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Comparison of Artificial Intelligence Applications of EEG Signals in Neuroscience

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ABSTRACT In recent years, there has been a growing interest in the artificial intelligence (AI)-based analysis of electroencephalography (EEG) signals. This surge has made the potential of EEG more evident, both in monitoring cognitive states and in the early diagnosis of neurological disorders. This review systematically evaluates the academic literature from the past decade focusing on the processing of EEG signals through machine learning (ML), deep learning (DL), and other alternative techniques. The study compares personalized ML models (e.g., SVM, Random Forest) with wavelet decomposition–based optimized approaches and further analyzes the performance of Hilbert transform–based Convolutional Neural Network (CNN) architectures, label-free autoencoder frameworks, and multi-architecture DL systems in contemporary brain–computer interface (BCI) applications. In addition, incremental learning models based on multimodal data fusion are reviewed in the context of diagnosing disorders such as Alzheimer's disease and epilepsy. The findings indicate that EEG–AI integration holds substantial potential for both research and clinical applications.

KEYWORDS
Artificial intelligence
Machine learning
Deep learning
Brain-computer interface
Neuroscience
EEG signals

INTRODUCTION

Electroencephalography (EEG) is a non-invasive neuroimaging technique that measures electrical fluctuations on the scalp resulting from action potentials generated during neuronal activity (Edelman *et al.* 2025; Kimmatkar and Babu 2021). The signals obtained through metal electrodes allow for high temporal resolution recording of electrical patterns in the brain. Owing to this feature, EEG stands out as a particularly valuable tool for real-time monitoring of mental and emotional processes.

The history of electroencephalography (EEG) dates back to 1875, when Richard Caton made the first observations on animals; following Hans Berger's successful recording of human EEG signals in 1924, it gained widespread clinical and scientific application (Wan *et al.* 2019). Today, EEG is effectively used in a wide range of areas, from epilepsy diagnosis to the analysis of sleep disorders, from detecting attention deficit, depression, and mood disorders to rehabilitation-oriented systems (Liu *et al.* 2025). This broad spectrum of applications has also facilitated the development of EEG devices with various electrode types, connectivity technologies, and user-friendly designs (Soufineyestani *et al.* 2020). In particular, brain-computer interfaces (BCIs) have attracted significant attention due to their potential to interpret EEG data and translate individuals' mental states into external system commands (Wan *et al.* 2019; Sozer and Fidan 2017; Sözer and Fidan 2019). Over the past five decades, research efforts have enabled brain–computer interface (BCI) systems to evolve from experimental foundations into applicable technologies across various domains, including clinical practice, rehabilitation, and human–machine interaction. This transformation has encompassed not only technical advancements but also sparked multidimensional discussions surrounding ethics, user experience, and societal acceptance (Kawala-Sterniuk *et al.* 2021). For example, motor imagery-based prosthetic control can be provided for paralyzed individuals, while alternative communication mechanisms can be developed for those with limited interaction abilities (Orban *et al.* 2022).

The integration of electroencephalography (EEG) into artificial intelligence (AI)-based systems, particularly for the diagnosis and monitoring of neurodegenerative diseases, represents a new paradigm in clinical decision-making (Mouazen *et al.* 2025). This integration is supported by digital tools that enable the preprocessing and enhancement of EEG signals for analytical purposes. Notably, open-source MATLAB-based platforms such as EEGLAB and Fieldtrip facilitate artifact removal, time–frequency analysis, and feature extraction through standardized modules. Extensions integrated into these platforms, such as MARA, AAR, ADJUST, clean rawdata, and icablinkmetrics, allow for the automatic detection and removal of artifacts caused by eye blinks, muscle activity, and environmental noise. This provides a robust preprocessing infrastructure that enhances the reliability and accuracy of downstream analyzes (Gu *et al.* 2021).

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With the advancement of AI algorithms, EEG data analysis has undergone a significant transformation. Machine learning (ML) and deep learning (DL) approaches have demonstrated high accuracy in classifying emotional states, cognitive levels, and mental tasks by learning spatiotemporal patterns from EEG signals (Khan *et al.* 2024; Nandakumar *et al.* 2025). In this context, AI-based analytical approaches involving multi-layered processes, such as feature extraction, classification, and even compression of EEG signals, are becoming increasingly comprehensive (Khlief and Idrees 2023). These developments not only enhance clinical diagnostic workflows but also expand the role of EEG in multidisciplinary applications, including human–computer interaction (HCI), driver fatigue detection, and emotion-aware user interfaces.

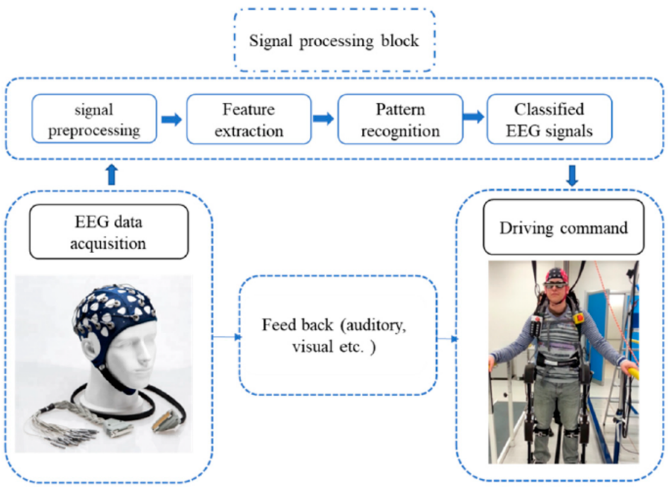

Figure 1 The rule of the EEG signal as the main element in the BCI-EEG rehabilitation system (Orban *et al.* 2022).

In this study, the scientific literature focusing on the analysis of EEG signals through AI-based methods is examined in depth. Within this scope, prominent machine learning and deep learning approaches are systematically categorized and compared, both in the context of individualized models and collective frameworks.

METHODOLOGY OF LITERATURE REVIEW

This review adopts a structured methodology to explore the recent advances in artificial intelligence applications on EEG signals. Academic articles published between 2018 and 2025 were systematically retrieved from reputable databases including PubMed, IEEE Xplore, Scopus, and SpringerLink. The search strategy involved Boolean keyword combinations such as "EEG + Deep Learning", "Brain-Computer Interface + AI", and "EEG + Classification"

Studies were included in the article based on the following criteria:

- Use of real EEG data (clinical or experiment in in most studies, traditional ML methods such as Support Vector Machines (SVM), k-nearest neighbors (kNN), and decision trees have been used for classification purposes due to their simplicity and interpretabilityental)
- Implementation of AI techniques (ML or DL)
- Focus on emotion recognition, mental task classification, BCI systems, or neurological diagnosis
  Studies were not included in the article based on the following criteria:
- Simulation-only data
- Hardware-only reviews without algorithmic analysis
- Articles lacking peer-review

After deduplication and abstract screening, 63 articles were included in this review.

RECENT ADVANCES IN AI-DRIVEN EEG APPLICATIONS

Electroencephalography (EEG) signals are currently evaluated in integration with disciplines such as artificial intelligence, bioinformatics, psychology (Elnaggar *et al.* 2025), and neuroscience, and are utilized across a wide variety of application domains. In this context, existing studies span a broad spectrum, ranging from the characterization of meditation to the diagnosis of neurological disorders, and from mental command recognition to human–robot interaction.

Meditation, Mental State, and Mindfulness Classifications

In a study aiming to distinguish techniques such as Vipassana, Isha Shoonya, and Himalayan Yoga, a one-dimensional convolutional neural network (1D-CNN) combined with chi-square–based feature selection achieved an accuracy rate of 60% (Jain *et al.* 2025). The differentiation of meditation states through EEG signals contributes to the objective assessment of individuals' levels of mental awareness.

Studies aimed at classifying cognitive states such as mental relaxation and concentration constitute the fundamental building blocks of BCI systems (Aggarwal and Chugh 2022; You 2021). In addition, in studies focusing on the classification of imagined words, classification was performed using CNN after Hilbert transformation; however, model complexity has been a limiting factor in real-time applications (Agarwal and Kumar 2024). In the field of mental task recognition, autoencoder architectures operating with unlabeled data have been proposed, where "abnormal" states are identified based on reconstruction errors (Dairi *et al.* 2022).

Classification of Emotional States

The classification of emotional states using EEG signals holds a significant place in the literature (Mendivil Sauceda *et al.* 2024). The biologically informed Spiking Neural Network-based BISNN model has improved emotional classification performance and enhanced sensitivity through the biological meaningfulness of synaptic parameters (Sun *et al.* 2025).

