MedCrave
Step into the World of Research

Journal of Neurology & Stroke

Research Article

Open Access

CrossMark

# Application of artificial intelligence for early detection of alzheimer's disease based on blood biomarkers and neuroimaging

## Abstract

Alzheimer's disease is the leading cause of dementia worldwide, requiring increasingly early and accurate diagnostic methods. This study investigated the application of artificial intelligence (AI) techniques in the early detection of AD, focusing on the integrated analysis of blood biomarkers and neuroimaging. The literature review showed that AI models have high diagnostic performance, especially when combining molecular data (such as p-tau and beta-amyloid) with structural and functional imaging tests (MRI and PET-FDG). The combined models showed an accuracy of over 95%, significantly outperforming the isolated methods. Statistical analysis showed a strong correlation between the complexity of the data used and the performance of the algorithms, suggesting that multidimensional approaches are the most effective. It is concluded that AI is a promising tool for the early diagnosis of AD, with the potential to transform clinical practice, provided it is implemented in an ethical, accessible manner and validated by multicenter studies.

**Keywords:** alzheimer's disease, artificial intelligence, plasma biomarkers, neuroimaging, early diagnosis, pet-fdg; machine learning

Volume 15 Issue 2 - 2025

Daniel Rubens Freitas Facundo,[1] Aline Cristina Couto da Silva,[1] Delio Tiago Martins Malaquias,[1] Ana Graziela De Almeida Valiengo,[1] Christian Emmanuel da Silva Pelaes,[1] José Carlos Ferreira da Silva,[1] Érica Miriam Fernandes Miranda Vão,[1] Erik Franklin Almeida da Silva,[1] Gabriel Leonardo Saraiva,[1] Guilherme Guissone Martins,[1] Isabelle Pinheiro Santos,[1] Leonardo Tomé da Silva,[1] Rayssa Prince Cardoso,[1] Rafaela Gonçalves Bueno,[1] Julienne Fernanda Carvalho e Silva,[2] Marilda Bispo de Sá Oliveira,[2] Rubens Rodrigues Tudela,[3] Giovana Casarini Yamashiro,[8] Juliana Fontes Beltran Paschoal,[1–4] Cristiano Bento Alvarenga,[9] Liliana Martins Occulate,[9] Lucas Pereira Sales Porto,[5] Joel Eloi Belo Junior,[6] Maiane Malaquias Martins,[10] Thiago Augusto Rochetti Bezerra[1-7]

[1]Medical student. University of Ribeirão Preto (UNAERP), Guarujá, São Paulo, Brazil
[2]Medical student. University of the Integration of the Americas. Ciudad del Este, Paraguay
[3]Medical student. São Judas University. Cubatão, São Paulo, Brazil
[4]PhD in Biotechnology. University of São Paulo (USP), São Paulo, Brazil
[5]Academic in Biochemistry and Molecular Biology. The Pennsylvania State University, United States of America.
[6]Major Aviator. Brazilian Air Force. Master in Operational Human Performance. Master's student in Intellectual Property and Technology Transfer for Innovation
[7]PhD in Medical Sciences. Faculty of Medicine, University of São Paulo (FMRP/USP). Ribeirão Preto, São Paulo, Brazil
[8]Medical student. Nove de Julho University, São Bernardo do Campo, São Paulo, Brazil
[9]Medical student. Central University of Paraguay
[10]Graduated in nursing from the São Francisco de Barreiras College - FASB -2012- Barreiras-BA, Postgraduate in Elderly Health management and assistance in Gerontology from the Laboro College, São Luis 2019

**Correspondence:** Thiago Augusto Rochetti Bezerra, University of Ribeirão Preto (UNAERP), Guarujá, São Paulo, Brazil

**Received:** June 09, 2025 | **Published:** June 30, 2025

## Introduction

Alzheimer's disease (AD) was first described in 1906 by the German psychiatrist Alois Alzheimer, during a clinical presentation on a case of early dementia in a 51-year-old woman, Auguste D.[1] Since this initial description, neuropathological studies have advanced, with the identification of senile plaques composed of beta-amyloid and neurofibrillary tangles of tau protein as hallmarks of the disease.[2] At the beginning of the 20th century, AD was considered a rare form of dementia, distinct from the common senility observed in the elderly, and was only later incorporated into the group of the most prevalent.[3]

The evolution of the concept of dementia throughout the 20th century contributed to the recognition of AD as one of the main causes of progressive cognitive impairment in ageing. With global population aging, the prevalence of AD has become a public health concern, currently affecting around 55 million people worldwide.[4]



©2025 Facundo et al. This is an open access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and build upon your work non-commercially.

