Identification of Students' Confusion in Classes from EEG Signals Using Convolution Neural Network

Rekha Sahu[1], Satya Ranjan Dash[2,*], and Amarendra Baral[3]
[1]Silicon Institute of Technology, Bhubaneswar, Odisha, India
[2]Kalinga Institute of Industrial Technology, Bhubaneswar, Odisha, India
[3]Trident Academy of Technology, Bhubaneswar, Odisha, India
E-mail:sahu_r@rediffmail.com, sdashfca@kiit.ac.in, hodmath@tat.ac.in
*Corresponding author

Keywords: students' confusion, predefined confusion, user-defined confusion, mismatch of confusion label, one-dimensional convolution neural network, electroencephalography signals

Received: January 7, 2023

For a student, classes are vital factors for gaining knowledge. The lectures may be online or offline, but getting knowledge without confusion is a major issue. The confusion labels can be measured from the electroencephalography signals and the confusion can be solved after knowing that students are suffering from confusion. Different machine learning approaches were implemented on electroencephalography signals to identify the suffering of students from confusion. The performance of traditional machine learning approaches in predicting confusion status is found as poor. In this paper, the one-dimensional convolution neural network is implemented on the electroencephalography signals to detect confusion of the students at the time of watching video classes. Students' attention, mediation, electroencephalography signals, delta, theta, alpha1, alpha2, beta1, beta2, gamma1 and gamma2 are taken into consideration to train a one-dimensional convolution neural network classifier. The one-dimensional convolution neural network approach has achieved better accuracy in detecting the confusion of the students. Besides finding confusion labels of students, the experiment is performed when understandable classes are creating confusion and the difficult classes are understandable for the students. This second experiment is also performed on electroencephalography signals of students and after identification of confusion status, the improvement of students' deficiencies can be possible. For future work, more data and different aspects of the students can be taken into consideration for identifying confusion and different obstacles respectively which helps to improve in achieving perfect knowledge from the classes.

Povzetek: Raziskava obravnava identifikacijo zmedenosti študentov med predavanji z uporabo EEG signalov in enodimenzionalne konvolucijske nevronske mreže, kar omogoča boljše razumevanje in obravnavo učnih ovir za izboljšanje pedagoškega procesa.

1 Introduction

Education influences society significantly and education is an essential aspect of a better society and comfortable life. To spread education all over society, the proper way of teaching, as well as students' perception levels, should be analyzed and emphasized for adopting the improvement approaches in teaching procedures. The teaching procedures and student perceptions are vital factors in creating an educated society. Investigations show that students are facing problems when learning from lectures. They suffer from confusion and are unable to understand the lectures. It is found that students can better learn only if the teaching procedure, as well as student perception, is better [8]. Further, the teaching process influences the educational system drastically and delivering a better lecture, appreciated by students, influences the educational system positively [30, 34]. By the way, students' attitudes in perceiving the contents of the lecture are also influencing the learning strategy [29]. Different observation shows that student confusion level is an important factor to certify whether a class is appreciable for better education or not. Again, the lectures are delivered either online or offline. Whatever may be the procedure of delivery of the lectures, mainly the students should understand and be clear on the concepts behind the lessons. Otherwise, the lectures are unnecessary, wastage of time, and meaningless. Since, nowadays, education is provided through online classes, experiments have been performed on the impact of online classes [6].During the pandemic, online classes were taken to overcome from discontinuous classes of the students. But, the students were suffering from confusion, down, sad, upset, excitement etc. in the classes [24]. Because of the online classes during covid-19, the perception of the students was less [7, 34]. Besides the deficiencies in students' perception of online classes, the instructors also showed their deficiencies in teaching, behaviours, emotions, attention, cognitive workload and trust [18]. Moreover, the relationship between the students' and instructors' behaviours, emotions, attentional, cognitive workloads, trust and collaboration was required to enhance the clarity, and understanding of the lectures in the classes [18]. By the way, online lectures are more useful since the lectures can be attended at any time and anywhere according to the flexibility of students. Even after the pandemic, online classes are appreciated for higher education along with the cognizance of staff and students which is essential [10]. It is needed to observe the impact on the understanding and confusion level of students automatically during classes for taking appropriate actions.

During the online classes, whether the student is in confusion or not, was a vital matter. In an experiment, the online class was shown as poor in participation, emotional, skill and performance engagement in contrast to face-to-face classes [37]. But, Ram´ırez-Moreno et.al. has found from electroencephalography (EEG) signals that online teaching is better than classroom teaching [26]. The EEG signals from the frontal lobes visualize the confusion level of a human. Hence, the EEG signals from the frontal lobes of students could state whether the student is in confusion or not during online teaching. Further, the experiment stated that the Fp1 channel is placed on the frontal lobe and it can be used to measure the concentration and confusion level of a subject [22]. Again, by manipulating raw EEG signals of the Fp1 channel, delta, theta, alpha, beta and gamma frequencies have been extracted for deep analysis [1].For classifying the EEG signals' pattern, traditional machine learning and deep learning have been applied to EEG signals datasets to find the pattern of EEG signals in recognizing the student state features [16].

The confusion labels of students can be measured from EEG signals and the deep learning approach implementation on EEG signals can find out the specific pattern for a specific target class [22, 16]. These influence to implementation of a deep learning approach on the EEG signals of students for detecting students' confusion labels. In our experiment, the EEG signals of students had been collected at the time of watching videos in online classes[35]. Intentionally, the videos were created as confused videos and non-confused videos. Those are called predefined confused and non-confused labels. After watching the videos for learning, the students labelled whether the videos are creating confusion or non-confusion in understanding the lessons. Those are called user-defined confusion and non-confusion labels. Both pre-defined labels and user-defined labels are mismatched in some cases. Hence, we have created three questions. Firstly, for which pattern of EEG signals, the students are suffering from confusion. Secondly, for which pattern of EEG signals, the students are not in confusion. Since in some cases, pre-defined labels and user-defined labels are mismatching, so thirdly, we have analysed the pattern of EEG signals for which signals are mismatched. The collected EEG signals are raw Fp1 EEG signals. From the raw Fp1 EEG signals, different features like, Attention, Meditation, Raw EEG signals, Delta frequency, Theta frequency, Alpha1, Alpha 2, Beta1, Beta 2, Gamma1, and Gamma2 are extracted for confused and non-confused students. Since deep learning approaches are implemented for finding the pattern for classification tasks [16], so we have applied a one-dimensional convolution neural network (1DCNN) on our extracted dataset to classify the EEG signals for confusion, non-confusion and mismatching labels of user-defined and pre-defined labels. The overall work performed in this paper is represented in Fig. 1.

The rest of the paper is as follows. In section 2, related work is stated. Our experiment details are represented in section 3. The description of the dataset is presented in section 3.1, the technology applied is elaborated in section 3.2 and the result analysis is presented in section 3.3. Finally, in section 4, a conclusion and possible future work are stated.

2 Related work

For developing teaching-learning procedures, different experiments and surveys are performed. Some surveys have concluded that students are suffering from academic stress drastically. Even achieving knowledge from the lectures of reputed universities is becoming hard for them [3]. Sometimes for improving learning, students were specially trained with some teaching-learning techniques and got good scores in comparison to direct attending the lecture [19]. Moreover, student confusion is a major factor in college lectures and the detection of confusion depends on attention and meditation [23]. It is hard to measure the attention of the student through self-report or from the behaviour of the students. The state of the students' minds can be analyzed and found from the EEG signals [20, 9].

