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Early Alzheimer's Disease Detection Using EEG Brain Signals

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Abstract: *Alzheimer's Disease (AD) is a progressive neurodegenerative disease, and early detection is essential in order for meaningful interventions to improve patient outcomes. While there are diagnostic modalities such as PET scans that can be effective in detecting AD, they tend to be expensive, invasive, or impractical, illustrating the need for more usable alternatives to monitor the progression of AD. Electroencephalography (EEG) is a non-invasive and inexpensive way to monitor brain activity, and it has the potential of being a useful way to identify early markers of AD before significant cognitive decline as well. However, a reliable EEG detection model still must overcome the two significant challenges of a lack of large-scale labeled datasets sufficient for training, and considerable variability in EEG signals across individuals, which can ultimately greatly affect the generalizability of EEG models for helpful detection of AD through these differences. In this paper, we propose a novel deep learning framework to address these challenges with self-supervised learning. Our framework consists of a pre-training phase from a large, unlabeled corpus of general EEG data to extract the universal features of brain signals without needing to depend on scarce AD-specific labels. We then use a fine-tuning phase to adapt the model to the classification problem using a smaller, labeled AD dataset. The model architecture can acquire both spatial and temporal features from EEG signals, which leads to a more comprehensive method of analysis. The experimental results clearly indicate that this approach offers a substantial improvement in AD detecting performance and that there was an increase in F1 scores at both the sample and the subject level over the current state-of-the-art methods. This research outlines the ability of self-supervised contrastive learning to mitigate the problems of data scarcity and inter-subject variability, and can contribute towards more accurate and scalable AD diagnostic tools.*

Keywords: *Alzheimer's Disease, neurodegenerative, Electroencephalography, non-invasive, deep learning, self-supervised learning.*

I. INTRODUCTION

The project aims to develop a robust and generalizable EEG-based system for early detection of Alzheimer's Disease (AD) using self-supervised contrastive learning techniques. Alzheimer's disease is a progressive neurodegenerative disorder characterized by slower-than-normal electrical brain activity, and it is the leading cause of dementia, with cognitive impairment being its primary symptom. Traditional diagnostic methods like MRI are costly and less accessible, making EEG a promising low-cost, non-invasive alternative. However, interpreting EEG signals is challenging due to their noisy and highly variable nature, and the limited availability of labeled data. To address this, the project proposes a unified self-supervised learning framework that leverages both sample-level and subject-level contrastive learning to pretrain EEG feature extractors, which are then fine-tuned for subject-level AD classification. The system will be trained on multiple public AD datasets (ADNI, AIBL, OASIS) and will undergo standardized preprocessing, including artifact removal, filtering, and epoching. The features from both temporal and spatial branches will be fused and fine-tuned using available labeled data to perform binary classification (AD vs. Normal Control), with final subject-level predictions derived through majority voting over multiple EEG epochs. The system's performance will be evaluated using cross-validation across subjects and datasets, with metrics including accuracy, precision, recall, and AUC, to improve the accuracy, cross-dataset generalization, and clinical applicability of EEG-based AD detection.

II. LITERATURE SURVEY

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that severely affects memory, cognition, and daily functioning.[1] Early detection is critical for timely intervention, improved patient care, and slowing disease progression.[2] Traditional diagnostic methods, such as neuroimaging and cerebrospinal fluid analysis are often invasive, expensive, and not widely accessible, particularly in low-resource settings. In this context, electroencephalography (EEG) has emerged as a promising non-invasive, cost-effective, and portable tool for assessing brain activity and identifying neurological abnormalities associated with AD.