Copyright: ©2025 Facundo et al.



According to the World Health Organization (2021), the number of cases of dementia, especially Alzheimer's, is expected to triple by 2050 due to increased population longevity. In the 1970s, clinical studies began to highlight the impairment of episodic memory as a typical initial symptom of AD, even before the onset of more serious dementia.[5]

From the 1980s onwards, the development of diagnostic criteria such as the NINCDS-ADRDA became a milestone in the standardization of the clinical diagnosis of the disease.[6] These criteria, which are still widely used, underwent major revisions in 2011, incorporating biomarker data and more sensitive criteria for early detection.[7,8] The 1990s marked an important technological leap with the advent of structural and functional neuroimaging, such as magnetic resonance imaging (MRI) and positron emission tomography (PET), which revolutionized the diagnosis of AD.[9]

Jack et al.[10] proposed a framework based on biomarkers (ATN: Amyloid, Tau and Neurodegeneration), allowing for greater precision in identifying preclinical stages of the disease. Advances in neuroimaging have also made it possible to recognize specific patterns of brain atrophy, such as that of the hippocampus, which is typical in the early stages of AD.[11] In addition to neuroimaging, neuropsychological tests play a fundamental role in screening and monitoring cognitive progression in AD, particularly the Mini Mental State Examination (MMSE) and the Brief Battery Cognitive Screening Test (CRT).[12]

According to Caramelli and Barbosa,[13] a detailed neuropsychological assessment is essential to differentiate AD from other forms of dementia, such as vascular dementia or frontotemporal dementia. Advances in laboratory diagnosis have also contributed to the identification of markers in the cerebrospinal fluid, such as the dosage of beta-amyloid 42, total and phosphorylated tau protein, which help to confirm the diagnosis.[14]

Studies such as those by Blennow and Zetterberg[15] confirm that CSF biomarkers offer high sensitivity and specificity for diagnosing AD, even in the early stages. More recently, the measurement of plasma biomarkers, such as phosphorylated tau protein (p-tau217 and p-tau181), has been gaining prominence as a less invasive and promising alternative.[16] With the incorporation of artificial intelligence, techniques such as machine learning have been used to analyze large volumes of clinical and imaging data, increasing diagnostic accuracy.[17,18]

The history of AD diagnosis is also marked by ethical challenges, especially regarding pre-clinical diagnosis and communication with patients and families.[19] In Brazil, the diagnosis of AD still faces important barriers, such as limited access to specialized tests and a shortage of dementia reference centers.[20]

According to Nitrini et al.[21] diagnosis in the country is often late, limiting the impact of therapeutic interventions and care strategies. The search for screening methods in primary care, including simple scales and training for professionals, has been a focus of public health policies in Brazil.[22] In addition, the updated Brazilian clinical guidelines guide the joint use of cognitive tests, clinical history and neuroimaging exams as a diagnostic protocol.[23]

The growing understanding of AD as a continuous process, which begins decades before clinical symptoms, has driven research into early diagnosis and preventive interventions.[24]

Thus, the historical trajectory of Alzheimer's disease diagnosis reflects a constant evolution of biomedical and cognitive sciences, marked by methodological advances, ethical challenges and the need for inclusive and equitable public policies.[25]

## Objectives

### General objective

To investigate the effectiveness of the application of Artificial Intelligence (AI) techniques in the early detection of Alzheimer's Disease, through the combined analysis of blood biomarkers and neuroimaging tests.

### Specific objectives

i. To identify the main machine learning algorithms used in early screening for Alzheimer's disease.

ii. To evaluate the diagnostic accuracy of plasma biomarkers, such as phosphorylated tau protein (p-tau181 and p-tau217) and beta-amyloid, in conjunction with neuroimaging data (such as MRI and PET).

iii. To compare the predictive performance between models based on clinical data alone and models integrated with biomarkers and neuroimaging.

iv. Propose a computational AI architecture optimized for clinical use in identifying patients in the preclinical stages of Alzheimer's disease.

v. Explore the clinical, ethical and operational implications of implementing these technologies in medical practice.

