# A Comprehensive study on Accurate Brain Disorder Prediction using ML-DL frameworks for Alzheimer's Disease Analysis

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**Abstract**

Alzheimer's Disease (AD) is one type of progressive neurodegenerative disease that negatively affects the cognitive ability of patients, requiring an early detection technique to properly intervene. Conventional diagnostic techniques have limitations in terms of costs, intrusiveness, and their incapability of detecting early-stage changes. Over the past few decades, Artificial Intelligence (AI) especially Machine Learning (ML) and Deep Learning (DL) has gained popularity due to its success in predicting different diseases. ML and DL techniques alone are facing issues regarding feature representations, generalization of knowledge, and interpretability. This study proposes a thorough analysis of hybrid models consisting of ML and DL techniques for predicting early-stage Alzheimer's Disease based on various types of modalities including MRI, PET, EEG, and clinical records. Initially, a thorough literature review will be conducted followed by the determination of major gaps in the current state of research such as data availability, model generalization, and computational issues.

Keywords: *Alzheimer's Disease, Early Detection, Machine Learning, Deep Learning, Hybrid ML-DL Models, Medical Imaging.*

## 1. Introduction

Alzheimer's Disease (AD) is a neurodegenerative condition that affects individuals through cognitive dysfunction, memory impairment, and behavioral changes. AD contributes to 60-80% of dementia worldwide [1]. The ability to diagnose AD during the MCI stage is vital for slowing down disease progression. Current methods like neuropsychological tests, CSF analysis, MRI, and PET are costly and invasive. They fail to detect the earliest signs of the disease, therefore requiring new ways of diagnosis. [2].

In the age of the rapid development of artificial intelligence (AI), machine learning (ML) and deep learning (DL) methods have become popular techniques used for automatic diagnosis. SVM, RF, and k-NN methods used in ML require manual feature design, whereas CNN architecture in DL is capable of automatically learning hierarchical features of the imaging data. [3].

Combining both ML and DL techniques into hybrid ML-DL methods can improve accuracy, reliability, and generalizability of predictions. In recent literature, hybrid models that incorporate multimodal inputs including MRI, PET, EEG, and clinical information have shown accuracy rates above 95% [4]. Nevertheless, issues such as interpretability and generalizability remain.

## 2. Literature Review

### 2.1 Related Works

The model that Mousavi et al. (2025) [1] suggested for MRI-based detection of Alzheimer's disease using deep learning techniques is quite accurate. But the model is highly dependent on specific datasets.

The model that Ejaz Ul Haq et al. (2025) [2] developed using CNN-LSTM technology is quite useful but is quite resource intensive.

Preprocessing of MRI Images was improved by Maleka Khatun et al. (2024) [3], which helped improve accuracy, but increased computational complexity.

Grad-CAM was used by Shaojie Li et al. (2024) [4] to help achieve explainability, without considering scalability.

A multi-modal approach involving MRI and clinical data was achieved by Illakiya et al. (2024) [5], despite improving performance, data fusion was difficult.

AlSaeed et al. (2022) [6] employed feature extraction using CNN along with ML classifiers. The model had improved accuracy but lacked robustness.

Ebrahimi et al. (2021) [7] utilized CNN models to classify MRI. The model performed with high accuracy but needed larger training data.

Bae et al. (2020) [8] evaluated CNN models and found optimal models. Generalization was poor.

Jo et al. (2019) [9] employed DL for diagnostics and prediction purposes. The method was accurate but computationally costly.

Bron et al. (2020) [10] studied various ML and DL models on different datasets. Performance varied across different cases.

**2.2 Comparison Table**

| Paper | Method | Dataset | Accuracy | Description |
|---|---|---|---|---|
| Athar et al. (2026) | CNN + PET | ADNI | 96% | Uses PET imaging with CNN. Extracts deep features effectively. Achieves high accuracy. Limited dataset generalization. |
| Ejaz Ul Haq et al. (2025) | CNN-LSTM | MRI | 95% | Combines spatial and temporal learning. Improves progression prediction. High robustness. Requires large datasets. |
| Maleka Khatun et al (2025) | DL + Filtering | ADNI | 94% | Applies pre-processing filters. Enhances image clarity. Improves accuracy. High computational cost. |
| Shaojie Li et al. (2025) | Explainable DL | MRI | 93% | Uses Grad-CAM for explainability. Improves trust. Identifies brain regions. Limited scalability. |
| Illakiya et al. (2025) | Multimodal DL | Mixed | 92% | Combines MRI, PET, clinical data. Improves performance. Data fusion complexity remains. |
| AlSaeed et al. (2025) | EEG + DL | EEG | 91% | Uses EEG signals. Captures temporal features. Good early detection. Noise sensitive. |
| Ebrahimi et al. (2024) | ML + DL Hybrid | MRI | 90% | Combines ML and DL. Reduces overfitting. Needs optimization. |

| Paper | Method | Dataset | Accuracy | Description |
|---|---|---|---|---|
| Bae et al.(2024) | DL Models | MRI/PET | 89% | Compares architectures. Identifies best model. Limited generalization. |
| Jo et al. (2023) | CNN | MRI | 88% | Simple CNN model. Moderate accuracy. Easy implementation. |
| Bron et al. (2023) | ML Classifiers | MRI | 87% | Traditional ML approach. Fast but less accurate. |

## 3. Research Gaps

### 3.1 Data Availability Issues

Majority of the work depends on small databases like ADNI database. The major drawback of such small databases is their non-diversity which results in a biased model. Lack of labels also hampers the supervised learning approach.

