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Methods for Identifying Epilepsy: A Comprehensive Review

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Abstract - Epilepsy, a widespread neurological disorder, has a substantial global impact, especially in low- and middle-income countries. Early and precise epilepsy detection could prevent around 70% of seizures. The Electroencephalogram (EEG) is a vital tool for recording neurological data in epilepsy patients. Recent advancements in automatic epilepsy detection methods, including signal processing, machine learning and deep learning, has gained significant attention. This paper provides a thorough examination of the most effective and precise method for detecting epilepsy, with a specific emphasis on utilizing EEG-based machine learning and deep learning approaches for diagnosing seizures.

Keywords - EEG, Epilepsy, Signal processing, machine learning, deep learning

1. Introduction

Epilepsy is a neurological condition marked by abnormal brain activity, leading to recurrent involuntary movements and associated symptoms. This can result in complications such as depression and cardiovascular problems, affecting both patients and their families. With approximately 50 million affected individuals worldwide, early detection is crucial for effective seizure management through medication [1]. Various tests, including EEG, high-density EEG, CT scans, MRI, fMRI, PET, and SPECT are used to diagnose epilepsy and determine the cause of seizures.

While EEG is a common diagnostic tool, it can be time-consuming for neurologists. Therefore, automated seizure detection methods have emerged, utilizing signal processing, machine learning, and deep learning algorithms. Analyzing and classifying EEG data are essential for epilepsy diagnosis, as EEG patterns offer real-time insights into the brain's electrophysiological state. EEG has advantages such as portability, affordability, high temporal resolution, tolerance to subject movement, and no radiation exposure risks. However, it has limitations in spatial resolution and signal-to-noise ratio.

Currently, epilepsy detection involves manual examination of EEG recordings, a process that can take several days. Diagnosis relies on intricate and lengthy EEG tests, with results subject to interpretation by the examining physician. Discrepancies may arise between novice and expert assessments, making this method time-consuming and error-prone. To address these challenges, robust and reliable techniques for detecting epileptic activity in EEG signals are crucial. Accurate identification of seizure type and location is vital for effective treatment.

Epilepsy detection methods, which encompass signal processing, machine learning, and deep learning, typically involve four key stages: 1. Signal pre-processing (including artifact removal), 2. Segmentation, 3. Feature extraction, and 4. Classification. The below figure-1 illustrate the overall system for epilepsy detection from EEG signals, incorporating all the techniques discussed. These methods primarily differ in the feature extraction stage. Traditional signal feature extraction with manual features is one category. Another involves automatic feature extraction combined with machine learning classifiers, falling under supervised or unsupervised machine learning algorithms. For methods that encompass data pre-processing, automatic segmentation, and the automatic feeding of self-learned features to classifiers, classifying epilepsy signals as black box classifiers, they are categorized as a deep learning approach.

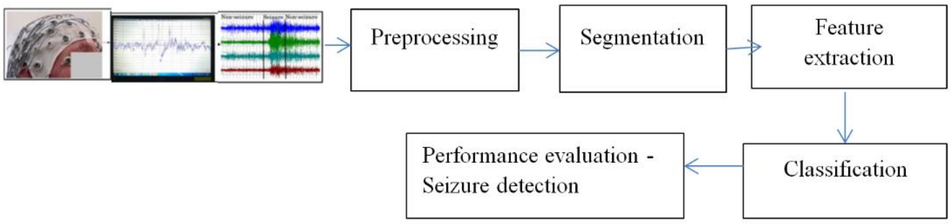

Fig.1 Overview of epilepsy detection process [23] [26]

Epilepsy detection follows a structured approach, beginning with data acquisition, often using EEG data that may contain significant noise. The next step is signal pre-processing, which focuses on noise removal. Segmentation comes next, where appropriate algorithms are used to extract segments. The subsequent phase is feature extraction, where crucial statistical features play a vital role in distinguishing EEG signals. Recent efforts aim to create stable representations of seizure presence to improve detection accuracy. Feature extraction condenses extensive EEG data into a feature vector while retaining information (feature reduction and selection).

Classification follows, involving the prediction or categorization of unknown observations based on criteria derived from known observations in the training group. Lastly, performance evaluation relies on standard measures like accuracy, sensitivity, specificity, and the area under the ROC curve, among others. The EEG analysis involves these stages, and the subsequent section provides a brief review of the related literature for each stage, followed by a discussion of the most effective technique employed within them.

