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EVALUATING AI FOR EPILEPSY DETECTION: AUTOMATED RECOGNITION OF CHARACTERISTIC EEG PATTERNS

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ABSTRACT

Electroencephalography (EEG) is a crucial diagnostic tool in epilepsy, providing high temporal resolution for detecting epileptic seizures and interictal discharges. Despite its significance, EEG analysis faces challenges such as susceptibility to artifacts, individual variability, and the need for specialized expertise.

In recent years, the rapid and intensive development of artificial intelligence (AI), in particular machine learning and deep learning methods, has shown that their application in EEG analysis can be useful in everyday clinical practice. The integration of artificial intelligence offers promising solutions to enhance EEG interpretation, automate routine analysis, and improve diagnostic accuracy. Machine learning algorithms, particularly convolutional neural networks, have demonstrated expertise-level performance in classifying EEG signals and predicting seizures, reducing clinician workload and increasing efficiency. AI applications extend to wearable devices and implantable systems for continuous seizure monitoring and personalized therapy.

However, challenges remain, including data quality, noise interference, privacy concerns, and the translation of research models into clinical practice. Future developments should focus on refining AI systems, improving dataset quality, and ensuring accessibility to enhance the diagnosis and management of epilepsy.

Methodology: For the purpose of this paper, electronic databases such as Scopus, Google Scholar, and PubMed were searched. The literature search covered publications released primarily between 2016 and 2025, with particular emphasis on studies published within the last decade, reflecting the dynamic development of artificial intelligence methods in EEG analysis. A literature review was conducted using the following keywords: electroencephalography (EEG), epilepsy diagnosis, Artificial Intelligence (AI), seizure detection, deep learning, machine learning, automated EEG analysis, neuroimaging.

Original research studies, case reports, and review articles were utilized. The search was limited to publications in Polish and English.

KEYWORDS

Electroencephalography (EEG), Epilepsy Diagnosis, Artificial Intelligence (AI), Seizure Detection, Deep Learning, Machine Learning, Automated EEG Analysis, Neuroimaging

CITATION

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Introduction

1. Diagnostic significance of EEG and emerging AI approaches

1.1. The importance of electroencephalography (EEG) in the diagnosis of epilepsy.

EEG (electroencephalography) is an electrophysiological method for recording the brain's electrical activity, distinguished by its high temporal resolution. This characteristic makes EEG a fundamental tool for evaluating dynamic neuronal processes. It holds particular significance in the diagnosis of patients with suspected epileptic seizures, epilepsy, and atypical paroxysmal events [1]. These signals also provide valuable insights into cognitive processes such as perception, attention, and memory. [2]

In the vast majority of epilepsy cases, EEG reveals characteristic changes both during seizures (ictal recordings) and in the interictal period. Most patients with epilepsy also exhibit interictal epileptiform discharges (IED), which include spike discharges (lasting <70 µs), sharp wave discharges (70–200 µs), and spike-wave complexes. The identification of these patterns in EEG plays a crucial role in the diagnosis and classification of epilepsy, enabling precise determination of the seizure focus type and location. Additionally, EEG is utilized during surgical procedures and in the assessment of postoperative complications such as ischemia or infarction. [1]

1.2. Challenges in EEG signal analysis.

Despite its numerous advantages, such as high temporal resolution, cost-effectiveness compared to other neuroimaging techniques[3,4], and flexibility, the use of EEG presents several challenges. One of these challenges is the integration of EEG with other methods, such as functional magnetic resonance imaging (fMRI). The simultaneous application of both techniques results in interactions between radiofrequency (RF) fields and gradient fields with the EEG leads, leading to the heating of individual components as well as the surrounding scalp tissue in contact with the electrodes. [5]

Another significant challenge in EEG recordings is the presence of artifacts—unwanted signals that interfere with the accurate interpretation of the data. The occurrence of artifacts is influenced by various factors, which are classified into internal and external artifacts. Internal artifacts originate from physiological processes within the body, such as heartbeat and muscle activity, while external artifacts result from environmental and methodological factors, including measurement errors, suboptimal recording conditions, or signal distortions caused by patient movement during the examination.[6]

During EEG analysis, it is also essential to consider individual differences in recordings, as the signal varies depending on factors such as skull thickness, conductivity, and brain structure. [2]

