Smart Learning System Based on EEG Signals

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Abstract. According to recent trends in information technology, classroom learning is transformed to Web based learning. This transformation helps learner to trigger digital technologies anywhere and anytime. This paper plan to build a system that can harness the power of the brain and build smart and meaningful applications to make life easier. The major problem is emerged during online education is loose the learner's active attention after some duration of time. This leads to the user getting distracted without having any mechanism to provide him with a feedback, as a result, online learning is not getting as much effective as classroom learning. Therefore, EEG device is used for data acquisition, to measure EEG signals and also to monitor the attention levels of user. Proposed project will collect the EEG data to calculate various parameters such as concentration level, attention level, etc. These parameters will be used in the smart applications to provide real-time analysis and feedback to the user. This technology will provide real-time feedback user who has enrolled in MOOCs. This should foresee whether the student struggles or not while learning to give convenient alarms.

Keywords: E-learning · EEG · MOOCs · Classroom education

1 Introduction

Advancement in technology leads to open various opportunities to enhance instructional procedures as well as e-learning platforms. Language learning relies upon intelligent guidance, tweaked learning maps, checking frameworks, or more all commitment and inspiration. In conventional classroom educating, an educator can pass judgment on the learning dimension of understudies by their signals and can alter according to students' pace. However, in web-based educating, the educator can't know consistently that student is really understanding the content or not. In this way, it has turned out to be important to consider intelligent tutoring system, where it can survey that how profoundly student is considering while at the same time learning. The analysts are taking a shot at this plan to construct a framework that can consequently gauge cognitive load (CL) progressively and streamline its systems to promote intrinsic cognitive load.

Brainwaves are profoundly connected with one's psychological state, including the level of concentration, emotional state, and degree of relaxation. Electroencephalograms

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(EEG) are a non-invasive neuroimaging method used to gauge the electrical movement of neurons in the mind utilizing electrodes put on the scalp.

Ongoing advancements in EEG innovation, for example, dry cathodes and remote transmission, have made it conceivable to apply these gadgets in the field of training to screen the psychological status of students occupied with learning.

The EEG device is used for data acquisition and to measure EEG signals and to monitor the attention levels of user as they interact with complex problems. Use of EEG is to capture the alpha and beta brain waves and analyze them with our machine learning models. To accomplish the above vision and goal, knowledge of the CL of a user can play a very crucial rule. CL relates to the effort being and amount of data that the working memory holds at one time. Cognitive load theory can be used by the tutors to design and improve the learning course materials, so that the learning material can be presented at a pace and at a level that is easy for the learner to understand.

1.1 Cognitive Load Theory (CLT)

CLT is based upon the broadly acknowledged model of human data handling. Three primary parts human data processing are shown in Fig. 1.

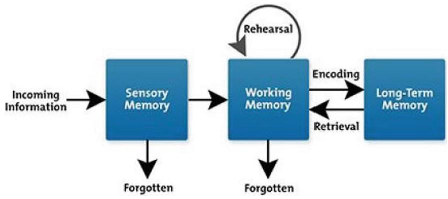

Fig. 1. Cognitive load theory (CLT)

The sensory memory keeps information about the relevant data and later transfer this information to working memory. The transferred information is either processed or discarded. The working memory of the brain can hold up to nine chunks of information at any one time. This is central to Cognitive Load Theory.

The brain starts processing information, after this it categorizes that information and moves it into long-term memory, where it is stored in schemas. The human concepts and their habits are built on these schemas. There are three types of cognitive load:

a. **Intrinsic load:** It is characterized as the essential cognitive load required to carry out a task. It is specifically relative to the trouble of the assignment and contrarily corresponding to the level of aptitude of the user.
b. **Extraneous load:** It is characterized as the squandered cognitive load that does not identify with the essential psychological learning exercises but rather rises reluctantly. It is caused by elements that are not vital to the material to be adapted, for example, introduction techniques or exercises that part consideration between

numerous wellsprings of data. Instructional techniques ought to abstain from overburdening it with extra exercises that don't straightforwardly add to learning.

c. **Germane load:** It is characterized as the load utilized for adapting, for example, for developing schema activities. These components help to encourage the advancement of a student's learning base. Every one of these loads ought to be inside the working memory.

1.2 Methodology Used

In this section, the various methodologies that have been used for the design and analysis of the application have been mentioned. Our project is majorly based CLT and we are also using EEG to collect data from the user. The proposed device when worn by the user will keep on analyzing the alpha and beta waves to measure the attention of the user. It will trigger an alert when the concentration falls under a specific threshold.

