

Alzheimer's Disease Detection Using Machine and Deep Learning: Empirical Evidence, Predictive Models, and Research Gaps, A Systematic Review

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Abstract. Alzheimer's disease is an irreversible neurodegenerative disorder that affects a growing proportion of the global population and represents a significant challenge for healthcare systems due to its gradual progression and the absence of a definitive cure, a context in which early detection through Machine Learning emerges as a promising strategy to support timely clinical interventions. This research aims to determine how Machine Learning models impact the detection of Alzheimer's disease through the systematic analysis of the available empirical evidence. A systematic review was conducted under the PRISMA 2020 framework, considering studies published between 2019 and 2025 in IEEE Xplore, Web of Science, Scopus, EBSCOhost, and ScienceDirect; after applying inclusion criteria and quality assessment, 73 papers were selected. Support Vector Machine (18.91%), Random Forest (16.92%), and Decision Tree (13.93%) predominate as hegemonic models, while Python accounts for 45% of the developments; the functional category groups 70.3% of the theoretical definitions, and Neuroimaging Classification emerges as the only specialized thematic cluster. The field shows a progressive transition toward multimodal deep

architectures, although critical gaps persist in clinical validation, interpretability, and ontological standardization, which guide future research.

Keywords. Machine learning, deep learning, alzheimer, alzheimer's disease, systematic review.

1 Introduction

Alzheimer's disease is an irreversible neurodegenerative disorder that affects a growing proportion of the population and represents a significant challenge for healthcare systems due to its gradual progression and the absence of a definitive cure.

In this context, early detection is essential to promptly identify signs of cognitive decline and support more appropriate clinical interventions. In the context of early Alzheimer's diagnosis through structural neuroimaging, several authors [2,17,29] have developed architectures based on

convolutional neural networks and 3D models applied to sMRI images, reporting AUC values above 88% and accuracies close to 100% in specific classifications, together with efficient handling of data leakage and preprocessing. Along the same line, the authors in [4,10,13] proposed transfer learning approaches that combine architectures such as ResNet-50, Inception-V3, VGG16, MobileNetV2, and DenseNet121, together with image enhancement techniques such as CLAHE and ESRGAN, achieving accuracies ranging from 87% to 97.93%. Complementarily, the studies in [3,11,28] introduced vision transformers (ViT), ADD-Net networks, and CNN ensembles with interpretability methods such as LIME, Saliency, and Grad-CAM, achieving accuracies above 98% while simultaneously strengthening the explainable artificial intelligence component, an essential aspect for clinical acceptance.

Likewise, the researchers in [9,18,34] focused on hybrid frameworks that integrate deep learning with feature fusion through CCA, gradient boosting, and multistage models based on residual networks with classifiers such as SVM, Random Forest, and SoftMax, reaching accuracies above 97.58% on datasets such as ADNI1, MIRIAD, and OASIS. Continuing along this line of robust predictive models, the authors in [6,24,26] developed a dual-attention autoencoder, a lightweight deep learning model, and a multifractal geometry technique with K-Nearest Neighbor, reporting accuracies ranging from 95.93% to 99.4%, as well as AUC values above 0.99 in binary and multiclass classifications. For their part, the authors in [16,19,38] examined morphometric aspects of the brain through hippocampal segmentation using the SWANS network, dimensionality reduction through harmony search, and cortical complexity analysis using fractal dimension combined with MoCA, achieving AUC values of up to 0.955 and successful external validations.

Regarding emerging modalities not based exclusively on MRI, the studies in [1,22,23] explored blood biomarkers (U-p532D3A8+ combined with MMSE and APOE ϵ 4), Raman spectroscopy of cerebrospinal fluid, and gene expression analyzed through deep learning, achieving accuracies between 80% and 86.67%,

which demonstrates the potential of alternative cost-effective sources for screening. Similarly, the authors in [7,21,87] applied machine learning to EEG signals, generative adversarial networks for data augmentation, and speech analysis with deep learning, demonstrating that these noninvasive modalities can reach accuracies of up to 99.98% and provide scalable tools for clinical settings with limited resources.

With respect to multimodal and longitudinal approaches, the authors in [25,43,85] have proposed frameworks based on LSTM, Dual-3DM3-AD models combining MRI and PET with Mixed-transformer and U-Net, as well as pipelines that integrate biomarkers, achieving accuracies of 98% and addressing the persistent challenge of multiclass classification among Alzheimer's disease, mild cognitive impairment, and its substages. Finally, regarding syntheses of the field, previous bibliometric studies and systematic reviews [80,82,98] analyzed between 530 and 2316 publications, documenting exponential growth since 2018-2019, the leadership of the United States and China, and the consolidation of key lines such as early diagnosis, risk prediction, and Clinical Decision Support Systems. In addition, the reviews in [84,86,89] examined predominant algorithms such as SVM, Ensemble, and CNN, as well as specific applications for mild cognitive impairment, identifying advances in remote monitoring and personalized medicine. Lastly, the authors in [88,96] focused their analysis on the challenges of security, explainability, and cerebral functional connectivity through fMRI, pointing out the imperative need for more interpretable, integrated, and accurate models that can guide future research toward clinically translatable tools.

Critical gaps remain: asymmetric performance between binary and multiclass classification of EMCI, sMCI, and pMCI stages; limited explainability; restricted multimodal fusion; an almost exclusive dependence on ADNI; and the low maturity of emerging modalities. This research is justified by the need to consolidate the dispersed evidence on machine learning and deep learning models for Alzheimer's disease, where high accuracies contrast with marginal clinical adoption. Under PRISMA 2020, it synthesizes architectures, modalities, and datasets, and identifies the gaps that will guide future developments. For this

reason, this paper proposes a systematic review aimed at examining the state of the art in Alzheimer's disease detection through the implementation of Machine Learning, with the intention of establishing a reference framework to contribute to future developments. The present review addresses relevant topics for the development of future research that may contribute to the existing literature on the subject. This paper is structured as follows. Section 2 contains the theoretical framework. Section 3 presents the methodology implemented for the review. Section 4 presents the results and discussion. Finally, Section 5 presents the conclusions, limitations, and recommendations for future work.

2 Background

This section presents the conceptual and contextual framework underpinning the study, providing the theoretical and technical elements required for a comprehensive understanding of the work developed.

2.1 Machine Learning

Machine learning is defined as an application of artificial intelligence (AI) that enables systems to learn and improve automatically from experience, without the need to be explicitly programmed [21, 57]. Likewise, it comprises the systematic study of algorithms and mathematical models capable of performing specific tasks based on data [79].

Among its main techniques, deep learning stands out as a type of machine learning that is particularly suitable for the analysis of complex medical images [24], due to its ability to extract relevant features from neurological data. For this purpose, the availability of a considerable volume of labeled data is essential [12]. In essence, machine learning is grounded in intelligent algorithms capable of learning autonomously, without relying on rule-based programming with predefined instructions [95].

2.2 Alzheimer's Disease Detection

Alzheimer's disease is a progressive neurodegenerative condition that causes a gradual

deterioration of cognitive and functional abilities [1]. In this context, its detection must be carried out at early stages, especially when the first symptoms appear [2], through the use of various diagnostic methods and techniques [36], such as clinical assessments [27], biomarker analysis [29], and brain imaging studies [32].

Early detection represents a key factor in reducing the incidence and morbidity associated with this disease [52]. Likewise, the need for accurate and low-cost diagnostic methods is emphasized [62], which is why the implementation of machine learning algorithms has been promoted in order to improve the understanding of the disease and contribute to a better quality of life for patients [68].

2.3 Integration of Machine Learning in Alzheimer's Disease Detection

Machine Learning has transformed the detection of Alzheimer's disease through the development of computational models capable of identifying complex patterns in medical images, biomarkers, and clinical data, significantly improving diagnostic accuracy and promoting the early detection of neurodegenerative alterations; this interaction is supported by theoretical approaches based on pattern recognition, supervised learning, and deep learning, which make it possible to automate classification and prediction processes from large volumes of biomedical data. However, the application of these techniques still faces challenges related to the availability of labeled data, the heterogeneity of clinical sources, model interpretability, and computational costs, thereby driving the development of more advanced approaches aimed at intelligent, explainable, and clinically robust diagnostic systems, which establishes a conceptual foundation for the following sections of the study.

3 Review Method

The present systematic literature review (SLR) was developed following the methodological guidelines proposed by Barbara Kitchenham and Stuart Charters [77], which made it possible to establish an organized structure for the planning, execution, and writing of the research. Likewise, this approach was complemented by the systematic

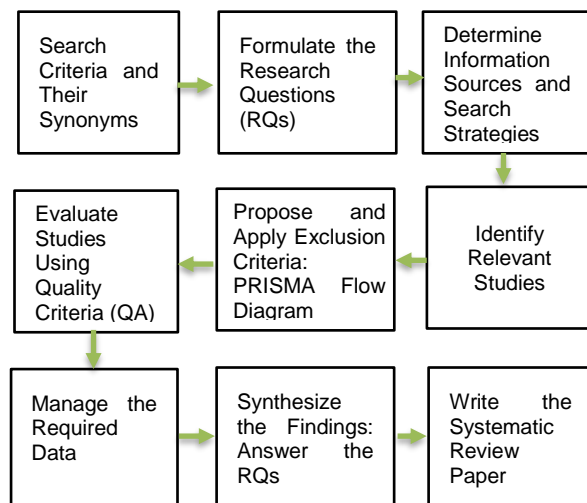


Fig. 1. Stages of the SLR

Table 1. Search descriptors and their synonyms organized by conceptual group

Conceptual Group	Descriptor
Machine Learning	machine learning/ ml/ deep learning/ neural networks
Alzheimer's Disease Detection	detection/identification/diagnosis + alzheimer/alzheimer's disease

mapping study (SMS) proposed by Kai Petersen and collaborators [78], which facilitated the implementation of additional strategies related to the identification, selection, and categorization of the analyzed studies. These methodological guidelines are presented in Figure 1.

3.1 Research Problems

The prior definition of the research questions (RQs) was intended to systematically guide the search, selection, and analysis process of the existing scientific literature.

The research questions are presented below, ensuring a structured and coherent approach that allows the review to be conducted properly.

RQ1: What types of Machine Learning-based models have been developed in the studies?

RQ2: At what quartile levels are the journals that publish research on the application of Machine Learning in Alzheimer's Disease Detection classified?

RQ3: Which programming languages are most frequently used in the development of Machine Learning-based solutions?

RQ4: What theoretical approaches and definitions have been formulated in studies analyzing the impact of Machine Learning on Alzheimer's disease detection?

RQ5: What thematic categories predominate in the research linking Machine Learning to Alzheimer's disease detection?

RQ6: Which countries stand out for their co-occurrence in collaborative studies on Machine Learning and its application to Alzheimer's disease detection?.

3.2 Information Sources and Search Strategies

The search strategy was structured systematically in order to identify highly relevant studies related to Alzheimer's disease detection through Machine Learning techniques. For this purpose, five high-quality academic sources were used: Scopus, ScienceDirect, Web of Science, IEEE Xplore, and EBSCOhost.

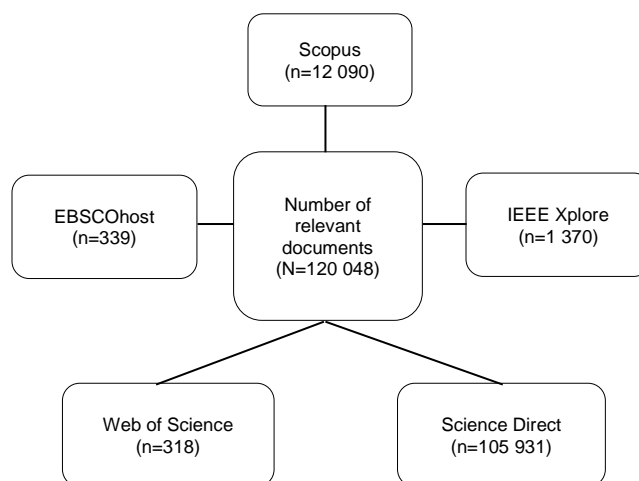
Likewise, a table of descriptors and their corresponding grouped synonyms was prepared in order to conduct systematic searches in each of the selected information sources, as shown in Table 1. It should be noted that the database search process was carried out until August 14, 2026, thereby establishing the temporal limit of the study.

