Journal of Theoretical and Applied Information Technology
15th February 2026. Vol.104. No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A COMPREHENSIVE ANALYSIS ON DEEP LEARNING TECHNIQUES FOR ELECTRO ENCEPHALOGRAM SIGNAL ANALYSIS AND APPLICATIONS

SYDA NAHIDA[1], SHAIK SAGAR IMAMBI[2]
Research Scholar,Department of CSE,Koneru Lakshmaiah Education Foundation,Vaddeswaram,Guntur,Andhra Pradesh,India[1,*]
Professor, Department of CSE & IRD,Koneru Lakshmaiah Education Foundation,Vaddeswaram,Guntur Andhra Pradesh,India[2]
nahidasyeda786@gmail.com[1,*],simambi@gmail.com[2]
Corresponding Author*: nahidasyeda786@gmail.com

ABSTRACT

Electroencephalogram (EEG) analysis has emerged as a cornerstone for understanding brain dynamics and diagnosing neurological and cognitive disorders. While recent years have witnessed a surge in deep learning–based EEG studies reporting high classification accuracy, existing literature largely remains descriptive and model-centric, offering limited critical insight into why certain approaches succeed or fail under real-world EEG constraints such as non-stationarity, inter-subject variability, and low signal-to-noise ratios. This gap limits both scientific understanding and clinical translation.This survey addresses this limitation by presenting a critical and integrative analysis of deep learning techniques for EEG signal processing, moving beyond architectural taxonomies to examine their methodological assumptions, robustness, interpretability, and deployment feasibility. Unlike prior surveys, this work systematically evaluates how preprocessing strategies, feature learning paradigms, and emerging architectures—such as attention mechanisms, transformers, and graph neural networks—interact with the intrinsic properties of EEG signals.The study synthesizes recent advances to identify unresolved challenges in generalization, explainability, and data scarcity, while highlighting emerging trends such as self-supervised learning, multimodal fusion, and privacy-preserving federated frameworks. By framing deep learning–based EEG analysis through a critical lens, this survey provides actionable insights for researchers and clinicians, and contributes new conceptual understanding required for the development of reliable, interpretable, and clinically deployable EEG-based AI systems.

Keywords: *EEG Signals, Deep Learning, Brain Wave Analysis, Neural Activity Classification, Machine Learning Algorithms, Emotion Recognition, Neurological Disorder Detection*

1. INTRODUCTION

Electroencephalography (EEG) is a common, noninvasive brain recording method. It quantifies electrical oscillations in the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz) and gamma (30–100 Hz) bands related to distinct neurological, cognitive processes. The high dimensional, time-varying, non-stationary and often contaminated by artifacts nature of the EEG signals adds further to their difficulty of understanding. To meet these challenges, computer scientists have proposed computational solutions rooted in classic machine learning and extended now to deep learning methodologies.

Originating studies were based on machine learning algorithms and handcrafted features. Models such as multilayer perceptrons and support vector machines that are based on permutation entropy, spectral power, or clustering showed preliminary positive results in identifying epileptic seizure, recognizing emotion, and classifying mental states [1–3]. Subsequent ensemble and wavelet-based trans- forms increased robustness and interpretability [4–6]. Following this introduction of deep learning after 2015, cognitive EEG signal analysis also trended towards convolutional neural networks (CNN) and recurrent neural networks (RNN). CNNs were good at space-based features extracting through raw EEG signal, and long short-term memory networks and gated recurrent units were capable of learning complex temporal dependencies [7–12]. The generalization to other subjects and sessions was improved by transfer learning methods [13–15].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Deep learning allowed the EEG research field to address different applications such as seizure detection, sleep stage classification, affective computing, BCI designs, cognitive load estimation and depression diagnosis [16–25]. Such trends also continued for online monitoring tasks, such as driver state identification and automatic artifact rejection [26–29]. The promise of EEG in human–computer interaction was further demonstrated by paradigms for thought-to-text translation, robotic control forecasting and fine-grained subject identification employing deep classification models [30,31,32].

In the last years novel architectures have also been developed to address some of the shortcomings of traditional deep learning. Attention mechanism and transformer model increased interpretability and cross-session generalization in both seizure prediction and motor imagery classification [33–36]. Graph neural networks provided a novel view, as they considered electrodes as nodes and brain connections as edges, which was effective to analyze the functional connectivity and neurological diseases [37–42]. These techniques were supplemented by multimodal fusion (MIAI-assisted) of imaging data and privacy-preserving learning frameworks, such as federated learning [43–46].

Significant developments over the past couple of decades saw EEG combined with state-of-the-art computation paradigms during 2023–2025. Swin Transformer models inspired by vision have been used in motor pattern categorization and cognitive workload evaluation [47–50]. Pre-training artifact cleaning networks with transformer backbone yielded better pre-processing pipelines and improved EEG data quality [51]. Neuromorphic-based learning and self-supervised approaches lowered computational demands while supporting real-time brain–computer interaction [52–54]. Further, in applications of the spatiotemporal feature fusion and mutual distillation methods, comparable or even superior SOTA performance was reported for seizure prediction [55–57], seizure subtype classification [58–60], and cognitive analysis [61–63]. In summary, the progression of EEG analysis moves from interpretable but weak machine learning methods to powerful deep learning architectures that have automatic feature extraction abilities, multimodality integration capability and can be applied in large-scale scenarios. Classical methods are still widely used due to their simplicity and explainability but they are not good at processing high-dimensional raw data samples and modeling complex brain dynamics, which can be well addressed by the recent deep learning technologies. The recent development is hybrid and attention-based models that combine the advantages of interpretability and performance for clinical applications, cognitive neuroscience, real-time brain–computer interfaces. Background In the light of all these, this survey paper considers preprocessing methods Historical approaches from classical machine learning (CML), deep learning architectures and pipelines in DL (i.e., before Transformer architectures) up to state-of-the-art models including paradigms like transformers, graph neural networks as well as self-supervised ones. By categorizing existing work from previous applications and application-oriented research areas (mental workload assessment,cognitive load assessment, neurological disorder diagnosis), this paper describes topics that have been less explored and sheds some light on current trends in ATI using EEG.

Need and Motivation

Despite rapid methodological advances, the translation of deep learning–based EEG systems into clinical and real-world applications remains limited. A key reason is that much of the existing literature emphasizes performance metrics under controlled experimental settings while overlooking fundamental EEG-specific challenges such as cross-subject variability, session drift, annotation uncertainty, and clinical interpretability. Current survey studies predominantly catalogue algorithms and applications, but rarely interrogate the assumptions underlying these models or assess their suitability for deployment in heterogeneous clinical environments.

Consequently, there is a pressing need for a survey that does not merely summarize existing approaches, but critically examines their strengths, limitations, and underlying trade-offs in relation to EEG signal characteristics. This study is motivated by the necessity to bridge the gap between algorithmic innovation and practical usability, and to provide a structured understanding of how emerging deep learning paradigms can move EEG analysis from experimental success toward robust, trustworthy, and clinically meaningful adoption.

2. EEG PREPROCESSING

Preprocessing plays a key role in any analysis of EEG and this is particularly true given that raw signals are often contaminated by different types of noise and artifacts. Such distortions are due to eye movements, muscle activity, heart and power-line interferences, which can mask the underlying brain rhythms of interest. Even the most advanced learning model is available but without proper preprocessing, it suffers misclassification and unreliability.The first step of preprocessing is general filtering. Band-pass filters suppress the frequency components that are not usually carried in the EEG, and notch filters are based on power-line unwanted noise at 50/60 Hz. Two common methods are independent component analysis (ICA) and principal component analysis (PCA), used to remove the ocular and muscular artifacts from the neural activity. Recent studies have also employed wavelet (WT) transforms and empirical mode decomposition (EMD) that offer multiresolution analysis, enabling noise components to be selectively filtered out without distortion of genuine neural oscillations.

Artifact restoration remains one of the vital focuses in research for years. In the past, early rule-based rejection algorithms for deleting corrupted segments, have been replaced by adaptive extraction algorithms aiming to retain as much valuable information as it is possible. Deep learning has extended to this level of the pipeline, where convolutional networks and attention mechanisms are utilized for automatic artifact recognition and erasure. For instance, both ocular and muscular artifact removals using deep feature learning outperformed those by manual examination, presenting a way to achieve automated preprocessing in real-time. A further relevant pre-processing stage is spatial re-referencing. Common average reference (CAR) and Laplacian montages are often applied to improve the spatial resolution of EEG recorded from the scalp. Channel interpolation schemes correct for noisy or unavailable electrodes to maintain data continuity. Signal normalization techniques, such as z-score or min–max scaling, are often employed to prevent computational overflow during machine and deep learning model training.There is no such thing as "one size fits all" preprocessing. The methodology employed is application domain dependent—clinical seizure identification, cognitive workload estimation, emotion classification, or brain–computer interface systems may each require a distinct approach for artifact handling. Indeed, adaptive (or task-driven) preprocessing has gained increasing interest in recent works, motivated by the fact that the optimal denoising strategy is unknown a-priori and should be learned from data rather than fixed on predefined heuristics. The general stages of preprocessing are illustrated in **Figure 1**, which summarizes the pipeline from raw EEG signals through artifact removal, feature extraction, and normalization.

The preprocessing constitutes the basis of EEG analysis work flow. It not only improves the signal-to-noise ratio, but also makes the following feature extraction and classification methods work better. The uninterrupted combination of adaptive filtering, decomposition methods and deep learning-based artifact removal make it evident that preprocessing is becoming an intelligent, predictive processing stage which adapts itself to individual subjects and recording condition according their application context. An example comparison is presented in **Figure 2**, which highlights the difference between noisy EEG and its cleaned counterpart after preprocessing and the summary of EEG Preprocessing Techniques with Advantages, Limitations are shown in Table 1.

