Electroencephalography (EEG) Signal Processing: A Systematic Review of Techniques, Applications, and Future Directions

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Abstract:

Electroncesefelography (EEG) is a powerful brain signal analysis tool widely used in neurological disorders, brain-computer interface (BCI), cognitive monitoring and biometric authentication. Despite its importance, EEG signal noise, low signal-to-show ratio (SNR) and inter-subject variability, advanced reserve so-up, functional extraction and classification techniques are necessary. This article presents a comprehensive, systematic review of EEG signal therapy, discusses pre-prosaic methods, functional extraction techniques, classification methods (traditional machine learning, deep learning and hybrid models), discussions and future research directions. A broad comparative analysis of existing methods is involved.

Keywords: EEG signal processing, feature extraction, machine learning, deep learning, hybrid models, brain-computer interface, neurological disorder detection.

١ Introduction

Electroencephalography (EEG) is a non-invasive neurophysiological technique that records brain activity through electrical signals. The first time introduced by Hans Berger in ١٩٢٩ [١], EEG has become an important tool in neurology, cognitive study and medical diagnosis. It is essential in monitoring epilepsy, neurodiac disease diagnosis, emotional recognition and interaction between humans and computers [٢]-[٤]. However, EEG signal analysis is challenging due to noise objects, poor spatial resolution and personal variability [٥]. The arrival of machine learning (ML) and Deep Learning (DL) have improved EEG processing to a large extent, which enables automatic functional extraction and real-time classification [٦]. The review examines advanced processing technology, functional extraction methods, classification models (including hybrid techniques) and EEG-based applications. A comparative analysis of traditional ML, DL, and hybrid methods is given, and challenges and future research directions are discussed.

٢ Methodology

This systematic review follows the prism (favourite reporting elements for systematic reviews and meta-analysis) guidelines.

٢,١ Literature Search Strategy

A comprehensive discovery was made for articles published between ١٩٩٠ and ٢٠٢٥ on Google Scholar, IEEE Xplore, PubMed and Springer, such as using keywords:

"EEG signal processing"

"Facilitation Survey in EEG"

"Machine Learning for EEG"

"Deep Learning EEG classification"

٢,٢ Inclusion and Exclusion Criteria

Inclusion criteria

EEG preparation, functional extraction and classification studies.

Research on ML/DL techniques for EEG-based applications.

Peer-Review Journal Articles and Conference Letters.

Exclusion criteria

Non-English publication.

Study without empirical confirmation.

Conference abstract with inadequate technical details

Traditional speech growth techniques include spectral subtraction, veneer filtration and MMSE estimates [٥], [٦]. The purpose of these methods is to reduce the noise in the background by preserving speech information.

٣. EEG Signal Processing Techniques

EEG signal treatment consists of three important stages:

Pre-treatment: Removal of noise and deformation certificates.

Functional extraction: Identify meaningful patterns from the signal.

Classification: Assign the features drawn to different categories.

Each step is essential to improve the accuracy and strength of EEG-based applications.

٣,١ Preprocessing Methods

EEG signals are often contaminated from internal and external noise sources, which must be removed for accurate analysis. The most common noise sources include:

Physical objects (e.g. flashes, muscle activity, cardiac signs).

Environmental noise (e.g., electrical intervention or movement of objects).

Electrode displacement (e.g. poor contact with the skull).

To reduce these effects, various pre-roses have been developed.

Table ١: Comparison of EEG Preprocessing Methods

Technique	Purpose	Advantages	Disadvantages	References
Bandpass Filtering	Removes unwanted frequency components	Simple, effective	Can distort signals	[٧], [٨]
Independent Component Analysis (ICA)	Identifies and separates artefact sources	High accuracy for artefact removal	Computationally expensive	[٩]

Wavelet Transform	Decomposes EEG into frequency sub-bands	Preserves time and frequency information	Requires parameter tuning	[١٠], [١١]
Common Spatial Pattern (CSP)	Enhances discriminative EEG features	Effective for BCI applications	Sensitive to noise variations	[١٢]
Adaptive Noise Cancellation	Eliminates specific noise sources adaptively	Works well with dynamic noise	Computational overhead	[١٣]

٣,٢ Feature Extraction Techniques

Functional extraction is essential to reduce the dimensions of EEG data while maintaining important information. Facilities can be classified as:

Time domain properties: Statistical properties for raw EEG signals.

