A Survey of Machine Learning Techniques for Accurate Seizure Detection and Future Forecasting

Abstract

Epilepsy affects approximately 50 million people worldwide, with seizures significantly impacting quality of life. Accurate seizure detection and forecasting could greatly improve patient care and outcomes. This survey provides a comprehensive review of machine-learning techniques for automated seizure detection and prediction from electroencephalogram (EEG) data. We examine various approaches including traditional machine learning models, deep learning architectures like convolutional and recurrent neural networks, and hybrid methods. Key challenges include EEG signal complexity, inter-patient variability, and limited labeled data. We analyze performance metrics, datasets, and clinical translation potential across studies. While deep learning shows promise, issues remain in generalizability and interpretability. Emerging directions like multimodal data fusion, federated learning, and explainable AI offer opportunities to advance the field. This survey aims to bridge the gap between technological advances and clinical application, providing researchers and clinicians with a comprehensive resource on the state-of-the-art in machine learning for epilepsy management.

Keywords:seizure detection; epilepsy; scalp electroencephalography; machine learning; deep learning; clinical translation; Convolution Neural Networks.

1. Introduction

Seizures, particularly those related to epilepsy, are among the most common neurological diseases, affecting approximately 50 million people worldwide, according to the World Health Organization. Their unpredictable nature not only disturbs everyday living but also offers substantial health concerns, such as damage and, in severe cases, sudden unexpected death from epilepsy (SUDEP). We might greatly improve patient care by enhancing seizure detection and prediction accuracy, allowing for prompt interventions, personalized treatment methods, and potentially even seizure prevention[1][2].

EEG is the primary diagnostic tool for epilepsy, providing crucial insights into brainwave dynamics and electrical activity[3][4]. Electrodes are strategically placed on different areas of the scalp to capture EEG signals, as illustrated in **Figure 1**. Various types of seizures exhibit distinct EEG patterns:

1. Interictal Spikes: Brief bursts of high-frequency activity between seizures, signaling an increased risk of seizure onset.

2. Ictal Activity: EEG patterns observed during a seizure, which vary depending on the type and location of the seizure.

3. Slow Waves: Low-frequency waves that appear after a seizure, reflecting reduced brain activity.

4. 4. High-Frequency Oscillations (HFOs): Rapid EEG oscillations often seen alongside interictal spikes, are associated with epileptic activity.

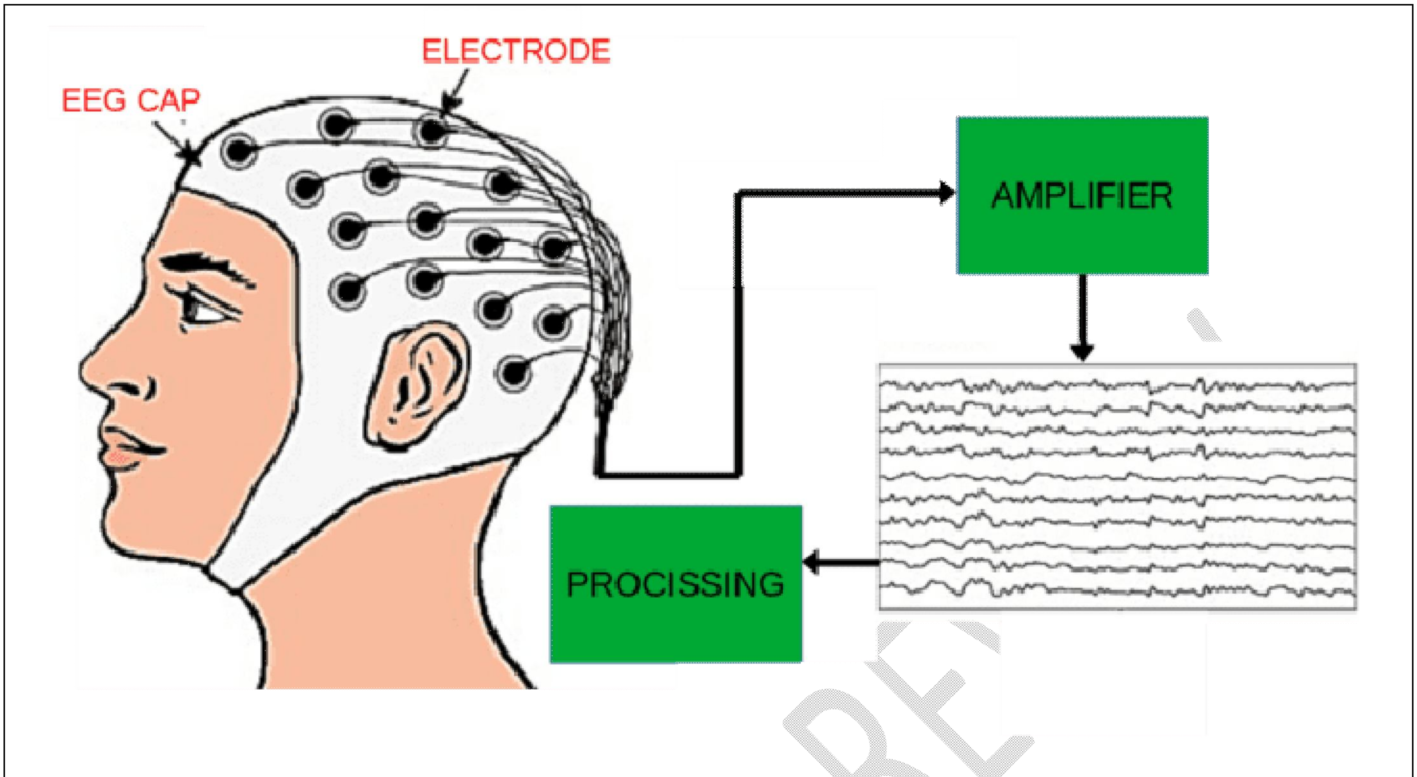


Figure.1.EEGrecordingsystem[5].

Particularly in the field of neurology, machine learning (ML) has emerged as a vital tool for improving predictive analytics and medical diagnostics in recent years. Traditional methods of seizure detection usually entail the manual examination of electroencephalograms (EEG) or video-EEG data by trained personnel. But in addition to being subjective and time-consuming, this approach lacks the scalability necessary for ongoing, real-time monitoring. The emergence of machine learning methodologies has presented the prospect of automated, real-time seizure detection, along with the additional possibility of predictive abilities. This technological advance is opening the door for a paradigm change in seizure disorder management, moving from a more reactive to a more proactive approach.

This survey aims to explore and evaluate the various machine-learning techniques employed for the detection and forecasting of epileptic seizures. We delve into how these techniques analyze complex datasets, typically derived from EEG, magnetoencephalography (MEG), or even wearable devices, to identify patterns indicative of pre-seizure states or seizure onset.

1.1 Scope of the Review

Approaches for Seizure Identification: This section will examine a variety of seizure identification algorithms, from sophisticated deep learning techniques to conventional signal processing techniques combined with well-known machine learning models like Random Forests and Support Vector Machines (SVM). Recurrent neural networks (RNNs) and convolutional neural networks (CNNs), which are especially useful for real-time seizure detection, will be covered in detail.

- **Predictive Models:** Let's look into predictive models, which are intended to identify seizures in advance. In addition to discussing various feature extraction techniques and highlighting intriguing machine learning models for forecasting seizure likelihood, this section will tackle the difficulties in detecting the preictal state. In this new area of predictive neurology, we'll also look at the special difficulties and intriguing developments.

- **Data Sources and Preprocessing:** A summary of the many forms of data that are utilized, along with feature engineering and preprocessing, which are essential to the effectiveness of machine learning models in seizure analysis.

- **Performance Measures:** Sensitivity, specificity, false positive rates, and the more recent metrics designed for the unbalanced datasets typical of seizure data are discussed in the evaluation of these models.

- **Challenges and Future Directions:** We will discuss the present constraints on machine learning (ML) applications for seizure detection and forecasting, including the necessity for individualized models as opposed to generalizable ones, interpretability issues with models, and the incorporation of multimodal data. We will also investigate new approaches to seizure pattern discovery, such as federated learning, transfer learning, and unsupervised learning.

1.2 Research Question
How can machine learning techniques be effectively applied to improve the accuracy of seizure detection and forecasting in epileptic patients, and what are the implications for clinical practice and patient outcomes?

1.3 Research Gap
Despite significant advancements in machine learning for seizure detection, there remains a gap in the comprehensive evaluation of these techniques, particularly in terms of their clinical translation and impact on patient care. Current research often focuses on technical achievements without sufficient exploration of how these technologies can be integrated into clinical workflows and improve patient outcomes.

