A Comprehensive Survey on Classification and Prediction Techniques for Alzheimer's Disease

Maga Vigna C.[1], Kavitha Devi M. K.[2], Vaira Suganthi G.[3]

[1]Department of Computer Science and Engineering, Thiagarajar College of Engineering, Madurai, India.

[2]Department of Applied Mathematics and Computational Science, Thiagarajar College of Engineering, Madurai, India.

[3]Department of Computer Science and Design, Sethu Institute of Technology, Kariapatti, India.

E-mail: [1]magavigna1053@gmail.com, [2]mkkdit@tce.edu, [3]vairasuganthi@gmail.com

Abstract

Alzheimer's disease (AD) is one of many disorders that affect the brain. It is thought to have a number of neurological and physical causes, including the loss of muscle memory. It is characterized by an aggregation of clinical features; memory loss, confusion, and personality changes tend to worsen over time. The WHO stated that in 2021 there were more than 55 million people living with dementia, and this figure is estimated to increase to as high as 139 million by the year 2050. Alzheimer's is responsible for 60-70% of dementia cases, with many other factors considered. Mild cognitive impairment (MCI) is a condition where individuals experience significant challenges in memory, cognition, and decision-making, often influenced by age and educational background. Individuals with MCI have two to three times the chance of advancing to Alzheimer's dementia compared to older adults, with an estimated annual transition rate of 3% to 15%. Various strategies across a range of AI tools, including machine learning and deep learning, are used for for AD diagnosis, particularly the application of machine learning algorithms. This paper presents the results of various research studies conducted in the last few years that particularly concern the path from MCI to AD. It focuses on reviewing machine learning and deep learning algorithms, covering convolutional neural networks and multitask learning techniques to predict Alzheimer's progression.

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1. Introduction

Alzheimer's is a degenerative brain disease that gradually takes away every existing mental function from memory, cognition, and learning to performing even the most basic tasks. This is the most prevalent form of dementia, accounting from 60% to 80% of all dementia cases, with millions of cases the whole world. The pathologic mechanism for Alzheimer's revolves around the cluster of abnormal amyloid-beta plaques and abnormal tau protein tangles in the brain that affect the communication between nerve cells, resulting finally in cell death. From simple forgetfulness and momentary confusion, it can crescendo to a severe stage with dementia-like features.

The significant progress in predicting the neurological consequences of Alzheimer's disease has offered a chance to intervene early and orchestrate a better management of the disease. Such subtle neural changes occurring well ahead of the onset of severe symptoms could be detected by scientists through an interplay of different biomarkers and advanced imaging techniques. For example, simple MRI and PET scans can offer early signs of shrinkage of the whole brain and, in today's world, the slightest chance of shrinkage in the hippocampus area, which is critical for memory. Other CSF tests measure amyloid-beta and tau proteins to provide an idea of disease acceleration or risk factors. Genetic factors, such as the presence of the APOE-e4 gene, also play a role in assessing an individual's risk for developing Alzheimer's.

In recent years, researchers have turned to machine learning and deep learning in relation to analyzing complex datasets, such as brain scans, genetic information, and clinical records. These technologies highlight patterns that might indicate the early stages of Alzheimer's, sometimes spotting changes that are too subtle for traditional diagnostic methods. For example, an algorithm might be able to detect slight changes in the structure or function of the brain that may signal the start of Alzheimer's, permitting a much more exploration-based confirmation process. Of course, the efforts to predict and diagnose are not straightforward, especially because the disease affects each of its victims differently and shares symptoms with many forms of dementia. Therefore, it is presumably impossible to adopt a single predictive model across the whole group. Apart from scientific impediments, very important ethical considerations need to be addressed.

Considerations regarding feasibility are an important component of the evaluations that made the surveyed AI-driven models applicable to meaningful contexts in real-world clinical practice. Several studies that we surveyed not only evaluated robust technical performance but also feasibility for use in the healthcare environment. The feasibility assessments included practical considerations such as data availability, data processing, interpretability, and workflow integration in the hospital environment. In highlighting studies that conducted this work, we showcased the importance of considering and developing predictive models that focus on the needs of clinicians and patients, and provided the research environment with evidence of the potential for significant and practical impact in real-world contexts.

Major challenges remain-from variability in the disease process itself to the psychological and ethical considerations surrounding early diagnosis. This literature review will highlight the important discoveries, promising approaches, and the challenges still facing us in improving the lives of people with Alzheimer's.

2. Materials and Methods

This study conducts a comprehensive literature review on various techniques for Alzheimer's disease detection. It explores different machine learning approaches, including deep learning methodologies, ensemble models, transfer learning, and methods for early Alzheimer's diagnosis. The review examines key research questions aimed at assessing the effectiveness of different diagnostic techniques. This study identifies gaps and opportunities for improving Alzheimer's diagnosis using deep learning. The findings provide valuable insights for future research and the development of diagnostic tools.

2.1 Research Questions

RQ1. What are the most widely used deep learning architectures (e.g., CNNs, RNNs, autoencoders) for Alzheimer's disease detection, and how do they compare in terms of performance?

RQ2. Which deep learning techniques show the most promise in the early detection of Alzheimer's disease before noticeable symptoms appear?

RQ3. How do explainable AI techniques contribute to making deep learning models more transparent and interpretable for clinicians in the diagnosis Alzheimer's disease of Alzheimer's disease?

