Leveraging machine learning techniques for student's attention detection: a review

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ABSTRACT

With the advances of the internet and today's innovation, it has become conceivable to conduct teaching and learning activities remotely through the online platform. Existing research says that student's attention state and learning result are strongly correlated. However, despite its importance, this can be a challenging task, as students in general taking an online class may be in a variety of different environments and may be multitasking or distracted by other factors. This review paper aims to address these challenges by exploring the opportunities offered by machine learning techniques in attention detection for effective online teaching and learning. By leveraging machine learning algorithms, which can analyze large volumes of data, including eye-tracking, facial expressions, and body movements, we can develop robust models for attention detection in online learning environments. This paper reviews the challenges specific to online learning, such as students' attention deficits and learning styles, and highlights the limitations of current attention detection methods. Furthermore, it provides recommendations to advance attention detection technology, emphasizing the potential of machine learning to enhance attention detection technology for effective online teaching and learning.

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1. INTRODUCTION

In recent years, online learning has gained significant popularity, offering flexible and accessible educational opportunities to a diverse range of students. Experiencing from COVID-19 pandemic, which is a past today, many things have changed cross the industry including education in terms of operations and services. Though students have returned to their respective education institutions, online teaching and learning is still practiced at least to some extent. However, one of the significant disadvantages is the student's attention that can be distracted by the external stimuli such as text messages and noises from the surrounding environment when attending online classes [1]. Research studies have indicated a positive association between attention level and academic performance, and poor attention may result in the students having difficulty following instructions, slow learning, and completing the tasks on time [2]. Hence, introducing a student's attention monitoring system during online learning process is crucial for student's learning success.

One of the challenges faced by educators in online learning environments is the ability to monitor and assess students' attention levels [3]. Understanding students' attention patterns is crucial for effective instruction, personalized feedback, and identifying potential learning difficulties. In a traditional classroom, teachers monitor students' body language or facial expressions to gauge their attentiveness, which can lead to incorrect conclusions [4]. Therefore, there is a growing interest in applying machine learning techniques to detect students' attention in real-time. The motivation of the review paper is to address the need of an effective attention monitoring way in online learning environments. As the demand of online learning continues to grow, it is important to understand student's mental state and optimize students' attention levels for enhanced learning outcomes in online learning context [5].

The purpose of this review paper is to provide an overview of the impact of attention in learning and the state-of-the-art machine learning algorithms employed for attention detection. We hope to discover the strengths, limitation, and the potential applications of these attention detection applications by reviewing the existing research. Furthermore, we also look at different type of data sources that being used in attention detection, such as eye-gaze data, facial expressions, and electroencephalography (EEG) signals. The combination of these data sources and machine learning algorithms holds promise for constructing effective attention detection models.

The objectives of this review paper are: (i) to identify the relationship of learning style and attention that influence students' attention in online learning (ii) to review the performance of the machine learning algorithms in terms of accuracy, reliability, and scalability in different attention detection approaches and (iii) to discuss the implications of attention detection in online learning environments. By reviewing the existing research, we hope to provide insights into the potential benefits and challenges associated with the use of machine learning techniques for attention detection in online learning.

The remainder of the paper is organized as follows. Section 2 is the impact attention in learning, that discuss about the importance of attention in student learning. Section 3, student's attention detection and prediction approaches, the finding and discussion is in section 4. Section 5 concludes the paper with some future recommendations.

2. THE IMPACT OF ATTENTION IN LEARNING

Attention is a fundamental cognitive function and a prominent area of research within the field of neuroscience. Attention deficits can significantly impact the learning process and various aspects of daily life. Individuals experiencing attention deficits often exhibit behavioral challenges, including difficulty following instructions, maintaining focus on tasks, and engaging in effective social interactions [6]. Such individuals may struggle to stay attentive to their responsibilities and assignments, resulting in reduced task completion and suboptimal learning outcomes. Concentration difficulties are a primary contributor to ineffective learning and hinder the successful completion of tasks. Past research has aimed to understand whether learners are more active during learning tasks or if they can better retain learned content at a later time [7]. Investing attention during learning processes can be highly beneficial, aiding learners in the more efficient processing and encoding of information. However, individuals with attention deficits may not always recognize their attention-related challenges. In response, various protocols and interventions have been developed to assist students with attention deficits, aiming to enhance their attention, reduce inattentiveness, and facilitate a more productive learning experience.