1.4 Contributions
1. Comprehensive Review: This survey provides a thorough analysis of the current state of machine learning techniques used for seizure detection and forecasting, covering both traditional and deep learning methods.
2. Clinical Translation Insights: By examining the challenges and opportunities in translating these techniques into clinical practice, this survey offers insights into the practical implications of machine learning in epilepsy management.
3. Future Directions: The survey identifies emerging trends and future research directions, such as the use of multimodal data and interpretability of models, which are crucial for advancing the field.
4. Practical Guidance: By providing a detailed overview of data sources, preprocessing techniques, and performance measures, this survey serves as a practical guide for researchers and clinicians interested in implementing or evaluating machine learning tools for seizure detection.

This survey aims to bridge the gap between technological advancements and clinical application, offering a comprehensive resource for understanding and advancing the use of machine learning in epilepsy care.

1.5 Impact and Applications:
The implications of accurate seizure detection and forecasting extend beyond clinical settings. They include the development of alert systems for patients, aiding in drug dosage adjustments, and even influencing the design of implantable devices for seizure control. This survey not only serves as a technical overview but also highlights the transformative potential of ML in enhancing the autonomy and safety of individuals with seizure disorders.

By systematically analyzing the strengths and weaknesses of existing machine learning techniques, this survey aims to provide a foundation for researchers and practitioners to innovate further in this critical area of medical technology. Epilepsy is a persistent neurological illness that is characterized by the abrupt and unexplained onset of signs or symptoms that are brought on by aberrant electrical activity in the brain, these symptoms or signs might bring on seizures.

Figure 2 presents a comprehensive overview of the application of electroencephalogram (EEG) recordings in various clinical contexts for the detection, diagnosis, and monitoring of seizures and epilepsy.

- In**ward** settings, EEG recordings are primarily used for the detection of seizures and the monitoring of patients with status epilepticus. The primary challenges in this context include ensuring patient generalizability, ease of use, and robustness to noise. Scalp EEG recordings, typically lasting from minutes to days, are the predominant modality used inwards.
- In **telemetry units**, EEG recordings are employed for seizure detection, epilepsy diagnosis, and pre-surgical planning. The key challenges in this setting are the robustness of EEG analysis to different seizure types and the spatial localization of seizure onset and spread. Both scalp and intracranial EEG recordings are utilized, often lasting for days.
- In **community** settings, EEG recordings are primarily used for seizure detection, epilepsy diagnosis, and patient safety alarms. The challenges in this context include the need for simple hardware suitable for ambulatory patients and the lack of a clear clinical correlate for EEG findings. Scalp, intracranial, and sub-cutaneous EEG recordings are used, with durations ranging from days to months.

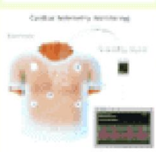
clinical context		USE CASE	SPECIFIC CHALLENGE	DURATION AND MODILITY
	ward	surveillance and seizure detection in epileptic states	generalization about the patient simple to operate resistant to noise and with a low false-positive rate for abnormal brain activity	continuous scalp EEG recording over an extended period
	telemetry unit	seizure detection, epilepsy diagnosis, and planning prior to surgery	resilience to seizure types, their regional localization, and their dissemination	long-term scalp or intracranial EEG recordings over several days
	community	epilepsy diagnosis, seizure detection, and patient safety alert	basic hardware not correlated clinically in ampulla patients	long-term EEG assessment incorporating scalp, intracranial, and subcutaneous recordings

Figure 2: Applications, Challenges, and Recording Modalities for Automated Scalp EEG-Based Seizure Detection

2. Challenges in Automated Scalp EEG-Based Seizure Detection

Automated scalp EEG-based seizure detection is an essential advancement in epilepsy care, providing continuous, real-time monitoring of brain activity. However, developing effective detection systems is fraught with challenges. These challenges arise from the inherent complexity of EEG data, the intricacies in defining seizures, and inconsistencies in data collection and labeling. EEG signals are highly variable, with non-stationary characteristics, frequent noise and artifacts, and significant variability both within and between patients, making seizure identification difficult. Defining what constitutes a seizure—especially in cases of subclinical events or seizure-like mimics—further complicates detection. Additionally, variations in recording quality, the potential for labeling errors, limited dataset sizes, and ethical considerations around data privacy create additional obstacles. Overcoming these challenges is crucial to improving the accuracy and reliability of automated seizure detection systems, ultimately enhancing patient care. The challenges for automated seizure detection from scalp EEG can be summarized as follows[6][7]:

1. Data Complexity

- **Non-Stationarity:** EEG signals are inherently non-stationary, meaning their statistical properties can change over time. This variability makes it difficult to develop models that consistently identify seizure patterns, as the EEG data does not adhere to fixed distributions or characteristics. Non-stationarity can arise due to various factors such as changes in brain state, alertness, or external influences, complicating the task of detecting seizures with high accuracy.
- **Noise and Artifacts:** EEG recordings are prone to contamination from various sources of noise and artifacts, which can mask or distort the signal of interest. Common sources of noise include muscle artifacts (e.g., from eye blinks or jaw movements), line noise from electrical interference, and motion artifacts. These contaminations can create false positives or obscure real seizure activity, posing a significant challenge for automated detection algorithms that must distinguish between true brain activity and extraneous noise.
- **Inter-patient Variability:** EEG patterns differ significantly between individuals due to variations in brain anatomy, physiology, and seizure types. This inter-patient variability makes it difficult to develop seizure detection models that generalize well across different patients. A model trained on one patient's data may not perform as effectively on another's, necessitating the development of more robust, adaptable algorithms that can accommodate this diversity.
- **Intra-patient Variability:** Even within the same patient, EEG patterns can change over time, influenced by factors such as medication, sleep, stress, or disease progression. These variations can lead to inconsistencies in seizure detection if the model is not designed to adapt to such changes. Intra-patient variability demands the development of dynamic models capable of adjusting to evolving EEG patterns without losing accuracy.

2. Seizure Definition

- **Subclinical Seizures:** Some seizures do not produce overt clinical symptoms, making them difficult to identify and label accurately. These subclinical seizures can be missed in manual reviews and pose a challenge for automated systems, which must detect subtle changes in EEG that may not correspond to obvious clinical signs. Detecting subclinical seizures is crucial for comprehensive monitoring and management of epilepsy[8].
- **Seizure Mimics:** Non-epileptic events, such as psychogenic nonepileptic seizures (PNES), can produce EEG patterns that resemble epileptic seizures. These seizure mimics can lead to false positives in automated detection systems, complicating the differentiation between true epileptic events and other phenomena. Accurate classification models are required to distinguish between epileptic and non-epileptic events to avoid misdiagnosis and inappropriate treatment[9].

- **Continuous Seizures:** Continuous or prolonged seizures, such as those seen in status epilepticus, present a unique challenge in distinguishing them from repeated discrete seizures. Automated systems must accurately identify the transition between seizure and non-seizure states to avoid misinterpreting a continuous event as multiple discrete seizures or vice versa. This requires sophisticated algorithms that can analyze the temporal dynamics of seizures with high precision[10].

3. Data Collection and Labeling Discrepancies

- **Variability in Recording Quality:** The quality of EEG recordings can vary due to differences in equipment, electrode placement, and recording settings. Variations in these factors can introduce inconsistencies in the data, making it difficult to develop standardized detection algorithms. Poor recording quality can lead to missed seizures or false detections, underscoring the importance of high-quality data collection protocols[11].
- **Labeling Errors:** Manual labeling of seizures in EEG data is a subjective process and prone to errors, particularly for subtle or atypical seizures. These errors can propagate through the training and validation of automated detection systems, reducing their accuracy and reliability. Ensuring accurate and consistent labeling is essential for the development of robust models[12].
- **Limited Dataset Size:** The availability of large, well-labeled EEG datasets is crucial for training effective seizure detection algorithms. However, such datasets are often limited in size, which can hinder the development and evaluation of models. Small datasets may not capture the full range of seizure variability, leading to overfitting and poor generalization to new patients or conditions[13].
- **Data Privacy and Ethical Considerations:** Collecting and sharing EEG data involve significant ethical and privacy concerns, particularly regarding patient confidentiality. The sensitive nature of medical data requires stringent protocols to ensure that data is handled appropriately, and patient consent is obtained[14].

These considerations can limit the availability of data for research and development, posing a challenge for advancing automated seizure detection technologies.

