ALZHEIMER’S DISEASE DETECTION USING EEG SIGNALS

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Introduction:

This project aims to develop a low-cost, efficient diagnostic system for the early detection of Alzheimer’s Disease (AD) by leveraging EEG signals combined with advanced machine learning and deep learning methods. The focus is to create a non-invasive, accessible tool that overcomes the limitations of traditional diagnostic approaches like MRI and PET, which are expensive, invasive, and time-consuming. By using EEG signals, this study seeks to harness the power of AI to provide accurate, early diagnosis, enabling timely intervention and improving the quality of life for patients and their families. The system will preprocess EEG data, extract meaningful features using techniques like wavelet transform and power spectral density analysis, and apply machine learning models such as Random Forest, SVM, and Naïve Bayes. Additionally, deep learning models, including CNN, LSTM, and hybrid CNN-LSTM architectures, will be employed for improved accuracy and real-time analysis. A user-friendly interface will be developed for easy input and visualization of results. The project will evaluate the models based on accuracy, precision, recall, and computational efficiency, aiming to create a scalable, cost-effective tool for early AD detection that can eventually be integrated into clinical practice.

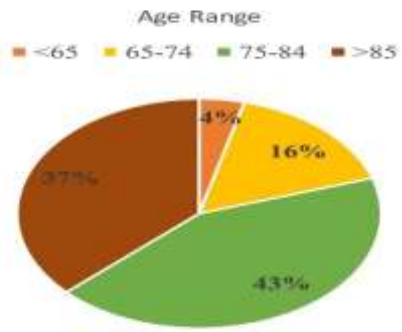

Figure 1: Proportion of people with Alzheimer’s disease by age

Objectives:

The process begins with data acquisition and preprocessing, where EEG data is collected and cleaned to ensure quality and consistency. Next, relevant features are extracted from the EEG signals to capture meaningful patterns associated with cognitive states. These features are then used to train machine learning models during the model development phase. Once trained, the models are evaluated using a separate test dataset to validate their performance. Finally, after thorough testing, the system undergoes clinical validation and is prepared for deployment in real-world clinical settings.

Methodology:

The project The methodology for the Alzheimer's Disease detection system involves several key stages: data acquisition, preprocessing, feature extraction, classification, and result visualization. Initially, EEG signals are acquired from publicly available datasets or real-time input devices, capturing signals from patients at different stages of cognitive health, including normal, mild cognitive impairment (MCI), and Alzheimer's Disease (AD). The preprocessing stage involves cleaning the raw EEG data by applying bandpass filtering to isolate relevant frequency ranges (0.5-50 Hz), removing artifacts such as eye blinks and muscle movements using Independent Component Analysis (ICA), and normalizing the data for consistent feature scaling.Feature extraction is performed using a combination of time-domain and frequency-domain techniques. Discrete Wavelet Transform (DWT) is applied to decompose signals into multi-resolution frequency bands, while Power Spectral Density (PSD) analysis examines the power distribution across different frequency components. Additionally, statistical measures such as mean, standard deviation, skewness, and kurtosis are computed. These features are combined into a composite vector for each EEG segment, which serves as input to the classification models.The classification engine utilizes a deep learning approach, employing Convolutional Neural Networks (CNNs) for automatic spatial feature learning and Long Short-Term Memory (LSTM) networks for temporal sequence modeling. A hybrid CNN-LSTM model is used to capture both spatial and temporal dependencies in the EEG signals, enhancing the system's ability to accurately classify the cognitive status of the patient as normal, MCI, or AD. The system outputs diagnostic results with confidence scores and integrates a user-friendly interface for clinicians, offering visualizations of the EEG signals and classification results.

Result and Conclusion:

The study found that Random Forest, LSTM, and Multi-Headed models achieved the highest classification accuracy of 96%, demonstrating strong effectiveness in detecting Alzheimer's Disease. The Multi-Headed Model, which combined EEG signals with image data, proved especially robust by capturing both spatial and temporal features, thus reducing false detections. CNN models performed well, particularly in identifying non-Alzheimer's cases, and showed promise for improvement through better feature extraction and recall optimization. The use of autoencoders and dimensionality reduction techniques notably enhanced model accuracy, benefiting traditional classifiers like SVM and k-NN. Overall, hybrid models that integrated deep learning architectures, advanced feature extraction, and multi-modal data sources delivered the most reliable classification outcomes for Alzheimer's detection.