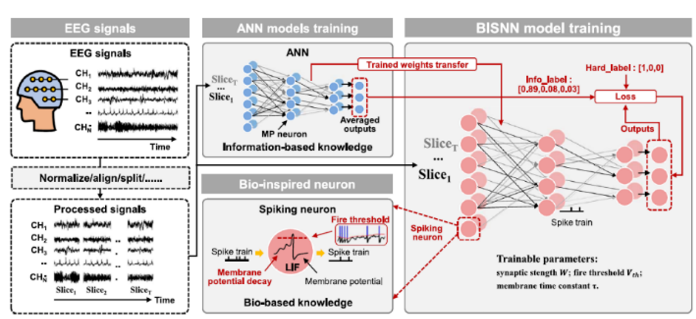

Figure 2 Overview of the training process of the proposed BISNN method for EEG-based emotion recognition. Pre-processed EEG signals are divided into T-slices to reduce temporal feature complexity. Pre-trained weights from a knowledge-based ANN model are transferred to a homogeneous BISNN model composed of biologically inspired neurons (Sun *et al.* 2025).

Similarly, models developed for the classification of emotions in the context of human-robot interaction (HRI) have achieved high accuracy through the use of global optimization algorithms, demonstrating that emotional intelligence can be integrated into HRI systems (Staffa *et al.* 2023)

Studies on the classification of anxiety levels have been conducted using algorithms such as SVM, kNN, and Decision Tree; the use of closed-loop neurofeedback systems for therapeutic purposes has also been evaluated (Chen et al., 2021). Additionally, a personalized machine learning approach was developed using the DEAP dataset, taking into account individual emotional differences (Barrowclough *et al.* 2025)

Additionally, a comprehensive study conducted by Reza et al. proposed a machine learning framework to classify four emotional states, positive, neutral, depressed, and anxiety, using EEG signals. The study utilized a dataset of 300 patients and addressed class imbalance through advanced data augmentation techniques including GAN, SMOTE, and ADASYN. Discrete Wavelet Transform and Shannon entropy were applied for feature extraction, and nine different ML/DL algorithms (MLP, CNN, RF, SVM, etc.) were compared. The highest accuracy of 98.8% was achieved with the MLP model (Sobhani *et al.* 2025).

Recent review studies have also highlighted the progress and limitations of deep learning techniques in EEG-based emotion recognition. In particular, Abgeena and Garg systematically analyzed more than one hundred studies published between 2018 and 2024, emphasizing that models such as BiLSTM, CNN, and hybrid CNN–LSTM architectures achieved the highest accuracy rates across datasets like SEED and DEAP (Abgeena and Garg 2025). Similarly, Li and Chen (2025) proposed a cross-modal alignment and fusion framework that combines EEG and visual features through a hybrid attention mechanism, achieving up to 96.49% accuracy on the SEED dataset.

The analysis of mental stress levels using EEG in virtual reality (VR) environments has also emerged as a prominent topic in recent years. In one study, stress levels were classified using EEG signals recorded in a VR environment, and the performances of algorithms such as SVM and Random Forest were compared (Albayrak-Kutlay and Bengisu 2025; Kamińska *et al.* 2021).

Diagnosis and Follow-up of Neurological Diseases

In the differentiation of neurodegenerative diseases such as Alzheimer's Disease (AD) and Frontotemporal Dementia (FTD), the Coherence-CNN method achieved three-class classification with over 94% accuracy by utilizing functional connectivity measures (Jiang *et al.* 2025). In another recent study, a wavelet-ML framework incorporating OTFL-THFB decomposition was proposed for Alzheimer's detection using EEG signals. With features derived from Hjorth Parameters and Higuchi's Fractal Dimension, the model achieved up to 98.91% accuracy, outperforming existing state-of-the-art classifiers (Puri *et al.* 2025).

Wang *et al.* (2025b) extracted effective connectivity information using the GRU-GC algorithm for pre-surgical focus localization in patients with refractory epilepsy, enabling the classification of epileptic foci through directional connectivity graphs. Pacia (2023) demonstrated that sub-scalp implantable telemetric EEG (SITE) systems enable the identification of diagnostic biomarkers and objective monitoring of treatment responses in neurological and behavioral disorders beyond epilepsy through long-term EEG recording. Tautan *et al.* (2025) systematically reviewed the use of unsupervised and self-supervised machine learning methods on EEG data for epilepsy, highlighting methodological trends and clinical application gaps in the field.

Shafiezadeh *et al.* (2024) evaluated patient-independent AI models for EEG-based epileptic seizure prediction and emphasized the lack of generalizability and methodological validation in most existing studies. Gurmessa and Jimma (2025) conducted a systematic review evaluating interpretable artificial intelligence (XAI) methods for EEG-based epileptic seizure diagnosis, emphasizing the balance between model performance and clinical interpretability. The study provided a comprehensive methodological framework for developing reliable, ethical, and explainable AI systems in epilepsy diagnosis. The study developed by Leela and Helenprabha (2025) stands out with the proposed TMDFILE model, a two-level multimodal data fusion and incremental learning approach aimed at the early diagnosis of Alzheimer's disease. By integrating different data types such as EEG, MRI/PET, speech, and written text, this approach dynamically optimizes inter-modality contribution levels through the use of a gating mechanism.

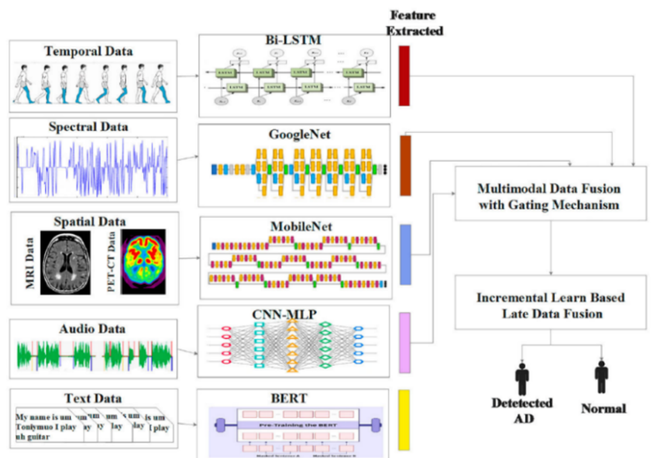

Figure 3 Overview of workflow process (Leela and Helenprabha 2025).

Thanks to its incremental learning structure, the model can adapt to newly incoming data and achieved 94.5% accuracy when tested on five different datasets (ADNI, OASIS, EEG, AUSD, BRATS). Compared to traditional methods such as CNN, SVM, and RF, TMDFILE demonstrated superior performance in terms of both accuracy and generalizability (Leela and Helenprabha 2025; Shang *et al.* 2024; Uyanik *et al.* 2025).

Brain-Computer Interfaces (BCI)

BCI systems are effectively utilized, particularly in the rehabilitation of individuals with limited motor abilities Fig. 4 A review study on these systems evaluated the performance of potentials such as P300 and SSVEP in terms of signal processing (Sözer and Fidan 2018), pattern recognition and control techniques (Orban *et al.* 2022).

In another study, EEG-based BCI applications for elderly and disabled individuals were examined, and the application methods of machine learning algorithms such as ANN, SVM, and LDA to EEG data were elaborated (Wan *et al.* 2019). Endogenous EEG-based BCI systems developed to enable online communication for individuals with complete loss of motor functions rely on paradigms that operate without external stimuli (Turi *et al.* 2021). In the study conducted by Han et al., a classification approach based on Riemannian geometry achieved an accuracy of 87.5% (Han *et al.* 2019; Ma *et al.* 2025; Remsik *et al.* 2022).

