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# Alzheimer’s Disease Detection and Severity Classification using Deep Learning Models

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**Abstract**

Alzheimer's disease is a neurodegenerative disease, and its diagnosis, especially in the initial stages, is extremely tough. The recent breakthroughs in deep learning techniques have generated a mania in research activities for better diagnosis with the use of neuroimaging and medical data. The three important facets of this comprehensive survey are, a) types of data used in research for AD, including MRI, PET and multimodal dataset, b) a range of deep learning techniques including CNNs, RNNs, Autoencoders, and Transformers, c) the effectiveness of these techniques in terms of accuracy, sensitivity, and specificity for the aforementioned datasets. The survey involves a comparison and analysis of various results obtained from benchmark datasets such as ADNI and OASIS, and indicates the state of research in this area, future research, and trends in this regard in a manner that would further enhance the use of Deep Learning in AD diagnosis.

**Keywords:** Alzheimer's Disease (AD), Deep Learning, Magnetic Resonance Imaging (MRI), Biomarkers, Early Diagnosis

## 1. Introduction

Alzheimer's disease (AD) is the leading cause of dementia worldwide, and accounts for 60 to 70 percent of all dementia cases. Furthermore, there are currently over 55 million people in the world who have dementia. Current projections estimate another three times this figure will occur without preventative measures being implemented [1]. Early diagnosis will improve the quality of life for the patient as well as slow the progression of the disease. However, many current methods to make a diagnosis include clinical assessment, neuropsychiatric evaluation which are all very time-consuming, are highly subjective and have very poor sensitivity when identifying people with mild cognitive impairment (MCI) and those who may still have symptoms associated with MCI [2]. Both machine learning (ML) and deep learning (DL) approaches to automating the detection of persons with AD have the potential of recognising patterns in both high dimensional multidimensional data.

### 1.1. Transitioning from Unimodal to Multimodal Methods

The majority of published research has explored only a unimodal data source including, MRI, PET, CSF biomarkers, or neuropsychological tests [3]. Each modality provides an independent view of the same aspects of Alzheimer's disease pathology such as: physical atrophy (with MRI), metabolic changes (with PET), and biochemical changes, but there is no single data source available which supplies the complete picture of the complexity of the disease [4]. These limitations can be overcome by combining existing data sources neuroimaging, biomarkers, genetics, clinical scores, and speech data into a single multi-modal data source, and thus provide a more complete characterization of the disease, assist with earlier prediction of the disease, and allow for a much finer granularity of disease severity classification [5].

### 1.2. Paradigms for Machine Learning, Deep Learning and Fusion

ML techniques such as SVM, Random Forests, and Logistic Regression have been applied to extract clinical markers from multimodal data [6]. Deep learning approaches CNNs, RNNs, and Transformers offer automatic feature learning from complex multi-source inputs [7]. Three fusion strategies are commonly employed (1) Early fusion, which concatenates features before model training (2) Intermediate fusion, which learns modality-specific embeddings combined at hidden layers and (3) Late fusion, which aggregates predictions from separate unimodal models. Emerging techniques including graph neural networks (GNNs), transformer-based architectures and cross-modal attention further enhance interdependency modelling. Figure 1 presents an overview of approaches to improve Alzheimer's detection.

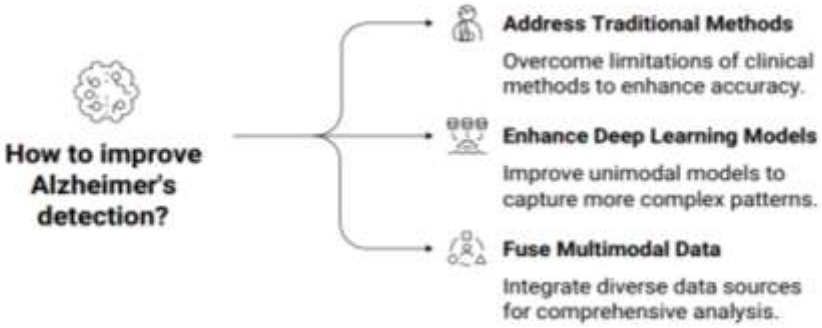


**Figure 1: How to Improve Alzheimer's Detection**

## 1.3. Motivation and Contributions

AD remains one of the most significant medical challenges globally due to its increasing prevalence, lack of a cure, and economic burden. This review addresses key shortcomings in the literature subjective neuropsychological assessments, single-modality DL limitations, exclusive focus on binary AD vs. control classification, and limited interpretability through (1) systematic synthesis of publicly available AD datasets (ADNI, OASIS) (2) a taxonomic framework of DL architectures (3) comparative performance evaluation across studies (4) identification of research trends and gaps; and (5) a roadmap for clinically relevant future research.