The interpretation and analysis of EEG require expertise and experience on the part of the examiner. In addition to the previously mentioned challenges, the specialist must differentiate false-positive IED detections. Improper filter settings can also affect the accuracy of the analysis—for instance, a low-frequency filter may suppress pathological delta waves, while a high-frequency filter may distort IED signals. [6]

1.3. Introduction to Artificial Intelligence Methods in EEG Analysis

The rapid advancement of artificial intelligence (AI) has led to its increasing application in medicine. The potential and capabilities offered by AI facilitate the daily work of physicians by assisting in accurate diagnosis and improving the efficiency of the diagnostic process.

AI refers to the simulation of human cognitive processes and reasoning by computers. It differs from traditional systems by utilizing machine learning and deep learning, enabling it to learn from mistakes and draw conclusions. As a result, artificial intelligence possesses the ability to continuously improve and refine its performance.[5]

The potential of artificial intelligence enables its increasingly widespread use as an auxiliary tool in EEG interpretation. This is particularly significant as AI contributes to enhancing the efficiency of medical centers by increasing the number of analyzed recordings. In addition to handling a larger volume of interpretations, AI also reduces the likelihood of diagnostic errors, thereby improving overall diagnostic accuracy. [6]

1.4 Aim of the study

In this study, we will explore the potential impact of artificial intelligence on EEG analysis in the diagnosis of epilepsy. We will examine the capabilities and advantages that AI offers in enhancing the accuracy and efficiency of electroencephalography interpretation. Additionally, we will address the challenges and future prospects associated with integrating AI as a standard auxiliary tool in clinical practice.

2. Basics of electroencephalography and EEG system characteristics

Electroencephalography (EEG) is the most commonly used tool in the diagnostic evaluation of patients with suspected epilepsy. When performed by skilled professionals, EEG provides crucial information that aids in both the diagnosis and classification of epilepsy, which is essential for making informed therapeutic decisions [7]. EEG can be categorized into two types based on the method of acquisition: intracranial EEG (iEEG) and scalp EEG (sEEG). Although sEEG is more prone to interference from external factors, its non-invasive nature and ease of use make it one of the most valuable tools in the diagnosis and treatment of epilepsy [8].

2.1 EEG examination procedure and its physiological foundations

The onset of an epileptic seizure occurs when a group of neurons synchronously discharge or misfire from several focal points, spreading to other hemispheres or the entire brain, leading to electrophysiological abnormalities. Diagnosis is primarily performed using EEG [9]. The EEG reflects a series of fluctuating field potentials produced by the synchronized activity of numerous neurons, detected by electrodes placed on the scalp.

The EEG system consists of 10–20 metal electrodes placed on the scalp, connected by 36 wires to a recording device. It measures the electrical potentials detected by each electrode. Electroencephalographic reactivity is assessed through simple tests, including eye-opening, hyperpnea, and intermittent light stimulation, which involves brief, intense light flashes with gradually increasing frequency. The EEG assessment typically takes around 20 minutes and does not require hospitalization [10].

2.2. Characteristic EEG patterns in epilepsy

Cortical excitability is usually assessed through the passive observation of interictal epileptiform discharges, including spikes, sharp waves, and high-frequency oscillations (HFOs). These discharges often occur frequently, sometimes several times per day or hour, and have long been utilized as markers of epilepsy, aiding both in diagnosis and in localizing epileptic brain tissue. These discharges are believed to result from the abnormal firing of a group of neurons, a phenomenon often referred to as "hyperexcitability" or "hypersynchronicity" [11].

Interictal spikes, including sharp waves and other epileptiform discharges detected with standard EEG electrodes, are brief paroxysmal events driven by cortical excitability. These spikes are valuable biomarkers for identifying epileptic regions, especially in surgical planning. The shared excitability underlying both spikes and seizures has led some to suggest that spikes can be viewed as "miniseizures," providing insight into the same disordered process that triggers full seizures [11].

EEG studies have primarily focused on the frequency range of 0.3–70 Hz. However, in recent years, there has been growing interest in higher frequencies. High-frequency activity refers to brain activity above 80 Hz, with high-frequency oscillations (HFOs) characterized as discrete EEG events containing at least four oscillations that clearly differentiate from the background activity. HFOs are further divided into ripples (80–250 Hz) and fast ripples (250–500 Hz). These oscillations can be either physiological or pathological and may occur spontaneously or be triggered.

