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A Current Perspective On Machine Learning Approaches For Early Alzheimer's Disease Detection Using Non-Invasive Cognitive Assessments Test Data

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Abstract: Alzheimer's disease (AD) is a progressive neurodegenerative illness that significantly impairs cognitive function, highlighting the need for early and accurate detection to enable timely intervention. Although a lot of research has concentrated on neuroimaging and biomarker-based diagnosis, these methods can be costly and less accessible in many clinical settings. Recent advances in machine learning (ML) have created new opportunities for leveraging clinical assessment data such as cognitive test scores, demographic information, and behavioral measures to detect AD in its early stages. This review synthesizes current developments in ML methodologies applied to noninvasive clinical data for Alzheimer's detection. We discuss a range of both supervised and unsupervised learning models, feature selection strategies, and evaluation metrics used in recent studies. The findings demonstrate that machine learning models trained on clinical and cognitive assessment data can achieve high accuracy in distinguishing early Alzheimer's from healthy aging, presenting a scalable and cost-effective alternative to imaging-based approaches. Challenges associated with data heterogeneity, model generalizability, and interpretability are also addressed, along with future directions for integrating ML into routine clinical screening for Alzheimer's disease.

Keywords: Machine learning, Alzheimer disease, Cognitive assessment test, mild cognitive impairment, Datasets, Transfer learning, Evaluation metrics

1.INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder and the most common cause of dementia, accounting for 60-80% of dementia cases worldwide. Its symptoms, primarily cognitive decline, memory loss, disorientation, and behavioral changes, profoundly affect patients' quality of life and present substantial challenges for caregivers and healthcare systems. With the global population aging rapidly, the number of people living with Alzheimer's disease is projected to triple by 2050, underscoring the urgent need for effective diagnostic tools and early intervention strategies.

Early detection of Alzheimer's disease is vital for several reasons. It enables the timely initiation of pharmacological and non-pharmacological interventions, which can help slow disease progression, manage symptoms, and improve patient outcomes. Moreover, early diagnosis allows patients and families to plan for the future, access support services, and participate in clinical trials for emerging therapies. Despite these benefits, the early and accurate identification of AD remains a significant clinical challenge. Alzheimer's disease typically develops slowly and insidiously, with initial symptoms often mistaken for normal aging or other conditions. As

a result, many individuals are diagnosed at moderate or advanced stages, when therapeutic options are more limited.

Traditional diagnostic methods for Alzheimer's disease include comprehensive clinical evaluations, neuroimaging techniques such as magnetic resonance imaging (MRI) and positron emission tomography (PET), and laboratory analyses of cerebrospinal fluid biomarkers. While these approaches can be highly informative, they are not without limitations. Neuroimaging and biomarker analyses are often expensive, invasive, and require specialized equipment and expertise, making them less accessible in primary care and resource-constrained settings. Moreover, these methods may not always detect subtle cognitive changes that occur in the earliest stages of the disease.

Cognitive assessments, on the other hand, represent a non-invasive, cost-effective, and widely applicable alternative for evaluating individuals at risk for Alzheimer's disease. Standardized neuropsychological tests—such as the Mini-Mental State Examination (MMSE), Montreal Cognitive Assessment (MoCA), and Alzheimer's Disease Assessment Scale-Cognitive Subscale (ADAS-Cog)—are commonly used to measure various cognitive functions, including memory, attention, language, executive function, and visuospatial skills. These assessments form an integral part of the diagnostic process and are used both in clinical practice and research settings to monitor disease progression.

However, despite their clinical utility, traditional cognitive assessments face several challenges. Test outcomes can be influenced by a variety of factors, such as an individual's education, cultural background, language proficiency, and comorbid conditions. Additionally, the interpretation of test results often relies on cutoff scores or qualitative judgments, which may not capture subtle cognitive changes characteristic of early-stage Alzheimer's disease. This inherent subjectivity and variability have prompted researchers to seek more objective, data-driven approaches to cognitive assessment interpretation.

Advances in machine learning (ML) have generated renewed interest in leveraging cognitive assessment data for Alzheimer's disease detection. Machine learning, a subfield of artificial intelligence, encompasses a range of computational techniques designed to learn patterns from data and make predictions or decisions without explicit programming. ML algorithms—ranging from traditional classifiers like logistic regression and support vector machines to complex deep learning architectures—have demonstrated remarkable success in biomedical applications, including disease diagnosis, prognosis, and biomarker discovery.