## 2. Related Work

AD research has progressively shifted from unimodal to multimodal approaches to overcome single-data-source limitations. Early DL work demonstrated the value of CNNs and transfer learning for MRI-based AD staging. An end-to-end DL system using VGG19 transfer learning achieved accuracies of 93.61% (2D CNN), 95.17% (3D CNN), and 97% (VGG19) on ADNI data, including a web application for remote AD screening [8]. A systematic review highlighted the dominance of CNNs and RNNs, noting persistent challenges such as small datasets and the need for discriminating biomarkers [9].Multicentre and federated learning approaches have also been explored. A Hybrid Federated Learning architecture with a Brain-region Attention Network (BANet) used self-supervised learning on structural MRI to achieve 85.69% (AD vs. NC) accuracy across five datasets while preserving data privacy [12]. CNN-based models have reached very high performance, a dual-CNN architecture reported 99.43–99.57% accuracy [13], the Pipelined LeNet (PLN) model with image fusion achieved 99.5% accuracy in 0.65 ms [14] and ADNet (3D-CNN) achieved 99.94% accuracy for four-stage dementia classification [15]. Gait analysis using CNN-RNN models demonstrated >90% accuracy for non-invasive early AD detection [16]. Transfer learning with pre-trained CNNs for six-stage MRI classification produced accuracies of 83–99.79% [17]. A lightweight EEG-based CNN model, LEADNet, achieved 99.24% accuracy with 150× fewer parameters than standard deep CNNs [18]. A hybrid model combining DenseNet feature extraction with ML voting achieved 91.75% accuracy on a Kaggle MRI dataset [20]. Table 1 summarizes related work on AD detection.

**Table 1: Summary of Related Work on Alzheimer's Disease Detection**

| Model | Application | Result | Highlight |
|---|---|---|---|
| CNN (2D/3D), VGG19 TL [8] | Early AD detection, ADNI MRI | 93.61% (2D), 95.17% (3D), 97% (VGG19) | End-to-end DL system with web app |
| CNN, CNN-LSTM, CNN-SVM, VGG16-SVM [11] | MRI-based early AD detection | 99.92% (CNN-LSTM best) | Superior CNN-LSTM for early diagnosis |
| Hybrid Federated Learning, BANet [12] | Multi-center MRI AD detection | 69.89% (AD vs MCI), 85.69% (AD vs NC) | Privacy-preserving with self-supervised loss |
| Dual CNN [13] | MRI multi-class AD classification | 99.43%, 99.57% | Parallel CNNs for local & global features |
| Pipelined LeNet (PLN) + image fusion [14] | Low-resolution MRI AD detection | 99.5% Acc, 0.65 ms | Fast fusion-based pipeline |
| ADNet (3D CNN) [15] | 3D MRI dementia stage detection | 99.94% accuracy | 4-stage volumetric classification |

| | | | |
|---|---|---|---|
| CNN-RNN [16] | Gait analysis for early AD | >90% accuracy | Non-invasive sensor-based detection |
| EfficientNet, DenseNet, ResNet, AlexNet [17] | MRI 6-stage AD classification | 83%–99.79% | Transfer learning across AD stages |
| LEADNet (Lightweight CNN) [18] | EEG-based AD detection | 99.24%, 150x fewer params | Low-complexity EEG model |
| DenseNet + SVM/NB/XGBoost voting [20] | MRI AD detection (Kaggle) | 91.75% Acc, 96.5% Sp | Hybrid TL+ML outperforms SOTA |

## 3. Data Modalities in AD Detection

AD is influenced by behavioral, genetic, biochemical, structural, and functional variables. No single modality can capture the full disease pathophysiology, making it necessary to use diverse data sources for accurate detection, staging, and progression tracking [21].

