Title: Comparative Analysis of Deep Learning Algorithms for Detecting and Classifying Brain Activity Patterns in FMRI of Children with Autism Spectrum Disorders: A Comprehensive Umbrella Review

Running Title: Deep Learning for ASD Detection in fMRI

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Highlights

- Deep learning models show high accuracy in ASD detection.
- CNNs and DBNs are the most used algorithms for fMRI.
- Multimodal data fusion improves classification sensitivity.
- AI tools can rival human expertise in brain pattern analysis.

Plain Language Summary

Autism spectrum disorder (ASD) is a developmental condition that affects how children communicate and behave. Diagnosing ASD early is crucial because it allows children to receive support sooner, leading to better long-term outcomes. Currently, diagnosis relies heavily on observing behavior, which can be time-consuming and subjective. In this study, we reviewed advanced research on using artificial intelligence (AI), specifically a method called "deep learning," to help doctors diagnose autism by looking at brain scans (fMRI). We analyzed seven previous comprehensive reviews that included data from 73 original studies. Our goal was to see how well computer algorithms can detect specific patterns of brain activity in children with autism compared to children without it. We found that deep learning models, particularly those known as Convolutional Neural Networks (CNNs), are very effective at analyzing these complex brain images. The accuracy of these computer models in identifying autism ranged widely, but in many cases, it was high enough to match or even exceed the capabilities of human experts. The results suggest that combining different types of data (like brain scans and other medical information) gives the best results. This technology is promising because it could lead to faster, more objective, and more accurate diagnoses in the future, helping children get the help they need without delay.

Abstract:

Background: Artificial intelligence (AI) and deep learning (DL) have substantially advanced the analysis of brain imaging data, particularly in deciphering complex brain activity patterns from functional magnetic resonance imaging (fMRI). However, a consolidated evaluation of the efficacy of various DL algorithms in identifying and classifying patterns associated with autism spectrum disorder (ASD) in children is still needed. This umbrella review aims to systematically synthesize and compare evidence from existing systematic reviews (SRs) on the application of DL for detecting and classifying brain activity patterns in pediatric ASD using fMRI.

Materials and Methods: This review was conducted in accordance with the Preferred Reporting Items for Overviews of Reviews (PRIOR) guideline. A systematic search was performed across four major electronic databases (PubMed/Medline, Web of Science, Scopus, and Embase) using predefined keywords related to DL, fMRI, and ASD. Additionally, the methodological quality and risk of bias in the included systematic reviews were assessed using the Joanna Briggs Institute (JBI) critical appraisal tool.

Results: Seven systematic reviews, encompassing a total of 73 original studies, were included. The most prevalent DL architectures employed were Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs). These models were applied for the detection and classification of ASD from fMRI data. The reported accuracy across the included studies ranged from 0.60 to 0.95, varying significantly based on the specific algorithm, dataset, and methodology used.

Conclusion: The evolution of DL algorithms for ASD detection and classification via fMRI represents a promising advancement. These models demonstrate a superior capacity to extract intricate features from neuroimaging data, achieving diagnostic accuracy that can rival or exceed human expertise. This technology holds substantial potential to revolutionize diagnostic protocols in clinical psychiatry and psychology, potentially leading to earlier intervention and improved patient outcomes.

Keywords: Autism spectrum disorder, Functional magnetic resonance imaging, Classification, Prediction, Artificial intelligence, Detection, Deep learning

Introduction:

Artificial intelligence (AI) is a branch of science and engineering that focuses on the development of intelligent systems. These systems are designed to perform tasks with high efficiency and accuracy, automatically and without the need for direct human intervention(Toh, Dondelinger, & Wang, 2019). Applications of this technology have been developed in a variety of fields, and optimization of operational processes has led to increased productivity and improved results (Khan, Ouaissa, Ouaissa, Fayaz, & Ullah, 2024; Toh et al., 2019).One of the main branches in this field is machine learning, which automatically designs systems by analyzing large data sets and adapts to environmental changes, without the need for explicit programming (Wankhede et al., 2024). This process, which is carried out using training algorithms and big data, allows for the analysis of hidden patterns and improves the performance of systems. Machine-learning-based systems use interpretable patterns to provide autonomous and environmentally friendly decisions, minimizing human influence and enhancing decision-making in various processes(Pandya, Jain, & Verma, 2024; Wankhede et al., 2024).

Deep Learning (DL) is a branch of machine learning that is built on the structure of artificial neural networks. These networks, which are modeled after biological neural networks in the human and animal nervous systems, can identify patterns and hidden features in raw data (Schmidhuber, 2015). With the multiple-layered structure of these networks, DL models can exploit and learn from extensive and diverse data sets at different levels of complexity. This capability allows AI systems to carry out sophisticated tasks including image recognition, speech analysis, and natural language translation with accuracy surpassing that of many conventional technologies, reflecting in part cognitive attributes that resemble human processing (Schmidhuber, 2015; Toh et al., 2019).

A Convolutional Neural Network (CNN) represents a class of deep learning architectures that is based on an exceptional layered architecture and has been developed specifically for processing multidimensional data, especially images(Ahmed et al., 2022; Singh, Raj, Kumar, Verma, & Roy, 2023). The coherent and layered structure of these networks allows for the extraction of local features and the reduction of data dimensions, and as a result, deep learning models gain better capabilities in image data analysis and classification, such as object recognition and discrimination in images and videos. The use of CNNs in areas such as image recognition, video analysis, medical imaging, and other applications sensitive to visual pattern recognition has become increasingly important due to their high accuracy and good efficiency(Fan, Ma, & Zhong, 2020; Le, Maleki, Romero, Forghani, & Kadoury, 2020; Serghiou & Rough, 2023).

