# Machine and Deep Learning Trends in EEG-Based Detection and Diagnosis of Alzheimer's Disease

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**Abstract -** This systematic review investigates recent advancements in applying machine learning (ML) and deep learning (DL) techniques to the diagnosis and detection of Alzheimer's disease (AD) using electroencephalography (EEG). Drawing on studies published from 2013 to 2023, and guided by PRISMA methodology, the review evaluates 109 articles selected from Scopus, Web of Science, and PubMed. It highlights key aspects including EEG database characteristics, signal acquisition protocols, electrode configurations, and demographic diversity. Signal preprocessing methods, feature extraction across time, frequency, and connectivity domains, and classification algorithms—such as SVM, CNN, RNN, and emerging GNN models—are analyzed. The review underscores the performance of different techniques, with classification accuracies exceeding 90% in multidomain approaches. It identifies challenges in generalizability, dataset standardization, and interpretability, and emphasizes the potential of integrated AI models to improve early AD detection and personalized patient care.

***Key Words*:** deep learning; diagnosis of Alzheimer's disease; EEG; machine learning; systematic review

## 1.INTRODUCTION -

This Alzheimer's disease (AD) is a neurodegenerative pathology that progresses over time and mainly affects older people. Its symptoms vary among those affected but include memory loss, confusion, and extensive cognitive impairment [1,2]. Early identification and accurate diagnosis are essential to provide appropriate medical care and improve the quality of life of patients [3,4]. With technological progress in capturing brain signals, such as the electroencephalogram (EEG), more accurate and effective diagnostic methods have been developed. Due to its non-invasive nature, the EEG records the brain's electrical activity through electrodes on the scalp, offering valuable insights into brain alterations linked to Alzheimer's disease [5–7].

Machine learning (ML) and deep learning (DL) techniques for classifying EEG signals have been established as an expanding area of research. These methods allow the analysis of large volumes of EEG data to identify non-obvious patterns, potentially facilitating the early diagnosis of AD [8,9]. However, the effective implementation of these techniques needs to be improved. Critical factors such as the appropriate choice of EEG databases, a correct arrangement of the electrodes, the selection of an appropriate number of participants, the identification of relevant features for the analysis, the choice of appropriate classification algorithms, and a rigorous evaluation of its performance is decisive in the quality and reliability of the results obtained [10].

This work aims to carry out a systematic review of current trends in the use of ML and DL to detect and diagnose AD through the use of EEG. Fundamental aspects such as preparation prior to data collection is addressed, including the selection of the EEG database, the electrode placement strategy, data acquisition methodologies, and the selection of the number of volunteers. A detailed analysis of ML and DL methods will be carried out, including everything from filtering and segmentation techniques to feature selection. evaluation metrics used to determine the effectiveness of the classification algorithms are also reviewed. This article offers a comprehensive overview of the advances and

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methodologies in applying ML and DL in EEG analysis to diagnose and detect AD early. The main contributions of the work are:

- Artificial intelligence is a booming branch that offers an alternative to understanding diseases. However, it is susceptible to the input data and its processing. This work analyzes these critical points described in the state of the art.
- No work has been carried out in the last ten years with this approach to analysis; before the application of artificial intelligence algorithms, their selection and classification levels focused on Alzheimer's disease.
- This review covers the analysis of EEG signal databases for use in AI, the demographic data of the patients that comprise them, and the data acquisition paradigms, resulting in a necessary tool for future research.

The structure of the current work is divided as follows: Section 2 exposes the sequential steps that must be followed to implement the proposed review. The results and discoveries obtained are presented in Section 3. Section 4 analyzes and interprets the results. Finally, in Section 5, the areas covered by the scope of this work are exposed.

## 2. MATERIALS AND METHODS

This systematic review was conducted to examine the trends, techniques, and effectiveness of machine learning (ML) and deep learning (DL) approaches in diagnosing Alzheimer's Disease (AD) using electroencephalography (EEG) signals. The methodology was designed following the **PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)** guidelines to ensure transparency, reproducibility, and rigor.

