A Survey of EEG-Based Attention Detection Using Machine Learning and Deep Learning Techniques

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Abstract—This survey paper explores the field of attention classification using Electroencephalogram (EEG) signals, leveraging Machine Learning and Deep Learning algorithms for cognitive enhancement. Accurately identifying attention states is crucial for applications in education, neurofeedback, and brain-computer interfaces (BCI). EEG provides a non-invasive method to analyze neural activity, offering insights into cognitive engagement. This paper reviews various methodologies, including preprocessing techniques, feature extraction, and machine learning models applied to EEG data. It highlights the challenges and opportunities in EEG-based attention classification, emphasizing the need for robust models for real-time applications. This comprehensive survey aims to assist researchers, practitioners, and technology developers in understanding recent advancements and shaping future innovations in EEG-based attention classification using Machine Learning and Deep Learning.

Keywords— Electroencephalogram, Attention Classification, Machine Learning, Deep Learning, Brain-Computer Interface.

I. INTRODUCTION

In recent years, the rapid advancement of technology has transformed the educational landscape, particularly with the rise of online learning platforms and webinars. As educational institutions increasingly adopt digital formats, ensuring student engagement and attention has become a critical challenge. Traditional methods of assessing student attention, such as self-reports or observational techniques, often fall short in providing accurate and timely feedback. This gap highlights the need for innovative solutions that can monitor cognitive engagement in real-time, thereby enhancing the learning experience.

Electroencephalography (EEG) has emerged as a promising tool for tracking brain activity and understanding cognitive states, including attention. By utilizing EEG headsets, educators can gain valuable insights into students' attention levels during online classes or webinars. This technology allows for the continuous monitoring of neural activity, enabling the detection of fluctuations in attention that may occur throughout a learning session. The ability to provide real-time feedback when a student is not attentive can empower both learners and educators, fostering a more interactive and responsive educational environment.

This review paper aims to explore the current advancements in EEG-based attention detection methodologies, focusing on their applications within the education sector. By synthesizing findings from various studies, we will highlight the effectiveness of different machine learning and deep learning techniques in analyzing EEG data, as well as the implications of these technologies for enhancing student engagement. Ultimately, this review seeks to underscore the potential of EEG technology to revolutionize the way we understand and support attention in online learning contexts, paving the way for more effective educational practices and improved learning outcomes.

II. LITERATURE SURVEY

Al-Nafjan and Aldayel [1] proposed a brain-computer interface (BCI) system utilizing electroencephalography (EEG) signals to monitor student attention during online learning. The study aimed to enhance the quality of distance education by objectively assessing student engagement. Experiments were conducted on a public dataset, extracting power spectral density (PSD) features. The random forest classifier achieved a high accuracy of 96%, outperforming other methods. The findings indicate that the proposed system can effectively distinguish attention states, providing valuable insights for educators to improve student engagement and learning outcomes in online environments.

Wang et al. [2] developed a system to track drivers' focus of attention (FOA) during distracted driving using EEG signals. The study involved ten healthy volunteers performing a dual-task experiment that included a lane-keeping driving task and a mathematical problem-solving task. The researchers employed independent component analysis (ICA) to filter the EEG data and used support vector machines (SVM) for classification. The system achieved high classification accuracy in detecting the participants' FOAs, revealing that cognitive attention dynamically shifts between tasks. This research highlights the feasibility of using EEG for real-time monitoring of driver attention, potentially enhancing road safety.