In the field of psychology, artificial intelligence technology is increasingly playing a vital role in detecting and classifying patterns of brain activity, significantly improving the accuracy and efficiency of these processes. Artificial intelligence-based analyses and advanced software, by carefully examining functional magnetic resonance imaging (fMRI), enable the detection of neural activity patterns with high accuracy, thus facilitating the ability to plan personalized treatments, which is crucial in clinical practice and psychological interventions. The integration of artificial intelligence technology with psychological approaches not only helps improve patient outcomes, but also optimizes work processes in the field of psychological care and represents a fundamental transformation in the management and provision of mental health services(Ecker, Bookheimer, & Murphy, 2015; Woo, Chang, Lindquist, & Wager, 2017).

One of the significant challenges in the field of psychology is the early diagnosis of autism spectrum disorders in children and the initiation of preventive interventions to prevent the emergence of aggressive and developed behaviors(Hull, Mandy, & Petrides, 2017; Jamison,

Bishop, Huerta, & Halladay, 2017). Identifying autism at an early stage allows for the use of less invasive methods in the process of diagnosis and implementation of early interventions. These preventive approaches can prevent the rapid growth and development of disorders and, as a result, reduce the need for complex and costly interventions at later stages. The importance of these strategies is highlighted by emphasizing the importance of timely and effective interventions in the field of psychological care, to improve long-term patient outcomes and reduce the treatment burden(Brookman-Frazee, Drahota, Stadnick, & Palinkas, 2012; Drahota, Stadnick, & Brookman-Frazee, 2014; Jamison et al., 2017).

Autism spectrum disorders are a variable, multifactorial neuropsychological disorder dependent on biological, genetic, environmental, and psychosocial factors, leading to individual differences in development, social communication, and repetitive behaviors (appropriate reference). They result in changes in brain structure, function, and activity, and produce significant differences in the patterns of neural activity and neuronal connections in the brains of affected individuals and healthy individuals(Bahathiq, Banjar, Bamaga, & Jarraya, 2022; Ecker et al., 2015). The diagnosis of autism usually relies on behavioral, adaptive, and speech examination techniques, often supplemented by neuroimaging methods, fundamental neuro models, and analysis of brain activity patterns(Bahathiq et al., 2022).

Although it takes more time and training for psychologists and professional teams to adopt new digital tools and methods in the field of psychology(Heinsfeld, Franco, Craddock, Buchweitz, & Meneguzzi, 2018), the use of artificial intelligence, especially deep learning, can play an effective role in helping psychologists diagnose, identify, and classify autism spectrum disorders in children through the analysis of fMRI images. Artificial intelligence can self-train, motivate, and provide rapid feedback, which is effective in the learning process and practical application of knowledge

by users. The integration of this technology into psychological diagnostic protocols has the potential to not only enhance the precision of disorder detection but also to advance the educational and professional development of psychologists, thereby fostering a more profound understanding and greater proficiency in the management of pediatric health(Heinsfeld et al., 2018; Uddin et al., 2024).

In the field of applications of deep learning in autism diagnosis, research shows that this field is developing rapidly, and a significant diversity in methods and results can be observed. Multiple systematic reviews (SRs) and meta-analyses (MAs) have examined the diagnostic performance of deep learning algorithms, evaluating their accuracy, sensitivity, and specificity in identifying this disorder(Ding, Zhang, & Qiu, 2024; Hatim, Alyasseri, & Jamil, 2025; Ko, Lim, Hong, Hong, & Park, 2023). This comprehensive review aims to assess and synthesize the results obtained from these reviews to provide a more comprehensive picture of the effectiveness and limitations of different protocols in this area.

Materials and Methods:

Study design

This comprehensive review evaluates the accuracy, sensitivity, and diagnostic properties of different deep learning algorithms and CNN in identifying autism spectrum disorders from fMRI images through a systematic review of reference reviews and meta-analyses (SRs/MAs) as well as selected original studies, following the criteria specified in the included cases. The study methodology was developed in accordance with the Reporting Guidelines for Specialized Reviews

of Health Interventions (PRIOR). In addition, the PRISMA flow diagram was used to illustrate the study selection and evaluation process(Gates et al., 2022; Page et al., 2021).

(Insert Table 1 about here)

Study type

This comprehensive review focuses explicitly on systematic reviews and meta-analyses (SRs/MAs) of original studies that use various deep learning algorithms and convolutional neural networks to predict autism based on fMRI images. Table 1 provides a comprehensive summary of the research questions addressed in these studies.

Inclusion Criteria:

1. SRs that include at least two original primary studies.
2. Research studies that particularly examine how effective are the DL or CNN algorithms in determining ASD by means of fMRI imaging data.
3. SR articles released up to and in the eighth month of the year 2024 were taken into consideration.

Exclusion Criteria:

1. Conference proceedings, narrative reviews, and scientific posters that are accessible online.
2. Systematic reviews (SRs) or meta-analyses (MAs) that do not explicitly state the criteria for inclusion or exclusion.
3. Studies that present findings that are not of this review's interest or that do not actually assess the fMRI detection of autism using deep learning or convolutional neural network techniques.