3. Domain-Specific Knowledge in EEG-Based Seizure Detection

3.1 EEG Recording Techniques

EEG, or electroencephalography, measures brain activity by detecting voltage fluctuations generated by neuronal activity. There are two primary EEG recording methods: extracranial and intracranial. Extracranial EEG involves placing electrodes on the scalp, while intracranial EEG involves placing electrodes directly in the brain or under the skin. Intracranial methods, such as electrocorticography (ECoG) and stereotaxic EEG, offer superior signal quality because they record activity directly from brain regions of interest, leading to a higher signal-to-noise ratio and fewer artifacts[15]. However, these methods are invasive, carry significant medical risks, and are primarily used in epilepsy surgery planning. As a result, intracranial EEG data is rare and typically patient-specific, limiting its general use in seizure detection.

Conversely, scalp EEG is the most common method for recording brain activity in seizure-related disorders. It typically involves about 20 electrodes placed on the scalp using the standardized 10-20 system. This system, however, has limitations, such as inadequate coverage of the lower brain regions, which can result in missed seizure activity. Scalp EEG primarily captures activity from cortical pyramidal neurons and offers a lower amplitude signal compared to intracranial recordings. Despite these limitations, scalp EEG is widely used due to its non-invasive nature and sufficient efficacy in clinical settings[16].

3.2 EEG Frequency Bands

EEG signals are categorized into frequency bands, each associated with different cognitive and physiological states. The five conventional frequency bands are shown in **Table 1**.

Table1:BasicBrainWavesCharacteristics[17]

Freq. Band	Details		
	Frq.HZ	Amp.mv	states
Gamma	Morethan30	5-10	Concentration
Beta	15-30	2-20	Anxietyis prevalent,energetic,focused onothers,andcalm.
Alpha	9-14	20-60	very calm,unresponsivefocus
Theta	4-8	2-100	internally concentratedand deeplyrelaxed
Delta	1-3	20-200	Sleep

3.3 Seizure Manifestations in Scalp EEG

Understanding the various manifestations of seizures in EEG is crucial for developing machine-learning algorithms for seizure detection. Seizures are characterized by abnormal, excessive electrical activity in the brain, and are classified as either focal (involving specific brain regions) or generalized (involving both hemispheres). Seizures can vary in duration, typically lasting from a few seconds to two minutes, but sometimes extending into a prolonged state known as status epilepticus, which requires immediate medical attention as shown in **Figure 3**.

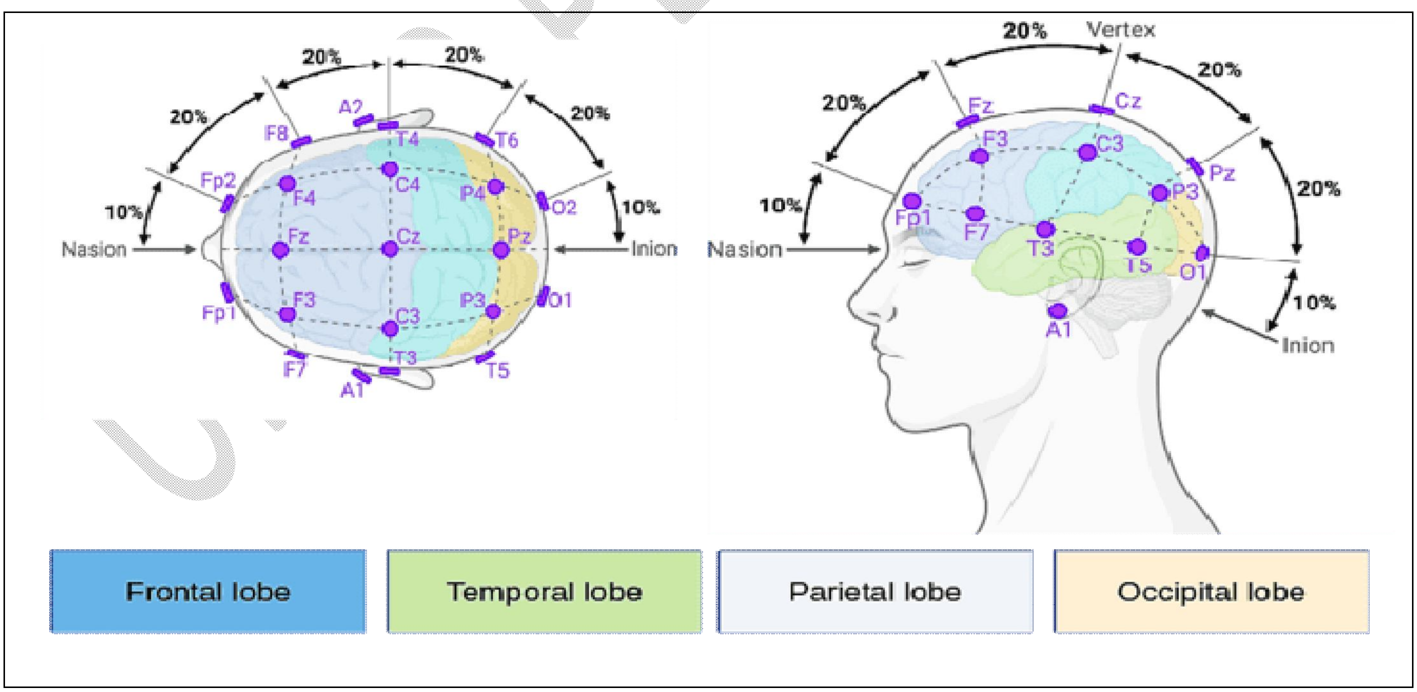


Figure 3: The 10-20 electrode placement system is based on front-back distances (from nasion to inion) of 10% and 20%. Scalp EEG setups can vary in spatial resolution, using anywhere from 1 to 256 channels. Each electrode is identified by one or two letters, followed by a digit, indicating its location. The letters

represent specific brain regions: Fp (frontal-polar), F (frontal), P (parietal), T (temporal), O (occipital), and C (central). Odd-numbered electrodes are positioned on the left side of the brain, even-numbered on the right, and Z electrodes are placed along the midline of the scalp[18].

Seizures progress through four phases as shown in **Figure 4**:

1. Inter-ictal: The baseline period between seizures, which may contain inter-ictal epileptiform discharges (IEDs) in patients with epilepsy.
2. Pre-ictal: The period immediately before a seizure, relevant for seizure prediction algorithms.
3. Ictal: The active seizure period, characterized by specific EEG patterns depending on the affected brain region.
4. Post-ictal: The recovery period after a seizure, often marked by distinct EEG abnormalities and patient confusion or drowsiness.