### 3.1. Neuroimaging Modalities

Neuroimaging is among the most widely used approaches for AD detection. MRI provides structural and functional brain information critical for identifying AD-related changes.

### 3.1.1. Magnetic Resonance Imaging (MRI)

MRI provides valuable structural, functional, and metabolic data relevant to diagnosing AD. Using structural MRI one can see signs of hippocampal atrophy and cortical thinning, as well as evidence of enlarged ventricles and loss of gray matter. Diffusion Tensor Imaging (DTI) explains how well white matter is intact. Functional MRI (fMRI) demonstrates a loss of functional connectivity, while Magnetic Resonance Spectroscopy (MRS) highlights metabolic changes resulting from the death of nerve cells. Because MRI is non-invasive, has a very high level of spatial resolution, and is widely used in the clinical setting to measure the severity and presence of an individual's dementia, it has remained one of the most effective imaging techniques for identifying people with AD and determining the severity of their disease [22-24].

### 3.1.2. Positron Emission Tomography (PET)

Functional and molecular information important to the pathophysiology of Alzheimer's disease can be provided through PET. PET allows one to visualize neuronal activity, glucose metabolism, and pathological proteins before the appearance of structural changes in the brain. The principal PET modalities include the following: [25, 26] FDG-PET, which measures decreased neuronal activity in AD-infected areas; [27, 28] Amyloid PET, which measures β-amyloid plaque accumulation; and Tau PET, which measures the accumulation of neurofibrillary tangles in order to assess severity of the disease and response to treatment [31]. A summary of the major modalities of neuroimaging used in the detection of AD is provided in Table 2.

**Table 2: Comparison of Neuroimaging Modalities in Alzheimer's Disease Detection**

| Modality | Information Captured | AD-related Findings | Advantages | Limitations |
|---|---|---|---|---|
| MRI | Structural anatomy | Hippocampal atrophy, cortical thinning [32], ventricular enlargement, white matter via DTI | High resolution, non-invasive, widely available | Structural changes appear late, inter-subject variability |
| PET | Functional and molecular activity | FDG-PET: hypometabolism; Amyloid PET: beta-amyloid plaques; Tau PET: neurofibrillary tangles [33] | Detects pathology before structural changes, useful for differential diagnosis | Radiation exposure, high cost, specialized facilities |
| fMRI | Neural activity (BOLD signals) | Disrupted DMN, hypoconnectivity in memory regions, abnormal activation [34] | Non-invasive, detects early functional changes, network biomarkers [35] | Sensitive to noise/motion, computationally demanding |

### 3.1.3. Clinical and Cognitive Assessments

Cognitive decline and dementia are assessed clinically to assess the degree of cognitive problems present. Common tools used in this process include the Mini-Mental State Examination (MMSE), the Montreal Cognitive Assessment (MoCA) and the Clinical Dementia Rating (CDR). These three methods evaluate memory, executive functioning, language and day-to-day activities. While the tests themselves tend to be low-cost and are used often, combining them with neuroimaging studies and biomarker data can improve the diagnostic accuracy for dementia significantly. Table 3 lists some of the more common clinical assessments that can be used in combination with neuroimaging and/or biomarker data [36-38].

**Table 3: Common Clinical and Cognitive Assessments in Alzheimer's Disease**

| Test/Assessment | Purpose / Focus | Strengths | Limitations |
|---|---|---|---|
| MMSE | Global cognition: orientation, memory, attention, language, visuospatial skills | Quick to administer, widely used, tracks progression | Low sensitivity for MCI, influenced by education and culture |
| MoCA | Detects MCI and early AD; evaluates executive function, memory, attention | More sensitive than MMSE for early detection, covers broader domains | Takes longer; still influenced by education and language |
| CDR (Clinical Dementia Rating) | Stages dementia severity across cognitive and functional domains | Effective for staging, incorporates functional decline | Relies on caregiver input, inter-rater variability |
| Clinical History & Behavioral Assessments | Evaluates ADL/IADL, behavioral symptoms (apathy, depression, agitation) | Captures real-world impact, provides functional context | Highly subjective, dependent on caregiver reports |