2. Literature review

This section provides a concise overview of the literature review concerning the most prominent technique that excels in each stage of epilepsy detection.

Anchal Yadav et.al [2] discussed ocular artifacts in EEG data collected from scalp electrodes and introduces an innovative method that combines Ensemble Empirical Mode Decomposition (EEMD) and Spatial Constraint Independent Component Analysis (SCICA). to effectively remove these artifacts while preserving EEG signals. The method involves EEMD to extract IMFs, distinguishing between artifactual and artifact-free IMFs using a correlation-based approach. Artifactual IMFs are then used to derive ICs through ICA with an Inverse Mixing Matrix. Thresholds for discrimination are set using Kurtosis and mMSE, with spatial constraints applied to adjust the mixing matrix. This approach outperforms existing methods in removing ocular artifacts, as shown in comparisons using Mutual Information, Correlation Coefficient, and Coherence measures.

Chao-Lin Teng et al [3] introduced EICA, a novel method for handling common EOG artifacts in EEG signals. EICA combines EEMD and ICA to address this challenge. In EICA, EEG signals are decomposed into ICs using ICA, EOG-related ICs are identified using kurtosis, and the EEMD algorithm targets these EOG-related ICs to remove EOG-related IMFs. Clean EEG signals are then reconstructed through ICA inversion. EICA's effectiveness is demonstrated on both simulated and real EEG data, offering an improved solution with higher signal-to-noise ratios and reduced errors in EOG artifact removal. This method enhances multichannel EEG signal processing and analysis by effectively eliminating blink artifacts.

Jakub Jirka et. al.[4] has developed the concept of adaptive segmentation, which was initially introduced by Silin and Skrylev in 1986, involved sliding Fast Fourier Transform (FFT) windows but proved inadequate for non-stationary EEG signals. Varri later improved this approach by incorporating two windows with variable signal amplitude summations, serving as a foundation for subsequent techniques named as modified varri. Various methods, including FFT, fuzzy c-means, linear prediction, autocorrelation, and fractal dimensions, are available for adaptive segmentation. Among these, fractal dimensions have shown remarkable efficiency in rapid signal segmentation. An advanced approach integrates fractal dimension (FD) with evolutionary algorithms (EAs) to address dynamic signals like EEG. This method utilizes discrete wavelet transform (DWT) and sliding windows to enhance segmentation accuracy.

Automatic epilepsy classification using EEG data was first presented by Mădălina-Giorgiana Murariu et al. [5]. It makes use of empirical mode decomposition (EMD) to extract EEG data and then analyses the spectral power density of the resulting intrinsic mode functions (IMFs). These IMF characteristics can tell the difference between localised and distributed EEG activity. K-nearest Neighbour (KNN) and Naive Bayes (NB) classifiers are used for classification, with impressively high accuracy: 99.90% and 99.80% for focal and non-focal data, and 99.49% and 99.20% for focal and generalized epilepsy data during wakefulness and sleep stages, respectively. This technique offers a major advancement in the classification of EEG signals for epilepsy, which may benefit in the making of clinical decisions for patients.

Muzaffer aslan et.al.[6] used Hilbert Huang Transformation (HHT) to extract distinctive features like mean Instantaneous Amplitude (IA) and mean Instantaneous Frequency (IF) from EEG signals. These features are classified using Extreme Learning Machine (ELM), resulting in highly accurate seizure detection. Furthermore, the method outperforms recent techniques with 0.5-1% higher classification accuracy and superior seizure detection accuracy.

Mokhtar Mohammadi et. al. [7] proposed a method which combines MEMD and the Hilbert transform, forming HHT, to analyse the spectral energy of IMFs in the signal. EMD adaptively breaks down signals into multiple IMFs based on their characteristics. Hilbert transforms (HTs) are then used to convert these IMFs into instantaneous frequencies (IFs), providing time-frequency-energy distributions. Detection of epileptic seizures in EEG signals is performed using a support vector machine. The algorithm was tested on intracranial EEG records from patients with refractory epilepsy and validated by the Epilepsy Center at the University Hospital of Freiburg. Experimental results show that this method efficiently identifies epileptic seizures in EEG signals with reasonable accuracy.

C.Jamunadevi et.al [8] has found that rising interest among researchers in developing automated methods to detect EEG signal abnormalities has led to an increased prevalence of EEG seizure detection. However, this endeavor demands a higher temporal resolution and is often constrained by limited data availability. Machine learning offers a promising avenue for extracting crucial information from EEG signals to aid in seizure detection. In this study, they conducted a performance analysis using different classifiers, including Random Forest, Gaussian Boosting, and AdaBoost. The findings demonstrate that Random Forest stands out as the most accurate classifier, delivering a high level of precision.