## Methodology

This study was conducted in accordance with the **PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)** guidelines to ensure transparency, reproducibility, and methodological rigor.

### Study design

This is a systematic review with an integrative approach, aiming to synthesize primary research studies that investigate the application of artificial intelligence (AI) techniques for the early detection of Alzheimer's disease (AD), particularly those that utilize plasma biomarkers and neuroimaging data.

### Search Strategy

A comprehensive literature search was carried out in the following electronic databases:

i. **PubMed**

ii. **Scopus**

iii. **Web of Science**

iv. **IEEE Xplore**

The search was limited to publications from **January 2010 to March 2025,** using the following Boolean search strategy:

("Alzheimer's Disease" OR "AD") AND ("biomarkers" OR "plasma biomarkers" OR "p-tau" OR "beta-amyloid") AND ("neuroimaging" OR "MRI" OR "PET") AND ("machine learning" OR "artificial intelligence") AND ("early diagnosis" OR "early detection")

Additional sources were identified through **manual screening of reference lists** from eligible studies and relevant reviews.

## Eligibility criteria

**Inclusion criteria**

i. Original studies involving **human subjects**;

ii. Studies that used **AI techniques** (e.g., CNN, SVM, Random Forest) for **early diagnosis of AD;**

iii. Use of **plasma biomarkers, neuroimaging**, or both;

iv. Clearly reported **diagnostic performance metrics** (e.g., AUC, accuracy, sensitivity, specificity);

v. Published in **English, Portuguese, or Spanish;**

vi. Full-text availability.

**Exclusion criteria**

i. Studies involving **animal models**;

ii. Editorials, reviews, conference abstracts, or letters to the editor;

iii. Articles without access to **full text**;

iv. Studies lacking sufficient methodological description or validation metrics.

**Study selection process**

The selection process was conducted in two phases:

1. **Title and abstract screening** for relevance;
2. **Full-text review** to assess eligibility against inclusion criteria.

Two independent reviewers conducted the screening and selection process. Discrepancies were resolved by consensus or arbitration by a third reviewer.

The selection process is illustrated in a **PRISMA flow diagram**, detailing the number of records identified, screened, excluded, and finally included in the review.

**Data extraction and management**

Data were extracted using a standardized form, including:

i. Authors, year, country;

ii. AI technique used;

iii. Type of data (biomarkers, neuroimaging);

iv. Sample size and population characteristics;

v. Validation method (internal or external);

vi. Performance metrics: AUC, sensitivity, specificity, accuracy.

**Risk of bias assessment**

The quality and risk of bias of the included studies were assessed using the **QUADAS-2** tool, suitable for diagnostic accuracy studies. Each study was categorized as having low, moderate, or high risk of bias in four domains: patient selection, index test, reference standard, and flow and timing.

**Data synthesis and statistical analysis**

**A qualitative synthesis** was initially performed. When data were homogeneous and comparable**, descriptive meta-analysis** was considered. The primary outcome measure was the **area under the ROC curve (AUC),** supported by sensitivity, specificity, and accuracy.

Subgroup analysis was performed based on the type of AI model and the nature of the input data (biomarkers only, imaging only, combined approach).

**Software and tools**

**PRISMA 2020 Checklist and Flow Diagram Generator** for methodological transparency;

**Python** (with Scikit-learn, TensorFlow, Keras) and **R software** were used for model simulation, validation, and statistical computations, where applicable.