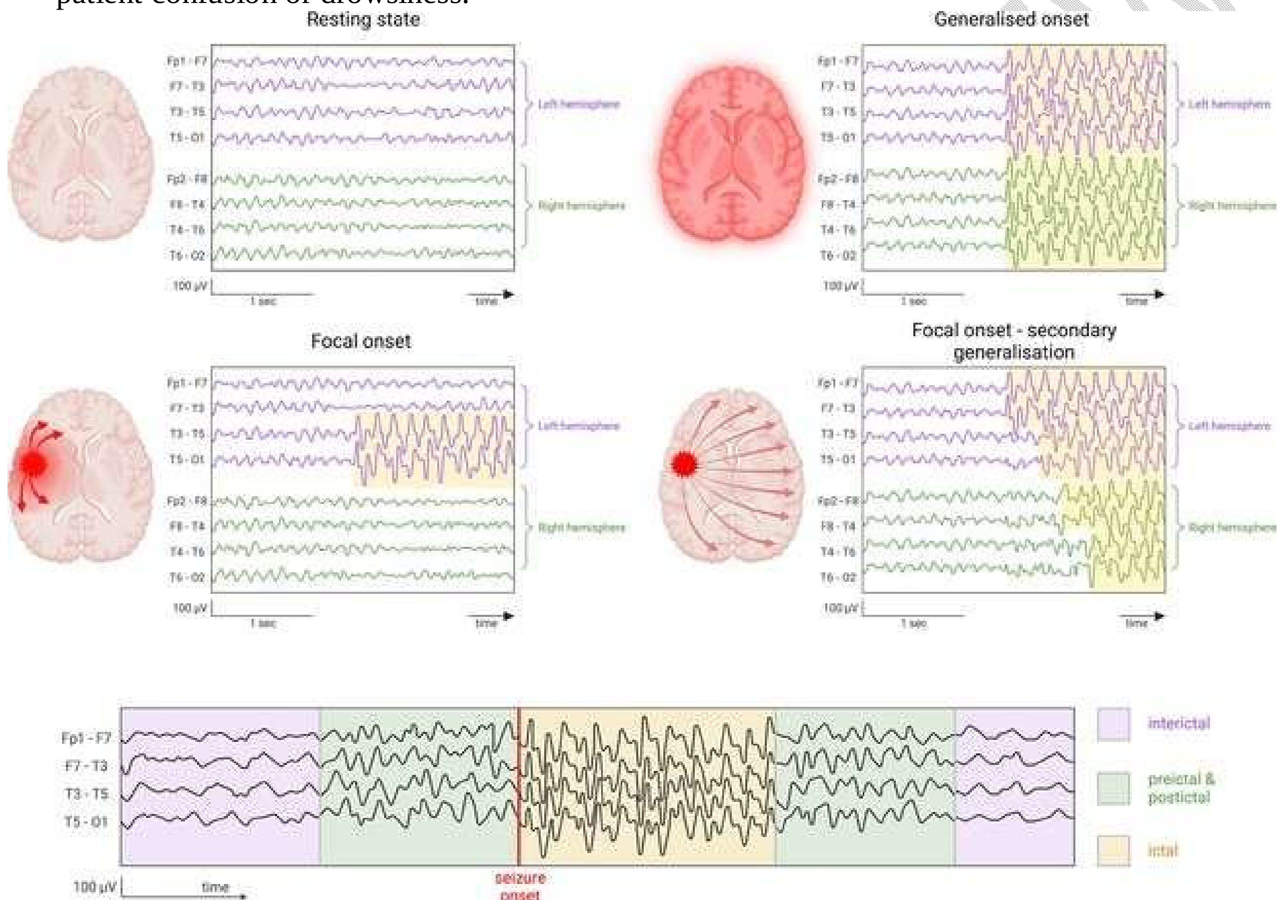


Figure 4. Main seizure types and some EEG characteristics. (Top) Normal brain activity, focal seizure,
andfocalonsetseizurewithsecondarygeneralizationalongsidetheirEEGcorrelate.(Bottom)Nomencla-ture of seizure phases including demonstrative EEG segments of inter-ictal, pre-ictal, ictal and post-ictal activity[18].

The detection of seizures is complicated by the fact that not all abnormal EEG activity is epileptiform, and not all epileptiform activity indicates a seizure.

3.4 Scalp EEG Artifacts

Scalp EEG recordings are prone to various artifacts that can interfere with accurate seizure detection. These include:

- Electrical and Environmental Interference: External electrical sources can introduce noise into the EEG signal.
- Ocular Artifacts: Eye movements and blinks can produce significant electrical potentials that contaminate the EEG.
- Muscle Artifacts: Movements such as jaw clenching or convulsions during seizures can introduce high-amplitude, high-frequency noise.
- Cardiac and Respiratory Artifacts: The heart's electrical activity and respiratory movements can also affect EEG recordings.

These artifacts can vary depending on the clinical setting and the patient's condition, and may even dominate the EEG signal during a seizure, potentially misleading detection algorithms.

Understanding these aspects of EEG recording and seizure manifestation is essential for the development of robust and accurate seizure detection algorithms.

4. Datasets

Electroencephalography (EEG) datasets are indispensable resources in the study and diagnosis of neurological disorders, particularly epilepsy. These datasets provide critical information about brain activity, captured through electrodes placed on the scalp, allowing researchers and clinicians to analyze patterns associated with various brain states. With the growing interest in artificial intelligence and machine learning for medical applications, the availability of diverse and high-quality EEG datasets has become increasingly important.

EEG datasets vary significantly in terms of patient demographics (such as age and species), the number of channels, sampling frequency, and the specific conditions recorded. Some datasets are publicly accessible, promoting open science and enabling widespread research collaboration. Others are private or require special access due to the sensitive nature of the data.

Table 2[19]provides a comprehensive overview of various EEG datasets, highlighting their availability, type, source, year of publication, size, number of channels, number of patients, sampling frequency, and the types of EEG segments included. This information is crucial for researchers selecting appropriate datasets for their studies, whether they are investigating seizure patterns, brainwave dynamics, or developing novel diagnostic tools.

Table 2: Overview of EEG Datasets

Ref.	Availability	Type	Source	Year	Size	No. of Channels	No. of Patients	Sampling Frequency	EEG Segments
[20]	Freely available	Adult	e-repositori upf.	2001	3.05 MB	100 single	5	173.61 Hz	Seizure states, healthy
[21]	Upon request	Pediatric and adult	–	2005	–	–	–	–	–
[22]	Freely available	Pediatric	PhysioNet repository	2010	42.6 GB	23–27	23	256 Hz	Intractable seizures
[23]	Freely available	Adult	e-repository upf.	2012	814 MB	64	5	512 Hz	Focal, Non-focal
[24]	Freely	Dog and	Kaggle	2014	105	–	–	–	Different types

Ref.	Availability	Type	Source	Year	Size	No. of Channels	No. of Patients	Sampling Frequency	EEG Segments
	available	human			GB				
[25]	Free but requires login	Adult	Website	2015	572 GB	20–31	10,874	250, 256, 512 Hz	Different types
[26]	Freely available	Adult	Researchgate	2016	604 KB	57	10	200 Hz	Ictal, inter-ictal, pre-ictal EEGs
[27]	Freely available	Paediatric (neonates)	Zenedo	2018	4.3 GB	19	79	256 Hz	Seizure onset
[28]	Requires registration	Adult	Website	2018	–	16	3	400 Hz	Seizure episodes
[29]	Private	Adult	–	2019	–	19	115	128 Hz	Epileptic and healthy
[30]	Private	Adult	–	2019	–	–	50	250, 256 Hz	Generalized and focal epilepsies
[31]	Private	Adult	–	2019	–	21	5	500 Hz	Focal and tonic-clonic
[32]	Private	Pediatric	–	2019	–	–	29	200, 500 Hz	Typical absence seizures
[33]	Private	Adult	–	2019	–	–	12	256 Hz	Seizure events
[34]	Private	–	–	2019	–	21	25	200 Hz	Seizure events
[35]	Private	–	–	2019	–	18	10	256 Hz	Seizure states
[36]	Private	–	–	2019	–	22	22	250 Hz	Ictal, non-ictal
[37]	Freely available	Adult	Zenedo	2020	20 MB	–	15	173.61 Hz	Inter-ictal
[38]	Private	–	–	2020	–	21	–	250 Hz	Seizure onsets
[39]	Private	Adult	–	2020	–	21	150	256 Hz	Seizure and normal
[40]	Freely available	Adult	PhysioNet repository	2020	20 GB	29	14	512 Hz	Epileptic seizures (focal onset, tonic-clonic)
[41]	Freely available	–	Figshare	2020	24.3 GB	–	39	–	Divided based on activity
[42]	Freely available	Adult	Mendeley repository	2021	3133 MB	21	6	500 Hz	Complex partial, electrographic, and video-detected seizures
[43]	Freely available	Pediatric and adult	Open neuro repository	2021	15 GB	52	30	2000 Hz	HFO markings
[44]	Freely available	Paediatric	IEEE data port	2021	5.12 GB	23–96	24	256 Hz	Ictal and pre-ictal EEGs
[45]	Private	Paediatric	–	2021	–	22	23	256 Hz	Peri-ictal and non-seizure EEGs

5. A. Modern Techniques for Epileptic Diagnosis

Advancements in technology have significantly transformed the landscape of epileptic diagnosis, particularly with the integration of Artificial Intelligence (AI) into healthcare systems. Among AI technologies, machine learning (ML) and deep learning (DL) have emerged as powerful tools for analyzing EEG data and diagnosing epilepsy.

5.1 Machine Learning vs. Deep Learning in Epileptic Diagnosis

ML and DL represent two distinct approaches to analyzing EEG data for epilepsy diagnosis. ML models typically involve a series of iterative processes, including feature selection, classification, and model evaluation. These models rely heavily on expert knowledge for selecting relevant features and tuning the parameters for classification. Despite their effectiveness, ML models often require extensive manual intervention and expertise.

In contrast, DL models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are designed to automatically learn features from raw data. However, they demand large datasets and substantial computational resources for effective training. DL models have shown great promise in capturing complex patterns in EEG data, often outperforming traditional ML methods when enough data is available.

5.2 Stages of Epileptic Diagnosis Using Deep Learning

The process of diagnosing epilepsy using deep learning involves several key stages, as illustrated in **Figure 5**. Each stage is crucial for developing an accurate and reliable model that can assist in clinical decision-making.

