Applying machine learning approach to detect confused mental state using EEG

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Abstract. In classroom teaching with primitive methods of imparting knowledge, it becomes easy to check if students are able to understand the topic which is taught by the teacher in the class or not. Today's scenario is different , apart from the old teaching techniques new effective techniques are used in classrooms to make the subject more understandable and interesting. One such technique is learning by watching video tutorials available on Internet. Problem arises when one want to calculate the effectiveness of such videos, as taking immediate feedback is not possible in such case. This work makes use of data collected from single-channel EEG headset to detect the mental state of students. The signal gathered from the students watching such videos is further used to find when a student becomes confused while watching such videos. A state of mind when one can't think clearly or one might feel disoriented is known as confusion.

Keywords: EEG, online video tutorials, confused mental state, student's feedback, machine learning

I. INTRODUCTION

In recent times, there is an increasing trend towards student's using online video tutorials for learning. Such videos are freely available on Internet, have large repository of content and are available in regional languages as well [1]. The main advantage of such video tutorials is that Students of any age, region, creed, caste, area can have access on them, there is no time constrain on watching such tutorials, there are no rules and regulations like college or schools, students are free to learn their course according to their comfort. Such courses serve many students of different areas simultaneously, but with so many advantageous they also have many shortcomings. Students opting for such courses generally report the problem of interaction and feedback in such video tutorials [2]. Many websites having such video tutorial courses also offer interactive sessions for question and answers, quizzes and also feedback forms but it's not same as in the class-room sessions [3].

A major gap between online education and class-room teaching can be seen [4], this work concentrates on : detecting the confusion level of the students'. In class-room teaching a teacher can judge that is student is able to understand the topic or not by asking questions in between the lecture delivery or by their body gestures, so an immediate feedback can be taken and action could be performed. This situation does not persist in online-education. This work tries to find the solution to this problem by using the dataset of EEG signal data collected from ten students, each watching ten online video tutorial videos.

Electroencephalogram (EEG) is a technique used to capture the brain activity of neurons. It is a voltage signal which can be caught from the outside of the scalp, emerging from huge gatherings of neurons terminating at a similar rate in the mind [3]. EEG reacts to the biological activities of brain tissues, thus it can indicate the functional status of the brain. The EEG signals gathered from different locations of the brain reflect variety of information [4-6]. For example, signals collected from frontal-lobe tell about attention, responsiveness and human memory [7].

The dataset is readied utilizing such online recordings which are expected not to be a lot of confusing for understudies. Each video used in data set is about 2 minutes long. Some clips from the middle of a topic are removed to make the video clippings more confusing for students. While data collection the students were made to wore a single-channel wireless EEG device by NeuroSky “Mindset” which measures the brain activity from the frontal lobe [8].

The limitation of this device is that it records the brain activity using a single sensor, but a previous study [9] found that this device “MindSet” differentiates two very common mental states (neutral and attentive) with an accuracy of 86% , which is fairly good . It has been also been used to detect the reading difficulty in persons [10] and human emotional responses [11] in the domain of online tutoring systems.

An EEG headset device with single-channel electrode currently costs around Rs. 6000 – Rs. 9,000 in India. By this work we propose that websites providing online video tutorial courses like NPTEL, spoken-tutorials, SWAYAM, Coursera, edX etc. must collaborate with educational institutes and setup special labs where EEG device should be made available to students. This setup initially may be an expensive stuff but in long run such labs will provide these websites the data collected of students’ brain activity as EEG signals which will be served as the direct feedback. Such feedback will be very important in making the videos more effective and in detecting those areas where the students are confused and are not able to understand the course material provided. Moreover, at current moment these EEG device is a luxury affair, but with increasing popularity of such headsets soon these consumer-friendly EEG devices will be like any other electronic accessory like audio headset, speakers, computers and T.V.

This work focuses on solving questions like: if brain signals collected from EEG device can help to distinguish between different mental states of a student. Can we find the confusion state of a student, and if so then up to what accuracy the results produced are.

II. EXPERIMENTAL DESIGN

This study is conducted on the EEG data collected from Kaggel. This data consist of EEG signal data of college students while watching online video tutorials. These videos were prepared such as a normal college student can be made confused assuming that the student does not have a prior knowledge about the topic. The data is collected from 10 students. Randomly five videos were picked and shown to randomly picked student; this was done so that the student is not able to guess the predefined level of confusion. In every session students rated their confusion level from 1-7, where 1 signifies least confusing and 7 as most confusing material. The understudies were made to wear a remote single-channel EEG gadget that deliberate action over the cerebrum's frontal projection. All the more precisely, the situation on the temple is Fp1 which is somewhere close to left eye forehead and the hairline, as expressed by the International 10-20 framework [12]. Following signal streams were collected using the API: The raw EEG signal which is sampled at 512 Hz, “MindSet’s” proprietary “attention” and “meditation” signals measures the mental focus and calmness of the user, at 1 Hz and finally , a power spectrum, acquired at 8 Hz, broken into the frequency bands: delta (1-3Hz), theta (4-7 Hz), alpha (8-11 Hz), beta (12-29 Hz), and gamma (30-100 Hz).

III. EEG FOR DETECTING CONFUSION

3.1 Training classifiers

This work uses Gaussian Naïve Bayes’ classifiers to estimate the probability that a given session/ video clip was confusing or not, based on the recorded EEG signal data. Particularly this method was chosen as it is assumed to be generally best technique for problems having noisy and sparse training data [13].

