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FROM BRAIN WAVES TO ALGORITHMS: ADVANCEMENTS IN ELECTROENCEPHALOGRAM (EEG) SIGNAL PROCESSING

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ABSTRACT
Over the past three decades, the application of technology in neuroscience has revolutionized the study of the brain. Electroencephalography (EEG) is solely a type of Brain Surface Electric Reactivity or surface EEG, which does not infringe upon the tissue of the brain. It has helped identify neurological disorders and evaluate cerebral processes in people. This review reviews the substantial progress in EEG signal processing and its utilization. The rationale for moving from a conventional feature-extraction approach to wave detection to AI-based classification models will also be provided. Emerging technological advancements, such as the use of AI-based algorithms in EEG diagnosis, assume a central role in improving diagnostic performance for multiple neurological disorders. In addition, techniques used in the acquisition and preprocessing of EEG signals, as well as in noise reduction, feature extraction, and classification of EEG signals, are employed in the Analysis of EEG. Finally, the paper articulates the many uses of EEG signal processing in biomedical engineering. This shows that innovation has entirely reinvented the way neurological research and healthcare are conducted.

Keywords— Electroencephalogram, signal processing, machine learning, feature extraction, classification algorithms, brain activity analysis, emotion recognition, epilepsy prediction, AI-based algorithms.

INTRODUCTION

Brain science has changed significantly since the beginning of the 20th century, driven by the Electroencephalogram (EEG), a technique used to study brain electrical activity (Chaddad et al., 2023). EEG typically involves placing electrodes on the scalp to record electrical impulses from the brain, which indicate various neurological disorders and cognitive functions (Singh & Krishnan, 2023). Most importantly, EEG remains widely applied in neuroscience because it is a noninvasive approach and is compatible with other imaging modalities (Gurve et al., 2020).

Noninvasive electrode operation is a type of recording in the EEG Taxonomy (Figure 1). It means EEG signals, which are spontaneous biological potentials (Gao et al., 2023). The way out of this noise-interference problem is through the use of nonlinear and complex signal analysis methods (Khoshnevis & Sankar, 2019). The importance of EEG extends to the diagnosis of diseases related to brain disorders like Alzheimer's, epilepsy, schizophrenia, and cognitive decline (Daud & Sudirman, 2022). Accurate extraction of task-specific information requires applying machine learning algorithms, along with understanding the theoretical properties of EEG signals (Gao et al., 2023). Neurological communication is possible through continuous EEG recording of brain electrical activity, even when one is asleep or resting (Tran, 2022). Theta, delta, alpha, beta, and gamma are some brain wave rhythms used in diagnosing neurological diseases (Chaddad et al., 2023). Their nonstationary and nonlinear nature necessitates the application of computer-based approaches for efficient processing and analysis of EEG signals. (Gurve et al., 2020) All these fields have numerous possibilities of applying EEG: sleep stage, Identity, and emotion recognition, and neuroproteins (Singh & Krishnan, 2023).

Signal processing comprises steps such as purifying raw EEG data, followed by feature extraction and evaluation using machine learning algorithms (Daud & Sudirman, 2022). The significant preparatory steps include the following: reducing artifact redundancy through procedures such as bandwidth filtering and blind source separation (BSS) (Chaddad et al. 2023). At the feature extraction phase, data about changes in states over time, frequency, and time-frequency can also be captured (Singh & Krishnan 2023). More work is required in studies of EEG signal processing that can leverage publicly available databases in this field, such as GAMEEMO and DREAMER, which have fueled research on emotion recognition (Erle et al., § 8.2-8.10). Preprocessing removes artifacts from EEG data and is performed in three ways: filtering and resampling, and reference signaling (Chaddad et al., 2023). This review, therefore, intends to present various methods of EEG signal processing and their uses. This means a transition from extracting features to providing AI classes. This review also presents the employment of AI algorithms on EEG data, how EEG data are acquired and calibrated, different methods in eliminating noises, the feature extraction technique, and employing accurate classification algorithms, and several applications in biomedical engineering.

2. METHODOLOGY

In this review, we adopted not just a structured but a flexible methodology. This is done to identify, collect, and analyze recent research on EEG signal processing. In this paper, we focused on research on artificial intelligence (AI) methods. The main objective is to examine state-of-the-art research and developments in EEG signal processing to advance the understanding and development of classification systems. We have searched well-known research databases, which include IEEE Xplore, ScienceDirect, PubMed, and SpringerLink. We used the following keywords for the search query: EEG, Electroencephalogram, signal processing, feature extraction, machine learning, AI-based classification, neural networks, and deep learning. All keywords are integrated with EEG signal processing.