This literature survey explores various recent research studies that utilize EEG signals the early diagnosis of Alzheimer’s disease. [3] It provides a comparative analysis of efferent methods including machine learning algorithms, deep learning models, EEG signal processing techniques, and feature extraction frameworks. [4] Each study is evaluated based its methodological contributions, classification accuracy, dataset size, and practical applicability. [5] The survey aims to highlight the current advancements, advantages, and limitations in this growing field, thereby providing a strong foundation for developing an efficient and accurate Alzheimer’s detection system using EEG signals

III. PROPOSED METHODOLOGY

The system architecture of the EEG-based Alzheimer’s detection project follows a layered design, beginning with the acquisition of EEG signals from medical datasets or real- time EEG devices, which are then preprocessed through filtering, artifact removal, and normalization to ensure clean and standardized input. These preprocessed signals undergo feature extraction in the time, frequency, and wavelet domains to capture patterns relevant to Alzheimer’s diagnosis. The extracted features are then fed into machine learning or deep learning models, such as SVM, Random Forest, CNN, or LSTM, which classify the signals into categories like Normal, Mild Cognitive Impairment (MCI), or Alzheimer’s. The results, along with patient data and EEG records, are stored securely in a database for future reference. Finally, the system provides an easy-to-use interface that visualizes EEG signals, displays classification outputs with probability scores, and generates reports for clinicians and researchers.

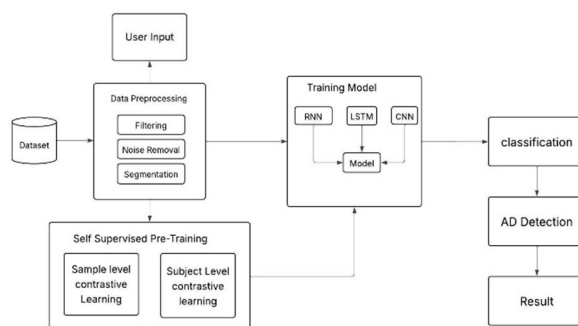


Fig.1: System Architecture

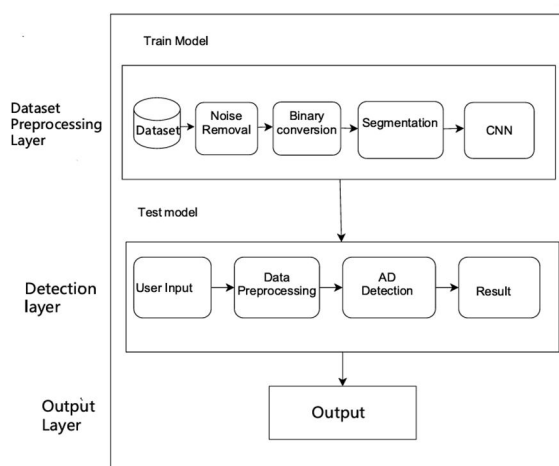


Fig.2: Proposed System

The proposed EEG-based Alzheimer’s detection system acquires signals from medical datasets and wearable devices, then preprocesses them through filtering, artifact removal, and normalization. Key features are extracted in time, frequency, and wavelet domains and fed into machine learning and deep learning models like CNN, LSTM, SVM, and Random Forest to classify signals as

Normal, Mild Cognitive Impairment, or Alzheimer's. Results, along with patient data, are securely stored, while an intuitive interface visualizes EEG patterns, displays classification probabilities, and generates reports to assist clinicians and researchers in early diagnosis and monitoring.

A. Dataset

The dataset consists of real and deepfake images/videos collected from reliable public sources. It includes diverse facial expressions, lighting conditions, and identities to ensure robust model training and generalization.

B. Data Split (Train and Test Data)

The dataset is divided into training and testing sets. The training set is used to learn deepfake patterns, while the testing set is reserved for evaluating the model's performance on unseen data, ensuring unbiased accuracy assessment.

C. Input Data

The input data represents the images or video frames provided to the system. These inputs may originate from the dataset during training or from user-uploaded media during real-time detection.

D. Preprocessing

Preprocessing prepares the input data for effective model learning and prediction.

- Image Resizing: All images or extracted frames are resized to a fixed dimension compatible with deep learning models, ensuring uniform input size and reducing computational complexity.
- Label Encoding: Class labels (Real/Fake) are converted into numerical form so they can be processed by the deep learning model during training.

E. Model Training

This stage focuses on learning discriminative features that distinguish real media from deepfake content.