3.3 Search Equations

In order to identify highly relevant papers for the present research, search equations were designed using the terms associated with the study variables and the Boolean operators AND and OR in each of the selected information sources. It should be noted that each database uses a particular structure for executing searches, an aspect detailed in Table 2.

Table 2. Search equations adapted to each source

Source	Search Equation
Scopus	TITLE-ABS-KEY ("machine learning" OR ml OR "deep learning" OR "neural networks") AND TITLE-ABS-KEY (detection OR identification OR diagnosis) AND TITLE-ABS-KEY (alzheimer OR "alzheimer's disease")
ScienceDirect	("machine learning" OR ml OR "deep learning" OR "neural networks") AND (detection OR identification OR diagnosis) AND (alzheimer OR "alzheimer's disease")
IEEE Xplore	("Document Title": "machine learning" OR "Document Title": ml OR "Document Title": "deep learning" OR "Document Title": "neural networks") AND ("Document Title": detection OR "Document Title": diagnosis OR "Document Title": identification) AND ("Document Title": alzheimer OR "Document Title": "alzheimer's disease") OR ("Author Keywords": "machine learning" OR "Author Keywords": ml OR "Author Keywords": "deep learning" OR "Author Keywords": "neural networks") AND ("Author Keywords": detection OR "Author Keywords": diagnosis OR "Author Keywords": identification) AND ("Author Keywords": alzheimer OR "Author Keywords": "alzheimer's disease") OR ("Abstract": "machine learning" OR "Abstract": ml OR "Abstract": "deep learning" OR "Abstract": "neural networks") AND ("Abstract": detection OR "Abstract": diagnosis OR "Abstract": identification) AND ("Abstract": alzheimer OR "Abstract": "alzheimer's disease")
Web of Science	((TS=("machine learning" OR ml OR "deep learning" OR "neural networks")) AND TS=(detection OR identification OR diagnosis)) AND TS=("alzheimer's disease")
EBSCOhost	TI ("machine learning" or ml or "deep learning" or "neural networks") AND TI (detection or diagnosis or identification) AND TI "alzheimer's disease"

**Fig. 2.** Number of relevant documents

3.4 Identified Studies

Figure 2 illustrates the initial results obtained from the advanced search conducted in each of the

selected information sources. The central part presents the total number of relevant documents retrieved from each source, evidencing a considerable volume of identified studies.

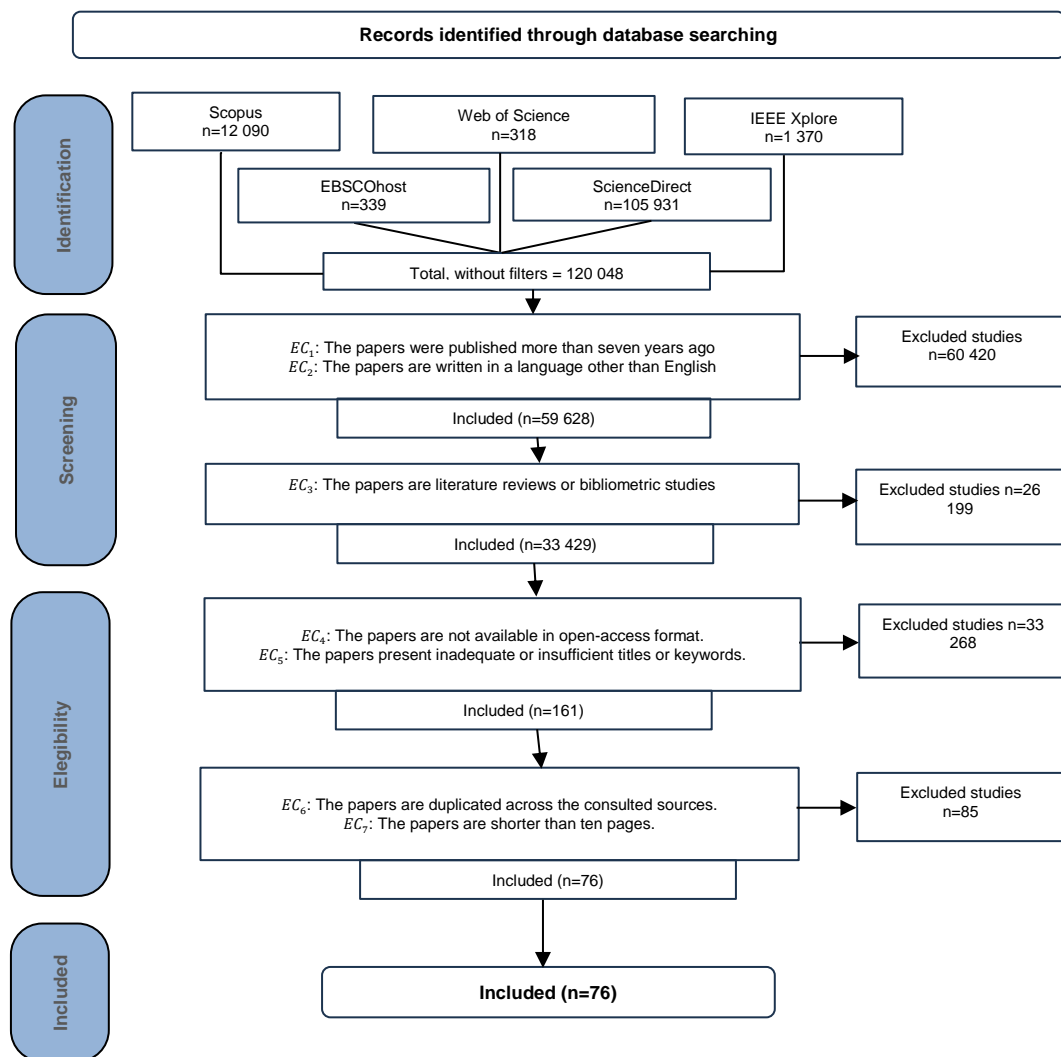


Fig. 3. PRISMA Flow Diagram

3.5 Selection Criteria

To ensure the relevance and quality of the papers included in this systematic review, a set of exclusion criteria was established based on the objectives previously defined.

EC1: The papers were published more than seven years ago.

EC2: The papers are written in a language other than English.

EC3: The papers are literature reviews or bibliometric studies.

EC4: The papers are not available in open-access format.

EC5: The papers present inadequate or insufficient titles or keywords.

EC6: The papers are duplicated across the consulted sources.

EC7: The papers are shorter than ten pages.

3.6 Study Selection

Due to the high number of papers retrieved from each of the information sources, the studies were sequentially subjected to the different exclusion criteria previously defined and applied directly in

Table 3. Results of the quality assessment

Ref.	Type	QA1	QA2	QA3	QA4	QA5	QA6	QA7	Score
[1]	Journal	3	2	1	1	2	2	2	13
[2]	Journal	2	2	2	1	2	2	2	13
[3]	Journal	3	2	1	3	2	3	2	16
[4]	Journal	3	2	2	3	1	2	2	15
[5]	Journal	3	3	2	3	2	3	1	17
[6]	Journal	2	3	1	2	1	2	2	13
[7]	Journal	2	2	2	1	2	3	2	14
[8]	Journal	3	1	2	3	2	1	1	13
[9]	Journal	3	3	2	3	2	3	2	18
[10]	Journal	3	2	2	3	1	2	2	15
[11]	Journal	2	2	2	3	1	3	1	14
[12]	Journal	3	2	1	2	3	3	1	15
[13]	Journal	3	3	2	1	1	1	1	12
[14]	Journal	2	2	3	1	3	3	2	16
[15]	Journal	3	3	2	3	3	3	2	19
[16]	Journal	3	1	3	2	3	3	1	16
[17]	Journal	3	3	2	3	3	3	1	18
[18]	Journal	2	3	2	3	1	3	2	16
[19]	Journal	3	2	2	2	2	2	1	14
[20]	Journal	2	1	1	3	2	3	2	14
[21]	Journal	3	2	2	2	2	3	2	16
[22]	Journal	2	2	3	2	3	3	1	16
[23]	Journal	2	2	1	2	2	2	1	12
[24]	Journal	2	2	3	3	3	2	3	18
[25]	Journal	3	3	2	2	2	1	1	14
[26]	Journal	2	2	3	2	1	2	1	13
[27]	Journal	2	3	3	1	2	2	2	15
[28]	Journal	3	2	2	1	2	2	2	14
[29]	Journal	2	2	3	3	1	1	2	14
[30]	Journal	2	2	2	2	1	2	2	13
[31]	Journal	3	2	3	1	2	3	2	16
[32]	Journal	2	3	2	2	1	1	2	13

[33]	Journal	2	2	3	3	1	1	1	13
[34]	Journal	2	2	3	2	2	1	2	14
[35]	Journal	3	2	3	2	2	2	2	16
[36]	Journal	3	3	2	3	2	2	1	16
[37]	Journal	2	2	3	1	2	1	2	13
[38]	Journal	3	3	2	3	1	2	2	16
[39]	Journal	2	2	3	3	1	3	2	16
[40]	Journal	2	2	3	2	2	1	1	13
[41]	Journal	2	2	2	2	3	1	1	13
[42]	Journal	2	3	1	2	1	2	1	12
[43]	Journal	1	3	3	1	1	2	1	12
[44]	Journal	3	2	2	3	2	1	2	15
[45]	Journal	2	2	3	2	2	1	1	13
[46]	Journal	3	2	3	2	2	1	1	14
[47]	Journal	3	2	2	2	2	2	2	15
[48]	Journal	2	3	3	3	1	2	2	16
[49]	Journal	2	2	1	2	1	2	2	12
[50]	Journal	3	2	2	2	3	1	1	14
[51]	Journal	3	2	1	2	1	2	1	12
[52]	Journal	2	3	3	1	1	2	1	13
[53]	Journal	2	2	3	2	2	1	2	14
[54]	Journal	3	2	2	2	1	1	2	13
[55]	Journal	3	2	3	3	2	2	1	16
[56]	Journal	3	3	2	3	2	1	1	15
[57]	Journal	2	2	3	2	2	2	2	15
[58]	Journal	2	2	2	2	1	2	2	13
[59]	Journal	2	2	1	2	1	2	2	12
[60]	Journal	3	3	2	1	1	2	1	13
[61]	Journal	3	3	2	2	1	1	1	13
[62]	Journal	2	2	2	2	2	1	2	13
[63]	Journal	2	2	3	2	2	1	2	14
[64]	Journal	2	3	3	1	2	2	1	14
[65]	Journal	2	2	2	2	2	2	1	13
[66]	Journal	3	2	3	2	2	1	2	15
[67]	Journal	2	2	2	2	2	1	2	13
[68]	Journal	2	3	2	2	1	1	1	12
[69]	Journal	2	2	2	3	3	2	2	16
[70]	Journal	3	2	3	3	2	2	1	16
[71]	Journal	2	2	2	2	2	1	1	12
[72]	Journal	2	3	2	2	1	2	3	15

