LOW ALPHA, LOW BETA, AND THETA BRAINWAVES BANDS TO PREDICT STUDENT ENGAGEMENT USING MACHINE LEARNING METHODS

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ABSTRACT

Recent developments in Brain-Computer Interface technologies have increased the ability to personalize Learning by detecting and recognizing participants' cognitive and emotional affective states. From a global point of view, working in monitoring and identifying the emotional and cognitive states of the students will establish the basis to incorporate a higher level of academic supervision and control of student performance. In this paper, the authors used an Open EEG (Electroencephalography) Dataset to analyze the correlation between student brainwaves in the frontal lobe when watching videos categorized in levels of confusion by using Machine Learning algorithms. It was found that alpha1, beta1, and theta bands are highest correlated to confusion with p=0.012, p=0.085, and p=0.0016, respectively. A comparison between some algorithms showed that the Convolutional Neural Network (CNN) + LSTM Model presented 75% highest accuracy. Furthermore, the level of student cognitive engagement was computed, in terms of those three brainwaves, obtaining a p= 0.625. The results suggest that Machine Learning is a powerful tool for analyzing brain activity. This paper contributes to neurosciences applied to Personalized Learning.

KEYWORDS

Cognitive Load. Task Complexity. Confusion. Engagement. EEG. Machine Learning. Personalized Learning.

1. INTRODUCTION

Psychophysiological measures during a virtual lecture may lead to new insights into the convergence between objectives and subjective measures. Cognitive engagement is susceptible to being affected by the levels of the cognitive load enforced by a task. Consequently, cognitive load is increased when excessive demands are imposed on the cognitive system. Such demands include inadequate instructional methods to educate students about a subject and unnecessary environmental disruptions. If the cognitive load becomes too high, the student becomes confused and obstructs Learning and transfer. Students typically can experiment with specific emotional states within a learning experience which affect levels of their focus and attention (Al-Nafjan et al., 2017). Therefore, emotional states are associated with directly impacting learning objectives. In this paper, an EEG headset will be used as an objective method to collect the brainwave activity and correlates it with cognitive and emotional states such as confusion (high cognitive load) or student engagement, which could affect the learning objectives. EEG-based emotion recognition systems provide researchers and educators with objective insights to face research directions for developing individualized and adapting learning systems. In this paper, we used different neural network architectures, including ConvNets and TCNs, to decode the level of confusion associated with cognitive load from the EEG recordings.

