Disease Prediction Using Artificial Intelligence Techniques: A Comprehensive Review of Alzheimer's Disease Detection.

Abstract

The nearby study analyses the solid waste management in Alzheimer's disease (AD) is a progressive neurodegenerative disorder and the leading cause of dementia worldwide, affecting millions of individuals and placing substantial burdens on healthcare systems, patients, and caregivers. Early and accurate detection of AD remains challenging due to the complexity of its pathology, the high cost of neuroimaging, and the invasive nature of traditional diagnostic methods. In recent years, artificial intelligence (AI) techniques have emerged as transformative tools for AD prediction, offering improved accuracy, accessibility, and interpretability. This paper provides a comprehensive review of AI-based approaches for Alzheimer's disease detection, examining machine learning and deep learning methodologies applied to diverse data modalities including neuroimaging, clinical assessments, behavioral markers, and handwriting analysis. Particular attention is given to recent advances in transfer learning, ensemble methods, explainable AI, and multimodal integration. The review synthesizes findings from cutting-edge research published between 2024 and 2025, highlighting state-of-the-art models achieving accuracy rates exceeding 99% in controlled settings. Key challenges including data imbalance, generalizability, and clinical translation are discussed, along with future directions for AI-driven AD diagnostics within emerging Healthcare 5.0 paradigms.

Key words:-

Alzheimer's disease, artificial intelligence, machine learning, deep learning, early detection, neuroimaging.

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Introduction:-

Alzheimer's disease (AD) is a progressive neurodegenerative disorder marked by beta-amyloid plaques and tau tangles, resulting in cognitive decline and loss of independence. AD is the leading cause of dementia, constituting 60-70% of over 55 million cases globally, with estimates of 139 million by 2050. The disease presents significant emotional and economic challenges, with the U.S. spending approximately $277 billion on AD care in 2018.

Despite extensive research, AD remains without a cure; however, pharmacological treatments can temporarily alleviate symptoms[1]. Early detection is crucial as it allows for timely intervention and improved patient outcomes. Artificial intelligence (AI) presents a transformative approach to AD detection, utilizing machine learning (ML) and deep learning (DL) to identify subtle biomarkers from complex data. Recent research indicates that AI models can achieve diagnostic accuracy over 95%, surpassing traditional methods and human practitioners in some cases. Additionally, AI integration offers interpretable insights that enhance clinician trust and promote clinical adoption[2].

This paper provides a thorough review of AI methodologies for predicting Alzheimer's disease. It explores current approaches across various data types, innovative methods such as transfer learning and ensemble strategies, the importance of explainability, and the challenges and prospects in the field. By compiling findings from the latest research (2025-2026), this review seeks to inform researchers and clinicians on the advancements in AI-based AD detection.

2. Background: Alzheimer's Disease and Diagnostic Challenges

2.1 Pathophysiology and Clinical Presentation

Alzheimer's disease is defined by progressive neurodegeneration, initiated in the medial temporal lobe and extending to cortical areas. Key pathological features include beta-amyloid plaques and tau protein tangles, which impair neuronal function and elicit inflammation. This neurodegenerative process results in synaptic dysfunction, neuronal death, and brain atrophy.

Clinically, Alzheimer's disease is marked by a gradual decline in cognitive abilities. Initial symptoms consist of short-term memory loss, executive function difficulties, and language issues. As the condition progresses, patients face disorientation, mood and behavioral alterations, and diminished daily independence. In its advanced stages, Alzheimer's results in profound cognitive decline, physical complications like dysphagia, and heightened infection risk[3].

2.2 Traditional Diagnostic Modalities

Current diagnostic approaches for AD encompass several modalities, each with inherent strengths and limitations:

Neuroimaging: Structural MRI detects cortical atrophy patterns characteristic of AD, particularly hippocampal shrinkage. Functional imaging including fluorodeoxyglucose PET (FDG-PET) reveals hypometabolism in affected regions, while amyloid PET directly visualizes plaque burden . While accurate, these methods are expensive, require specialized equipment, and are often unavailable in resource-limited settings[4].

Biomarker Analysis: Cerebrospinal fluid (CSF) analysis measures concentrations of amyloid-beta and tau proteins, providing molecular evidence of AD pathology . However, lumbar puncture is invasive and carries procedural risks[5].