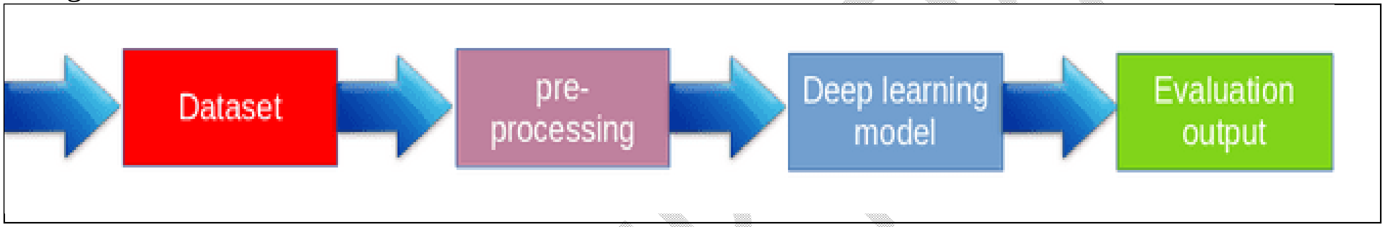


Figure 5.Stagesofepilepticdiagnosisbydeeplearning.

Data Preprocessing:

- Noise Removal: The first step involves cleaning the EEG data to eliminate noise and artifacts, which could otherwise distort the analysis.
- Signal Segmentation: EEG signals are then segmented into smaller epochs or windows, making it easier to analyze specific time intervals.
- Data Conversion: The segmented signals are converted into numerical arrays or other formats suitable for input into deep learning models.

Feature Extraction:

- Identifying Relevant Features: In this stage, features that are indicative of different types of epileptic activity are extracted. These may include spectral features (such as power in different frequency bands), statistical measures (like mean and variance), and time-domain features (such as amplitude and duration of spikes).

Data Augmentation (Optional):

- Enhancing Data Diversity: When the original dataset is limited, data augmentation techniques like rotation, scaling, or adding noise can be applied. This step increases the diversity of training samples, which can improve the generalization of the model.

5.3 Deep Learning Model Development

Once the data is preprocessed and features are extracted, the focus shifts to developing and training the deep learning model.

Model Selection:

- Choosing the Right Architecture: Selecting an appropriate deep learning architecture is crucial. This could involve experimenting with various architectures, such as CNNs for spatial patterns or RNNs for temporal sequences, to determine which is most effective for the specific EEG classification task.

Model Training:

- Training the Model: The selected model is trained using the preprocessed and augmented data. During training, appropriate loss functions and optimization techniques are employed to fine-tune the model's parameters.
- Validation and Monitoring: The training process is closely monitored, with regular validation on a separate dataset to ensure that the model is not overfitting. This helps in achieving a model that generalizes well to unseen data.

Evaluation:

- Performance Assessment: After training, the model is evaluated on a separate test dataset to assess its performance metrics, including accuracy, sensitivity, specificity, and F1 score. These metrics provide insights into the model's effectiveness in diagnosing epilepsy.

5.4 Deployment (Optional)

- Clinical Integration: If the model demonstrates satisfactory performance, it can be deployed in clinical settings to assist healthcare professionals in diagnosing epilepsy. Deployment involves ensuring the model's robustness, reliability, and compliance with security and privacy regulations, especially when patient data is involved.

Research in this field has produced a variety of deep learning models for EEG classification, each designed with specific objectives, datasets, preprocessing techniques, and classification methods. **Figure6**represents a Standard pipeline for automated seizure detection using ML algorithms.

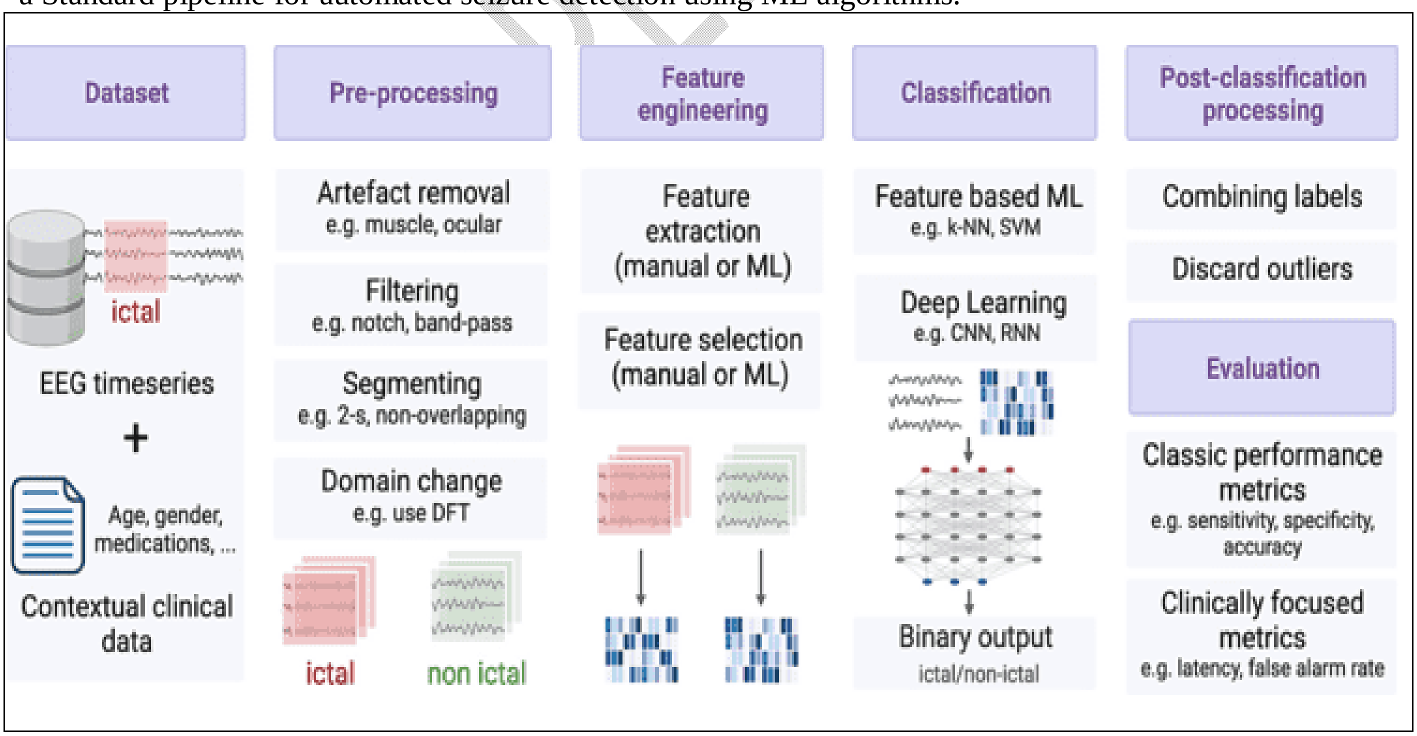


Figure6. Standardpipelineforautomatedseizuredetectionusing MLalgorithms[18]

6. Machine Learning Algorithms for Classification

After data pre-processing, feature extraction, and feature selection, the data is prepared for classification. It's important to note that deep learning (DL) models don't always require pre-extracted features as input. This section explores three common feature-based machine learning (ML) algorithms used for automated seizure detection, while the following section focuses on DL models. **Tables 3** summarize the feature-based ML models found in the literature.

Table3. Feature-based ML methods from a systematic review of literature for seizure detection in scalp EEG data

Classifier	Feature(s)	Dataset(s)	Performance	Validation	Segment	Year	Reference
LDAG-SVM	Entropy, largest Lyapunov exponent, correlation dimension	CHB-MIT, Bonn	Accuracy: 95%, Sensitivity: 99%, Specificity: 96%, Run time: 98ms	50-50 train-test	N/A	2019	[46]
SVM	DWT-based sigmoid entropy (time and frequency domain)	CHB-MIT, Bonn, RMCH	Sensitivity: 94.21%	LOO	1s	2019	[47]
SVM, ELM (SVM is best)	Weighted FPE complexity-based feature (W-FPE-F)	CHB-MIT (12 patients), Bonn	Accuracy: 98.99%, Specificity: 89.33%, Sensitivity: 94.17%	10-fold CV	4s, 3s overlap	2019	[48]
k-NN	The energy of signal after DCT	CHB-MIT (21 patients, 5 electrodes)	Accuracy: 93.64%, Sensitivity: 94.77%, Specificity: 92.21%, F-score: 93.12%, FPR: 0.07, FNR: 0.05	10-fold CV	1s, no overlap	2020	[49]
Hidden Markov Model	DMD power, sum of 2D PSD, variance, KFD features	CHB-MIT, AIIMS	Average CHB-MIT: Accuracy: 99.60%, MCC: 0.97, Kappa: 0.97, FPR: 0.12%, NPV: 99.69%, PPV: 98.73%, Sensitivity: 96.64%, Specificity: 99.88%	N/A	5s, no overlap	2020	[50]
XGBoost	Mean, std, signal envelope, kurtosis, skewness, complexity, mobility, TKEO, fractal dimension, band power, sum of relative beta and gamma	TUSZ (4 channels)	Sensitivity: 20%, FA/24h: 15.59	N/A	1s, 0.5 overlap	2020	[51]
LDA	Univariate features (kurtosis, mean absolute deviation, interquartile range, semivariance), bivariate features (correlogram)	CHB-MIT (14 patients)	Sensitivity: 100%, Specificity: 99.8%, Accuracy: 99.6%	3-fold CV	1s, no overlap	2020	[52]
k-NN	Discrete cosine transform energies	CHB-MIT (5 channels)	Accuracy: 93.64%	N/A	3s overlap	2020	[53]
k-NN	Dual-tree discrete wavelet transform features	CHB-MIT	Accuracy: 74.03%	N/A	3s overlap	2020	[54]
RF	Hjorth parameters,	CHB-MIT	Accuracy: 98.03%,	Leave-5-	4s, 2s	2020	[55]