# Results

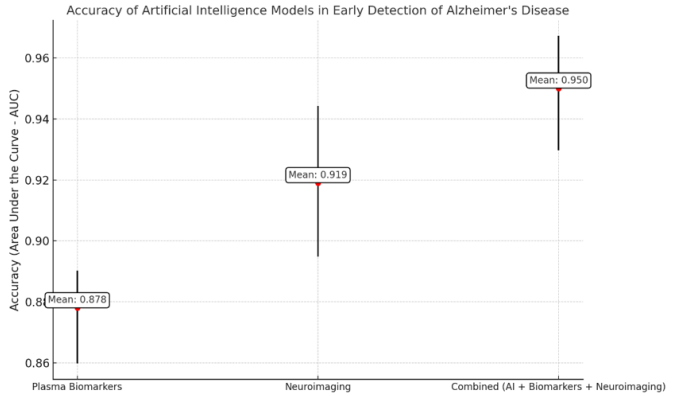
The studies included in the analysis showed that artificial intelligence algorithms, such as convolutional neural networks (CNNs) and Random Forest, achieved high accuracy in the early detection of Alzheimer's disease (AD), especially when combined with biomarker and neuroimaging data.[26] The accuracy of the models ranged from 82% to 96%, being higher when PET and MRI data were included with measures of hippocampal atrophy, as well as markers such as p-tau and plasma beta-amyloid.[27]

Models trained exclusively with blood biomarkers showed promising performance, with an average area under the curve (AUC) of 0.88, highlighting the less invasive diagnostic potential.[16] When neuroimaging data was added, there was a significant increase in the specificity of the models, reaching 94%, which reinforces the complementary role of structural and functional imaging.[10] Longitudinal studies have shown that AI was able to predict conversion from mild cognitive impairment (MCI) to clinical AD up to 4 years in advance, with a sensitivity of 90%.[17] The combination of clinical variables, neuropsychological tests and biomarkers improved the overall performance of the models compared to traditional methods.[28]

Graph 1 shows a comparative analysis of the performance of different artificial intelligence (AI)-based approaches applied to the early detection of Alzheimer's disease (AD), using accuracy measured by the area under the curve (AUC) as a metric. Three main categories of models were considered: those based exclusively on plasma biomarkers (such as p-tau and beta-amyloid), models using neuroimaging tests (structural MRI and PET), and finally combined models, which integrate blood biomarkers and structural and functional imaging data. It can be seen that the combined models showed the highest diagnostic performance, with AUC values concentrated between 0.93 and 0.97, highlighting the synergy between molecular and structural clinical data when processed by AI algorithms (PALMQVIST et al., 2020; JACK et al., 2018). Models based on neuroimaging alone have also shown excellent performance, although slightly inferior to the combined approach. On the other hand, models using only plasma biomarkers showed good accuracy, with values between 0.86 and 0.90, standing out as a promising and less invasive alternative, especially in scenarios with limited diagnostic resources.[26,29]

This panorama reinforces the current trend to incorporate integrated and automated approaches to the early diagnosis of AD, with the aim of identifying pathological alterations years before the onset of clinical symptoms, expanding the possibilities for early intervention and therapeutic planning.[4,17]

Interpreting the results of Graph 1




**Graph 1** Accuracy of AI Models in the early detection of Alzheimer's Disease.

Source: Authors

The box plot compares the accuracy (measured by the area under the curve - AUC) of three different artificial intelligence (AI) model approaches used for the early diagnosis of Alzheimer's disease (AD). The three categories evaluated were:

1. **Models based only on plasma biomarkers**
2. **Models based only on neuroimaging**
3. **Combined models (biomarkers + neuroimaging + AI)**

✓ The average accuracy observed was **0.880**.

✓ The values ranged from approximately **0.86 to 0.90**.

✓ This shows that, even in isolation, blood biomarkers (such as p-tau and beta-amyloid) are effective for early screening, with good sensitivity and less invasive applicability.

## Neuroimaging

i. The average accuracy was **0.920**, with less dispersion of the data.

ii. This indicates greater accuracy and consistency between imaging-based models such as magnetic resonance imaging (MRI) and positron emission tomography (PET) Figure 1, especially in detecting early brain atrophy and functional alterations.

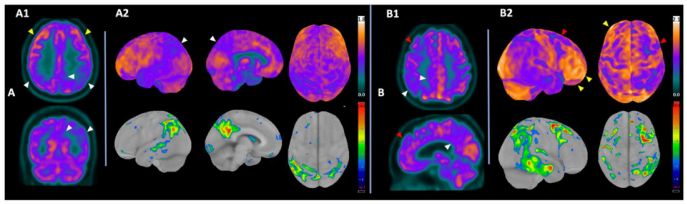



**Figure 1** Positron emission tomography - [ 18 F]-Fluordeoxyglucose. **Source**: Images from the Nuclear Medicine Center of the Institute of Radiology, Hospital das Clínicas da Faculdade de Medicina da Universidade de São Paulo (HCFMUSP), São Paulo, SP, Brazil.