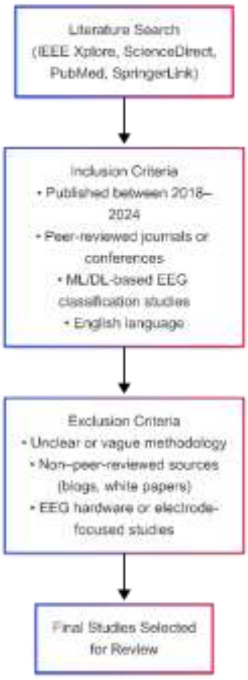

Figure 1. Search for inclusion and exclusion criteria.

After the inclusion and exclusion process as given in Figure 1, we began by reviewing the titles and abstracts. Once the paper is selected, a detailed analysis is done to understand its objectives, methodology, and results. The preceding sections were selected and reviewed in detail in the following sections.

2.1 EEG Algorithm Taxonomy

The paper is organized systematically according to its technical methodologies. The taxonomy of EEG classification algorithms is depicted in Figure 2. The taxonomy divided the existing approaches into ML, DL, and hybrid models. Each class of methods encompasses state-of-the-art classifiers, providing a clear and structured comparison of the algorithms used in EEG signal analysis.

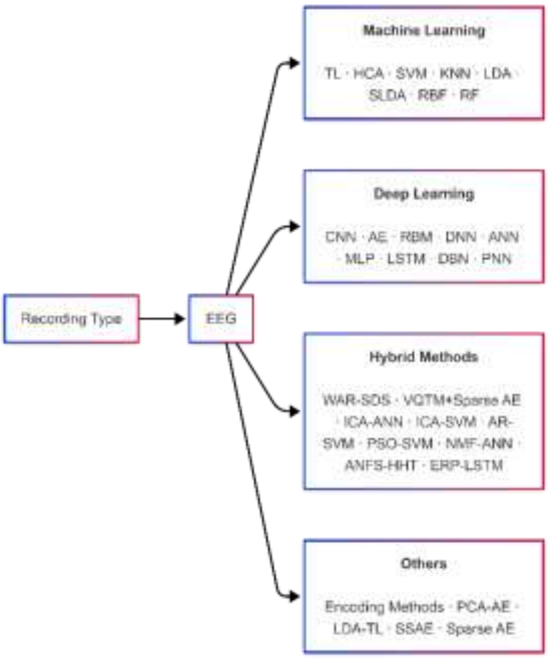

Figure 2.1EEG Taxonomy

3. LITERATURE REVIEW

Electroencephalography (EEG) is a neurophysiological technique used to measure microvolt-level electrical activity. Ionic currents in the human brain generate this activity (Smith et al., 2018). EEG helps understand brain function by capturing electromagnetic patterns associated with different mental and cognitive states. Several research works have established a strong understanding regarding brain regions and their corresponding EEG sub-bands (Jones and Brown, 2016).

Traditional methods first analyze the EEG signal and identify patterns, which then lead to the classification of the EEG signals. Signal features and manual visual inspection are essential in this. Classical ML classifiers are often limited in terms of accuracy and, architecturally. Further scalability limitations, with increasing computational overhead, also hurt the use of these classifiers (Wang et al., 2020). To address these limitations, more advanced branches of artificial intelligence (AI), such as deep learning, have emerged as highly scalable solutions and shown strong potential by automatically extracting meaningful features from large EEG datasets without manual intervention (Chen et al., 2019). The ability of DL methods to understand nonlinear, complex patterns enables improved performance in complex EEG classification problems, including seizure detection and mental state recognition. Recent advances in DL methods can handle large EEG datasets and automate processing without manual feature extraction (Chen et al., 2019).

