

Deep Learning-Powered Electrical Brain Signals Analysis: Advancing Neurological Diagnostics

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Abstract—Neurological disorders represent significant global health challenges, driving the advancement of brain signal analysis methods. Scalp electroencephalography (EEG) and intracranial electroencephalography (iEEG) are widely used to diagnose and monitor neurological conditions. However, dataset heterogeneity and task variations pose challenges in developing robust deep learning solutions. This review systematically examines recent advances in deep learning approaches for EEG/iEEG-based neurological diagnostics, focusing on applications across 7 neurological conditions using 46 datasets. We explore trends in data utilization, model design, and task-specific adaptations, highlighting the importance of pre-trained multi-task models for scalable, generalizable solutions. To advance research, we propose a standardized benchmark for evaluating models across diverse datasets to enhance reproducibility. This survey emphasizes how recent innovations can transform neurological diagnostics and enable the development of intelligent, adaptable healthcare solutions.

Index Terms—Deep learning, Neural Signal Analysis, Electroencephalography, Neurological Disorder Diagnosis

I. INTRODUCTION

Neurological disorders represent one of the most significant challenges to global health today, with profound consequences for both individuals and healthcare systems. According to the World Health Organization (WHO), neurological disorders affect over one-third of the global population, making them a leading cause of illness and disability worldwide [1]. Dementia, which affects 47.5 million people worldwide, is a primary concern, with Alzheimer's disease being the most common form. Seizure impacts more than 50 million individuals, while sleep disorders are widespread yet often underdiagnosed. Other significant disorders, including Parkinson's disease, schizophrenia, depression, and ADHD, further exacerbate the global burden, placing additional strain on healthcare systems [2]. In low- and middle-income countries,

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Manuscript received 24 February 2025. This work is supported by NSFC (62322606) and Zhejiang NSF (LR22F020005).

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where limited resources constrain access to neurological care and treatment, the situation is particularly dire.

Practical diagnostic tools are essential to alleviate the growing global burden of neurological disorders, and electrical brain signals are indispensable among them. Electrical brain signals, specifically electroencephalography, are critical for understanding and diagnosing neurological disorders. Electroencephalography evaluates electrical activity in the brain and is categorized into scalp electroencephalography (EEG) and intracranial electroencephalography (iEEG). EEG is non-invasive, recording brain activity from electrodes placed on the scalp. iEEG includes inserting electrodes into the brain (stereo-electroencephalography, SEEG) or onto the brain's surface (electrocorticography, ECoG), providing more detailed and localized information [3].

The analysis of brain signals such as EEG/iEEG poses significant challenges for traditional machine learning (ML) approaches. These methods typically rely on manually engineered features that may not fully capture the complex patterns in neurophysiological data, while their performance is often compromised by inherent noise and artifacts in raw neural recordings. Deep learning (DL) addresses these limitations by automatically extracting features, modeling temporal dependencies, and improving robustness against signal variability. The ability of DL methods to detect and classify neurological disorders with high accuracy has driven widespread adoption in brain signal analysis. This survey systematically examines the workflow of DL models in brain signal analysis, focusing on their applications in diagnosing neurological disorders.

A. General Workflow

The general workflow of electrical brain signal analysis in neurological diagnostics, as illustrated in Fig. 1, consists of three main stages: signal collection, signal preprocessing, and analysis and diagnosis.

In the signal collection stage, electrical brain activity is recorded using EEG, ECoG, or SEEG systems (Fig. 1.a). These signals are typically captured across multiple channels at specific sampling frequencies and are often accompanied by labeled tasks and corresponding labels.

The signal preprocessing stage (Fig. 1.b) involves a series of low-level techniques, including denoising, filtering, artifact removal, and normalization. These steps are crucial for reducing noise and artifacts, enhancing relevant patterns, and structuring the data for effective feature extraction.

In the analysis and diagnosis stage (Fig. 1.c), the preprocessed signals undergo feature extraction and neurodiagnostic

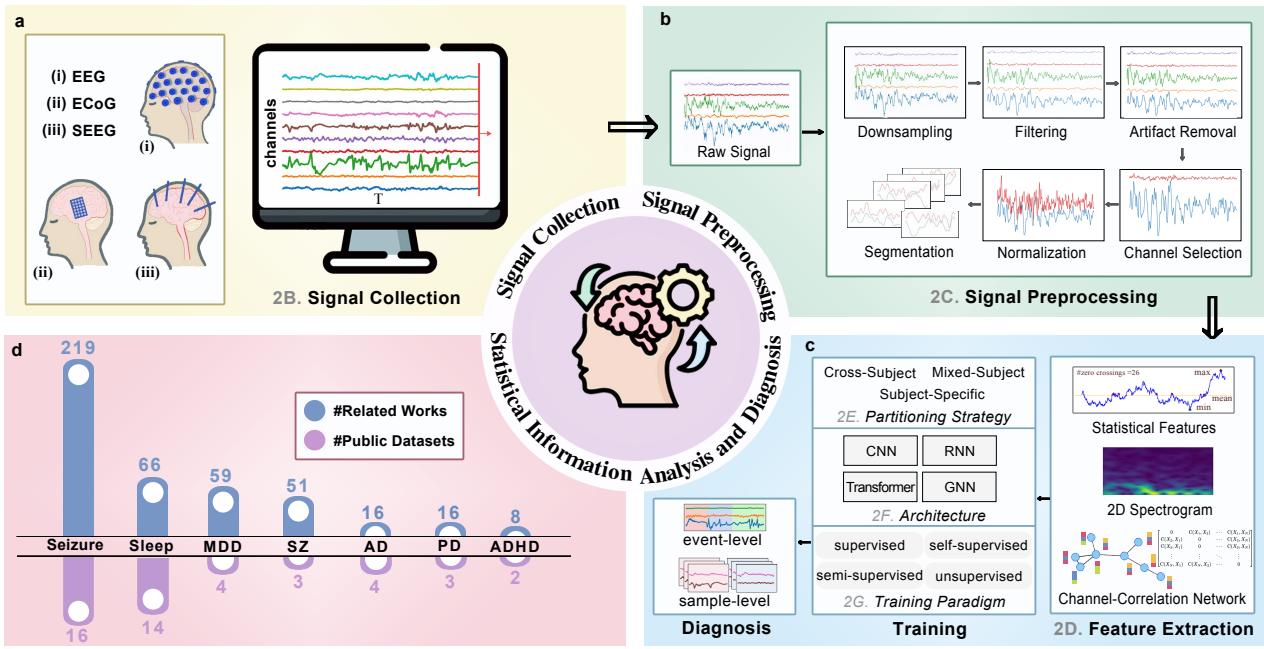


Fig. 1: General Workflow of Electrical Brain Signals Analysis in Neurological Diagnostics. a. Signal Collection:

Acquisition of EEG/iEEG signals from patients using non-invasive scalp electrodes or invasive intracranial electrodes, capturing brain electrical activity for clinical purposes. **b. Signal Preprocessing:** A feasible workflow to process raw signals, ensuring their suitability for subsequent analysis. **c. Analysis and Diagnosis:** Extraction of features from the preprocessed signals, followed by the application of deep learning techniques for model training and neurological classification.

d. Statistical Information: A statistical summary of related work and publicly available datasets, illustrating their contributions to the field and providing essential resources for future research, model development, and validation.

classification. Feature extraction transforms the signals into representations suitable for diagnosis. Traditional methods extract spatial, temporal, and spectral features manually, while deep learning approaches automatically learn complex, diagnostically relevant patterns. These features are then fed into classifiers for specific neurodiagnostic tasks. The training phase involves careful consideration of network backbones, training paradigms and data partitioning strategies.

Finally, the extracted features are applied to downstream tasks. Fig. 1.d highlights the distribution of related research efforts and publicly available datasets across various neurological conditions, including seizure, sleep disorders, major depressive disorder (MDD), schizophrenia (SZ), Alzheimer's disease (AD), Parkinson's disease (PD), and attention deficit hyperactivity disorder (ADHD).

B. Related Studies and Our Contributions

Existing brain signal analysis surveys exhibit diverse scopes and focuses. Some focus specifically on EEG signals, emphasizing their wide availability [4]–[6]. Others broaden the scope to include brain signals like magnetic resonance imaging (MRI) [7], [8], which differ from EEG and iEEG in acquisition methods, temporal resolution, and preprocessing requirements. From a task perspective, some reviews focus specifically on diseases such as seizure [9], [10], providing in-depth insights into disease-specific applications. Others take a broader view, covering diverse brain-computer interface (BCI)

applications [11], [12], which focus on interaction and control, differing fundamentally from neurological diagnostic tasks.

Our work establishes three foundational contributions to advance deep learning-driven neurodiagnosis: First, we systematically curate and analyze 46 public EEG/iEEG datasets across seven neurological conditions, establishing the most comprehensive data landscape to date. We also unify fragmented methodologies by standardizing data processing, model architectures, and evaluation protocols. Besides, we identify self-supervised learning as the optimal paradigm for developing multi-task diagnostic frameworks, offering a comprehensive overview of pre-trained multi-task frameworks and their advancements. Additionally, we propose a benchmarking methodology to evaluate brain signal models across tasks, providing a foundation for scalable and versatile solutions in EEG/iEEG-based neurological diagnostics applications.

II. METHODS

A. Problem Definition

In this survey, we classify neurological diagnostic tasks into sample-level classification and event-level classification, both of which fall under the broader framework of classification problems. Sample-level classification involves assigning a single label to an entire signal, which typically represents a specific subject or sample (e.g., Alzheimer's disease diagnosis). By comparison, event-level classification focuses on identifying and classifying distinct temporal segments within a more

extended signal, thereby introducing an implicit segmentation process by associating each segment with a specific event or state (e.g., seizure detection or sleep staging).

Electrical brain signals, which capture the brain's electrical activity over time, can be modeled as multivariate time series. Specifically, let $\mathbf{X} \in \mathbb{R}^{C \times T}$ represent the EEG/iEEG time series, where C is the number of channels, and T is the number of sampling points. Each channel $\mathbf{x}^c = \{x_1^c, x_2^c, \dots, x_T^c\}$ corresponds to the measurements from a specific source, such as an EEG electrode or a contact of an iEEG electrode.

1) *Sample-Level Classification*: In sample-level classification, the objective is to assign a single label $y \in \mathcal{Y}$ to the entire signal \mathbf{X} . This can be formulated as:

$$y = \Phi_{\text{sample}}(\mathbf{X}; \theta), \quad y \in \mathcal{Y},$$

where Φ_{sample} represents the deep learning model parameterized by θ , and \mathcal{Y} denotes the set of possible classes. Here, \mathbf{X} is treated as a unified entity, capturing sample-level or subject-level characteristics.

2) *Event-Level Classification*: In event-level classification, the goal is to classify smaller temporal segments of the signal. The signal \mathbf{X} is divided into K segments $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_K$, where $\mathbf{X}_k \in \mathbb{R}^{C \times T_k}$ and T_k is the duration of the k -th segment. A classification model is applied to each segment to produce a sequence of labels $\mathbf{Y} = \{y_1, y_2, \dots, y_K\}$, $y_k \in \mathcal{Y}$:

$$y_k = \Phi_{\text{segment}}(\mathbf{X}_k; \theta), \quad \mathbf{Y} = \bigcup_{k=1}^K \{y_k\},$$

where Φ_{segment} denotes the deep learning model parameterized by θ . This process associates each segment \mathbf{X}_k with a specific label y_k , allowing the temporal localization of events within the signal. Event-level classification captures natural temporal dependencies between consecutive segments, reflecting the continuity of events in time [13].

B. Signal Collection

EEG have evolved significantly since Hans Berger first recorded EEG signals from the human scalp in 1924 [14]. While EEG signals are typically collected non-invasively using scalp electrodes placed according to the 10-20 system [15], more recent studies employ higher-density EEG electrode configurations for enhanced spatial resolution and detailed brain activity mapping. EEG captures brain oscillations across frequency bands, each linked to specific neural states: delta (deep sleep), theta (light sleep), alpha (relaxation), beta (focus), and gamma (higher cognition) [16]. Depending on the study, participants may perform tasks or rest to elicit relevant brain activity. Resting-state EEG evaluates baseline activity, while specific tasks can highlight disease-related abnormalities [17].

iEEG involves implanting electrodes either within deep and superficial brain structures via burr holes (SEEG) or on the brain's surface by placing grids during craniotomy (ECoG). Compared to EEG, iEEG offers excellent spatial resolution and reduced susceptibility to artifacts from scalp muscle activity and eye movements. SEEG allows recording from deep and distributed brain regions with minimal invasiveness, while ECoG provides higher spatial resolution for cortical surface

TABLE I: Signal Preprocessing Techniques

Techniques	Details	Reference
Noise Reduction & Filtering	FIR Filter	[18]
	IIR Filter	[19]
	Adaptive Filters	[20]
	Manual & Custom	[21]
Artifact Removal	Blind Source Separation	[22]
	Artifact Correction	[23]
Baseline Correction & Detrending	Baseline Correction	[24]
	Baseline Removal	[25]
	Detrending	[26]
Channel Processing	Channel Selection	[27]
	Channel Mapping	[28]
	Re-Referencing	[25]
Normalization & Scaling	Z-Normalization	[29]
	Quantile Normalization	[30]
	Scaling & Shifting	[28]
Sampling Adjustment	Downsampling	[31]
	Resampling	[32]
	Interpolation	[33]
	Imputation	[34]
Segmentation	Windowing	[35]
Signal Alignment & Synchronization	Time Synchronization	[36]
	Temporal Alignment	[36]

activity due to its densely packed electrode grids. However, iEEG can still be affected by cardiac artifacts, electrode shifts, and other forms of noise. Rigorous preprocessing techniques are essential to ensure the accuracy and reliability of EEG and iEEG signals in clinical and research applications.

C. Signal Preprocessing

EEG/iEEG signals require low-level preprocessing to address challenges such as noise and artifact removal, normalization for consistency, and segmentation into analyzable time windows. These steps refine raw data, ensuring it accurately reflects brain activity and provides a robust foundation for analysis. Representative methods are summarized in Table I, with one key work per category highlighted.

1) *Noise Reduction and Filtering*: Filtering techniques, such as Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters, are employed to isolate specific frequency components. Advanced methods like MSEC noise reduction and wavelet transforms [21] provide specialized solutions for effective denoising and precise data refinement.

2) *Artifact Removal*: Artifact removal strategies include Blind Source Separation techniques, such as Independent Component Analysis (ICA), Principal Component Analysis (PCA), and Multiple Component Analysis (MCA) [37], along with Artifact Correction methods, including Ocular Correction and Artifact Subspace Reconstruction. Wavelet decomposition is also commonly used mitigate artifacts.

3) *Baseline Correction and Detrending*: Baseline correction and detrending address baseline drift caused by eye movements, breathing, and subject motion. Baseline correction standardizes power data, baseline removal reduces subject-independent noise, and detrending eliminates linear or non-linear trends, enhancing signal reliability.

TABLE II: Feature Extraction Techniques

Techniques	Details	Reference
Data Augmentation	Oversampling	[32]
	ELM-AE	[39]
Signal Decomposition & Transformation	Time-Frequency Analysis	[40]
	Empirical Decomposition	[41]
Spectral & Power Analysis	Power Spectrum	[42]
	Spectral Density	[43]
	Partial Directed Coherence	[44]
Time-Domain Features Extraction	Statistical Measures	[45]
	Amplitude & Range	[46]
	Hjorth Parameters	[47]
Frequency-Domain Features Extraction	Band Power Features	[48]
	Spectral Measures	[49]
Time-Frequency Features Extraction	Wavelet Coefficients	[50]
	STFT Features	[51]
	Multitaper Spectral	[52]
Other Features Extraction	Nonlinear Features	[53]
	Spatial Features	[54]
	Transform-Based Features	[55]
Graph Analysis	Clustering Coefficient	[56]
	Other Graph Metrics	[57]

4) *Channel Processing*: Neurological disorders often affect specific brain regions, making channel processing techniques, including selection, mapping, and re-referencing, essential for enhancing the specificity and interpretability of analyses.

5) *Normalization and Scaling*: Normalization standardizes the amplitude of raw EEG and iEEG signals, which often vary in voltage. Common methods include Z-score and quantile normalization, while linear scaling and shifting minimize spurious amplitude variations across channels.

6) *Sampling Adjustment*: Sampling adjustments optimize data for analysis while reducing computational demands. Downsampling reduces memory and processing requirements, whereas interpolation handles missing data, insufficient training samples, and pulse artifacts [38].

7) *Segmentation*: Segmentation divides EEG and iEEG data into smaller sections for localized information extraction and data augmentation to enhance sample diversity. Overlap windows ensure continuity and capture transitional features, while non-overlapping segments prioritize computational efficiency and maintain distinct temporal boundaries.

8) *Signal Alignment and Synchronization*: Signal alignment ensures temporal consistency across signals from different sources, improving the reliability of findings. Fine-grained temporal alignment further corrects residual discrepancies after initial synchronization, ensuring data precision.

D. Feature Extraction

Feature extraction techniques reconfigure data into alternative representations by isolating key features or decomposing it into core components essential for modeling and analysis. This process effectively primes the data for more sophisticated, abstract analytical tasks. Representative methods are summarized in Table II, with one key work per category highlighted.

1) *Data Augmentation*: Data augmentation generates new samples to increase dataset diversity and improve classification

accuracy and stability. Oversampling is commonly used to address class imbalances, while the Extreme Learning Machine Autoencoder (ELM-AE) employs autoencoders to synthesize data by reconstructing input features [39].

2) *Spectral and Power Analysis*: Spectral and power analysis focuses on examining the frequency components and energy distribution of signals. Key techniques include power spectrum calculation, frequency band energy analysis, and partial-directed coherence for evaluating signal causality.

3) *Time Domain Feature Extraction*: Time domain features, such as statistical measures, Hjorth parameters, and Zero-Crossing Rate, effectively represent signal amplitude, time scale, and complexity. These features provide valuable insights into signal distribution, intensity, and rate of change.

4) *Frequency Domain Feature Extraction*: Frequency domain features, such as band power, band energy, median frequency, spectral edge frequency, and power spectral density (PSD), provide insights into the spectral content of signals.

5) *Time-Frequency Feature Extraction*: Time-frequency features capture both temporal and spectral information, providing a comprehensive signal representation. Short-time Fourier Transform (STFT) analyzes frequency variations over time, while Continuous and Discrete Wavelet Transforms (CWT, DWT) offer detailed time-frequency representations. Advanced techniques like FBSE-EWT filter banks [58] and Smoothed Pseudo Wigner Ville Distribution (SPWVD) [59] enhance analysis precision.

6) *Other Feature Extraction*: Nonlinear features, such as entropy measures, fractal dimensions, and Lyapunov exponents, capture complex patterns that linear methods may miss. Spatial features, including Common Spatial Patterns and connectivity measures like phase-locking value (PLV) and phase-lag index (PLI), represent spatial domain activities. Transform-based features further enhance analysis by reconstructing signals into more informative representations.

7) *Signal Decomposition and Transformation*: Signal decomposition and transformation techniques decompose complex signals to facilitate detailed analysis, such as wavelet transforms, Gabor Transform [40], Fast Fourier Transform, Empirical Mode Decomposition, and Hilbert-Huang Transform.

8) *Graph Analysis*: Graph analysis evaluates connectivity between channels. Metrics like degree measure connections and node importance, while the clustering coefficient quantifies local network density, revealing network structure.

E. Data Partitioning Strategies

Building on the detailed definition of $\mathbf{X}^{(i)} \in \mathbb{R}^{C \times T}$ in Section II-A, where $\mathbf{X}^{(i)}$ represents the EEG or iEEG signal of subject i , we further introduce additional notations to formalize the data partitioning strategies:

- $\mathcal{P} = \{1, 2, \dots, N\}$: The set of N subjects in the dataset.
- $\mathcal{X}_{\text{train}}, \mathcal{X}_{\text{val}}, \mathcal{X}_{\text{test}}$: The training, validation, and testing sets, respectively.
- $\alpha_{\text{train}}, \alpha_{\text{val}}, \alpha_{\text{test}} \in (0, 1)$: The proportion of data used for training, validation and test, and $\alpha_{\text{train}} + \alpha_{\text{val}} + \alpha_{\text{test}} = 1$.
- $K^{(i)}$: The total number of temporal segments or events derived from subject i 's data.

Using these definitions, we classify data partitioning strategies into three categories: subject-specific methods, mixed-subject methods, and cross-subject methods.

1) *Subject-Specific Methods*: Subject-specific methods focus on capturing individual characteristics by partitioning each subject's data independently into training, validation, and testing sets. Formally,

$$\mathcal{X}_{\text{train}} \cup \mathcal{X}_{\text{val}} \cup \mathcal{X}_{\text{test}} = \{\mathbf{X}_k^{(i)}\}_{k=1}^{K^{(i)}},$$

where i denotes a specific subject. This method is particularly useful in the early stages of development, as it enables rapid iteration on small datasets and captures individual patient patterns. It is commonly used in closed-loop seizure detection systems, where personalization is critical.

2) *Mixed-Subject Methods*: Mixed-subject methods leverage signals from all subjects in \mathcal{P} for training, validation, and testing, aiming to create models with broad applicability. The data partitioning method is as follows:

$$\mathcal{X}_{\text{set}} \subset \bigcup_{i \in \mathcal{P}} \bigcup_{k=1}^{K^{(i)}} \{\mathbf{X}_k^{(i)}\}, \quad |\mathcal{X}_{\text{set}}| = \alpha_{\text{set}} \sum_{i=1}^N K^{(i)},$$

where $\text{set} \in \{\text{train, val, test}\}$. By pooling data across subjects, this approach maximizes training efficiency and improves the model's robustness to inter-subject variability. However, it also introduces the risk of data leakage, as segments from the same subject may appear in different sets.

3) *Cross-Subject Methods*: Clinical applications demand models that generalize across unseen patients. Cross-subject methods explicitly enforce subject separation between training, validation, and testing by partitioning \mathcal{P} into disjoint subsets:

$$|\mathcal{P}_{\text{set}}| = \alpha_{\text{set}} |\mathcal{P}|, \quad \mathcal{X}_{\text{set}} = \bigcup_{i \in \mathcal{P}_{\text{set}}} \bigcup_{k=1}^{K^{(i)}} \{\mathbf{X}_k^{(i)}\},$$

where $\text{set} \in \{\text{train, val, test}\}$. This ensures that models are evaluated on entirely unseen subjects.

Extending subject-level partitioning strategies, dataset-level partitioning includes three approaches: **dataset-specific** (independent partitioning per dataset), **mixed-dataset** (pooling data across datasets), and **cross-dataset** (disjoint datasets for training, validation, and testing). Dataset-specific methods capture individual dataset characteristics, while mixed-dataset methods enhance robustness to inter-dataset variability. Cross-dataset partitioning is crucial for universal models, rigorously assessing generalization and closely aligning with real-world clinical deployment.

F. Deep Learning Architectures

Neurological data processing relies on several key architectures: **Convolutional Neural Networks (CNNs)** [60] excel at extracting spatial/spectral features through hierarchical convolutions. **Recurrent Neural Networks (RNNs)** [61] capture temporal dependencies via recurrent connections. **Transformers** [62] model long-range spatiotemporal relationships using self-attention. **Graph Neural Networks (GNNs)** [63] analyze functional connectivity in graph-structured data. **Autoencoders (AEs)** [64] learn compressed representations through

encoder-decoder structures. **Generative Adversarial Networks (GANs)** [65] synthesize signals through adversarial training. **Spiking Neural Networks (SNNs)** [66] leverage spike-based computation for temporal dynamics.

G. Deep Learning Paradigms

Deep learning applications in neurological diagnostics can be categorized into four paradigms: supervised learning, self-supervised learning, unsupervised learning, and semi-supervised learning. Each paradigm addresses specific challenges in processing brain signals by leveraging architectures tailored to data availability and task requirements. These paradigms will be further discussed in detail in Section III.

1) *Supervised Learning*: Supervised learning is the dominant paradigm for neurological diagnostics tasks, training models to map signals $\mathbf{X} \in \mathbb{R}^{C \times T}$ to labels $y \in \mathcal{Y}$.

2) *Unsupervised Learning*: Unsupervised learning is essential for uncovering intrinsic data structures in signals \mathbf{X} , enabling representation learning without relying on labels.

3) *Semi-Supervised Learning*: Semi-supervised learning combines a small set of labeled examples $\{(x_i, \hat{y}_i)\}_{i=1}^l$, where \hat{y}_i denotes the provided labels, with a larger set of unlabeled examples $\{x_j\}_{j=l+1}^{l+u}$ to learn a mapping from \mathbf{X} to \mathcal{Y} .

4) *Self-Supervised Learning*: Self-supervised learning (SSL) leverages unlabeled EEG/iEEG data by constructing pretext tasks that generate pseudo-labels \hat{y} from intrinsic properties of the raw signals \mathbf{X} . These tasks enable models to learn robust representations, which can be fine-tuned for downstream tasks. SSL methods fall into three main categories: contrastive, predictive, and reconstruction-based learning. **Contrastive-based methods**, such as Contrastive Predictive Coding (CPC) [18] and Transformation Contrastive Learning [67], learns by maximizing similarity between related views while minimizing it between unrelated ones, capturing distinguishing signal features. **Predictive-based learning** employs pretext tasks such as Relative Positioning and Temporal Shuffling to extract structural patterns across temporal, frequency, and spatial domains [68], [69]. By predicting transformations applied to the data, it enhances domain-specific feature learning. **Reconstruction-based learning** trains models to reconstruct masked signal segments. Methods like Masked Autoencoders (MAE) reconstruct temporal or spectral components, learning intrinsic patterns in the process [28], [70]. Studies have also explored hybrid methods, which combine elements from contrastive, predictive, and reconstruction-based approaches [18], [71].

III. APPLICATIONS

This section systematically reviews neurological disease diagnosis methodologies. Each subsection starts with an introduction to the disease's background, including its characteristics, diagnostic tasks, and relevant public datasets. We will then review representative works for each disease, highlighting disease-specific features in the context of deep learning-based diagnosis, such as data types, frequency bands, brain regions, and methodological trends. Given their extensive research history, seizure detection and sleep staging receive dedicated

TABLE III: Public EEG/iEEG datasets for seizure detection, with **Seizures** indicating the number of episodes, **Length** the duration of each record, and **Size** the total duration of recording.

Dataset	Type	Subjects	Seizures	Length	Size	Frequency (Hz)	Channels
Bonn [72]	EEG	10	-	23.6 sec	≈ 3.3 hours	173.61	1
Freiburg [73]	iEEG	21	87	4 sec	≈ 504 hours	256	128
Mayo-UPenn [74]	iEEG	2	48	1 sec	583 min	500-5000	16-76
CHB-MIT [75]-[77]	EEG	22	198	1 hour	≈ 686 hours	256	23 / 24 / 26
Bern-Barcelona [78]	iEEG	5	3750	20 sec	57 hours	512	64
Hauz Khas [79]	EEG	10	-	5.12 sec	87 min	200	50
Melbourne [80]	iEEG	3	-	10 min	81.25 hours	400	184
TUSZ [81]	EEG	642	3050	-	700 hours	250	19
SWEC-ETHZ [82], [83]	iEEG	18 / 16	244 / 100	1 hour / 3 min	2656 hours / 48 min	512 / 1024	24-128 / 36-100
Zenodo [84]	EEG	79	1379	74 min	≈ 97 hours	256	21
Mayo-Clinic [85]	iEEG	25	-	3 sec	50 hours	5000	1
FNUSA [85]	iEEG	14	-	3 sec	7 hours	5000	1
Siena [86]	EEG	14	47	145-1408 min	≈ 128 hours	512	27
Beirut [87]	EEG	6	35	1 sec	130 min	512	19
HUP [88]	iEEG	58	208	300 sec	≈ 27 hours	500	52-232
CCEP [89]	iEEG	74	-	-	89 hours	2048	48-116

sections, while other disorders are analyzed through focused comparative discussions to eliminate redundancy. Technical implementation details across studies (preprocessing pipelines, network architectures, training protocols) are systematically cataloged in supplementary tables.