Raveendra kumar t. H. et.al. [9] Proposed an automated classification method using a modified XGBoost classifier with a focal loss function to improve efficiency since diagnosis of epilepsy is a challenging task, often relying on time-consuming manual seizure detection guided by neurologists. This model evaluation, based on the CHB-MIT Scalp EEG dataset from all 24 patients, compares 2-class seizure results with state-of-the-art approaches. Cross-validation experiments determine seizure or non-seizure predictions, resulting in nearly 100% average sensitivity and specificity. Importantly, this model enhances average sensitivity by 0.05% and boosts average specificity by 1%, outperforming existing seizure detection techniques.

As described by Puja Dhar et al. [10], due to their superior categorization abilities, Machine Learning and Deep Learning techniques have lately gained traction in the automatic identification of epileptic episodes. Neurologists can benefit greatly from the precise categorization of different seizure disorders in large EEG datasets by means of ML and DL algorithms. Using many features, researchers in this study implemented a convolutional neural network (CNN) to detect seizures in EEG data. The classification performance of the hybrid CNN-RNN model is thoroughly examined by simulation analysis, proving its efficacy in seizure detection using measures like accuracy, precision, recall, F1 score, and false-positive rate.

In brief, the review of the literature on epilepsy EEG signals reveals a common practice of using ICA in the preprocessing stage, modified varri for segmentation, and EMD-HHT for feature extraction. Further details regarding the utilization of XG Boost for classification will be elaborated in the subsequent section.

3. A comprehensive overview of best techniques employed at various stages.

3.1 Stage-1

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3.1.1 EEG Pre-processing or the elimination of artifacts:

EEG signals are pre-processed to enhance quality by eliminating noise, correcting baselines, filtering, and handling artifacts. Decisions regarding artifact management prioritize preserving clinical information for visual signal interpretation. Noise reduction, while essential, must not compromise overall artifact removal. EEG's high temporal resolution makes it prone to noise and diverse artifacts from instruments and subjects, excessive electrode impedance, line noise, and defective electrodes are all potential causes. Physiological artefacts such as eye movements, blinks, heart activity, and muscular activity can affect EEG data but are difficult to manage despite advances in instrumentation and systems and methods.

Artifacts can be classified as internal (physiological) and external (non-physiological). Handling internal artifacts like ocular electro-oculogram (EOG) and muscular (EMG) artifacts is challenging due to their signal characteristics. Effective artifact management is crucial in EEG-based research, particularly in diagnosing neurological disorders. While numerous artifact removal methods exist, a consensus on optimal approaches to enhance signal quality remains elusive. Recent developments focus on refining algorithms, combining techniques, and automating denoising. Traditional methods like regression, ocular artifact correction, and blind source separation remain prevalent. However, static filtering approaches struggle with noise elimination due to subject-specific EEG sub-band variations. The following section briefly discusses used EEG artifact removal method.