Classifier	Feature(s)	Dataset(s)	Performance	Validation	Segment	Year	Reference
	time correlation coefficient matrix, eigenvalues of correlation, sub-band signal energy		Specificity: 99.04%, Sensitivity: 97.02%	patient-out	overlap		
Genetic Algorithm - Binary Grey Wolf Optimization	Std, Shannon entropy, kurtosis, Hjorth parameters, skewness, energy and nonlinear energy, Higuchi fractal dimension, Katz fractal dimension, spectral entropy	TUH	Accuracy: 85%	N/A	1.8s, no overlap	2021	[56]
Multi-layer Perceptron	Riemannian tangent space map features	TUSZ (18 channels)	Accuracy: 98.94%, Kappa: 0.916	6s, 3s overlap		2021	[57]
RF	Mean value and peak-to-peak value of wavelet energy (PDWC)	CHB-MIT, NICU, Pone_pat, Bonn	TPR: 99.42%, PPV: 99.71%, TNR: 99.71%, NPV: 99.71%, Accuracy: 99.67%, F1: 99.54%	80-20 train-test	4s	2021	[58]
LDA (classification), bagging	Spectral edge frequencies, spectral edge powers, IQR, MAD, PCC	CHB-MIT (18 channels), AIIMS (private)	Accuracy: 84.83%, FDR: 1.2/hour, Mean latency: 1.43s	N/A	1s, no overlap	2021	[59]
XGBoost	WAF-based hybrid extracted features, SSA, and time-domain features	CHB-MIT (18 channels, 10 patients)	Accuracy: 94.46%, Sensitivity: 88.61%, Specificity: 88.61%, Precision: 99.81%, MCC: 89.54%, Kappa: 89.03%	5-fold CV	6s, no overlap	2022	[60]
SVM (Classification)	Covariance matrices of channels (Riemannian geometry)	CHB-MIT (22 channels)	Accuracy: 99.87%, Sensitivity: 99.91%, Specificity: 99.82%	10-fold CV	2s, no overlap	2022	[61]
Naive Bayes	Relative amplitude, spectral entropy, logarithmic band power, tonal power ratio, 1D local binary pattern, PSD, spectrogram	CHB-MIT, TUEP	TUEP: Accuracy >90%, Sensitivity >85%, Specificity >85%, CHB-MIT: Accuracy 90%, Sensitivity >92%, Specificity >92%	90-10 train-test	N/A	2022	[62]
Naive Bayes	10 geometric features extracted in each frequency band (θ, β, δ, α)	CHB-MIT	Accuracy: 94.54%	10-fold CV	20s, 15s overlap	2022	[63]
NN	AM bandwidth, FM bandwidth, frequency, kurtosis, Hjorth complexity, Hjorth mobility, skewness, spectral centroid, spectral entropy, spectral peak	Bonn, NSC-HK	Accuracy: 98.1%, Sensitivity: 98.21%, Specificity: 97.65%	70-30 train-test	N/A	2022	[64]
Fuzzy k-NN	GNMF decomposed SSTFT maps	CHB-MIT, Bonn	Accuracy: 98.99%, Sensitivity: 99.27%, Specificity: 98.53%	10-fold CV	1s, no overlap	2023	[65]

Classifier	Feature(s)	Dataset(s)	Performance	Validation	Segment	Year	Reference
k-NN (feature selection), RF	Weighted degree, clustering coefficient	CHB-MIT, Siena scalp	CHB-MIT: F1: 86.69%, AUC: 84.33%, Accuracy: 84.83%, Precision: 85.60%, Sensitivity: 87.81%, Specificity: 81.01%	5-fold CV	4s	2023	[66]
SVM	Kurtosis, skewness, line length, quartile values, correlation coefficient matrix (PCA dimensionality reduction)	CHB-MIT, Siena	Accuracy: 96.67%, Specificity: 95.62%, Sensitivity: 97.72%	Bootstrap	1s, 0.5s overlap	2023	[67]
RF	Power of 6 PSD brain wave bands, vs coherence coefficient	TUEP (8 channels)	Coherence coefficients: Accuracy: 90.87%, PSD: Accuracy: 95.73%	70-30 train-test	10s, no overlap	2023	[68]
RF	Hjorth parameter, time correlation coefficient matrix, eigenvalues, sub-band signal energy, fuzzy entropy	CHB-MIT	Accuracy: 98.03%, Specificity: 99.04%, Sensitivity: 97.02%	Leave-5-patient-out	4s, 2s overlap	2023	[69]

The analysis of various classifiers used for seizure detection across different datasets reveals a range of performance metrics and methodologies.

- K-Nearest Neighbors (k-NN) is employed with discrete cosine transform energies and dual-tree discrete wavelet transform features on CHB-MIT data. The accuracy varies significantly: 93.64% with discrete cosine transform features but drops to 74.03% with wavelet transform features. Both approaches use a 3-second segment length with overlap, indicating that feature choice can significantly influence the classifier's performance.

- Support Vector Machine (SVM), using covariance matrices of channels processed through Riemannian geometry, achieves an impressive accuracy of 99.87%, with high sensitivity (99.91%) and specificity (99.82%). This classifier benefits from a 2-second segment length without overlap, highlighting the effectiveness of using geometric features in high-dimensional space.

- Random Forest (RF), leveraging multiple features such as Hjorth parameters and sub-band signal energy, shows strong performance with an accuracy of 98.03% and a high specificity of 99.04%. Validation is performed using a leave-5-patient-out method with 4-second segments and 2-second overlap, which provides robust results across diverse patient data.

- Linear Discriminant Analysis (LDA) achieves perfect sensitivity (100%) and high specificity (99.8%) with univariate and bivariate features. This classifier is validated with 3-fold cross-validation and 1-second segments without overlap, suggesting its efficiency in distinguishing seizure events when using well-selected features.

- XGBoost demonstrates varied results. With hybrid features and SSA, it reaches an accuracy of 94.46%, but it drops to a sensitivity of only 20% with different feature sets on the TUSZ dataset. This classifier uses a 6-second segment length without overlap for one set of features and a 1-

second segment with 0.5-second overlap for another, illustrating the impact of feature selection and segment length on performance.

- ➢ Naive Bayes shows high accuracy (up to 94.54%) and good sensitivity (>85%) with different feature sets across CHB-MIT and TUEP datasets. The 10-fold cross-validation and longer segments (20 seconds with 15-second overlap) used in some studies suggest a balance between accuracy and practical classification needs.

- ➢ Genetic Algorithm - Binary Grey Wolf Optimization provides an accuracy of 85% with a diverse set of features, using a 1.8-second segment length without overlap. This method demonstrates that optimization algorithms can be effective in feature selection, though its accuracy is slightly lower compared to other methods.

- ➢ Hidden Markov Model achieves high accuracy (99.60%) and excellent performance metrics such as MCC and Kappa. It uses a 5-second segment without overlap and a range of features, including 2D power spectra and variance. This suggests that Hidden Markov Models can effectively model complex temporal dynamics in seizure data.

- ➢ Neural Networks (NN), utilizing a variety of features, including bandwidths and spectral properties, achieve high accuracy (98.1%) on the Bonn and NSC-HK datasets. This method uses a 70-30 train-test split, demonstrating its robustness in handling various feature sets.

- ➢ Multi-layer Perceptron (MLP), with Riemannian tangent space map features, achieves an accuracy of 98.94% on the TUSZ dataset with a 6-second segment and 3-second overlap. This highlights the classifier's ability to capture complex feature interactions effectively.

Overall, the choice of classifier, feature set, and validation method significantly impacts performance. While methods like SVM and RF show high accuracy and sensitivity, classifiers such as k-NN and XGBoost demonstrate the importance of feature selection and segment length in achieving optimal results.