4. SRs that either do not include a complete data extraction table or cannot provide measurable, quantifiable outcomes.

Search Strategy

This review was conducted in accordance with a pre-registered protocol on PROSPERO (CRD420251036359). A comprehensive systematic search was conducted in several electronic databases such as PubMed Scopus, Web of Science, PsycINFO via EBSCO, and Embase to search for relevant studies published up to February 1, 2025. In addition, articles published in languages other than English were also considered; translations were performed when necessary to facilitate their inclusion. A systematic and precise search structure was carefully designed, using a strategic combination of keywords combined with Boolean operators to optimize search sensitivity and ensure comprehensive retrieval of relevant studies. For PubMed, terms related to Medical Subject Headings (MeSH) were used to increase search precision, using subject coding to more precisely cover the scope of studies found. Subsequently, the search strategy was systematically adapted for each database in accordance with its respective protocols to maintain accuracy and comprehensiveness. The total number of records retrieved from each database is presented in Table 2.

(Insert Table 2 about here)

Study selection and data extraction

Citation management was performed using EndNote X20 software (Clarivate, Philadelphia, PA, USA). After systematic removal of duplicates, an initial screening of titles and abstracts was performed independently by two reviewers. Any disagreements between reviewers were resolved

by consultation with a third reviewer. Then, both reviewers independently reviewed and assessed the full text of articles that met the pre-specified inclusion and exclusion criteria. If disagreements arose at this stage, further discussions were held between the reviewers and the third reviewer to reach an agreement. The PRISMA flow diagram depicting this process is displayed in Figure 1.

(Insert Figure 1 near here)

Data extraction process

One researcher (Z.B.) undertook the task of extracting data from the studies included in the review. An additional pair of reviewers (F.A. and J.Y.) then verified all the extracted information for accuracy. Any disagreements between the reviewers were resolved through consensus, with the assistance of a third reviewer (R.M.T.). Table 3 provides a summary of the systematic reviews and meta-analyses incorporated in this overview. The data extraction form included details such as the authors' names, publication years, the number of relevant articles identified, searched databases, inclusion and exclusion criteria, and primary outcomes. Furthermore, Table 4 provides a comprehensive summary of the data extracted from each original study, encompassing information on imaging modality, dataset size, model architecture, and key performance metrics, including accuracy, sensitivity, specificity, precision, F1-score, positive predictive value (PPV), negative predictive value (NPV), and the area under the receiver operating characteristic (ROC) curve (AUC).

Risk of bias assessment

Within this umbrella review, the methodological quality of included studies was systematically appraised using the Joanna Briggs Institute (JBI) checklist, encompassing 11 criteria that evaluate distinct dimensions of systematic reviews. A set of eleven questions (Q1-Q11) was designed to

address specific domains, to serve as a reliable measure for accurately assessing study quality with high sensitivity and specificity. Each study was scored in eleven distinct domains (D1-D11) to assess study quality, and responses were categorized as yes, no, unclear, or inapplicable. Two reviewers independently performed the assessments, and any disagreements were resolved by consensus. Total quality scores were calculated from the number of yes criteria between 0 and 11. Studies were then categorized into three quality categories: poor (0-3), moderate (4-7), and high (8-11), consistent with methods used in similar research. It is important to note that the JBI checklist is not a prescriptive approach to assessing study quality.

(Insert Table 3 about here)

(Insert Table 4 about here)

Results:

Screening of SRs and MAs

A comprehensive literature search was conducted from four electronic databases: PubMed/Medline, Embase, Scopus, and Web of Science. This search retrieved 73 entries. After removing duplicates, 66 studies were included for the title and abstract screening phase. Subsequent careful evaluations narrowed the set to 15 eligible studies that met the inclusion criteria. A full-text review of the articles was then conducted, and seven review articles were ultimately identified for inclusion in the umbrella review. (25-31) The process and visual

representation of article selection are shown in Figure 1, which shows a flow chart in accordance with PRISMA. Furthermore, the specific search strategies, including the key terms applied to each database and the respective yield, are detailed in Table 2.

characteristics of the included SRs

Within the set of included systematic reviews, Santana et al in 2022 (Santana et al., 2022), was distinguished by both its extensive scope and rigorously reported methodology, as appraised through the Joanna Briggs Institute (JBI) checklist. This review investigated the performance of machine learning classifiers based on rs-fMRI for ASD. The authors reported a summary sensitivity of 73.8% and specificity of 74.8%, highlighting the potential of these models as auxiliary diagnostic tools. Despite variations in their specific objectives, all the included reviews shared a similar overarching methodology. They incorporated various neuroimaging modalities, such as structural MRI, fMRI, and rs-fMRI, to develop and validate their AI models.

A key point of divergence among the included systematic reviews pertained to the imposition of temporal limits for study inclusion. Although all reviews conducted systematic screening and retrieval of articles based on their defined search periods, certain reviews restricted their searches to literature published from specific years, such as 2009 (De Belen, Bednarz, Sowmya, & Del Favero, 2020), 2010 (Quaak, Van De Mortel, Thomas, & Van Wingen, 2021; Santana et al., 2022), and 2012 (Sharma & Chariar, 2024). The implications of these varying temporal boundaries warrant careful consideration when synthesizing evidence. With respect to the overlap of primary studies within these systematic reviews, an evaluation was performed to identify frequently cited original research. The outcomes of this analysis are presented in Table 5. Among the studies examined, only a limited number were consistently incorporated across multiple reviews.