From the EEG signal information a few highlights were figured to quantify the state of factual dispersions of the data, like: variance, minimum, maximum, kurtosis and skewness. To improve the performance of the classifier, mean is used as the classifier feature. The below table shows the classifier features.

Table 1. Classifier features

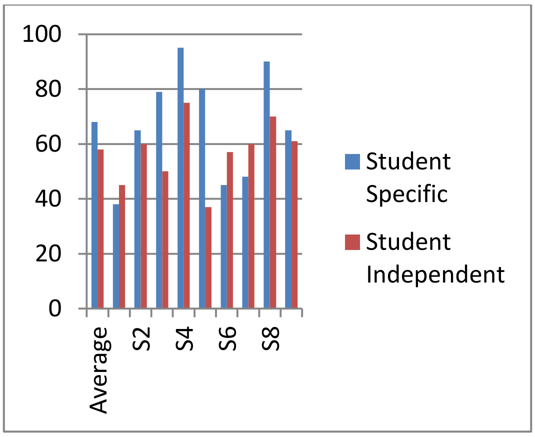
Extracted Features	Sampling rate
Attention	1 Hz
Meditation	1 Hz
Raw EEG	512 Hz
Delta frequency band	8 Hz
Theta frequency band	8 Hz
Alpha frequency band	8 Hz
Beta frequency band	8 Hz
Gamma frequency band	8 Hz

To avoid over fitting of data, cross validation was used to evaluate the performance of the classifier. The student-*specific* classifiers of a single student collected while watching one specific video were trained and then tested on all other videos. This procedure was repeated for every student and the result was averaged to cross-validate accuracy within reader. Thus, the *student-independent* classifiers were prepared on the information gathered from one understudy, and afterward tried on every single other understudy, this was rehashed for every understudy, and resulting accuracies were averaged to cross-validate across students.

3.2 Detect pre-defined confusion level

For finding the levels of pre-defined confusion the classifiers were trained and tested. The average accuracies achieved for student-specific and student-independent classifiers are 67% and 57%, respectively. Both classifier performances achieved were statistically significant better than a chance level of 0.5 ($p < 0.05$). **Fig. 1** plots the classifier accuracy for each student. Blue bars indicate the accuracy of student-specific classifiers and red bars indicate the accuracy of student-independent classifiers. The figure also shows that 6 out of 9 students' classifiers performed significantly above chance.

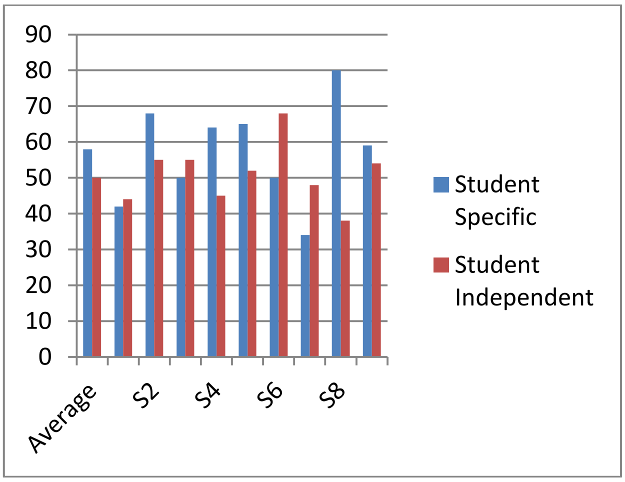
Figure 1. Pre defined confusion level



3.3 Detect user-defined confusion level

In the same fashion, classifiers were trained and tested for student-defined confusion. The average accuracies of student-specific and student-independent classifiers were 56% and 51%, respectively. We found that the performance of the student-specific classifier achieved was statistically significant better than a chance level of 0.5 ($p < 0.05$), but the situation with the student-independent classifier was not the same. Fig. 2 plots the accuracy for each student for user defined confusion levels. It also shows that in student-specific classifier 5 out of 9 students performed significantly above chance while in student-independent classifier only 1 out of 9 students performed significantly above chance.

Figure 2. User defined confusion level



IV. CONCLUSION AND FUTURE WORK

This paper conducts a study on EEG brain signal data collected from students while they were learning from online video tutorials. The work prepared and tried the classifiers to distinguish the confounded mental condition of an understudy. The work closes a feeble yet above-chance execution for utilizing EEG to recognize whether an understudy is confused or not.

The proposed work has many limitations, like the video clips which are selected for experimental setup may not be confusing for the student who is watching it. Therefore the videos selected must be chosen very carefully by discussing the topics with the teachers and students. Another limitation is that the data set used in this study is small, for better performance accuracy we have to target a large set of dataset. The duration of the videos which were selected in data during data collection process were also on 2 minute timing. In the future work, this duration will be increased so that long EEG brain signal could be gathered for research purpose.

On applying Cross validation through all the trials and afterward arranging them as per the precision it was seen that THETA signal assumed a significant job in all the main blends. THETA signal is a brain signal which corresponds to errors, correct responses and feedback, suggesting what we are classifying is indeed confusion.

At long last we can reason that the exactness of the classifier can be improved by leading a progressively thorough investigation, expanding the information size, and by improving the classifier by including great element choice techniques and by improving pre handling of the crude EEG sign to decrease noise.

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