A. Seizure Disorder

1) *Task Description:* Epilepsy, a neurological disorder affecting 50 million people globally, is characterized by recurrent seizures caused by abnormal brain activity. Seizures range from brief confusion or blanking out to severe convulsions and loss of consciousness. According to the World Health Organization (WHO), up to 70% of epilepsy cases can be effectively treated with proper care. However, in low-income regions, limited resources and stigma often hinder access to treatment, heightening the risk of premature death [90].

Seizure detection primarily relies on standardized EEG/iEEG datasets, summarized in Table III. The key challenge is distinguishing seizure events from background activity, typically framed as binary classification where $y_k \in \{0, 1\}$. Most approaches segment long EEG sequences into smaller windows for sample-level classification, aggregating segment predictions to form event-level outcomes as $\mathbf{Y} = \bigcup_{k=1}^K \{y_k\}$ [91], [92]. Another approach detects optimal cut points within continuous recordings to identify the boundaries of meaningful segments $\{\mathbf{X}_k\}_{k=1}^K$, and each segment is classified individually [56]. The final event-level prediction is obtained by combining these event-level labels $\mathbf{Y} = \bigcup_{k=1}^K \{\Phi_{\text{segment}}(\mathbf{X}_k; \theta)\}$.

More detailed classifications have also been explored, including three-class tasks, where $y_k \in \{A, D, E\}$ represents interictal (A, the period between seizures), preictal (D, the time before seizure onset), and ictal (E, seizure) states [93]. Five-class tasks refine this further by subdividing the preictal state into early, middle, and late stages [94]. The Temple University Seizure Corpus (TUSZ) [81] supports detailed epilepsy studies, classifying events into pathological patterns

like epileptiform discharges and seizure types (e.g., focal, generalized, tonic-clonic), as well as non-pathological signals such as background activity and artifacts (e.g., eye movements). A detailed overview of all related works is provided in Appendix Table XI.

2) *Supervised Methods:* Supervised seizure detection using EEG/iEEG data has advanced alongside growing datasets and improved technology. Early studies relied on subject-specific or mixed-subject evaluations using short, pre-segmented EEG clips. For example, the Bonn dataset [72] consists of manually labeled seizure/non-seizure segments, leading to models optimized for fixed-length inputs. Approaches based on raw signals employ CNNs or RNNs to automatically extract spatiotemporal features from these standardized segments [29], [95], while feature-based methods derive handcrafted or transformed representations, such as scalograms [94] and wavelet-based features [96], which are more suited for shallow classifiers. These techniques inherently assume limited temporal context and avoided segmentation challenges.

With the adoption of long-term recordings like CHB-MIT [76], the focus shifts toward cross-subject paradigms. These datasets provide extensive seizure examples within continuous, long-term EEG streams, necessitating more flexible detection frameworks capable of handling variable-length inputs and identifying seizure boundaries in unsegmented data. Approaches integrate temporal modeling through sliding windows [91], sequence-aware architectures such as Transformers [97], or hybrid feature fusion techniques [98]. Concurrently, cross-subject validation becomes standard, reflecting clinical requirements that generalize across diverse conditions.

The necessity of cross-subject modeling in seizure detection stems from its critical role in ensuring clinical generalization. The invasive nature of iEEG fundamentally differentiates its modeling requirements from EEG through distinct acquisition paradigms and neurophysiological characteristics, as its patient-specific recording conditions and electrode configurations lead to substantial inter-subject heterogeneity in temporal features and spatial sampling properties, unlike EEG's

standardized scalp placement [99]. Balancing high-resolution spatiotemporal capture with robustness across patients, iEEG requires specialized methodologies to enhance generalizability while addressing its inherent complexities. Spatial modeling is essential for capturing three-dimensional epileptogenic networks with depth electrodes. Graph-based methods model inter-channel dependencies via neuroanatomical [100] or dynamic functional connections [101], while Transformer architectures use attention mechanisms to adapt to varying electrode configurations [102]. DMNet [103] improves domain generalization through self-comparison mechanisms.

3) Semi- and Unsupervised Methods: Semi-supervised and unsupervised learning techniques have become increasingly applied in deep learning for seizure detection, particularly when labeled data is limited. A common approach incorporates clustering paradigms for event-level segmentation, allowing the model to identify and segment seizure events [56]. Another notable application involves using models such as Autoencoders, DBNs and GANs to automatically extract relevant features or augment the dataset, thereby enhancing the model's robustness and generalizability [104]–[106].

4) Self-supervised Methods: Self-supervised learning has emerged as an effective approach for seizure detection. Contrastive learning captures seizure-related patterns by forming positive pairs through segment augmentation and negative pairs based on feature differences. For example, SLAM [107] generates negative pairs by pairing the anchor with a randomly selected window from a distant time point. SPP-EEGNET [108] calculates the absolute difference between pairs to classify them as positive or negative. Wagh et al. [109] employs cross-domain contrastive learning to mitigate individual differences by comparing subjects based on factors such as age. They use the delta/beta power ratio to estimate EEG-based behavioral states and distinguish pre- and post-seizure characteristics. Zheng et al. [110] employ predictive-based SSL by designing classification pretext tasks that simulate key epileptic features, such as increased amplitude and abnormal frequencies, enabling the model to recognize epilepsy-related patterns. Tang et al. [111] first combine graph-based modeling with pre-training for EEGs, where the model predicts the next set of EEG signals for a given time period.

EpilepsyNet [97] employs reconstruction-based SSL, using Pearson Correlation Coefficients to capture spatial-temporal embeddings while preserving contextual features. Wavelet2Vec [92] utilizes a frequency-aware masked autoencoder that reconstructs wavelet-transformed EEG patches in the time-frequency domain. By leveraging seizure-specific abnormal discharge patterns across frequency bands, it enhances feature extraction for seizure subtype classification. EEG-CGS [57] adopts a hybrid graph-based SSL approach, framing seizure detection as anomaly detection, integrating random walk-based subgraph sampling with contrastive and reconstruction-based learning.

The SSL paradigm is also commonly used in iEEG-based modeling. BrainNet [112] employs bidirectional contrastive predictive coding to capture temporal correlation in SEEG signals. MBrain [71] models time-varying propagation patterns and inter-channel phase delays characteristic of epileptic

TABLE IV: Public Sleep EEG Datasets, where **Recordings** denotes the number of whole-night PSG recordings.

Dataset	Recordings	Frequency (Hz)	Channels
Sleep-EDF [77], [114]	197	100	2
MASS [115]	200	256	4-20
SHHS [116], [117]	8362	125	2
SVUH_UCD [77], [118]	25	128	3
HMC [77], [119]	151	256	4
PC18 [77], [120]	1985	200	6
MIT-BIH [77], [121]	16	250	1
DOD-O [122]	55	250	8
DOD-H [122]	25	250	12
ISRUIC [123]	126	200	6
MGH [124]	25941	200	6
Piryatinska [125]	37	64	1
DRM-SUB [126]	20	200	3
SD-71 [127]	142	500	61

activity through a multivariate contrastive-predictive learning framework, leveraging graph-based representations for spatial-temporal correlations across EEG and SEEG channels. PPi [113] accounts for regional seizure variability, employing a channel discrimination task to ensure the model captures distinct pathological patterns across brain regions rather than treating all channels uniformly.

B. Sleep Staging

1) Task Description: Sleep staging is critical to understanding sleep disorders like insomnia and sleep apnea, as well as the impact on overall health. It is estimated that 20% to 41% of the global population is affected by sleep disorders, which are linked to an increased risk of obesity, cardiovascular diseases, and mental health issues [128]. Therefore, accurately identifying sleep stages is essential for addressing these concerns.

Sleep staging involves segmenting signals into 30-second epochs and classifying them into stages: awake (W), rapid eye movement (REM), and three non-REM (NREM) stages (N1, N2, N3). Wake is characterized by high-frequency β and α waves. In N1, the transition from wakefulness to sleep, low-amplitude θ waves appear. N2, the light sleep stage, is marked by sleep spindles and K-complexes associated with sensory processing and memory consolidation. N3, or deep sleep, features slow-wave δ activity. REM sleep, essential for emotional regulation and dreaming, is characterized by rapid, low-voltage brain activities.

Multimodal modeling is fundamental for sleep analysis, as polysomnography (PSG) integrates EEG (e.g., Fpz-Cz, Pz-Oz), Electrooculography (EOG), and Electromyography (EMG) to enhance staging accuracy. The public datasets listed in Table IV are frequently employed in sleep analysis. A detailed overview of all related works is provided in Appendix Table XII.

2) Supervised methods: Selecting biosignal modalities is critical for designing supervised learning frameworks in PSG-based sleep staging. Two primary paradigms are widely used. Single-channel EEG methods, preferred in resource-constrained settings, offer hardware simplicity, reduced cross-modal interference, and enhanced computational

TABLE V: Public EEG Datasets for Depression Detection, where **Exp (n)** represents the number of depressed individuals and **Ctrl (n)** represents the healthy control group.

Dataset	Exp (n)	Ctrl (n)	Frequency (Hz)	Channels
HUSM [139]	34	30	256	22
PRED+CT [140]	46	75	500	64
EDRA [141]	26	24	500	63
MODMA [142]	24	29	250	128
	26	29		3

efficiency [129], [130]. However, relying solely on EEG limits the detection of complementary cues—such as ocular and muscular activities—essential for identifying ambiguous sleep stages like REM sleep. Multimodal architectures integrating EEG, EOG, and EMG signals emulate the integrative analysis performed by sleep experts [131], [132]. Chambon et al. [131] employs techniques like spatial filtering to mitigate cross-modal interference. These designs align with clinical scoring protocols and compensate for the limited contextual information of individual modalities. Beyond these dominant approaches, hybrid models, such as EEG-EOG, balance diagnostic accuracy with computational efficiency [133].

3) *Self-supervised methods:* Self-supervised contrastive-based methods enhance sleep representation by leveraging temporal and contextual patterns in unlabeled EEG data. Early works explore tasks such as relative positioning, temporal shuffling, and autoregressive latent feature predictions to extract temporal structures from multivariate signals [68], [69]. Jiang and et al. [134] extends these efforts with augmentation-based contrastive learning, generating positive and negative pairs from augmented EEG segments. ContraWR [135] adopts constructing contrastive pairs from distinct time windows, prioritizing window-level temporal dependencies. mulEEG [136] and CoSleep [137] introduce multi-view contrastive strategies to integrate time-series and spectrogram representations of EEG data. mulEEG emphasizes cross-view consistency while encouraging modality-specific features, whereas CoSleep develops a time-frequency dual-view contrastive learning framework that implicitly captures sleep-staging-related temporal dynamics and spectral rhythmic patterns in EEG signals.

Multimodal modeling improves sleep staging accuracy by integrating complementary EEG, EOG, and EMG insights. Brant-X [138] address alignment challenges using EEG foundation models and contrastive learning. By aligning EEG and EXG signals at both the local and global levels, Brant-X effectively bridges the semantic gaps between modalities.

C. Depression Identification

1) *Task Description:* Depression, particularly Major Depressive Disorder (MDD), is a psychological condition affecting 5% of individuals worldwide, with a higher prevalence among women. In low- and middle-income countries, up to 75% of individuals lack adequate care due to limited resources and stigma, despite effective treatments being available [143].

Depression severity is quantified using standardized scales like the Beck Depression Inventory (BDI) to differentiate clinical depression from normal mood variations. Existing

TABLE VI: Public EEG Datasets for Schizophrenia, where **Exp (n)** represents the number of schizophrenia patients and **Ctrl (n)** represents the control group.

Dataset	Exp (n)	Ctrl (n)	Frequency (Hz)	Channels
CeonRepod [147]	14	14	250	19
NIMH [148]	49	32	1024	64
MHRC [149]	45	39	128	16

studies adopt heterogeneous classification criteria: some focus on binary discrimination (e.g., patients vs. healthy controls), while others stratify cohorts by treatment status (medicated vs. non-medicated) or severity levels (mild vs. moderate/severe). Table V summarizes datasets used in MDD research. A detailed overview of all related works is provided in Appendix Table XIII.

2) *Approach overview:* Depression impacts both superficial and deeper brain structures, presenting challenges for traditional handcrafted features. Acharya introduces the first end-to-end DL model for EEG-based depression detection, showing that right-hemisphere signals are significantly more distinctive than left-hemisphere ones, which aligns with clinical findings [144]. This insight has driven further studies analyzing hemispheric EEG separately, often confirming similar patterns. For example, Ay et al. introduces a hybrid CNN-LSTM architecture, with experimental results revealing a more pronounced performance improvement in the right cerebral hemisphere [21]. DeprNet [35] employs a CNN-based architecture with visualizations highlighting prominent activity in right-hemisphere electrodes for depressed subjects.

Spiking neural networks (SNNs) excel in EEG-based depression diagnosis, capturing brain-inspired spatiotemporal dynamics with biologically interpretable insights. Shah et al. [145] employ the NeuCube SNN framework to encode EEG signals into temporal spike trains, mapping them onto a 3D spiking neural network reservoir (SNNr) aligned with the Talairach brain atlas. The SNNr models spatiotemporal relationships between EEG channels using unsupervised spike-timing-dependent plasticity (STDP), offering interpretable brain connectivity visualizations. Sam et al. [146] integrates a 3D brain-inspired SNN with an LSTM, leveraging SNN's energy efficiency with LSTM's temporal modeling capabilities.

D. Schizophrenia Identification

1) *Task Description:* Schizophrenia (SZ) is a psychiatric disorder affecting 24 million people worldwide, characterized by cognitive impairments, including memory deficits, delusions, and hallucinations [150]. SZ is associated with disruptions in structural and functional brain connectivity, marked by decreased global efficiency, weakened strength, and increased clustering [151]. These abnormalities are detectable in EEG signals, making them useful for binary classification to distinguish SZ patients from healthy controls. Table VI summarizes publicly available datasets for SZ research. A detailed overview of all related works is provided in Appendix Table XIV.

2) *Approach overview:* Transfer learning has emerged as a powerful technique for fine-tuning pre-trained computer

TABLE VII: Public EEG Datasets for Alzheimer’s Diagnosis, where **AD (n)** and **MCI (n)** represent the experimental groups, and **Ctrl (n)** represents the control group.

Dataset	AD (n)	MCI (n)	Ctrl (n)	Frequency (Hz)	Channels
FSA [155]	160	-	24	128	21
AD-65 [156]	36	-	29	250	19
Fiscon [157]	49	37	14	1024	19
AD-59 [158]	59	7	102	128-256	21

vision (CV) models in EEG-based schizophrenia diagnosis, enhancing performance with minimal training. A common approach is converting EEG signals into 2D images for CNN-based models. Aslan et al. [152] feed spectrograms into a pre-trained VGG-16, applying Grad-CAM to highlight critical frequency components. SchizoGoogLeNet [153] fine-tunes the pre-trained GoogLeNet to process 2D EEG feature matrices, which are generated from preprocessed EEG signals through average filtering and resizing to align with the model’s input dimensions. Shalbaf et al. [154] transform EEG into scalogram images via CWT, using ResNet-18 and VGG-19 to extract spatial-temporal features for classification.

E. Alzheimer’s Disease Diagnosis

1) *Task Description:* Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that starts with mild memory loss and advances to severe cognitive impairment, affecting daily life. While medical interventions can improve quality of life, a definitive cure remains elusive [159]. Alzheimer’s disease (AD) progresses through three stages: preclinical, mild cognitive impairment (MCI), and Alzheimer’s dementia. Classification tasks typically distinguish MCI or Alzheimer’s dementia from healthy controls. EEG abnormalities, such as slowed brain rhythms and desynchronization, serve as biomarkers for AD-related neurodegeneration [160]. Table VII summarizes publicly available datasets. A detailed overview of all related works is provided in Appendix Table XV.

2) *Approach overview:* EEG abnormalities in Alzheimer’s disease, such as disrupted functional connectivity and altered brain rhythms, provide critical insights into the neurological changes. Brain connectivity modeling in AD can be approached from several angles. One approach, as seen in ST-GCN [161], generates functional connectivity matrices that incorporate metrics like wavelet coherence and phase-locking value to simulate spatial and temporal dependencies in EEG signals. Alves et al. [162] uses functional connectivity matrices derived from Granger causality and correlation measures to emphasize the spatial structure of brain networks. Additionally, some studies focus on spectral analysis, such as Morabito et al. [163], who convert EEG data into 2D spectral images using FFT and process these images with techniques like discriminative DCssCDBM to identify hybrid features that highlight EEG patterns associated with AD.

F. Parkinson’s Disease Diagnosis

1) *Task Description:* Parkinson’s disease (PD) is a progressive neurodegenerative disorder marked by motor symptoms

TABLE VIII: Public EEG Datasets for Parkinson’s Disease Diagnosis, where **Exp (n)** represents the number of patients and **Ctrl (n)** represents the healthy control group.

Dataset	Exp (n)	Ctrl (n)	Frequency (Hz)	Channels
UCSD [164]	15	16	512	32
UNM [165]	27	27	500	64
UI [166]	14	14	500	59

(tremors, rigidity, bradykinesia) and non-motor symptoms (depression, sleep disturbances, cognitive decline). In 2019, over 8.5 million people worldwide were living with PD [167]. EEG is widely used in PD research due to its noise resistance and sensitivity to neurological changes, such as slowing cortical oscillations and increased low-frequency power [168]. Most studies focus on supervised learning for binary classification, with some incorporating transfer learning. Table VIII summarizes publicly available datasets. A detailed overview of all related works is provided in Appendix Table XVI.

2) *Approach overview:* Transforming raw EEG signals into 2D representations is a well-established approach for PD classification, with various techniques offering distinct insights. Spectrograms, generated via Gabor Transform, as in GaborPDNet [40], preserve time-frequency characteristics while minimizing information loss. Scalograms, created using CWT, provide another effective representation [169]. According to Chu et al. [170], power spectral density (PSD) mapping is another method, where specific frequency bands like high- δ and low- α can serve as potential biomarkers for early PD diagnosis. Connectivity-based 2D representations can be obtained, like those applied by Arasteh et al. [171], compute directional connectivity and produce heatmaps that effectively capture inter-channel relationships across frequency bands.

G. ADHD Identification

1) *Task Description:* Attention-deficit/hyperactivity disorder (ADHD) is a neurodevelopmental disorder affecting around 3.1% of individuals aged 10–14 and 2.4% of those aged 15–19 [174]. It is categorized into three subtypes: Inattentive (ADHD-I), Hyperactive-Impulsive (ADHD-H), and Combined (ADHD-C) [175]. EEG is widely used alongside neuroimaging and physiological measures for ADHD diagnosis. However, deep learning remains underexplored, with most existing approaches relying on supervised learning and feature-based classification. Research focuses on binary classification tasks, and Table IX lists two publicly available datasets. A detailed overview of all related works is provided in Appendix Table XVII.

2) *Approach overview:* Studies on ADHD diagnosis identify distinct EEG neurophysiological markers, particularly

TABLE IX: Public EEG Datasets for ADHD Identification, where **Exp (n)** represents the number of ADHD patients and **Ctrl (n)** represents the healthy control group.

Dataset	Exp (n)	Ctrl (n)	Frequency (Hz)	Channels
ADHD-79 [172]	37	42	256	2
ADHD-121 [173]	61	60	128	19

abnormalities in specific frequency bands. Chen et al. [176] and Dubreuil-Vall et al. [177] demonstrate the effectiveness of CNNs for ADHD detection. Chen et al. report θ and β abnormalities in children with ADHD, while Dubreuil-Vall et al. observe altered α and $\delta - \theta$ in frontal electrodes during executive function tasks, aligning with medical findings. They also find that EEG data from executive function tasks outperform resting-state EEG for ADHD detection.

IV. UNIVERSAL PRE-TRAINED MODELS

In recent years, SSL has revolutionized EEG/iEEG analysis in neurological diagnosis. Emerging methods focus on generalizable SSL frameworks that integrate heterogeneous datasets during pre-training, overcoming the limitations of task- and dataset-specific models and enabling seamless adaptation to multiple downstream tasks. These innovations bring us closer to the development of universal neurodiagnostic models capable of addressing challenges across diverse clinical settings.

Table X summarizes pre-trained SSL frameworks for multi-task neurodiagnosis, organized by the SSL paradigms to align with their technical evolution analyzed in this section. While some frameworks extend to broader time-series data, such as BCI signals and motion sensor data, we focus on datasets and tasks directly relevant to neurological applications. Below, we further explore these frameworks, examining their contributions to unified pre-training strategies, multitask adaptability, and their potential to impact real-world applications.

A. Contrastive- and Predictive- Based Learning

a) Contrastive Predictive Coding: Early SSL approaches in EEG/iEEG analysis are largely based on the Contrastive Predictive Coding (CPC) paradigm [18], [71], which learns robust representations by predicting signal segments through contrastive learning. While these models employed generic architectures across neurophysiological tasks, they fail to achieve true cross-task generalization. As a result, they are trained separately on specific datasets, limiting their clinical applicability across diverse neurodiagnostic applications. CPC variants like TS-TCC [178] introduce a one-to-one feature transfer mechanism. This framework enables feature migration across tasks such as human activity recognition, sleep staging, and epileptic seizure detection, paving the way for broader multi-domain diagnostic generalization.

Building on the foundational principles of CPC, two distinct approaches have emerged: contrastive learning (CL) and predictive-based variants. CL retains CPC's contrastive framework but emphasizes explicit instance-level discrimination through hand-crafted augmentations for positive/negative pairs, instead of CPC's autoregressive future state prediction. Predictive variants inherit CPC's structure but replace its auto-learned latent contexts with manually defined features.

b) Contrastive-Based learning: SeqCLR [67], inspired by SimCLR, employs contrastive learning to EEG data, enhancing similarity between augmented views of the same channel through domain-specific transformations. Adopting a mixed-dataset training approach, it unifies diverse EEG

datasets for robust representation learning. TF-C [179] incorporates dual time-frequency contrastive learning with a cross-domain consistency loss to align embeddings across temporal and spectral representations. It further evaluates one-to-many paradigms, highlighting the potential of cross-task feature sharing for universal neural signal models. BIOT [180] integrates contrastive learning, unifying multimodal biosignals (e.g., EEG, ECG) via tokenization and linear attention to learn invariant physiological patterns for cross-task generalization.

c) Predictive-Based Learning: Jo et al. [181] proposes a channel-aware predictive-based framework, which leverages stopped band prediction for spectral feature learning and employs temporal trend identification to capture dynamic patterns. By integrating mix-dataset pretraining, it enhances generalization through cross-domain feature fusion. However, the pretraining scale remains limited.

B. Reconstruction-Based Learning

a) Masked Autoencoding: The paradigm shift from CPC to masked reconstruction in SSL aims for higher data efficiency and scalability, inspired by cross-domain advances like masked language modeling in NLP (e.g., BERT [189]), with MAE's generative approach enhancing classification performance while avoiding complex negative sampling.

Neuro2vec [70] extends masked reconstruction by integrating EEG-specific spatiotemporal recovery and spectral component prediction into a unified framework, utilizing a CNN-ViT hybrid architecture for patch embedding and reconstruction. CRT [182] further introduces multi-domain reconstruction through cross-domain synchronization of temporal and spectral features, replacing conventional masking with adaptive input dropping to preserve data distribution integrity, thereby improving robustness in physiological signal modeling. NeuroBERT [183] introduces Fourier Inversion Prediction (FIP), reconstructing masked signals by predicting their Fourier amplitude and phase, then applying an inverse Fourier transform. The spectral-based prediction framework inherently matches the physiological nature of EEG signals.

b) Large-Scale Continuous-Reconstruction Models: Transformer architectures excel in neurodiagnostics due to their scalability and attention mechanisms, which adaptively capture global dependencies in irregular neural signals. BERT-style pretraining, particularly masked reconstruction, enhances neurodiagnostic classification by enforcing robust contextual learning of latent bioelectrical patterns, which is crucial for distinguishing subtle neurological signatures. Their parallelizable training and tokenized time-frequency representations pave the way for scalable foundation models, driving large-scale pretraining in neural signal analysis.

Inspired by Bert, BENDR [28] integrates CPC with MAE-inspired reconstruction for temporal feature learning. Pre-trained on the Temple University Hospital EEG Corpus (TUEG)—a diverse dataset containing 1.5 TB of raw clinical EEG recordings from over 10,000 subjects—BENDR represents the emergence of large-scale pretraining for neurodiagnostics, showcasing the cross-subject scalability of transformers. It demonstrates how foundation models can unify

TABLE X: Summary of pre-trained SSL frameworks for multi-task neurodiagnosis, focusing on relevant datasets and tasks, with paradigms such as Contrastive Learning (CL), Contrastive Predictive Coding (CPC), and Masked Autoencoding (MAE)

Work	SSL Paradigm	Backbone	Data Type	Partitioning	pre-training Dataset	Downstream Tasks
Banville et al. [18]	CPC	CNN	EEG	dataset-specific	TUSZ, PC18	Seizure, Sleep
MBrain [71]	CPC	CNN+LSTM+GNN	EEG, iEEG	dataset-specific	TUSZ, private	Seizure, etc.
TS-TCC [178]	CPC	CNN+Transformer	EEG	cross-dataset	Bonn, Sleep-EDF, etc.	Seizure, Sleep, etc.
SeqCLR [67]	CL	CNN+GRU	EEG	mixed-dataset	TUSZ, Sleep-EDF, ISRUC, etc.	Seizure, Sleep, etc.
TF-C [179]	CL	CNN	EEG	cross-dataset	Sleep-EDF, etc.	Seizure, Sleep, etc.
BIOT [180]	CL	Transformer	EEG, etc.	cross-dataset	SHHS, etc.	Seizure, etc
Jo et al. [181]	Predictive	CNN	EEG	mixed-dataset	CHB-MIT, Sleep-EDF	Seizure, Sleep
neuro2vec [70]	MAE	CNN+Transformer	EEG	cross-dataset	Bonn, Sleep-EDF, etc.	Seizure, Sleep
CRT [182]	MAE	Transformer	EEG	dataset-specific	Sleep-EDF, etc.	Sleep, etc.
NeuroBERT [183]	MAE	Transformer	EEG, etc.	dataset-specific	Bonn, SleepEDF, etc,	Seizure, Sleep,etc.
BENDR [28]	CPC+MAE	CNN+Transformer	EEG	cross-dataset	TUEG	Sleep, etc.
CBRAMOD [184]	MAE	Transformer	EEG	cross-dataset	TUEG	Seizure, Sleep, MDD
Brant [99]	MAE	Transformer	iEEG	cross-dataset	private	Seizure, etc.
Brainwave [185]	MAE	Transformer	EEG, iEEG	cross-dataset	TUEG, Siena, CCEP, Sleep-EDF, NIMH, FSA, private, etc.	Seizure, Sleep, MDD, SZ, AD, ADHD
EEGFormer [186]	VQ+MAE	Transformer	EEG	cross-dataset	TUEG	Seizure, etc.
LaBraM [187]	VQ+MAE	Transformer	EEG	cross-dataset	TUEG, Siena, etc.	Seizure, etc.
NeuroLM [188]	VQ+MAE +Predictive	Transformer	EEG	cross-dataset	TUEG, Siena, etc.	Seizure, Sleep, etc.

heterogeneous neural signal paradigms, advancing generalized and scalable EEG analysis. CBRAMOD [184] introduces a criss-cross transformer framework to explicitly model EEG’s spatial-temporal heterogeneity. Using patch-based masked EEG reconstruction, it separately processes spatial and temporal patches through parallel attention mechanisms, preserving the structural dependencies unique to EEG.