### 3.1.4. Biomarkers (CSF, Blood, and Genetic Data)

Objective data regarding the pathological basis for Alzheimer's disease (AD) are provided by biomarkers [36]. Biomarkers in CSF such as Aβ42, total tau and phosphorylated tau are representative of the biological processes involved in the aetiology of AD [37], while blood-based biomarkers can provide a less invasive alternative for large-scale screening. Genetic risk factors such as APOE ε4 can help inform individual risk for AD and assist in developing personalized treatment strategies [38]. The major categories of biomarkers are outlined in Table 4.

**Table 4: Biomarkers in Alzheimer's Disease Detection**

| Type | Key Indicators | Strengths | Limitations |
|---|---|---|---|
| CSF | Decreased Aβ42, elevated total tau, elevated phosphorylated tau | High diagnostic accuracy, reflects core AD pathology | Invasive (lumbar puncture), impractical for screening |
| Blood-Based Biomarkers | Plasma Aβ42/40 ratio, plasma tau, neurofilament light chain (NfL) | Minimally invasive, cost-effective, scalable | Under validation, may be affected by comorbidities |
| Genetic Data | APOE ε4 allele, GWAS variants, polygenic risk scores | Predictive of susceptibility, supports personalized medicine | Non-diagnostic alone, raises ethical/privacy concerns |

### 3.2. Multimodal Datasets

Major publicly available datasets are significant contributors to the field of AD research. The ADNI data set is composed of MRI, PET, CSF biomarker, genetics data and cognitive assessments, making it the benchmark for multimodal fusion within the context of the AD research community. The OASIS provides structural MRI data from both aging and individuals with AD. The OASIS-3 data set has added longitudinal imaging and clinical information for both age and AD subjects. The primary multimodal datasets that are utilized within AD research are provided in Table 5.

**Table 5: Key Multimodal Datasets for Alzheimer's Disease Research**

| Dataset | Modalities | Highlights | Limitations |
|---|---|---|---|
| ADNI | MRI, PET, CSF biomarkers, genetics, cognitive tests | Gold-standard multimodal dataset, longitudinal, benchmark for fusion research | High complexity, not fully representative of diverse populations |
| OASIS / OASIS-3 | Structural MRI, clinical data | Covers aging spectrum; OASIS-3 adds longitudinal data | Primarily imaging, limited biochemical/genetic data |

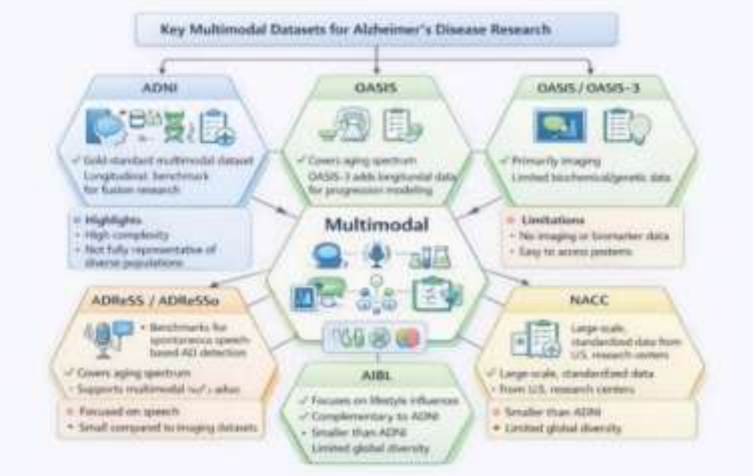


**Figure 2: Representative Multimodal Datasets Used for Computational Alzheimer's Disease Research**

## 4. Methodological Framework for Alzheimer's Disease (AD) Detection

Detecting Alzheimer’s Disease early and accurately is important as currently, there is no cure for it [8,11]. As a result of this lack of an existing solution, every step taken to slow down the progression of the disease is essential. AI-based solutions utilizing ML and DL/ have proven effective, in that they provide high-quality results with multiple imaging approaches such as MRI scans, EEGs, and gait data. There are three categories of AI-based solutions: Machine Learning, Deep Learning, and Autoencoder-based/Self-Supervised.

