ISSN (O): 2320-5407
ISSN (P): 3107-4928

Journal Homepage: - www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

Article DOI: 10.21474/IJAR01/23132
DOI URL: http://dx.doi.org/10.21474/IJAR01/23132

RESEARCH ARTICLE

DISEASE PREDICTION USING ARTIFICIAL INTELLIGENCE TECHNIQUES: A COMPREHENSIVE REVIEW OF ALZHEIMER'S DISEASE DETECTION

Wijdan A. Khaleel

1. Ministry of Education /Basra Education Directorate /Human Resources Department, Basrah, Iraq.

……

Manuscript Info

Manuscript History
Received: 16 January 2026
Final Accepted: 18 February 2026
Published: March 2026

Key words:-
Alzheimer's disease, artificial intelligence, machine learning, deep learning, early detection, neuroimaging.

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 2026, highlighting state-of-the-art models achieving accuracy rates exceeding 99% in controlled settings. Key challenges including data imbalance, generaliz ability, bias, and clinical translation are discussed, along with future directions for AI-driven AD diagnostics within emerging Healthcare 5.0 paradigms.

……

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. This clinical need has spurred the exploration of advanced computational tools to address the limitations of traditional diagnostic methods. Artificial intelligence (AI) presents a transformative approach to AD detection, utilizing

Corresponding Author:- Wijdan A. Khaleel
Address**:-**Ministry of Education /Basra Education Directorate /Human Resources Department, Basrah, Iraq.

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 (2024-2026), this review seeks to inform researchers and clinicians on the advancements in AI-based AD detection.

Background: Alzheimer's Disease and Diagnostic Challenges:-

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].

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]

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].

Artificial Intelligence Techniques in Alzheimer's Disease Prediction:-

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.

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].

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 dual-attention 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].

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] .

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].

Performance Evaluation and Comparative Analysis:-

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].

State-of-the-Art Performance:-

Table 1 summarizes performance of recent high-impact studies:

Research	Data Modality	Model Architecture	Accuracy	Architecture Details
[14]	MRI (ADNI	CAPCBAM (Capsule Networks + CBAM)	99.95%	Combines Capsule Networks (preserves spatial hierarchies and part-whole relationships) with Convolutional Block Attention Modules (CBAM) that refine feature maps by highlighting clinically relevant regions. Dual attention mechanism focuses on both spatial and channel-wise features.

[13]	Structural MRI	Siamese DenseNet with GAN, GCN, optimization	98.42%	Combines DenseNet-201 (dense connectivity for efficient feature reuse) with Siamese architecture (learns similarity metrics between pairs, effective with limited data). Integrates GANs for data augmentation and Graph Convolutional Networks (GCN) for capturing relational features.
[1]	MRI (Kaggle)	ResNet152 with transfer learning + XAI	97.77%	ResNet152 (152-layer residual network with skip connections to prevent vanishing gradients) pre-trained on ImageNet. Fine-tuned on AD MRI data. Integrated with XAI (SHAP, LIME, Grad-CAM) for interpretability. Designed for IoMT (Internet of Medical Things) in Healthcare 5.0.
[2]	Voice/simulated	Hybrid (RF, SVM, GB, MLP, CNN, RNN)	95%	Combines 6 models: Random Forest, SVM, Gradient Boosting, Multi-Layer Perceptron, CNN, and RNN. Uses OpenAI's Whisper for speech transcription. Soft voting ensemble aggregates predictions. Designed for voice-based cognitive testing.
[17]	Handwriting (DARWIN)	Neural Network (with PCA, 10 models compared)	91%	Uses Principal Component Analysis (PCA) for dimensionality reduction. Compares 10 different algorithms (including Neural Networks, SVM, Random Forest) with hyperparameter tuning. Key predictors: "air_time" (pen movement above tablet) and "paper_time" (contact time).
[15]	Clinical/demographic (2149 patients)	Soft voting ensemble with SMOTE variants	93.26%	Soft voting ensemble combining multiple classifiers (RF, SVM, XGBoost, etc.). Integrates advanced resampling techniques: SMOTE, ADASYN, and BorderlineSMOTE to address class imbalance. Features: demographic, medical history, lifestyle, cognitive scores.
[16]	Clinical/behavioral	Gradient Boosting with SHAP	93.9%	Gradient Boosting sequentially builds decision trees correcting previous errors. Integrated with SHAP (SHapley Additive exPlanations) for model interpretability. Identified MMSE scores and activities of daily living as key predictors.

