

REVIEW ARTICLE

From neuroimages to insights: Artificial intelligence-powered hybrid models for Alzheimer's disease detection

Gracy Singh^{1†*}, Nidhi Verma^{1†}, Sonali Bhatt^{2†}, and Saurabh Mukherjee³¹Centre of Artificial Intelligence, Banasthali Vidyapith, Tonk, Rajasthan, India²Department of Biosciences and Biotechnology, Banasthali Vidyapith, Tonk, Rajasthan, India³Department of Mathematics and Computing, Banasthali Vidyapith, Tonk, Rajasthan, India

Abstract

Alzheimer's disease (AD), a progressive neurodegenerative disease, is a major global public health problem. Early and accurate diagnosis is crucial for timely intervention, especially with the prevalence of the condition expected to triple by 2050. Traditional methods have been enhanced by artificial intelligence (AI)-driven techniques, particularly Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). These approaches enhance the early detection and classification of diseases by evaluating complex neuroimaging data. Using Matrix Laboratory, we developed hybrid models integrating CNNs and SVMs to detect AD, focusing on feature extraction, predictive accuracy, and model interpretability for clinical use. While Internet of Things-based wearable devices are reviewed for their potential in large-scale data processing and real-time monitoring, our empirical work emphasizes practical AI solutions. In conclusion, integration of multimodal neuroimaging data and advanced feature selection techniques holds the potential to enhance diagnostic precision of AD.

Keywords: Alzheimer's disease; Neuroimaging data; Convolutional Neural Network; Support Vector Machine; Matrix laboratory

[†]These authors contributed equally to this work.

***Corresponding author:**

Gracy Singh
(abmta24010_gracy@banasthali.in)

Citation: Singh G, Verma N, Bhatt S, Mukherjee S. From neuroimages to insights: Artificial intelligence-powered hybrid models for Alzheimer's disease detection. *Artif Intell Health*. 2026;3(2):025400087. doi: 10.36922/AIH025400087

Received: October 5, 2025

Revised: November 24, 2025

Accepted: December 1, 2025

Published online: December 10, 2025

Copyright: © 2025 Author(s). This is an Open-Access article distributed under the terms of the Creative Commons Attribution License, permitting distribution, and reproduction in any medium, provided the original work is properly cited.

Publisher's Note: AccScience Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

1. Introduction

Dementia presents a significant global health issue, impacting more than 50 million individuals, with estimates suggesting the number could rise to 152 million by 2050 as a result of global aging.¹ According to the World Health Organization, dementia is classified as a syndrome rather than a disease.² It is characterized by a progressive decline in the cognitive function of an individual across multiple cognitive domains, consequently impairing functional abilities. The term "dementia" has been replaced by "major neurocognitive disorder" in the Diagnostic and Statistical Manual of Mental Disorders-5.³ Alzheimer's disease (AD) is the leading cause of dementia, accounting for 60–80% of all dementia cases. In the United States, the yearly financial burden of AD and other types of dementia amounts to US\$305 billion, with expectations to exceed US\$1.1 trillion by 2050.⁴ This includes costs associated with healthcare, hospice care, and lost productivity.⁵ AD is a progressive neurodegenerative condition characterized

by a decline in cognitive abilities, functionality, and behavior, with notable pathological indicators including the presence of extracellular amyloid-beta ($A\beta$) plaques and intracellular neurofibrillary tangles (NFTs). $A\beta$ plaques are formed due to either inefficient clearance or excessive production and can be observed almost two decades before the onset of symptoms.⁶ NFTs are generated from hyperphosphorylated tau protein and appear roughly 10–15 years before the symptoms manifest.⁷ AD advances from a stage without symptoms marked by biomarkers (preclinical AD) to mild cognitive impairment (MCI) and/or mild behavioral impairment, eventually resulting in AD dementia.⁸ Different staging systems categorize AD along the continuum, varying in their definitions but taking into account pathological $A\beta$, NFTs, and cognitive, functional, and behavioral deficits, with differences in terminology based on clinical and research classifications.⁹

AD is a gradual, degenerative illness characterized by progressively worsening symptoms. Initial indicators include memory loss regarding recent events, mood changes, difficulties in understanding new information, confusion, communication challenges, and a decline in the ability to perform routine tasks. As the condition advances, symptoms become more severe, resulting in significant memory loss, difficulties recognizing family and friends, agitation, difficulties with reading and writing, negligence of personal hygiene, decreased appetite, changes in personality, and a growing reliance on others. In advanced stages, individuals may lose the ability to speak, experience incontinence, fail to recognize themselves or others, undergo severe disorientation, lose mobility, and enter prolonged periods of sleep.¹⁰ Because similar symptoms can occur with other conditions, seeking timely medical advice is vital. Particularly for those with several affected family members, this disease exerts pressure on the healthcare systems.¹¹ With the incidence of dementia anticipated to increase significantly by 2050, improving detection and treatment methods is critical.¹²

The timely and precise identification of AD is essential for successful treatment and management. A range of diagnostic and detection approaches has been created, including cognitive evaluations and sophisticated neuroimaging methods. Emerging diagnostic tools include biomarker-based tools, such as magnetic resonance imaging (MRI), positron emission tomography (PET), computed tomography (CT), blood-based biomarkers, cerebrospinal fluid-based biomarkers, ocular testing, and salivary biomarkers. The majority of these tools are in the research phase, although imaging is often used in combination with cognitive testing to diagnose AD.¹³

Research on AD encounters hurdles concerning data protection, ethics, and the incorporation of AI.¹⁴ The

identification of the disease in its early stages depends on biomarkers, MRI, and PET imaging,¹⁵ while the Internet of Things (IoT) and ambient intelligence improve AI assessment and continuous monitoring.¹⁶

2. Motivation and scope

As a significant global health challenge, early detection of AD is crucial for enhancing patient outcomes. Existing diagnostic techniques have limitations, particularly during the initial phases of the disease. This research investigates the potential of machine learning (ML) and AI to overcome these obstacles. The study intends to improve the diagnosis of AD by utilizing advanced imaging techniques (including MRI, PET, and electroencephalography), hybrid AI models (such as Convolutional Neural Network [CNN]-Support Vector Machine [SVM]), and wearable IoT devices. In addition, the research tackles ethical considerations of AI in clinical environments and the difficulties of data integration to advance early detection, tailored care, and the management of neurodegenerative disorders.

3. Literature review

3.1. ML techniques in AD diagnosis

ML is frequently applied in biomedical research to forecast and classify diseases, including AD.¹⁷ Classifiers aid in identifying AD using clinical, MRI, and speech information, with continuous improvements expected to enhance diagnosis and treatment.¹¹ Traditional ML techniques have provided the foundation for AD diagnosis, with research concentrating on automated algorithms to identify neural lesions associated with the disease.¹⁸

Gray *et al.*¹⁹ created a multimodal classification approach employing random forest (RF) classifiers, whereas Feng *et al.*¹⁸ suggested a multilayer classification system to analyze feature-label correlations and introduced a sparse learning method for AD classification, though both techniques require significant computational resources.

Deep learning techniques, such as the fully stacked bidirectional long short-term memory model by Feng *et al.*,¹⁸ have addressed these challenges, enhancing diagnostic accuracy by preserving spatial and semantic data in MRI and PET scans. Models such as SVMs, Decision Tree, and CNNs build on these principles, further advancing AD detection and classification.

3.1.1. SVM

SVM is an effective technique for AD classification, achieving 70–80% accuracy and demonstrating robustness to noise, particularly in small datasets.²⁰ SVMs have historically shown strong theoretical grounding and real-world performance in classification tasks.²¹ They have also

been applied to identify patients with and without rapid cognitive decline,²² a condition associated with accelerated cognitive deterioration, higher institutionalization rates, and increased mortality.²³

3.1.2. CNN

CNNs are widely used deep learning architectures known for sparse interactions, shared parameters, and translation-equivalent representations.²⁴ CNNs excel in extracting hierarchical and spatial information from MRI scans, enabling more accurate characterization of brain structures.²⁵ Their effectiveness in medical imaging, including neuroimaging for AD detection, has been demonstrated in multiple studies.²⁰ Despite their strengths, CNNs often require large datasets and may benefit from integration with classical classifiers to improve generalization.