The application of machine learning to cognitive assessment data offers several advantages. By analyzing multidimensional and longitudinal test data, ML models can uncover complex, non-linear relationships that may elude conventional statistical analyses. These models can automate the interpretation of cognitive assessments, reduce human error and bias, and potentially provide individualized risk predictions for Alzheimer's disease. Furthermore, ML techniques can integrate cognitive scores with other data types—such as demographic, genetic, or imaging data—to improve diagnostic accuracy and enable more personalized clinical decision-making.

In recent years, a growing body of research has explored the utility of machine learning methods for Alzheimer's disease detection based on cognitive assessment data. Studies have applied a variety of algorithms, including decision trees, random forests, support vector machines, k-nearest neighbors, and artificial neural networks, to classify individuals as cognitively normal, mildly cognitively impaired, or having Alzheimer's disease. These studies have utilized publicly available datasets, such as those from the Alzheimer's Disease Neuroimaging Initiative (ADNI) and other longitudinal cohort studies, as well as data collected in clinical settings. Reported outcomes suggest that ML models can achieve high levels of sensitivity and specificity, often surpassing traditional cutoff-based approaches.

Despite these promising findings, challenges remain in translating machine learning approaches from research to clinical practice. Issues such as small sample sizes, heterogeneous data sources, lack of external validation, and potential overfitting can limit the generalizability and robustness of ML models. Interpretability and transparency are also critical concerns, as clinicians require clear explanations of model predictions to inform their decision-making. There are also ethical and privacy considerations regarding the use of patient data in model training and deployment.

This systematic review aims to provide a comprehensive and up-to-date overview of machine learning approaches for Alzheimer's disease detection using cognitive assessment data. We summarize the different types of cognitive assessments employed, discuss the various ML algorithms implemented, and examine the datasets, feature selection methods, and validation strategies used in recent studies. We also critically evaluate the

performance metrics reported, highlight the strengths and limitations of current approaches, and discuss key challenges in this evolving field.

Ultimately, this review seeks to inform researchers, clinicians, and policymakers about the current state of the art in machine learning-based Alzheimer's detection using cognitive data. By synthesizing the existing literature, we aim to identify gaps in current knowledge, suggest directions for future research, and contribute to the ongoing effort to improve early diagnosis and patient outcomes in Alzheimer's disease.

2. Review Protocol and Methodology

This section outlines the detailed review protocol and methodology employed to conduct in this systematic review. Our approach is designed to ensure a comprehensive and objective analysis of the existing literature. The process begins with the formulation of specific research questions that guide our investigation into the use of machine learning for the early detection of Alzheimer's Disease (AD) using clinical assessments.

The answers to these research questions are derived from a thorough examination of relevant papers published in academic databases. A strict search strategy is followed to identify the most pertinent studies. The initial search is conducted on key databases such as PubMed, Scopus, and Web of Science using a combination of keywords, including "Alzheimer's disease clinical assessment," "early detection with machine learning," and " Early Detection of Alzheimer's."

2.1 Search Strategy

A comprehensive literature search was conducted to identify relevant studies focusing on the application of machine learning techniques to cognitive assessment data for Alzheimer's disease detection. Electronic databases including ACM, Academia, PubMed, ArXiv, Scopus, Web of Science, and IEEE Xplore were systematically searched for articles published up to 2025. The search terms combined keywords related to Alzheimer's disease ("Alzheimer's disease," "dementia," "cognitive impairment"), machine learning ("machine learning," "artificial intelligence," "deep learning," "classification," "prediction"), and cognitive assessments ("cognitive test," "neuropsychological assessment," "MMSE," "MoCA," "ADAS-Cog," etc.). Boolean operators (AND, OR) were used to refine the search. Additional studies were identified by screening the reference lists of relevant papers and reviews [4]. The records identified by searching as on 01/08/2025 with the keywords in each journal are given in table 1.

Table 1: Number of records found for each query in journal search engines as on from 2020-2025.

Search Engine	Keywords	Number of Records Found
Google Scholar	Alzheimer's disease assessment data	19000
	Early Detection of MCI to AD Conversion Using Machine Learning	17700
	Early Detection of Alzheimer's	16900
Pubmed	Alzheimer's disease assessment data	8000
	Early Detection of MCI to AD Conversion Using Machine Learning	750
	Early Detection of Alzheimer's	7014
IEEE Xplore	Alzheimer's disease assessment data	401
	Early Detection of MCI to AD Conversion Using Machine Learning	190
	Early Detection of Alzheimer's	1408
Arxiv	Alzheimer's disease assessment data	5500
	Early Detection of MCI to AD Conversion Using Machine Learning	5610
	Early Detection of Alzheimer's	5890

ACM	Alzheimer's disease assessment data Early Detection of MCI to AD Conversion Using Machine Learning Early Detection of Alzheimer's	3500 2610 5100

2.2. Study selection

To ensure the selection of relevant studies, specific inclusion and exclusion criteria were established and applied throughout the study selection process. These criteria guided the screening and evaluation of studies at each stage. The inclusion and exclusion criteria used in this review are detailed below.

