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Review

Machine and deep learning methods for epileptic seizure recognition using EEG data: A systematic review

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ABSTRACT

Epilepsy is a neurological disorder affecting millions worldwide, characterized by recurrent and unpredictable seizures. Electroencephalography (EEG) is a widely used tool for seizure diagnosis, but the complexity and variability of EEG signals make manual analysis challenging. Machine Learning (ML) and Deep Learning (DL) techniques have emerged as powerful methods for automated Epileptic Seizure (ES) detection, classification, and prediction. However, questions remain regarding their effectiveness, interpretability, and clinical applicability. This systematic review critically examines ML and DL approaches applied to EEG-based seizure recognition, highlighting key challenges such as feature extraction, dataset selection, and model generalization. We analyze peer-reviewed studies from 2013 to 2023, sourced from the PubMed database, to compare various methodologies and evaluate their performance. Unlike prior reviews that focus on a single aspect of seizure recognition, this work provides a comprehensive overview of detection, classification, and prediction tasks. We also discuss the strengths and limitations of different ML and DL models, emphasizing the trade-offs between computational complexity, accuracy, and real-world implementation. Furthermore, this study outlines emerging trends, including the integration of explainable AI, transfer learning, and privacy-preserving techniques such as federated learning. By synthesizing the latest advancements, this review serves as a guide for researchers and clinicians seeking to enhance the reliability and efficiency of seizure recognition systems. Our findings aim to bridge the gap between AI-driven methodologies and clinical applications, paving the way for more robust and interpretable ES detection frameworks.

1. Introduction

Epilepsy is a neurological disorder characterized by frequent and unpredictable disturbances in typical brain function, resulting in epileptic seizures affecting approximately 50 million people worldwide (Siddiqui et al., 2019). These seizures entail abnormal and heightened neuronal activity in the brain, which may manifest as involuntary body jerking or loss of consciousness, posing risks, especially during hazardous activities (Contributors, 2024). Approximately 70 % of patients manage their seizures with anti-epileptic medications, but about 30 % do not respond well, necessitating surgery (Munakomi and Das, 2024). It has been reported that there is a shortage of neurologists and the essential neurological services they provide. This can impact the timely delivery of treatment to the patients in need (Majersik, 2021). Hence, the automatic recognition of seizures is important to assist neurologists and other healthcare professionals in the patients' diagnosis process and specify necessary treatments, if applicable.

1.1. Seizure types

Two types of seizures are generally distinguished: focal and generalized. Focal seizures are divided into two types: simple partial seizures, and complex partial seizures. Simple partial seizures affect a small part of the brain while individuals remain fully aware of their surroundings.

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These seizures may cause brief movements like a jerk in an arm or hand. In contrast, complex partial seizures affect a larger area of the brain, often the temporal lobe, and lead to impaired awareness. During these seizures, people might display a glassy stare, fail to respond to questions, or give inappropriate or confused answers. They may also move aimlessly, make lip-smacking or chewing motions, produce unusual vocal sounds, or fidget (Wachtel, 2024). On the other hand, generalized epileptic seizures begin simultaneously on both sides of the brain and are often linked to genetic or hereditary causes (Siddiqui, 2018). They include absence seizures, tonic-clonic seizures, myoclonic seizures, and atonic seizures (drop attacks). Absence seizures (petit mal) are brief and marked by staring spells with no motor movements, typically leaving the individual appearing confused or "out of it" before normal functioning returns. Generalized tonic-clonic seizures (grand mal) involve dramatic convulsions, starting with total body stiffening, followed by rhythmic jerking, with confusion or drowsiness afterward. Myoclonic seizures cause sudden, brief jerks of the body or parts of the body, often occurring in clusters, particularly in children with infantile spasms. Atonic seizures are short and cause a sudden fall to the ground due to either stiffening or loss of tone, and are difficult to treat, with a high risk of injury (Wachtel, 2024). Fig. 1.1 shows the spread of seizures across the brain regions in both focal and generalized seizures.

1.2. Diagnosis

Electroencephalography (EEG) was first discovered by the German psychiatrist Hans Berger. It was used to measure the electrical activity of the brain which in turn may be very practical to diagnose different types of brain injuries (Tudor et al., 2024). Such a tool assists neurologists in examining the brain's fluctuations during epileptic seizures. Analyzing these changes helps distinguish between healthy and abnormal brain activity accurately. In typical applications, five EEG frequency bands are analyzed: delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), sigma (12–16 Hz), and beta (13–30 Hz) and the EEG signal amplitude varies between 10 μV and 100 μV (Nayak and Anilkumar, 2024).

Analyzing epileptic seizures requires long-term EEG data spanning days to months, demanding extensive clinical experience to avoid diagnostic errors. Interference from external noise and eye movements can affect the quality of the EEG signal, complicating the diagnostic process (Moien-Afshari, 2013), especially as EEG signals are characterized by low voltage, making them all the more sensitive to disturbances. When EEG signals are contaminated by noise, their waveform can undergo unpredictable variations, drawing extreme challenges in the diagnostic process (Sharma and Pachori, 2015). Furthermore, a large amount of EEG signals is necessary for diagnosing epilepsy. Clinically speaking, EEG signals are typically recorded together with video signals to assist in diagnosis by observing behavioral signs. Clinicians spend a minimum of 16 h reviewing the EEG signals of patients to have a clear diagnosis of the result (Sharma and Pachori, 2015). Interruptions during the review of EEG signals and the workload can impact the clinician's ability to analyze the signals, potentially leading to misdiagnosis (Thurman, 2011).

1.3. Epileptic seizure recognition tasks

ES recognition tasks include a range of complicated approaches that play an important role in improving patient care and management. ES recognition systems designed using ML or DL models include mainly three tasks:

- ES detection: involves real-time detection of the ictal state in an EEG recording. In this task, the model is designed to trigger an alarm at the beginning of the ictal state or after a very short duration of its starting time. Fig. 1.2 shows a visualization of ES detection task.
- ES classification: In this task, the model can identify different types of seizures or their stages. Sometimes, the term "classification" is used to describe the process of recognizing different seizure phases, which is also called EEG/phase classification in research.
- ES prediction: Seizure prediction is when a model can detect early signs of an upcoming epileptic seizure by recognizing the patient's preictal state. Fig. 1.3 shows an overview of the seizure prediction task.

1.4. Utilizing AI models for ES recognition

AI is making significant advances in the diagnosis and treatment of various conditions, including schizophrenia, Attention deficit hyperactivity disorder (ADHD), autism spectrum disorder (ASD), epilepsy, COVID-19, and diabetes (Shoeibi, 2023; "Sensors | Free Full-Text | Epileptic Seizures Detection in EEG Signals Using Fusion Handcrafted and Deep Learning Features." Accessed: Sep. 04, 2024; Shoeibi, 2024; Sharifrazi, 2021; Shoeibi, 2022) . AI, through Machine Learning (ML) and Deep Learning (DL), is revolutionizing how these disorders are detected and managed. Specifically, in the context of epilepsy, AI-driven techniques for analyzing EEG signals are proving to be transformative. These methods significantly reduce the workload on clinicians by providing objective and precise diagnosis, thereby mitigating the subjectivity inherent in traditional interpretation approaches. The rapid growth in research into AI applications for EEG diagnostics underscores its potential to revolutionize clinical practice, not only for epilepsy but also for a wide range of neurological and physiological conditions. Moreover, the integration of Explainable AI (XAI) is improving the transparency, speed, and reliability of AI diagnostic systems. It enables

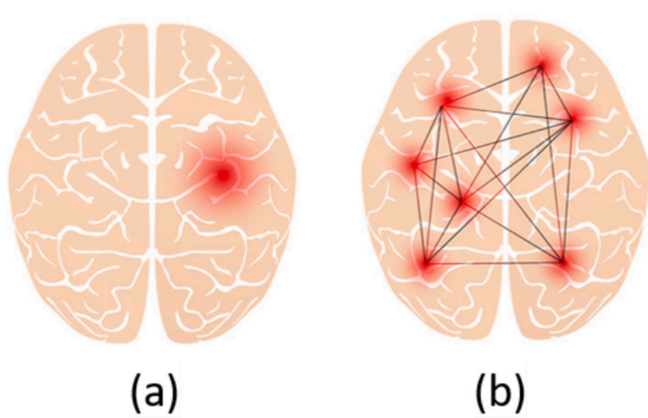

Fig. 1.1. Seizure spread in (a) focal seizure, and (b) generalized seizure ("Understanding different kinds of seizures," NIH MedlinePlus Magazine. Accessed: Jan. 08, 2025).

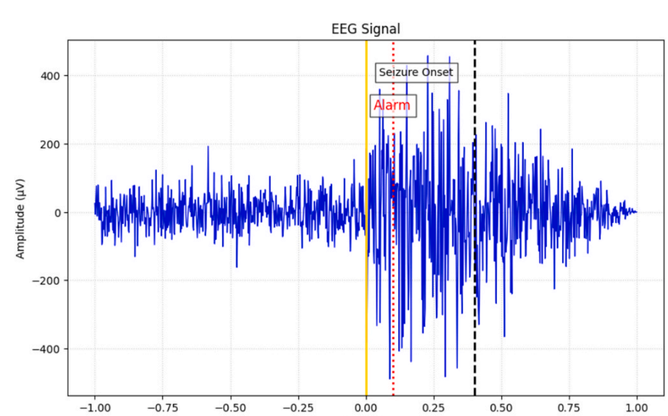

Fig. 1.2. Visualization of seizure detection task. A successful detection occurs when raising an alarm instantly at the beginning of the ictal state.

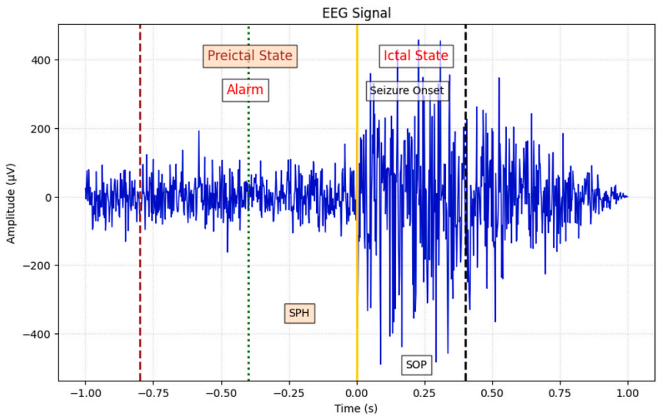

Fig. 1.3. Visualization of Seizure Occurrence Period (SOP) and Seizure Prediction Horizon (SPH). With a precise prediction, a seizure must occur after SPH and within the SOP.

clinicians to understand the rationale behind model predictions, offering interpretations into which EEG features influenced the decision-making of the model (Barredo Arrieta, et al., 2020; Khan et al., Aug. 2024) . It also assists doctors identifying patients that are at high risk of developing epilepsy and helps them create a customized treatment plan.

1.5. Contributions of the review

EEG remains the primary non-invasive method for diagnosing and monitoring epilepsy, yet its interpretation is significantly challenged by signal noise, low amplitude, and the sheer volume of data generated during long-term monitoring. As highlighted in the diagnosis part, the diagnostic process is time-consuming, error-prone, and heavily reliant on expert interpretation, leading to the need for automated, accurate, and interpretable solutions.

To address these challenges, numerous ML and DL techniques have been proposed for ES recognition. However, a gap remains in the existing literature: prior reviews tend to either focus narrowly on specific models or tasks (e.g., detection or prediction) (Xu, 2024) (Rasheed, 2021), overlook critical aspects such as dataset characteristics (Ahmad, 2022), or fail to incorporate both ML and DL models in a unified framework (Farooq et al., 2023) (Siddiqui et al., 2020).

Thus, this review aims to bridge that gap by providing a comprehensive comparative analysis of ML and DL models across all three core ES recognition tasks: detection, classification, and prediction. Unlike previous works, we critically examine:

- The model-specific suitability for each task.
- The influence of dataset quality and structure on model performance.
- The trade-offs between traditional ML models and modern DL architectures.
- The role of Explainable AI (XAI) in ensuring model interpretability.

The rest of the paper is divided as follows: Section 2 presents the research methodology adopted to develop this review paper. Section 3 shows the results obtained from the research methodology that was followed. Section 4 shows a background on the necessary steps to achieve a functional ML or DL models. Section 5 discusses ML and DL methods presented in the literature. Section 6 discusses the challenges facing the recognition tasks. Finally, section 7 concludes the review.

2. Research methodology

2.1. Introduction

A common approach for gathering, evaluating, and interpreting significant research on specific topics or methods is the comprehensive and systematic literature review method. This method aims to assess the challenges addressed and solutions proposed in studies with similar scopes. The review was conducted systematically following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines (Moher et al., 2009). PRISMA is mostly used since it is an evidence-based minimum set of papers for reporting in systematic literature reviews and *meta*-analyses research (Nafea and Ismail, 2022). In this paper, a plan has been formed that consists of 3 stages: research questions, execution process, and articles eligibility.

2.2. Research Questions

Before moving to the execution process, it is necessary to understand the research questions and their importance. Hereafter are the research questions that were answered when emphasizing the findings of the articles studied. They form the key areas for utilizing ML/DL for ES.

- Q1: What are the challenges facing detection, classification, and prediction of ES?
- Q2: What are the preprocessing techniques used?
- Q3: What are the feature extraction methods used?
- Q4: What are the ML/DL classifiers used?
- Q5: What dataset(s) is(are) used in the study?

2.3. Execution process

The database search process was performed using a combination of keywords that directly describe the topic such as “epileptic”, “seizure”, “EEG”, “detection”, “classification”, “prediction”. Pubmed search engine uses “()” to search entities. Thus, the search key terms for searching the database were (Epileptic) AND (Seizure) AND (EEG) AND ((Detection) OR (Classification) OR (Prediction)). Review articles and articles older than 10 years were excluded.