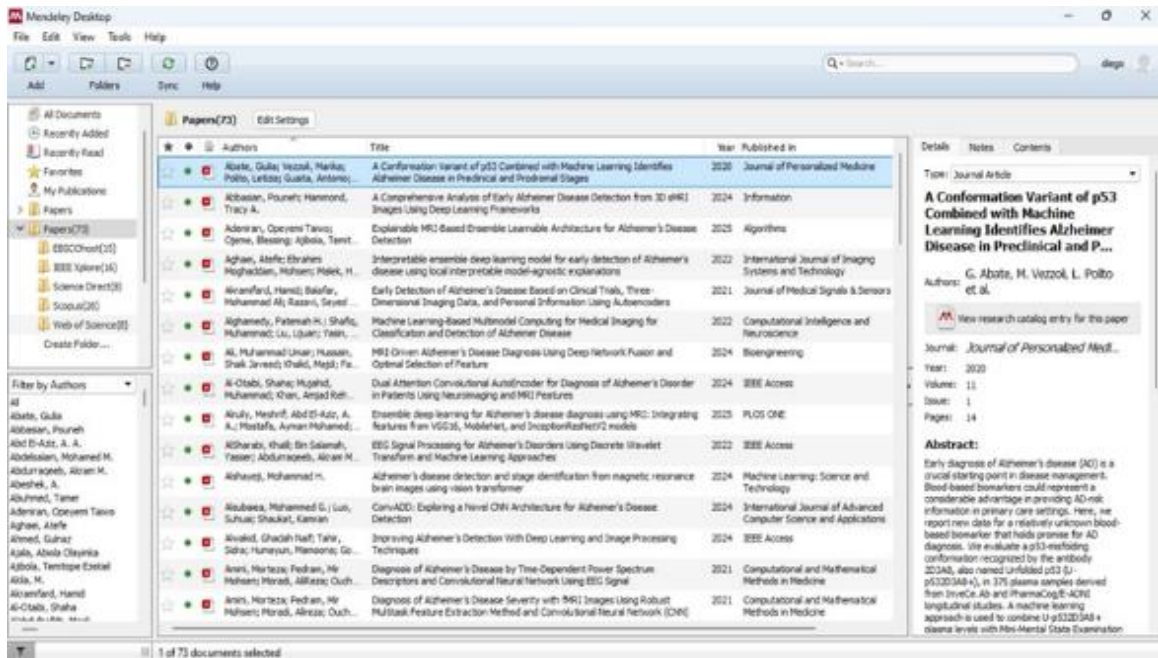


Fig. 4. Report Management with Mendeley Desktop

[73]	Journal	3	2	2	2	2	2	1	14
[74]	Journal	2	2	1	2	1	1	1	10
[75]	Journal	2	1	1	1	2	2	1	10
[76]	Journal	2	1	2	1	1	2	1	10

the selected platforms. Likewise, the number of resulting documents was recorded at each stage of the filtering process. As a result, a total of 76 papers were preselected after PRISMA for quality assessment. These details are presented more precisely in Figure 3.

3.7 Quality Assessment

A series of quality assessment questions (QAs) was formulated to evaluate the quality of the 76 papers identified through the PRISMA flow diagram.

- QA1: Are the study objectives stated explicitly and precisely?
- QA2: Is there coherence between the methodological design and the stated objectives?
- QA3: Are the applied techniques described in sufficient detail and is their selection justified?

- QA4: Were appropriate procedures applied for measuring the study indicators?
- QA5: Are the procedures used for data collection properly documented?
- QA6: Is a clear and comprehensive characterization of the collected data presented?
- QA7: Is the purpose of the data analysis clearly defined?

For each paper, 7 criteria were used to verify its quality through a scoring system ranging from 1 to 3 (1 = Poor, 2 = Fair, and 3 = Excellent). For the exclusion of a paper, a minimum score of 11.5 was established. This assessment is shown in Table 3.

As a result of the evaluation of the 76 papers, it was concluded that 3 studies [74, 75, 76] did not meet the minimum required score of 11.5 or higher; therefore, only 73 papers will be used in this research.

3.8 Data Extraction Strategies

Figure 4 presents the process of managing and organizing the identified papers through the use of Mendeley Desktop. After conducting an exhaustive

review of the selected information sources, the collected records were systematically organized using this bibliographic tool, allowing a structured and efficient management of the papers included in the review.

Likewise, in order to answer the research questions, relevant information was extracted from the final list of selected papers, including the paper title, authors, affiliations, countries, URL, publication source, ISSN, type and name of the publication, quartile, H-index, abstract, keywords, methodology, and conclusions.

Additionally, RAj (Research Assistant j), an artificial intelligence tool developed by Javier Gamboa Cruzado, was used. This tool contributed to the processing, analysis, and organization of the collected information, thereby strengthening the quality of the study conducted.

3.9 Synthesis of Findings

The answers corresponding to each research question (RQ1–RQ6) were organized into tables and presented through quantitative data in order to develop a comparative analysis of the statistical results obtained.

4 Results and Discussion

This section presents a detailed analysis of the results obtained, relating them to the research objectives and contrasting them with the evidence reported in the existing scientific literature.

Likewise, Figure 5 shows the stages used for the processing of unstructured texts.

4.1. General Description of the Studies

Figure 6 presents the distribution of the objectivity of the conclusions reported in the analyzed papers according to the scientific information source used, classifying them into neutral, objective, and subjective approaches.

As shown in the findings, Scopus concentrates the largest number of papers with neutral and objective conclusions, which may be associated with its high editorial standards and with the predominance of indexed journals that prioritize rigorous methodological structures and

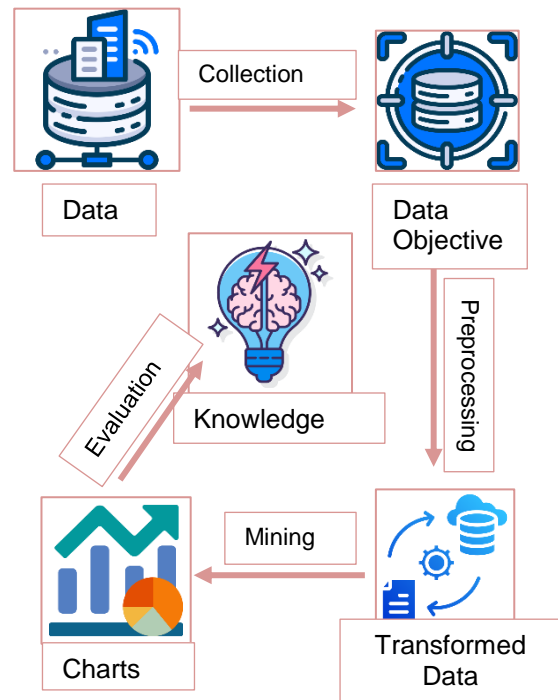


Fig. 5. Additional processing of selected studies

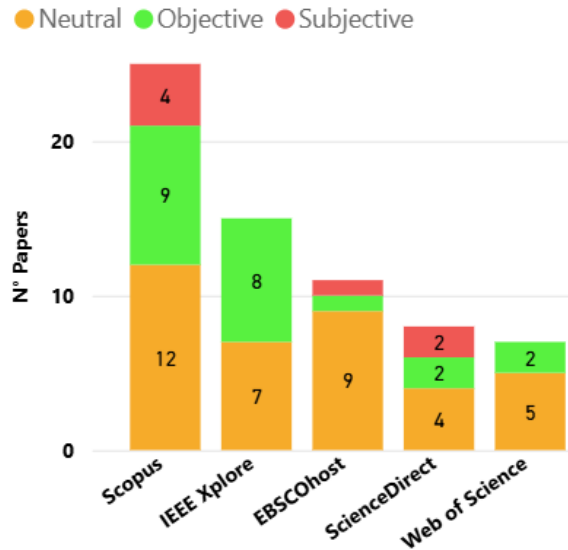


Fig. 6. Objectivity of Conclusions by Source

discussions grounded in empirical evidence. According to the observed distribution, IEEE Xplore and EBSCOhost maintain a significant

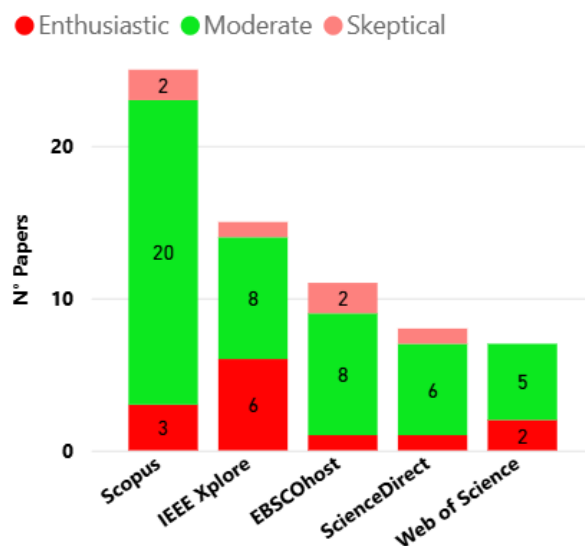


Fig. 7. Polarity of conclusions by source

presence of objective conclusions, although with a lower overall publication volume, which reflects a technical orientation centered on verifiable results and computational models applied to the biomedical field. In line with the identified pattern, subjective conclusions show a considerably lower frequency across all analyzed sources, indicating a general tendency in the literature toward more structured analytical approaches and less dependence on speculative interpretations, particularly in research related to Machine Learning and the detection of neurodegenerative diseases.

These results highlight the importance of prioritizing scientific sources with high levels of objectivity in research applied to other sectors, such as digital health, finance, logistics, or intelligent manufacturing, where the reliability of conclusions is decisive for strategic decision-making.

Likewise, the observed pattern may serve as a methodological reference for future studies developed in different geographic contexts and time periods, promoting more robust literature selection processes and scientific evaluation criteria aimed at strengthening the quality of systematic reviews.

Figure 7 presents the distribution of the polarity of conclusions in the analyzed papers according to

the scientific information source, classifying them into enthusiastic, moderate, and skeptical approaches. This representation is relevant because it makes it possible to identify the predominant orientation of the conclusions reported in the literature related to Machine Learning applied to Alzheimer's disease detection, thereby facilitating a deeper evaluation of the scientific positioning present in each database.

As shown in the findings, moderate polarity clearly predominates across all the analyzed sources, especially in Scopus, which suggests a tendency within the scientific community toward balanced and cautious interpretations regarding the performance of Machine Learning models in clinical settings. According to the observed distribution, IEEE Xplore shows a relatively higher proportion of enthusiastic conclusions compared with other databases, a situation that may be related to the technological and experimental focus of the published studies, where accuracy metrics, algorithmic optimization, and computational validations are usually prioritized. Based on the analyzed evidence, skeptical conclusions maintain a limited presence across all sources, which could be explained by the progressive consolidation of advanced deep learning techniques and by the increasing availability of biomedical data that strengthens confidence in the obtained results, although it could also reflect a certain editorial tendency to favor studies with more promising results.

These results highlight the need to maintain balanced analytical approaches in other artificial intelligence-intensive sectors, such as digital health, finance, logistics, and intelligent manufacturing, where excessively optimistic interpretations could affect strategic and operational decision-making. Likewise, the identified pattern may serve as a methodological reference for future research developed in different geographic regions and time periods, promoting more critical evaluations of the applicability, robustness, and sustainability of Machine Learning-based solutions.