3.1.3. Hybrid models combining SVMs and CNNs

Hybrid approaches combining CNNs and SVMs have shown strong performance in AD diagnosis by leveraging the strengths of both methods. CNNs automatically extract rich, high-level features from MRI data, while SVM enhances classification stability and accuracy, particularly in small or imbalanced datasets.^{20,26}

For example, Kumar *et al.*²⁷ introduced a hybrid model that uses CNN-based feature extraction combined with SVM classification to distinguish between moderate cognitive impairment and non-demented individuals. Similarly, Yang and Mohammed²⁸ utilized CNN autoencoders to derive low-dimensional representations of MRI and PET scans, which were then classified using SVM to differentiate AD, MCI, and normal cognition. Murugan *et al.*²⁶ also demonstrated that a CNN–SVM framework improves detection across various AD stages compared to standalone CNNs. Subasi²⁹ further highlighted the potential of hybrid models, suggesting the need for comparative evaluation to better assess their performance.

In a related context, Yang and Mohammed²⁸ emphasize the application of CNN-based autoencoders in predicting early AD. Their analysis demonstrates that CNNs create low-dimensional representations of MRI and PET scans, which are then classified with SVMs for distinguishing between AD, MCI, and normal cognition, thereby enhancing diagnostic precision.

In a similar vein, Murugan *et al.*²⁶ utilized a hybrid model combining CNN and SVM to analyze MRI images for the purpose of detecting various stages of AD. The CNN focused on identifying intricate patterns associated with AD, while the SVM contributed to greater accuracy throughout the different phases of cognitive decline, such

as MCI and advanced AD. This approach surpassed the performance of conventional CNN models and enhanced the diagnosis of early-stage AD.

Furthermore, Subasi²⁹ highlighted the promise of hybrid CNN–SVM models, indicating that the application of AI methods to imaging data yields important insights into the progression of AD. These approaches utilize data-driven techniques that enhance diagnosis by effectively classifying imaging information for dependable identification of AD. While the precision of these hybrid models has improved, a comparative analysis is required to evaluate their overall performance.

3.1.4. Comparison of ML approaches

Table 1 presents a comparative evaluation of traditional ML classifiers for AD detection. Logistic regression (LR), SVM, and RF achieved high and consistent performance, each with 96% accuracy, indicating that the extracted feature set is well-suited for classical methods. Adaptive Boosting (AdaBoost) also performed competitively with an accuracy of 94.66%, while K-Nearest Neighbors (KNN) showed lower performance due to its sensitivity to high-dimensional MRI data. Although these models are effective, they rely on manually engineered features and lack the capacity to learn deeper spatial patterns from neuroimaging data. CNN architectures address this limitation through automated feature learning, and their integration with SVM classifiers offers a balanced strategy—leveraging CNN’s representational power and SVM’s robustness. This hybridization strengthens early AD detection and provides a more reliable framework for handling real-world variability in MRI datasets.

Recent studies published between 2021 and 2025 highlight a clear shift toward multimodal neuroimaging, explainable AI, and hybrid architectures for AD diagnosis. Researchers have explored transformer-based models for MRI–PET fusion, interpretable CNNs for clinical transparency, and lightweight deep networks suitable for limited datasets. These advancements reveal ongoing challenges such as the need for high-quality annotated MRI data, improved generalization, and better integration between handcrafted features and deep representations. Although CNN–SVM hybrids have shown considerable promise, very few studies have compared their performance alongside traditional classifiers using a consistent feature extraction pipeline. This gap motivates the present work, which systematically evaluates classical ML models (LR, SVM, RF, AdaBoost, and KNN) and relates their performance to insights from recent deep learning developments to better understand their suitability for early AD diagnosis.

3.2. Dataset analysis

Cognitive evaluations play a key role in AD research by helping assess disease severity and steering subsequent studies.³¹ Large-scale projects such as National Alzheimer's Coordinating Center, Layton Aging and Alzheimer's Center, Alzheimer's Disease Neuroimaging Initiative, the UK Biobank, and the Vienna–Trans–Danube Ageing Project gather comprehensive longitudinal and multimodal information. These initiatives aim to identify clinical, biochemical, genetic, and imaging biomarkers to enhance early detection, predict disease progression, and support the development of therapies.³²

3.3. Description of MRI and other medical imaging datasets used in studies

Medical imaging datasets are fundamental to AD research, providing structural and multimodal information essential for developing reliable diagnostic and predictive models. MRI remains the primary modality due to its high anatomical resolution, while PET, CT, and integrated datasets offer complementary insights. A brief overview of

key MRI and multimodal datasets used in AD studies is summarized in [Table 2](#).

3.4. Evaluation of ML

The comparative analysis of ML algorithms for AD detection relies on widely used performance metrics, including accuracy, precision, recall, F1-score, sensitivity, and specificity.³⁶ These metrics collectively provide a comprehensive assessment by capturing different aspects of classification behavior. Accuracy reflects the overall correctness of predictions but fails to distinguish between positive and negative cases, making it insufficient on its own, especially in imbalanced datasets.³⁷ Precision, recall, and the F1-score—computed based on true positives, false positives, and false negatives—offer deeper insight by quantifying the model's ability to correctly identify AD cases while minimizing misclassifications.³⁸ Sensitivity and specificity further enhance the evaluation by measuring the model's capability to detect actual positive cases and correctly reject non-positive instances. Together, these metrics enable a balanced, reliable, and clinically meaningful evaluation of model performance.

Table 1. Comparison of different ML approaches and their accuracy³⁰

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Key limitations
RF	96	96	96	96	Can overfit noisy features; limited ability to capture spatial MRI patterns; interpretability decreases with more trees
AdaBoost	94.66	95	95	95	Sensitive to noise/outliers; weak learners' misclassification affects entire model
SVM	96	96	96	96	High computational cost; performance depends on kernel choice; requires manual feature engineering
KNN	90.66	93	89	90	Suffers in high-dimensional data; sensitive to feature scaling; slow predictions
LR	96	96	96	96	Assumes linear decision boundaries; cannot capture complex MRI patterns; depends on hand-crafted features

Abbreviations: AdaBoost: Adaptive boosting; KNN: K-nearest neighbors; LR: Logistic regression; MRI: Magnetic resonance imaging; RF: Random forest; SVM: Support vector machine.

Table 2. Summary of MRI and multimodal medical imaging datasets for AD studies

Dataset Name	Description	Features	Ref.
DNI	CNNs used to classify AD stages, including unbalanced and healthy cases	MRI images	27
EEG Signal	FFT features extracted and fed to CNN for disease stage classification	EEG signals from PhysioNet (European format)	22
ADNI	Temporal analysis of MRI, PET, and DTI to predict disease progression	Cortical thickness, volume, and surface area features	33
Basic	Early detection using T2-Star MRI with augmentation (rotation, scaling, and flipping)	1,101 MRI samples augmented to 10,025; XAI (Score-CAM, Grad-CAM)	34
Augmented ADNI Handwritten dataset	Handwriting from 54 participants recorded through WACOM tablet	1D time-series: timestamp, x/y coordinates, pressure, azimuth, altitude	35

Abbreviations: AD: Alzheimer's disease; CNN: Convolutional Neural Network; DTI: Diffusion tensor imaging; EEG: Electroencephalography; FFT: Fast Fourier transform; Grad-CAM: Gradient-weighted class activation mapping; MRI: Magnetic resonance imaging; PET: Positron emission tomography; Score-CAM: Score-weighted class activation mapping; XAI: Explainable artificial intelligence.

A list of formulas used for evaluating ML model are given below:³⁹

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

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

where FN = False negative; FP = False positive; TN = True negative; TP = True positive.

3.5. Overview of IoT in healthcare

The emergence of IoT in the healthcare sector brings considerable opportunities.^{40,41} It is essential for the remote monitoring of patients, both within healthcare facilities and at home.⁴² IoT plays a key role in the digital transformation of medicine, providing innovative business models that improve operational efficiency, decrease expenses, enhance performance, and boost patient satisfaction.⁴³ The concept and functionality of such systems are illustrated in Figure 1.

3.5.1. IoT applications in healthcare

To provide a clear understanding of the evidence base, Table 3 brings together key information from the articles that we selected, facilitating comparison of topics such as antimicrobial resistance, dementia care, and emerging diagnostic technologies.

3.5.2. Types of wearable devices for AD patients

Wearable sensor technologies, along with the IoT, have the potential to provide affordable, objective, and reliable methods for monitoring and understanding functionality.⁶⁷ An overview of these capabilities is presented in Table 4 which outlines the diverse services offered by modern wearable devices.

IoT-based wearable devices present a valuable opportunity for enhancing AD monitoring by capturing real-time physiological and behavioral indicators such as mobility patterns, sleep quality, or daily activity levels. Integrating these continuous data streams with MRI-based diagnostic models could significantly improve early detection accuracy.