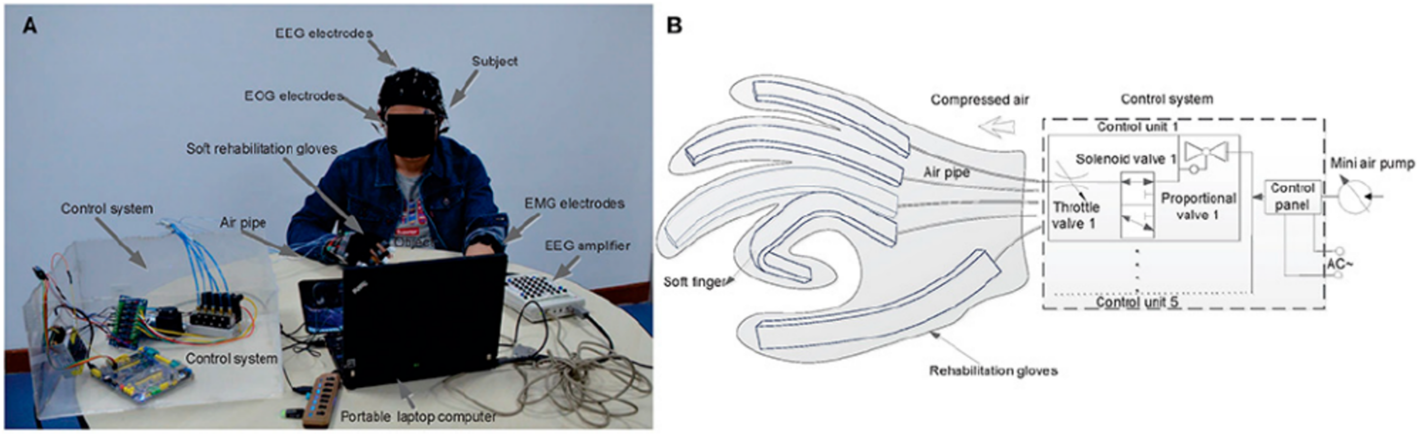

Figure 4 (a) Shows the prototype model BCI and its experimental conditions, (b) is the control scheme of the soft robot hand (Orban *et al.* 2022).

Furthermore, a comprehensive review on EEG-based BCI systems systematically presented the strengths and weaknesses of deep learning architectures such as CNN, RNN, LSTM, GAN, and Transformer models (Alshehri *et al.* 2025; Hossain *et al.* 2023). Another noteworthy study on the classification of motor movements from EEG signals was conducted by Al-Dabag and Ozkurt (2019). In this study, classification was performed using statistical features obtained from EEG signals through artifact removal, wavelet-based frequency band decomposition, and cross-correlation with effective channels (Al-dabag and Ozkurt 2019). In experiments conducted on both the BCI Competition III Dataset IVa and data recorded using the Emotiv device, classification accuracies exceeding 98% were achieved with ANN and SVM algorithms (Al-dabag and Ozkurt 2019). Similar signal processing approaches contribute to the development of BCI systems used not only in clinical settings but also in various application areas such as gaming, education, and marketing (Maiseli *et al.* 2023).

Mental Command and Human-Machine Interaction

Mental command recognition using EEG expands the possibilities of thought-based control in human–machine interaction. Classification of EEG signals preprocessed with EMD using deep neural networks has enabled the differentiation of various mental commands (Agrawal *et al.* 2024). In another study, biometric identification based on individuals' EEG signals was achieved, where a multi-band deep embedding learning network provided high-accuracy identification using features extracted from SSVEP signals (Gu *et al.* 2025). In a study based on a hybrid BCI architecture, motor imagery (MI) and steady-state visual evoked potential (SSVEP) signals were combined to control a quadcopter in 3D space. The system, which switches between two modes using an eye-blinking signal, is capable of controlling flight directions through eight different EEG commands, achieving a classification accuracy of 87.09%. Enhanced with real-time feedback and offline optimization, this architecture offers a high level of control capacity based on mental commands in human–machine interaction (Yan *et al.* 2020).

Sleep, Fatigue, and Mental State Monitoring

In studies focusing on tracking time-dependent cognitive states, fatigue levels were successfully detected using a spatial–temporal CNN and a bidirectional LSTM-based model (Ahn *et al.* 2016; Jeong *et al.* 2019). Building on EEG-derived cognitive state models, a vocal fatigue detection system was developed for air traffic controllers using SVM and Random Forest classifiers. The system performs cognitive state classification based on speech signal features such as MFCCs, fundamental frequency, and energy (Kouba *et al.* 2023).

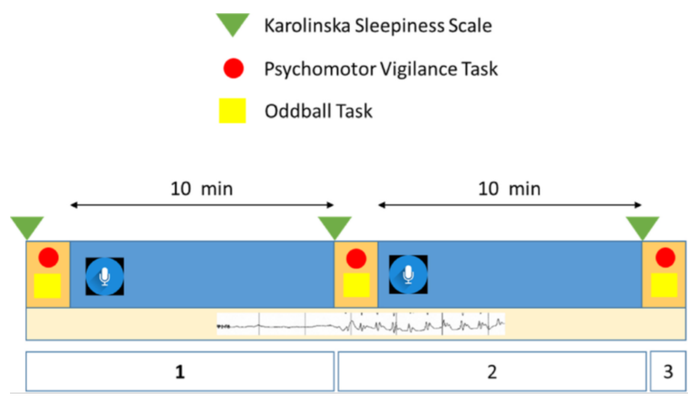

Figure 5 The experimental session representation (Kouba *et al.* 2023).

Additionally, wavelet transform-based multilayer models were employed to classify mental states such as alertness and drowsiness by enhancing time–frequency resolution (Joo *et al.* 2025; Khare *et al.* 2023). In a study on the detection of driver fatigue using EEG signals, the fatigue state was classified with high accuracy through the fusion of four different entropy measures (spectral, approximate, sample, and fuzzy). Using selected classifiers (SVM, BP, RF, and kNN), an accuracy of up to 98.3% was achieved, and effective results were obtained with only four channel regions. These findings highlight the traceability of mental states in human–machine interaction systems and their potential contribution to driving safety (Kouba *et al.* 2023).

In this context, Hassan et al. conducted a comprehensive survey summarizing the current progress and key challenges in electroencephalogram (EEG)-based driver fatigue detection. The review systematically analyzed 87 studies published between 2015 and 2025, focusing on signal preprocessing, feature extraction, and classification techniques. Commonly adopted classifiers such as

Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) networks were found to achieve accuracies ranging from 85% to 99%. The study emphasized that increased power in theta (4–8 Hz) and alpha (8–13 Hz) frequency bands is strongly correlated with fatigue onset. Moreover, the authors highlighted critical limitations, including inter-subject variability, real-time implementation challenges, and a lack of standardized EEG acquisition protocols, suggesting the need for adaptive and wearable EEG systems for practical applications (Hassan *et al.* 2025).

Unique Sensory Experiences and Neurophysiological Representations

The study by Shen *et al.* (2025) investigated the effects of acupuncture sensation on brain functional connectivity using EEG data and analyzed this sensory experience through graph theory metrics. Based on the obtained measures, acupuncture sensation was predicted with a mean absolute error (MAE) of 0.65%. EEG-based investigations conducted on individuals with high autistic traits revealed the neurophysiological foundations of social interaction difficulties and identified a negative correlation between low alpha coherence in the occipital region and AQ scores (Wang *et al.* 2025a).

Music, as a form of expression capable of eliciting strong emotional responses, enables the recognition of music-evoked emotions through EEG signals, contributing to a deeper understanding of the underlying neural mechanisms of such responses. Artificial intelligence plays a crucial role in this process by facilitating the extraction of characteristic frequencies (Su *et al.* 2024) and the identification of novel features, thereby enhancing the development of emotion recognition models.

The studies presented demonstrate that the analysis of EEG signals using AI-assisted approaches plays a significant role in the objective assessment of cognitive, emotional, and neurological states. Deep learning and graph theory-based methods reveal the versatile potential of EEG in clinical, rehabilitation, and human–computer interaction domains. In this context, the development of personalized EEG analyses and real-time systems represents a significant advancement in literature.

ARTIFICIAL INTELLIGENCE APPLICATIONS ON EEG SIGNALS

Several studies identified in the literature that utilize artificial intelligence methods are comparatively examined in the following section.

Machine Learning Method (ML)

Comprehensive reviews are also available in the literature regarding the role of machine learning (ML) algorithms in enhancing the processing, interpretation, accuracy, and effectiveness of EEG signals (Hosseini *et al.* 2021). The methods used in the study conducted by Joseph et al. (2025) are as follows:

Preprocessing: In this section, the researchers explain that the four-channel signals obtained from the MUSE EEG device were converted into microvolts using the BlueMuse and Muse-lsl software and then standardized by resampling them to 200 Hz through a Fourier transform. Each EEG recording, approximately one minute in duration, was segmented using a one-second "sliding window" with a 0.5-second overlap to capture temporal variations. Statistical features (such as skewness and variance) were extracted from these windows and subsequently used for signal analysis and emotional state classification.

The graph in Figure 6 illustrates the segmentation of the EEG signal over time for analysis. In other words, the continuous signal is divided into overlapping small segments (windows). Each segment (for instance, one second in length) serves as an analytical unit from which statistical features are extracted.