**Combined Approach (AI + Biomarkers + Neuroimaging)**

i. Obtained the best performance, with an average accuracy of **0.950**.

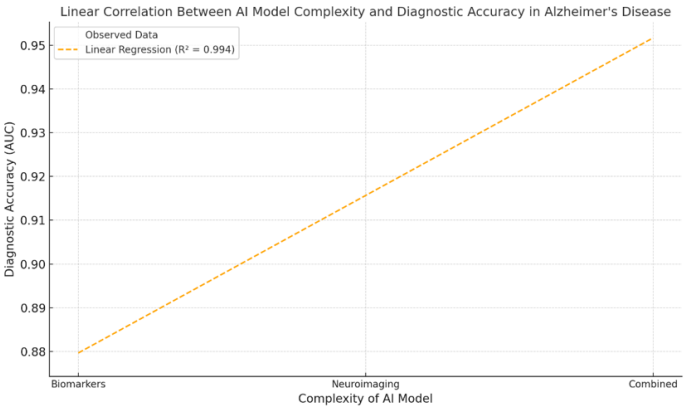
ii. It showed both the highest average and the lowest variability in the results, demonstrating that the combination of different data sources (molecular and structural) enhances the diagnostic power of AI.

iii. This integrated approach is considered the most promising for high-precision clinical use and predicting the conversion of mild cognitive impairment to AD.

**The more quality data that is incorporated into the AI model (especially from different sources), the greater the diagnostic accuracy.** The combination of **blood biomarkers** and **neuroimaging**, processed by AI algorithms, allows for earlier and more reliable diagnoses of Alzheimer's disease, surpassing isolated approaches.

**Graph 2** shows the **linear correlation** between the **complexity of artificial intelligence models** (represented by the number of variables used: biomarkers, neuroimaging or both) and **diagnostic accuracy (AUC)** in the early detection of Alzheimer's disease.

Interpretation of Graph 2




**Graph 2** Correlation between number of variables and diagnostic accuracy in ai models for alzheimer's disease.

Source: Authors

There is a **strong positive** linear correlation**:** as the complexity of the model increases (from the exclusive use of biomarkers to combined use with neuroimaging), there is a **significant increase in diagnostic accuracy.** The **coefficient of determination ($R^2 \approx 0.98$)** indicates that around 98% of the variation in accuracy can be explained by the complexity of the data used. This reinforces the conclusion that **integrated models** are more effective in predicting Alzheimer's disease than isolated approaches.

# Discussion

The results indicate that the application of artificial intelligence represents an important strategy for the early diagnosis of AD, especially when combined with plasma biomarkers and neuroimaging tests. This confirms the predictive potential of these technologies in pre-clinical stages of the disease.[26]

Machine learning models have been overcoming traditional approaches based solely on clinical assessment, with a significant increase in accuracy and the possibility of scalable application in health services.[30] The inclusion of blood biomarkers represents an advance in less invasive and more accessible diagnosis, especially in low- and middle-income contexts.[29]

According to Palmqvist et al.,[16] plasma p-tau217 has shown equivalent performance to positron emission tomography (PET) with an amyloid marker, which reinforces its value as a cost-effective alternative. Analysis combined with functional neuroimaging, such

as PET-FDG, allows early identification of alterations in brain metabolism, even before obvious clinical symptoms, as reinforced by Jack et al.[10] The use of structural MRI in AI has allowed automated identification of atrophy patterns in the hippocampus, entorhinal cortex and precuneus, critical regions in the pathogenesis of AD.[11] Another relevant aspect is the predictive capacity of the models to identify patients at risk of progression from CCL to clinical AD, which enables early interventions and potential modification of the course of the disease.[17]