2.2.1. Inclusion Criteria

After getting the results from the databases for the keywords as mentioned in Table 1, Studies were included in this review if they met the following criteria:

- ✓ Original research articles published in peer-reviewed journals or conference proceedings.
- ✓ Investigated the use of machine learning algorithms for the detection or classification of Alzheimer's disease or related cognitive impairments.
- ✓ Utilized cognitive assessment data (e.g., MMSE, MoCA, ADAS-Cog) as primary input features for model development.
- ✓ Reported performance metrics such as accuracy, sensitivity, specificity, or AUC.

2.2.2. Exclusion criteria were:

- ➢ Studies not focused on Alzheimer's disease or not involving cognitive assessment data.
- ➢ Studies using only neuroimaging, genetic, or other non-cognitive data as input features.
- ➢ Reviews, editorials, letters, or non-peer-reviewed articles.

3. Results and discussion

This section contains detailed information about the results and discussions.

3.1. Study Selection Process

A comprehensive search was conducted across multiple electronic databases, including Google Scholar, PubMed, IEEE Xplore, Arxiv, and ACM. The search utilized the keywords "Alzheimer's disease assessment data," "Early Detection of Alzheimer's diesease Using Machine Learning," and "Early Detection of Alzheimer's." This yielded a total of 98,282 records (Google Scholar: 53,600; PubMed: 15,764; IEEE Xplore: 1,999; Arxiv: 17,000; ACM: 11,919).

After removing 2,215 duplicate records, 96,067 unique articles remained. Titles and abstracts were screened, resulting in the exclusion of 30,215 articles based on irrelevance. Subsequently, articles that focused solely on the scientific or clinical aspects of MCI and Alzheimer's Disease (AD) without any application of artificial intelligence or machine learning were excluded at the abstract screening stage.

A total of 65,852 articles were then assessed for eligibility through full-text review. Of these, studies were excluded for the following reasons: lack of focus on MCI to AD conversion (n = 18,500), absence of longitudinal cognitive assessment data (n = 21,000), insufficient methodological details or feature specification (n = 20,000), and lack of reported performance metrics such as accuracy, sensitivity, or specificity (n = 6,310). Ultimately, 42 studies met all inclusion criteria and were included in this systematic review. The detailed exclusion criteria used throughout the paper selection process are illustrated in Fig. 1.

4. Data Extraction

For each study meeting the inclusion criteria, a comprehensive data extraction process was undertaken to ensure systematic and consistent collection of relevant information. A standardized data extraction form was developed and pilot-tested on a subset of included articles to confirm its suitability and comprehensiveness. Two reviewers independently performed the data extraction, with discrepancies resolved through discussion or, when necessary, consultation with a third reviewer [5].

The following categories of information were extracted from each study:

4.1. Bibliographic Information:

Details including the first author's name, year of publication, title, journal or conference name, and country of study origin were recorded. This information helps contextualize the study within the broader literature and allows for geographical and temporal trends to be identified.

4.2. Study Population and Sample Characteristics:

Data on the number of participants, age range, gender distribution, and any relevant inclusion or exclusion criteria were extracted. Where available, details about the diagnostic criteria for Alzheimer's disease or cognitive impairment, such as DSM or NINCDS-ADRDA guidelines, were also noted.

4.3. Datasets and Sources of Cognitive Assessment Data:

Publicly Available Datasets for the Detection of Alzheimer's Disease Using Cognitive Assessment Test Data A