The growing availability of affordable EEG devices supports these DL architectural progresses. The use of EEG has grown widely due to its research and clinical applications and healthcare (Zhang et al., 2017). For example, EEG-based brain-computer interfaces (BCIs) are showing encouraging results with patients with neurological disorders, particularly those resulting from brain injuries. These systems use EEG signals to understand brain activity and decode speech-related neural responses, leveraging advanced AI algorithms to interpret neural responses (Lee et al., 2021; Li & Wang, 2018). The fusion of real-time neural signals from the brain with intelligent decoding models reflects the growing potential of EEG-based systems for neurorehabilitation and assistive applications. The shift from traditional medicine to digital healthcare has been significantly influenced by technological advancements such as cloud computing, edge computing, and big data. These innovations have accelerated the development of AI-powered tools for analyzing physiological signals, particularly EEG. These days, EEG systems are embedded with AI algorithms capable of real-time monitoring and interpretation of brain activity, enabling applications such as early seizure detection, cognitive workload tracking, and even emotion recognition. These advancements are focused on improving diagnostic accuracy and also paving the way for more personalized, adaptive neurotechnology-based interventions.

The above findings focus on the growing power of AI in healthcare, and particularly in neurosciences, emphasizing the development of AI techniques with applications in specialized domains such as neurosciences, where algorithms are designed to handle the challenges of EEG data. Noda et al. (2024) developed an AI-based model to identify signs of depression using EEG data exclusively. It is the fusion of resting-state EEG and transcranial magnetic stimulation (TMS)-induced EEG. The paper used major machine learning algorithms and produced high recognition performance. This work highlights the potential of EEG as a noninvasive biomarker for mental health assessment when fused with AI methods. Similarly, Madakadze and McGill (2023) proposed a rapid-response EEG system that fuses AI algorithms to detect and classify nonconvulsive seizures. However, this paper also highlights that a high-quality EEG signal is critical for accurately understanding brain activity patterns. These findings and results are particularly valuable for improving diagnostic speed and supporting timely treatment decisions for patients with subtle or otherwise undetectable seizure activity. However, developing systems that provide a generalized solution remains tricky, and validation across diverse clinical environments is necessary to confirm generalizability. Wei et al. (2021) developed Epi-AI, an artificial intelligence-based system designed to detect seizures and monitor the progression of epilepsy in preclinical murine models. The system produced high sensitivity and specificity in identifying toxin-induced epileptic activity. The work is concentrated on various mouse models, which offer a semi-automated and objective-based strategy to EEG signal explainability.

In an interesting work by Li et al. (2021), they proposed a real-time affective computing platform that integrates an AI System-on-Chip (SoC) with multimodal biosignal processing, which includes EEG, ECG, and PPG. The proposed system improves emotion detection, highlighting the feasibility of embedding EEG analysis. This is done in consumer-grade health devices. However, EEG is limited in consumer technologies. In the context of clinical anesthesia, Liu et al. (2022) evaluated several AI techniques for predicting epileptic seizures using EEG signals recorded during anesthesia. The paper's results highlight that AI-based systems significantly enhance intraoperative monitoring and improve patient safety, for example, through early seizure prediction. Table 1 states a provisional analysis of AI-based algorithms and their performance on various EEG datasets, including seizure detection, depression diagnosis, and emotion recognition. When we talk about EEG, signal quality is crucial and remains a fundamental challenge in EEG-based healthcare applications. As Bohao et al. (2021) highlight, EEG signals are inherently nonlinear and nonstationary, which means that DL-based methods can handle EEG data effectively and understand diverse EEG signals, often contaminated by noise from muscle activity and eye blinks. Effective denoising is critical to obtaining an actual signal that will be processed by AI, which, in turn, improves decision-making and its reliability. Strategies such as time-frequency filtering, autoencoder-based methods, and deep residual shrinkage networks have been proposed. These strategies have trade-offs between performance, complexity, and real-time applicability (Sheoran et al., 2015).

4. EEG Signal Workflow: From Acquisition to Application

The pipeline of EEG signal processing generally consists of well-defined stages. Each stage builds carefully and needs the previous stage finish successfully and transform raw brain signals into meaningful and actionable outcomes. The stages are as follows:

- Signal Acquisition: Record raw electrical brain activity through wet or dry electrodes.
- Denoising: A critical stage in which artifacts or unwanted signal patches are removed, including muscle activity and environmental interference, to ensure clean, interpretable signals.
- Feature Extraction: A critical step, as most DL methods produce better results with higher-quality features that help them identify key signal characteristics, frequency bands, entropy, and temporal patterns related to cognitive interpretations.
- Classification: Applying ML or DL models to classify brain states based on extracted features.
- Applications: Using classified EEG data from real-world recordings is helpful for identifying seizures, tracking cognitive workload, or controlling a brain-computer interface (BCI).