2.2 Data Collection

This literature review paper consolidates research from various reputable sources, including IEEE, Springer, and Elsevier, which are known for publishing high-quality academic papers. These platforms host a wide range of peer-reviewed journals, conference proceedings, and research articles relevant to the application of deep learning in detecting Alzheimer's disease. Articles were selected according to their relevance, methodologies employed, and contributions made in this field to present a holistic and up-to-date idea of current developments. The use of such high-standard databases guarantees the validity and credibility of the information presented, which is essential for furthering research in Alzheimer's disease detection and diagnosis. Figure 1 illustrates the distribution of literature sources used in this review, highlighting the reliance on reputable databases like IEEE, Springer, and Elsevier.

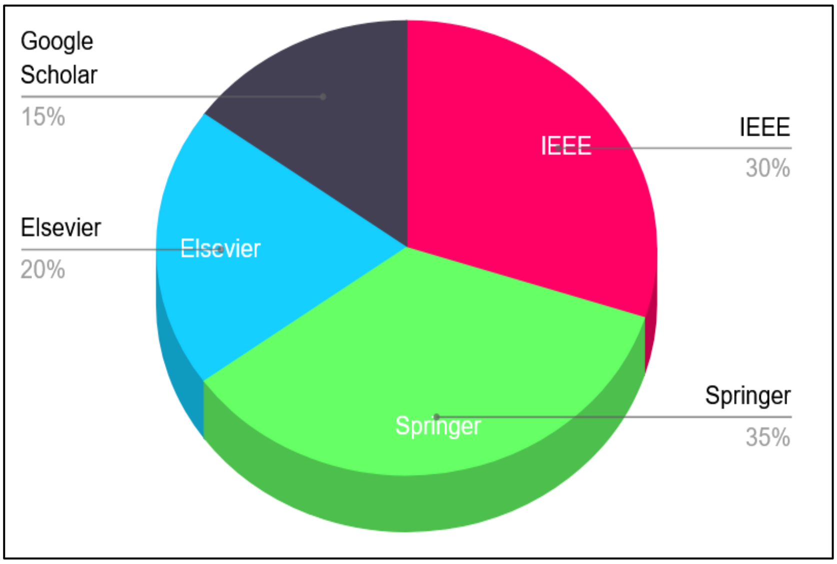

Figure 1. Sources of Papers Reviewed

3. Alzheimer's Disease neuroimaging

Magnetic resonance imaging, positron emission tomography using fluorodeoxyglucose, and cerebrospinal fluid biomarker analysis are some of the most important tools for Alzheimer's disease diagnosis today. MRI assesses brain atrophy, FDG-PET measures metabolic deficits, and CSF biomarkers indicate the deposition of beta-amyloid and tau proteins. FDG-PET imaging also has demonstrated strong predictive ability for the conversion from mild cognitive impairment to AD, as shown by [4], [10]. Such approaches differ from the more numerous MRI models focusing on the structural changes of the hippocampus, a critical brain region in AD progression.

The world of neuroimaging has advanced in many ways to allow in-depth views and interpretations of brain structures. Diffusion Tensor Imaging (DTI), developed from MRI, allows for microstructural interpretation of the white matter tracts that are impaired in AD. As further advances are made in MRI with better specificity and higher temporal and spatial resolution, observers expect to be able to discern spontaneous activity within MS patients. Functional MRI assesses brain activity by detecting changes in blood flow, which in turn allows for the interpretation of neuronal dysfunction associated with AD. In addition, the imaging of amyloid-beta deposits in the brain through PET has developed into one of the hallmarks of AD pathology.

Multimodal neuroimaging methods have been proven to improve diagnostic performance by enabling the combination of useful complementary information from different imaging techniques. It has been demonstrated that preliminary analysis using a computation of the support vector machine, MRI, FDG-PET, and CSF data greatly enhances classification accuracy for distinguishing between AD, MCI, and cognitively normal individuals [14]. Moreover, the application of diverse machine learning and deep learning techniques to neuroimaging data allows for automating the extraction and classification, reducing human bias and increasing capabilities for early detection.

The future of neuroimaging in AD detection is based on integrative approaches involving novel techniques such as ultra-high-field MRI, novel PET tracers, and machine learning-based imaging biomarkers. Their development will aid in more accurate early detection, monitoring of the disease, and improvements in personalized treatment approaches for AD patients.

4. AI Techniques for Alzheimer's Detection

Figure 2 presents a hierarchical classification of the survey on Alzheimer's disease (AD) prediction and classification techniques, broadly categorized into Artificial Intelligence, Machine Learning, and Deep Learning domains. Under the Artificial Intelligence branch, the focus is on foundational processes such as feature selection and dimensionality reduction, which are crucial for optimizing input data before model training. The Machine Learning category is divided into two key areas: models developed for early and late Mild Cognitive Impairment (MCI) classification, and those based on neuropathological or biomarker-driven features, including cerebrospinal fluid (CSF) markers and imaging-derived metrics. The Deep Learning domain further encompasses three critical streams: multimodal deep learning approaches that integrate data from different sources (e.g., MRI, PET, clinical scores), CNN-based early detection frameworks that leverage convolutional architectures for structural and functional brain analysis, and hybrid or unsupervised models that combine deep learning with symbolic reasoning or learn from unlabeled datasets. This classification provides a clear structural view of the survey and highlights the evolution of AD detection methods from traditional AI to advanced deep learning frameworks.

