Artificial Intelligence Technology Based on EEG Signals for Monitoring the Online Education Industry

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A wearable Neurosky device that uses learner EEG data in real-time to detect attentiveness during online learning. An adaptive learning environment can control low cognitive and mental attention duration by responding to learner requests. The student's level of involvement has a substantial impact on online learners' propensity to study. The efficacy of the proposed method is explicitly evaluated based on its classification accuracy in predicting engagement. The online teaching approach can be automatically changed by modifying the content and communication approaches when distraction, disinterest, or superficial involvement occurs during an online session with the learner. The novel technique involves acquiring EEG data, focusing specific attention on movements, eye blinks, and facial expressions at frequencies linked to concentration or attention. An AI and machine learning technique based on EEG data is used to predict learner attention. A government or independent organization employs this technology to monitor and control the online education sector.

Keywords: EEG, Machine learning, SVM, AI.

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1 Introduction

The sporadic closure of universities and other institutions brought on by the epidemic has impacted more than 500 million pupils. Technological innovations have completely changed the outdated educational system. Everything from exam preparation to higher education to elementary, secondary, and informal learning, online learning platforms have grown significantly in all areas of education. It is a tremendously fragmented online education market. Start-ups selling innovative items are becoming more popular, and a few specialist companies specialize in different sectors. Online education has benefited from technological advancements over the last decade. Examples include using cloud-based platforms, virtual reality (VR), augmented reality (AR), and information and communication technology (ICT) in the classroom. The online education market was projected to have cost INR 108.79 billion in 2021. Between 2022 and 2027, it is expected to increase at a compound annual growth rate (CAGR) of around 22.67% reaching INR 299.18 billion.

The ability of the brain to pay attention to one thing while disregarding others is referred to as attention in a certain context. Attention is the first step toward learning. Planned, previewed, monitored, and regulated thoughts and behaviours v are key skills that students need to concentrate on. Students' degree of attentiveness during the online learning process is an essential aspect of their academic performance. Real-time feedback is often interpreted as either a compliment or a warning sign he instructor may decide to use a different teaching strategy to re-engage learners in online classes. The purpose of Shen et al.'s large-scale expert assessment systems (Scholar, n.d.-a) [1] was to look at how studying instructional videos by online learners affected their overall learning outcomes. These systems were based on user behaviour and the Delphi technique. Hu et al.'s qualitative research (Scholar, n.d.-b) [2] explored the relationship between online participants' knowledge, time and budgetary constraints, and learning performance.

The researchers constructed a structural equation model. To validate the step of the appropriate dataset and the classifier, the statistical processing tool known as AMOS was utilized. The model's predictability coefficient was 0.8, and the chi-square proportionate to the degrees of freedom ratio was determined to be 2.7. and by merging the outcomes of users' questions and answers with the behaviours of users. An innovative network learning process assessment approach was developed by Wang et al. (Liang et al., 2023) [3] to investigate users' learning states when they are learning online. A decision tree model was developed using Rapid Miner; the model's accuracy was determined and the outcome showed how well the learning state analysis methodology works. Namita and Ajit Kumar (Tambe&Khachane, 2016) [4] proposed a method to anticipate a learning video based on the emotions of the learner, aiming to improve the effectiveness of traditional e-learning. They employed five different classification methods and examined the accuracy of each. In another study, Alirezaei and Sardouie (2017) [5] investigated how attention can be identified using EEG signals. Data were collected from twelve individuals, and features were extracted using Fisher parameters and forward feature selection algorithms. The use of an SVM classifier resulted in excellent accuracy.

Aci et al. (2019) [6] proposed a passive EEG-based brain-computer interface (BCI) to observe the mental states of learners, identifying three levels of mental attention: tiredness, disengagement, and passive attention. Five individuals performed a low-intensity control task, and a dataset of EEG readings was collected over 25 hours. In the context of e-learning, Nandi et al. (2021) [7] proposed a real-time emotion classification approach using EEG signals, based on stochastic gradient descent and logistic regression. They validated their method using the DEAP dataset, reporting that their approach outperforms other offline and online methods.EEG data can be utilized to determine cognitive features, aiding researchers in understanding human behavior. This knowledge has applications in psychology, neurology, and human-computer interaction. Advances in EEG-based technologies enable teachers to monitor students' cognitive load without disrupting e-learning (Erdoğan et al., 2021; Qiu et al., 2022) [8] [9]. An automated learning system can adapt e-learning content to students' attention levels by precisely monitoring them (Li et al., 2022) [10].