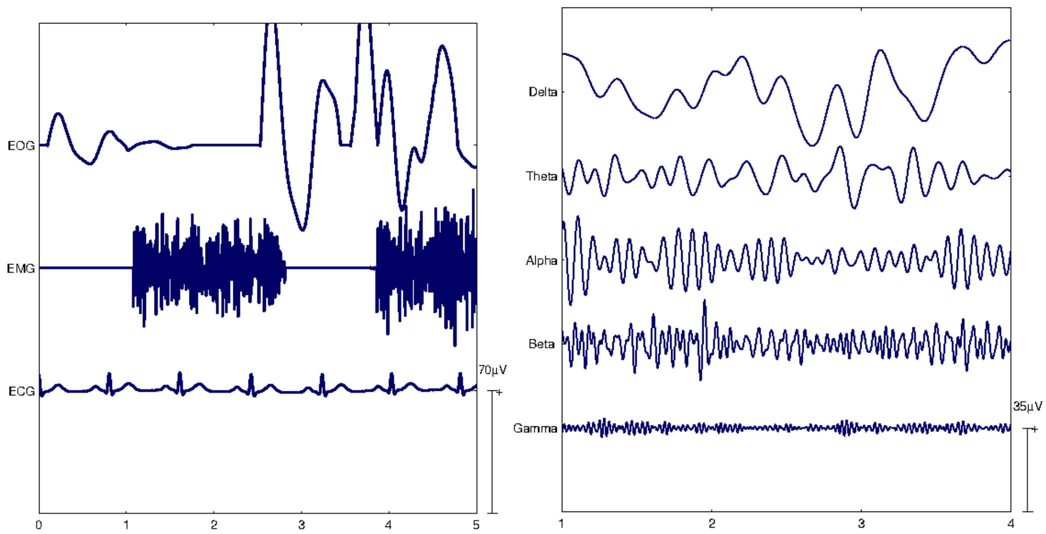

Fig. 2 (a) Brain Rhythms (b) Artifacts

In Fig.2 (a), we see the full range of frequencies that make up the background EEG spectrum, from Delta through Theta, Alpha, Beta, and Gamma. Most physiological disturbances in EEG artefact removal investigations fall into one of three categories: (b) ocular artefacts, (c) muscle artefacts, or (d) cardiac artefacts. [11].

3.1.2 Independent component analysis (ICA)

Blind source separation techniques, such as ICA and PCA, process data from all electrodes simultaneously (X), whereas methods like without managing source separation explicitly, channels can be processed via regression, filtering, empirical mode decomposition, and the wavelet transform. ICA is commonly used to remove EEG artifacts by breaking down multi-channel EEG data into temporally independent components with fixed spatial patterns. In epilepsy research, ICA assists in separating EEG signals into distinct components, improving artifact removal, and identifying abnormal sources associated with seizures. However, ICA may inadvertently remove eye-related signals from the electrooculogram (EOG), potentially impacting brain activity in the EOG. Detecting and eliminating transient artifacts like muscle spasms and movements with ICA can be challenging. Real-time processing with ICA demands substantial computational resources but offers the advantage of not requiring a reference channel.

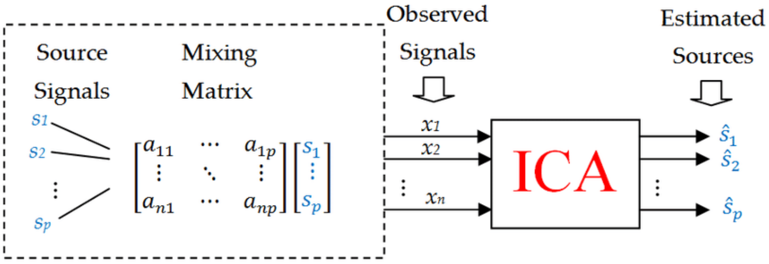

Fig. 3. Block diagram of standard independent component analysis [12]

In summary, Independent Component Analysis (ICA) is a machine learning technique used to decompose multivariate signals into independent, non-Gaussian components. It assumes that the signals result from a linear combination of distinct, non-Gaussian sources. Its primary goal is to identify a linear transformation that produces independent components, achieved by utilizing an unmixing matrix (W) to reconstruct the original sources.

$$S = W X \qquad (1)$$

In this context, S represents the ICA source activity, with dimensions of components multiplied by time. W represents the ICA unmixing matrix, characterized by components multiplied by channels, and X denotes the data matrix with dimensions of channels multiplied by time.

3.2 Stage-2

3.2.1 EEG Signal Segmentation

EEG signal segmentation is essential for exploring brainwave data systematically. It divides continuous EEG data into shorter segments, enabling in-depth analyses like event-related potentials and spectral assessments. Various methods are employed; each chosen based on research objectives and data features.

The Adaptive Segmentation technique, particularly the Modified Varri method, customizes segment lengths according to EEG signal characteristics. It adapts to non-stationary EEG data, typical during changes in brain states. This technique uses two sliding windows to create segments, focusing on amplitude summation and frequency analysis. The adaptation ensures that segments capture relevant signal properties, making it especially useful for events like epileptic seizures that alter signal characteristics [04].

Modified-Varri enhances EEG signal understanding, catering to non-stationary signals and aiding research in EEG-based studies. This method is pivotal for precise analysis and interpretation of EEG data.

3.2.2 Adaptive Segmentation (Modified Varri):

Adaptive Segmentation adapts segment lengths based on signal characteristics like peaks or spectral shifts. On the other hand, Sliding Window Segmentation uses a continuous, fixed window that moves along the EEG signal, providing a balance between time and frequency for ongoing analysis.