Figure 8 presents the annual distribution of scientific documents according to the analyzed information sources, complemented by a Pareto diagram that makes it possible to identify the years with the highest concentration of publications

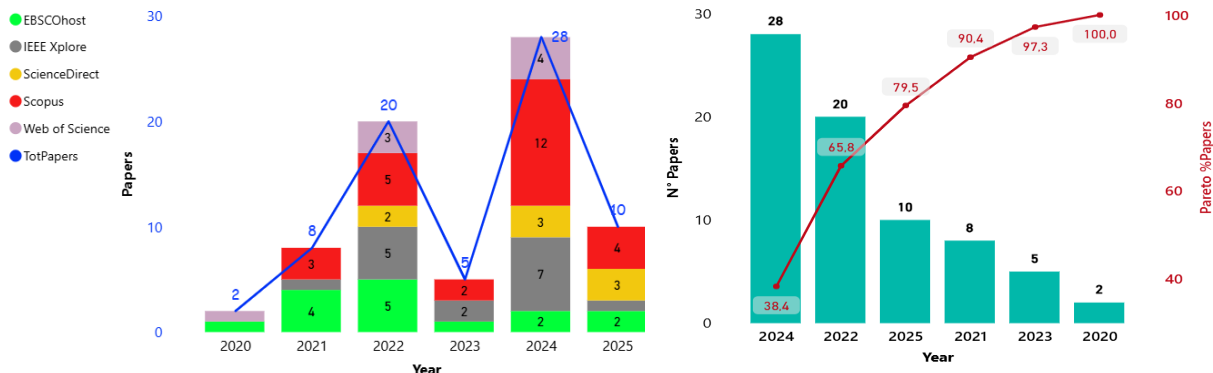


Fig. 8. Distribution of Evaluation Criteria

Table 4. Impact of papers by year

Year	N° Papers	% Papers	N° Citations	% Citations	H-Index	% H-Index	Citations/ Paper
2024	28	38,4%	152	11,1%	3505	33,2%	5,4
2022	20	27,4%	607	44,3%	3432	32,5%	30,4
2025	10	13,7%	5	0,4%	1751	16,6%	0,5
2021	8	11,0%	475	34,7%	1041	9,9%	59,4
2023	5	6,8%	102	7,5%	518	4,9%	20,4
2020	2	2,7%	28	2,0%	313	3,0%	14,0
Total	73	100,0%	1369	100,0%	10560	100,0%	18,8

within the studied period. In turn, Table 4 shows the impact of papers by year through indicators related to the number of papers, citations, H-index, and average citations per paper, providing a comprehensive view of the evolution and scientific relevance of the analyzed academic production.

As shown in the findings, 2024 concentrates the largest number of publications, accounting for 38.4% of the total papers analyzed, which indicates a recent acceleration in scientific interest in the use of Machine Learning for Alzheimer's disease detection, probably driven by advances in deep learning models and the growing availability of digital biomedical data. Based on the reported results, 2022 records the highest number of citations and one of the highest H-index values, a result that may be linked to longer academic exposure and to the publication of studies with high

methodological and clinical influence within the analyzed domain. Based on the presented evidence, although 2025 shows a lower number of citations and citations per paper, it still maintains relevant scientific production, which suggests that the most recent works are still in an early stage of dissemination and accumulation of bibliometric impact within the international scientific community.

In the study by Chamakuri and Janapana [80], 2020 concentrated the highest scientific production on the topic, with 27 papers, followed by 2021 with 21 papers; in contrast, Al-Hammadi and co-authors [81] identified 2018 and 2022 as the years with the highest number of publications, which stood out as the most productive periods within the analyzed interval. For their part, Song and their team [82] documented an accelerated growth in publications

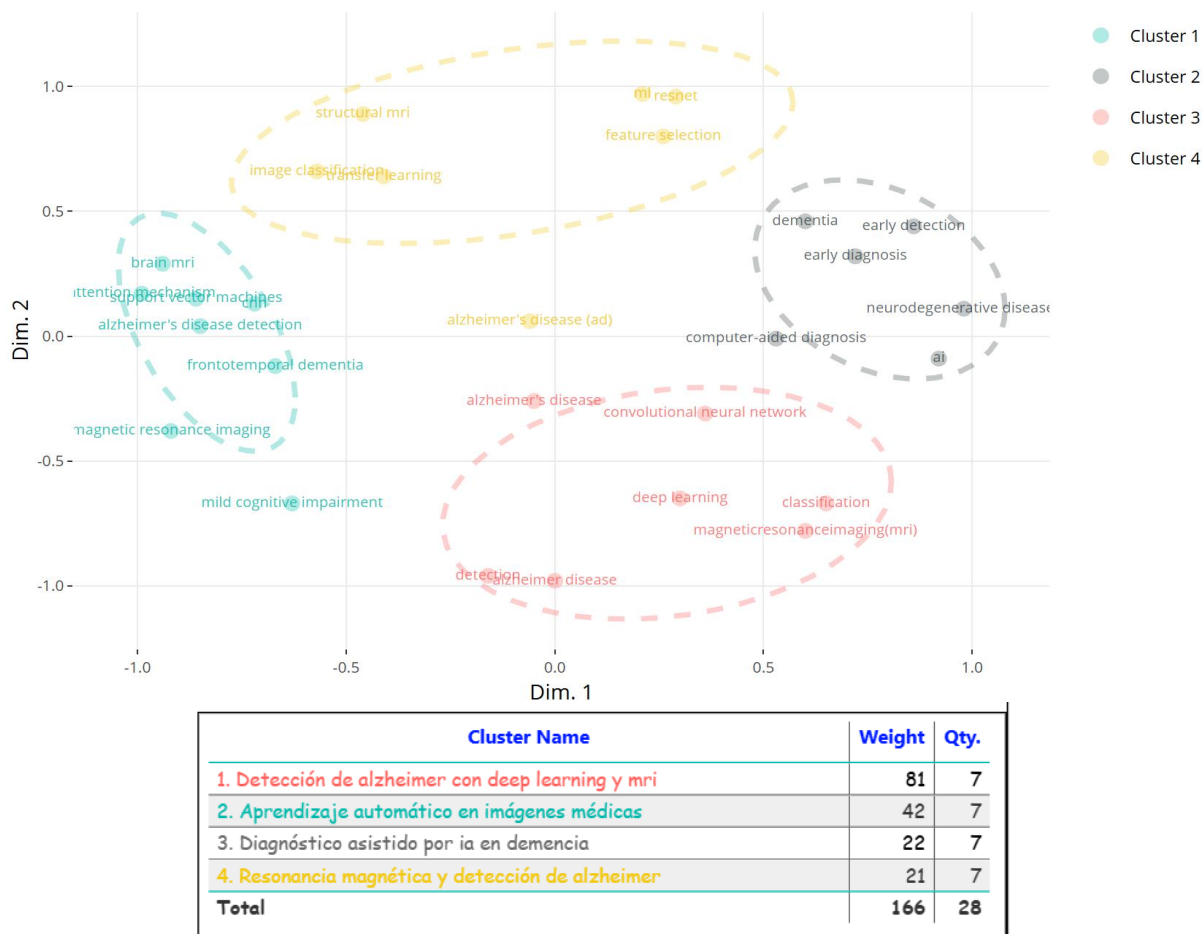


Fig. 9. Keyword Clusters

beginning in 2019, reaching its highest point in 2022 with more than 500 publications, which reflects a considerable expansion of academic interest in the field.

Although Alarjani and Almarri [96] reported a greater concentration of papers in 2018 and 2019, with more than 20 publications per year, Rojas Valdivia and collaborators [97] showed that 2021 represented the peak of productivity, with 44 publications, followed by 2020 with 18 papers and 2019 with 14, configuring an accelerated growth curve in the domain of API deployment through Machine Learning; nevertheless, 2017 and 2018 had a marginal participation, with only 1 and 6 publications, respectively. Finally, An and the research team [98] identified 2023 as the year with

the highest production, with 139 papers, followed by 2024 with 133, whereas 2016 recorded the lowest contribution, with only 1 paper.

Taken together, the reviewed studies show differentiated temporal patterns of scientific production, although they converge in showing a progressive growth of academic interest in recent years; therefore, the evolution of publications suggests a gradual consolidation of the field, with productivity peaks associated with recent periods and with the intensification of Machine Learning-based applications.

These results show that artificial intelligence-based technologies continue to consolidate across different data-intensive sectors, such as digital health, finance, advanced manufacturing, and

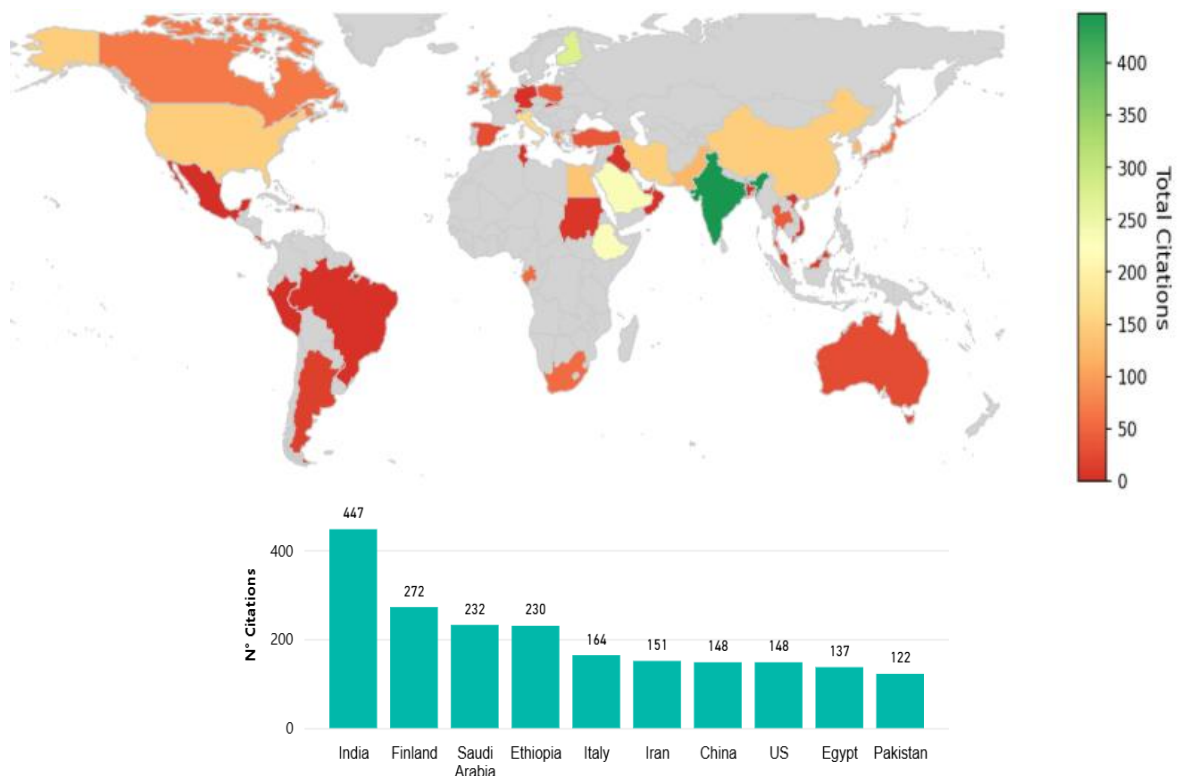


Fig. 10. Distribution of Citations by Country

cybersecurity, where the sustained growth in publications reflects processes of technological transformation and the progressive adoption of predictive models.

Likewise, the observed temporal concentration and the bibliometric impact indicators may serve as a strategic reference for future research developed in different geographic regions and time periods, favoring the identification of emerging trends and priority areas for interdisciplinary development.

Figure 9 presents the grouping of keywords through cluster analysis, making it possible to identify the main thematic lines and conceptual relationships present in the analyzed scientific literature on Machine Learning applied to Alzheimer's disease detection.

This representation is relevant because it facilitates the understanding of the predominant research areas, as well as the interaction between computational techniques, diagnostic methods, and approaches based on medical imaging.

As shown in the findings, the cluster related to Alzheimer's detection through deep learning and MRI has the greatest thematic weight, which reveals a strong concentration of research oriented toward the use of deep neural networks and magnetic resonance imaging to improve diagnostic accuracy and the early identification of neurodegenerative patterns.

According to the observed distribution, the clusters linked to machine learning in medical imaging and magnetic resonance imaging show a high conceptual proximity, a pattern that may be attributed to the methodological dependence on classification and feature extraction algorithms applied to complex biomedical data.

In line with the identified pattern, the cluster associated with AI-assisted diagnosis in dementia has a lower relative weight, although it maintains relevant connections with terms related to early detection and neurodegenerative diseases, which suggests a progressive evolution toward intelligent

clinical support systems with greater interpretive and predictive capacity.