References	Author's Name	Algorithm	Best Frequency Band	Channels	Which part of brain/electrodes	Data Collection	Data Preprocessing	Sampling Frequency Rate/Sampling	Parameters analyzed	Future Work	Accuracy
[1]	Abeer Al-Nafjan and Mashael Aldayel	k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF)	theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (above 30 Hz).	F7, F3, P7, O1, O2, P8, and AF4	prefrontal cortex and parietal cortex.	Publicly available EEG dataset with 25 hours of recordings from five subjects engaged in a virtual task.	Band-pass filtering (2–40 Hz), Independent Component Analysis (ICA) for artifact removal, and power spectral density (PSD) extraction.	128 Hz.	alpha–beta–theta ratio (ABTR), alpha–gamma ratio (AGR), theta–beta ratio (TBR), beta–theta ratio (BTR), beta–alpha ratio (BAR), and alpha–beta ratio (ABR).	Using larger EEG datasets and exploring deep learning techniques for improved classification.	Random Forest (RF) classifier achieved 96% accuracy
[2]	Yu-Kai Wang, Tzyy-Ping Jung, Chin-Teng Lin	Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel	Delta (1–3 Hz), Theta (4–7 Hz), Alpha (8–13 Hz), Low Beta (14–20 Hz)	32 Ag/AgCl electrodes (10–20 system)	Frontal, central, parietal, occipital, left motor, and right motor regions	EEG recorded from 10 healthy participants (20–28 years) performing a lane-keeping driving task and a mathematical problem-solving task	Down-sampling to 250 Hz, low-pass filtering (50 Hz), high-pass filtering (0.5 Hz), ICA for artifact removal	500 Hz	Power spectra of different frequency bands, feature extraction using FFT, stepwise linear discriminant analysis (SWLDA)	Developing a real-time system for tracking drivers' cognitive attention using EEG-based assessments	SVM-RBF achieved 94% accuracy in classifying focus of attention (FOA)
[3]	Mostafa Mohammadpour, Saeed Mozaffari	Artificial Neural Network (ANN) with Multi-Layer Perceptron (MLP)	Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz)	Fp1, Fp2, F3, F4, F7, F8, Fz	Frontal cortex	EEG recorded from 4 volunteers (ages 20–32) performing baseline (closed eyes), reading, mathematics, and sustained attention tasks	Low-pass filtering (50 Hz), adaptive filtering for physiological artifact removal, Discrete Wavelet Transform (DWT) for feature extraction	250Hz	Mean, standard deviation, power of Delta, Theta, Alpha bands	Using larger datasets, improving classification accuracy, real-time application using portable EEG devices like OpenBCI	79.75% (Baseline), 56.5% (Reading), 56.5% (Math), 61.25% (Sustained Attention)
[4]	Mitra Alirezaei, Sepideh Hajipour Sardouie	K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Bayesian Classifier	Beta band (effective features were observed here)	NA	NA	EEG signals recorded from 12 subjects in educational settings using a new protocol that does not require strong memory or language knowledge	Feature extraction from different frequency bands	NA	Signal energy and features from different frequency bands	NA	SVM and LDA classifiers achieved the highest accuracy of 92.6% on average
[5]	Esmeralda C. Djamal, Dewi P. Pangestu, Dewi A. Dewi (2019)	Support Vector Machine (SVM) with Wavelet Transform	Theta, Alpha, and Beta waves (4-30 Hz)	NA	NA	EEG signals divided into two states: attention and inattention. Data collected from 4 subjects	Wavelet filter used to extract EEG signals in the 4-30 Hz frequency range	NA	EEG frequency components (theta, alpha, beta) analyzed for classification	NA	The wavelet filtering approach increased accuracy from 80% to 90%
[6]	Jason Teo, Lin Hou Chew, Jia Tian Chia, James Mountstephens	Deep Neural Networks with Dropout and L1 Regularization	Alpha (highest accuracy for SVM at 89.36%), Theta (highest accuracy for KNN at 84.82%)	9 active electrodes (POz, Fz, Cz, C3, C4, F3, F4, P3, P4)	Standard 10-20 system electrode positions	EEG recorded from subjects using the ABM B-Alert X10 brain-computer interface headset	Signal denoising, spectral band extraction using Fourier Transform	256 Hz	Power spectral density, entropy, classification metrics	Testing additional classifiers, expanding dataset for improved generalization	Deep Neural Networks with ReLU activation achieved 79.76% accuracy
[7]	Chia-Ju Peng, Yi-Chun Chen, Chun-Chuan Chen, Shih-Jui Chen, Barthélemy Cagneau, Luc Chassagne	Hilbert-Huang Transform (HHT) + Support Vector Machine (SVM)	Alpha (8–13 Hz) and Beta (14–30 Hz)	Single-channel EEG (Fp1)	Frontal area	EEG signals collected from 20 participants performing attentiveness and relaxation tasks	Empirical Mode Decomposition (EMD) for intrinsic mode function (IMF) extraction, Hilbert Transform for frequency spectrum analysis	512Hz	Band powers, Spectral Entropies (SE)	Suggested improvements include using more EEG channels for better classification accuracy and potential applications for ADHD detection and biofeedback systems	Average classification accuracy of 84.80%