Brant [99] and Brainwave [185] represent a unified effort to establish foundation models for neural signal analysis. Brant focuses on SEEG signals, employing a masked autoencoding framework with dual Transformer encoders to capture temporal dependencies and spatial correlations, enabling applications such as seizure detection and signal forecasting. Brainwave pioneers large-scale pretraining with an unprecedented multimodal corpus of over 40,000 hours of EEG and iEEG data from 16,000 subjects, marking a significant milestone in neural signal foundation models. Its pre-training strategy follows a masked modeling paradigm that randomly masks time-frequency patches of neural signals, and the model is trained to reconstruct the missing regions. To enhance generalizability across different types of neural data, Brainwave employs a shared encoder for both EEG and iEEG, coupled with modality-specific reconstruction decoders. These innovations position Brainwave as the first comprehensive foundation model capable of unifying EEG and iEEG analysis, with transformative implications for neuroscience research.

c) *Large-Scale Discrete-Reconstruction Models:* Vector Quantized Variational Autoencoder (VQ-VAE) is a powerful framework for learning discrete representations of continuous data by mapping inputs to a predefined codebook, which has been widely adopted in domains like speech and image processing [190]. By tokenizing raw data into discrete codes, this approach enhances cross-subject generalization while preserving interpretable spatiotemporal patterns.

LaBraM [187] trains its discrete codebook by reconstructing both Fourier spectral magnitudes and phases of EEG seg-

ments, then pretrains with a symmetric masking task that predicts masked code indices bidirectionally. NeuroLM [188] further extends this approach by introducing VQ Temporal-Frequency Prediction, aligning EEG tokens with textual representations through adversarial training. After tokenization, it employs multi-channel autoregressive modeling, enabling an LLM to predict the next EEG token in a manner analogous to language modeling. EEGFormer [186] focuses on reconstructing raw temporal waveforms for codebook training, followed by BERT-style masked signal reconstruction pretraining. These methods demonstrate how VQ-based tokenization adapts to EEG modeling—whether prioritizing spectral synchrony (LaBraM), fusing time-frequency features (NeuroLM), or preserving temporal fidelity (EEGFormer).

C. BrainBenchmark

The development of universal pre-trained frameworks represents a transformative advancement in healthcare, enabling the integration of heterogeneous datasets and generalization across diverse diagnostic tasks. To systematically evaluate and advance this field, we have established an open benchmark, currently comprising 8 models and 9 public datasets focused on neurological diagnostics, with ongoing expansions planned. This benchmark supports comprehensive performance evaluation, custom model integration, and dataset extensibility, fostering reproducible research and innovation. The implementation is publicly available at <https://github.com/ZJU-BrainNet/BrainBenchmark>. Future work will include a detailed analysis of benchmark results to further advance universal frameworks in EEG/iEEG analysis.

V. CONCLUSION

This survey systematically reviews 448 studies and 46 public datasets to advance deep learning-driven analysis of EEG/iEEG signals across seven neurological diagnostic tasks:

seizure detection, sleep staging and disorder, major depressive disorder, schizophrenia, Alzheimer’s disease, Parkinson’s disease, and ADHD. Our work establishes three foundational contributions: First, we unify fragmented methodologies across neurological conditions by standardizing data processing, model architectures, and evaluation protocols. Second, we identify self-supervised learning as the most promising paradigm for multi-task neurodiagnosis, providing a comprehensive overview of pre-trained SSL frameworks and their advancements. Third, we introduce BrainBenchmark to enhance reproducibility by integrating neurological datasets and universal models under standardized evaluations.

Looking back, the pursuit of universal models capable of learning from diverse, multimodal data reflects the field’s growing ambition. It lays the groundwork for a new era of intelligent and adaptable healthcare systems. Over the past decades, significant progress in traditional methods has established a strong foundation for neurological diagnostics based on electrical brain signals. Key contributions include advances in signal preprocessing techniques, curating large-scale, well-annotated datasets, and developing deep learning architectures for specific tasks. Building on this foundation, the integration of self-supervised pretraining marks a paradigm shift, enabling models to extract rich and meaningful representations from vast amounts of unlabeled, heterogeneous data.

Looking forward, the ultimate goal is to develop genuinely universal and adaptable frameworks capable of transcending individual tasks and datasets to address a broader range of neurological disorders. These advancements will pave the way for intelligent diagnostic tools that deliver precise, efficient, and accessible healthcare solutions globally, driving transformative progress in biomedical research and clinical applications.

ACKNOWLEDGMENT

This work is supported by NSFC (62322606) and Zhejiang NSF (LR22F020005).

In this section, we provide summaries of deep learning-based frameworks for the seven neurodiagnostic tasks mentioned earlier. These summaries include details on preprocessing methods, extracted features, deep learning backbones, training paradigms, downstream task datasets, classification tasks, data partitioning strategies, and reported performances. The relevant tables are as follows: seizure detection in Table XI, sleep staging in Table XII, depression identification in Table XIII, schizophrenia identification in Table XIV, Alzheimer’s disease diagnosis in Table XV, Parkinson’s disease diagnosis in Table XVI, and ADHD identification in Table XVII.

TABLE XI: Summary of deep learning frameworks for seizure detection

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[191]	Image generation	2D Image	2D-CNN	supervised	Bern-Barcelona, private	binary	mixed-subject	100%
[93]	FFT	Frequency-domain features	2D-CNN	supervised	Freiburg, CHB-MIT	binary 3-class	subject-specific	98.2%- 99.4% 95.3%
[192]	Filtering,Downsampling	Raw	2D-CNN	supervised	private	binary	cross-subject	AUC=0.94
[193]	FSST,WSST	Time-Frequency matrix	2D-CNN	supervised	Bern-Barcelona	binary	mixed-subject	99.94%
[194]	Filtering,EMD,FWT,FT	Raw,IMFs, Wavelet Coefficients, Module Values	2D-CNN	supervised	Bern-Barcelona, private	binary	mixed-subject	98.9%
[195]	Z-norm,STFT	2D Spectrograms	2D-CNN	supervised	Bern-Barcelona, private	binary	mixed-subject	91.8%
[46]	Filtering	2D Images	2D-CNN	supervised	Bonn	binary	mixed-subject	99.6%
[94]	CWT	2D Scalograms	2D-CNN	supervised	Bonn	binary 3-class 5-class	mixed-subject	93.60%
[196]	Windowing	Raw Segments	2D-CNN	supervised	CHB-MIT	binary	mixed-subject	99.07%
[197]	Image construction	intensity Image	2D-CNN	supervised	CHB-MIT	binary	mixed-subject	99.48%
[198]	Windowing,Normalization	Raw	2D-CNN	supervised	CHB-MIT	binary	cross-subject	98.05%
[199]	FFT,WPD	Time-Frequency features	2D-CNN	supervised	CHB-MIT	binary	subject-specific	98.33%
[200]	STFT,Filtering, MAS calculation	MAS Map Image	2D-CNN	supervised	CHB-MIT, private	binary 3-class 5-class	mixed-subject	99.33% 98.62% 87.95%
[201]	MPS	2D Spectrograms	2D-CNN	supervised	CHB-MIT, private	binary	mixed-subject	SEN>90%
[202]	Filtering,Segmentation	2D Image	2D-CNN	supervised	private	binary	cross-subject	TPR=74%
[203]	Filtering,Normalization, Image generation	2D Image	2D-CNN	supervised	private	binary	mixed-subject	87.65%
[204]	FFT	2D Spectrograms	2D-CNN	supervised	TUSZ	binary	cross-subject	F1=59.2%
[205]	Segmentation, Image generation	RPS Image	2D-CNN	supervised	Bonn	binary 3-class	mixed-subject	98.5% 95%
[206]	CWT	Scalograms	2D-CNN	supervised	Bonn	binary	mixed-subject	72.49%
[207]	Hilbert Transform, GASF,GADF	2D Images	2D-CNN	supervised	Bonn	binary	mixed-subject	98%
[208]	Filtering,DWT	2D Image	2D-CNN	supervised	Bonn	binary	mixed-subject	97.74%
[209]	Segmentation	Raw Segments	2D-CNN	supervised	CHB-MIT	binary	cross-subject	99.72%
[210]	Segmentation,DWT	PSDED	2D-CNN	supervised	CHB-MIT	4-class	mixed-subject	92.6%
[211]	Channel selection, Image generation	2D Image	2D-CNN	supervised	CHB-MIT	3-class	mixed-subject	94.98%
[212]	Segmentation,STFT	2D Spectrograms	2D-CNN	supervised	CHB-MIT	binary	subject-specific	95.65%
[213]	Filtering,Segmentation, STFT	2D Spectrograms	2D-CNN	supervised	CHB-MIT	binary	subject-specific	SEN=92.7%
[214]	Segmentation,STFT	2D Spectrograms	2D-CNN	supervised	CHB-MIT	binary	mixed-subject	98.26%
[215]	Filtering,FT,Welch's,WPD	Fusion feature Image	2D-CNN	supervised	CHB-MIT, private	5-class	mixed-subject	98.97%
[216]	Normalization,DWT, S-Transform	2D Spectrograms	2D-CNN	supervised	Freiburg	binary	subject-specific	98.12%
[217]	Segmentation,CWT	scalograms	2D-CNN	supervised	Melbourne	binary	mixed-subject	AUC=0.928
[218]	Filtering,STFT	2D Spectrograms	2D-CNN	supervised	TUSZ	binary	cross-subject	88.3%
[219]	Filtering,Segmentation	Raw Segments	2D-CNN	supervised	TUSZ	binary	cross-subject	70.38%
[220]	Segmentation,STFT,CWT	2D Spectrogram, Scalogram	2D-CNN	supervised	Bonn	binary	mixed-subject	99.21%

(Continued) Summary of deep learning frameworks for seizure detection

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[221]	Segmentation, FNSW	2D Image	2D-CNN	supervised	Bonn	binary 3-class 5-class	mixed-subject	100%
[222]	Segmentation,EMD,WOG	Graph representation	2D-CNN	supervised	Bonn, private	binary	mixed-subject	100% 97.65%
[223]	Z-norm,Windowing	RPS Image	2D-CNN	supervised	Bonn	binary	mixed-subject	92.3%
[224]	Filtering,CWT	2D Scalograms	2D-CNN	supervised	Bonn	binary	mixed-subject, cross-subject	99.5%
[225]	STFT	2D Spectrograms	2D-CNN +Attention	supervised	CHB-MIT	binary	mixed-subject	96.61%
[226]	Filtering,Z-norm	Raw Segments	2D-CNN +Attention	supervised	SWEC-ETHZ,private	binary	subject-specific	AUC=0.92 AUC=0.96
[51]	STFT	Spectrograms	3D-CNN	supervised	CHB-MIT, private	binary	cross-subject	99.4%
[227]	Segmentation,WT	Relative Energy matrix	Bi-GRU	supervised	CHB-MIT, private	binary	cross-subject, subject-specific	SEN=95.49
[228]	Segmentation, Time-GAN	Enhanced Segments	BiLSTM	supervised	private	binary	cross-subject	78.5%
[229]	Filtering,Frequency feature extraction	Linear features	Bi-LSTM	supervised	Bonn	binary	mixed-subject	98.56%
[230]	Z-norm,Filtering, Segmentation	Raw Segments	Bi-LSTM	supervised	Bern-Barcelona	binary	mixed-subject	99.6%
[231]	Segmentation,LMD	Statistical features	Bi-LSTM	supervised	CHB-MIT	binary	subject-specific	SEN=93.61%
[232]	Segmentation, S-transform	Spectrogram	Bi-LSTM	supervised	Freiburg	binary	subject-specific	98.69%
[233]	Segmentation	Segments	Bi-LSTM	supervised	CHB-MIT	binary	mixed-subject, cross-subject	87.8%
[234]	Normalization, Instantaneous frequency	Spectral entropy	Bi-LSTM	supervised	Bonn	binary 5-class	mixed-subject	100% 96%
[26]	Baseline Correction, Windowing,linear detrending	Raw Segments	CNN	supervised	private	binary	cross-subject	87.51%
[235]	Downsampling, Filtering	Raw	CNN	supervised	private	binary	cross-subject	97.1%
[29]	Z-norm	Raw	CNN	supervised	Bonn	binary	mixed-subject	88.67%
[236]	Segmentation,EMD	IMFs of EMD	CNN	supervised	Bonn	binary 3-class	mixed-subject	100% 98.6%
[237]	Segmentation	Raw Segments	CNN	supervised	Bonn	binary	mixed-subject	99.1%
[238]	Normalization	Raw Segments	CNN	supervised	Bonn	binary 5-class	cross-subject	97.38% 93.67%
[239]	Filtering,Segmentation	Raw Segments	CNN	supervised	CHB-MIT	binary	cross-subject	SEN=86.29%
[240]	Filtering,Downsampling, CAR montage	Raw	CNN	supervised	private	binary	cross-subject	AUC=93.5%
[241]	Segmentation, Normalization, Standardization	Segments	CNN	supervised	TUSZ	binary	cross-subject	79.34%
[96]	DWT	Wavelet Coefficients	CNN	supervised	Bonn	binary	mixed-subject	100%
[242]	Filtering, Z-norm	Raw	CNN	supervised	Bonn	binary	mixed-subject	99%
[243]	Data Augmentation, feature enhancement	Enhanced Segments	CNN	supervised	CHB-MIT	binary	cross-subject	SEN=74.08%
[244]	Filtering,Windowing	Raw Segments	CNN	supervised	CHB-MIT, private	binary	mixed-subject	AUC=0.8
[245]	Filtering,Windowing	Raw Segments	CNN	supervised	private	binary	cross-subject	AUC=0.83
[246]	Downsampling,Z-norm, Windowing,Data Augmentation	Raw Segments	CNN	supervised	private	binary	cross-subject	SEN=95.8%
[247]	Z-norm,Filtering, Segmentation	Raw Segments	CNN	supervised	private	binary	cross-subject	AUC=0.961
[248]	Normalization, Segmentation	Raw Segments	CNN	supervised	Bern-Barcelona	binary	mixed-subject	91.5%
[249]	Filtering, Data Augmentation	Augmented data	CNN	supervised	Bern-Barcelona	binary	mixed-subject	89.28%

(Continued) Summary of deep learning frameworks for seizure detection

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[48]	Filtering,DWT, Power Spectrum Band Calculation,Frequency Band Calculation	2D Image	CNN	supervised	Bonn	binary	cross-subject	99.99%
[250]	Segmentation,Filtering	ApEn and RQA vector	CNN	supervised	Bonn	binary	mixed-subject	99.26%
[251]	Normalization,CWT	2D Scalograms	CNN	supervised	Bonn	binary	mixed-subject	98.78%
[252]	Filtering	Raw	CNN	supervised	Bonn	binary	mixed-subject	100% 99.8%
[253]	-	Raw	CNN	supervised	Bonn	3-class	mixed-subject	98.67%
[254]	Segmentation, Data Augmentation	Raw Segments	CNN	supervised	Bonn	binary	mixed-subject	AUC=0.92%
[255]	Z-norm	Raw	CNN	supervised	Bonn	binary 5-class	mixed-subject	99.93% 94.01%
[256]	Normalization	Raw	CNN	supervised	Bonn	binary 3-class 5-class	mixed-subject	98.5-100%
[257]	Segmentation, Normalization	Raw Segments	CNN	supervised	Bonn	binary 3-class 5-class	mixed-subject	97.63%-99.52% 96.73%-98.06% 93.55%
[258]	Z-norm	Raw	CNN	supervised	Bonn, CHB-MIT	binary	mixed-subject	98.67%
[259]	Segmentation,Baseline Removal,Resampling, Detrending,Filtering	Raw Segments	CNN	supervised	Bonn, TUSZ, CHB-MIT	binary	subject-specific	99.8% 92% 95.96%
[260]	Channel selection	Raw	CNN	supervised	CHB-MIT	binary	subject-specific	96.1%
[261]	Filtering,Segmentation, Spectrogram generation	2D Spectrograms	CNN	supervised	CHB-MIT	binary	subject-specific	77.57%
[262]	Segmentation	Raw Segments	CNN	supervised	CHB-MIT	binary	mixed-subject	96.74%
[263]	Normalization, Segmentation	Raw Segments	CNN	supervised	CHB-MIT	binary	cross-subject	97%
[264]	Segmentation,Filtering, FFT,WT	spectral data	CNN	supervised	CHB-MIT	binary	mixed-subject	97.25%
[265]	Filtering,resampling, Segmentation	Raw Segments	CNN	supervised	CHB-MIT	binary	subject-specific	84.1%
[266]	Segmentation	Raw Segments	CNN	supervised	CHB-MIT, Mayo-Upenn	binary	subject-specific	AUC=0.970 AUC=0.915
[267]	Downsampling,Filtering, Artifact Removal	Raw Segments	CNN	supervised	private	binary	cross-subject, subject-specific	99.6%
[268]	Z-norm,Filtering	Raw Segments	CNN	supervised	private	binary	cross-subject	80%
[269]	Segmentation,Filtering, Data Augmentation	Raw	CNN	supervised	private	binary	cross-subject, subject-specific	96.39%
[270]	Filtering,Segmentation	Raw Segments	CNN	supervised	private	binary	cross-subject	-
[271]	Filtering,Downsampling, Segmentation	Raw Segments	CNN	supervised	private	binary	subject-specific	AUC=98.9
[272]	Windowing,Normalization	Raw Segments	CNN	supervised	private	binary	cross-subject	77%
[273]	Downsampling,Windowing	Raw, Periodogram, Spectrograms, Image	CNN	supervised	Mayo-Upenn	binary	cross-subject, subject-specific	99.9%
[274]	Segmentation	Raw Segments	CNN	supervised	Mayo-UPenn, CHB-MIT	binary	subject-specific	AUC=0.981 AUC=0.988
[275]	Time-Frequency feature extraction	Pattern Matrices	CNN	supervised	TUSZ	binary	cross-subject	AUC=0.74
[276]	Segmentation	Raw Segments	CNN	supervised	TUSZ	binary	cross-subject	80.5%
[277]	1D-AaLBP,1D-AdLBP	Histogram-based feature	CNN	supervised	Bonn, CHB-MIT	binary 5-class	mixed-subject	98.8% - 99.65% 99.11%
[278]	Filtering,Segmentation, FFT	Frequency-domain features	CNN	supervised	Mayo-Upenn	binary	subject-specific	94.74%
[103]	Normalization,Differencing	Difference Matrix	CNN	supervised	MAYO, FNUSA, private	binary	cross-subject	F2=55.93-81.54

(Continued) Summary of deep learning frameworks for seizure detection

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[279]	Filtering,GPSO	Time- & Freq-domain features	CNN	supervised	Bonn	binary	mixed-subject	99.65%
[280]	Z-norm,FFT	Raw,features	CNN	supervised	Bonn	binary	mixed-subject	98.23%
[281]	Normalization,Filtering, STFT	RPSD,SampEn,SI	CNN	supervised	CHB-MIT	binary	subject-specific	96.33%
[282]	Normalization, Segmentation	Raw Segments	CNN	supervised	private	binary	mixed-subject	94.5%
[283]	Filtering,Segmentation	Freq-features, Time-Freq Image	CNN 3D-CNN	supervised	Helsinki	binary	cross-subject	99.61%
[284]	Filtering,Segmentation, Artifact rejection	Raw Segments	CNN 2D-CNN	supervised	private	binary	cross-subject	90.06%
[285]	Normalization	Raw	CNN CNN-LSTM	supervised	CHB-MIT	binary	subject-specific	91.50%
[286]	Segmentation	Raw	CNN,LSTM	supervised	CHB-MIT	binary	92.11%	
[287]	Segmentation, Normalization	Nan	CNN LSTM GRU	supervised	Bonn	binary	mixed-subject	89.21%
[288]	STFT	2D Spectrograms	CNN+Attention	supervised	CHB-MIT	binary	cross-subject	96.67%
[289]	Filtering,Downsampling, Segmentation	Raw Segments	CNN+Attention	supervised	private	binary	cross-subject	AUC=0.97
[290]	Downsampling, Segmentation	Raw Segments	CNN-BiGRU	supervised	CHB-MIT, Bonn, Mayo-Upenn	binary	mixed-subject	0.985
[53]	DWT	Statistical,Freq-, Nonlinear features	CNN-BiGRU +Attention	supervised	Freiburg	binary	mixed-subject	98.35%
[291]	Filtering,Segmentation, Normalization	Raw Segments	CNN-BiLSTM	supervised	private	binary	cross-subject	AUC=0.9042
[292]	Normalization,K-means SMOTE	Raw Segments	CNN-BiLSTM	supervised	Bonn	binary	mixed-subject	99.41%
[293]	Downsampling,Bipolar Reference,Segmentation	Raw Segments	CNN-BiLSTM +Attention	supervised	Mayo-UPenn, private	binary	cross-subject	84.10%
[98]	Windowing	Raw Segments	CNN-BiLSTM +Attention	supervised	CHB-MIT	binary	subject-specific	94.12%
[294]	Filtering,S-transform	Adjacency matrix	CNN-GCN	supervised	CHB-MIT	binary	cross-subject	96.61%
[295]	TCP	Raw	CNN-GRU	supervised	TUSZ	binary	cross-subject	98%
[296]	Segmentation,WPT	Multi-view feature matrix	CNN-GRU	supervised	CHB-MIT	binary	subject-specific	SEN=94.50%
[297]	Filtering,CWT	2D Scalograms	CNN-GRU	supervised	Bonn	binary	mixed-subject	100%
[91]	Windowing,Filtering, Z-norm	-	CNN-GRU	supervised	CHB-MIT	binary	subject-specific	100%
[298]	Frequency Decomposition,Image generation	2D Image	CNN-LSTM	supervised	CHB-MIT	binary	cross-subject, subject-specific	99.4%
[299]	Segmentation,PCA	LFCCs	CNN-LSTM	supervised	TUSZ,private	6-class	cross-subject	SEN=96%
[300]	-	Raw	CNN-LSTM	supervised	Bonn	binary	mixed-subject	100%
[301]	Segmentation	Raw Segments	CNN-LSTM	supervised	Bonn	binary	mixed-subject	98.33%
[302]	Normalization	Raw	CNN-LSTM	supervised	Bonn	binary	mixed-subject	98.8%
[303]	Filtering,Segmentation	Raw Segments	CNN-LSTM	supervised	Bonn, Freiburg, CHB-MIT	binary	mixed-subject	99.39%
[304]	Segmentation, Image generation	2D Image	CNN-LSTM	supervised	CHB-MIT	4-class	cross-subject	95.29%
[305]	Segmentation,FFT,DWT	Time-Frequency features	CNN-LSTM	supervised	Freiburg	binary	mixed-subject	99.27%
[306]	Segmentation, Format Conversion	EEG video	CNN-LSTM	supervised	private	binary	cross-subject	SEN=88%

(Continued) Summary of deep learning frameworks for seizure detection

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[307]	Filtering,Segmentation, CWT,STFT	2D Spectrogram, Scalogram	CNN-LSTM	supervised	Bonn CHB-MIT Bern-Barcelona	binary	mixed-subject	99.94% 93.77% 95.08%
[308]	Filtering,STFT	2D Spectrograms	CNN-LSTM	supervised	CHB-MIT	binary	subject-specific	94.5%
[309]	Filtering,Difference	Raw,Differential signal	CNN-LSTM +Attention	supervised	Bonn	binary 5-class	mixed-subject	98.87% 90.17%
[310]	Filtering,Resampling,TCP	Segments	CNN-RNN	supervised	TUSZ	binary	cross-subject	82.27%
[311]	Segmentation	Raw Segments	CNN-RNN +Attention	supervised	CHB-MIT	binary	mixed-subject	SEN=92.88%
[312]	Normalization	Raw Segments	CNN-Transformer	supervised	TUSZ	various	cross-subject	AUC=0.72
[313]	Channel selection, Windowing	Raw Segments	CNN-Transformer	supervised	CHB-MIT	binary	cross-subject, subject-specific	SEN=65.5%
[102]	Filtering,resampling, Windowing	Raw Segments	CNN-Transformer	supervised	SWEC-ETHZ, private	binary	subject-specific	SEN=97.5%
[314]	Filtering,Z-norm,DWT	Rhythm Signals	CNN-Transformer	supervised	CHB-MIT	binary	cross-subject	SEN=91.7%
[315]	Filtering,Windowing	Raw Segments	CNN-Transformer	supervised	CHB-MIT	binary	subject-specific	AUC=0.937
[316]	Filtering,Downsampling, Bipolar Reference	Raw Segments	CNN-Transformer	supervised	TUSZ, CHB-MIT	binary	cross-subject	49.1%- 85.8%
[317]	Filtering,Segmentation, STFT	Time-Frequency features	CNN-Transformer	supervised	CHB-MIT	binary	cross-subject	94.75%
[318]	Bipolar referencing, Filtering,Z-norm	Raw Segments	CNN-Transformer	supervised	SWEC-ETHZ HUP	binary	cross-subject	91.15% 88.84%
[319]	DWT	Wavelet-based features	DBN	supervised	private	binary	cross-subject	96.87%
[320]	Segmentation,GASF	GASF Image	Pre-Trained Networks, Deep ANN	supervised	Bern-Barcelona	binary	mixed-subject	AUC=0.92
[321]	Min-max Normalization	Raw	DNN	supervised	Bonn	binary	mixed-subject	97.17%
[322]	Normalization	Raw	DNN	supervised	Bonn	binary	mixed-subject	80%
[323]	Filtering,Segmentation,ToC	SAE-based	DNN	supervised	Bonn	binary 3-class 5-class	mixed-subject	100% 99.6% 97.2%
[324]	DWT,Normalization	Nonlinear and entropy features	DNN	supervised	Bonn, Bern-Barcelona, CHB-MIT	binary 3-class	mixed-subject	93.61%(Bonn)
[325]	Filtering,Z-norm,DWT	Wavelet Coefficients	DWT-Net	supervised	TUSZ	binary	cross-subject	SEN=59.07%
[326]	Filtering,Z-norm, Network construction	Adjacency matrix	GAT	supervised	CHB-MIT	binary	subject-specific	98.89%
[327]	Filtering,Network construction	Node Feature matrix,Adjacency matrix	GAT+GRU	supervised	CHB-MIT, private	binary	cross-subject, subject-specific	98.74%
[328]	Filtering,Z-norm, Network construction	Adjacency matrix,Raw	GAT +Transformer	supervised	CHB-MIT	binary	cross-subject, subject-specific	98.3%
[329]	Filtering,Z-norm	Node Feature matrix,Adjacency matrix	GAT-BiLSTM	supervised	CHB-MIT	binary	subject-specific	98.52%
[330]	ICA	Correlation matrix	GCN	supervised	Bonn, CHB-MIT	binary 3-class	mixed-subject	99.8% 99.2%
[331]	FFT,VG	Frequency-domain Network	GCN	supervised	Bonn, private	binary	mixed-subject	100%
[332]	Filtering,Segmentation, Network construction	Raw Segments, Adjacency matrix	GCN	supervised	CHB-MIT	binary	subject-specific	99.3%
[333]	Filtering,Z-norm, Segmentation,Network construction	EEG Network	GCN	supervised	private	binary	mixed-subject	AUC=0.91

