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A Survey on EEG Signal Analysis Using Machine Learning

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Abstract

Electroencephalogram (EEG) signals provide a window through which we can view brain activity, are of great importance for neurological diagnosis, developing Brain-Computer Interface (BCI), and cognitive neuroscience. Despite the importance of EEG data, they being complex and non-stationary make it difficult for analysis. With the development of machine learning (ML) and deep learning (DL) as state-of-the-art methods for decoding EEG signals, attempting to provide optimal performance in both accuracy and computational time costs when it comes to the problem of extreme complexity such as classification of huge dataset sizes. This paper presents a comprehensive review of the most recent ML and DL techniques in EEG signal analysis. We examine the latest methods — Convolutional Neural Networks (CNNs), Transformer models, Recurrent Neural Networks (RNNs), and both hybrid and traditional architectures with their individual undertakings in tasks of seizure detection, emotion classification, and motor imagery to evaluate each approach efficiency. Overall, the results validate the high transformative efficacy of ML and DL in the EEG signal domain which might provide a key towards optimizing our current knowledge of brain function, as well as serving to increase diagnostic accuracy in clinical environments.

Keywords—Electroencephalogram, Machine learning, Convolutional Neural Networks, Transformer-Based Models, Recurrent Neural Networks, Hybrid Architectures.

1 Introduction

Electroencephalography (EEG) is a non-invasive method of measuring brain activity, it produces a visual representation of the electrical activity of the human brain, by taking measurements of the voltage difference between various brain regions and graphically displaying the results over time. Known as scalp or surface EEG, this type of standard clinical EEG uses multiple electrodes placed on the subject's scalp to detect low energy signals which are the field potential created by the fluctuations of large groups of cortical neurons (Sherman et al., 2020) and (Siuly et al., 2016). Clinical professionals use EEG extensively for diagnostic and treatment purposes, including diagnosing various neurological conditions and abnormalities of the brain and also the treatment of neurodegenerative diseases. For tasks such as accurately diagnosing epilepsy, the physician will use EEG to observe the abnormal activity of the brain, which indicates an epileptic seizure, it is also used by them

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for diagnosing other disorders such as sleep disorders, dementia, Alzheimer's disease, brain trauma, and neurofeedback. Additionally, EEG is widely used in the applications of Brain-Computer interfaces (BCI). A path for communication between the brain and a computer is created by BCI technology to help those with severe neuromuscular disorders to communicate by analyzing their brain activity (Angulo-Sherman et al., 2023) and (Sharma et al., 2024). This large number of EEG applications is a confirmation of the importance of its usage in various settings, but along with its simplicity to use and its potential, EEG produces large amounts of data that need to be analyzed by experts and monitored continuously, because of this, an automated signal analysis methods have been developed, but due to the non-stationary and multi-component nature of the EEG signal, the traditional signal analysis methods are not suitable for this task.

On the other hand, this is exactly where the machine learning and deep learning tools have appeared and been applied. Having shown their efficiency in multiple areas, the two techniques have proven their success in working with brain signals and have made impressive contributions to all of the areas listed above (Zhang et al., 2023). When it comes to processing and analyzing very complicated and rich EEG data, deep learning and machine learning systems can complete this process of extracting the types of information and patterns that are required in an effective manner (Shoorangiz et al., 2021). This survey aims to determine and get an overview of what are the most recent and effective approaches to the analysis of EEG data using deep learning. The research is to examine what approaches of EEG analysis are known at present and how their performance varies in different tasks, as well as what special architectures, pre-processing techniques, and problems can be noted in the light of the most recent researches and developments.

2 Literature Review

In this section, we go over the most recent techniques used in EEG signal analysis based on the models used.

2.1 Convolutional Neural Network (CNN)-Based Models

The reason behind why CNN-based models are used widely in the task of EEG analysis is because they have a good ability to learn the spatial features that exist in a signal. For example, (Dose et al., 2018) used Motor Imagery (MI) data, with a system that uses CNN layers in addition to the traditional Fully Connected (FC) layer for classification, to build an EEG-based system that can be used to improve rehabilitation strategies for people with stroke, the leading cause of disability in adults.

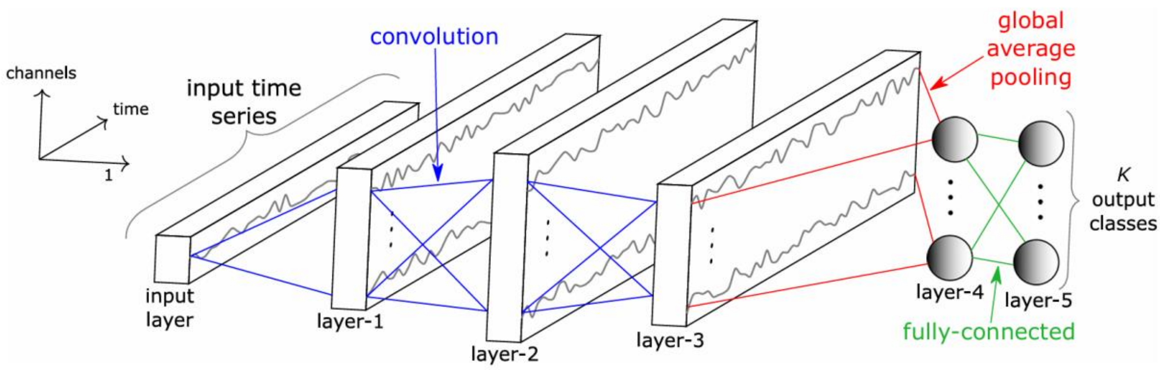

Figure 1: Fully Convolutional Neural Network architecture, image from (Fawaz et al., 2019)

EEGNet, a compact CNN for EEG-based brain–computer interfaces, introduced by (Lawhern et al., 2018), to design a single CNN architecture and accurately classify EEG signals from different BCI paradigms, while simultaneously being as compact as possible , it starts with the temporal convolution to learn frequency-specific spatial filters and a wide variety of interpretable features over a range of BCI tasks, achieving high performance with SP300, MRCP, and ERN datasets allowing for capturing frequency information at 2 Hz and above.