Since the report of students or observers is not sufficient to measure mind state and the mind state of a student can be measured from EEG recording [20, 9], so we have experimented with EEG recording to find out the confused students. Our survey helps to find how different factors like Attention, Meditation, Raw EEG signals, Delta frequency, Theta frequency, Alpha1, Alpha 2, Beta1, Beta 2, Gamma1, and Gamma2 are extracted from EEG signals. J. K. Grammer, et.al. stated that from EEG signals, the measurement of student attention can be quantified [13]. Moreover, from the channel Fp1 EEG signals, the attentive & inattentive students are classified and Ning-Han Liu, et.al. implemented Support Vector Machine (SVM) approach to classify the EEG signals pattern to visualize the attention of the student [17]. It is found out Meditation describes the state of calmness and focused attention of mental activity and this can be identified from EEG signals[32] and it is observed that Mindfulness meditation can be quantified from the frequency of EEG signals [2]. The above-mentioned Fp1 channel is placed on the frontal lobe and it can be used to measure the concentration of a subject. Again, memory retrieval, decision-making, planning, response evalua-

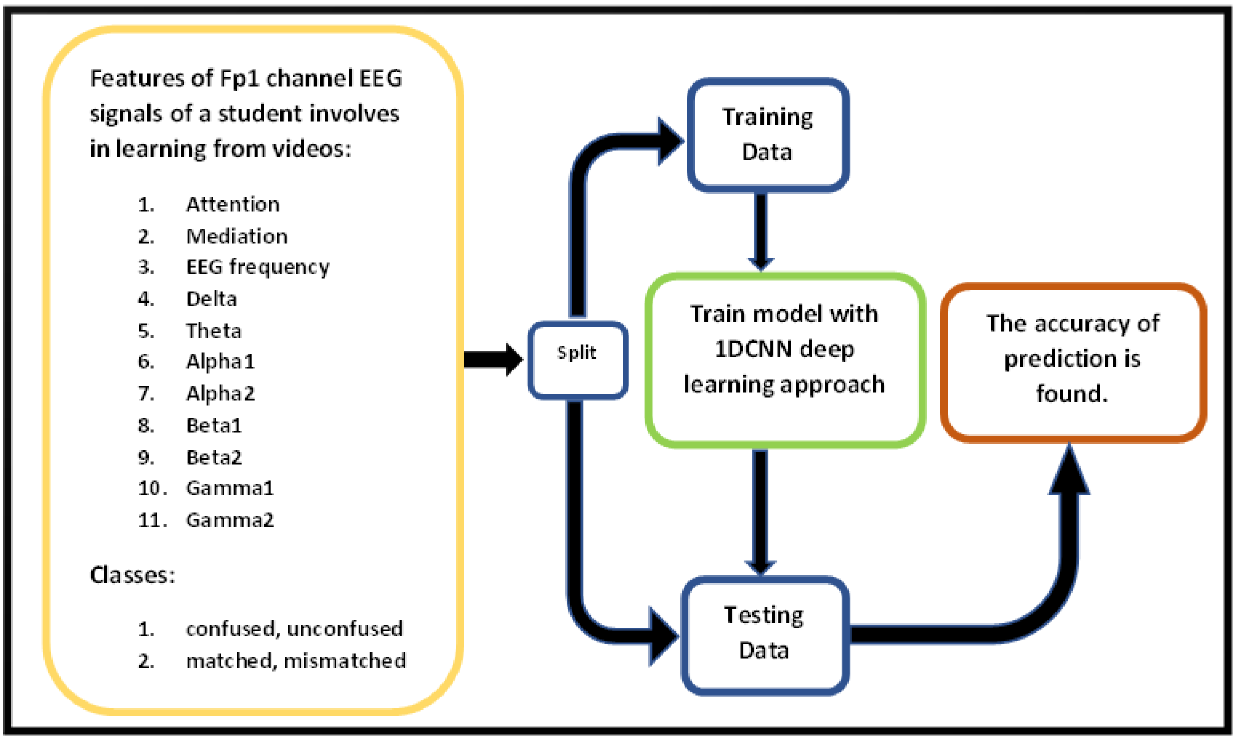

Figure 1: Overall workflow diagram: It is representing different attribute values generated from EEG signals taken as input. The class values as confused vs unconfused and matched vs mismatched are included. Input data are split as training dataset and testing dataset. 1DCNN classifier is trained using a training dataset and implemented on a testing dataset to find the accuracy of prediction.

tion, and reflection of a subject are studied through channel frequency[22]. At the same time, EEG signals can display five types of EEG waves i.e., gamma, beta, alpha, theta, and delta [1]. Generally in the case of the gamma wave, higher processing tasks and cognitive functioning are performed. The gamma waves are responsible for cognitive functioning, learning, memory, information processing, attention, focus, consciousness, mental processing, and perception. In other sites, Beta waves are related to conscious thought, logical thinking, stimulating effect, conscious focus, memory, and problem-solving. Again, Alpha waves lead to the feeling of deep relaxation and calm down whereas, Theta waves involve improving intuition, creativity and a more natural feel. Lastly, Delta waves involve feeling rejuvenated, promoting the immune system, natural healing, and restorative/deep sleep[25]. To find out the delta, theta, alpha, beta and gamma frequency, we manipulate raw EEG signals [1] and hence by manipulating Fp1 EEG recording, we can find the delta, theta, alpha, beta and gamma band frequency for Fp1 EEG channel. To study the pattern of EEG signals to recognize the student state features, both traditional machine learning and deep learning can be applied to EEG signal datasets [16].

From the literature survey, we have found that machine learning and deep learning approaches are applied to EEG signals to find different patterns [14, 27, 28]. The Machine learning approaches like logistic regression, random forest, decision tree, K- nearest neighbour (KNN) and SVM are applied to Brain-Computer Interface (BCI) data set and found out logistic regression has given better performance in the detection of students' confusion in Massive Open Online Course (MOOC)[5]. Again, the attention of students is studied from the EEG signals when the students were involved in MOOC and traditional classrooms and the SVM approach was implemented on the EEG data [32]. The experiment result concluded that the MOOC learning process maintains higher attention. Besides, different traditional machine learning approaches like the random forest, SVM and KNN are applied to the EEG signals dataset to classify students' attention levels when involve in online classes [4]. Not only traditional machine learning, but deep learning approaches have also given better performance in identifying a specific EEG signal pattern. The experiment on EEG signals of nineteen students is performed to identify their emotions like happiness, sadness, anger, fear, disgust, and surprise. In this experiment, the deep learning approaches i.e., Long Short Term Machine (LSTM) and Convolution Neural Network (CNN) are applied to the EEG signals to identify the emotions and found 99.8% classification accuracy with implementing CNN [14]. Again, the Students' attentiveness towards the lectures is measured from EEG signals patterns, and it was fruitful by analysing EEG signals data using three-dimensional CNN [15]. With the above survey, we also found out that Bidirectional LSTM Recurrent

Neural Networks were implemented on the EEG signals dataset to identify the confused and non-confused students when involve in online courses. It was observed that the classification accuracy was 73.3% and the gamma 1 wave can be used to identify the confusion [23]. A deep learning approach can also be implemented on EEG signals to find out the attention level of a student[33]. Thus, the survey concludes that the traditional machine learning, deep learning and spiking neural network analysed and classified the EEG signals for extracting specific patterns [27, 28]. It is observed that the one-dimensional convolution neural network (1DCNN) is implemented on the EEG signals and given higher accuracy in detecting the different pattern EEG signals [27]. Again, the CNN approach is implemented on the raw EEG signals of one channel to detect sleep disorders[31]. Besides, fear, fun and sad emotions are identified from the EEG signals using the CNN approach [12]. After going through the above literature, we have proposed a 1DCNN model applied to EEG signals data set to detect confusion of students when involve in video classes. In the next section, we have stated our experiment and compared our novel approach with other works and also the different aspect, we have experimented, with is elaborated.

