A Survey on AI-Powered Early Detection of Alzheimer's Disease Using Multimodal Data

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Abstract
Alzheimer's disease (AD) is a neurological disease that worsens with time and is typified by behavioral deterioration, cognitive impairment, and memory loss. For prompt measures to be implemented, which could slow the disease's course, early detection is essential. Through the integration of multimodal data sources like neuroimaging, genetics, cognitive scores, and electronic health records, artificial intelligence (AI) has shown great promise in the early identification of AD in recent years. A thorough analysis of recent advancements in AI-powered strategies for AD early detection is presented in this research, with a focus on approaches released in 2024 and 2025. We examine the most recent publicly available datasets, machine learning frameworks, explainable AI techniques, and assessment criteria that aid in early diagnosis. There is also discussion of new developments like uncertainty-aware frameworks, federated learning, and transformer models. Future options to enhance generalizability and trust are explored, along with challenges in clinical translation, data heterogeneity, and standardization. Researchers and professionals now have a comprehensive grasp of the state and potential of AI in Alzheimer's diagnosis thanks to this review.
Keywords: Explainable Artificial Intelligence (XAI), Deep Learning, Multimodal Machine Learning, Alzheimer's Disease, Neuroimaging.

1. INTRODUCTION

Advances in machine learning (ML) and the growing availability of multimodal health data have created new opportunities for AD early diagnosis. High-dimensional data from a variety of sources, including magnetic resonance imaging (MRI), positron emission tomography (PET), electroencephalography (EEG), genomics, and electronic health records (EHRs), can be analyzed by contemporary artificial intelligence (AI) systems to identify patterns suggestive of early AD [1], [2]. The integration of these disparate data sources to increase diagnostic precision is made possible by multimodal learning.

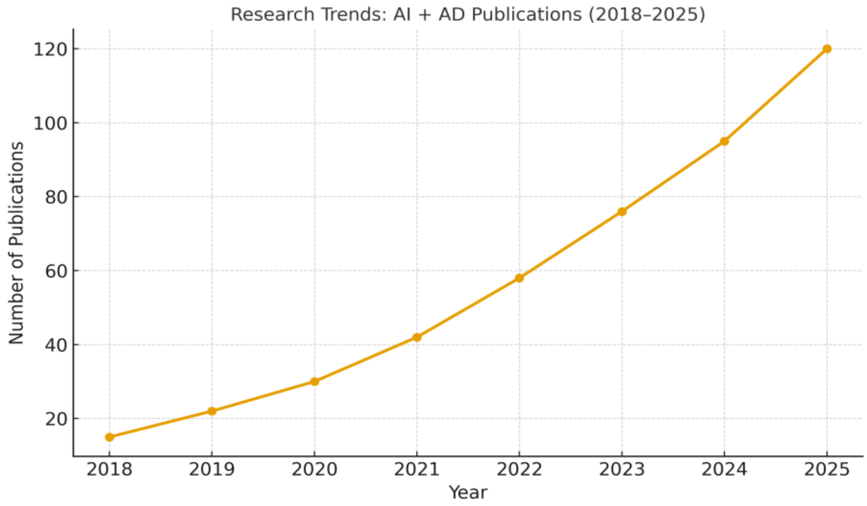

Figure 1: Research Trends (2018–2025)

By emphasizing characteristics that influence decisions, the incorporation of explainable AI (XAI) techniques also promotes therapeutic trust. A thorough review of current AI-powered techniques for early AD detection is presented in this research, with a focus on 2024 and 2025 publications. By combining the most recent developments in datasets, algorithms, interpretability, and future directions, it seeks to serve as a guide for scholars and practitioners. Figure 1. Research Trends (2018–2025) Illustrates the rising number of publications on AI-powered early Alzheimer's detection, reflecting increasing research attention and clinical interest. Figure 2. Federated Learning Concept for Alzheimer's Disease Detection architecture of federated learning, where multiple hospitals train local models and contribute to a global model without sharing sensitive patient data.