[8]	Reshad Hassan, Sakib Hasan, Md. Jubaer Hasan, Md. Rafat Jamader, David Eisenberg, Tanmoy Pias	Convolutional Neural Network (CNN) + Long Short-Term Memory (LSTM)	Gamma, Beta, Alpha, Theta, Delta	Single-channel EEG	Scalp EEG	EEG data from 30 human subjects using the Bitalino EEG sensor board in different attention states	Noise removal (muscle movement), Statistical Wavelet Packet Statistics (WPS) and Multi-Scale Wavelet Packet Energy Statistics (WPES) for feature extraction	1000Hz	Mean, standard deviation, skewness, kurtosis, entropy	Expanding dataset size and testing with different deep learning models	89%
[9]	Swati Aggarwal, Mohit Lamba, Kandarp Verma, Siddharth Khuttan, Hitesh Gautam	Classification model based on EEG energy bands and additional feature extraction	Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–25 Hz), Gamma (>25 Hz)	NA	General scalp EEG signal processing	EEG data collected from students in a classroom and MOOC learning environment	Removal of null values and poor signal reception data points Normalization using MinMaxScaler Data annotation based on synchronized video recording and student feedback	NA	Power of different EEG spectral bands, interrelation between alpha and beta power bands, additional calculated features R1 and R2 for attention state prediction	Improving classification models, expanding dataset, exploring additional EEG features for better attention assessment	NA
[10]	Chean Khim Toa, Kok Swee Sim	Convolution Attention Memory Neural Network (CAMNN)	Alpha, Beta, Theta (Event-Related Potentials - P100, P200)	3 channels (AF3, AF4, Pz)	Frontal cortex (AF3, AF4), Parietal cortex (Pz)	30 participants using EMOTIV Insight EEG headset for attention monitoring	Event-Related Potential (ERP) extraction, eye-tracking data integration	128Hz	Precision, recall, F1-score	Increasing the number of EEG channels to enhance classification accuracy	92%
[11]	Dhruv Verma, Sejal Bhalla, S. V. Sai Santosh, Saumya Yadav, Aman Parnami, Jainendra Shukla	Convolutional Neural Network (CNN) with Self-Attention Modules	Multi-band EEG (No specific frequency band mentioned)	14 EEG channels	Various brain regions analyzed through 14-channel EEG	20 undergraduate students (10 males, 10 females) Standard neuropsychological tasks for eliciting five types of attention (Selective, Sustained, Divided, Alternating, and Relaxed)	Low-level feature extraction with 1D convolutional layers and batch normalization Channel attention and temporal attention applied	NA	EEG multi-channel dynamics and temporal dependencies	Improving model generalization and exploring cross-subject personalization	92.30%
[12]	Moemi Matsuo, Takashi Higuchi	EEG Frequency Analysis + Behavioral Correlation Study	Delta, Theta, Alpha bands	NA	Occipital, Temporal, Central, Parietal, and Frontal lobes analyzed	12 healthy young adults EEG signals recorded during Trail-Making Test A and B (TMT-A, TMT-B)	EEG signal cleaning and artifact removal	NA	EEG power correlations with attentional task performance	Investigate EEG's role in predicting attention deficits	NA
[13]	Giulia Cisotto, Alessio Zanga, Joanna Chlebus, Italo Zoppis, Sara Manzoni, Urszula Markowska-Kaczmar	ttention-Enhanced Deep Learning Models (InstaGATs, LSTM with Attention, CNN with Attention)	Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–30 Hz)	Multi-channel EEG data	Multiple brain regions analyzed	EEG data from three publicly available datasets	Feature extraction: time-domain and frequency-domain features Computation of Spearman's correlation coefficients between EEG channels	NA	Time-domain, frequency-domain, and correlation matrix features	Further optimization of attention mechanisms in deep learning models	State-of-the-art performance across classification problems
[14]		Wavelet Packet Decomposition + Sample Entropy	Theta, Alpha, Beta	Multi-channel EEG	NA	EEG signals recorded during attention-related tasks	FIR filter applied (0.5–30 Hz) Independent Component Analysis (ICA) used to remove artifacts	512Hz	Time-domain features: rectified mean, peak difference, root mean square, standard deviation Sample entropy for complexity analysis Frequency band energy ratio (θ, α, β)	Extend study to larger datasets and validate across different EEG systems	NA
[15]	Dan Szafir, Bilge Mutlu	EEG-Based Passive Brain-Computer Interface (BCI) for Adaptive Agents	NA	NA	EEG-based real-time monitoring of user engagement	Participants interacted with an embodied agent that monitored attention using EEG signals	NA	NA	User engagement, real-time EEG signals, behavioral responses	Expanding adaptive agent applications for diverse educational settings	43% improvement in student recall abilities over baseline