However, certain limitations exist. IoT sensors differ in precision, calibration, and sampling frequency, which may introduce noise into the dataset. Continuous monitoring also raises privacy concerns, as long-term behavioral data are highly sensitive. In addition, elderly patients may face usability difficulties, potentially affecting data reliability.

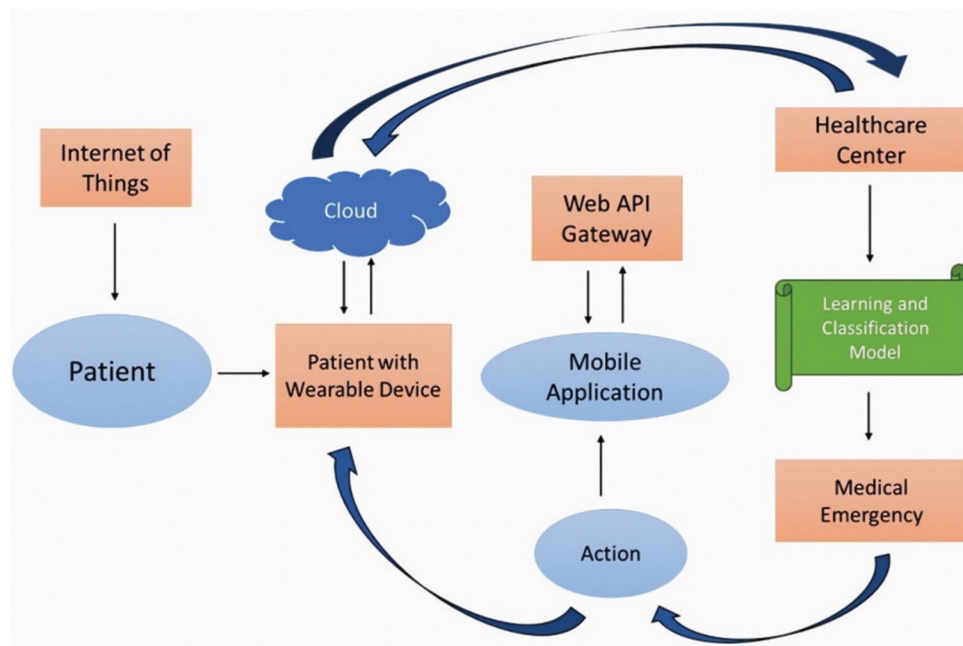


Figure 1. Internet of Things-powered intelligent health tracking device. Image created by the authors.

Table 3. Applications of IoT in healthcare

Section	Study/Focus	Brief description	Ref.
Remote monitoring	IoT-based portable physiological monitoring	Portable physiological monitoring integrated with expert systems.	44
	IoT+Cloud long-suffering monitoring	Continuous monitoring, abnormality detection, alerts, and real-time data transmission were validated.	45
	Body-temperature remote monitoring	Infrared sensors+WiFi, accurate temperature measurement, guidance on ideal body sites.	46
	Secure IoT-healthcare integration	Smartwatch+server+app using secure communication for vital sign monitoring.	47
	ML-based patient surveillance	ML improves remote monitoring, data mining, and healthcare service delivery.	48
	Remote ECG monitoring system	Cloud-linked ECG system enabling doctor–patient remote interaction, alarms, and reduced hospital visits.	49
	IoT for post-COVID monitoring	IoT wearables+ML algorithms for remote monitoring and early medical assistance.	50
	Private backend IoT monitoring server	Backend server uploads vital sign data to the cloud with high accuracy and success rate.	51
	CNN–LSTM patient activity monitoring	CNN–LSTM model yields 99.53% accuracy for human action recognition.	52
	IoT for influenza/COVID-19 suspicion	Smart tracking system assists influenza/COVID-19 patients and tracks mobility for risk behavior.	53
Locating systems	UAV-based source localization	Deep neural networks+radar array for accurate, real-time localization.	54
	RFID+NB-IoT for specimen logistics	Tracks specimen locations and environmental conditions in hospitals.	55
	Wearable tracking system for AD	Indoor/outdoor tracking, step detection, anomaly alerts for AD patients.	56
	Ontology-based location and wellness sensing	Sensor-agnostic APIs for environmental and patient-location monitoring.	57
	IoT for COVID-19 remote monitoring	A COVID-19–based patient tracking system enables timely clinical decisions.	58
	IoT for public bin waste levels	Embedded device tracks trash levels; potential for hospital biomedical waste management.	59
Personalized medicine	IoT adoption and patient engagement	Validates IoT's role in personalized care and secure computing environments.	60
	LDA-based diabetes personalization	The LDA model predicts future diabetic treatment approaches.	61
	Type-1 diabetes pediatric care	IoT+mHealth predicts glucose variation for individualized diet plans.	62
	Personalized dental caries model	ML-based personalized prediction of dental caries risk.	63
	5G-enabled diabetic monitoring	Real-time diabetic monitoring with alerts and personalization.	64
	VOC-based health monitoring	Exhaled VOC analysis for personalized disease diagnosis.	65
	Meta-learning personalization	Meta-learning model for individualized vital sign and activity detection.	66

Abbreviations: AD: Alzheimer's disease; CNN: Convolutional neural network; COVID-19: Coronavirus disease 2019; ECG: Electrocardiography; IoT: Internet of Things; LDA: Linear discriminant analysis; LSTM: Long short-term memory; mHealth: Mobile health; NB-IoT: Narrowband Internet of Things; ML: Machine learning; RFID: Radio-frequency identification; UAV: Unmanned aerial vehicle; VOC: Volatile organic compound.

Table 4. Variety of services offered by wearable technology¹⁶

Wearable device	Description of services	Key features/Connectivity
Smart biomedical system	Provides clock monitoring, location tracking, medication time reminders, and an emergency call button.	Integrated with a mobile app for data access and alerts
Smart assistive health system	Offers audiovisual alerts; stores medication schedules in nonvolatile memory; displays medicine info on LCD; equips with sound effect for attention; and sends message alerts to physicians.	LCD and wireless communication
Environment-aware system	Monitors environment and user activity; provides GPS localization; detects falls; and enables mobile app interaction.	Mobile app service with real-time GPS tracking
Halcyon device	Focuses on patient-device interactions, including instruction assignment, delivery, and movement tracking.	Connected to the mobile app for task management
Intelligent assistive tool	Tracks heart rate; provides medication reminders; monitors patient location; helps find lost items.	Smartphone-linked mobile application

A deeper exploration of standardized protocols, secure data transmission, and multimodal fusion techniques would strengthen future studies in this direction.

3.5.3. AI integration with wearable devices for real-time monitoring

The emergence of AI and wearable technology has revolutionized healthcare, offering innovative solutions for diabetes management.⁶⁸ AI, broadly defined as the ability of computer systems to perform tasks typically requiring human intelligence, is playing an important role in healthcare.⁶⁹ AI-powered systems can analyze vast amounts of data, identify patterns, and make predictions, enabling them to support clinical decision-making,⁷⁰ predict outcomes, and personalize treatment approaches.⁷¹ This ability to process and interpret complex datasets is particularly valuable in diabetes management, where individual patient needs and responses to treatment vary widely.⁷⁰ The use of AI and wearable technology facilitates immediate patient monitoring, supporting the early identification of diseases and fostering recovery.⁷² ML and AI algorithms that analyze data from wearable devices provide valuable health insights, enabling the early detection of illnesses and the development of tailored treatment options.⁷³

4. Research gaps

Even though AD research has advanced tremendously, there are still several important problems that remain unresolved:

4.1. Limited exploration of multimodal and standardized data

Many earlier studies utilized only MRI scans and did not combine them with other useful types of information such as PET scans, medical test results, or long-term data from wearable devices. Although studies by Fernandez Montenegro and Argyriou⁷⁴ and Kumar *et al.*²⁷ demonstrated the potential benefits of using multiple data sources, they did not fully implement or standardize these methods. As a result, developing robust diagnostic systems capable of capturing both the physical changes in the brain and how the disease affects its function remains challenging.

4.2. Insufficient focus on early and subtle AD detection

Some recent research, including Yang and Mohammed,²⁸ do not focus on the detection of early-stage or preclinical AD, where structural changes are subtle. There is still a need for models capable of identifying minute volumetric and cortical alterations before clear symptoms manifest.