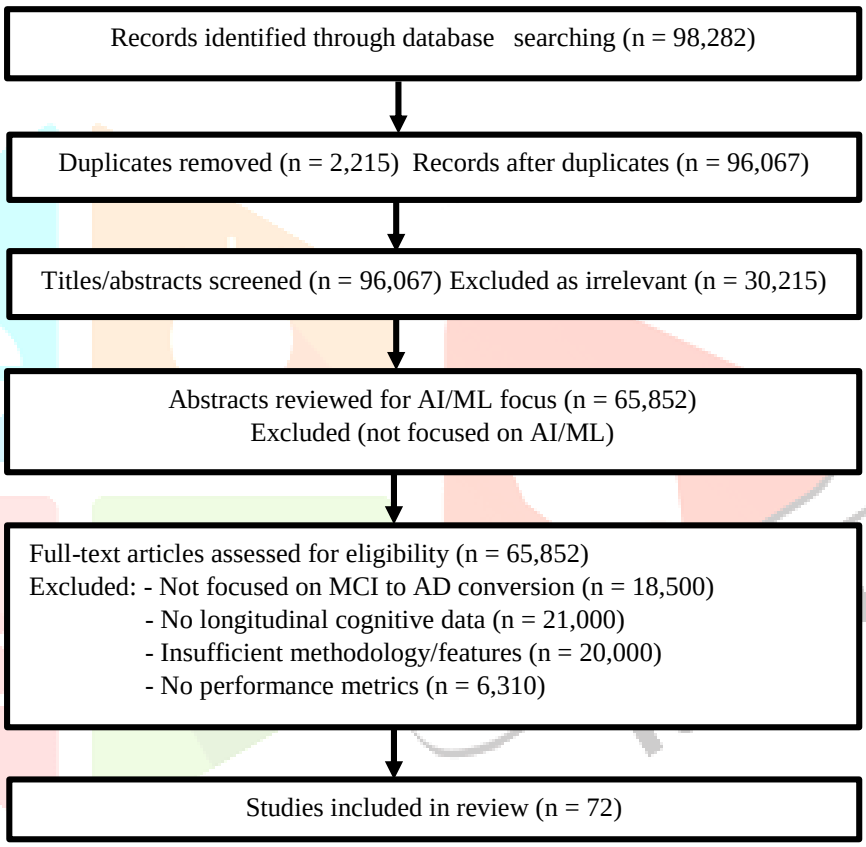

Figure. 1. Exclusion criteria used in the paper selection process.

variety of publicly accessible datasets are commonly employed in research focused on the early detection of Alzheimer's disease (AD) using cognitive assessment test data. These datasets provide a rich source of longitudinal, multimodal, and demographic information that enables the development and validation of machine learning models for the identification of cognitive decline and AD conversion. Below, we describe several of the most widely used resources:

4.3.1. Alzheimer's Disease Neuroimaging Initiative (ADNI)

The ADNI is one of the most prominent and comprehensive datasets used in Alzheimer's research. While its primary focus is on neuroimaging biomarkers, the ADNI database also contains extensive cognitive assessment data, including scores from the Mini-Mental State Examination (MMSE), Alzheimer's Disease Assessment Scale-Cognitive Subscale (ADAS-Cog), Clinical Dementia Rating (CDR), and an array of other neuropsychological batteries. The dataset includes longitudinal follow-ups, allowing researchers to track cognitive decline and conversion from mild cognitive impairment (MCI) to AD. Participants are recruited from multiple centers across North America, ensuring a diverse demographic representation. The open-access nature of the ADNI has made it a cornerstone for benchmarking machine learning approaches in cognitive assessment-based AD detection.

4.3.2. National Alzheimer's Coordinating Center (NACC)

The NACC database aggregates data collected from Alzheimer's Disease Centers across the United States. It provides a wide scope of standardized cognitive assessment instruments, such as MMSE, MoCA (Montreal Cognitive Assessment), and CDR, along with detailed clinical, demographic, and diagnostic information. The NACC's Uniform Data Set (UDS) offers longitudinal cognitive test results, enabling studies on disease progression and early detection using machine learning techniques. The size and diversity of the NACC cohort make it valuable for developing robust and generalizable models.

4.3.3. Open Access Series of Imaging Studies (OASIS)

While OASIS is primarily known for its neuroimaging data, it also includes cognitive assessment scores such as MMSE and CDR for each participant. The OASIS-3 dataset, in particular, comprises longitudinal clinical and cognitive data for older adults, including both healthy controls and individuals across the spectrum of cognitive impairment. The availability of these cognitive scores alongside demographic and imaging features supports research into early AD detection based solely on test data or in combination with other modalities.

4.3.4. Australian Imaging, Biomarkers & Lifestyle Flagship Study of Ageing (AIBL)

The AIBL study collects comprehensive cognitive assessment data from Australian participants aged 60 and above, including longitudinal MMSE, ADAS-Cog, and CDR scores. The dataset also integrates information on lifestyle factors, genetics, and medical imaging, but the cognitive test data alone have been widely used to model cognitive decline and AD onset. The AIBL cohort's follow-up assessments (typically at 18-month intervals) enable the study of subtle cognitive changes and support the development of predictive algorithms for early AD diagnosis.