2. BACKGROUND

Student engagement is a multidimensional concept with all the dimensions dynamically interrelated. According to Crosslin "It typically includes three dimensions: 1) Behavioral engagement: focusing on participation in academic, social, and co-curricular activities. 2) Emotional engagement: focusing on the extent and nature of positive and negative reactions to teachers, classmates, academics, and school, and; 3) Cognitive engagement: focusing on students' level of investment in learning" (Crosslin et al., 2018). Confusion could be considered within emotional engagement since it refers to emotional reactions to academic content and context (Bent et al., 2017). Some researchers have been designing different ways to get real data to explore student engagement in a classroom (Bobby Hoffman & Louis Nadelson, 2010). For instance, in (Xu et al., 2020), they incorporated a commercial platform into the educational system, allowing students to provide real-time, continuous, and anonymous feedback on their comprehension levels using a mobile application. It enables instructors to visualize the student comprehension in terms of confusion on a web dashboard used as real-time feedback permitting instructors to perform the necessary changes in the instructional material or methods during the actual lecture. They proposed a three buttons-system representing students' comprehension status: sad, neutral, and happy, corresponding to confused, neutral, and confident, respectively. They found that the system improved student confidence in the material and the class pace. Additionally, it encouraged more responsible student learning behavior. This feedback system can improve the classroom experience for both instructors and students. The mental state changes due to the level of imparted Cognitive Load, and a student's performance may drastically reduce if the load surpasses a critical point (Grassmann et al., 2017). Cognitive load theory aims to clarify how the information processing load stimulated by learning tasks can affect students' proficiency in processing new information and building knowledge in long-term memory. Sweller argument states that "human cognitive processing is heavily restricted by our limited working memory, which can only process a limited number of information elements at a time" (Sweller et al., 2019). The working memory capacity can be extended and thus help to process more intellectual activities like problem-solving, storing knowledge in the form of schemata, that is, knowledge organized by chunking. Therefore, the objective of training must be to support the construction of schemata in working memory by not overloading its capacities (Buchner et al., 2022). Most neurocognitive EEG research focused on Event-Related Potential (ERP) indices (Prinzel et al., 2003). Antonenko and colleagues mentioned "ERPs reflect brain responses to certain events and are calculated by averaging the continuous EEG signal over many trials so that the oscillatory background activity, considered noise, is canceled out. During an EEG, small electrodes and wires are attached to a subject's head" (Antonenko et al., 2010). The electrodes detect the brain waves, and the EEG machine amplifies the signals and records them in a wave pattern on graph paper or a computer screen. An EEG measures the brain's electricity; it does not measure thoughts or feelings. Many researchers have found an association between theta, alpha, and beta channels with task difficulty (confusion levels). According to (Gevins et al., 1997) "high-resolution EEG topographic maps showed the deblurred topography of the frontal midline theta rhythm, while performing easy and difficult tasks". The most prominent and consistent task-related variation of spectral power happened in the theta and alpha bands. The maximum amplitude individual bursts were observed in the most difficult task conditions (higher confusion). On average, across the subjects, theta signal was higher in amplitude in the more difficult task conditions than in the easy task conditions and was higher after practice. In (Klimesch, 1997), they found by performing several experiments that alpha frequency varies as a function of memory performance. Klimesch results indicate "that alpha frequency may be a permanent and not only a functional parameter that controls the speed with which information can be retrieved from memory". Changes in alpha band power (amplitude) reveal further that the upper alpha band is susceptible to semantic memory demands and the lower alpha band, on the other hand, appears to reflect attentional processes. A literature review conducted by Sinha suggests that "cognitive load variations for tasks having different difficulty levels are most clearly visible if we consider the frontal and parietal lobes" (Sinha et al., 2014). Studies have reported that seven leads (Cz, P3, P4, Pz, O2, PO4, and F7) are the most important for the cognitive load. Cognitive load considering alpha and theta waves from the four selected channels will get a simple measurement of cognitive load (Anderson et al., 2011). In (Jensen et al., 2002), (Sauseng et al., 2005), they also reported that alpha power decreases with increased cognitive load. This effect is most prominent at the central parietal (Pz) location, whereas theta power increases with increased cognitive load and is most prominent at the central frontal (Fz) location. The increased beta response in healthy subjects under cognitive workload implies that beta oscillations could move the system to an attention state and have an important function in cognitive activity. The authors proposed to open a way to consider the beta activity as an important operator in brain cognitive processes. The results support the hypothesis that the increase in beta responses is also related to attention and the cognitive process (Güntekin et al., 2013). Tyng states that the "state of mind which can vary widely. Emotional information appears to enhance LongTime Memory (LTM), with pronounced effects deriving from positive emotions compared with negative emotions" (Tyng et al., 2017). Researchers have studied emotions for years by measuring brain waves using ECG signals, facial recognition (eyes, mouth), and shoulder movements using image processing and computer machine learning techniques (Dzedzickis et al., 2020). Typically, emotions affect human cognition, which is how people process information. Different channels have been used to define cognitive states and emotions. Using a portable EEG headset (*Emotiv PRO*, n.d.), it is possible to get the student performance metrics taken from stress, engagement, focus, and relaxation levels, among others. Engagement is qualified as attentiveness and the conscious direction of attention towards task stimuli. Engagement is characterized by increased physiological arousal, beta waves, and attenuated alpha waves. The greater the attention, focus, and workload, the greater the output score reported by the detection. Focus is a measure of fixed attention to one specific task. Many researchers have demonstrated the correlation between various EEG parameters and such psychological variables as arousal, attention, and workload. Pope and his colleagues (Pope et al., 1995) developed a closed-loop method to enable an index of engagement that is maximally sensitive to changes in workload. They studied the consequences of various engagement indices based on their relative ability to generate stable operations under negative feedback and unstable operation under positive feedback, concluding that the beta / (alpha + theta) index exhibits expected feedback-control behavior. Many machine learning algorithms have been used to classify and predict EEG for various tasks. In (Ranzato et al., n.d.), they proposed a Deep Belief Network (DBN) that is based on learning from high-level features based on raw EEG signals and can predict high-order dependencies among variables. The research developed by (Petrosian et al., 2001) showed that Recurrent Neural Networks could detect early signs of cognitive impairment disease in long-term EEG recordings. other studies have shown that confusion can be seen using Deep Neural Networks (DNNs). Also, LSTM has gained popularity among many researchers as it can be used in quickly analyzing time-series data.