(Continued) Summary of deep learning frameworks for seizure detection

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[334]	Segmentation,Network construction	Adjacency matrix	GCN	supervised	CHB-MIT	binary	subject-specific	98.38%
[335]	Filtering,Z-norm	Node Feature matrix,Adjacency matrix	GCN+Attention	supervised	CHB-MIT	binary	subject-specific	98.7%
[336]	Filtering,Windowing	Raw Segments	GCN-Transformer	supervised	CHB-MIT	binary	subject-specific	AUC=0.935
[101]	Filtering,Segmentation,FFT	Node Feature matrix,Adjacency matrix	GNN	supervised	TUSZ	binary	cross-subject	81.77%
[337]	Filtering,Segmentation, Network construction	NaN	GNN+Transformer	supervised	CHB-MIT	binary	subject-specific	98.43%
[338]	Segmentation	Raw Segments	GRU	supervised	Bonn	3-class	mixed-subject	98%
[339]	DWT	Wavelet Coefficients	GRU	supervised	Bonn	binary	subject-specific	98.5%
[340]	-	Raw	GRU	supervised	Bonn	binary	mixed-subject	97.5%
[341]	Segmentation	Raw Segments	LSTM	supervised	Bonn	3-class	mixed-subject	100%
[342]	-	Raw	LSTM	supervised	Bonn	binary	mixed-subject	95.54%
[343]	Data Augmentation, Segmentation	Raw Segments	LSTM	supervised	Bonn	binary	mixed-subject	100%
[344]	Z-norm,DCT	Hurst & ARMA features	LSTM	supervised	Bonn	binary	mixed-subject	99.17%
[345]	DWT	20 Eigenvalue features	LSTM	supervised	Bonn	binary	mixed-subject	94.81% 99%
[346]	Filtering,Segmentation,FFT	Freq-domain features	LSTM	supervised	CHB-MIT	binary	subject-specific	98.14%
[347]	DWT,CFS	Time-Frequency features	LSTM	supervised	TUSZ	binary	cross-subject	98.08% 95.92%
[348]	Filtering,decomposition	Time- & Freq-domain features	LSTM	supervised	CHB-MIT, Siena, Beirut, Bonn	binary	mixed-subject, cross-subject	94.69%
[349]	Filtering	Montage grid	RNN	supervised	CHB-MIT	binary	subject-specific	SEN=100%
[350]	Segmentation	Raw Segments	RNN	supervised	CHB-MIT	binary	cross-subject	88.7%
[351]	Segmentation	Raw Segments	RNN	supervised	CHB-MIT	binary	mixed-subject	87%
[352]	-	Raw	RNN	supervised	Bonn	3-class	mixed-subject	99.33% 98.2%
[353]	Filtering,Z-norm, Windowing	Raw Segments	RNN-Transformer	supervised	Bonn, CHB-MIT	binary	subject-specific	98.2% 81.33%
[354]	STFT	Spectrogram	RNN-Transformer	supervised	Bonn, CHB-MIT	binary	subject-specific	95.06% 99.75%
[355]	STFT	Spectrograms	TGCN	supervised	private	binary	cross-subject	AUC=0.928
[356]	Resampling,Segmentation	Raw Segments	Transformer	supervised	TUSZ	binary	cross-subject	SEN=9.03%
[357]	STFT,Bipolar Montage	Time-Frequency Graph	Transformer	supervised	TUSZ	binary	cross-subject	AUC=0.921
[20]	Subspace Filtering, ICLabel	Raw,Subspace Filtering,ICLabel	U-net	supervised	TUSZ	binary	cross-subject	-
[358]	Filtering,PSD	PSD	DNN	supervised	private	binary	subject-specific	-
[359]	Filtering	Hypergraph-based HSO	DNN	supervised	private	binary	mixed-subject	90.70%
[109]	Filtering,Downsampling, Segmentation	2D Topomap	2D-CNN	self-supervised	TUSZ	binary	cross-subject	AUC=0.92
[110]	-	Raw Segments	CNN	self-supervised	CHB-MIT, Mayo-UPenn, private	binary	mixed-subject, cross-subject	AUC=0.92-0.95
[112]	Windowing	Raw Segments	CNN-GNN	self-supervised	private	binary	cross-subject	F2=76.87%

(Continued) Summary of deep learning frameworks for seizure detection

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[113]	Downsampling, Segmentation	Time- & Freq-domain features, Raw	CNN-LSTM	self-supervised	Mayo-UPenn, FNUSA, private	binary	cross-subject	F1=85.6% F1=82.3% F1=87.1%
[111]	Z-norm,FFT	Adjacency matrix,Frequency-domain features	GNN	self-supervised	TUSZ	binary	cross-subject	AUC=0.875
[57]	FFT,graph construction	EEG Network	GNN	self-supervised	TUSZ	binary	cross-subject	F1=0.534%
[97]	Segmentation,PCC	PCC matrix	Transformer	self-supervised	Turkish	binary	cross-subject	85%
[107]	Filtering,Z-norm, Windowing	Raw Segments	Transformer	self-supervised	CHB-MIT	binary	cross-subject	97.07%
[108]	Filtering,Segmentation	Raw Segments	CNN	self-supervised	TUSZ	binary	cross-subject	-
[92]	DWPT	Wavelets	Transformer	self-supervised	TUSZ	4-class	cross-subject	73%
[360]	Normalization, Data Enhancement	AE-based	AE	semi-supervised	Bonn	binary	cross-subject	99.6% 96.4%
[361]	Segmentation,Filtering, Data Augmentation	Raw Segments	CNN	semi-supervised	CHB-MIT, private	binary	mixed-subject	90.58%
[362]	Artifacts removal,FFT	2D Spectrograms	CNN	semi-supervised	private	binary	cross-subject	95.70%
[363]	STFT	SSDA-based	2D-CNN	unsupervised	CHB-MIT	binary	cross-subject	94.37%
[364]	FFT	BP-ASE-based	2D-CNN	unsupervised	CHB-MIT	binary	cross-subject	99.4%
[104]	-	AE-based	CNN	unsupervised	Bonn	binary	cross-subject	100% 99.33%
[27]	Normalization	AE-based	CNN	unsupervised	Bonn, CHB-MIT	binary	cross-subject	100% 92%
[365]	Segmentation,STFT	GAN-based	CNN	unsupervised	CHB-MIT, EPILEPSIAE, Freiburg	binary	subject-specific	77.68% 75.47% 65.05%
[56]	FT,WT	Spectrograms	CNN	unsupervised	Freiburg	clustering	subject-specific	97.38%
[366]	Filtering,Segmentation	AE-based	CNN	unsupervised	private	3-class	subject-specific	98.84%
[367]	Filtering,Segmentation	AE-based	CNN	unsupervised	Bonn	binary	cross-subject	99.8%
[368]	Normalization	Raw	DBN	unsupervised	private	5-class	cross-subject	F1=0.93%
[105]	Min-max Normalization	Time-domain features	DBN	unsupervised	private	binary	cross-subject, subject-specific	F1=90%
[369]	Filtering,Normalization	DCAE-based	DCAE	unsupervised	Bonn, Bern-Barcelona	binary	mixed-subject	96% 93.21%
[370]	Segmentation, Normalization	SSAE-based	DNN	unsupervised	Bonn	binary	mixed-subject	96%
[371]	Filtering	SAE-based	DNN	unsupervised	Bonn	binary 3-class 5-class	mixed-subject	100%
[372]	STFT	SSDA-based	DNN	unsupervised	CHB-MIT	binary	mixed-subject	93.92%
[373]	Taguchi Method	SSAE-based	DNN	unsupervised	Bonn	binary	mixed-subject	100%
[374]	Segmentation,Z-norm	DSAE-based	DNN	unsupervised	Bonn	binary	mixed-subject	100%
[375]	Filtering,Segmentation, HWPT,FD	AE-based	DNN	unsupervised	Bonn	binary	mixed-subject	98.67%
[376]	Segmentation,CWT	SAE-based	DNN	unsupervised	CHB-MIT	binary	mixed-subject	93.92%
[377]	Downsampling,Filtering, Z-norm	AE-based	DNN	unsupervised	private	binary	subject-specific	SEN=100%
[43]	ESD	DSAE-based	DNN	unsupervised	private	binary	mixed-subject	100%
[58]	FBSE-EWT	SAE-based	DNN	unsupervised	Bern-Barcelona	binary	mixed-subject	100%
[106]	Filtering,Segmentation, Z-norm,STFT	2D Spectrograms	GAN	unsupervised	private	binary	subject-specific	AUC=0.9393

TABLE XII: Summary of deep learning frameworks for sleep staging

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[378]	Filtering,Feature Extraction	Time- & Freq-features	3D-CNN	supervised	ISRUC	5-class	cross-subject	82%-83.2%
[130]	AFR	Raw Segments	CNN	supervised	Sleep-EDF, SHHS	5-class	cross-subject	82.9%-86.6%
[379]	Filtering,Resampling	Raw Segments	CNN-Transformer	supervised	Sleep-EDF, ISRUC, private	5-class	cross-subject	84.76%-86.32%
[380]	Resampling,Segmentation	Raw Segments	CNN	supervised	Sleep-EDF, SHHS	5-class	cross-subject	85.3% 88.1%
[381]	DCT	DCT Coefficients	CNN-LSTM	supervised	SleepEDF, DRM-SUB, ISRUC	5-class	cross-subject	85.47%-87.11%
[382]	Segmentation	Raw Segments	CNN-BiLSTM	supervised	Sleep-EDF, MASS	5-class	cross-subject	82.0% 86.2%
[383]	Filtering,Spectrogram Generation	2D Spectrogram	2D-CNN	supervised	Sleep-EDF, SHHS	5-class	mixed-subject	83.02%-94.17%
[384]	Filtering,Downsampling	Complex Values	CNN	supervised	UCD, MIT-BIH	5-class	cross-subject	92%
[385]	Filtering,DE Calculation	DE matrix	GCN	supervised	MASS	5-class	cross-subject	88.90%
[386]	Filtering,Segmentation, PCC,PLV	EEG Network	CNN+Attention	supervised	Sleep-EDF	5-class	cross-subject	81%-85.8%
[387]	-	Raw Segments	CNN-biLSTM	supervised	Sleep-EDF, MASS, SHHS	5-class	cross-subject	83.9%-86.7%
[388]	feature extraction	Freq- features	CNN	supervised	Sleep-EDF	5-class	cross-subject	81.5%-86.6%
[389]	Segmentation	Raw Segments	CNN	supervised	Sleep-EDF, SHHS	5-class	cross-subject	79.5%-83.3%
[390]	Segmentation,Network construction	Spatial-Temporal features	GCN+Attention	supervised	MASS, ISRUC	5-class	cross-subject	88.1% 90.5%
[32]	Resampling,Filtering,HHT	Time-Frequency Image	2D-CNN	supervised	SVU_UCD, MIT-BIH	5-class	cross-subject	88.4% 87.6%
[391]	Filtering	Spatial-Temporal features	CNN-GAT	supervised	Sleep-EDF	5-class	cross-subject	81.6%-84.9%
[392]	Downsampling,STFT	Time-Freq Image	BiRNN +Attention	supervised	MASS	5-class	cross-subject	87.1%
[393]	Segmentation, Normalization	Raw Segments	CNN-BiRNN	supervised	Sleep-EDF	5-class	cross-subject	80.03%-84.26%
[394]	Segmentation,Multitaper Spectral Analysis	Raw,Spectrogram	CNN	supervised	MGH	5-class	cross-subject	85.76%
[395]	Filtering,Segmentation	Raw Segments	CNN-CRF	supervised	Sleep-EDF	5-class	cross-subject	86.81%
[396]	Segmentation	Raw Segments	CNN-LSTM	supervised	Sleep-EDF, MASS	5-class	cross-subject	83.1%-87.5%
[52]	Multitaper Spectral Estimation,Image Construction	RGB Image	2D-CNN	supervised	Sleep-EDF	5-class	cross-subject	88%
[397]	Segmentation	Raw Segments	CNN-BiLSTM	supervised	Sleep-EDF	5-class	cross-subject	85.07%-87.02%
[398]	Segmentation	Raw Segments	BiLSTM +Attention	supervised	Sleep-EDF, DRM-SUB	5-class	cross-subject	83.78% 81.72%
[399]	Filtering,Segmentation, Normalization,Hilbert	Stat. features, Spectrogram	CNN	supervised	Sleep-EDF	2-class	mixed-subject	96.94%
[400]	Downsampling, Segmentation	Time- & Freq-features	CNN-BiLSTM	supervised	MASS	5-class	cross-subject	87.8%
[133]	Downsampling, Segmentation	Raw Segments	CNN-LSTM	supervised	Sleep-EDF	5-class	cross-subject	83.7%
[401]	Standardization	Raw Segments	CNN-Transformer	supervised	Sleep-EDF	5-class	cross-subject	79.5%
[402]	Filtering,Windowing,DFT	Spectral Coefficients	GRU+Attention	supervised	Sleep-EDF	5-class	cross-subject	82.5%
[129]	-	Raw Segments	CNN	supervised	Sleep-EDF	5-class	cross-subject	74%
[131]	Filtering,Downsampling, Normalization	Raw Segments	CNN	supervised	MASS	5-class	cross-subject	82%
[403]	-	Raw Segments	CNN	supervised	SHHS	5-class	cross-subject	87%
[404]	Segmentation	Raw Segments	CNN	supervised	Sleep-EDF	5-class	cross-subject	81%

(Continued) Summary of deep learning frameworks for sleep staging

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[132]	Downsampling, Normalization, Segmentation	Raw segments	CNN-LSTM	supervised	SHHS, ISRUC, DRM-SUB, SVUH_UCD, HMC, Sleep- EDF	5-class	cross-subject	$\kappa=0.8$
[405]	Downsampling,STFT	Time-Frequency Image	CNN	supervised	Sleep-EDF, MASS	5-class	cross-subject	82.3% 83.6%
[406]	Segmentation	Raw Segments	CNN	supervised	Sleep-EDF	5-class	cross-subject	92.67%
[407]	Z-norm	Raw Segments	CNN+Attention	supervised	Sleep-EDF	5-class	mixed-subject	82.8%-93.7%
[408]	DE Calculation	DE matrix	CNN-GCN	supervised	Sleep-EDF, ISRUC	5-class	cross-subject	91.0% 87.4%
[409]	Windowing,STFT,PSD Calculation	Spectral & Tem- poral features	LSTM	supervised	MASS	5-class	cross-subject	89.4%
[410]	Filtering,Segmentation, Normalization	Raw Segments	CNN	supervised	ISRUC	(2-5)- class	mixed-subject	98.93%-99.24%
[31]	Filtering,Windowing	Raw Segments	CNN	supervised	Sleep-EDF	(2-6)- class	mixed-subject	92.95%-98.1%
[135]	Filtering,Segmentation, STFT	Raw Segments, 2D Spectrogram	2D-CNN	self-supervised	Sleep-EDF, SHHS, MGH	5-class	cross-subject	72.03%-86.90%
[137]	Filtering,Hilbert Transform	Raw Segments, 2D Spectrogram	CNN	self-supervised	Sleep-EDF, ISRUC	5-class	cross-subject	71.6% 57.9%
[411]	Normalization	Raw Segments	CNN-RNN	self-supervised	Sleep-EDF, ISRUC	5-class	mixed-subject	80.0% 71.4%
[412]	Segmentation	Raw Segments	Transformer	self-supervised	Sleep-EDF	5-class	cross-subject	90%
[136]	Resampling,Filtering,STFT	2D Spectrogram	CNN	self-supervised	Sleep-EDF, SHHS	5-class	cross-subject	78.06% 81.21%
[413]	Segmentation,Channel Selection,Normalization	Raw Segments	CNN-RNN	self-supervised	Sleep-EDF, ISRUC	5-class	mixed-subject	80.8% 74.4%
[414]	Segmentation, Normalization	Raw Segments	CNN-RNN	self-supervised	Sleep-EDF, ISRUC	5-class	cross-subject	70.1% 53.6%
[415]	Normalization, Segmentation	Raw Segments	CNN- Transformer	self-supervised	Sleep-EDF, MASS	5-class	cross-subject	83.12% 84.23%
[416]	Segmentation, Augmentation	Augmented Segments	CNN+Attention	self-supervised	Sleep-EDF, ISRUC	5-class	cross-subject	82.0% 79.9%
[68]	Filtering,Segmentation, Normalization	Raw Segments	CNN	self-supervised	Sleep-EDF, MASS	5-class	cross-subject	76-79%
[134]	Normalization,Filtering, Segmentation	Raw Segments	CNN	self-supervised	Sleep-EDF	5-class	mixed-subject	88.16%
[30]	Filtering,Normalization, Segmentation	Raw Segments, 2D Spectrogram	CNN	self-supervised	Sleep-EDF	5-class	cross-subject	86.8%
[417]	Segmentation, Normalization	Raw Segments	CNN	self-supervised	Sleep-EDF, PC18	5-class	cross-subject	72.5%
[418]	Normalization, Segmentation	Raw Segments	CNN	semi-supervised	Sleep-EDF, private	5-class	mixed-subject	91%
[419]	Filtering,STFT	2D Spectrogram	CNN	semi-supervised	Sleep-EDF, private	5-class	mixed-subject	84%
[420]	Segmentation,FFT	2D Spectrogram	2D-CNN	semi-supervised	Sleep-EDF	5-class	cross-subject	89%
[421]	Filtering,Normalization, Segmentation	Raw Segments	CNN- BiGRU	semi-supervised	Sleep-EDF, DRM-SUB	5-class	mixed-subject	82.3% 81.6%
[422]	Multi-tapered Spectrogram Generation	Time-Frequency Image	GMM	semi-supervised	Sleep-EDF	4-class	subject-specific	73%
[423]	Filtering	Raw Segments	CNN	semi-supervised	Sleep-EDF	5-class	mixed-subject	80%
[424]	Filtering,Downsampling	Raw Segments	CNN	unsupervised	Sleep-EDF, UCD	5-class	cross-subject	83.4% 77.2%
[425]	Segmentation,Filtering	Complex Values	CNN	unsupervised	UCD, MIT-BIH	5-class	cross-subject	87%
[426]	Filtering,Segmentation, feature extraction	Time-Frequency domain features	AE	unsupervised	Piryatinska	3-class	mixed-subject	80.4%
[427]	Filtering,Downsampling, Segmentation	Raw Segments	DBN	unsupervised	UCD	5-class	cross-subject	91.31%
[428]	Morlet Calculation, Normalization	SSAE-based	DNN	unsupervised	Sleep-EDF	5-class	cross-subject	78%
[429]	Filtering,feature extrac- tion	Time- & Freq- features,Raw	DBN	unsupervised	UCD	5-class	cross-subject	67.4%-72.2%

TABLE XIII: Summary of deep learning frameworks for depression identification

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[430]	Filtering,ICA,STFT	Connectivity Graph	GCN-LSTM	supervised	PRED+CT, MODMA	binary	cross-subject	90.38% 90.57%
[431]	ICA,DWT,Segmentation	Frequency-domain matrix	CNN-LSTM	supervised	HUSM	binary	mixed-subject	99.15%
[432]	Filtering,ICA,Z-norm, STFT	2D Spectrogram	CNN-LSTM	supervised	HUSM	binary	mixed-subject	99.9%
[34]	ICA,FFT,Windowing	Time-Frequency features	CNN-LSTM	supervised	private	binary	mixed-subject	99.1%
[35]	Filtering,ICA,Segmentation	Raw Segments	CNN	supervised	private	binary	mixed-subject	99.37%
[433]	Filtering,Segmentation	Raw Segments	CNN-Transformer	supervised	HUSM, private	binary	cross-subject	93.7% 96.2%
[434]	Filtering,ICA,Band Filter,CSP	Raw Segments	Transformer	supervised	private	binary	mixed-subject	92.25%
[435]	Z-norm,Welch	Psd features	CNN-GRU+Attention	supervised	MODMA, EDRA	binary	mixed-subject	97.56% 98.33%
[436]	Downsampling,Z-norm, Segmentation	Raw Segments	2D-CNN	supervised	private	3-class	mixed-subject	79.08%
[437]	Filtering,Downsampling, Normalization	Raw Segments	CNN-LSTM	supervised	private	binary	cross-subject	94.69%
[438]	Filtering,ICA,Wpt	Brain Network	GCN	supervised	MODMA, EDRA, HUSM	NaN	mixed-subject	91.11%-93.75%
[439]	Baseline Removal, Detrending,Filtering,STFT	Time-Frequency Image	GCN	supervised	HUSM, MODMA	binary	cross-subject	99.19% 95.53%
[440]	Normalization, Segmentation,Network construction	Node Feature matrix,Adjacency matrix	GNN	supervised	MODMA	binary	cross-subject	84.91%
[441]	Filtering,DE Calculation	Differential Entropy,Adjacency matrix	GCN	supervised	PRED+CT, MODMA	binary	cross-subject	83.17% 92.87%
[442]	Filtering,ICA,CAR, U-NET	Multi-scale Saliency-encoded Spectrogram	CNN	supervised	HUSM	binary	cross-subject	99.22%
[443]	Downsampling,Filtering, Segmentation	Raw Segments	CNN-RSE	supervised	private	binary	mixed-subject	98.48%
[444]	Segmentation	Raw Segments	2D-CNN	supervised	HUSM, private	3-class	mixed-subject	98.59%
[445]	Filtering,Min-max Norm,Segmentation, Welch	Asymmetry matrix Images	2D-CNN	supervised	HUSM	binary	mixed-subject	98.85%
[446]	Filter,Image Construction	2D Image	CNN-LSTM	supervised	HUSM	binary	cross-subject	99.245%
[447]	Denoising,Filtering,STFT	2D Spectrogram	2D-CNN	supervised	HUSM	binary	mixed-subject	99.58%
[448]	Band-pass Filter	Frequency bands	2D-CNN	supervised	HUSM	binary	mixed-subject	96.97%
[449]	Filtering,MPWD,Network construction	Adjacency matrix Of Fdmb Network	2D-CNN	supervised	HUSM	binary	mixed-subject	97.27%
[450]	MSEC,Segmentation	Raw Segments	CNN,CNN-LSTM	supervised	HUSM	binary	mixed-subject	98.32%
[451]	Filtering,PLV,Welch	Multilayer Brain Network	GCN	supervised	HUSM	binary	mixed-subject	99.29%
[452]	ICA,Rereferencing,Filtering	2D Image	2D-CNN	supervised	HUSM	binary	mixed-subject	99.11%
[453]	Filtering,Z-norm, Segmentation	Connectivity matrix	2D-CNN+Attention	supervised	HUSM	binary	cross-subject	91.06%
[454]	ICA,Z-norm,Band Filter	Frequency bands	CNN	supervised	HUSM	binary	cross-subject	99.6%
[455]	Filtering,ASR	Raw Segments	Inception	supervised	HUSM	binary	cross-subject	91.67%
[456]	Filtering,CWT,WCOH	RGB Image	2D-CNN	supervised	HUSM	binary	mixed-subject	98.1%
[457]	Filtering,Windowing, SWC,PLV	P-mSWC	2D-CNN	supervised	HUSM, PRED+CT	binary	mixed-subject	93.93%- 99.87%
[444]	Filtering,Z-norm	Raw Segments	CNN	supervised	private	binary	mixed-subject	95.96%

(Continued) Summary of deep learning frameworks for depression identification

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[458]	Filtering,STFT	2D Spectrogram	2D-CNN	supervised	private	binary	mixed-subject	96.43%
[459]	Filtering,ICA,Segmentation	Mixed Feature matrix	CNN	supervised	private	binary	mixed-subject	94.13%
[47]	ICA,LMS,AR,Hjorth	2D Image	CNN	supervised	private	binary	cross-subject	84.75%
[460]	Filtering,Segmentation	Raw Segments	CNN	supervised	private	binary	mixed-subject	75.29%
[461]	Filtering,Segmentation, PLV,PLI	Connectivity matrix	2D-CNN	supervised	private	binary	cross-subject	80.74%
[462]	Filtering,PLI	Connectivity matrix	2D-CNN	supervised	private	binary	mixed-subject	67.67%
[44]	Denoising,Segmentation, PDC matrix Calculation	3D CPC	3D-CNN	supervised	private	binary	cross-subject	100%
[21]	Manual Denoising, Filtering	Raw Segments	CNN-LSTM	supervised	private	binary	mixed-subject	99.12%
[463]	Filtering,Segmentation	Raw Segments	CNN-RNN	supervised	private	binary	mixed-subject	99.66%
[464]	Filtering,Image Construction	Spatial-Temporal Image	2D-CNN	supervised	private	binary	mixed-subject	92.66%
[465]	Filtering,DWT	Wavelet features	BiLSTM	supervised	private	binary	mixed-subject	99.66%
[466]	Band Filter, Normalization	Raw Segments	CNN	supervised	private	binary	mixed-subject	98.13%
[467]	Filtering,ICA,Hanning	2D Frames	2D-CNN	supervised	private	binary	cross-subject	77.2%
[468]	Filtering,LMS	Raw Segments	CNN-LSTM	supervised	MODMA	binary	cross-subject	95.1%
[469]	Filter,Image Construction	2D Image	DAN	supervised	MODMA	binary	cross-subject	77%
[470]	Filtering,Windowing,PLI	Time- & Spatial-domain features	CNN-RNN	supervised	MODMA	binary	mixed-subject	96.33%
[471]	Filtering,Z-norm	Time-Frequency features	2D-CNN	supervised	PRED+CT	binary	mixed-subject	93.33%
[472]	ICA,Z-norm	Raw Segments	CNN-LSTM	supervised	PRED+CT	binary	mixed-subject	99.07%
[42]	Filtering,ICA,Power Spectrum Calculation	Topographical Activity Map, Frequency bands	2D-CNN	supervised	private	binary	cross-subject	85.62%
[446]	Filtering,ICA	Spike Trains	SNN-LSTM	supervised	PRED+CT	4-class	cross-subject	98%
[473]	Filtering,downsampling	Frequency bands	CNN-LSTM	supervised	private	binary	cross-subject	95%
[474]	Filtering,feature extraction	Adjacency matrix,Node features	GCN	supervised	private	binary	cross-subject	97%
[475]	Image construction	2D Image	2D-CNN	supervised	MODMA	binary	mixed-subject	74%
[476]	Filtering,ICA	Graph	GCN	self-supervised	MODMA, EDRA	binary	cross-subject	99.19%
								98.38%
[477]	ICA,Filtering, DE Calculation	Differential Entropy	GCN	semi-supervised	MODMA	binary	cross-subject	92.23%
[45]	ICA,Filtering	AE-based	DNN	unsupervised	private	binary	cross-subject	83.42%
[145]	ICA,Segmentation	Spike Trains	SNN	unsupervised	private	binary	mixed-subject	72.13%
[478]	Filtering,DWT,PCC	Adjacency matrix	GCN	unsupervised	MODMA	binary	mixed-subject	97%

TABLE XIV: Summary of deep learning frameworks for schizophrenia identification

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[54]	Connectivity Measures,Complex Network construction	VAR,PDC,CN	CNN	supervised	MHRC	binary	cross-subject	91.69%
[479]	Z-norm,Segmentation	Raw Segments	CNN	supervised	CeonRepod	binary	mixed-subject	98.07%
[480]	Segmentation, Margenau–Hill	Time-Frequency Image	CNN	supervised	MHRC, CeonRepod, NIMH	binary	mixed-subject	96.35%-99.75%
[481]	Connectivity Networks Construction	WOC-Based features	CNN	supervised	MHRC	binary	cross-subject	90%
[482]	Filtering,Segmentation, Welch Method	Spectrum matrix	CNN	supervised	private	binary	cross-subject	91.12%
[483]	Filtering	Raw Segments	CNN	supervised	CeonRepod	binary	mixed-subject	98.05%
[22]	Filtering,Segmentation, ASR,ICA	Connectivity features	CNN	supervised	CeonRepod	binary	mixed-subject	99.84%
[484]	CWT,STFT,SPWVD	Scalogram,TFR, Spectrogram	CNN	supervised	NIMH	binary	mixed-subject	93.36%
[485]	Filtering,Segmentation, Z-norm	Raw Segments	CNN	supervised	CeonRepod	binary	mixed-subject	99.18%
[486]	Filtering,ICA	Trend Time Series	CNN	supervised	CeonRepod	binary	cross-subject	93%
[487]	Mspca,Filtering,Multitaper	Frequency features	CNN	supervised	CeonRepod	binary	mixed-subject	98.76%
[488]	Filtering,Segmentation, Connectivity Measures	FC matrix	CNN	supervised	MHRC	binary	cross-subject	94.11%
[489]	Filtering,Windowing, Z-norm,CWT	2D Scalogram	CNN	supervised	CeonRepod, NIMH	binary	mixed-subject	99% 96%
[490]	Re-Referencing, Filtering,Segmentation	Raw Segments	2D-CNN	supervised	private	3-class	cross-subject	81.6%-99.2%
[491]	Filtering,Segmentation,FFT	Spectral Power, Variance,Mobility, Complexity,Mean Spectral Amp.	2D-CNN	supervised	MHRC, CeonRepod	binary	mixed-subject	94.08%-98.56%
[152]	Segmentation,STFT	2D Spectrogram	2D-CNN	supervised	MHRC, CeonRepod	binary	mixed-subject	95% 97%
[50]	CWT	2D Scalogram	2D-CNN	supervised	MHRC, CeonRepod	binary	mixed-subject	98% 99.5%
[41]	Segmentation,EMD,HHT	Hilbert Spectrum	2D-CNN	supervised	MHRC, CeonRepod	binary	mixed-subject	96.02% 98.2%
[39]	WT,1D-LBP,ELM-AE	EEG Image	2D-CNN	supervised	MHRC	binary	mixed-subject	97.73%
[55]	Z-norm	EEG Image	2D-CNN	supervised	NIMH	binary	mixed-subject	93.2%
[153]	Filtering	Image matrix	2D-CNN	supervised	NIMH	binary	mixed-subject	98.84%
[154]	Filtering,CWT	2D Scalogram	2D-CNN	supervised	CeonRepod	binary	mixed-subject	99%
[492]	Filtering,Segmentation	Raw Segments	2D-CNN	supervised	NIMH, private	binary	cross-subject	80%
[493]	Baseline Correction, Filtering,Segmentation	Time-Frequency features	2D-CNN	supervised	NIMH	binary	mixed-subject	92%
[494]	Segmentation,PCC	Correlation matrix	2D-CNN	supervised	MHRC	binary	mixed-subject	90%
[495]	Segmentation,Phase Reconstruction	RPS Portrait	2D-CNN	supervised	CeonRepod	binary	mixed-subject	99.37%
[33]	Filtering,Interpolation	EEG Image	2D-CNN	supervised	NIMH	binary	mixed-subject	99.23%
[496]	Normalization,DSTFT	DSTFT Spectrogram	2D-CNN	supervised	MHRC	binary	cross-subject	83%
[497]	LSDI	2D Spectrogram, Scalogram	2D-CNN	supervised	MHRC	binary	mixed-subject	98.3%
[498]	Segmentation,Feature Selection	Nonlinear features	2D-CNN	supervised	CeonRepod	binary	mixed-subject	95.85%
[499]	Filtering,CWT,CMI	Connectivity matrix	3D-CNN	supervised	MHRC	binary	cross-subject	97.74%
[500]	Normalization,DAF	2D Image	CNN, Transformer	supervised	CeonRepod	binary	mixed-subject	98.32%-99.04%
[501]	Filtering,Segmentation, Z-norm	PSD features	CNN CNN-LSTM	supervised	private	binary	cross-subject	75.9% 71.5%
[502]	Filtering,Min-Max Norm	Raw	CNN-LSTM	supervised	private	binary	cross-subject	89.98%