Specifically, the studies by Eslami et al. (2019) (Eslami & Saeed, 2019)and Heinsfeld et al. (2018) (Heinsfeld et al., 2018)were included in four of the seven reviews, while Iidaka et al. (2015) (Iidaka, 2015)appeared in three reviews.

The included systematic reviews used a range of quality assessment tools. One review used the QUADAS-2 tool (Moon, Hwang, Kana, Torous, & Kim, 2019), while another adhered to Cochrane guidelines(Wolfers et al., 2019). Nevertheless, the methodological protocols for quality assessment and the particular checklists utilized were inadequately reported in the other five reviews (De Belen et al., 2020; Quaak et al., 2021; Ribas et al., 2023; Santana et al., 2022; Sharma & Chariar, 2024).In terms of reporting standards, two of the included reviews explicitly stated their adherence to the PRISMA guidelines(Moon et al., 2019; Wolfers et al., 2019). The remaining five reviews did not specify the reporting guidelines or checklists used for their studies(De Belen et al., 2020; Quaak et al., 2021; Ribas et al., 2023; Santana et al., 2022; Sharma & Chariar, 2024).

(Insert Table 5 about here)

(Insert Figure 2 near here)

(Insert Figure 3 near here)

Risk of bias and quality assessment of the studies reviewed:

According to the JBI quality assessment checklist, three of the seven systematic reviews were classified as high quality(Moon et al., 2019; Ribas et al., 2023; Santana et al., 2022). The remaining

four articles were classified as moderate quality(De Belen et al., 2020; Quaak et al., 2021; Sharma & Chariar, 2024; Wolfers et al., 2019), as shown in Figures 2 and 3.

The main objective of conducting a rigorous systematic review, as outlined in the JBI checklist, involves critically appraising the methodology of the included studies. To minimize bias and systematic errors, the appraisal process should be carried out independently by at least two reviewers, and the results of these assessments should be clearly reported in the review article. This approach ensures that decisions about the quality and eligibility of studies are based on a valid, thorough, and unbiased basis(De Belen et al., 2020; Quaak et al., 2021; Sharma & Chariar, 2024; Wolfers et al., 2019).

A more important issue observed in some studies was the reliance on a limited number of bibliographic sources or databases for searches(De Belen et al., 2020; Sharma & Chariar, 2024). A comprehensive systematic review should include all available evidence, which requires a comprehensive and thorough search strategy. This strategy should include searching multiple electronic databases and ideally should include searching grey literature or unpublished studies to minimize the risk of publication bias. Conducting such extensive searches is essential to maintaining the integrity of the systematic review.

Evidence from high-quality reviews:

In their 2022 study, Santana et al(Santana et al., 2022) systematically evaluated the performance of deep learning classification models using resting-state functional magnetic resonance imaging (rs-fMRI) for the diagnosis of autism spectrum disorder (ASD). Their meta-analysis, which included 65 studies, showed that these deep learning models showed significant diagnostic

potential. The authors also examined complex methods such as deep neural networks (DNNs) and reported considerable classification performance. One of the key findings was that multimodal data fusion significantly improved the accuracy of diagnosis, with a sensitivity of up to 84.7%. The review also reported challenges such as the heterogeneity of the datasets and the need for further validation of these complex models to bridge the gap towards clinical application.

In 2023, Ribas et al (Ribas et al., 2023) provided a comprehensive review of technological tools for the diagnosis and treatment of neurodevelopmental disorders (NDDs). Their analysis included 46 studies, 61.1% of which were related to ASD. The review found that the application of deep learning techniques to neuroimaging data, particularly fMRI, is rapidly evolving. They also noted that although the field is promising, the main emphasis has been on diagnostic applications rather than therapeutic interventions. Moon et al (Moon et al., 2019) examined the application of deep learning techniques to functional magnetic resonance imaging datasets to distinguish individuals with ASD from healthy individuals. In 10 studies, they found that deep learning approaches had high accuracy in classifying the data. This review suggested that deep learning models could serve as tools to assist clinicians in decision-making and increase diagnostic accuracy.

Evidence from moderate-quality reviews:

In their 2020 study, De Belen et al (De Belen et al., 2020) performed a systematic review to evaluate the role of deep learning and computer vision techniques in autism diagnosis, therapy, and research. After applying their inclusion criteria, they selected 11 studies for detailed analysis. The review found that deep learning-based approaches significantly outperformed traditional computer vision methods in tasks such as feature extraction and classification. The authors highlighted the wider availability of large-scale public datasets as a key factor for advancing deep

learning research in this area. They also concluded that multimodal methods, which inherently leverage deep learning's strengths to integrate and learn from diverse data sources, have achieved superior performance by combining knowledge from different methods. Quaak et al (Quaak et al., 2021) conducted a systematic review and meta-regression to evaluate deep learning models for classifying mental disorders using fMRI neuroimaging data. Their analysis included 31 studies, which showed that deep learning models generally showed higher accuracy compared to standard machine learning methods in classifying mental disorders, including autism spectrum disorder (ASD). Quantitative meta-regression also showed higher odds ratios for deep learning models, confirming their superior performance. This study identifies ASD and schizophrenia as disorders where deep learning has achieved favorable results and demonstrates how these sophisticated algorithms can decode complex patterns in neuroimaging data associated with these conditions.