Recent studies examined the impact of remote learning practices and difficulties during initial stay-at-home orders during the COVID-19 pandemic in adolescents with and without attention deficit hyperactivity disorder (ADHD). Teaching and learning are conducted via online platforms for remote learning. A total of 238 adolescents (132 males; 118 with ADHD) aged 15.64–17.99 years and their parents participated in this study. Students were self-rate their experience about remote learning. The result shows that adolescents with and without ADHD are facing concentrating difficulties while attending remote learning [8]. As remote learning starts gaining its popularity, the studies for attention detection is important to help the students to overcome the difficulties to stay attentive during the online learning.

In the education field, research has consistently demonstrated the significant influence of sustained attention on learners' performance and motivation, especially in the context of online instruction. A study conducted by Chen and Wang [9], highlighted the potential of attention monitoring through electroencephalogram (EEG) brain wave signals to enhance individual learners' performance. This approach offers valuable support to teaching assistants and online instructors, enabling them to boost the sustained attentiveness of learners, particularly those with lower attention levels during online instructional activities.
The study's findings revealed that learners in the experimental group outperformed their counterparts in the control group, exhibiting not only better learning performance but also improved sustained attentiveness. These results affirm the pivotal role of attention monitoring in promoting attentiveness and, consequently,

enhancing overall learning performance. These studies collectively underscore the profound impact of learners' attention levels on their learning styles within educational contexts. Understanding students' unique learning styles not only aids educators in tailoring their instructional approaches but also empowers students to adapt more effectively to successful learning practices. Given that attention plays a central role in prioritizing and applying concepts and information, it follows that individuals with attention deficits may struggle to efficiently process and apply information. Therefore, the level of attention significantly influences individuals' learning styles, and by enhancing attentiveness, we can aspire to achieve the learning outcomes.

2.1. The relationship of learning style and attention during learning

Attention represents the early phase in the process of learning. We constantly confronted with a multitude of sensory information or stimuli which is impossible to receive and process all of them [10]. Consequently, we engage in a cognitive process known as selectivity, wherein we choose which stimuli to focus our attention on. This selective mechanism is orchestrated by the brain's attention control system [11], which serves the dual purpose of swiftly responding to abrupt environmental stimuli and aiding us in aligning our attention with our goals and the demands of varying situations. This facet of the brain also plays a crucial role in regulating alertness and arousal within the reticular activating system (RAS), located in the frontal lobe. Information that gains priority in our attention is subsequently stored and subjected to the learning process, giving rise to distinctive learning styles that differ among individuals [12].

Attention is a mental process that enables us to focus our attention on one thing while ignoring other things. In the classroom, we use various strategies to direct students' attention to the learning tasks and activities. These include directing students' attention toward a specific activity or task by using visual cues (e.g., pointing out a word in the text), auditory cues (e.g., singing a song) or verbal cues (e.g., telling students about an upcoming quiz). Hence, various studies have been conducted to understand student's learning style in order to facilitate their learning.

A learning style can be understood as an approach that optimizes an individual's learning process [13]. The extent of a learner's attentiveness significantly influences their learning style. Attention serves as the gateway through which information is received, and working memory processes this incoming information, imparting meaning to it [14]. The level of attention, therefore, undeniably impacts a student's success, as it shapes their learning style. Various frameworks for learning styles have been devised to examine how learners assimilate information through their selective attention mechanisms. However, each person possesses a unique preference for particular learning styles, irrespective of their deficits and abilities. This preference reflects an individual's favored approach to learning. These learning style frameworks [15]–[17] have found application in the fields of education and health sciences, with a particular emphasis on distinct learning outcomes, each influenced by the level of attentiveness.