Frequency domain properties: Analysis using Fourier Transform (FT) and Power Spectral Density (PSD).

Time enemy properties: Time and frequency analysis (e.g. Wavelet, short-term furrier transformation).

Nonlinear features: Measures of brain signal complexity, such as entropy and fractal dimension.

Table ٢: Feature Extraction Techniques in EEG Analysis

Feature Type	Methods	Advantages	Disadvantages	References
Time-Domain	Mean, variance, skewness	Simple, computationally efficient	Low classification accuracy	[١٤]
Frequency-Domain	PSD. FFT, Welch's method	Effective for steady-state analysis	Loses temporal information	[١٥]
Time-Frequency	STFT, wavelets, Hilbert-Huang Transform	Captures transient patterns	High computational complexity	[١٦]
Nonlinear Features	Entropy, fractal dimension, Lyapunov exponent	Useful for chaotic EEG patterns	Difficult to interpret	[١٧]

٤. Machine Learning and Deep Learning for EEG Classification

EEG classification is essential for epilepsy detection, motor imagery recognition, sleep staging, and emotion classification. Traditional ML techniques, deep learning models, and hybrid approaches have been developed to improve accuracy.

٤,١ Traditional Machine Learning Approaches

Traditional ML models require manual feature extraction before classification.

Table ٣: Comparison of Traditional Machine Learning Methods for EEG

Algorithm	Advantages	Disadvantages	Application	References
Support Vector Machines (SVM)	Works well with high-dimensional data	Requires tuning	BCI, epilepsy detection	[١٨], [١٩]
k-Nearest Neighbors (KNN)	Simple, interpretable	Computationally expensive	Emotion recognition	[٢٠]
Random Forest (RF)	Robust to overfitting	Computationally expensive	Cognitive load classification	[٢١]

٤,٢ Deep Learning-Based Methods

Deep learning eliminates manual feature extraction by learning patterns directly from EEG signals.

Table ٤: Deep Learning Models for EEG Classification

DL Model	Advantages	Disadvantages	Application	References
Convolutional Neural Networks (CNNs)	Extracts spatial EEG features	Requires large datasets	Seizure detection	[٢٢],[٢٣]
Recurrent Neural Networks (RNNs)	Captures temporal EEG patterns	Vanishing gradient problem	Emotion recognition	[٢٤]
Graph Convolutional Networks (GCNs)	Analyzes EEG connectivity	Computationally expensive	Motor imagery	[٢٥]

٤,٣ Hybrid Methods for EEG Classification

Hybrid models combine ML and DL approaches to improve classification accuracy and robustness.

Table ٥: Hybrid EEG Classification Models

Hybrid Model	Components	Advantages	Disadvantages	Application	References
CNN- SVM	CNN for feature extraction + SVM for classification	High accuracy	Computational cost	Epilepsy detection	[٢٦],[٢٧]
LSTM- RF	LSTM for sequential analysis + Random Forest for classification	Captures temporal dependencies	Prone to overfitting	Emotion recognition	[٢٨],[٢٩]
Graph Convolutional Networks (GCNs)	CNN for spatial features + LSTM for temporal dependencies	Handles both spatial and sequential patterns	Requires large datasets	Seizure prediction	[٣٠],[٣١]

٥. Applications of EEG Signal Processing

EEG classification has numerous real-world applications, spanning medical diagnostics, human-computer interaction, and security systems.

٥,١ Brain-Computer Interfaces (BCIs)

BCIs enable direct communication between the brain and external devices.

Applications include:

Neuroprstiika: controlling robotic organs [٣٢].

Smart Home Control: EEG-driven home automation [٣٣].

Virtual reality: Improve gaming experiences [٣٤].