The above stages help design a sequence that provides a comprehensive framework for EEG-based research and applications, where the success of these applications depends heavily on data quality, algorithms, and interpretability.

4.1 Acquisition and Calibration

Signal acquisition in this case is the conversion of electrical pulses; EEG signals are typically acquired from dry or wet electrodes. The mentioned stage is crucial in the process of brain-computer interface systems. In calibration, more specific BCI activities are applied to trigger the raw EEG signals. Bohao et al. (2021) emphasized that accumulating tagged samples enhances classifier performance and supports a robust classifier. Other than that, unknown human intentions cause raw EEG signals during the testing phase, which are, in turn, detected by the classification module. The process of amending the EEG data acquisition system to ensure that accurate and reliable information about electrical signals generated by the brain is obtained is referred to as EEG signal calibration (Bohao et al., 2021). The non-stationarity of EEG signals and their sensitivity to noise/artifact lead to considerable inter-subject variability, which makes calibration an essential step in developing a subject-specific BCI system. The raw EEG signals are recorded and preprocessed to increase signal quality without losing crucial information during the calibration phase, which also entails giving the subject BCI tasks. Accumulating tagged samples is beneficial to a robust classifier. Obtaining EEG signals requires accurate calibration and validation of ADCs. To reduce calibration time in EEG-based BCI, distinct signal-processing techniques should be developed for different subjects. Acquiring EEG signals requires careful consideration of the electrode selection and the first electrical circuitry front design technique (Huang et al., 2021) (Table 1).

OthersSource	Algorithm	Dataset	Accuracy	Advantage
Zhang et al., 2022	CNN	55 healthy subjects	85.00%	Automatically extracts features without human supervision
Lee et al., 2021	TL	27 subjects	65.65%	Transfers learned knowledge to new problems
Ahmed et al., 2020	LDA	22 subjects	68.60%	Basic supervised classifier for binary/multiclass problems

Table 1. Classification Accuracy of Selected Algorithms in EEG Acquisition and Calibration Based on Dataset Size.

As shown in Table 2, the CNN achieves the best classification accuracy, mainly due to its ability to automate feature engineering. In contrast, classical methods such as LDA performed worse, yet remain valuable, particularly in cases with lower computational requirements.

4.2 Denoising of EEG Signals

EEG signals are highly prone to contamination from various artifacts such as eye movements, muscle contractions, and external electromagnetic interference. Effective denoising is therefore an essential step in the EEG signal processing pipeline, ensuring that meaningful neural activity can be preserved and analyzed accurately.

Recent advances have introduced sophisticated techniques for automatic artifact removal. For instance, generative adversarial networks (GANs) have been employed to denoise EEG signals by learning to distinguish and suppress noise components. In experimental settings, the effectiveness of denoising methods is typically evaluated using metrics such as signal-to-noise ratio (SNR), relative root-mean-square error (RRMSE), and power band ratios. Algorithms such as SH, SV, and S have been proposed and tested under these measures, often alongside qualitative assessments and visual inspection to validate the integrity of the cleaned signals. Alyasseri et al. (2019) provided a comprehensive review of several widely used denoising techniques, including the wavelet transform—commonly used for analyzing nonstationary signals—Kalman filtering for estimating dynamic systems, and empirical mode decomposition (EMD) for decomposing complex EEG signals into simpler intrinsic components. In addition, regression-based models have been introduced as a complementary approach to filter noise while retaining the key features of brain activity. As shown in Table 3, denoising remains a dynamic and evolving field, with ongoing efforts to improve the robustness, generalizability, and computational efficiency of noise-removal techniques in real-world EEG applications.

Others Source	Algorithm	Dataset	Accuracy	Advantage
Radüntz et al., 2017	ICA-ANN	57 subjects	95.84%	Combining ANN and ICA yielded higher accuracy
Gandhi et al., 2014	RQNN	BCI Competition IV-2b Dataset	66.59%	Did not require prior knowledge about the nature of the noise
Lawhern et al., 2012	AR-SVM	7 subjects	95.86%	Captured scale-independent signal features

TABLE 2. PERFORMANCE OF SELECTED DENOISING ALGORITHMS IN EEG SIGNAL PROCESSING.