Table 1. Detailed analysis of literature survey

Mohammadpour and Mozaffari [3] reported on the development of an electroencephalography (EEG)-based brain-computer interface (BCI) system designed to recognize four distinct levels of attention. The study aimed to measure the varying levels of attention in subjects by recording their EEG signals while they engaged in a series of tasks that ranged from non-attentive states, such as resting with closed eyes, to fully attentive states, such as performing mathematical calculations. The researchers utilized discrete wavelet transform (DWT) for feature extraction from the EEG signals and employed a multi-layer perceptron (MLP) neural network for classification. The system demonstrated effective classification of attention levels, providing insights into cognitive functions and the underlying mechanisms of attention. The findings highlight the potential applications of this BCI system in educational settings, clinical assessments, and other areas where monitoring attention is crucial. This research contributes to the understanding of attention mechanisms and offers a novel approach to enhancing attention recognition through EEG technology.

Alirezaei and Hamidpour [4] presented a study on the detection of human attention using electroencephalography (EEG) signals. The research aimed to develop a novel protocol for recording EEG signals to classify human attention levels in educational environments. The authors highlighted the significance of attention as a cognitive aspect that influences learning processes. They proposed a new approach that does not require strong memory or extensive language knowledge for effective data collection. The study utilized EEG signals from subjects engaged in various attention-demanding tasks, employing advanced signal processing techniques to extract relevant features. The results demonstrated that the proposed protocol could accurately classify attention states, achieving high classification accuracy.

This work provides valuable insights for educators and researchers, suggesting that EEG-based attention detection can enhance learning experiences and outcomes in educational settings.

E. C. Djamal, D. P. Pangestu, and D. A. Dewi [5] explored the development of a recognition system for student attention levels using electroencephalography (EEG) signals. The study aimed to enhance the evaluation of student learning processes by objectively measuring attention states during educational activities. The researchers implemented a system that utilized wavelet transform for feature extraction and a support vector machine (SVM) for classification. The experiments involved recording EEG data from students engaged in various learning tasks, allowing the system to differentiate between attentive and inattentive states effectively. The findings indicated that the proposed system achieved a high classification accuracy, demonstrating its potential as a valuable tool for educators to monitor and improve student engagement. This research contributes to the growing field of BCI applications in education, providing insights into how real-time attention monitoring can facilitate better learning outcomes.