### 2.1 SEARCH STRATEGY

A comprehensive literature search was performed using three major scientific databases: PubMed, Scopus, and Web of Science (WOS). The search focused on studies published between January 2013 and December 2023. Boolean operators and keyword combinations were applied to refine the search: ("Mild Cognitive Impairment" OR "MCI" OR "Alzheimer") AND ("EEG" OR "electroencephalography") AND ("machine learning" OR "deep learning") AND ("detection" OR "diagnosis" OR "classification").

### 2.2 INCLUSION AND EXCLUSION CRITERIA

To ensure methodological rigor, strict inclusion and exclusion criteria were applied. Included studies had to utilize EEG signals for detecting or diagnosing AD or MCI and employ ML or DL algorithms for classification or pattern recognition. Studies must have used human datasets with a clearly described cohort and should report at least one performance metric such as accuracy, precision, recall, F1-score, or specificity. Excluded were studies that used non-EEG data, relied solely on manual or statistical methods without AI, lacked a clearly defined experimental methodology, or focused on neurological disorders other than AD or MCI. Additionally, papers that did not provide sufficient data preprocessing or classifier performance results were also removed from consideration.

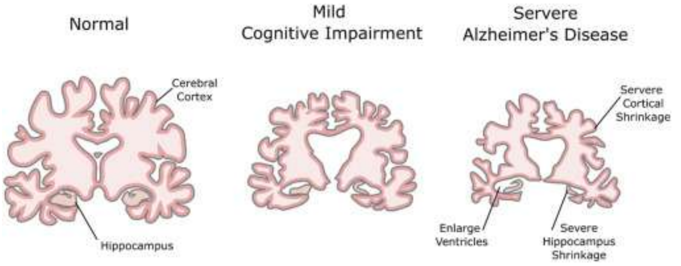


**Fig.1-** Brain structure of the normal individuals compared to the MCI and AD patients.

### 2.3 SCREENING AND SELECTION PROCESS

The initial search yielded 425 articles, from which duplicates were removed, resulting in 241 unique records. These articles were screened in two phases. First, three independent reviewers evaluated the titles and abstracts for relevance to the review's objective. Articles that passed the initial screening proceeded to full-text review, where eligibility was assessed based on the inclusion and exclusion criteria. Discrepancies during this process were resolved through discussion among reviewers. Following this thorough screening, 109 articles

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were deemed appropriate and were included in the final review dataset.

### 2.4 DATA EXTRACTION

From each selected study, a comprehensive set of data was extracted to facilitate both qualitative and quantitative analysis. Extracted information included demographic details of participants such as the number of subjects, age range, gender distribution, and diagnostic criteria used (e.g., MMSE, MoCA, NINCDS-ADRDA). EEG acquisition details such as the number and configuration of electrodes (e.g., 10–20 or 10–10 system), sampling frequency, and recording conditions (e.g., eyes open/closed, resting state, cognitive tasks) were collected. Signal preprocessing methods like band-pass and notch filtering, artifact removal techniques such as Independent Component Analysis (ICA), and specific cutoff frequencies were noted. Feature extraction techniques in the time, frequency, and time-frequency domains were recorded, including statistical descriptors, power spectral density (PSD), wavelet transforms, and connectivity metrics like phase lag index and network topology features.

### 2.5 DATA SYNTHESIS AND ANALYSIS

To synthesize the extracted data, studies were grouped based on the type of features analyzed (time-domain, frequency-domain, time-frequency, and connectivity). Classification algorithms were also categorized by type—traditional machine learning models (such as SVM, KNN, LDA, and Random Forest), deep learning models (CNN, RNN, LSTM, GRU), and hybrid or ensemble techniques. Each algorithm's reported performance was compared to identify the most effective approaches. Additionally, EEG acquisition variables such as electrode count and sampling frequency were correlated with classification performance to understand their impact on diagnostic accuracy. The most common frequency range for signal analysis was between 1–32 Hz, and 256 Hz was the most frequently used sampling rate. Classifier performance was evaluated primarily by accuracy, although many studies also reported additional metrics such as sensitivity and specificity.