٥,٢ Neurological Disorder Diagnosis

EEG is widely used in medical diagnosis:

Epilepsidetection: Automatic seizure spread [٣٥].

Alzheimer's disease: to detect cognitive decline [٣٦].

Depression diagnosis: EEG-based evaluation of mental health [٣٧].

٥,٣ Biometric Authentication

EEG-based certification provides increased security:

Identification verification: EEG biometry for safe access [٣٨].

Continuous certification: Verification of real-time [٣٩].

٦: Challenges and Future Directions

Despite the significant progress of EEG signal therapy, many challenges broadly prevent EEG-based technologies. These challenges include noise objects, variation between subjects, computational obstacles and large-scale data set deficiency. It is important to address these boundaries to improve the reliability, accuracy and factual purposes of EEG-based systems.

٦,١ Key Challenges

٦,١,١ Noise and Artifacts in EEG Signals

EEG signals are receptive to different noise sources, including physical, environmental and movement objects. These objects affect the quality of EEG registration, reduce the signal-to-show ratio (SNR) and affect classification performance.

Common types of artwork include:

Electromyography (EMG) objects: Muscular contraction mainly affects high-frequency ribbon tape.

Electroculography (EOG) objects: Results from eye movements affect the frontal electrode reading to a large extent.

Movement artefacts: Electrodes are caused by displacement or subject movement, which is usually seen by using EEG applications.

Streamline intervention: Environmental noise from electrical sources (٥٠-٦٠ Hz frequency range) can distort EEG signals.

Despite the advanced prepricing techniques such as independent component analysis (ICA) and Wavelet Danoizing, deformation is calculated and time-consuming. Future EEG systems must include real-time noise filtering algorithms to increase EEG's praise in real-world applications [٤٠].

٦,١,٢ Inter-Subject and Intra-Subject Variability

EEG signals show significant inter-subject variability, which means that EEG patterns can vary widely in individuals due to the difference in brain structure, cognitive function and electrode placement. Similarly, intra-subject variability refers to a person's change in EEG patterns over time due to fatigue, emotional conditions, and external factors.

Effects of variability on the EEG model:

Poor normalization: Trained models in one subject can perform poorly on the other and limit cross-topic adaptability.

Increase in calculation complexity: Extensive privatization and calibration are needed before the real-world placement.

Need for domain optimization: Many studies detect transmission and adaptive functional extraction techniques to reduce subject variation [٤١]. A promising approach to addressing the difference between the subjects is the development of adaptive and individual EEG models that dynamically adjust the parameters based on real-time response.

٦,١,٣ Data Scarcity and Limited Public Datasets

The success of Machine Learning (ML) and Deep Learning (DL) models depends on a large dataset. However, the EEG dataset is often limited in size, making it difficult to train a model with high demonstrations without overmass.

Challenges in EEG data collection:

High costs for data collection: EEG experiments require special equipment and trained professionals.Lack of Standardized Datasets: Many studies use different electrode configurations and preprocessing pipelines, making cross-study comparisons difficult.

Ethical and Privacy Concerns: EEG data contains sensitive information about brain activity, raising concerns about data sharing and subject privacy [٤٢].

Potential Solutions:

Data Augmentation Techniques: Synthetic EEG data generation using Generative Adversarial Networks (GANs) can help expand training datasets.

Federated Learning Approaches: Allow decentralized model training while preserving privacy.

Development of Open-Source EEG Repositories: Encouraging the collection and sharing of large-scale multi-subject EEG datasets.

٦,١,٤ Real-Time EEG Processing and Computational Constraints

Many EEG applications, such as brain-computer interfaces (BCIs) and neurofeedback systems, require real-time processing. However, EEG signal analysis often involves computationally intensive steps, including:

High-dimensional feature extraction (e.g., wavelet decomposition).

Deep learning-based EEG classification (e.g., CNNs, LSTMs).

Artefact removal algorithms that require significant processing power.

Wearable EEG devices like consumer-grade headsets have limited processing power, making real-time inference challenging. Optimized lightweight deep learning models, such as MobileNets and TensorFlow Lite, can help improve efficiency while maintaining high classification accuracy.