3 Experiment

For fair teaching procedure, emphasis should be given to observing how fairly lecturers are delivered and how much students can able to perceive from lectures. Hence, the student's understanding and confusion status is essential to observe. Our experiment is performed to find out whether a student is in a confused or non-confused state when watching online lectures. Therefore, EEG signals are collected from the students when they were watching the lectures. Those signals are used to train the models for classification tasks. Here, confusion and non-confusion of a student are interpreted according to predefined or user-defined labels. Predefined implies the videos of the lecture are recorded intentionally as either confused or not confused lectures. User-defined implies students practically labelled that the lecture is either confusing or not confusing. With this dataset, a deep learning model is trained. The model predicts whether the student is in confusion according to the predefined or confusion according to the user-defined. Also, a model is trained to find out the pattern of signals for which predefined opinions and user-defined opinions are the same and for which they have mismatched. The explanation of experiments is as follows. We have described the dataset in section 3.1, the description of the method applied to the dataset is represented in section 3.2 and finally in section 3.3 result of the experiment is discussed.

3.1 Dataset and its analysis

For finding whether the students suffering from confusion, the EEG signals pattern is required to study when they are involved in watching MOOC video clips. We have collected EEG brain wave dataset from the Kaggle database [35]. To collect the dataset of students' EEG signals, twenty videos were prepared and each video was of two minutes. Again, a two-minute clip in the middle of a topic is chopped to make the videos more confusing. Out of twenty videos, ten videos are prepared to confuse a normal student and ten videos are prepared to not confuse a normal student. These videos are shown to ten students to test their confusion labels. However, one student is not considered for missing data due to a technical defect. Among twenty videos, randomly five videos of each category are picked and those are presented to a student in random sequence. This was the procedure that was followed for each student. Then, the students were instructed to learn as much as possible from the video clip. When the students were watching the video clip, the body language of the students was observed and the confused state of the students was noted. In general, after each video, the student rated the confusion label as well as an observer of the student rated the corresponding confusion label. The confusion label was defined on a scale of 1-7, where 1 stands for least confusing and 7 stands for most confusing.

EEG signals from each student were collected from the frontal lobe (Fp1) that lies between the left eyebrow and hairline. Using a wireless single-channel Mindset, EEG signals of Fp1 were collected and those are depicted in figure. 2. Besides, using NeuroSky's API, the following signals' information is collected.

1. The raw EEG signal, sampled at 512 Hz
2. An indicator of signal quality, reported at 1 Hz
3. MindSet's proprietary "attention" and "meditation" signals are said to measure the user's level of mental focus and calmness, reported at 1 Hz
4. A power spectrum, reported at 8 Hz, clustered into the standard named frequency bands: delta (1-3Hz), theta (4-7 Hz), alpha (8-11 Hz), beta (12-29 Hz), and gamma (30-100 Hz)

Finally, from the Fp1 channels recording, the attributes Attention, Meditation, Raw EEG signals, Delta frequency, Theta frequency, Alpha1, Alpha 2, Beta1, Beta 2, Gamma1, and Gamma2 are taken into consideration. To characterize the overall values of the attributes, the mean statistic is calculated. We have 100 data points for 9 subjects and each watch 10 videos. The class value for the corresponding instance is the label based on a predefined confusion label as the experiment designed and the user-defined confusion label as the user's subjective rating. Hence, for one instance we have two labels one is a predefined confusion label and another is user defined confusion label. Besides, a mismatch label is generated to differentiate the predefined confusion label and the user-defined confusion label. In the dataset, the number of instances is 12811 and the number of attributes is 16. The attributes are the serial number of subjects, the serial number of videos, Attention, Meditation, Raw EEG signals, Delta frequency, Theta frequency, Alpha1, Alpha 2, Beta1, Beta 2, Gamma1, Gamma2, the pre-

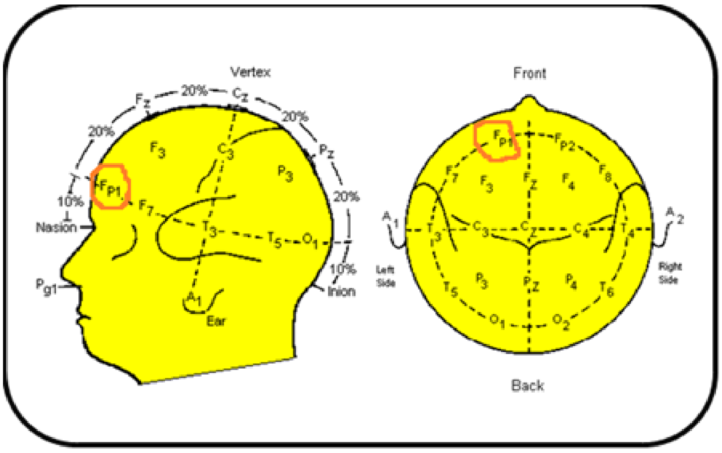

Figure 2: Fp1 channel location is shown on the head which is between the left eyebrow and hairline.

defined, user-defined and the mismatched labels. Attention, Meditation, Raw EEG signals, Delta frequency, Theta frequency, Alpha1, Alpha 2, Beta1, Beta 2, Gamma1, and Gamma2 are the frequency values and the pre-defined and user-defined attributes contain either 0 or 1, where 0 stands for the student is not confused and 1 stand for the student is confused. Again, the mismatch attribute contains 1 or -1 or 0, where 1 implies confused according to predefined but not confused according to the user-defined, -1 in mismatch implies not confused according to predefined but confused according to the user-defined and 0 implies both have the same label. All information about the dataset is summarized in the table. 1.

The graphical analysis of 11 attributes of three types of class i.e., predefined confused, user-defined confused and mismatched labels, are depicted in figs. 3, 4, 5, 6, 7, 8, 9, 10.

3.2 One-dimensional convolution neural network approach (1DCNN)

We have proposed a variant of the CNN approach called 1DCNN to identify the confused student against the unconfused. 1DCNN is a sequence of layers: convolution layer, pooling layer, flatten layer and dense layer followed by activation function [27]. The purpose of the convolution layer is to filter the data. For the convolution operation, we have the kernel, the dot product is performed between the input data and kernel. The stride and padding are performed and finally get a new filter dataset. Then, the dataset is reduced by doing the max pooling operation in the pooling layer. After pooling, we flatten the pooling data into a column. Then those column data are the input for the artificial neural network that is the dense layer of the proposed approach. On the output of the dense layer, we use the activation functions like the Re LU function and soft-max function, which are defined in equations 1 and 2 respectively.

$$f(x) = \begin{cases} 0 & \text{when } x < 0 \\ 1 & \text{when } x \geq 0 \end{cases} \quad (1)$$

$$S(x) = \frac{e^x}{\Sigma_{x=1}^{n} e^x} \quad (2)$$

In the convolution layer, one-row data (1×n) is filtered using the convolution operation with a one-dimensional filter (1×m). The maximum value of one pad is taken for max pooling. Besides, the ReLU function gives the output value when the value is positive otherwise it gives zero and the softmax function predicts the probability of input data belonging to a class. The diagrammatical representation of the CNN model is represented in Fig. 11.