Akaneme *et al.* [18], conducted a comparative analysis to assess students' learning style preferences, both with and without attention deficits. The study employed a survey research design in which 158 students participated, with 73 having attention deficits and 85 without. The research utilized the Fleming VARK questionnaire and ADHD questionnaire to gather data. The results showed that a majority of students displayed a preference for the visual learning style. Among students without attention deficits, the preference leaned toward learning through watching, listening, and reading text materials. In contrast, students with attention deficits exhibited a preference for hands-on activities, followed by watching and visual demonstrations. Educators can utilize these questionnaires to tailor their teaching strategies, aligning them with the specific learning styles of the students, and thereby, enhancing the potential for academic success.

Another recent study conducted by Rawandale *et al.* [19], it was found that urban students, in the age group of 14-16 years in Dhule, Maharashtra, India, had a preference for the visual learning style over kinesthetic and auditory styles. In contrast, rural students within the same age group exhibited a preference for auditory learning over kinesthetic and visual styles. The study collected data from 50 students each from rural and urban schools. The study's implications suggest that recognizing students' learning preferences can empower them to employ effective learning strategies and become more self-motivated, thus maximizing their learning potential. Furthermore, the study underscores the critical connection between teaching content, attention, and effective learning. Student learning attention is significantly influenced by the configuration of the online teaching platform, as well as the teaching content and methods employed [20].

Amid the COVID-19 pandemic, an experiment investigating the impact of various online instructional styles on students' learning attention levels was conducted [21]. The researcher collected EEG signals to assess the subjects' attention levels during their engagement in online learning, enabling subsequent analysis. These attention level signals were then harmonized with Mayer's theories of multimedia technology for a comprehensive analysis. The study enlisted four students who participated in the experiment, which involved the utilization of three distinct styles of instructional videos. The results revealed that online course videos featuring an instructor and content simultaneously on the screen, with the instructor pinpointing the location of the content while explaining it, were more likely to elicit higher levels of student attention.

2.2. Challenges of student's attention in online learning

Online learning environment has gained its popularity over the years. One of the examples is massive open online course (MOOC) where it offers learners to acquire new knowledge anytime and anywhere on the online platforms [22]. The online learning systems are usually web-based applications that distribute, track, and manage courses over the Internet. The demand of MOOC is still increasing over time [23]. Despite huge numbers of learners participated on MOOC learning platform, research showed that only 5%-10% of the learners completed their courses on a MOOC platform [24] and facing high dropout rate [25]. One of the main challenges that faced by MOOC platform is the learners loss their attention during the learning process and bring disastrous impact to learning efficiency [23].

One of the challenges that students experience in both physical and online classes is keeping their attention on the subject being presented to them. Online learning platforms can be conducted as synchronous and asynchronous approaches. Instructors use online meeting tool such as Zoom, Microsoft Teams, Cisco Webex, or Google Meet for synchronous online learning. For the synchronous approach, teachers can provide immediate feedback to students about their learning. One of the drawback when students have the option to attend the online classes by using their phone, they tend to being distracted by the text messages from the phone [26]. In contrast, for asynchronous approach, the online learning contents are uploaded to the online platform and the students access the learning content at their own pace [22]. The content being presented to the students in asynchronous approach may be overwhelmed and them to shift their focus elsewhere and have negative impact on some student's attention span [27], [28]. However, students find that short videos (with the length of 3 minutes) are less informative or contain insufficient information for their learning [29]. Hence, an appropriate length of instructional video is important to maximize the student's learning impact.

3. STUDENT'S ATTENTION DETECTION AND PREDICTION APPROACHES

Online learning/e-learning has grown at a fast pace especially due to the global pandemic. Monitoring student conduct is essential so that teachers may easily identify and rectify inappropriate behaviour. Student attention monitoring is a process that allows educator to observe and record the amount of time students are spending on various tasks during online classes. This data can be used to help improve student learning by giving educators insight into how students are performing in their classes. Various methods and studies have been conducted by using mobile devices, sensors, and with the aids of machine learning to helps the educator to understand student's attention in the class. However, it is still a challenging task to estimate student's attention in the various dynamic learning environments [30].