### 4.1. Machine Learning Approaches

Various conventional methods of machine learning including Support Vector Machines (SVM), Random Forests (RF), Logistic Regression, Gradient Boosting (GB), and XGBoost have all been implemented to successfully classify patients with Alzheimer's Disease (AD) from MRI, EEG, and clinical data sets. These conventional methods provide some interpretability and can be processed quickly; nevertheless their classification performance is generally inferior to that of contemporary deep learning techniques (Such as CNNs) [6, 29, 30]. An image comparison of the various methods of machine learning for AD is shown in Figure 3.

**Figure 3: Machine Learning Models for Alzheimer's Disease Detection**

### 4.2. Deep Learning Based Approaches for Alzheimer's Disease Detection

The predominant way of detecting AD is using deep learning methods as they can automatically develop layers of features from neuroimages, EEG and gait data. As a result, there have been great success using CNNs, CNN-LSTM hybrids, transfer learning methods, lightweight networks for EEG and volumetric 3D CNNs demonstrating diagnostic accuracies for many different datasets. A summary of how the representative models compare against each other and their major contribution as represented in Table 6 and Figure 4.

**Table 6: Deep Learning–Based Approaches for Alzheimer's Disease Detection**

| Model | Data Modality | Application | Performance | Key Contribution |
|---|---|---|---|---|
| 2D CNN / 3D CNN / VGG19 TL [8] | MRI | Early AD Detection | 93.61% (2D), 95.17% (3D), 97% (VGG19) | Transfer learning for end-to-end AD screening |
| CNN-LSTM [11] | MRI | Early AD Detection | 99.92% Acc | Joint spatial-temporal modeling |
| Dual CNN [13] | MRI | Multi-class AD Classification | 99.43–99.57% Acc | Local + global feature extraction |
| PLN + Image Fusion [14] | Low-res MRI | AD Detection | 99.5% Acc, 0.65 ms | Fast fusion-based pipeline |
| ADNet (3D CNN) [15] | 3D MRI | Dementia Stage Classification | 99.94% Acc | Efficient volumetric learning |
| CNN-RNN [16] | Gait Data | Early AD Detection | >90% Acc | Non-invasive sensor-based diagnosis |
| LEADNet [18] | EEG | AD Detection | 99.24% Acc | 150x fewer parameters |