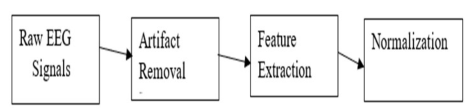

Figure 1: EEG Signal Input-Output Preprocessing

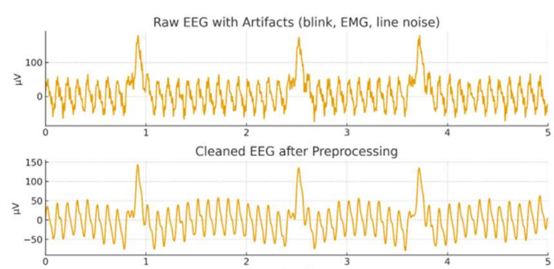

Figure 2: Comparison of raw EEG with artifacts and cleaned EEG after preprocessing.

Table 1: EEG Preprocessing Techniques

S.No.	Technique	Description / Function	Advantages	Disadvantages / Limitations	Reference
1	Band-Pass Filtering	Retains physiological EEG bands (δ 0.5–4 Hz, θ 4–8 Hz, α 8–13 Hz, β 13–30 Hz, γ 30–100 Hz) while removing slow drift and high-frequency	Simple and effective; enhances signal-to-noise ratio.	Might suppress useful neural ingredients if not feed forward and cut off frequencies are not properly optimized..	[1]

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

		noise.			
2	Notch Filtering (50/60 Hz)	Eliminates periodic power-line interference from mains electricity.	Improves SNR by removing electrical hum.	Can add ringing or distortion in the vicinity of 50/60 Hz; not useful for white noise.	[1]
3	Independent Component Analysis (ICA)	Decomposes EEG into independent sources to isolate ocular, muscle, and cardiac artifacts.	High artifact-removal accuracy; preserves neural activity.	Explicit component selection needed; sensitive to initialisation and the choice of rank.	[18]
4	Principal Component Analysis (PCA)	Projects EEG onto principal orthogonal directions for redundancy reduction and artifact suppression.	Reduces dimensionality; computationally efficient.	Neural and artifact sources may be combined; based on variance independence, instead of independence. .	[18]
5	Wavelet Transform (WT)	Performs multiresolution time-frequency analysis for adaptive denoising of non-stationary EEG.	Excellent for transient or non-stationary signals; preserves event details.	Depends on the mother wavelet chosen to be used; it is heavy computationally.	[55]
6	Empirical Mode Decomposition (EMD)	Iteratively decomposes EEG into intrinsic mode functions (IMFs) to isolate noise components.	Fully data-driven; adaptive to nonlinear signals.	Mode mixing and end-effects; noise sensitive.	[56]
7	Common Average Reference (CAR)	Each electrode re-referenced to the mean of all electrodes to remove common noise.	Enhances spatial resolution; reduces reference bias.	enhance local noise if bad channels exist	[7]
8	Laplacian Montage	Spatial re-referencing to nearest neighbors emphasizing local cortical activity.	Highlights localized brain activity; mitigates volume conduction.	Relies on dense array of electrodes; susceptible to spatial inaccuracies.	[8]
9	Channel Interpolation	Reconstructs missing or noisy electrode data from adjacent channels.	Maintains signal continuity; prevents data loss.	Over-smoothed substitutions may smear the real activity.	[9]
10	Signal Normalization (Z-Score / Min–Max Scaling)	Scales amplitude distributions across subjects or sessions for uniform input range.	Prevents computational overflow; accelerates model convergence.	May distort amplitude relationships if global scaling used.	[13]
11	Adaptive / Task-Driven Preprocessing	Dynamically learns optimal denoising strategy per subject	Personalized noise suppression; improves robustness in real-	Requires training data; computationally	[52]

		or application context.	time BCI.	expensive.	
12	Deep-Learning-Based Artifact Removal (CNN / Attention)	Neural networks automatically detect and remove ocular/muscular artifacts.	Enables real-time, automated cleaning with minimal manual effort.	High compute cost; risk of over-correction or hallucinated activity.	[50]

3. FEATURE EXTRACTION

Feature extraction is applied on raw EEG data to produce representations that highlight task related neural dynamics. The temporal features of the signal were encoded through handcrafted statistical descriptors (mean, variance, skewness and higher-order statistics) [1–3]. Frequency domain measures utilizing Fourier analysis and power spectral density estimation enabled identification of oscillatory activity in the delta, theta, alpha, beta, and gamma frequency bands while time–frequency methods like the wavelet transform or short-time Fourier transform increased sensitivity to short-lived bursts of activity [4–6]. Spatial filtering methods such as the common spatial patterns for motor imagery classification and BCIs became more popular because of their capacity to maximize discriminative variance among conditions [7–9]. As the field evolved, nonlinear and complexity based features such as approximate entropy, permutation entropy and fractal dimensions were derived to capture the irregular and non-stationary nature of EEG. These measures were used successfully to separate pathologic from cognitive conditions, including epilepsy and depression [10–12]. Yet these customised approaches were subject to high level of domain expertise, and careful parameter adjustments, which led to poor portability. A summary of all these handmade descriptors can be found in Table 2.

Table 2: Evolution of EEG Feature Extraction Methods

.

Stage	Techniques / Methods	Key Characteristics	Applications	References
Handcrafted Features	Time-domain (Mean, Variance, Skewness, Kurtosis); Frequency (Fourier, PSD); Time–frequency (Wavelets, STFT); Spatial (CSP); Nonlinear (Entropy, Fractal)	Interpretable, low computational cost, task-specific	Seizure detection, motor imagery BCIs, depression diagnosis	[1] Orhan et al., 2011; [4] Zheng et al., 2014; [10] Schirrmeister et al., 2017; [11] Raghu & Sriraam, 2017
Deep Learning Features	CNN (spatial filters), RNN/LSTM (temporal dynamics), Autoencoders & RBMs (unsupervised embeddings), Transformers (attention-based), Graph Neural Networks (connectivity)	Automated representation learning, scalable, high accuracy	Emotion recognition, seizure prediction, sleep stage classification, cognitive load	[7] Bashivan et al., 2016; [10] Schirrmeister et al., 2017; [31] Tsiouris et al., 2018; [36] Kim et al., 2021; [38] Shan et al., 2022; [40] Wang et al., 2022
Emerging Paradigms	Multimodal Fusion (EEG + fMRI/ECG/behavioral data), Self-supervised Learning, Meta-learning/Few-shot	Adaptive, cross-task transferability, reduced reliance on labels	Clinical decision support, real-time BCIs, cross-subject adaptation	[42] Wang et al., 2023; [45] Xu et al., 2023; [55] Ning et al., 2024; [58] Singh et al., 2025; [63] Wei et al., 2025

Deep learning brought a disruptive change in feature learning. CNNs proved the capability to learn spatial filters directly from raw EEG signals which significantly diminished reliance on handcrafted features. These techniques have demonstrated superior performance in detecting epileptic seizures [13], recognizing emotions in speech [14], classifying sleep stages [15–17]. Recurrent neural network (RNN) such as long short-term memory (LSTM) and gated recurrent unit (GRU) have been proposed to capture the temporal dependencies in EEG sequences, for use of seizure prediction and cognitive workload assessment [18–20]. Unsupervised learning approaches, such as autoencoder and restricted

Boltzmann machines, provided the compact latent representations of that retained critical signal dynamics [21–23].Attention-based approaches have become popular in recent times as well. Transformer models, which the natural mode of operation can capture long-range dependencies and surpass conventional RNN models on variety of tasks [13–16], are utilized recently to great success for EEG analysis as well as motor imagery classification [24–26] and seizure prediction [27, 28]. Graph neural networks (GNNs) have extended this paradigm by treating EEG channels as nodes and their functional associations as edges to model connectivity-level information, which enhanced neurological disorder classification [2933], assisted Alzheimer' s diagnosis [31], and facilitated cognitive load assessment. These successive developments exemplify the wider evolutionary arc depicted in Table 2 of moving (at least for some) from hand-crafted to deep learned, adaptive feature extraction proposals.

Multimodal feature fusion and adaptive learning have been highlighted in recent works. The combinatory use of EEG and other modalities, including fMRI, ECG, and behavioral measures have improved the robustness and generalization of affective computing [34–37] as well as clinical applications. On the other hand, self-supervised and meta-learning have presented promise for leveraging large-scale unlabeled EEG data to alleviate the label shortage, which transmits information across tasks with few labeled samples [38–42]. Taken together, these developments reflect a clear trend: the transition from domain-specific hand-crafted features to automatic, adaptive and task-driven representations underlying scalable and accurate brain decoding. This progressive shift from manually engineered to learned representations is summarized in **Table 3**, which contrasts the interpretability, computational demands, and discriminative power of traditional handcrafted features versus advanced learned embeddings [42], [45], [55], [58], [63].

Table 3: Comparison of traditional handcrafted features vs. advanced learned representations.