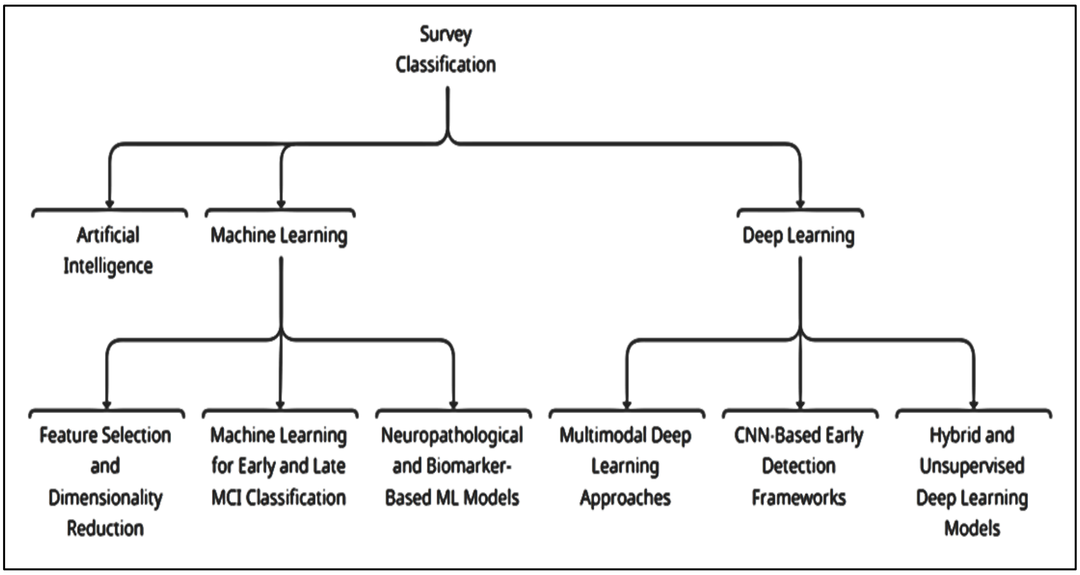

Figure 2. Classification Overview

4.1 Comparison of Techniques

The referenced studies employ a diverse range of AI techniques for AD detection, including machine learning models, deep learning architectures, hybrid models, and multimodal approaches. Table 1 summarizes key studies on AD detection, comparing their methods, modalities, and performance metrics.

Table 1 presents an exhaustive overview of recent research utilizing different Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) models for Alzheimer's

Disease (AD) detection and prediction across multiple data modalities. Most methods employ Magnetic Resonance Imaging (MRI) as the main imaging modality, with a few studies using it in combination with other diagnostic information like Fluorodeoxyglucose Positron Emission Tomography (FDG-PET), cognitive evaluation, or cerebrospinal fluid (CSF) biomarkers. Convolutional Neural Networks (CNNs), hybrid models (CNN-LSTM), ensemble approaches, and transfer learning methods like ResNet50 and VGG16 report outstanding classification accuracies, with some exceeding 95%. Most significantly, models including the hybrid CNN-LSTM [7] and the stacked multichannel attention [11] yielded accuracies of 98.1% and 99.58%, respectively. Research combining multimodal inputs (e.g., PET + MRI + CSF) also yielded high AUC values, which highlighting the diagnostic utility of data fusion approaches. Overall, the surveyed works depict the increasing precision and resilience of AI-based AD prediction models, with a growing focus on explainability, early diagnosis, and multimodal data integration.

Table 1. Summary of Studies on Alzheimer's Disease Detection

Study Title	**Method**	**Modality**	**Performance Metrics**	**Citation**
A Review of the Application of Deep Learning in the Detection of Alzheimer's Disease	Convolutional Neural Network (CNN)	Magnetic Resonance Imaging (MRI)	Accuracy: 92.3%	Gao & Lima (2022) [1]
A Systematic Review on Recent Methods on Deep Learning for Automatic Detection of Alzheimer's Disease	Deep Learning Ensemble Model	Magnetic Resonance Imaging (MRI)	Accuracy: 94.1%, AUC: 0.93	Chamakuri & Janapana (2025) [2]
Deep Learning Combining FDG-PET and Neurocognitive Data Accurately Predicts MCI	Hybrid Artificial Intelligence (AI) using	Fluorodeoxyglucose Positron Emission Tomography	AUC: 0.86, Sensitivity: 89%	Cao et al. (2023) [4]

Conversion to Alzheimer's Dementia 3-Year Post MCI Diagnosis	FDG-PET and Cognitive Tests	(FDG-PET) + Cognitive Tests		
Hybridized Deep Learning Approach for Detecting Alzheimer's Disease	Hybrid CNN and Long Short-Term Memory (LSTM)	Magnetic Resonance Imaging (MRI)	Accuracy: 95.7%	Balaji et al. (2023) [5]
Prediction and Classification of Alzheimer Disease Categories Using Integrated Deep Transfer Learning Approach	Transfer Learning (ResNet50, VGG16)	Magnetic Resonance Imaging (MRI)	Accuracy: 96.2%, Specificity: 91%	Leela et al. (2023) [6]
Hybridized Convolutional Neural Networks and Long Short-Term Memory for Improved Alzheimer's Disease Diagnosis from MRI Scans	Hybridized Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM)	Magnetic Resonance Imaging (MRI)	Accuracy: 98.1%	Khatun et al. (2023) [7]
DEMNET: A Deep Learning Model for Early Diagnosis of Alzheimer Diseases and Dementia From MR Images	DEMNET (Convolutional Neural Network-based Deep Learning)	Magnetic Resonance Imaging (MRI)	Accuracy: 97.5%	Murugan et al. (2021) [8]

