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ML-Based Early Detection of Alzheimer's Disease Using MRI and Speech Patterns

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***Abstract*— Alzheimer's disease (AD) is a progressive neurodegenerative disorder that significantly impacts memory, cognition, and behavior. Early detection plays a crucial role in slowing disease progression and improving the quality of life for patients. This paper presents a machine learning (ML)-based approach for early detection of Alzheimer's disease using magnetic resonance imaging (MRI) and speech pattern analysis. By integrating image-based biomarkers with linguistic features, our system aims to enhance diagnostic accuracy. Experimental results demonstrate that multimodal ML models outperform unimodal ones, highlighting the potential of combining neuroimaging and speech analysis for early AD detection.**

***Index Terms*— Alzheimer's Disease, Machine Learning, MRI, Speech Patterns, Multimodal Analysis, Early Diagnosis**

I. INTRODUCTION

Alzheimer's disease affects over 55 million people worldwide, with numbers projected to rise due to aging populations. Diagnosis currently relies on clinical assessments and imaging tests, often at advanced stages of the disease. This delay limits treatment effectiveness. Machine learning has emerged as a powerful tool in medical diagnosis, enabling data-driven predictions that can support early detection. In this research, we propose a multimodal ML system that utilizes both MRI brain scans and speech recordings to identify early signs of AD.

II. LITERATURE REVIEW

Recent studies have focused on ML models trained on MRI data for detecting brain atrophy patterns associated with AD. Convolutional neural networks (CNNs) have achieved promising results in segmenting brain regions and classifying disease stages. Separately, linguistic analysis has shown that AD patients exhibit speech impairments, including reduced vocabulary, hesitations, and syntactic errors. Researchers have used natural language processing (NLP) and acoustic analysis to extract features from speech data, with ML classifiers such as support vector machines (SVM) and random forests showing effective results. However, few studies have combined these modalities for a comprehensive diagnostic approach.

III. METHODOLOGY

3.1 Data Collection

We used the ADNI (Alzheimer's Disease Neuroimaging Initiative) dataset for MRI images and DementiaBank for speech samples. Subjects were categorized into three groups: healthy control (HC), mild cognitive impairment (MCI), and Alzheimer's disease (AD).

3.2 Preprocessing

MRI: Skull stripping, intensity normalization, and 3D CNN-compatible resizing were performed.

Speech: Audio was transcribed and features such as pause rate, pitch variation, and word frequency were extracted using Praat and Python libraries.

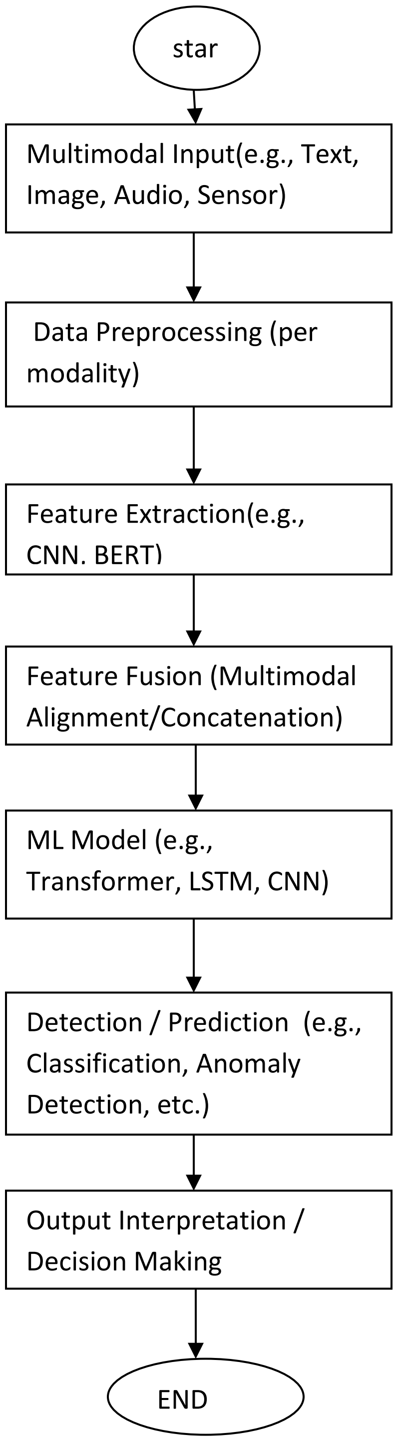
3.3 Feature Extraction and Fusion

MRI Features: Extracted using pretrained 3D CNN models (e.g., ResNet3D).