3. DATASET BACKGROUND

The EEG dataset used for this study was collected by a set of researchers working towards studying the cognitive (confusion) levels, focused on identifying if the students were confused or not confused after watching a specific material from Massive Open Online Courses (MOOC). This Dataset is also available online on the Kaggle website (*Confused Student EEG Brainwave Data*, n.d.). Kaggle provides many open data sources for various causes. EEG dataset contains two types of videos, one that is not confusing for students like simple algebra and geometry, and the other, which is confusing for students like Quantum Mechanics and Stem Cell Research. After the completion of the experiment, ten sets of data from 10 different students were collected while watching ten random materials. Researchers used the device to collect EEG data from the students was a wireless single-channel EEG sensor Neurosky Mindset EEG Headset (Wang et al., n.d.). The collected data will be used to perform a correlational study between variables and to build a preliminary classification model for the student as a complex system.

Within the dataset, column (EEG channels) "delta", "alpha", "theta", "beta", "gamma" is used as label and the column "predefined labeled" is used as target with value "0" for not-confused and "1" for confused. The study proposes a cognitive (confused or not-confused) load detection framework using machine learning methods.

4. Methods

To analyze student cognitive state in terms of confused or not-confused. The study proposes a student cognitive load framework using Machine Learning methods, as shown in Fig 1.

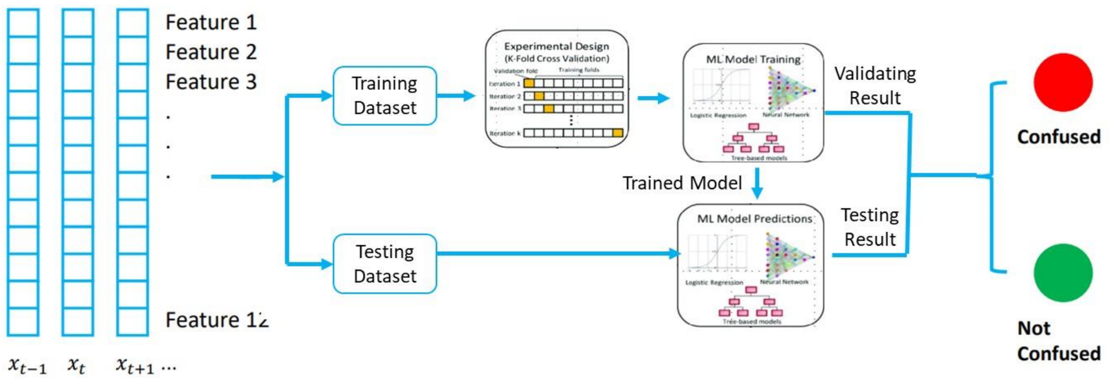

Fig. 1. Framework based on Machine Learning methods.

The data collected from the EEG dataset is first preprocessed using the feature selection process. Feature selection is a crucial step for any data processing model. The primary purpose of feature selection is to select a subset of features that are more important to the target variable. Hence by using feature selection, we can improve model learning algorithms by reducing redundant and irrelevant data. Then, different feature selection methods are applied to obtain the most relevant features; each feature is compared with the target variable to see its importance. Fig. 2 shows the feature rank after using the feature selection.