CL theory is based upon the broadly acknowledged model of data handling. Three primary parts human data processing are the sensory memory, working memory, and long-term memory.

Consistently, we are barraged with heaps of tactile data on daily basis. The sensory memory keeps information about the relevant data and later transfer this information to working memory. The transferred information is either processed or discarded. The working memory of the brain can hold up to nine chunks of information at any one time.

In the human cerebrum, every individual neuron speaks with the others by sending small electrochemical signs. At the point when a huge number of neurons are enacted, each contributing with little electrical flow, they produce a flag that is solid enough to be recognized by an EEG device. The ongoing accessibility of basic, minimal effort and compact EEG observing gadgets makes it conceivable to take this innovation from the lab into schools/universities.

These devices collect the data from human scalp by putting electrodes at number of positions. It is a universally perceived strategy to portray and apply the area of scalp electrodes with regards to an EEG test or trial. This framework depends on the connection between the location of an electrode and the hidden zone of the cerebral cortex. 10% or 20% of the aggregate front–back or right–left separation of the skull. The variation of this standard is known as Modified Combinatorial Nomenclature.

Since EEG signals are exceptionally frail and normally contain a considerable measure of noise. Therefore, these signs should be intensified and separated. To evacuate potential EEG antiquities, regularly band-pass channel 3–100 Hz is connected to the crude EEG signal. A Notch channel can likewise be connected to dispose of electrical noises from the power source, which fluctuates from 50 to 60 Hz relying upon the geological location (Table 1).

Table 1. Summary and research studies

S. No	Paper title	Tools/Technology	Findings	Citation
1	Brain machine interface system automation considering user preferences and error perception feedback	Machine learning, Deep learning, BCI, EEG	Experiments were done to design BCI systems that gradually become autonomous	Penaloza *et al.* [1]
2	Machine learning based detection of user specific brain states	Machine learning and BCI	System robustly transfers The discrimination of mental states	Blankertz *et al.* [2]
3	On the need for online learning in brain-computer interfaces	BCI and EEG processing	Performance is increased	Millan [3]
4	Toward brain-computer interfacing	Survey on EEG dataset	Research indicates there are several approaches that may provide alternatives for individuals with severe motor disabilities	Dornhege *et. al.* [4]
5	General signal processing and machine learning tools for BCI	Machine learning and EEG	Tested various regression and classification machine learning algorithms	Dornhege *et al.* [5]
6	Speed control of Festo Robotino mobile robot using NeuroSky MindWave EEG headset based brain-computer interface	Neurosky, EEG and BCI	Implementing speed control using neurosky, have been finished with positive results	Katona *et al.* [6]
7	Evaluating the ergonomics of BCI devices for research and experimentation	BCI, EEG	Compared various ergonomics of 2 different BCI devices	Ekandem *et al.* [7]
8	EEG-based brain controlled prosthetic arm	BCI, EEG, Robotics	The movement of the finger can be controlled	Bright *et al.* [8]
9	Brain robot using neurosky mindwave	Robotics, EEG, BCI	ROBOT will move forward when attention and ROBOT will move backward when meditation value crosses a certain limit	Tiwari and Saini [9]
10	A user-friendly wearable single channel EOG-based human-computer interface for cursor control	Neurosky, BCI, EEG	The NeuroSky MindWave headset can control cursor navigations and actions	Ang *et. al.* [10]

(*continued*)

Table 1. (*continued*)

S. No	Paper title	Tools/Technology	Findings	Citation
11	A wearable real-time BCI system based on mobile cloud computing	Cloud computing, BCI, EEG	Facial expression interface can indicate the user's mental States according to the analysis of EEG data on the server	Blondet *et al.* [11]
12	Replacing the computer mouse	BCI, EEG and machine learning	It shows ways to move mouse cursors and clicks using BCI	Dernoncourt [12]
13	A novel EEG for alpha brain state training, neurobiofeedback and behavior change	EEG, BCI	Alpha brain waves were used to provide real time, Easily interpretable feedback to the user	Stinson and Arthur [13]
14	Brain-controlled home automation system	Raspberry Pi, EEG device, IOT	Able to control various appliance like light bulbs using raspberry pi and AWS	Ghodake and Shelke [14]

1.3 Literature Survey

In human brain, every individual neuron communicates with the others by passing a small electrochemical signs. At the point when a huge number of neurons are enacted, each contributing with little electrical flow, they produce a flag that is solid enough to be recognized by an EEG device. These devices collect the data from human scalp by putting electrodes at number of positions. The positions to gauge EEG signals are characterized by the International 10–20 system. It is a universally perceived strategy to depict and apply the location of scalp electrodes with regards to an EEG test or analysis. This framework depends on the connection between the location of the electrode and the basic zone of the cerebral cortex.