In the study by Song and co-authors [82], the predominant keywords were “machine learning,” “convolutional neural network,” and “alzheimer disease,” which evidences a thematic orientation centered on the use of machine learning techniques and convolutional neural networks applied to the study of Alzheimer’s disease. In contrast, An and collaborators [98] identified “deep learning” and “neurodegenerative disease” as the main keyword clusters, whereas “machine learning” ranked fifth and “disease diagnosis” ranked eighth, which suggests a broader focus on neurodegenerative diseases and diagnostic processes supported by advanced deep learning models. Taken together, both studies agree in recognizing the relevance of machine learning in the biomedical field; however, they differ in thematic emphasis, since Song and their team [82] focus more specifically on Alzheimer’s disease, whereas An and collaborators [98] present a broader perspective linked to neurodegenerative diseases and clinical diagnosis.

These results show that the integration of artificial intelligence techniques and medical image analysis can be extended to other sectors intensive in visual data processing, such as computational radiology, precision agriculture, industrial safety, and intelligent manufacturing. Likewise, the identified thematic structure may serve as a reference for future research developed in different geographic regions and time periods, favoring the consolidation of interdisciplinary approaches and the design of research strategies focused on advanced diagnostic technologies.

Figure 10 presents the geographic distribution of cumulative citations by country in the studies, complemented by a bar chart showing the countries with the highest number of citations. This representation is relevant because it makes it possible to identify the main centers of scientific impact and recognize the regions with the greatest academic influence within the analyzed domain.

Based on the presented evidence, India concentrates the highest number of citations, reaching a total of 447, which reflects strong scientific participation and a growing consolidation of research oriented toward the use of artificial intelligence in biomedical and neurodegenerative

applications. As shown in the findings, countries such as Finland, Saudi Arabia, and Ethiopia also present important citation levels, a situation that may be related to the strengthening of international collaborations, investments in digital health, and the expansion of research infrastructures based on medical data analysis. From the reported results, the heterogeneous distribution of citations shows that scientific impact is not concentrated exclusively in traditionally dominant economies, but also emerges in regions with active strategies of technological innovation and interdisciplinary academic production.

Compared with the study by Song and collaborators [82], the United States records the highest share of citations, with 36.1%, whereas Canada presents the lowest proportion, with 3.4%. Similarly, in the study by Liu and co-authors [84], the U.S. also leads the citation distribution, with 31.3%, in contrast to France, which reaches the lowest value, with 3.8%. For their part, An and colleagues [98] again report the leadership of the U.S., although with a lower share, equivalent to 17.86%, whereas Saudi Arabia ranks in the last position, with 7.83%. Taken together, the three studies show a consistent trend: the United States maintains a dominant position in terms of citations, although with percentage variations across studies; in contrast, the countries with the lowest participation differ depending on the study analyzed, which suggests an uneven distribution of international scientific influence in the field.

These results reflect that the adoption of Machine Learning-based technologies and predictive analytics continues to expand into different geographic contexts and strategic sectors, such as digital health, bioinformatics, advanced manufacturing, and intelligent monitoring systems. Likewise, the identified citation patterns may serve as a reference for future research developed over different time periods, facilitating the identification of emerging countries with high scientific potential and promoting international strategies for collaboration and technological innovation.

Table 5 synthesizes the methodological findings of the included studies, grouping techniques, datasets, performance, limitations, and references by analytical category. This organization makes it possible to compare the

Table 5. Synthesis of Findings by Methodological Category

Method Category	Methods used	Datasets	Performance	Limitations	Refs.	Qty. (%)
Biofluid, Genomic, Spectroscopy, and Omics-based ML	ELISA biomarker modeling; Raman spectroscopy; ATR-FTIR; GWAS; WGCNA; Random Forest; SVM; LASSO; SHAP	InveCe.Ab; PharmaCog/E-ADNI; ANZIANI INRETE; CSF Raman spectra; Xiangya/Liuyang cohorts; ADNI GWAS; GEO datasets; Japanese speech recordings	AUC=0.99; Accuracy=86%; AUC=0.92–0.93; Accuracy=89%; AUC=0.824–0.918; AUC up to 0.977	Small or retrospective cohorts; limited ethnic/geographic diversity; acquisition variability; need for external validation	[1] [22] [39] [44] [46] [53]	6 (9.5)
Decision-support, Chatbot, and MCDM AI	CoCoSo; AHP; SVNSs; LSTM; Seq2Seq; Attention; Bag of Words; Beam search	Telecommunication chatbot data; custom Arabic corpus; public organization case studies; Dialog dataset	Case-study validation; sensitivity analysis; BLEU-4=0.8537; accuracy/response-time improvements reported	Limited fit to AD-specific diagnosis; weak clinical integration; privacy/security and social factors insufficiently considered	[23] [25] [26] [31] [33] [35] [38] [40] [56]	9 (14.3)
Deep CNN and Transfer Learning for Neuroimaging	2D/3D CNN; ResNet; Inception; MobileNet; DenseNet; VGG; autoencoders; GAN; SMOTE/ADASYN; Grad-CAM	ADNI; ADNI3; OASIS; Kaggle MRI; AIBL; MIRIAD; Alzheimer's Disease Neuroimaging Dataset	Accuracy=81.80%–99.92%; AUC=0.91–0.99; Dice=0.885; Specificity up to 99.12%	Generalizability limits; small or single-source datasets; 2D-slice dependency; computational cost; limited clinical validation	[2] [4] [6] [10] [12] [13] [16] [17] [20] [21] [24] [27] [28] [30] [32] [34] [36] [37] [50]	19 (30.2)
EEG and Biomedical Signal-based ML/DL	DWT; PSD; FIR filtering; SSVEP biomarkers; CNN; DICE-net; CNN-LSTM-attention; SVM; KNN; RF	Hospital EEG datasets; EEG-SSVEP recordings; OpenNeuro EEG; Spanish multi-hospital EEG; ERP datasets	Accuracy=75%–99.98%; AUC=100%; F1-score=86.87%; LOSO validation=83.28%	Small samples in several studies; EEG noise and artifacts; limited external validation; lower multiclass performance	[7] [14] [45] [48] [55] [58] [60]	7 (11.1)
Feature Engineering, Optimization, and Hybrid ML	CLAHE; k-means; PCA; CCA; WOA; QMFT; rMTFL; Harmony Search; SVM; KNN; DT; RF	MRI brain images; Kaggle MRI; ADNI fMRI; ADNI sMRI	Accuracy=77.5%–98.12%; CNN=96.7%; AD/HC accuracy=95.5%; pMCI/sMCI accuracy=78.5%; NR in one study	Dataset source sometimes NR; optimization cost; limited cross-dataset validation; incomplete performance reporting	[8] [9] [15] [19]	4 (6.3)
Gait, Handwriting, and Behavioral Sensing ML	Kinect v.2 gait capture; TUG analysis; signal processing; stacking; RF; SVM; ANOVA; RFE	DARWIN; Kinect skeletal joint datasets; TUG test data	Accuracy=85.50%–98.68%; F-score=83.9%–98.67%; AUC-ROC=97.5%	Small samples; sensor-placement sensitivity; not standalone diagnosis; generalizability not established	[49] [61] [62]	3 (4.8)
Supervised Clinical, Cognitive, and Multimodal ML	SVM; Random Forest; Logistic Regression; Gradient Boosting; XGBoost; LightGBM; stacking; PCA; autoencoder imputation; SHAP; LIME	ADNI; OASIS longitudinal MRI; ADNI-1/2/3/GO; Kaggle clinical AD dataset; reviewed MRI/biomarker datasets	Accuracy=89.63%–97.60%; AUC=0.964–0.981; Accuracy range across review=62.64%–99.77%	Missing data dependency; single-dataset validation; overfitting risk; heterogeneous metrics across studies	[5] [18] [41] [42] [47] [51] [63]	7 (11.1)
Transformer, Attention, Graph, and Multimodal Deep Architectures	ViT; Swin Transformer; MobileViTv3; GCN; multi-head attention; mixed-transformer U-Net; CNN-LSTM; multimodal CNN-LSTM fusion	ADNI; OASIS; Kaggle MRI; PET images; MRI/PET datasets; OASIS-1/3; NACC	Accuracy=83.28%–99.83%; AUC up to 99.31%; Specificity up to 99.89%	Computational complexity; limited external validation; heterogeneous modalities; incomplete full-system metrics in some studies	[3] [11] [29] [43] [52] [54] [57] [59]	8 (12.7)

relative maturity of the approaches employed in Alzheimer's disease detection through Machine Learning and Deep Learning. In addition, the Qty.

(%) values show the methodological concentration of the field and make it possible to identify dominant, emerging, and peripheral lines.

Method Category: The taxonomy shows a clear concentration in *Deep CNN and Transfer Learning for Neuroimaging*, which groups 19 studies (30.2%), confirming that research has been structured primarily around medical imaging, especially MRI, as the dominant source for Alzheimer's disease detection. In contrast, categories such as *Gait, Handwriting, and Behavioral Sensing ML* include only 3 studies (4.8%), which shows that noninvasive approaches based on behavioral signals still occupy a peripheral position compared with neuroimaging models. This distribution suggests that the availability of public datasets such as ADNI, OASIS, and Kaggle has favored the expansion of visual models, whereas methods based on behavior, biofluids, or omics require greater efforts in validation, standardization, and multicenter data collection.

Methods used: The methods employed reveal a strong predominance of CNN architectures, deep networks, transfer learning, class-balancing mechanisms, and explainability techniques, especially in the dominant neuroimaging category, which accounts for 30.2% of the studies. The categories *Transformer, Attention, Graph, and Multimodal Deep Architectures*, with 8 studies (12.7%), and *EEG and Biomedical Signal-based ML/DL*, with 7 studies (11.1%), show an evolution toward models capable of capturing more complex spatial, temporal, and multimodal dependencies. This pattern may be explained by the need to improve diagnostic sensitivity in early stages, where neurodegenerative changes are subtle and require models with greater representational capacity.

Datasets: The datasets are concentrated mainly in ADNI, OASIS, Kaggle MRI, and other widely used biomedical repositories, which explains the high presence of neuroimaging studies and deep models. This dependence on recurrent sources favors experimental comparability, but it may also restrict clinical generalizability due to the repetition of cohorts, controlled conditions, and possible overfitting to specific domains. The categories with lower frequency, such as biofluids, gait, handwriting, and speech, show greater data diversity, but also greater fragmentation, which

limits replicability and the consolidation of stable benchmarks.

Performance: The reported performance shows high values across several categories, with accuracies reaching levels close to 99% and AUC values above 0.90, especially in neuroimaging models, biofluids, and advanced deep architectures. However, these results must be interpreted with caution, because the most frequent categories, such as CNN and transfer learning, which account for 30.2%, usually rely on public, preprocessed, or relatively controlled datasets, whereas approaches involving biomedical signals, behavior, or clinical data face greater variability and lower standardization. This difference suggests that high technical performance does not always equate to clinical robustness, especially when there are reduced sample sizes, limited external validations, or heterogeneous metrics.

Limitations: The limitations are concentrated in recurrent problems of generalizability, reduced sample size, dependence on single datasets, heterogeneity of metrics, overfitting, computational complexity, and limited clinical validation. These constraints are particularly relevant in the categories with the greatest weight, such as *Deep CNN and Transfer Learning for Neuroimaging*, with 19 studies (30.2%), and *Transformer, Attention, Graph, and Multimodal Deep Architectures*, with 8 studies (12.7%), because their high performance usually depends on complex architectures and highly structured data. Consequently, the main gap in the field lies not only in achieving greater accuracy, but in demonstrating stability, interpretability, transferability, and clinical utility in real-world scenarios.