4.3. Lack of model interpretability and clinical explainability

A common problem in studies like those by Sai Krishna *et al.*,⁷⁵ Gupta *et al.*,²⁰ and Feng *et al.*¹⁸ is that very minimal attention was paid to explainable AI. Many deep learning models function as “black boxes,” making their decision-making processes difficult to interpret and challenging for clinicians to trust or validate.

4.4. Dataset bias, imbalance, and poor generalization

Many studies did not attempt to address problems such as dataset imbalance, demographic bias, and cross-scanner variability. Without proper testing on diverse groups of people, the models may overfit and will not work well in real-world situations.

4.5. Limited scalability and lack of ethical considerations

Very few studies look at how these models would actually work in real hospital settings or consider important ethical issues such as patient privacy, consent, and bias in the algorithms. As Sai Krishna *et al.*⁷⁵ pointed out, safely and ethically using AI in diagnosis is important but not well studied yet.

5. List of objectives

The purpose of this paper is to investigate the current limitations in diagnosing AD and to explore how contemporary technology can solve these issues.

- To test how well a CNN-SVM model works when using advanced medical imaging techniques, such as MRI scans
- To explore whether combining different types of data can improve early detection of AD and lead to better patient care and treatment
- To increase the diversity of the dataset and use advanced methods to choose the most important features.

6. Research methodology

This work uses structural MRI data derived from the Open Access Series of Imaging Studies (OASIS)⁷⁶ dataset, which was accessed through its standard version on Kaggle. The dataset contains 9488 pre-processed MRI slices categorized into four AD stages—non-demented, very mild demented, mild demented, and moderate demented—based on Clinical Dementia Rating (CDR) scores. The MRI scans originate from a cohort of 416 individuals aged 18–96 years, including 100 participants above 60 years clinically diagnosed with varying levels of cognitive impairment.

Although OASIS dataset is well-known for its high-quality T1-weighted MRI scans, it has some limitations. The scans were taken using different machines and settings, which can cause differences in image quality, structure, and feature extraction. Problems such as movement during scanning, uneven image intensity, and normal age-related changes in the brain can also affect MRI-based diagnosis.

The Kaggle version of the dataset only includes MRI scans, without other types of data such as PET scans, which could make diagnosis more reliable. There are also fewer cases of mild and moderate AD, which can make it harder for models to generalize well.

Preprocessing steps such as removing the skull, normalizing intensity, resizing images, and reducing noise help reduce some of these issues, but they cannot fix everything. All of these factors can affect how well the ML models perform and how reliably they work on new data.

The block diagram in Figure 2 illustrates the complete workflow followed in this work. The original MRI scans were provided as 3D volumes, which were converted into NIfTI (.nii) format using FSL and segmented along the z-axis (slices 100–160) to generate 2D JPEG images suitable for model training. All MRI slices were standardized to 224×224 resolution and denoised to ensure uniformity across samples. Exploratory data analysis was performed

on the dataset to examine label distribution, image quality, and basic demographic characteristics. Feature extraction was conducted using a pretrained ResNet-50 model to obtain high-level imaging features. These features were then combined with available clinical annotations and split into training and testing sets using an 80:20 ratio. Normalization was applied before feeding the feature vectors into the ML classifier.

The performance of each classifier was evaluated using accuracy, precision, recall, F1-score, and confusion matrices. This integrated pipeline ensured systematic preprocessing, robust feature extraction, and reliable evaluation for AD classification using the OASIS MRI dataset.

7. Results and discussion

7.1. Quantitative performance analysis

The proposed classification model showed slight variations in performance across different tests, with overall accuracy ranging from 75% to 99%. This shows that the model is sensitive to changes in the dataset but can adapt to different types of input. In the first test, the model had a precision of 0.79 and a recall of 0.72, meaning it was moderately good at distinguishing AD cases from non-AD cases. In the next test, it performed perfectly with both precision and recall at 1.0, showing that under ideal conditions, the model can make very reliable predictions. In the final test, the model

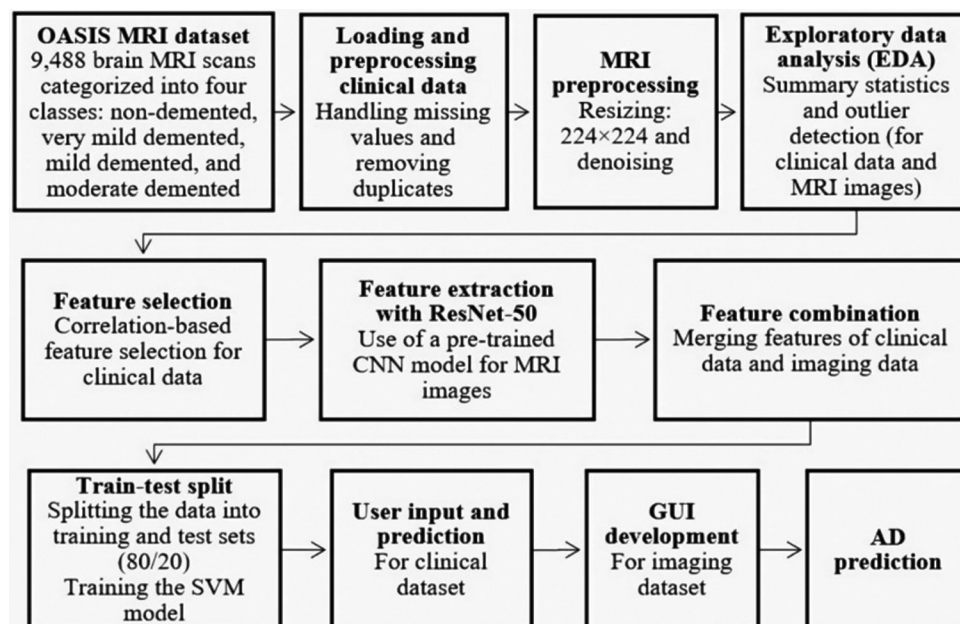


Figure 2. Block diagram of AD prediction workflow. Image created by the authors.

Abbreviations: AD: Alzheimer's disease; CNN: Convolutional neural network; GUI: Graphical user interface; MRI: Magnetic resonance imaging; OASIS: Open Access Series of Imaging Studies; SVM: Support vector machine.

achieved an accuracy of 83.33%, a precision of 0.875, and a recall of 0.7. This shows overall strong performance, though it also highlights that the model struggles slightly with less common cases due to class imbalance. These variations emphasize the need for better-balanced datasets and more robust sampling methods to strengthen the model's reliability. Overall, the results show that AI has strong potential for early AD detection, but improvements in datasets, feature selection, and the use of explainable AI are needed to make the results more interpretable and useful for clinicians.

7.2. Behavior of clinical and imaging features

The dataset was thoroughly analyzed using histograms, correlation matrices, and example MRI images:

- Histograms show how key clinical and demographic measures are distributed. Mini-mental state examination (MMSE) scores, for example, are skewed, indicating that there are more people with lower cognitive function
- Box plots highlight outliers in MMSE, socioeconomic status (SES), and CDR scores, showing that the data are quite variable and emphasizing the need for careful preprocessing
- Correlation matrices show strong relationships between certain variables, especially between estimated total intracranial volume (eTIV) and normalized whole-brain volume (nWBV), indicating that brain volume measures are important predictors
- Sample MRI slices display noticeable structural changes at different stages of AD, helping to visually

track how the disease progression.

The AD classification model was thoroughly evaluated using sample images, correlation matrices, histograms, and box plots of important numerical variables.

- Histograms (Figure 3) show how key clinical and demographic measures are distributed. MMSE scores are skewed, indicating that many AD patients have lower cognitive performance
- Box plots (Figure 4) show outliers in MMSE, SES, and CDR, indicating profound variability in the data and highlighting the need for careful preprocessing
- Correlation matrix (Figure 5) shows strong relationships between some variables. For example, eTIV and nWBV are highly correlated, suggesting that these brain-volume measures are closely related and may both play a role in classification
- Representative MRI images (Figure 6) show structural brain changes at different AD stages, helping to visually interpret disease progression and complement the numerical analysis.