Epileptic or pathological HFOs are considered promising biomarkers for identifying epileptogenic tissue in candidates for epilepsy surgery. Despite this, distinguishing between pathological and physiological HFOs remains difficult. HFOs that occur alongside spikes or during seizures are typically pathological, while those triggered by sensorimotor or cognitive tasks are usually physiological. Unfortunately, at present, it remains challenging to reliably differentiate between the two [12].

Apart from clear epileptic events such as spikes and HFOs, the continuous brain activity recorded during the interictal period may be altered in epileptic tissue. One objective and quantitative approach to assess this is through the measurement of EEG band power. The underlying principle of examining EEG band power is that abnormal cortical excitability is expected to manifest as a spectral pattern that differs from the normal spectral features of a brain region. By quantifying this deviation, we can identify markers of abnormal cortical excitability [11].

2.3 Traditional EEG analysis methods in epilepsy diagnosis

Epilepsy is one of the most prevalent and serious neurological disorders, yet the specialized skill required to interpret clinical EEGs is not commonly available. Even in countries with advanced healthcare systems, most EEGs are reviewed by physicians who lack formal training in EEG analysis [7]. Typically, neurophysiologists perform the task of visually inspecting EEG recordings to identify epileptiform patterns and their onset across the time series. However, this manual process is time-intensive and inefficient, particularly in cases involving long-term EEG monitoring. Additionally, the overlap of epilepsy symptoms with other neurological conditions and the contamination of EEG signals by artifacts (particularly those from extracranial or scalp sources) makes the visual analysis a highly demanding task, even for experienced neurophysiologists [9].

Literature Review Results

1. Artificial Intelligence in EEG Analysis

1.1. A Brief Overview of AI Methods

Modern methodologies for analyzing bioelectrical brain activity, particularly EEG signals, increasingly incorporate artificial intelligence techniques capable of capturing complex, nonlinear relationships inherent to neurophysiological data. The rapid progression of machine learning and the emergence of deep neural network architectures have significantly transformed conventional diagnostic paradigms in neurology, enabling automated recognition of pathological brain activity patterns with high accuracy. These approaches, firmly rooted in the principles of statistical learning theory, support not only classification tasks, but also regression, dimensionality reduction, and the modeling of temporal dynamics embedded in EEG time series. [13]

1.1.1. Machine Learning

Machine learning (ML) encompasses a set of methods that enable the construction of predictive models based on data, without the need for explicit programming of decision rules. In the context of EEG analysis, classical algorithms such as Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN) have demonstrated high effectiveness in signal classification, particularly when combined with appropriate feature extraction techniques such as Discrete Wavelet Transform (DWT), Independent Component Analysis (ICA), or Principal Component Analysis (PCA). Due to their low computational complexity and reduced susceptibility to overfitting, these models are particularly well suited for applications in resource-constrained environments, such as embedded systems or clinical settings with limited computational infrastructure.

In the study by Guharoy et al., the combination of DWT and ICA with classical ML classifiers (SVM, k-NN, and Naive Bayes) enabled seizure detection with an accuracy ranging from 94.5% to 100%, while maintaining low algorithmic complexity. [14]

1.1.2. Artificial Neural Networks

Artificial neural networks (ANN) represent a class of computational models inspired by the structure of the biological nervous system, capable of recognizing complex patterns in high-dimensional data. In EEG analysis, both classical architectures such as the multilayer perceptron (MLP) and deeper models—including convolutional neural networks (CNN) and recurrent neural networks (RNN), including long short-term memory (LSTM) networks—are commonly employed. MLP networks have shown high performance particularly in binary classification tasks when supported by carefully selected input features. In contrast, deep neural networks enable automatic extraction of spatial and temporal representations from EEG signals without the need for handcrafted feature engineering, making them especially effective in seizure detection and seizure-type classification.