2.4. Article eligibility

To acquire relevant data for this comprehensive literature review, all articles were carefully assessed that addressed the research inquiries. The determination of eligible articles for inclusion in the study was based upon the following criteria:

2.4.1. Inclusion criteria

The following set of constraints has been considered as inclusion criteria for the articles, ensuring timeframe compatibility (I1), focused research topic (I2), human applicability (I3):

- **I1: Papers published between 2013 and 2023;** Restricting the publication period to 2013–2023 ensures that the review includes recent and up-to-date research. This helps capture current trends, advancements, and state-of-the-art methods in the field, while excluding outdated studies that might not reflect the latest developments.
- **I2: Emphasis on epileptic seizure detection, prediction, or classification using EEG signals (intracranial or scalp);** Focusing on epileptic seizure detection, prediction, and classification using EEG signals ensures that the articles directly align with the study’s primary objective. Including both intracranial and scalp EEG covers the most common sources of data in this domain while maintaining a clear focus on epilepsy-related applications. These types of data acquisition systems have very high temporal resolution compared to other data like imaging data.
- **I3: Methods conducted on human brains;** Limiting the review to methods conducted on human brains ensures that the findings and methodologies are relevant to clinical applications or real-world scenarios involving humans.

2.4.2. Exclusion criteria

The following set of constraints has been considered as exclusion criteria for the articles, ensuring relevance to the research focus (E1 and E2), novelty and contribution (E3), human-specific context (E4), article type and scientific validity (E5 and E6), and language accessibility (E6):

- **E1: Developed/implemented approaches other than ML/DL;** This ensures the focus remains on articles that directly align with the study's aim of analyzing ML or DL models in ES detection, classification, and prediction. Including different approaches would weaken the analysis.
- **E2: Analyzed signals other than EEG signals;** Limiting to EEG signals keeps the research relevant to the specific signal type under investigation. Including other signals (e.g., ECG or EMG) would broaden the scope unnecessarily and introduce variability in methodologies and findings.
- **E3: Implemented with no new methodology;** Excluding articles that do not propose new methodologies ensures that the review highlights innovative and original contributions, avoiding repetition of existing knowledge or mere applications of known techniques.
- **E4: Analyzed other than human brains;** Excluding analysis on animal brains ensures the findings and methodologies are directly applicable to human brain studies, which is often the primary focus in neuroscience and medical applications.
- **E5: Presented a review paper;** Excluding review papers focuses the literature review on original research and empirical studies rather than secondary summaries. This ensures the study is grounded on primary data and methodological advancements.
- **E6: Articles were not available;** Articles that are unavailable (*i.e.* no provided access) are excluded because they cannot be fully reviewed, ensuring the analysis is clear and complete.
- **E7: Articles not written in English;** Since the article is written in English, excluding non-English articles ensures accessibility and comprehensibility for the researcher and the intended audience.

3. Database search results

After setting up all the constraints (inclusion and exclusion criteria) on the research methodology, the PRISMA diagram is illustrated in Fig. 3.1. The diagram consists of 3 main stages; (1) articles identification which holds the primary filtering steps without assessing the full text (filtering by date and removing duplicates), (2) articles screening which holds the exclusion process of irrelevant articles by assessing the title and abstract, then assessing the full text of the remaining articles, and (3) the inclusion phase which records the final number of the included articles.

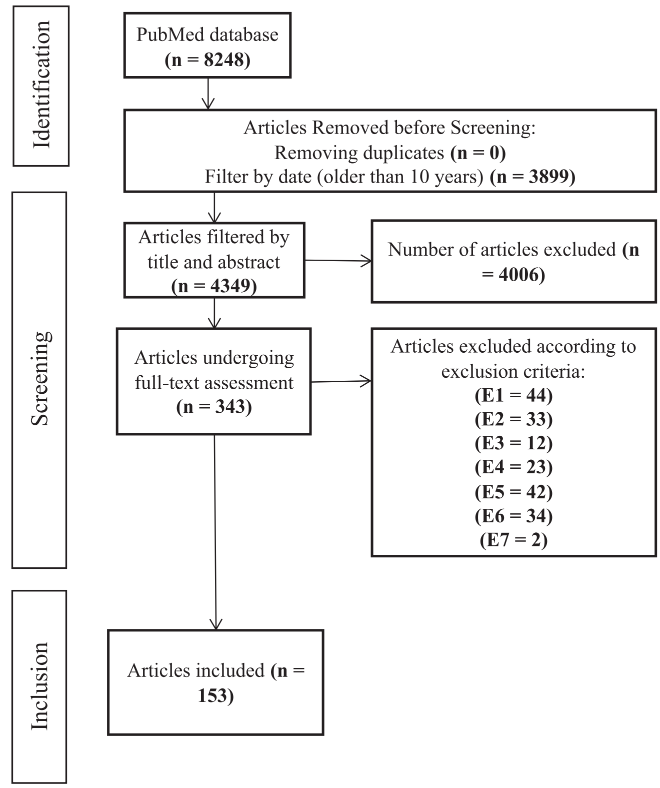

Fig. 3.1. PRISMA diagram of literature selection.

4. Background

ML involves teaching computational machines to utilize previous data exposure to solve problems. Recent advancements in processing power and memory affordability have spurred interest in applying ML across domains to outperform humans. Accessible computational resources enable large-scale data processing and analysis, uncovering insights autonomously. ML relies on algorithms enabling abstraction formation based on prior knowledge, requiring manual feature extraction expertise in the problem domain. While DL employs sophisticated multi-layer structures for automatic data extraction, surpassing ML in complexity. While ML offers effective classification techniques, DL's advanced methods are gaining more popular (Nafea and Ismail, 2022). In the field of ES recognition, the process is illustrated in Fig. 4.1 and outlined afterwards.

4.1. Data acquisition

For seizure recognition, data collection begins with using an EEG monitoring device to gather EEG signals from the brain. Following the 10–20 international system, electrodes are positioned on the scalp, connected to the monitoring device via wires. These scalp EEG signals, though noisy, undergo careful examination by neuro-experts who classify them into "seizure" and "non-seizure" states. Alternatively, intracranial EEG (iEEG) electrodes, placed inside the brain via special surgery, capture less noisy signals with diverse voltage and spatial information (Ahmad, 2022; Herwig et al., 2003) .

4.2. Datasets

The utilization of datasets holds significant importance for data scientists and experts as it enables them to assess the performance of their proposed models. Publicly available datasets play an important role as they provide a benchmark for result analysis through comparison across different datasets. There are numerous epilepsy-related datasets accessible online that are summarized in Table 4.1.

The pie chart in Fig. 4.2 proves that CHB-MIT and Bonn datasets mostly used to validate the performance of the proposed models in the literature. However, these datasets lack variability which lead to models not able to generalize. To ensure consistency, it is always recommended to use a benchmark available dataset such as CHB-MIT for training along with a private dataset for testing. This approach was taken by several authors (Raghu et al., 2019; Qaisar and Hussain, 2021; Yang et al., 2021; Pandey et al., 2022) to ensure that their model is performing well on new patients and increase the generalizability of their models.

For seizure detection, datasets like CHB-MIT and TUH are widely used due to their well-defined seizure annotations, but over-reliance on them can introduce biases (Asadi-Pooya et al., 2023; Roy et al., 2018) . TUH and TUSZ provide more diversity but require advanced preprocessing to handle noise. Private datasets from sources like Kaggle and Zenodo can improve robustness but lack standardization. In classification tasks, structured datasets like Bonn and Freiburg are useful for their balanced classes and low computational demands, though their small size limits scalability. TUH and TUSZ, with diverse seizure types,

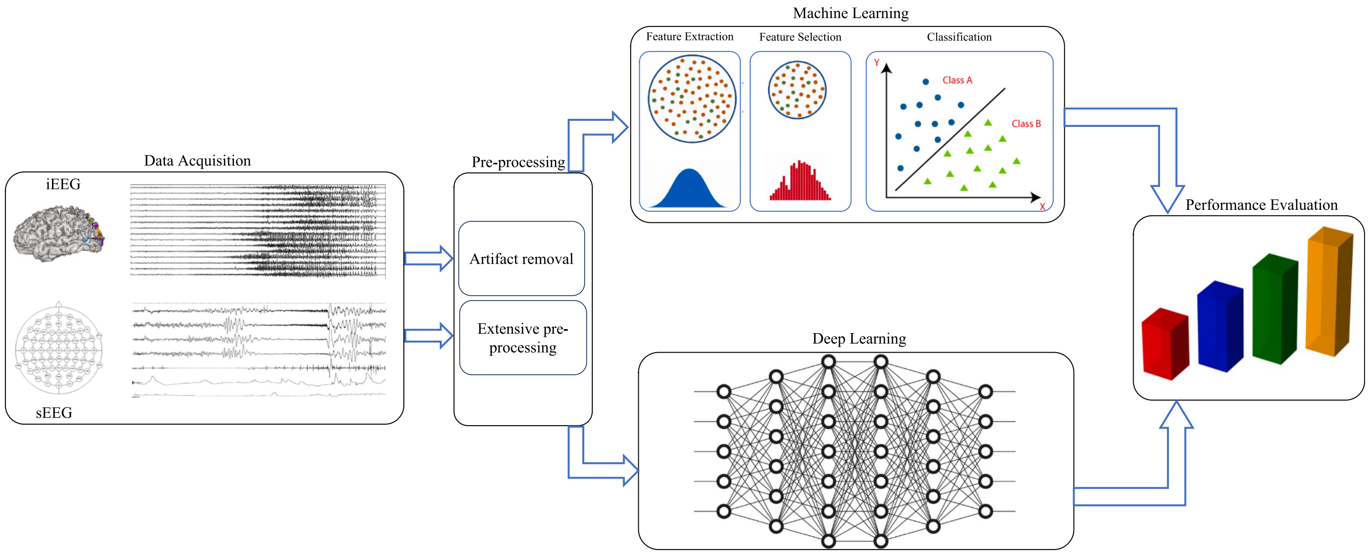

Fig. 4.1. High-level overview of automated ES model.

Table 4.1
List of publicly available epileptic seizure datasets.

Dataset	Recording	Number of Seizures	Sampling Frequency	Time	Type of seizure	Number of Patients
CHB-MIT (Guttag, 2010)	Scalp EEG	163	256 Hz	844 min	Intractable seizures	22
Bonn ("The Bonn EEG time series download page," Nonlinear Time Series Analysis. Accessed: Apr. 11, 2024)	Scalp and iEEG	NA	173.61 Hz	39 min	–	10
Freiburg ("Seizure Prediction Project Freiburg." Accessed: Apr. 11, 2024)	iEEG	87	256 Hz	708 min	Medically intractable focal epilepsy	21
Kaggle ("Epileptic seizures dataset." Accessed: Apr. 11, 2024)	iEEG	48	400/5 kHz	627 min	–	5 dogs, 2 patients
Zenodo (Stevenson et al., 2018)	Scalp EEG	460	256 Hz	74 min	Neonatal seizures	79 neonatal
Bern Barcelona ("The Bern-Barcelona EEG database," Nonlinear Time Series Analysis. Accessed: Apr. 11, 2024)	iEEG	3750	512	83 min	–	5
Temple University Seizure Corps (TUSC) (I. Obeid and J. Picone, "The Temple University Hospital EEG Data Corpus," Front. Neurosci., vol. 10, 2016)	–	3050	250–1000 Hz	Mean: 97 sec	–	300
UCI (Masum et al., 2020; "Home - UCI Machine Learning Repository." Accessed: Jan. 21, 2024)	Scalp EEG	4097	256 Hz	543 sec/ patient	–	500

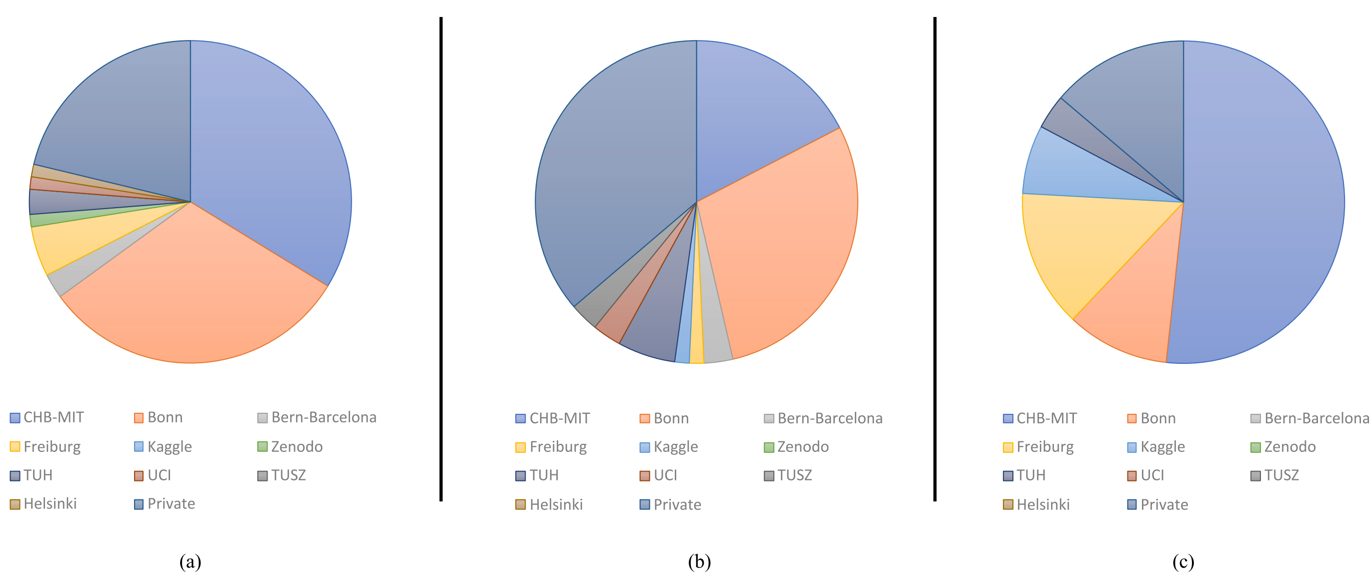

Fig. 4.2. The dataset occurrence in the literature for seizure (a) detection, (b) classification, and (c) prediction tasks.

support better generalization but require more computational resources (Wang and Mengoni, 2022; Selvaraj et al., 2023) . For seizure prediction, datasets must capture pre-ictal phases, which public datasets often lack, making private datasets valuable despite accessibility challenges. To improve model generalization, it is recommended to train on benchmark datasets like CHB-MIT and test on private datasets, a strategy adopted in several studies (Raghu et al., 2019; Qaisar and Hussain, 2021; Yang et al., 2021; Pandey et al., 2022) .