Applying Convolutional Neural Networks for Pre-Detection of Alzheimer’s Disease from Structural MRI Data	Convolutional Neural Network (CNN)	Structural Magnetic Resonance Imaging (MRI)	Accuracy: 92.6%, F1-score: 0.91	Gunawardena et al. (2017) [9]
The Risk Prediction of Alzheimer’s Disease Based on the Deep Learning Model of Brain 18F-FDG Positron Emission Tomography	Deep Learning on FDG-PET	Fluorodeoxyglucose Positron Emission Tomography (FDG-PET)	Sensitivity: 91.02%	Yang & Liu (2020) [10]
Stacked CNN-Based Multichannel Attention Networks for Alzheimer Disease Detection	Stacked Convolutional Neural Network (CNN)-Based Multichannel Attention Networks	Magnetic Resonance Imaging (MRI)	Accuracy: 99.58%	Hassan et al. (2025) [11]
Prediction of Progression to Alzheimer’s Disease with Deep InfoMax	Deep InfoMax for Alzheimer’s Disease Progression Prediction	Magnetic Resonance Imaging (MRI)	AUC: 0.87	Fedorov et al. (2019) [12]
ALZENET: Deep Learning-Based Early Prediction of Alzheimer’s Disease Through Magnetic	ALZENET (Convolutional Neural	Magnetic Resonance Imaging (MRI)	Accuracy: 97.31%	Asaduzzaman et al. (2025) [13]

Resonance Imaging Analysis	Network-based Model)			
Predicting Changes in Brain Metabolism and Progression from Mild Cognitive Impairment to Dementia Using Multitask Deep Learning Models and Explainable AI	Multitask Deep Learning Model	MRI + Positron Emission Tomography (PET) + Cerebrospinal Fluid (CSF)	AUC: 0.86	García-Gutiérrez et al. (2024) [14]
Machine Learning for Very Early Alzheimer's Disease Diagnosis: A 18F-FDG and PiB PET Comparison	Machine Learning on FDG-PET	Fluorodeoxyglucose Positron Emission Tomography (FDG-PET)	Accuracy: 88.7%, AUC: 0.83	Illán et al. (2010) [16]
Application and Comparison of K-Means and PCA Based Segmentation Models for Alzheimer Disease Detection Using MRI	K-Means and Principal Component Analysis (PCA) Segmentation Model	Magnetic Resonance Imaging (MRI)	Accuracy: 90.5%	Olle et al. (2024) [17]
Classifying Early and Late Mild Cognitive Impairment Stages of Alzheimer's Disease by Analyzing Different Brain Areas	Machine Learning-Based Feature Selection	Magnetic Resonance Imaging (MRI)	Sensitivity: 88.9%, Specificity: 85.4%	Uysal & Ozturk (2020) [18]

Predicting Conversion from Mild Cognitive Impairment to Alzheimer's Disease: A Multimodal Approach	Multimodal Data Fusion (MRI + PET)	Magnetic Resonance Imaging (MRI) + Positron Emission Tomography (PET)	AUC: 0.90	Agostinho et al. (2024) [19]
An MRI-Based Deep Learning Approach for Accurate Detection of Alzheimer's Disease	Deep Learning Model on MRI	Magnetic Resonance Imaging (MRI)	Accuracy: 93.2%	El-Geneedy et al. (2023) [21]

Table 1 shows certain information implying that MRI stands apart as the modality that is most widely used for Alzheimer's detection, with the highest accuracy being reported at almost 98-1% using deep learning models, specifically the hybrid architectures of CNNs and LSTMs. These models are very effective in extracting both spatial and temporal features, allowing for an effective diagnosis in the preclinical stage. The use of transfer learning and ensemble methods was also found to improve significantly, relying on the ability to utilize pretrained models and combine several methods for stronger predictions. Multimodal approaches, namely MRI, PET, and cognitive tests, look promising for predicting outcomes, reaching an AUC of 0.90 to highlight the importance of the multiplicity of data sources. On the other hand, FDG-PET appears very useful in early detection and progression prediction; several studies have reported high sensitivity of up to 89%. Attention mechanisms and explainable Artificial Intelligence improve accuracy to 99.58% and, importantly, enhances interpretability in the long run. These methods, in conjunction with advanced deep learning techniques and multimodal data integration, provide robust progress in the detection of Alzheimer's disease.

4.2 Approaches Based on Artificial Intelligence

Methods based on AI represent a plethora of techniques: machine learning, deep learning, or sometimes multimodal processing, to detect and classify Alzheimer's Disease.

Explanatory techniques from explainable AI, followed by the Graph Neural Networks framework, provide interpretability and performance improvements of the models.