7. Deep Learning Algorithms for Classification

While feature-based ML requires pre-defined features, DL can automatically identify patterns and features from various data types. DL algorithms can use raw or filtered EEG data, domain representations, or a set of extracted EEG features as input. Common DL architectures for automated seizure detection include artificial neural networks (ANN), convolutional neural networks (CNN), and graph machine learning (GML). Different architectures classify EEG segments based on specific signal properties. This section reviews these DL methods. Notably, some studies combine different DL architectures (in parallel or series) to leverage their strengths and address weaknesses. **Tables 4**summarize the encountered DL models.

Table4.DLmethodsfromsystematicreviewofliteratureforseizuredetectioninscalpEEG data

Classifier	Dataset(s)	Performance	Validation	Segment Length	Year	References
Hybrid Probabilistic Graphical Model CNN (PGM-CNN)	CHB-MIT, Johns Hopkins Hospital (JHH)	TPR: 0.61, FPR: 0.0067, AUC: 0.8, F1: 0.67, Precision: 0.83	5-fold CV	1s	2019	[70]
CNN	NYP-WC, CHB-MIT	-	5-fold CV	120s, 119s overlap	2019	[71]
ANN	CHB-MIT	-	-	100s, no overlap	2019	[72]
Attention-based CNN-	CHB-MIT	No missing channels:	10-fold CV	23s	2019	[73]

Classifier	Dataset(s)	Performance	Validation	Segment Length	Year	References
BiRNN		Specificity: 93.94%, Sensitivity: 92.88% 2 missing channels: Specificity: 90%, Sensitivity: 95%				
CNN + MIDS, CNN + Data Augmentation	CHB-MIT	CNN+MIDS: Sensitivity: 74.08%, Specificity: 92.46% CNN+Data Augmentation: Sensitivity: 72.11%, Specificity: 95.89%	LOO	5s	2019	[74]
CNN	CHB-MIT	Sensitivity: 97.25%, Specificity: 97.25%, Accuracy: 97.25%	10-fold CV	3s	2020	[75]
CNN	CHB-MIT	Accuracy: 96.74%, Specificity: 100%, Sensitivity: 82.35%	5-fold CV	100s	2020	[76]
GCN	CHB-MIT	Accuracy: 98.35%	10-fold CV	60s	2020	[77]
U-net (Feature Extraction), LSTM (Classification)	TUSZ (16 channels)	Sensitivity: 12.37%, FA/24hr: 1.44, TAES score: 2.46	10-fold CV	20s	2020	[78]
AttVGGNet-RC	CHB-MIT (23 channels, remove patient 12)	Sensitivity: 93.84% ± 0.63%, Specificity: 95.84% ± 0.74%, Accuracy: 95.12% ± 0.20%	10-fold CV	1s	2020	[79]
CNN (Feature Extraction), LSTM (Classification)	TUSZ	Accuracy: 82%, Precision: 71.69%, Sensitivity: 85%	LOO	N/A	2020	[80]
RNN	CHB-MIT, TUEP	TUEP: Accuracy: 84.7%, Sensitivity: 89.2%, Specificity: 82.2% CHB-MIT: Accuracy: 85.3%, Sensitivity: 93.0%, Specificity: 79.7%	90-10 train-test	N/A	2021	[81]
CNN	CHB-MIT	Accuracy: 87.4%, Sensitivity: 88.10%, Specificity: 87.10%, F1: 87.40%, Precision: 86.98%	10-fold CV	8s	2021	[82]
2D-DCAE (Feature Extraction), Bi-LSTM (Classification)	CHB-MIT (16 patients)	Accuracy: 98.79% ± 0.53%, Sensitivity: 98.72% ± 0.77%, Specificity: 98.86% ± 0.53%, Precision: 98.86% ± 0.53%, F1: 98.79% ± 0.53%	10-fold CV	4s	2021	[83]
CNN	CHB-MIT, Bonn	Accuracy: 98.80%, Sensitivity: 98%, Specificity: 98%	10-fold CV	N/A	2021	[84]
CNNs, FC Layer	CHB-MIT (remove patient 12, 21 channels), TUSZ (28 patients)	CHB-MIT: Accuracy: 96.17%, Sensitivity: 56.83%, Specificity: 96.97%, F1: 38.26% TUSZ: Accuracy: 67.68%, Sensitivity: 59.21%, Specificity: 75.30%, F1: 47.55%	5-fold CV	4s, 1s overlap	2021	[85]
CNN Aided Factor Graph	CHB-MIT	AUC-ROC: 90.23%, AUC-PR: 76.77%, F1: 90.42%	6-fold, leave 4 patients out	4s	2021	[86]
2D-PCANet (Feature Extraction), SVM (Classification)	CHB-MIT, Bonn	Accuracy: 98.47%, Sensitivity: 98.28%, Specificity: 98.50%	10-fold CV	1s	2021	[87]

Classifier	Dataset(s)	Performance	Validation	Segment Length	Year	References
GBDT, Attention-based CNN-BiRNN, FC Layer for Classification	CHB-MIT	Accuracy: 97.56%, Sensitivity: 90.97%, Specificity: 91.93%	Train-val-test (70-15-15)	20s	2021	[88]
ResNest18	TUSZ (20 channels)	Sensitivity: 42.05%, FAR/day: 5.78	CV	250 samples	2021	[89]
Multilayer Deep Convolutional Neural Network (MDCNN)	CHB-MIT (18 subjects, 23 channels)	Accuracy: 71.60%	LOO	1s, 0.5s overlap	2021	[90]
Asymmetrical Back Propagation Neural Network (ABPN)	CHB-MIT	Sensitivity: 96.32%, Specificity: 95.12%, Accuracy: 98.36%	-	-	2021	[91]
AE (Feature Extraction), RF (Classification)	Siena	F1 (ictal): 91%, F1 (non-ictal): 90.1%	Leave-2-out	6s, 1s overlap	2021	[92]
Deep Stacked AE	CHB-MIT, TUEP	TUEP: Accuracy: 91.5%, Sensitivity: 85.2%, Specificity: 86.0% CHB-MIT: Accuracy: 91.4%, Sensitivity: 85.5%, Specificity: 85.3%	90-10 train-test	N/A	2021	[93]
CNN Aided Factor Graph	CHB-MIT	AUC-ROC: 83.8%, AUC-PR: 50.38%, F1: 93.42%	6-fold, leave 4 patients out	4s, 32s	2022	[94]
CNN-SVM	CHB-MIT	Accuracy: 98.31%	Train-test-val (70/15/15)	N/A	2022	[95]
CNN, LSTM	CHB-MIT (22 patients, 8 channels)	Accuracy: 94.6%, Recall: 97.15%, Precision: 95.78%	10-fold CV	N/A	2022	[96]
1D CNN	CHB-MIT (21 channels)	Accuracy: 97.09%, Sensitivity: 96.49%, Specificity: 97.09%	10-fold CV	2s, 1s overlap	2022	[97]
ResNet-based	TUSZ (20 channels)	Accuracy: 69% (segment level), Accuracy: 61.67%	3-fold CV	1s, 0.75s overlap	2022	[98]
Medium Weight Deep CNN	CHB-MIT	Accuracy: 96%	10-fold CV	300ms, 20ms overlap	2022	[99]
CNN vs Xception	CHB-MIT	CNN: Accuracy: 98.47%, Precision: 99.79%, Recall: 98.93%, F1: 98.51% Xception: Accuracy: 95.52%, Precision: 99.93%, Recall: 98.63%, F1: 97.05%	CV	N/A	2022	[100]
Multi-fuse Reduced Deep CNN (MF-RDCNN)	Bonn, CHB-MIT, Neurology Sleep Centre Delhi	CHB-MIT: Accuracy: 99.29%, Sensitivity: 99.29%, Specificity: 99.86%, FPR: 0.71%	Train-test-val (40-40-20)	N/A	2022	[101]
ConvLSTM	TUEP	Accuracy: 92.17%, Sensitivity: 93.27%, Specificity: 90.96%, Precision: 91.23%, F1: 0.93	5-fold CV, LOO	3s	2022	[102]
Convolution Attention Layer, BiRNN Classification	CHB-MIT (Patients 1-11, 14, 20-24)	Accuracy: 97.62%, Sensitivity: 96.69%, Specificity: 98.41%, F1: 97.38%	N/A	1s	2022	[103]
AE (Feature Extraction), RF (Classification)	Siena	Accuracy: 97.22%	LOO	6s, 1s overlap	2022	[104]
CNN (Feature Extraction), ANN, LR,	CHB-MIT, Bonn	ANN: 94.4%, LR: 91.7%, RF: 92.4%, SVM: 95.7%, GB:	10-fold CV	5s, no overlap	2022	[105]