7.3. Model interpretation and clinical applicability

Figure 7 provides case studies illustrating clinical detection of AD using the proposed model. This system operates as a binary classifier, requiring essential clinical parameters—age, CDR, years of education (Educ), MMSE, and SES—to generate diagnostic predictions categorizing individuals as AD-positive or AD-negative. The Dementia Detection App interface (Figure 8) further showcases a user-friendly design enabling healthcare professionals to upload brain scans and

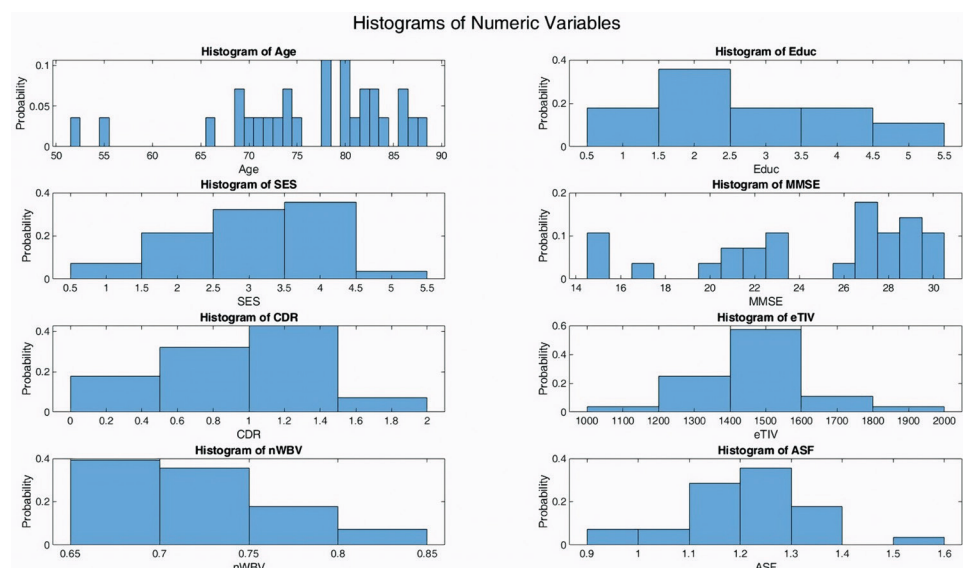


Figure 3. Histograms of clinical variables. Image created by the authors.

Abbreviations: ASF: Atlas scaling factor; CDR: Clinical dementia rating; Educ: Years of education; eTIV: Estimated total intracranial volume; MMSE: Mini-mental state examination; nWBV: Normalized whole-brain volume; SES: Socioeconomic status.

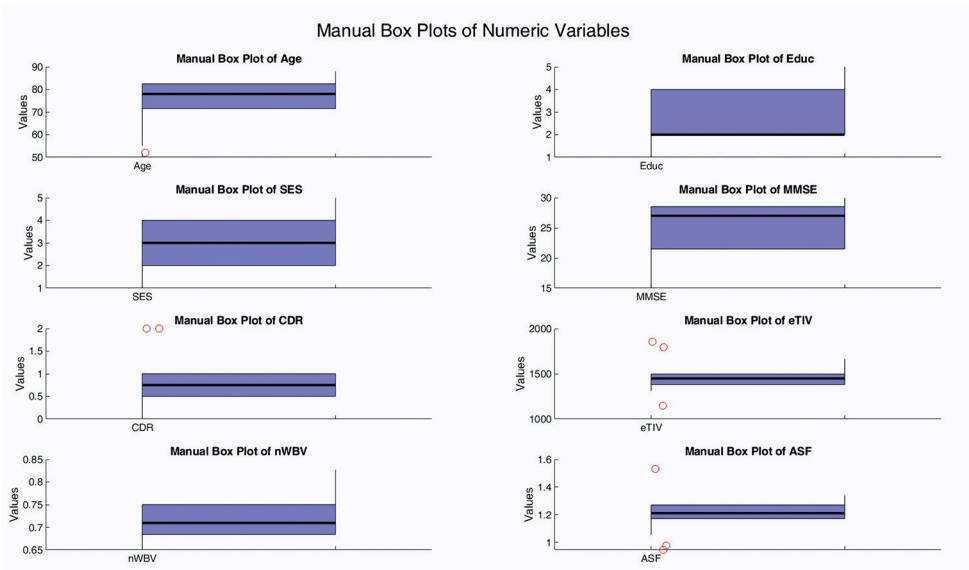


Figure 4. Distribution of key predictors. Image created by the authors.
Abbreviations: ASF: Atlas scaling factor; CDR: Clinical dementia rating; Educ: Years of education; eTIV: Estimated total intracranial volume; MMSE: Mini-mental state examination; nWBV: Normalized whole-brain volume; SES: Socioeconomic status.

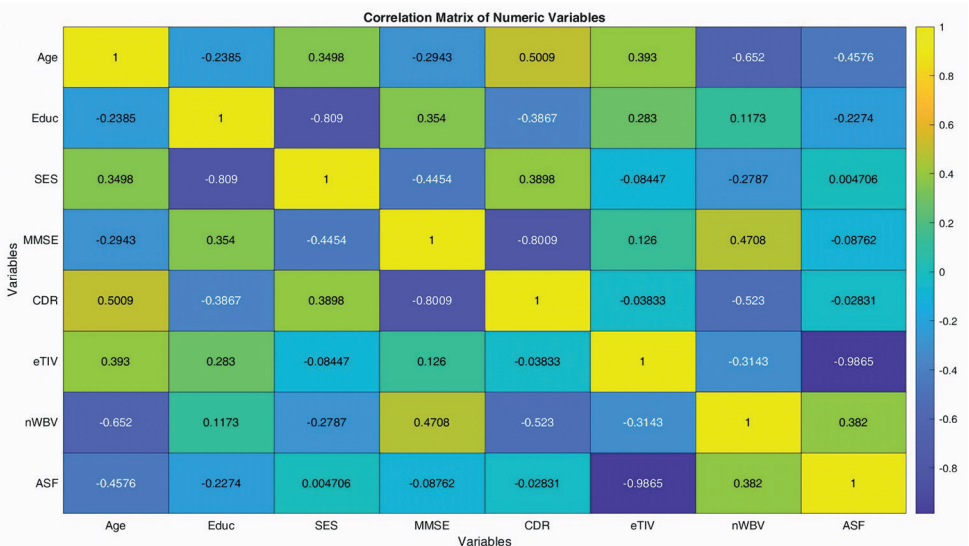


Figure 5. Correlation matrix of clinical variables. Image created by the authors.
Abbreviations: ASF: Atlas scaling factor; CDR: Clinical dementia rating; Educ: Years of education; eTIV: Estimated total intracranial volume; MMSE: Mini-mental state examination; nWBV: Normalized whole-brain volume; SES: Socioeconomic status.

receive immediate binary classification results (“Dementia Detected” or “No Dementia Detected”). By offering rapid, image-based preliminary screening, the application enhances clinical workflow efficiency while maintaining interpretability through its streamlined binary output.

7.4. Ethical considerations in AI-based AD diagnosis

Using AI to detect AD brings up important ethical issues that need careful attention to ensure that it is used safely in hospitals and clinics.

- Patient privacy is a key concern because MRI scans and medical records contain sensitive health information. Strong data protection, anonymization, and compliance with rules such a HIPAA and GDPR are needed to prevent misuse
- Informed consent is essential, so patients understand how their data will be used, stored, and incorporated into AI tools
- Algorithmic bias can happen if certain groups (by age, gender, or ethnicity) are underrepresented in datasets