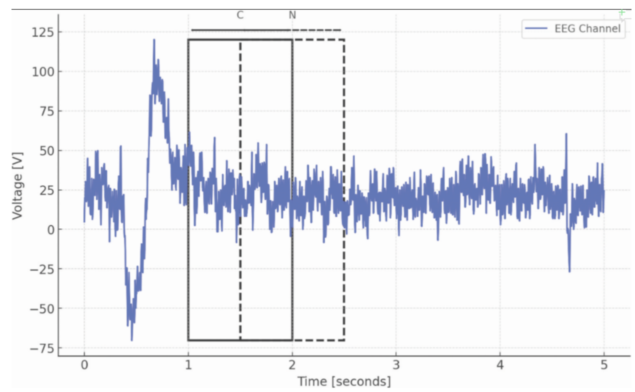

Figure 6 Sliding window approach (Barrowclough *et al.* 2025).

$$\tilde{\mu}_3 = \frac{\sum_i^N (x_i - \bar{x})^3}{(N-1) * \sigma^3} \tag{1}$$

$$S^2 = \frac{\sum (x_i - \bar{x})^2}{n-1} \tag{2}$$

Overall, the data processing procedure involves standardizing the raw EEG signals, segmenting them into time windows, and extracting statistical features (such as skewness and variance) from each window. These features were then utilized in the affective classification model.

Feature Extraction: To capture different dimensions of emotions (e.g., valence and arousal), features were extracted from the signals in the time–frequency domain. Among the prominent techniques are methods such as Empirical Mode Decomposition (EMD) and Wavelet Transform.

Classification: For personalized models, the best results were obtained using Support Vector Machines (SVM) and Random Forest algorithms. The researchers also experimented with ensemble learning strategies to improve classification performance. According to the results, personalized models performed significantly better than general models.

Performance Criteria: Classical evaluation metrics such as accuracy, sensitivity, and specificity were used as performance measures. The SVM-based personalized model achieved an accuracy of up to 85%, which outperforms many general models reported in the literature.

Evaluation and Observation: Based on the assumption that each individual's EEG signal structure differs, the researchers investigated whether personalized models outperform generic ones. To this end, six machine learning algorithms were tested on the MUSE and DEAP datasets: K-NN, Decision Tree, Random Forest, SVM, Naïve Bayes, and Stacking Ensemble Classifier. The experiments aimed to enhance prediction performance by accounting for EEG features specific to each individual.

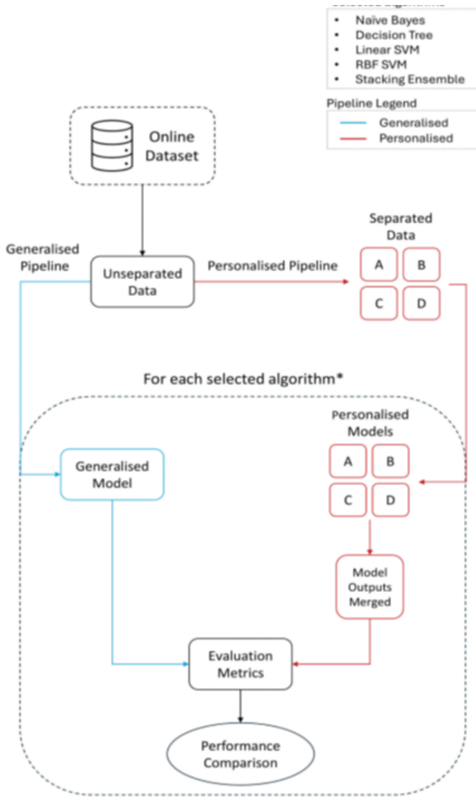

Figure 7 High level method pipeline (Barrowclough *et al.* 2025)

The experimental design of the study is visualized in Fig. 7. This diagram illustrates, step by step, how both the generic and personalised model pipelines are implemented with the machine learning algorithms. The fundamental mathematical foundations of the algorithms (e.g., Minkowski distance, Gini impurity, Bayesian distributions, SVM kernel functions) are also provided; during evaluation, confusion matrices were used and accuracy rates were compared.

Table 1 Summary of Methods and Techniques Used in the Study by Joseph et al.

Feature	Methods Used	Advantages	Disadvantages
Feature Extraction	EMD, Wavelet Transform	High time-frequency resolution	High computational cost
Classifier	SVM, Random Forest, Ensemble Methods	High accuracy with personalized modeling	Slow due to the need for training multiple models
Dataset	DEAP	Widely used, suitable for comparative analysis	Limited number of subjects
Model Structure	Personalized models	Able to capture individual differences	Not suitable for generalization

The methodological contribution of this study lies in demonstrating that a personalized modeling strategy can substantially enhance the performance of EEG-based emotion classification. Such approaches are particularly well-suited for applications such as user-specific neurofeedback systems, mental health monitoring, and human–computer interaction.

The methods used in the study conducted by Khare *et al.* (2023) are as follows:

Dataset and Preprocessing: In this part of the study, a publicly available EEG dataset from the Kaggle platform was utilized. Five participants performed experiments using a train simulator (Amtrak–Philadelphia route). The participants' mental states were categorized into three classes: Focused, Unfocused, and Drowsy. EEG recordings were collected using the Emotiv EPOC EEG system with a sampling frequency of 128 Hz, a bandwidth of 0.2–43 Hz, and a resolution of 0.51 µV. Each 10-minute session was divided into 30-second segments, resulting in 680 EEG segments per class.

The raw EEG signals were processed using an ensemble wavelet decomposition approach to remove noise and artifacts. In this process, three different wavelet-based methods were employed in combination:

• MDWT (Multilevel Discrete Wavelet Transform): It separates low- and high-frequency components.

• TQWT (Tunable Q Wavelet Transform): It performs parameter-based (q, R, B) decomposition without requiring the selection of a main wavelet.

• FAWT (Flexible Analytic Wavelet Transform): It analyzes complex signals such as EEG through two high-pass and one low-pass channels.

• The combination of these methods allows for precise analysis of the signals in both time and frequency domains.

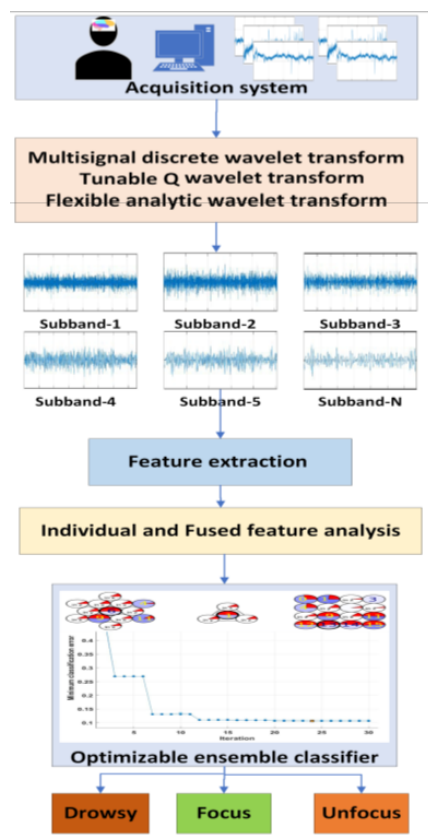

Figure 8 Proposed ensemble model for mental state detection (Khare *et al.* 2023)

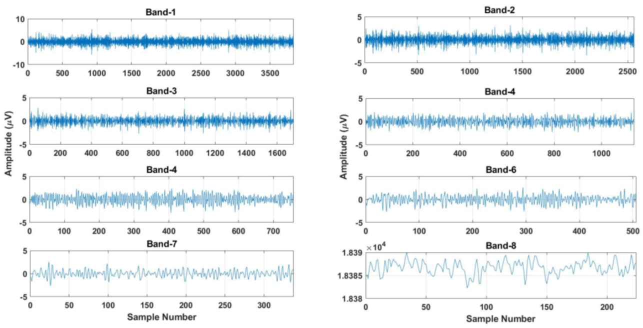

Figure 9 A typical example of SBs generated by the TQWT (Khare *et al.* 2023)

Feature Extraction and Wavelet-Based Decomposition: A total of 27 statistical, fractal, and nonlinear features were extracted from the decomposed EEG signals. These features include indicators such as mean energy, variance, skewness, Hurst exponent, Hjorth mobility, Higuchi fractal dimension, Lyapunov exponent, and zero-crossing rate. The extracted features represent the dynamics of brain activity and were utilized to differentiate between various mental states.

Classification: Optimized ensemble classifiers were employed in the study. The classifiers used included models such as boosted trees, bagged trees, ensemble discriminant, and subspace KNN. Feature fusion was applied to achieve dimensionality reduction and enhance performance.

During the training and testing phases, holdout, 5-fold, and 10-fold cross-validation techniques were implemented.