A 13-layer Deep Convolutional Neural Network (DCCN) is proposed by (Acharya et al., 2018) For detecting normal, preictal, and seizure classes by using Z-score normalization, zero mean, and standard deviation of 1 as pre-processing techniques for the signal before feeding it into the CNN, which consisted of three different types of layers: convolutional layer, pooling layer, and a fully connected layer.

In another study, (Raghu et al., 2020) aimed to classify seven types of seizures and non-seizure EEG patterns CNNs and transfer learning. EEG signals are converted into spectrograms using Short-Time Fourier Transforms (STFT) and then fed into the network. STFT is utilized to analyze the frequency content of nonstationary signals, such as EEG data, over time. It can be mathematically
expressed as:

$$X(t,\omega)=\int_{-\infty}^{\infty}x(\tau)w(\tau-t)e^{-j\omega\tau}d\tau \tag{1}$$

where $X(t,\omega)$ represents the STFT of the signal $x(\tau), w(\tau-t)$ is a window function centered at time t, ω is the angular frequency, and j is the imaginary unit. Classification is performed through two methods: firstly, using 10 different pre-trained CNN networks; secondly, extracting image features utilizing the same networks followed by Support Vector Machine (SVM) as a classifier.

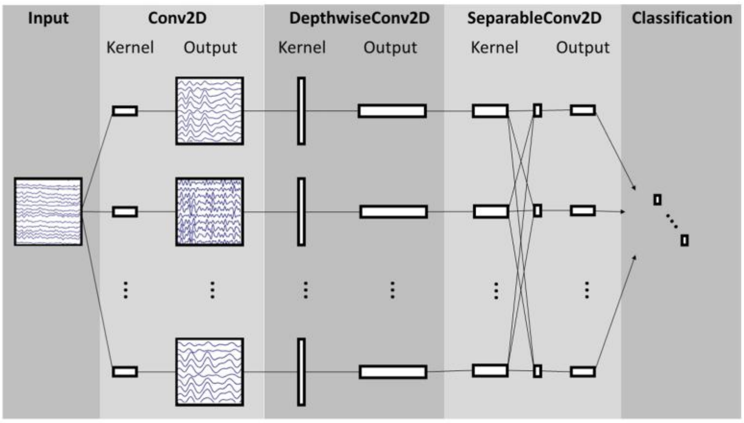

Figure 2: EEGNet architecture, image from (Lawhern et al., 2018)

A study by (Chambon et al., 2018) applies spatial filtering to enhance the signal-to-noise ratio, then uses CNNs to capture spectral features from three modalities (EEG, Electrooculography (EOG), and Electromyography (EMG) signals), these features are then fed to the softmax to classify sleep stages, it found that using 6 EEG with 2 EOG and 3 EMG channels and exploiting one minute of data before and after each segment which significantly improves classification performance when a limited number of channels is available.
(Jonas et al., 2022) explored the potential of DL for diagnostic and predictive assessment based on EEG and to analyze serious diseases and those suffering from different etiologies of ACI through EEG signals. A basic CNN was used to predict the patient's condition. Two methods were employed to detect the decision. First, a visual analysis of all EEGs containing epochs was classified with a certainty factor ≥ 0.9. Second, the so-called Gradient-weighted Class Activation Mapping (Grad-CAM) algorithm was used to highlight discriminative patterns.
(Shoka et al., 2023) built an encrypted system to classify and recognize EEG data using Chaotic Baker and Arnold map transformation algorithms with CNNs, to protect sensitive medical EEG signals from detection. In the proposed system, the first phase describes an automated encrypted spectral model for mapping EEG. It includes three main modules: Signal Preprocessing and Handling (SPH) module to convert EEG signals into encoded 2D spectral images, EEG Spectral Classification Module (E2SC) encoded to classify the encoded images using the trained networks AlexNet, DarkNet19, GoogleNet, ResNet50, and QuesqueNet. Then, the final layers are replaced with new layers that adapt to the new encoded dataset. Seizure Detection Assessment (SDA) module evaluates the performance of the proposed approach with different experimental scenarios.

The study presented by (Siuly et al., 2023) aimed to solve the problem of the time-consuming traditional manual feature extraction methods, to do that, they presented a feature extraction design based on a deep residual network (ResNet) that consists of three stages: signal pre-processing, extraction of hidden patterns of EEG signals, and classification by softmax layer. This design can automatically extract features from EEG signal data with high accuracy in order to find out if a person has schizophrenia or not.

2.2 Transformer-Based Models

Transformer architectures were initially developed for Natural Language Processing (NLP) tasks, they have been applied to EEG signal processing and they show the potential to effectively capture long-range dependencies.

The main component in the transformer models is the use of attention mechanisms to capture temporal-spatial dependencies in EEG data effectively and demonstrate relatively competitive performance when compared with other methods. For example, one method proposed the Gated Transformer Networks (GTN) by (Liu et al., 2021) is an extension of the standard transformer architecture, but here it is developed for multivariate time series classification. Using two encoder towers to model attention and masking across step-wise and channel-wise correlation. A step-wise encoder is used to encode temporal features by self and multi-head attention with positional encoding used, as well as a channel-wise encoder without positional encoding to compute the attention weights across different channels.
In a study by (Hussain et al., 2022) a Multichannel Vision Transformer (MViT) architecture was proposed to classify preictal and interictal EEG activities. EEG segmentation and Continuous Wavelet Transform (CWT) to convert each segment into an image-like representation known as scalograms, which are then split into fixed-size patches and inputted into the MViT which consists of multiple branches, each serving as a transformer encoder to process a distinct EEG scalogram image. The resulting features are fed into a Multi-Layer Perceptron (MLP) for EEG classification.