In the study by Gupta et al., a single-layer neural network was applied to classify EEG data while preserving its one-dimensional structure. The model achieved 99.9% specificity and 99.5% sensitivity in seizure classification, along with approximately 81% accuracy in a multiclass task—demonstrating its potential for deployment in embedded systems and Internet of Things (IoT) applications.[15]

1.1.3. Deep Learning

Deep learning refers to a class of models based on multilayer neural networks capable of automatically extracting complex data representations. In EEG analysis, deep learning techniques—such as CNN, recurrent LSTM networks, and hybrid architectures (e.g., CNN-LSTM)—allow for the direct processing of raw signals without the need for manual feature engineering. These models have demonstrated high effectiveness in epileptic seizure detection, and their ability to model spatiotemporal dependencies makes them particularly suitable for tasks involving the classification of dynamic brain activity.

This is supported by the study conducted by Darankoum et al., in which a deep learning pipeline based on a CNN and a Transformer encoder achieved an F1-score of approximately 93% on the publicly available Bonn EEG dataset, demonstrating strong generalization capabilities across animal and human EEG data. [16]

1.2. Models Used for EEG Signal Analysis

The rapid advancement of artificial intelligence methods has led to the development of a wide spectrum of analytical models successfully applied in the processing and interpretation of EEG signals. Due to their complexity, temporal variability, and susceptibility to noise, electroencephalographic signals pose significant computational challenges, requiring advanced techniques for feature extraction and classification. In response to these challenges, the literature typically distinguishes three main categories of models: classical machine learning algorithms, deep neural network architectures, and hybrid approaches that integrate the strengths of multiple methodologies.

Each of these categories is characterized by distinct representational capacity, computational complexity, and susceptibility to overfitting, all of which are critical considerations in the context of limited availability of medical data.

1.2.1. Classical Machine Learning Algorithms

Despite advances in deep learning, classical machine learning methods continue to be widely applied in EEG signal analysis, particularly in the context of epilepsy diagnosis. Models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest (RF) offer solid performance while maintaining relatively low computational complexity and modest requirements regarding the size of training datasets.

- **SVM**

SVM is a supervised learning method based on maximizing the classification margin in the feature space. In EEG classification, it is commonly applied using transformed features—such as power spectral densities, statistical descriptors, or entropy-based measures—to distinguish between ictal and non-ictal EEG segments. In the study by Abdullayeva and Örnek, the effectiveness of the SVM algorithm was demonstrated when combined with spectral analysis using Welch's method. [17] The model achieved an accuracy exceeding 93% in detecting epileptic activity. The utility of SVM for EEG classification was further confirmed in the work by Li et al., where a lightweight approach for classifying neurological states from single-channel EEG recordings was proposed. [18] The SVM classifier, employing entropy features extracted from time–frequency matrix representations, achieved high accuracy comparable to other classical classifiers while maintaining low computational complexity.

- **k-NN**

k-NN is a non-parametric algorithm based on measuring distances between observations in the feature space. In the context of EEG analysis, it is frequently used to classify signals transformed using methods such as Discrete Wavelet Transform (DWT) or entropy-based coefficients. Although less scalable than SVM or RF, k-NN often achieves high sensitivity on relatively simple datasets.

In the study conducted by T. Monsoor, k-NN was shown to perform well in classifying preictal states based on time–frequency domain features, particularly in the analysis of single- and multi-channel EEG signals. [19] This is further supported by research by Wang et al., where both standard and improved versions of the k-NN algorithm were applied to epilepsy diagnosis based on EEG recordings.[20] The model achieved accuracy comparable to more complex methods, while maintaining significantly lower computational costs. These characteristics make k-NN a valuable tool in resource-constrained environments and mobile systems.

- **RF**

RF, an ensemble of decision trees, offers strong resistance to overfitting and provides mechanisms for assessing feature importance. In EEG applications, it is frequently used for the classification of sleep–wake states, epileptic seizures, and differential diagnosis in clinical contexts. In Shah's dissertation, RF was successfully implemented as part of a remote health monitoring system. The model achieved over 91% accuracy in seizure detection using simple statistical features. [21]

The effectiveness of RF in EEG analysis was also confirmed by Khan et al., who employed the algorithm to classify epileptic seizures within the framework of Internet of Medical Things (IoMT) systems. [22] RF delivered competitive classification performance, and its ensemble structure enabled robust processing of heterogeneous EEG data collected from multiple channels. The authors also highlighted the utility of RF in systems with automated feature extraction, particularly where minimizing the risk of overfitting is critical.