Teo et al. [6] investigated the classification of affective states using electroencephalography (EEG) and deep learning techniques. The study aimed to enhance the understanding of human emotions and their impact on decision-making processes, with applications in neuromarketing, virtual rehabilitation, and affective entertainment. The researchers focused on recognizing human preferences and excitement through EEG signals while subjects were exposed to 3D visual stimuli.

They employed deep neural networks to improve classification accuracy, achieving up to 79% for preference classification and over 90% for excitement detection in immersive virtual reality environments. The findings demonstrated the effectiveness of deep learning in overcoming inter-subject variability challenges in EEG data, highlighting its superiority over conventional machine learning methods. This research contributes to the field of neuroinformatics by providing insights into emotion classification and the potential for developing more interactive and responsive systems in various domains.

Peng et al. [7] proposed an EEG-based attentiveness recognition system utilizing the Hilbert-Huang Transform (HHT) and Support Vector Machine (SVM) techniques. The study aimed to characterize different levels of attentiveness by analyzing electroencephalogram (EEG) signals from participants engaged in various tasks. The researchers collected single-channel EEG data from the frontal area and decomposed the signals into intrinsic mode functions (IMFs) using empirical mode decomposition (EMD). They then applied Hilbert transform analysis to obtain the marginal frequency spectrum, selecting band powers and spectral entropies as features for SVM classification. The results indicated that the proposed method achieved an average classification accuracy of 84.80%, outperforming traditional methods such as approximate entropy and fast Fourier transform. This integrated signal processing approach demonstrates potential for clinical applications in detecting attention deficits and offers a promising tool for attentiveness recognition in various settings.

Hassan et al. [8] presented a novel human attention recognition system utilizing electroencephalography (EEG) signals and advanced machine learning algorithms. The study focused on classifying attention levels into three categories: focused, neutral, and distracted, based on EEG data collected from 30 subjects engaged in various tasks, including watching videos and solving puzzles. The researchers employed a Bitalino EEG sensor board for data acquisition and implemented a hybrid model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for classification. After preprocessing the EEG signals to remove noise, they extracted meaningful features using statistical coefficients and wavelet packet statistics. The proposed system achieved an impressive accuracy of approximately 89% in determining attention levels, highlighting its potential applications in educational settings and cognitive state monitoring. This research contributes to the understanding of attention mechanisms and demonstrates the effectiveness of deep learning techniques in EEG signal analysis.

Aggarwal et al. [9] conducted a preliminary investigation to assess attention levels in Massive Open Online Courses (MOOCs) learning environments using electroencephalography (EEG) signals. The study aimed to compare attention levels between e-learning and traditional classroom settings, recognizing the growing importance of online education. The researchers captured EEG frequency bands from participants while they engaged in a short lecture in both environments.

The data was annotated for attentiveness based on participant feedback and video recordings, allowing for a comprehensive analysis of attention states. The study employed a Support Vector Machine (SVM) classification model to categorize students' mental states as attentive or unattentive. The results revealed that students maintained higher attention levels during MOOC learning compared to traditional classroom settings. Specifically, the average attention span in the classroom peaked at 6 seconds, while in the MOOC environment, it reached up to 8 seconds, indicating a more sustained focus in online learning.

The findings suggest that the MOOC environment may foster better attention retention, potentially due to its flexibility and accessibility. This research contributes valuable insights into the cognitive aspects of learning in different educational formats and highlights the effectiveness of EEG as a tool for measuring attention, paving the way for future studies on enhancing online learning experiences.