An extensive review of literature was done in order to study already existing work and the kind of research that is being done in the field. Penaloza *et al.* [1] addresses the problem of mental fatigue caused by the excessive use of brain machine interface systems. Blankertz *et al.* [2] talked about how BCI can be used to translate brain signals to commands. Millan [3] mentioned the use of BCI in online learning to improve the learning process. Dornhege *et al.* [4] gave a detailed analysis of the use and improvements in the field of brain computer interface. Dornhege *et al.* [5] addressed the issue of noise in EEG data and how can it be removed or minimized to the maximum. It mentions how signal processing can be used to improve the quality of the data. Katona *et al.* [6] and Ekandem *et al.* [7] mentions the use of neurosky headset. The same headset is being used by the smart learning system. Bright *et al.* [8] mentions how BCI can be used in understanding various human thoughts and shows how it is used in controlling a prosthetic arm. Tiwari and Saini [9] mentions the use of neurosky mindwave eeg device to control a robot. Ang *et al.* [10] and Blondet *et al.* [11] addresses the development in the field of portable and low-cost EEG devices and how such devices can be made. Dernoncourt [12] showed how BCI can be used to control a mouse cursor and replaced the traditional mouse cursor by an EEG device. Stinson and Arthur [13] gave a deep analysis of how EEG devices are being used to detect calmness in the human body and provide feedback to the user about the state of mind. Ghodake and Shelke [14] proposed a home automation system using brain computer interface that uses EEG device.

2 Methodology Adopted

2.1 Investigative Techniques

Experimental investigation technique was enforced on this system to get the best possible accuracy with the as minimum latency as possible. Various machine learning model was used on the data generated to get the best possible result. The devised algorithm was able to give real-time results with best accuracy.

2.2 Proposed Solution

The proposed solution consists of a web application and a device which when worn by the user will keep on analyzing the alpha and beta waves to measure the attention of the user. It will trigger an alert when the concentration falls under a specific threshold along with monitoring the eye movements of the user. This will make sure that the user is able to get constant feedback from the system according to his performance and the system will adopt the appropriate pedagogy to adjust to the users' learning curve and hence improving the overall learning experience of the user (Fig. 2).

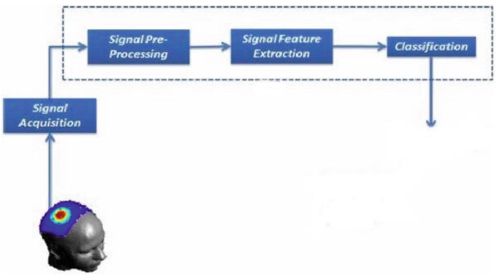

Fig. 2. EEG data processing

3 Design Specifications

3.1 System Architecture

The architecture of our system is divided into 2 parts which are interdependent on each other. One is our MVC structure and other is the web application which talks to the desktop application. Figure 3 shows the basic system architecture and Fig. 4 shows the MVC architecture.

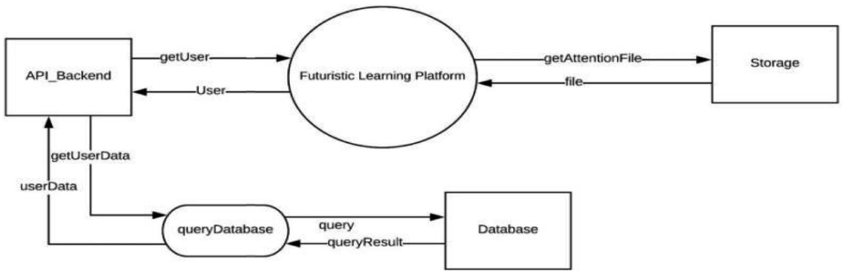

Fig. 3. System architecture

The user comes to the smart learning platform with an EEG device connected to the system. To fetch the required videos by the user several backend APIs are called. The user opens the desktop app where he enters the video id and obtains the analysis of his performance.