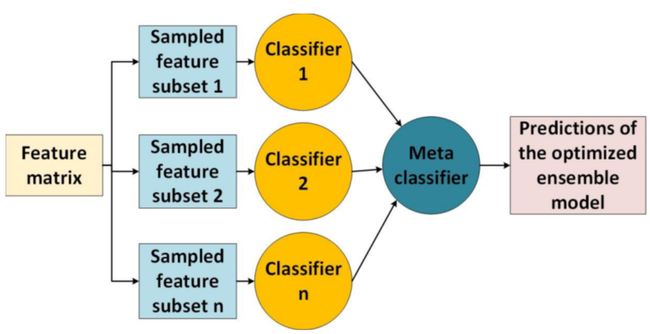

Figure 10 Typical working of ensemble classifier techniques (Khare *et al.* 2023)

Success Performance and Results:

- The best performance was achieved using FAWT, yielding 97.8% accuracy with the Iterative Majority Voting technique.
- In the three-class analysis (F, UF, D), FAWT-based features provided higher separability compared to other methods.
- Feature fusion achieved the highest F1 score (98.18%) particularly for the drowsy class.
- The best-performing subband (SB) levels were as follows:
  - B-1 for MDWT and TQWT
  - SB-7 for FAWT

Evaluation and Observation: This study demonstrates how the combination of wavelet transform techniques and optimized ensemble classification can yield robust results in EEG-based mental state classification. In particular, the high time–frequency resolution of FAWT has proven to be ideal for complex and oscillatory signals such as EEG.

Table 2 Summary of Methods, Features, and Classification Performance in the Study by Khare *et al.* (2023)

Feature	Methods Used	Advantages	Disadvantages
Feature Extraction	MDWT, TQWT, FAWT	Versatile time–frequency decomposition	Parameter tuning is complex
Feature Type	27 statistical/chaotic features	Rich info, high discriminative power	Large features → reduction may be required
Classifier	Ensemble (optimized)	High accuracy and generalization	High computational cost
Accuracy (with IMV)	97.8%	Superior performance in the literature	Limited number of subjects

Compared to previous studies, this work adopts an ensemble wavelet decomposition with feature fusion strategy rather than personalization. While personalized models focus on capturing individual variations, the advantage of the present study lies in providing a more generalizable classification model.

The two studies considered (Barrowclough *et al.* 2025; Khare *et al.* 2023) focus on the machine learning-based classification of mental states from EEG signals and present distinct methodological approaches. Although the objectives of both studies are similar, they demonstrate significant differences in the signal processing and classification strategies employed.

Modeling Approach:

- The first study, "Personalised Affective Classification Through Enhanced EEG Signal Analysis," focused on individual-specific emotion classification and developed personalized machine learning models (Khare *et al.* 2023). Training a separate model for each participant aimed to enhance classification accuracy by accounting for personal variations in EEG signals.
- The second study, "Ensemble Wavelet Decomposition-Based Detection of Mental States," aimed to establish a generalizable model and adopted an ensemble wavelet decomposition combined with an optimizable ensemble classifier approach rather than personalization (Ma *et al.* 2025). In this study, mental states such as focused, unfocused, and drowsy were classified into three distinct classes.

The first study emphasizes personalized models, whereas the second focuses on generalized models. While the former highlights individual adaptation, the latter underscores the power of signal processing and algorithm optimization.

Feature Extraction and Signal Processing Techniques:

- In the first study, features were extracted from EEG signals using conventional time–frequency decomposition methods, such as Empirical Mode Decomposition (EMD) and Wavelet Transform. These extracted features were used to model affective dimensions, such as valence and arousal.
- In the second study, a more sophisticated approach was adopted. Multilevel Discrete Wavelet Transform (MDWT),

Tunable Q Wavelet Transform (TQWT), and Flexible Analytic Wavelet Transform (FAWT) were used in combination to perform ensemble decomposition. Each of these techniques excels at decomposing different frequency bands and signal characteristics. A total of 27 statistical and chaotic features were extracted, and dimensionality reduction was achieved using a feature fusion method.

In the second study, the feature space is considerably richer and more diverse. In particular, the use of FAWT provides a significant advantage in analyzing the temporal complexity of EEG signals. The methods employed in the first study are comparatively more basic in nature.

Table 3 Machine learning based Comparative Performance and Methodological Analysis of Barrowclough *et al.* (2025) and Khare *et al.* (2023)

Feature	Study 1: Personalized Model	Study 2: Ensemble Wavelet Model
Modeling Approach	Individual-specific	Generalizable + optimized
Feature Extraction	EMD, Wavelet	MDWT, TQWT, FAWT
Classifier	SVM, RF	Ensemble + IMV
Accuracy	~85%	97.8%
Signal Type	DEAP dataset	Kaggle EEG
Strengths	Captures individual variations	Advanced decomposition + fusion
Limitations	Limited generalization	Small number of participants

Classification Methods:

- In the first study, Support Vector Machines (SVM) and Random Forest classifiers were primarily employed, and personalization increased the accuracy to approximately 85% (Khare *et al.* 2023).
- In the second study, optimized ensemble classifiers were preferred. A combination of methods, including bagged trees, boosted trees, and subspace KNN, was applied, and the final decision mechanism was implemented using Iterative Majority Voting (IMV). This framework increased the accuracy rate to 97.8%. The classification approach in the second study demonstrated superior performance due to its more advanced framework and inclusion of hyperparameter optimization. Despite the use of personalized models in the first study, the overall accuracy remained lower.

Deep Learning Method (DL)

In the literature review section, three key studies employing deep learning (DL) approaches for EEG-based classification problems were analyzed (Agarwal and Kumar 2024), and their methodological differences and performances were compared in detail. Prabhakar et al. in 2024, the methods employed are as follows:

Preprocessing:

- The preprocessing stage aimed both to enhance signal quality and to provide a suitable foundation for feature extraction.
- The signals were divided into segments of equal length to enable meaningful analysis.
- Each segment was time-normalized to ensure consistent learning by the model.
- The preprocessing stage aimed both to enhance signal quality and to provide a suitable basis for feature extraction.

Feature Extraction:

- The Hilbert Transform was applied to the EEG signals to obtain the envelopes of each signal.
- This transformation provided both instantaneous amplitude and phase information, offering a richer representation compared to classical time–frequency analysis methods.
- The resulting envelopes were converted into a suitable matrix format to serve as input for the classification model.
- In this way, both the neural and semantic components of the signals were successfully represented

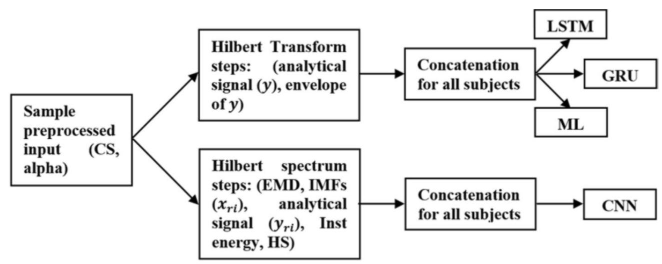

Figure 11 Detailed steps for feature extraction (Agarwal and Kumar 2024)

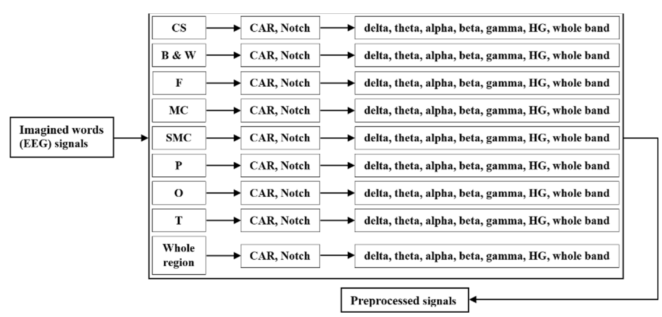

Figure 12 Detailed steps for preprocessing (Agarwal and Kumar 2024).

Classification:

- A deep neural network (DNN) based on a multilayer perception (MLP) was employed for classification.
- The model was trained under a supervised learning paradigm and optimized using the backpropagation algorithm.
- The network architecture enabled the deep processing of features, allowing for successful discrimination of imagined word tasks.

Performance Criteria:

- The model's performance was primarily evaluated in terms of accuracy. Additionally, its cross-subject generalizability was tested to assess the ability for participant-independent classification.