4.3. Data preprocessing

Data preprocessing is the step of transforming raw data into an interpretable format. It includes data filtering (*i.e.*, removing noises from raw EEG data), removing null values, scaling and normalizing data, and data splitting. In addition, it may involve converting the raw EEG data into a more interpretable format such as frequency domain (spectrograms). However, the transformed data alone do not contain enough information to identify seizures. To achieve accurate seizure identification, a range of features and modalities are employed for precise information extraction.

4.3.1. Filtering

Filtering ensures that no artifacts are present in EEG recordings. A common approach is the use of bandpass filter between 1 Hz to remove heart signals related to pulse effect and low frequency noises related to nearby electromagnetic field, and 40 Hz to discard the AC power line effects (Gonçales, 2021).

4.3.2. Normalization

Data normalization before training is essential to ensure that all features contribute equally to the learning process and are on the same scale. Optimization algorithms such as gradient decent, converge faster when trained on normalized data. It also helps the model learn weights or patterns accurately. The commonly used normalization methods are:

- Min-max scaling: Rescales the data to values between 0 and 1.
- Z-score normalization: Centers the data around 0 with unit variance.
- MaxAbs scaling: Scales data by its maximum absolute value.

4.3.3. Data splitting

Data splitting is a common approach followed to help the model perform well not only on training data, but also on unseen data. A common technique is to split the data into 70 % training, 10 % validation, and 20 % testing. By doing so, the model can be evaluated whether it is learning real patterns or just memorizing the training data. If it performs well on training data, but poorly on test data, it is likely to be overfitted. In addition, it is very important to split the data in a way that no training data are present in the test data and vice versa, where this is important to provide unbiased model evaluation.

4.3.4. Advanced preprocessing

Advanced preprocessing techniques vary according to the task (*i.e.*, detection, classification, or prediction). In seizure detection, Techniques such as Empirical Mode Decomposition (EMD) and Hilbert-Huang Transform (HHT) are frequently employed due to their adaptability in analyzing non-linear and non-stationary signals. EMD decomposes EEG signals into intrinsic mode functions, isolating seizure-relevant oscillatory components, while HHT offers a precise time–frequency representation for seizure detection (Alickovic et al., 2018; Muhammad Usman et al., 2021; Acar Demirci et al., 2023; Muhammad Usman et al., 2021) . Preprocessing is designed to ensure that features discriminating between seizure types (e.g., focal vs. generalized seizures) or patient-specific patterns are emphasized. Fractal Dimension Analysis and Entropy-based Techniques are commonly applied to capture the complexity and irregularity of EEG signals associated with different seizure types (Janjarasjitt, 2014; Desri et al., 2021; Lahmiri, 2018) . On the other hand, prediction tasks require techniques that highlight signal changes preceding seizures. In this context, methods such as Nonlinear Dynamical System Analysis and Phase-Synchronization Analysis are extensively used. These techniques quantify variations in EEG signal dynamics or synchronization levels between brain regions, which are often indicative of an impending seizure. Additionally, Wavelet Packet Decomposition (WPD) is particularly effective for seizure prediction as it provides a hierarchical representation of EEG signals, enabling the identification of low-energy shifts or frequency transitions preceding seizures. Predictive features such as fractal dimension changes, phase shifts, and long-term signal trends are extracted following these preprocessing step (Selvaraj et al., 2023; L. Sui, X. Zhao, Q. Zhao, T. Tanaka, and J. Cao, "Localization of Epileptic Foci by Using Convolutional Neural Network Based on iEEG," in Artificial Intelligence Applications and Innovations, J. MacIntyre, I. Maglogiannis, L. Iliadis, and E. Pimenidis, Eds., in IFIP Advances in Information and Communication Technology. Cham: Springer International Publishing, 2019; Rashed-Al-Mahfuz et al., 2021; Choi, et al., 2019) .

4.4. Feature extraction

Feature extraction is a crucial process in Epileptic Seizure (ES) detection systems, as it utilizes mathematical algorithms to extract relevant information from raw or pre-processed datasets, improving pattern description accuracy. Integrating feature extraction enhances the performance of pattern recognition systems in distinguishing different patterns efficiently. Various techniques are employed during feature extraction from raw EEG signals to gather necessary information for analysis (Asadi-Pooya et al., 2023). In this context, feature extraction plays a vital role in creating an intelligent system for detecting epileptic seizures efficiently. During the feature extraction phase of such a system, multiple techniques have been employed to process the raw EEG signals and acquire the necessary information for a thorough analysis of the phenomenon we are interested in. In the literature, researchers have utilized different feature extraction strategies, each having its own pros and cons upon the task. In this review, the most used feature extraction techniques were combined and are shown in Fig. 4.3 with the lower box illustrating the preprocessing methods used to extract relevant features in the time–frequency domain. Once the feature extraction task is accomplished, the resulting signals become more accessible and significantly enhance their informativeness for classifying seizures (Liang et al., 2017). As previously mentioned, it is important to recognize that applying machine learning algorithms directly to the raw dataset can yield low accuracy, potentially resulting in inconsistent results and usually demanding a longer time to complete the prediction task (Gao and Mosalam, 2024). Hence, it becomes important to employ a feature extraction method while simultaneously making a wise selection among the available techniques. This is crucial because various types of features exist for characterizing physiological signals, and the choice of efficient statistical features becomes indispensable when dealing with a demanding task.

Time-domain features are fundamental in EEG signal analysis and include variance, mean, median, standard deviation, skewness, kurtosis, peak amplitude, and minimal amplitude. These features are extracted directly from raw EEG signals without transformation, making them computationally efficient. However, they are highly sensitive to noise, requiring extensive preprocessing to mitigate artifacts (Sánchez-Hernández et al., 2022; Logesparan et al., 2015) . Additionally, they struggle to capture dynamic changes in brain activity due to their fixed-window computation and lack spectral information, making it difficult to analyze transitions between frequency bands. To address these limitations, many studies integrate both time-domain and frequency-domain features for improved robustness (Raghu et al., 2019; Pandey et al., 2022; Selvaraj et al., 2023; Sánchez-Hernández et al., 2022; Boonyakitanont et al., 2021; Büyükçakır et al., 2020; Malekzadeh et al., 2021; Hussain, 2018; Abbaszadeh et al., 2019; Savadkoohi et al., 2020; Lopes,

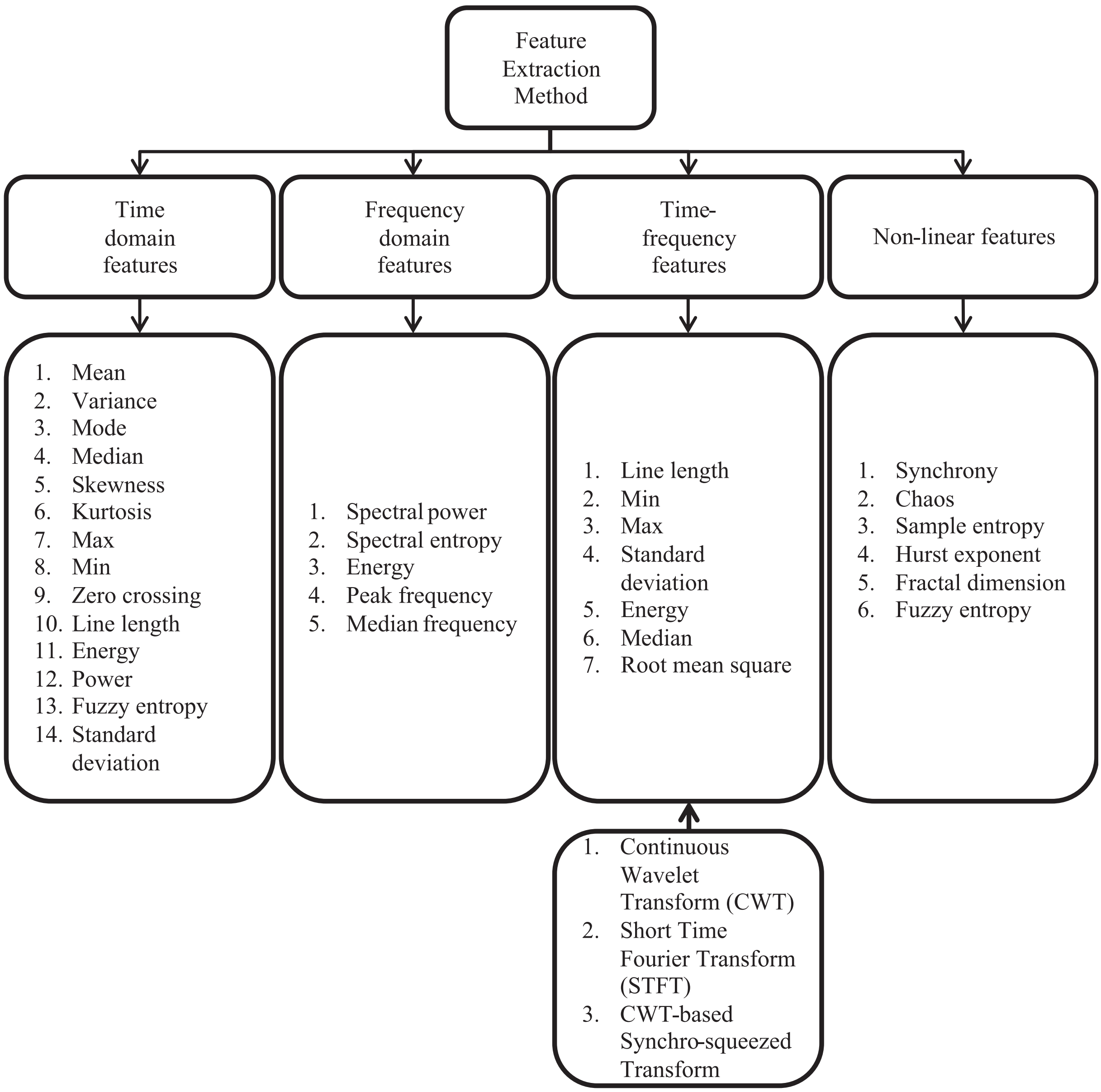

Fig. 4.3. Commonly used feature extraction methods for EEG data.

2023; Kiranyaz et al., 2013) .

Frequency-domain features are extracted from EEG signals transformed into the frequency domain using FFT, enabling the analysis of spectral components such as relative power, peak frequency, and median frequency (Zabihi and Kiranyaz, 2023). While FFT is computationally efficient, it does not provide precise temporal localization of frequency variations. To bridge this gap, time–frequency domain (TFD) features use transformations like STFT or wavelet analysis to represent how frequency content changes over time (Selvaraj et al., 2023; L. Sui, X. Zhao, Q. Zhao, T. Tanaka, and J. Cao, "Localization of Epileptic Foci by Using Convolutional Neural Network Based on iEEG," in Artificial Intelligence Applications and Innovations, J. MacIntyre, I. Maglogiannis, L. Iliadis, and E. Pimenidis, Eds., in IFIP Advances in Information and Communication Technology. Cham: Springer International Publishing, 2019; Rashed-Al-Mahfuz et al., 2021; Choi, et al., 2019) . Features such as line length, root mean square, and standard deviation are then derived from the time–frequency spectrogram. However, TFD methods face challenges related to the choice of sliding window size, where wider windows enhance frequency resolution at the cost of temporal precision, and individual variability, as EEG patterns differ significantly across subjects.

Given the non-linear and complex nature of brain activity, non-linear features provide valuable insights into EEG signals. Fractal Dimension (FD), including Higuchi and Petrosian methods, measures signal complexity and has been used to distinguish between seizure and non-seizure states (Janjarasjitt, 2014; Desri et al., 2021; Lahmiri, 2018; "Multifractals and Chronic Diseases of the Central Nervous System | SpringerLink." Accessed: Sep. 04, 2024) . Detrended fluctuation analysis (DFA) quantifies self-affinity in non-stationary time-series EEG data, with the Hurst exponent offering insights into signal trends (Yang, 2020; "Sensors | Free Full-Text | Integration of 24 Feature Types to Accurately Detect and Predict Seizures Using Scalp EEG Signals." Accessed: Sep. 04, 2024) . Line length (LL), a simplified FD measure, has shown promise in detecting seizure-related burst changes (Anuragi et al., 2021; "Processes | Free Full-Text | Performance Evaluation of Epileptic Seizure Prediction Using Time, Frequency, and Time–Frequency Domain Measures." Accessed: Sep. 04, 2024) . Fuzzy Entropy (FuzzyEn) quantifies signal irregularities and has been effective in differentiating between epileptic and healthy individuals, achieving 93 % accuracy in distinguishing seizure states in certain studies ("Detection of epileptic seizure based on entropy analysis of short-term EEG | PLOS ONE." Accessed: Sep. 04, 2024; Shoeibi, 2022) . When combined with adaptive neuro-fuzzy inference systems (ANFIS), FuzzyEn enhances classification performance by capturing the intrinsic patterns in ictal EEG signals.

For seizure detection, classification, and prediction, feature selection is crucial. Studies recommend using a combination of time-domain, frequency-domain, and non-linear features for robust seizure detection (Sánchez-Hernández et al., 2022; Logesparan et al., 2015) , with line length being particularly effective in capturing EEG complexity (Siddiqui et al., 2020). In classification and prediction, transforming signals into frequency representations using STFT, WT, or EMD help differentiate seizure and non-seizure events. Statistical features extracted from these transformations enhance model performance. Window size is another critical factor—detection and classification tasks benefit from a 2-second window for rapid identification, while prediction tasks require longer windows (up to 30 s) to accurately capture pre-ictal phase characteristics. These strategies ensure effective seizure detection, classification, and prediction by utilizing different EEG features.

4.5. ML/DL models for predicting outputs

ML and DL models are trained to predict a specific output. Training these models can be categorized into 2 categories (Rasheed, 2021):

- Supervised Learning: training the model is coupled with input labels assigned by experts (*i.e.* neurologists) and the model learns to extract relation between the data and the labels. Hence, the model can classify input data according to each category. Support Vector Machine is a common example used in supervised learning.
- Unsupervised Learning: The model receives inputs without any label. The model is trained to develop, by repetition of information, a perception of the input data. This perception is then used to detect similar patterns in new input data.