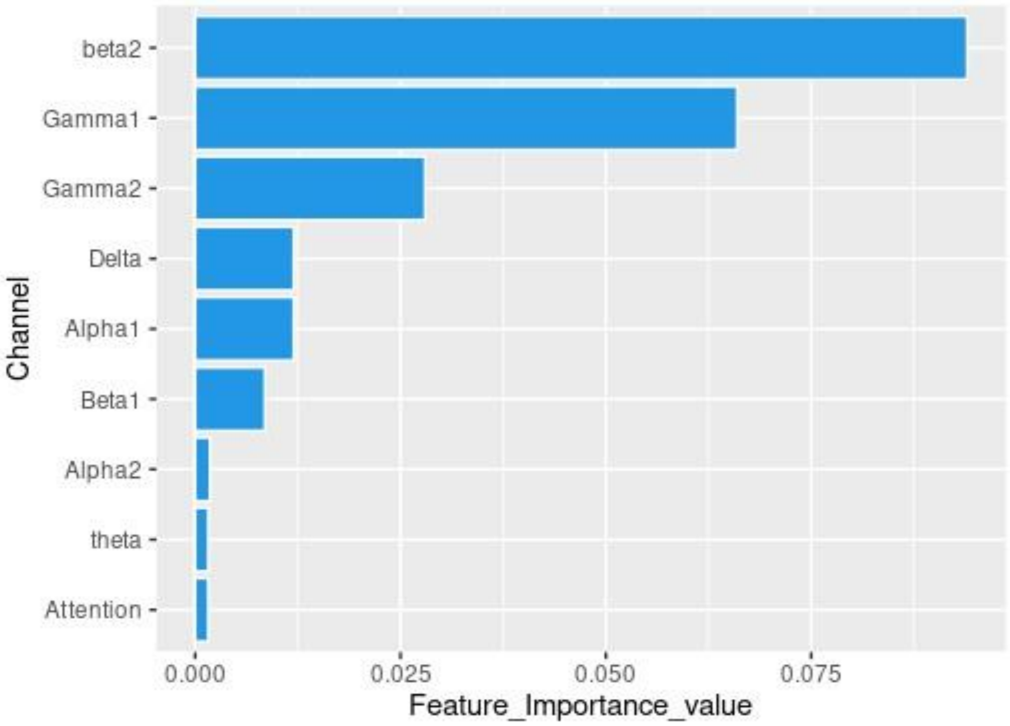

Fig 2. Filter-based feature selection evaluation

Another feature selection method implemented is a correlation matrix with a heatmap. The correlation matrix evaluates if the features within the Dataset are positively (increase one's value with increased value in target variable) or negatively (increase one's value with the decreased value in target variable) related to the target variable. For example, shown below is the figure for the Correlation matrix using the heatmap:

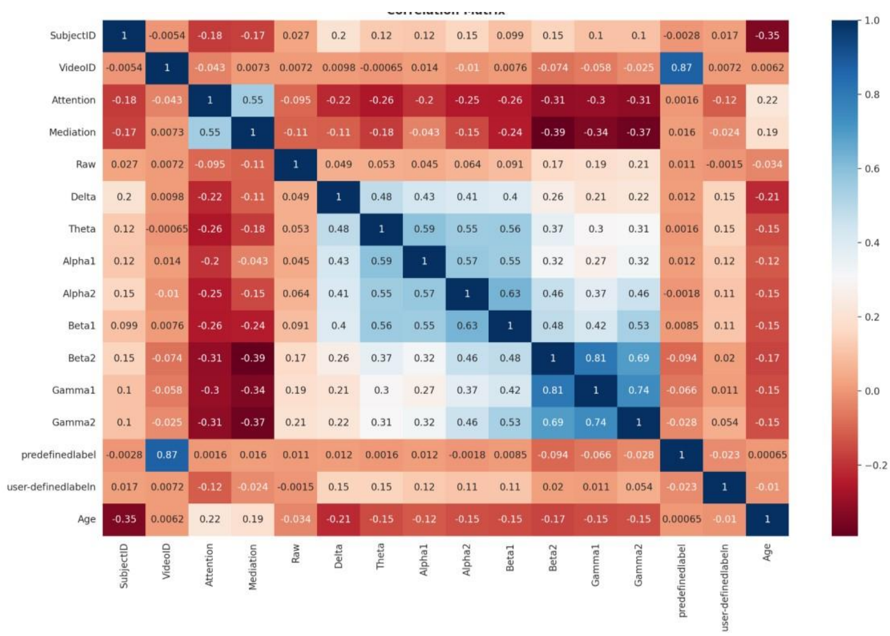

Fig 3. correction matrix using heatmap

To conclude on the correlation matrix, it can be said that beta2 is highly negatively correlated and alpha1 is highly positively correlated in the EEG channel band.

5. RESULTS

The intrinsic cognitive load is reflected by the material's intrinsic nature and depends on the student's level of expertise. The student's comprehension level is affected by the task's intrinsic load. Task complexity level and student expertise will reflect the confused brainwave behavior while watching the complete videos. In our approach and based on the literature review, emotions such as confusion, frustration, anxiousness, etc., are associated with learning failing when a task imposes a high cognitive load, decreasing student engagement. The data were collected on the forehead Fp1, defined by the International 10-20 system. An analysis of the correlation is shown in the following table:

Table 1. Correlation between brainwaves Task Complexity/Confusion.

	Correlation with CL	**Waves + correlated**	ρ	**Waves - correlated**	ρ
1	Highest	$\alpha 1$	0.012	$\beta 2$	-0.094
2	Medium	$\beta 1$	0.0085	$\gamma 1$	-0.066
3	Lower	θ	0.0016	$\gamma 2$	-0.028

The highest positive correlation was ρ=0.012, corresponding to the lower alpha band ($\alpha 1$). $\alpha 1$ appears to reflect attentional processes. The second highest correlation (ρ = 0.0085) corresponds to the low beta waves ($\beta 1$), which are associated chiefly with quiet, focused, introverted concentration. This result is aligned with the literature review and the intrinsic load imposed by the task (video). According to the literature review, theta power increases with increased cognitive load, which is most prominent at the central frontal location. All three bands strongly correlate with cognitive load; thus, these results prove our theoretical frame based on neurosciences. It is essential to point out that the negatively correlated brainwaves are highly correlated.

To evaluate the model performance, we design the model using three machine learning approaches: Long Short-Term Memory (LSTMs) which are capable of learning long-term dependencies, making RNN advance in remembering things that have happened in the past, and finding patterns across time to make its next guesses make sense; Deep Neural Networks (DNNs) in which data flows from the input layer to the output layer without going backward and the links between the layers is one way which is in the forward direction, and they never touch a node again and, also, LSTM combined with Convolutional Neural Networks (CNNs) to improve data processing.

It can be seen that LSTM model achieved 65.39% accuracy with 50 epochs, the DNN model achieved 66% accuracy with 74 epochs, and CNN+LSTM achieved 75% accuracy with 100 epochs; the result is shown in Table 2.

Table 2: Average accuracy using different machine learning methods.

Type of Classifier	**Epochs**	**Accuracy (%)**
Long short-term memory (LSTM)	50	65.39%
Deep neural network (DNN)	74	66.00%
Convolutional neural network (CNN) + LSTM	100	75%

The results show that CNN+LSTM outperforms the other two methods indicating that a combination of Convolution Neural Network and LSTM can give better results when compared with individual models such as LSTM or DNN.

6. CONCLUSION

Low alpha, low beta, and theta are the most correlated bands with student cognitive confusion. Based on this; the student engagement index was calculated using the formula beta / (alpha + theta) developed by (Pope et al., 1995). We realized that cognitive confusion and engagement are strongly correlated (p= 0.625). A CNN+LSTM model based on Machine Learning has been proposed to analyze student brainwaves correlated with cognitive confusion. The accuracy achieved by our model using the CNN+LSTM algorithm is higher than other machine learning methods.

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