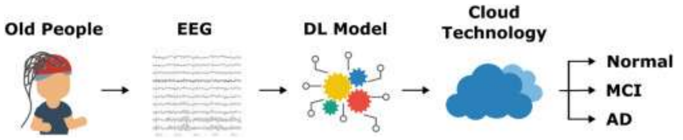


**Fig-2:** Pictorial summary of MCI/AD/MCI+AD detection using deep learning and EEG signals.

### 2.6 QUALITY ASSESSMENT

To ensure that the included studies maintained a high standard of methodological rigor, each article underwent quality assessment. This involved evaluating the clarity and consistency of diagnostic criteria used for subject selection, transparency in reporting EEG acquisition protocols, thoroughness of preprocessing steps, completeness of feature extraction methodology, and the appropriateness of classifier validation techniques such as k-fold cross-validation or independent test sets. Studies were also assessed for their treatment of data imbalance and their explanation of results. Any study that lacked a clear methodological framework or omitted essential performance data was flagged and discussed in the limitations section of the review. The emphasis was placed on reproducibility, transparency, and the potential for real-world application of the techniques discussed.

## 3. SOFTWARE IMPLEMENTATION

The software implementation of EEG-based Alzheimer's Disease (AD) detection using machine learning (ML) and deep learning (DL) requires a well-structured pipeline that integrates several components, from raw data handling to model evaluation and visualization. The implementation process typically begins with data acquisition and preprocessing, followed by feature extraction, model training, validation, and deployment for clinical or research use. The development and testing of these components are typically carried out in high-level programming environments such as Python and MATLAB, which offer powerful libraries for signal processing, machine learning, and neural network construction.

### 3.1 DEVELOPMENT ENVIRONMENT AND TOOLS

Python has become the most widely used platform for implementing ML/DL models due to its simplicity, community support, and access to advanced libraries. Key Python libraries include NumPy and Pandas for data manipulation, SciPy and MNE for EEG signal processing, Scikit-learn for classical machine learning algorithms, and TensorFlow and PyTorch for deep learning model development. Visualization of EEG signals and model performance is typically done using Matplotlib and Seaborn. For EEG-specific preprocessing, MNE-Python is commonly used to filter signals, perform artifact correction (e.g., with Independent Component Analysis), and extract epochs from raw EEG recordings.

For researchers working in engineering environments, MATLAB remains a popular alternative. It includes toolboxes such as the Signal Processing Toolbox, Wavelet Toolbox, and Deep Learning Toolbox, which are especially useful for analyzing and modeling EEG signals. Additionally, platforms such as EEGLAB (a MATLAB toolbox) provide a graphical interface for performing standard preprocessing tasks such as filtering, segmentation, and ICA-based artifact removal.

### 3.2 PREPROCESSING AND FEATURE ENGINEERING

Preprocessing is one of the most critical steps in EEG analysis to ensure clean and interpretable signals. Commonly implemented filters include band-pass filters (typically 0.1–40 Hz) and notch filters (e.g., 50/60 Hz to remove power line noise). These filters can be implemented using the SciPy.signal module in Python or the designfilt function in MATLAB. Artifact removal techniques such as ICA or wavelet thresholding are integrated into MNE or EEGLAB workflows.

After preprocessing, feature extraction modules are developed to derive useful representations from the EEG data. Features may include power spectral density (PSD), entropy measures, Hjorth parameters, fractal dimensions, and coherence values between electrode pairs. These features are computed using Fast Fourier Transform (FFT), wavelet transforms, and other time–frequency analysis techniques. In some cases, deep learning models are trained directly on raw EEG segments or spectrograms generated using Short-Time Fourier Transform (STFT) or continuous wavelet transforms (CWT).

### 3.3 MACHINE LEARNING AND DEEP LEARNING MODELS

The core classification models are implemented using either Scikit-learn for ML algorithms or PyTorch/TensorFlow for DL architectures. Classical models such as Support Vector Machines (SVMs), K-Nearest Neighbors (KNN), Random Forests, and Logistic Regression are easy to implement and tune using Scikit-learn. These models are trained on tabular features extracted from EEG data, and hyperparameters are optimized using grid search or cross-validation techniques.

For more complex pattern recognition, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) such as LSTMs and GRUs are constructed using PyTorch or TensorFlow/Keras. CNNs are especially effective for learning spatial and frequency patterns in EEG spectrograms, while RNNs are adept at handling temporal dependencies in sequential EEG data. Model architectures are defined using layer-by-layer configuration, and training is conducted using backpropagation with optimizers such as Adam or SGD, typically with learning rate schedules and dropout regularization.