The Modified Varri technique utilizes two sliding windows and is based on the summation of amplitude values within these windows. It also incorporates a frequency measure derived from the summation of differences between consecutive signal samples [13].

$$\boldsymbol{A_{dif}} = \sum_{k=1}^{N} |\boldsymbol{X_k}| \qquad (2)$$

$$\boldsymbol{F_{dif}} = \sum_{k=1}^{N} |\, \boldsymbol{X_k} - \boldsymbol{X_{k-1}} \,| \qquad (3)$$

Here, N represents the window length, and X_k corresponds to the k^{th} signal point. Consequently, the difference function (G) is defined as follows:

$$G_m = A_l \,|\, A_{difm+1} - A_{difm} \,| + F_l \,|\, F_{difm+1} - F_{difm} \quad (4)$$

In this context, "m" represents the window number, while the constants A1 and F1 may vary in different applications. Segment boundaries are determined by detecting local maxima in the G function exceeding a predefined threshold.

Fractal dimension is a valuable metric for assessing signal complexity and identifying new segments when it surpasses a predefined threshold. In EEG analysis, the Hilbert-Huang Transform (HHT) is chosen for its ability to handle EEG data's nonlinearity. Singular Spectrum Analysis (SSA) is vital for noise reduction, enhancing data quality. However, for precise EEG analysis, the Modified Variability (mVAR) method excels. This statistical approach specializes in capturing signal variability, proving advantageous, especially in noisy EEG data, and enhancing our understanding of brain dynamics.

Modified Variability (mVAR) is a customized and indispensable technique for EEG analysis. Its enhancement of variability estimation provides deeper insights, particularly in complex scenarios. This technique significantly contributes to the progress of neuroscience research and clinical applications. Following segmentation, each segment allows for a multitude of analyses, such as exploring frequency components, studying temporal patterns, and making statistical comparisons across different conditions or subjects.

3.3 Stage-3

3.3.1 EEG Feature extraction and feature selection

In this section, we explore distinct approaches to extract features from EEG signals, primarily for the purpose of seizure detection. Feature extraction can be categorized into two main methods: manual and automatic extraction. Manual extraction involves the creation of features through manual processes, spanning various forms within both frequency and temporal domains. In contrast, automatic feature extraction relies on the utilization of parameters like mean, kurtosis, skewness, entropy, statistical moments, variance, correlation, and more. These features are often analyzed within common feature domains, consisting of not only the time domain but also the time-frequency domain and the frequency domain.

The Fourier transform (FT), discrete wavelet transforms (DWT), and continuous wavelet transforms (CWT) are often used for this purpose. In the feature extraction stage of epilepsy detection, literature suggests the utilization of EMD, PCA, Hilbert Huang Transform (HHT), and DWT methods as highly suitable choices. These techniques excel in extracting essential features from EEG signals, which can then be applied in the subsequent classification phase. The following section provides detailed explanations for HHT used for feature extraction [6].

3.3.2 Hilbert Huang Transform (HHT):

The utilization of the Hilbert-Huang Transform (HHT) for feature extraction is a powerful method for analyzing intricate and non-linear signals, including EEG data. HHT dissects these signals into Intrinsic Mode Functions (IMFs), effectively capturing their inherent oscillatory components. These IMFs serve as a foundation for feature extraction across various applications, particularly in the domain of epileptic seizure detection. HHT-based feature extraction facilitates the identification of crucial characteristics like signal energy, frequency distribution, and temporal patterns, all contributing to the distinction between normal and abnormal brain activity. This approach provides valuable insights for understanding EEG signal dynamics, making it a valuable asset in both neuro-scientific research and clinical applications [6].

The Hilbert Huang Transform (HHT) is carried out in a two-step procedure, combining the Hilbert transform (HT) with the empirical mode decomposition (EMD) technique. In the first step, EMD disassembles the signals into intrinsic mode functions (IMFs), each representing distinct time scales. In the second step, the Hilbert transform is individually applied to each IMF, resulting in the creation of the Hilbert spectrum. This spectrum serves as the fundamental source for subsequent feature extraction processes [6][7].

The Hilbert Transform H[X(t)] of a signal X(t) is defined as,

$$H[X(t)] = X(t)^* \frac{1}{\pi t} = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{X(\tau)}{t-\tau} d\tau = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{X(t-\tau)}{\tau} d\tau \quad (5)$$

The Hilbert transform of X(t) is obtained by convolving X(t) with the signal 1/πt, representing the reaction of X(t) to a linear time-invariant filter known as a Hilbert transformer with an impulse response of 1/πt. After applying the Hilbert transform to every intrinsic mode function (IMF), features, including statistical parameters (mean, median, standard deviation, minimum, maximum, energy) and Hjorth features (activity, mobility, complexity), are extracted. Cumulative features (cumulative mean, cumulative minimum, cumulative maximum), and additional metrics (Shannon entropy, Rényi entropy, approximate entropy, Sample entropy, Higuchi fractal dimension, Katz fractal dimension) are computed from both the IMFs and residual waves. The averages of these features are determined across segments. These features are calculated for each Hilbert-transformed signal and then averaged across the segments.