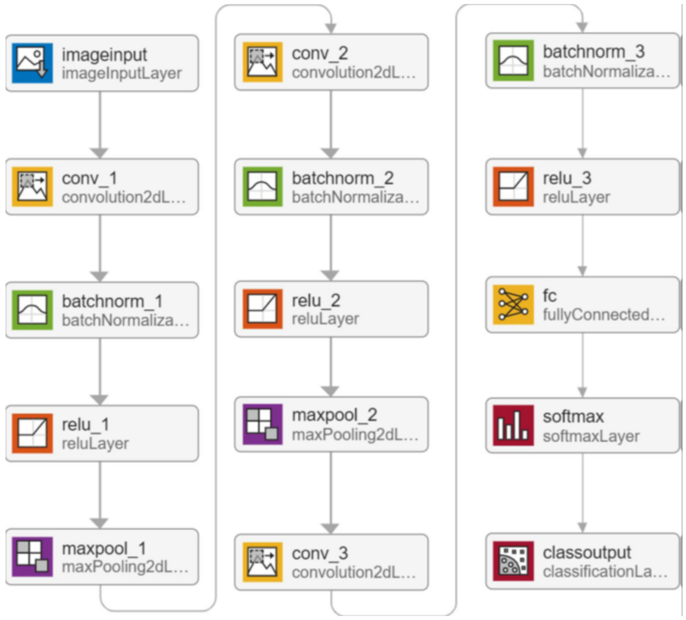

Figure 13 Proposed CNN architecture (Agarwal and Kumar 2024).

Table 4 Summary of Preprocessing, Feature Extraction, and Classification Methods Used by Remsik *et al.* (2022)

Feature	Methods Used	Advantages	Disadvantages
Preprocessing	Band-pass filtering, segmentation, time normalization	Signals cleaned from noise and artifacts; suitable for analysis	Filter parameters may not be universal due to individual variations
Feature Extraction	Envelope extraction via Hilbert Transform	Rich representation containing both phase and amplitude info	Computational load of Hilbert Transform can be high
Classification	MLP-based Deep Neural Network, backpropagation	Strong classification capability; parametric flexibility	Deep learning models require large datasets; risk of overfitting
Performance Evaluation	Accuracy, cross-subject generalizability tests	Effective performance across different individuals	Despite high accuracy, not yet tested in real-time applications

- The study demonstrated high performance with similar accuracy rates across different individuals. However, the applicability of the model in real-time systems has not yet been experimentally tested.
- The F1 score is not directly reported as a metric in the article content and tables; the study focuses more on accuracy and Network Prediction Time (NPT).
- Accuracy Percentage:
  - Maximum Accuracy: 94.29% was achieved.
  - Average Accuracy: An average accuracy of 71.75% was achieved throughout the study.

In the study conducted by (Dairi *et al.* 2022), the methods employed are as follows:

Preprocessing:

- In this section of the study, the Multi-Channel Wiener Filter (MWF) algorithm was applied for artifact removal. MWF has been shown to perform effectively on both real and hybrid EEG data, offering superior performance compared to conventional techniques.
- The fundamental principle of the algorithm involves modifying the artifact covariance matrix using a low-rank approximation and processing it through generalized eigenvalue decomposition. This approach provides a generalizable and robust solution for the removal of various types of EEG artifacts.

Feature Extraction:

- In this study, conventional manual feature extraction was not performed. Instead, the task of feature extraction was directly handled by the encoder layers of the model.
- In particular, the convolutional layers (CNN) acted as a structure that automatically learned the spatial and temporal patterns of the EEG signals to extract features. This approach aligns with the deep learning capability to reduce the need for manual feature engineering.
- Consequently, the data was fed directly into the neural network, allowing the model itself to generate meaningful representations without relying on hand-crafted features.

Classification:

- The novelty of the study lies in employing an anomaly detection approach instead of conventional classifiers. In this context, the developed system is based on an autoencoder architecture. The encoder–decoder model aims to summarize and reconstruct the input signal.
- During training, the model was allowed to learn only "normal" mental tasks. In the testing phase, reconstruction errors were measured to identify "anomalous" patterns. This approach is particularly effective for high-variance data such as EEG signals, providing both the ability to work with unlabeled data and robustness to individual differences.

Performance Criteria:

- The success of the DBN-iF model proposed in this study has proven its superiority compared to other results in the literature:
  - DBN-iF (This study): 98.5%
  - LS-SVM (Closest competitor): 97.56%
  - KNN: 92.8%
  - CNN-SAE: 90.0%
- The model's performance was evaluated primarily based on reconstruction error rather than conventional accuracy metrics. Anomalous events were identified when this error exceeded a predefined threshold, enabling functional output even on unlabeled samples.
- Experimental results demonstrate the system's high capacity both for discriminating between different tasks and for adapting to inter-subject variations.However, the absence of

Table 5 Summary of Preprocessing, Feature Extraction, and Classification Methods Used by (Dairi *et al.* 2022)

Feature	Methods Used	Advantages	Disadvantages
Preprocessing	Multi-Channel Wiener Filter (MWF); low-rank covariance; eigenvalue decomposition	Superior denoising on real/hybrid EEG; robust to multiple artifacts	More complex than classical filtering; requires expertise
Feature Extraction	Automatic extraction via CNN layers; no manual features	Eliminates manual engineering; learns spatial-temporal patterns	Requires large data; less interpretable than handcrafted features
Classification / Detection	Autoencoder-based anomaly detection; reconstruction error	Learning from unlabeled data; robust to inter-subject variability	Lack of softmax makes direct comparison difficult; threshold selection issues
Performance Evaluation	Reconstruction error and anomaly thresholding	Enables detection without labels; shows generalization	No classical metrics (accuracy, etc.) reported; limited comparability

comparison using traditional metrics such as class-wise accuracy limits the direct comparability of these results with conventional systems.

- According to the findings of this article, combining QTFD (Quadrificial Time-Frequency Distribution) feature extraction with DBN-based Anomaly Detector (Isolation Forest) can achieve higher accuracy in recognizing mental tasks compared to traditional supervised learning models (such as CNN or SVM).

In the study conducted by Khondoker Murad et al. (Hossain *et al.* 2023), the techniques employed are as follows:

Preprocessing: The raw EEG signals inherently contain noise, artifacts, and low signal-to-noise ratios, which complicate their direct use in BCI applications. Therefore, among the prominent preprocessing methods highlighted in the studies reviewed, the following are commonly employed:

- Frequency filtering (particularly band-pass filtering between 0.5–45 Hz).
- Artifact removal (especially signals arising from eye blinks and muscle movements).
- Manual cleaning and methods such as Independent Component Analysis (ICA) and Discrete Wavelet Transform (DWT).

Feature Extraction. One of the main advantages of deep learning is its ability to eliminate the need for manually defined feature extraction. In the studies reviewed, feature extraction was primarily performed automatically by the initial layers of CNN, RNN, LSTM, or even Transformer architectures.

However, some hybrid approaches employed time–frequency representations to support model learning, applying transformations such as STFT, CWT, or Morlet wavelets as a pre-processing step. Notably, in tasks such as motor imagery or emotion recognition, these rich representations were observed to significantly enhance classification performance.

Classification: In the review, various deep learning architectures employed for EEG-based BCI applications are presented in detail. The most frequently used classifiers include:

- Convolutional Neural Networks (CNN) – effective for capturing spatial features.
- Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) – suitable for temporal signals such as EEG.
- Generative Adversarial Networks (GAN) – employed for data augmentation and balancing.
- Transformer architectures – offer potential for modeling long-range dependencies.

Performance Criteria: In this study, deep learning models demonstrated different success levels depending on the application type:

- Driver Fatigue Detection: Studies in this area have resulted in high accuracy rates between 83% and 98%.
- Epileptic Seizure Detection: Accuracy rates of over 99% have been reported using CNN and RNN models.
- Emotion Recognition: Most researchers have achieved accuracy rates above 90% in datasets such as DEAP and SEED.
- Motor Imagery (MI): While classical machine learning methods struggle in this area (between 72% and 86%), deep learning (especially LSTM and CNN) has significantly improved performance.

Table 6 Summary of Preprocessing, Feature Extraction, and Classification Methods Used by (Hossain *et al.* 2023)

Feature	Methods Employed	Advantages	Limitations
Preprocessing	Frequency filtering, artifact removal (ICA, DWT), manual visual inspection	Noise reduction and improved signal quality	Standardization is challenging due to methodological diversity
Feature Extraction	CNN, LSTM, Transformer architectures; time–frequency transformations (CWT, STFT)	Automatic learning instead of manual extraction; rich representations	Loss of interpretability and high computational cost in some models
Classification	CNN, LSTM, GAN, Transformer; hybrid architectures (e.g., CNN+LSTM)	High accuracy with task-specific selection; captures patterns	Model selection depends on task type; no universal architecture
Performance Evaluation	Accuracy, F1-score, sensitivity, specificity, cross-validation	Multi-dimensional analysis; improved generalization via transfer learning	Direct comparison is difficult due to differences in datasets

Additionally, some approaches employed cross-validation strategies to assess generalizability. It has also been highlighted that increasing the amount of data, as well as applying domain adaptation and transfer learning techniques, has a significant impact on accuracy. However, the lack of methodological consistency among the datasets used has led to inconsistencies in comparative results.