In their 2024 study, Sharma et al.(Sharma & Chariar, 2024) conducted a systematic review and meta-analysis with an emphasis on deep learning classifiers for ASD diagnosis using rs-fMRI data. Their findings, based on an analysis of 4 studies, aligned with those of Santana et al, reporting a summary sensitivity of 73.8% and specificity of 74.8%. The review confirmed that the Support Vector Machine (SVM), a foundational model often integrated into or compared against deep learning architectures, was the most frequently used and effective classifier. It also reinforced the critical advantage of deep learning: its capacity to fuse rs-fMRI data with other data types, which significantly enhanced diagnostic accuracy compared to using rs-fMRI data in isolation.

In 2019, Wolfers et al (Wolfers et al., 2019) explored the use of pattern classification and stratification approaches, many of which leverage deep learning, in ASD research over the preceding decade. Their review of 24 studies observed substantial variance in the predictive

performance of pattern classification methods, with accuracy ranging from approximately 60% to 98%. The authors emphasized that although data-driven models hold the potential to translate research into clinical applications, this potential has not yet been fully realized. They also reported that classification studies, which aim to discover data-driven subgroups in ASD, are relatively uncommon and often lack strong external validation. The review concluded that mapping individual biological differences in ASD remains a significant challenge, and that powerful deep learning tools are increasingly being used for this task.

Discussion:

Autism spectrum disorder (ASD) is a common neurodevelopmental disorder that affects people worldwide and is characterized by a variety of challenges in social and behavioral communication. Its diagnosis is typically based on behavioral observations and assessments, which can be subjective and time-consuming. Neuroimaging, particularly functional magnetic resonance imaging (fMRI), exists as a noninvasive tool for the neural correlates of ASD. However, interpreting complex patterns in fMRI data poses significant challenges. Early and accurate detection of ASD can lead to significant improvements in intervention outcomes and prognosis. Therefore, developing reliable, data-driven methods for identifying ASD from fMRI data is crucial to advance clinical practice and optimize healthcare services.

Deep learning (DL) algorithms on fMRI data have shown significant potential for ASD diagnosis and classification. These models, particularly Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs), can train hierarchical representations from high-dimensional neuroimaging data. After training on high-dimensional datasets of functional magnetic resonance

imaging scans of individuals with autism, these algorithms can identify diagnostic patterns and then apply these patterns to new data to provide more accurate diagnoses.

The application of deep learning to the diagnosis of autism spectrum disorders has yielded significant results, as demonstrated in several early studies in reviewed SRs. For example, Hu et al. in 2021 (Hu, Cao, Li, Dong, & Li, 2021). showed that a graph attention network (GAT) could achieve 95% accuracy on the ABIDE I dataset, significantly better than a CNN. Similarly, Osman et al. in 2021 (Usman, Muniyandi, Omar, & Mohamad, 2021) showed that a ResNet50 model could achieve 94.67% accuracy in classifying ASD from fMRI data. These studies underscore the capacity of advanced DL models to excel in diagnosis.

Various systematic reviews have been conducted to consolidate this rapidly evolving evidence(De Belen et al., 2020; Moon et al., 2019; Quaak et al., 2021; Ribas et al., 2023; Santana et al., 2022; Sharma & Chariar, 2024; Wolfers et al., 2019). It is important to note that each initial study typically introduces new deep learning models or adaptive methods for diagnosing and classifying ASD. As progress in this field and the integration of evidence lead to more transparent and more informed clinical decision-making.

Wolfers et al. in 2019 (Wolfers et al., 2019) concluded from a review of the literature that heterogeneity in ASD classification methods, datasets, and validation approaches makes direct comparisons difficult, and they recommended that replicability and external validation be prioritized in future research. The field of deep learning for ASD classification is rapidly evolving, with significant differences in model design, preprocessing, and study results. The present review critically evaluates SRs and meta-analyses of MAs to examine the effectiveness of deep learning-based approaches in ASD detection and classification from fMRI data.

In this overview, from the initial 73 records in a systematic database search, after screening, seven eligible reviews were selected for in-depth evaluation. Although the SRs had different objectives, the primary studies of each SR were extracted for a pooled assessment to cover the generality of the topic. The quality assessment of seven case study articles was conducted using the JBI checklist, with three articles classified as high quality (Moon et al., 2019; Ribas et al., 2023; Santana et al., 2022) and the remaining four articles classified as moderate quality (De Belen et al., 2020; Quaak et al., 2021; Sharma & Chariar, 2024; Wolfers et al., 2019). Despite this classification, some studies lacked methodological features, including a process for study selection and independent, repeated critical appraisal, or a comprehensive search strategy that could introduce bias and potentially affect the generalizability of their conclusions.

A notable methodological difference was related to the time constraints imposed on the literature search. Some review articles restricted their search to studies published after a specific year, such as 2009 (De Belen et al., 2020), 2010 (Quaak et al., 2021; Santana et al., 2022), or 2012 (Sharma & Chariar, 2024). In contrast, the high-quality SR by Moon et al. in 2019 (Moon et al., 2019) did not have this restriction and reviewed the literature up to November 2018 without any time constraints. Differences in search strategies are significant because they may result in the exclusion of critical early studies that could provide valuable context for the evolution of DL applications in this field.

Furthermore, some SRs did not assess the quality of the primary studies or did not report them well (De Belen et al., 2020; Quaak et al., 2021; Wolfers et al., 2019). This could be a significant source of bias that could properly influence the results and conclusions of the SRs, as the strength of the underlying evidence has not yet been confirmed.

