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A Review of Artificial Intelligence Methods for Diagnosing and Classifying Schizophrenia Using EEG Signals

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ABSTRACT

Schizophrenia (SZ) is a chronic and severe mental disorder characterized by impairments in cognitive skills, perceptions, emotions, and social interactions. A timely and accurate diagnosis is crucial for improving prognosis and developing effective treatment strategies. Recently, researchers have utilized computational models to enhance the effectiveness and speed of schizophrenia diagnosis using electroencephalogram (EEG), consequently reducing clinical workload. This research investigates the integration of traditional signal processing techniques, feature extraction methods, and artificial intelligence (AI), including machine learning (ML) and deep learning (DL), for the categorization of schizophrenia (SZ) utilizing EEG data. The electroencephalogram, a crucial tool for assessing cerebral activity, has demonstrated importance in mental health research. Upon acquiring brain data, various signal-processing techniques are employed to extract pertinent information from the temporal, frequency, and spatial domains. The gathered properties, encompassing mean, variance, and band power, are the basis for recognizing EEG signals. Traditional machine learning techniques, such as Decision Trees and Support Vector Machines (SVMs), provide interpretability and effectiveness with constrained datasets. In contrast, deep learning techniques, such as convolutional neural networks (CNNs) and extended short-term memory networks (LSTMs), excel in analyzing complex EEG patterns; however, they require extensive data and significant computational resources. The study examines the challenges associated with implementing AI in the diagnosis of schizophrenia, including ethical concerns and issues with data quality. These difficulties require collaborative and ethically sound approaches to ensure reliable advancement in the area. The research highlights the importance of employing many approaches to improve diagnosis accuracy, showcasing the potential of AI-driven solutions in the classification of schizophrenia. This review offers a comprehensive examination of contemporary literature, encompassing themes, approaches, and conclusions. The aim is to identify significant advancements and provide insights that help researchers and clinicians understand and tackle schizophrenia through innovative AI-driven approaches.

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1. Introduction

Schizophrenia (SZ) is a devastating mental illness and a degenerative neurological ailment that profoundly influences social situations, healthcare systems, and the quality of life for affected individuals and their families [1].

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It affects cognitive functions, social interactions, and perception of reality, leading to symptoms such as delusions, hallucinations (e.g., auditory or visual distortions), and cognitive deficits that obstruct thought processes. Furthermore, SZ patients often exhibit reduced emotional expression, less motivation, difficulties in social interaction, motor deficits, and impaired daily functioning [2]. The precise etiology of schizophrenia remains unknown; nonetheless, it is unequivocally influenced by a confluence of biological, environmental, and genetic variables, impacting around 21 million individuals worldwide [3]. The illness is a major contributor to disability and imposes considerable economic and societal burdens due to increased healthcare costs and increasing morbidity and mortality rates. An expedient and accurate diagnosis is essential for enhancing patient outcomes and improving their quality of life. The increasing demand has led to the development of automated and efficient diagnostic methods to differentiate individuals with schizophrenia from healthy individuals. The diagnosis of schizophrenia has traditionally relied on clinical interviews and behavioral assessments conducted by professionals. Nevertheless, these methods are subjective, laborious, and prone to human error [4]. Neuroimaging techniques, such as electroencephalography (EEG), computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET), have been assessed to improve diagnostic accuracy [5]. EEG has become a favored instrument owing to its remarkable temporal resolution, non-invasive nature, and cost efficiency. Electroencephalogram (EEG) signals obtained from scalp electrodes represent the brain's electrical activity, producing extensive data that necessitates advanced analytical methods for interpretation [6].

Recently, artificial intelligence (AI) has exhibited considerable potential in various fields, including cybersecurity, virtual reality therapy, medical diagnostics, disease management, and healthcare optimization. In medical research, artificial intelligence, particularly machine learning and deep learning, has revolutionized the analysis of complex biomedical data. The advanced computational power of graphics processing units (GPUs) has accelerated the processing and analysis of EEG signals, hence improving diagnostic accuracy for schizophrenia and other neurological disorders [7]. Fig. 1 illustrates a block diagram for classifying schizophrenia using AI. AI-based SZ classification consists of several stages, including preprocessing, feature extraction, feature selection, and classification. In traditional machine learning (ML) approaches, features are extracted from EEG signals using various methods, such as time, frequency, time-frequency, and nonlinear techniques[8]. While ML methods yield reliable results, deep learning (DL) models are particularly effective with large datasets as they can automatically learn hierarchical feature representations. However, DL models typically require significant computational resources and longer training times [9]. This review offers a thorough examination of AI-based methods for classifying EEG signals associated with schizophrenia.

The key contributions of this work are as follows:

- A systematic comparison of machine learning (ML) and deep learning (DL) techniques, to evaluate their effectiveness in schizophrenia detection.
- The paper explores different feature extraction methods (time, frequency, and time-frequency domains) and their impact on classification performance, helping researchers select optimal feature sets.
- This study evaluates the most efficient EEG preprocessing methods, encompassing filtering, normalization, and artifact elimination, to enhance model efficacy.
- Identification of principal obstacles, including dataset variability and interpretability, along with suggestions for future study, such as hybrid models and multimodal data fusion.

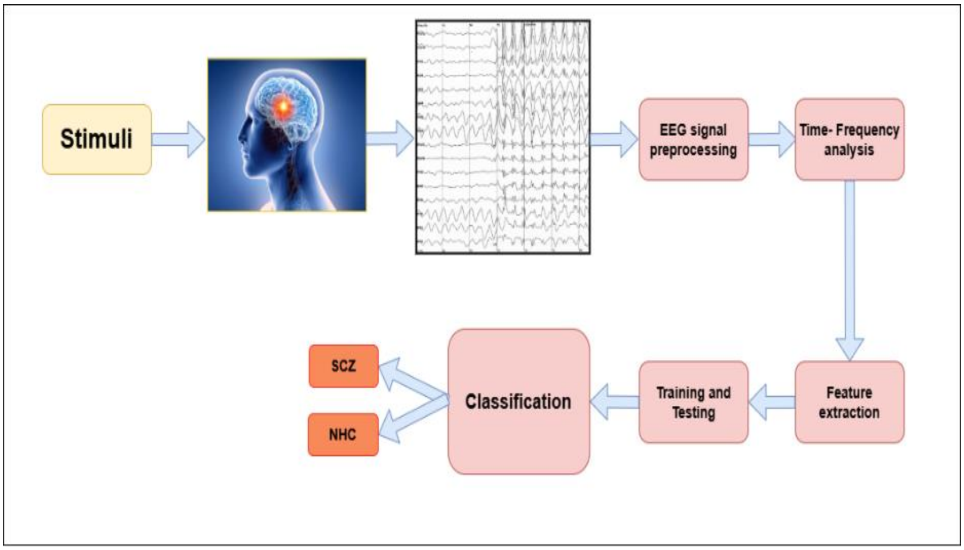

Fig. 1- Block diagram for classifying schizophrenia using AI.

2. Related Work

Multiple studies have examined the classification of schizophrenia via EEG patterns, employing both machine learning and deep learning techniques. This section summarizes the most pertinent studies, organized by their use of diverse methodologies. (Jahmunah et al., 2019) examined EEG classification employing Support Vector Machines (SVM) with Radial Basis Function (RBF) and polynomial kernels, attaining a maximum accuracy of 92.91%. Support Vector Machine models necessitate meticulous kernel selection, and their efficacy is significantly influenced by the selected features [10]. (Siuly et al.,2020) employed Empirical Mode Decomposition (EMD) to analyze EEG data by decomposing it into intrinsic mode functions (IMFs). They subsequently conducted feature selection using the Kruskal-Wallis test. The Ensemble Bagged Tree (EBT) had the highest efficacy as a classifier, achieving an accuracy of 93.21%. The EMD-based decomposition method may produce extraneous or irrelevant features, potentially leading to increased computational complexity [11]. (Sunil Kumar Prabhakar et al., 2020) improved Isometric Mapping (Isomap) features with the Flower Pollination Algorithm and classified them with Real AdaBoost, achieving an accuracy of 98.77%. Feature optimization enhances accuracy while concurrently increasing computational complexity, hence challenging real-time applications [12].

Similarly, (Manish Sharma & U. Rajendra Acharya, 2021) developed a computer-aided diagnostic (CAD) system utilizing single-channel EEG. They derived normative features from wavelet-decomposed sub-bands and classified these features using the K-nearest neighbors (KNN) algorithm, with a remarkable accuracy of 99.21%. Nonetheless, dependence on single-channel EEG may constrain the depiction of spatial characteristics, thereby undermining classification efficacy in multi-channel configurations [13]. (Mehmet Baygin et al.,2021) proposed a three-stage framework employing the Collatz pattern, maximal absolute pooling (MAP) decomposition, iterative neighborhood component analysis (INCA), and K-nearest neighbors (KNN) for classification purposes. Their model achieved exceptional accuracies of 99.47% and 93.58% on two separate datasets. The iterative feature selection method escalates processing requirements, rendering it less practical for real-time applications [14]. (Keihani et al. , 2022) extracted twenty microstate features, including occurrence, duration, and mean global field power (GFP). Using Chi-square tests for feature selection and a Bayesian-optimised SVM classifier, the study achieved an accuracy of 90.93% [15].