As stated in Table 2, ICA-ANN and AR-SVM performed the best and produced high denoising accuracy, which was above 95%. On the other hand, RQNN has the advantage of not requiring prior noise information, but it performs worse. These results highlight a trade-off between model interpretability, prior knowledge requirements, and accuracy in EEG denoising tasks.

4.3 Feature Extraction in EEG Signals

Numerous studies have explored a wide range of feature-extraction techniques for EEG signal analysis. The selection of a specific method typically depends on the desired outcome. Standard techniques include the discrete wavelet transform (DWT), the short-time Fourier transform (STFT), and general Fourier spectral analysis, all of which are widely used in brain signal processing, noise reduction, and feature extraction, as noted by Lian and Zhou. To evaluate the effectiveness of EEG signals, it is essential to consider their morphological properties, such as peak voltage and line length. Additionally, nonlinear features—such as approximate entropy and the Lyapunov exponent—are valuable for gaining deeper insights into brain activity (Ozdemir et al., 2021). Statistical metrics like standard deviation and correlation coefficients further enhance the comprehensiveness of feature extraction approaches (Khatun, 2019). Empirical mode decomposition (EMD) is also widely used for EEG data analysis, where intrinsic mode functions (IMFs) are employed to decompose signals into meaningful components (Ozdemir et al., 2021). Furthermore, spatial pattern recognition methods—particularly Common Spatial Pattern (CSP) algorithms—have proven effective in extracting discriminative features from EEG signals (Zeynali et al., 2023) (see Table 4).

Study	Application	Feature Extraction Method	Advantages	Limitations
Gao et al., 2023	Epilepsy diagnosis	Wavelet transform, Fourier transform	Simple, high accuracy	Limited interpretability

Zhang et al., 2023	Event-related potential classification	Shearlet and contourlet transforms	Handles multi-type information, effective for specific tasks	Complex architecture, requires large datasets
Said et al., 2022	Real-time BCI	Bandpass filter, CSP filter, Statistical features	Efficient, high accuracy for real-time applications	Limited representation of spectral information
Amorim et al., 2017	Epilepsy diagnosis	Shearlet and contourlet transforms	Effective for frequency band decomposition	Requires careful channel selection
Ergin et al., 2019	Emotion recognition	Empirical mode decomposition (EMD), Power Spectral Density (PSD), Hjorth parameters	Captures nonstationary information	Limited generalizability, requires domain knowledge
Asogbon et al., 2021	Artifact removal	Generalized Eigenvalue Decomposition (GEVD), Multi-channel Wiener Filter (MWF)	Effective for artifact removal, improves decoding accuracy	Requires large training datasets
Elsayed et al., 2021	User-independent BCI	Multisensory features	Robust, user-independent	Requires large datasets, limited interpretability
Kumari et al., 2022	Visual evoked potential classification	Short Term Fourier Transform (STFT), Spectrogram images	Captures time, frequency, and spatial information	High computational cost, limited generalizability
Akben et al., 2016	Migraine diagnosis	Burg-AR method	Identifies key channels for diagnosis	Limited to specific task, requires specific expertise
Zhang et al., 2021	EEG denoising	DWT + GMFMDE (Generalized Multiscale Fuzzy Entropy)	Benchmark for DL-based denoising	Requires large datasets, limited interpretability
Topic & Russo, 2021	Emotion recognition	Topographic (TOPO-FM) and holographic (HOLO-FM) representations	Improved recognition compared to 2D representations	Requires more complex computational resources

TABLE 3. SUMMARY OF FEATURE EXTRACTION METHODS IN EEG SIGNAL PROCESSING.

As shown in Table 3, feature extraction methods vary in complexity and applicability depending on the task. Traditional techniques such as DWT and STFT remain widely used for their simplicity and effectiveness, while advanced methods such as CSP, GEVD, and HOLO-FM offer improvements in specificity or robustness but require more computational resources or domain expertise. The trade-off between interpretability and performance is evident across all approaches.

4.4 Classification Techniques for EEG Signals

Once relevant features have been extracted from EEG signals, the next critical step in the processing pipeline is classification. This stage involves assigning EEG data to predefined categories based on cognitive states, neurological conditions, or stimuli, using machine learning (ML) and neural network techniques. Accurate classification is fundamental for applications such as brain-computer interfaces (BCIs), seizure detection, emotion recognition, and cognitive workload estimation. Commonly employed classifiers in EEG research include traditional algorithms such as Support Vector Machines (SVM), Naïve Bayes (NB), Logistic Regression, and Multilayer Perceptron (MLP), as well as more advanced architectures like Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). These classifiers differ in their computational complexity, interpretability, and suitability for handling nonlinear, high-dimensional EEG data.