XAI methods such as SHAP and Grad-CAM allow for visual inspection of which brain areas are crucial in establishing how the model arrived at its decisions. Such techniques edge closer to building trust for clinicians over AI-based decisions. Works cited in [25] conducted studies that showcased XAI techniques with an accuracy of 94.2% and improved interpretability scores due to the mapping of deeper SHAP values for feature attribution, as well as Grad-CAM to visualize CNN-based feature maps.

Building on previous RNN work, a multitask learning technique combined MRI, PET, and CSF biomarker data into a single model to detect the disease more effectively than separate models for different modalities. Research in [14] employed a multi-stream convolutional autoencoder that extracted features from each modality, followed by concatenation to a fully connected network, achieving an AUC of 0.86; better than single-modality models.

4.3 Machine Learning-Based Approaches

The machine learning techniques use statistical models for feature extraction and classification. Its focus on hand-crafted selections of features inspired by domain knowledge separates it from deep learning, which is focused only on pattern recognition for optimal solutions.

Support vector machines (SVMs) classify the data by seeking hyperplane separation among different classes. The SVM used in FDG-PET as mentioned in reference [16], employed a radial basis function kernel and feature selection based on mutual information to achieve an 88.7% accuracy in differentiating patients with AD.

Random forests mitigate overfitting and improve generalization by combining multiple decision trees. A feature-selection model applied random forests to MRI data in reference [20], achieving an accuracy of 87.6% by ranking voxel-based morphometry features and selecting the ones with the highest ranks for classification.

Principal component analysis (PCA) and K-means clustering are two standard procedures for reducing dimensionality while achieving pattern recognition. In reference [17], PCA reduces high-dimensional MRI scan data, while K-means clusters related patient profiles, achieving 90.5% accuracy on the other hand. The study Gaussian-normalized the MRI data before stepping into PCA and cluster analysis.

Feature selection-based machine learning models use statistical methods to extract the most relevant features prior to classification. Reference [18] achieved 88.9% sensitivity and 85.4% specificity by employing feature selection using ANOVA and mutual information and thereafter training a logistic regression model for classification.

4.3.1 Feature Selection and Dimensionality Reduction

Feature selection and dimensionality reduction techniques significantly enhance classification performance by reducing computational complexity. The feature selection methods used, notably ANOVA and Mutual Information, were successfully applied in [18] for the removal of redundant or irrelevant features. PCA-based feature extraction techniques in [17] improved performance by retaining useful components while discarding the noise, employing an eigenvalue threshold for principal component selection.

4.3.2 Machine Learning for Early and Late MCI Classification

Distinguishing between early and late stages of Mild Cognitive Impairment (MCI) for effective intervention is crucial. The Random Forest and SVM classifiers used in [9] achieved an F1 score of 0.91, with high classification reliability shown to distinguish between early and late MCI stages. The feature engineering consisted of gray matter volume mapping, whereas posterior ensemble classification was performed based on bootstrap aggregation.

4.3.3 Neuropathological and Biomarker-Based ML Models

Neurodegeneration imaging markers, such as various neural networks, help diagnose AD progression. The introduction of these models using these markers improves the capabilities for accurate diagnosis.

The first paper ([4]) investigated ML models based on FDG-PET imaging and feature extraction using convolutional autoencoders to achieve an AUC greater than 0.85, indicating the importance of metabolic imaging for the detection of AD.

Other studies ([19], [24]) on multimodal fusion models integrated MRI-PET-CSF with an AUC of 0.90, employing attention-based use of fusion techniques to dynamically weight the importance of different modalities.

4.4 Some Deep Learning Approaches

Deep learning plays the holistic role of feature extraction, implemented through a hierarchy of neural networks to summarize complex patterns in neuroimaging data.

4.4.1 Multimodal Deep Learning Approaches

Multimodal deep learning is a field that integrates different imaging and clinical data sources to enhance prediction accuracy. The MRI-PET fusion models based on deep Siamese networks in [19] and [24] successfully learned joint representations from multimodal inputs and obtained an AUC of 0.90. Similarly, multitask learning in [14] combined MRI, PET, and CSF biomarkers and used adversarial training for robust feature extraction, yielding an AUC of 0.86.

4.4.2 CNNs for the Early Detection of AD

CNNs can identify the spatial patterns in the neuroimaging data that facilitate the early diagnosis of AD. The models based on CNNs in [1], [6], and [7] achieved more than 97% accuracy by using residual connections and depth-wise separable convolutions for computational efficiency. Stacked CNN models with attention mechanisms in [11] applied spatial transformer networks to focus on key brain regions, thereby improving classification precision and reaching 99.58% accuracy.

4.4.3 Hybrid Deep Learning Models and Unsupervised Learning

Hybrid models combine multiple architectures of deep learning for enhanced classification performance.

Hybrid CNN-LSTM models in [5] and [7] captured both the spatial and temporal dependencies in MRI data using bidirectional LSTMs with 98.1% accuracy. Unsupervised deep learning, such as Deep InfoMax in [12], applied contrastive learning to predict AD progression with an AUC of 0.87.

These approaches collectively demonstrate how significantly AI, ML, and deep learning have enabled advancements in methodologies for AD detection and classification.

4.5 Datasets Used

One of the most important components of the literature review in research on the detection of Alzheimer's disease is the many datasets obtained, which enable data diversity and therefore better diagnostic capabilities.