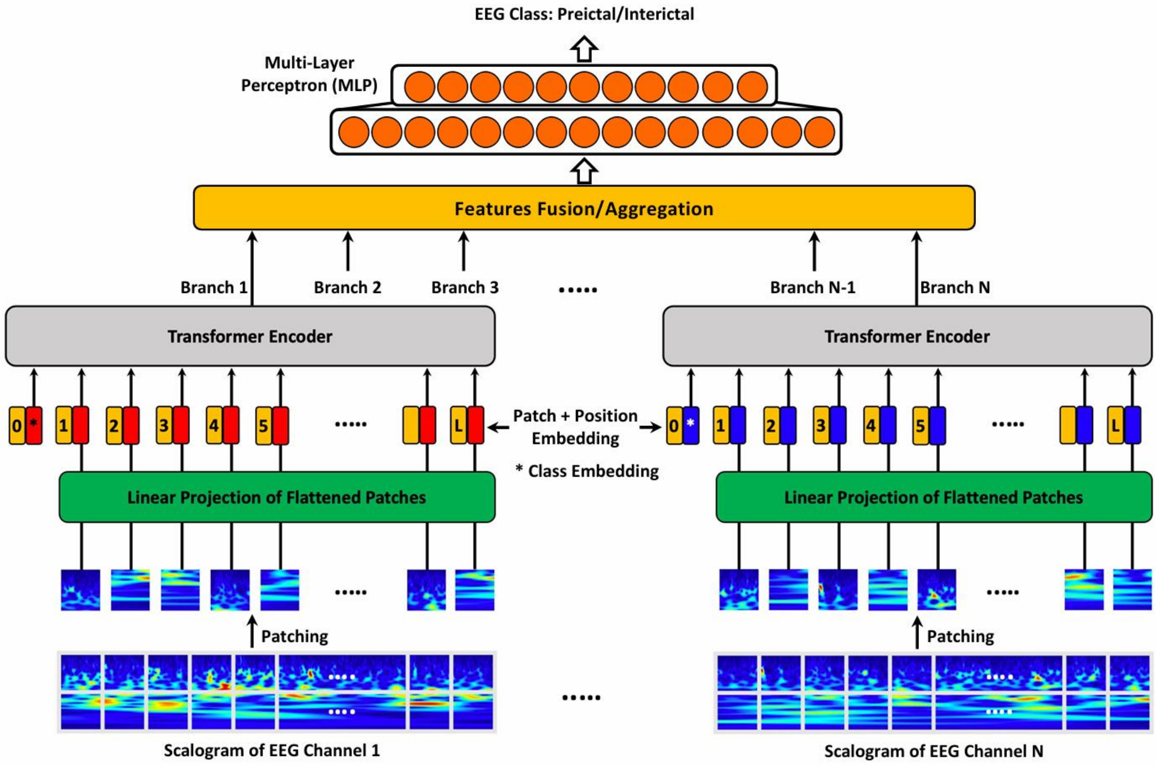

Figure 3: Framework of MViT for multi-channel EEG feature learning, image from (Hussain et al., 2022)

A transformer-based unsupervised learning approach for seizure identification in EEG data is introduced by (Potter et al., 2022) By reframing the problem as anomaly detection, an autoencoder involving a transformer encoder is trained via an unsupervised loss function, incorporating a masking strategy specifically designed for multivariate time series. The autoencoder learns meaningful latent representations from EEG recordings, reconstructing input data with minimal error in the absence of seizures and higher reconstruction errors for records with seizures.
In (Qi et al., 2020), the authors described an automatic epilepsy detection method by using multi-scale wavelet analysis to decompose EEG signals into components of different frequency bands, followed by feature extraction and CNNs with an attention mechanism for classification.

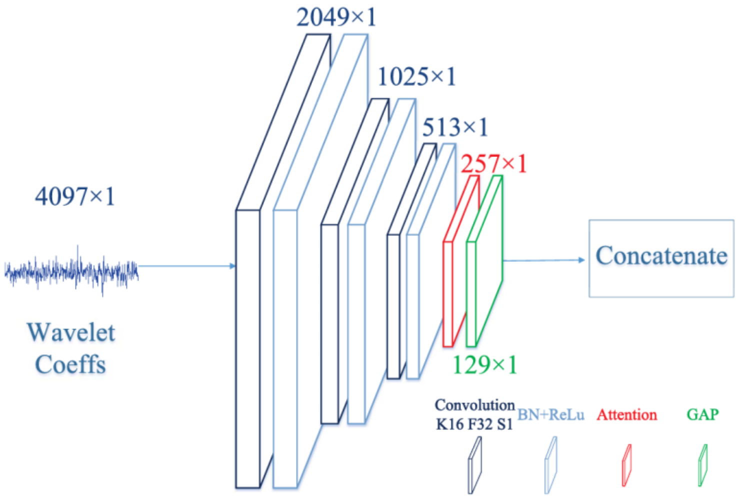

Figure 4: Attention mechanism-based CNN, image from (Qi et al., 2020)

(Ying et al., 2024) on the other hand, emphasize the usefulness of attention mechanisms in sequence data analysis as they investigate the use of electrophysiological methods to examine brain activity for accurate symptom evaluation. It presents the EEG-based Depression Transformer (EDT) model, which is based on EEG data extraction and reliably differentiates depressed people from healthy controls by identifying specific traits. The effectiveness of the EDT model is attributed to capture depression-specific information using information extraction and attention modules.
The study conducted by (Yan et al., 2022) highlights the design of a model to predict epileptic seizures for patients with epilepsy. This model relied on transformer networks to extract and integrate 3D features of EEG signals. STFT has been used to extract time-frequency information from EEG signals and automatically generate enhanced features. It also converts the EEG signal into a two-dimensional matrix that includes time and frequency domains. Time-frequency features were extracted from the EEG signals using the wavelet transform tool. The seizure prediction task is completed after post-processing. Here the design will work to predict seizures with high efficiency, and this will help a lot in maintaining the quality of life.
In (Zhou and Pan, 2021), the authors proposed Spectrum Attention Mechanism (SAM) and Segmented-SAM (SSAM) for Time Series Classification (TSC). SAM integrates adaptive filtering into deep learning models by transforming time series data into the frequency domain using a Discrete Cosine Transform (DCT)
DCT is employed to transform a signal into a sum of cosine functions of different frequencies. For a 1-dimensional signal $x(n)$ of length N, the DCT is expressed as:

$$X_k = \sum_{n=0}^{N-1} x_n cos\left[\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right] \tag{2}$$

where X_k is the DCT coefficient at index k, x_n is the input signal, N is the length of the signal, and k is frequency index. The benefit of this transformation is to effectively compress the signal energy into a few coefficients. Apply a trainable mask to filter out the noise and transform it back into the time domain. For SSAM on the other hand, similarly divides the TC data into a number of segments to keep the time-domain characteristics by using a heuristic strategy that applies SAM to each segment on an individual level and then combines the results, here these results are considered as features that will be processed using a CNN.