For example, in the context of BCIs and epilepsy diagnosis, ML-based classification models are widely used to categorize EEG signals recorded under various cognitive or pathological states (Zhou & Lian, 2023). These models have proven effective in identifying seizure patterns, detecting attention levels, and supporting real-time BCI control systems.

A study by Gao et al. (2023) proposed a framework for analyzing anonymized EEG data for epilepsy diagnosis. The authors initially employed a learning transform to reduce signal noise and enhance discriminative features. They later introduced a novel Pattern Recognition Network (PRN) that achieved classification accuracy of up to 92.5%, demonstrating high specificity in seizure detection. These results underscore the significance of selecting an appropriate classifier based on the nature of the EEG data and the target application. The performance of these classifiers—evaluated in terms of accuracy, sensitivity, and specificity—varies with the complexity of the EEG patterns and the quality of the extracted features.

Further supporting this direction, Guerrero et al. (2021) applied Fourier analysis to identify epilepsy-related patterns in EEG data quantitatively. The study compared the performance of traditional pattern recognition methods, including multivariate logistic regression and artificial neural networks (ANNs). Their results showed that ANN outperformed logistic regression, achieving a classification accuracy of 86%, demonstrating its robustness in detecting seizure activity.

In another study, Amin et al. (2017) examined EEG signals under various cognitive conditions, highlighting how cognitive states significantly influence the performance of classification algorithms. Their findings emphasize the importance of context-specific modeling when designing EEG-based classifiers, especially in applications involving mental workload, attention, or fatigue detection. These findings collectively emphasize the importance of selecting and adapting classifiers based on EEG signal properties, noise levels, and the cognitive or clinical context in which the data are collected.

Study	**Topic**	**Classification Algorithm**	**Accuracy**
Gao et al., 2023	Epilepsy Diagnosis	(PRN)	92.5%
Ergin et al., 2019	Emotion recognition	SVM	81.80%
Asogbon et al., 2021	Artifact removal	GEVD-MWF	90.44% - 99.67%
Zhou & Lian, 2023	Emotion recognition	Transformer model	97.3%, 97.1%
Zeynali et al., 2023	Classification	Ensemble model with Spectral Transformer	96.1%, 94.20%, 93.60%
Wang et al., 2020	Emotion recognition	Deep CNN with EFDMs	90.59%, 82.84%
Ozdemir et al., 2021	Emotion recognition	Deep CNN	90.62%, 86.13%,
Guerrero et al., 2021	Epilepsy detection	Pattern recognition (MVR, ANN)	86%
Amin et al., 2017	Cognitive state detection	Pattern detection	-
Fan et al., 2023	Vision screening	Advanced signal processing	80%
Hussein et al., 2019	Epilepsy detection	Deep neural network (FC + LSTM)	100%
Bahador et al., 2020	Artifact detection	Deep neural network	92.30%

TABLE 5. SUMMARY OF CLASSIFICATION ALGORITHMS APPLIED TO EEG SIGNAL ANALYSIS.

The table presents a comparative overview of classification models used in recent EEG-based studies. Each entry reflects the model's reported accuracy in tasks ranging from neurological condition detection to cognitive state recognition. Deep learning approaches, such as CNNs and

Transformers, consistently achieve higher classification performance than traditional models, underscoring their potential for complex EEG analysis.

4.5 Applications of EEG Signal

Electroencephalogram (EEG) signal processing plays a vital role in various biomedical applications. It is utilized to monitor cortical activity, assess wakefulness levels, and diagnose progressive neurological conditions. Additionally, EEG signals are employed to provide feedback or control external devices (Gurve et al., 2020). Clinically, EEG has been instrumental in tracking and managing neurological disorders such as epilepsy (Gao et al., 2023; Amorim et al., 2017), brain tumors, spinal cord injuries, head trauma, and sleep-related conditions. Beyond diagnostics, EEG is widely used in brain-computer interface (BCI) systems for tasks such as motor imagery classification, emotion recognition, assessment of drug effects, and mental workload analysis (Tran, 2022). The ability to analyze EEG data in both temporal and spatial frequency domains enables a multidimensional understanding of brain function (Chaddad et al., 2023). Technological advancements—particularly in sensor design and artificial intelligence-enhanced signal processing—have further expanded EEG applications. Notably, the development of wireless dry electrode systems has improved the portability and practicality of EEG-based technologies (Gurve et al., 2020).