In 2023, Megha Agarwal and Amit Singhal introduced a Fourier-based method for real-time detection of SZ. Their approach utilizes a boosted trees (BT) classifier combined with Look Ahead Pattern (LAP) features, achieving accuracy rates of 98.62% and 99.24% on two different datasets. However, the study relies entirely on the Fourier transform, which may not effectively capture the complex non-stationary characteristics of EEG signals when compared to wavelet-based techniques [16]. (Ruiz de Miras et al., 2023) proposed a pipeline that extracts both linear and non-linear features from sliding EEG windows. They identify the most discriminative attributes via principal component analysis (PCA) and subsequently classify these features using a support vector machine (SVM) classifier. Their methods achieved an accuracy of 89%. Nonetheless, a limitation of this technique is that the feature selection process depends on PCA, which may not consistently identify the most pertinent EEG data. This constraint may impact the reliability of the classification [17]. (T. Sunil Kumar et al., 2023) discerned two feature categories from EEG signals: Histogram of Local Variance (HLV) and Symmetrical Weighted Local Binary Patterns (SLBP). They employed correlation-based techniques for feature selection and classified the data using AdaBoost, attaining accuracies of 92.85% and 99.36% on two distinct datasets. Nonetheless, the work relies on manually constructed features, which may lack robust generalizability to other EEG datasets [18].

(Bethany Gosala & colleagues 2023) investigated the use of Continuous Wavelet Transform (CWT) for feature extraction and the diagnosis of schizophrenia (SZ) employing Decision Trees (DT). Their model achieved an impressive accuracy of 97.98%. However, the study is deficient in a comparative examination with alternative classifiers, which would augment the evaluation of the robustness of their approaches [19]. (Athar Alazzaw et al., 2024) employed four machine learning algorithms: "ensemble classifier (EC), quadratic discriminant analysis (QDA), support vector machine (SVM), and K-nearest neighbor (KNN)" to classify individuals with schizophrenia (SZ) utilizing EEG data acquired from 19 channels at a frequency of 250 Hz. The SVM attained a maximum accuracy of 99.9% when used with Log En features and a 1-second window size. However, the study was based on a small dataset consisting of only 14 SZ patients and 14 healthy controls, which raises concerns regarding overfitting and the generalizability of the results [20]. Finally, (Elfarsy et al., 2024) divided the data into five-second epochs with one-second overlap. They measured the minimum, maximum, mean, standard deviation, variance, mean square, root mean square, absolute signal difference, skewness, and peak-to-peak. Then, the performance of three machine learning classifiers was evaluated. "The Random Forest" classifier achieved the highest accuracy of 96% [21]. Table 1 summarizes the methodologies and results of recent studies on schizophrenia classification using EEG signals with machine learning strategies.

Table 1- Summary of related work on schizophrenia classification using Machine Learning.

Study	Method	Signal	Dataset	Accuracy (%)
Jahmunah et al. (2019) [10].	SVM-RBF	EEG	IPN (Olejarczyk and Jernajczyk, 2017)	92.91
Siuly Siuly et al. (2020) [11].	EMD -EBT	EEG	Laboratory for Neurophysiology and Neuro-Computer Interfaces	93.21
Sunil Kumar Prabhakar et al. (2020) [12]	Flower Pollination Algorithm	EEG	IPN (Olejarczyk and Jernajczyk, 2017)	98.77
M. Sharma et al. (2021) [13].	Wavelet and KNN	EEG	IPN (Olejarczyk and Jernajczyk, 2017)	99.21
Mehmet Baygin et al. (2021) [14].	Collatz pattern and MAP	EEG	Private	99.47
Keihani et al. (2022)[15]	Microstate features with SVM and Bayesian optimization	EEG	IPN (Olejarczyk and Jernajczyk, 2017)	90.93
Megha Agarwal et al. (2023) [16].	Look-ahead pattern (LAP) features and boosted trees (BT)	EEG	IPN (Olejarczyk and Jernajczyk, 2017)	99.24
Ruiz de Miras at el. (2023) [17].	SVM	EEG	SanAgustin (Linares, Jaen)	89.00
T. Sunil Kumar et al. (2023) [18].	HLV, SLBP, and AdaBoost	EEG	(Anon, 2021) And (Olejarczyk and Jernajczyk, 2017)	99.36
Bethany Gosala et al. (2023) [19].	CWT and DT	EEG	Laboratory for Neurophysiology and Neuro-Computer Interfaces	97.98

Athar Alazzaw et al. (2024) [20].	LogEn features and SVM	EEG	IPN (Olejarczyk and Jernajczyk, 2017)	99.9
Elfarsy et al. (2024) [21].	Statistical features and RF	EEG	IPN (Olejarczyk and Jernajczyk, 2017)	96.00

Conversely, deep learning (DL) has been widely employed for various applications and consistently demonstrated positive results across numerous fields. In the classification of schizophrenia, deep learning systems have shown significant potential by autonomously extracting and learning features from complex datasets. This accomplishment has established deep learning as a preferred method in contemporary research focused on analyzing EEG signals to distinguish between schizophrenia patients and healthy individuals. (Shu Lih Oh & his associates, 2019) developed an eleven-layer Convolutional Neural Network (CNN) for the processing of EEG signals. The model independently extracted features by convolution, with the most prominent features acquired during the max-pooling phase. The fully connected layer was employed for classification, achieving an accuracy of 81.26% in subject-specific testing and 98.07% in non-subject-specific testing. The significant disparity between subject-based and non-subject-based accuracy indicates possible challenges in model generalization, potentially affecting its reliability in practical applications [22]. (Ahmad Shalbaf & his associates, 2020) advocated for the application of pre-trained ResNet-18 convolutional neural networks (CNNs) in the interpretation of EEG signal images. They extracted significant attributes from the convolutional and pooling layers and employed these features as input for a Support Vector Machine (SVM) classifier. This approach achieved exceptional results, exhibiting an accuracy of 98.60% and a sensitivity of 99.65% [23].

(Smith K. Khare & his associates, 2021) employed time-frequency analysis and Convolutional Neural Networks (CNNs) for categorizing EEG signals. They used the Smoothed Pseudo-Wigner-Ville Distribution (SPWVD) to generate spectrograms, scalograms, and SPWVD-based time-frequency representation (TFR) plots, therefore alleviating the limitations of traditional feature extraction methods. The proposed CNN model achieved an accuracy of 93.36% using the SPWVD-based time-frequency representation. The technique effectively gathers complex time-frequency data; nonetheless, its subpar accuracy suggests that employing more advanced CNN architectures or exploring alternative preprocessing techniques could enhance performance [24]. (Hesam Akbari & his associates, 2021) analyzed EEG data via phase space dynamics (PSD) and employed a Generalized Regression Neural Network (GRNN) in conjunction with a K-Nearest Neighbors (KNN) classifier. The KNN employing City-block distance demonstrated superior performance, achieving an average classification accuracy of 94.80% via a 10-fold cross-validation technique. Although the methodology is clear and comprehensible, the middling accuracy suggests that more sophisticated procedures or feature extraction methods could improve performance [25]. (Jie Sun & his team, 2021) derived fuzzy features from EEG time series to serve as input for a hybrid deep learning model that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM). This method analyzed RGB pictures of the signals to distinguish between schizophrenia patients, with a remarkable accuracy of 99.22% through Fuzzy Entropy (Fuzzy En). The technique demonstrated outstanding performance; nevertheless, integrating fuzzy features with intricate hybrid models may elevate computational complexity. This may restrict its use in real-time or resource-limited settings [26].

(Bagherzadeh et al., 2022) employed a hybrid methodology that integrates a pre-trained convolutional neural network (CNN) with a long short-term memory (LSTM) model, leveraging Transfer Entropy (TE) for effective connection, to differentiate between schizophrenia (SZ) and healthy controls (HC). The EfficientNetB0-LSTM model attained a remarkable average accuracy of 99.90%. Nonetheless, the intricacy of this hybrid model may constrain its practical implementation in clinical environments [27]. (Rinku Supakar et al., 2022) developed a deep learning model utilizing a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) to categorize individuals with schizophrenia using their EEG data autonomously. The model consisted of a 100-dimensional LSTM layer followed by three thick layers, with an exceptional accuracy of 98%. The dataset used for this research was sourced from the EEG recordings repository at the Laboratory for Neurophysiology and Neuro-Computer Interfaces at M.V.

Lomonosov Moscow State University [28]. (Zülfkar Aslan et al., 2022) introduced a technique for converting EEG signals into two-dimensional representations to extract time-frequency components. They generated scalogram pictures to delineate essential characteristics and trained a Visual Geometry Group-16 (VGG16) network. The model attained accuracies of 99.5% and 98% on two distinct datasets. This strategy, albeit highly accurate, restricts the investigation of possibly superior models that could improve performance by depending exclusively on the VGG16 model [29].