4.3.5. Dementia Bank (Pitt Corpus)

Dementia Bank is a unique resource containing both structured neuropsychological test data and spontaneous speech recordings from individuals with Alzheimer's disease, other dementias, and healthy controls. The dataset includes transcripts, MMSE scores, and results from other cognitive assessments. It is particularly valuable for studies aiming to integrate linguistic and cognitive features in machine learning models for early AD detection.

Related to the above dataset's summary can be given in Table2.

Table2: Each datasets of Alzheimer's disease are given below.

Dataset	Key Cognitive Tests	Sample Size	Follow-up	Main Features
ADNI	MMSE, ADAS-Cog, CDR	~2000+	Yes	Extensive longitudinal cognitive & clinical data
NACC	MMSE, MoCA, CDR	~40,000+	Yes	Large, diverse, US-based, standardized assessments
OASIS	MMSE, CDR	1000+	Yes	Imaging + cognitive, longitudinal
AIBL	MMSE, ADAS-Cog, CDR	2000+	Yes	Lifestyle, genetics, regular cognitive testing
DementiaBank	MMSE + speech/language	250+	Yes	Transcripts, audio, cognitive test scores

These datasets provide a robust foundation for the development, validation, and benchmarking of machine learning models aimed at the early detection of Alzheimer's disease using cognitive assessment data. Researchers can leverage the longitudinal and multimodal nature of these resources to improve the sensitivity and specificity of early diagnosis, facilitate comparative studies, and advance the field toward clinically viable solutions.

4.4. Types and Features of Cognitive Assessment:

Each study's use of cognitive assessment tools was documented in detail, with particular attention given to the specific neuropsychological tests administered and the aspects of cognition they were designed to evaluate. The most frequently used standardized cognitive assessments in the context of Alzheimer's disease detection include the following:

4.4.1. Mini-Mental State Examination (MMSE):

The Mini-Mental State Examination (MMSE) is a well-known tool used to screen for cognitive impairment. It looks at several different areas of a person's thinking skills, such as knowing the time and where they are, their ability to remember new information, how well they can pay attention and do calculations, and their skills with language and seeing things in a spatial way.

A person's total MMSE score gives a simple idea of their overall cognitive function. Basically, the lower the score, the more significant the cognitive impairment might be. When researchers use the MMSE in machine learning studies, they often use both the total score and the scores from individual sections of the test as features for their models.

4.4.2. Montreal Cognitive Assessment (MoCA):

The MoCA was developed to detect mild cognitive impairment and is considered more sensitive than the MMSE for early-stage Alzheimer's disease. It covers a broader range of cognitive domains, including executive functions, visuospatial abilities, naming, memory, attention, language, abstraction, delayed recall, and orientation. Studies may use the total MoCA score, as well as subscores or specific item responses, to capture subtle cognitive deficits.

4.4.3. Alzheimer's Disease Assessment Scale–Cognitive Subscale (ADAS-Cog):

The ADAS-Cog is a comprehensive and widely used tool in clinical trials for Alzheimer's disease. It evaluates memory, language, praxis, comprehension, and orientation, with higher scores indicating greater impairment. The ADAS-Cog provides detailed subscale scores for various cognitive domains, and these granular features are often leveraged in machine learning analyses.

4.4.4. Clinical Dementia Rating (CDR):

The CDR is used to stage the severity of dementia. It is based on a structured interview and rates cognitive and functional performance in six domains: memory, orientation, judgment and problem solving, community affairs, home and hobbies, and personal care. The CDR sum of boxes score and global score are common features extracted for analysis.

4.4.5. Other Common Assessments:

Additional neuropsychological tests such as the Logical Memory Test (for episodic memory), Trail Making Test (for attention and executive function), Boston Naming Test (for language), and Rey Auditory Verbal Learning Test (for verbal memory) are also used in some studies. These tests provide domain-specific information that can be valuable for early detection and differentiation of Alzheimer's disease from other conditions.

5. Machine learning and Deep Learning models

A diverse range of machine learning (ML) and deep learning (DL) models have been employed by researchers for the early detection of Alzheimer's Disease (AD) using clinical assessments. A common approach involves utilizing Support Vector Machines (SVMs) as the final classifier, which is a popular choice for its effectiveness in binary classification tasks, such as distinguishing between healthy controls (HC), cognitively normal (CN) individuals, and those with mild cognitive impairment (MCI). Researchers have used SVMs with various kernels, including the Radial Basis Function (RBF) kernel and polynomial kernels, to classify patients based on features derived from tests like the Mini-Mental State Examination (MMSE) and the Montreal Cognitive Assessment (MoCA). SVMs are frequently combined with other techniques, with extracted features from deep learning models being fed into an SVM for final classification. This approach is noted in studies by researchers in Refs. [34, 36–40, 42, 43, 47, 48, 64].