Research studies on students' attention detection can be found in the literature. To review them, we propose a taxonomy which is shown in Figure 1. First, we divided the existing attention detection methods into two main categories-objective and subjective methods, based on the degree of student's involvement in the attention detection process. Objective methods use external measurements and observations in data collection that are quantifiable and less influenced by personal biases. Neurophysiological, oculomotor, and behavioral data are the example of the data using objective method. In contrast, subjective method relies on students providing subjective feedback on their own attention levels. Self-reporting and interview are the examples of subjective method of data collection, as it involves students' personal opinions and perceptions of their own attention levels. In this review, we are focused into objective methods which are computer vision, eye gaze tracking, and EEG.

3.1. Computer-vision method

Computer vision is a field of study within artificial intelligence that focuses on enabling computers to understand and interpret visual information. In the context of student attention detection, computer vision methods can be employed to analyze various visual cues associated with attention and engagement during learning. In general, this attention detection systems captured the video streams while the students participated in a learning activity and then analyze the student's attention during the learning process. The common indicators for attention detection using this method are facial expression analysis and posture tracking [31], [32].

The common tools are webcams or surveillance cameras to detect facial expression of the student during online learning [33]. Typically, webcams are used to provide a constant and non-intrusive manner of gathering face photos of the students while they are using mobile devices or personal computers for the learning activities. The sequence of photos is captured to understand the attention state of the students. Over the past decade, the application of machine learning and computer vision methods has made tremendous progress in various areas such as automated assessment, security, image data investigation, identity verification, and surveillance. Mindoro *et al.* [34] suggested to apply You Only Look Once, Version 3

(YOLOv3) algorithms in predicting students attentive and non-attentive state based on the face recognition during class session. However, this system is sensitive to the student's facial position because the attentiveness level of the student is determined by whether the students are looking at the camera. Another attention detection study conducted for offline classes [20] which also incorporated head pose, audio components, and class state in analysing student's attention state. Cameras were installed in the classroom and the students were aware that the cameras were capturing images for data analysis but were not informed for attention detection purposes. Environmental sound is recorded to capture the different class state namely lecturing, practice, interaction, and transcription state. Both data were analysed using deep learning algorithm and the combination of voice and image information improves the accuracy of the learning attention recognition.

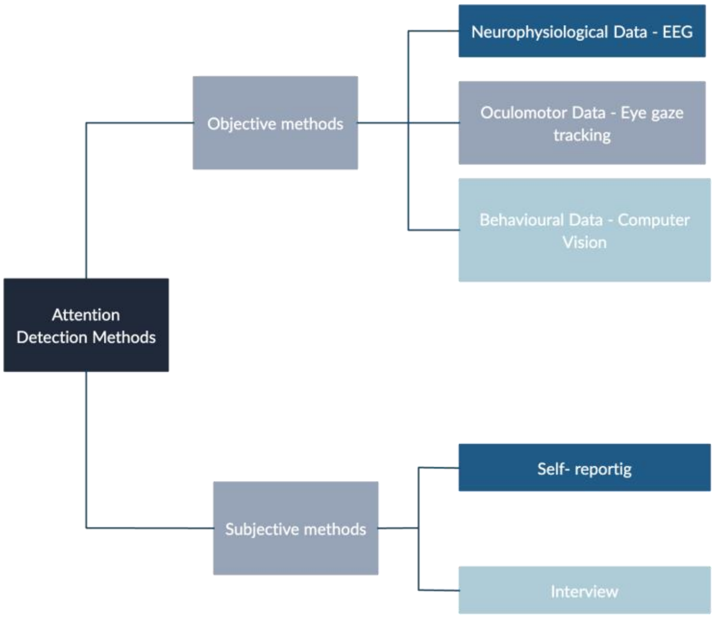

Figure 1. Type of data collection for attention detection

Another study being done to predict student's attention level is by using Kinect One sensor [35]. The sensor is used to capture the class activities and then to create a feature set that characterizes a student's facial and body features. These features are then being used to build the machine learning attention model includes gaze point, lean back, head displacement, eye closed, face deformation, and mouth open. Seven classifiers were deployed including decision tree, k-nearest neighbors, and decision trees to predict three attention states, namely high, medium, and low. Despite the combination of Kinnect One sensor and machine learning methods providing remarkable results, however, the drawback of this approach is the inter-personal differences among the individuals that make the model difficult to be generalized.