(Ko & Yang, 2022) employed the Gramian Angular Field (GAF) method to convert EEG signals into pictures, which were then examined using Convolutional Neural Networks (CNNs) employed on the VGGNet architecture. This method attained an accuracy of 93.2% in the diagnosis of schizophrenia. The technique successfully captures temporal information; however, its middling accuracy suggests that more sophisticated CNN architectures or supplementary preprocessing techniques may enhance performance [30]. (Shen & his team, 2023) extracted EEG features in the alpha band (8–12 Hz) using cross-mutual information and time-frequency functional connectivity analysis. They employed a 3D convolutional neural network (3D-CNN) to classify patients with schizophrenia (SZ) and healthy controls (HC), achieving an impressive accuracy of 97.74%, with a sensitivity of 96.91% and specificity of 98.53%. However, focusing exclusively on the alpha band may overlook valuable information present in other frequency ranges [31]. Finally, (Bhadra et al., 2024) proposed a novel methodology in which complexity features were extracted using DWT and Multivariate Empirical Mode Decomposition (MEMD), followed by classification with Convolutional Neural Networks (CNNs). Features were fused and optimized using "Principal Component Analysis (PCA) and Canonical Correlation Analysis (CCA)", achieving an accuracy of 90.64% [32]. Table 2 summarizes the methodologies of recent studies on SZ classification using EEG signals with deep learning strategies.

Table 2 - summarizes related work on schizophrenia classification using deep learning.

Authors	Method	Signal	Dataset	Accuracy (%)
Oh et al. (2019) [22].	CNN models	EEG	IPN(Olejarczyk and Jernajczyk, 2017)	98.07
Shalbaf et al. (2020) [23].	ResNet-18 and SVM classifier	EEG	IPN(Olejarczyk and Jernajczyk, 2017)	98.60
Khare et al. (2021) [24].	Traditional features with SPWVD-based TFR	EEG	Kaggle SZ	93.36
Akbari et al. (2021) [25].	PSD with GRNN and KNN	EEG	IPN(Olejarczyk and Jernajczyk, 2017)	94.80
Sun et al. (2021) [26].	Fuzzy features with a hybrid deep learning model (CNN) and LSTM	EEG	IPN(Olejarczyk and Jernajczyk, 2017)	99.22
Bagherzadeh et al. (2022) [27].	Transfer Entropy with a hybrid deep learning model (CNN) and LSTM	EEG	IPN(Olejarczyk and Jernajczyk, 2017)	99.90
Supakar et al. (2022) [28].	RNN and LSTM	EEG	Laboratory for Neurophysiology and Neuro-Computer Interfaces	98.00
Aslan et al. (2022) [29].	scalogram images and VGG16	EEG	IPN (Olejarczyk and Jernajczyk, 2017)	99.50
Ko et al. (2022) [30].	GAF and VGG Net	EEG	Kaggle SZ	93.20
Shen et al. (2023) [31]	Time-frequency functional connectivity analysis by CWT with 3D-CNN	EEG	Laboratory for Neurophysiology and Neuro-Computer Interfaces (Shishkin et al., 2011)	97.74
Bhadra et al. (2024) [32].	DWT and MEMD combined	EEG	IPN (Olejarczyk and Jernajczyk, 2017	90.64

3. Acquisition of brain and EEG signals

The brain is comprised of the brainstem, cerebellum, and cerebrum. More specifically, the left and right hemispheres of the cerebrum are responsible for higher functions, including vision, touch, hearing, learning, and reasoning [33]. The cerebellum, located beneath the cerebrum, controls posture and balance. The brainstem serves as a link between the spinal cord and the brain, acting as a relay center. It regulates automatic processes, including breathing, digestion, and sleep cycles. A bundle of fibers known as the corpus callosum connects the two hemispheres, allowing communication between them [34]. Spatial orientation, nonverbal communication, emotions, creativity, intuition, and artistic expression are all associated with the right hemisphere. In contrast, the more complex left hemisphere is primarily associated with science, logic, abstract thinking, speech, verbal expression, and symbols [35]. As shown in Fig. 2, the frontal, parietal, temporal, and occipital lobes are the primary divisions of the hemispheres. Each lobe is further divided into regions responsible for specific functions. Numerous intricate connections exist between the lobes and between the left and right hemispheres, indicating that the brain does not function independently within this region.

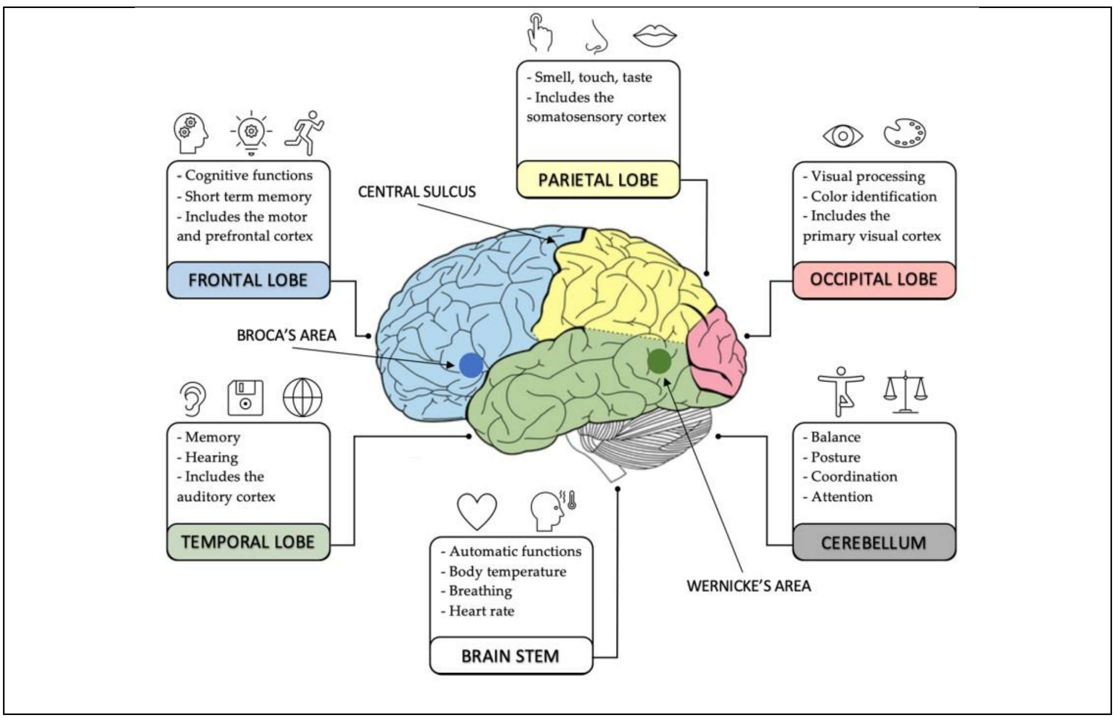

Fig. 2- Brain sub-regions and lobes. An image of the brain taken from [36].

The frontal lobe is located in the forward region of the brain. It affects intellect, emotion, language, and motor control. The prefrontal cortex, responsible for cognitive processes, the motor cortex, which is engaged in movement, and Broca's area, located in the left hemisphere and crucial for language creation, are all parts of the frontal lobe. Directly behind the frontal lobe lies the parietal lobe. It interprets information from the senses [36]. The tiny voltage waves and impulses that can be recorded and tracked using various methods enable brain control and monitoring, summarized in Table 1. Large volumes of pictures and signals are currently stored using a variety of invasive and noninvasive recording techniques. The patterns of the brain can be generally recorded and imaged using a variety of complementary methods, including brain stimulation recordings, magnetic resonance imaging (MRI), electrical, and neuroimaging [37]. (See Table 3).

Table 3- Recording technique Neuronal

Recording technique	Specific mechanism
Electrical recordings	(EEG) Electroencephalography
	(ECoG) Electrocorticography
	(LFP) Local field potential
	(spikes) Single-unit recordings
Neuroimaging recordings	(fNIR) Functional near-infrared recordings
	(fMRI) Functional magnetic resonance imaging
	(PET) Positron emission tomography
Brain stimulations	(TMS) Transcranial magnetic stimulation
	(tDCS) Transcranial direct current stimulation
	(DBS) Deep brain stimulation
Magnetic recordings	(MEG) Magnetoencephalography

Measurements of electric fields (consequently related electric currents), electric recordings are based on the signals released by active populations of neurons that exist in the brain during activity. Local field potential (LFP) involves placing arrays of electrodes inside the brain. Electrocorticography (ECoG) involves placing implanted electrodes on the upper layers of the cerebral cortex, electroencephalography (EEG) involves placing electrodes on the scalp, and single-unit recordings or spikes involve inserting arrays of microelectrodes near neurons. The most common method for magnetic recordings is magnetoencephalography (MEG), which measures the magnetic field created by brain electrical activity [37].

On the order of seconds, blood flow and oxygen uptake are comparatively slow. Functional near-infrared recordings (fNIR), which measure hemoglobin's near-infrared light absorbance, functional magnetic resonance imaging (fMRI), which identifies changes in blood hemoglobin levels, both oxygenated and deoxygenated, and positron emission tomography (PET), which detects radioactive substances because of the brain's metabolic activity, are examples of commonly used imaging techniques. Neurostimulation can be used in conjunction with previous neural recording methods [37]. To elicit the desired brain response, external electrical or magnetic stimulation is used to activate a specific area of the brain. It is essential to note that recording electrodes can also be used for stimulation. Brain stimulation techniques include deep brain stimulation (DBS), transcranial direct current stimulation (TDCS), and transcranial magnetic stimulation (TMS), which relies on variations in the magnetic field of a coil placed next to the skull and uses electrodes placed in specific brain regions to excite specific brain areas. Electroencephalography (EEG) and magnetoencephalography (MEG) have some of the best temporal resolution among non-invasive methods. However, when compared to EEG and MEG, functional magnetic resonance imaging (fMRI) has the highest spatial resolution but the lowest temporal resolution. Finally, positron emission tomography (PET) and functional near-infrared (fNIR) exhibit the lowest temporal and spatial resolution, respectively [38].