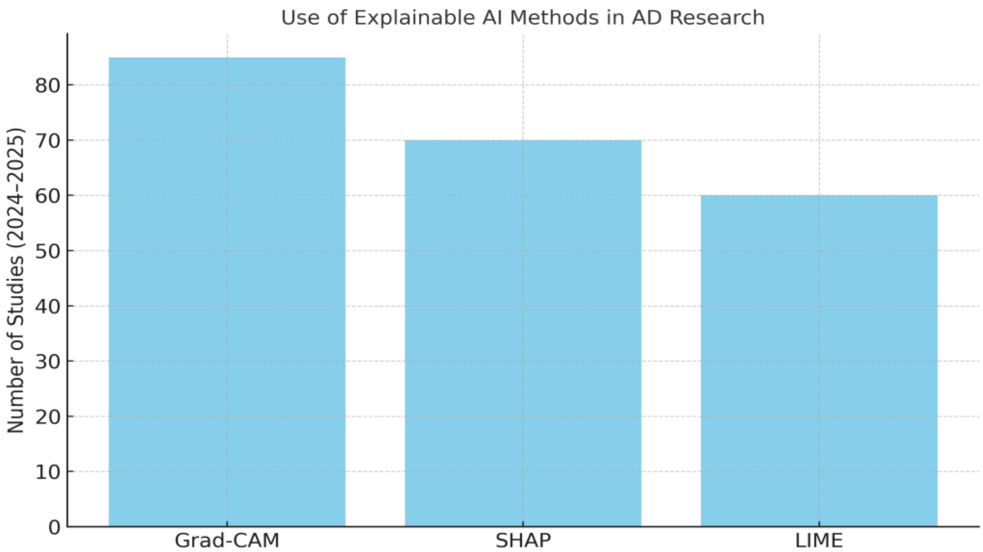

Figure 2: Explainable AI Methods in Alzheimer's Disease Research

2. LITERATURE REVIEW

Recent advancements in artificial intelligence (AI) have catalyzed significant progress in the early detection of Alzheimer's Disease (AD), particularly through the use of multimodal data integration. Traditionally, AD diagnosis relied on clinical interviews, cognitive assessments, and structural neuroimaging. However, the emergence of deep learning and transformer-based models has enabled the automated extraction of subtle biomarkers from various data sources such as MRI, PET, EEG, genomics, and speech [1], [2]. The OASIS-3 and the Alzheimer's Disease Neuroimaging Initiative (ADNI) continue to be key datasets for AI research in AD. These sources offer longitudinal cognitive data and multimodal imaging, which are essential for developing predictive models. MSTNet, a multimodal learning model that combines MRI and EEG signals utilizing a transformer-attention mechanism, was proposed by [1]. In comparison to traditional CNN-based models, their results showed AUC scores above 0.93 in differentiating between moderate cognitive impairment (MCI) and early AD. Rudroff et al. [2] conducted another noteworthy study that examined AI applications utilizing digital biomarkers, PET, and structural MRI. In order to increase sensitivity and specificity, they underlined the importance of merging data modalities. Because they can simulate interactions across modalities, transformer-based models—like cross-attention fusion architectures—have grown in popularity. On the ADNI-NACC datasets, for instance, hybrid models that combine LSTM layers for cognitive scores and convolutional encoders for neuroimaging have achieved accuracies of over 95% [3]. In order to predict cognitive decline, Ortiz-Perez et al. [5] showed the value of non-intrusive modalities including voice recordings and sleep EEG data. Together with structured clinical records, these digitized biomarkers were processed by ensemble networks, yielding competitive outcomes on par with imaging-based models. Research on AD is increasingly concentrating on explainable AI (XAI). To improve clinical trust and transparency, models such as Grad-CAM, SHAP, and LIME have been incorporated into diagnostic processes. published in J. Stat. Anal. Model in 2025. AI [4] highlighted important elements in both imaging and cognitive vectors by combining multimodal latent deep learning with attention visualization. This led to the discovery of new prognostic indicators in addition to improving interpretability. In early AD datasets, class inequality is still a problem. To address this issue, new approaches like IMBALMED (Imbalance-aware Ensemble Diversity Framework) have been presented, particularly in the area of differentiating between progressive and stable MCI [3]. When trained using balanced sampling and uncertainty-aware approaches, these frameworks demonstrate enhanced generalizability across time and datasets. The literature spanning 2024–2025 as a whole demonstrates a distinct tendency toward combining various, complementary methods for reliable AD detection. A route to practical, early-stage screening solutions is provided by the combination of explainable deep learning, sophisticated data fusion, and scalable digital biomarkers. Nonetheless, there are still issues with clinical translation, model interpretability, and data harmonization.