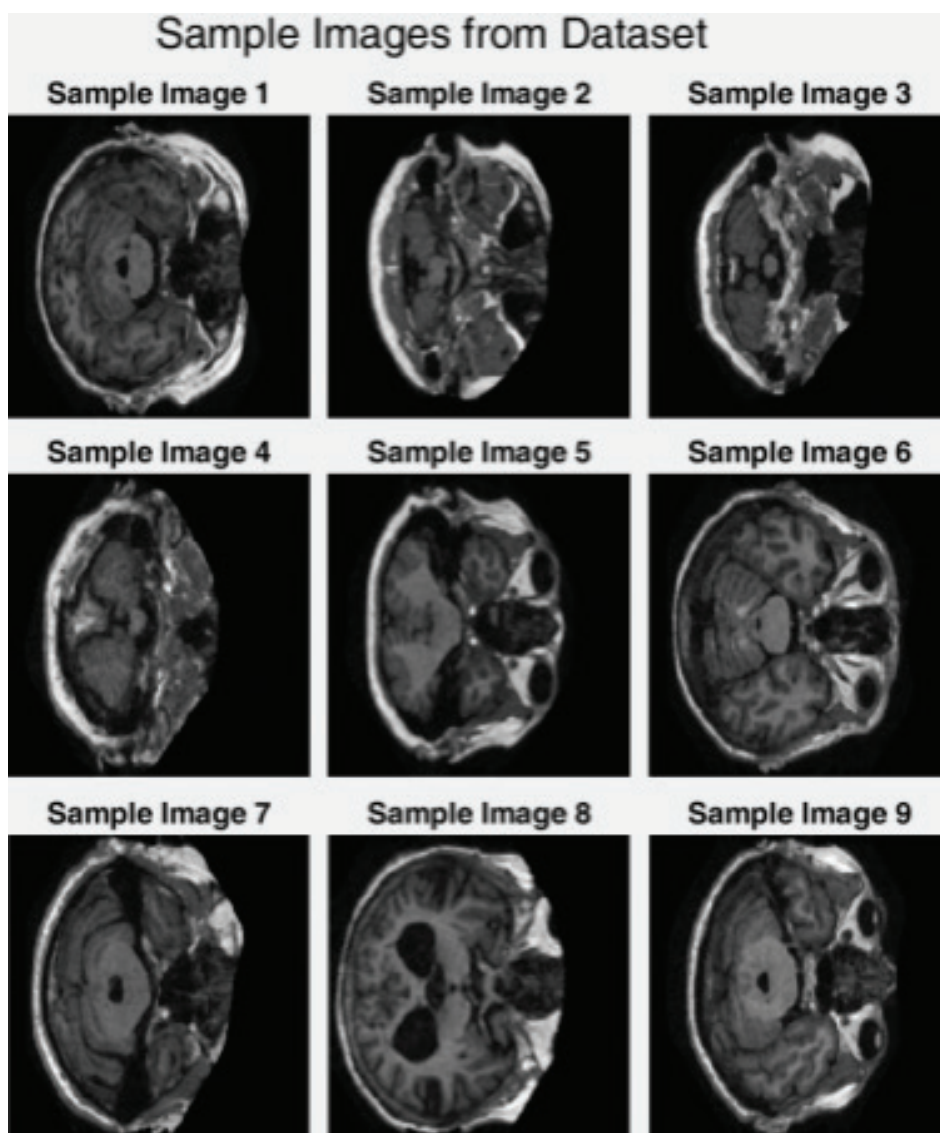


Figure 6. Representative MRI images. Image created by the authors.
Abbreviation: MRI: Magnetic resonance imaging.

```
Enter 1 for Clinical Data or 2 for Image Data: 1
Enter value for Age: 45
Enter value for CDR: 0
Enter value for Educ: 6
Enter value for MMSE: 26
Enter value for SES: 3
The model predicts: The person does not have Alzheimer's disease based on clinical data.
Enter value for Age: 80
Enter value for CDR: 3
Enter value for Educ: 6
Enter value for MMSE: 9
Enter value for SES: 1
The model predicts: The person has Alzheimer's disease based on clinical data.
```

Figure 7. A representative clinical case of Alzheimer's disease detection. Image created by the authors.

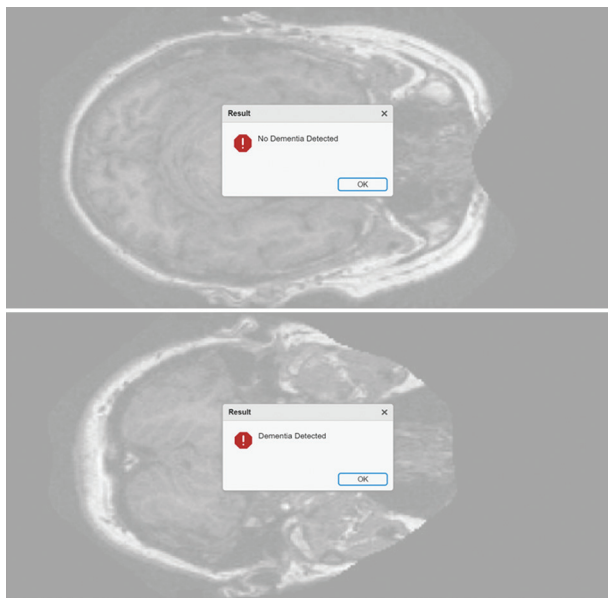


Figure 8. Interface of an App for detecting dementia with prediction and outcome modules. Image created by the authors.

like OASIS. This could make the AI less accurate for some people, raising fairness concerns

- Interpretability is also an important factor. Helping clinicians to understand AI predictions and gaining, there is critical trust before such an approach can be deployed in clinical practice. Using explainable AI and transparent decision-making helps make the technology safer and more reliable in healthcare settings.

8. Conclusion

This work shows that AI, especially the hybrid CNN-SVM models, can improve AD diagnosis by combining different types of data. The model performed well, with accuracy between 75% and 99%, though changes in precision and recall show it is sensitive to uneven datasets and feature differences. Testing with the OASIS MRI dataset confirmed that the model can reliably tell the difference between dementia and non-dementia cases under different conditions. The Dementia Detection App demonstrates the potential for using such models in clinical settings for quick MRI-based screening. However, the performance variations highlight the need for better-balanced datasets, improved feature-selection methods, and the use of explainable AI to make the model's decisions clearer and more trustworthy for doctors. Improving these areas is important to make the model reliable for early detection of AD in real-world settings.

Future research can expand on this study in several important ways. First, creating datasets that combine MRI, PET scans, medical records, and data from wearable devices would give a more complete picture of AD

progression and help detect the disease earlier. Next, it is important to standardize MRI preprocessing steps, such as skull stripping, intensity normalization, and segmentation, because inconsistencies in these steps can affect model performance and make it hard to compare results across studies. In addition, it is necessary to develop strong, generalizable deep learning models that perform well across different MRI scanners, age groups, and diverse populations. This will make AI-based AD diagnosis more reliable and fairer for real-world clinical use.

Acknowledgments

None.

Funding

None.

Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Saurabh Mukherjee

Visualization: Gracy Singh, Sonali Bhatt

Writing—original draft: Gracy Singh, Nidhi Verma, Sonali Bhatt

Writing—review & editing: Sonali Bhatt

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

The dataset used in this study is the OASIS MRI dataset, which is a publicly available dataset on Kaggle.

References

1. Parra MA, Butler S, McGeown WJ, Brown Nicholls LA, Robertson DJ. Globalising strategies to meet global challenges: The case of ageing and dementia. *J Glob Health*. 2019;9(2):020310. doi: 10.7189/jogh.09.020310
2. Al Mani TY, Sallam AM, Aldosary RA, AlGhamdi JA, Ghulam BM, Shamah WF. Impact of palliative care for dementia patients in tertiary hospitals among Saudi Arabia: A systemic review. *Arch Pharm Pract*. 2022;13(3):134-140. doi: 10.51847/2gfkzkb1m
3. Emmady PD, Schoo C, Tadi P. *Major Neurocognitive Disorder (Dementia)*. In: StatPearls [Internet]. Treasure Island (FL):