EEG is one of the most frequently utilized technologies in practice for recording neural signals since it is inexpensive, easy to use, subject-motion-tolerant, and radiation-free. Hans Berger first introduced the EEG in 1927. He described it as a method for functional investigation of the central nervous system that records the brain's electrical activity in real-time. The individual is wearing an EEG hat on top of their head to record and store their brain's electrical activity. This requires the electrodes on their scalp to be positioned consistently in space to capture the electrical activity as waves. One globally accepted technique used for this is the 10-20 EEG positioning system [39]. Typically, EEG signals acquired during measurements are separated into frequency bands. Five primary brain waves can be identified primarily by the frequency band and signal amplitude. First, within the range of 0.5 to 4 Hz, the delta band has the lowest frequency with a maximum amplitude of between 20 and 200 μV. It can manifest in a waking state and is associated with deep slumber. Theta waves, which have an amplitude more significant than 20 μV and fall between 4 and 7.5 Hz, are primarily used to indicate arousal in adults or sleepiness in young children. Deep meditation and creative inspiration are also associated with these waves[40].

4. Common EEG Datasets for Schizophrenia Research

Several publicly available EEG datasets have been used in schizophrenia research to investigate the neural correlates of the disorder, develop diagnostic models, and evaluate treatment responses. The datasets vary in sample size, recording methodologies, and preprocessing procedures, influencing their appropriateness for different research aims. We emphasize two significant EEG datasets that are commonly cited in schizophrenia research:

4.1 The Warsaw SZ Dataset

Data were gathered at the Institute of Psychiatry and Neurology in Warsaw, Poland. The study comprised 14 patients diagnosed with schizophrenia, consisting of seven men with a mean age of 27.9 ± 3.3 years and seven females with a mean age of 28.3 ± 4.1 years. The study also had 14 healthy participants, consisting of seven males with a mean age of 26.8 ± 2.9 years and seven females with a mean age of 28.7 ± 3.4 years. EEG signals were acquired during a 15-minute resting state with closed eyelids (EC) at a sample rate of 250 Hz, in accordance with the international 10-20 system standard. The FCz electrode served as the reference electrode, and the EEG recordings included all 19 channels: Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2, and T2. Patients who had consumed medicine within the seven days before data collection, pregnant women, those with organic or severe neurological disorders, and participants under the age of 18 were excluded. Individuals in the first phases of schizophrenia or those undergoing their first episode were excluded from the study. This data set is a standard reference in studies related to the automatic diagnosis of schizophrenia [41].

4.2 The Kaggle SZ Dataset

This open-source dataset comprises EEG data from 49 patients diagnosed with schizophrenia (8 females and 41 males, average age of 40.02 ± 13.55 years) and 32 healthy control participants (6 females and 26 males, average age of 38.37 ± 13.69 years). The data were recorded using a Biosemi Active Two system, which captures signals from 64 scalp electrodes and 8 external sites at a sampling rate of 1024 Hz. With multiple trials conducted under various conditions, this dataset provides detailed insights into temporal dynamics. However, it also requires extensive preprocessing to address artifacts and outliers [41].

Overall, selecting the right EEG dataset is essential for obtaining reliable and generalizable results in schizophrenia research. However, the datasets reviewed provide valuable insights, several challenges, such as limited sample sizes, variability in recording protocols, and issues with data quality. Future efforts to combine multiple datasets and standardize preprocessing techniques could enhance the robustness of models and improve our understanding of schizophrenia through EEG analysis.

5. Preprocessing and Feature Extraction

In medical studies focused on brain signal analysis, the key procedure involves feature extraction and preprocessing. Brain signals are obtained using several electrodes placed on the scalp. Once these signals are collected, they undergo preprocessing to address the inevitable presence of noise and external interference. Sources of this noise can include the electrical distribution network, nearby electronic devices, or even bodily processes. Effective filtering techniques are utilized to eliminate undesired noise components from the signals, hence enhancing data quality [42]. One type of filter commonly used in EEG analysis is the frequency filter. This filter processes the EEG signal by breaking it down and removing unnecessary frequency components. Specifically, the bandpass filter allows only selected frequency ranges to pass through, separating the data into different frequency sub-bands, such as delta, theta, gamma, alpha, and beta rhythms. This filtering process enables the exclusion of frequencies that are either too high or too low in frequency. Filtering is particularly beneficial when the original brain data contains a significant amount of high-frequency noise. It helps to isolate and clarify the detailed information within the EEG signals. The bandpass filter effectively removes high-frequency noise before categorizing the EEG data into various window widths [43]. Fig. 3 illustrates the results of the EEG signals both before and after applying the bandpass filter.

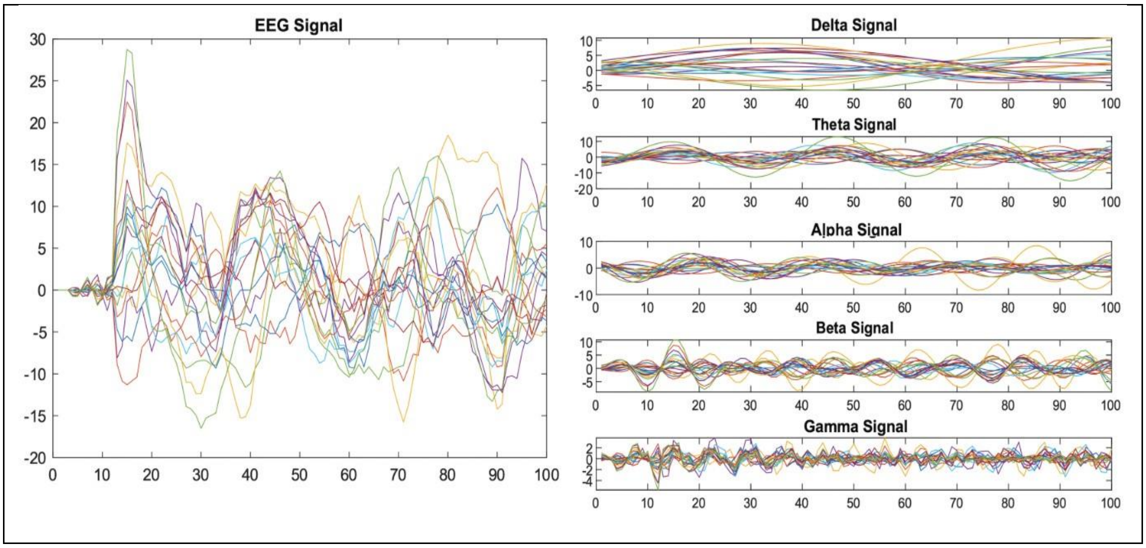

Fig. 3- A band-pass filter for decomposing EEG signals [20].

Additionally, another filtering method is the average filter (AF), which is used to eliminate noise and artifacts from EEG signals. This technique smooths the signals and reduces intensity variations, helping to remove unwanted details. It is also simple, easy to understand, and straightforward to implement [44]. Accurately extracting features from EEG signals is a challenging yet crucial step in the classification process, as it directly impacts classification accuracy. Both frequency-domain and time-domain feature extraction techniques can be employed to identify EEG signals linked to schizophrenia. Feature extraction is a method employed to diminish data volume by generating new features from the original dataset. These new features are non-redundant and preserve pertinent information from the original data, facilitating improved classification through the simplified representation rather than the complete initial dataset. This procedure is crucial for reducing data dimensionality, thereby converting it from a high-dimensional space to a low-dimensional space [45]. Numerous techniques exist for feature extraction, and we will elucidate a few of them.

4.3 Time Domain

EEG data are examined by time-domain feature extraction techniques that emphasize fluctuations in the signal time series. The intricacy of EEG signifies the chaotic and unexpected characteristics of cerebral function. Owing to the continuous advancement of nonlinear theory, numerous researchers are utilizing nonlinear analytical methods to examine EEG data. A method for quantifying complexity is entropy. Entropy is the most commonly utilized feature index among the numerous time-domain features, especially in disease diagnosis. Fuzzy entropy (Fuzzy En), derived from several entropy metrics, is frequently employed. In comparison to other forms of entropy, like information entropy, sample entropy, and Fuzzy En, these types exhibit superior noise resistance, enhanced resilience, and reduced computational complexity [46] . Fuzzy entropy is very effective for the analysis of chaotic signals due to its stable entropy value, which is less influenced by noise in EEG data. Prior research has shown that FuzzyEn exhibits enhanced signal identification and recognition abilities compared to alternative entropy metrics, especially in the context of epilepsy and schizophrenia. The temporal domain is advantageous for research focused on prompt seizure detection, such as real-time patient monitoring systems. Nonetheless, utilizing the time domain presents constraints, such as the inability to discern frequency information or spectral components, as well as difficulties in studying unstable signals. As a result, numerous researchers in this domain prefer more sophisticated analytical techniques, such as those grounded in the frequency domain or time-frequency domain[47].