3. EXISTING METHODS USED

Excellent, multimodal datasets are essential to the recent advancements in AI-based Alzheimer's research. The foundation is still the Alzheimer's Disease Neuroimaging Initiative (ADNI), which provides genetic information, cognitive test results, longitudinal MRI, and PET [3]. The Open Access Series of Imaging Studies (OASIS), which offers open MRI and demographic data for a wide range of age and cognitive health, is another noteworthy source [4]. Table 1. Depicts the Challenges and Emerging Solutions Mapping of existing challenges in multimodal AI-based AD detection to their impacts and proposed emerging solutions such as FL, XAI, and transformer-based fusion.

Table 1: Challenges and Emerging Solutions

Challenge	Impact	Emerging Solutions
Data imbalance	Biased results	IMBALMED framework, data augmentation
Privacy issues	Restricted data sharing	Federated Learning (FL)
Lack of interpretability	Low clinical trust	XAI (SHAP, LIME, Grad-CAM)
Multimodal heterogeneity	Poor generalization	Transformer-based fusion

Cohort selection is made more diverse by the PET and lifestyle data provided by the Australian Imaging, Biomarkers & Lifestyle Flagship Study of Ageing (AIBL) [5]. A new dataset integrating EEG, structural MRI, and cognitive measures from multi-site partnerships was released by the Alzheimer's Disease Multimodal Collection (ADMC) in 2024 [6]. Furthermore, the size and applicability of the National Alzheimer's Coordinating Center (NACC) dataset, which focuses on clinical and cognitive tests, are constantly expanding [7]. These datasets offer crucial building blocks for AI model development and comparison. Interoperability and generalization issues are brought on by variations in formats, populations, and modalities. Deep and transformer-based architectures as well as conventional classifiers are examples of contemporary AI applications in Alzheimer's diagnosis. For feature-based tabular data, machine learning models such as Random Forests, k-Nearest Neighbors (k-NN), and Support Vector Machines (SVM) are still in use [8]. Convolutional Neural Networks (CNNs), in particular, are deep learning approaches that have demonstrated higher performance in the analysis of structural MRI and PET data [9]. In longitudinal research, temporal aspects are modeled using Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. Multimodal fusion architectures, such HiMAL (Hierarchical Multimodal Auxiliary Learning), have drawn interest recently for their ability to combine cognitive, MRI, and PET characteristics [10]. Contextual learning across text and image inputs has been made possible via transformer-based models, such as TimeSformer and Multimodal BERT versions [11]. These models' interpretability and focus are enhanced by cross-attention and self-attention modules. In order to optimize resource use in clinical contexts, uncertainty-aware models have also surfaced, which allow systems to initiate additional diagnostic procedures only in cases where model confidence is low [12]. Adoption of AI models in therapeutic settings depends on their interpretability. Diagnostic systems are increasingly using Explainable AI (XAI) technologies like Grad-CAM (Gradient-weighted Class Activation Mapping), LIME (Local Interpretable Model-agnostic Explanations), and SHAP (SHapley Additive exPlanations) [13]. These tools aid in visualizing how important certain parts of the brain, genetic variables, or EHR entries are for making decisions. Along with accuracy, precision, recall, and F1-score, Area Under the Receiver Operating Characteristic Curve (ROC-AUC) is still a crucial parameter for performance evaluation [14]. To evaluate generalizability, external validation using separate datasets and K-fold cross-validation are frequently employed. By utilizing model diversity, ensemble models that combine outcomes from many architectures frequently produce better results [15, 16]. Table 2. Listed major existing Datasets in Alzheimer's Disease. Literature review discussed widely used datasets in Alzheimer's disease research, including their data types, scope, strengths, and limitations