This technology offers numerous opportunities for enhancing virtual learning experiences by streamlining the evaluation process and providing informative feedback. This work describes how a government or independent agency uses artificial intelligence (AI) combined with EEG techniques to monitor and regulate the online education sector. To achieve this, the study first collects EEG data from a random sample of students, which is then processed and analyzed in real-time. The processed data is sent to a centralized monitoring system to measure the quality and standards of online coaching. The research paper is organized as follows: Section 2 presents the background information and basic principles of the study; Section 3 covers the research methodology, including the EEG data experiments; Section 4 analyzes the assessment results; and Section 5 presents the conclusions.

2 Material and Method

The Neurosky device is used to record EEG signals. EEG signals must be pre-processed before they can be extracted into refined brainwaves at various frequencies. The five basic types of human EEG waves are alpha, beta, gamma, theta, and delta. We use EEG frequencies to assess a learner's attention level over a given period. The Neurosky device records EEG data from a certain spot point on the head. Electric impulses were identified by EEG signals that occur during mental tasks. Neurosky records impulses at 512 Hz/s. The Neurosky gadget amplifies EEG data up to 8000 times before filtering them to the 1-50 Hz range. The EEG information is processed in real-time to identify and improve upon noise artifacts continuously. EEG signal analysis is carried out utilizing the Fast Fourier Technique. The EEG signal's properties are predicted via power spectral density value assessment. The Fourier transform can be utilized when calculating PSD value. This incorporates nonparametric methods for analyzing variation in autocorrelation. Welch's method is the most widely used and traditional methodology.

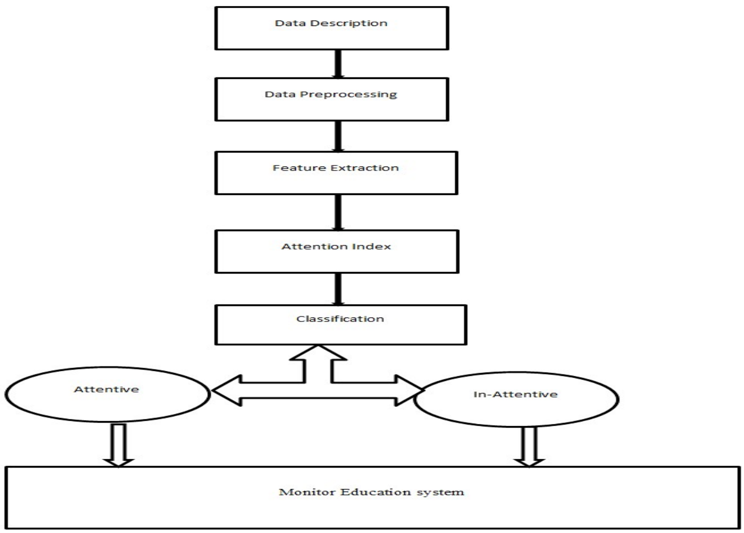

Figure 1. Block diagram of AI based monitoring of online education industry

Several machine learning methods may be employed in real-time learning sessions to determine how much the learner is paying attention figure. 1 above shows the process through a block diagram. These techniques, including logistic regression, support vector machines, and ridge regression, are well-known for their ability to tackle complex problems. EEG waves arise in several frequency ranges that are generated while conducting tasks. A student's level of focus in an online course can be evaluated using EEG waves. Analyzing a student's attention span more precisely is made possible by the characterization of EEG waves. The methods we use to evaluate attentiveness are based on prediction and classification. Logistic regression, support vector machines, and ridge regression are examples of traditional machine-learning techniques used to forecast complex actions.

Identifying whether an EEG signal data point reflects attentiveness or inattention, Prior to extracting particular frequency waves from unprocessed EEG data, noise is reduced. These frequencies are then used by the various machine learning algorithms to predict attentiveness and inattention. Many brain waves are seen as inattentive by human attention standards, despite the fact that α and β waves are attentive. Stratified sampling is utilized to balance the projection before ML methods are applied. Next, the segmented data is utilized to train machine learning systems that can forecast both attention and inattention. The innovative approach is to first gather EEG data that is specifically focused on eye blinks, head movement, and facial gestures with specific frequencies that are primarily responsible for concentration or attention. An artificial intelligence and machine learning-based technique is used to forecast learner attentiveness based on acquired EEG data, and the results are then transferred to an independent agency or government for further analysis figure 2 shows that the suggested approach to monitoring online education industry.