4.4 Frequency Domain

The frequency-domain feature extraction method is initiated by transforming the original time-domain EEG signal into a frequency-domain representation. This version facilitates a more profound examination of signal characteristics and demonstrates the correlation between frequency and amplitude [48]. The Fourier Transform (FT) is a commonly employed method for this conversion, noted for its straightforward implementation and comparatively low computational cost relative to other frequency-domain techniques. For the Fourier Transform to be effective, it is crucial that the EEG data are obtained in the frequency domain. This method is particularly suitable for EEG signals. Despite the prevalence of continuous signals, they must be discretized for processing, as computers are incapable of directly handling continuous signals. The discrete variant of the Fourier Transform, applicable in both time and frequency domains, is known as the Discrete Fourier Transform (DFT). The Fast Fourier Transform (FFT) is an efficient method for computing the Discrete Fourier Transform (DFT) and has been favored by several researchers in previous studies for assessing EEG signals regarding frequency-domain characteristics [49]. Recent research in relevant fields indicates that fuzzy entropy (fuzzyEn) and FFT are critical methods for information extraction in both temporal and frequency domains. Both methodologies have demonstrated considerable effectiveness and are widely employed in various biological signal research initiatives.

4.5 Time-Frequency Domain

The time-frequency domain concurrently encompasses a signal's temporal and spectral attributes. The time-frequency domain examines the temporal variations of a signal's frequency components in contrast to the conventional time or frequency domain analysis. This offers a thorough examination of non-stationary signals, encompassing EEG data. Time-frequency analysis is essential for EEG signals because of the inherently dynamic and non-stationary characteristics of brain activity, which is marked by oscillating patterns that vary with time [50]. Techniques such as the Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Smoothed Pseudo-Wigner-Ville Distribution (SPWVD) are commonly utilized to convert signals into the time-frequency domain. These approaches produce a time-frequency representation (TFR), a two-dimensional graph with one axis representing time, the other representing frequency, and the intensity indicating amplitude. The time-frequency domain is crucial in EEG analysis for detecting transient events, analyzing brain rhythms over several frequency bands (e.g., delta, theta, alpha, beta, gamma), and understanding the dynamic properties of neural oscillations. This technique can reveal subtle anomalies associated with neurological illnesses, including schizophrenia, epilepsy, and Alzheimer's disease. The time-frequency domain enables a more sophisticated and dynamic understanding of signals, making it an essential tool in biological signal processing and neurodiagnostics [51].

6. Machine Learning VS. Deep Learning for EEG

A methodical two-phase approach is frequently utilized in conventional machine learning-based EEG analysis. Initially, attributes such as power spectral density (PSD), statistical metrics, or entropy values are manually extracted from EEG data. The effectiveness of machine learning models primarily relies on the quality of feature engineering. Common algorithms include Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), Logistic Regression (LR), K-Nearest Neighbors (KNN), Naive Bayes (NB), Boosting Techniques (BT), and AdaBoost. A significant benefit of classical machine learning is its interpretability. The well-defined, domain-specific extracted characteristics facilitate comprehension for researchers and physicians on the variables that influence the model's decisions. Moreover, these models frequently exhibit strong performance with minimal datasets, rendering them advantageous in scenarios of data scarcity. Nevertheless, dependence on manual feature extraction may be a constraint. The necessity for subject expertise in crafting efficient feature extraction methodologies may induce biases and risk neglecting significant information inherent in raw EEG data. Moreover, the efficacy of these models is limited by the quality and pertinence of the chosen features. [52]. The following are the principal machine learning techniques frequently employed in EEG analysis:

Support Vector Machine (SVM)

Support Vector Machine (SVM) has been employed in several studies in recent years to classify diverse datasets. It is a robust supervised learning technique frequently used for classification and regression applications. The primary goal of SVM is to identify the ideal dividing hyperplane that categorizes the data into separate classes. It seeks to optimize the separation or margin between the hyperplane and the closest data points from each class. The critical data points, referred to as support vectors, substantially affect the placement and alignment of the hyperplane. The term "kernel trick" refers to the diverse kernels utilized by Support Vector Machines (SVMs), such as Polynomial, Gaussian, Radial Basis Function (RBF), Laplace RBF, Sigmoid, and Anova RBF, among others [53].

K-Nearest Neighbours (KNN)

The K-Nearest Neighbors (K-NN) algorithm is a widely used machine learning technique for classification and regression, which depends on closeness to ascertain the class of a new sample. This method calculates the distance between the unknown sample and each sample in the training set, typically using the Euclidean distance [58]. The

Euclidean distance between two points X = {x_1, x_2, ..., x_n} and Y = {y_1, y_2, ..., y_n}, each possessing n characteristics, is defined as follows:

$$E_{dist}(X,Y) = \sqrt{\sum_{i=1}^{n}(xi - yi)^2} \tag{1}$$

After identifying the K nearest neighbors, the new sample is classified based on the majority class among those neighbors, mostly depending on the distribution of nearby data. K-NN is characterized by its simplicity and effectiveness in various applications, since it does not require complex training processes, but instead relies on the preservation of training data for categorization. The careful selection of the K value is crucial for the algorithm's effectiveness, as small values may result in inaccurate classification due to reliance on an inadequate number of neighbors, while large values may obscure class distinctions by incorporating more distant points [54]. This technique is employed in multiple fields, including pattern recognition, image classification, and bioinformatics, particularly for categorizing of EEG data and the investigation of brain processes, making it a powerful tool in medical and scientific applications.

Decision Trees (DT) Algorithm

The decision tree model is a supervised classification technique that employs hierarchical decision rules articulated as IF-THEN-ELSE statements. The regulations are organized hierarchically, resulting in definitive classification outcomes. This approach involves breaking down a major problem into several minor issues and resolving them sequentially. The terminal nodes, or leaves, signify the possible output classes, whereas each internal node encompasses a condition that assesses a particular feature-value pair. The branches emanating from each node represent the diverse results of specific events. A decision tree is developed during the training phase by distinguishing potential output classes at each node. Node-splitting criteria generally depend on two metrics: information gain and the Gini index. At each node, the feature-value combination is selected to either limit information gain or enhance the Gini index [55].

Quadratic Discriminant Analysis (QDA)

Quadratic Discriminant Analysis (QDA) is a classification technique used to separate data into distinct classes based on their feature distributions. Unlike Linear Discriminant Analysis (LDA), which assumes that all classes share the same covariance matrix, QDA allows for different covariance matrices for each class. This flexibility enables QDA to model more complex class boundaries, making it suitable for non-linear problems. However, this adaptability can also result in overfitting, particularly when there is a limited amount of training data. In the context of EEG signal classification, QDA can be effective if there is enough data to accurately estimate the covariance matrices [56].

Random Forest (RF)

The Random Forest classifier is a type of ensemble learning algorithm originally introduced by Breiman, and it combines multiple decision trees. Each decision tree functions as an independent classifier, and the final classification result is determined through a majority voting process across all the trees in the ensemble. This non-parametric machine learning algorithm typically builds its trees using the classification and regression tree method. Random Forest operates based on the concept of bagging, where multiple subsets of the original training data are generated through random sampling with replacement. Each subgroup is utilized to independently train a distinct decision tree. During the classification phase, each decision tree produces an independent prediction for the test data, and the final classification is determined by a majority vote among all trees [57].

In contrast, deep learning eliminates the need for manual feature extraction by training artificial neural networks to automatically learn hierarchical features from raw EEG data. Commonly used models include Convolutional Neural Networks (CNNs) for capturing spatial patterns, Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks for temporal dependencies. The primary advantage of deep learning lies in its ability to automatically learn features and effectively process complex, high-dimensional EEG data. These models often outperform traditional techniques, especially when dealing with large and diverse datasets. However, deep learning also has its drawbacks. It typically requires large datasets for effective training, and data augmentation techniques may be necessary to address data scarcity. Training deep networks demands substantial computational power, usually requiring high-performance GPUs, which may not be accessible in all research settings. Furthermore, deep learning models are often considered "black boxes," making it challenging to comprehend their decision-making processes. This lack of transparency is a significant concern in medical applications where clarity is crucial [58]. The main difference between ML and DL approaches is shown in Fig. 4.

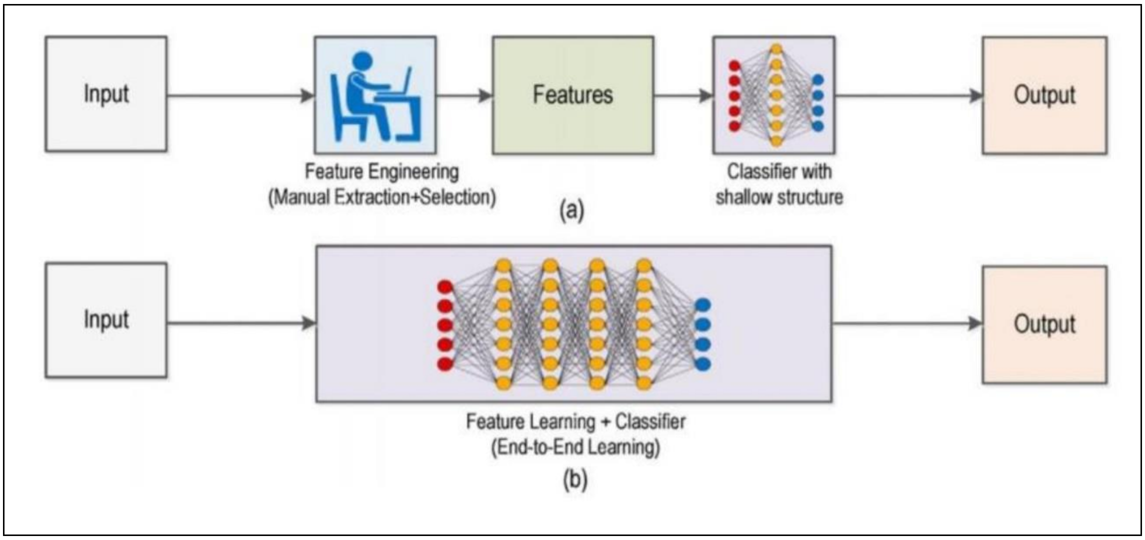

Fig. 4- The main difference between (a) conventional ML; (b) DL.