The work of (Hao et al., 2022) proposes an improvement for deep learning networks with an additional module called class-specific attention (CSA) which is incorporated into the feature extraction stage. It consists of transforming the input features into keys, queries, and values, and then performing class-specific feature importance calculations for each feature. To highlight all the unique class features, this module utilizes class differentiation element, the generated attention weights are then used to modulate the features and as a result, increase the emphasis on useful class-specific information.

2.3 Recurrent Neural Network (RNN)-Based Models

To process best the sequential data like natural language, time-series data, and EEG, the RNN-based models are employed, specifically Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), In addition, the RNN networks are capable of capturing and modeling effectively the temporal dynamics of EEG signals and enabling accurate classification of emotional states and abnormal EEG patterns and other useful EEG patterns. A general form of an RNN calculates the state at time t and the hidden state h_{t-1} from previous time step based on x_t which represents the input, the h_t is hidden state at time step t and the output o_t is computed from the hidden state h_t

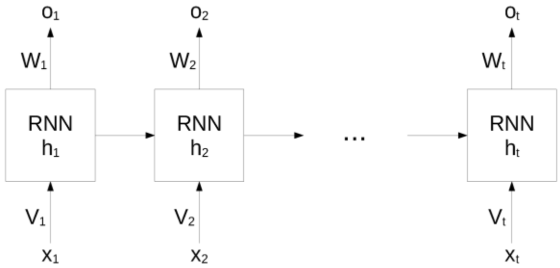

Figure 5: Structure of an RNN block, image from (Alessandrini et al., 2021)

For a time series data $\{x_1, x_2, \dots, x_t\}$, the hidden state h_t at time step t is computed as:

$$h_t = f(W_h h_{t-1} + V_h x_t + b_h) \tag{3}$$

Here, the input at the time t is represented by x_t and h_{t-1} is the hidden state from previous time step, V and W considered as the weight matrices for the hidden layers, b is the bias for the hidden and output states, and f is the activation function (tanh or ReLU). The output o_t is calculated as:

$$o_t = f(h_t + b_o) \tag{4}$$

where f is the output function (a softmax function or other activation function).

The LSTM cell consists of several gates which the purpose of is regulating the flow of information in modeling long sequences. Mathematically, the LSTM cell operations are defined as follows:
For a time series data $\{x_1, x_2, \dots, x_t\}$, the LSTM cell computes the forget gate as:

$$f_t = \sigma\left(W_x^T f \cdot x_t + W_h^T f \cdot h_{t-1} + b_f\right) \tag{5}$$

the input gate is defined as :

$$i_t = \sigma(W_x^T i \cdot x_t + W_h^T i \cdot h_{t-1} + b_i) \tag{6}$$

and the candidate cell state is defined as:

$$\widetilde{c_t} = tanh\ tanh\ (W_x^T c \cdot x_t + W_h^T c \cdot h_{t-1} + b_c) \tag{7}$$

where W_f, W_i, and W_C considered as weight matrices, b_f, b_i, and b_C are biases, σ is the sigmoid activation function, and tanh is the hyperbolic tangent function. Then, the cell state is updated as:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{8}$$

where c_{t-1} is the previous cell state and $\odot$ denotes element-wise multiplication. The output gate is computed as:

$$g_t = \sigma\left(W_x^T g \cdot x_t + W_h^T g \cdot h_{t-1} + b_g\right) \tag{9}$$

and the hidden state is updated as:

$$o_t, h_t = g_t \odot tanh\ (c_t) \tag{10}$$

where W_o and b_o are the weight matrix and bias for the output gate, respectively (Alessandrini et al., 2021).

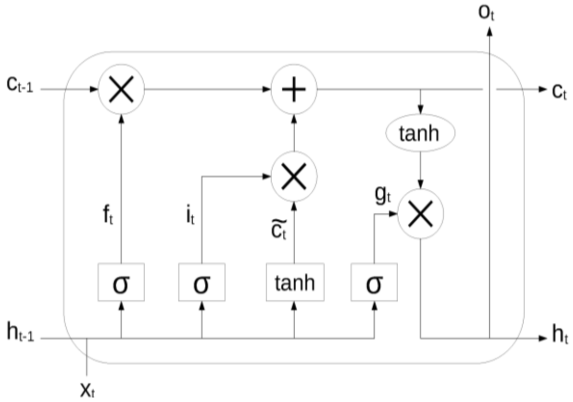

Figure 6: LSTM cell unit, image from (Alessandrini et al., 2021)

Roy et al. proposed a network called ChronoNet to identify abnormal brain activity in the TUH dataset, the network combined Conv1D layers that included multiple filters with exponentially changing lengths, following that, stacked layers of GRUs connected in a feedforward way using skip connections, where these connections will guide the network to ignore some GRU layers where the demand of model complexity is less required by the data (Roy et al., 2019). In a study after that by (Chowdary et al., 2022), the authors tried to classify emotions using different RNNs on the EEG Brain Wave Dataset with three different emotional states, positive, negative, and neutral. They applied three RNN models which are RNN, LSTM, and GRU where all three are trained using Adam optimizer with sparse categorical cross-entropy as a loss function.