For feature selection and classification, Least Absolute Shrinkage and Selection Operator (LASSO) regression has been employed. This method is effective for identifying the most predictive clinical features from a large set of assessment scores. One study [31] used LASSO to build a feature selection framework and a classifier to distinguish between different stages of cognitive decline.

In addition, regression models have been developed for AD prediction. For example, a linear Sparse Regression model was proposed by researchers in Ref. [41]. Cox regression models, specifically designed for survival analysis, have also been adapted for classifying patients. These models, used in Refs. [33, 45], can predict the time to conversion from MCI to AD. One study [33] used a Cox regression model as a classifier to predict the conversion from stable MCI (sMCI) to progressive MCI (pMCI) using clinical data. Similarly, a Cox hazard model was implemented in Ref. [45] to identify whether a patient belongs to the sMCI or pMCI category based on the calculated Cox probability value.

Longitudinal classifiers are crucial for analyzing data collected over multiple patient visits [6]. Researchers in Refs. [35, 63] utilized these models to capture the progression of cognitive decline. A Mixed Effects Model was proposed in Ref. [63] to account for varying visit intervals and individual patient trajectories. Furthermore, a sliding window-based approach [35] was used to measure the influence of one visit's assessment results on the prediction of subsequent cognitive states.

The use of ensemble methods has shown promise in improving classification accuracy. An ensemble of ML classifiers, such as a combination of SVM and Logistic Regression (LR), was used by researchers in Refs. [27, 50] to better helping doctors tell the difference between people who have different levels of thinking ability.

Deep Learning (DL) architectures are used for both feature extraction and as direct classifiers. Convolutional Neural Networks (CNNs), while traditionally used for image analysis, have been adapted to process structured clinical data by treating it as a one-dimensional signal. Researchers in Refs. [28, 30, 44, 46, 49, 52–62, 65] used CNNs for feature extraction from clinical assessment batteries. These extracted features can then be used by traditional classifiers like SVMs, as shown in studies [32, 33, 35, 36, 39, 65], or directly classified by the deep learning architecture itself. A table summarizing the purpose and configurations of these models is provided below.

Table 3: Configuration of ML and DL algorithms used in previous works.

Reference	Model Configuration	Purpose
[27, 50]	**Ensemble of SVM and Logistic Regression (LR)**: SVM with RBF kernel, Binary Logistic Regression	Classification of AD progression based on clinical and neuropsychological test scores.
[28–30, 47, 54, 66]	**Convolutional Neural Network (CNN)**: Variable number of fully connected layers (FCLs), activation functions like Sigmoid or ReLU	Feature extraction from clinical data and direct classification of cognitive status.
[31, 32]	**Sparse Autoencoder (SAE)**: Rectified Linear Unit (ReLU) activation	Capturing latent features from neuropsychological data for dimensionality reduction and classification.
[34, 44]	**Cox Regression Models**	Calculating the survival time to AD conversion from multimodal clinical data.
[40, 61]	**CNN, SVM, Support Vector Regression (SVR)**	CNN for automatic feature extraction; SVR for estimating cognitive decline rates; SVM for classification.
[42]	**Sparse Learning Regression**	Causal inference model for identifying the relationship between different clinical features and cognitive decline.
[48]	**Bayes Classifier**	Probabilistic model for classifying AD using speech features from clinical interviews.
[49]	**CNN + Graph Networks**: Tanh activation function	CNN for feature extraction; Graph Networks for analyzing connectivity measures from clinical data.
[60]	**Ensemble Voting Classifier**: SVM, KNN, MLP	Combining multiple models (SVM with RBF kernel, KNN, MLP) for enhanced classification accuracy.
[53]	**CNN with Attention Mechanism**	Focusing on more significant clinical assessment scores or regions of interest (ROI) for better classification.

[55]	**CNN**	Extracting features from Electroencephalography (EEG) data as part of a multi-modal clinical assessment.
[44, 49, 65]	**CNN + Recurrent Neural Network (RNN)**	CNN for feature extraction from clinical data; RNN for capturing temporal features and dependencies over multiple visits.