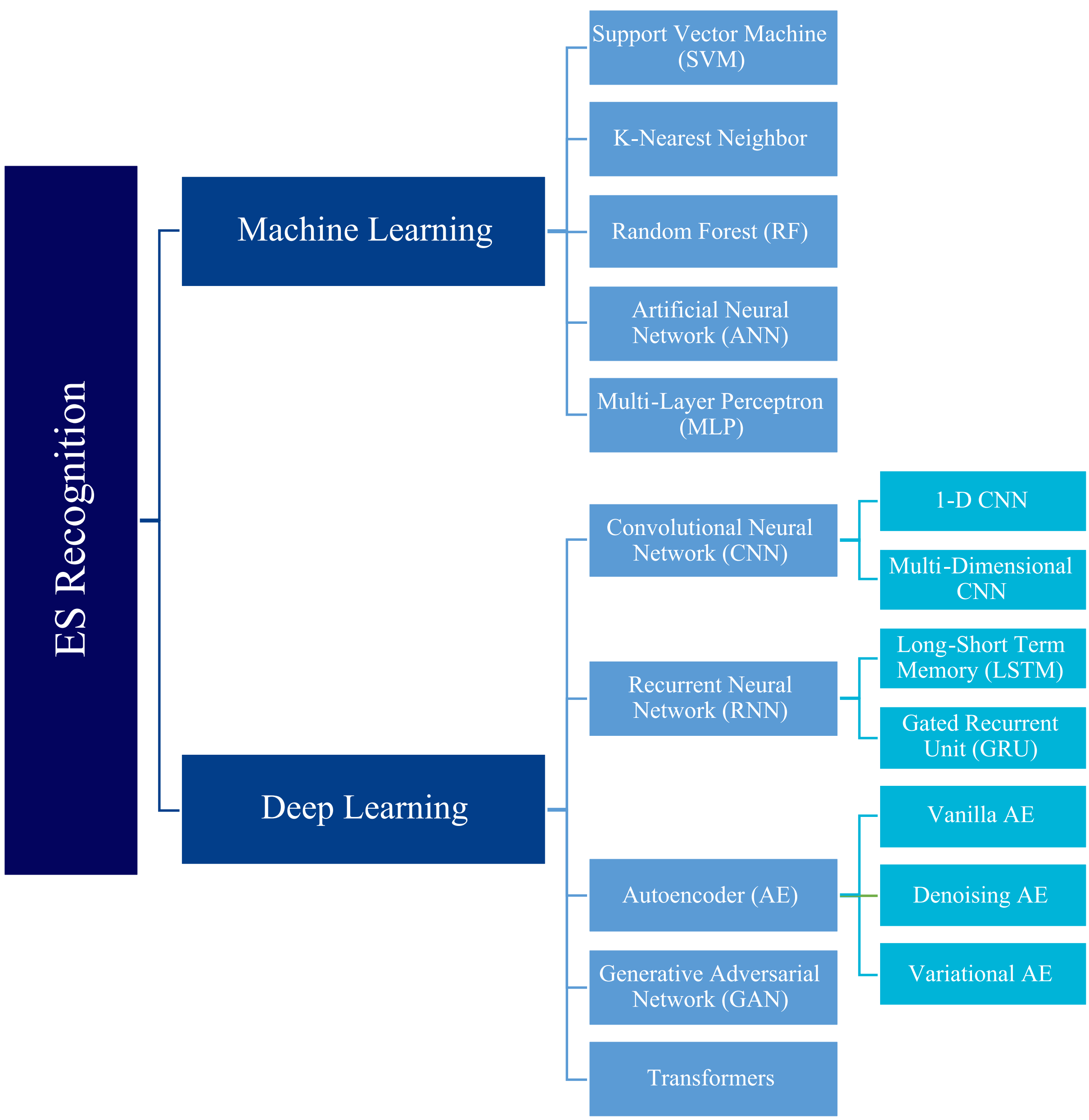

Fig. 4.4. Popular ML and DL models used in the literature.

Fig. 4.4 Shows the most used ml and dl models in es detection, prediction, and classification.

4.6. Performance evaluation

In order to evaluate the performance of the ML or DL models, the methods require a performance and quality check using different evaluation metrics. The most common evaluation metrics throughout the literature are the accuracy, sensitivity, specificity and precision respectively defined by: (Rasheed, 2021)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Precision = \frac{TP}{TP + FP}$$

Where, in terms of detection, classification, or prediction:

- True Positive (TP): is the number of positive class samples the model outputs correctly. In case of seizure prediction for example, TP is the number of correct predictions of the seizure events.
- True Negative (TN): is the number of negative class samples the model outputs correctly. In case of seizure detection for example, TN is the number of non-seizure events detected successfully.
- False Positive (FP): is the number of negative class samples the model outputs incorrectly. In case of seizure detection, FP is the number of non-seizure events detected incorrectly.
- False Negative (FN): is the number of positive class samples the model outputs incorrectly. In terms of seizure detection, FN is the number of seizure events detected incorrectly.

In the literature, there are also other widely used evaluation metrics for detecting, classifying, and predicting ES (Masum et al., 2020; Sánchez-Hernández et al., 2022; Boonyakitanont et al., 2021; Büyükçakır et al., 2020; Hosseini et al., 2018; Yuan et al., 2019; Liu et al., 2020; Daoud and Bayoumi, 2019) . They are described as follow (Bajaj, 2024):

$$TPR = Sensitivity$$

$$FPR = \frac{FP}{FP + TN}$$

$$F1_{score} = \frac{2}{\frac{1}{precision} + \frac{1}{sensitivity}}$$

where:

- True Positive Rate (TPR): is the same as sensitivity and corresponds to the ratio of positive data samples which are correctly output by the model with respect to all positive data samples.
- False Positive Rate (FPR): corresponds to the ratio of negative data samples that are incorrectly output by the model with respect to all negative data samples.

5. Literature review

Based on the aforementioned challenges facing the ES detection, classification, and prediction, this section introduces a short summary of the solutions presented by all the articles selected via the PRISMA diagram. This section is divided by the most used ML and DL models in literature.

5.1. Conventional ML methods

This section explores different ML classifiers used to detect, classify, or predict ES. Fig. 5.1 illustrates the distribution of the most used ML algorithms in three core areas: seizure detection (a), classification (b), and prediction (c). It is shown that SVM classifier was mostly used in detection and prediction tasks while K-NN classifier was majorly used in classification. The following subsections will introduce each model and present some techniques stated in the literature among each classifier.

5.1.1. SVM

SVM has played a crucial role in ES recognition by serving as a primary classifier in various studies. Researchers have used SVM in combination with Wavelet Transformation (WT) and Discrete Wavelet Transformation (DWT) to extract time–frequency domain features such as energy, entropy, and statistical metrics. Table 5.1 lists numerous studies utilizing SVM for epileptic seizure analysis. For instance, Chen et al. (Chen et al., 2017) optimized DWT settings to enhance detection accuracy while maintaining low computational cost, achieving an 86.83 % accuracy rate. In addition, Siddiqui *et al.* (M. K. Siddiqui, M. Z. Islam, and M. A. Kabir, "Analyzing performance of classification techniques in detecting epileptic seizure: The 13th International Conference on Advanced Data Mining and Applications (ADMA)," Adv. Data Min. Appl., vol., 2017) detected seizures from CHB-MIT dataset using four different classifiers (SVM and KNN as black-box) and decision tree and Ensemble classifiers (as non-black-box). They extracted nine features from EEG data including min, max, mean, entropy, line length, standard deviation, kurtosis, skewness, and energy. These features were also used in their previous work (Siddiqui and Islam, 2016). They claimed that the ensemble classifier can assist for seizure detection in shorter windows of 0.5 s with high accuracy rate.

In terms of seizure detection, most studies refer to the use of time domain and frequency domain features along with SVM classifier. authors in (Hussain, 2018; Raghu et al., 2019; Malekzadeh et al., 2021; Sánchez-Hernández et al., 2022; M. K. Siddiqui, M. Z. Islam, and M. A. Kabir, "Analyzing performance of classification techniques in detecting epileptic seizure: The 13th International Conference on Advanced Data Mining and Applications (ADMA)," Adv. Data Min. Appl., vol., 2017) and (Kiranyaz et al., 2013) tested different SVM parameters with min, max, kurtosis, skewness, energy, line-length, root mean square, and amplitude features and with frequency domain features, resulting in the highest accuracy of 99.71 % when using wavelet transforms.

For seizure classification, Moctezuma and Molinas (Moctezuma and Molinas, 2020) employed a genetic algorithm to select optimal EEG channels and used SVM to classify seizure states, achieving 100 % accuracy with DWT features. Ali et al. (Asadi-Pooya et al., 2023) used SVM in a stacking approach with other classifiers to distinguish between Idiopathic Generalized Epilepsy (IGE) and focal epilepsy, reaching 81 % sensitivity and precision.

In seizure prediction, Syed et al. (Muhammad Usman et al., 2021) combined handcrafted features and CNN-based automatic features to predict seizures 30 min before onset, achieving a sensitivity of 96.28 % with SVM as the final classifier. Furthermore, clustering methods such as those used by Sunil and Dong-Ok (Prabhakar and Won, 2023) incorporated SVM alongside learning-based techniques like K-means and bio-inspired methods, where Cuckoo search clustering with SVM attained a 99.48 % classification accuracy. These studies highlight the versatility of SVM in ES analysis, from raw EEG classification to hybrid feature extraction and deep learning integration.

5.1.2. K-NN

K-NN is a simple, non-parametric, and instance-based machine learning algorithm widely used for classification and regression tasks. In the context of ES detection and classification, K-NN identifies patterns in

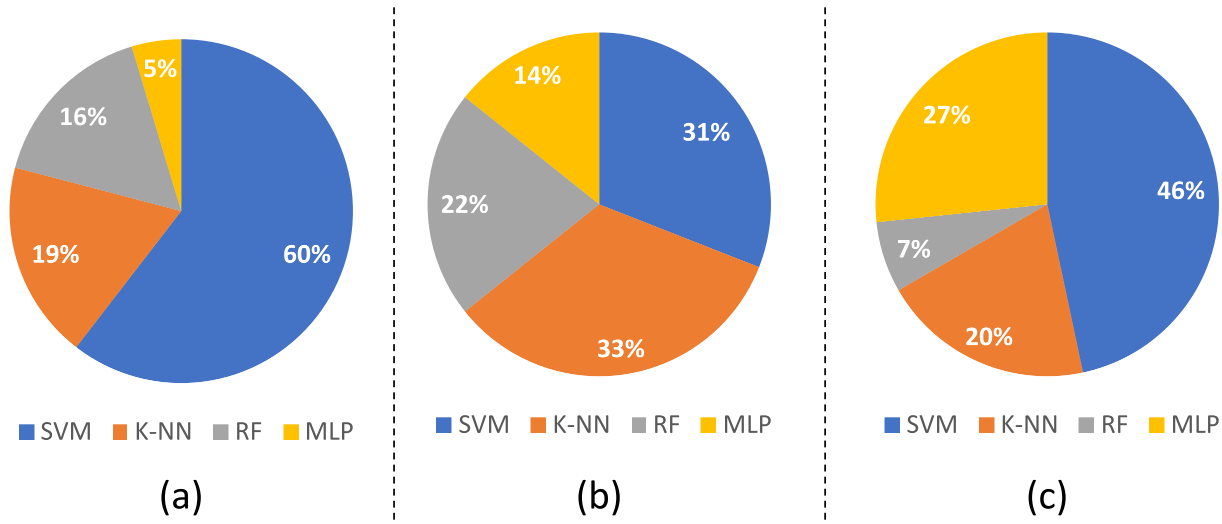

Fig. 5.1. Commonly used ML classifiers in (a) detection, (b) classification, and (c) prediction tasks.

Table 5.1
List of existing literature using SVM model.

Work	Classifier	Feature Extraction	Preprocessing	Dataset	Accuracy (%)
(Chen et al., 2017)	SVM	DWT	–	Bonn	86.83
(Dastgoshadeh and Rabiei, 2022)	SVM	DWT Approximate Entropy and Sample Entropy	DWT	Bonn (sEEG and iEEG)	99.5
(Zabihi and Kiranyaz, 2023)	SVM NB	PCA	PCA	CHB-MIT	95.63
(Ahmad et al., 2014)	SVM	DWT	PCA	CHB-MIT	94.8
(Tran et al., 2022)	SVM K-NN	DWT BPSO	DWT	Bonn (sEEG)	98.4
(Raghu et al., 2019)	SVM	TD FD	Notch filter/ bandpass filter (0.5——40 Hz)/ ICA/ DWT/ window = 1 s overlapping	sEEG of 115 patiens	96.34
(Yuan et al., 2018)	SVM	Global PCAstacked denoising AE	WT scalogram	CHB-MITBonn (sEEG)	95.71
(Tapani et al., 2022)	SVM	22 statistical features	window = 16 s	sEEG of 107 neonates	90
(Al-Salman et al., Mar. 2022)	LS-SVM	FFT	DT-CWT	Bonn (sEEG)Bern-Barcelona	97.7 96.8

Table 5.2
List of existing literature using K-NN model.

Work	Classifier	Feature Extraction Method	Preprocessing	Dataset	Accuracy (%)
(Zazzaro and Pavone, 2022)	K-NN	TD	Bandpass filter Window = 2 s overlapping	Freiburg	98
(Luo, 2022)	K-NN	GLCM	CWT	CHB-MITBonn (sEEG)	99.67
(Malekzadeh et al., 2021)	SVM K-NN CNN-RNN	TD FD	TQWT Window = 5 s (Bonn) Window = 4 s (Freiburg)	Bonn (sEEG) Freiburg	99.71 99.13
(Amin, 2015)	SVM K-NN MLP	DWT	–	Epilepsy	98.75
(Savadkoohi et al., 2020)	K-NN	TD FDTF	FT/ WT/ Butterworth filter	Bonn (sEEG)	99.5
(Liu et al., 2023)	K-NN	FD	Segmented-EEG/ PSD/ FOOOF/ Window = 10 s (overlapping)	Bonn (sEEG) CHB-MIT	98.83 99.95
(Hussain, 2018)	K-NN	TD FD nonlinearwavelet-based entropy	–	Bonn (sEEG)	98
(Tran et al., 2022)	K-NN	DWT BPSO Window = 5 s overlapping	DWT	Bonn (sEEG)	98.4
(Alalayah et al., 2023)	K-NN	DWT	PCA t-SNE	UCI	98.98

EEG signals by comparing them to the closest data points in the feature space. While K-NN can effectively detect complex patterns in time-series EEG data, its lack of interpretability and sensitivity to irrelevant features often limit its standalone use in seizure prediction and detection tasks. Consequently, it is frequently combined with other machine learning models or advanced feature extraction techniques to enhance its performance (Bzdok et al., 2018). Table 5.2 shows some studies utilizing K-NN for ES recognition tasks.