Qty. (%): The percentages show an uneven methodological structure: CNN and transfer learning account for 30.2%, followed by decision support and MCDM with 14.3%, *Transformer/Attention/Graph* architectures with 12.7%, and EEG or multimodal clinical models with 11.1% each. This concentration indicates that the field is dominated by visual and computationally intensive approaches, whereas behavioral, biochemical, and feature engineering alternatives remain less represented. The pattern suggests a

Table 6. Machine Learning Models

Model	Reference	Qty. (%)
Support Vector Machine	[5][7][8-11][26][27][29-36][38][39][41][55][57][60-64][68][72]	[42][44][47-55] 38 (18.91)
3D CNN	[10][11][12][27][29][32][36][37][40][52][54][63][73]	13 (6.47)
ResNet50	[2][4][6][9][11][27][30][32][34][37][51][71]	12 (5.97)
VGG16	[2][6][9][10][11][12][28][32][34][47][50][51][63][68][71]	15 (7.46)
InceptionV3	[6][11][28][31][59][71]	6 (2.99)
MobileNet	[3][6][9][10][11][28][71]	7 (3.48)
Vision Transformer	[3][6][11][29][32][48][52][59]	8 (3.98)
Random Forest	[7-11][27][29][31-34][37][39][41-50][52][53][54][57][60][61][63][67][68][69][71]	34 (16.92)
Decision Tree	[1][2][4][7][8][11][26][30-34][41][42][43][45][46][47][49][50][51][53][55][57][60][61][63][68]	28 (13.93)
XGBoost	[6][26][30][32][38][47][48][49][51][57]	10 (4.98)
Multinomial Logistic Regression	[42]	1 (0.50)
K-Nearest Neighbors	[2][26][30][31][39][42][44][47][48][49][51][60][63]	13 (6.47)
Logistic Regression	[8][30][38][39][41][42][44][45][47][48][49][53][57][61][67][68]	16 (7.96)

gradual transition from classical models and specific pipelines toward deep, multimodal, and explainable architectures, although important methodological gaps still remain for their clinical adoption.

The results suggest that future research should prioritize external validations, multicenter cohorts, and comparable protocols in order to reduce dependence on recurrent datasets. The concentration in neuroimaging confirms its technical maturity, but also highlights the need to integrate biofluids, EEG signals, clinical data, and behavioral biomarkers. In sectors such as digital health, insurance, telemedicine, and hospital management, these findings may guide the design

of more robust and explainable predictive systems. The low representation of behavioral and noninvasive approaches opens opportunities for applications in home monitoring, healthy aging, and assisted diagnosis in areas with limited medical infrastructure.

From a methodological perspective, the field must move from the maximization of metrics toward reproducible, interpretable, clinically transferable, and sustainable models in real-world scenarios.

4.2. Answers to the Research Questions

The following subsection provides answers to the research questions formulated in the initial stage.

RQ1: What types of Machine Learning-based models have been developed in the studies?

Table 6 presents the distribution of the main Machine Learning and Deep Learning models used in studies related to Alzheimer's Disease Detection, showing the frequency of use of each algorithm within the analyzed literature. This representation is relevant because it makes it possible to identify the predominant computational approaches in the development of intelligent diagnostic systems, as well as to recognize the methodological evolution of the field toward more complex and specialized architectures.

The synthesis of the information corresponding to the machine learning models is presented in Figure 11.

As shown in the findings, Support Vector Machine accounts for the highest proportion of studies, with 38 records (18.91%), followed by Random Forest with 34 studies (16.92%) and Decision Tree with 28 studies (13.93%), which suggests a strong persistence of classical models due to their interpretability, statistical stability, and adequate performance with biomedical datasets of moderate size and high dimensionality. Based on the reported results, deep architectures oriented toward medical image processing, such as VGG16 with 15 studies (7.46%), 3D CNN and K-Nearest Neighbors with 13 studies each (6.47%), as well as ResNet50 with 12 records (5.97%), reflect a progressive consolidation of models capable of extracting complex spatial features from MRI and other neuroimaging modalities.

Based on the presented evidence, more recent models such as Vision Transformer with 8 studies (3.98%) and XGBoost with 10 studies (4.98%) still show lower relative adoption, although they reveal a methodological transition toward hybrid architectures and advanced attention mechanisms aimed at improving diagnostic accuracy, generalization capacity, and the automation of neurodegenerative pattern extraction.

According to Cárdenas-Quispe and co-authors [83], the predominant algorithms were Support Vector Machine (23.14%), Random Forest Regression (16.16%), and Naive Bayes Classifier (14.85%), a pattern partially convergent with the findings of the present study regarding the

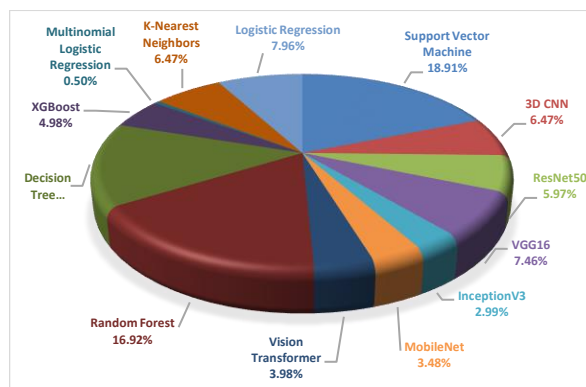


Fig. 11. Synthesis of Machine Learning Models

prominence of SVM and Random Forest, although divergent due to the incorporation of deep architectures such as VGG16, 3D CNN, and Vision Transformer, which are absent in the domain of Android malware detection. In a similar line, Shukla, R. Tiwari, and S. Tiwari [85] argue that, in recent years, models such as SVM and VBM have gained broad popularity due to their high accuracy, whereas CNN-based models showed comparatively lower performance. This is consistent with what was reported by Kantayeva, Lima, and Pereira [86], who identified SVM as the most frequent model in their studies, with a total of 15 records, while CNNs reached 6 studies. Nevertheless, Yang and collaborators [87] point out that, although SVM continues to be used, there is a growing trend toward convolutional neural networks and pretrained models applied to unstructured data, which have achieved accuracies above 90%. In contrast, Toumaj and colleagues [88] reported that CNNs were the most popular models, with 25.7%, followed by SVM and LSTM, with 11.4% each. In the same direction, Mohammed and their team [89] maintain that CNN and ResNet models showed a clear predominance, with 18 papers each, followed by VGG with 13 papers, whereas SVM showed only marginal presence, being considered in just 1 paper. For their part, Aparcana-Tasayco and Gamboa-Cruzado [90] identified Support Vector Machine (14.4%), Naive Bayes (9.3%), and Reinforcement Learning (7.9%) as the predominant algorithms, a pattern convergent with the present study regarding the leadership of SVM, but divergent due to the incorporation of deep

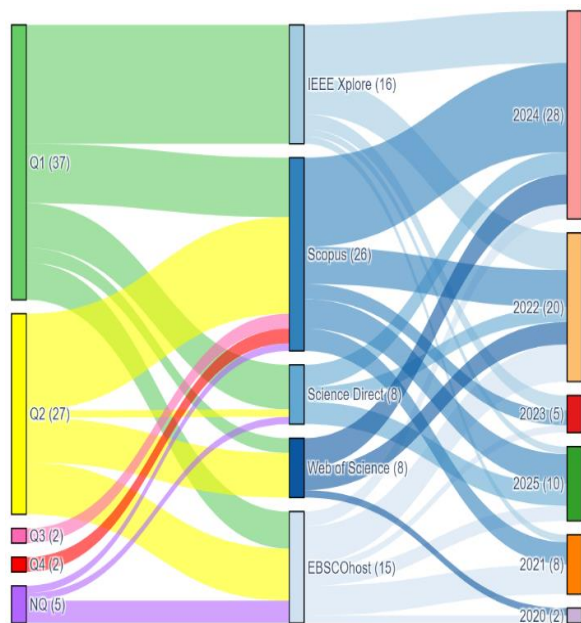


Fig. 12. Quartile Levels by Journal

architectures for neuroimaging. Finally, in the study by Rojas Valdivia and co-authors [97], the predominant algorithms were Decision Tree, with 17 publications (21.25%); K-means, with 16 studies (20%); and Logistic Regression, with 14 records (17.5%), which shows a hegemony of classical models in the domain of API deployment; in contrast, the present study shows greater architectural diversification by integrating traditional models such as SVM and Random Forest together with deep architectures such as VGG16 and 3D CNN.

Taken together, the reviewed studies show a progressive transition from classical Machine Learning models toward deep architectures and pretrained models, although the intensity of this transition varies according to the application domain, the type of data analyzed, and the reported performance criteria.

This points to the fact that the Machine Learning techniques used in Alzheimer's Disease Detection have a high transfer potential toward other data-intensive sectors, such as digital health, cybersecurity, finance, intelligent manufacturing, and business predictive analytics. Likewise, the coexistence of classical models and deep

architectures suggests that future research developed in different geographic regions and time periods should prioritize hybrid, interpretable, and multimodal strategies that make it possible to balance predictive performance, clinical robustness, and computational feasibility in real-world scenarios.

RQ2: At what quartile levels are the journals that publish research on the application of Machine Learning in Alzheimer's Disease Detection classified?

Figure 12 presents a Sankey diagram that visualizes the flows among journal quartile levels, indexing databases, and publication years.

Table 7 synthesizes the quantitative distribution of scientific production by quartile together with its associated bibliometric indicators, while Table 8 breaks down these same indicators according to the source of origin. This representation is essential for the analysis, since it makes it possible to simultaneously evaluate the editorial quality, bibliometric impact, and traceability of scientific production on the application of Machine Learning to Alzheimer's disease detection.

As shown in the findings, the Q1 quartile accounts for the largest proportion of scientific production, with 37 papers and a total of 821 citations, reaching an H-index of 7796, which indicates that the most influential research in this domain is published predominantly in journals with high editorial visibility, a phenomenon explained by the rigorous peer-review processes and the methodological standards required by these publications, which act both as quality filters and as amplifiers of academic impact.

According to the identified pattern, Q2 journals contribute 27 papers and an average of 16 citations per paper, whereas the Q3 and Q4 quartiles show only marginal participation, with just 2 papers each, an asymmetry explained by the consolidation of a core group of journals specialized in artificial intelligence applied to neuroscience that channels the most rigorous production, relegating lower-quartile publications to peripheral or emerging contributions. Based on the reported results,

Scopus ranks as the source with the highest volume of papers (26) and an average H-index of

Table 7. Distribution of Scientific Production by Quartile and Bibliometric Indicators

Quartil	N° Papers	N° Citations	Citations/ Paper	H-Index
Q1	37	821	22	7796
Q2	27	429	16	2391
NQ	5	98	20	269
Q3	2	18	9	91
Q4	2	3	2	13
Total	73	1369	19	10560

Table 8. Distribution of Scientific Production and Bibliometric Indicators by Source

Source	Avg H-Index	Total Papers	Total Citations	Citations /Paper	PY Start
Scopus	86,69	26	391	15	2021
IEEE Xplore	260,13	16	569	36	2021
EBSCOhost	153,47	15	270	18	2020
ScienceDirect	109,38	8	41	5	2022
Web of Science	120,88	8	98	12	2020
Total	144,66	73	1369	19	2020

Table 9. Machine Learning Programming Languages

Programming Language	Reference	Qty. (%)
Matlab	[5][7][9][26][30][33][37][39][48][55][58][60] [61][62][69][70]	16 (26.6)
Python	[2][4][6][11][27][29][31][33][35][36][38][39] [40][41][45][47][48][49][51][52][53][55][57] [58][67][69][70]	27 (45)
Java	[2]	1 (1.6)
R	[67]	1 (1.6)
Scala	[11][12][31][32][35][47][48][51][56][59][66] [67][68][70][71]	15 (25)

86.69, whereas IEEE Xplore, despite contributing only 16 papers, exhibits the highest average H-index (260.13) and the highest citation-to-paper ratio (36), a result associated with the technical and applied nature of this database, which concentrates biomedical engineering and

computational intelligence research with strong resonance in the scientific community.