Cognitive Assessments: Standardized tests such as the Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA) evaluate cognitive function across multiple domains . These tools are inexpensive and widely available but subject to practice effects, educational and cultural biases, and inter-rater variability[5]

2.3 The Early Detection Imperative

The progressive nature of AD creates a critical window for intervention. Pathological changes begin decades before symptom onset, and by the time clinical symptoms emerge, substantial neuronal loss has already occurred . Early detection enables:

- Timely initiation of symptomatic treatments
- Participation in clinical trials of disease-modifying therapies
- Lifestyle modifications to reduce risk factors
- Advance care planning and family preparation

This imperative has driven intensive research into novel biomarkers and computational approaches capable of identifying preclinical AD[2].

3. Artificial Intelligence Techniques in Alzheimer's Disease Prediction

3.1 Overview of AI Approaches

Artificial intelligence encompasses a broad spectrum of computational techniques that enable machines to learn from data and make predictions or decisions. In the context of AD detection, AI methods can be broadly categorized into traditional machine learning and deep learning approaches, each with distinct architectures, data requirements, and applications.

3.2 Machine Learning Methods

Traditional machine learning algorithms have been extensively applied to AD prediction using structured data including clinical assessments, demographic information, and extracted imaging features . Common algorithms include:

Support Vector Machines (SVM) : SVM constructs hyperplanes in high-dimensional space to separate classes, proving effective for binary classification tasks such as distinguishing AD patients from healthy controls. Research utilizing SVM on MRI data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) achieved accuracies of approximately 81-83%[6, 7] .

Random Forest (RF) : This ensemble method constructs multiple decision trees and aggregates their predictions, offering robustness against overfitting and the ability to handle mixed data types. In comparative studies, RF has consistently performed well, achieving 91.19% accuracy in recent work utilizing clinical and demographic features . The algorithm also provides intrinsic feature importance rankings, offering initial interpretability[6, 8].

Gradient Boosting (GB) : GB sequentially builds decision trees, each correcting errors of its predecessors, achieving high predictive accuracy. A gradient boosting classifier applied to clinical and behavioral data achieved 93.9% accuracy and an F1-score of 91.8%, identifying MMSE scores and activities of daily living as key predictors[9, 10].

3.3 Deep Learning Architectures

Deep learning, particularly convolutional neural networks (CNNs), has revolutionized medical image analysis by automatically learning hierarchical features from raw data. Recent advances in AD detection leverage increasingly sophisticated architectures:

Convolutional Neural Networks (CNNs) : Standard CNN architectures learn spatial features from neuroimages through successive convolutional and pooling layers. Applied to MRI data, CNNs have achieved balanced accuracy of 88% on the OASIS dataset . More recent implementations demonstrate that CNNs can effectively analyze non-image data as well—for example, analyzing visual representations of conversational dynamics to detect AD with over 95% accuracy [2, 11].

ResNet and Transfer Learning: Residual networks (ResNet) incorporate skip connections enabling training of much deeper networks without vanishing gradients. The ResNet152 architecture, pre-trained on large image datasets and fine-tuned on Alzheimer's MRI data, achieved 97.77% accuracy in classifying four stages of dementia (non-demented, very mild, mild, and moderate) . This approach, known as transfer learning, dramatically reduces training time and data requirements while maintaining high performance[1, 12].

Siamese Networks and DenseNet: Siamese architectures learn similarity metrics between pairs of inputs, proving valuable when training data is limited. A Siamese DenseNet model combining DenseNet-201 with graph convolutional networks and advanced feature selection achieved 98.42% accuracy on structural MRI data[13].

Capsule Networks with Attention Mechanisms: The CAPCBAM framework represents a significant advance, combining capsule networks—which preserve spatial hierarchies and part-whole relationships—with convolutional block attention modules (CBAM) that refine feature maps by highlighting clinically relevant regions . This dualattention approach achieved remarkable 99.95% accuracy on the ADNI dataset, with precision and recall both at 99.8%, demonstrating the power of architectural innovation[14].