- StatPearls Publishing. Updated Nov 19, 2022. Available from: <https://www.ncbi.nlm.nih.gov/books/NBK557444/>
4. 2016 Alzheimer's disease facts and figures. Alzheimer's & Dementia. 2016;12(4):459-509.
doi: 10.1016/j.jalz.2016.03.001
5. Deb A, Thornton JD, Sambamoorthi U, Innes K. Direct and indirect cost of managing Alzheimer's disease and related Dementias in the United States. *Expert Rev Pharmacoecon Outcomes Res.* 2017;17(2):189-202.
doi: 10.1080/14737167.2017.1313118
6. Surguchov A, Emamzadeh FN, Titova M, Surguchev AA. Controversial properties of amyloidogenic proteins and peptides: New data in the COVID ERA. *Biomedicines.* 2023;11(4):1215.
doi: 10.3390/biomedicines11041215
7. Jack CR, Bennett DA, Blennow K, *et al.* NIA-AA research framework: Toward a biological definition of Alzheimer's disease. *Alzheimers Dement.* 2018;14(4):535-562.
doi: 10.1016/j.jalz.2018.02.018
8. Dubois B, Feldman HH, Jacova C, *et al.* Revising the definition of Alzheimer's disease: A new lexicon. *Lancet Neurol.* 2010;9(11):1118-1127.
doi: 10.1016/s1474-4422(10)70223-4
9. Porsteinsson AP, Isaacson RS, Knox S, Sabbagh MN, Rubino I. Diagnosis of early Alzheimer's disease: Clinical practice in 2021. *J Prev Alzheimers Dis.* 2021;8(3):371-386.
doi: 10.14283/jpad.2021.23
10. Kumar A. *Alzheimer Disease*. StatPearls; 2024. Available from: <https://www.ncbi.nlm.nih.gov/books/nbk499922> [Last accessed on 2025 Dec 02].
11. Ammar RB, Ayed YB. Language-related features for early detection of Alzheimer disease. *Proc Comput Sci.* 2020;176:763-770.
doi: 10.1016/j.procs.2020.09.071
12. Scheltens P, De Strooper B, Kivipelto M, *et al.* Alzheimer's disease. *Lancet.* 2021;397(10284):1577-1590.
doi: 10.1016/s0140-6736(20)32205-4
13. Wells C, Horton J. An Overview of New and Emerging Technologies for Early Diagnosis of Alzheimer Disease. *Can J Health Technol.* 2022;2(5).
doi: 10.51731/cjht.2022.330
14. Kale M, Wankhede N, Pawar R, *et al.* AI-driven innovations in Alzheimer's disease: Integrating early diagnosis, personalized treatment, and prognostic modelling. *Ageing Res Rev.* 2024;101:102497.
doi: 10.1016/j.arr.2024.102497
15. Akpinar E. Quantum machine learning in the cognitive domain: Alzheimer's disease study. In: *2024 IEEE High Performance Extreme Computing Conference (HPEC); 2024:1-6.*
doi: 10.1109/hpec62836.2024.10938482
16. Salehi W, Gupta G, Bhatia S, Koundal D, Mashat A, Belay A. IOT-based wearable devices for patients suffering from Alzheimer disease. *Contrast Media Mol Imaging.* 2022;2022(1):3224939.
doi: 10.1155/2022/3224939
17. Balamurugan M, Nancy A, Vijaykumar S. Alzheimer's disease diagnosis by using dimensionality reduction based on Knn classifier. *Biomed Pharmacol J.* 2017;10(4):1823-1830.
doi: 10.13005/bpj/1299
18. Feng C, Elazab A, Yang P, *et al.* Deep learning framework for Alzheimer's disease diagnosis via 3D-CNN and FSBI-LSTM. *IEEE Access.* 2019;7:63605-63618.
doi: 10.1109/access.2019.2913847
19. Gray KR, Aljabar P, Heckemann RA, Hammers A, Rueckert D. Random Forest-based similarity measures for multi-modal classification of Alzheimer's disease. *NeuroImage.* 2013;65:167-175.
doi: 10.1016/j.neuroimage.2012.09.065
20. Gupta M, Kumar R, Abraham A. Adversarial network-based classification for Alzheimer's disease using multimodal brain images: A critical analysis. *IEEE Access.* 2024;12:48366-48378.
doi: 10.1109/access.2024.3381956
21. Hearst MA, Dumais ST, Osuna E, Platt J, Scholkopf B. Support vector machines. *IEEE Intellig Syst Application.* 1998;13(4):18-28.
doi: 10.1109/5254.708428
22. Deepthi LD, Shanthi D, Buvana M. An Intelligent Alzheimer's Disease Prediction Using Convolutional Neural Network (CNN). *Int J Adv Res Eng Technol.* 2020;11(4):12-22.
23. Soto ME, Andrieu S, Arbus C, *et al.* Rapid cognitive decline in Alzheimer's disease. Consensus paper. *J Nutr Health Aging.* 2008;12(10):703-713.
doi: 10.1007/bf03028618
24. Agrawal S, Pandharkar NS, Khandelwal PA, Pandhare PA, Deoghare JS. Alzheimer's disease classification using deep CNN. *Int J Sci Res Comput Sci Eng Inform Technol.* 2021;7:325-331.
doi: 10.32628/cseit217371
25. Salomi M, Wadhwa D, Madan P. Diagnosis of Alzheimer Stages by using CNN Architecture. In: *2024 5th International Conference for Emerging Technology (INCET); 2024:1-6.*
doi: 10.1109/incet61516.2024.10593422
26. Murugan S, Venkatesan C, Sumithra MG, *et al.* DEMNET:

- A deep learning model for early diagnosis of Alzheimer diseases and dementia from Mr Images. *IEEE Access*. 2021;9:90319-90329.
doi: 10.1109/access.2021.3090474
27. Kumar MS, Azath H, Velmurugan AK, Padmanaban K, Subbiah M. Prediction of Alzheimer's disease using hybrid machine learning technique. In: *AIP Conference Proceedings*. Vol 2613. AIP Publishing; 2023:020091.
doi: 10.1063/5.0110283
28. Yang K, Mohammed EA. A Review of Artificial Intelligence Technologies for Early Prediction of Alzheimer's Disease. *arXiv*. Preprint posted online 2021.
doi: 10.48550/arXiv.2101.01781
29. Subasi A. Use of artificial intelligence in Alzheimer's disease detection. In: *Artificial Intelligence Precision Health*. United States: Academic Press; 2020:257-278.
doi: 10.1016/b978-0-12-817133-2.00011-2
30. Cabanillas-Carbonell M, Zapata-Paulini J. Evaluation of machine learning models for the prediction of Alzheimer's: In search of the best performance. *Brain Behav Immun Health*. 2025;47:100957.
doi: 10.1016/j.bbih.2025.100957
31. Khan S, Barve KH, Kumar MS. Recent advancements in pathogenesis, diagnostics and treatment of Alzheimer's disease. *Curr Neuroparmacol*. 2020;18(11):1106-1125.
doi: 10.2174/1570159x18666200528142429
32. Bellio M, Oxtoby NP, Walker Z, et al. Analyzing large Alzheimer's disease cognitive datasets: Considerations and challenges. *Alzheimers Dement (Amst)*. 2020;12(1):e12135.
doi: 10.1002/dad2.12135
33. Hong X, Lin R, Yang C, et al. Predicting Alzheimer's disease using LSTM. *IEEE Access*. 2019;7:80893-80901.
doi: 10.1109/access.2019.2919385
34. Jahan S, Saif Adib R, Mahmud M, Kaiser MS. Comparison between explainable AI algorithms for Alzheimer's disease prediction using efficient net models. In: *Lecture Notes in Computer Science*. Berlin: Springer; 2023:357-368.
doi: 10.1007/978-3-031-43075-6_31
35. Dao Q, El-Yacoubi MA, Rigaud AS. Detection of Alzheimer disease on online handwriting using 1D convolutional neural network. *IEEE Access*. 2023;11:2148-2155.
doi: 10.1109/access.2022.3232396
36. Srivastava S, Divekar AV, Anilkumar C, Naik I, Kulkarni V, Pattabiraman V. Comparative analysis of deep learning image detection algorithms. *J Big Data*. 2021;8(1):66.
doi: 10.1186/s40537-021-00434-w
37. Dalianis H. Evaluation metrics and evaluation. In: *Clinical Text Mining*. Berlin: Springer; 2018:45-53.
doi: 10.1007/978-3-319-78503-5_6
38. Bari Antor M, Jamil AH, Mamtaz M, et al. A comparative analysis of machine learning algorithms to predict Alzheimer's disease. *J Healthc Eng*. 2021;2021:9917919.
doi: 10.1155/2021/9917919
39. Rainio O, Teuhio J, Klén R. Evaluation metrics and statistical tests for machine learning. *Sci Rep*. 2024;14(1):6086.
doi: 10.1038/s41598-024-56706-x
40. Ray PP. A survey on internet of things architectures. *J King Saud Univ Comput Inform Sci*. 2018;30(3):291-319.
doi: 10.1016/j.jksuci.2016.10.003
41. Rejeb A, Rejeb K, Treiblmaier H, et al. The internet of things (IOT) in healthcare: Taking stock and moving forward. *Int Things*. 2023;22:100721.
doi: 10.1016/j.iot.2023.100721
42. Jara AJ, Zamora-Izquierdo MA, Skarmeta AF. Interconnection framework for mHealth and remote monitoring based on the internet of things. *IEEE J Select Areas Commun*. 2013;31(9):47-65.
doi: 10.1109/jsac.2013.sup.0513005
43. Rayan RA, Tsagkaris C, Iryna RB. The internet of things for healthcare: Applications, selected cases and challenges. In: *Studies in Computational Intelligence*. Berlin: Springer; 2021:1-15.
doi: 10.1007/978-981-15-9897-5_1
44. Valsalan P, Hasan NU, Baig I, Zghaibeh M. Remote healthcare monitoring using expert system. *Int J Adv Comput Sci Appl*. 2022;13(3):593.
doi: 10.14569/ijacsa.2022.0130370
45. Sahu ML, Atulkar M, Ahirwal MK, Ahamad A. Cloud-based remote patient monitoring system with abnormality detection and alert notification. *Mobile Netw Appl*. 2022;27(5):1894-1909.
doi: 10.1007/s11036-022-01960-4
46. Boonsong W, Senajit N, Prasongchan P. Contactless body temperature monitoring of in-patient department (IPD) using 2.4 GHz microwave frequency via the internet of things (IOT) network. *Wireless Personal Commun*. 2022;124(3):1961-1976.
doi: 10.1007/s11277-021-09438-4
47. Imtyaz Ahmed M, Kannan G. Secure and lightweight privacy preserving internet of things integration for remote patient monitoring. *J King Saud Univ Comput Inform Sci*. 2022;34(9):6895-6908.
doi: 10.1016/j.jksuci.2021.07.016
48. Deepa S, Sridhar KP, Baskar S, Mythili KB, Reethika A,