3.3 Experiment result and discussion

1DCNN approach applies to predefined confusion EEG signal datasets and user-defined confusion EEG signal datasets to identify the confused students according to predefined confusion and user-defined confusion of students respectively. Videos are intentionally recorded as confused videos and unconfused videos. Some confused videos are rated as unconfused by the students and some unconfused videos are rated as confused by the students. 1DCNN is also applied to find the signal pattern for the mismatch of the user-defined and predefined class labels.

For the predefined confused EEG signals dataset, the structure of 1DCNN is as follows. The kernel size is 1×3, the number of filters is 10, and the input shape is 1×12. The Max pooling size is 4. After flattening, two dense layers are structured with 500 neurons with a ReLU activation function followed by 2 neurons with a SoftMax activation function. For optimization, Adam's version of the gradient descent learning approach is implemented. 80% data is used for training and 20% is used for testing. With one epoch, we have got 100% classification accuracy in finding confused students' EEG patterns in contrast to unconfused ones.

For the user-defined confused EEG signals dataset, the

Number of subjects	9
Number of Videos	20 (10 for confused and 10 for not confused)
EEG recording duration per subject and video	2 min (total 6 hours recording)
Channel recorded	One channel Fp1
Number of attributes	17
Number of instances	12811
Class label	Confused and not confused mismatched of pre-defined and user-defined opinion

Table 1: Dataset descriptions of the students' online classes and their confusion labels.

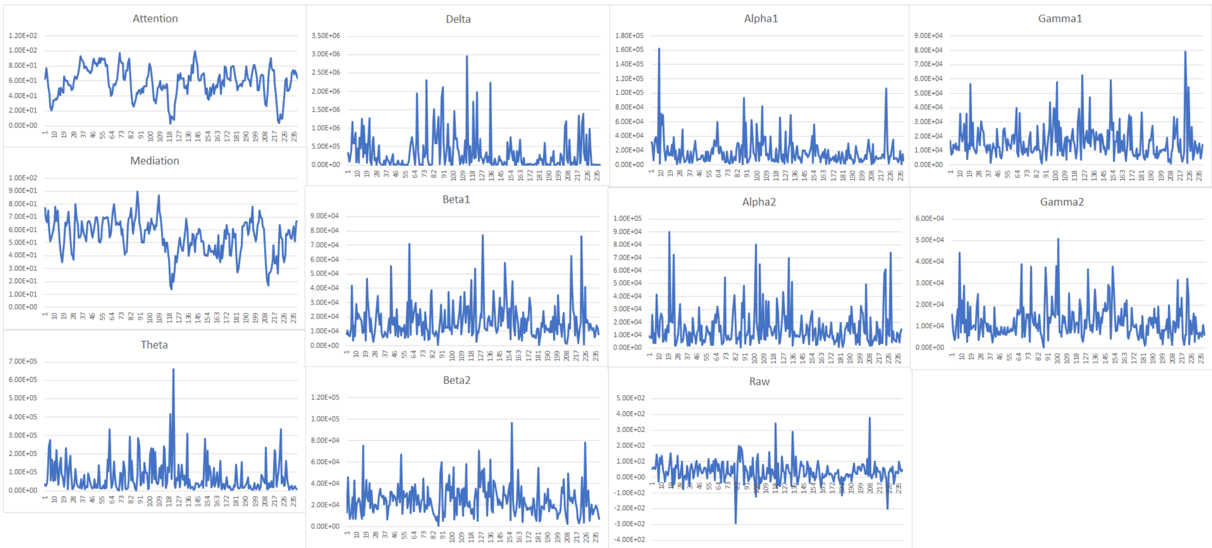

Figure 3: Attributes value representation for user defined non-confused labels.

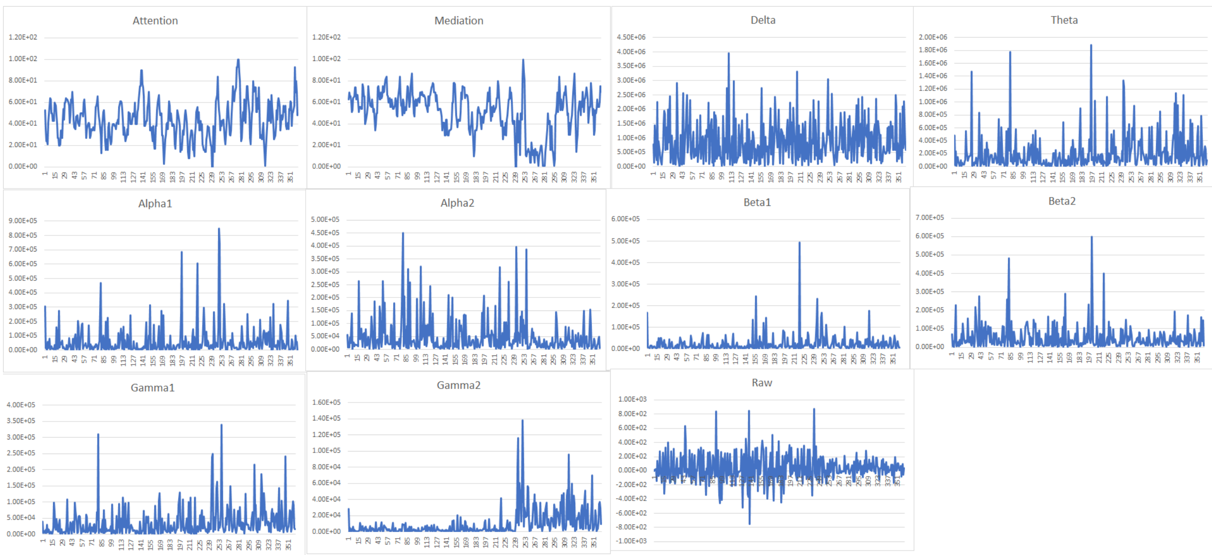

Figure 4: Attributes value representation for user-defined confused labels.

structure of 1DCNN is as follows. The kernel size is 1×3, the number of filters is 10, and the input shape is 1×11. The max pooling is 4. After flattening, two dense layers are structured with 1000 neurons with a ReLU activation function followed by 2 neurons with a SoftMax activation function. For optimization, Adam's version of the gradient descent learning approach is implemented. 80% data is used for training and 20% is used for testing. With 1500 epochs, we have got 99% classification accuracy in finding confused students' EEG patterns in contrast to unconfused