In the study by Song and collaborators [82], the predominant quartiles corresponded to Q1 and Q2, which indicates a greater concentration of studies published or referenced in journals with high and

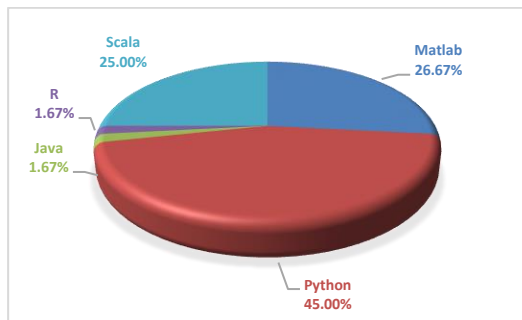


Fig. 13. Synthesis of Programming Languages

upper-middle academic impact; consequently, this pattern suggests an orientation toward sources with greater scientific recognition and more rigorous editorial standards.

The high proportion of Q1 and Q2 papers supports the strength and reliability of the findings on machine learning in Alzheimer's disease detection. However, the presence of NQ studies in some cases may introduce bias and limit the overall applicability of the results.

RQ3: Which programming languages are most frequently used in the development of Machine Learning-based solutions?

Table 9 provides a comprehensive record of the bibliographic references associated with each programming language, together with their absolute and relative frequencies. This characterization is methodologically significant, since it makes it possible to identify the predominant technological ecosystem in the implementation of algorithmic models and to project the adoption trajectory of computational tools in the applied neuroscientific domain. Figure 13 presents, through a three-dimensional pie chart, the percentage distribution of the programming languages used in the development of Machine Learning-based solutions for Alzheimer's disease detection.

Python accounts for 45% of the reported developments, with 27 references, positioning itself as the hegemonic language, a fact attributable to the maturity of its ecosystem of specialized libraries, TensorFlow, PyTorch, Keras, Scikit-learn, and NiBabel, which facilitate the implementation of deep architectures on structural

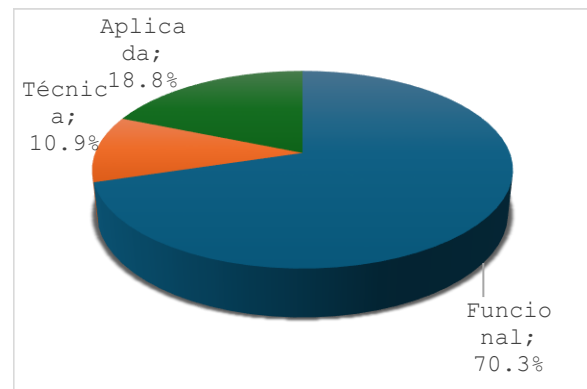


Fig. 14. Percentage Synthesis of Definitions by Category

and functional neuroimaging data, as well as to the active open-source community that supports the experimental reproducibility required in biomedical research. According to the identified pattern, Matlab and Scala maintain significant shares of 26.67% and 25.00%, respectively, which responds to differentiated factors: Matlab persists because of its historical consolidation in biomedical signal processing and the availability of specialized toolboxes such as SPM and FieldTrip for magnetic resonance analysis, whereas Scala emerges as an alternative for distributed processing on frameworks such as Apache Spark when working with large-scale longitudinal cohorts. Based on the reported results, Java and R exhibit marginal shares of 1.67% each, an asymmetry explained by the syntactic verbosity of Java, which hinders the iterative prototyping characteristic of deep learning research, and by the classical statistical orientation of R, which is less competitive than Python in representational learning tasks on unstructured data such as volumetric images and electroencephalographic time series.

In the study by Gamboa-Cruzado and the research team [92], Python reached a share of 32%, followed by Java with 25%, a result that contrasts with the findings of the present study, where Python reaches 45%, whereas Java accounts for only 1.6%. In contrast, Wang and collaborators [93] report a different pattern, since MATLAB exceeds Python by one paper, and Python shows the same frequency as C++; however, it is worth noting that the number of studies considered in that research was smaller than in the compared reviews.

Table 10. Categorization of Definitions

Synthesized Definition	Category	Reference	Qty. (%)
The ability of machines to learn and improve automatically from data without explicit programming.	Functional	[1][3][4][7][9][11][16-19][21][23][25][26][28-31][33-38][40][42-45][48][50][52][55][57-62][65][66][67][69][71][73]	45 (70.3)
The use of algorithms and statistical models to solve tasks through advanced computational methods.	Technical	[22][24][27][32][53][56][70]	7 (10.9)
The implementation of ML in specific domains such as medicine, diagnosis, or clinical analysis.	Applied	[2][6][10][13][39][41][46][47][49][64][68][72]	12 (18.8)

For their part, Zhang and Saber [94] identified a clear superiority of Java, with 52.9% out of a total of 104 analyzed papers, whereas Python represented only 8.9%, which reflects an orientation more closely linked to development environments and software systems. In contrast, Talebi and co-authors [99] show a pattern closer to the predominance of Python, reporting its presence in 51 papers, followed by MATLAB with 18 papers. Similarly, Bhushan and their team [91] indicate that Python was present in 72% of the studies, followed by MATLAB and R, with 11% and 9%, respectively. Reinforcing this dominance, Poursaeed and colleagues [101] identified that Python appeared in 64 papers, whereas MATLAB and R registered 14 and 26 papers, respectively; therefore, Python exceeds even the combined total of both languages.

Taken together, these studies show that Python tends to consolidate itself as the predominant language in research associated with scientific analysis, machine learning, and data processing; nevertheless, the relevant presence of MATLAB, R, Scala, Java, C++, Ruby, and Node.js shows that language choice depends on the application domain, distinguishing contexts oriented toward scientific analysis, such as neuroimaging, from production environments linked to e-commerce systems and chatbots.

These findings guide development teams in sectors such as healthtech, neurotechnology,

Figure 14 visualizes, through a three-dimensional pie chart, the percentage distribution of these conceptual perspectives. This taxonomic characterization is epistemologically significant, since it makes it possible to map the predominant theoretical frameworks that guide the

digital pharmaceuticals, and AI-assisted diagnosis toward the consolidation of Python-based pipelines, replicable in emerging geographic contexts where limited computational infrastructure requires low-cost and highly interoperable solutions, as well as in prospective periods in which integration with cloud platforms and GPU accelerators will continue to intensify. Additionally, the persistence of Matlab and Scala suggests strategic opportunities for technological hybridization in projects that combine legacy biomedical signal processing with distributed analytics, a model transferable to analogous domains such as early detection of Parkinson's disease, multiple sclerosis, mild cognitive impairment, and neuropsychiatric disorders in which large volumes of multimodal data and rigorous clinical validation requirements converge.

RQ4: What theoretical approaches have been formulated in studies analyzing the impact of Machine Learning on Alzheimer's disease detection?

Table 10 systematizes the conceptual definitions of Machine Learning identified in the reviewed corpus, classifying them into three epistemological categories, functional, technical, and applied, together with their associated bibliographic references and relative frequencies.

conceptualization of machine learning in research on Alzheimer's disease detection and to reveal the paradigmatic orientations that articulate the scientific production of the domain.

Based on the obtained results, the functional category accounts for 70.3% of the formulated

definitions, with 45 references, a predominance attributable to the consolidation of an operational conception of Machine Learning centered on the autonomous ability to learn from data without explicit programming, a perspective that is cognitively accessible to interdisciplinary audiences and facilitates communication among neurologists, radiologists, and computational engineers involved in translational projects.

According to the identified pattern, the applied category groups 18.8% of the conceptualizations, with 12 references, positioning itself as the second dominant orientation due to the growing demand for clinical validation in real-world scenarios, which has shifted academic discourse from purely abstract formulations toward contextualized definitions in specific biomedical domains such as neuroimaging, biomarkers, and cognitive analysis.

Based on the reported results, the technical category exhibits the lowest representation, with 10.9% and 7 references, an asymmetry that can be explained by the interdisciplinary nature of the analyzed corpus, in which authors tend to avoid deep algorithmic and statistical formalizations in favor of narratives that are accessible to clinical communities, a phenomenon that reveals a conceptual gap between the mathematical rigor underlying the implemented models and their effective communication in the biomedical literature.

This study constitutes a pioneering effort in the systematization and classification of definitions of Machine Learning in the context of Alzheimer's disease detection.

No previous studies were identified that address this conceptual dimension in a structured manner. The analysis conducted provides a clear and consistent definitional framework that strengthens the theoretical understanding of the field and serves as a basis for future academic inquiry.

A generalist approach to Machine Learning prevails, which may hinder its effective use in clinical settings. It is essential to consolidate the theoretical and technical aspects in future studies. In this way, a more solid and appropriate implementation in Alzheimer's disease detection will be promoted.

RQ5: What thematic categories predominate in the research linking Machine Learning to Alzheimer's disease detection?

Figure 15 represents, through a Callon strategic diagram, the distribution of the thematic clusters identified from the keyword co-occurrence analysis in the reviewed corpus, articulating on the horizontal axis the degree of centrality, which measures the relevance and level of interaction of each theme with other topics in the network, and on the vertical axis the degree of density, which quantifies the internal cohesion and conceptual development of the cluster. This is complemented by Table 11, which synthesizes the numerical values of both dimensions together with total citations, associated documents, and the corresponding strategic categorization. This visualization is methodologically significant, since it makes it possible to map the intellectual structure of the field, identify emerging, consolidated, and peripheral topics, and project the evolutionary trajectories of the research agenda surrounding Machine Learning applied to Alzheimer's disease detection.

As shown in the findings, the Marginal category concentrates the largest proportion of topics, with seven thematic clusters, Deep Learning Alzheimer, Deep Learning Diagnostics, Alzheimer Detection, Deep Neuroimaging, Dementia Diagnosis, Alzheimer Diagnosis, and Alzheimer Imaging, which present centrality values below 0.50 and low densities despite accumulating substantial citation volumes ranging from 904 to 1880 citations, an asymmetry attributable to the conceptual fragmentation characteristic of a domain in an early stage of consolidation, where multiple research groups address related problems without unified terminological articulation, thereby generating isolated subgroups despite their high productivity. densities despite accumulating substantial citation volumes ranging from 904 to 1880 citations, an asymmetry attributable to the conceptual fragmentation characteristic of a domain in an early stage of consolidation, where multiple research groups address related problems without unified terminological articulation, thereby generating isolated subgroups despite their high productivity. According to the identified pattern, Neuroimaging Classification stands out as the only specialized

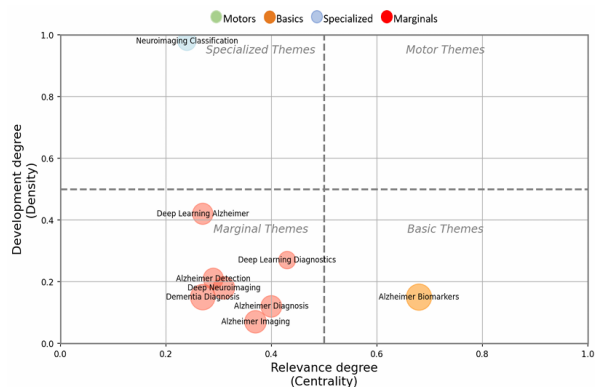


Fig. 15. Thematic Map of Topic Categories

Table 11. Topic Categories

Theme	Density	Centrality	Total Citations	Total Documents	Category
Neuroimaging Classification	0,98	0,24	1336	60	Specialized
Deep Learning Alzheimer	0,42	0,27	1659	73	Marginal
Deep Learning Diagnostics	0,27	0,43	1130	44	Marginal
Alzheimer Detection	0,21	0,29	1616	59	Marginal
Deep Neuroimaging	0,18	0,31	1880	73	Marginal
Alzheimer Biomarkers	0,15	0,68	953	37	Basic
Dementia Diagnosis	0,15	0,27	904	36	Marginal
Alzheimer Diagnosis	0,12	0,40	1732	63	Marginal
Alzheimer Imaging	0,07	0,37	1866	62	Marginal

topic, with the highest density in the network (0.98) but low centrality (0.24), a configuration typical of topics that are highly developed internally but show limited cross-cutting interaction, a behavior explained by the technical maturity of convolutional architectures applied to the classification of structural and functional images, which have reached methodological consensus that paradoxically distances them from the exploratory frontier of the field. Based on the reported results, Alzheimer Biomarkers emerges as the only basic topic, with the highest centrality in the network (0.68) and moderate density (0.15), revealing a cross-cutting conceptual core that articulates multiple lines of research, a phenomenon supported by the interdisciplinary convergence among molecular neuroscience, multimodal neuroimaging, and artificial intelligence, where

biomarkers such as amyloid-beta, phosphorylated tau, and hippocampal atrophy constitute the fundamental inputs that feed predictive models.