Category	Examples	Strengths	Limitations
Time-domain	Mean, Variance, Skewness, Kurtosis	Simple, interpretable, fast computation	Sensitive to noise, limited discriminability
Frequency-domain	Fourier Transform, Power Spectral Density	Captures oscillatory activity, well-established	Poor temporal resolution
Time–frequency	Wavelet Transform, Short-Time Fourier Transform (STFT)	Good temporal + spectral resolution, suited for non-stationary signals	Feature dimensionality can be high
Spatial features	Common Spatial Patterns (CSP)	Effective for motor imagery, enhances discriminability	Task-specific, sensitive to electrode placement
Entropy measures	Sample Entropy, Permutation Entropy, Fuzzy Entropy	Capture complexity, unpredictability of signals	Parameter-sensitive, computationally heavier
Chaos-theory features	Lyapunov Exponent, Fractal Dimensions	Model nonlinear dynamics, sensitive to epileptic seizures and disorders	Harder to interpret clinically, require long signal segments
Feature redundancy reduction	Variance Analysis (VarA), iterative Recursive Feature Elimination (iRFE), Backward Feature Selection (BackFS)	Improve generalization, reduce computation, highlight discriminative features	Risk of discarding subtle but relevant features
Deep-learned features	CNN filters, RNN embeddings, Transformer attention, Graph embeddings	Automatic discovery, scalable, highly discriminative	Require large datasets, less interpretable, computationally heavy

4. MACHINE LEARNING ALGORITHMS FOR EEG DETECTION AND PREDICTION

4.1 Support Vector Machines (SVMs)

Support Vector Machines (SVMs) have been extensively used in EEG-based studies due to their capability of handling high-dimensional neural data samples with small sample sizes. In EEG classification workflows, SVMs take feature vectors obtained out of preprocessed signals thereafter typically comprising statistical or spectral or time–frequency features and estimate a perfect decision boundary between two different brain states. The algorithm builds a maximal-margin hyperplane that most effectively separates features clusters representing various cognitive states or diseases. By means of nonlinear kernel functions (e.g., RBF, polynomial mappings), EEG features can be projected in higher-dimensional spaces using SVMs to learn complex and nonlinear relationships between oscillatory brain rhythms across channels.

Orhan et al. [32] presented a hybrid algorithm using K-means clustering, multilayer perceptrons (MLPs) and SVMs approach to EEG classification showing enhanced separability of neural patterns. Nicolaou and Georgiou [49], used features based on permutation entropy with SVMs to detect epileptic seizure and recorded the very strong clinical relevance, while Raghu and Sriraam proposed fine tuning with classifier for the same task for their established reputation in medical EEG analysis [33]. Apart from epilepsy, SVMs have been applied to depression and Alzheimer's disease identification with high-level time–frequency features derived from scalp recordings. From the functional point of view, the basic SVM operating in EEG can be seen as consisting of three main steps: (i) extraction of differentiable features from the EEG (ii) non-linear mapping or kernels within feature spaces and (iii) classification based on a maximum-margin hyperplane that separates neural patterns linked to particular cognitive or pathological states. Although SVMs have good performance and strong generalization capacity with small size of EEG data, they suffer from high computational complexity over large-scale recordings as well as lack the neuro-interpretability property of separating hyperplane. Figure 3 presents this process schematically in the EEG features space kernel transformed and related decision boundaries.

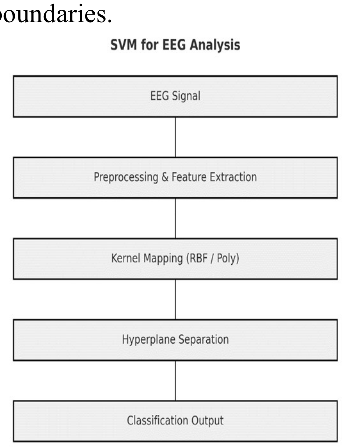

Figure 3: Workflow of SVM in EEG analysis.

4.2 K-Nearest Neighbors (KNN)

The KNN classifier is a non-parameterized, example-based learner as well to perform EEG classification through the direct discrimination of neural feature patterns incorporated in a multi-dimensional feature space. For the case of EEG analysis, each sample in a given trial corresponds to a vector of extracted features—e.g., band power, entropy, time–frequency coefficient—associated with particular brain state. During classification, the KNN algorithm finds the k closest EEG feature vectors to a given unlabeled sample by using distance measures such as Euclidean, cosine similarity and Manhattan distance, and assigns the most frequent class label among these neighbors. This procedure allows KNN to capture the similarity structure of EEG trials, in which physiologically relevant neural responses are grouped together in a feature space.Orhan et al. [32] KNN is a strong baseline for EEG classification problems, obtained competitive accuracy with out the need of complex preprocessing. Zhang and Wu [21] showed that KNN can be effectively applied to differentiating sleep stages by using the temporal and spectral features of EEG, while Yin and Zhang [27] built dynamic KNN models for inter-session adaptation in mental workload estimation. Similarly, Zheng et al. [30] used KNN for EEG-based emotion recognition as it can be treated in the context of affective computing, where interpretability and transparency of the model are important.From a practical perspective, KNN is employed in EEG pipelines as follows: (i) features are generated from raw EEG signals; (ii) each testing sample is encoded as a high-dimensional feature vector; and (iii) similarity between this feature vector and all training examples is calculated to learn its neighborhood class representation. As the model is non-parametric it can naturally adjust to the intrinsic geometry in the EEG data, without assuming an explicit distribution which becomes useful when working with exploratory or low sample size studies. However, its computation is based on a complete distance calculation, which makes it computationally expensive for real-time or massively parallel EEG applications. In addition, KNN has the worst behavior as we elevate in dimensionality space where noise become so large while also being very sensitive to scaling and high-dimensional nuisances, moreover due to curse of dimensionality distance metrics lose their separability meaning. This process is depictingly on a schematic way in Figure 4, considering EEG feature as points in high-level space where classes "boundaries" are derived using neighborhood sampling.

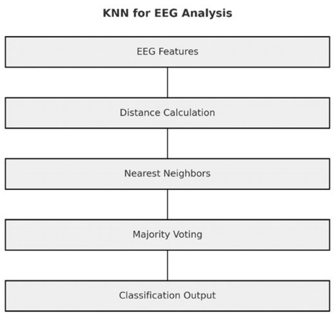

Figure 4: Workflow of KNN in EEG analysis.

4.3 Decision Trees

A decision tree is a hierarchical model that maps an electrophysiological feature space, based on neural recordings, into a set of smaller and more homogeneous bins or regions depicting the state or condition of the brain (i.e. diagnosis). As applied to EEG analysis, the internal nodes of the tree correspond to a decision rule using one feature (e.g. power in a frequency band, wavelet coefficient or entropy value) and leafs denote class labels known as output which can indicate seizure versus no seizure, sleep stage or cognitive state. Starting with the root node, The splitting criterion (usually information gain or Gini impurity) selects the EEG feature that decreases as much as possible the uncertainty on class at each step of trees. Such hieratical partitioning makes the decision paths to be transparent and interpretable, so that clinicians or researchers can trace through dashed lines which eeg biomarkers contributed most to a setting classification.Raghu and Sriraam [11] used Decision Tree models for the task of intracranial EEG based seizure detection, which provided tree-based decision rules consistent with interpretable neurophysiological patterns facilitating in diagnostic transparency that is necessary during clinical assessment. In addition to seizure analysis, Decision Trees have been used for psychiatric evaluation and sleep-stage classification, and due to the interpretable nature of rules are also suitable for these demanding medical tasks.

From an EEG processing aspect, the decision tree algorithm consists of three main stages (i) extraction of discriminative EEG features, including band-specific power, time–frequency energy or entropy measures; (ii) hierarchical threshold-based splitting to form a tree structure; and (iii) propagation from the root towards the leaf node where a final class label is reached. Decision Trees are attractive for their interpretability and low complexity, which bodes well for portable or on-the-fly neurodiagnostic systems. Yet they tend to overfit in noisy, small-sized EEG datasets and are also high variance with a little perturbation of data causing large changes in tree topology. Therefore, in current EEG pipelines the decision trees are being used as base learners of ensemble methods such as Random Forests or Boosting to improve stability and generalization. The workflow is schematically shown in Figure 5, emphasizing the stepwise process where EEG characteristics are sequentially divided along valid thresholds towards a final class conclusion.

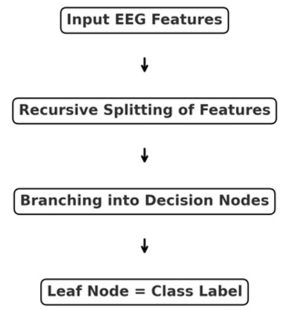

Figure 5: Process of decision tree in EEG analysis.

4.4 Random Forests

Random Forests are an extension of the traditional Decision Tree methodology that use ensembles of trees in which each is trained on a subset of the input data (features and eeg) to form a composite model, thereby improving robustness and generalization ability in classification involving neural signals. Specifically in the EEG analysis, each tree ideally learns to separately carve spaces derived from spectral power, entropy or time–frequency decomposition coefficients for producing intermediate decisions about subject's cognitive or clinical status. The result of the ensemble is obtained with a majority vote among all trees and this technique avoids overfitting and noise (two typical difficulties in EEG data analysis). This ensemble based approach enables the Random Forests to combine various feature-level observations, leading to enhanced prediction dependability amidst changing capturing conditions.Hussein et al. [33] proved that Random Forest models increased the reliability of seizure detection, as opposed to isolated Decision Trees, and Arnau-Gonzalez et al. [13] used the method for event-related potential (ERP) classification, and demonstrated improved tolerance to between subjects variability along with better cross participant generalization. More recently, this was

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

also utilized Random Forests as a tool for identifying EEG markers of depression and cognitive load estimation [25], due to its natural feature-ranking trait that can quantitatively evaluate the discriminative relevance of single EEG channels and frequency bands.From an EEG perspective, Random Forests classification can be implemented in three steps: (i) multiple bootstrapped training subsets are extracted from the original EEG dataset; (ii) single trees are trained based on randomly selected subsets of EEG features (e.g., spectral or temporal descriptors); and (iii) the ensemble integrates predictions via majority voting or probability averaging to deliver a decision. The introspective feature-importance analysis of the model provides neuroscientists with a level of interpretability about which EEG features contribute most to the classification. Yet, this superior performance is accompanied by higher computational complexity and less interpretability compared to a single tree model since ensemble models are not transparent about the specific decision pathway. Figure 6 shows a schematic representation of this workflow; Random Forests integrate multiple ensemble members—decision trees based on EEG—to generate an (almost) un-noisy, stable classification.