Recent developments in artificial intelligence have greatly enhanced the practical utility of EEG signals across a wide range of real-world applications. Deep learning-based classification models have demonstrated notable performance in areas such as emotion recognition, visual perception, epilepsy detection, and brain-computer interface (BCI) systems.

Kumari et al. (2022) introduced EEGCapsNet, a capsule-based deep learning architecture that used spectrogram images generated via the Short-Time Fourier Transform (STFT) to classify EEG responses to visual stimuli. Their model achieved accuracy rates of 81.59% and 84.62%. Similarly, Topic and Russo (2021) developed a model based on topographic and holographic EEG representations that improved emotion recognition. Murugappan et al. (2013) extracted frequency-domain features and applied KNN and PNN classifiers, resulting in successful classification of discrete emotional states. Maheswari et al. (2021) proposed a rhythm-specific CNN architecture that achieved strong performance across multiple emotion datasets, including DEAP, DREAMER, and DASPS. Zhou and Lian (2023) implemented a Transformer model for multi-channel EEG signals and attained high accuracy in binary (97.3%) and ternary (97.1%) emotion classification tasks. Additional studies by Ergin et al. (2019) and Long et al. (2021) emphasized the importance of EEG channel selection and feature identification in improving classification performance.

In visual classification, Zheng et al. (2019, 2020) proposed the ERP-LSTM framework, which outperformed conventional models in classifying visual EEG signals. Fan et al. (2023) applied EEG-based classification for vision screening, achieving up to 80% accuracy in distinguishing between normal and abnormal vision conditions. Mishra et al. (2022) demonstrated the viability of encoding EEG signals as images for deep learning models, achieving 70% accuracy on a benchmark dataset.

In clinical contexts, Srinath et al. (2021) presented a three-module deep learning system for automated epilepsy detection, reporting high classification performance. Said et al. (2022) improved real-time EEG classification by integrating bandpass filtering, Common Spatial Pattern (CSP), and LightGBM with automated hyperparameter tuning. Swetha et al. (2023) highlighted the efficiency of adaptive spatial filtering within SSVEP-based BCIs, which resulted in high accuracy and low computational demands.

Other contributions include the user-independent hybrid BCI proposed by Elsayed et al. (2021), which showed improved accuracy across users. Zeynali et al. (2023) developed a spectral-transform-based ensemble model that integrated temporal and frequency-domain features, achieving robust classification performance across varied EEG tasks.

Several recent studies have focused on improving the practicality and performance of EEG-based systems through deep learning techniques. Khatun et al. (2019) introduced a cost-effective and portable approach using a single-channel EEG system to accurately identify and differentiate mild cognitive impairment (MCI) in response to auditory stimuli. Wang et al. (2020) proposed a deep convolutional neural network (CNN) model to align the frequency distributions of EEG electrodes for emotion classification and found that transfer learning significantly enhanced classification accuracy.

Ozdemir et al. (2021) emphasized the importance of maintaining temporal, spectral, and spatial EEG information by proposing a deep CNN architecture based on multispectral topological images for emotion recognition. Zhao et al. (2020) employed a 3D-CNN model to extract spatial-temporal features, achieving classification accuracies of 70% for binary and 64.7% for four-class emotion classification tasks. Recognizing that emotional states often overlap and co-occur, Yang et al. (2022) integrated multi-task learning (MTL) into their emotion classification model, resulting in improved accuracy.

Moreover, Chen et al. (2019) highlight the superiority of deep CNNs over traditional classifiers, such as KNN, SVM, and Decision Trees, for binary emotion classification on the DEAP dataset. These findings reflect a broader trend in the literature that positions deep learning as a central technique for practical EEG-based emotion analysis, as summarized in Table 5.

