Report: AI-powered EEG System for Early Alzheimer’s Detection

**Introduction**

Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that causes memory loss, cognitive decline, and behavioral changes. It is the leading cause of dementia globally, affecting millions of people. Current diagnostic approaches rely on neuroimaging (MRI, PET scans), clinical evaluation, and neuropsychological testing. These methods are costly, time-consuming, and often detect the disease only after significant progression.

Electroencephalography (EEG) offers a non-invasive, portable, and cost-effective alternative, capable of capturing real-time brain activity. However, manual interpretation of EEG signals is challenging due to high variability and noise. Artificial Intelligence (AI), especially deep learning models, can learn discriminative patterns from EEG data to support early detection.

This project proposes an AI-powered EEG-based Alzheimer’s detection system that integrates preprocessing, feature extraction, deep learning classification, and explainability tools to provide clinically interpretable predictions.

**Problem Statement**

The absence of accessible, accurate, and scalable tools for early Alzheimer’s detection limits timely diagnosis and treatment. While neuroimaging provides detailed insights, it is not practical for large-scale screenings. EEG-based detection offers potential, but conventional methods fail to extract reliable biomarkers. There is a need for an AI-driven system that can:

* Process raw EEG signals,
* Extract meaningful features linked to cognitive decline,
* Detect early Alzheimer’s with high accuracy, and
* Provide explainable predictions for clinical use.

**Objectives**

The main objectives of this project are:

1. Develop a robust EEG preprocessing pipeline to remove noise and artifacts.
2. Extract time-domain, frequency-domain, and nonlinear features from EEG signals.
3. Design and train deep learning models (CNN, RNN/LSTM, and hybrid models).
4. Incorporate Explainable AI (XAI) techniques for clinical interpretability.
5. Validate the system on benchmark EEG datasets to ensure accuracy and generalizability.

**Literature Review (Brief)**

* Dauwels et al. (2010): Highlighted EEG biomarkers for AD diagnosis but noted challenges in accuracy.
* Taran and Bajaj (2017): Applied wavelet-based features with traditional ML classifiers for AD detection.
* Subasi and Kevric (2021): Used hybrid deep learning models on EEG for Alzheimer’s with improved accuracy.
* Recent Advances (2018–2024): Shift towards CNN and RNN architectures with explainability methods to improve clinical trust.

**Proposed Framework**

**System Framework**

The proposed system consists of five major stages:

Data Acquisition

* + Public EEG datasets such as Temple University EEG Corpus, DementiaBank EEG, or ADNI.

Preprocessing

* + Band-pass filtering (0.5–45 Hz).
  + Independent Component Analysis (ICA) for artifact removal (eye blinks, muscle noise).
  + Normalization to standardize signals.

Feature Extraction

* + Time-domain: Mean, variance, Hjorth parameters.
  + Frequency-domain: Power spectral density, band power across delta, theta, alpha, beta, gamma.
  + Nonlinear features: Entropy, fractal dimension.

Deep Learning Model

* + CNN layers for spatial feature extraction.
  + LSTM/GRU layers for temporal dynamics.
  + Hybrid CNN-LSTM architecture to capture both spatial and temporal EEG patterns.
  + Transfer learning from pre-trained EEG/EEGNet architectures.

Explainability Module

* + Grad-CAM, LRP, or SHAP for visualizing relevant EEG electrodes contributing to the classification.

**Model Architecture**

Proposed Hybrid CNN-LSTM Model

* Input Layer: Preprocessed EEG signal (multichannel time-series).
* CNN Block:
  + 2D convolution layers with ReLU activation.
  + Max-pooling for dimensionality reduction.
  + Batch normalization.
* LSTM Block:
  + Sequential LSTM layers to capture temporal dependencies.
* Dense Layers:
  + Fully connected layers with dropout for regularization.
* Output Layer:
  + Softmax activation for classification (Healthy vs. Early AD).

**Diagram (Conceptual Flow):**

EEG Input → Preprocessing → CNN (spatial features) → LSTM (temporal features)

→ Dense Layers → Softmax → Alzheimer’s Prediction

**Evaluation Metrics**

* Accuracy – Percentage of correct predictions.
* Precision & Recall – Sensitivity to Alzheimer’s cases.
* F1-score – Balance between precision and recall.
* ROC-AUC – Area under the curve for classification robustness.
* Cross-validation – Ensures generalization across datasets.

**Expected Outcomes**

* A validated AI-powered EEG detection system for early Alzheimer’s.
* Identification of clinically interpretable EEG biomarkers.
* A low-cost, scalable, and portable solution for healthcare providers.
* Contribution towards timely interventions improving patient outcomes.

**Novelty of the Project**

* Hybrid CNN-LSTM architecture for joint spatial-temporal EEG analysis.
* Integration of multi-domain feature extraction with deep learning.
* Use of explainable AI (XAI) for building trust with clinicians.
* Focus on early detection, before severe cognitive decline.

**Conclusion**

This project proposes an innovative framework that leverages AI, EEG analysis, and explainable deep learning to enable early detection of Alzheimer’s disease. The hybrid CNN-LSTM model, combined with advanced preprocessing and feature extraction, ensures accurate classification of EEG patterns. Explainability modules will further ensure clinical interpretability, making the system both effective and trustworthy.

If successfully implemented, this solution can serve as a scalable, cost-effective, and portable tool for Alzheimer’s screening in hospitals and community healthcare settings.