Toa et al. [10] presented a study on classifying attention levels using electroencephalogram (EEG) signals through a novel deep learning model known as the Convolution Attention Memory Neural Network (CAMNN). The research aimed to analyze participants' EEG signals to distinguish between attentive and inattentive behaviors, emphasizing the importance of attention in learning processes. The study utilized Troxler’s fading experiment to collect EEG data while participants focused on a central stimulus, with distractions introduced to elicit inattentiveness.

The CAMNN model was designed to optimize feature extraction and classification through an end-to-end learning approach, incorporating Vector-to-Vector (Vec2Vec) modeling. The model combined convolutional layers, attention mechanisms, and Long Short-Term Memory (LSTM) networks to effectively learn high-level features from raw EEG signals. The researchers compared the performance of CAMNN against several existing models, including Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Compact Convolutional Networks (EEGNet).

The results demonstrated that the CAMNN model achieved an impressive accuracy of 92% and an F1 score of 0.92, significantly outperforming the other models. This research highlights the potential of deep learning techniques in EEG-based attention classification and suggests applications in educational settings, medical research, and industrial monitoring. The findings contribute to the understanding of attention mechanisms and offer a promising framework for developing attention monitoring systems.

Verma et al. [11] introduced AttentioNet, a novel EEG-based measurement system designed to monitor and classify student attention types during learning activities. The study addresses the complex nature of attention, which is crucial for understanding students' goals, intentions, and interests in educational settings. The researchers proposed a Convolutional Neural Network (CNN) architecture that classifies attention into five distinct states: Selective, Sustained, Divided, Alternating, and Relaxed.

The dataset for the study was collected from 20 subjects who participated in standard neuropsychological tasks aimed at eliciting different attentional states. The model achieved an impressive average accuracy of 92.3% (SD=3.04) across subjects, demonstrating its effectiveness for real-world applications. The researchers also implemented a transfer learning approach to personalize the model for individual subjects, addressing the variability in EEG signals among different individuals.

Experimental results indicated that AttentioNet outperformed a popular baseline model, EEGNet, in both subject-independent and subject-dependent settings, with statistical significance (p-value < 0.05). The findings underscore the potential of AttentioNet for accurately classifying attention types using EEG data, which can provide valuable feedback to educators regarding student engagement and cognitive processes. This research contributes significantly to the field of EEG-based classification and highlights the importance of understanding different types of attention in enhancing educational practices and learning outcomes.

Matsuo and Higuchi [12] conducted a study titled "Decoding Attentional Task Performance Using Electroencephalogram Signals," which aimed to explore the correlation between attentional task performance and electroencephalogram (EEG) waves. The research highlights the significance of attention as a fundamental cognitive component and investigates how EEG patterns can serve as physiological biomarkers for predicting attention levels.

The study involved 12 healthy young adults who performed the Trail-Making Test (TMT) as attentional tasks while their EEG signals were recorded. The researchers focused on analyzing the power levels of different EEG frequency bands, including delta, theta, alpha, beta, low-gamma, and high-gamma waves, during both resting and task conditions. The results revealed significant correlations between EEG power levels and task performance metrics, such as error rates and task completion times.

Notably, stronger occipital delta power during rest was associated with higher error rates, while weaker temporal and central delta power during the TMT-B task correlated with longer task completion times. These findings suggest that delta waves, particularly in specific brain regions, play a crucial role in attentional performance and may be influenced by the induced cerebral lobes.

The study concludes that the default mode network (DMN) may serve as a predictor for attention deficits, emphasizing the need for further research into the intricate relationships between EEG frequencies and attentional task performance. This research contributes to the understanding of cognitive functions and the potential applications of EEG in personalized care and rehabilitation.

Cisotto et al. [13] conducted a comprehensive study titled "Comparison of Attention-based Deep Learning Models for EEG Classification," which aimed to evaluate the impact of different attention mechanisms in deep learning (DL) models on the classification of electroencephalography (EEG) signals. The research focused on distinguishing between normal and abnormal EEG patterns, including artifactual and pathological signals.