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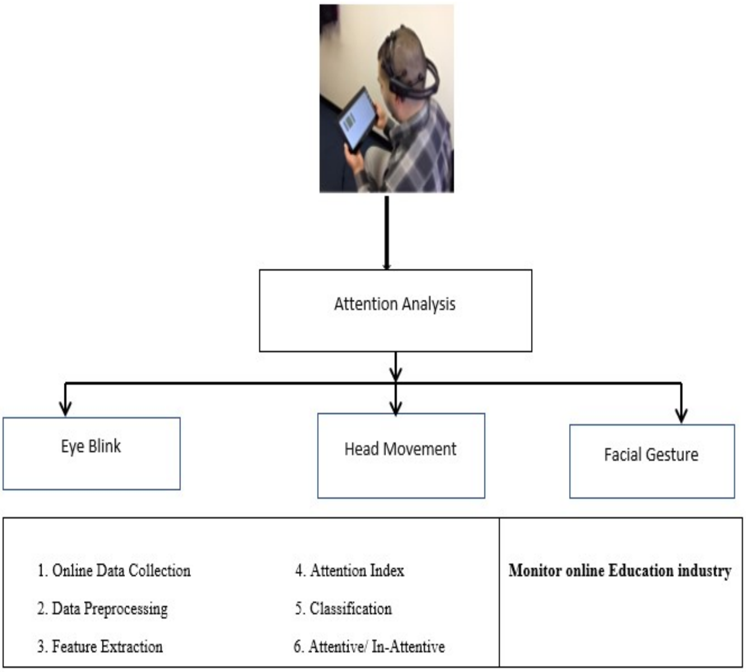

Figure 2. Process of Monitor student's attentiveness step by step

3 Result and Discussion

The benchmark dataset from the Kaggle website was utilized for attention-detection testing, as described in the previous Section because each classifier in the prior study was trained independently;

the subject-specific paradigm resulted in poor algorithm generalization. Although these classifiers perform well, it is impossible to train one for each individual in practical scenarios. We trained a single classifier for all topics using the common-subject paradigm. A variety of cross-validation methods were used to evaluate the categorization algorithms' efficacy. The dataset was split into 70% training and 30% testing, these views were considered divergent. The ROC/AUC curve and confusion matrix are used in Figure 3 to illustrate the accuracy results for the SVM classifier.