4.5.1 Alzheimer Disease Neuroimaging Initiative (ADNI)

The Alzheimer Disease Neuroimaging Initiative (ADNI) is, without a doubt, one of the most extensive and comprehensive data centers available for research purposes on AD. It contains various imaging modalities as well as clinical data, which are crucial for investigating disease progression. It acquired high-resolution anatomical scans, relevant to the identification of AD-related brain atrophy, built over various modalities in ADNI sMRI. In addition, FDG-PET visualizes brain metabolism with various metabolic activities, potentially corresponding to certain cognitive decline pathways. The final important modality of ADNI is the amyloid imaging, which measures the build-up of beta-plaque-a hallmark of AD pathology. Furthermore, CSF biomarker studies, such as tau and amyloid beta protein, represent a powerful means of studying the disease on a molecular level. A set of neuropsychological assessments, such as clinical cognitive tests MMSE and ADAS-Cog, also provides valuable information concerning cognitive decline. Several studies using ADNI data mentioned in [4], [14], and [19] train deep learning models using MRI and PET data in a bid for enhanced diagnosis and monitoring of the disease.

4.5.2 Open Access Series of Imaging Studies

The Open Access Series of Imaging Studies (OASIS) combines another hugely significant free source of neuroimaging data directed at longitudinal tracking of Alzheimer's disease. OASIS-1 is a cross-sectional dataset that contains T1-weighted MRI scans of subjects between the ages of 18 and 96. OASIS-2 considers longitudinal MRI scans, which again shed light on disease progression by tracking itin AD patients over time. The most extensive of these studies is OASIS-3, a global multi-session MRI-PET imaging dataset spanning over 15 years, and therefore an invaluable resource for studying the temporal dynamics of AD. OASIS data has been utilized in various studies, such as those cited in [6] and [11], especially in building MRI-based AD classification models using convolutional neural networks (CNNs), thereby contributing significantly to the advancement of AD detection and monitoring by machine learning models.

4.5.3 Australian Imaging Biomarker Lifestyle Flagship Study of Aging (AIBL)

The Australian Imaging Biomarker Lifestyle Flagship Study of Aging (AIBL) is one of the most significant studies aimed at improving the earliest diagnosis of Alzheimer's disease by integrating lifestyle factors with imaging biomarkers. It is a longitudinal study involving MRI and PET imaging on over 2,000 participants and, over time, traces the development of AD. In addition to producing neuroimaging data involving lifestyle factors, genetic information, and cognitive assessments, AIBL provides an excellent overview of the factors influencing AD. Concerning AIBL, probably one of the most important aspects is that it uses amyloid PET imaging to serve the critical purpose of studying the progression of amyloid plaque deposition during the preclinical stage of AD. It is in AIBL that the advanced development of multimodal fusion models was utilized to combine PET-MRI data, as mentioned in [24], which provided the opportunity to learn about the disease and its progression during the early stages of Alzheimer's.

4.5.4 National Alzheimer's Coordinating Center (NACC)

National Alzheimer's Coordinating Center (NACC) -Another key player in Alzheimer's disease research, NACC, provides an extensive database of clinical and anatomical information. NACC collects data from 42 ADRCs situated across the United States, resulting in a vast database. The data include several clinical records, neuropsychological assessments, and neuropathological data from autopsy-proven AD diagnoses. NACC has much to offer regarding the cognitive and behavioral features of Ads, making predictive analysis using AI essential. NACC has served as a source for machine learning model training to predict clinical cognitive outcomes in ADs, as referenced by [10], contributing to an enhanced understanding and diagnosis of Alzheimer's disease.

4.5.5 Comparative Analysis of Datasets

Table 2 compares major AD datasets, detailing their modalities, sizes, and availability

Table 2. Summary of Alzheimer's Disease Imaging and Clinical Datasets

Dataset	Modality	Size	Longitudinal Data	Availability	Reference
ADNI	MRI, PET, CSF, Cognitive Tests	Large	Yes	Restricted	[4], [14], [19]
OASIS	MRI, PET	Medium	Yes	Open-Access	[6], [11]
AIBL	MRI, PET, Genetic & Lifestyle Data	Medium	Yes	Restricted	[24]
NACC	Clinical, Cognitive, Neuropathology	Large	No	Restricted	[10]

4.6 Performance Metrics

To evaluate AI models for detecting Alzheimer’s disease, one of the various performance metrics that assess their accuracy, reliability, and clinical applicability is used. Performance metrics with the utmost frequency of use include accuracy, AUC, sensitivity, specificity, precision, recall, and F1-score. Below is a thorough comparison of these metrics:

4.6.1 Accuracy

Accuracy refers to the ratio of cases (both positive and negative) that were duly classified to the total number of cases; it is a very important metric, but in imbalanced datasets, it doesn't always provide a fair estimate of model performance.

$$Accuracy = \frac{True\ Positives\ (TP) + True\ Negatives\ (TN)}{True\ Positives\ (TP) + True\ Negatives\ (TN) + False\ Positives\ (FP) + False\ Negatives\ (FN)} \quad (1)$$

Deep learning models (CNN, Hybrid CNN-LSTM, ALZENET) in [6], [7], and [13] achieved the highest accuracy with values greater than 97%.