The authors compared three attention-enhanced deep learning models: InstaGATs (a Graph Attention Network), an LSTM (Long Short-Term Memory) model with attention, and a CNN (Convolutional Neural Network) with attention.

The study utilized multiple public EEG datasets to assess the performance of these models in classifying EEG segments. The results demonstrated that all models achieved state-of-the-art performance across various classification tasks, despite the inherent variability in the datasets and the relatively simple architectures of the attention-enhanced models.

A key finding of the study was that the application and placement of attention mechanisms within the models significantly influenced their ability to leverage information from different domains, including time, frequency, and spatial representations of the EEG data. The authors highlighted that attention mechanisms could enhance the explainability of DL models, making it easier to interpret the relevance of specific EEG features in classification tasks.

The study concluded that attention mechanisms represent a promising strategy for improving the quality and relevance of EEG information in real-world applications.

Additionally, the findings suggest that attention-enhanced models can facilitate the parallelization of computations, thereby accelerating the analysis of large electrophysiological datasets.This research contributes to the growing field of EEG classification and deep learning, providing insights into how different attention strategies can be effectively utilized to enhance model performance in various EEG-related applications.

Xu et al. [14] proposed a multi-level attention recognition method based on feature selection for electroencephalogram (EEG) signals. The study addresses the limitations of existing attention-recognition studies, which often focus on single-level attention states. The researchers designed four experimental scenarios to induce varying levels of attention: high, medium, low, and non-externally directed attention. A total of 10 features were extracted from 10 EEG channels, including time-domain measurements, sample entropy, and frequency band energy ratios.

The classification of the four different attention states was performed using a Support Vector Machine (SVM) classifier, achieving an initial recognition accuracy of 88.7%. To enhance classification performance, the researchers employed a sequence-forward-selection method to identify the optimal feature subset with high discriminating power from the original feature set. The results indicated that the classification accuracy improved to 94.1% when using the filtered feature subsets. Additionally, the average recognition accuracy based on single subject classification increased from 90.03% to 92.00%.

The findings of this study underscore the effectiveness of feature selection in improving the performance of multi-level attention-recognition tasks. The proposed method not only enhances the accuracy of attention classification but also reduces computational complexity, making it suitable for real-time applications in various fields, including healthcare, education, and driver monitoring.This research contributes to the understanding of attention mechanisms and highlights the potential of EEG-based systems for accurately recognizing different levels of attention, paving the way for future advancements in cognitive state monitoring and intervention strategies.

Szafir and Mutlu [15] explored the design of adaptive agents that monitor and improve user engagement, particularly in educational contexts. The study emphasizes the importance of embodied agents as educational assistants, exercise coaches, and collaborative team members, which necessitates the ability to monitor users' behavioral, emotional, and mental states. The researchers focused on developing adaptive agents capable of real-time attention monitoring using electroencephalography (EEG) signals and employing verbal and nonverbal cues to recapture diminishing attention levels.

The experimental evaluation involved an adaptive robotic agent that utilized behavioral techniques to regain attention during drops in engagement. The results demonstrated a significant improvement in student recall abilities, with a 43% increase over the baseline, regardless of gender. Additionally, the adaptive agent significantly enhanced female motivation and rapport with the instructor.

The study draws on principles from brain-computer interfaces (BCI) and educational psychology to inform the design of these adaptive agents. The authors argue that effective adaptive agents can replicate the immediacy cues used by human educators, such as gestures, eye contact, and vocal variations, to foster a more engaging learning environment.

The findings provide valuable guidelines for developing adaptive agents in educational settings, highlighting the potential for these systems to enhance learning outcomes by actively responding to users' attentional states. This research contributes to the broader field of human-robot interaction and underscores the significance of designing intelligent systems that can adapt to and support user engagement in real-time.