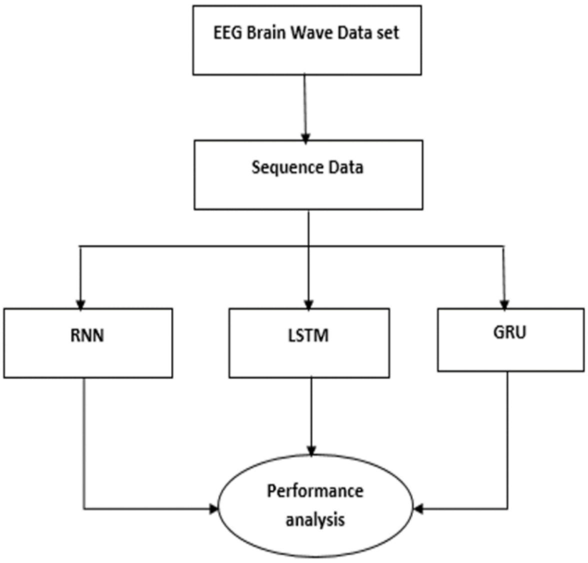

Figure 7: Emotion Recognition from EEG Signals Using RNN, image from (Chowdary et al., 2022)

(Ma et al., 2021) proposes a recurrent t-distributed Stochastic Neighbor Embedding (t-SNE) neural network model to predict customer decision-making behavior in the market field. This was done by implementing the t-SNE algorithm to extract features, and then a recurrent neural network is created with an LSTM layer. SoftMax was used for feature training and EEG signal classification. This model could predict customers' thinking well.
The study conducted by (Alessandrini et al., 2022) confirmed the development of a method for automatic classification of incomplete or corrupted data. The Robust Principal Component Analysis (RPCA) algorithm was used with an RNN for classification. This network was used with corrupted data as outliers and was processed during RPCA to remove outliers from the signal for diagnosing Alzheimer's disease (AD). Even with corrupted data, they confirmed that the accuracy increased by about 5% with respect to the Robust Principal Component (RPC) that was tested on the RNN with EEG data, which was correctly processed through traditional PCA.

2.4 Deep Learning Models Based on Hybrid Architectures

The applications of one model for learning spatial features (such as CNN-based models) and another in processing the temporal characteristics of a signal (such as an RNN-based model) may constrain their capacity to process and understand both spatio-temporal patterns of EEG signals that vary in time domain and frequency domain. Consequently, some of the researchers began to combine a variety of models and architectures together to take benefit from their strengths. The authors, for example, (Spampinato et al., 2017) followed a two-stage approach where they intended to investigate how well we can express human visual capabilities using both RNN and CNN models. In the first stage, the RNN is used as an encoder trained to learn the temporal features of raw EEG evoked by a subject looking at an image, and using a CNN-based regression in the second stage to project images into the learned features manifold representation.
Another research was done by (Xu et al., 2020), in which a One-Dimensional Convolutional Neural Network-Long Short-Term Memory (1D CNN-LSTM) model was proposed to detect epileptic seizures by analyzing the EEG signal with high accuracy and timeliness. This model is done by pre-processing the EEG signal data and then designing a one-dimensional CNN to extract data features. To process these extracted features, LSTM layers are used. Then, the output features are fed to several fully connected layers for final seizure recognition. A three-pass hybrid deep learning system presented by (Golmohammadi et al., 2019), its objective was to identify significant clinical patterns in the TUH dataset by extracting features from the data using Linear Frequency Cepstral Coefficients (LFCCs) and processing them through their proposed system that captures the temporal features in the first stage using Hidden Markov Models (HMMs), followed by spatial and temporal context analysis using Stacked Denoising Autoencoders (SdAs), and a statistical language model at the end to enhance the accuracy of EEG event classification.

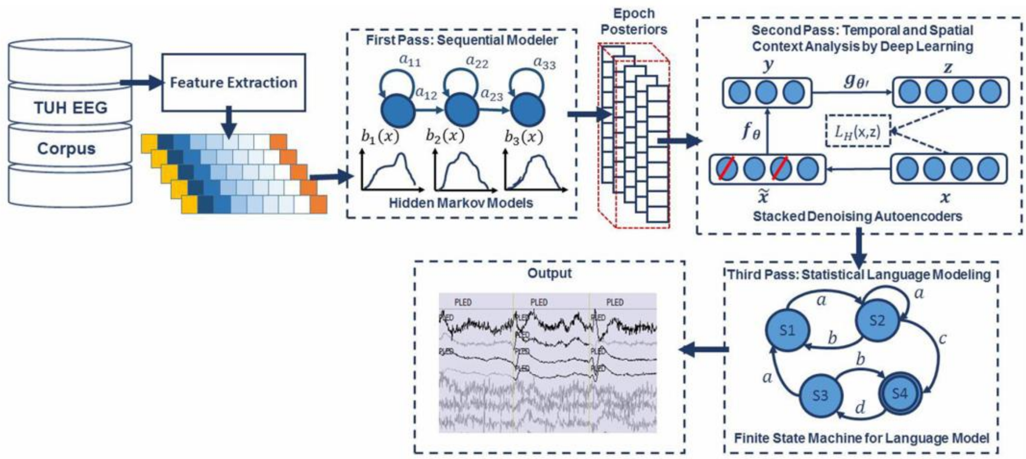

Figure 8: A three-pass architecture for automatic interpretation of EEG, image from (Golmohammadi et al., 2019)

NeuroNet described in (Lee et al., 2024), is ahybrid self-supervised learning framework for sleep stage classification using single-channel EEG, combining NeuroNet with the mamba-based temporal context module with Sleep-EDFX, SHHS, and ISRUC-Sleep datasets, demonstrated the highest performance across all datasets, with the exception of Sleep-EDFX. Compared to other SSL. The use of NeuroNet exceeds most recent supervised learning methods, even with minimally labeled data. Furthermore, it uses multi-resolution CNNs to extract features from both high- and low-frequency EEG data, and STFT Encoder performs admirably on most datasets. Sanchita et al. used electrocardiogram (ECG) and EEG data analysis to identify and evaluate depression. The primary characteristics examined in the brain signal are band power alpha, entropy, standard deviation, and Hjorth activity (HA). Performance was enhanced by combining the CNN, KNN, and SVM classifiers with the LSTM autoencoder model. After preprocessing the signal to eliminate artifacts, the RNN learned the data then sent it out for further training by the LSTM autoencoder while a minimal test was done in the end for categorizing and predicting depression (Sanchita et al., 2023).
A hybrid deep learning approach for detecting sleep arousal events has been demonstrated in (Foroughi et al., 2023). To begin with, this technique requires separating the signal in the Discrete Wavelet Transform (DWT) and further windowing for simplification. After that, the combined feature extraction is performed by Inception-ResNet-v2 structure and classification by SVM. To optimize the SVM, Gray Wolf Optimization method is used.