3.4 Ensemble and Hybrid Approaches

Ensemble methods combine multiple models to achieve superior performance by leveraging diverse algorithmic strengths. The AlzStack framework employs a soft voting ensemble of multiple classifiers, integrating advanced resampling techniques including SMOTE (Synthetic Minority Oversampling Technique), ADASYN, and BorderlineSMOTE to address class imbalance . This approach achieved 93.26% accuracy with an AUC of 94.27% on a dataset of 2,149 patients incorporating demographic, medical, lifestyle, and cognitive variables [15].

The Neuro framework exemplifies hybrid modeling, combining random forest, SVM, gradient boosting, multi-layer perceptron, CNN, and recurrent neural networks (RNN) for voice-based AD detection . This multimodal ensemble achieved 95% accuracy with 95% recall and an AUC of 0.931, demonstrating the value of integrating diverse model architectures[2] .

3.5 Data Modalities for AI-Based Detection

AI techniques have been successfully applied to diverse data types, each offering unique advantages:

Neuroimaging (MRI, PET) : Structural and functional neuroimaging remain the most extensively studied modalities, providing direct visualization of brain pathology. Deep learning models applied to MRI achieve the highest reported accuracies, with recent studies exceeding 99%[13, 14].

Clinical and Demographic Data: Structured data including age, medical history, genetic risk factors (particularly APOE-e4), and cognitive test scores provide accessible, low-cost prediction. Gradient boosting and random forest models applied to such data achieve 91-94% accuracy[13, 16] .

Behavioral and Functional Assessments: Activities of daily living (ADL), functional assessment scores, and behavioral markers have proven highly predictive, often ranking among the most important features in explainable models[15] .

Handwriting Analysis: Fine motor control deteriorates in early AD due to cognitive-motor integration deficits. The DARWIN dataset, comprising handwriting samples from 174 participants across 25 structured tasks, enabled a neural network classifier to achieve 91% accuracy and 94% AUC . Variables including "air_time" (pen movement above tablet) and "paper_time" consistently emerged as critical predictors across multiple algorithms[17] .

Speech and Conversational Analysis: Voice-based biomarkers offer non-invasive, scalable screening. The Neuro framework analyzes vocal cognitive tests using hybrid ML models and OpenAI's Whisper for transcription, achieving 95% accuracy . An innovative approach analyzing the topological and kinetic structure of conversations—without requiring full transcription—applied CNNs to visual representations of conversational dynamics, achieving over 95% accuracy in distinguishing AD patients from healthy controls . This method identified distinctive discursive patterns in AD patients, including excessive digression and altered transition probabilities between conversational topics[2].

4. Performance Evaluation and Comparative Analysis

4.1 Evaluation Metrics

AI-based AD detection studies employ standardized metrics enabling cross-study comparison:

- **Accuracy**: Overall proportion of correct predictions.
- **Precision (Positive Predictive Value)** : Proportion of positive identifications that are correct.
- **Recall (Sensitivity)** : Proportion of actual positives correctly identified.
- **Specificity**: Proportion of actual negatives correctly identified.
- **F1-Score**: Harmonic mean of precision and recall.
- **AUC-ROC**: Area under the receiver operating characteristic curve, measuring discriminative ability across thresholds[18].

4.2 State-of-the-Art Performance

Table 1 summarizes performance of recent high-impact studies:

Research	Data Modality	Model Architecture	Accuracy	Key Metrics
[14]	MRI (ADNI	CAPCBAM (Capsule Networks + CBAM)	99.95%	Precision: 99.8%, Recall: 99.8%, F1: 99.92%, AUC: 0.99
[13]	Structural MRI	Siamese DenseNet with GAN, GCN, optimization	98.42%	
[1]	MRI (Kaggle)	ResNet152 with transfer learning + XAI	97.77%	Precision: 0.981, Recall: 0.987, F1: 0.983, Specificity: 99.13%
[2]	Voice/simulated	Hybrid (RF, SVM, GB, MLP, CNN, RNN)	95%	Recall: 95%, Precision: 82.6%, F1: 88.3%, AUC: 0.931
[17]	Handwriting (DARWIN)	Neural Network (with PCA, 10 models compared)	91%	AUC: 94%
[15]	Clinical/demographic (2149 patients)	Soft voting ensemble with SMOTE variants	93.26%	Precision: 89.17%, Recall: 92.11%, F1: 90.61%, AUC: 94.27%
[16]	Clinical/behavioral	Gradient Boosting with SHAP	93.9%	F1: 91.8%
[13]	Clinical (Kaggle, 35 features)	Random Forest with feature selection	91.19%	