(Continued) Summary of deep learning frameworks for schizophrenia identification

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[24]	Filtering,Segmentation, Baseline Correction, Ocular Correction	FuzzyEn Image	RGB	CNN-LSTM	supervised	private	binary	mixed-subject 99.22%
[503]	Filtering,Segmentation	Raw Segments	CNN-LSTM	supervised	MHRC, CeonRepod	binary	cross-subject	91% 96.1%
[504]	MSST	Time-Frequency Feature Image	CNN-LSTM	supervised	CeonRepod	binary	mixed-subject	84.42%
[505]	Filtering,TE	2D Image	CNN-LSTM	supervised	CeonRepod	binary	mixed-subject	99.9%
[506]	Artifact Removal, Filtering	Raw	CNN-LSTM	supervised	NIMH	binary	cross-subject	98.2%
[507]	Segmentation,Z-norm	Raw Segments	CNN-LSTM	supervised	CeonRepod	binary	mixed-subject	99.25%
[508]	Filtering,PCA,ICA	Raw,features	CNN-TCN	supervised	CeonRepod	binary	mixed-subject	99.57%
[509]	Filtering, feature extraction	Frequency features	DNN	supervised	private	binary	mixed-subject	97.5%
[510]	Connectivity Measures,Complex Network construction	DC,CN	DNN-DBN	Supervised	MHRC	binary	cross-subject	95%
[511]	Filtering,ICA	PLI,PCI	GNN	Supervised	private	binary	cross-subject	84.17%
[512]	Filtering,TVD	Time- and Non-linear features	LSTM	Supervised	CeonRepod	binary	mixed-subject	99%
[513]	Dimension Reduction	End-to-end	RNN-LSTM	Supervised	MHRC	binary	mixed-subject	98%
[514]	Filtering,Normalization	Spatial Feature matrix	Transformer	Supervised	CeonRepod	binary	mixed-subject	98.99%
[515]	Filtering,Segmentation, Connections calculation	Connection matrix	2D-CNN	supervised	private	binary	mixed-subject	100%
[516]	Z-norm,Filtering	AE-based	CNN	Unsupervised	CeonRepod	binary	cross-subject	81.81%
[517]	Segmentation	SAE-based	DNN	Unsupervised	CeonRepod	binary	mixed-subject	97.95%
[518]	Filtering	AE-based	DNN	Unsupervised	MHRC, CeonRepod, NIMH	binary	mixed-subject	95.01%-99.99%

TABLE XV: Summary of deep learning frameworks for Alzheimer's Disease Diagnosis

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[162]	Filtering,Segmentation, Connections Calculation	Connection matrix	2D-CNN	Supervised	private	binary	mixed-subject	100%
[519]	Filtering,Segmentation	Raw Segments	2D-CNN	Supervised	FSA_Alzheimer's	binary	mixed-subject	97.9%
[161]	Filtering,Segmentation, Network construction	Adjacency matrix,Segments	GCN	Supervised	private	binary	mixed-subject	92.3%
[520]	Filtering,Segmentation	Raw Segments	2D-CNN	Supervised	private	binary	mixed-subject	69.03%-85.78%
[163]	Filtering,Segmentation, CWT	Time-Frequency features	2D-CNN	Supervised	private	binary	cross-subject	85% 82%
[521]	Filtering,FFT	2D Spectrograms	2D-CNN	Supervised	private	binary	mixed-subject	97.11% 95.04%
[522]	Filtering,FFT	Frequency-domain features	2D-CNN	Supervised	private	binary	-	93.7%
[523]	Filtering,Segmentation, ICA,CWT	RGB Image	2D-CNN	Supervised	private	3-class	mixed-subject	98.9%
[524]	Filtering,Downsampling, ICA	Frequency-domain features	CNN	Supervised	Fiscon	3-class	mixed-subject	97.1%
[525]	Normalization, Segmentation,DWT	2D Spectrograms	CNN	Supervised	AD-59	3-class	cross-subject	98.84%
[526]	Filtering,Segmentation,FT	PSD Image	2D-CNN	Supervised	private	Binary 3-class	mixed-subject	84.62%-92.95% 83.33%
[527]	Filtering,EMD	Time-Frequency features	CNN	Supervised	private	Binary 3-class	mixed-subject	99.3%-99.9% 94.8%
[528]	Filtering,Segmentation,RP	Frequency-domain features	DNN	Supervised	private	binary	cross-subject	75%
[529]	Denoising	AE-Based	RBM	Unsupervised	private	binary	mixed-subject	92%
[530]	Filtering,ICA, Morlet Wavelet	VAE-Based	VAE	Unsupervised	private	binary	cross-subject	98.1%
[531]	Filtering,Segmentation, CWT	SAE-Based	MLP-NN	Unsupervised	private	binary	cross-subject	88%

TABLE XVI: Summary of deep learning frameworks for Parkinson's Disease Diagnosis

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[532]	Segmentation,Embedding Reconstruction	Reconstructed Segments	CNN-LSTM	supervised	UNM	binary	mixed-subject	99.22%
[40]	Gabor Transform	2D Spectrograms	2D-CNN	supervised	UCSD	3-class	mixed-subject	92.6%-99.46%
[533]	SPWVD,Artifact Removal,Segmentation	TFR	2D-CNN	supervised	UCSD, private	binary	mixed-subject	99.84%-100%
[534]	Denoising,TQWT,WPT	Time-Frequency features	CNN	supervised	private	3-class	mixed-subject	92.59%-99.92%
[535]	Artifact rejection, Filtering,Segmentation	Raw Segments	CNN-RNN	supervised	private	binary	cross-subject	82.89%
[169]	CWT,Segmentation	2D Image	CNN	supervised	UCSD	3-class	mixed-subject	99.6%-99.9%
[170]	ICA,Filtering,P-Welch	PSD Image	2D-CNN	supervised	private	binary	mixed-subject	99.87%
[171]	Artifacts Removal, Filtering,Segmentation	DC Image	2D-CNN	supervised	private	binary	mixed-subject	99.62%
[536]	CWT,VMD	Time-Frequency features	2D-CNN	supervised	private	binary	mixed-subject	92%-96%
[537]	Filtering,Segmentation	Raw Segments	ANN	supervised	UCSD	binary	mixed-subject	98%
[19]	Artifact Removal, Filtering	Raw Segments	CNN	supervised	private	binary	mixed-subject	88.25%
[538]	Filtering,Z-norm	Raw Segments	CNN	supervised	UNM, UI	binary	cross-subject	82.8%
[539]	Artifact rejection, Filtering,Normalization, Segmentation	Raw Segments	CNN-GRU	supervised	private	binary	mixed-subject	99.2%
[540]	Segmentation	Raw Segments	CNN-LSTM	supervised	private	binary	mixed-subject	96.9%
[541]	FFT	2D Spectrograms	CNN-LSTM	supervised	private	binary	mixed-subject	99.7%
[542]	Artifact rejection, Filtering,Segmentation	Functional connectivity matrix	GCN	supervised	private	binary	mixed-subject	90.2%

TABLE XVII: Summary of deep learning frameworks for ADHD identification

Ref.	Preprocessing	Feature	Backbone	Training	Dataset	Task	Partitioning	Accuracy
[176]	segment screening	PSD	CNN	Supervised	private	Binary	mixed-subject	90.29%
[177]	Filtering,Segmentation, wavelet transform	Spectrogram	CNN	Supervised	private	Binary	cross-subject	88%
[23]	Resampling,filtering, ASR>windowing, Freq. bands separation	Frequency bands, RGB Images	CNN	Supervised	ADHD-Child	Binary	cross-subject	98.48%
[49]	PSD	PSD,SE	LSTM	Supervised	private	Binary	mixed-subject	92.15%
[543]	Filtering,Segmentation, ICA,segment screening	End-to-end	CNN	Supervised	private	3-class	mixed-subject	99.46%
[544]	FIR,filtering,ICA, Segmentation	Dynamic connectivity tensor (DCT)	ConvLSTM +Attention	Supervised	ADHD-Child	Binary	mixed-subject	99.75%
[25]	Re-referencing,filtering, Baseline rejection, downsampling,Segmentation	PSD	CNN	Supervised	ADHD-Child	Binary	mixed-subject	94.52%
[545]	Filtering,Segmentation, CWT	Time-Frequency Image	ConvMixer, ResNet50, ResNet18	Supervised	ADHD-Child	Binary	mixed-subject	72.58%

REFERENCES

- [1] World Health Organization, "Over 1 in 3 people affected by neurological conditions, the leading cause of illness and disability worldwide," 2024.
- [2] ———, "Mental health: Neurological disorders."
- [3] G. Ramantani and et al., "Correlation of invasive eeg and scalp eeg," *Seizure*, vol. 41, pp. 196–200, 2016.
- [4] Y. Roy and et al., "Deep learning-based electroencephalography analysis: a systematic review," *Journal of neural engineering*, vol. 16, no. 5, p. 051001, 2019.
- [5] G. Amrani and et al., "Eeg signal analysis using deep learning: A systematic literature review," in *2021 Fifth International Conference On Intelligent Computing in Data Sciences (ICDS)*, 2021, pp. 1–8.
- [6] N. S. Amer and S. B. Belhaouari, "Eeg signal processing for medical diagnosis, healthcare, and monitoring: A comprehensive review," *IEEE Access*, 2023.
- [7] X. Zhang and et al., "A survey on deep learning-based non-invasive brain signals: recent advances and new frontiers," *Journal of neural engineering*, vol. 18, no. 3, p. 031002, 2021.
- [8] P. Khan and et al., "Machine learning and deep learning approaches for brain disease diagnosis: principles and recent advances," *Ieee Access*, vol. 9, pp. 37622–37655, 2021.
- [9] A. Shocibei and et al., "Epileptic seizures detection using deep learning techniques: a review," *International journal of environmental research and public health*, vol. 18, no. 11, p. 5780, 2021.
- [10] J. Rahul and et al., "A systematic review of eeg based automated schizophrenia classification through machine learning and deep learning," *Frontiers in Human Neuroscience*, vol. 18, p. 1347082, 2024.
- [11] K. M. Hossain and et al., "Status of deep learning for eeg-based brain-computer interface applications," *Frontiers in computational neuroscience*, vol. 16, p. 1006763, 2023.
- [12] W. Weng and et al., "Self-supervised learning for electroencephalogram: A systematic survey," *arXiv preprint arXiv:2401.05446*, 2024.
- [13] J. Chen and et al., "Con4m: Context-aware consistency learning framework for segmented time series classification," *The Thirty-Eighth Annual Conference on Neural Information Processing Systems*, 2024.
- [14] H. Berger, "Über das elektroenzephalogramm des menschen," *Archiv für psychiatrie und nervenkrankheiten*, vol. 87, no. 1, pp. 527–570, 1929.
- [15] H. H. Jasper, "Ten-twenty electrode system of the international federation," *Electroencephalogr Clin Neurophysiol*, vol. 10, pp. 371–375, 1958.
- [16] G. Buzsaki and A. Draguhn, "Neuronal oscillations in cortical networks," *science*, vol. 304, no. 5679, pp. 1926–1929, 2004.
- [17] J. Jeong, "Eeg dynamics in patients with alzheimer's disease," *Clinical neurophysiology*, vol. 115, no. 7, pp. 1490–1505, 2004.
- [18] H. Banville and et al., "Uncovering the structure of clinical eeg signals with self-supervised learning," *Journal of Neural Engineering*, vol. 18, no. 4, p. 046020, 2021.
- [19] S. L. Oh and et al., "A deep learning approach for parkinson's disease diagnosis from eeg signals," *Neural Computing and Applications*, vol. 32, pp. 10927–10933, 2020.
- [20] C. Chatzichristos and et al., "Epileptic seizure detection in eeg via fusion of multi-view attention-gated u-net deep neural networks," in *2020 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*, 2020, pp. 1–7.
- [21] B. Ay and et al., "Automated depression detection using deep representation and sequence learning with eeg signals," *Journal of medical systems*, vol. 43, pp. 1–12, 2019.
- [22] N. Grover and et al., "Schizo-net: A novel schizophrenia diagnosis framework using late fusion multimodal deep learning on electroencephalogram-based brain connectivity indices," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 464–473, 2023.
- [23] M. Moghaddari and et al., "Diagnose adhd disorder in children using convolutional neural network based on continuous mental task eeg," *Computer Methods and Programs in Biomedicine*, vol. 197, p. 105738, 2020.
- [24] J. Sun and et al., "A hybrid deep neural network for classification of schizophrenia using eeg data," *Scientific Reports*, vol. 11, no. 1, p. 4706, 2021.
- [25] A. Nouri and Z. Tabanfar, "Detection of adhd disorder in children using layer-wise relevance propagation and convolutional neural network: An eeg analysis," *Frontiers in Biomedical Technologies*, vol. 11, no. 1, pp. 14–21, 2024.
- [26] A. Antoniades and et al., "Deep learning for epileptic intracranial eeg data," in *2016 IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP)*. IEEE, 2016, pp. 1–6.
- [27] T. Wen and Z. Zhang, "Deep convolution neural network and autoencoders-based unsupervised feature learning of eeg signals," *IEEE Access*, vol. 6, pp. 25399–25410, 2018.
- [28] D. Kostas and et al., "Bendr: Using transformers and a contrastive self-supervised learning task to learn from massive amounts of eeg data," *Frontiers in Human Neuroscience*, vol. 15, p. 653659, 2021.
- [29] U. R. Acharya and et al., "Deep convolutional neural network for the automated detection and diagnosis of seizure using eeg signals," *Computers in Biology and Medicine*, vol. 100, pp. 270–278, 2018.
- [30] W. Ko and H.-I. Suk, "Eeg-oriented self-supervised learning and cluster-aware adaptation," in *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, 2022, pp. 4143–4147.
- [31] Z. Mousavi and et al., "Deep convolutional neural network for classification of sleep stages from single-channel eeg signals," *Journal of neuroscience methods*, vol. 324, p. 108312, 2019.
- [32] J. Zhang and et al., "Orthogonal convolutional neural networks for automatic sleep stage classification based on single-channel eeg," *Computer Methods and Programs in Biomedicine*, vol. 183, p. 105089, 2020.
- [33] S. Siuly and et al., "Exploring deep residual network based features for automatic schizophrenia detection from eeg," *Physics in Engineering and Science Medicine*, vol. 46, pp. 561–574, 2023.
- [34] G. Sharma and et al., "Dephn: a novel hybrid neural network for electroencephalogram (eeg)-based screening of depression," *Biomedical signal processing and control*, vol. 66, p. 102393, 2021.
- [35] A. Seal and et al., "Depnnet: A deep convolution neural network framework for detecting depression using eeg," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–13, 2021.
- [36] S. Iwama and et al., "Two common issues in synchronized multimodal recordings with eeg: Jitter and latency," *Neuroscience Research*, 2023.
- [37] K. A. Robbins and et al., "How sensitive are eeg results to preprocessing methods: A benchmarking study," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 5, pp. 1081–1090, 2020.
- [38] T. Tuncer and et al., "A novel ensemble local graph structure based feature extraction network for eeg signal analysis," *Biomed. Signal Process. Control.*, vol. 61, p. 102006, 2020.
- [39] N. Sobahi and et al., "A new signal to image mapping procedure and convolutional neural networks for efficient schizophrenia detection in eeg recordings," *IEEE Sensors Journal*, vol. 22, no. 8, pp. 7913–7919, 2022.
- [40] H. W. Loh and et al., "Gaborpdnet: Gabor transformation and deep neural network for parkinson's disease detection using eeg signals," *Electronics*, vol. 10, no. 14, p. 1740, 2021.
- [41] A. Zülfikar and A. Mehmet, "Empirical mode decomposition and convolutional neural network-based approach for diagnosing psychotic disorders from eeg signals," *Applied Intelligence*, vol. 52, no. 11, pp. 12103–12115, 2022.
- [42] X. Li and et al., "Eeg-based mild depression recognition using convolutional neural network," *Medical & biological engineering & computing*, vol. 57, pp. 1341–1352, 2019.
- [43] A. M. Karim and et al., "A new framework using deep auto-encoder and energy spectral density for medical waveform data classification and processing," *Biocybernetics and Biomedical Engineering*, vol. 39, no. 1, pp. 148–159, 2019.
- [44] D. M. Khan and et al., "Automated diagnosis of major depressive disorder using brain effective connectivity and 3d convolutional neural network," *Ieee Access*, vol. 9, pp. 8835–8846, 2021.
- [45] J. Zhu and et al., "Multimodal mild depression recognition based on eeg-em synchronization acquisition network," *IEEE Access*, vol. 7, pp. 28196–28210, 2019.
- [46] J. Liu and B. Woodson, "Deep learning classification for epilepsy detection using a single channel electroencephalography (eeg)," in *Proceedings of the 2019 3rd International Conference on Deep Learning Technologies*, 2019, pp. 23–26.
- [47] X. Li and et al., "Depression recognition using machine learning methods with different feature generation strategies," *Artificial intelligence in medicine*, vol. 99, p. 101696, 2019.
- [48] I. Bhattacherjee, "Epileptic seizure detection using multicolumn convolutional neural network," in *2020 7th International Conference on Computing for Sustainable Global Development (INDIACom)*. IEEE, 2020, pp. 58–63.

- [49] M. Tosun, "Effects of spectral features of eeg signals recorded with different channels and recording statuses on adhd classification with deep learning," *Physical and Engineering Sciences in Medicine*, vol. 44, no. 3, pp. 693–702, 2021.
- [50] Z. Aslan and M. Akin, "A deep learning approach in automated detection of schizophrenia using scalogram images of eeg signals," *Physical and Engineering Sciences in Medicine*, vol. 45, no. 1, pp. 83–96, 2022.
- [51] G. Choi and et al., "A novel multi-scale 3d cnn with deep neural network for epileptic seizure detection," in *2019 IEEE International Conference on Consumer Electronics (ICCE)*, 2019, pp. 1–2.
- [52] A. Vilamala and et al., "Deep convolutional neural networks for interpretable analysis of eeg sleep stage scoring," in *2017 IEEE 27th international workshop on machine learning for signal processing (MLSP)*, 2017, pp. 1–6.
- [53] J. Xu and et al., "Epileptic seizure detection based on feature extraction and cnn- bigru network with attention mechanism," in *International Conference on Intelligent Computing*. Springer, 2023, pp. 308–319.
- [54] C.-R. Phang and et al., "A multi-domain connectome convolutional neural network for identifying schizophrenia from eeg connectivity patterns," *IEEE journal of biomedical and health informatics*, vol. 24, no. 5, pp. 1333–1343, 2019.
- [55] D.-W. Ko and J.-J. Yang, "Eeg-based schizophrenia diagnosis through time series image conversion and deep learning," *Electronics*, vol. 11, no. 14, 2022.
- [56] Q. Zhan and W. Hu, "An epilepsy detection method using multiview clustering algorithm and deep features," *Computational and Mathematical Methods in Medicine*, vol. 2020, p. 5128729, 2020.
- [57] T. K. K. Ho and N. Armanfard, "Self-supervised learning for anomalous channel detection in eeg graphs: Application to seizure analysis," in *Proceedings of the AAAI conference on artificial intelligence*, vol. 37, no. 7, 2023, pp. 7866–7874.
- [58] T. Siddharth and et al., "Eeg-based detection of focal seizure area using fbse-ewt rhythm and sae-svm network," *IEEE Sensors Journal*, vol. 20, no. 19, pp. 11 421–11 428, 2020.
- [59] E. Ebrahimbzadeh and et al., "A novel approach for detection of deception using smoothed pseudo wigner-ville distribution (spwvd)," *Journal of Biomedical Science and Engineering*, vol. 2013, pp. 8–18, 2013.
- [60] Y. LeCun and et al., "Convolutional networks for images, speech, and time series," *The handbook of brain theory and neural networks*, vol. 3361, no. 10, p. 1995, 1995.
- [61] J. L. Elman, "Finding structure in time," *Cognitive science*, vol. 14, no. 2, pp. 179–211, 1990.
- [62] A. Vaswani and et al., "Attention is all you need," *Advances in neural information processing systems*, vol. 30, 2017.
- [63] F. Scarselli and et al., "The graph neural network model," *IEEE Transactions on Neural Networks*, vol. 20, no. 1, pp. 61–80, 2009.
- [64] G. E. Hinton and R. Zemel, "Autoencoders, minimum description length and helmholtz free energy," *Advances in neural information processing systems*, vol. 6, 1993.
- [65] I. Goodfellow and et al., "Generative adversarial nets," *Advances in neural information processing systems*, vol. 27, 2014.
- [66] W. Maass, "Networks of spiking neurons: the third generation of neural network models," *Neural networks*, vol. 10, no. 9, pp. 1659–1671, 1997.
- [67] M. N. Mohsenvand and et al., "Contrastive representation learning for electroencephalogram classification," in *Machine Learning for Health*, 2020, pp. 238–253.
- [68] H. Banville and et al., "Self-supervised representation learning from electroencephalography signals," in *2019 IEEE 29th International Workshop on Machine Learning for Signal Processing (MLSP)*, 2019, pp. 1–6.
- [69] A. v. d. Oord and et al., "Representation learning with contrastive predictive coding," *arXiv preprint arXiv:1807.03748*, 2018.
- [70] D. Wu and et al., "neuro2vec: Masked fourier spectrum prediction for neurophysiological representation learning," *arXiv preprint arXiv:2204.12440*, 2022.
- [71] D. Cai and et al., "Mbrain: A multi-channel self-supervised learning framework for brain signals," in *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, 2023, pp. 130–141.
- [72] R. G. Andrzejak and et al., "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Physical Review E*, vol. 64, no. 6, p. 061907, 2001.
- [73] M. Ihle and et al., "Epilepsiae – A European epilepsy database," *Computer Methods and Programs in Biomedicine*, vol. 106, no. 3, pp. 127–138, 2012.
- [74] bbrinkm and et al., "Upenn and mayo clinic's seizure detection challenge," 2014.
- [75] J. Guttig, "CHB-MIT Scalp EEG Database (version 1.0.0)," 2010.
- [76] A. Shoeb, "Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment," Ph.D. dissertation, Massachusetts Institute of Technology, September 2009.
- [77] A. Goldberger and et al., "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.
- [78] R. G. Andrzejak and et al., "Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients," *Physical Review E*, vol. 86, p. 046206, 2012.
- [79] P. Swami and et al., "Eeg epilepsy datasets," 09 2016.
- [80] L. Kuhlmann and et al., "Melbourne university aes/mathworks/nih seizure prediction," 2016.
- [81] V. Shah and et al., "The Temple University Hospital Seizure Detection Corpus," *Frontiers in Neuroinformatics*, vol. 12, p. 83, 2018.
- [82] A. Burrello and et al., "One-shot learning for ieeg seizure detection using end-to-end binary operations: Local binary patterns with hyperdimensional computing," in *Proceedings of the IEEE Biomedical Circuits and Systems Conference (BioCAS)*, October 17–19 2018.
- [83] ———, "Hyperdimensional computing with local binary patterns: One-shot learning of seizure onset and identification of ictogenic brain regions using short-time ieeg recordings," *IEEE Transactions on Biomedical Engineering (TBME)*, 2019.
- [84] N. Stevenson and et al., "A dataset of neonatal EEG recordings with seizure annotations," *Scientific Data*, vol. 6, p. 190039, 2019.
- [85] P. Nejedly and et al., "Multicenter intracranial eeg dataset for classification of graphoelements and artifactual signals," *Scientific Data*, vol. 7, no. 1, p. 179, June 2020.
- [86] P. Detti and et al., "Eeg synchronization analysis for seizure prediction: A study on data of noninvasive recordings," *Processes*, vol. 8, no. 7, p. 846, 2020.
- [87] W. Nasreddine, "Epileptic eeg dataset," 2021.
- [88] J. M. Bernabei and et al., "'hup ieeg epilepsy dataset,'" 2022.
- [89] D. van Blooij, M. van den Boom, J. van der Aar, G. Huiskamp, G. Castegnaro, M. Demuru, W. Zweiphenning, P. van Eijnsden, K. J. Miller, F. Leijten, and D. Hermes, "'cceg ecog dataset across age 4–51,'" 2023.
- [90] World Health Organization, "Epilepsy," 2024.
- [91] X. Xu and et al., "Patient-specific method for predicting epileptic seizures based on drsn-gru," *Biomedical Signal Processing and Control*, vol. 81, p. 104449, 2023.
- [92] R. Peng and et al., "Wavelet2vec: a filter bank masked autoencoder for eeg-based seizure subtype classification," in *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2023, pp. 1–5.
- [93] M. Zhou and et al., "Epileptic seizure detection based on eeg signals and cnn," *Frontiers in neuroinformatics*, vol. 12, p. 95, 2018.
- [94] Ö. Türk and M. S. Özerdem, "Epilepsy detection by using scalogram based convolutional neural network from eeg signals," *Brain sciences*, vol. 9, no. 5, p. 115, 2019.
- [95] I. Ullah and et al., "An automated system for epilepsy detection using eeg brain signals based on deep learning approach," *Expert Systems with Applications*, vol. 107, pp. 61–71, 2018.
- [96] R. Akut, "Wavelet based deep learning approach for epilepsy detection," *Health Information Science and Systems*, vol. 7, no. 1, pp. 1–9, 2019.
- [97] O. S. Lih and et al., "Epilepsynet: Novel automated detection of epilepsy using transformer model with eeg signals from 121 patient population," *Computers in Biology and Medicine*, vol. 164, p. 107312, 2023.
- [98] A. K. Dutta and et al., "Deep learning-based multi-head self-attention model for human epilepsy identification from eeg signal for biomedical traits," *Multimedia Tools and Applications*, pp. 1–23, 2024.
- [99] D. Zhang and et al., "Brant: Foundation model for intracranial neural signal," *Advances in Neural Information Processing Systems*, vol. 36, 2024.
- [100] J. Guo and et al., "Detecting high frequency oscillations for stereoelectroencephalography in epilepsy via hypergraph learning," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 587–596, 2021.