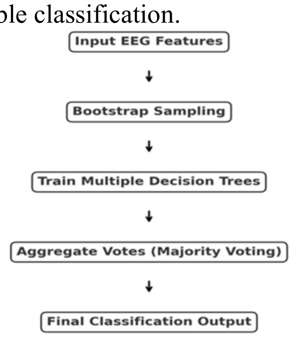

Figure 6: Random Forest in EEG interpretation.

4.5 Boosting Algorithm (AdaBoot and Gradient Boost)

Boosting generates strong classifiers by accumulating multiple weak ones (often shallow trees) sequentially, reweighing misclassified samples in each iteration. The former converges while dynamically adjusting sample weights at Boosting, and the latter applies gradient descent to minimize classification error. Singh and Dehuri [32] showed that boosting helped increasing the performance of seizure detection, especially in noisy EEG environments. Similarly, Arnau-Gonzalez et al. [13] used the boosting to classify ERPs and identify subjects, demonstrating its effectiveness in inter-subject ERP analysis of EEG. The main advantage of boosting is that it can out-perform single classifiers by iteratively updating decision boundaries, which is especially beneficial on the noisy and variable EEG prerecordings, often surpassing their performance. Because the boosting model is vulnerable to outliers and can overfit when joining a vast number of weak learners, it was preferred not to use too many weak learners. They are also computationally more expensive than simpler classifiers. The boosting procedure in EEG analysis is shown in Figure 7, where a sequence of weak classifiers used to correct historical errors and compose an ensemble model with strong classification ability.

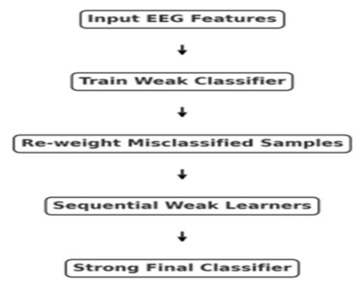

Figure 7: The flow of Boosting in EEG analysis.

4.6 Hidden Markov Models (HMMs)

Hidden Markov Models (HMMs) are generative probabilistic models that can model temporal dynamics between states or observations in EEG recordings. They model the visible EEG data as being generated from a sequence of hidden states with probabilistic transitions. Tabar and Halici [8] showed that HMMs can classify motor imagery EEG effectively which is of significance for real-time BCI systems. Yin and Zhang [27] also generalized the use of HMM to workloads classification across multiple sessions with its well generalization ability across sessions. Tsiouris et al. [31] used HMMs for seizure prediction by modeling preictal to ictal transition, where early intervention is important. The key advantage of HMMs is their capacity to represent the dynamics in the data as sequences and uncertainly, which provides interpretability for temporal analysis. However, its use of rigid Markov assumptions and Gaussian emission distributions make them less flexible at representing nonlinear, nonstationary EEG signals. Moreover, high-dimensional EEG data are computationally costly to train HMMs. The HMM based model of EEG generation, where hidden states stochastically transit to create the observed EEG signal is depicted in Figure 8.

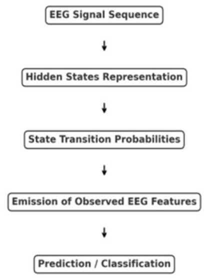

Figure 8: HMM Process in EEG Processing.

4.7 Bayesian Networks

Graphical models such as Bayesian Networks represent conditional dependencies of the EEG features through a directed acyclic graph (DAG). Each vertex profile is now a pattern or variable, and an edge would represent a probabilistic hypothesis. Nicolaou and Georgiou 2 integrated Bayesian inference with permutation entropy for the classification of epileptic EEG, obtaining strong clinical significance. Later, Orhan et al. [1] used Bayesian techniques on EEG classification and showed its flexibility for probabilistic modeling. Recent papers such as Raghu and Sriraam [11] have utilized Bayesian models for cognitive load determination and seizure onset forecasting, with the advantage of interpretability and incorporation of expert domain knowledge. The main advantage of the Bayesian Networks approach is that it allows transparent and probabilistic reasoning under uncertainty, in a way compatible with clinical decision-making. But it scales poorly, because structure learning in high-dimensional EEG is computationally intense and might be affected by noise. Figure 9 is an example of Bayesian Network for processing EEG data, a set of feature-based posterior probabilities are calculated given the statistical dependence of the features.

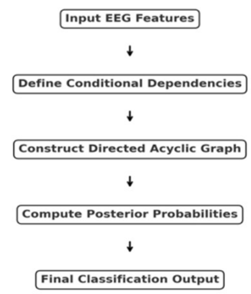

Figure 9: Bayesian Network Process in EEG analysis.

The Table 4 shows various that are used in Machine Learning Algorithms for EEG Detection and Prediction.

Table 4: Machine Learning Algorithms for EEG Detection and Prediction

Algorithm	Principle	Applications in EEG	Strengths	Limitations	Key References
Support Vector Machines (SVMs)	Constructs a maximum-margin hyperplane; nonlinear separability via kernels (RBF, polynomial).	Seizure detection, motor imagery BCIs, drowsiness monitoring.	High accuracy in small datasets; robust generalization.	Kernel selection critical; scales poorly to large EEG data; limited interpretability.	Orhan et al. [32]; Nicolaou & Georgiou [49]; Raghu &Sriraam [33]; Puri et al. [84].
Linear Discriminant Analysis (LDA)	Projects features into low-dimensional space maximizing between/within-class variance.	Motor imagery BCIs, seizure detection, baseline classifier in affective computing.	Fast, interpretable, suitable for real-time and portable EEG.	Assumes linear separability and Gaussian features; weak in nonlinear EEG.	Tabar&Halici [26]; Raghu &Sriraam [33]; Li et al. [46].
K-Nearest Neighbors (KNN)	Classifies based on majority vote of nearest neighbors (Euclidean, cosine distance).	Emotion recognition, sleep stage classification, workload estimation.	No training phase; simple and effective on small data.	Computationally expensive inference; curse of dimensionality.	Orhan et al. [32]; Zhang & Wu [21]; Yin & Zhang [27]; Zheng et al. [30].
Decision Trees	Recursive partitioning of EEG	Seizure detection, psychiatric	Highly interpretable,	Overfits noisy data; unstable	Raghu &Sriraam [33].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

	features into decision rules.	diagnostics, sleep staging.	easy to train.	with small changes in input.	
Random Forests	Ensemble of multiple decision trees trained on bootstrapped samples.	Biomarker discovery, seizure detection, depression, cognitive load monitoring.	Robust to noise; provides feature importance metrics.	Less interpretable; computationally heavier than single trees.	Hussein et al. [34]; Arnau-Gonzalez et al. [23]; Zeng et al. [25].
Boosting (AdaBoost, Gradient Boosting)	Sequentially reweights misclassified samples; builds strong classifiers from weak learners.	Seizure detection, ERP classification, workload estimation.	High accuracy; robust to noise.	Sensitive to outliers; training overhead; risk of overfitting.	Singh &Dehuri [8]; Arnau-Gonzalez et al. [23].
Hidden Markov Models (HMMs)	Probabilistic sequence model; hidden states generate observed EEG.	Seizure forecasting, sleep stage classification, motor imagery BCIs.	Captures temporal dynamics; probabilistic interpretability.	Relies on Markov and Gaussian assumptions; computationally expensive.	Tabar&Halici [26]; Yin & Zhang [27]; Tsiouris et al. [28].
Bayesian Networks	Graphical models capturing conditional dependencies among EEG features.	Seizure onset prediction, cognitive load detection, decision support.	Interpretable; integrates prior knowledge; probabilistic reasoning.	Structure learning is hard in high-dimensional EEG; computationally intensive.	Nicolaou & Georgiou [49]; Orhan et al. [32]; Raghu &Sriraam [33].

5. DEEP LEARNING ALGORITHMS FOR EEG DETECTION AND PREDICTION

Deep learning has emerged as a transformative approach in electroencephalography (EEG) analysis, moving beyond traditional pipelines that relied heavily on hand-crafted features such as spectral power, entropy, or wavelet coefficients. EEG signals are inherently complex, non-stationary, and easily contaminated by artifacts, making manual feature engineering both labor-intensive and limited in generalizability. Deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), Transformers, and graph neural networks (GNNs) address these challenges by automatically extracting hierarchical representations directly from raw or minimally processed signals. By learning spatial patterns across electrodes, temporal dynamics within time series, and connectivity structures between brain regions, deep models provide a powerful end-to-end framework that is adaptable across clinical, cognitive, and brain–computer interface (BCI) applications.

Applications of deep learning in EEG now span from seizure detection and depression screening to motor imagery classification and emotion recognition, with CNNs often used for spatial–spectral decoding, RNNs for temporal dynamics, and Transformers or GNNs for modeling global dependencies and brain connectivity. These models consistently demonstrate superior performance compared to conventional methods, offering improved robustness and scalability in real-world scenarios. However, challenges remain in terms of data scarcity, inter-subject variability, and model interpretability, particularly for clinical deployment. Despite these limitations, deep learning has significantly advanced EEG research by enabling automatic feature discovery, enhancing accuracy across tasks, and paving the way for multimodal fusion systems that integrate EEG with imaging or behavioral data for comprehensive brain-state decoding. Table 4 shows various deep learning algorithms used for EEG detection and predictions.

