set for the SVM algorithm. The testing set, on the other hand, constitutes 25% of the data sample [36]. We select 72 decisions out of 120 decisions in the experiment, as these 72 decisions represent the questions, which

Table 1. Descriptive statistics.

	δ		θ		α		β		γ	
	Illogical	Logical	Illogical	Logical	Illogical	Logical	Illogical	Logical	Illogical	Logical
Valid	40	32	40	32	40	32	40	32	40	32
Missing	0	0	0	0	0	0	0	0	0	0
Mean	0.508	0.543	0.731	0.732	1.063	1.108	1.936	1.957	2.003	1.575
Std. Deviation	0.167	0.199	0.352	0.239	0.399	0.371	0.847	0.650	0.649	0.530
IQR	0.147	0.366	0.609	0.291	0.578	0.452	0.791	0.856	1.096	0.576
Minimum	0.097	0.252	0.133	0.108	0.398	0.453	0.486	0.650	0.752	0.378
Maximum	0.986	0.885	1.460	1.132	2.211	2.040	4.056	3.464	3.104	3.088

Table 3. Descriptive statistics.

Confusion Matrix		
Observed	Predicted	
	Illogical	Logical
Illogical	29	11
Logical	16	16

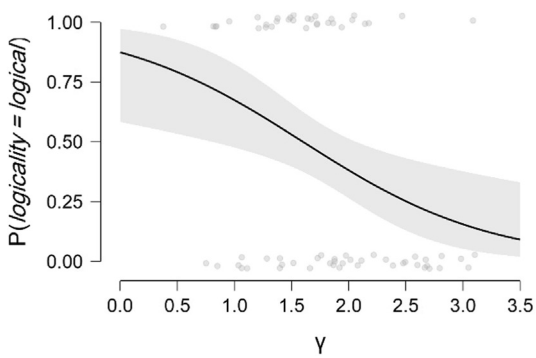

Fig. 6. Estimate of rationality of decisions.

require basic logic and rationality to solve. We provide the training set with the standard deviation of the gamma band and the corresponding answers.

After the SVM algorithm was executed, it was able to recognise 67% of correct decisions, but failed to map the remainder to their group of results. Improving these results can be achieved by increasing the training set. In this experiment, the questions relate to a specific type of decision making, i.e. the lottery problem. Changing the types of questions or answers might alter the results. The recognition of logical decisions has variant properties which depend on a participant's experience, their psychological state, the time of day, and other influential factors.

Table 4. Values of standard deviation for gamma frequency and decision results.

ID	Standard Deviation of Gamma Freq. for All Channels	Decision by Answers	Decision Detection by SVM	Final Result
1	2.983322802	1	1	1
2	1.946932887	0	1	0
3	2.078947693	1	1	1
4	2.325302215	1	1	1
5	1.035876827	0	0	1
6	1.723045099	1	0	0
7	1.876601525	0	0	1
8	1.111300979	0	0	1
9	1.275020968	1	0	0
10	1.759853928	0	0	1
11	1.642175071	1	0	0
12	0.851481458	0	0	1
13	1.837390109	0	0	1
14	2.048140324	0	1	0
15	2.796501136	1	1	1

Table 4 contains the results of the data set after running the SVM versus a participant's answer. Moreover, it contains the standard deviation of the gamma frequency for each participant and their decision by the answers and by the classification algorithm. We categorise the decisions into two groups: 1 represents logical decisions, whereas 0 represents illogical ones. The last column shows the final result. When the decision making in both the classification algorithm and the answers are identical, then the result will be 1. Otherwise, when the classification algorithm fails to identify the correct decision, the result will be 0.

The results show that it is difficult to distinguish the threshold that splits logical and illogical standard deviations. For example, most of the results with a standard deviation above or approximately 2 belong to logical decisions. However, results with a standard deviation below 2 are illogical decisions. Nonetheless, there are results with a standard deviation below 2 that have logical decisions, such as participant no. 2. His standard deviation is below or approximately 2 and his answer is logical. But the classification algorithm fails to map it to the correct logical group. Furthermore, it fails to map some illogical decisions to their group. Yet, this error is acceptable for the aforementioned reasons.

7. Conclusions

In this paper, we study the recognition of brain state patterns in a lottery experiment through analysing EEG signals. We recorded the signal frequencies when making a decision. Thereafter, we filtered out the unnecessary data, and selected the HPO of frequencies to find out the frequency bands. We analysed and recognised the most affected frequency band during decision-making. It appears that the gamma band is highly affected during the decision-making process. Applying this criterion through statistical analysis and SVM proves that 67% of the results were correct. This means that we were able to predict answers through the brain signal pattern. Both approaches, however, could not predict all of the correct answers, due to the nature of the experiment and because the training set was limited. In addition, the results showed that the beta band does have an influence, yet it is lesser than that of the gamma band.

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