1.2.2. Neural Networks and Deep Learning Models

With the increasing availability of large-scale EEG datasets and advances in parallel computing, deep learning models have become the foundation of modern systems for seizure detection and classification. Architectures such as CNN, RNN, and their advanced variants—such as LSTM—demonstrate exceptional performance in analyzing both the spatial and temporal dimensions of EEG signals.

- **CNN**

CNN architectures are capable of detecting local and structural patterns in data, which makes them particularly useful for analyzing EEG time–frequency representations such as spectrograms or scalograms. Through the use of convolutional layers, these models can autonomously extract relevant features without the need for manual feature engineering.

In the study by Mekruksavanich et al., an enhanced deep learning model based on CNN with a Convolutional Block Attention Module (CBAM), supported by BiGRU layers, was proposed. [23] The model achieved exceptionally high accuracy (99.14%) in detecting epileptic seizures from EEG data, confirming the effectiveness of CNNs in capturing complex spatiotemporal features from bioelectrical signals. Similarly, Shoji et al. proposed a compact convolutional network (mEEGNet) optimized for seizure detection in patients with absence epilepsy. [24] The model achieved performance comparable to or better than standard CNNs in terms of AUC, sensitivity, and F1-score, while using significantly fewer parameters, making it particularly suitable for embedded systems and portable medical devices.

- **RNN**

RNN represents a fundamental class of deep learning architectures designed for processing sequential data where temporal structure is essential. Through their recurrent loops, these networks propagate information across time steps, enabling the modeling of dependencies between successive states in the signal—making them a natural fit for EEG analysis, where data streams exhibit strong temporal dynamics.

Despite their theoretical appeal, classical RNNs are limited in their ability to retain long-term dependencies due to the vanishing gradient problem. In practical EEG applications, their effectiveness often depends on appropriate preprocessing steps, such as the extraction of statistical features or signal transformations.

In the study by Talathi, the use of recurrent neural networks with Gated Recurrent Units (GRU) was proposed for seizure detection and early seizure prediction based on EEG signals. [25] The model, composed of two GRU layers, achieved 99.6% accuracy on the publicly available Bonn EEG dataset and was able to detect 98% of seizures within 5 seconds of onset. These results confirm the utility of classical RNN architectures for processing sequential EEG data and classifying brain states in the context of epilepsy.

- **LSTM**

The LSTM architecture is an extension of classical RNNs, specifically designed to effectively model long-term dependencies in sequential data. A defining feature of LSTM networks is the use of gate mechanisms that regulate the flow of information through the network—allowing it to retain or discard information based on previous states. These mechanisms consist of an input gate, a forget gate, and an output gate, which collectively control the state of the so-called memory cell.

In the context of EEG signal processing, LSTM networks are particularly valuable due to their ability to capture complex, dynamic, and nonlinear patterns characteristic of transitions between preictal, ictal, and postictal states. Moreover, LSTM models do not require extensive preprocessing, making them suitable for real-time applications.

The use of LSTM for epileptic seizure detection was thoroughly examined in the study by Hussein et al., where an architecture based solely on LSTM was proposed to classify seizures using data from the Bonn EEG dataset. [26] After appropriate signal segmentation, a model composed of an LSTM layer and a Softmax classifier achieved near-perfect classification accuracy. Notably, the LSTM network demonstrated strong robustness against common EEG artifacts, including muscle activity, eye movements, and white noise, highlighting its suitability for clinical environments and real-world detection systems.

1.2.3. Hybrid Approaches and Ensemble Models

An example of an advanced hybrid approach is the MP-SeizNet model - a deep learning architecture combining a CNN with a bidirectional LSTM (Bi-LSTM), designed to classify seizure types from EEG signals. [27] The model was trained on both wavelet-decomposed features and raw EEG signals, enabling the efficient fusion of time–frequency and sequential representations. MP-SeizNet achieved an F1-score of 98.1% in seizure-type classification and 87.6% in cross-patient validation, confirming the strong performance of CNN-LSTM architectures in automated EEG analysis.

In the study by Mansour et al., a composite deep learning model was proposed for seizure detection, combining CNN, Bi-LSTM, and an attention mechanism. [28] The input consisted of diverse functional and directional brain connectivity metrics, including Phase Locking Value (PLV) and Directed Coherence. The model achieved 97.03% accuracy on the CHB-MIT dataset, demonstrating high performance and offering interpretability through explainable AI mechanisms by identifying the relevance of extracted features.