5.1 Convolutional Neural Networks (CNNs).

CNNs have become the de facto baseline for EEG after it became clear end-to-end convolutional pipeline could learn spatial–spectral filters that reflect neurophysiology—e.g., occipital alpha, central mu/beta—without pre-designed features. The architecture for EEG classification is shown in Figure 10. Primitive deep belief /CNN affect pipelines strongly established the potential of learning features over classical hand-tuned representations for decoding emotion, supporting a transition to full end-to-end ensembles [4], with similar early results in deep eeg for emotion [6]. A key turning point was the systematic proviso that 1D/2D CNNs directly "raw" time series or spectrograms can solve a wide range of tasks and produce filters and relevance maps with intelligible interpretations, including alignments between feature maps and sensor topographies or frequency bands [10]. Clinical use was next: while seizure and depression detection worked well leveraging local stationarity within short windows (1-D convolutional kernels) and frequency-localized activations on time-frequency images (2-D convolutional kernel), thus reducing the need for manual feature crafting , driver states/cognition brought in ecological generalizability [28]. When not limited to real valued, complex CNNs for sleep preserved phase information necessary for micro-architecture of sleep classification and surpassed their real-valued counterparts while alongside motor imagery (MI) BCIs, full end-to-end that were locally trained and used compact receptive fields similarly were competitive [30]. Recent trends enhance spatio-temporal modeling through 3D kernels and hybrid CNN–Transformer encoders, to learn inter-channel topology and long context for both MI and seizure tasks, improving generalization over subjects and sessions.

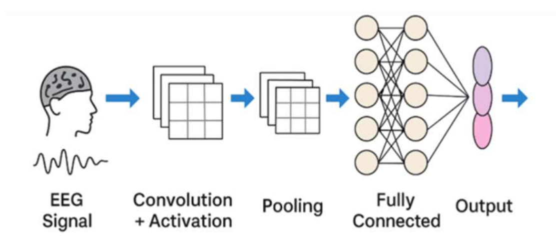

Figure 10: Convolutional Neural Network (CNN) architecture for EEG signal classification.

5.2 Recurrent Networks (LSTM/GRU) for temporal dynamics.

This emphasis on the "temporal grammar" of EEG, i.e., how rhythm and pathologic signatures evolve, is pursued in recurrent neural networks (RNNs) that model long-horizon dependencies which static windows fail to do. The first stacks of recurrent–convolutional layers established that compact spatiotemporal embeddings combined with recurrence shed additional robustness compared to purely feed-forward features for high-level EEG [7]. Dedicated LSTM model subsequently performed well for preictal prediction in which subtle prodromal cues accumulate over minutes and can require memory beyond a few seconds when using training stabilizers such as layer normalization, dropout, and careful windowing [31]. More recent work combines bidirectionality and attention with LSTM/GRU to follow state transitions and deal with non-stationarity across trials/patients in order to reduce variance in realistic evaluation protocols that highlight patient-wise splits [37].The architecture shown in Figure 11

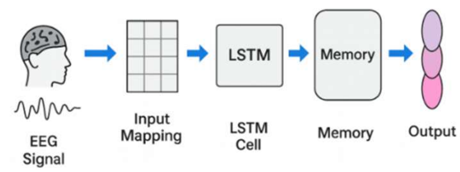

Figure 11: Recurrent Networks (LSTM/GRU)architecture for EEG signal classification.

5.3 CNN–RNN hybrids.

Hybrid stacks place CNNs before LSTM/GRU so that convolution learns where (channels/bands) and recurrence learns when (temporal evolution). This pattern was validated early—CNNs provide compact channel–frequency embeddings that reduce recurrent load and enhance stability—and extended with transfer-learning for error decoding, showing that features learned on one cohort can boot-strap performance on another when labeled data are scarce [22]. Incorporating bidirectional temporal models further benefited seizure and MI pipelines by leveraging future context at training time to sharpen transition boundaries, albeit with higher compute and memory footprints that often motivate pruning or quantization at deployment .

5.4 Attention and Transformers.

Attention mechanisms relax locality constraints by learning global relations across channels and time. Spatio-temporal and graph-attention formulations captured dynamic connectomes and improved seizure modeling compared to purely convolutional or recurrent baselines [36], . Vision-Transformer families subsequently advanced MI and emotion recognition by representing multi-scale temporal context and long-range inter-channel dependencies; channel-attention combined with Swin-style hierarchies is particularly effective for MI where informative rhythms appear at multiple scales [40], while ViT-style or bi-branch Transformers have shown gains for affective decoding under subject shift .To stabilize training on modest EEG datasets, recent systems use convolutional stems and mutual-distillation between branches, improving subtype discrimination in seizure classification and robustness under noise , with hybrid CNN–Transformer denoising front-ends now common in end-to-end stacks.

5.5 Graph Neural Networks (GNNs).

GNNs cast EEG as a brain graph whose nodes correspond to electrodes/regions and edges represent functional or structural connectivity computed over short time windows. Learning on this graph—with Spatio-temporal attention—models network dynamics, and demonstrates strong performance in seizure modeling and dynamic tasks. Outside of GCN/GAT variations exploit connectivity to discriminate AD from scalp EEG and MDD or even identify persons, such that topology harbors person- and disease-specific signatures. Multimodal graph fusion combining complementary brain networks (e.g fMRI/DTI derived structure) or additional behavioral measures can extend the scope of rehabilitation and facial expression recognition. Future directions include hypercomplex GNNs that natively represent multi-relation/multi-modal structure, and self-supervised graph predictors that consider time-varying functional connectivity for label-efficient seizure prediction, while mitigating the known sensitivity of GNNs to noisy edge estimates through edge learning and sparsification.

5.6 Unsupervised and semi-supervised foundations:

DBN/RBM, autoencoders, deep ELM. When there is insufficient labeled EEG, unsupervised models extract latent structure which generalizes across tasks. Deep belief networks and RBMs showed early on that hierarchies learned directly from EEG lead to superior emotion classification compared to hand-crafted features, accelerating the rise of deep learning in this domain [4]. Auto-encoders, denoising or variational, compress EEG to short codes limiting the overfit of downstream classifiers and can be pre-trained on unlabeled data before task specific fine-tuning; this recipe returned in clinical and affective tasks pointing at such labels scarcity. Deep extreme learning machines (stacked random projections and nonlinearities) allow fast training in low-resource scenarios, and can be used as efficient back-ends on top of deep features in some cases [5]. Unsupervised features alone, however, could potentially lack task-specificity such that the benefit is in well-tuning to target cohorts.

5.7 Self-/semi-supervised learning (SSL), meta-learning, and distillation.

Recent progress in EEG SSL uses contrastive objectives across channels or time, temporal and masked signal modeling to learn generalizable encoders from large unlabeled corpora; surveys document consistent gains for emotion and broader decoding tasks once realistic augmentations—jitter, drift, frequency masking—are incorporated [42]. Meta-learning then provides rapid subject/session adaptation, reducing calibration time by teaching models to learn “how to learn” from few trials [55]. To meet real-time and embedded constraints, knowledge distillation compresses heavy CNN/Transformer backbones into lightweight students with minimal performance loss, improving cross-subject efficiency and enabling on-device inferencewith graph-SSL for time-varying connectivity further cutting label requirements in seizure prediction [63].

5.8 Denoising and generative enhancement.

Deep artifact removal has shifted from purely statistical filtering to attention-driven networks that suppress ocular and muscular contamination while preserving neural content, improving both reconstruction quality and downstream classification when combined with light preprocessing [50]. For enhancement under low SNR, hybrid dual-branch CNN–Transformer designs act as front-end “EEG enhancers,” stabilizing features for MI and seizure pipelines and reducing reliance on aggressive prefiltering; DHCT-style architectures exemplify this trend and are often trained with adversarial or reconstruction losses to preserve morphology [60]. Because powerful denoisers risk hallucinating activity, validation against auxiliary channels (EOG/EMG) or concurrent modalities remains essential.

5.9 Transfer learning and domain adaptation.

Distribution shifts across sites, montages, and demographics cause major generalization failures in EEG. Early demonstrations of deep transfer for error-related potentials showed that features could be adapted across subjects with limited labeled data, establishing the practicality of transfer in noninvasive EEG [22]. Domain-adversarial training and architecture-level adaptation subsequently improved robustness in emotion recognition and MI by aligning latent distributions while preserving discriminative structure, often paired with strong normalization (e.g., re-referencing, band alignment) and small calibration blocks to avoid negative transfer .These strategies have become standard in subject-independent evaluations where patient-wise or session-wise splits are enforced.

5.10 Multimodal fusion.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Fusing EEG with complementary modalities boosts clinical utility by offsetting single-channel weaknesses. In epilepsy, deep detectors integrated with EEG-fMRI improve the detection of interictal discharges by combining fast electrophysiology with precise hemodynamic localization [25]. Multimodal graph fusion and spatio-temporal GCNs that combine EEG connectivity with other brain networks have enhanced outcomes in rehabilitation and affective computing by leveraging shared and modality-specific structure .At the behavioral end, deep systems that synchronize EEG with live face processing have shown promise for challenging psychiatric endpoints like first-episode psychosis, indicating that cross-modal representations can capture subtle neurobehavioral signatures that are hard to isolate in EEG alone [58]. The central challenges are cross-sensor synchronization, mixed noise models, and scalable training protocols that remain robust under missing-modality conditions