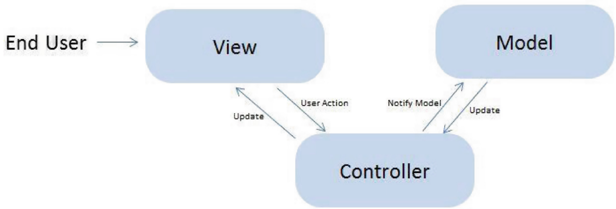

Fig. 4. MVC architecture

Model-View-Controller is a software design pattern or a software development methodology. The main objective of this architecture is to promote code usability and also to implement separation of concerns so that the software becomes easily testable. There are 3 components Model, View, and Controller.

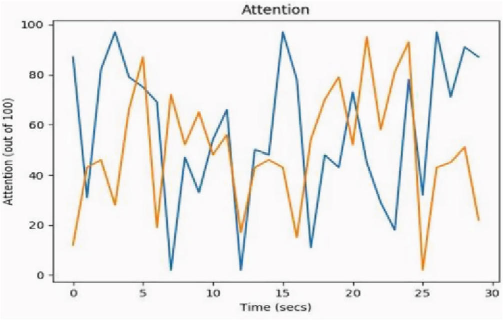

Fig. 5. Analysis of EEG data

The above Fig. 5 is a visual representation of the user attention level compared with the average attention level of all the users.

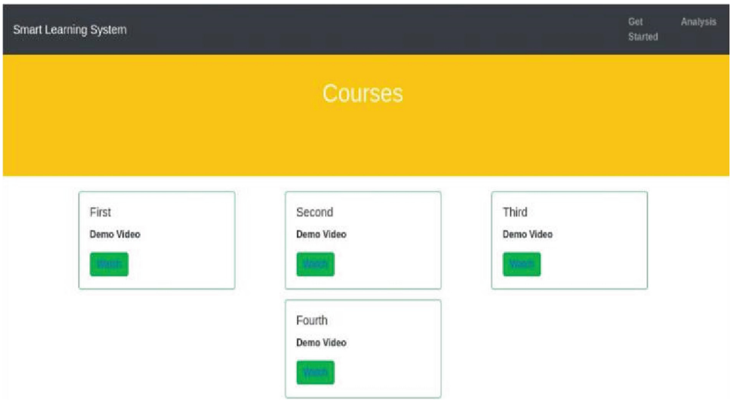

Fig. 6. Screenshot of web app

The above Fig. 6 shows the available courses on the platform. The users can click on the course of their choice and watch online lectures for that particular course.

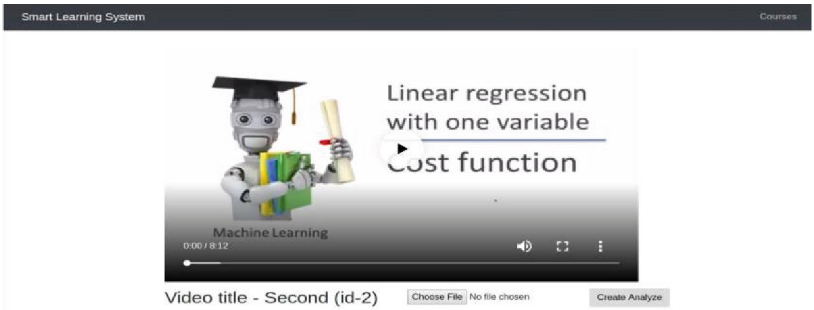

Fig. 7. Video player of web app

The above Fig. 7 shows the screenshot of the video player where the user will watch lectures of the courses of their choice.

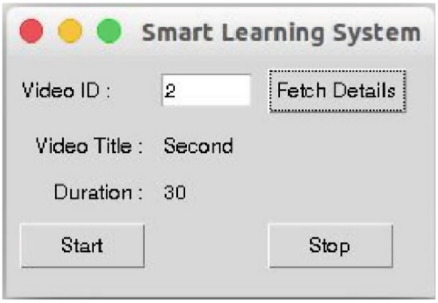

Fig. 8. Desktop app

The Fig. 8 shows the desktop app where the user is the required type the id of the video they are watching to get the analysis of their performance.

4 Experimental Results

4.1 Experimental Setup and Simulation

EEG device: The Neurosky Mindwave EEG device has flexible rubber sensor arms and rounded forehead sensor tip, T-shaped headband, and ear clip contacts. The user will wear the device on the forehead and connect the device with the laptop through Bluetooth.