Classifier	Dataset(s)	Performance	Validation	Segment Length	Year	References
RF, SVM, GB, k-NN, SGD, Ensembles (Classification)		94.6%, k-NN: 96.8%, SGD: 87%, Ensembles: 97%				
BERT (LLM)	TUSZ	Accuracy: ~77%	-	1s	2022	[106]
CNViT (Convolutional Vision Transformer)	CHB-MIT	Sensitivity: 96.71%, Specificity: 97.23%, Accuracy: 97.15%, AUC: 99.54%	-	2s	2022	[107]
Graph Isomorphism Network (GIN)	CHB-MIT	Accuracy: 96.2%, Sensitivity: 95.4%, Specificity: 97.0%	10-fold CV	20s	2022	[108]
Graph-Generative Neural Network (GGN)	TUH	Accuracy: 91%	Train-test (70-30)	5s	2022	[109]
GAT and BiLSTM	CHB-MIT, TUH	CHB-MIT: Accuracy: 98.52%, Specificity: 94.34%, Sensitivity: 97.75% TUH: Accuracy: 98.02%, Specificity: 99.06%, Sensitivity: 97.7%	5-fold CV	1s, 0.5s overlap	2022	[110]
Deep Convolutional Autoencoder Bi-LSTM	CHB-MIT	Sensitivity: 99.7%, Accuracy: 99.8%, Specificity: 99.9%, Precision: 99.9%, F1: 99.6%	10-fold CV	4s	2023	[111]
CNN	CHB-MIT, Bonn	Accuracy: 96.69%, Sensitivity: 96.19%, Specificity: 97.08%	k-fold CV	2s	2023	[112]
CNN and RNN	CHB-MIT, Bonn, Bern-Barcelona	Accuracy: 96.23%	8-fold CV	N/A	2023	[113]
CNNs with an Attention Mechanism	TUH	Accuracy: 86%, F1: 81%	LOO	3s, no overlap	2023	[114]
CNN and CBAM (Feature Extraction), GRU (Classification)	CHB-MIT (13 patients)	Accuracy: 91.73%, Sensitivity: 88.09%, FPR: 0.053/h, Specificity: 92.09%, AUC: 91.56%	10-fold CV	30s, 1s overlap	2023	[115]
CNN	CHB-MIT (8 channels, 16 patients)	Accuracy: 97.57%, Sensitivity: 98.90%, FPR: 2.13%, Delay: 10.46s	LOO	5s, 1s overlap	2023	[116]
Scalp Swarm Algorithm (SSA) (Feature Selection), LSTM (Classification)	TUSZ	Sensitivity: 98.99%, FDR: 98.43%, Specificity: 99.01%, Accuracy: 99.2%, F1: 97.54%	80-20 train-test	1s	2024	[117]

- Convolutional Neural Networks (CNNs) are widely used for seizure detection, with many studies reporting high accuracy on the CHB-MIT dataset. Performance metrics like sensitivity and specificity are often in the 90-98% range. Segment lengths vary but are commonly 1-5 seconds. 10-fold cross-validation is frequently used for validation.

- Some studies combine CNNs with other techniques like RNNs, LSTMs, or attention mechanisms. These hybrid approaches also tend to achieve strong results, with accuracies over 95% in many cases. The CHB-MIT dataset remains very popular, but some work uses other datasets like TUSZ or Bonn.

- Graph-based approaches like Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) have shown promise, with accuracies over 96% reported on CHB-MIT data. Transformer-based models like BERT and CNViT have also been applied successfully.

- Autoencoders are sometimes used for feature extraction before classification. Random Forests are a common choice for the classification stage when using autoencoders. This approach has achieved over 97% accuracy on the Siena dataset.

Overall, deep learning approaches dominate recent seizure detection research. While CNNs remain very popular, there is increasing diversity in model architectures as researchers explore graph-based, transformer-based, and hybrid approaches. Performance continues to improve, with many studies now reporting accuracies well over 95% on standard datasets.

8. Discussion and Future Work

This comprehensive survey has highlighted the significant progress made in applying machine learning techniques to seizure detection and forecasting. Several key themes have emerged:

1. Deep learning dominance: Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have shown superior performance compared to traditional machine learning methods on many benchmark datasets. Their ability to automatically learn relevant features from raw EEG data is particularly valuable given the complexity of seizure patterns.
2. Challenges with generalizability: While many studies report high accuracy on specific datasets, there remains a significant challenge in developing models that generalize well across different patients and recording conditions. Inter-patient and intra-patient variability in EEG signals continues to be a major hurdle.
3. Data limitations: The field is still constrained by the limited availability of large, high-quality, labeled EEG datasets. Many studies rely on relatively small patient cohorts, which may limit the robustness and generalizability of the developed models.
4. Clinical translation gap: Despite the promising results in research settings, there remains a significant gap in translating these technologies into clinical practice. Issues around interpretability, real-time performance, and integration with existing clinical workflows need to be addressed.
5. Multimodal approaches: Some of the most promising recent work has involved combining EEG data with other modalities such as clinical information, imaging data, or signals from wearable devices. This multimodal approach may be key to improving overall system performance.
6. Emerging architectures: While CNNs and RNNs dominate the field, newer architectures like graph neural networks and transformer models are showing promise in capturing the complex spatio-temporal dynamics of seizures.

Based on the current state of the field and identified challenges, several key areas for future research emerge:

- Larger, more diverse datasets: There is a critical need for larger, multi-center EEG datasets that capture a wider range of patient demographics, seizure types, and recording conditions. Efforts to standardize data collection and annotation protocols across institutions would be valuable.
- Personalized models: Given the high variability between patients, developing approaches for efficiently adapting or fine-tuning models to individual patients could significantly improve real-world performance. This may involve techniques like transfer learning or few-shot learning.
- Interpretable AI: As these systems move closer to clinical deployment, there is a growing need for interpretable or explainable AI techniques that can provide clinicians with insight into how decisions are being made. This is crucial for building trust and enabling effective human-AI collaboration.
- Real-time, low-power implementations: For practical use in wearable devices or implantable systems, there is a need to develop models that can operate in real time with low computational and power requirements. This may involve techniques like model compression or neuromorphic computing.

- Multimodal integration: Further research into effectively combining EEG data with other modalities (e.g., clinical data, neuroimaging, wearable sensors) could lead to more robust and accurate seizure detection and forecasting systems.
- Longitudinal studies: Most current research focuses on short-term seizure detection or prediction. Longer-term studies examining how these models perform over extended periods and how they might adapt to changes in a patient's condition over time are needed.
- Standardized evaluation: Developing standardized benchmarks and evaluation protocols would enable more direct comparisons between different approaches and accelerate progress in the field.
- Federated learning: Given privacy concerns around medical data, exploring federated learning approaches that allow models to be trained across multiple institutions without sharing raw patient data could be valuable.
- Causal inference: Moving beyond pure prediction, developing models that can provide insights into the causal mechanisms underlying seizures could have significant implications for treatment.

9. Conclusion

This comprehensive survey has examined the current state-of-the-art in machine-learning techniques for automated seizure detection and forecasting from EEG data. We have explored a wide range of approaches, from traditional machine learning models to advanced deep learning architectures and hybrid methods. Several key themes and findings have emerged from this review. Deep learning approaches, particularly convolutional and recurrent neural networks, have shown great promise in improving the accuracy and robustness of seizure detection compared to traditional machine learning methods. The ability of deep networks to automatically learn relevant features from raw EEG data has been particularly advantageous. However, challenges remain in terms of model interpretability and generalizability across patients and recording conditions.There is a clear trend towards multimodal approaches that combine EEG with other data sources like ECG, accelerometry, and video. These multimodal systems aim to provide a more comprehensive view of seizure activity and reduce false positives. However, integrating heterogeneous data streams remains technically challenging.While seizure detection has seen significant advances, accurate seizure forecasting remains an elusive goal. The inherent difficulty in identifying reliable pre-ictal biomarkers and the need for personalized models present ongoing challenges. Emerging techniques like transfer learning and online adaptive algorithms show promise in this area but require further investigation.A key gap identified in this survey is the limited clinical translation of many of the proposed techniques. Most studies focus on retrospective analysis of pre-recorded datasets rather than prospective, real-time implementation. More research is needed on practical considerations like computational efficiency, integration with clinical workflows, and long-term performance in real-world settings.

Looking to the future, several promising directions emerge:

1. Explainable AI techniques to improve the interpretability of complex deep learning models and build trust with clinicians.
2. Federated learning approaches to leverage data from multiple institutions while preserving patient privacy.
3. Unsupervised and self-supervised learning methods to extract insights from large unlabeled EEG datasets.
4. Closed-loop systems that combine seizure detection/forecasting with automated treatment delivery.
5. Wearable and minimally invasive EEG technologies to enable long-term ambulatory monitoring.

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