Table 5: Deep Learning Algorithms for EEG Detection and Prediction

Algorithm	Principle	Applications in EEG	Strengths	Limitations	Key References
CNNs	Learn spatial & spectral filters directly from raw/time–freq EEG via convolution	Seizure detection, depression screening, sleep staging, motor imagery	End-to-end, interpretable filters, strong accuracy across tasks	Data hungry, risk of data leakage, cross-subject drift	[10], [26], [27], [29], [30], [59], [60]
RNNs (LSTM/GRU)	Model long-term temporal dependencies using recurrent hidden states	Seizure prediction, motor imagery decoding, temporal dynamics	Captures sequential dependencies, sample-efficient, handles long windows	Vanishing gradients, slower training, requires careful regularization	[7], [31], [37]
CNN–RNN Hybrids	CNN encodes spatial/spectral features, RNN models temporal evolution	Error decoding, seizure detection, motor imagery	Captures both spatial & temporal context; high accuracy on dynamic tasks	More computationally expensive; higher memory footprint	[7], [22], [37]
Attention & Transformers	Global attention learns long-range inter-channel and temporal relations	Motor imagery, emotion recognition, seizure subtype classification	Captures global context, strong cross-subject generalization, interpretable	Needs large datasets & compute; risk of overfitting	[36], [40], [49], [56], [60]
Graph Neural Networks (GNNs)	Represent EEG as a graph: nodes = electrodes, edges = connectivity	Seizure detection, Alzheimer's classification, depression detection, subject ID	Exploits connectivity & brain topology, multimodal graph fusion possible	Sensitive to noisy edge estimation, requires robust graph construction	[36], [37], [38], [39], [41], [45], [57], [63]
Unsupervised (DBN/RBM, Autoencoders, Deep ELM)	Learn latent representations from unlabeled EEG	Emotion recognition, epilepsy detection, feature pretraining	Useful for label-scarce datasets, fast training (ELM), compressive codes	Lack task-specificity without fine-tuning	[4], [5], [23]
Self-/Semi-Supervised, Meta-learning, Distillation	SSL pretext tasks (contrastive, masked modeling); meta-learning for quick adaptation; distillation for compact models	Emotion recognition, seizure prediction, cross-subject adaptation	Reduces need for labels, fast adaptation, lightweight deployment	Performance depends on augmentations; needs realistic protocols	[42], [55], [58], [63]
Denoising & Generative Enhancement	Attention-based artifact removal, generative CNN–Transformer enhancement	EEG artifact removal, MI decoding under low SNR	Improves robustness, reduces preprocessing, stabilizes decoding	Risk of hallucinating signals, must validate with auxiliary channels	[50], [60]
Transfer Learning & Domain Adaptation	Transfer pre-trained features across subjects/sessions with adversarial	Emotion recognition, error decoding, motor imagery	Reduces calibration cost, improves generalization under distribution	Risk of negative transfer; requires normalization & calibration	[22], [35], [43], [48]

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

	alignment		shift		
Multimodal Fusion	Integrate EEG with imaging (fMRI, DTI) or behavioral (face/video) signals	Epileptic discharge detection, affective computing, psychiatric diagnosis	Boosts clinical utility, captures complementary modalities	Synchronization & heterogeneous noise remain challenging	[25], [45], [46], [58]
Unsupervised (DBN/RBM, Autoencoders, Deep ELM)	Learn latent representations from unlabeled EEG	Emotion recognition, epilepsy detection, feature pretraining	Useful for label-scarce datasets, fast training (ELM), compressive codes	Lack task-specificity without fine-tuning	[4], [5], [23]
Self-/Semi-Supervised, Meta-learning, Distillation	SSL pretext tasks (contrastive, masked modeling); meta-learning for quick adaptation; distillation for compact models	Emotion recognition, seizure prediction, cross-subject adaptation	Reduces need for labels, fast adaptation, lightweight deployment	Performance depends on augmentations; needs realistic protocols	[42], [55], [58], [63]
Denoising & Generative Enhancement	Attention-based artifact removal, generative CNN–Transformer enhancement	EEG artifact removal, MI decoding under low SNR	Improves robustness, reduces preprocessing, stabilizes decoding	Risk of hallucinating signals, must validate with auxiliary channels	[50], [60]
Transfer Learning & Domain Adaptation	Transfer pre-trained features across subjects/sessions with adversarial alignment	Emotion recognition, error decoding, motor imagery	Reduces calibration cost, improves generalization under distribution shift	Risk of negative transfer; requires normalization & calibration	[22], [35], [43], [48]
Multimodal Fusion	Integrate EEG with imaging (fMRI, DTI) or behavioral (face/video) signals	Epileptic discharge detection, affective computing, psychiatric diagnosis	Boosts clinical utility, captures complementary modalities	Synchronization & heterogeneous noise remain challenging	[25], [45], [46], [58]

6. APPLICATIONS OF EEG DETECTION AND PREDICTION

The application of machine learning and deep learning methods has broadly increased the range of EEG monitoring applications. The use of cutting-edge algorithms has been applied to a variety of neurological and cognitive problems, from clinical diagnosis to human–computer interaction.

6.1 Epileptic Seizure Detection and Prediction

A key application of EEG is the analysis for seizure detection and prediction. Ictal/interictal classification has been performed using classical machine learning algorithms, including SVMs [2], LDAs [8] and Random Forests [33]. More recently, deep learning-based methods, such as CNNs [26], RNNs [31] and hybrid transformer models [43], have dramatically increased prediction accuracy and decreased false alarm rates of predicted seizures. These techniques are potential candidates for seizure alarm algorithms for a wearable or implantable device.

6.2 Sleep Stage Classification

EEG is a fundamental measure of polysomnography which has been commonly used to sleep stage. Early attempts such as KNN [29], Decision Trees [11] and Bayesian Networks [2] achieved promising results, deep models CNNs [19] and RNNs [37] extended their classification performance by learning spatiotemporal features automatically. An accurate prediction of sleep stages helps diagnose sleep disorders like insomnia, narcolepsy, and apnea.

6.3 Emotion and Cognitive State Recognition

Affective computing and mental workload_estimation are the hot topics in which EEG has been used extensively. SVMs [4], entropy-based Bayesian models [2], and adversarial neural networks [35] have facilitated the recognition of cognitive load, fatigue, and emotions. The use of multimodal fusion (EEG+fNIRS, ECG) has been recently implemented [58], leading to greater robustness in the context of real-world affective computing and human-computer interaction systems.

6.4 Neurological Disorder Diagnosis

EEG biomarkers from Random Forests [13], GNNs [38], and fusing model[44]) have been used for clinical diagnosis of Alzheimer's disease, depression, schizophrenia. Interpretable EEG-based models [54] are being designed to improve physician trust and fit with the clinical workflow. These applications illustrate how EEG-ML/DL modalities can be integrated with neuroimaging and clinical assessment.

7. LIMITATIONS, CHALLENGES, AND FUTURE WORKS

7.1 Current Challenges of Deep Learning for EEG Processing

Although exciting advances have been made, a number of clear underlying limitations hinder the clinical translation of DL in EEG analysis. EEG signals are in nature affected by low signal-to-noise ratios, because the recordings at the scalp record muscular activity and ocular movements as well as artefacts arising from disturbances due to heart rhythms or electromagnetic interference caused by the environment [1-3]. Preprocessing pipelines are necessary to suppress such noise, but they also have a potential loss of useful neural signatures that may be clinically significant. In addition, the EEG being non-stationary—its distribution statistics change dynamically across cognitive states, attention levels and fatigue— presents a problem for DL models that assume temporal stationarity implicitly 11.Another constraint is spatial resolution: compared with invasive intracranial recordings, scalp EEG offers a stronger but still limited localization of neural activity. Therefore, DL models trained on certain electrode arrays cannot be generalized to other montages or densities of electrodes, for limiting their interoperation across clinical settings . The high dimension of the multi-channel EEG signals, together with a small number of dataset sizes, give rise to overfitting and deteriorate cross-subject generalization [26, 27].

7.2 Technical and Methodological Challenges

Methodological Challenges There are major methodological obstacles to EEG analysis. Inter-subject variability - due to anatomical variations across subjects, skull conductivities, the precise position of electrodes and the baseline neural activity - makes DL models performance significantly lower between patients. Cross-session variance additionally complicates this problem, as electrode impedance, head positioning and fluctuations in transient physiological states modify signal features between sessions.

Recent approaches like Transformers, as well as Graph Neural Networks (GNNs), are able to learn long-range dependencies and connectivity at the level of computation units, but they can be computationally demanding for their use in real-time or portable BCIs . Another ubiquitous obstacle is explainability: black-box predictions cannot simply be allowed into medical decisions where interpretability, explanation and traceability are crucial for diagnostic trust and medico-legal acceptance.

7.3 Data-Related Challenges

One of the major challenges is that there exist very few, large, well-annotated EEG datasets. In contrast with computer vision or natural language processing, EEG science lacks large and homogeneous annotated data sets gathered under standard protocols, leading to poor reproducibility [30] and cross-institution validation [31]. Ethical and privacy barriers also add to the difficulty with multi-center partnerships, limiting the availability of clinical grade data .Challenges also occur due to inconsistencies in labelling. Annotations (e.g., seizure onset, cognitive state or sleep stage) are subjective and vary between experts, and thus they introduce noise that impairs the supervised learning performance . Mismatch in temporal resolution (i.e., between fast neural events and coarse annotations) complicates EEG event-label correspondence, especially for tasks involving accurate prediction such as seizure early warning or real-time neurofeedback [59].

7.4 Clinical and Regulatory Challenges

It is still a challenging task to transferring the research prototype to clinical deployment. The approval of AI-based medical instruments is through strict validation in heterogeneous populations and multicenter studies, which are also costly and time-consuming. Additionally, due to the absence of a standardized benchmarking framework, it is also difficult to objectively compare algorithms or define clinically relevant performance measures .

There are further challenges when it comes to integrating these into hospital workflows. Automated EEG systems should also integrate with electronic medical records and current neurodiagnostic practices. While DL-driven insights can also require training for clinicians to interpret, particularly when such decisions affect diagnosis and treatment planning . It is very hard to get it widely embraced in the clinic if you don't have explainability and robust validation."

7.5 Future Research Directions

7.5.1 Advanced Architectural Innovations

Emerging trends shift to the hybrid and neuromorphic architectures. Neuro-symbolic techniques could integrate the interpretability of symbolic reasoning with the representational capabilities of DL . Quantum machine learning may offer to model high-dimensional EEG spaces as well as represent complex correlations. Neuromorphic hardware and spike-based networks offer the potential of ultra-low power real-time EEG processing viable for wearble BCI.