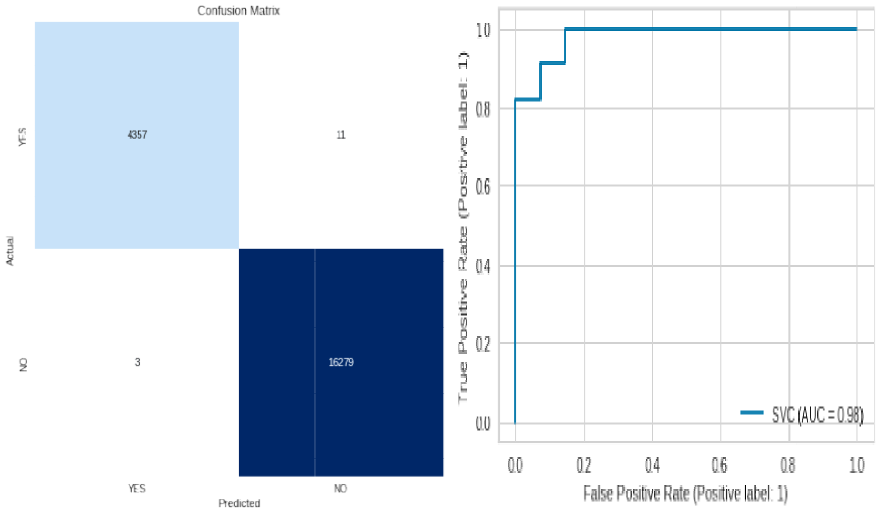

Figure 3. (a) Confusion matrix for classifier (b) ROC/AUC curve with value

The attention levels of students in real-world classrooms were extracted using an EEG-based technology, and their academic achievement was correlated with those attention levels. According to these findings, our platform can be an effective means of assessing student's academic success in the classroom as well as the capacity to raise student performance via the efficiency of the teaching-learning process. More importantly, we have opted for a safe and reliable approach that combines multiple methods because the amount of noise in EEG signals cannot be estimated beforehand. Although perfect performance was lost, this method allowed for coexistence at high noise levels. This has verified our main promise, which was to create a platform that could function in environments similar to a real secondary school. Its resilience and adaptability are excellent, despite the expectedly high levels of EEG noise. Table 1 compares all the approaches used to try and various levels of attention. The technique described by the authors of (Scholar, n.d.-c)(Peng et al., 2020) [12](Gupta et al., 2023a)[13] was used to identify the three separate learning stages: rest, no attention, and attention.

Table 1. Comparison table for accuracy value

S. No	Researcher	Classification	Accuracy value (%)
1	Swadha Gupta et. al.	SVM	91.68
2	T. A. Suhail et. al.	SVM	90.11
3	C. J. Peng et. al.	SVM	84.80
4	Proposed Approach	SVM	99.00

The entropy was calculated using power spectrum features and nonlinear parameters, while the amount of attentiveness was estimated using SVM. 85.24% accuracy was achieved. The attention was measured using band power and spectral entropy on single-channel EEG data. An individual's mental state may be identified with 84.80% accuracy. After examining 20 individuals, a cognitive state-based attention approach was proposed with an overall accuracy rate of 90.11%. To predict attention levels, the algorithm identified characteristics based on the attention index AITABG, the Hjorth parameter (spectral entropy), and EEG band ratios. A consistent method for assessing learner attentiveness was established by identifying the best two frequencies based on important feature assessments (Gupta et al., 2023b) [14]. Decision assistance technology visualizes data points to help learners focus to achieve an accuracy of 91.68%. Our proposed approach yields the best results when compared to the previous method comparison graph displayed in Figure 4. This accuracy value is gathered from several students and transmitted to a central system, which aggregates all the data for assessment of a particular online coaching industry.

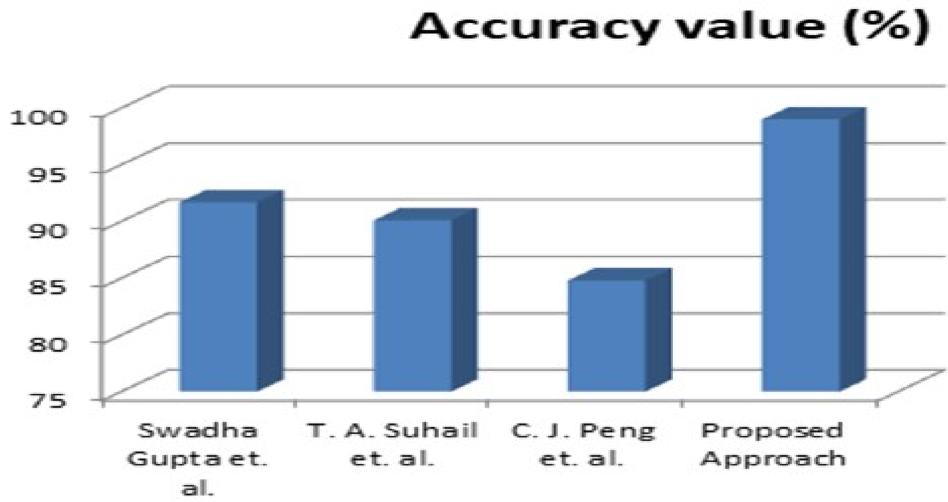

Figure 4. Comparison chart with previous method

4 Conclusion

This research work offers an efficient and impartial method for evaluating the results of machine learning and EEG signal-based online learning assessment in real-time. First, while the learners complete tests of their mental effort focused on online learning, EEG signals are recorded of them and then pre-process the EEG signals. Finally, the EEG signals are extracted from various tests with the help of power spectral density, fuzzy entropy, wavelet analysis, and SVM classifier to predict learner attention to compute overall efficiency. The results indicate that the learning efficiency of the experiment subjects is within the public evaluation's range when paired with statistics from the public assessment. This accuracy result compared with previous methods recommended methodology has shown an advantage over the previous method. A central monitoring system operated by a government agency or an impartial third party gathers this accurate data from some selected learner who has been chosen. This organization is capable of researching findings, verifying authenticity, and grading specific online education businesses.

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