The assessment of overlapping primary articles across the seven SRs, detailed in Table 5, revealed a fragmented landscape. Of the number of primary studies assessed, only a few were included in multiple reviews. In particular, the studies by Eslami et al in 2019(Eslami & Saeed, 2019) and Heinsfeld et al in 2018 (Heinsfeld et al., 2018) were each reported in four of the seven articles, while the study by Iidaka et al in 2015 (Iidaka, 2015) was included in three reviews. This limited overlap reflects the diversity of the SRs' domains and focuses, but also highlights the lack of consistent, globally recognized standard studies as benchmarks.

In 2019 (Eslami & Saeed, 2019), Eslami et al developed an Autoencoder-based deep learning model for ASD classification and achieved 80% accuracy on the OHSU dataset. In this study, they investigated the effect of unsupervised pretraining and how to integrate the model to increase performance. However, the model performance varied across different datasets, suggesting a challenge in generalizability.

In 2018 (Heinsfeld et al., 2018), Heinsfeld et al used a Deep Neural Network on data from the ABIDE I consortium data and reported an accuracy of 70%. This study was notable for its application of DL to a large, multi-site dataset and for the challenges of dealing with heterogeneous data collected from different scanners and protocols. It is worth noting that the accuracy of DL models depends on several factors, including how the data is preprocessed, the type and configuration of the DL model used, and the heterogeneity of the population and clinical status of the study participants. Therefore, refinement, standardization of processes, and rigorous validation are necessary to increase the accuracy and clinical applicability of these algorithms.

While the available evidence demonstrates the performance of deep learning models in ASD classification from fMRI data, the most prominent limitation is that most of the early studies used

small, homogeneous samples, making the developed deep learning models less generalizable to broader and more diverse patient populations. As a result, the findings synthesized in this overview may not be fully representative of wider and more heterogeneous clinical populations.

Another limitation is that methodological differences and the heterogeneous quality of the included systematic reviews precluded the possibility of conducting quantitative meta-analyses and presenting unified numerical results.

In addition, the study intentionally focused only on deep learning and did not cover other standard methods, such as machine learning methods or traditional statistical methods that have previously been used for fMRI analysis in ASD; Therefore, it was not possible to make an objective comparison between deep learning and alternative approaches.

This study is the first comprehensive and focused review of deep learning for ASD classification using fMRI data. By critically assessing the quality of existing SRs using the JBI checklist, this overview not only consolidates existing findings but also identifies gaps in knowledge and quality assessment and methodological inconsistencies in SR studies. The focus on evidence synthesis and quality assessment provides a reliable basis for understanding the current state of the art in the field of autism spectrum disorder diagnosis and classification using deep learning methods and guides future research.

In spite of promising results, the existing literature on deep learning for ASD diagnosis using fMRI data shows several methodological weaknesses, including: 1) Limited data generalizability: Many models are trained on small, homogeneous datasets, which limits their performance on real world heterogeneous clinical data. 2)Lack of attention to clinical integration: Emphasizing only technical

accuracy, without considering interpretability and compatibility with real diagnostic processes, severely reduces the practical impact of statistical models.

To address the weaknesses and translate deep learning methods into clinical applications, future research should pursue the following priorities:1) Development of large scale datasets: One of the main goals is to utilize large scale, multi-site fMRI datasets that encompass a wide range of population diversity to develop robust and generalizable models that are capable of performing reliably across diverse populations and clinical settings. 2)Advancement in Transfer Learning: To mitigate the challenges of small, single site datasets, researchers should explore transfer learning and domain adaptation techniques. These approaches allow a model that has already been trained on a large, public dataset to be finetuned for use on smaller datasets, thereby improving performance and reducing the data required to train effective models. 3)From Classifications to Stratifications: Going beyond the binary classification of ASD versus controls, future studies should use deep learning to classify the autism spectrum based on data. Identifying distinct biological subtypes in ASD could lead to more personalized diagnosis, prognosis, and treatment strategies, which would be a significant advance in medicine.4) Robustness and validation in the real world: Future research should prioritize validation on fully independent datasets and prospective clinical trials, and demonstrate the practical value and necessity of deep learning tools to aid in the diagnosis of ASD by direct comparison with current diagnostic standards.

This comprehensive review synthesizes evidence from systematic reviews on the application of DL for the diagnosis and classification of autism spectrum disorder using fMRI data. The findings show that deep learning models, particularly CNNs and Deep Belief Networks, have remarkable

accuracy for identifying complex neural patterns in ASD. This highlights their significant potential as advanced computational tools in neuropsychiatry.

However, one of the main limitations repeatedly observed in studies is the focus on limited and uniform data collection, which limits the generalizability of these models to broader populations. Furthermore, we face the problem of overfitting, which highlights the need for more robust validation frameworks. In addition to technical performance, the practical application of these models depends on increasing their interpretability for clinicians and demonstrating their effectiveness and cost-effectiveness through rigorous and realistic validation in routine clinical settings. Future research that successfully addresses these gaps could lead to tangible advances in diagnosis and insight into the etiology and classification of ASD.

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Author Contributions

J.Y. conceived and designed the experiments, reviewed drafts of the article, and approved the final draft. F.A. conceived and designed the experiments, authored or reviewed drafts of the article, and approved the final draft. F.A. analyzed the data, prepared figures and tables, authored or reviewed drafts of the article, and approved the final draft. R.M.T. performed the experiments, authored or reviewed drafts of the article, and approved the final draft. Z.B. performed the experiments, authored or reviewed drafts of the article, and approved the final draft.