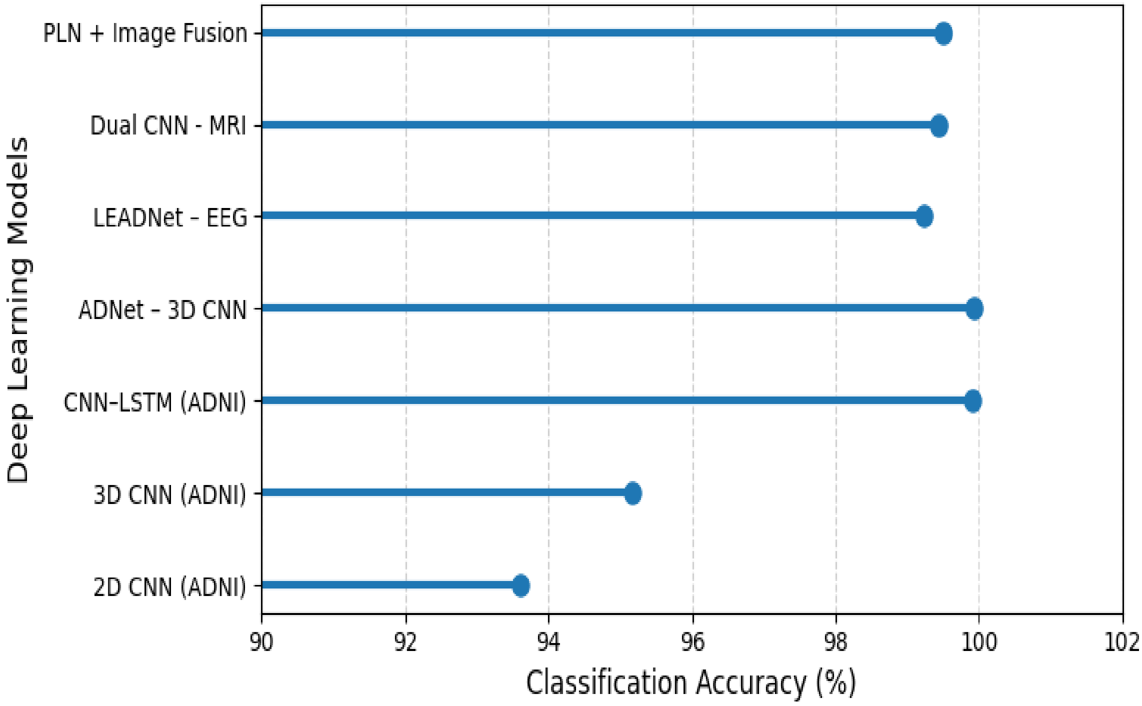


**Figure 4: Accuracy Comparison of Deep Learning Models for Alzheimer's Disease Detection**

## 4.3. Autoencoder-Based and Self-Supervised Approaches

Self-supervised learning methods and autoencoder architectures have been shown to provide a robust way to create valuable feature representations, even when the amount of labelled data available is limited. Various approaches using the Bi-Vision Transformer, CVAE-ViT architecture, Masked Autoencoder, and Graph-based Self-supervised frameworks have yielded significantly better results than traditional supervised learning methods using magnetic resonance imaging (MRI), electroencephalography (EEG), and functional magnetic resonance imaging (fMRI). More detail on the results for each study is available in Table 7 and Figure 5.

**Table 7: Comparison of Autoencoder-Based and Self-Supervised AD Detection Methods**

| Ref | Modality | Core Method | Learning Strategy | Dataset | Accuracy (%) |
|---|---|---|---|---|---|
| Fonseka et al., 2025 [41] | Structural MRI | CVAE + Vision Transformer | Unsupervised + Transformer | ADNI, SCAN (~14k) | 93.3 |
| Shah et al., 2024 [42] | 2D MRI | Bi-Vision Transformer (MLF + PCES) | Autoencoder-assisted | AD MRI datasets | 96.38 |
| Xiang et al., 2025 [43] | EEG | Masked Autoencoder + ViT + MLP | Self-Supervised | EEG (65 subjects) | 96.92 |
| Zhang et al., 2025 [44] | fMRI | Spatiotemporal Graph Autoencoder + SSL | Self-Supervised | Multi-cohort fMRI (5,687) | +5.1% vs SOTA |