3.3.3 Mutual Information (MI) Score:

Mutual Information (MI) is derived from information theory and functions as a valuable tool for feature selection, akin to the concept of information gain in constructing decision trees. MI measures the reduction in uncertainty of one variable when the value of another variable is known. While it is inherently suitable for discrete variables like categorical data, it can be adapted for numerical data as well. MI quantifies the decrease in entropy related to the target value. The MI score ranges from 0 to ∞, with higher scores indicating stronger associations between features and the target variable, underscoring their significance in model training. Conversely, lower scores, including 0, imply weaker associations [5].

3.4 Stage-4

3.4.1 EEG Classification and epilepsy detection

Numerous studies have been devoted to the identification of epileptic seizures by analyzing EEG data, examining a wide array of approaches encompassing statistical, nonlinear, and machine learning methods. These methods include diverse classifiers like Artificial neural networks (ANN), convolutional neural networks (CNN), recurrent neural networks (RNN), and autoencoders (AE) have all been tested and compared to traditional methods like random forests, SVMs, K-NNs, and Gradient Boosts. Conducting a comprehensive assessment of various factors is crucial for epilepsy classification. The selection of metrics relies on specific application needs. Notably, Random Forest (RF) and XG-Boost have exhibited strong performance, and the subsequent section delves deeper into their exploration.

3.4.2 X-treme Gradient boost classifier

Gradient Boosting (GB) is a potent machine learning approach, creating robust ensemble models by combining multiple weaker prediction models, often in the form of decision trees, primarily focusing on improving classification tasks. It operates iteratively, training new models to rectify previous model deficiencies, with each subsequent model predicting gradients or residuals of the loss function associated with prior models' predictions. The final classification decision aggregates all models' predictions [9].

The Gradient Boosting Classifier's mathematical foundation involves step-by-step loss function reduction by fitting weak classifiers to negative gradients. This iterative process progressively improves model accuracy errors in prediction.

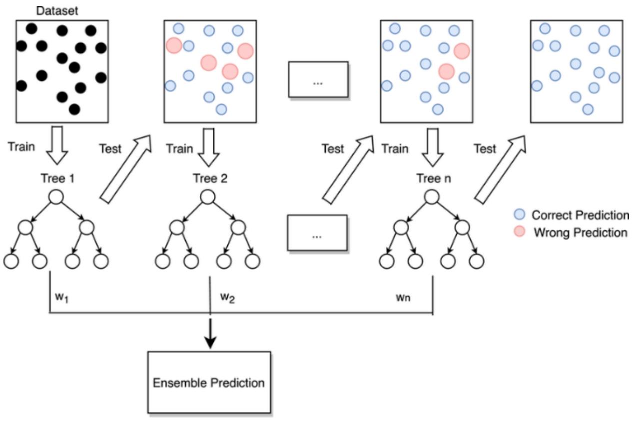

Fig. 4. Flow diagram of gradient boosting machine learning method [14]

Gradient Boosting (GB) is a robust ensemble machine learning method, primarily focused on enhancing classification tasks by combining multiple weak prediction models, often in the form of decision trees. This process involves iterative model training to address deficiencies in prior models, with each model predicting gradients or residuals of the loss function tied to previous predictions. The ultimate classification result is an aggregation of predictions from all the models [14].

GB's mathematical foundation relies on sequentially reducing a loss function by fitting weak classifiers to the negative gradients, leading to gradual improvements in model accuracy. These core principles underlie Gradient Boosting, systematically enhancing prediction accuracy by iteratively reducing residual errors through weak classifier fitting. The final prediction combines their forecasts, with the combination weighted according to the learning rate.

XGBoost, or eXtreme Gradient Boosting, is an advanced evolution of gradient boosting, tailored for enhanced efficiency and precision. It prioritizes gradient information and integrates multiple optimizations while building upon the fundamental principles of gradient boosting with its unique refinements.