Recurrent Neural Networks (RNNs)

RNNs are a kind of deep learning model used in biological signal processing, natural language processing, and speech recognition. CNN models fall into the Feed-Forward category. They are primarily employed in voice processing and natural language processing (NLP). Unlike traditional neural networks, RNNs process data sequentially. This structure allows RNNs to incorporate contextual information, which can be valuable in various applications. To understand the significance of a word within a phrase, it is essential to grasp the meaning of the entire statement. RNNs can be viewed as short-term memory units, with 'x' representing the input layer, 'y' denoting the output layer, and 's' standing for the hidden state layer [60].

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are among the most impactful and extensively utilized methodologies in deep learning for medical imaging. A standard CNN design comprises several essential components, including convolutional layers, pooling layers, batch normalization, fully connected layers, and a concluding SoftMax layer for classification. The convolutional layers are essential for obtaining feature maps. Pooling layers are designed to down-sample feature maps using maximum or average procedures, emphasizing the most salient characteristics. The fully connected layers subsequently analyze the aggregated features, enabling the SoftMax layer to do the final classification. Especially the ReLU function, nonlinear activation functions enhance the network's capacity to address nonlinear challenges. After every convolutional and fully connected layer, a ReLU is the activation function. Additionally, methods used to reduce overfitting in the network include dropout and batch normalization methods [61].

Ultimately, for organized, feature-rich data, conventional machine learning approaches are usually more interpretable and efficient, but deep learning approaches shine in handling raw, complex EEG data via automatic feature extraction. Among these two approaches, data availability, computational resources, and the significance of model interpretability in clinical environments have to be among the choices.

7. Evaluation Metrics in Machine Learning and Deep Learning

Determining the efficacy, dependability, and suitability for therapeutic uses, such as the diagnosis of schizophrenia from machine learning and deep learning models, depends on their performance evaluation. Different evaluation techniques help clarify certain facets of model performance, allowing a more complete knowledge of the categorization outcomes [62].

7.1 Confusion matrix

A comprehensive technique for showing the link between expected and actual classes is the confusion matrix. "True Positive (TP)", which denotes events whereby the model correctly predicts the positive class; "True Negative (TN)", which refers to events whereby the model correctly identifies the negative class; "False Positive (FP)", which denotes events whereby the model mistakenly classifies the positive class; and "False Negative (FN)", which pertains to events whereby the model incorrectly classifies the negative class [62].

7.2 Accuracy

Accuracy is the proportion of accurate model forecasts to the overall number of predictions—that is, both right and wrong outcomes. As equation (2) [63].

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \tag{2}$$

7.3 Sensitivity (Recall)

Recall, also known as sensitivity, is the percentage of precisely found positive cases to the total count of true positive cases. Equation (3) rates the model's accuracy in spotting affirmative cases [63].

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

7.4 Specificity

Specificity measures the relative frequency of precisely expected negative cases to the overall count of real negative cases. As shown in the next equation (4), it assesses the model's ability in consistently spotting bad circumstances [63].

$$Specificity(SPE) = \frac{TN}{TN + FP} \tag{4}$$

7.5 Precision

Precision gauges the proportion of actual positive forecasts to all the positive forecasts generated. As stated in the following equation (5), the computation is expressed as the ratio of true positive forecasts to the sum of true positive and false positive predictions [63].

$$Precision(Prec) = \frac{TP}{TP + FP} \tag{5}$$

7.6 F-Score (F1-Score)

Using a weighted average of sensitivity and accuracy, the F-score, also known as the F1-score, effectively balances recall and precision. It is helpful for imbalanced class distributions since it takes false positives as well as real positive predictions. The F-score is expressed by equation (6) [63].

$$F1\_Score = \frac{2\times(Precision\times Sensitivity}{(Precision+Sensitivity)} \tag{6}$$

7.7 *Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC)*

The ROC curve illustrates that the false positive rate relates to the actual positive rate. The area under the curve (AUC) measures the general capacity of the model to differentiate across multiple classes [64].

8. Challenge the Classification of Schizophrenia

EEG wave diagnosis of schizophrenia presents numerous challenges.

- Signal Variability: Due to natural variations and external factors, including noise and internal influences such as mood or medication, EEG readings exhibit significant variability and display considerable variation among individuals. These variances make it difficult to find consistent biomarkers for the disease.
- Complex and Non-linear Nature: The complex and non-linear nature of EEG waves makes it challenging to identify key traits that distinguish individuals with schizophrenia from healthy.
- Low Signal-to-Noise Ratio (SNR): Muscle artifacts and environmental disturbances are among the various forms of noise present in EEG readings that can obscure important information.
- Data Limitations: Ethical constraints and patient accessibility hinder the procurement of extensive, high-quality, accurately annotated datasets from individuals with schizophrenia.
- Overlap with Other Disorders: Accurate classification is complicated by the intersection of the symptoms and cerebral activity patterns linked with schizophrenia with those of several neurological and mental diseases.
- Inter-Subject Variability: Cerebral activity among individuals exhibits significant variability, complicating the development of generalized models that can effectively assist every patient.
- Feature Selection: Individual cerebral activity differs widely, making it challenging to create broad models that would benefit every patient.
- Computational Complexity: Advanced deep learning models for analyzing EEG data require substantial computational resources, which may not be readily available in all research or clinical environments.
- Interpretability: Many deep learning models function as opaque systems, therefore impairing doctors' ability to evaluate data and use it in good decision-making.

9. Directions and Recommendations

Future studies on the diagnosis of schizophrenia using EEG signals could investigate several potential strategies to solve present difficulties and improve the therapeutic value of artificial intelligence models.

- Formulating Hybrid Models: Combine the deep learning pattern recognition capability with the interpretability of conventional machine learning. To enhance clinical decisions, aim for a mix of accuracy and comprehensibility.
- Enhancing Data Quality and Quantity: Utilize generative adversarial networks (GANs) or sophisticated data augmentation methods to handle limited datasets. Use longitudinal studies to better understand the temporal dynamics of schizophrenia, thereby producing more complete datasets.
- Feature Engineering: Methods combining graph-theoretical metrics with time-frequency domain properties. To further clinical application, also design more interpretable deep learning models, including explainable artificial intelligence (XAI) systems.
- Integrating Clinical Applications: Install AI-based diagnostic tools in real-time monitoring systems to offer quick identification and tailored therapy options. Moreover, it promotes multidisciplinary cooperation among doctors, neuroscientists, and computer scientists to offer therapeutically applicable treatments.
- Addressing Ethical Considerations: Give data security first priority; cut artificial intelligence model biases; and apply appropriate AI in clinical settings. Improve model decision-making transparency and validate artificial intelligence models by means of multi-center clinical trials, thereby promoting more general acceptability.
- Following these guidelines will help future studies to generate more accurate, interpretable, clinically useful solutions using EEG data for the diagnosis and management of schizophrenia.

10. Conclusion

This work employs artificial intelligence techniques, particularly machine learning and deep learning, for the classification of schizophrenia (SZ) based on EEG signals. Several methods for processing EEG data, including signal capture, preprocessing, feature extraction, and classification, are evaluated in this work. While deep learning techniques such as "Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)" excel at identifying complex, non-linear patterns in raw EEG signals, conventional machine learning models, including "SVM and DT," provide interpretability and perform well with limited datasets. The principal finding of the examined studies is that, despite high classification accuracy, deep learning techniques encounter challenges such as the necessity for extensive datasets, substantial computational resources, and difficulty with interpretability. While ML models offer greater openness, they may struggle to sufficiently evaluate the complexity of EEG data without the use of sophisticated feature extraction techniques. The paper emphasizes the need to employ a balanced strategy that leverages the advantages of both machine learning (ML) and deep learning (DL) to address the difficulties in schizophrenia diagnosis. Future research paths could involve the creation of hybrid models that combine the excellent pattern recognition capacity of deep learning with the interpretability of machine learning. Moreover, while examining more interpretable artificial intelligence models may help clinical applications, enhancing data augmentation techniques could help alleviate data restrictions. This study has implications for improved clinical decision-making in three ways: it enhances diagnosis accuracy, optimizes patient therapy, and helps to identify schizophrenia early on.

References

[1] M. A. Vázquez, A. Maghsoudi, and I. P. Mariño, "An Interpretable Machine Learning Method for the Detection of Schizophrenia Using EEG Signals," *Front Syst Neurosci*, vol. 15, May 2021, doi: 10.3389/fnsys.2021.652662.