Comparison of Deep Learning-Based Studies

These three studies collectively illustrate the multidimensional utilization of deep learning techniques in EEG signal analysis. The first study introduces a CNN-based framework focusing on a specific task (imagined words), whereas the second emphasizes an anomaly detection paradigm rather than direct classification. The third article provides a higher-level synthesis encompassing multiple studies, underscoring that the selection of an appropriate methodological approach should be determined contextually, depending on the experimental design and target application.

Explanations of Technical Terms:

- Hilbert Transform: An analytical signal approach used to extract the temporal amplitude and phase components of EEG signals. It enhances temporal resolution.
- Autoencoder: An unsupervised learning architecture that identifies anomalies by learning low-dimensional representations of data and minimizing reconstruction error.
- STFT / CWT / Wavelet Transforms: Fundamental time-frequency transformation techniques used in EEG signal analysis. They facilitate the generation of more meaningful inputs for deep learning models.
- Domain Adaptation: A subfield of transfer learning employed to maintain model consistency across EEG data collected from different individuals.

Similarities and Differences Between Methods:

- CNN architecture plays a significant role in all three studies. In the first study, it is employed directly for classification purposes, whereas in the second study, it is incorporated within an autoencoder structure for reconstruction. In the third study, CNN is discussed within the context of a literature review as a commonly used method in EEG applications.
- Noticeable differences emerge in terms of pre-processing techniques. The first study enriches the data using advanced signal processing methods such as the Hilbert transform, whereas the second study employs simpler, more basic preprocessing procedures. This distinction clearly demonstrates the impact of data preparation methods on the resulting model performance.
- In terms of learning paradigms, the first study is based on supervised learning and utilizes labeled data. In contrast, the second study employs an unsupervised learning approach applied to unlabeled datasets. The third study compares these two methods and discusses which approach may be more appropriate depending on the type of application.
- Advanced techniques such as generalizability and transfer learning are discussed in detail particularly in the third study. Since EEG signals exhibit substantial inter-individual variability, these strategies are crucial for ensuring that models remain effective across different subjects. In contrast, the other two studies address this topic in a more limited manner.

Results: Although these three studies serve different objectives, they collectively demonstrate that deep learning–based analyses of EEG signals encompass a broad methodological spectrum. The common use of CNN-based architecture indicates that such models can effectively capture and represent spatial patterns within EEG data. However, the adaptation of these architectures to dataset-specific characteristics, such as preprocessing strategies, labeling schemes, and levels of architectural complexity, constitutes a critical factor influencing application performance. As a consequence of this methodological diversity, models such as autoencoders tend to offer advantages in scenarios emphasizing unsupervised learning, whereas CNN-based models enriched with information-dense inputs yield more efficient outcomes in contexts requiring linguistic imagery or complex classification.

Studies Utilizing Alternative Modeling Approaches

The methods and techniques used in the studies of Al-Dabag and Ozkurt (Al-dabag and Ozkurt 2019),

Preprocessing:

- Artifact Removal (EEG Subtraction): Noise was suppressed by subtracting the resting-state (motionless) EEG signal from the EEG signal containing movement. This procedure was applied to enhance signal clarity and make it suitable for classification.
- Channel Selection: EEG channels located near the motor cortex were pre-identified and selected. In particular, the F3 and F4 channels were utilized as "effective channels.

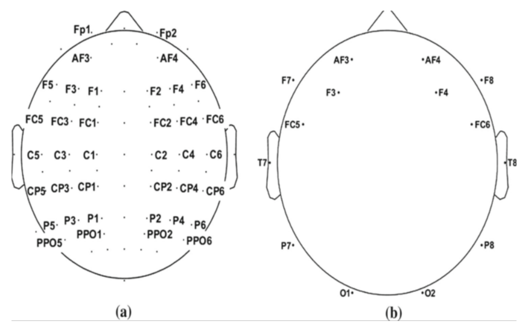

Figure 14 Selected EEG channels in both datasets. (A) Selected channels of BCI datasets, (b) selected channels of Emotiv datasets (Al-dabag and Ozkurt 2019).

Feature Extraction:

- Discrete Wavelet Transform (DWT): EEG signals were decomposed into beta and gamma bands using the DWT method. This decomposition allowed the extraction of frequency components related to movement.
- Cross-Correlation: The selected effective channels (F3, F4) were subjected to cross-correlation with other channels in the right and left hemispheres, thereby extracting information on similarity/synchronization between two channels.
- Statistical Features: From the cross-correlation outputs, 10 normalized statistical features were calculated, including minimum, maximum, mean, median, mode, standard deviation, variance, entropy, and the first and third quartiles.

Classification:

- Artificial Neural Network (ANN): A multilayer ANN was implemented. The number of nodes in the hidden layer was optimized through multiple trials (e.g., 14 nodes yielded the best performance).

Table 7 Comparative Deep Learning-Based EEG Applications

Criterion / Study	Imagined Words Classification (Hilbert Transform + CNN)	Mental Task Recognition (Autoencoder-Based Anomaly Detection)	Comprehensive Literature Review (Multiple Deep Learning Architectures)
Application Domain	Recognition of mentally imagined words (*Imagined Speech BCI*)	Identification of different cognitive tasks (*Mental Task Recognition*)	General methodological categorization for EEG-based BCI systems
Preprocessing Approach	Extraction of instantaneous amplitude and phase components using the Hilbert Transform	Z-norm–based standardization and basic spectral filtering	Time–frequency transformations (STFT, CWT, Wavelet Decompositions)
Modeling Architecture	Deep Convolutional Neural Network (Deep CNN)	Encoder–decoder–based Autoencoder structure (CNN embedded)	Advanced DL architectures such as CNN, LSTM, GAN, and Transformer
Methodological Contribution / Innovation	Enriched input representation via Hilbert Transform for meaningful signal encoding	Mental state differentiation through unsupervised detection of anomalous patterns	Architecture–application mapping and architecture recommendations based on task type
Data Labeling Requirement	Moderate (requires labeled data for supervised learning)	Low (suitable for unsupervised or anomaly detection tasks)	High (requires extensively labeled data or transfer learning scenarios)
Generalizability / Subject Independence	Cross-participant generalizability tested	Proposed structure tolerant to participant variability	Discussion of domain adaptation and transfer learning strategies
Highest Accuracy	%94.29	%98.50	99.00%+ (Epilepsy)
Average / Other Results	Average: 71.75%	LS-SVM: %97.56, KNN: %92.8, CNN-SAE: %90.0	Driver Fatigue: 83–98%, Emotion Recognition: >90%, Motor Imagery: 72–86%

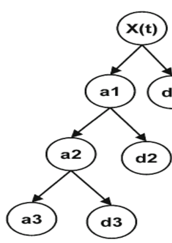

Figure 15 Three-level DWT decomposition (Al-dabag and Ozkurt 2019)

- Support Vector Machine (SVM): An SVM with a Radial Basis Function (RBF) kernel was employed. The kernel scale was determined automatically.
- Datasets: Classification was performed using both the BCI Competition III Dataset IVa (imagined movements) and Emotiv Epoc+ data (actual movements).

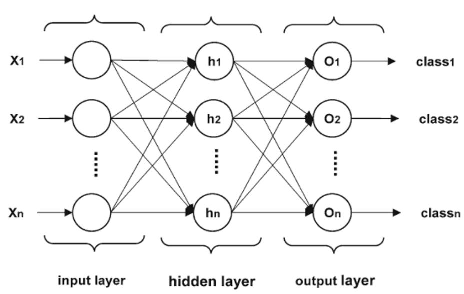

Figure 16 ANN architecture (Al-dabag and Ozkurt 2019)

Performance Criteria:

- Accuracy: An accuracy of 99.33% was achieved with the ANN, and 99.69% with the SVM (BCI dataset).
- Cross-Validation (10-Fold): A 10-fold cross-validation was performed for both classifiers to assess their validity.
- User Independence: Both subject-specific (patient-based) and pooled-subject (movement-based) classifications were tested. In movement-based classification, accuracy did not drop below 92%.