- [101] A. Rahmani and et al., "A meta-gnn approach to personalized seizure detection and classification," in *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2023, pp. 1–5.
- [102] Y. Sun and et al., "Continuous seizure detection based on transformer and long-term ieeg," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 11, pp. 5418–5427, 2022.
- [103] S. Tu and et al., "Dmnet: Self-comparison driven model for subject-independent seizure detection," in *The Thirty-eighth Annual Conference on Neural Information Processing Systems*.
- [104] A. M. Abdelhameed and et al., "Epileptic seizure detection using deep convolutional autoencoder," in *2018 IEEE international workshop on signal processing systems (SiPS)*, 2018, pp. 223–228.
- [105] J. Turner and et al., "Deep belief networks used on high resolution multichannel electroencephalography data for seizure detection," in *2014 aaai spring symposium series*, 2014.
- [106] S. You and et al., "Unsupervised automatic seizure detection for focal-onset seizures recorded with behind-the-ear eeg using an anomaly-detecting generative adversarial network," *Computer Methods and Programs in Biomedicine*, vol. 193, p. 105472, 2020.
- [107] T. Xiao and et al., "Self-supervised learning with attention mechanism for eeg-based seizure detection," *Biomedical Signal Processing and Control*, vol. 87, p. 105464, 2024.
- [108] X. Li and V. Metsis, "Spp-eegnet: An input-agnostic self-supervised eeg representation model for inter-dataset transfer learning," in *International Conference on Computing and Information Technology*, 2022, pp. 173–182.
- [109] N. Wagh and et al., "Domain-guided self-supervision of eeg data improves downstream classification performance and generalizability," in *Machine Learning for Health*, 2021, pp. 130–142.
- [110] Y. Zheng and et al., "Task-oriented self-supervised learning for anomaly detection in electroencephalography," in *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, 2022, pp. 193–203.
- [111] S. Tang and et al., "Self-supervised graph neural networks for improved electroencephalographic seizure analysis," *10th International Conference on Learning Representations (ICLR'22)*, 2022.
- [112] J. Chen and et al., "Brainnet: Epileptic wave detection from seeg with hierarchical graph diffusion learning," pp. 2741–2751, 2022.
- [113] Z. Yuan and et al., "Ppi: Pretraining brain signal model for patient-independent seizure detection," *Advances in Neural Information Processing Systems*, vol. 36, 2024.
- [114] B. Kemp and et al., "Analysis of a sleep-dependent neuronal feedback loop: The slow-wave microcontinuity of the EEG," *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 9, pp. 1185–1194, 2000.
- [115] C. O'Reilly and et al., "Montreal Archive of Sleep Studies: An open-access resource for instrument benchmarking and exploratory research," *Journal of Sleep Research*, vol. 23, no. 6, pp. 628–635, 2014.
- [116] S. F. Quan and et al., "The Sleep Heart Health Study: Design, rationale, and methods," *Sleep*, vol. 20, no. 12, pp. 1077–1085, 1997.
- [117] G. Q. Zhang and et al., "The National Sleep Research Resource: Towards a sleep data commons," *Journal of the American Medical Informatics Association*, vol. 25, no. 10, pp. 1351–1358, October 2018.
- [118] "St. Vincent's University Hospital / University College Dublin Sleep Apnea Database," 2007.
- [119] D. Alvarez-Estevez and R. Rijsman, "Haaglanden medisch centrum sleep staging database (version 1.1)," 2022.
- [120] M. M. Ghassemi and et al., "You Snooze, You Win: The PhysioNet/Computing in Cardiology Challenge 2018," in *2018 Computing in Cardiology Conference (CinC)*, 2018, pp. 1–4.
- [121] Y. Ichimaru and G. B. Moody, "Development of the polysomnographic database on CD-ROM," *Psychiatry and Clinical Neurosciences*, vol. 53, pp. 175–177, April 1999.
- [122] A. Guillot and et al., "Dreem open datasets: Multi-scored sleep datasets to compare human and automated sleep staging," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. PP, pp. 1–1, 07 2020.
- [123] S. Khalighi and et al., "ISRUUC-Sleep: A comprehensive public dataset for sleep researchers," *Computer Methods and Programs in Biomedicine*, vol. 124, pp. 180–192, 2016.
- [124] S. Biswal and et al., "Expert-level sleep scoring with deep neural networks," *Journal of the American Medical Informatics Association*, vol. 25, no. 12, pp. 1643–1650, 2018.
- [125] A. Piryatinska and et al., "Automated detection of neonate eeg sleep stages," *Computer methods and programs in biomedicine*, vol. 95, no. 1, pp. 31–46, 2009.
- [126] S. Devuyst, "The dreams databases and assessment algorithm," 2005.
- [127] C. Xiang and et al., "A resting-state eeg dataset for sleep deprivation," <https://doi.org/10.18112/openneuro.ds004902.v1.0.5>, <https://doi.org/10.18112/openneuro.ds004902.v1.0.5>.
- [128] The Recovery Village, "Sleep disorders statistics," 2023.
- [129] O. Tsinalis and et al., "Automatic sleep stage scoring with single-channel eeg using convolutional neural networks," *arXiv preprint arXiv:1610.01683*, 2016.
- [130] E. Eldele and et al., "An attention-based deep learning approach for sleep stage classification with single-channel eeg," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 809–818, 2021.
- [131] S. Champon and et al., "A deep learning architecture for temporal sleep stage classification using multivariate and multimodal time series," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 4, pp. 758–769, 2018.
- [132] D. Alvarez-Estevez and R. M. Rijsman, "Inter-database validation of a deep learning approach for automatic sleep scoring," *PloS one*, vol. 16, no. 8, p. e0256111, 2021.
- [133] K. H and et al., "Accurate deep learning-based sleep staging in a clinical population with suspected obstructive sleep apnea," *IEEE journal of biomedical and health informatics*, vol. 24(7), pp. 2073–2081, 2019.
- [134] X. Jiang and et al., "Self-supervised contrastive learning for eeg-based sleep staging," in *2021 International Joint Conference on Neural Networks (IJCNN)*, 2021, pp. 1–8.
- [135] C. Yang and et al., "Self-supervised electroencephalogram representation learning for automatic sleep staging: model development and evaluation study," *JMIR AI*, vol. 2, no. 1, p. e46769, 2023.
- [136] V. Kumar and et al., "muleeg: a multi-view representation learning on eeg signals," in *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 2022, pp. 398–407.
- [137] J. Ye and et al., "Cosleep: A multi-view representation learning framework for self-supervised learning of sleep stage classification," *IEEE Signal Processing Letters*, vol. 29, pp. 189–193, 2021.
- [138] D. Zhang and et al., "Brant-x: A unified physiological signal alignment framework," in *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, 2024, pp. 4155–4166.
- [139] W. Mumtaz, "MDD Patients and Healthy Controls EEG Data (New)," 11 2016.
- [140] J. Cavanagh and et al., "The patient repository for eeg data + computational tools (pred+ct)," *Frontiers in Neuroinformatics*, vol. 11, p. 67, Nov 2017.
- [141] L. Yang and et al., "Automatic feature learning model combining functional connectivity network and graph regularization for depression detection," *Biomedical Signal Processing and Control*, vol. 82, p. 104520, 2023.
- [142] H. Cai and et al., "A multi-modal open dataset for mental-disorder analysis," *Scientific Data*, vol. 9, no. 1, p. 178, 2022.
- [143] World Health Organization. (2024) Depression.
- [144] U. R. Acharya and et al., "Automated eeg-based screening of depression using deep convolutional neural network," *Computer methods and programs in biomedicine*, vol. 161, pp. 103–113, 2018.
- [145] D. Shah and et al., "Deep learning of eeg data in the neucube brain-inspired spiking neural network architecture for a better understanding of depression," in *Neural Information Processing: 26th International Conference, ICONIP 2019, Sydney, NSW, Australia, December 12–15, 2019, Proceedings, Part III 26*, 2019, pp. 195–206.
- [146] A. Sam and et al., "Depression identification using eeg signals via a hybrid of lstm and spiking neural networks," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 4725–4737, 2023.
- [147] E. Olejarczyk and W. Jernajczyk, "Graph-based analysis of brain connectivity in schizophrenia," *PloS one*, vol. 12, no. 11, p. e0188629, 2017.
- [148] J. M. Ford and et al., "Did i do that? abnormal predictive processes in schizophrenia when button pressing to deliver a tone," *Schizophrenia bulletin*, vol. 40, no. 4, pp. 804–812, 2014.
- [149] S. Borisov and et al., "Analysis of eeg structural synchrony in adolescents with schizophrenic disorders," *Human Physiology*, vol. 31, pp. 255–261, 2005.
- [150] World Health Organization. (2024) Schizophrenia.
- [151] A. Zalesky and et al., "Disrupted axonal fiber connectivity in schizophrenia," *Biological psychiatry*, vol. 69, no. 1, pp. 80–89, 2011.
- [152] Z. Aslan and M. Akin, "Automatic detection of schizophrenia by applying deep learning over spectrogram images of eeg signals," *Traitement du Signal*, vol. 37, no. 2, 2020.

- [153] S. Siuly and et al., "Schizogogenet: The googlenet-based deep feature extraction design for automatic detection of schizophrenia," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, p. 1992596, 2022.
- [154] A. Shalbaf and et al., "Transfer learning with deep convolutional neural network for automated detection of schizophrenia from eeg signals," *Physical and Engineering Sciences in Medicine*, vol. 43, pp. 1229–1239, 2020.
- [155] M. L. Vicchietti and et al., "Data from: Computational methods of eeg signals analysis for alzheimer's disease classification," Feb 2023.
- [156] A. Miltiadous and et al., "'a dataset of 88 eeg recordings from: Alzheimer's disease, frontotemporal dementia and healthy subjects'", 2023.
- [157] G. Fiscon and et al., "In alzheimer's disease patients classification through eeg signals processing," in *Computational Intelligence & Data Mining*, 2014, pp. 105–112.
- [158] M. Cejnek and et al., "Novelty detection-based approach for alzheimer's disease and mild cognitive impairment diagnosis from eeg," *Medical & Biological Engineering & Computing*, vol. 59, no. 11, pp. 2287–2296, 2021.
- [159] M. A. BETTER, "Alzheimer's disease facts and figures," *Alzheimer's Dement*, vol. 20, pp. 3708–3821, 2024.
- [160] D. Labate and et al., "Eeg complexity modifications and altered compressibility in mild cognitive impairment and alzheimer's disease," in *Recent Advances of Neural Network Models and Applications: Proceedings of the 23rd Workshop of the Italian Neural Networks Society (SIREN)*, 2014, pp. 163–173.
- [161] X. Shan and et al., "Spatial-temporal graph convolutional network for alzheimer classification based on brain functional connectivity imaging of electroencephalogram," *Human Brain Mapping*, vol. 43, no. 17, pp. 5194–5209, 2022.
- [162] A. C. L and et al., "Eeg functional connectivity and deep learning for automatic diagnosis of brain disorders: Alzheimer's disease and schizophrenia," *Journal of Physics: complexity*, vol. 3(2), p. 025001, 2022.
- [163] F. C. Morabito and et al., "Deep convolutional neural networks for classification of mild cognitive impaired and alzheimer's disease patients from scalp eeg recordings," in *2016 IEEE 2nd International Forum on Research and Technologies for Society and Industry Leveraging a better tomorrow (RTSI)*. IEEE, 2016, pp. 1–6.
- [164] A. P. Rockhill and et al., "'uc san diego resting state eeg data from patients with parkinson's disease'", 2021.
- [165] J. F. Cavanagh and et al., "Diminished eeg habituation to novel events effectively classifies parkinson's patients," *Clinical Neurophysiology*, vol. 129, no. 2, pp. 409–418, Feb 2018.
- [166] A. Singh and et al., "Frontal theta and beta oscillations during lower limb movement in parkinson's disease," *Clinical Neurophysiology*, vol. 131, pp. 694–702, 2020.
- [167] World Health Organization, "Parkinson disease," 2023.
- [168] A. Morita and et al., "Relationship between slowing of the eeg and cognitive impairment in parkinson disease," *Journal of Clinical Neurophysiology*, vol. 28, no. 4, pp. 384–387, 2011.
- [169] M. Shaban and A. W. Amara, "Resting-state electroencephalography based deep-learning for the detection of parkinson's disease," *Plos one*, vol. 17, no. 2, p. e0263159, 2022.
- [170] C. Chu and et al., "Deep learning reveals personalized spatial spectral abnormalities of high delta and low alpha bands in eeg of patients with early parkinson's disease," *Journal of Neural Engineering*, vol. 18, no. 6, p. 066036, 2021.
- [171] E. Arasteh and et al., "Deep transfer learning for parkinson's disease monitoring by image-based representation of resting-state eeg using directional connectivity," *Algorithms*, vol. 15, no. 1, p. 5, 2021.
- [172] G. S. Bajestani and et al., "A dataset of eeg signals from adults with adhd and healthy controls: Resting state, cognitive function, and sound listening paradigm," 2023.
- [173] M. Nasrabadi and et al., "Eeg data for adhd / control children," 2020.
- [174] World Health Organization. (2021) Adolescent mental health.
- [175] National Institute of Mental Health. (2023) Attention-deficit/hyperactivity disorder (adhd). U.S. Department of Health and Human Services.
- [176] H. Chen and et al., "Use of deep learning to detect personalized spatial-frequency abnormalities in eegs of children with adhd," *Journal of neural engineering*, vol. 16, no. 6, p. 066046, 2019.
- [177] L. Dubreuil-Vall and et al., "Deep learning convolutional neural networks discriminate adult adhd from healthy individuals on the basis of event-related spectral eeg," *Frontiers in neuroscience*, vol. 14, p. 251, 2020.
- [178] E. Eldele and et al., "Time-series representation learning via temporal and contextual contrasting," *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, IJCAI-21*, 2021.
- [179] X. Zhang and et al., "Self-supervised contrastive pre-training for time series via time-frequency consistency," *Advances in Neural Information Processing Systems*, vol. 35, pp. 3988–4003, 2022.
- [180] C. Yang and et al., "Biot: Biosignal transformer for cross-data learning in the wild."
- [181] S. Jo and et al., "Channel-aware self-supervised learning for eeg-based bci," in *2023 11th International Winter Conference on Brain-Computer Interface (BCI)*. IEEE, 2023, pp. 1–4.
- [182] W. Zhang and et al., "Self-supervised time series representation learning via cross reconstruction transformer," *IEEE Transactions on Neural Networks and Learning Systems*, 2023.
- [183] D. Wu and et al., "Neuro-bert: Rethinking masked autoencoding for self-supervised neurological pretraining," *IEEE Journal of Biomedical and Health Informatics*, 2024.
- [184] J. Wang and et al., "Cbramod: A criss-cross brain foundation model for eeg decoding," *The Thirteenth International Conference on Learning Representations*, 2025.
- [185] Z. Yuan and et al., "Brainwave: A brain signal foundation model for clinical applications," 2024.
- [186] Y. Chen and et al., "Eegformer: Towards transferable and interpretable large-scale eeg foundation model," in *AAAI 2024 Spring Symposium on Clinical Foundation Models*, 2024.
- [187] W.-B. Jiang and et al., "Large brain model for learning generic representations with tremendous eeg data in bci," *The Twelfth International Conference on Learning Representations*, 2024.
- [188] W. Jiang and et al., "Neurolm: A universal multi-task foundation model for bridging the gap between language and eeg signals," *The Thirteenth International Conference on Learning Representations*, 2025.
- [189] J. Devlin, "Bert: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint arXiv:1810.04805*, 2018.
- [190] A. Van Den Oord and et al., "Neural discrete representation learning," *Advances in neural information processing systems*, vol. 30, 2017.
- [191] A. M. Taqi and et al., "Classification and discrimination of focal and non-focal eeg signals based on deep neural network," in *2017 International Conference on Current Research in Computer Science and Information Technology (ICCIT)*. IEEE, 2017, pp. 86–92.
- [192] M. C. Tjepkema-Cloostermans and et al., "Deep learning for detection of focal epileptiform discharges from scalp eeg recordings," *Clinical Neurophysiology*, vol. 129, no. 10, pp. 2191–2196, 2018.
- [193] S. Madhavan and et al., "Time-frequency domain deep convolutional neural network for the classification of focal and non-focal eeg signals," *IEEE Sensors Journal*, vol. 20, no. 6, pp. 3078–3086, 2019.
- [194] R. San-Segundo and et al., "Classification of epileptic eeg recordings using signal transforms and convolutional neural networks," *Computers in Biology and Medicine*, vol. 109, pp. 148–158, 2019.
- [195] L. Sui and et al., "Localization of epileptic foci by using convolutional neural network based on ieeg," in *IFIP International Conference on Artificial Intelligence Applications and Innovations*. Springer, 2019, pp. 331–339.
- [196] P. Boonyakitanont and et al., "A comparison of deep neural networks for seizure detection in eeg signals," *bioRxiv*, p. 702654, 2019.
- [197] B. Bouaziz and et al., "Epileptic seizure detection using a convolutional neural network," in *Digital Health Approach for Predictive, Preventive, Personalised and Participatory Medicine*. Springer, 2019, pp. 79–86.
- [198] M. S. Hossain and et al., "Applying deep learning for epilepsy seizure detection and brain mapping visualization," *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, vol. 15, no. 1s, pp. 1–17, 2019.
- [199] X. Tian and et al., "Deep multi-view feature learning for eeg-based epileptic seizure detection," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 10, pp. 1962–1972, 2019.
- [200] J. Cao and et al., "Epileptic signal classification with deep eeg features by stacked cnns," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 12, no. 4, pp. 709–722, 2019.
- [201] P. Z. Yan and et al., "Automated spectrographic seizure detection using convolutional neural networks," *Seizure*, vol. 71, pp. 124–131, 2019.
- [202] A. Emami and et al., "Seizure detection by convolutional neural network-based analysis of scalp electroencephalography plot images," *NeuroImage: Clinical*, vol. 22, p. 101684, 2019.
- [203] R. Zuo and et al., "Automated detection of high-frequency oscillations in epilepsy based on a convolutional neural network," *Frontiers in Computational Neuroscience*, vol. 13, p. 6, 2019.

- [204] U. Asif and et al., "Seizurenet: A deep convolutional neural network for accurate seizure type classification and seizure detection," arXiv preprint arXiv:1903.03232, 2019.
- [205] N. Ilakiyaselvan and et al., "Deep learning approach to detect seizure using reconstructed phase space images," *Journal of Biomedical Research*, vol. 34, no. 3, p. 240, 2020.
- [206] W. Mao and et al., "Eeg dataset classification using cnn method," in *Journal of Physics: Conference Series*, vol. 1456. IOP Publishing, 2020, p. 012017.
- [207] A. Shankar and et al., "Epileptic seizure classification based on gramian angular field transformation and deep learning," in *2020 IEEE Applied Signal Processing Conference (ASPCON)*. IEEE, 2020, pp. 147–151.
- [208] A. Singh and et al., "Cnn-based epilepsy detection using image like features of eeg signals," in *2020 International Conference on Electrical and Electronics Engineering (ICE3)*. IEEE, 2020, pp. 280–284.
- [209] P. Boonyakantanont and et al., "Automatic epileptic seizure onset-offset detection based on cnn in scalp eeg," in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2020, pp. 1225–1229.
- [210] Y. Gao and et al., "Deep convolutional neural network-based epileptic electroencephalogram (eeg) signal classification," *Frontiers in Neurology*, vol. 11, 2020.
- [211] F. George and et al., "Epileptic seizure prediction using eeg images," in *2020 International Conference on Communication and Signal Processing (ICCP)*. IEEE, 2020, pp. 1595–1598.
- [212] Y. Qin and et al., "Patient-specific seizure prediction with scalp eeg using convolutional neural network and extreme learning machine," in *2020 39th Chinese Control Conference (CCC)*. IEEE, 2020, pp. 7622–7625.
- [213] S. M. Usman and et al., "Epileptic seizures prediction using deep learning techniques," *IEEE Access*, vol. 8, pp. 39998–40007, 2020.
- [214] B. Zhang and et al., "Cross-subject seizure detection in eegs using deep transfer learning," *Computational and Mathematical Methods in Medicine*, vol. 2020, 2020.
- [215] D. Hu and et al., "Epileptic state classification by fusing hand-crafted and deep learning eeg features," *IEEE Transactions on Circuits and Systems II: Express Briefs*, 2020.
- [216] G. Liu and et al., "Automatic seizure detection based on s-transform and deep convolutional neural network," *International Journal of Neural Systems*, vol. 30, no. 04, p. 1950024, 2020.
- [217] R. Hussein and et al., "Epileptic seizure prediction: A semi-dilated convolutional neural network architecture," arXiv preprint arXiv:2007.11716, 2020.
- [218] S. Raghu and et al., "Eeg based multi-class seizure type classification using convolutional neural network and transfer learning," in *Neural Networks*, vol. 124, 2020, pp. 202–212.
- [219] T. Uyttenhoeve and et al., "Interpretable epilepsy detection in routine, interictal eeg data using deep learning," in *Machine Learning for Health*. PMLR, 2020, pp. 355–366.
- [220] M. Rashed-Al-Mahfuz and et al., "A deep convolutional neural network method to detect seizures and characteristic frequencies using epileptic electroencephalogram (eeg) data," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 9, pp. 1–12, 2021.
- [221] M. Zeng and et al., "Grp-dnet: A gray recurrence plot-based densely connected convolutional network for classification of epileptiform eeg," *Journal of Neuroscience Methods*, vol. 347, p. 108953, 2021.
- [222] T. Luo and et al., "Emd-wog-2dcnn based eeg signal processing for rolandic seizure classification," *Comput. Methods Biomed. Eng.*, vol. 25, no. 14, pp. 1565–1575, 2022.
- [223] T. Jagadesh and et al., "Early prediction of epileptic seizure using deep learning algorithm," in *Brain-Computer Interface*. Wiley, 2023, pp. 157–177.
- [224] T. Kaur and T. K. Gandhi, "Automated diagnosis of epileptic seizures using eeg image representations and deep learning," *Neuroscience Informatics*, vol. 3, no. 3, p. 100139, 2023.
- [225] Y. Yuan and et al., "A novel channel-aware attention framework for multi-channel eeg seizure detection via multi-view deep learning," in *2018 IEEE EMBS international conference on biomedical & health informatics (BHI)*, 2018, pp. 206–209.
- [226] X. Si and et al., "Patient-independent seizure detection based on long-term ieeg and a novel lightweight cnn," *J. Neural Eng.*, vol. 20, no. 1, p. 016037, 2023.
- [227] Y. Zhang and et al., "Epileptic seizure detection based on bidirectional gated recurrent unit network," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 135–145, 2022.
- [228] B. Ganti and et al., "Time-series generative adversarial network approach of deep learning improves seizure detection from the human thalamic seeg," *Frontiers in Neurology*, vol. 13, p. 755094, 2022.
- [229] X. Hu and Q. Yuan, "Epileptic eeg identification based on deep bi-lstm network," in *2019 IEEE 11th International Conference on Advanced Infocomm Technology (ICAIT)*. IEEE, 2019, pp. 63–66.
- [230] L. Friwan and M. Alkhodari, "Classification of focal and non-focal epileptic patients using single channel eeg and long short-term memory learning system," *IEEE Access*, vol. 8, pp. 77255–77262, 2020.
- [231] X. Hu and et al., "Scalp eeg classification using deep bi-lstm network for seizure detection," *Computers in Biology and Medicine*, vol. 124, p. 103919, 2020.
- [232] M. Geng and et al., "Epileptic seizure detection based on stockwell transform and bidirectional long short-term memory," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 3, pp. 573–580, 2020.
- [233] X. Yao and et al., "A robust deep learning approach for automatic classification of seizures against non-seizures," *Biomedical Signal Processing and Control*, vol. 64, p. 102215, 2021.
- [234] E. Tunçer and E. Bolat, "Classification of epileptic seizures from electroencephalogram (eeg) data using bidirectional short-term memory (bi-lstm) network architecture," *Biomed. Signal Process. Control*, vol. 73, p. 103462, 2022.
- [235] A. O'Shea and et al., "Neonatal seizure detection using convolutional neural networks," in *2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP)*. IEEE, 2017, pp. 1–6.
- [236] H. G. Daoud and et al., "Automatic epileptic seizure detection based on empirical mode decomposition and deep neural network," in *2018 IEEE 14th international colloquium on signal processing & its applications (CSPA)*. IEEE, 2018, pp. 182–186.
- [237] I. Ullah and et al., "An automated system for epilepsy detection using eeg brain signals based on deep learning approach," *Expert Systems with Applications*, vol. 107, pp. 61–71, 2018.
- [238] J. Zhang and et al., "A new approach for classification of epilepsy eeg signals based on temporal convolutional neural networks," in *2018 11th International Symposium on Computational Intelligence and Design (ISCID)*, vol. 2. IEEE, 2018, pp. 80–84.
- [239] R. Yuvaraj and et al., "A deep learning scheme for automatic seizure detection from long-term scalp eeg," in *2018 52nd Asilomar Conference on Signals, Systems, and Computers*. IEEE, 2018, pp. 368–372.
- [240] J. Thomas and et al., "Eeg classification via convolutional neural network-based interictal epileptiform event detection," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, pp. 3148–3151.
- [241] O. Yıldırım and et al., "A deep convolutional neural network model for automated identification of abnormal eeg signals," *Neural Computing and Applications*, pp. 1–12, 2018.
- [242] D. Lu and J. Triesch, "Residual deep convolutional neural network for eeg signal classification in epilepsy," *arXiv preprint arXiv:1903.08100*, 2019.
- [243] Z. Wei and et al., "Automatic epileptic eeg detection using convolutional neural network with improvements in time-domain," *Biomedical Signal Processing and Control*, vol. 53, p. 101551, 2019.
- [244] J. Craley and et al., "Integrating convolutional neural networks and probabilistic graphical modeling for epileptic seizure detection in multichannel eeg," in *International Conference on Information Processing in Medical Imaging*. Springer, 2019, pp. 291–303.
- [245] A. H. Ansari and et al., "Neonatal seizure detection using deep convolutional neural networks," *International Journal of Neural Systems*, vol. 29, no. 04, p. 1850011, 2019.
- [246] M. T. Avcu and et al., "Seizure detection using least eeg channels by deep convolutional neural network," in *2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2019, pp. 1120–1124.
- [247] K. Fukumori and et al., "Fully data-driven convolutional filters with deep learning models for epileptic spike detection," in *2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2019, pp. 2772–2776.
- [248] S. Wang and et al., "Time-resnext for epilepsy recognition based on eeg signals in wireless networks," *EURASIP Journal on Wireless Communications and Networking*, vol. 2020, no. 1, pp. 1–12, 2020.
- [249] X. Zhao and et al., "Classification of epileptic ieeg signals by cnn and data augmentation," in *2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2020, pp. 926–930.