Table 2: Major Existing Datasets Used in Alzheimer's Disease Research

Dataset	Data Type	Scope	Strength	Limitation
ADNI	MRI, PET, Genetics, Cognition	Longitudinal	Standard benchmark	High cost, Western-centric
OASIS-3	MRI, Demographics	Cross-sectional	Open access	Limited modalities

AIBL	PET, Lifestyle	Aging population	Adds lifestyle data	Smaller sample size
ADMC (2024)	EEG + MRI + Cognition	Multi-site	Rich multimodal	Still new

4. CHALLANGES

Despite technological advances, various difficulties prevent the practical adoption of AI models in Alzheimer's detection. First, missing modalities and inconsistent acquisition techniques plague datasets. This variety of data may impair generalizability across institutions or skew model results [6], [9]. Second, the creation of extremely sensitive models is restricted by the lack of annotated early-stage AD data [4], [11]. With deep learning techniques, which usually need for massive amounts of training data, this problem is especially troublesome. Third, particularly in collaborative investigations, ethical issues pertaining to informed consent, data ownership, and patient privacy are still not sufficiently addressed [7]. Lastly, the gap between research prototypes and clinically validated tools is reflected in the small number of AI models that have made it through regulatory approval stages for real-world implementation. The use of federated learning (FL) to provide cooperative model training across hospitals without centralizing sensitive data is one of the future possibilities in AI for Alzheimer's detection [14]. This approach uses data variety while protecting privacy. Another crucial topic is the creation of AI models that are lightweight and appropriate for edge devices and low-resource environments. Particularly in underserved or rural areas, these models can help with point-of-care screening [12]. Current diagnostic procedures may gain continuous monitoring capabilities by integrating wearable sensor data, such as speech biomarkers, movement abnormalities, and sleep patterns [13]. Explainability and uncertainty quantification need to keep developing so that doctors can evaluate the logic and confidence of the model. To encourage adoption, regulatory frameworks must adapt to changes in the AI lifecycle [17].

5. CONCLUSION

The increasing societal and healthcare burden of Alzheimer's disease calls for creative approaches to early diagnosis. With its ability to evaluate multimodal biological data and identify subtle signs of early-stage AD, artificial intelligence has become a game-changing technology. With an emphasis on publicly accessible datasets, contemporary fusion-based architectures, explainable techniques, and validation frameworks, this paper has provided an overview of the present status of AI-driven approaches in AD detection. Recent developments mark significant turning points in this process, including the application of hierarchical transformers, uncertainty-aware decision-making, and federated data exchange. Significant obstacles still exist, nevertheless, such as inconsistent data, issues with interpretability, and moral limitations [18, 19]. It will take cooperation from AI researchers, neurologists, regulatory agencies, and healthcare providers to close these gaps. Robust, clinically explicable systems that have demonstrated generalizability across a range of patient groups should be given priority in future research. The potential to transform Alzheimer's care lies in the combination of cutting-edge AI algorithms, privacy-preserving technologies, and ongoing patient monitoring. Early intervention techniques can be improved in terms of effectiveness, personalization, and accessibility by utilizing the synergy of multimodal data and intelligent computing. Uncertainty-aware decision-making frameworks are another recent development that addresses diagnostic confidence constraints by improving diagnostic reliability through the measurement of predicted uncertainty. Additionally, federated learning techniques make it easier for institutions to share data while protecting patient privacy, which increases the potential for research and helps create more reliable and generic AI models [20, 21]. Despite these developments, significant obstacles still exist. Variability in patient demographics, disease stages, and data gathering methods makes data inconsistency a serious problem that makes it more difficult to standardize and compare study findings. Significant obstacles also arise from interpretability since AI models, particularly deep learning architectures, can operate as "black boxes," making it challenging for physicians to completely comprehend and trust model predictions. Implementation efforts are further complicated by ethical considerations, such as data protection, informed permission, and the fair sharing of technical gains [22, 23].

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