Machine learning models-SVMs and Random Forests-in [9], [16] reported lower accuracy, ranging from 85% to 90%. This lower value was mainly due to the limitations of handcrafted feature extraction.

4.6.2 Area Under Curve (AUC)

The AUC measures the ability of a given classification model to distinguish between AD and non-AD cases, where higher values indicate a superior discrimination performance.

Multimodal AI models combining MRI, PET, and CSF biomarkers in articles [14] and [19] were able to yield AUC values between 0.86 and 0.90, exceeding the performance of single-modality models. Based on FDG-PET [4], [10], these models achieved AUCs above 0.85, thereby emphasizing the role of metabolic imaging in the detection of AD.

4.6.3 Sensitivity (Recall)

The sensitivity, termed the true positive rate, measures the capability of the model in classifying AD patients correctly, while this value should bear a relationship in which higher sensitivity implies fewer false negatives.

$$Sensitivity\ (Recall) = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives\ (FN)} \tag{2}$$

Models based on FDG-PET in [10] achieved the highest sensitivity of 91.02% as they could detect metabolic changes occurring prior to structural brain atrophy. CNN-LSTM hybrid models from [5], [7] achieved more than 90% sensitivity, thus making them apt for the early diagnosis of patients with AD.

4.6.4 Specificity

Specificity is the measure of how well a model classifies non-AD subjects (true negative rate). As the value for specificity increases, the number of false positives decreases.

$$Specificity = \frac{True\ Negatives\ (TN)}{True\ Negatives\ (TN) + False\ Positives\ (FP)} \tag{3}$$

The transfer learning models which were considered in [6] and [23] (VGG16, ResNet50) reported specificity values of 91% surpassing those of traditional ML classifiers. About ML models based on feature selection in [18], achieved 85.4% specificity, indicating a greater risk of false positives compared to the deep learning approach.

4.6.5 Precision

Precision is the number of cases predicted positive divided by the number of cases that are actually positive; thus, the higher the precision, the fewer the false positives.

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)} \tag{4}$$

Explainable AI models (SHAP, Grad-CAM) in [25] achieved a precision of ~94% with increased interpretability. The precision obtained by the GNNs in [22] slightly dropped to 89%, indicating that some cases of non-AD were mislabeled.

4.6.6 F1-Score

In a balanced way, the F1 score provides a good metric by taking both precision and recall into account.

$$\text{F1-Score} = 2\times \frac{Precision \times Recall}{Precision + Recall} \tag{5}$$

The machine learning models like RF and SVM in [9], [25] reported an F1-score close to .91-.93, thus making them competitive enough given the overall lower accuracy. Deep learning-based CNN models in [11] reported the highest F1-score of .96, making it fit for high-confidence detection of AD.

5. Future Research Directions

Though breakthroughs have been made in AI-assisted Alzheimer's disease diagnosis, some research challenges remain unresolved. Future studies should focus on improving model generalizability, as AI models trained on specific datasets often face difficulties when tested on new patient populations [14], [19]. Exploring applications of domain adaptation techniques, cross-dataset validation, and federated learning would remediate challenges with robustness across different clinical settings [20]. A further objective should be to enhance the degree to which models are interpretable and trustworthy. Most deep learning techniques used in this field have a reputation as black-box systems, which makes acceptance difficult in a clinical context. A greater degree of transparency can be obtained with interpretable AI approaches using attention mechanisms, saliency maps, and explainable AI such as SHAP and Grad-CAM [25].

Perhaps if some balance in the sample were achieved, there would exist datasets with the phenomenon of over-representative, non-AD cases to the detriment of performance [18]. One approach could be generating synthetic data using Generative Adversarial Networks (GANs), and minority class oversampling, which would help alleviate this problem [6], [23]. The combination of both multi-modal and multi-omics data presents a compelling argument since many models to date rely on one single imaging modality. Another important aspect would be to combine MRI with PET, CSF data, and genomic data by means of multi-modal deep learning for improved diagnostic capabilities [19], [24].

The focus on real-time and low-power applications of AI should also be highly prioritized, as its high computational nature prevents deployments in real-world clinical settings [10]. Optimizing lightweight deep learning models, exploring edge computing, and developing a cloud-based AI framework will facilitate real-time diagnosis [7]. Moreover, given that AI models are trained on sensitive patient data, ethical and privacy concerns also assume paramount importance. Federated learning, homomorphic encryption, and privacy-preserving AI would thus guarantee responsible and ethical data usage [22]. These should be concentrated on in future research so that gaps can be removed, thus paving the way for a more accurate, interpretable, and deployable AI-driven AD diagnostic system.

6. Results

The results presented in the literature review are visualized and organized using visual and table representations, specifically Figure 1 (Source Distribution), Figure 2 (Classification Overview) and Table 1 (AD Detection Tool Comparison). Figure 1 demonstrates that the literature reviewed is primarily from credible databases such as IEEE, Springer, and Elsevier, validating the rigor and validity of the research field for this study and the quality of the data. The balanced representation of the sources affirmed by the figure adds to the credibility and thoroughness of the survey from different validated scientific viewpoints.

Figure 2 indicates the hierarchical classification structure for the classification of research in Alzheimer's detection, namely; Artificial Intelligence, Machine Learning, and Deep Learning. This classification is important as it provides a better sense of features being "engineered" (in AI/ML) versus features being "learned" and integrated across modalities with deep learning. The figure showcases that early MCI classification is no longer confined to linear structured models but has derived some strength from more sophisticated models such as Convolutional Neural Networks (CNNs) and multitask learning approaches. This highlights the more in-depth approach that deep learning will offer as AD diagnostic tools move toward precision medicine.