- [250] X. Gao and et al., "Automatic detection of epileptic seizure based on approximate entropy, recurrence quantification analysis and convolutional neural networks," *Artificial Intelligence in Medicine*, vol. 102, p. 101711, 2020.
- [251] D. Kaya, "The mrrmr-cnn based influential support decision system approach to classify eeg signals," *Measurement*, vol. 156, p. 107602, 2020.
- [252] J. Lian and et al., "Pair-wise matching of eeg signals for epileptic identification via convolutional neural network," *IEEE Access*, vol. 8, pp. 40 008–40 017, 2020.
- [253] H. Qin and et al., "Deep multi-scale feature fusion convolutional neural network for automatic epilepsy detection using eeg signals," in *2020 39th Chinese Control Conference (CCC)*. IEEE, 2020, pp. 7061–7066.
- [254] A. Torfi and E. A. Fox, "Corgan: Correlation-capturing convolutional generative adversarial networks for generating synthetic healthcare records," *arXiv e-prints*, pp. arXiv–2001, 2020.
- [255] G. Zhang and et al., "Mnl-network: A multi-scale non-local network for epilepsy detection from eeg signals," *Frontiers in Neuroscience*, vol. 14, 2020.
- [256] W. Zhao and et al., "Seizurennet: A model for robust detection of epileptic seizures based on convolutional neural network," *Cognitive Computation and Systems*, vol. 2, no. 3, pp. 119–124, 2020.
- [257] —, "A novel deep neural network for robust detection of seizures using eeg signals," *Computational and Mathematical Methods in Medicine*, vol. 2020, p. Article 2020, 2020.
- [258] R. Abiyev and et al., "Identification of epileptic eeg signals using convolutional neural networks," *Applied Sciences*, vol. 10, no. 12, p. 4089, 2020.
- [259] Y. Li and et al., "Epileptic seizure detection in eeg signals using a unified temporal-spectral squeeze-and-excitation network," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 4, pp. 782–794, 2020.
- [260] H. Daoud and et al., "Iot based efficient epileptic seizure prediction system using deep learning," in *2020 IEEE 6th World Forum on Internet of Things (WF-IoT)*. IEEE, 2020, pp. 1–6.
- [261] G. C. Jana and et al., "A cnn-spectrogram based approach for seizure detection from eeg signal," *Procedia Computer Science*, vol. 167, pp. 403–412, 2020.
- [262] O. Kaziha and T. Bonny, "A convolutional neural network for seizure detection," in *2020 Advances in Science and Engineering Technology International Conferences (ASET)*. IEEE, 2020, pp. 1–5.
- [263] S. Khalilpour and et al., "Application of 1-d cnn to predict epileptic seizures using eeg records," in *2020 6th International Conference on Web Research (ICWR)*. IEEE, 2020, pp. 314–318.
- [264] R. V. Sharan and S. Berkovsky, "Epileptic seizure detection using multichannel eeg wavelet power spectra and 1-d convolutional neural networks," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2020, pp. 545–548.
- [265] A. H. Thomas and et al., "Noise-resilient and interpretable epileptic seizure detection," in *2020 IEEE International Symposium on Circuits and Systems (ISCAS)*. IEEE, 2020, pp. 1–5.
- [266] S. Zhao and et al., "Binary single-dimensional convolutional neural network for seizure prediction," in *2020 IEEE International Symposium on Circuits and Systems (ISCAS)*. IEEE, 2020, pp. 1–5.
- [267] M. Abou Jaoude and et al., "Detection of mesial temporal lobe epileptiform discharges on intracranial electrodes using deep learning," *Clinical Neurophysiology*, vol. 131, no. 1, pp. 133–141, 2020.
- [268] L.-C. Lin and et al., "Alternative diagnosis of epilepsy in children without epileptiform discharges using deep convolutional neural networks," *International Journal of Neural Systems*, vol. 30, no. 05, p. 1850060, 2020.
- [269] F. Pisano and et al., "Convolutional neural network for seizure detection of nocturnal frontal lobe epilepsy," *Complexity*, 2020.
- [270] T. Sakai and et al., "Scalpnet: Detection of spatiotemporal abnormal intervals in epileptic eeg using convolutional neural networks," in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2020, pp. 1244–1248.
- [271] J. Thomas and et al., "Automated detection of interictal epileptiform discharges from scalp electroencephalograms by convolutional neural networks," *International Journal of Neural Systems*, vol. 30, no. 11, p. 2050030, 2020.
- [272] C. Vance and et al., "Learning to detect the onset of slow activity after a generalized tonic-clonic seizure," *BMC Medical Informatics and Decision Making*, vol. 20, no. 12, pp. 1–8, 2020.
- [273] K.-O. Cho and H.-J. Jang, "Comparison of different input modalities and network structures for deep learning-based seizure detection," *Scientific Reports*, vol. 10, no. 1, pp. 1–11, 2020.
- [274] Y. Xu and et al., "An end-to-end deep learning approach for epileptic seizure prediction," in *2020 2nd IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS)*. IEEE, 2020, pp. 266–270.
- [275] T. Ic̄ smantas and R. Alzbutas, "Convolutional neural network for detection and classification of seizures in clinical data," *Medical & Biological Engineering & Computing*, vol. 58, no. 9, pp. 1919–1932, 2020.
- [276] X. Zhang and et al., "Adversarial representation learning for robust patient-independent epileptic seizure detection," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 10, pp. 2852–2859, 2020.
- [277] S. Ramakrishnan and et al., "Seizure detection with local binary pattern and cnn classifier," in *Journal of Physics: Conference Series*, vol. 1767. IOP Publishing, 2021, p. 012029.
- [278] K. Singh and J. Malhotra, "Prediction of epileptic seizures from spectral features of intracranial eeg recordings using deep learning approach," *Multimed. Tools Appl.*, vol. 81, no. 20, pp. 28 875–28 898, Aug 2022.
- [279] D. K. Atal and M. Singh, "Effectual seizure detection using mbbf-gpso with cnn network," *Cogn. Neurodyn*, pp. 1–12, 2023.
- [280] Y. Zaid, M. Sah, and C. Direkoglu, "Pre-processed and combined eeg data for epileptic seizure classification using deep learning," *Biomedical Signal Processing and Control*, vol. 84, p. 104738, 2023.
- [281] I. Assali and et al., "Cnn-based classification of epileptic states for seizure prediction using combined temporal and spectral features," *Biomedical Signal Processing and Control*, vol. 82, p. 104519, 2023.
- [282] S. Mekruksavanh and A. Jitpattanakul, "Deep learning approaches for epileptic seizures recognition based on eeg signal," in *46th International Conference on Telecommunications and Signal Processing (TSP)*. IEEE, 2023, pp. 33–36.
- [283] D. Raab, A. Theissler, and M. Spiliopoulou, "Xai4eeg: Spectral and spatio-temporal explanation of deep learning-based seizure detection in eeg time series," *Neural Comput. Appl.*, vol. 35, no. 14, pp. 10 051–10 068, May 2023.
- [284] T. Prasanth and et al., "Deep learning for interictal epileptiform spike detection from scalp eeg frequency sub bands," in *Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2020, pp. 3703–3706.
- [285] S. Poorani and P. Balasubramanie, "Deep learning based epileptic seizure detection with eeg data," *Int. J. Syst. Assur. Eng. Manag.*, pp. 1–10, 2023.
- [286] X. Liu and A. G. Richardson, "Embedded deep learning for neural implants," *arXiv preprint arXiv:2012.00307*, 2020.
- [287] X. Chen, J. Ji, T. Ji, and P. Li, "Cost-sensitive deep active learning for epileptic seizure detection," in *ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*, 2018, pp. 226–235.
- [288] Y. Yuan and K. Jia, "Fusionatt: Deep fusional attention networks for multi-channel biomedical signals," *Sensors*, vol. 19, no. 11, p. 2429, 2019.
- [289] D. Y. Isaev and et al., "Attention-based network for weak labels in neonatal seizure detection," in *Proc. Mach. Learn. Res.*, vol. 126, 2020, p. 479.
- [290] M. Natu and et al., "Hclu_cbigru: Hybrid convolutional bidirectional gru based model for epileptic seizure detection," *Neurosci. Inform.*, p. 100135, 2023.
- [291] J. Craley, E. Johnson, C. Jouny, and A. Venkataraman, "Automated inter-patient seizure detection using multichannel convolutional and recurrent neural networks," *Biomed. Signal Process. Control*, vol. 64, p. 102360, 2021.
- [292] I. Ahmad and et al., "A hybrid deep learning approach for epileptic seizure detection in eeg signals," *IEEE Journal of Biomedical and Health Informatics*, 2023.
- [293] Y. Wang and et al., "Seeg-net: An explainable and deep learning-based cross-subject pathological activity detection method for drug-resistant epilepsy," *Computers in Biology and Medicine*, vol. 148, p. 105703, 2022.
- [294] F. A. Jibon and et al., "Epileptic seizure detection from electroencephalogram (eeg) signals using linear graph convolutional network and densenet based hybrid framework," *J. Radiat. Res. Appl. Sci.*, vol. 16, no. 3, p. 100607, 2023.

- [295] S. Roy and et al., "Chrononet: A deep recurrent neural network for abnormal eeg identification," in *Conference on Artificial Intelligence in Medicine in Europe*. Springer, 2019, pp. 47–56.
- [296] L. Tang and et al., "Seizure prediction using multiview features and improved convolutional gated recurrent network," *IEEE Access*, vol. 8, pp. 172 352–172 361, 2020.
- [297] S. P. Kumar and et al., "Automatic detection of epilepsy using cnn-gru hybrid model," in *Biomed. Signals Based Comput.-Aided Diagn. Neurol. Disord.* Springer, 2022, pp. 165–186.
- [298] P. Thodoroff and et al., "Learning robust features using deep learning for automatic seizure detection," in *Machine Learning for Healthcare Conference*. PMLR, 2016, pp. 178–190.
- [299] M. Golmohammadi and et al., "Deep architectures for automated seizure detection in scalp eegs," *arXiv preprint arXiv:1712.09776*, 2017.
- [300] U. B. Baloglu and et al., "Convolutional long-short term memory networks model for long duration eeg signal classification," *J. Mech. Med. Biol.*, vol. 19, no. 01, p. 1940005, 2019.
- [301] Y. Liu and et al., "Deep c-lstm neural network for epileptic seizure and tumor detection using high-dimension eeg signals," *IEEE Access*, vol. 8, pp. 37495–37504, 2020.
- [302] G. Xu and et al., "A one-dimensional cnn-lstm model for epileptic seizure recognition using eeg signal analysis," *Frontiers in Neuroscience*, vol. 14, p. 1253, 2020.
- [303] Y. Li and et al., "Automatic seizure detection using fully convolutional nested lstm," *International Journal of Neural Systems*, vol. 30, no. 04, p. 2050019, 2020.
- [304] W. Liang and et al., "Scalp eeg epileptogenic zone recognition and localization based on long-term recurrent convolutional network," *Neurocomputing*, vol. 396, pp. 569–576, 2020.
- [305] W. Hussain and et al., "Epileptic seizure detection using 1d-convolutional long short-term memory neural networks," *Appl. Acoust.*, vol. 177, p. 107941, 2021.
- [306] Y. Yang and et al., "Video-based detection of generalized tonic-clonic seizures using deep learning," *IEEE Journal of Biomedical and Health Informatics*, 2021.
- [307] M. Varli and et al., "Multiple classification of eeg signals and epileptic seizure diagnosis with combined deep learning," *J. Comput. Sci.*, vol. 67, p. 101943, 2023.
- [308] Y. P. Singh and et al., "Automatic prediction of epileptic seizure using hybrid deep resnet-lstm model," *AI Commun.*, vol. 36, no. 1, pp. 57–72, Feb 2023.
- [309] X. Qiu and et al., "A difference attention resnet-lstm network for epileptic seizure detection using eeg signal," *Biomed. Signal Process. Control*, vol. 83, p. 104652, 2023.
- [310] S. Roy and et al., "Deep learning enabled automatic abnormal eeg identification," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, pp. 2756–2759.
- [311] C. Huang and et al., "Automatic epileptic seizure detection via attention-based cnn-birnn," in *2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE, 2019, pp. 660–663.
- [312] D. Kostas and et al., "Bendr: Using transformers and a contrastive self-supervised learning task to learn from massive amounts of eeg data," *Frontiers in Human Neuroscience*, vol. 15, p. 653659, 2021.
- [313] P. Busia and et al., "Eegformer: Transformer-based epilepsy detection on raw eeg traces for low-channel-count wearable continuous monitoring devices," in *2022 IEEE Biomedical Circuits and Systems Conference (BioCAS)*. IEEE, 2022, pp. 640–644.
- [314] S. Hu and et al., "Exploring the applicability of transfer learning and feature engineering in epilepsy prediction using hybrid transformer model," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 1321–1332, 2023.
- [315] Z. Deng and et al., "Eeg-based seizure prediction via hybrid vision transformer and data uncertainty learning," *Engineering Applications of Artificial Intelligence*, vol. 123, p. 106401, 2023.
- [316] W. Y. Peh and et al., "Six-center assessment of cnn-transformer with belief matching loss for patient-independent seizure detection in eeg," *International Journal of Neural Systems*, vol. 33, no. 03, p. 2350012, 2023.
- [317] C. Dong and et al., "Eeg-based patient-specific seizure prediction based on spatial-temporal hypergraph attention transformer," *Biomedical Signal Processing and Control*, vol. 100, p. 107075, 2025.
- [318] Y. Sun and et al., "Multi-task transformer network for subject-independent ieeg seizure detection," *Expert Systems with Applications*, p. 126282, 2024.
- [319] T. X. Le and et al., "Deep learning for epileptic spike detection," *VNU Journal of Science: Computer Science and Communication Engineering*, vol. 33, no. 2, pp. 1–13, 2018.
- [320] K. P. Thanaraj and et al., "Implementation of deep neural networks to classify eeg signals using gramian angular summation field for epilepsy diagnosis," *arXiv preprint arXiv:2003.04534*, 2020.
- [321] K. Akyol, "Stacking ensemble based deep neural networks modeling for effective epileptic seizure detection," *Expert Systems with Applications*, vol. 148, p. 113239, 2020.
- [322] A. Guha and et al., "Epileptic seizure recognition using deep neural network," in *Emerging Technology in Modelling and Graphics*. Springer, 2020, pp. 21–28.
- [323] R. Sharma and et al., "Seizures classification based on higher order statistics and deep neural network," *Biomedical Signal Processing and Control*, vol. 59, p. 101921, 2020.
- [324] H. A. Glory and et al., "Ahw-bgoa-dnn: A novel deep learning model for epileptic seizure detection," *Neural Computing and Applications*, pp. 1–29, 2020.
- [325] Z. Zhang and et al., "Dwt-net: Seizure detection system with structured eeg montage and multiple feature extractor in convolution neural network," *Journal of Sensors*, 2020.
- [326] Y. Zhao and et al., "Graph attention network with focal loss for seizure detection on electroencephalography signals," *International Journal of Neural Systems*, vol. 31, no. 07, p. 2150027, 2021.
- [327] Y. Wang and et al., "A spatiotemporal graph attention network based on synchronization for epileptic seizure prediction," *IEEE Journal of Biomedical and Health Informatics*, vol. 27, no. 2, pp. 900–911, 2023.
- [328] Y. Zhao and et al., "Hybrid attention network for epileptic eeg classification," *International Journal of Neural Systems*, vol. 33, no. 06, p. 2350031, 2023.
- [329] J. He and et al., "Spatial-temporal seizure detection with graph attention network and bi-directional lstm architecture," *Biomedical Signal Processing and Control*, vol. 78, p. 103908, 2022.
- [330] X. Chen and et al., "Epilepsy classification for mining deeper relationships between eeg channels based on gcn," in *2020 International Conference on Computer Vision, Image and Deep Learning (CVIDL)*. IEEE, 2020, pp. 701–706.
- [331] J. Wang and et al., "A sequential graph convolutional network with frequency-domain complex network of eeg signals for epilepsy detection," in *2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE, 2020, pp. 785–792.
- [332] Y. Zhao and et al., "Eeg-based seizure detection using linear graph convolution network with focal loss," *Computer methods and programs in biomedicine*, vol. 208, p. 106277, 2021.
- [333] D. Nhu and et al., "Graph convolutional network for generalized epileptiform abnormality detection on eeg," in *2021 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*. IEEE, 2021, pp. 1–6.
- [334] J. Lian and F. Xu, "Spatial enhanced pattern through graph convolutional neural network for epileptic eeg identification," *International Journal of Neural Systems*, vol. 32, no. 09, p. 2250033, 2022.
- [335] C. Dong and et al., "Attention-based graph resnet with focal loss for epileptic seizure detection," *Journal of Ambient Intelligence and Smart Environments*, vol. 14, no. 1, pp. 61–73, 2022.
- [336] Y. Wang and et al., "Dynamic multi-graph convolution based channel-weighted transformer feature fusion network for epileptic seizure prediction," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2023.
- [337] J. Lian and F. Xu, "Epileptic eeg classification via graph transformer network," *International Journal of Neural Systems*, vol. 33, no. 8, p. 2350042, 2023.
- [338] S. S. Talathi, "Deep recurrent neural networks for seizure detection and early seizure detection systems," *arXiv preprint arXiv:1706.03283*, 2017.
- [339] A. Verma and R. R. Janghel, "Epileptic seizure detection using deep recurrent neural networks in eeg signals," in *Advances in Biomedical Engineering and Technology*. Springer, 2021, pp. 189–198.
- [340] O. Ramwala and et al., "Gru-based parameter-efficient epileptic seizure detection," *Biomedical Signal Processing and Artificial Intelligence*, pp. 73–86, 2023.
- [341] R. Hussein and et al., "Robust detection of epileptic seizures using deep neural networks," in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2018, pp. 2546–2550.
- [342] D. Ahmed-Aristizabal and et al., "Deep classification of epileptic signals," in *2018 40th Annual International Conference of the IEEE*, 2018.

- [343] R. Hussein and et al., "Optimized deep neural network architecture for robust detection of epileptic seizures using eeg signals," *Clinical Neurophysiology*, vol. 130, no. 1, pp. 25–37, 2019.
- [344] M. U. Abbasi and et al., "Detection of epilepsy seizures in neo-natal eeg using lstm architecture," *IEEE Access*, vol. 7, pp. 179 074–179 085, 2019.
- [345] I. Aliyu and C. Lim, "Selection of optimal wavelet features for epileptic eeg signal classification with lstm," *Neural Computing and Applications*, pp. 1–21, 2021.
- [346] K. Singh and J. Malhotra, "Two-layer lstm network-based prediction of epileptic seizures using eeg spectral features," *Complex Intelligence Systems*, vol. 8, no. 3, pp. 2405–2418, Jun 2022.
- [347] E. Tunçer and E. Bolat, "Channel based epilepsy seizure type detection from electroencephalography (eeg) signals with machine learning techniques," *Biocybernetics and Biomedical Engineering*, vol. 42, no. 2, pp. 575–595, 2022.
- [348] A. Pandey and et al., "An intelligent optimized deep learning model to achieve early prediction of epileptic seizures," *Biomedical Signal Processing and Control*, vol. 84, p. 104798, Jul 2023.
- [349] L. Vidyarathne and et al., "Deep recurrent neural network for seizure detection," in *2016 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2016, pp. 1202–1207.
- [350] X. Yao, Q. Cheng, and G.-Q. Zhang, "Automated classification of seizures against nonseizures: A deep learning approach," arXiv preprint arXiv:1906.02745, 2019.
- [351] X. Yao and et al., "A novel independent rnn approach to classification of seizures against non-seizures," arXiv preprint arXiv:1903.09326, 2019.
- [352] Y. Singh and D. Lobiyal, "A comparative study of deep learning algorithms for epileptic seizure classification," in *2022 International Conference on Computing, Communication Security and Intelligent Systems (IC3SIS)*. IEEE, 2022, pp. 1–6.
- [353] R. Chiranjeevi and et al., "Identification of epileptic seizures using recurrent neural networks and time series transformer," in *2024 7th International Conference on Circuit Power and Computing Technologies (ICCPCT)*. IEEE, 2024, pp. 1546–1553.
- [354] R. Zhu and et al., "Epileptic seizure prediction via multidimensional transformer and recurrent neural network fusion," *Journal of Translational Medicine*, vol. 22, no. 1, p. 895, 2024.
- [355] I. C. Covert and et al., "Temporal graph convolutional networks for automatic seizure detection," in *Machine Learning for Healthcare Conference*. PMLR, 2019, pp. 160–180.
- [356] J. Pedoeem and et al., *TabS: Transformer based Seizure Detection*. Cham: Springer International Publishing, 2022.
- [357] Y. Ma and et al., "Tsd: Transformers for seizure detection," *bioRxiv*, p. 2023.01.24.525308, 2023.
- [358] C. Meisel and K. A. Bailey, "Identifying signal-dependent information about the preictal state: A comparison across ecog, eeg and ekg using deep learning," *EBioMedicine*, vol. 45, pp. 422–431, 2019.
- [359] J. Guo and et al., "Detecting high frequency oscillations for stereoelectroencephalography in epilepsy via hypergraph learning," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 587–596, 2021.
- [360] A. Gogna and et al., "Semi-supervised stacked label consistent autoencoder for reconstruction and analysis of biomedical signals," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 9, pp. 2196–2205, 2016.
- [361] C. Park and et al., "Epileptic seizure detection for multi-channel eeg with deep convolutional neural network," in *2018 International Conference on Electronics, Information, and Communication (ICEIC)*. IEEE, 2018, pp. 1–5.
- [362] W. Barry, S. Arcot Desai, T. K. Tcheng, and M. J. Morrell, "A high accuracy electrographic seizure classifier trained using semi-supervised labeling applied to a large spectrogram dataset," *Frontiers in neuroscience*, vol. 15, p. 667373, 2021.
- [363] Y. Yuan and et al., "A multi-view deep learning framework for eeg seizure detection," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 1, pp. 83–94, 2018.
- [364] P. N. Bhagat and et al., "Robust prior stage epileptic seizure diagnosis system using resnet and backpropagation techniques," *International Journal*, vol. 8, no. 5, 2020.
- [365] N. D. Truong and et al., "Epileptic seizure forecasting with generative adversarial networks," *IEEE Access*, vol. 7, pp. 143 999–144 009, 2019.
- [366] H. Takahashi and et al., "Convolutional neural network with autoencoder-assisted multiclass labelling for seizure detection based on scalp electroencephalography," *Computers in Biology and Medicine*, vol. 125, p. 104016, 2020.
- [367] A. Shoeibi and et al., "A comprehensive comparison of handcrafted features and convolutional autoencoders for epileptic seizures detection in eeg signals," *Expert Systems with Applications*, vol. 163, p. 113788, 2021.
- [368] D. Wulsin and et al., "Modeling electroencephalography waveforms with semi-supervised deep belief nets: Fast classification and anomaly measurement," *J. Neural Eng.*, vol. 8, no. 3, p. 036015, 2011.
- [369] H. Daoud and M. Bayoumi, "Deep learning approach for epileptic focus localization," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 14, no. 2, pp. 209–220, 2019.
- [370] Q. Lin and et al., "Classification of epileptic eeg signals with stacked sparse autoencoder based on deep learning," in *International Conference on Intelligent Computing*. Springer, 2016, pp. 802–810.
- [371] B. Yan and et al., "An eeg signal classification method based on sparse auto-encoders and support vector machine," in *2016 IEEE/CIC International Conference on Communications in China (ICCC)*. IEEE, 2016, pp. 1–6.
- [372] Y. Yuan and et al., "A multi-view deep learning method for epileptic seizure detection using short-time fourier transform," in *Proceedings of the 8th ACM International Conference on Bioinformatics, Computational Biology, and Health Informatics*, 2017, pp. 213–222.
- [373] A. M. Karim and et al., "A new generalized deep learning framework combining sparse autoencoder and taguchi method for novel data classification and processing," *Mathematical Problems in Engineering*, vol. 2018, 2018.
- [374] Y. Qiu and et al., "Denoising sparse autoencoder-based ictal eeg classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26, no. 9, pp. 1717–1726, 2018.
- [375] V. Sharathappriyaa and et al., "Auto-encoder based automated epilepsy diagnosis," in *2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*. IEEE, 2018, pp. 976–982.
- [376] Y. Yuan and et al., "Wave2vec: Deep representation learning for clinical temporal data," *Neurocomputing*, vol. 324, pp. 31–42, 2019.
- [377] A. Emami and et al., "Autoencoding of long-term scalp electroencephalogram to detect epileptic seizure for diagnosis support system," *Computers in Biology and Medicine*, vol. 110, pp. 227–233, 2019.
- [378] J. X and et al., "3dsleepnet: A multi-channel bio-signal based sleep stages classification method using deep learning," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2023.
- [379] W. J and et al., "Caresleepnet: a hybrid deep learning network for automatic sleep staging," *IEEE Journal of Biomedical and Health Informatics*, 2024.
- [380] L. F and et al., "End-to-end sleep staging using convolutional neural network in raw single-channel eeg," *Biomedical Signal Processing and Control*, vol. 63, p. 102203, 2021.
- [381] E. E and O. S., "Cosleepnet: Automated sleep staging using a hybrid cnn-lstm network on imbalanced eeg-eog datasets," *Biomedical Signal Processing and Control*, vol. 80, p. 104299, 2023.
- [382] S. A and et al., "Deepsleepnet: A model for automatic sleep stage scoring based on raw single-channel eeg," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 25(11), pp. 1998–2008, 2017.
- [383] L. C and et al., "A deep learning method approach for sleep stage classification with eeg spectrogram," *International Journal of Environmental Research and Public Health*, vol. 19(10), p. 6322, 2022.
- [384] Z. J and W. Y., "A new method for automatic sleep stage classification," *IEEE transactions on biomedical circuits and systems*, vol. 11(5), pp. 1097–1110, 2017.
- [385] Z. Jia and et al., "Graphsleepnet: Adaptive spatial-temporal graph convolutional networks for sleep stage classification," in *Ijcai*, vol. 2021, 2020, pp. 1324–1330.
- [386] F. Y and et al., "A dual-stream deep neural network integrated with adaptive boosting for sleep staging," *Biomedical Signal Processing and Control*, vol. 79, p. 104150, 2023.
- [387] S. H and et al., "Intra-and inter-epoch temporal context network (iitnet) using sub-epoch features for automatic sleep scoring on raw single-channel eeg," *Biomedical signal processing and control*, vol. 61, p. 102037, 2020.
- [388] Y. C and et al., "Lwsleepnet: A lightweight attention-based deep learning model for sleep staging with singlechannel eeg," *Digital Health*, vol. 9, p. 20552076231188206, 2023.
- [389] L. G and et al., "Micro sleepnet: efficient deep learning model for mobile terminal real-time sleep staging," *Frontiers in Neuroscience*, vol. 17, p. 1218072, 2023.