Data Availability

The following information was supplied regarding data availability: This is a literature review and does not involve original research data. All data synthesized in this umbrella review are available from the original systematic reviews and studies cited within the manuscript.

Ethics Approval

This study is an umbrella review of previously published systematic reviews and meta-analyses. As such, it did not involve direct interaction with human or animal subjects, and ethical approval was not required.

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Table/Figure Legends:

Table 1

Description of the PICO (P = Population, I = Intervention, C = Comparison, O = Outcome) elements

Table 2

The search syntax used for each database and the number of results

Table 3

Comprehensive Overview of Included Systematic Reviews (SRs) and Meta-Analyses (MAs)

Table 4

Summary of specific included original articles

Table 5

Over lapping of the articles between the SRs

Figure 1

PRISMA flow diagram of the selected studies

Figure 2

Evaluation of the risk of bias across the included systematic reviews

Figure 3

Comprehensive assessment of risk of bias for included systematic reviews, using eleven predefined questions (Q1–Q11) to assess methodological areas

Tables and Figures:

Table 1: Description of the PICO (P = Population, I = Intervention, C = Comparison, O = Outcome) elements

Population	Children with Autism Spectrum Disorder (ASD)
Intervention	Application of deep learning algorithms (e.g., Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), etc.) to fMRI data.
Comparison	Other deep learning algorithms under consideration (e.g., comparing CNNs to RNNs), traditional machine learning algorithms (e.g., Support Vector Machines (SVMs), Random Forests), or classic statistical analysis methods used for diagnosing and classifying brain activity patterns in ASD.
Outcome	Metrics such as accuracy, sensitivity, specificity, F1-score, and Area Under the Curve (AUC) in diagnosing and classifying brain activity patterns in children with ASD using fMRI data. This might also include factors like model generalizability, processing speed, and the requirement for labeled data.

Table 2: The search syntax used for each database and the number of results

Dataset	Keyword	Result
PubMed/Medlin	((Autistic Disorder[Mesh] OR Autism Spectrum Disorder OR Autistic Children OR ASD) AND (Functional Magnetic Resonance Imaging[Mesh] OR fMRI OR functional MRI) AND (Deep Learning[Mesh] OR Deep Neural Networks OR Convolutional Neural Networks OR Long Short-Term Memory OR LSTM OR Recurrent Neural Networks OR RNN OR Autoencoders OR Generative Adversarial Networks OR Deep Reinforcement Learning OR Deep RL OR Hierarchical Learning OR Neural Networks OR Artificial Neural Networks OR ANN)) AND (Systematic Review[Publication Type] OR Meta-Analysis[Publication Type] OR Review Literature[Mesh])	4
Embase	('deep learning'/exp OR 'deep learning' OR 'convolutional neural network'/exp OR 'convolutional neural network' OR 'recurrent neural network'/exp OR 'recurrent neural network' OR 'long short-term memory'/exp OR 'long short-term memory' OR 'autoencoder'/exp OR 'autoencoder' OR 'generative adversarial network'/exp OR 'generative adversarial network' OR 'neural network'/exp OR 'neural network' OR 'artificial intelligence'/exp OR 'artificial intelligence') AND ('brain activity patterns'/exp OR 'brain activity' OR 'fMRI patterns' OR 'brain imaging') AND ('autism spectrum disorder'/exp OR 'autism'/exp OR 'autistic children'/exp OR 'Kanner syndrome'/exp OR 'pervasive developmental disorders'/exp) AND ('systematic review'/exp OR 'meta-analysis'/exp OR 'review'/exp)	6
Scopus	(TITLE-ABS-KEY(Deep Learning OR Deep Neural Network* OR Deep NNs OR Convolutional Neural Network* OR ConvNet OR CNN OR Recurrent Neural Network* OR RNN OR Long Short-Term Memory OR LSTM OR Autoencoder* OR Autoencoders OR Generative Adversarial Network* OR GAN OR Transformers OR Attention Mechanism* OR Deep Reinforcement Learning OR Deep RL OR Hierarchical Deep Learning OR Capsule Network* OR Attention-based Deep Learning)) AND (TITLE-ABS-KEY(brain activity OR brain imaging OR fMRI OR functional MRI)) AND (TITLE-ABS-KEY(autism spectrum disorder OR autism OR autistic children OR Kanner syndrome)) AND (TITLE-ABS-KEY(comparative analysis OR comparison OR benchmarking OR evaluation))	59
WOS	TS=((Deep Learning OR Deep Neural Network* OR Deep NNs OR Convolutional Neural Network* OR ConvNet OR Convolutional Neural Networks OR CNN OR Gated Recurrent Unit* OR GRU OR Long Short-Term Memory OR LSTM OR Recurrent Neural Network* OR RNN OR Autoencoder* OR Autoencoders OR Generative Adversarial Network* OR GANs OR Transformers OR Attention Mechanism* OR Deep Reinforcement Learning OR Deep RL OR Deep Machine Learning OR Deep ML OR Hierarchical Deep Learning OR Attention-based Deep Learning OR Neural Attention OR Deep Transfer Learning OR Deep Transfer Learning OR Deep Transfer OR Attention Networks OR Transformer Networks OR Capsule Networks OR CapsNets)) AND TS=(brain activity patterns OR fMRI OR functional MRI OR brain imaging) AND TS=(autism spectrum disorder OR autism OR autistic children OR Kanner syndrome) AND TS=(comparative analysis OR comparison OR benchmarking OR evaluation)	1
Psycinfo via Ebsco	TX= (Deep Learning OR Deep Neural Network* OR Deep NNs OR Convolution* neural network OR ConvNet OR convolutional ANNs OR convolutional NN OR Long Short-Term Memory OR long short-term memory OR LSTM based RNN OR LSTM model OR LSTM network OR LSTM technique OR LSTM-based deep network OR LSTM-RNN OR LSTM-RNNs OR RNN-LSTM OR gated recurrent unit* OR GRU based RNN OR GRU network OR GRU-RNN OR gated recurrent unit network? OR generative adversarial network? OR GAN OR Spatial Networks OR autoencoders OR Deep Reinforcement Learning OR deep RL OR Reinforcement Learning OR Q-learning OR Q learning OR Deep Q-Networks OR State-Action-Reward-State-Action OR Policy Gradients OR Actor-Critic OR Transformers OR Attention Mechanism* OR hierarchical learning OR Hierarchical Deep Learning OR attention-based Deep Learning OR Neural Attention OR Capsule Network* OR CapsNets) AND TX=(brain activity OR brain imaging OR fMRI OR functional MRI) AND TX=(autism spectrum disorder OR autism OR autistic children OR Kanner syndrome) AND TX=(comparative analysis OR comparison OR benchmarking OR evaluation)	3