2. Effectiveness of AI in recognizing epileptic patterns in EEG

2.1 Application of AI in the Classification of Normal and Pathological EEG Signals

The capacity of machine learning to handle vast and intricate data structures has made it a valuable tool in the field of EEG analysis. This has led to significant progress in developing automated systems for detecting epileptic seizures. In addition to identifying seizures in real time, these models are increasingly being applied to predict upcoming epileptic activity, offering a forward-looking approach to epilepsy management [29]. Importantly, the primary goal of AI in healthcare is not to replace clinicians, but to enhance their performance by alleviating routine burdens and assisting with tasks that might otherwise be overlooked. In the context of EEG interpretation, AI can automate the labor-intensive process of visually inspecting and annotating hours of EEG recordings. By categorizing signal segments into predefined classes - such as discharges, ictal and interictal phases, artifacts, and normal background - AI systems can generate structured summaries for clinical review, including lists of spikes, discharges, and seizures [9].

One notable implementation of this concept is SCORE-AI, an AI model developed and validated for the comprehensive assessment of routine clinical EEGs. Beyond the binary classification of normal versus abnormal EEGs, SCORE-AI is designed to further subcategorize abnormal recordings into clinically meaningful groups: epileptiform-focal, epileptiform-generalized, nonepileptiform-focal, and nonepileptiform-diffuse abnormalities. The expert-level performance achieved by SCORE-AI supports its use in remote and underserved regions. Additionally, in well-resourced centers, SCORE-AI has the potential to reduce workload by allowing experts to focus more on complex ICU or epilepsy monitoring unit (EMU) cases, while spending less time on EEGs classified as normal with near-perfect accuracy [7].

Scalp EEG remains a critical diagnostic modality, particularly in intensive care settings. Supporting this, a deep learning model developed by Jing et al. was trained on over 6,000 scalp EEGs from 2,711 patients and demonstrated expert-level reliability in identifying seizures and seizure-like patterns. Their study also introduced the concept of the "ictal-interictal-injury continuum," encompassing seizures, periodic discharges, and rhythmic delta activity. The model's performance, evaluated using calibration and discrimination metrics, matched or exceeded that of clinicians, underscoring its potential for accelerating EEG review processes [30].

Progress in AI applications has also extended to invasive EEG obtained from chronically implanted devices. These systems are evolving from open-loop configurations to advanced brain coprocessors that integrate real-time neural sensing and stimulation with cloud computing and machine learning algorithms. Classification systems, refined through extensive ambulatory EEG data, have proven effective in detecting epileptiform spikes and seizures, as well as classifying behavioral states such as sleep and wakefulness. When paired with patient self-reporting and behavioral tracking tools, these devices represent a promising step toward personalized, adaptive neuromodulation therapies [30].

2.2. Comparison of the accuracy of AI methods and traditional EEG analysis methods

Artificial intelligence (AI) has enabled the development of automated algorithms capable of efficiently processing high-dimensional, nonstationary EEG data, offering a significant advantage over traditional manual visual inspection by clinicians. These algorithms operate under expert supervision, progressively acquiring domain-specific knowledge and refining their internal parameters over time. This continuous learning process allows for incremental improvements in performance. When supplied with sufficiently large and high-quality datasets, and when appropriately optimized, AI systems can achieve a level of diagnostic accuracy comparable to that of domain experts [9].

Models such as SCORE-AI exemplify this capability, having demonstrated expert-level performance in the automated interpretation of routine clinical EEGs [7]. Similar findings were reported in a study by Tveit et al., in which an AI model designed for the analysis of routine outpatient scalp EEGs achieved high diagnostic accuracy across a large, multi-institutional holdout dataset, performing at a level equivalent to that of human experts [30].

2.3 Problems and limitations in epilepsy detection using AI.

Despite the considerable promise and vast potential of artificial intelligence (AI), a number of challenges and limitations must be carefully considered to ensure its safe and effective application in electroencephalography (EEG) analysis. The training of AI models necessitates exposure to large datasets comprising thousands of cases to achieve sufficient reliability and generalizability. However, epileptic seizures occur infrequently in routine clinical practice, which significantly limits the number of available annotated cases for AI training purposes. This scarcity of representative data slows the learning process[31], particularly in the context of more complex or atypical seizure presentations [34].