- Hariharan PR. IOT-enabled smart healthcare data and health monitoring based machine learning algorithms. *J Intellig Fuzzy Syst.* 2023;44(2):2927-2941.
doi: 10.3233/jifs-221274
49. Bushnag A. A wireless ECG Monitoring and analysis system using the IOT Cloud. *Intellig Autom Soft Comput.* 2022;33(1):51-70.
doi: 10.32604/iasc.2022.024005
50. Rahman S, Parveen S, Sofi SA, Zahoor S. Post-covid remote patient monitoring using medical internet of things and machine learning analytics. *Scalable Comput Pract Exp.* 2023;24(1):1-16.
doi: 10.12694/scpe.v24i1.2008
51. Ali FI, Ali TE, Al-Dahan ZT. Private backend server software-based Telehealthcare Tracking and monitoring system. *Int J Online Biomed Eng.* 2023;19(01):119-134.
doi: 10.3991/ijoe.v19i01.32433
52. Balasubramanian K, Prabu AV, Shaik MF, Naik RA, Suguna SK. A hybrid deep learning for patient activity recognition (PAR): Real time body wearable sensor network from healthcare monitoring system (HMS). *J Intellig Fuzzy Syst.* 2023;44(1):195-211.
doi: 10.3233/jifs-212958
53. Abdulhussein TA, Al-Falahi HA, Ahmed Smaït D, Alani S, Mahmood SN, Mustafa MS. Early coronavirus disease detection using internet of things smart system. *Int J Electr Comput Eng.* 2023;13(1):1161.
doi: 10.11591/ijece.v13i1.pp1161-1168
54. Cong J, Wang X, Yan C, Yang LT, Dong M, Ota K. CRB weighted source localization method based on deep neural networks in Multi-UAV network. *IEEE Int Things J.* 2023;10(7):5747-5759.
doi: 10.1109/jiot.2022.3150794
55. Le NT, Thwe Chit MM, Truong TL, *et al.* Deployment of smart specimen transport system using RFID and Nb-IOT technologies for hospital laboratory. *Sensors (Basel).* 2023;23(1):546.
doi: 10.3390/s23010546
56. García-Requejo A, Pérez-Rubio MC, Villadangos JM, Hernández Á. Activity monitoring and location sensory system for people with mild cognitive impairments. *IEEE Sens J.* 2023;23(5):5448-5458.
doi: 10.1109/jsen.2023.3239980
57. Zappatore M, Longo A, Martella A, Di Martino B, Esposito A, Gracco SA. Semantic models for IOT sensing to infer environment-wellness relationships. *Fut Gen Comput Syst.* 2023;140:1-17.
doi: 10.1016/j.future.2022.10.005
58. Yoganapriya R, Deepthi P, Dhinakaran M. IOT based COVID patient health monitoring system. *Int J Eng Technol Manage Sci.* 2023;7(1):82-87.
doi: 10.46647/ijetms.2023.v07i01.015
59. Karthik M, Sreevidya L, Nithya Devi R, Thangaraj M, Hemalatha G, Yamini R. An efficient waste management technique with IOT based smart garbage system. *Mater Today Proceed.* 2023;80:3140-3143.
doi: 10.1016/j.matpr.2021.07.179
60. Bhatt V, Chakraborty S. Improving service engagement in healthcare through internet of things based healthcare systems. *J Sci Technol Policy Manag.* 2021;14(1):53-73.
doi: 10.1108/jstpm-03-2021-0040
61. Ni Ki C, Hosseinian-Far A, Daneshkhah A, Salari N. Topic modelling in precision medicine with its applications in personalized diabetes management. *Exp Syst.* 2021;39(4):e12774.
doi: 10.1111/exsy.12774
62. Zholdas N, Mansurova M, Postolache O, Kalimoldayev M, Sarsembayeva T. A personalized mHealth monitoring system for children and adolescents with T1 diabetes by utilizing IOT sensors and assessing physical activities. *Int J Comput Commun Control.* 2022;17(3):2-14.
doi: 10.15837/ijccc.2022.3.4558
63. Kang IA, Ngamsie Njimbouom S, Lee KO, Kim JD. DCP: Prediction of dental caries using machine learning in personalized medicine. *Appl Sci.* 2022;12(6):3043.
doi: 10.3390/app12063043
64. Sravani MVS, Poojitha P, Joshi P, Prathyusha B. 5G-smart diabetes: Toward personalized diabetes diagnosis with healthcare big data clouds. *IEEE Commun Magaz.* 2018;56:16-23.
doi: 10.1109/MCOM.2018.1700788
65. Karthick GS, Pankajavalli PB. Chronic obstructive pulmonary disease prediction using internet of things-spiro system and fuzzy-based quantum neural network classifier. *Theor Comput Sci.* 2023;941:55-76.
doi: 10.1016/j.tcs.2022.08.021
66. Jia Z, Shi Y, Hu J. Personalized neural network for patient-specific health monitoring in IOT: A metalearning approach. *IEEE Trans Comput Aided Design Integr Circuits Syst.* 2022;41(12):5394-5407.
doi: 10.1109/tcad.2022.3162182
67. Stavropoulos TG, Lazarou I, Diaz A, *et al.* Wearable devices for assessing function in Alzheimer's disease: A European public involvement activity about the features and preferences of patients and caregivers. *Front Aging Neurosci.* 2021;13:643135.

- doi: 10.3389/fnagi.2021.643135
68. Sarma AD, Devi M. Artificial Intelligence in diabetes management: Transformative potential, challenges, and opportunities in healthcare. *Hormones (Athens)*. 2025;24(2):307-322.
doi: 10.1007/s42000-025-00644-4
 69. Ahmed A, Aziz S, Abd-alrazaq A, Farooq F, Sheikh J. Overview of artificial intelligence-driven wearable devices for diabetes: Scoping review. *J Med Internet Res*. 2022;24(8):e36010.
doi: 10.2196/36010
 70. Makroum MA, Adda M, Bouzouane A, Ibrahim H. Machine learning and smart devices for diabetes management: Systematic review. *Sensors (Basel)*. 2022;22(5):1843.
doi: 10.3390/s22051843
 71. Iftikhar M, Saqib M, Qayyum SN, *et al*. Artificial intelligence-driven transformations in diabetes care: A comprehensive literature review. *Ann Med Surg (Lond)*. 2024;86(9):5334-5342.
doi: 10.1097/ms9.0000000000002369
 72. LaBoone PA, Marques O. Overview of the future impact of wearables and artificial intelligence in healthcare workflows and technology. *Int J Inform Manag Data Insights*. 2024;4(2):100294.
doi: 10.1016/j.jjimei.2024.100294
 73. Briganti G, Le Moine O. Artificial intelligence in medicine: Today and tomorrow. *Front Med (Lausanne)*. 2020;7:27.
doi: 10.3389/fmed.2020.00027
 74. Fernandez Montenegro JM, Argyriou V. Cognitive evaluation for the diagnosis of Alzheimer's disease based on turing test and virtual environments. *Physiol Behav*. 2017;173:42-51.
doi: 10.1016/j.physbeh.2017.01.034
 75. Sai Krishna K, Sarma KJ, Bamane KD, Prasad J, Tiwari M, Karthikeyan T. Alzheimer disease detection using AI with deep learning based features with development and validation based on data science. *J Adv Zool*. 2023;44(S4):91-99.
doi: 10.17762/jaz.v44is4.2174
 76. Marcus DS, Wang TH, Parker J, Csernansky JG, Morris JC, Buckner RL. Open access series of imaging studies (OASIS): Cross-sectional MRI data in young, middle aged, nondemented, and demented older adults. *J Cogn Neurosci*. 2007;19(9):1498-1507.
doi: 10.1162/jocn.2007.19.9.1498