A machine learning system was presented by (Yogarajan et al., 2023) to analyze EEG patterns and detect seizure-indicative asymmetry. They derived the statistical and Hjorth parameters of signals decomposed using the Stationary Wavelet Transform (SWT). To identify essential characteristics of SWT-compressed data that are vital for further classification with Deep Neural Networks (DNNs), the Binary Dragonfly was proposed.
Varalakshmi et al. present an approach to predict epileptic seizures, which involves decomposing EEG signals using Tunable Q Factor Wavelet Transformation (TQWT), extracting statistical, temporal, and global features. Techniques like Continuous Bag of Words (CBoW) and dimensionally reduced using autoencoders are applied to extract temporal features, while global features are Identified using PCA across different sub-bands of the signals to identify the signals, a basic Artificial Neural Network (ANN) is employed (Varalakshmi et al., 2021).

2.5 Traditional Machine Learning Models

In the examination of EEG rhythms, standard BCI, traditional methods are used, like SVM, KNN and Naïve Bayes (NB). For tasks such as mental stress detection, a study by (AlShorman et al., 2022) aimed to use Fast Fourier Transform (FFT) as a feature extraction stage, along with applying SVM-assisted learning classifiers to achieve high accuracy in detecting mental stress accurately using frontal lobe and total EEG signals. The posterior probability of the prior, the predictor probability of the target, and the prior probability of the predictor were also computed using NB, which offers a Bayes hypothesis. This approach is simple and may be utilized as a real-time and continuous monitoring technique for medical purposes.
(Bashivan et al., 2016) investigated robust representations of EEG data. Data is transformed into a sequence of multispectral pictures that preserve topology. They used different techniques, such as SVM, Deep Belief Networks (DBN), Random Forest Ensemble, and Logistic Regression, to determine which hyperplane best splits data points into discrete groups. Furthermore, Jang et al attempt exact EEG classification. DEAP and DREAMER were the two EEG datasets for emotional and psychological states used by the scientists who did not employ Graph Neural Networks (GNN) but only conventional approaches. The algorithms used were Spatial-Temporal Graph Convolutional Network (ST-GCN), ChebNet, and Deep Graph Convolutional Neural Network (DGCNN) among others. KNN, SVM, Recurrent Attention Convolutional Neural Network (RACNN) were among the methods applied for data analysis. Besides this model showed significantly better performance when compared to its own version that did not learn graphs (Jang et al., 2021).
(Abdullah et al., 2019) searched different classification algorithms for analyzing data related to epilepsy. It utilized the Hilbert-Huang Transform (HHT) for purpose of data extraction, also it uses the Gaussian Deep Boltzmann Machine (GDBM) for classification purpose. GDBM exhibits the highest accuracy as if it compared to SVM, NB, and logistic regression.

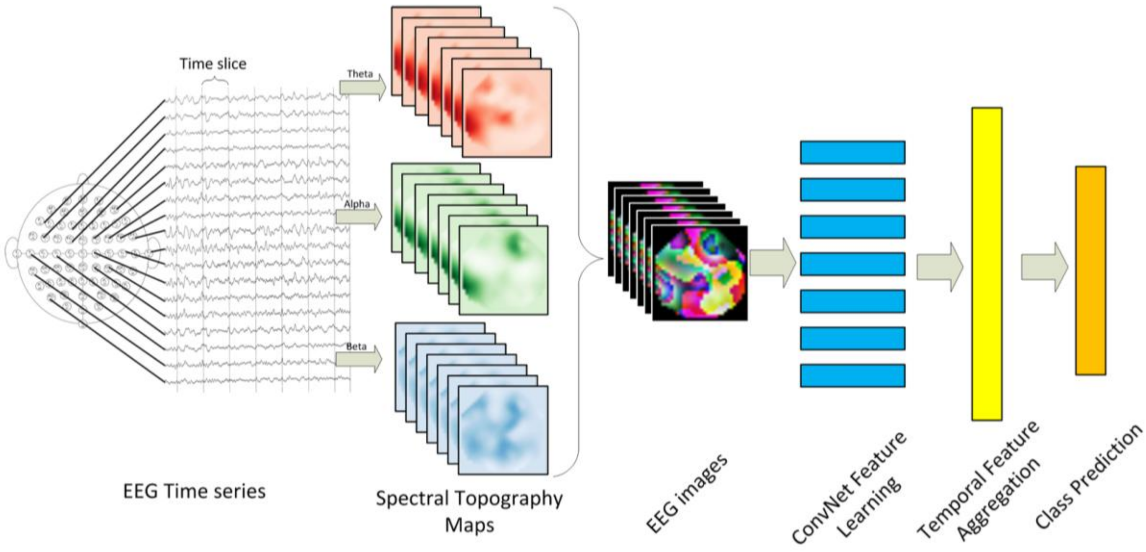

Figure 9: Overview of the approach by (Bashivan et al., 2016)

Finally, (Savadkoohi et al., 2020) concerned the implementation of feature extraction and selection in three domains: time, frequency, and time-frequency. EEG signals were filtered using a third-order Butterworth bandpass filter for the time-domain aspects, and statistical characteristics such as mean, skewness, variance and kurtosis were extracted from five brain wave categories, which are: Delta, Theta, Alpha, Beta, and Gamma.

Fourier and Wavelet Transforms were used to extract features related to both frequency and time-frequency features resulting in a total of 60. feature selection was performed using the T-test and Sequential Forward Floating Selection (SFFS), the selected features were then fed into SVM and KNN for classification.