[2] F. S. Racz, O. Stylianou, P. Mukli, and A. Eke, "Multifractal and Entropy-Based Analysis of Delta Band Neural Activity Reveals Altered Functional Connectivity Dynamics in Schizophrenia," *Front Syst Neurosci*, vol. 14, p. 554337, Jul. 2020, doi: 10.3389/fnsys.2020.00049.

[3] S. Siuly, Y. Guo, O. F. Alcin, Y. Li, P. Wen, and H. Wang, "Exploring deep residual network based features for automatic schizophrenia detection from EEG," *Phys Eng Sci Med*, vol. 46, no. 2, pp. 561–574, Jun. 2023, doi: 10.1007/s13246-023-01225-8.

[4] C. Zhuo *et al.*, "The genomics of schizophrenia: Shortcomings and solutions," *Prog Neuropsychopharmacol Biol Psychiatry*, vol. 93, pp. 71–76, Jul. 2019, doi: 10.1016/j.pnpbp.2019.03.009.

[5] J. W. Lai, C. K. E. Ang, U. R. Acharya, and K. H. Cheong, "Schizophrenia: A Survey of Artificial Intelligence Techniques Applied to Detection and Classification," *Int J Environ Res Public Health*, vol. 18, no. 11, p. 6099, Jun. 2021, doi: 10.3390/ijerph18116099.

[6] G. Xu *et al.*, "A Deep Transfer Convolutional Neural Network Framework for EEG Signal Classification," *IEEE Access*, vol. 7, pp. 112767–112776, 2019, doi: 10.1109/ACCESS.2019.2930958.

[7] M. Bracher-Smith *et al.*, "Machine learning for prediction of schizophrenia using genetic and demographic factors in the UK biobank," *Schizophr Res*, vol. 246, pp. 156–164, Aug. 2022, doi: 10.1016/j.schres.2022.06.006.

[8] G. Li, D. Han, C. Wang, W. Hu, V. D. Calhoun, and Y.-P. Wang, "Application of deep canonically correlated sparse autoencoder for the classification of schizophrenia," *Comput Methods Programs Biomed*, vol. 183, p. 105073, Jan. 2020, doi: 10.1016/j.cmpb.2019.105073.

[9] K. Kim, N. T. Duc, M. Choi, and B. Lee, "EEG microstate features for schizophrenia classification," *PLoS One*, vol. 16, no. 5, p. e0251842, May 2021, doi: 10.1371/journal.pone.0251842.

[10] V. Jahmunah *et al.*, "Automated detection of schizophrenia using nonlinear signal processing methods," *Artif Intell Med*, vol. 100, p. 101698, Sep. 2019, doi: 10.1016/j.artmed.2019.07.006.

[11] S. Siuly, S. Khare, V. Bajaj, … H. W.-I. T. on, and undefined 2020, "A computerized method for automatic detection of schizophrenia using EEG signals," *ieeexplore.ieee.orgS Siuly, SK Khare, V Bajaj, H Wang, Y ZhangIEEE Transactions on Neural Systems and Rehabilitation Engineering, 2020•ieeexplore.ieee.org*, Accessed: Oct. 13, 2024. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9187840/

[12] S. K. Prabhakar, H. Rajaguru, and S.-W. Lee, "A Framework for Schizophrenia EEG Signal Classification With Nature Inspired Optimization Algorithms," *IEEE Access*, vol. 8, pp. 39875–39897, 2020, doi: 10.1109/ACCESS.2020.2975848.

[13] M. Sharma and U. R. Acharya, "Automated detection of schizophrenia using optimal wavelet-based $$l_1$$ norm features extracted from single-channel EEG," *Cogn Neurodyn*, vol. 15, no. 4, pp. 661–674, Aug. 2021, doi: 10.1007/s11571-020-09655-w.

[14] M. Baygin, O. Yaman, T. Tuncer, S. Dogan, P. D. Barua, and U. R. Acharya, "Automated accurate schizophrenia detection system using Collatz pattern technique with EEG signals," *Biomed Signal Process Control*, vol. 70, Sep. 2021, doi: 10.1016/j.bspc.2021.102936.

[15] A. Keihani, S. S. Sajadi, M. Hasani, and F. Ferrarelli, "Bayesian Optimization of Machine Learning Classification of Resting-State EEG Microstates in Schizophrenia: A Proof-of-Concept Preliminary Study Based on Secondary Analysis," *Brain Sci*, vol. 12, no. 11, Nov. 2022, doi: 10.3390/brainsci12111497.

[16] M. Agarwal and A. Singhal, "Fusion of pattern-based and statistical features for Schizophrenia detection from EEG signals," *Med Eng Phys*, vol. 112, p. 103949, Feb. 2023, doi: 10.1016/j.medengphy.2023.103949.

[17] J. Ruiz de Miras, A. J. Ibáñez-Molina, M. F. Soriano, and S. Iglesias-Parro, "Schizophrenia classification using machine learning on resting state EEG signal," *Biomed Signal Process Control*, vol. 79, p. 104233, Jan. 2023, doi: 10.1016/j.bspc.2022.104233.

[18] T. S. Kumar, K. N. V. P. S. Rajesh, S. Maheswari, V. Kanhangad, and U. R. Acharya, "Automated Schizophrenia detection using local descriptors with EEG signals," *Eng Appl Artif Intell*, vol. 117, Jan. 2023, doi: 10.1016/j.engappai.2022.105602.

[19] B. Gosala, P. Dindayal Kapgate, P. Jain, R. Nath Chaurasia, and M. Gupta, "Wavelet transforms for feature engineering in EEG data processing: An application on Schizophrenia," *Biomed Signal Process Control*, vol. 85, p. 104811, Aug. 2023, doi: 10.1016/j.bspc.2023.104811.

[20] A. Alazzawı *et al.*, "Schizophrenia diagnosis based on diverse epoch size resting-state EEG using machine learning," *PeerJ Comput Sci*, vol. 10, p. e2170, Aug. 2024, doi: 10.7717/peerj-cs.2170.

[21] A. Elfarsy and S. El-Metwally, "Leveraging EEG Signals and Machine Learning for Schizophrenia Classification," in *2024 6th International Conference on Computing and Informatics (ICCI)*, IEEE, Mar. 2024, pp. 23–27. doi: 10.1109/ICCI61671.2024.10485176.

[22] S. L. Oh, J. Vicnesh, E. J. Ciaccio, R. Yuvaraj, and U. R. Acharya, "Deep Convolutional Neural Network Model for Automated Diagnosis of Schizophrenia Using EEG Signals," *Applied Sciences*, vol. 9, no. 14, p. 2870, Jul. 2019, doi: 10.3390/app9142870.

[23] A. Shalbaf, S. Bagherzadeh, and A. Maghsoudi, "Transfer learning with deep convolutional neural network for automated detection of schizophrenia from EEG signals," *Phys Eng Sci Med*, vol. 43, no. 4, pp. 1229–1239, Dec. 2020, doi: 10.1007/s13246-020-00925-9.

[24] S. K. Khare, V. Bajaj, and U. R. Acharya, "SPWVD-CNN for Automated Detection of Schizophrenia Patients Using EEG Signals," *IEEE Trans Instrum Meas*, vol. 70, pp. 1–9, 2021, doi: 10.1109/TIM.2021.3070608.

[25] H. Akbari, S. Ghofrani, P. Zakalvand, and M. Tariq Sadiq, "Schizophrenia recognition based on the phase space dynamic of EEG signals and graphical features," *Biomed Signal Process Control*, vol. 69, p. 102917, Aug. 2021, doi: 10.1016/j.bspc.2021.102917.

[26] J. Sun *et al.*, "A hybrid deep neural network for classification of schizophrenia using EEG Data," *Sci Rep*, vol. 11, no. 1, p. 4706, Feb. 2021, doi: 10.1038/s41598-021-83350-6.

[27] S. Bagherzadeh, M. S. Shahabi, and A. Shalbaf, "Detection of schizophrenia using a hybrid of deep learning and brain effective connectivity image from electroencephalogram signal," *Comput Biol Med*, vol. 146, p. 105570, Jul. 2022, doi: 10.1016/j.compbiomed.2022.105570.

[28] R. Supakar, P. Satvaya, and P. Chakrabarti, "A deep learning-based model using RNN-LSTM for the Detection of Schizophrenia from EEG data," *Comput Biol Med*, vol. 151, p. 106225, Dec. 2022, doi: 10.1016/j.compbiomed.2022.106225.

[29] Z. Aslan and M. Akin, "A deep learning approach in automated detection of schizophrenia using scalogram images of EEG signals," *Phys Eng Sci Med*, vol. 45, no. 1, pp. 83–96, Mar. 2022, doi: 10.1007/s13246-021-01083-2.

[30] D. W. Ko and J. J. Yang, "EEG-Based Schizophrenia Diagnosis through Time Series Image Conversion and Deep Learning," *Electronics (Switzerland)*, vol. 11, no. 14, Jul. 2022, doi: 10.3390/electronics11142265.

[31] M. Shen, P. Wen, B. Song, and Y. Li, "Automatic identification of schizophrenia based on EEG signals using dynamic functional connectivity analysis and 3D convolutional neural network," *Comput Biol Med*, vol. 160, p. 107022, Jun. 2023, doi: 10.1016/j.compbiomed.2023.107022.