Moreover, AI systems demonstrate a higher propensity for interpretative errors when analyzing datasets contaminated with noise and artifacts, compared to those with minimal signal disturbances [35]. In some instances, AI algorithms may erroneously classify artifacts as epileptic seizures. Although the incidence of such false positives remains relatively low, ongoing efforts are essential to minimize misclassifications in order to meet safety standards and clinical acceptability [32].

Another critical concern is the inadvertent leakage of validation data into training datasets. Such data contamination can artificially inflate the model's performance metrics and lead to an overestimation of its interpretative accuracy in EEG analysis, thereby undermining the validity of reported outcomes [31].

Furthermore, cybersecurity presents a significant and evolving challenge. Although anonymized datasets are typically used in AI development, there remains a risk of re-identification through data triangulation or malicious cyberattacks targeting electronic health records. Such breaches pose serious ethical and legal implications by compromising patient confidentiality and data integrity [33].

3. Practical Applications and Future of AI in Epilepsy Diagnosis

3.1 Automated Diagnostic Support Systems in Clinics

Artificial intelligence (AI) in epilepsy diagnosis utilizes machine learning techniques to analyze EEG signals for seizure detection. The referenced study investigates the application of a convolutional neural network (CNN) for EEG signal analysis in epilepsy diagnosis. Traditional EEG analysis relies on visual inspection, which is time-consuming and prone to errors. The proposed system in the study employs a 13-layer convolutional neural network to classify EEG signals into normal, pre-seizure, and seizure classes. The achieved accuracy, specificity, and sensitivity were 88.67%, 90.00%, and 95.00%, respectively, demonstrating the effectiveness of this approach in epilepsy diagnosis [36].

Recently, deep learning technology has been widely applied to image processing tasks, enabling the extraction of useful features from data and the automatic processing of multi-channel signals. To ensure an effective automatic seizure detection system, a novel three-dimensional (3D) convolutional neural network (CNN) architecture has been proposed, where multi-channel EEG signals serve as inputs [37].

3.2 Implementation Potential of AI in Portable Devices (e.g., Home Monitoring Systems)

Wearable devices placed on the wrist or ankle are less invasive compared to traditional electroencephalographic (EEG) systems used for seizure monitoring. By utilizing specially designed seizure detection models based on deep learning, the feasibility of detecting various types of seizures using signals from wearable devices has been demonstrated.

Electrodermal activity, accelerometry (ACC), and photoplethysmography (PPG) data were collected from patients, with blood volume pulse (BVP) derived from PPG. Board-certified epileptologists identified seizure onset, offset, and classification based on video and EEG recordings following the International League Against Epilepsy (ILAE) 2017 classification. The fusion of ACC and BVP data achieved the highest detection performance, with a sensitivity of 83.9% and a false positive rate of 35.3%. Nineteen out of twenty-eight seizure types were detectable using at least one data modality, as measured by the area under the receiver operating characteristic (ROC) curve [38].

3.3 Future Developments and Potential Enhancements

Recent findings highlight the feasibility of seizure prediction using intracranial EEG (iEEG) recordings. The transition from the interictal to ictal state involves a "buildup" phase, which can be tracked using advanced feature extraction techniques and AI-based methods. However, before current approaches can be translated into real-world clinical devices, further research is required in areas such as feature extraction, electrode selection, hardware implementation, and deep learning algorithm optimization [39].

3.4 Challenges and Limitations

Although artificial intelligence (AI) offers numerous benefits, it is still in its early stages of development. Electroencephalography (EEG) plays a crucial role in detecting and analyzing epileptic seizures, which affect over 70 million people worldwide. However, the visual interpretation of EEG signals for epilepsy detection remains labor-intensive and time-consuming. Future research efforts should focus on simplifying diagnostic frameworks, not only for epilepsy but also for other neurological disorders [40].

Despite significant progress, there is still a lack of sufficient studies to fully harness AI's potential in epilepsy diagnosis and seizure prevention. More time is needed before AI-based devices capable of predicting seizures become widely adopted in clinical practice. In addition to improving accuracy and efficacy, manufacturers should also prioritize accessibility, as epilepsy affects an estimated 50 million people worldwide, often severely impacting their daily lives [41,42].