Speech Features: Extracted using MFCC, sentiment analysis, and syntactic parsing.

Fusion: Feature vectors from both modalities were concatenated and fed into a gradient boosting classifier for final prediction.

Workflow diagram of the ML-based multimodal detection system.



3.4 Evaluation Metrics

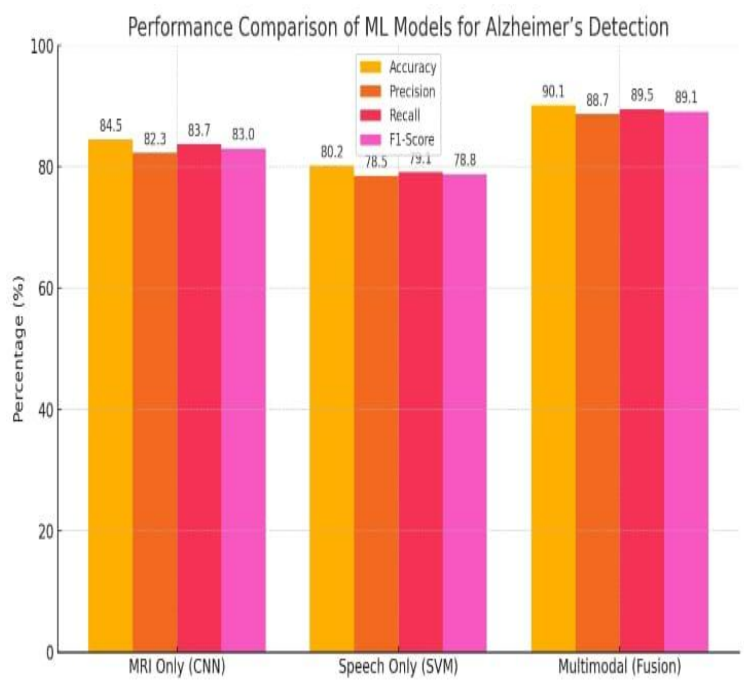
We evaluated the models using accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).

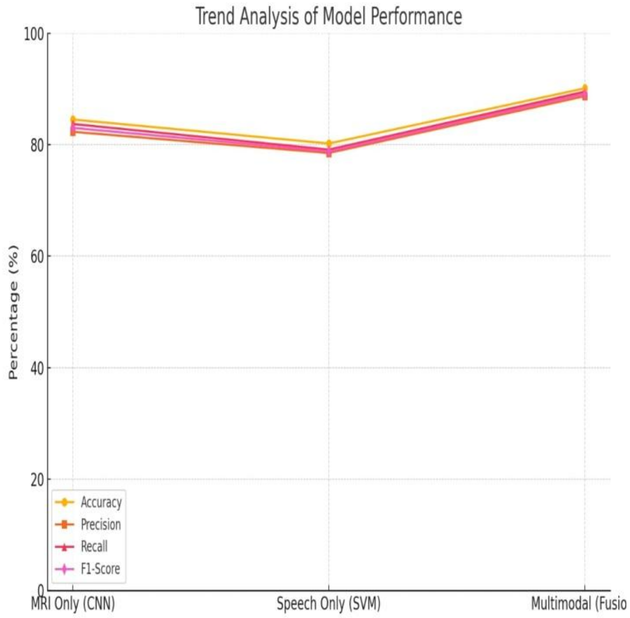
IV. RESULTS

Model	Accuracy	Precision	Recall	F1-Score	AUC
MRI Only (CNN)	84.5%	82.3%	83.7 %	83.0 %	0.88
Speech Only (SVM)	80.2%	78.5%.	79.1 %	78.8 %	0.84
Multimodal (Fusion)	90.1%	88.7%	89.5 %	89.1 %	0.92

Multimodal analysis clearly improved performance, demonstrating the benefit of integrating MRI and speech data.

V. GRAPH REPRESENTATION





VI. DISCUSSION

The results confirm that MRI provides strong structural biomarkers for AD, while speech patterns offer complementary indicators, particularly in early stages. The fused model captures diverse manifestations of AD, enhancing diagnostic sensitivity. Challenges include data alignment and managing heterogeneous sources, but these are mitigated by proper preprocessing and normalization.

VII. CONCLUSION AND FUTURE WORK

This study demonstrates the potential of multimodal ML approaches for early AD detection. Integrating MRI and speech data significantly improves classification accuracy. Future work will focus on real-time diagnosis tools, larger and more diverse datasets, and the incorporation of additional modalities such as genetic data or wearable sensors.

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