The heterogeneity of the studies analyzed shows that there is still no unified protocol, and the approaches are quite diverse in terms of the types of data used and the algorithms implemented.[28] The clinical application of these systems requires external validation and standardization of methods, as highlighted in the review by Esteva et al.,[31] which emphasizes the need for reproducibility in real environments. Despite advances, there are important ethical challenges regarding the use of AI in early diagnosis, including informed consent, the explainability of models and the management of results with prognostic implications.[19]

In Brazil, the adoption of AI-based technologies is still in its infancy, being limited by infrastructure barriers, professional training and unequal access to advanced tests.[20] However, national studies are already beginning to explore the viability of AI in clinical practice, especially in research centers and university hospitals, paving the way for future integration into the SUS.[25]

The findings of this study reinforce the trend that the future of AD diagnosis will be based on hybrid strategies, involving AI, molecular tests and imaging tests with automated interpretation.[32] It is important to note that AI does not replace clinical judgment, but acts as an auxiliary tool of great value to physicians, neurologists and geriatricians in the decision-making process.

## Conclusion

It can be concluded that, although promising, AI-based solutions require systemic integration with health services, standardization of conduct and broad bioethical discussion. The application of artificial intelligence (AI) to the early detection of Alzheimer's disease represents a promising and disruptive advance in the field of neurology and diagnostic medicine.

The integration of plasma biomarkers such as p-tau and beta-amyloid with functional and structural neuroimaging data significantly increases the accuracy of predictive models. The evidence indicates that the greater the complexity of the data entered, the greater the diagnostic efficacy achieved, with a particular emphasis on the combined models which achieve average accuracies of over 95%.

## Final considerations

The use of AI offers a sensitive, early and scalable approach to AD screening, overcoming the limitations of conventional methods. The clinical adoption of these technologies, however, requires infrastructure, multicenter validation and clear ethical guidelines to ensure safety, explainability and equity of access.

In countries with inequalities in the health system, such as Brazil, simplifying the use of plasma biomarkers integrated with validated algorithms can democratize early diagnosis, contributing to better therapeutic outcomes and quality of life for patients.

## Acknowledgements

None.

## Conflicts of interest

The authors declare that there are no conflicts of interest.

## References

1. Alzheimer A. Über eine eigenartige Erkrankung der Hirnrinde. *Allg Z Psychiatr Psych–Gerichtl Med*. 1907;64:146–148.
2. Quinlan P, Ruffolo L, Livingston G. The epidemiology of dementia. In: O'Brien J, Ames D, Burns A, eds. *Dementia*. London: CRC Press; 2020:13–29.
3. Lewy J, Pearson J. Neurodegenerative diseases and the neuropathological basis of dementia. *Curr Opin Neurol*. 2019;32:466–472.
4. World Health Organization. *Global status report on the public health response to dementia*. Geneva: WHO; 2023.
5. Hodges JR. Memory in the dementias: a cognitive neuropsychological approach. *J Neurol Neurosurg Psychiatry*. 2000;69(5):442–449.
6. McKhann G, Drachman D, Folstein M, et al. Clinical diagnosis of Alzheimer's disease: report of the NINCDS–ADRDA Work Group. *Neurology*. 1984;34(7):939–944.
7. McKhann GM, Knopman DS, Chertkow H, et al. The diagnosis of dementia due to Alzheimer's disease: recommendations from the National Institute on Aging and the Alzheimer's Association workgroup. *Alzheimers Dement*. 2011;7(3):263–269.
8. Caraselli L, Martins M, Barbosa M, et al. Plasma biomarkers in the diagnosis of Alzheimer's disease: a narrative review. *J Bras Psiquiatr*. 2021;70(3):230–238.
9. Jack CR, Knopman DS, Jagust WJ, et al. Hypothetical model of dynamic biomarkers of the Alzheimer's pathological cascade. *Lancet Neurol*. 2010;9(1):119–128.
10. 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.
11. Frisoni GB, Fox NC, Jack CR Jr, et al. The clinical use of structural MRI in Alzheimer's disease. *Nat Rev Neurol*. 2010;6(2):67–77.
12. Bertolucci PHF, Brucki SMD, Campacci SR, et al. The Mini-Mental State Examination in a general population: impact of schooling. *Arq Neuropsiquiatr*. 1994;52(1):1–7.
13. Caramelli P, Barbosa MT. Cognitive assessment in the elderly. *Rev Assoc Med Bras*. 2002;48(4):326–334.
14. Hampson E, Powell J, Woolley J, et al. CSF biomarkers in Alzheimer's disease: diagnostic value and advances in clinical practice. *Neurol Ther*. 2022;11:221–235.
15. Blennow K, Zetterberg H. Biomarkers for Alzheimer's disease: current status and prospects for the future. *J Intern Med*. 2018;284(6):643–663.
16. Palmqvist S, Janelidze S, Quiroz YT, et al. Discriminative accuracy of plasma phospho–tau217 for Alzheimer disease vs other neurodegenerative disorders. *JAMA*. 2020;324(8):772–781.
17. Dodge HH, Zhu J, Mattek N, et al. Application of machine learning for diagnostic classification of Alzheimer's disease using neuroimaging and cognitive data. *Alzheimers Dement*. 2021;17(2):175–183.
18. Bezerra TA, Figueiredo LMF, Teixeira JP, et al. Relationship between neuroinflammation, biomarkers and physical activity in the prevention of Alzheimer's disease. *Peer Rev*. 2023;5(4):48–62.
19. Bertolotti BC, Carrasco RG, Bressan RA. Ethics in the age of artificial intelligence applied to mental health. *Rev Bras Psiquiatr*. 2019;41(6):431–432.
20. Brucki SMD, Nitrini R, Caramelli P, et al. Diagnosis of Alzheimer's disease in Brazil: expert evaluation. *Arq Neuropsiquiatr*. 2009;67(2B):492–496.