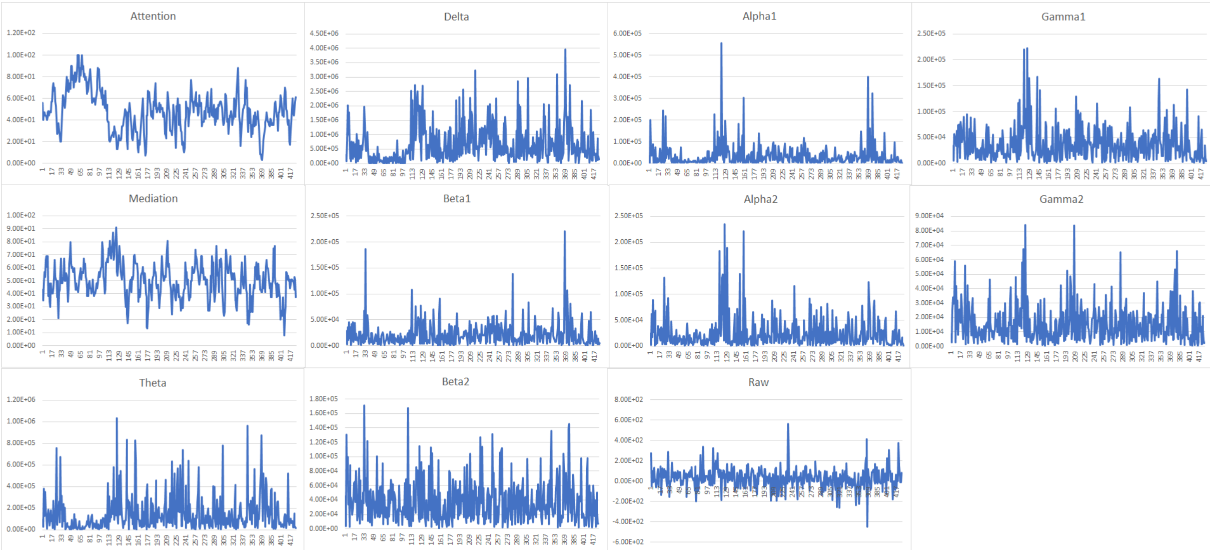

Figure 5: Attributes value representation for predefined non-confused labels.

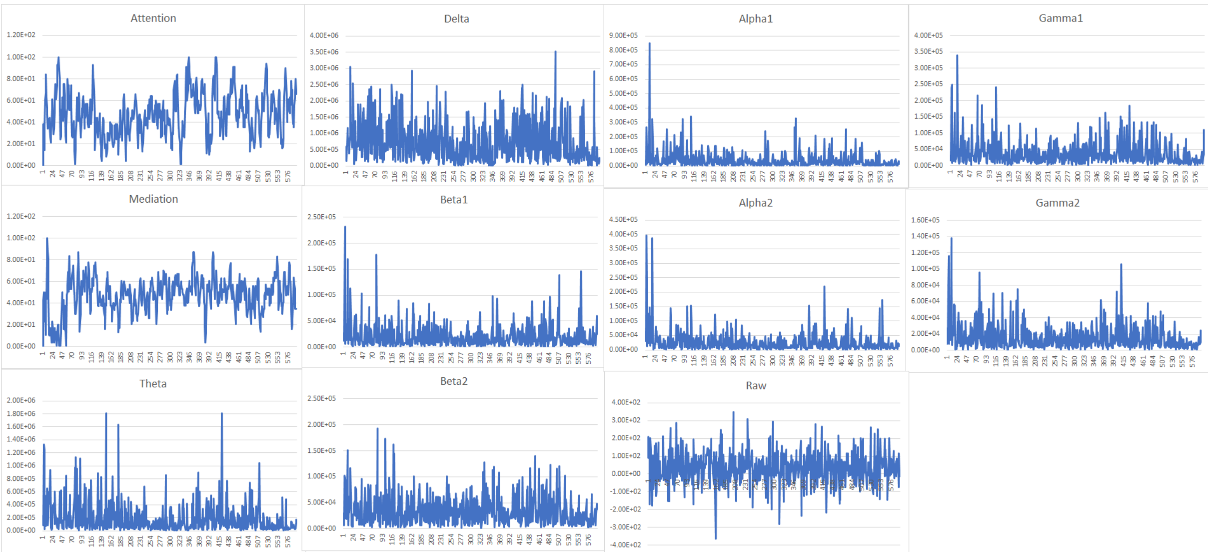

Figure 6: Attributes value representation for predefined confused labels.

ones.

For mismatched user-defined and pre-defined confused rate EEG signals dataset, the structure of 1DCNN is as follows. The kernel size is 1×3, the number of filters is 10, and the input shape is 1×11. The max pooling is 4. After flattening, two dense layers are structured with 500 neurons with a ReLU activation function followed by 3 neurons with a SoftMax activation function. For optimization, Adam's version of the gradient descent learning approach is implemented. 80% data is used for training and 20% is used for testing. With 10000 epochs, we have got 99% classification accuracy in finding mismatches.

Some works are performed on the EEG signals confused dataset [23, 21, 11]. The probability-based features approach utilizes the probabilistic output from the random forest and gradient-boosting machine to train machine learning models to detect the confused student [11]. Again, Gaussian Naïve Bayes classifiers are trained with the dataset to find out the confused students. The accuracy of the classification pattern of EEG signals for the confused student was less than 70% [36]. The bidirectional LSTM Recurrent Neural Networks approach is applied to the confused EEG signal data to detect the confused student and the classification accuracy is found to as 73.3% [23]. The experiments with different traditional machine learning approaches and deep learning approaches on the dataset have given less accuracy in comparison to our experiment except for the probability feature-based approach and the performances are summarized in table. 2.

Thus, from the summary in table. 2, it is concluded our proposed approach has efficiency to identify the confused students. Besides, the experiments with different traditional

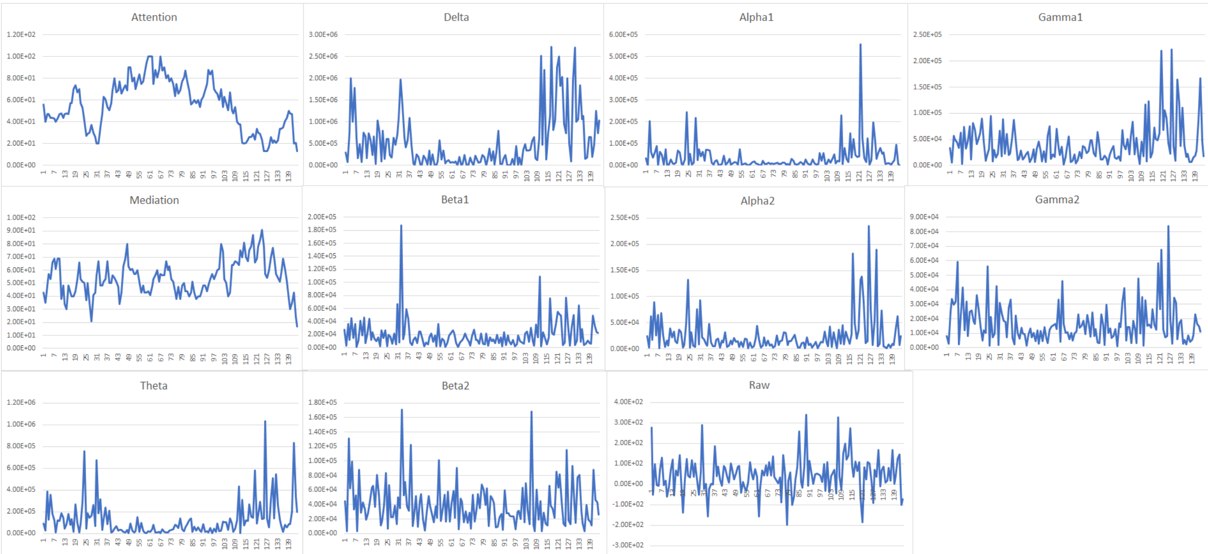

Figure 7: Attributes value representation for user-defined and pre-defined labels are matched (not confused).