5.1. Research Challenges

- **Identifying Precise Clinical Biomarkers**: A major challenge is pinpointing the most accurate and specific biomarkers for **early AD detection** from clinical assessment data. It's particularly difficult to distinguish between **MCI to AD converters** and those who remain stable (non-converters). This requires identifying subtle, yet significant, changes in neuropsychological test scores over time, which can be easily confused with normal aging or other conditions.
- **Feature Selection from Multimodal Data**: When integrating data from various clinical assessments, such as cognitive tests, functional questionnaires, and demographic information, the challenge lies in identifying the most relevant and non-redundant features. This is often referred to as a "curse of dimensionality" problem, where an abundance of features can introduce noise and reduce model performance. Effectively combining these different data modalities while selecting only the most predictive features is a critical task.
- **Predicting Rapid Conversion**: There is an urgent need to identify patients who are likely to progress from MCI to AD in a short timeframe (e.g., within 6 months to 1 year). Predicting this rapid conversion is difficult because the data often lacks sufficient granularity and long-term follow-up to capture these accelerated changes. This necessitates the development of advanced **longitudinal models** that can effectively capture subtle, quick-onset changes in patient data.

5.2. Future Directions

- **Advanced Feature Engineering**: Future research should focus on developing more sophisticated methods for feature engineering that go beyond standard test scores. This could include creating new composite scores or metrics that capture the rate of change in cognitive function. Techniques like Principal Component Analysis (PCA) or Sparse Autoencoders (SAEs) could be used to discover latent, more predictive features from the raw clinical assessment data.
- **Longitudinal Deep Learning Models**: While traditional ML models like SVMs have been effective, future work should explore more powerful deep learning architectures capable of handling time-series data. Models such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks can be designed to analyze the temporal evolution of clinical scores, capturing dependencies between different patient visits.
- **Explainable AI (XAI) for Clinical Adoption**: To build trust among clinicians, it is crucial to move beyond "black-box" models. Future research should integrate **Explainable AI** techniques (e.g., SHAP, LIME) to highlight which specific clinical features or test questions are most influential in a model's prediction. This will help clinicians understand the model's reasoning and better interpret the results.
- **Developing Comprehensive Multimodal Frameworks**: While the provided data focuses on clinical assessments, a key future direction is the creation of unified frameworks that seamlessly integrate clinical data with other modalities like neuroimaging (MRI, PET) and genetic data. This involves developing sophisticated multi-modal fusion techniques that can process heterogeneous data types to create more robust and accurate predictive models.
- **Cross-Cultural and Diverse Datasets**: The data provided primarily comes from the USA and Canada. A significant future direction is to validate models on diverse, multi-ethnic, and multi-national datasets to ensure that the findings are generalizable and not biased toward a specific population. This will improve the clinical applicability of the models globally.

Table 4: Summary of Machine Learning and Deep Learning Models for AD Detection Using Clinical Assessments

Reference	Country	Year	Data Modalities	Machine Learning Model	Deep Learning Model	Ensemble Learning	Result
[1]	Bangladesh	2023	Clinical (Non-MRI), MRI	Random Forest, GaussianNB, LinearSVC, Logistic Regression, KNeighbors, Adaboost	X	Hybrid model	96.07% accuracy (with MRI), 93.37% accuracy (without MRI)
[2]	India	2022	Clinical (OASIS dataset)	focuses on feature extraction/selection	X	X	90.20% accuracy (with MRI), 89.42% accuracy (without MRI)
[3]	India	2022	Clinical (Normalized Whole Brain Volume, CDR,MMSE)	SVM, Decision Tree, Gradient Booster, Random Forest, Gaussian Naive Bayes	MLP	Voting Classifier	Random Forest and Gradient Boosting: 83.92% accuracy
[4]	India	2023	Clinical (behavioral, clinical, lifestyle)	SVM, Random Forest, Decision Tree, Logistic Regression	ANN	X	Random Forest: 95% accuracy
[27]	USA, Canada	2021	Single (Clinical)	SVM: RBF kernel, no feature selection	X	X	Accuracy 71%, Sensitivity 96%, Specificity 53%
[28]	USA, Canada	2021	Single (Clinical)	X	CNN with 93 ROI patches (automatic feature selection)	X	Accuracy 74%, Sensitivity 70%, Specificity 78%
[29]	USA, Canada	2021	Single (Clinical)	Regression on whole image patches	CNN (automatic feature selection)	X	Accuracy 76%, Sensitivity 42%, Specificity 82%
[30]	USA, Canada	2021	Single (Clinical)	X	SAE on gray/white matter patches	X	Accuracy 82%, Sensitivity 81%,