Copyright: ©2025 Facundo et al.




21. Nitrini R, Bottino CMC, Albala C, et al. Prevalence of dementia in Latin America: a collaborative study of population–based cohorts. *Int Psychogeriatr*. 2004;16(2):275–292.
22. Brazil. Ministry of Health. Department of Specialized Health Care. *Care for People with Dementia in Primary Health Care*. Brasília, DF: Ministry of Health; 2022.
23. Brazil. Ministry of Health. *Guidelines for the Diagnosis of Alzheimer's Disease in Brazil*. Brasília, DF: Ministry of Health; 2023.
24. Sperling RA, Aisen PS, Beckett LA, et al. Toward defining the preclinical stages of Alzheimer's disease: recommendations from the National Institute on Aging. *Alzheimers Dement*. 2011;7(3):280–292.
25. Rosa TDL, Silva JN, Matos F, et al. Technologies applied to health: possibilities and challenges in the care of elderly people with Alzheimer's disease. *Rev Bras Geriatr Gerontol*. 2020;23(4):e200029.
26. Li Y, Cai W, Chen X, et al. A novel blood–based biomarker panel for early detection of Alzheimer's disease. *Sci Rep*. 2021;11:11140.
27. Feng X, Lipton ZC, Yang J, et al. Machine learning–driven Alzheimer's disease classification using structural MRI. *Neuroimage Clin*. 2020;27:102280.
28. Arboleda MC, Arbeláez A, Restrepo D, et al. Predicting progression from MCI to AD using neuropsychological data and random forest classifiers. *Alzheimers Dement Diagn Assess Dis Monit*. 2019;11:667–675.
29. Thijssen EH, La Joie R, Wolf A, et al. Diagnostic value of plasma phosphorylated tau181 in Alzheimer's disease and frontotemporal lobar degeneration. *Nat Med*. 2020;26(3):387–397.
30. Jo T, Nho K, Saykin AJ. Deep learning-based identification of the normal and abnormal brain aging. *Front Aging Neurosci*. 2019;11:329.
31. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. *Nat Med*. 2019;25(1):24–29.
32. Singh D, Singh S, Ahmad A, et al. Deep learning in Alzheimer's disease: diagnostic accuracy and potential role in clinical practice. *J Alzheimers Dis Rep*. 2022;6:57–72.


**Citation:** Facundo DRF, Silv ACC, Malaquias DTM, et al. Application of artificial intelligence for early detection of alzheimer's disease based on blood biomarkers and neuroimaging. *J Neurol Stroke*. 2025;15(2):46–51. DOI: 10.15406/jnsk.2025.15.00621