In conclusion Alzheimer's Disease remains challenging to diagnose at an early stage due to limited access to affordable and non-invasive diagnostic tools. This study presents an automated EEG-based system that leverages both machine learning and deep learning techniques to detect cognitive impairments associated with Alzheimer's. Through rigorous preprocessing—using normalization, Butterworth band-pass filtering, and feature extraction methods like Power Spectral Density and Discrete Wavelet Transform—the system enhanced EEG signal clarity and representation. A range of classifiers, including Random Forest, SVM, Naïve Bayes, Decision Tree, k-NN, CNN, LSTM, and hybrid models such as Autoencoder-CNN and LSTM-CNN-MLP, were evaluated for performance. The Random Forest model showed strong test accuracy, while hybrid deep learning models exceeded 95% accuracy, affirming the potential of EEG-based approaches as reliable, non-invasive tools for early Alzheimer's diagnosis.

Project Outcome & Industry Relevance: The outcome of this project is the development of an Alzheimer's Disease detection system based on EEG signals, leveraging advanced machine learning and deep learning techniques for accurate early-stage detection. The system integrates data acquisition, preprocessing, feature extraction, and classification, offering a modular, scalable, and user-friendly tool for clinicians with real-time diagnostic capabilities. Its industry relevance is significant, as it provides a cost-effective, non-invasive alternative to traditional diagnostic methods like PET scans and MRIs, which are expensive and require specialized facilities. By integrating AI with EEG analysis, the system addresses the growing demand for AI-driven healthcare tools and aligns with the need for early detection in Alzheimer's Disease, improving quality of life for patients. Additionally, it can be integrated with electronic health records (EHRs), making it suitable for large-scale screenings, research, and long-term patient monitoring in clinical environments.

Working Model vs. Simulation/Study: This project can be classified as a simulation/study, as it primarily focuses on evaluating the performance and feasibility of an Alzheimer's Disease detection system using EEG signals in a controlled research environment. The system's components, including data acquisition, preprocessing, feature extraction, and machine learning classification, were tested and validated using pre-recorded EEG data, assessing the effectiveness of various algorithms like CNNs, LSTMs, and hybrid models. The project involved testing classification accuracy, feature extraction techniques, and model performance in a non-clinical setting. While the system has the potential for real-world application, it has not yet been fully deployed for clinical use, making it more aligned with a simulation/study aimed at proving the system's viability before potential deployment in actual healthcare environments.

Project Outcomes and Learnings: The project resulted in the development of an Alzheimer's Disease detection system using EEG signals and advanced AI techniques. Key learnings included the integration of machine learning models like CNNs and LSTMs for accurate classification, along with the importance of preprocessing and feature extraction techniques such as wavelet transforms and Power Spectral Density

(PSD). The use of explainable AI (XAI) methods for model interpretability was a crucial learning point, ensuring the system’s transparency for clinical use. A user-friendly interface was developed to provide real-time insights for clinicians. Challenges included ensuring data security and integrating the system with Electronic Health Records (EHRs). The project showcased the potential of AI in improving early detection and treatment of Alzheimer’s disease.

Future Scope:

The future scope of this project aims to significantly enhance the Alzheimer's Disease detection system by incorporating advanced technologies and methodologies. First, integrating multi-channel EEG data can provide greater spatial resolution, enabling more accurate detection, especially in early stages like Mild Cognitive Impairment (MCI). Additionally, the development of portable EEG headsets with lightweight, mobile-optimized models could allow for real-time monitoring in both home and clinical settings, increasing accessibility and patient comfort. The incorporation of transformer-based models and attention mechanisms could further enhance diagnostic accuracy by dynamically focusing on the most relevant parts of the EEG signals, thereby improving the system's interpretability and performance. The adoption of Explainable AI (XAI) techniques such as SHAP and LIME would allow clinicians to understand and interpret the model's decision-making process, ensuring greater trust and usability. Furthermore, future work will focus on improving the system’s performance, expanding its real-world applications, and integrating it with Electronic Health Records (EHRs) for seamless use in hospitals and clinics. Ultimately, these advancements aim to create a more robust, scalable, and user-friendly diagnostic tool for Alzheimer’s Disease detection.