Comparative Insights:-

Several patterns emerge from cross-study comparison, revealing important trade-offs between different approaches:

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, specialized acquisition protocols, and significant expertise for interpretation. This limits their utility as screening tools in primary care or resource-limited settings. In contrast, 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]The choice of modality thus involves a trade-off between diagnostic certainty and practical deployability.

Architectural Complexity vs. Interpretability: 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[14]. However, more complex models often sacrifice interpretability—a critical requirement for clinical adoption. Studies incorporating explainable AI techniques (SHAP, LIME, Grad-CAM) demonstrate that high performance need not preclude transparency, though explainability methods for capsule networks and attention mechanisms remain less mature than those for simpler architectures [1, 16]

Generalizability Concerns: The highest accuracies are reported on well-curated research datasets (ADNI, Kaggle) under controlled conditions. Performance may degrade significantly 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]. This gap between research performance and clinical effectiveness represents perhaps the most significant barrier to translation.

Practical Clinical Considerations: For deployment in clinical settings, factors beyond raw accuracy become paramount: ease of use, integration with existing workflows, processing time, and cost per prediction. Handwriting analysis [17]and voice-based approaches [2] offer advantages in scalability and patient acceptability, while neuroimaging-based methods provide greater diagnostic confidence for challenging cases. Future research should explicitly evaluate these practical dimensions rather than focusing solely on accuracy metrics.

Challenges and Limitations:-

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.

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.

Bias and Fairness in AI Models:-

A critical yet often overlooked challenge is the potential for AI models to perpetuate or amplify healthcare disparities. Most publicly available AD datasets are derived from predominantly White, highly educated, and clinically referred populations. Models trained on such data may underperform in underrepresented groups, including different ethnicities, socioeconomic backgrounds, or education levels.

This bias can manifest in several ways:

- **Detection bias**: Models may be less accurate for populations not well-represented in training data
- **Measurement bias**: Cognitive assessments and biomarkers may have different baseline distributions across populations

- **Accessibility bias**: Deploying models requiring expensive neuroimaging may benefit only patients with access to advanced healthcare

Addressing these concerns requires intentional efforts to collect diverse, representative datasets; rigorous auditing of model performance across subgroups; and development of equitable AI systems that do not exacerbate existing health disparities. Explainable AI techniques can help identify when models rely on biased or spurious correlations, but ultimately the responsibility lies with researchers and developers to ensure fairness in both development and deployment[1, 15].

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[14]; ResNet152 with transfer learning reaches 97.77% while providing multi-method explainability[1]; voice-based hybrid models attain 95% accuracy with accessible, non-invasive data collection [2]; and handwriting analysis offers cost-effective screening with 91% accuracy[17]. 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. Furthermore, the field must actively address concerns about bias and fairness to ensure that AI-driven diagnostics benefit all populations equitably. 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.