Discussion

The incorporation of artificial intelligence (AI) into the analysis of electroencephalographic (EEG) data represents a significant development in the field of epilepsy diagnostics. Recent advancements in machine learning—particularly deep learning—have demonstrated the capacity of AI models to interpret complex EEG signals with diagnostic accuracy that approaches, and in some cases exceeds, that of experienced clinicians. Systems such as SCORE-AI exemplify the practical application of such technologies, offering automated classification of EEG patterns into clinically relevant categories and thereby supporting more efficient diagnostic workflows.

AI-based tools offer considerable potential to enhance diagnostic throughput, particularly in settings where access to specialized neurological expertise is limited. By automating the labor-intensive process of EEG interpretation, these systems may alleviate the workload of clinicians, enabling them to allocate greater attention to diagnostically challenging cases. This redistribution of clinical resources could, in turn, expedite the diagnostic process and improve patient outcomes through earlier intervention.

Nevertheless, several critical limitations must be addressed before AI can be widely and reliably integrated into routine clinical practice. Chief among these is the dependency of AI systems on large, diverse, and high-quality datasets for training. The relative infrequency of epileptic events in routine EEG recordings constrains the availability of annotated data, particularly for atypical or rare seizure types. This limitation may hinder the generalizability and robustness of AI models across varied clinical contexts.

Moreover, the presence of artifacts and noise in EEG data presents a persistent challenge. AI algorithms may be susceptible to misclassifying such artifacts as epileptiform activity, thus generating false positives that compromise diagnostic specificity. This underscores the necessity for rigorous preprocessing, artifact reduction techniques, and model validation across heterogeneous datasets.

In addition to technical constraints, ethical and security considerations remain paramount. Although anonymization is standard practice in AI model development, the risk of re-identification through data triangulation or cyberattacks on healthcare infrastructure cannot be discounted. Ensuring data security, patient confidentiality, and compliance with relevant legal and ethical standards is essential to fostering trust in AI-assisted diagnostics.

Future directions in the field are likely to include the integration of multimodal data—such as wearable sensor outputs and intracranial recordings—to enable continuous, real-time seizure detection and prediction. These developments may facilitate a shift toward personalized, adaptive epilepsy management, though substantial research remains necessary to refine algorithmic accuracy, hardware compatibility, and clinical usability.

In conclusion, while AI holds transformative potential in the realm of EEG-based epilepsy diagnostics, its successful clinical translation requires the resolution of current methodological, ethical, and infrastructural challenges. Ongoing interdisciplinary collaboration between clinicians, data scientists, and policymakers will be essential in ensuring the safe, equitable, and effective implementation of these technologies in neurological practice.

Conclusions

Electroencephalography (EEG) remains a cornerstone in the diagnosis and management of epilepsy due to its exceptional temporal resolution and ability to detect characteristic epileptiform discharges. Despite its diagnostic value, EEG analysis poses significant challenges, including vulnerability to internal and external artifacts, difficulties in signal interpretation due to individual variability, and the need for specialized expertise.

Recent advancements in artificial intelligence (AI), particularly machine learning and deep learning methods, have introduced new possibilities for automating EEG analysis. AI algorithms, such as convolutional neural networks, have demonstrated high accuracy in classifying EEG signals into normal, preictal, and ictal states, thereby reducing clinician workload and improving diagnostic consistency. One notable model, SCORE-AI, has achieved expert-level performance in classifying EEG abnormalities and is particularly valuable in remote or underserved clinical settings.

AI's application extends beyond traditional EEG analysis, encompassing wearable technologies and implanted devices for real-time seizure detection and prediction. These systems leverage multimodal data sources—such as electrodermal activity and accelerometry—and aim to support home-based monitoring and personalized neuromodulation therapies. However, limitations persist, including the need for extensive, high-quality datasets, risks of misclassification due to noise and artifacts, data privacy concerns, and challenges in translating research models into clinically deployable tools.

Future efforts must prioritize the refinement of AI models, ensure ethical handling of patient data, and improve accessibility and hardware integration to fully realize AI's potential in enhancing epilepsy diagnosis and management.

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