For seizure detection, Mahshid and Rabiei (Dastgoshadeh and Rabiei, 2022), and Tran *et al.* (Tran et al., 2022), claimed that SVM classifier gave better results compared to K-NN. For example, (Dastgoshadeh and Rabiei, 2022) addressed the challenge of time-consuming visual interpretation and the need for early diagnosis of epilepsy. They extracted wavelet sub-bands with useful features related to epileptic seizure. They described these features through 2 entropy methods (approximate and sample entropy). Then, they performed an analysis of variance test to rank the extracted features which in turn will form an optimal feature table with the help of forward sequential feature selection technique. They achieved a detection accuracy of 98 % when using SVM and NB and 94.5 % when using K-NN.

In terms of ES classification, Zazzaro and Pavone (Zazzaro and Pavone, 2022) and Luo *et al.* (Luo, 2022) examined the use of K-NN alone and achieved a classification sensitivity of 92 % and a classification accuracy of 99.67 % respectively. (Zazzaro and Pavone, 2022) proposed a method that combines different statistical, spectral, and entropy features to extract useful features from EEG signals. They tested their algorithm on 23 patients with epilepsy. While, (Luo, 2022) proposed a method that uses time–frequency analysis to decompose EEG signal into 5 rhythms (delta, theta, alpha. beta. and gamma). They then used local binary pattern and gray level co-occurrence matrix to extract, respectively, local pattern and spatial relationships between gray levels in the signals. Then, they used improved Harris Hawks optimization method to select the most discriminative features from the features.

5.1.3. RF

RF is an ensemble learning method that combines multiple Decision Trees (DTs) to improve classification performance. By aggregating the outputs of several DTs, RF reduces variance and minimizes the risk of overfitting, particularly when working with large datasets (Uddin et al., 2019). Its robust performance in handling noisy data and complex features makes it a popular choice in machine learning tasks. However, in the context of ES recognition, many studies have not relied solely on RF. Table 5.3 lists some studies utilizing RF model for ES recognition tasks.

For instance, in detection task, Liu et al. (L. X, W. J, S. J, L. J, D. L, and Y. S, Epileptic Seizure Detection based on Variational Mode Decomposition and deep Forest using EEG Signals Brain Sci. 12 10, 2022) utilized a 4-second overlapping window to apply Variational Mode Decomposition (VMD), effectively decomposing EEG signals into time–frequency components for noise filtering. They then employed a Log-Euclidean Covariance Matrix (LECM) transformation to extract interpretable features, achieving a detection sensitivity of 99.32 % using the Bonn dataset. Nevertheless, other studies (Alickovic et al., 2018; Sánchez-Hernández et al., 2022; Boonyakitanont et al., 2021; Tran et al., 2022) combined RF with different classifiers, concluding that SVM often delivered superior performance for ES detection.

In ES classification, RF has been effectively applied to differentiate between various states of epilepsy. Xiashuang et al. (Wang et al., 2019) developed a model to classify three epilepsy states: no epilepsy, intermittent, and severe, using time–frequency features with an RF classifier. To enhance the performance of RF, they employed an improved Grid Search Optimization (GSO) technique. This optimization method begins with a broad search using large step sizes across all training parameters and then refines the search using a finer mesh for critical parameters. The improved GSO identifies the most optimal parameter sets with minimal penalties, leading to better model performance. They trained their model using a 10-fold cross-validation strategy to ensure robustness and adaptability. By implementing GSO, the classification accuracy of their RF model increased from 88 % to 96.7 %, demonstrating the potential of RF when combined with effective optimization techniques for ES classification tasks.

5.1.4. MLP

MLP is a type of Artificial Neural Network (ANN) that consists of multiple hidden layers, enabling it to model complex, non-linear relationships between input features. Like other ANNs, MLPs excel at detecting intricate patterns in data, making them well-suited for tasks like ES detection and classification. By utilizing multiple layers of interconnected neurons, MLPs can process high-dimensional EEG data and extract meaningful features that help distinguish between seizure and non-seizure events. Table 5.4 shows some studies utilizing MLP for ES recognition tasks.

Several studies have demonstrated the effectiveness of MLPs in seizure detection. For example, Khaled M. Alalayah et al. (Alalayah et al., 2023) achieved a 98.98 % detection accuracy using MLP after decomposing EEG signals with Discrete Wavelet Transform (DWT) and applying dimensionality reduction techniques such as PCA and t-SNE. Similarly, Sriraam et al. (Sriraam, 2018) used Teager energy features, sensitive to sudden changes in EEG signals, and achieved a detection sensitivity of 99.66 % with MLP. In seizure classification and prediction, Jee *et al.* (Siddiqui and Islam, 2016) utilized Synchro-Extracting Transformation (SET) and Singular Value Decomposition (SVD) to enhance EEG time–frequency representation, reaching an accuracy of

Table 5.3
List of existing literature using RF model.

Work	Classifier	Feature Extraction	Preprocessing	Dataset	Accuracy (%)
(L. X, W. J, S. J, L. J, D. L, and Y. S, Epileptic Seizure Detection based on Variational Mode Decomposition and deep Forest using EEG Signals Brain Sci. 12 10, 2022)	RF	VMD	LECM Window = 4 s overlapping	Bonn (sEEG) Freiburg	99.32 95.2
(Sánchez-Hernández et al., 2022)	RF	TD FD	Butterworth high pass filter Butterworth bandpass pass filter Window = 2 s overlapping	CHB-MITSeina (sEEG)	90 93
(Alickovic et al., 2018)	RF	Statistical Methods	EMD DWT WPD	Freiburg CHB-MIT	100
(Wang et al., 2019)	RF	TF	STFTPCA	sEEG of 5 patients	96.7
(Jacobs et al., 2018)	RF	cross-frequency coupling	window = 2 s non-overlapping	sEEG of 12 patients	82.4

Table 5.4
List of existing literature using MLP model.

Work	Classifier	Feature Extraction	Preprocessing	Dataset	Accuracy (%)
(Alalayah et al., 2023)	MLP	DWT	PCA t-SNE	UCI	98.98
(Sriraam, 2018)	MLP	Teager energy	Notch filter ICAwindow = 1 s overlapping	sEEG of 14 patients	96.66
(Ra and Li, 2023)	MLP	SET SET-SVD	–	CHB-MITBonn (sEEG)	99.71 100
(Roy et al., 2018)	MLP	TF	Filtering Spectrogram GAF	TUH	82.27
(Hosseini et al., 2018)	MLP	I-ICA	–	Bonn (sEEG) CHB-MIT	97 94
(Wang and Mengoni, 2022)	MLP	STFT NLP	STFT/ NLP/ Window = 2 s overlapping	TUSZ	85
(Cao et al., 2021)	MLP	SENet LSTM	Window = 2 s non-overlapping	TUH EEG CHB-MIT	96.3 86.7

99.71 %.

In terms of ES classification and prediction, MLP classifier was coupled with another ML or DL model as a final stage to generate the final output (Hosseini et al., 2018; Daoud and Bayoumi, 2019; Amin, 2015; Wang and Mengoni, 2022; Ra and Li, 2023; Roy et al., 2018; Dissanayake et al., 2022) . For instance, Jee *et al.* (Ra and Li, 2023) focused on improving the prediction accuracy, sensitivity, and specificity of epileptic seizures using the Synchro-Extracting Transformation (SET), which is a time–frequency analysis method that belongs to a post-processing procedure of STFT and can generate a more energy-concentrated Time-Frequency (TF) representation and Singular Value Decomposition (SET-SVD) to enhance the time–frequency resolution of EEG signal and achieved an accuracy up to 99.71 %. Also, Mohammad *et al.* (Hosseini et al., 2018) developed a model aiming to solve the problem of fast epileptic seizure classification in real time. They focused on extracting independent features from EEG data through Infinite Independent Component Analysis (I-ICA), which is a method used to separate independent sources from mixed data. Hence, extracting independent features from EEG data and passing each feature space into a separate classifier (*i.e.*, SVM, K-NN, MLP) can significantly decrease the classification time of the model. They achieved a classification accuracy of 97 % with the use of MLP model.

5.2. DL models

This section explores the most used DL models in ES detection, classification, and prediction tasks, which are summarized in the pie chart of Fig. 5.2. It is clearly visible that Convolutional Neural Network (CNN) model is majorly used in all tasks followed by LSTM model. In the following subsections, each DL model will be introduced, highlighting different techniques used in the literature among each model.

5.2.1. CNN

CNN, a type of feedforward neural network, have shown great skill in image analysis and feature extraction (Zhang et al., 2024). They were first known for their ability to recognize detailed spatial patterns and complex structures in images, which quickly made them a popular choice in the field. Recently, more research has focused on using CNNs for EEG data, where they have shown strong performance in identifying epileptic seizure signals from non-seizure signals. In the literature, both 1D-CNN and 2D-CNN architectures have been widely explored for this purpose, each offering unique advantages depending on the nature of the input representation and the task at hand.

In 1D-CNN, EEG signals serve as an input to the model in 1D format. The model was used to reduce the computational complexity associated with higher dimension CNN models and thus is better suited for wearable devices. Fig. 5.3 shows a typical 1D CNN architecture. Qiu et al. (Qiu et al., 2023) employed a 1D CNN with a model pruning mechanism to enhance seizure detection and localization tasks. This approach significantly reduced the computational load of their model, achieving a complexity of only 3.7 million MACs. In comparison, a similar 1D CNN without pruning required 10.1 million MACs, as noted in a study by (Wang et al., 2021). This efficiency gain, however, was achieved through model optimization rather than the inherent structure of 1D-CNN.

It is important to note that the choice between 1D and 2D CNN should be informed by the nature of the input data and the specific features of interest. While 2D-CNN can capture spatial features in 2D representations, 1D-CNN may excel at modeling temporal patterns and inter-channel dynamics directly from raw time-series data. Roy et al. (Roy et al., 2018) tested and compared various ML and DL models to classify epileptic seizures including LR, MLP, 1D-CNN, 2D-CNN, 1D-CNN-RNN, and Time-distributed CNN-RNN. They compared their performance under different preprocessing approaches including 4th order

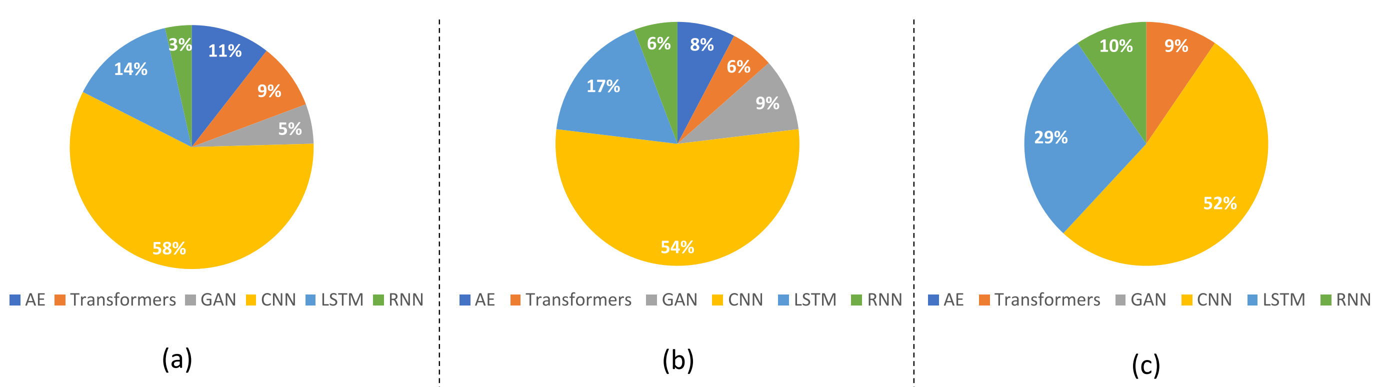

Fig. 5.2. Commonly used DL models in (a) detection, (b) classification, and (c) prediction tasks.

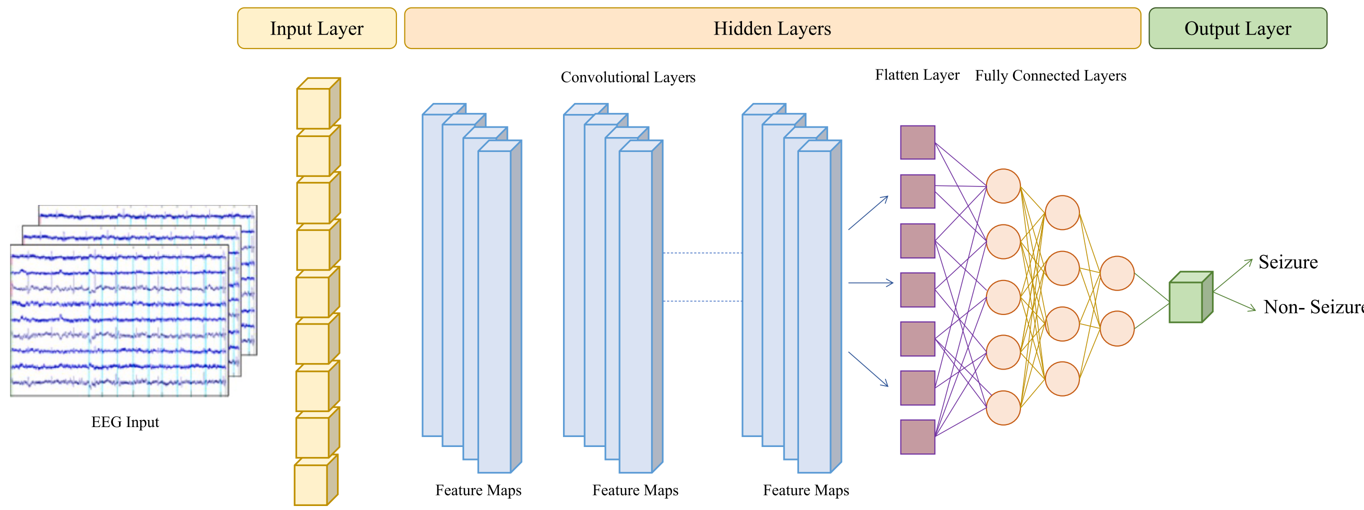

Fig. 5.3. Typical 1D CNN architecture.