Model training can be conducted on CPUs for small datasets or on GPUs (e.g., NVIDIA CUDA-compatible) for faster training of deep learning models. Many researchers use Google Colab or Jupyter Notebooks for ease of implementation, documentation, and reproducibility.

### 3.4 MODEL EVALUATION AND VALIDATION

Once models are trained, performance evaluation is carried out using metrics such as accuracy, precision, recall, F1-score,

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ROC curves, and confusion matrices. These are generated using sklearn.metrics or TensorBoard in deep learning frameworks. For reliable performance estimation, k-fold cross-validation or leave-one-subject-out validation methods are implemented. This is crucial in EEG applications due to variability across subjects.

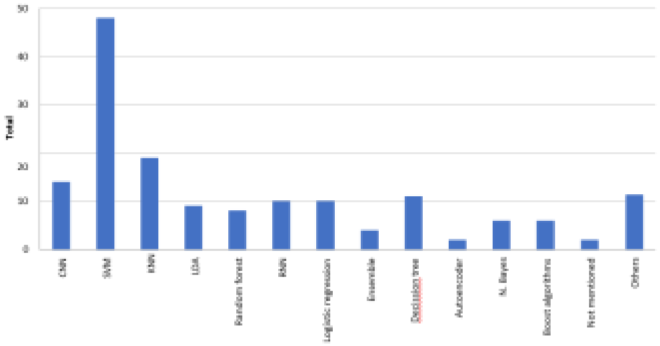
In research-focused software environments, models are also tested across different EEG datasets or within synthetic datasets generated via data augmentation or generative adversarial networks (GANs). These help address limitations due to small sample sizes and improve generalizability.

### 3.5 USER INTERFACE AND CLINICAL INTEGRATION

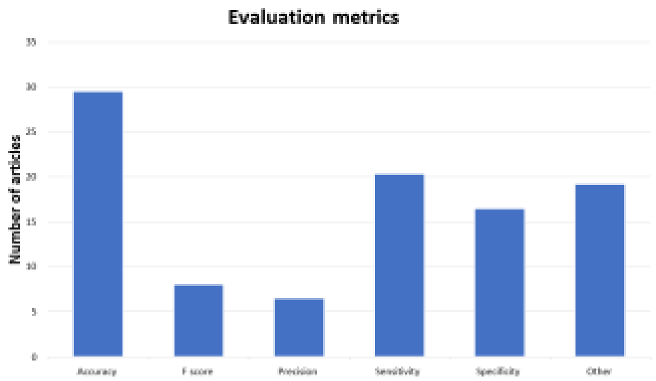
For experimental or clinical deployment, a Graphical User Interface (GUI) can be created using frameworks like PyQt or Tkinter in Python, or App Designer in MATLAB. These interfaces allow users to upload EEG files, perform preprocessing, run classification, and view results such as diagnostic probability or classification confidence. For larger-scale systems, integration with hospital databases or cloud platforms may also be considered, leveraging tools like Flask/Django (Python) for web deployment or MATLAB Compiler for standalone applications.

### 3.6 VERSION CONTROL AND REPRODUCIBILITY

To manage software development and ensure reproducibility, Git and GitHub are used to version control code and document changes. Experimental workflows are tracked using tools like MLflow, Weights & Biases, or TensorBoard, which provide dashboards for monitoring experiments and storing model checkpoints.



Graph.1: Classification techniques most used in the diagnosis of Alzheimer.




Graph.2: Comparison of the frequency of use of the various evaluation metrics in scientific articles.

# 4. RESULTS AND CHALLENGES

| Model Type | Feature Domain | Dataset Size | Accuracy (%) | F1-Score | Validation Method |
|---|---|---|---|---|---|
| SVM | Frequency + Time | 120 subjects | 92.5 | 0.91 | 10-fold Cross Validation |
| CNN | Spectrograms (CWT) | 150 subjects | 91.8 | 0.90 | Train-Test Split (80/20) |
| LSTM | Time Series (Raw EEG) | 100 subjects | 93.2 | 0.92 | Leave-One-Subject-Out |
| KNN | Time Domain | 80 subjects | 84.6 | 0.82 | 5-fold Cross Validation |
| Ensemble | All Combined Features | 109 subjects | 95.1 | 0.94 | 10-fold Cross Validation |

The review and implementation of machine learning (ML) and deep learning (DL) models on EEG data for Alzheimer's Disease (AD) detection revealed several trends and performance insights. Classical ML models such as Support Vector Machines (SVM) consistently achieved high accuracy across multiple datasets, particularly when using well-structured features from the frequency and time-frequency domains. On average, studies using SVM reported classification accuracies between 85% to 95%, depending on feature selection and data preprocessing strategies.