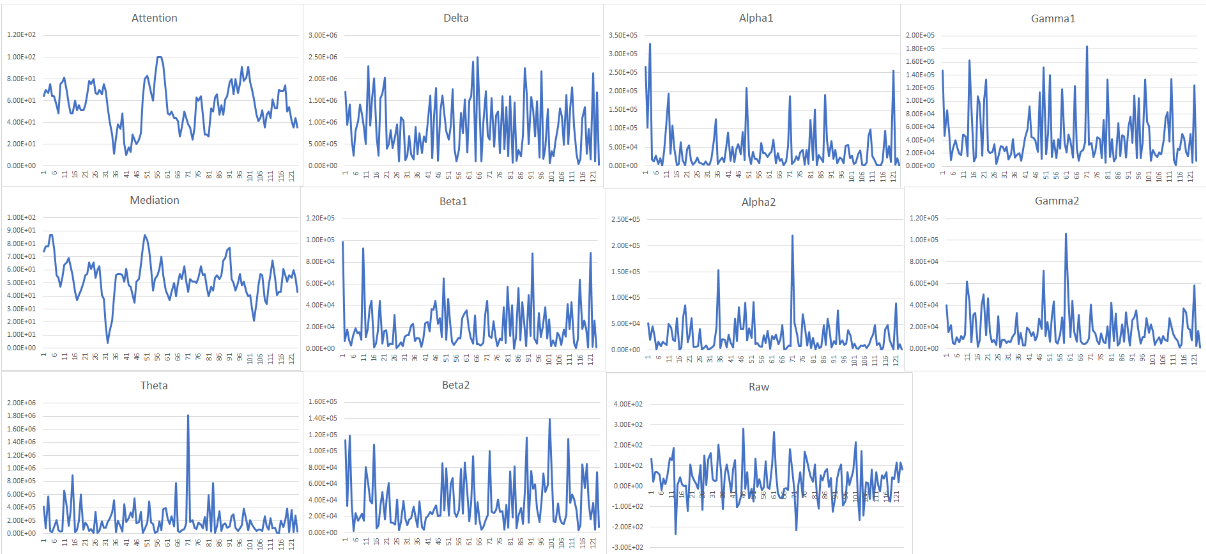

Figure 8: Attributes value representation for user-defined and pre-defined labels are matched (confused).

Approach Implemented	Purpose of the Approach	Accuracy
1DCNN	Detect confused student (according to predefined)	100%
1DCNN	Detect confused student (according to user-defined)	99%
1DCNN	Detection of mismatch of user-defined and pre-defined confused label	99%
The probability-based features approach utilizes the probabilistic output from the random forest and gradient-boosting method	Detect confused student	99%
Gaussian Naïve Bayes method	Detect confused student	70%
The bidirectional LSTM Recurrent Neural Networks approach Neural Networks approach	Detect confused student	73.3%

Table 2: Summary of the performances of different approaches.

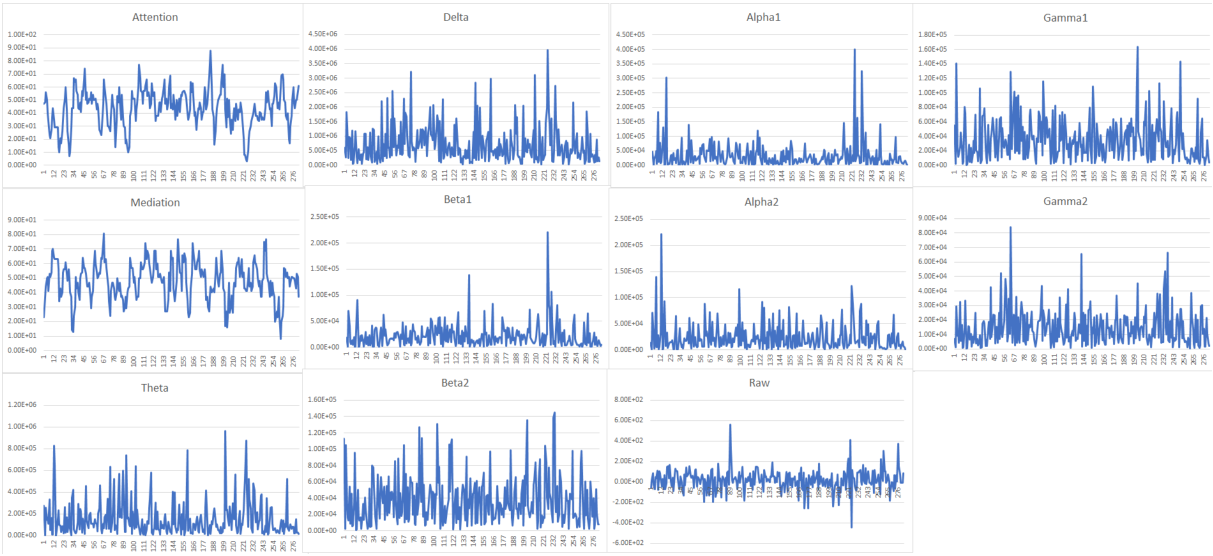

Figure 9: Attributes value representation for user-defined and pre-defined labels are matched (when predefined is not confused and user-defined is confused).

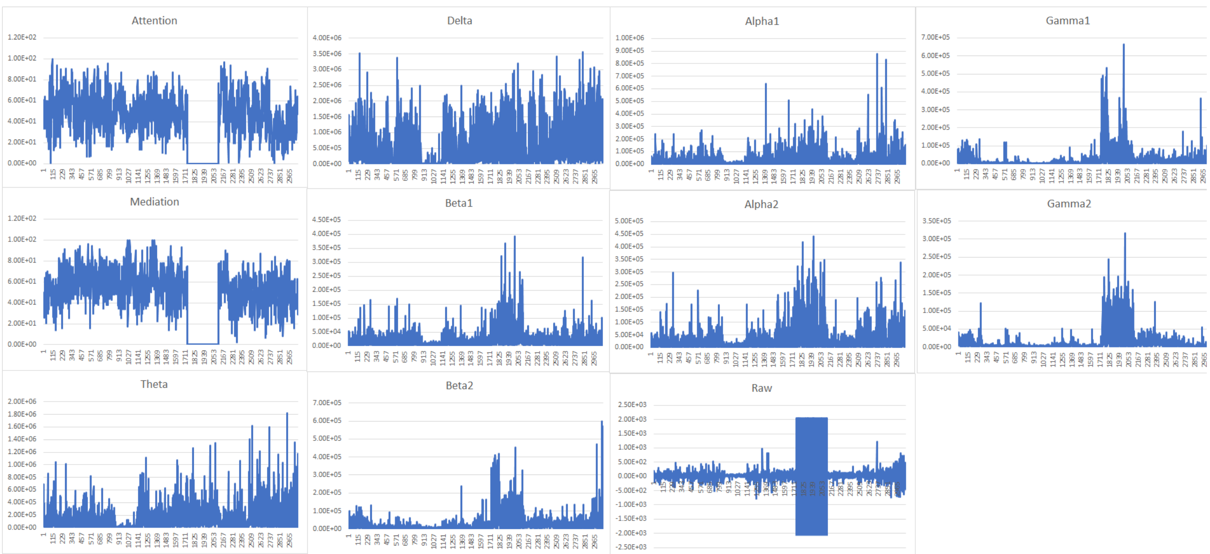

Figure 10: Attributes value representation for user-defined and pre-defined labels are matched (when predefined is confused and user-defined is not confused).