3 Discussion of Previous Findings

In the previous section, we discussed various machine learning algorithms which were developed by many researchers to find ways that would help improve the accuracy and reliability of diagnostic tools for categorizing EEG signals. Below we state and discuss the outcomes from the previously mentioned studies which introduced different ML and DL models that demonstrate their applicability in this area. Many studies highlight the effectiveness of RNN and hybrid models in EEG classification. Roy et al. achieved accuracies of 90.60% and 86.57%, on the TUH Abnormal EEG Corpus surpassing previous accuracy benchmarks by 1.17% showcasing the efficacy of using Conv1D and GRU layers. Chowdary et al. reported LSTM at 97% accuracy, GRU at 96%, and RNN at 95% for classifying emotional states. Vinay et al. showed promising results with RNNs, while Spampinato et al. combined RNNs and CNNs to achieve 83% accuracy. Alessandrini et al. demonstrated 97.9% accuracy using PCA. Whereas the results related to CNN models are varied. For example, Raghu et al. 's Inceptionv3 obtained an 88.30% accuracy while Chambon et al. utilized spatial filtering and CNNs to advance sleep stage classification. On the other hand, Qi et al. acquired 98.89% for triple and 99.70% for binary classification accuracies respectively in Bonn and Bern-Barcelona datasets although EEGNet has been shown to have good performance with all BCI paradigms.

Other studies show the effectiveness of transformer-based and hybrid models in the analysis of EEG data. Using the CHB–MIT dataset, Hussein et al. employed MViT to achieve over 99% sensitivity, specificity, and accuracy with a low false positive rate. Yan et al. predicted epileptic events with a sensitivity of 96.01% and a low rate of false positives. By integrating attention mechanisms with EEG data, Ying et al. succeeded in classifying depression with high accuracy. High precision was achieved by Xu et al. in binary and multi-class tasks related to seizures. More than 90% of neurological diseases were identified by Golmohammadi et al. Using hybrid architectures, Lee et al. were able to successfully capture temporal relationships. Pange et al. used an LSTM autoencoder and achieved 97% accuracy. Employing integrated RNNs with CNN, Spampinato et al. were able to recognize cognitive tasks with an accuracy of almost 83%.

However, other results which are related to SVM methods show that AlShorman et al. achieved accuracies between 90% and 98.21% using SVM classifiers, showcasing robust performance. Savadkoohi et al. compared SVM and KNN classifiers, with SVM demonstrating superior accuracy of 100% accuracy, sensitivity, and specificity.

Lastly, other studies showed high performances using different models and techniques, for example, Acharya et al. achieved an accuracy of 88.67%, along with sensitivity and specificity rates of 95.00% and 90.00%, respectively, for seizure detection. Potter et al. achieved an AUC of 0.93 ± 0.005 on the MIT dataset, highlighting strong performance. Liu et al. 's GTN achieved accuracies ranging from 88.9% to 100% across diverse datasets. Foroughi et al. achieved an average accuracy of 93.82%, ensuring computational efficiency gains. Abdullah et al. reported 100% accuracy using GDBM, for demonstrating significant diagnostic potential. Shoka et al. achieved accuracies of 86.11% and 84.72% using GoogleNet with Arnold and Chaotic methods, respectively. Zhou and Pan's SSAM-CNN model showed superior performance over traditional and deep learning methods. Jang et al. achieved accuracies of 73.5% ± 8.07% for DEAP and 55.5% ± 7.59% for DREAMER. and Varalakshmi et al. improved the accuracy using their methodologies, achieving accuracies up to 98% with ANN classifiers.

Table 1: Summary of Previous Studies

Author(s)	Year	Application	ML Model(s)	Feature Extraction	Dataset	Results
Bashivan et al.	2016	BCI	CNNs and VGG (Visual Geometry Group) and LSTM	CNNs	EEG data during a working memory experiment	Single-Frame Classification Test Error:12.39% Multi-Frame Classification Test Error: 8.89%
Acharya et al.	2017	Detect normal, preictal, and seizure classes	CNNs	CNNs	/	CNN model obtained 88.67% accuracy, 95.00% sensitivity, and 90.00% specificity.
Spampinato et al.	2017	Automated visual classification.	RNN CNN	CNNs	ImageNet	83% classification accuracy
Lawhern et al.	2018	BCI	CNNs	CNNs	SP300, MRCP and ERN	EEGNet generalizes across paradigms better than when only limited training data is available
Dose et al.	2018	Rehabilitation of stroke survivors using BCI and motor imagery	CNNs	Temporal and spatial convolutional filters	EEG Motor Movement /MI	The selected global classifier reached 80.38%, 69.82%, and 58.58% mean accuracies for datasets with two, three, and four classes, respectively.
Chambon et al.	2018	Sleep stages classification	CNNs	CNNs followed by maxpooling	MASS dataset (Montreal Archive of Sleep Studies)	Found that exploiting one minute of data before and after each segment significantly improves classification performance when a limited number of channels is available.
Roy et al.	2019	Identification of abnormal brain activity	CNNs and GRU	CNN for frequency feature extraction	TUH Abnormal EEG	90.60% training Accuracy and 86.57% testing accuracy
Golmohammadi et al.	2019	EEG classification	Hidden Markov Models	Linear frequency cepstral	The TUH EEG Corpus	sensitivity above 90% while maintaining a

			(HMMs) and SdAs	coefficients (LFCCs)		specificity below 5%
Abdullah et al.	2019	EEG classification	GDBM, Logistic regression, Naïve Bayes, and SVM	Hilbert-Huang Transform (HHT)	Epileptic EEG data	The classification accuracies were 97%, 98%, 97% and 100%. GDBM showed the highest performance
Raghua et al.	2020	Classification of seven types of seizures alongside non-seizure EEG patterns	CNN and SVM	Pretrained CNN	TUH	Accuracy using the Inceptionv3 pretrained network: 88.30%
Xu et al.	2020	Epileptic seizures detection	1D Convolutional Neural Network (1D CNN)	1D CNN	UCI epileptic seizure dataset	This method achieved high accuracy of 99.39% and 82.00% on the binary system and epileptic seizure recognition tasks
Savadkoohi a et al.	2020	Epileptic seizures detection	SVM and KNN	Statistical feature: mean, variance, skewness, and kurtosis, Fourier Transform, and Wavelet Transform	Bonn EEG database	SVM: 100% accuracy, sensitivity, and specificity KNN: accuracy of 99.5, sensitivity of 99%, and 100% specificity.
Jang et al.	2021	Emotional video classification	CNN, RNN, GNN, LSTM, and RACNN	Converts the raw EEG signals to features for end-to-end learning	DEAP database DREAMER database	The accuracy results for DEAP were 56.6±8.39%, while for Accuracy for DEAP were 73.5±8.07% and for DREAMER 55.5±7.59%.
Liu et al.	2021	Multivariate time series classification	Two Tower Transformer NN	/	13 different datasets	The GTN achieved accuracy of 88.9% to 100% for 13 different datasets
Vinay et al.	2021	Audio onset prediction	RNN FCN	A spectral flux-based novelty function	NMED-T	/
AlShorman et al.	2021	Automatic mental stress detection	SVM Naive Bayes	FFT	Najran University EEG Dataset	Accuracy: 90-98.21%