Web Application: After connecting the device the user has to open the web application on the laptop and start a lecture of choice. There is a desktop app where the user has to enter the id of the video lecture that he is watching to get a detailed analysis of his performance and attention level.

4.2 Experimental Analysis

4.2.1 Data

The data in the application is generated by the EEG device which reads the brain waves and then converts them into numeric data which is further processed by the application to convert it from raw EEG data to usable and clean data.

4.2.2 Performance Parameters

- Time Delay: Time between notification alerts is taken as one of the important performance parameters. The lesser the delay the more the efficiency of the system. The time delay occurs during transmission of the signal from the surveillance area to the app via a server or vice versa.

- Accuracy: The accuracy of the EEG data and the calculation of the performance of the user are also an important parameter that can generate unexpected results if not taken into consideration.
- Ease of use: Ultimately user is the one who will benefit from the system. So, it becomes more important to make a system according to the user's perspective. Our system takes care of this by using a simple application that can be modified according to user behavior.

4.2.3 Test Cases

S. No.	Test Case	Input	Expected output	Actual output	Result
1	The user enters a valid video id	Valid video id	The user will be able to generate an analysis of the attention level	Analysis generated	Successful
2	The user enters an invalid video id	Invalid video id	The desktop app will show −1 in video title and duration	−1 is shown on the desktop app	Successful
3	User presses pause/stop button	Button pressed	Data will not be written to the file	Data is not written on the file	Successful
4	User uploads data	Data file	Graphs will be displayed	Graphs are displayed	Successful

4.2.4 Test Results

All the test cases were successful. The application worked as expected and if there were any bug or corner cases, they were fixed while testing. Figures 9, 10, 11 and 12 shows the screenshots of the test cases.

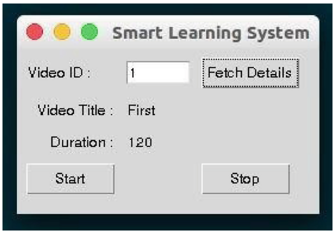

Fig. 9. Valid video id

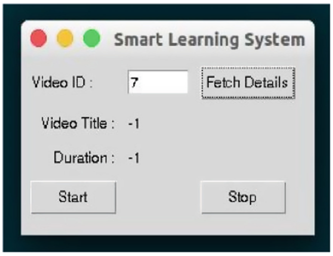

Fig. 10. Invalid video id

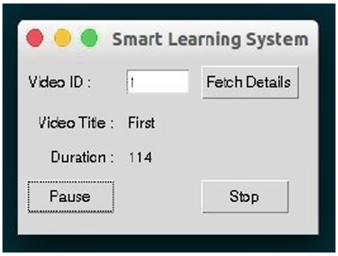

Fig. 11. Pausing the application

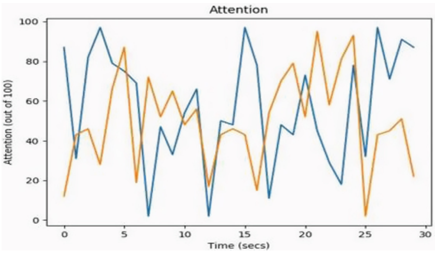

Fig. 12. Uploading the data

5 Conclusion and Future Directions

In this paper we developed a smart learning system based on EEG that has capabilities of monitoring the active attention of learner. The main focus to this paper is to enhance the progress of students by improving attention and concentration level. So, we have used EEG signal to calculate various parameters such as concentration level, attention level, etc. These parametric values further used for real-time analysis and provides feedback to the user. This system improves the learner's active attention during online learning. It may also use to improve learning through MOOCs, making driving safer, etc. Brain Computer Interface is prepared to significantly affect instruction, human services, diversion, security, and numerous different ventures and will no uncertainty advance our lives in manners we can't yet predict for ages to come. Currently, the EEG device gives good accuracy with data and analysis. But following features can be added and improved:

i. By applying machine learning algorithms, we can give better recommendations for the video lectures to the user. This will help them in learning efficiently.
ii. The collected of users can also be used to improve the online courses.
iii. The BCI technology can be used in different projects such as making brain controlled robots, giving attention triggers while driving, manipulating a computer cursor etc.

The EEG technology is still a huge research-oriented field and will continue to make immense leaps and bounds in the future. The tools like NeuroSky Mindwave and other EEG devices provide a low budget and user-friendly solution for conducting EEG oriented research.

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