machine learning approaches and deep learning approaches on the dataset have given less accuracy in comparison to our experiment, except for the probability feature-based approach. The probability feature-based approach and other machine learning approaches have emphasized the finding of confused students from the signals whereas our experiment has performed on more than finding confused students i.e., when user-defined confusion is found, when predefined confusion is found and when predefined & user-defined labels are mismatched. For all three cases, EEG signals' patterns are trained using the 1DCNN model and have given 100%, 99% and 99% classification accuracies respectively. Besides, no discussion is shown in any paper still now on mismatched labels of user-defined and predefined labels. In finding a mismatch, it is possible to analyze more on the reason for the mismatch. The reason for the mismatch may be due to misinterpretation or more talented students. If the predefined confusion level is 0 but the user-defined confusion level is 1, then it will be assumed the student is more talented or had knowledge of the lecture before. If the predefined confusion level is 1 but the user-defined confusion level is 0, then those students should be analyzed to study the reason for confusion and their EEG signals pattern predict the student is in confusion although the lecture is very simple to understand. This issue can be analyzed more to treat the student's deficiency.

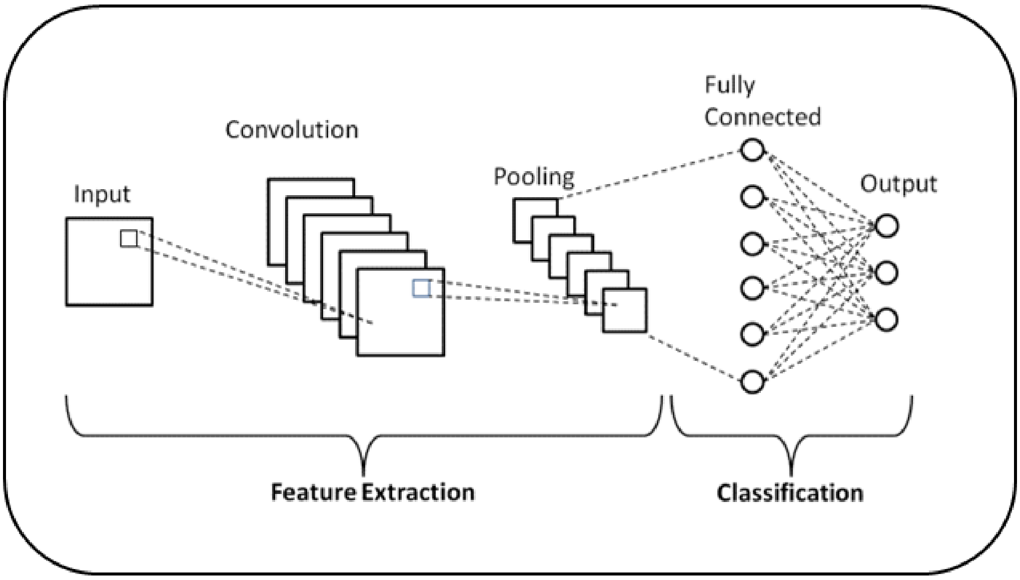

Figure 11: Convolution Neural Network Architecture with the input layer, convolution layer, pooling layer, dense layer followed by output layer.

4 Conclusion and future work

Students learn from the lectures in the classes and so the lectures should be understandable without confusion. Due to covid 19 pandemic, classes were online mode and nowadays also video lectures are influencing students. In this work, the confusion labels were studied when the student was watching video lectures. Twenty videos were collected out of which, ten were confused videos and ten were non-confused videos. Nine students' EEG recordings were collected and the attributes' values were extracted to find the patterns for confused students according to predefined, non-confused students according to predefined, confused students according to the user-defined, and non-confused students according to the user-defined. Besides, the mismatched patterns of user-defined and predefined are extracted. For extracting the patterns, 1DCNN is implemented and found to have better classification accuracy. For pre-defined labels, it has given 100% classification accuracy. For user-defined labels, it has given 99% classification accuracy. Finally, the mismatched confusion label of user-defined and predefined has shown classification accuracy as 99%. In all three cases, 80% data is used for training with 1DCNN and 20% data is used for testing. Thus, the proposed deep learning approach has given better accuracy in finding confused students when pre-defined confused labels are mismatched with the student-defined confusing label. The experiments were performed to identify the pattern of EEG signals for confused students but no discussion was emphasized for the pattern that causes mismatched and our paper has discussed mismatch in confusion labels. By applying the approach to more datasets, we can extract more information for analyzing students' confusion. As a result, the deliberation of lectures can be improved and the students can be treated accordingly.

More research can be performed relating to confusion and other problems of the students when involved in offline or online classes or watching videos. We have taken less amount of EEG datasets, and more experiments with more datasets can give better conclusions regarding the confusion of students and correspondingly we may treat the students for better achievement in education. The major study of mismatches of user-defined confusion and pre-defined confusion labels tends to analyze the different characteristics of the students to check whether the student is more talented (user defined is 0 but predefined is 1) or not talented (user defined is 1 but predefined is 0) or any other issues (previously know about the contains of lectures). Hence, mismatch leads to more analysis on the features of students and this can be kept as feature work. Moreover, if the user-defined label is the same as the predefined label, then there will not require more analysis, otherwise, more analysis will require on the attribute values or some other criteria are taken into consideration to find the reason for the mismatch like a student is more talented. Besides confusion, researchers focus on other attributes for finding deficiencies like attention, interest etc. for better improvement of the students in classes (online/offline) or watching videos.

References

[1] 5 types of brain waves frequencies: gamma, beta, alpha, theta, delta. Access: November 2022. `https://mentalhealthdaily.com/2014/04/15`.

[2] S. Aggarwal, M. Lamba, K. Verma, S. Khuttan, and H. Gautam. A preliminary investigation for assessing attention levels for massive online open courses learning environment using eeg signals: An experimental

study. *Human Behavior and Emerging Technologies*, 3(5):933–941, 2021.

[3] J. Agolla and H. Ongori. Assesment of academic stress among undergraduate students: The case of university of botswana. pages 63–70, 2009.

[4] A. Al-Nafjan and M. Aldayel. Predict students' attention in online learning using eeg data. *Sustainability*, 14(11):6553, 2022. http://dx.doi.org/10.3390/su14116553.

[5] V. A. S. M. Anala and G. Bhumireddy. Comparison of machine learning algorithms on detecting the confusion of students while watching moocs, 2022.

[6] R. P. Baral. The digital divide in online learning: A case study of university students in nepal. *Prithvi Academic Journal*, pages 88–99, 2022. http://dx.doi.org/10.3126/paj.v5i1.45043.

[7] H. Beyari. Predicting the saudi student perception of benefits of online classes during the covid-19 pandemic using artificial neural network modelling. *IJCSNS*, 22(2):145, 2022. http://dx.doi.org/10.31235/osf.io/3vwcu.

[8] B. Cerbin. Improving student learning from lecture. November 2019. https://takinglearningseriously.com/2019/11/16/improving-student-learning-from-lecture/.