3.2. Eye-tracking method

Eye tracking is another popular method being used to measure student's attentiveness in class. This method measures the movements of the eyes and/or body while students are positively or negatively interacting with the learning environments in a time-varying manner. By analyzing gaze patterns, fixations, saccades, and other eye movement metrics, researchers can gain insights into students' attention levels and their engagement with learning materials. The other attentiveness indicator is the blink rate. The blink rate is low when the students contact with object of interest. In contrast, high blinking rate associate with fatigue [36]. A study conducted by Veliyath [37] which focus on eyetrackers to model students attention. Tobii 4c Eyetracker is used to collect eye-gaze data. The environment setup was in a computer lab where students either to pay attention to lecture or looking at the computer. Throughout the class session, students were to self-report their engagement state through a pop-up survey from the computer screen. At the end, a machine learning model that to determine student's attention level is built in the combination of eye-gaze data collected and the self-reported data.

The other research investigates the use of eye gaze to predict mind wandering during computer-based learning. Mind wandering can be considered as an indicator of attention lapse during learning tasks. The study aimed to determine whether gaze data could be used to predict student's mind wandering when interact with computer-based learning and also help the student to re-gain the attention. This research covered different types of classroom setting (online and offline) to identify student's mind wandering while interacting with an Intelligent Tutoring System-GuruTutor. The study achieved success rates of 93% in real-time wandering detection in classroom for online model [38]. By identifying patterns associated with mind wandering, educators and researchers can gain insights into students' attention levels and adapt their instructional approaches accordingly.

3.3. EEG data

With the advancement of EEG detection tools, it has become increasingly feasible and cost-effective to detect attention by monitoring the variations in attention states. Leveraging attention as a bio-signal of the brain, a feedback mechanism can be devised, allowing learners to recognize physiological changes occurring during the learning process. This approach is commonly known as EEG-based Neurofeedback for measuring attention [39]. Studies have been conducted about children who are attending puberty to study about sleep disorders causing inattention [40]. The results indicated increased theta waves (θ) associated with attention. The brainwaves frequency can be divided into five waves, namely delta, theta, alpha, beta, and gamma [41], [42]. Each type of brain wave represents its mental states, and the value can be varied. When one of the five types of brain waves in our brain is either overproduced or underproduced, it can cause problems [43].

Everyone's attentiveness is different to the same learning, and that result the EEG signals of everyone is vary during the learning process. In a study conducted by George *et al.* [44], EEG data was collected using mobile sensors, and features were extracted from raw data. Support vector machine (SVM) classifier was used to calculate and analyse characteristic features that described students' attentiveness. . Thorugout the learning process, brain wave signals were adopted for collecting EEG signals of the subjects. Data processing modules and EEG sensing were used for filtering and preparing the collected data. Subsequently, the EEG signal features were extracted and organized into categories of attentiveness and inattentiveness. Although EEG-based attention applications aimed at controlling assistive devices through the utilization of brain waves, new challenges are emerging such as pre-processing strategies [45], techniques to reduce the noise [46], and types of electrodes to be used in data collection [47].

4. DISCUSSION

Online learning has the advantages of flexibility that allowing the students at their self-pace. It is also a great opportunity for university or education provide to reach wider range of students locally and internationally. Technology plays a vital role in term of planning, designing, and delivering of the online learning. Apart of student motivation and engagement, this review paper explores different learning style which can be incorporate into online learning which can contribute to the success of online learning. Subjective attention detection methods such as self-reporting or human observation mechanism are cost effective but not entirely reliable because the observers may have misinterpretation on everyone's behavior and does not provide real time result [37], [48]. Furthermore, monitoring attentiveness of online students remain challenging because the absence of physical class engagement and feedback from the instructors. Besides that, People may be unaware of their attention deficit condition, and therefore, it is difficult to measure using self-reporting instruments. Whether the students are attentizzve throughout the learning process or not greatly influences their self-efficacy.