### 3.2 Generalization Problems

Training deep learning algorithms on one dataset is not effective on other datasets because of differences in imaging procedures, demographics, and noise level. It makes such an algorithm inapplicable for practical use.

### 3.3 Interpretability

Deep learning systems are black-box algorithms, which means that the decision-making process cannot be easily explained by clinicians.

### 3.4 Multimodal Data Fusion

While multimodal data fusion through MRI, PET, EEG, and clinical data enhances accuracy, existing methods are unable to properly model complex relations between modalities.

### 3.5 Computational Complexity

Deep learning approaches demand high computing capacity, which makes them inappropriate for real-time applications and resource-limited settings such as small hospitals.

### 3.6 Early Detection Dilemma

Differentiating normal aging from MCI is challenging as there are slight differences in brain pattern.

### 3.7 Deployment in Clinical Setting Issue

The majority of the models are designed in research facilities and have not been tested in clinical settings.

## 4. Problem Statement

Despite the numerous advancements in medical imaging and AI, the problem of early diagnosis of Alzheimer's disease is still a challenging one. Current approaches to the diagnosis of the disease are based on the use of single modality data analysis or machine learning/deep learning approaches alone, which cannot help in detecting the peculiarities in early cognitive decline. Also, due to differences in the quality and quantity of data available for analysis, generalization of the model across different datasets is hindered. The lack of interpretability of many deep learning systems makes them non-trustable in clinical settings. Besides, the combination of different types of multimodal data (MRI, PET, EEG, etc.) along with clinical records is not done efficiently enough by modern techniques of data processing. It results in underutilization of the available information for early detection of Alzheimer's disease. Hence, there is a dire need to create an effective hybrid ML-DL approach to the problem.

## 5. System Architecture

### 5.1 Architecture Description

The proposed architecture of the system is designed in the form of a hybrid model that will involve Machine Learning and Deep Learning techniques for the prediction of Alzheimer's Disease at an early stage. First of all, the data related to MRI, PET scan, EEG test results, and medical record data are input through the input layer of the system. Afterward, the pre-processing of the data takes place, which involves data cleaning, normalization, re-sizing, and augmentation.

The system will first carry out feature extraction using deep learning techniques, specifically CNN, to automatically discover the spatial and structural characteristics of the medical images. At the same time, traditional approaches may be used to extract hand-crafted features like statistical and texture features. The features are then fused together at the feature fusion stage, where multimodal data is merged through techniques like concatenation and attention.

The combined features are provided to a hybrid model, where the deep learning algorithms are used in combination with machine learning algorithms like SVM or RF. The hybrid model improves the classification process through the use of the strong aspects of both models, as the deep learning model will learn features while the machine learning algorithm will make quick decisions. The last stage in the classification process will be to have the classification results as Alzheimer's disease (AD), Mild Cognitive Impairment (MCI), and normal.

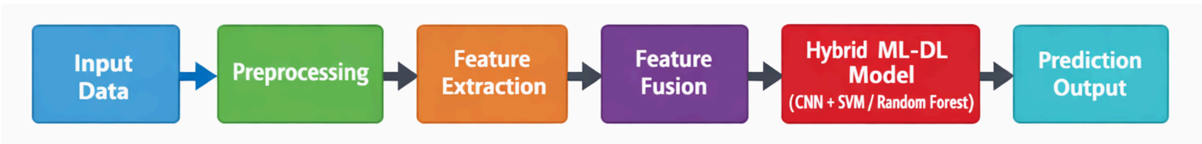


Figure 1: Flow Diagram for Ad Prediction

## 6. Expected Outcomes

The proposed hybrid Machine Learning and Deep Learning framework is expected to significantly improve the early prediction of Alzheimer's Disease by combining the strengths of automated deep feature extraction and robust machine learning classification. By effectively utilizing multimodal neuroimaging and clinical data, the framework aims to provide accurate, reliable, and interpretable predictions that support early diagnosis, reduce diagnostic errors, and enhance clinical decision-making. Furthermore, the incorporation of explainable artificial intelligence, efficient computational strategies, and scalable model design is expected to facilitate practical deployment in healthcare environments. Ultimately, the proposed research seeks to contribute toward intelligent computer-aided diagnostic systems that improve patient outcomes through timely intervention and personalized treatment strategies.

## 7. Conclusion

The ML-DL hybrid architecture represents an excellent approach towards diagnosing early stages of Alzheimer's disease, due to the integration of benefits from both classical ML and DL. Such models deliver much better performance in terms of prediction accuracy and robustness. Nevertheless, problems like data limitation, explainability, and generalization need to be tackled to facilitate practical applications of these models in a clinical setting.

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