7.5.2 Self-Supervised and Few-Shot Learning

Due to the limited availability of labeled EEG data, self-supervised learning is a promising approach which leverages temporal dependencies and inter-channel correlations for learning transferable embeddings . Few-shot and meta-learning schemes may be able to help on fast subject adaptation that is crucial for personalized medicine. Motivated by the NLP and CV breakthroughs, EEG base models pretrained on large multi-center datasets could serve as universal backbones to be fine-tuned for clinical tasks .

7.5.3 Multimomdal Fusion and Federated Learning

In the future, ETV techniques will merge EEG with gases (and other modalities; e.g. fMRI or NIRS 1, MEG) and behavior data in combined imaging of whole brain. Federated learning and differential privacy techniques will support cooperation in model training across institutions without compromising patient's privacy. Blockchain-enabled data-sharing platforms can enable secure and transparent access in the EEG databases.

7.5.4 Real-Time and Edge Computing Usage

Pruned, quantized and knowledge distilled lightweight models can be used for real-time EEG processing on the edge The robustness to long-term signal variation will be further enhanced through hardware– software co-design approaches and adaptive learning algorithms, which in turn would enable applications such as closed-loop neurofeedback and wearable BCIs.

7.5.5 Clinical Translation and Standardization

Consistent data collection, pre-processing and benchmarking protocols are necessary to speed up the clinical translation. Validating models and fairness with large-scale shared data sets across different populations will make these processes robust and fair. The establishment of a regulatory framework dedicated to AI-facilitated-EEG systems would enable the acceleration of approval process . Explainable AI and uncertainty quantification techniques should be incorporated in EEG models to promote clinician trust and safe integration with decision-support systems.

7.6 Critical Reflection on This Survey

While this survey aims to provide a comprehensive and critical synthesis of deep learning techniques for EEG analysis, certain limitations must be acknowledged. First, the analysis is primarily architecture-driven, which may underrepresent the role of neurophysiological validation and domain-specific experimental protocols that are crucial for clinical credibility. Second, performance comparisons across studies rely on reported results that are often derived from heterogeneous datasets, evaluation metrics, and preprocessing pipelines, limiting direct comparability.

Additionally, although this work identifies emerging methodological trends and conceptual gaps, it does not propose a unified benchmarking framework or standardized evaluation protocol—an aspect that remains an open research challenge for the community. Nonetheless, by explicitly highlighting these limitations, the survey aims to promote transparency and encourage future research that moves toward reproducible, interpretable, and clinically aligned EEG–AI systems.

8. DIFFERENCE FROM PRIOR WORK

Existing surveys on EEG signal analysis predominantly focus on categorizing algorithms, reporting benchmark accuracies, or summarizing application domains such as seizure detection, emotion recognition, and brain–computer interfaces. While informative, such studies often adopt a descriptive perspective and provide limited

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

guidance on model selection, generalization challenges, or clinical readiness.

In contrast, this study differentiates itself by adopting a critical, systems-level perspective. Rather than treating deep learning models as isolated components, the survey analyzes EEG pipelines holistically—linking preprocessing strategies, feature learning mechanisms, architectural choices, and deployment constraints. Furthermore, this work explicitly examines why recent paradigms such as transformers and graph neural networks represent structural shifts in EEG modeling, rather than incremental performance improvements.

By emphasizing interpretability, robustness, and translational feasibility alongside accuracy, this survey addresses unmet needs in the literature and aligns methodological advances with real-world neurodiagnostic requirements.

9. CONCLUSION

This survey has critically examined the evolution of machine learning and deep learning approaches for EEG signal analysis, highlighting both their transformative potential and persistent limitations. While classical methods established interpretable and computationally efficient baselines, modern deep learning architectures—including CNNs, recurrent networks, transformers, and graph neural networks—have enabled automated extraction of complex spatiotemporal and connectivity patterns that were previously inaccessible.

The key scientific contribution of this work lies in reframing EEG–deep learning research from an accuracy-centric viewpoint to a capability- and applicability-driven perspective. By analyzing how architectural choices interact with EEG-specific challenges such as non-stationarity, inter-subject variability, and low signal-to-noise ratios, this survey provides deeper insight into why many high-performing models fail to generalize beyond controlled datasets. Furthermore, the study highlights that emerging hybrid and attention-based models are not merely algorithmic trends, but necessary responses to structural limitations of earlier approaches.

Importantly, this article adds to existing knowledge by synthesizing methodological, clinical, and regulatory considerations into a unified framework, offering actionable guidance for future EEG research. The findings underscore the need for explainable, adaptive, and privacy-aware models supported by standardized benchmarks and large-scale collaborative datasets. With continued progress along these directions, deep learning–powered EEG systems can transition from experimental success to reliable clinical and real-time neurotechnology applications.

REFERENCES:

[1] U. Orhan, M. Hekim, and M. Ozer, "EEG signals classification using the K-means clustering and a multilayer perceptron neural network model," Expert Syst. Appl., 38(10), 13475–13481, Sep. 2011.

[2] N. Nicolaou and J. Georgiou, "Detection of epileptic electroencephalogram based on permutation entropy and support vector machines," Expert Syst. Appl., 39, 202–209, 2012.

[3] R. N. Duan, J. Y. Zhu, and B. L. Lu, "Differential entropy feature for EEG-based emotion classification," in 2013 6th Int. IEEE/EMBS Conf. Neural Eng. (NER), 81–84, 2013.

[4] W. L. Zheng, J. Y. Zhu, Y. Peng, and B. L. Lu, "EEG-based emotion classification using deep belief networks," in IEEE Int. Conf. Multimedia and Expo (ICME), 1–6, Jul. 2014.

[5] S. Ding, N. Zhang, X. Xu, L. Guo, and J. Zhang, "Deep extreme learning machine and its application in EEG classification," Math. Probl. Eng., 2015, Article ID 103068, 2015.

[6] Y. Gao, H. J. Lee, and R. M. Mehmood, "Deep learning of EEG signals for emotion recognition," in IEEE Int. Conf. Multimedia and Expo Workshops (ICMEW), 1–5, Jun. 2015.

[7] P. Bashivan, I. Rish, M. Yeasin, and N. Codella, "Learning representations from EEG with deep recurrent-convolutional neural networks," ICLR 2016 (preprint 2015).

[8] Y. R. Tabar and U. Halici, "A novel deep learning approach for classification of EEG motor imagery signals," J. Neural Eng., 14(1), 016003, Nov. 2016.

[9] E. Nurse, B. S. Mashford, A. J. Yepes, I. Kiral-Kornek, S. Harrer, and D. R. Freestone, "Decoding EEG and LFP signals using deep learning: Heading TrueNorth," Proc. ACM Int. Conf. Computing Frontiers, 259–266, May 2016.

[10] R. T. Schirrmeister, J. T. Springenberg, L. D. J. Fiederer, M. Glasstetter, K. Eggensperger, M. Tangermann, and T. Ball, "Deep learning with convolutional neural networks for EEG decoding and visualization," Hum. Brain Mapp., 38(11), 5391–5420, Nov. 2017.

[11] S. Raghu and N. Sriraam, "Optimal configuration of multilayer perceptron neural network classifier for recognition of

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

intracranial epileptic seizures," Expert Syst. Appl., 89, 205–221, Dec. 2017.

[12] M. J. Van Putten, J. Hofmeijer, B. J. Ruijter, and M. C. Tjepkema-Cloostermans, "Deep learning for outcome prediction of postanoxic coma," in EMBEC and NBC, 506–509, Jun. 2017.

[13] P. Arnau-Gonzalez, S. Katsigiannis, N. Ramzan, D. Tolson, and M. Arevalillo-Herrez, "ES1D: A deep network for EEG-based subject identification," Proc. IEEE 17th Int. Conf. Bioinformatics and Bioengineering (BIBE), 81–85, Oct. 2017.

[14] A. Vilamala, K. H. Madsen, and L. K. Hansen, "Deep convolutional neural networks for interpretable analysis of EEG sleep stage scoring," Proc. IEEE 27th Int. Workshop Machine Learning for Signal Processing (MLSP), 2017.

[15] S. R. Carvalho, I. Cordeiro Filho, D. O. De Resende, A. C. Siravenha, C. De Souza, H. G. Debarba, and R. Boulic, "A deep learning approach for classification of reaching targets from EEG images," 30th SIBGRAPI Conf. Graphics, Patterns and Images (SIBGRAPI), 178–184, Oct. 2017.

[16] J. Birjandtalab, M. Heydarzadeh, and M. Nourani, "Automated EEG-based epileptic seizure detection using deep neural networks," Proc. IEEE Conf. Healthcare Informatics (ICHI), 552–555, Aug. 2017.

[17] M. C. Tjepkema-Cloostermans, R. C. de Carvalho, and M. J. van Putten, "Deep learning for detection of focal epileptiform discharges from scalp EEG recordings," Clin. Neurophysiol., 129(10), 2191–2196, Jul. 2018.

[18] B. Yang, K. Duan, C. Fan, C. Hu, and J. Wang, "Automatic ocular artifacts removal in EEG using deep learning," Biomed. Signal Process. Control, 43, 148–158, May 2018.

[19] J. A. Mioranda-Correa and I. Patras, "A multi-task cascaded network for prediction of affect, personality, mood and social context using EEG signals," 13th IEEE Conf. FG 2018, 373–380, May 2018.

[20] X. Zhang, L. Yao, Q. Sheng, S. S. Kanhere, T. Gu, and D. Zhang, "Converting your thoughts to texts: Enabling brain typing via deep feature learning of EEG signals," IEEE PerCom, 1–10, 2018.

[21] J. Behncke, R. T. Schirrmeister, W. Burgard, and T. Ball, "The signature of robot action success in EEG signals," 6th Int. Conf. Brain-Computer Interface (BCI), Jan. 2018.