[9] K.-m. Chang, J. Nelson, U. Pant, and J. Mostow. Toward exploiting eeg input in a reading tutor. *International Journal of Artificial Intelligence in Education*, 22(1-2):19–38, 2013. http://dx.doi.org/10.1007/978-3-642-21869-9_31.

[10] N. Connon and E. Pirie. Home-based learning (hbl) in higher education post covid: an analysis from staff and student perspectives. *Journal of innovation in polytechnic education*, 4(1), 2022.

[11] T. Daghriri, F. Rustam, W. Aljedaani, A. H. Bashiri, and I. Ashraf. Electroencephalogram signals for detecting confused students in online education platforms with probability-based features. *Electronics*, 11 (18):2855, 2022. http://dx.doi.org/10.3390/electronics11182855.

[12] H. Donmez and N. Ozkurt. Emotion classification from eeg signals in convolutional neural networks. In *2019 Innovations in Intelligent Systems and Applications Conference (ASYU)*, pages 1–6. IEEE, 2019. http://dx.doi.org/10.1109/asyu48272.2019.8946364.

[13] J. K. Grammer and A. Lenartowicz. What do we know about student attention in the classroom? July 2021. https://www.sciencedirect.com/topics/neuroscience/gamma-wave.

[14] A. Hassouneh, A. Mutawa, and M. Murugappan. Development of a real-time emotion recognition system using facial expressions and eeg based on machine learning and deep neural network methods. *Informatics in Medicine Unlocked*, 20:100372, 2020. http://dx.doi.org/10.1016/j.imu.2020.100372.

[15] J. Hemphill, A. Myers, and M. K. Warman. Uc-19 comparison of active and passive attention based tasks using eeg with convolutional neural network. 2021.

[16] H. Jingchao and H. Zhang. Recognition of classroom student state features based on deep learning algorithms and machine learning. *Journal of Intelligent & Fuzzy Systems*, 40(2):2361–2372, 2021. http://dx.doi.org/10.3233/jifs-189232.

[17] N.-H. Liu, C.-Y. Chiang, and H.-C. Chu. Recognizing the degree of human attention using eeg signals from mobile sensors. *sensors*, 13(8):10273–10286, 2013. http://dx.doi.org/10.3390/s130810273.

[18] S. Ma, T. Zhou, F. Nie, and X. Ma. Glancee: An adaptable system for instructors to grasp student learning status in synchronous online classes. In *CHI Conference on Human Factors in Computing Systems*, pages 1–25, 2022. http://dx.doi.org/10.1145/3491102.3517482.

[19] L. A. Moreno López, M. Somacarrera Pérez, M. Díaz Rodríguez, J. Campo Trapero, and J. Cano Sánchez. Problem-based learning versus lectures: Comparison of academic results and time devoted by teachers in a course on dentistry in special patients. 2009. http://dx.doi.org/10.4317/medoral.14.e583.

[20] J. Mostow, K.-m. Chang, and J. Nelson. Toward exploiting eeg input in a reading tutor. In *Artificial Intelligence in Education: 15th International Conference, AIED 2011, Auckland, New Zealand, June 28–July 2011 15*, pages 230–237. Springer, 2011. http://dx.doi.org/10.1007/978-3-642-21869-9.

[21] J. Murphy. An overview of convolutional neural network architectures for deep learning. *Microway Inc*, pages 1–22, 2016.

[22] T. A. Nguyen and Y. Zeng. Analysis of design activities using eeg signals. In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, volume 44137, pages 277–286, 2010. http://dx.doi.org/10.1115/detc2010-28477, DOI=10.1115/detc2010-28477.

[23] Z. Ni, A. C. Yuksel, X. Ni, M. I. Mandel, and L. Xie. Confused or not confused? disentangling brain activity from eeg data using bidirectional lstm recurrent neural networks. In *Proceedings of the 8th acm*

international conference on bioinformatics, computational biology, and health informatics, pages 241–246, 2017.

[24] D. L. A. Prastini, S. Supiani, and R. Ratna. The emotional experiences of english student teachers'practicum in learning to teach during covid-19 pandemic. *Proceeding: Islamic University of Kalimantan*, 2022.

[25] B. W. G. Priyanka A. Abhang and S. C. Mehrotra. Technical aspects of brain rhythms and speech parameters. 2016. `https://www.sciencedirect.com/topics/neuroscience/gamma-wave`.

[26] M. A. Ramírez-Moreno, M. Díaz-Padilla, K. D. Valenzuela-Gómez, A. Vargas-Martínez, J. C. Tudón-Martínez, R. Morales-Menendez, R. A. Ramírez-Mendoza, B. L. Pérez-Henríquez, and J. d. J. Lozoya-Santos. Eeg-based tool for prediction of university students' cognitive performance in the classroom. *Brain sciences*, 11(6):698, 2021. `http://dx.doi.org/10.3390/brainsci11060698`.

[27] R. Sahu, S. R. Dash, L. A. Cacha, R. R. Poznanski, and S. Parida. Epileptic seizure detection: a comparative study between deep and traditional machine learning techniques. *Journal of integrative neuroscience*, 19(1):1–9, 2020. `http://dx.doi.org/10.31083/j.jin.2020.01.24`.

[28] R. Sahu, S. R. Dash, L. A. Cacha, R. Poznanski, and S. Parida. Classifier implementation for spontaneous eeg activity during schizophrenic psychosis. *Computación y Sistemas*, 25(3):493–514, 2021. `http://dx.doi.org/10.13053/cys-25-3-3874`.

[29] R. Sahu, S. R. Dash, and S. Das. Career selection of students using hybridized distance measure based on picture fuzzy set and rough set theory. *Decision Making: Applications in Management and Engineering*, 4(1):104–126, 2021. `http://dx.doi.org/10.31181/dmame2104104s`.

[30] A. H. Sequeira. Introduction to concepts of teaching and learning. *Available at SSRN 2150166*, 2012. url-http://dx.doi.org/10.2139/ssrn.2150166.

[31] A. Sors, S. Bonnet, S. Mirek, L. Vercueil, and J.-F. Payen. A convolutional neural network for sleep stage scoring from raw single-channel eeg. *Biomedical Signal Processing and Control*, 42:107–114, 2018. `http://dx.doi.org/10.1016/j.bspc.2017.12.001`.

[32] J. Tee and W. Leong. Eeg extraction for meditation. *Journal of Engineering Science and Technology*, 13(7):2125–2135, 2018. `http://dx.doi.org/10.1049/pbhe016e_ch1`.

[33] C. K. Toa, K. S. Sim, and S. C. Tan. Electroencephalogram-based attention level classification using convolution attention memory neural network. *IEEE Access*, 9:58870–58881, 2021. `http://dx.doi.org/10.1109/access.2021.3072731`.

[34] S. Vikas and A. Mathur. An empirical study of student perception towards pedagogy, teaching style and effectiveness of online classes. *Education and Information Technologies*, 27(1):589–610, 2022. `http://dx.doi.org/10.1007/s10639-021-10793-9`.

[35] H. Wang. Confused student eeg brainwave data. Access: November 2022. `https://www.kaggle.com/datasets/wanghaohan/confused-eeg`.

[36] H. Wang, Y. Li, X. Hu, Y. Yang, Z. Meng, and K.-m. Chang. Using eeg to improve massive open online courses feedback interaction. In *AIED Workshops*, 2013.

[37] A. Whiting. Investigating the impact on student engagement from converting face-to-face classes to online in response to covid-19. *Atlantic Marketing Journal*, 11(1):9, 2022.