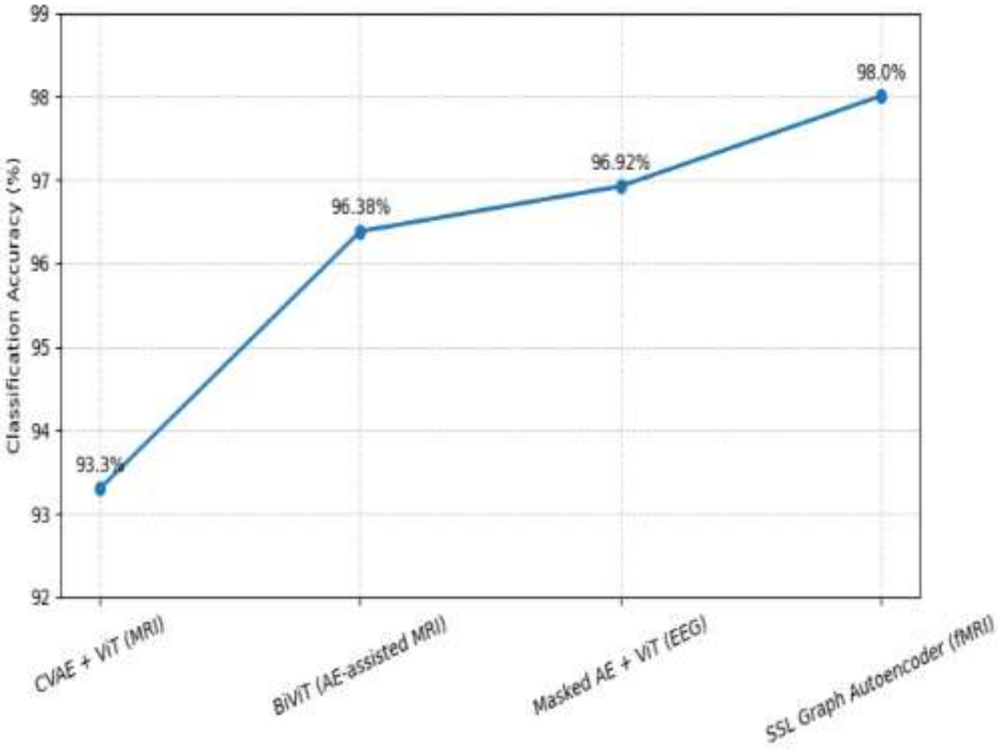
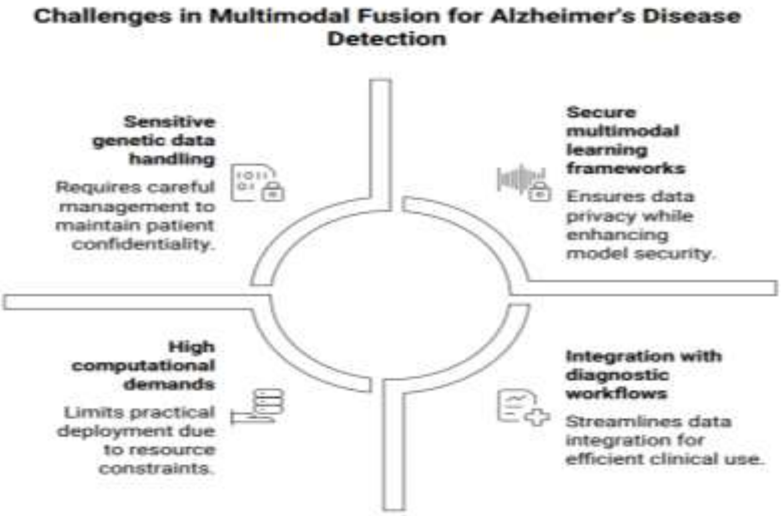


**Figure 5: Accuracy versus Learning Paradigm in Autoencoder-Based Alzheimer's Disease Diagnosis**

## 5. Challenges and Future Research Directions

Although multimodal fusion methods have significant potential for Alzheimer's disease (AD) detection, their effectiveness is limited by challenges such as integrating heterogeneous data (MRI, PET, CSF, genetic, and speech), incomplete patient records, small and imbalanced datasets, and variations in data acquisition protocols [21]. Additionally, fusion strategy selection involves computational trade-offs [7], while the lack of model interpretability, poor generalization across datasets, high computational requirements, and privacy concerns related to clinical and genetic data further hinder their clinical adoption and large-scale deployment [40].Future research should focus on: (1) developing explainable AI (XAI) frameworks for clinical interpretability, (2) designing robust missing-modality handling via cross-modal knowledge distillation, (3) leveraging self-supervised and semi-supervised learning to address labelled data scarcity [41, 44], (4) standardizing multimodal acquisition protocols to improve cross-dataset generalizability and (5) incorporating privacy-preserving federated learning to enable large-scale multi-institutional collaboration [12].

**Figure 6: Major Challenges in Multimodal Fusion for Alzheimer's Disease Detection**



## 6. Conclusion

Alzheimer's disease diagnosis remains challenging because of the diverse nature of neuroimaging, cerebrospinal fluid, genetic, and cognitive biomarkers. Multimodal fusion techniques provide an effective way to integrate these heterogeneous data sources using early, intermediate, late, and attention-based fusion strategies. Recent advances in deep learning, attention mechanisms, and graph architectures have improved the modeling of complex cross-modal relationships. There are still issues that relate to the lack of interpretability, missing modalities, high-dimensional data, and too few large datasets to use. If we can figure out how to fix these, we will be able to use explanatory, privacy-preserved, and self-supervised methods to help increase the adoption of AI in the clinic and provide accurate, reliable and timely AD diagnoses.

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