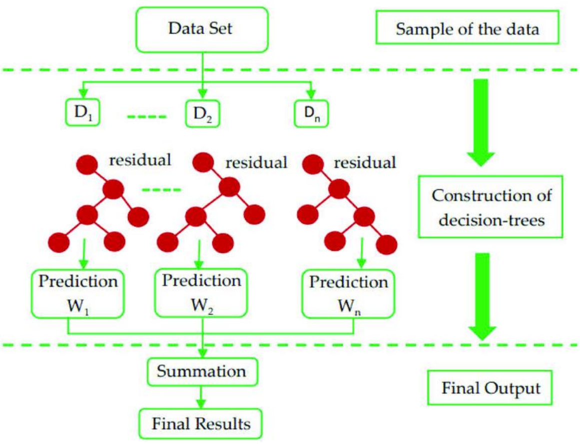

Fig. 5 XGBoost (extreme gradient-boosting) algorithm structure [15]

3.4.3 Evaluation Metrics for Epilepsy Detection Classification Methods

The evaluation of epilepsy classification encompasses a diverse set of machine learning metrics, collectively providing insights into the model's ability to distinguish between epileptic and non-epileptic signals.

In the mathematical assessment of a classifier model, performance metrics occupy a pivotal role. This section is dedicated to evaluating the model's effectiveness and quantifying its predictive accuracy using quantitative data.

Specifically, four metric functions - accuracy, precision, F1 score, and recall - are employed for this purpose [5].

Having previously provided detailed explanations of the stages and techniques commonly utilized in typical epilepsy detection methods, along with a brief overview of relevant literature, we now shift our focus to delve into deep learning -an advanced machine learning approach that holds relevance in epilepsy detection.

4.1 Deep Learning (DL) Approach

Epilepsy detection initially relied on traditional signal processing and human expertise. The term "machine learning" (ML) emerged in computer science and AI in the 1950s and 1960s, with pioneers like Arthur Samuel introducing algorithms that allow computers to learn from experience rather than explicit programming. Over the time, the machine learning especially deep learning, transformed epilepsy detection, automating feature extraction, enhancing EEG analysis accuracy, and fostering automation. This evolution, driven by computational progress and data availability, established machine learning as a fundamental component in various applications. Machine learning comprises diverse algorithms that facilitate learning from data and making predictions without explicit programming, significantly impacting contemporary technology. However, it thrives in structured data tasks but may face limitations in unstructured domains like images, audio, and text.

Deep learning (DL) is a subfield of machine learning that uses convolutional neural networks (ANNs) with many hidden layers, as shown in the figure, to autonomously extract hierarchical features from raw data. This approach is particularly effective for handling unstructured data, such as images, audio, and natural language. In natural language processing (NLP), notable deep learning architectures include transformer-based models and recurrent neural networks (RNNs). CNNs are used for image analysis[10].

It's worth mentioning that deep learning typically requires a significant amount of labeled data and substantial computational resources, such as GPUs or TPUs. In summary, deep learning, a subset of machine learning, excels in automatically learning relevant features from unstructured data through deep neural networks. In contrast, machine learning encompasses a broader range of algorithms, often requiring manual feature engineering and being better suited for structured data.