Butterworth filtering, spectrograms, and Gramian Angular Field (GAF). They have proved that training the models with the first 11 min of recordings is the most efficient as performance drops after 11 min of recordings. They achieved the best classification accuracy of 82.27 % when combining normal filter (Butterworth filter) with 1D-CNN-RNN.

On the other hand, 2D-CNNs are often employed when EEG data is transformed into image-like formats such as spectrograms or topographical brain maps. These architectures are well-suited for capturing spatial relationships across channels and have been used effectively in seizure detection tasks involving time–frequency representations. For example, Nadalin et al. (Nadalin et al., 2021) developed a model that outputs a probability that a spectrogram image (extracted from an EEG signal) contains a spike ripple. Thus, this image was classified as a subject with high seizure risk. They first divided the EEG signals into 1 s window and subtracted the original signal from the mean within a 0.2 s subinterval and computed the spectrograms. The generated spectrograms represented spikes as heat maps above a frequency threshold and thus they were classified as high probability of seizure events. They targeted the AUC metric and acquired an AUC of 99 %. In addition, researchers employed 2D-CNN along with TD and FD features to reduce the computational cost of the model with preserving its capabilities with feature capturing (Selvaraj et al., 2023; L. Sui, X. Zhao, Q. Zhao, T. Tanaka, and J. Cao, "Localization of Epileptic Foci by Using Convolutional Neural Network Based on iEEG," in Artificial Intelligence Applications and Innovations, J. MacIntyre, I. Maglogiannis, L. Iliadis, and E. Pimenidis, Eds., in IFIP Advances in Information and Communication Technology. Cham: Springer International Publishing, 2019; Roy et al., 2018; Sadiq, 2021; Guerrero et al., 2021; Agarwal et al., 2022; "Epilepsy Detection by Using Scalogram Based Convolutional Neural Network from EEG Signals - PMC." Accessed: Oct. 14, 2023; L. g. m, 2022; Shah et al., 2022; Gao et al., 2020; Zhang, 2020; Lo Giudice, et al., 2022; null Raghu, N. Sriraam, Y. Temel, S. V. Rao, and P. L. Kubben, "A convolutional neural network based framework for classification of seizure types," Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Int. Conf., vol., 2019; Wang et al., 2019; Cui, 2022; Gong et al., 2020) . While others transformed EEG time series into images since 2D-CNN networks are best-suited for image classification ("Epilepsy Detection by Using Scalogram Based Convolutional Neural Network from EEG Signals - PMC." Accessed: Oct. 14, 2023; Li et al., 2021; Ilakiyaselvan et al., 2020; Shankar et al., 2022; Hao et al., 2021; Shankar et al., 2021) . Table 5.5 lists several studies in literature that use 1D and 2D CNN models.

Overall, the selection between 1D and 2D CNN architectures largely depends on the data representation strategy and the intended application. Literature suggests that 1D-CNNs are typically favored when working directly with raw EEG time-series data due to their lower computational complexity and ability to capture temporal dynamics, making them suitable for real-time or embedded systems. Conversely,

Table 5.5
List of existing literature using 1D and 2D CNN models.

Work	Classifier	Feature Extraction	Preprocessing	Dataset	Accuracy (%)
(Lih, 2023)	CNN	PCC	PCC Positional Encoding	Dataset of 121 patients	85
(Qiu et al., 2023)	1D-CNN	Max-Pooling GAP	Band-pass filter	CHB-MIT	97.09
(Antoniades et al., 2024)	2D-CNN	TD	–	Bonn	87.5
("Epileptic seizure detection for multi-channel EEG with deep convolutional neural network | IEEE Conference Publication | IEEE Xplore." Accessed: Oct. 14, 2023)	1D-CNN 2D-CNN	CNN	Low pass filter	CHB-MIT SNUH-HYU	85.6 90.5
(Liang et al., 2020)	1D-CNN	LRCN	–	CHB-MIT	99
(X. Chen, J. Ji, T. Ji, and P. Li, "Cost-Sensitive Deep Active Learning for Epileptic Seizure Detection," in Proceedings of the, 2018)	1D-CNN	DWT	–	Bonn	97.27
(Ibrahim, 2022)	CNN	PSR spectrograms	–	CHB-MIT	94.5
(Zhao, 2020)	1D-CNN	CNN	–	Bonn (sEEG)	99.52
(Burelo et al., 2022)	SNN	CNN	Band-pass filter (50–250 Hz) Bandpass filter (500–900 Hz)	sEEG of 11 patients	80
(Emami et al., 2019)	CNN	–	bandpass filter (0.3—–60 Hz) window = 0.5 s, 1 s, 2 s, 5 s, 10 s	sEEG of 24 patients	81

2D-CNN is often employed when EEG signals are transformed into two-dimensional formats such as spectrograms, time–frequency images, or topographical brain maps. These representations allow 2D-CNN models to use their strength in capturing spatial correlations and complex frequency-domain patterns. While both approaches have demonstrated strong performance in seizure recognition tasks, current research does not indicate a universally superior model; rather, performance outcomes appear to be task-specific and closely tied to the nature of the input features and the chosen preprocessing methods.

5.2.2. RNN

RNN models are a basic type of neural network designed to work well with sequential and time-based data. They are good at recognizing patterns and connections over time, which makes them useful for analyzing time-series data like EEG signals in detecting epileptic seizures ("Deep recurrent neural network for seizure detection | IEEE Conference Publication | IEEE Xplore." Accessed: Feb. 03, 2025). RNN models have two main variants: LSTM and GRU. Table 5.6 lists some studies utilizing RNN models for ES recognition tasks.

5.2.2.1. LSTM. LSTM networks are a special type of RNN designed to solve the vanishing gradient problem and better capture long-term dependencies in data using gated mechanisms. LSTM models are popular because they can effectively model patterns in sequential data while remembering important information over longer periods. Studies have shown that LSTMs perform well in both binary classification (inter-ictal vs. ictal) and three-class classification (pre-ictal, inter-ictal, and ictal) tasks ("Detection of Epilepsy Seizures in Neo-Natal EEG Using LSTM Architecture | IEEE Journals Magazine | IEEE Xplore." Accessed: Feb. 03, 2025).

For ES detection, Aliyu and Lim also developed an LSTM model, using a feature selection algorithm to pick the best wavelet features from EEG signals (Aliyu and Lim, 2023). Another commonly used variant is Bidirectional LSTM (BiLSTM), which processes data in both forward and backward directions. In (Fraiwan and Alkhodari, 2020), pre-processed data (using z-score normalization and Savitzky-Golay filtering) was fed into a BiLSTM network to detect seizures, achieving 99.6 % accuracy. Tuncer and Bolat also used BiLSTM, extracting features like instantaneous frequency and spectral entropy, and highlighted the importance of tuning BiLSTM hyperparameters (Tuncer and Doğru Bolat, 2022).

As far as ES classification is concerned, most articles combined CNN with LSTM (Li et al., 2021; Shankar et al., 2022; Craley et al., 2022; Xu et al., 2020; Huang, 2022) . For instance, Huang *et al.* (Huang, 2022) improved the training efficiency and reduced the data input dimensions by presenting a 1D Depth-wise Separable CNN (DSCNN)-2LSTMs model. The DSCNN, compared to other methods, requires a smaller number of parameters and operations. It accepts simple network matrix as input, thus reducing the input dimensions. It extracts spatial features from EEG signals. They trained their LSTM model using five different EEG data samples. Two of them were collected from scalp EEG for healthy subjects (one for eyes closed and the other for eyes opened) and the other three inter-ictal recordings were collected using iEEG signals (1: healthy hippocampal area, which was collected from hippocampal region, 2: site of the epileptic's brain tumor, which was collected from tumor tissue, and 3: seizure activities from epileptic patients). The classification task was done as binary and multiclass. They acquired a binary classification accuracy of 99.57 % and a quintuple (multi-class) accuracy of 81.3 %.

In the field of ES prediction, Xiang *et al.* (Lu et al., 2023), Fábio *et al.* (Lopes, 2023), and Theekshana *et al.* (Dissanayake et al., 2022) used a CNN-LSTM hybrid model where the CNN model extracts pre-ictal and inter-ictal dependency features and LSTM model performs output prediction. Lu *et al.* (Lu et al., 2023) addressed the issue of timely prediction of epileptic seizures using both temporal and spatial EEG signal features. They used 3D Convolutional Block Attention Module (CBAM) to extract temporal and spatial EEG features and focus only on the relevant features, unlike 2D CNNs which only extract spatial features, from inter-ictal and pre-ictal states. The extracted features were in form of spectrograms extracted from varying window STFT, and they used CNN-BiLSTM model to perform prediction. They achieved a prediction accuracy of 97.95 %.

5.2.2.2. GRU. Another type of RNN is GRU which is designed to address the vanishing gradient issue and enhance the modelling of sequential dependencies. It offers a streamlined architecture with simplified gating mechanisms, which balances the trade-off between modelling capacity and computational complexity (Xu, 2024). In the study of (Zhang, 2022), they proposed a method that combines wavelet

Table 5.6
List of existing literature using RNN models.

Work	Classifier	Feature Extraction	Preprocessing	Dataset	Accuracy (%)
("Detection of Epilepsy Seizures in Neo-Natal EEG Using LSTM Architecture | IEEE Journals Magazine | IEEE Xplore." Accessed: Feb. 03, 2025)	LSTM + BiLSTM	Hurst and ARMA	DCT	Bonn (sEEG)	99.17
(Ahmedt-Aristizabal et al., 2018)	LSTM	–	–	Bonn (sEEG)	95.54
(Aliyu and Lim, 2023)	LSTM	20 eigenvalues features	DWT	Bonn (sEEG)	98
(Fraiwan and Alkhodari, 2020)	BiLSTM	–	Z-score normalization	Bern-Barcelona	99.6
(Tuncer and Doğru Bolat, 2022)	BiLSTM	Instantaneous frequency and spectral entropy	Min-Max normalization	Bonn (sEEG)	99
(Verma and Janghel, 2021)	5-layer GRU	–	DWT	Bonn (sEEG)	98.5
(Ramwala et al., 2023)	4-layer GRU	–	–	Bonn (sEEG)	97.5
(Y. P. Singh and D. K. Lobiyal, "A Comparative Study of Deep Learning Algorithms for Epileptic Seizure Classification," in, 2022)	GRU	–	–	Bonn (sEEG)	98.6
(Zhang, 2022)	BiGRU	Energy value	DWT	CHB-MIT	98.49
(X. Chen, J. Ji, T. Ji, and P. Li, "Cost-Sensitive Deep Active Learning for Epileptic Seizure Detection," in Proceedings of the, 2018)	LSTM	DWT	–	Bonn (sEEG)	97.27
(Geng et al., 2021)	Bi-LSTM	CNN	Normalization [0,1] Window = 1 s, 2 s, and 4 s non-overlapping	CHB-MIT	98.79
(Yang et al., 2021)	LSTM	CNN	–	CHB-MIT	88
(Pan et al., 2022)	LSTM	CNN STFT DFTDWT	STFT DFTDWT	100 EEG recordings	99.08
(Khan et al., 2021)	LSTM	amplitude and statistical features	HVD	Bonn (sEEG)	96

transform and GRU to detect the ictal state in EEG signals. They used wavelet transform to transform raw EEG data into five segments where they focused on segments three to segment five since they hold the ictal state information (3–30 Hz). They calculated the relative energy for each detection window (0.5 s) and passed it to a bidirectional GRU network. They targeted the specificity and sensitivity of the model achieving a specificity of 98.49 % and a sensitivity of 93.89 %. While, the authors of (Verma and Janghel, 2021) created a 5-layer GRU (Gated Recurrent Unit) neural network for EEG data after applying DWT (Discrete Wavelet Transform), achieving 98.5 % accuracy. Similarly, (Ramwala et al., 2023) proposed a 4-layer GRU network for automatic seizure detection without using hand-crafted features. In (Y. P. Singh and D. K. Lobiyal, "A Comparative Study of Deep Learning Algorithms for Epileptic Seizure Classification," in, 2022), GRU and BiGRU (Bidirectional GRU) networks were compared, with BiGRU showing slightly better accuracy (99.3 %) than GRU (98.6 %) on the Bonn dataset.

5.2.3. Autoencoder

AE models are multilayer neural networks which learn an encoded representation of one sample in an unsupervised way (Yue, 2024). In other words, AEs learn to compress input into a latent space then decode it back to its original shape. During training, the model calculates the output reconstruction error and adjusts its weights to minimize this error. The learned latent space can then be used to generate input-like samples and, hence, solve the problem of class imbalance. Another significant strength of AE, like CNN, is that it can learn robust features from raw EEG data with less computational complexity than the CNN model. Fig. 5.4 illustrates the typical architecture of an AE model.

Khan *et al.* (Khan et al., 2023) implemented an AE model that was trained on raw EEG channels of CHB-MIT dataset. They segmented each recording into a 1-second window (256 samples per window). They tested different dimensions for the latent space, reporting the best result is with 64-dimensional latent space. They were also able to detect and localize seizure events with average accuracy of 98.85 %. Also, Daoud *et al.* (Daoud and Bayoumi, 2020) classified between focal and non-focal seizure classes of Bonn and Bern datasets. They developed two models, *i. e.*, simple convolution AE, and deep VAE. They reported a classification accuracy of 96 %, sensitivity of 93 %, and specificity of 99 % when using the VAE model, outperforming the simple convolution AE. Authors in (Yıldız et al., 2022) utilized an AE model as an anomaly detector. They trained the model only on non-seizure data, and during testing if the test signal was decoded (by the decoder) with higher reconstruction error, that means the input has seizure-like characteristics. In another study (de Sousa et al., 2024), they trained the AE model on inter-ictal signals only and when testing, they computed the reconstruction error at the decoder's output with large error leading to non-seizure state and slightly larger error leading to ictal state.