[22] M. Völker, R. T. Schirrmeister, L. D. Fiederer, W. Burgard, and T. Ball, "Deep transfer learning for error decoding from non-invasive EEG," 6th Int. Conf. BCI, Jan. 2018.

[23] I. Ullah, M. Hussain, and H. Aboalsamh, "An automated system for epilepsy detection using EEG brain signals based on deep learning approach," Expert Syst. Appl., 107, 61–71, Oct. 2018.

[24] A. Antoniades, L. Spyrou, D. Martin-Lopez, A. Valentin, G. Alarcon, S. Sanei, and C. C. Took, "Deep neural architectures for mapping scalp to intracranial EEG," Int. J. Neural Syst., 28(8), 1850009, Mar. 2018.

[25] Y. Hao, H. M. Khoo, N. von Ellenrieder, N. Zazubovits, and J. Gotman, "DeepIED: An epileptic discharge detector for EEG-fMRI based on deep learning," NeuroImage Clin., 17, 962–975, Jul. 2018.

[26] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals," Comput. Biol. Med., 100, 270–278, Sep. 2018.

[27] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, H. Adeli, and D. P. Subha, "Automated EEG-based screening of depression using deep convolutional neural network," Comput. Methods Programs Biomed., 161, 103–113, Jul. 2018.

[28] H. Zeng, C. Yang, G. Dai, F. Qin, J. Zhang, and W. Kong, "EEG classification of driver mental states by deep learning," Cogn. Neurodyn., 12(6), 597–606, 2018.

[29] J. Zhang and Y. Wu, "Complex-valued unsupervised convolutional neural networks for sleep stage classification," Comput. Methods Programs Biomed., 164, 181–191, Oct. 2018.

[30] H. Dose, J. S. Møller, H. K. Iversen, and S. Puthusserypady, "An end-to-end deep learning approach to MI-EEG signal classification for BCIs," Expert Syst. Appl., 114, 532–542, Dec. 2018.

[31] K. M. Tsiouris, V. C. Pezoulas, M. Zervakis, S. Konitsiotis, D. D. Koutsouris, and D. I. Fotiadis, "A long short-term memory deep learning network for the prediction of epileptic seizures using EEG signals," Comput. Biol. Med., 99, 24–37, Aug. 2018.

[32] N. Singh and S. Dehuri, "Usage of deep learning in epileptic seizure detection through EEG signal," in Nanoelectronics, Circuits and Communication Systems, 219–228, 2019.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[33] R. Hussein, et al., "Optimized deep neural network architecture for robust detection of epileptic seizures using EEG signals," Clin. Neurophysiol., 130(1), 25–37, Jan. 2019.
[34] V. Gupta, M. D. Chopda, and R. B. Pachori, "Cross-Subject Emotion Recognition Using Flexible Analytic Wavelet Transform From EEG Signals," IEEE Sensors J., 19(6), 2266–2274, 2019.
[35] Y. Li, W. Zheng, Y. Zong, Z. Cui, T. Zhang, and X. Zhou, "A bi-hemisphere domain adversarial neural network model for EEG emotion recognition," IEEE Trans. Affect. Comput., 12, 494–504, 2021.
[36] B. H. Kim, J. C. Ye, and J. J. Kim, "Learning dynamic graph representation of brain connectome with spatio-temporal attention," NeurIPS, 34, 4314–4327, 2021.
[37] J. He, J. Cui, G. Zhang, M. Xue, D. Chu, and Y. Zhao, "Spatial–temporal seizure detection with graph attention network and bi-directional LSTM architecture," Biomed. Signal Process. Control, 78, 103908, 2022.
[38] X. Shan, J. Cao, S. Huo, L. Chen, P. G. Sarrigiannis, and Y. Zhao, "Spatial–temporal graph convolutional network for Alzheimer classification based on EEG functional connectivity," Comput. Biol. Med., 148, 105631, 2022.
[39] X. Sun, C. Ma, P. Chen, M. Li, H. Wang, W. Dang, C. Mu, and Z. Gao, "A Novel Complex Network-Based Graph Convolutional Network in Major Depressive Disorder Detection," IEEE Trans. Instrum. Meas., 71, 1–12, 2022.
[40] H. Wang, et al., "Channel-attention mechanism with Swin Transformer for motor pattern classification," Expert Syst. Appl., 198, 116834, 2022.
[41] W. Tian, M. Li, X. Ju, and Y. Liu, "Applying Multiple Functional Connectivity Features in GCN for EEG-Based Human Identification," Brain Sci., 12(8), 1072, 2022.
[42] X. Wang, Y. Ren, Z. Luo, W. He, J. Hong, and Y. Huang, "Deep learning-based EEG emotion recognition: Current trends and future perspectives," Front. Psychol., 14, 1126994, 2023.
[43] J. Luo, Y. Wang, S. Xia, N. Lu, X. Ren, Z. Shi, and X. Hei, "A shallow mirror transformer for subject-independent motor imagery BCI," Comput. Biol. Med., 164, 107254, 2023.
[44] Q. Xue, Y. Song, H. Wu, Y. Cheng, and H. Pan, "Graph neural network based on brain inspired forward-forward mechanism for motor imagery classification," Front. Neurosci., 17, 1219988, 2023.
[45] R. Xu, Q. Zhu, S. Li, Z. Hou, W. Shao, and D. Zhang, "MSTGC: Multi-channel spatio-temporal GCN for multi-modal brain networks fusion," IEEE Trans. Neural Syst. Rehabil. Eng., 31, 2359–2369, 2023.
[46] M. Li, M. Qiu, W. Kong, L. Zhu, and Y. Ding, "Fusion Graph Representation of EEG for Emotion Recognition," Sensors (Basel), 23(3), 1404, 2023.
[47] Y. Cai, et al., "Multi-scale Swin Transformer model for cognitive load assessment," IEEE Access, 11, 78984–78993, 2023.
[48] J. Zhang, K. Li, B. Yang, and X. Han, "Local and global convolutional transformer-based motor imagery EEG classification," Front. Neurosci., 17, 1219988, 2023.
[49] W. Lu, T.-P. Tan, and H. Ma, "Bi-branch vision transformer network for EEG emotion recognition," IEEE Access, 11, 36233–36243, 2023.
[50] R. Jiang, S. Tong, J. Wu, et al., "A novel EEG artifact removal algorithm based on an advanced attention mechanism," Sci. Rep., 15, 19419, 2024.
[51] A. C. Filip, T. Azevedo, L. Passamonti, N. Toschi, and P. Lio, "A novel graph attention network architecture for modeling multimodal brain connectivity," Front. Neurosci., 17, 1288433, 2024.
[52] C. Zhang, X. Deng, and S. H. Ling, "Next-Gen Medical Imaging: U-Net Evolution and the Rise of Transformers," Sensors (Basel), 24(14), 4668, 2024.
[53] D. V. Puri, P. H. Kachare, and S. L. Nalbalwar, "Metaheuristic optimized time–frequency features for enhancing Alzheimer's disease identification," Biomed. Signal Process. Control, 94, 106244, 2024.
[54] D. V. Puri, S. L. Nalbalwar, and P. P. Ingle, "EEG-based systematic explainable Alzheimer's disease and mild cognitive impairment identification using novel rational dyadic biorthogonal wavelet filter banks," Circuits Syst. Signal Process., 43(3), 1792–1822, 2024.
[55] X. Ning, J. Wang, Y. Lin, X. Cai, H. Chen, H. Gou, et al., "MetaEmotionNet: spatial–spectral–temporal-based attention 3-D dense network with Meta-learning for EEG emotion recognition," IEEE Trans. Instrum. Meas., 73, 1–13, 2024.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[56] R. Peng, Z. Du, C. Zhao, J. Luo, W. Liu, X. Chen, and D. Wu, “Multi-Branch Mutual-Distillation Transformer for EEG-Based Seizure Subtype Classification,” IEEE Trans. Neural Syst. Rehabil. Eng., 32, 831–839, 2024.
[57] Y. Yang, C. Ye, G. Cai, K. Song, J. Zhang, Y. Xiang, and T. Ma, “Hypercomplex Graph Neural Network: Towards Deep Intersection of Multi-modal Brain Networks,” IEEE J. Biomed. Health Inform., 2024 (early access).
[58] R. Singh, Y. Zhang, D. Bhaskar, V. Srihari, C. Tek, X. Zhang, J. A. Noah, S. Krishnaswamy, and J. Hirsch, “Deep multimodal representations and classification of first-episode psychosis via live face processing,” Front. Psychiatry, 16, 1518762, 2025 (online 2024).
[59] X. Deng, H. Huo, L. Ai, D. Xu, and C. Li, “A Novel 3D Approach with a CNN and Swin Transformer for Decoding EEG-Based Motor Imagery Classification,” Sensors (Basel), 25(9), 2922, 2025.
[60] Y. Cai, Z. Meng, and D. Huang, “DHCT-GAN: Improving EEG Signal Quality with a Dual-Branch Hybrid CNN-Transformer Network,” Sensors (Basel), 25(1), 231, 2025.
[61] D. Ji, L. He, X. Dong, H. Li, X. Zhong, G. Liu, and W. Zhou, “Epileptic Seizure Prediction Using Spatiotemporal Feature Fusion on EEG,” Int. J. Neural Syst., 34, 2450041, 2025.
[62] D. V. Puri, J. P. Gawande, P. H. Kachare, and I. Al-Shourbaji, “Optimal time-frequency localized wavelet filters for identification of Alzheimer’s disease from EEG signals,” Cogn. Neurodyn., 19(1), Article 12, 2025.
[63] B. Wei, L. Xu, and J. Zhang, “A self-supervised graph network with time-varying functional connectivity for seizure prediction,” Biomed. Signal Process. Control, 102, 107375, 2025.