Zhou and Pan	2021	Time series classification (TSC)	CNNs	Discrete Cosine Transform (DCT	/	/
Qingguo Ma et al.	2021	Customer behavior prediction	Recurrent t-SNE Neural Network	/	/	Accuracy: 87%
Varalakshmi et al.	2021	Epileptic seizures detection	Simple ANN	Tunable Q Factor Wavelet Transformation (TQWT) Continuous Bag of Words (CBoW)	/	Accuracy: 98%
Hussein et al.	2022	Classification of preictal and interictal EEG activities	MLP and Multi head attention Transformer Encoders	CWT, and Transformer Encoders	CHB–MIT Kaggle/American Epilepsy Society (AES) Dataset Kaggle/Melbourne University	On the CHB–MIT Dataset Accuracy was 99.8% and FPR of 0.004 On Kaggle/AES sensitivity: 90.28 AUC Score Public/Private: 0.940/0.885
Potter et al.	2022	Seizure detection	Transformer Encoder, t Distributed Stochastic Neighbor Embedding (t-SNE), K-means Clustering, and XGBoost	/	CHB-MIT UPenn TUH	AUC of 0.93 ± 0.005 on the MIT dataset Outperformed supervised methods by up to 16% recall, 9% accuracy, and 9% AUC on UPenn and MIT datasets
Chowdary et al.	2022	Emotions classification	RNN, LSTM, and GRU	CNNs	EEG Brain Wave Dataset: Feeling Emotions	An average accuracy of 95% for RNN, 97% for LSTM, and 96% for GRU for emotion detection problems is achieved
Qi et al.	2022	Epileptic seizures detection	CNNs with attention	Discrete Wavelet Transform (DWT)	Bonn EEG database and Bern-Barcelona EEG database.	The proposed algorithm achieved 98.89% accuracy in triple classification on the Bonn EEG database and 99.70% accuracy in binary classification on the Bern-

						Barcelona EEG database.
Jonas et al.	2022	Diagnosis of Acute Consciousness Impairment (ACI)	CCNs	CNNs	CERTA	The accuracy for predicting was 54.5 % and increased to 67.7 %, 70.3 % and 84.1 %, respectively
Athar A. Ein Shoka et al.	2022	EEG classification with encryption	CNNs (Alexnet, Darknet, GoogleNet, Resnet50, squeezenet)	Pretrained CNN	CHB-MIT	Accuracy: 86.11 % and 84.72% using GoogleNet with Arnold and chaotic methods respectively.
Alessandrini et al.	2022	Alzheimer's disease classification	RNNs	PCA RPCA	20 subjects diagnosed with Alzheimer's disease (AD). 15 healthy subjects (Normal)	97.9% versus 79.3% in the best cases
Yan et al.	2022	Epileptic seizures detection	Three-tower Transformer	STFT	CHB-MIT	sensitivity: 96.01% false positive rate: 0.047/h
Hao et al.	2022	TSC	FCN, MLSTM, MLSTM-FCN, CNN-ATN, and TapNet	/	40 datasets 28 multivariate time series (MTS) and 12 univariate time series (UTS) datasets.	The inclusion of the CSA module led to significant improvements in classification accuracy across most datasets.
Pange et al.	2023	Depression recognition	LSTM, KNN, SVM, and CNN	FFT for EEG wavelet transform for ECG	PhysioNet	Accuracy of 84% for ECG signal and 96% for EEG
Yogarajan et al.	2023	Automatic seizure detection	DNN	Stationary Wavelet Transform (SWT)	Bonn EEG dataset	100% accuracy, sensitivity, specificity, and F1 score, with only 13% of the features used.
Foroughi et al.	2023	Detecting sleep arousal events	CNNs (Inception-ResNet-v2) architecture	Convolution filters	2018 Challenge Physiobank sleep dataset	Accuracy: 93.82%
Siuly et al.	2023	Automatic detection of schizophrenia	Deep residual network (Deep ResNet)	/	Kaggle data	Accuracy: 99.23%.

Ying et al.	2024	Depression recognition	EDT	Extract features from the frequency, spatial, and temporal domains of EEG data	ImageNet	Accuracy: 92.25 ± 4.83 %
Lee et al.	2024	Sleep stages classification	Mamba space model	low-frequency and high-frequency features through multi-resolution CNNs	Sleep-EDFX, SHHS, and ISRUC-Sleep	The STFT Encoder demonstrated the highest performance across all datasets, with the exception of Sleep-EDFX. Compared to other SSL

4 Conclusion

This survey aimed to review the intervention of machine learning and deep learning, and mentioned its importance in many uses, including analyzing brain signals, from which many aspects appear, including predicting a condition before it occurs, such as epilepsy, or predicting the thoughts and behavior of humans, or whether an individual has Alzheimer’s, and much of that kind. This was done by using some complex techniques and processors to give valuable results. Among the techniques that were used was CNN because of its ability to capture spatial features in a very efficient way. RNN, hybrid learning, and other techniques that have the ability to classify and analyze were also used. It was noted in all of them that the results were good, with high accuracy and efficiency. Based on these conclusions, the importance of these technologies and their use and development must be considered further in our current reality because of the accuracy of the results. In future studies, we must focus on increasing the accuracy and effectiveness of networks and introducing them into more systems.

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