5.2.4. GAN

GAN is a DL architecture that trains two neural networks (discriminator and generator) to compete each other to generate more real-like new data from a training dataset ("What is a GAN - Generative Adversarial Networks Explained - AWS," Amazon Web Services, Inc. Accessed: Dec. 26, 2024). In terms of EEG signals, new signals may be generated using GANs that are comparable to the real ones in order to increase the balancing between non-seizure and seizure parts. The generator generates new data by taking the input sample of an EEG signal, and modifies it as much as possible. Then, the discriminator tries to predict if the generated data at the output follows similar characteristics of the real input. Many researchers used GAN for epileptic seizure detection as part of dataset balancing strategy. For example, Gao et al. (Gao et al., 2022) addressed data imbalance issue with three datasets (CHB-MIT, Bonn, and New Delhi). They proposed a GAN model along with a 1D-CNN to perform detection. They generated synthetic seizure data from GAN and led to a significant improvement in the sensitivity of the model. Their hybrid model achieved sensitivity of 93.53 %, and specificity of 99.05 % on the CHB-MIT dataset outperforming the standalone 1D-CNN. Moreover, Liu (Xiaojia, n.d) detected ES in signals with limited labeled data using an improved GAN model, named semi-supervised GAN (SGAN). The generator takes 100-dimensional random noise vector as input and outputs synthetic EEG signals matching the real data dimensions while the discriminator employs convolutional layers to classify data while distinguishing between real and synthetic samples. Then, the model output underwent moving mean filtering and thresholding to improve the accuracy of seizure classification. The model's performance was assessed using sensitivity, specificity, and accuracy metrics on the CHB-MIT dataset scoring 90.36 %, 93.72 %, and 93.72 %, respectively.

5.2.5. Transformers

Transformers are a foundational architecture in Natural Language

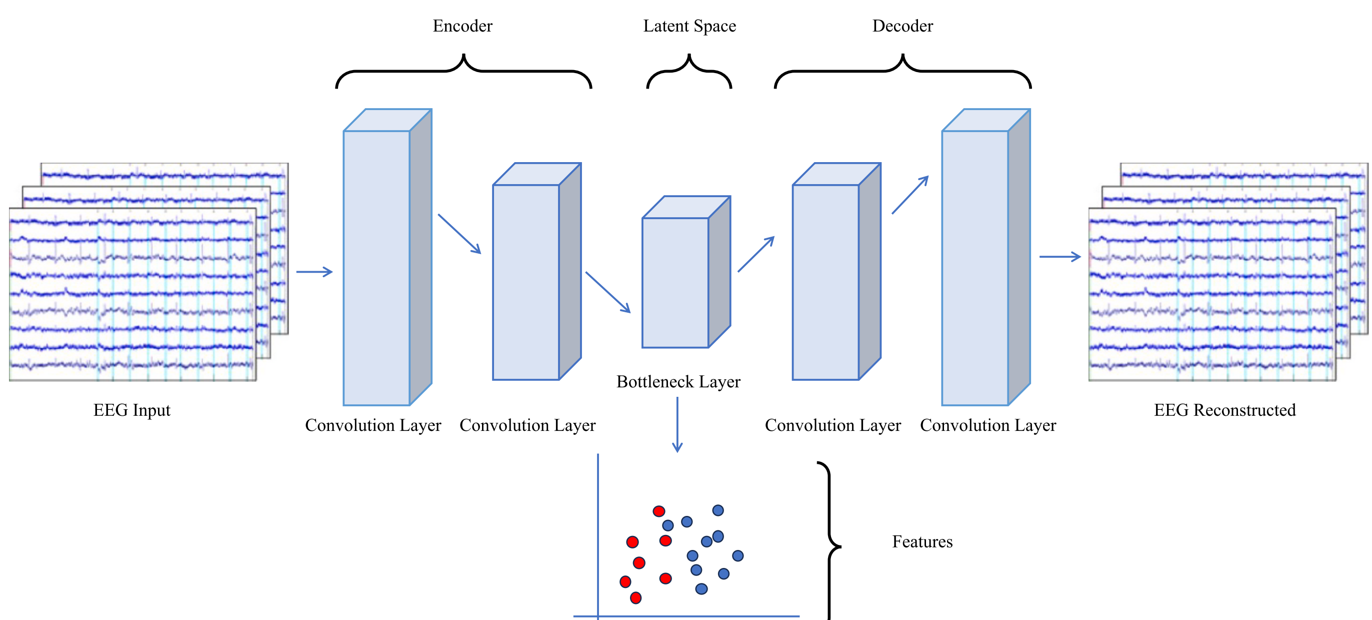

Fig. 5.4. Typical AE model architecture.

Processing (NLP) that have revolutionized sequence modeling tasks. Unlike traditional RNNs, transformers process entire input sequences simultaneously, enabling better parallelization and the efficient handling of long-range dependencies. The core innovation of transformers lies in the attention mechanism, particularly self-attention, which calculates the relationships between all elements in a sequence, allowing the model to weigh their importance in context. To address the lack of inherent sequence order awareness, transformers utilize positional encoding to incorporate positional information into the model ("How Transformers Work: A Detailed Exploration of Transformer Architecture." Accessed: Dec. 27, 2024). Building on this architecture, recent studies started to explore the application of transformers in the field of ES detection, showing their potential to model complex temporal patterns in EEG signals with improved accuracy and efficiency. For example, Zhong *et al.* (Zhong, et al., 2024) combined the time–frequency analysis capabilities of the Stockwell Transform (ST) with the advanced sequence modeling of transformers. The ST captures both time and frequency information from EEG signals while this representation is then fed into the transformer model, which uses self-attention mechanisms to identify complex patterns indicative of seizures. Moreover, Yandong et al. (Ru et al., 2024) used STFT to convert the recording of CHB-MIT into time–frequency representation, and then used a CNN to acquire local information and used transformer's multi-head self-attention to capture global dependencies in order to reduce the computational cost while extracting multi-scale features. They recorded detection accuracy of 92.89 %, sensitivity of 96.17 %, and specificity of 92.99 %. Also, Lih et al. (Lih, 2023) used a 35-channel EEG signal, from a private dataset, to train a transformer model. For each training iteration, they sampled 1-minute data from each participant. Each 5-second segment was transformed into a matrix using Pearson Correlation Coefficient (PCC), where only the upper triangle of the matrix was used as input data. The resulting data was then converted into a 1D array. Positional encoding was added before feeding it into the model. Ten-fold cross-validation was used to assess the model's performance. Their model achieved an accuracy of 85 %, sensitivity of 82 %, specificity of 87 %, and positive predictive value of 82 %. In addition, Li *et al.* (Chang et al., Nov. 2022) proposed a Transformer-guided CNN (TGCNN) for EEG-based seizure prediction. This model combines the strengths of CNNs in capturing local features and Transformers in modeling global dependencies. TGCNN achieved a sensitivity of 91.5 % and an AUC of 93.5 % on the CHB-MIT dataset, demonstrating its efficacy in seizure prediction tasks.

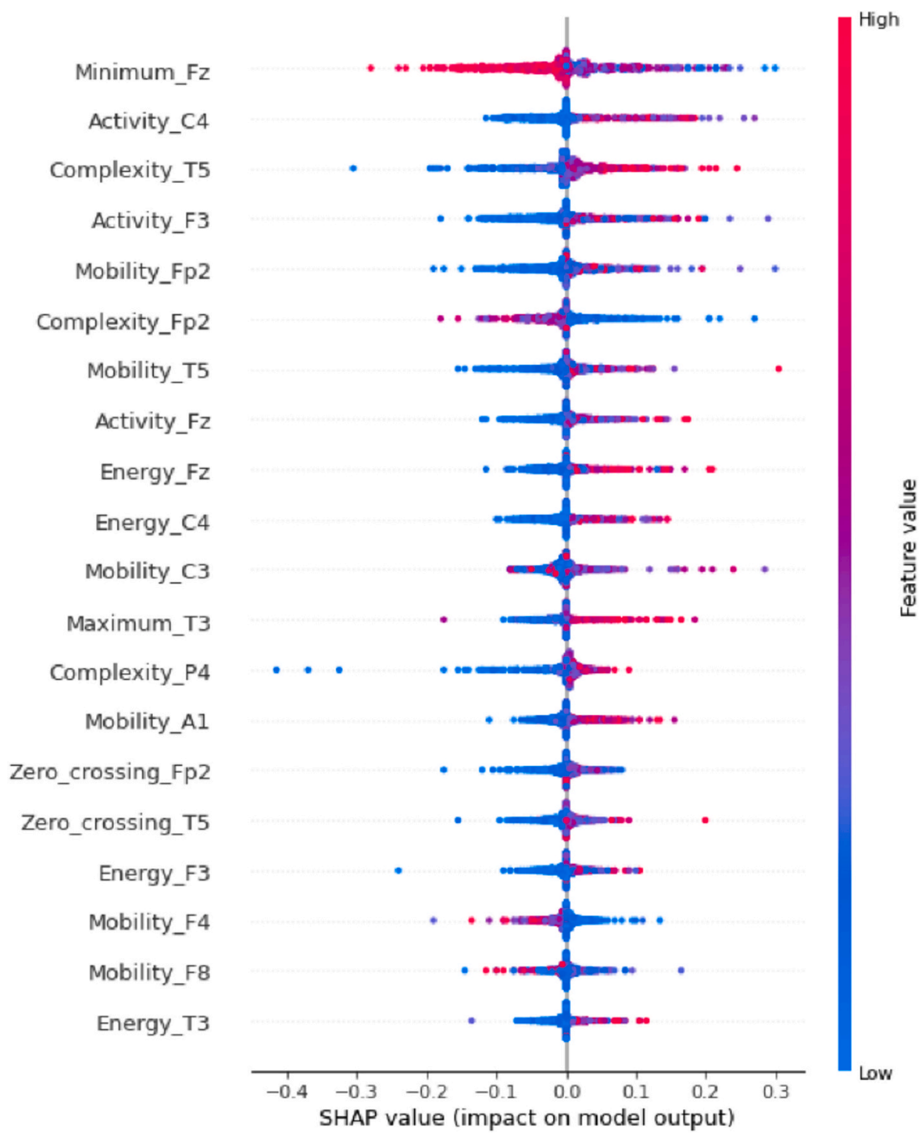

Fig. 5.5. SHAP output for seizure detection task (Vieira et al., 2023).

5.3. Explainable AI

XAI is a collection of techniques and methods designed to help human users understand and trust the outcomes produced by machine and deep learning algorithms. XAI means understanding how an AI model works, what impact it might have, and what biases it might contain. It helps check if the model is accurate, fair, clear, and makes good decisions. This is important for building trust when using AI in real-world tasks. It also helps organizations develop AI in a responsible way ("What is Explainable AI (XAI) | IBM." Accessed: Dec. 22, 2024). In the field of XAI, SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) offer unique approaches to understand complex model output ("LIME vs SHAP: A Comparative Analysis of Interpretability Tools." Accessed: Dec. 22, 2024). LIME is a technique that generates local approximations to model predictions, while SHAP assigns a value for each feature, indicating its contribution to model's prediction. XAI not only improves the reliability and accuracy of the seizure detection system but also enhances trust and interpretability (Khan et al., Aug. 2024). XAI algorithms can also provide an explanation of how they arrive at their prediction, which can help clinicians interpret the data and make more informed decisions about patient care (Rathod and Naik, 2022).

Fig. 5.5 Shows a shap output obtained by(Vieira et al., 2023) to detect seizures in EEG segments. Authors extracted activity, amplitude, complexity, energy, kurtosis, maximum value, mean, median, minimum value, mobility, root mean square, skewness, and zero crossing upon EEG segments. The SHAP output represented in the figure lists on the Y-axis the features that mostly affected the decision of the model (top to bottom = most to least impactful feature on the model's prediction). The X-axis shows the SHAP value where a positive value increases the model's prediction while a negative value decreases the model's prediction. Each dot in the graph indicates one EEG window with red dot being higher value of the feature and a blue dot being a low value of the feature. For instance, high value of "minimum_Fz" feature pushes the model negatively (to the left) meaning a high minimum value in channel Fz leads to a lower seizure prediction. In addition, Khan et al. (Khan et al., Aug. 2024) used both LIME and SHAP to interpret the predictions obtained by several ML classifiers. LIME helped them identify the most important features that influenced the classification results for three classifiers: SVM, KNN, and Random Forest by building a simple, easy-to-understand model that explained how complex classifiers behaved for specific data points, giving local explanations for individual predictions. SHAP was used to analyze how features interacted with each other through dependency graphs. This provided a clearer view of how the model made decisions. Authors found that LIME identified features such as mean, variance, kurtosis, and mean-square have high importance in detecting the normal class, while mean, std, rms, skewness, variance, and maximum contribute significantly to the identification of the seizure class. Also, Raab et al. (Raab et al., 2023) presented an explainable representation of spectral, spatial, and temporal dimensions, named XAI4EEG, to provide an intuitive identification of decision-relevant regions for these dimensions. They proposed two deep learning models (1D-CNN and 3D-CNN) that were fused with XAI4EEG which incorporates SHAP as an explainer. Both models were trained using k-fold-cross-validation. They found that 1D-CNN achieved higher specificity of 97.55 % and precision of 84.24 % compared to 3D-CNN while 3D-CNN had slightly higher sensitivity of 86.00 % compared to 1D-CNN. They reported that the explanation module significantly reduced the validation time for prediction compared to standard SHAP visualization.

6. Discussion and challenges

In this survey, different ML and DL models have been investigated to solve the task of ES recognition. Among the classifiers and models used in literature, it is challenging to tell what is the best classifier or model to use, which is highly dependent upon the task. It is also challenging to compare between features that are best-suited for a specific model due to their heterogenous nature. Table 6.1 lists a comparison between the most used ML and DL models used in ES recognition tasks.

For seizure detection, CNN is recommended due to its ability to automatically extract spatial features and detect seizure activity in time-series data, outperforming SVM and RF in capturing temporal dynamics. Similarly, CNN is the preferred choice for ES classification as it effectively learns patient-specific variations without extensive feature engineering, though RF remains useful in clinical settings for its interpretability, which can be enhanced by XAI. For seizure prediction, both CNN and LSTM were widely used, with LSTM excelling in modeling long-term dependencies, while CNN can be effective when combined with temporal features. Despite CNN achieving lower accuracy in some cases, it is recommended for all tasks due to its robustness in feature extraction. However, to optimize CNN for real-world applications, computational efficiency must be addressed using pruning techniques, hyperparameters should be fine-tuned with methods like grid search or Bayesian optimization, and data augmentation should be employed to improve generalization, particularly with limited datasets.

Both traditional machine learning and deep learning have their strengths and weaknesses in seizure recognition. While DL models excel in automatic feature extraction, handling large-scale data, and achieving high accuracy, it also comes with challenges such as high computational costs and lack of interpretability. Similarly, traditional ML models rely heavily on feature engineering and may struggle with capturing complex patterns in EEG data. Despite their potential, both approaches face

Table 6.1
Comparison between ML and DL models.