References:-

1. A. H. Khan, D. Ali, S. Ahmed, A. Alhumam, M. F. Khan, and S. Y. Siddiqui, "IoMT driven Alzheimer's prediction model empowered with transfer learning and explainable AI approach in healthcare 5.0," Scientific Reports, vol. 15, no. 1, p. 35382, 2025.
2. I. Liu, F. Ramirez, and K. Liu, "Neuro: Machine Learning Optimized to Detect Neurodegenerative Diseases Pilot Study," medRxiv, p. 2025.09. 29.25336770, 2025.
3. A. Y. Kim, S. Al Jerdi, R. MacDonald, and C. R. Triggle, "Alzheimer's disease and its treatment–yesterday, today, and tomorrow," Frontiers in pharmacology, vol. 15, p. 1399121, 2024.
4. G. Svanishvili, "Revolutionising Alzheimer's Diagnostics: AI Tool Shows Superior Accuracy Over Traditional Methods," Journal of Neuroscience, vol. 2, p. 100004, 2025.
5. B. Babu et al., "Comparing the artificial intelligence detection models to standard diagnostic methods and alternative models in identifying Alzheimer's disease in at-risk or early symptomatic individuals: A scoping review," Cureus, vol. 16, no. 12, p. e75389, 2024.
6. J. Biswas et al., "Performance-optimized Alzheimer's detection using machine learning with SMOTE and randomized hyperparameter tuning," Discover Artificial Intelligence, 2026.
7. O. O. Olatunde, K. S. Oyetunde, J. Han, M. T. Khasawneh, H. Yoon, and A. s. D. N. Initiative, "Multiclass classification of Alzheimer's disease prodromal stages using sequential feature embeddings and regularized multikernel support vector machine," NeuroImage, vol. 304, p. 120929, 2024.
8. A. A. Soladoye, N. Aderinto, B. A. Omodunbi, A. O. Esan, I. A. Adeyanju, and D. B. Olawade, "Enhancing Alzheimer's disease prediction using random forest: A novel framework combining backward feature elimination and ant colony optimization," Current Research in Translational Medicine, vol. 73, no. 4, p. 103526, 2025.

9. R. Govindarajan, K. Thirunadanasikamani, K. K. Napa, S. Sathya, J. S. Murugan, and K. C. Priya, "Development of an explainable machine learning model for Alzheimer’s disease prediction using clinical and behavioural features," MethodsX, vol. 15, p. 103491, 2025.
10. S. P. Praveen, S. BHUKYA, S. VALLEM, S. GORIKAPUDI, K. K. R. PENUBAKA, and V. SHARIFF, "Enhanced predictive modeling for alzheimer’s disease: Integrating cluster-based boosting and gradient techniques with optimized feature selection," Journal of Theoretical and Applied Information Technology, vol. 103, no. 8, pp. 3285-3296, 2025.
11. K. Velu and N. Jaisankar, "Design of a CNN–Swin transformer model for Alzheimer’s disease prediction using MRI images," IEEE Access, 2025.
12. S. B. Francis and J. Prakash Verma, "Deep CNN ResNet-18 based model with attention and transfer learning for Alzheimer's disease detection," Frontiers in Neuroinformatics, vol. 18, p. 1507217, 2025.
13. R. Viswanathan and N. K. Nallabala, "Siamese DenseNet: Unveiling interpretable insights in Alzheimer’s disease (AD) detection through structural MRI with explainable artificial intelligence (XAI)," Computers and Electrical Engineering, vol. 129, p. 110734, 2026.
14. H. Slimi, S. Abid, and M. Sayadi, "Revolutionizing Alzheimer’s disease detection with a cutting-edge CAPCBAM deep learning framework," Scientific Reports, vol. 15, no. 1, p. 13925, 2025.
15. V. A. Modali et al., "AlzStack: Forecasting early-onset Alzheimer's with an explainable AI system using multiple data balancing techniques," Global Epidemiology, p. 100235, 2025.
16. A. Trognon, C. Duman, G. Vittart, N. Stortini, L. Mahdar-Recorbet, and H. Altakroury, "Deep learning of conversation-based ‘filmstrips’ for robust Alzheimer’s disease detection," npj Aging, vol. 11, no. 1, p. 77, 2025.
17. H. Wenzheng, E. F. Agyemang, S. K. Srivastav, J. G. Shaffer, and S. Kakraba, "Artificial Intelligence–Enhanced Multi-Algorithm R Shiny Application for Predictive Modeling and Analytics: Case Study of Alzheimer Disease Diagnostics," JMIR aging, vol. 8, no. 1, p. e70272, 2025.
18. D. M. Powers, "Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation," arXiv preprint arXiv:2010.16061, 2020.