4.3 Comparative Insights

Several patterns emerge from cross-study comparison:

Data Modality and Performance: Neuroimaging-based approaches consistently achieve the highest accuracy (97-99%), reflecting the rich diagnostic information in structural brain images. However, these methods require expensive equipment and specialized acquisition protocols. Non-invasive modalities including handwriting analysis (91%), voice analysis (95%), and clinical data (91-94%) achieve competitive performance at substantially lower cost and greater accessibility[2, 16, 17] .

Architectural Complexity: Increasing model sophistication generally correlates with improved performance, though with diminishing returns at the highest levels. The CAPCBAM framework's 99.95% accuracy may approach the theoretical maximum given irreducible label noise and biological variability in the ADNI dataset[4] .

Generalizability Concerns: The highest accuracies are reported on well-curated research datasets (ADNI, Kaggle) under controlled conditions. Performance may degrade in real-world clinical populations with greater heterogeneity, comorbidities, and data quality variation. The Neuro study's use of synthetic data, while achieving 95% accuracy, explicitly acknowledges the need for validation on real patient data [2].

5. Challenges and Limitations

5.1 Data-Related Challenges

Data Scarcity and Quality: Despite progress in transfer learning and data augmentation, medical AI requires large, diverse, high-quality datasets for robust training. Public datasets including ADNI, OASIS, and Kaggle resources have accelerated research but may not fully represent global population diversity[13] .

Class Imbalance: AD is less prevalent than healthy aging in screening populations, creating class imbalance that can bias models. While SMOTE and GAN-based approaches mitigate this issue, they introduce synthetic samples that may not perfectly capture true data distributions[1, 15] .

Heterogeneity and Standardization: MRI acquisition protocols vary across sites, scanners, and sequences, introducing non-biological variance that can confound models. Similarly, cognitive assessments and clinical measures lack standardization across healthcare systems.

5.2 Model-Related Challenges

Overfitting: Complex deep learning models with millions of parameters risk overfitting to training data, particularly when datasets are modest in size. The Neuro study's hybrid model achieved 95% accuracy on simulated data but acknowledged computational complexity contributing to overfitting risk[6] .

Generalizability: Models trained on research cohorts may not generalize to clinical populations with different demographic characteristics, comorbidity profiles, or disease stage distributions. External validation on independent, diverse datasets remains essential but underutilized.

6. Conclusion

Artificial intelligence has emerged as a transformative force in Alzheimer's disease detection, offering the potential for earlier, more accurate, and more accessible diagnosis than traditional methods alone. This review has examined the landscape of AI techniques applied to AD prediction, from traditional machine learning algorithms on clinical data to sophisticated deep learning architectures analyzing neuroimages, handwriting, speech, and conversational dynamics.

Recent advances demonstrate remarkable progress: CAPCBAM achieves 99.95% accuracy on MRI data ; ResNet152 with transfer learning reaches 97.77% while providing multi-method explainability ; voice-based hybrid models attain 95% accuracy with accessible, non-invasive data collection ; and handwriting analysis offers cost-effective screening with 91% accuracy . The integration of explainable AI techniques including SHAP, LIME, and Grad-CAM addresses historical concerns about model interpretability, building the trust necessary for clinical adoption.

However, substantial challenges remain. Highest reported accuracies come from research datasets under controlled conditions; real-world performance may be lower. Data scarcity, class imbalance, and heterogeneity across acquisition protocols demand continued methodological innovation. Clinical translation requires rigorous validation, regulatory approval, workflow integration, and demonstrated improvement in patient outcomes.

The path forward lies in multimodal integration, continuous monitoring within Healthcare 5.0 frameworks, foundation models leveraging self-supervised learning, and causal approaches that move beyond prediction to mechanistic understanding. As these technologies mature, AI-driven Alzheimer's detection holds promise not merely as a research tool but as a clinical reality—enabling earlier intervention, better patient outcomes, and ultimately reducing the global burden of this devastating disease.

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