Model	Strengths	Limitations
SVM	Effective for high-dimensional data and robust to overfitting ("What is a Support Vector Machine (SVM) | Definition from TechTarget," WhatIs. Accessed: Apr. 21, 2025).	May require extensive tuning of hyperparameters (such as the kernel and regularization parameters) to achieve optimal performance, particularly when working with large datasets.
RF	Selected due to its robustness, ease of use, and interpretability.	Performance might fall with very high-dimensional data or when precise temporal patterns are crucial, as in seizure prediction.
MLP	Can handle non-linear relationships between features, which is beneficial for modeling complex patterns in EEG data.	May require a significant amount of training data to avoid overfitting and achieve good generalization.
CNN	Can automatically extract features from raw and high-dimensional data. Its ability to learn spatial hierarchies makes it powerful for identifying seizure activity in EEG signals.	Computationally intensive and requires large, labeled datasets for effective training and it is less interpretable compared to other models like SVM or RF.
LSTM	Can handle sequential data where it retains long-term dependencies of input data.	Requires large datasets to train effectively and is computationally expensive. Additionally, it can be prone to vanishing gradients if not properly tuned or designed.
Autoencoder	Can automatically extract features from raw data while reducing their dimensions. The computational cost depends on the architecture (e.g., fully connected vs. convolutional AE)	Prone to overfitting when latent dimensions are not properly set.

limitations that need to be addressed for more effective seizure recognition and can be summarized as follows:

- **EEG Signal Complexity:** EEG signals are chaotic and nonlinear, making visual inspection difficult. Scalp EEGs also suffer from noise and artifacts due to minor physical activities like eye blinks, heartbeats, and muscle movements (Sazgar and Young, 2019). These artifacts make feature engineering more challenging and thus more difficult to ML models to perform the task. Preprocessing is needed to clean EEG signals from noise and artifacts. Direct use of EEG signals in machine learning is limited, so feature extraction techniques, from statistical to non-linear methods, are employed to transform the signals for better analysis (Stancin et al., 2021). However, methods that rely on deep learning techniques do not necessitate the manual creation of features.
- **Computational Complexity:** One important factor to take into consideration when designing a ML or DL model in ES detection, classification, and prediction is its complexity. It is a direct indicator whether this model can be implemented on wearable devices or clinical settings with limited hardware resources. One way to measure the model's complexity is by presenting the number of Multiply-Accumulate (MAC) operations which quantify the total multiplications followed by additions required for the model's computations (Hoang et al., 2024). Table 6.2 shows the variations of MACs for different ML classifiers and DL models (Qiu et al., 2023; Pathak et al., 2023) . In terms of ML classifiers (SVM, K-NN, and RF), they generally have lower computational complexity compared to DL models. In case of utilizing DL models, it is always recommended to use lightweight models such as 1D CNN to reduce the computational complexity. In addition, exploring the use of cloud-based solutions such as federated learning could significantly improve the deployment process in resource-limited scenarios.
- **Class Imbalance:** Class imbalance is another factor impacting the quality of ES recognition task. This issue is raised because the duration of EEG recording is long, time-consuming and seizure durations last for few seconds, which results in being prone to errors (Siddiqui et al., 2020). This imbalance often leads traditional classifiers to become biased toward the majority class (non-seizure), which may result in skewed high overall accuracy while failing to detect actual seizure events. Consequently, accuracy alone becomes an unreliable metric in such settings, and alternative evaluation measures like recall, F1-score, or area under the precision-recall curve (AUC-PR) are more appropriate for assessing model performance. Researchers have tackled the problem of imbalanced seizure datasets using various methods. For example, the authors in (Yuan et al., 2019) used VAE to create new samples, while another study in (Amin and Kamboh, 2016) combined SMOTE and RUSTBoost techniques to achieve 97 % accuracy in seizure detection. Strategies like padding, interpolation, and data augmentation were also applied in (Masum et al., 2020; Guo, 2022) . Siddiqui et al. (Siddiqui et al., 2020) introduced penalties for false negatives based on EEG recording duration, achieving a 100 % recall on the CHB-MIT dataset. However, balancing datasets remains challenging, with no one-size-fits-all solution. It's important to consider the dataset's characteristics and avoid overfitting, especially when using oversampling methods like SMOTE. Combining different techniques can sometimes yield the best results.
- **Generalization and Overfitting:** Variability in EEG signals and seizure infrequency make it hard for automated seizure models to work across patients. Patient-specific models improve accuracy but overfit to training data, leading to poorer performance with new patients due to less robust decision boundaries (Alotaiby et al., 2015; Li et al., 2022; Khatami et al., 2020) . Overfitting occurs when a model performs well on training data but fails to generalize to new data, often due to small or imbalanced datasets, excessive noise in EEG signals, and poor training strategies that do not properly separate patients during testing. Patient-specific approaches require clinicians to record new EEG data associated to each new patient. While achieving generalization across various patients is desirable, the trade-off between accuracy and generalization has consistently posed a challenge (Cao et al., 2021; Alotaiby et al., 2015; Quon, 2022) . Furthermore, creating a distinct model for each patient becomes impractical as the patient population expands. While achieving model generalization across extensive patient groups is a challenging undertaking, clinicians often find it more feasible, even if it entails a slight decrease in performance (Quon, 2022). Several studies (Qaisar and Hussain, 2021; Alickovic et al., 2018; Savadkoohi et al., 2020; Anuragi et al., 2021; Moctezuma and Molinas, 2020; Yuan et al., 2018; Karabiber Cura et al., 2020) have reported 100 % accuracy, suggesting overfitting due to data repetition. To mitigate overfitting and improve generalization, various strategies have been implemented, including regularization techniques (Ma, 2021), early stopping (Islam et al., 2022; Liu et al., 2020) , data augmentation (Liang et al., 2022), ensemble learning (Muhammad Usman et al., 2021), transfer learning (Daoud and Bayoumi, 2019), multi-view learning (Pan et al., 2022; Tian, 2019; Tang et al., 2020) , and subject-independent approaches (Dissanayake et al., 2022; Yang, 2020; "Deep Learning for Patient-Independent Epileptic Seizure Prediction Using Scalp EEG Signals | IEEE Journals Magazine | IEEE Xplore." Accessed: Feb. 09, 2025; Thuwajit, 2022) . Regularization, such as adversarial training (Nasiri and Clifford, 2021) and batch normalization in LSTM models (BN-LSTM) (Ma, 2021), mitigates overfitting by stabilizing training dynamics. Data augmentation, including GAN models ("Multichannel Synthetic Preictal EEG Signals to Enhance the Prediction of Epileptic Seizures | IEEE Journals Magazine | IEEE Xplore." Accessed: Feb. 09, 2025) and perturbation-based methods (Liang et al., 2022), artificially expands the dataset and improves robustness. Ensemble learning (Muhammad Usman et al., 2021) utilizes multiple models to reduce variance, while transfer learning (Daoud and Bayoumi, 2019) accelerates training by reusing pre-trained features. Multi-view learning (Tian, 2019; Pan et al., 2022) extracts diverse feature representations, improving discrimination across different domains. Structural CNN modifications (Jia et al., 2022; Hussein et al., 2021; Song et al., 2022) enhance adaptability by introducing dynamic weight mechanisms and optimized convolutions. Lastly, subject-independent approaches (Yang, 2020; "Deep Learning for Patient-Independent Epileptic Seizure Prediction Using Scalp EEG Signals | IEEE Journals Magazine | IEEE Xplore." Accessed: Feb. 09, 2025; Dissanayake et al., 2022; Thuwajit, 2022) train models on diverse patient data, boosting generalizability across individuals. These combined techniques significantly improve seizure recognition performance while addressing data scarcity and variability challenges.

Table 6.2
ML and DL models computational complexity.

Model	Average MACs (Million)	Notes
SVM	~1–50	Complexity depends on kernel type; typically, efficient for smaller datasets.
K-NN	~30–100	Higher MACs due to the need to compute distances for all samples.
RF	~50–150	Increases with the number of trees and tree depth.
MLP	~100–300	Relatively simple structure, but MACs depend on the number of hidden layers and neurons per layer.
ANN	~150–400	Slightly higher due to more complex architectures compared to basic MLPs.
AE	~200–800	Complexity depends on the encoder-decoder structure and size of latent features.
CNN	~300–1000+	Highly efficient for feature extraction but expensive with larger filter sizes or deeper architectures.
RNN	~500–1200+	Complexity scales with sequence length and hidden units; suitable for temporal features.
LSTM	~1000–1500+	Higher complexity than RNN due to additional gates for memory handling.

- **Interpretability**: The lack of transparency in deep learning models remains a major challenge. Models like CNN and RNN are very effective but are often seen as "black boxes," making it hard to understand how they make decisions or what features they focus on. Improving the interpretability and trustworthiness of these models is an important research area. Techniques like Layer-wise Relevance Propagation (LRP), Grad-CAM, or SHAP values can help explain their decision-making process. Additionally, using simpler models or combining deep learning with more explainable approaches can create a better balance between accuracy and clarity (Xu, 2024).
- **Task-Specific Challenges:** Despite the challenges mentioned above that are common for all tasks (detection, classification, and prediction), each task presents unique difficulties that affect the performance of the designed ML and DL models:
  - o For detection task, the requirement for real-time performance introduces a critical challenge: selecting an appropriate processing window length. This choice directly impacts the model's responsiveness and accuracy, as too short window may miss relevant features, while too long window can delay detection. Authors in (Emami et al., 2019) experimented with different detection windows such as 0.5, 1, 2, 5, and 10 s and claimed the highest detection accuracy was when using larger windows. And another study in (Khan et al., 2023) claimed that the choice of detection window should be between 1 and 30 s. However, selecting lower lengths significantly improves the detection speed but it requires special attention to the features extracted. To solve the issue of real-time detection, authors in (Sharan and Berkovsky, 2020) and (Nadalin et al., 2021) used frequency features (wavelet transforms and STFT) over 2-seconds windows to best describe the short length EEG windows and acquired an accuracy of 97.25 % and an AUC of 0.99 respectively, while (Sánchez-Hernández et al., 2022) used time domain features such as max, min, energy, kurtosis, skewness, and amplitude and get a 0.9 F1-score. To sum up, short detection windows require extra attention to feature extraction, applying overlapping windows, and data augmentation to better describe the short segments that can positively affect the detection speed.
  - o For classification tasks, a major challenge lies in the limited availability of annotated training data. Unlike seizure detection, which can utilize unsupervised learning approaches, seizure classification requires expert-labeled EEG recordings for each seizure type which requires an effort that is both time-consuming and resource-intensive. As a result, many studies rely on private datasets to carry out this task at the cost of reduce generalizability (Qaisar and Hussain, 2021; Cui, 2022; Agarwal et al., 2022; "Machine learning detects EEG microstate alterations in patients living with temporal lobe epilepsy - PubMed." Accessed: Jan. 02, 2024) . Moreover, Transitions between different seizure types can be gradual and hard to define in an EEG recording. Thus, feature extraction and selection techniques such as Gramian angular summation field (Shankar et al., 2021), wavelet transform (Lo Giudice, et al., 2022; Karabiber Cura et al., 2020) , and empirical mode decomposition (Pandey et al., 2022) are suggested to better let the model distinguish between different seizure types. Another possible mitigation for annotation-limited datasets was developed by (Wu et al., 2024), where they have shown the effectiveness of self-supervised learning for EEG signals by reconstructing masked EEG segments in the Fourier domain. This approach reduces the reliance on annotated data and supports the need for pretraining methods in label-limited clinical settings.
  - o For prediction task, the challenging part is determining the boundaries of the pre-ictal state where there is no general rule for this. Authors in (Wang, et al., 2020) defined the pre-ictal state 30 min prior of the ictal state where in (Dissanayake et al., 2022), they supposed the pre-ictal is 1 h prior of the ictal state. This lack of unified definition over the pre-ictal state raises the false alarm rates resulting in less confidence in the system (Yg, 2020). In addition, and while determining the pre-ictal state boundaries is still ambiguous, different patients have different pre-ictal characteristics limiting the model's ability to generalize which constitutes another seizure prediction challenge.

7. Conclusion

This paper presented a systematic review of ES detection, classification, and prediction using ML and DL models, highlighting advancements and persistent challenges such as computational complexity, class imbalance, generalization issues, and model interpretability. Among the most effective models, SVM demonstrated strong classification performance but required extensive feature engineering, CNN excelled in feature extraction from image-like EEG representations, and LSTM proved effective for seizure prediction when combined with robust temporal features at the cost of high computational demand. Additionally, wavelet-based transformation was found to outperform STFT in capturing EEG frequency variations, while time and frequency features such as energy, min/max frequency, and line length were identified as the most discriminative. CHB-MIT, Bonn, and private datasets were the most widely used, with CHB-MIT aiding generalization, Bonn supporting multi-class classification, and private datasets enhancing robustness but increasing the risk of overfitting.

Despite progress, challenges remain in deploying seizure recognition models in clinical settings. DL models often demand high computational resources, necessitating optimization techniques such as model compression and lightweight architectures for real-time applications. Class imbalance continues to affect model reliability, with GANs and VAEs emerging as potential solutions for synthetic data generation. To improve generalization, domain adaptation, transfer learning, and federated learning should be explored, while XAI techniques like SHAP and LIME can enhance model transparency for clinical trust. Additionally, hybrid models integrating LSTMs with CNNs or advanced time–frequency analysis methods can refine seizure prediction accuracy. Future research should focus on privacy-preserving, interpretable, and efficient AI models, bridging the gap between AI-driven methodologies and real-world clinical applications.

8. The use of Generative AI

During the preparation of this work, the authors used ChatGPT in order to check on grammatical mistakes in some sentences and summarize some other sentences. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

CRediT authorship contribution statement

Raja Mourad: Conceptualization, Data collection, Data analysis, and Writing. **Ahmad Diab:** Conceptualization, Data collection, Data analysis, Writing – review & editing, Supervision. **Zaher Merhi:** Conceptualization, Data collection, Data analysis, Writing – review & editing, Supervision. **Mohammad Khalil:** Supervision. **Régine Le Bouquin Jeannès:** Conceptualization, Data collection, Data analysis, Writing – review & editing, Supervision.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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