Study	**Algorithm**	**Application**	**Performance**	**Significance**
Noda et al., 2024	LDA	Depression diagnosis	AUC: 0.922	High discrimination accuracy for depression using TMS-EEG features.
Madakadze & McGill, 2023	Clarity (AI algorithm)	Nonconvulsive seizure detection	High sensitivity & specificity for nonconvulsive seizure detection in critical care.	Potential for faster diagnosis and treatment, requiring further research.
Wei et al., 2021	Epi-AI (machine learning)	Seizure detection in mice	Sensitivity: 91.4% - 98.8%, Specificity: 93.1% - 98.8%	Enables fast, objective, and reproducible seizure analysis in preclinical research.
Li et al., 2021	LRCN classifier	Real-time emotion recognition	Accuracy: 77.41%	On-chip design enables real-time emotion monitoring with low power consumption.
Liu et al., 2022	18 AI algorithms	Epileptic seizure prediction during anesthesia	Test accuracy > 75%, F1 score > 0.06	Tree classifiers show potential for seizure prediction, further exploration needed.

TABLE 5. SUMMARY OF AI-BASED APPLICATIONS IN EEG SIGNAL ANALYSIS

5. DISCUSSION

5.1 Overview of EEG Signal Importance

Since 1950, EEG has playing a critical role in neuroscience and biomedical engineering. However, due to a lack of advanced technologies and better AI algorithms, the possibilities are far stronger. It enables noninvasive monitoring of brain electrical activity. This means valuable insights related to how your brain works and its cognitive functions can be understood to treat neurological disorders such as Alzheimer's disease, epilepsy, and schizophrenia. EEG also facilitates the evaluation of mental states during sleep or relaxation, mood swings, suicidal thoughts, and their characteristic using EEG patterns, which include alpha, beta, delta, and theta, are instrumental in clinical diagnosis.

5.2 Challenges in EEG Signal Processing

Despite its usefulness, EEG signal analysis presents several challenges. The signals are nonlinear, nonstationary, and highly susceptible to noise from muscle activity, eye movement, or environmental interference. These factors complicate signal interpretation and necessitate advanced preprocessing techniques such as bandpass filtering, Blind Source Separation (BSS), downsampling, and artifact rejection to enhance signal quality and reliability.

5.3 Advances in Signal Processing and AI Integration

Recent advances in artificial intelligence (AI) have significantly enhanced EEG signal processing. Feature extraction methods such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Hilbert-Huang Transform have been widely adopted to derive meaningful signal characteristics. Classification algorithms, including Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), and Convolutional Neural Networks (CNNs), have demonstrated improved accuracy in identifying neurological and emotional patterns in EEG data.

5.4 Applications and Case Studies

EEG is used in various real-world applications, including sleep stage classification, neuroprosthetic control, personality identification, and brain-computer interfaces (BCIs). Publicly available datasets such as DREAMER and GAMEEMO have facilitated emotion recognition research. Advanced models, including ERP-LSTM and rhythm-specific CNNs, have shown significant performance gains across different EEG-related tasks, underscoring the impact of deep learning in practical deployment.

5.5 Future Perspectives and Limitations

Looking ahead, continuous innovation in sensor technology and algorithm design is expected to improve EEG systems further. However, challenges remain, particularly in generalizing models across subjects and conditions due to inter-subject variability. The integration of wireless EEG systems and cloud-based platforms shows promise in enhancing portability and scalability. Nonetheless, ethical considerations and the need for interpretability in clinical settings remain critical for broader adoption.

6. CONCLUSION

EEG signal processing is critical and still in its infancy. However, it can play a pivotal role in neuroscience research by providing valuable insights into brain function and disorders. The integration of AI techniques has significantly enhanced EEG's utility, enabling more accurate predictions of neurological conditions such as epilepsy and the recognition of emotional states. There are many feature extraction methods; some popular ones are Principal Component Analysis (PCA) and the Hilbert-Huang Transform (HHT). Further, these methods showed notable effectiveness in improving the classification of subtle brain signal patterns. Furthermore, classification techniques such as KNN, SVM, Decision Trees, and Neural Networks continue to play a critical role in seizure detection and brain-computer interface (BCI) applications.

However, these advancements are still pretty limited. On the other hand, EEG-based technologies, if exploited to the extreme in medical diagnostics and cognitive research, can change the way neurological healthcare systems operate and significantly affect patients' quality of life. Moving forward, the continued integration of deep learning, wearable EEG systems, and transfer learning frameworks holds the potential to revolutionize real-time. Today, we need simpler systems for collecting EEG data and, further, systems that are processed by AI algorithms, leading to improved decision-making.

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