					(automatic feature selection)		Specificity 82%
[31]	USA, Canada	2022	Single (Clinical)	SVM on metabolic intensity values	X	X	Accuracy 83%, Sensitivity 87%, Specificity 78%
[32]	USA, Canada	2022	Multi (Clinical & Imaging)	SVM on 93 ROI GM	CNN (automatic feature selection)	✓	Accuracy 73%, Sensitivity 69%, Specificity 77%
[33]	USA, Canada	2022	Multi (Clinical & Imaging)	Cox Regression Models	X	X	Accuracy 84%, Sensitivity 86%, Specificity 82%
[34]	USA, Canada	2022	Single (Clinical)	SVM on structural volume ratios (no feature selection)	X	X	Accuracy 92%, Sensitivity 95%, Specificity 90%
[35]	USA, Canada	2023	Single (Clinical)	SVM (sliding window approach)	X	X	Accuracy 76%, Sensitivity 70%, Specificity 81%
[36]	USA, Canada	2023	Single (Clinical)	SVM on amygdala distance (no feature selection)	X	X	Accuracy 88%, Sensitivity 86%, Specificity 90%
[37]	USA, Canada	2023	Multi (Clinical & Imaging)	SVM on structural MRI and FDG-PET	X	✓	Accuracy 90%, Sensitivity 86%, Specificity 83%
[38]	USA, Canada	2023	Single (Clinical)	SVM on gray matter regions (automatic feature selection)	X	X	Accuracy 92%, Sensitivity 93%, Specificity 92%

[39]	USA, Canada	2023	Multi (Clinical & Imaging)	Logistic Regression on selected voxels	X	✓	Accuracy 79%, Sensitivity 87%, Specificity 73%
[40]	USA, Canada	2024	Multi (Clinical & Imaging)	SVM, SVR	X	✓	Accuracy 74%, Sensitivity 54%, Specificity 88%
[41]	USA, Canada	2024	Multi (Clinical, Imaging & Biomarkers)	Sparse Learning Method	X	✓	Accuracy 89%, Sensitivity 89%, Specificity 92%
[42]	USA, Canada	2024	Multi (Clinical & Imaging)	SVM on MTL, Etorhinal cortex	X	✓	Accuracy 91%, Sensitivity 95%, Specificity 87%
[43]	Germany, Europe	2024	Multi (Clinical, Imaging & Biomarkers)	SVM on structural MRI, PET, and CSF biomarkers	X	X	Accuracy 82%, Sensitivity 85%, Specificity 70%
[46]	USA, Canada	2024	Multi (Clinical, Imaging & Biomarkers)	SVM on VBM, DBM, PET, CSF, clinical variables	X	X	Accuracy 73%, Sensitivity 72%, Specificity 74%
[47]	USA, Canada	2024	Multi (Clinical & Imaging)	X	CNN + RNN	X	Accuracy 96%

6.CONCLUSION

machine learning (ML) for early **Alzheimer's disease** (AD) detection using cognitive assessment data shows significant promise, offering a **cost-effective** and accessible alternative to neuroimaging and biomarker-based methods. While traditional cognitive assessments face challenges with subjectivity, ML models can uncover subtle, complex patterns in data that may be missed by conventional methods.

The studies reviewed demonstrate that ML models can achieve high accuracy in distinguishing early AD from healthy aging. Diverse algorithms, including SVM, logistic regression, and deep learning architectures like CNNs, have been applied to various publicly available datasets such as ADNI, NACC, and OASIS. The review highlights that models using multiple modalities of data, such as a combination of clinical assessments and neuroimaging, tend to report better results.

Previously, some studies utilized a limited number of assessment tests. However, including a greater number of tests, which measure a wider range of cognitive functions, could lead to a significant increase in the accuracy and performance of existing models. Expanding the number of features with more comprehensive tests like the

Montreal Cognitive Assessment (MoCA) and Alzheimer's Disease Assessment Scale–Cognitive Subscale (ADAS-Cog) could provide ML models with a richer dataset, allowing them to capture more subtle cognitive deficits.

It's exciting to see the progress in using AI to detect Alzheimer's early, but we still have a lot of work to do before these tools can be used in doctor's offices. One of the biggest hurdles is the need for more and better data. Right now, many of the models are trained on smaller datasets that don't represent the wide variety of people in the world, which means the models might not work as well for everyone.

Another tough problem is figuring out which biological markers and data points from different sources—like brain scans, genetic information, and cognitive tests—are the most important. It's a real challenge to sort through all that information to find the precise signals of the disease. Finally, we need to get much better at predicting who will progress from MCI to full-blown Alzheimer's in a very short period, say in just a few months. That's a difficult task that will require us to build more sophisticated models that can analyze changes over time.

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