[32] S. Bhadra, C. J. Kumar, and D. K. Bhattacharyya, "Multiview EEG signal analysis for diagnosis of schizophrenia: an optimized deep learning approach," *Multimed Tools Appl*, Sep. 2024, doi: 10.1007/s11042-024-20205-y.

[33] M. Hu *et al.*, "Structural and diffusion MRI-based schizophrenia classification using 2D pretrained and 3D naive Convolutional Neural Networks," *Schizophr Res*, vol. 243, no. June, pp. 330–341, 2022, doi: 10.1016/j.schres.2021.06.011.

[34] J. Rahul, D. Sharma, L. D. Sharma, U. Nanda, and A. K. Sarkar, "A systematic review of EEG-based automated schizophrenia classification through machine learning and deep learning," *Front Hum Neurosci*, vol. 18, p. 1347082, Feb. 2024, doi: 10.3389/FNHUM.2024.1347082/BIBTEX.

[35] W. Yassin *et al.*, "Machine-learning classification using neuroimaging data in schizophrenia, autism, ultra-high risk and first-episode psychosis," *Transl Psychiatry*, vol. 10, no. 1, p. 278, Aug. 2020, doi: 10.1038/s41398-020-00965-5.

[36] M. Luján, M. Jimeno, J. Mateo Sotos, J. Ricarte, and A. Borja, "A Survey on EEG Signal Processing Techniques and Machine Learning: Applications to the Neurofeedback of Autobiographical Memory Deficits in Schizophrenia," *Electronics (Basel)*, vol. 10, no. 23, p. 3037, Dec. 2021, doi: 10.3390/electronics10233037.

[37] Z. Rustam and G. S. Saragih, "Prediction schizophrenia using random forest," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 18, no. 3, p. 1433, Jun. 2020, doi: 10.12928/telkomnika.v18i3.14837.

[38] G. Li, D. Han, C. Wang, W. Hu, V. D. Calhoun, and Y.-P. Wang, "Application of deep canonically correlated sparse autoencoder for the classification of schizophrenia," *Comput Methods Programs Biomed*, vol. 183, p. 105073, Jan. 2020, doi: 10.1016/j.cmpb.2019.105073.

[39] M. Yadava, P. Kumar, R. Saini, P. P. Roy, and D. Prosad Dogra, "Analysis of EEG signals and its application to neuromarketing," *Multimed Tools Appl*, vol. 76, no. 18, pp. 19087–19111, Sep. 2017, doi: 10.1007/s11042-017-4580-6.

[40] I. J. Rampil, "A Primer for EEG Signal Processing in Anesthesia Introduction-The Rationale for Monitoring," 1998.

[41] J. M. Ford, V. A. Palzes, B. J. Roach, and D. H. Mathalon, "Did I Do That? Abnormal Predictive Processes in Schizophrenia When Button Pressing to Deliver a Tone," *Schizophr Bull*, vol. 40, no. 4, pp. 804–812, Jul. 2014, doi: 10.1093/schbul/sbt072.

[42] J. P. Pijn, J. Van Neerven, A. Noest, and F. H. Lopes da Silva, "Chaos or noise in EEG signals; dependence on state and brain site," *Electroencephalogr Clin Neurophysiol*, vol. 79, no. 5, pp. 371–381, Nov. 1991, doi: 10.1016/0013-4694(91)90202-F.

[43] B. Boashash and G. Azemi, "A review of time–frequency matched filter design with application to seizure detection in multichannel newborn EEG," *Digit Signal Process*, vol. 28, pp. 28–38, May 2014, doi: 10.1016/j.dsp.2014.02.007.

[44] S. Golestan, M. Ramezani, J. M. Guerrero, F. D. Freijedo, and M. Monfared, "Moving Average Filter Based Phase-Locked Loops: Performance Analysis and Design Guidelines," *IEEE Trans Power Electron*, vol. 29, no. 6, pp. 2750–2763, Jun. 2014, doi: 10.1109/TPEL.2013.2273461.

[45] I. Guyon and A. Elisseeff, "An Introduction to Feature Extraction," in *Feature Extraction*, Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 1–25. doi: 10.1007/978-3-540-35488-8_1.

[46] S. Capuozzo *et al.*, "Automating parasite egg detection: insights from the first AI-KFM challenge," *Front Artif Intell*, vol. 7, Aug. 2024, doi: 10.3389/frai.2024.1325219.

[47] L. Hu and Z. Zhang, Eds., *EEG Signal Processing and Feature Extraction*. Singapore: Springer Singapore, 2019. doi: 10.1007/978-981-13-9113-2.

[48] S. Guo, J. Wu, M. Ding, and J. Feng, "Uncovering Interactions in the Frequency Domain," *PLoS Comput Biol*, vol. 4, no. 5, p. e1000087, May 2008, doi: 10.1371/journal.pcbi.1000087.

[49] V. K. Rai and A. R. Mohanty, "Bearing fault diagnosis using FFT of intrinsic mode functions in Hilbert–Huang transform," *Mech Syst Signal Process*, vol. 21, no. 6, pp. 2607–2615, Aug. 2007, doi: 10.1016/j.ymssp.2006.12.004.

[50] K. T. Tapani, S. Vanhatalo, and N. J. Stevenson, "Time-Varying EEG Correlations Improve Automated Neonatal Seizure Detection," *Int J Neural Syst*, vol. 29, no. 04, p. 1850030, May 2019, doi: 10.1142/S0129065718500302.

[51] S. A. Neild, P. D. McFadden, and M. S. Williams, "A review of time-frequency methods for structural vibration analysis," *Eng Struct*, vol. 25, no. 6, pp. 713–728, May 2003, doi: 10.1016/S0141-0296(02)00194-3.

[52] M. Rezapour and S. K. Elmshaeuser, "Artificial intelligence-based analytics for impacts of COVID-19 and online learning on college students' mental health," *PLoS One*, vol. 17, no. 11, p. e0276767, Nov. 2022, doi: 10.1371/journal.pone.0276767.

[53] B. Scholkopf *et al.*, "Comparing support vector machines with Gaussian kernels to radial basis function classifiers," *IEEE Transactions on Signal Processing*, vol. 45, no. 11, pp. 2758–2765, 1997, doi: 10.1109/78.650102.

[54] A. E. Maxwell, T. A. Warner, and F. Fang, "Implementation of machine-learning classification in remote sensing: an applied review," *Int J Remote Sens*, vol. 39, no. 9, pp. 2784–2817, May 2018, doi: 10.1080/01431161.2018.1433343.

[55] N. S. Bastos, B. P. Marques, D. F. Adamatti, and C. Z. Billa, "Analyzing EEG Signals Using Decision Trees: A Study of Modulation of Amplitude," *Comput Intell Neurosci*, vol. 2020, pp. 1–11, Jul. 2020, doi: 10.1155/2020/3598416.

[56] W. Wu *et al.*, "Comparison of regularized discriminant analysis linear discriminant analysis and quadratic discriminant analysis applied to NIR data," *Anal Chim Acta*, vol. 329, no. 3, pp. 257–265, Aug. 1996, doi: 10.1016/0003-2670(96)00142-0.

[57] T. C. de Brito Guerra, T. Nóbrega, E. Morya, A. de M. Martins, and V. A. de Sousa, "Electroencephalography Signal Analysis for Human Activities Classification: A Solution Based on Machine Learning and Motor Imagery," *Sensors*, vol. 23, no. 9, p. 4277, Apr. 2023, doi: 10.3390/s23094277.

[58] A. Chahal* and P. Gulia, "Machine Learning and Deep Learning," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 12, pp. 4910–4914, Oct. 2019, doi: 10.35940/ijitee.L3550.1081219.

[59] E. Ueda, Y. Hirohata, T. Hino, and T. Yamashina, "Lower limit of pressure measurement using a spinning rotor gauge," *Vacuum*, vol. 44, no. 5–7, pp. 587–589, May 1993, doi: 10.1016/0042-207X(93)90102-G.

[60] A. C. Tsoi, "Recurrent neural network architectures: An overview," 1998, pp. 1–26. doi: 10.1007/BFb0053993.

[61] R. Yamashita, M. Nishio, R. Kinh, G. Do, and K. Togashi, "Convolutional neural networks : an overview and application in radiology," pp. 611–629, 2018.

[62] Mohan Patro and M. Ranjan Patra, "A Novel Approach to Compute Confusion Matrix for Classification of n-Class Attributes with Feature Selection," *Transactions on Machine Learning and Artificial Intelligence*, Apr. 2015, doi: 10.14738/tmlai.32.1108.

[63] D. W. Betebenner, Y. Shang, Y. Xiang, Y. Zhao, and X. Yue, "The Impact of Performance Level Misclassification on the Accuracy and Precision of Percent at Performance Level Measures," *J Educ Meas*, vol. 45, no. 2, pp. 119–137, Jun. 2008, doi: 10.1111/j.1745-3984.2007.00056.x.

[64] A. P. Bradley, "The use of the area under the ROC curve in the evaluation of machine learning algorithms," *Pattern Recognit*, vol. 30, no. 7, pp. 1145–1159, Jul. 1997, doi: 10.1016/S0031-3203(96)00142-2.