Previous research conducted on the vision-based for objective attention detection method. This method mainly apply face detection, face recognition, face features, and pose estimation for attention detection [49]. The accuracy of face recognition is highly affected by maintaining the uniformity and the quality of input images. This method may be useful because students are most likely having lesser movement during the online class. With that advantage, a study suggested a student's attention monitoring and alert system for online classes. The system applied machine learning algorithms to process the image/video of the students during attending the online class, and then detect their attention level from attentive, yawning, and dozing state through face landmark [50]. To enhance the precision of the machine learning data analysis, a study was undertaken that integrated computer vision and EEG data sources [51]. The study investigated the correlation of the facial expression and the region of the brain activities.

Implementing computer vision methods for attention detection may require specialized hardware or software to capture high quality image in the online learning context, which can be costly for the students. Besides, there's possible raise of ethical concerns related to privacy and data security concern when the visual of the student attending the online class is being capture.

Despite studies showing that eye-tracking is effective in attention detection, however, the key challenge of this method is proper eye-calibration especial for students who are wearing glasses. In order to produce a more precision result, the calibration needs to repeat a few times for each participants [48]. Another significant disadvantage of video-based eye tracker is the low resolution of the image capture from the camera [52] and restricting the movement of the students within the range of eye tracking compound [53].

Hence, wearable eye trackers such as mobile eye trackers and head-mounted system are gaining popularity and more suitable for the real-world applications [30]. One of the concerns of eye gaze method is the biometrics identification of the student may be exploited during the tracking process [54].

Table 1. Summary of attention detection methods

Author	Objective	Method	Instrument	Analysis/Algorithm	Result
Mindoro *et al.* [34]	To predict student behavior (attentive or not attentive) based on the face recognition during class session.	Computer Vision based on facial expression	Web-camera	YOLOv3 Algorithm	The proposed model acheived 88.6% accuracy
Zaletelj and Košir [35]	To detect student's attention during lectures in the classroom.	Computer Vision based on facial and body features	Kinect One sensor	Decision Tree, K-nearest Neighbour (KNN)	The proposed model achieved moderate accuracy of 75.3%
George *et al.*[44] Al-Nafjan and Aldayel [55]	To use EEG signals for the detection of student's attention during online classes.	EEG Data (F7, F3, P7, O1, O2, P8, AF4)	Participant controlled and engaged in simulated train	KNN, SVM, Random Forest (RF)	RF obtained the best result and achieved 96% of accuracy
Gupta *et al.* [56]	To detect student engagement based on multimodal information in e-learning context	Computer Vision based on facial expression, eyes blinking, and head movement.	Web-camera and instructional video	Deep Convolutional Neural Network (CNN) model	The proposed system achieved 92.58% of accuracy
Gao and Tan [21]	To analyze the impact of different styles of online political course videos on students' attention during the COVID-19 pandemic using EEG	EEG data (FT7, FT8, T7, T8, C5, C6, TP7, TP8, CP5, CP6, P7, P8)	Instructional videos	SampEN, Statistical Analysis (Kruskal-Walli's test, Mann-Whitney U test)	The instructional video that shows the appearance of instructor pointing at the content is more likely to elicit higher levels of students' attention.
Abate *et al.*[36]	To monitor student's attention during online learning.	Blink, gaze, and student's expression	Web camera, synchronous online learning, video recording, "attention prober" application	Eye Aspect Ratio (EAR), statistical analysis	The heat-map from the attention monitoring application indicates the attention level of students towards to material
Veliyath *et al.* [37]	To predict a student's attention using eye-tracker method.	Eye tracker	Tobii 4c Eyetracker, Self-report survey questions popup from screen for student to answer.	RF, SVM, Adaptive Boosting (AdaBoost), and Extreme Gradient Boosting (XGB)	XGB and SVM achieved higher accuracy 78%
Srivastava *et al.*[57]	To examine the use of eye-tracking to understand about learners' attention patterns.	Eye- tracking data while watching instructional video	Tobii Pro X230 eye-tracker, a Logitech RGB web camera, and an Optris PI-400 thermal camera.	Statistical analysis	Learners fixated on the same area of the video-lecture slide.