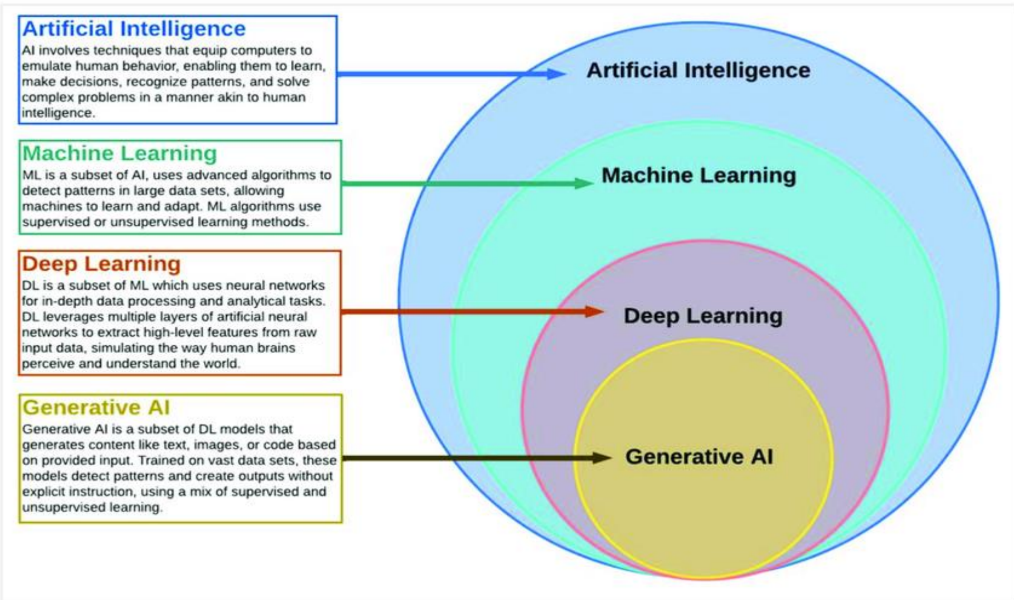

Fig. 6. ML vs DL vs AI: Overview [16]

4.1.1 CNN model:

CNNs, initially designed for visual data, have showcased their adaptability in handling non-image data, especially in NLP and text classification. While sharing core neural network principles with multilayer perceptron's (MLPs), CNNs differ in design, drawing inspiration from the animal visual system for exceptional image processing capabilities. In deep learning, CNNs have become prominent, excelling in one- and two-dimensional applications, such as disease prognosis from biological signals and the detection of epileptic seizures in EEG data.

Two-dimensional Convolutional Neural Networks (2D-CNNs) utilize visualization techniques like spectrograms and wavelet transforms to convert one-dimensional EEG signals into two-dimensional representations. In contrast, convolutional networks analyze one-dimensional EEG signals in their raw format. This distinction warrants a separate examination of both 2D and 1D-CNNs in the context of epileptic seizure detection [17].

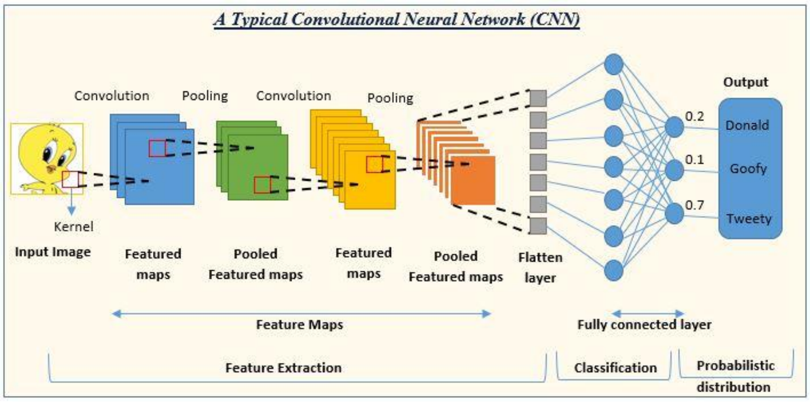

Fig. 7. Convolutional-neural-network-an-overview [17]

4.2 *Contrast Between Deep Learning (DL) and Traditional Machine Learning (ML) in Epilepsy Detection*

In traditional machine learning, feature and classifier selection often require a trial-and-error approach, making it suitable for small datasets but less effective with large volumes of data. On the other hand, deep learning methods, which depend on extensive training data, operate across multiple feature spaces, posing challenges with limited data availability. Historically, traditional machine learning models were developed primarily using Mat-lab, while deep learning models rely heavily on Python, often supported by open-source toolboxes. Python's accessibility and cloud computing resources have facilitated the creation of sophisticated automated systems [18].

To summarize, epilepsy detection has transitioned from traditional machine learning to deep learning due to increased data availability and the pursuit of precision. Traditional machine learning excels with small datasets but struggles with larger ones, requiring manual feature extraction and classifier selection. Deep learning streamlines these processes, benefiting from extensive data for complex models [18] [19].

Deep learning's demand for ample training data aligns with its exploration of various feature spaces, promoting data-centric research. This shift to deep learning is marked by the use of Python and open-source toolboxes, making it more accessible and conducive to system development. Implementing deep learning in epilepsy detection enhances accuracy and efficiency, potentially revolutionizing epilepsy pattern identification. Staying current with technological advancements in medical signal analysis is crucial.

Conclusion

Epileptic seizure detection bridges the realms of traditional signal processing and deep learning. Although there is no universally accepted framework declaring one approach superior in epilepsy detection, this review study aims to identify effective techniques within deep learning and signal processing to optimize epilepsy diagnosis based on multiple investigations. This thorough review study has made researcher to get insight of superior technique which is used in each stage of the epilepsy detection techniques.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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