٦,٢ Future Research Directions

٦,٢,١ Explainable AI (XAI) for EEG Models

Deep learning models in EEG classification often lack interpretability, making them challenging to deploy in clinical and neuroscience applications. Explainable AI (XAI) aims to enhance model transparency by providing human-readable insights into EEG-based decision-making.

Key areas for XAI in EEG analysis:

Feature Importance Visualization: Identifying which EEG channels or frequency bands contribute most to classification.
Model Interpretability Techniques: Using SHAP (Shapley Additive Explanations) or Layer-wise Relevance Propagation (LRP) to understand deep learning model predictions.
Clinical Acceptance: Physicians require AI models to provide interpretable and trustworthy outputs for EEG-based diagnostics.
By incorporating XAI techniques, EEG-based ML/DL models can become more transparent, trustworthy, and clinically relevant.

٦,٢,٢ Real-Time Processing for Wearable EEG Devices

The development of portable and wearable EEG devices is a growing research area, enabling applications in mental health monitoring, cognitive state assessment, and brain-computer interfaces. The current EEG classification in real-time faces many challenges, including:
Problems with delay: Most deep teaching models require high calculation power and limit real-time performance.
Edge AI for EEG processing: Distribution of models on built-in systems such as Raspberry Pie or Nvidia Jetson can increase efficiency.
Cloud-based EEG analysis: Cloud closing for Clouds enables more complex EEG analysis without hardware restrictions.
Future EEG systems should focus on real-time processing and allow natural integration into everyday applications such as neurofeedback training and cognitive charge monitoring.

٦,٢,٣ Multimodal EEG-fMRI Fusion for Advanced Brain Mapping

Combining EEG -is with other neuroimaging forms, such as functional magnetic resonance imaging (fMRI) and Magnetoencephalography(MEG), can provide deep insight into brain function.
Benefits of EEG-fMRI Integration:

EEG provides high temporary resolution, while FMRI offers high spatial resolution.

Better neurological disease diagnosis: Alzheimer's accuracy helps detect Parkinson's and epilepsy.

A better understanding of cognitive functions: EEG-FMRI studies can show how brain networks interact in real time.

Challenges of EEG-fMRI Fusion:

Problems with signal synchronization: EEG and FMRI work on different scales, making it challenging to coordinate data.

High costs and complexity: FMRI scanners are expensive and limit mass studies.

Data integration algorithms: Advanced deep learning models must effectively combine EEG and FMRI functions.

Future research should focus on developing effective deep learning frameworks that can initially integrate EEG and FMRI data, leading to more accurate activity of brain activity.

Conclusion

The EEG signal treatment has experienced significant progress in recent decades, which improves the preaching of techniques, functional extraction methods, machine learning (ML), Deep Learning (DL) and hybrid classification models. Despite these advances, EEG-based systems face significant challenges related to signal noise, variation between subjects, data shortages, real-time treatment limits and model lecturers.

This systematic review provided a comprehensive analysis of the EEG signal treatment techniques, covering:

Independent ingredient analysis (ICA), Wavelet transformation and preprocessing techniques such as adaptive noise reduction, which help reduce speed objects, muscle noise (EMG) and eye blink artefacts
(EOG) .

Extraction methods, time domains, frequency domains, time-frequency representatives, and nonlinear functions provide unique benefits for each EEG application.

From classification models, traditional ML (SVM, KNN, Random Forest) to DL-based approach (CNN, LSTM, GCN) and hybrid methods (CNN-SVM, LSTM-RF, CNN-LSTM).

Critical EEG applications include brain-computer cleaning (BCIS), neurological disorder diagnosis (epilepsy, Alzheimer's, depression), cognitive condition monitoring and biometric authentication.

Challenges related to noise objects, professional variability, data set limits, and computational obstacles hinder the distribution of EEG-based solutions in the real world.

Future research directions include the development of Explainable AI (XAI) for EEG models, real-time processing for wearable EEG devices, and EEG-fMRI fusion for enhanced brain mapping.

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