With the development of EEG detection tools, it became quite feasible and affordable to measure attention owing to variations in attention states [58]. Using attention as brain ware bio-signals, a feedback mechanism can be designed where learners can notice the changes in physiological states happening during the learning process referred to as EEG-based neurofeedback for measuring attention [39]. The evidence presented thus far supports the idea that use of EEG for online synchronous classes achieved good result to detect student’s attention level and maintain the student’s attentiveness during the lesson [9]. One significant advantage of using EEG in attention detection is the incorporation machine learning in the analysing the EEG data. Summary from Table 1 has indicated that deep learning models, such as CNN and recurrent neural networks (RNNs), have proven effective in processing EEG signals to identify patterns associated with attention levels.

On the other hand, despite these recent findings about the role of EEG in attention detection, this system also has its constraints. EEG modalities, headsets and data analysis methods are the most prominent challenges face by EEG-based BCI protocol. The preferred modalities in EEG, namely P300, MI, and steady state visual evoked potential (SSVEP), face issues in signal processing, especially in identifying methods for feature extraction and reduction [59]. This is because EEG signals are extremely artefact prone, non-stationary, and non-linear. For delivering remarkable outcomes, plenty of trials are required to concentrate on cutting down the period of calibration and effective training approaches [60]. Furthermore, EEG headsets require either liquid or gels on electrodes that are quite uncomfortable for the user. Dry electrodes can also be used between the scalp and pad [47]. However, the type of electrode to be used in EEG for attention measurement is a matter of open debate. It has been observed in previous studies that dry electrodes offer more noise and artefacts as compared to wet electrodes [61]. Besides that, EEG signals can vary significantly between individuals [62], and thus causing the attention measurement for each student may be challenging in online learning settings. Investigation about adaptive algorithms that can learn from individual data and provide personalized attention estimates may be conducted to overcome this issue.

The growth of machine learning has been significant in recent years, and it is expected to continue to grow in the future. There are huge opportunities for research in student’s attention detection and prediction in online learning. It has been observed that current short-term studies such as using small sample size of participants and in a constraint setup, may not necessarily show subtle changes over time. Machine learning is a type of artificial intelligence that involves training algorithms to make predictions or decisions based on data. With the increasing availability of data, the development of more powerful and efficient algorithms could benefit the development of attention monitoring in the context of online learning. Predicting a student's learning attention is a complex task, as there are many factors that can affect a student's ability to pay attention and learn. Some potential factors that could be considered when trying to predict a student's learning attention include their individual learning style, their current level of engagement with the material, their motivation and interest in the topic, and any external factors that may be impacting their ability to concentrate. Additionally, machine learning algorithms could be trained on data about a student's behavior, such as their test scores and performance on assignments, to predict their performances from student’s learning attention.

5. CONCLUSION

Online learning can reach to a wider audience due to its flexibility and customized time management for the participants. There are numerous advantages for the educational institutes to adopt online education as exclusive or complementary teaching tools. However, online learning also faces various of challenges such as keeping the students’ attentiveness due to the lack of face-to-face interaction and potential distractions from the online environment. Educators can help to mitigate these challenges by setting clear expectations and guidelines for the online behavior, providing regular feedback and support, and engaging learning environment. Understanding the students learning style also can help students stay engaged and focused on the online learning environment and reduce the potential distraction. Our finding also shows that machine learning methods hold significant potential for advancing the field of attention detection, due to their ability to effectively process and analyze complex data from multiple sources of data such as EEG, eye-tracking devices, facial expression analysis, and body movement sensors. These techniques allow for the extraction of meaningful patterns and features that can be used to infer students' attention levels. By integrating machine learning to the existing attention detection techniques, researchers can develop more effective strategies to enhance student engagement in online learning, adapt teaching materials to individual needs, and ultimately, improve learning outcomes. As the field of attention detection continues to evolve, it is essential for future research to explore the potential synergies between these methods, with the goal of creating a more holistic understanding of student attention and its role in the learning process. Future direction of the study can be expanded with multimodal data analysis that involved data from various sources, such as EEG, eye-tracking, webcam, and behavioral data, to create comprehensive models for understanding and predicting students' attention.

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