No previous reviews were identified that would allow a direct comparison of the predominant thematic categories in studies on Machine Learning applied to Alzheimer’s disease detection. This absence reveals a specific gap in the literature, given that existing reviews have focused on models, metrics, data sources, or general clinical applications. Consequently, the present study expands the literature by incorporating a thematic dimension of analysis that makes it possible to map the conceptual organization of the field and guide future research agendas.

These findings guide researchers, funding agencies, and developers in sectors such as healthtech, neurotechnology, AI-assisted

diagnosis, and precision pharmaceuticals toward the consolidation of strategic lines centered on digital and multimodal biomarkers, replicable in emerging geographic contexts where advanced neuroimaging infrastructure is limited and approaches based on accessible physiological signals, longitudinal clinical data, and low-cost peripheral biomarkers are required. Likewise, this analytical framework constitutes a methodological tool transferable to analogous domains such as early detection of Parkinson's disease, multiple sclerosis, mild cognitive impairment, and neuropsychiatric disorders, offering guidelines for anticipating thematic maturation in prospective periods in which integration with multimodal foundation models, federated learning, and explainable architectures will transform the current marginal fragmentation into fully consolidated motor clusters.

RQ6: Which countries stand out for their co-occurrence in collaborative studies on Machine Learning and its application to Alzheimer's disease detection?

Figure 16 represents, through an international co-authorship bibliometric network, the collaborative links among the countries that have contributed to the development of research on Machine Learning applied to Alzheimer's disease detection.

Table 12 quantifies the co-occurrence weights between pairs of nations, Table 13 synthesizes the centrality and cohesion metrics of the network, and Table 14 breaks down scientific production and bibliometric indicators by country. This analytical triangulation is methodologically significant, since it makes it possible to characterize the scientific geopolitics of the domain, identify nodes that articulate transnational collaboration, and evaluate the asymmetry between raw productivity and relational integration within the research community.

As shown in the findings. Saudi Arabia emerges as the central articulating node of the network. with a degree of 0.75. a strength of 16.00. and a betweenness centrality of 0.36. positioning itself as a structural bridge among multiple geographic groupings despite contributing 13 papers and 232 citations. This relational hegemony may be attributed to the implementation of Vision 2030.

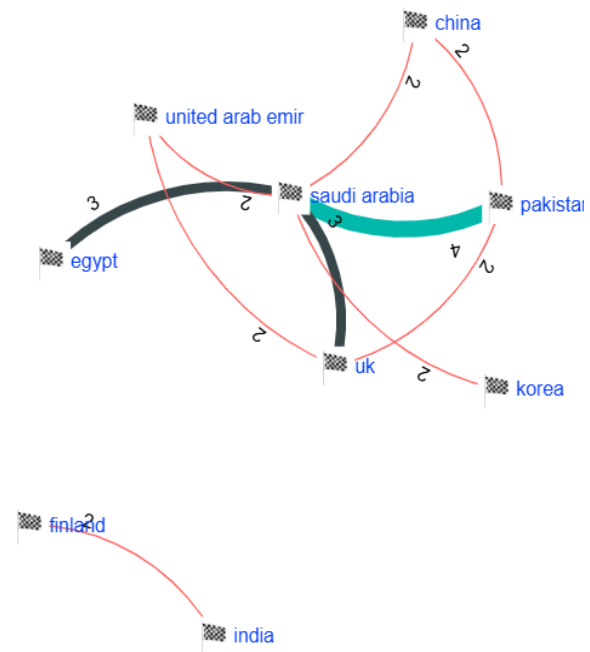


Fig. 16. Bibliometric Network by Country

Table 12. Co-occurrence between Countries

Country 1	Country 2	Weight
Pakistan	Saudi Arabia	4
Egypt	Saudi Arabia	3
Saudi Arabia	United Kingdom	3
China	Pakistan	2
China	Saudi Arabia	2
Finland	India	2
Korea	Saudi Arabia	2
Pakistan	United Kingdom	2
Saudi Arabia	United Arab Emirates	2
United Kingdom	United Arab Emirates	2
Total		24

which has mobilized substantial investments in biomedical artificial intelligence through institutions such as KAUST and KFUPM. complemented by active scientific internationalization policies that prioritize co-authorship with partners from South Asia, the Middle East and Europe.

According to the identified pattern. Pakistan and India display differentiated roles: Pakistan reaches the second-highest degree (0.38) with a

Table 13. Centrality and Cohesion Metrics in the Country Network of the Studies

Country	Degree	Strength	ClustCoeff	Betweenness
saudi arabia	0.75	16.00	0.13	0.36
pakistan	0.38	8.00	0.45	0.04
uk	0.38	7.00	0.43	0.04
china	0.25	4.00	0.63	0.05
united arab emirates	0.25	4.00	0.57	0.00
egypt	0.13	3.00	0.00	0.00
finland	0.13	2.00	0.00	0.00
india	0.13	2.00	0.00	0.00
korea	0.13	2.00	0.00	0.00
Total	2.50	48.00	2.21	0.48

Table 14. Distribution of Scientific Production and Bibliometric Indicators by Country

Country	N° Papers	% Papers	No Citations	% Citations	Citations/ Paper	H-Index
India	13	10%	447	14%	34	1,724
Saudi Arabia	13	10%	232	8%	18	2,393
China	12	9%	148	5%	12	1,528
US	9	7%	148	5%	16	1,461
Egypt	6	5%	137	4%	23	1,264
Iran	6	5%	151	5%	25	443
Korea	6	5%	121	4%	20	1,194
Italy	5	4%	164	5%	33	641
Pakistan	5	4%	122	4%	24	836
UK	5	4%	82	3%	17	1,205
Total	127	100%	3087	100%	24	19,558

strength of 8.00. derived from its preferential link with Saudi Arabia (weight 4) and its connections with the United Kingdom and China. whereas India leads in absolute productivity with 13 papers. 447 citations. and an H-index of 1.724. but presents comparatively modest relational integration (degree 0.13). An asymmetry explained by the consolidation of self-sufficient national ecosystems in computational biomedical research that reduce structural dependence on international collaborations.

Based on the reported results. China records the highest clustering coefficient (0.63) and the United Arab Emirates the second highest (0.57). showing the formation of densely interconnected subcommunities operating under logics of Asian regional and pan-Arab cooperation. a phenomenon reinforced by strategic initiatives such as the Belt and Road Initiative and the scientific agreements of the Gulf Cooperation

Council. In contrast. countries such as Egypt, Finland, South Korea, and India maintain null clustering coefficients, which reflects linear connections without closed triads and suggests latent opportunities to densify multilateral cooperation.

Consistent with Liu and co-authors [84]. the countries showing the greatest collaboration in that study are the United States and China. whereas cooperation is more limited in Canada and India. Likewise. for Kantayeva and colleagues [86]. the greatest coincidence in publications is observed between the United States and the United Kingdom. whereas a low coincidence persists between India and Canada. Nigeria. and other peripheral nations. In another study by Song and their team [82]. The countries with the greatest collaboration are the United States, China, and England, whereas lower cooperation is observed in countries such as Bangladesh, Egypt, and Iran.

On the other hand, in the study by An and collaborators [98], the main collaborators identified are the United States and China, whereas cooperation is scarcer with Macedonia. In the study by Villavicencio and co-authors [100], the countries with the highest production were China (10.6%), the United States (9.84%), and the United Kingdom (7.38%), in contrast with the present study, where Saudi Arabia and Pakistan emerge as central relational articulators despite their lower absolute production. Beyond the biomedical domain, Andrade-Mogollon and the research team [102] identify an analogous pattern in their review on Generative AI and IoT in Precision Agriculture, where Saudi Arabia and Pakistan again emerge as central articulating nodes, with a bilateral link of weight 3, suggesting that their relational centrality constitutes a cross-cutting structural phenomenon attributable to active scientific internationalization policies such as Vision 2030.

These findings guide science policy managers, funding agencies, and research consortia in sectors such as healthtech, neurotechnology, computational pharmaceuticals, and AI-assisted diagnosis toward the formulation of strategic South-South and North-South alliances that take advantage of existing articulating nodes, especially Saudi Arabia and Pakistan, to channel technological transfer toward regions with a high epidemiological burden of dementia and low installed research capacity, such as Latin America, Sub-Saharan Africa, and Southeast Asia. Likewise, this relational analysis model constitutes a methodological framework transferable to analogous domains such as early detection of Parkinson's disease, multiple sclerosis, mild cognitive impairment, and neuropsychiatric disorders, offering guidelines for designing scientific internationalization policies in prospective periods in which the convergence of artificial intelligence, multimodal neuroimaging, and precision medicine will require denser and more diversified multilateral collaborative schemes.

5 Conclusions and Future Research

Regarding the Machine Learning models developed (RQ1), the findings show a strategic

coexistence between classical algorithms and deep architectures, where Support Vector Machine (18.91%), Random Forest (16.92%), and Decision Tree (13.93%) retain hegemony because of their interpretability, whereas VGG16 (7.46%), 3D CNN (6.47%), and Vision Transformer (3.98%) reflect a transition toward models capable of capturing complex spatial dependencies; this duality suggests that the maturity of the field will be achieved through interpretive hybridization capable of reconciling predictive accuracy with diagnostic explainability.

With respect to the most widely used programming languages (RQ3), Python consolidates itself as hegemonic with 45% due to the maturity of its ecosystem, TensorFlow, PyTorch, Keras, and Scikit-learn, whereas Matlab (26.6%) and Scala (25%) preserve niches in biomedical signal processing and distributed analytics, and Java (1.6%) and R (1.6%) remain marginal; this pattern raises the structural challenge of ensuring interoperability among heterogeneous pipelines in clinical contexts where legacy systems and cloud platforms coexist.

Regarding the formulated theoretical approaches (RQ4), the functional category accounts for 70.3% of the definitions, a hegemony explained by its interdisciplinary cognitive accessibility, compared with 18.8% for the applied category and 10.9% for the technical category; this asymmetry reveals a critical epistemological gap between the underlying mathematical rigor and its effective communication in the biomedical literature, a structural obstacle to responsible clinical adoption, since narrative simplification compromises the understanding of the inductive biases and statistical assumptions of the field.

Regarding the predominant thematic categories (RQ5), the Callon analysis shows an asymmetric structure in which seven marginal clusters accumulate between 904 and 1880 citations despite centrality values below 0.50, whereas Neuroimaging Classification emerges as the only specialized topic (density 0.98) and Alzheimer Biomarkers consolidates itself as a cross-cutting core (centrality 0.68); this pattern reflects a field in early consolidation with terminological fragmentation that requires ontological standardization and multimodal integrative

frameworks capable of transforming marginal dispersion into motor clusters with translational impact.

Future research should prioritize multicenter cohorts with rigorous external validation that incorporate currently underrepresented Latin American, African, and Southeast Asian populations, together with methodological harmonization protocols under reproducible metrics. Likewise, it is essential to move toward hybrid multimodal models that integrate neuroimaging, peripheral biomarkers, EEG signals, and genomic data under federated learning paradigms and explainable architectures. Finally, epistemological frameworks that articulate the functional, technical, and applied dimensions of Machine Learning need to be consolidated, strengthening transferability toward analogous domains such as Parkinson's disease, multiple sclerosis, and neuropsychiatric disorders.

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