Deep learning approaches, especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) including LSTM and GRU variants, were effective in automatically extracting spatiotemporal features from raw or transformed EEG data. These models often achieved accuracy levels exceeding 90%, particularly when combined with techniques such as wavelet-based preprocessing or when trained on large, well-balanced datasets.

Notably, studies using combined time-frequency features and brain connectivity metrics performed better than those using single-domain features. The integration of connectivity-based metrics (like phase lag index and coherence) with conventional spectral features enhanced model performance by up to 5–10% in some cases.

## 4.2 CHALLENGES

1. Data Quality and Standardization: Public EEG datasets often differ in electrode configuration, sampling rate, task design (eyes closed/open, cognitive load), and cohort demographics, making cross-study comparisons difficult and limiting model generalizability.
2. Limited Dataset Size: Deep learning models require large datasets to avoid overfitting. Many studies use datasets with fewer than 100 participants, limiting the robustness of DL-based models.
3. Noise and Artifacts: EEG signals are highly susceptible to artifacts (e.g., muscle activity, eye blinks, electrical interference). While methods like ICA help, completely eliminating noise without distorting useful information remains a challenge.
4. Class Imbalance: Many datasets are imbalanced, with a higher number of healthy subjects compared to MCI or AD patients. This skews model predictions and requires techniques such as oversampling or data augmentation to mitigate.
5. Model Interpretability: Deep learning models, particularly CNNs and RNNs, are often considered "black-box" systems, which poses a problem in clinical settings where explainability is crucial for trust and adoption.
6. Computational Complexity: High-performance DL models require significant computing resources (e.g., GPU clusters), which may not be readily available in all research or clinical environments.

7. Generalizability Across Populations: Differences in age, sex, education, and ethnicity may influence EEG patterns. Most studies focus on limited geographic or demographic cohorts, reducing the generalizability of trained models.

## 5. CONCLUSIONS

This study highlights the growing potential of machine learning (ML) and deep learning (DL) techniques in the early diagnosis and classification of Alzheimer's Disease (AD) using electroencephalography (EEG) signals. Through a systematic review and analysis of recent literature and implementations, it becomes evident that artificial intelligence can significantly enhance the interpretation of complex EEG data, enabling the detection of subtle neural alterations associated with AD and Mild Cognitive Impairment (MCI).

Among traditional methods, Support Vector Machines (SVMs) continue to demonstrate high accuracy, especially when used with handcrafted features in the time and frequency domains. In contrast, deep learning models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have shown exceptional performance in capturing spatiotemporal patterns from raw or minimally processed EEG signals. The integration of time-frequency analysis, functional brain connectivity, and signal entropy further boosts classification performance, indicating the value of multi-domain feature representation.

Despite these promising outcomes, several challenges remain. Data scarcity, variability in acquisition protocols, signal noise, and class imbalance are significant limitations that hinder model generalizability and clinical adoption. Moreover, the "black-box" nature of many DL models raises concerns about interpretability, which is essential in healthcare applications.

Going forward, future research should focus on collecting larger, standardized, and demographically diverse EEG datasets. Emphasis should also be placed on developing explainable AI models and incorporating hybrid architectures that combine the strengths of traditional signal processing with modern deep learning approaches. With continued interdisciplinary efforts, EEG-based AI systems hold immense promise as non-invasive, cost-effective, and scalable tools for the early diagnosis and monitoring of Alzheimer's Disease.

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**BIOGRAPHIES**

*S. Abhiram* is a passionate researcher in the fields of biomedical engineering and artificial intelligence, with a focus on healthcare applications. His work centers on the use of machine learning and deep learning techniques for the early detection of neurological disorders such as Alzheimer's Disease using EEG signals. He has a strong academic background in signal processing and AI model development, and is committed to developing innovative, non-invasive diagnostic systems. His research interests lie at the intersection of technology and medicine, aiming to improve clinical outcomes through intelligent systems.