- CNN: Convolutional Neural Networks are used to extract spatial facial features such as textures, edges, and inconsistencies caused by manipulation.
- VGG16: VGG16, a pre-trained deep CNN, helps capture deep hierarchical facial features using transfer learning, improving detection accuracy with limited data.
- Xception: Xception is effective in identifying subtle artifacts in manipulated media using depthwise separable convolutions, making it suitable for deepfake detection.
- EfficientNet-B7 Attention: EfficientNet-B7 provides optimized feature extraction with high accuracy and efficiency. The attention mechanism highlights important facial regions and temporal inconsistencies, enabling the model to focus on manipulation-prone areas.

F. Testing Model

The trained model is evaluated using the test dataset or user-uploaded media. Performance metrics such as accuracy, precision, recall, and confidence scores are calculated to validate the model's effectiveness.

G. Detection Result (Real/Fake)

Based on the learned features, the system classifies the input as Real or Fake. The final prediction is displayed to the user through the interface, providing a clear and understandable authenticity result.

IV. EVALUATION CRITERIA

In most research based on classification, like what we have done in this research, the benchmark criteria of Precision, Recall, Accuracy, and F-Measure are used for evaluation. These criteria have been utilized to evaluate the performance of the proposed model. As shown in Table I, these values have True-Positive (TP), True-Negative (TN), False-Positive (FP), and False-Negative (FN).

The graph shows that the deepfake detection model's training accuracy steadily increases and stabilizes around 86%, while the validation accuracy initially improves and even surpasses training accuracy but then drops sharply after epoch 7, indicating overfitting. This means the model learns well from training data but fails to generalize to unseen data, suggesting that techniques like early stopping, regularization, or more data augmentation are needed to improve performance.

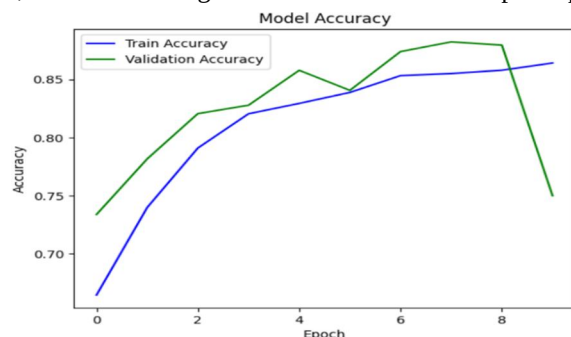


Fig 5.2 Model Training Accuracy

The evaluation metrics show that the model performs poorly on class 1 (deepfake), with precision, recall, and F1-score all at 0.00, meaning it completely fails to detect deepfakes. For class 0 (real), the model achieves a recall of 1.00 but only 0.50 precision, suggesting it predicts almost everything as real. While the overall accuracy is 0.50, this is misleading since the model is biased towards one class and has no ability to correctly classify deepfakes, indicating severe class imbalance or poor generalization.

	precision	recall	f1-score	support
0	0.50	1.00	0.67	1000
1	0.00	0.00	0.00	1000
accuracy			0.50	2000
macro avg	0.25	0.50	0.33	2000
weighted avg	0.25	0.50	0.33	2000