The methods and techniques used in the studies of Leela and colleagues (Leela and Helenprabha 2025),

Preprocessing: Since different data modalities (temporal, spectral, spatial, audio, and text data) were used for Alzheimer's disease prediction, specific preprocessing procedures were applied for each data type:

- Temporal (gait) data: Erroneous and missing data were removed using statistical methods, and outliers were eliminated based on standard deviation thresholds.
- Spectral (EEG) data: Signals were filtered within the 1–45 Hz band and subsequently prepared for time-frequency transformation.
- Spatial (MRI/PET/CT) data: Imaging data underwent size standardization and resampling procedures.
- Audio data: Noise reduction and normalization were performed.
- Text data: After converting audio data to text, tokenization, stop-word removal, and vectorization were carried out.

Feature Extraction: The study employed deep learning models that extract distinctive representations from multimodal datasets:

- Temporal (gait) data: A BiLSTM (Bidirectional Long Short-Term Memory) network was used for the time series data.

Table 8 Summary of Preprocessing, Feature Extraction, and Classification Methods Used by (Al-dabag and Ozkurt 2019)

Feature	Methods Used	Advantages	Disadvantages
Preprocessing	Resting-state EEG subtraction, channel selection	Noise was suppressed, resulting in cleaner signals. Focus on motor cortex regions was enhanced.	Manual channel selection may require expert knowledge. Performance may depend on recording conditions.
Feature Extraction	Frequency decomposition using DWT, cross-correlation, statistical parameter extraction	Provided meaningful and effective features with low computational cost. A comprehensive feature set was created.	Features were intuitively extracted from the signal; additional optimization may be required for universal generalization.
Classification	ANN (Levenberg-Marquardt), SVM (RBF kernel)	Tested with two different classifiers, achieving high accuracy. Comparison between ANN and SVM was conducted.	ANN results show run-to-run variability; parameter tuning may require careful adjustment.
Performance Evaluation	98–99+% accuracy, 10-fold cross-validation, two datasets (BCI and Emotiv), subject-specific and pooled classification	Method generalizability was tested, achieving success across different individuals and devices. High performance achieved with a simple approach.	Slight drop in accuracy observed in pooled classification scenarios (~92%); individual differences may have a stronger effect.

- Spectral (EEG) data: Frequency-dynamic features were extracted from EEG images using the GoogLeNet convolutional neural network.
- Spatial data: Imaging data were analyzed using the MobileNet architecture, achieving high-accuracy representations with low computational cost.
- Audio data: Audio files were analyzed using a CNN-MLP (convolutional neural network combined with a multilayer perceptron).
- Text data: Semantic information was captured using the BERT (Bidirectional Encoder Representations from Transformers) model.

A two-level data fusion approach was implemented:

- Level 1: Temporal, spatial, and spectral data were combined through a gating mechanism to generate an intermediate representation.
- Level 2: This intermediate representation was then integrated with audio and text representations to obtain the final fusion vector.

Classification: The final feature vector was given to the Incremental Learner Ensemble Classifier (TMDFILE) model, which was specifically developed for Alzheimer's prediction. The main characteristics of this model are as follows:

- Ensemble structure: It combines different classifiers (e.g., decision trees, SVM) to enable more robust decision-making.
- Incremental learning: The model can be updated with newly incoming data; in other words, it is not static but has an adaptive learning process.
- Gating mechanism: It assigns weights by determining which modality is more effective in the classification process.

Performance Metrics: ADNI, OASIS, EEG Emotion, Aberystwyth Dementia, and BRATS. The obtained performance metrics:

- Accuracy: %94.5
- Precision: %93.5
- Recall: %95.1
- F1 Score: %94.1

Table 9 Summary of Preprocessing, Feature Extraction, and Classification Methods Used by (Leela and Helenprabha 2025)

Feature	Methods Used	Advantages	Disadvantages
Data Types	Temporal, spectral, spatial, audio and text data	Integrated analysis of disease dimensions	Complex data collection and synchronization
Preprocessing	Band-pass filtering, outlier removal, resampling	Modality-specific cleaning improves quality	Long processing time; high technical expertise
Feature Extraction	BiLSTM, GoogLeNet, MobileNet, CNN-MLP, BERT	Optimized DL architectures for each modality	High hardware requirements; long training time
Data Fusion Approach	Two-level: hierarchical fusion with gating	Optimized modality contribution	Complex structure; limited explainability
Classification Method	Incremental Learner Ensemble (TMDFILE)	Updatable, adaptive system; high accuracy	Needs additional management for real-time
Performance Metric	Acc: 94.5%, Prec: 93.5%, Recall: 95.1%, F1: 94.1%	High success rates across datasets	High system complexity for integration
Clinical App.	Multimodal neurological imaging system	Evaluates cognitive and motor symptoms	Access to all data sources may not be feasible

Comparative Analysis in Terms of Methods and Techniques Al-Dabag and Ozkurt (2018) proposed a simple and low-cost method that can be integrated into online BCI systems for motor movement classification based on EEG data. By utilizing DWT, cross-correlation, and statistical features, high accuracy was achieved without the need for complex optimization processes, and classical models such as ANN and SVM were employed for classification. On the other hand, Leela et al. (2025) introduced an incremental learning-based system called TMDFILE, which integrates EEG, MRI, speech, text, and gait data for Alzheimer's diagnosis. This approach is grounded in multidisciplinary data fusion. The two studies differ significantly in terms of data diversity, scale, and intended application.

Table 10 Comparative Analysis of EEG-Based Studies by (Al-dabag and Ozkurt 2019) and (Leela and Helenprabha 2025)

Comparison	Al-Dabag & Ozkurt (2018)	Leela et al. (2025)
Application Area	EEG-based motor movement recognition, BCI systems	Alzheimer's disease diagnosis, multi-modal biomedical data
Data Type	EEG only (BCI Dataset & Emotive)	EEG, MRI/PET, gait, audio, and text data
Preprocessing	EEG subtraction, channel selection	Modality-specific preprocessing: filtering, normalization, resampling, etc.
Feature Extraction	DWT, cross-correlation, 10 statistical features	BiLSTM, GoogLeNet, MobileNet, CNN-MLP, BERT, two-level data fusion
Classification Algorithms	Artificial Neural Network (ANN), Support Vector Machine (SVM)	TMDFILE (Ensemble & Incremental Learning Classifier)
AI Level	Traditional ML techniques	Advanced deep learning and incremental learning
Fusion Usage	None	Two-level data fusion (EEG + MRI → + audio + text)
Accuracy	99.33% (ANN), 99.69% (SVM)	94.5% on average (across five datasets)
Advantages	Simple, low computational cost, suitable for online BCI applications	Comprehensive modality analysis, adaptive learning, clinical generalizability
Disadvantages	EEG-only usage → limited information representation, sensitivity to individual data	High computational and data requirements, system complexity
Generalizability	Limited (restricted to BCI systems)	High (broad clinical application with data from multiple sources)

CONCLUSION

This review systematically classified the literature from the past decade on AI-based EEG analysis and provided comprehensive methodological comparisons. The findings highlight that personalized machine learning models, supported by advanced signal representation techniques such as Hilbert-based analytic signal extraction and time–frequency decompositions using STFT, CWT, and wavelet transforms, significantly improve sensitivity to individual neural dynamics. In parallel, representation learning approaches based on autoencoders contribute to robust feature extraction and dimensionality reduction in high-dimensional EEG data. Moreover, advanced multichannel signal enhancement techniques, particularly the Multi-Channel Wiener Filter (MWF), play a critical role in artifact suppression, signal-to-noise ratio improvement, and preservation of physiologically meaningful neural information, thereby strengthening the robustness of downstream machine learning and deep learning models. Deep learning architectures such as CNN, LSTM, and Transformer networks demonstrate strong capability in capturing both spatial and temporal dependencies inherent in multichannel EEG recordings.

Beyond conventional clinical diagnosis and monitoring, EEG-based AI systems are increasingly applied in interdisciplinary domains, including emotional state recognition, human–computer interaction, and driving safety. In this context, incremental learning frameworks combined with multimodal data fusion show promising potential for the early detection of complex neurological disorders such as Alzheimer's disease. Looking forward, the more systematic integration of domain adaptation and transfer learning strategies that explicitly address inter-subject and cross-session variability is strongly recommended. Additionally, the development of low-latency, optimized software–hardware co-design solutions remains essential for real-time EEG applications. Finally, the adoption of ethical data practices and explainable AI frameworks is critical to ensure the safe, transparent, and clinically reliable translation of EEG–AI technologies into real-world healthcare systems.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Availability of data and material

Available upon request.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

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