- [390] J. Z and et al., "Multi-view spatial-temporal graph convolutional networks with domain generalization for sleep stage classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 1977–1986, 2021.
- [391] J. Lu and et al., "Pearnet: A pearson correlation-based graph attention network for sleep stage recognition," in *2022 IEEE 9th International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE, 2022, pp. 1–8.
- [392] H. Phan and et al., "Seqsleepnet: end-to-end hierarchical recurrent neural network for sequence-to-sequence automatic sleep staging," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 3, pp. 400–410, 2019.
- [393] M. S and et al., "Sleeppegnnet: Automated sleep stage scoring with sequence to sequence deep learning approach," *PloS one*, vol. 14(5), p. e0216456, 2019.
- [394] B. S and et al., "Sleepnet: automated sleep staging system via deep learning," *arXiv preprint arXiv:1707.08262*, 2017.
- [395] D. M and et al., "Sleepxai: An explainable deep learning approach for multi-class sleep stage identification," *Applied Intelligence*, vol. 53(13), pp. 16830–16843, 2023.
- [396] A. Supratak and Y. Guo, "Tinysleepnet: An efficient deep learning model for sleep stage scoring based on raw single-channel eeg," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2020, pp. 641–644.
- [397] J. N and et al., "Zleepanlystnet: a novel deep learning model for automatic sleep stage scoring based on single-channel raw eeg data using separating training," *Scientific Reports*, vol. 14(1), p. 9859, 2024.
- [398] F. M and et al., "Deep learning in automatic sleep staging with a single channel electroencephalography," *Frontiers in Physiology*, vol. 12, p. 628502, 2021.
- [399] H. M. N and K. I, "Mixed-input deep learning approach to sleep/wake state classification by using eeg signals," *Diagnostics*, vol. 13(14), p. 2358, 2023.
- [400] S. C and et al., "A hierarchical neural network for sleep stage classification based on comprehensive feature learning and multi-flow sequence learning," *IEEE journal of biomedical and health informatics*, vol. 24(5), pp. 1351–1366, 2019.
- [401] Z. Yao and X. Liu, "A cnn-transformer deep learning model for real-time sleep stage classification in an energy-constrained wireless device," in *2023 11th International IEEE/EMBS Conference on Neural Engineering (NER)*. IEEE, 2023, pp. 1–4.
- [402] H. Phan and et al., "Automatic sleep stage classification using single-channel eeg: Learning sequential features with attention-based recurrent neural networks," in *2018 40th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, 2018, pp. 1452–1455.
- [403] S. A and et al., "A convolutional neural network for sleep stage scoring from raw single-channel eeg," *Biomedical Signal Processing and Control*, vol. 42, pp. 107–114, 2018.
- [404] S. M and et al., "Deep learning for automated feature discovery and classification of sleep stages," *IEEE/ACM transactions on computational biology and bioinformatics*, vol. 17(6), pp. 1835–1845, 2019.
- [405] P. H and et al., "Joint classification and prediction cnn framework for automatic sleep stage classification," *IEEE Transactions on Biomedical Engineering*, vol. 66(5), pp. 1285–1296, 2018.
- [406] F.-B. E and et al., "Convolutional neural networks for sleep stage scoring on a two-channel eeg signal," *Soft Computing*, vol. 24, pp. 4067–4079, 2020.
- [407] Z. T and et al., "Convolution-and attention-based neural network for automated sleep stage classification," *International Journal of Environmental Research and Public Health*, vol. 17(11), p. 4152, 2020.
- [408] L. M and et al., "An attention-guided spatiotemporal graph convolutional network for sleep stage classification," *Life*, vol. 12(5), p. 622, 2022.
- [409] D. H and et al., "Mixed neural network approach for temporal sleep stage classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 26(2), pp. 324–333, 2017.
- [410] S. S. K and L. D, "Automated classification of multi-class sleep stages classification using polysomnography signals: a nine-layer 1d-convolution neural network approach," *Multimedia Tools and Applications*, vol. 82(6), pp. 8049–8091, 2023.
- [411] C. S and et al., "Dssnet: a deep sequential sleep network for self-supervised representation learning based on single-channel eeg," *IEEE Signal Processing Letters*, vol. 29, pp. 2143–2147, 2022.
- [412] C. H. Y. S and et al., "Maeeg: Masked auto-encoder for eeg representation learning," *arXiv preprint arXiv:2211.02625*, 2022.
- [413] Y. Y and et al., "Psnsleep: a self-supervised learning method for sleep staging based on siamese networks with only positive sample pairs," *Frontiers in Neuroscience*, vol. 17, p. 1167723, 2023.
- [414] Q. Xiao and et al., "Self-supervised learning for sleep stage classification with predictive and discriminative contrastive coding," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2021, pp. 1290–1294.
- [415] H. Zhang and et al., "Expert knowledge inspired contrastive learning for sleep staging," in *2022 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2022, pp. 1–6.
- [416] H. Lee, E. Seong, and D. K. Chae, "Self-supervised learning with attention-based latent signal augmentation for sleep staging with limited labeled data," in *IJCAI*, 2022, pp. 3868–3876.
- [417] T. Brüschi and et al., "Multi-view self-supervised learning for multivariate variable-channel time series," in *2023 IEEE 33rd International Workshop on Machine Learning for Signal Processing (MLSP)*. IEEE, 2023, pp. 1–6.
- [418] L. Y and et al., "Adversarial learning for semi-supervised pediatric sleep staging with single-eeg channel," *Methods*, vol. 204, pp. 84–91, 2022.
- [419] L. Y. and et al., "Mtclss: Multi-task contrastive learning for semi-supervised pediatric sleep staging," *IEEE Journal of Biomedical and Health Informatics*, vol. 27(6), pp. 2647–2655, 2022.
- [420] Z. C and et al., "Hybrid manifold-deep convolutional neural network for sleep staging," *Methods*, vol. 202, pp. 164–172, 2022.
- [421] Z. Y and et al., "Shnn: A single-channel eeg sleep staging model based on semi-supervised learning," *Expert Systems with Applications*, vol. 213, p. 119288, 2023.
- [422] A. M. Munk and et al., "Semi-supervised sleep-stage scoring based on single channel eeg," in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2018, pp. 2551–2555.
- [423] B. Haoran and L. Guanze, "Semi-supervised end-to-end automatic sleep stage classification based on pseudo-label," in *2021 IEEE International Conference on Power Electronics, Computer Applications (ICPECA)*. IEEE, 2021, pp. 83–87.
- [424] Z. J and W. Y, "Competition convolutional neural network for sleep stage classification," *Biomedical Signal Processing and Control*, vol. 64, p. 102318, 2021.
- [425] Z. J. and W. Y., "Complex-valued unsupervised convolutional neural networks for sleep stage classification," *Computer methods and programs in biomedicine*, vol. 164, pp. 181–191, 2018.
- [426] L. Fraiwan and K. Lweesy, "Neonatal sleep state identification using deep learning autoencoders," in *2017 IEEE 13th International Colloquium on Signal Processing & its Applications (CSPA)*. IEEE, 2017, pp. 228–231.
- [427] Z. J and et al., "Automatic sleep stage classification based on sparse deep belief net and combination of multiple classifiers," *Transactions of the Institute of Measurement and Control*, vol. 38(4), pp. 435–451, 2016.
- [428] T. O and et al., "Automatic sleep stage scoring using time-frequency analysis and stacked sparse autoencoders," *Annals of biomedical engineering*, vol. 44, pp. 1587–1597, 2016.
- [429] L. M and et al., "Sleep stage classification using unsupervised feature learning," *Advances in Artificial Neural Systems*, vol. 2012(1), p. 107046, 2012.
- [430] H.-G. Wang and et al., "Amgcn-l: an adaptive multi-time-window graph convolutional network with long-short-term memory for depression detection," *Journal of Neural Engineering*, vol. 20, no. 5, p. 056038, 2023.
- [431] C. Y and et al., "Dctnet: hybrid deep neural network-based eeg signal for detecting depression," *Multimedia Tools and Applications*, vol. 82(26), pp. 41307–41321, 2023.
- [432] S. G and et al., "Depcap: a smart healthcare framework for eeg based depression detection using time-frequency response and deep neural network," *IEEE Access*, vol. 11, pp. 52327–52338, 2023.
- [433] Y. Wang and et al., "Diffmdd: A diffusion-based deep learning framework for mdd diagnosis using eeg," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2024.
- [434] Y. M and et al., "Edt: An eeg-based attention model for feature learning and depression recognition," *Biomedical Signal Processing and Control*, vol. 93, p. 106182, 2024.
- [435] L. Yang and et al., "A gated temporal-separable attention network for eeg-based depression recognition," *Computers in Biology and Medicine*, vol. 157, p. 106782, 2023.

- [436] W. Z and et al., "Hybrideegnet: A convolutional neural network for eeg feature learning and depression discrimination," *IEEE Access*, vol. 8, pp. 30 332–30 342, 2020.
- [437] X. Song and et al., "Lsdd-eegnet: An efficient end-to-end framework for eeg-based depression detection," *Biomedical Signal Processing and Control*, vol. 75, p. 103612, 2022.
- [438] X. Sun and et al., "Multi-granularity graph convolution network for major depressive disorder recognition," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 32, pp. 559–569, 2023.
- [439] W. Cui and et al., "A multiview sparse dynamic graph convolution-based region-attention feature fusion network for major depressive disorder detection," *IEEE Transactions on Computational Social Systems*, vol. 11, pp. 2691–2702, 2023.
- [440] C. T and et al., "Exploring self-attention graph pooling with eeg-based topological structure and soft label for depression detection," *IEEE transactions on affective computing*, vol. 13(4), pp. 2106–2118, 2022.
- [441] Z. Z and et al., "A novel eeg-based graph convolution network for depression detection: incorporating secondary subject partitioning and attention mechanism," *Expert Systems with Applications*, vol. 239, p. 122356, 2024.
- [442] C. Yang and et al., "Tsunet-cc: Temporal spectrogram unet embedding cross channel-wise attention mechanism for mdd identification," in *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2023, pp. 1–4.
- [443] X. Y and et al., "Depressive disorder recognition based on frontal eeg signals and deep learning," *Sensors*, vol. 23(20), p. 8639, 2023.
- [444] K. H and et al., "Cloud-aided online eeg classification system for brain healthcare: A case study of depression evaluation with a lightweight cnn," *Software: Practice and Experience*, vol. 50(5), pp. 596–610, 2020.
- [445] K. M and et al., "Deep-asymmetry: Asymmetry matrix image for deep learning method in pre-screening depression," *Sensors*, vol. 20(22), p. 6526, 2020.
- [446] S. A and et al., "Major depressive disorder diagnosis based on effective connectivity in eeg signals: a convolutional neural network and long short-term memory approach," *Cognitive Neurodynamics*, vol. 15(2), pp. 239–252, 2021.
- [447] L. H. W and et al., "Decision support system for major depression detection using spectrogram and convolution neural network with eeg signals," *Expert Systems*, vol. 39(3), p. e12773, 2022.
- [448] M. Kang and et al., "Low channel electroencephalogram based deep learning method to pre-screening depression," in *2020 International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, 2020, pp. 449–451.
- [449] D. W and et al., "Multilayer brain network combined with deep convolutional neural network for detecting major depressive disorder," *Nonlinear Dynamics*, vol. 102(2), pp. 667–677, 2020.
- [450] M. W and Q. A., "A deep learning framework for automatic diagnosis of unipolar depression," *International journal of medical informatics*, vol. 132, p. 103983, 2019.
- [451] S. X and et al., "A novel complex network-based graph convolutional network in major depressive disorder detection," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–8, 2022.
- [452] A. A and et al., "Automated major depressive disorder diagnosis using a dual-input deep learning model and image generation from eeg signals," *Waves in Random and Complex Media*, 2023: 1–16.
- [453] X. M and et al., "An end-to-end deep learning model for eeg-based major depressive disorder classification," *IEEE Access*, vol. 11, pp. 41 337–41 347, 2023.
- [454] A. I. A and et al., "A robust deep-learning model to detect major depressive disorder utilising eeg signals," *IEEE Transactions on Artificial Intelligence*, 2024.
- [455] A. Rafiei and et al., "Automated detection of major depressive disorder with eeg signals: A time series classification using deep learning," *IEEE Access*, vol. 10, pp. 73 804–73 817, 2022.
- [456] D. M. Khan and et al., "Development of wavelet coherence eeg as a biomarker for diagnosis of major depressive disorder," *IEEE Sensors Journal*, vol. 22, pp. 4315–4325, 2022.
- [457] L. Li and et al., "An eeg-based marker of functional connectivity: Detection of major depressive disorder," *Cognitive Neurodynamics*, vol. 18, pp. 1671–1687, 2024.
- [458] P. Sandheep and et al., "Performance analysis of deep learning cnn in classification of depression eeg signals," in *TENCON 2019-2019 IEEE Region 10 Conference*. IEEE, 2019, pp. 1339–1344.
- [459] L. Duan and et al., "Machine learning approaches for mdd detection and emotion decoding using eeg signals," *Frontiers in Human Neuroscience*, vol. 14, 2020.
- [460] X. Zhang and et al., "Eeg-based depression detection using convolutional neural network with demographic attention mechanism," in *2020 42nd annual international conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2020, pp. 128–133.
- [461] L. X and et al., "A deep learning approach for mild depression recognition based on functional connectivity using electroencephalography," *Frontiers in neuroscience*, vol. 14, p. 192, 2020.
- [462] Y. Xie and et al., "Anxiety and depression diagnosis method based on brain networks and convolutional neural networks," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2020, pp. 1503–1506.
- [463] A. Qayyum and et al., "Hybrid deep shallow network for assessment of depression using electroencephalogram signals," in *Neural Information Processing: 27th International Conference, ICONIP 2020, Bangkok, Thailand, November 23–27, 2020, Proceedings, Part III 27*. Springer, 2020, pp. 245–257.
- [464] U. C and et al., "Major depressive disorder classification based on different convolutional neural network models: deep learning approach," *Clinical EEG and neuroscience*, vol. 52(1), pp. 38–51, 2021.
- [465] H. D. S. B. A and et al., "Integration of deep learning for improved diagnosis of depression using eeg and facial features," *Materials Today: Proceedings*, vol. 80, pp. 1965–1969, 2023.
- [466] A. O. Khadidos and et al., "Machine learning and electroencephalogram signal based diagnosis of depression," *Neuroscience Letters*, vol. 809, p. 137313, 2023.
- [467] W. Mao and et al., "Resting state eeg based depression recognition research using deep learning method," in *Proceedings of the International Conference on Brain Informatics (BI)*, Arlington, TX, USA, December 2018, pp. 329–338.
- [468] J. Zhang and et al., "Depression screening using hybrid neural network," *Multimedia Tools and Applications*, vol. 82, pp. 26 955–26 970, 2023.
- [469] W. Wu and et al., "Few-electrode eeg from the wearable devices using domain adaptation for depression detection," *Biosensors*, vol. 12, p. 1087, 2022.
- [470] B. Zhang and et al., "Spatial-temporal eeg fusion based on neural network for major depressive disorder detection," *Interdisciplinary Science: Computational Life Sciences*, vol. 15, pp. 542–559, 2023.
- [471] D. A and et al., "Deep learning in computer aided diagnosis of mdd," *Int J In-novat Technol Explor Eng*, vol. 8(6), pp. 464–468, 2019.
- [472] T. P. P and et al., "Eeg-based deep learning model for the automatic detection of clinical depression," *Physical and Engineering Sciences in Medicine*, vol. 43, pp. 1349–1360, 2020.
- [473] X. Song, D. Yan, L. Zhao, and L. Yang, "Lsdd-eegnet: An efficient end-to-end framework for eeg-based depression detection," *Biomedical Signal Processing and Control*, vol. 75, p. 103612, 2022.
- [474] J. Zhu and et al., "Eeg based depression recognition using improved graph convolutional neural network," *Computers in Biology and Medicine*, vol. 148, p. 105815, 2022.
- [475] B. Wang, Y. Kang, D. Huo, D. Chen, W. Song, and F. Zhang, "Depression signal correlation identification from different eeg channels based on cnn feature extraction," *Psychiatry Research: Neuroimaging*, vol. 328, p. 111582, 2023.
- [476] S. Zhang and et al., "Multi-view graph contrastive learning via adaptive channel optimization for depression detection in eeg signals," *International Journal of Neural Systems*, vol. 33, p. 2350055, 2023.
- [477] D. Wang and et al., "Identification of depression with a semi-supervised gcn based on eeg data," in *2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE, 2021, pp. 2338–2345.
- [478] W. Li and et al., "Gcns-fsmi: Eeg recognition of mental illness based on fine-grained signal features and graph mutual information maximization," *Expert Systems With Applications*, vol. 228, p. 120227, 2023.
- [479] O. S. L and et al., "Deep convolutional neural network model for automated diagnosis of schizophrenia using eeg signals," *Applied Sciences*, vol. 9(14), p. 2870, 2019.
- [480] K. S. K and et al., "Schizonet: a robust and accurate margenau-hill time-frequency distribution based deep neural network model for schizophrenia detection using eeg signals," *Physiological Measurement*, vol. 44(3), p. 035005, 2023.
- [481] K. M. R and et al., "Weighted ordinal connection based functional network classification for schizophrenia disease detection using eeg signal," *Physical and Engineering Sciences in Medicine*, vol. 46(3), pp. 1055–1070, 2023.
- [482] W. Z and et al., "Automated rest eeg-based diagnosis of depression and schizophrenia using a deep convolutional neural network," *IEEE Access*, vol. 10, pp. 104 472–104 485, 2022.

- [483] H. F and et al., "Fusion of multivariate eeg signals for schizophrenia detection using cnn and machine learning techniques," *Information Fusion*, vol. 92, pp. 466–478, 2023.
- [484] K. S. K and et al., "Spwyd-cnn for automated detection of schizophrenia patients using eeg signals," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–9, 2021.
- [485] L. I and et al., "Identification and diagnosis of schizophrenia based on multichannel eeg and cnn deep learning model," *Schizophrenia Research*, vol. 271, pp. 28–35, 2024.
- [486] E. Lillo and et al., "Automated diagnosis of schizophrenia using eeg microstates and deep convolutional neural network," *Expert Systems with Applications*, vol. 209, p. 118236, 2022.
- [487] H. Göker, "1d-convolutional neural network approach and feature extraction methods for automatic detection of schizophrenia," *Signal, Image and Video Processing*, vol. 17, no. 5, pp. 2627–2636, 2023.
- [488] A. Khodabakhsh and et al., "U-net based estimation of functional connectivity from time series multi-channel eeg from schizophrenia patients," in *2021 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC)*, 2021.
- [489] G. Sahu and et al., "Scz-scan: an automated schizophrenia detection system from electroencephalogram signals," *Biomedical Signal Processing and Control*, vol. 86, p. 105206, 2023.
- [490] L. Chu and et al., "Individual recognition in schizophrenia using deep learning methods with random forest and voting classifiers: insights from resting state eeg streams," *arXiv preprint arXiv:1707.03467*, 2017.
- [491] S. K and et al., "Spectral features based convolutional neural network for accurate and prompt identification of schizophrenic patients," *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*, vol. 2021, Part H: Journal of Engineering in Medicine.
- [492] B. C and et al., "From sound perception to automatic detection of schizophrenia: an eeg-based deep learning approach," *Frontiers in Psychiatry*, vol. 12, p. 813460, 2022.
- [493] Z. Guo and et al., "Deep neural network classification of eeg data in schizophrenia," in *Proc 2021 IEEE 10th Data Driven Control Learn Syst Conf (DDCLS)*, 2021, pp. 1322–1327.
- [494] C. A. T. Naira and et al., "Classification of people who suffer schizophrenia and healthy people by eeg signals using deep learning," *International Journal of Advanced Computer Science and Applications*, vol. 10, pp. 511–516, 2019.
- [495] N. Ilakiyaselvan and et al., "Reconstructed phase space portraits for detecting brain diseases using deep learning," *Biomedical Signal Processing and Control*, vol. 71, p. 103278, 2022.
- [496] D. Calhas and et al., "On the use of pairwise distance learning for brain signal classification with limited observations," *Artificial Intelligence in Medicine*, vol. 105, p. 101852, 2020.
- [497] E. Nsugbe and et al., "Intelligence combiner: a combination of deep learning and handcrafted features for an adolescent psychosis prediction using eeg signals," in *2022 IEEE Int Work Metrol Ind 4.0 IoT (MetroInd4.0IoT)*, 2022, pp. 92–97.
- [498] V. Divya and et al., "Signal conducting system with effective optimization using deep learning for schizophrenia classification," *Computer Systems Science and Engineering*, vol. 45, pp. 1869–1886, 2023.
- [499] M. Shen and et al., "Automatic identification of schizophrenia based on eeg signals using dynamic functional connectivity analysis and 3d convolutional neural network," *Computers in Biology and Medicine*, vol. 160, p. 107022, 2023.
- [500] M. Saeedi and et al., "Schizophrenia diagnosis via fft and wavelet convolutional neural networks utilizing eeg signals," 2022.
- [501] C. A. Ellis and et al., "Examining effects of schizophrenia on eeg with explainable deep learning models," in *2022 IEEE 22nd Int Conf Bioinformatics Bioengineering (BIBE)*, 2022, pp. 301–304.
- [502] A.-A. D and et al., "Identification of children at risk of schizophrenia via deep learning and eeg responses," *IEEE Journal of biomedical and health informatics*, vol. 25(1), pp. 69–76, 2020.
- [503] S. G and J. A. M., "Szmn: a novel and scalable deep convolution hybrid neural network framework for schizophrenia detection using multichannel eeg," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–9, 2022.
- [504] K. Jindal and et al., "Bi-lstm-deep cnn for schizophrenia detection using msst-spectral images of eeg signals," in *Artificial Intelligence-Based Brain-Computer Interface*. Elsevier, 2022, pp. 145–162.
- [505] B. S and et al., "Detection of schizophrenia using hybrid of deep learning and brain effective connectivity image from electroencephalogram signal," *Computers in Biology and Medicine*, vol. 146, p. 105570, 2022.
- [506] S. S and J. S. D., "A novel approach to schizophrenia detection: Optimized preprocessing and deep learning analysis of multichannel eeg data," *Expert Systems with Applications*, vol. 246, p. 122937, 2024.
- [507] A. Shoeibi and et al., "Automatic diagnosis of schizophrenia in eeg signals using cnn-lstm models," *Frontiers in Neuroinformatics*, vol. 15, pp. 1–16, 2021.
- [508] G. Sharma and et al., "A smart healthcare framework for accurate detection of schizophrenia using multichannel eeg," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–9, 2023.
- [509] S. Guhan and et al., "Eeg based classification of children with learning disabilities using shallow and deep neural network," *Biomedical Signal Processing and Control*, vol. 82, p. 104553, 2023.
- [510] C. R. Phang and et al., "Classification of eeg-based effective brain connectivity in schizophrenia using deep neural networks," in *Int IEEE/EMBS Conf Neural Engineering (NER)*, 2019, pp. 401–406.
- [511] Q. Chang and et al., "Classification of first-episode schizophrenia, chronic schizophrenia and healthy control based on brain network of mismatch negativity by graph neural network," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 1784–1794, 2021.
- [512] A. Nikhil Chandran and et al., "Eeg-based automated detection of schizophrenia using long short-term memory (lstm) network," in *Advances in Machine Learning and Computational Intelligence: Proceedings of ICMLCI 2019*. Springer Singapore, 2021, pp. 229–236.
- [513] S. R and et al., "A deep learning based model using rnn-lstm for the detection of schizophrenia from eeg data," *Computers in Biology and Medicine*, vol. 151, p. 106225, 2022.
- [514] L. B and et al., "Automatic detection of schizophrenia based on spatial-temporal feature mapping and levit with eeg signals," *Expert Systems with Applications*, vol. 224, p. 119969, 2023.
- [515] C. L. Alves and et al., "Eeg functional connectivity and deep learning for automatic diagnosis of brain disorders: Alzheimer's disease and schizophrenia," *Journal of Physics: complexity*, vol. 3, no. 2, p. 025001, 2022.
- [516] Y. Wu and et al., "Schizophrenia detection based on eeg using recurrent auto-encoder framework," in *International Conference on Neural Information Processing*. Springer, 2022, pp. 62–73.
- [517] P. S. K and L. S. W., "Sasd1 and rbatq: sparse autoencoder with swarm based deep learning and reinforcement based q-learning for eeg classification," *IEEE open journal of engineering in medicine and biology*, vol. 3, pp. 58–68, 2022.
- [518] S. Parija and et al., "Autoencoder-based improved deep learning approach for schizophrenic eeg signal classification," *Pattern Analysis and Applications*, vol. 26, no. 2, pp. 403–435, 2023.
- [519] N. M and et al., "A novel hybrid model in the diagnosis and classification of alzheimer's disease using eeg signals: Deep ensemble learning (del) approach," *Biomedical Signal Processing and Control*, vol. 89, p. 105751, 2024.
- [520] Ieracitano and et al., "A convolutional neural network based self-learning approach for classifying neurodegenerative states from eeg signals in dementia," in *2020 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2020, pp. 1–8.
- [521] B. X and W. H., "Early alzheimer's disease diagnosis based on eeg spectral images using deep learning," *Neural Networks*, vol. 114, pp. 119–135, 2019.
- [522] D. L. D and et al., "An intelligent alzheimer's disease prediction using convolutional neural network (cnn)," *International Journal of Advanced Research in Engineering and Technology (IJARET)*, vol. 11(4), pp. 12–22, 2020.
- [523] Huggins and et al., "Deep learning of resting-state electroencephalogram signals for three-class classification of alzheimer's disease, mild cognitive impairment and healthy ageing," *Journal of Neural Engineering*, vol. 18, no. 4, p. 046087, 2021.
- [524] X. W and et al., "A novel method for diagnosing alzheimer's disease using deep pyramid cnn based on eeg signals," *Heliyon*, vol. 9(4), 2023.
- [525] R. K and Z. M., "Diagnose alzheimer's disease and mild cognitive impairment using deep cascadenet and handcrafted features from eeg signals," *Biomedical Signal Processing and Control*, vol. 99, p. 106895, 2025.
- [526] I. C and et al., "A convolutional neural network approach for classification of dementia stages based on 2d-spectral representation of eeg recordings," *Neurocomputing*, vol. 323, pp. 96–107, 2019.
- [527] A. K and et al., "Eeg-based clinical decision support system for alzheimer's disorders diagnosis using emd and deep learning techniques," *Frontiers in Human Neuroscience*, vol. 17, p. 1190203, 2023.
- [528] D. Kim and K. Kim, "Detection of early stage alzheimer's disease using eeg relative power with deep neural network," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2018, pp. 352–355.

- [529] Y. Zhao and L. He, "Deep learning in the eeg diagnosis of alzheimer's disease," in *Computer Vision-ACCV 2014 Workshops: Singapore, Singapore, November 1-2, 2014, Revised Selected Papers, Part I* 12. Springer, 2015, pp. 340–353.
- [530] L. K and et al., "Feature extraction and identification of alzheimer's disease based on latent factor of multi-channel eeg," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 1557–1567, 2021.
- [531] M. F. C and et al., "Deep learning representation from electroencephalography of early-stage creutzfeldt-jakob disease and features for differentiation from rapidly progressive dementia," *International journal of neural systems*, vol. 27(02), p. 1650039, 2017.
- [532] S. S. A. A and et al., "Dynamical system based compact deep hybrid network for classification of parkinson disease related eeg signals," *Neural Networks*, vol. 130, pp. 75–84, 2020.
- [533] K. S. K and et al., "Pdcnnet: An automatic framework for the detection of parkinson's disease using eeg signals," *IEEE Sensors Journal*, vol. 21(15), pp. 17017–17024, 2021.
- [534] Z. R and et al., "Eeg analysis of parkinson's disease using time-frequency analysis and deep learning," *Biomedical Signal Processing and Control*, vol. 78, p. 103883, 2022.
- [535] X. Shi, T. Wang, L. Wang, H. Liu, and N. Yan, "Hybrid convolutional recurrent neural networks outperform cnn and rnn in task-state eeg detection for parkinson's disease," in *2019 Asia-Pacific signal and information processing association annual summit and conference (APSIPA ASC)*. IEEE, 2019, pp. 939–944.
- [536] P. M and et al., "Deep-learning detection of mild cognitive impairment from sleep electroencephalography for patients with parkinson's disease," *Plos one*, vol. 18(8), p. e0286506, 2023.
- [537] M. Shaban, "Automated screening of parkinson's disease using deep learning based electroencephalography," in *2021 10th international IEEE/EMBS conference on neural engineering (NER)*. IEEE, 2021, pp. 158–161.
- [538] S. R. J and D. P, "Generalizable electroencephalographic classification of parkinson's disease using deep learning," *Informatics in Medicine Unlocked*, vol. 42, p. 101352, 2023.
- [539] L. S and et al., "A convolutional-recurrent neural network approach to resting-state eeg classification in parkinson's disease," *Journal of neuroscience methods*, vol. 361, p. 109282, 2021.
- [540] S. Lee, R. Hussein, and M. J. McKeown, "A deep convolutional-recurrent neural network architecture for parkinson's disease eeg classification," in *2019 IEEE global conference on signal and information processing (GlobalSIP)*. IEEE, 2019, pp. 1–4.
- [541] L. K and et al., "Parkinson's disease detection and classification using eeg based on deep cnn-lstm model," *Biotechnology and Genetic Engineering Reviews*, vol. 40(3), pp. 2577–2596, 2024.
- [542] Z. S and et al., "An interpretable model based on graph learning for diagnosis of parkinson's disease with voice-related eeg," *NPJ Digital Medicine*, vol. 7(1), p. 3, 2024.
- [543] A. Ahmadi and et al., "Computer aided diagnosis system using deep convolutional neural networks for adhd subtypes," *Biomedical Signal Processing and Control*, vol. 63, p. 102227, 2021.
- [544] M. Bakhtyari and S. Mirzaei, "Adhd detection using dynamic connectivity patterns of eeg data and convlstm with attention framework," *Biomedical Signal Processing and Control*, vol. 76, p. 103708, 2022.
- [545] B. Karakaş and et al., "Convmixer ve sdd kullanılarak dehb hastalığının eeg sinyalleri ile otomatik olarak tespit edilmesi," *Türk Doğa ve Fen Dergisi*, vol. 13, no. 1, p. 19–25, 2024.