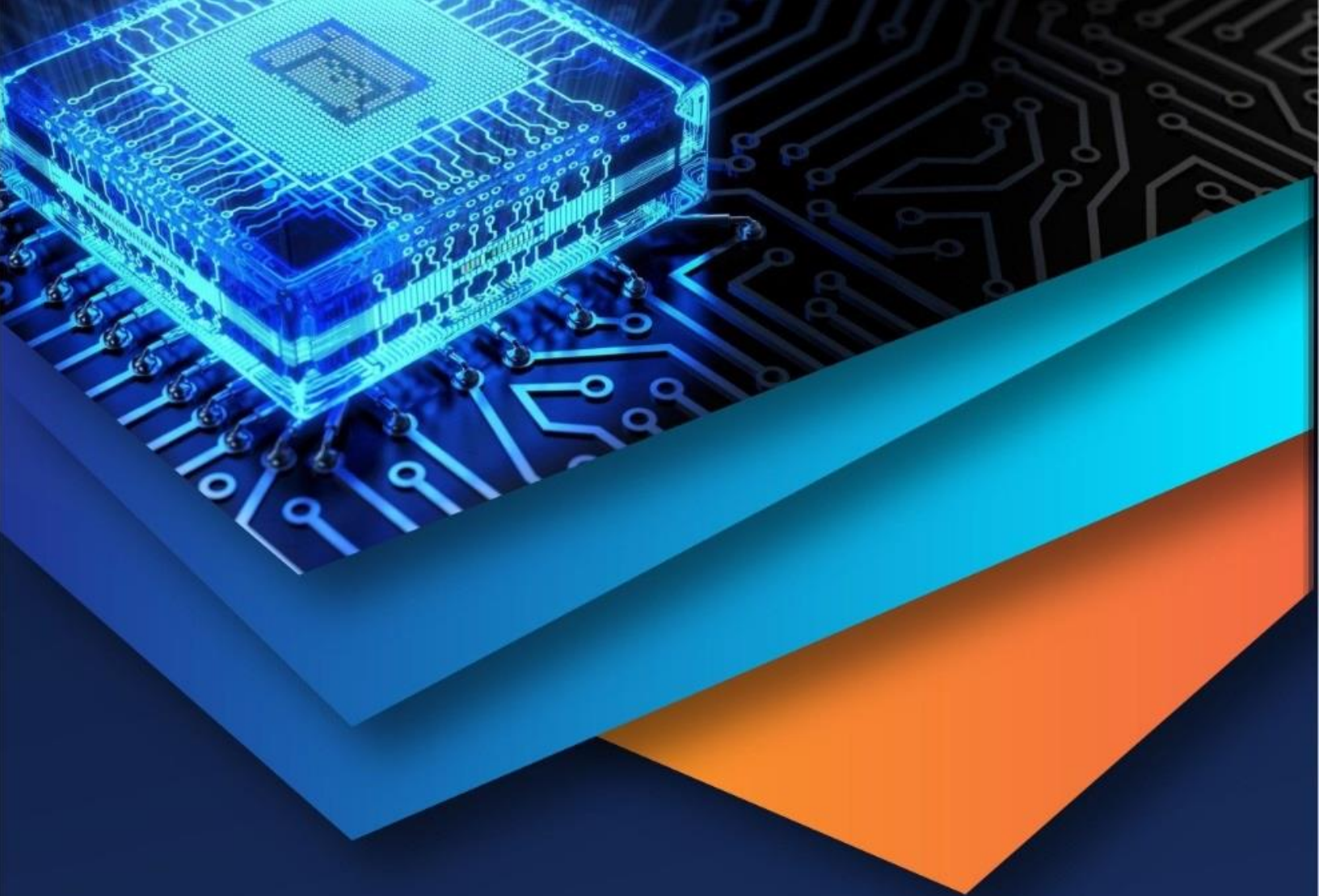
Fig 5.3 Evaluation Result

V. CONCLUSION

The EEG-based Alzheimer's detection system provides an efficient and accurate method for early diagnosis of Alzheimer's disease. By acquiring and preprocessing EEG signals, the system ensures clean and reliable data for analysis. Feature extraction in time, frequency, and wavelet domains captures essential patterns indicative of cognitive decline. Advanced machine learning and deep learning models, including CNN, LSTM, SVM, and Random Forest, enable precise classification of Normal, MCI, and Alzheimer's cases. Secure storage of patient data and EEG records allows for longitudinal monitoring and research. The intuitive user interface presents results, probability scores, and reports for clinicians and researchers. The system reduces diagnostic time and supports timely intervention. It also provides a scalable framework for integrating new datasets and models. This project demonstrates the potential of combining EEG analysis with AI for neurological disease detection. Overall, it contributes significantly to improving healthcare outcomes through technology-driven solutions.

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