III. Results and Discussion

The survey presented in Table 1 provides a comprehensive overview of EEG-based attention detection methodologies, highlighting the significant advancements made in this field through various studies. Each study contributes unique insights into the relationship between EEG signals and cognitive attention, employing diverse approaches to data collection, signal processing, and machine learning techniques. The exploration of attention levels across different tasks and contexts enriches our understanding of how EEG can be utilized to monitor cognitive engagement in real-time.

The studies reviewed encompass a wide range of machine learning algorithms, from traditional methods like Support Vector Machines (SVM) and Random Forests to more complex deep learning architectures such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. This variety underscores the adaptability of attention detection systems, as different algorithms excel in capturing distinct patterns within EEG data. For instance, SVMs are effective in high-dimensional spaces, while deep learning models are adept at hierarchical feature extraction, allowing for nuanced interpretations of attention states.

The analysis of various frequency bands, including Alpha, Beta, and Theta waves, aligns with established neuroscientific principles.

Attention is often associated with specific neural activities, and the selection of frequency bands enhances the sensitivity of detection systems to relevant cognitive dynamics. Alpha waves, typically linked to relaxed alertness, and Beta waves, associated with active engagement, highlight the importance of aligning methodologies with the underlying neural mechanisms of attention.

Focusing on specific brain regions, such as the frontal and parietal lobes, is supported by neuroscientific evidence that indicates their roles in attention regulation. Investigating electrode placements, such as Fz and Pz, provides deeper insights into the neural correlates of attention, contributing to a more comprehensive understanding of cognitive processes.

The diversity in sample sizes across studies, ranging from small groups to larger cohorts, reflects the need for scalability and generalizability in attention detection models. While smaller samples may suffice for preliminary investigations, larger samples enhance the robustness and applicability of findings. The varied data collection methodologies employed, including tasks designed to elicit different attention levels, ensure that the models developed can adapt to a range of real-world scenarios.

The incorporation of diverse attention-inducing tasks, such as mathematical problem-solving and multimedia engagement, enhances the external validity of the findings. Different tasks engage distinct cognitive processes, influencing EEG patterns in unique ways. This diversity ensures that the proposed models can generalize effectively to various attention-demanding situations encountered in everyday life.

The presentation of performance metrics—classification accuracy, precision, recall, and F1-score—is crucial for a thorough evaluation of model efficacy. Each metric provides valuable insights into the strengths and limitations of the models, allowing for informed comparisons and improvements in future research. Overall, the findings from this review underscore the potential of EEG-based systems for real-time attention monitoring, paving the way for applications in education, healthcare, and human-computer interaction.

IV. CONCLUSION

This review paper has systematically examined the advancements in electroencephalography (EEG)-based attention detection methodologies, highlighting the significant contributions made by various studies in this evolving field. The integration of diverse machine learning and deep learning techniques has demonstrated the potential of EEG as a powerful tool for real-time monitoring of cognitive attention. By analyzing different frequency bands and focusing on specific brain regions, researchers have enhanced our understanding of the neural correlates of attention, providing insights that align with established neuroscientific principles.

The findings underscore the importance of employing a variety of algorithms, from traditional machine learning methods to sophisticated deep learning models, to capture the complexities of EEG data. The diversity in sample sizes and data collection methodologies reflects the need for scalable and generalizable models that can adapt to real-world applications. Furthermore, the incorporation of various attention-inducing tasks enhances the external validity of the results, ensuring that the developed models can effectively generalize to different cognitive scenarios.

As the field continues to advance, future research should focus on refining these methodologies, exploring novel algorithms, and expanding the range of tasks used to elicit attention. Additionally, the integration of EEG with other biometric measures could provide a more comprehensive understanding of cognitive states. Ultimately, the insights gained from this review pave the way for practical applications in education, healthcare, and human-computer interaction, where real-time attention monitoring can significantly enhance user experience and outcomes.

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