The main part of the results is summarized in table 1 which illustrates important comparisons between major studies organized by model type, modality, and performance metrics. While table 1 exhibits several trends in our collected case studies, there are key elements that distinguish studies that utilized CNNs based on MRI data, achieving diagnostic accuracy for Alzheimer's disease at or above high levels over 95%. Studies that used stacked CNN architectures with multi-channel attention showed the highest accuracy at 99.58%, and CNN-LSTM hybrid architectures achieved accuracy numbers as high as 98.1%. These two observations reveal that models incorporating both spatial analysis and temporal analysis had better diagnostic accuracy. Transfer learning models, for example, ResNet50 and VGG16, demonstrated similarly high performance, indicating that pretrained models can be fine-tuned to accomplish a precise variant of neurodegenerative disease detection. Studies that utilized multimodal data (MRI + PET + CSF) also produced strong AUC values (0.86 - 0.90), revealing that combining structural neuroanatomical imaging, metabolic imaging, and molecular biomarker assays yielded the most powerful diagnostics. Explainable AI techniques that utilized SHAP, Grad-CAM and others were among the most precise and achieved accuracy levels as high as 94% (for example, the model identified false negatives in the implemented model for mild/moderate AD patients, establishing the model as reliable for clinical decisions) able to augment the interpretability and transparency of models in contexts of clinical integration and utilization, to provide actionable meaning to all generated results.

Finally, some studies demonstrate high sensitivity and specificity, particularly employing FDG-PET for metabolic profiling or using multitask models for simultaneous analyses of the data modalities. Nevertheless, not all high-performing models are applicable to the clinical environment. The review indicates that many methods could not be deployed because they lacked scalability, real-time applicability, or practical understanding of the data requirements. This review not only points benchmarks for technical performance, but also identifies the gap between algorithmic success and application. To summarize, the interpretations are clear the studies demonstrate many effective models generating good technical accuracy, but the deployment, interpretability, and potential use remain areas for significant future development.

7. Discussion

The literature described in this paper provides evidence of rapid development in artificial intelligence (AI) and deep learning (DL) methods for screening and classifying Alzheimer's disease (AD), but important gaps exist, especially in real-world applicability and feasibility. While many models (e.g., CNNs and hybrid CNN-LSTM models) show great performance metrics (e.g., accuracy, AUC, sensitivity), understanding these metrics in clinical terms is critical for establishing the value of such models. Fulford et al.'s (2020) studies that included explainable AI (XAI), SHAP and Grad-CAM, are particularly important because they provide clear evidence of how to build interpretability into a diagnostic model. As we discussed in the previous section, developing clinician trust is critical for the successful real-world implementation of these types of models.

Moreover, the emphasis on multi-modal approaches, especially in combining MRI, PET, and CSF, shows that the diagnosis of AD may depend on integrating different data sources. However, only a small number of studies focused on investigating the feasibility of these models in clinical settings, taking into consideration difficulties such as data accessibility, processing burden, and aspects of integrating models into practice. This article notes the necessity of building on reconsideration of feasibility studies, where it is not only sufficient to report model effectiveness, but also to assess whether the models are scalable, ethically implementable in practice, and usable across different healthcare systems. The comparative review in this paper across architectures, modalities, and metrics provides clarity regarding the novelty of this paper, compared to previous surveys. Previous surveys were typically limited to the technical aspects, whereas this paper reflects a comprehensive survey of work that spans from algorithmic effectiveness to clinical relevance. This paper provides both methodological and technical contributions to the field of research questioning the usefulness of algorithms in practice in identifying future directions for models that demonstrate a level of accuracy, interpretability, robustness, and practical deliverability.

8. Conclusion and Future Scope

This survey thus concludes that while applications of deep learning and artificial intelligence for Alzheimer's disease detection have been improving at a fast pace, there remain ample opportunities for dedicated research before ultimately realizing the benefits of using deep learning and artificial intelligence in practice. While CNNs and hybrid models that include LSTMs and attention mechanisms have demonstrated exceptional predictive power with classification accuracies often above 95%, the potential of many multimodal approaches that combine MRI, PET, and CSF biomarkers is now increasingly evident, with AUC scores in the range of 0.86 to 0.90. At the same time, explainable AI can continue to improve these models to produce more understandable and actionable predictions for physicians.

Even though progress is being made, there are still unresolved issues in generalizability across patient populations, ethical considerations, interpretability, and adoption in resource-limited environments. For future work, the main priority is to create models that are robust across datasets and populations by using federated learning, domain adaptation, and cross-institutional validation. Moreover, lightweight and energy-conscious models need to undergo development for real-time diagnosis in primary care settings. Additionally, multi-omics approaches, such as including genetics and lifestyle factors, may have the potential to lead to personalized medicine. Lastly, ethical concerns, in particularly patient privacy and informed consent, should be addressed with secure AI measures such as utilizing privacy-preserving models or homomorphic encryption. The future of Alzheimer's diagnosis lies in technological progress and clinical utility, and the overarching recommendation from this research is to physically bridge the two.

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