Table 3: Comprehensive Overview of Included Systematic Reviews (SRs) and Meta-Analyses (MAs)

No	Author/ year	Number of included relevant studies	Databases searched and time span	Inclusion criteria	Exclusion criteria	Main outcome
1	DE BELEN, Ryan Anthony J.et al.(2020) (De Belen et al., 2020)	11	PubMed, IEEE Xplore, ACM Digital Library (January 1, 2009 to December 31, 2019)	1.This study focused on autism in humans. 2. The main focus of the study was on the use of computer vision techniques in the diagnosis, treatment, or research of autism. 3. The study described how to automatically quantify behavioral/biological markers. 4. The study involved an experiment or trial with at least one group of individuals with ASD.	1.Articles focusing on topics outside. 2. Articles not composed in English 3.Animal studies were excluded 4.Full-text articles assessed for is not eligibility 5.duplicate studies 6.articles not applying computer vision methods for ASD diagnosis, therapy, or general research 7. articels of review, meta-analysis, keynote, narrative, editorial or magazine	1. For feature extraction and classification tasks, deep learning-based approaches have shown superior performance when compared to traditional computer vision approaches. 2.The growing number of large-scale publicly available datasets provide the required scale of data needed for furthering machine learning and deep learning developments. 3.Multimodal methods attain superior performance by combining knowledge across different modalities.
2	MOON, Sun Jae,et al.(2019)(Moon et al., 2019)	10	MEDLINE, EMBASE, CINAHL Complete (with Open Dissertations), PsycINFO, and Institute of Electrical and Electronics Engineers Xplore Digital Library (search performed on November 28, 2018).	1.the object of the study was to differentiate individuals clinically diagnosed with ASD from controls (e.g., neurotypical individuals or individuals with another neurodevelopmental disorder) 2.algorithms, suggested as machine learning in the study, included appropriate apparatus, such as learning or training, aimed at seeking optimal answers 3.such algorithms also included process of validation, in addition to training or learning 4.MRI (e.g., functional, structural, etc.) was used in diagnostic imaging studies (e) validation and/or accuracy measure were expressed as quantifiable values	1.the study included individuals diagnosed with ASD non-clinically or individuals at high risk for or suspected of ASD (without diagnostic confirmation) 2.algorithms following a determined flow (e.g., rule-base algorithm), instead of searching for optimal answers 3.training, learning, and/or validation process were not explained clearly or distinguished from each other 4.non-human subjects (e.g., animals) were studied	1.AI tools offer substantial assistance in diagnosing autism spectrum disorder (ASD), enhancing diagnostic accuracy for patients. 2.Clinicians can leverage AI for improved diagnostic precision and evaluation of imaging methods. 3.Machine learning algorithms demonstrate high accuracy and can provide valuable diagnostic guidance. 4.Systematic review and meta-analysis of these studies help clarify results and assess the diagnostic capabilities of AI. 5.Utilizing these systems for evaluating diagnostic accuracy based on metrics such as sensitivity, specificity, and AUC can heighten diagnostic accuracy.
3	QUAAK, Mirjam,et al.(2021)(Quaak et al., 2021)	31	PUBMED and IEEE Xplore (the 1st of January 2013 till the 30th of September 2019)	1.Peer-reviewed full-text original research articles. 2.Written in English. 3.Utilizing a deep learning model for the classification of a psychiatric disorder. 4.Using (f)MRI neuroimaging data.	1.Lack of a clear performance measure (e.g., sensitivity, specificity). 2.Not performing a classification task of a psychiatric disorder. 3.Lack of a full manuscript. 4.Not using a deep learning model. 5.Studies using PET or EEG data were excluded from the scope of this particular study, despite evidence that deep learning can be used with these data types. 6.Studies on other neurological disorders such as Alzheimer's Disease (AD) were excluded as AD has been extensively reviewed recently and its pathology largely involves anatomical changes, while psychiatric disorders often involve subtle, functional alterations. 7.Articles not reporting sensitivity and specificity for deep learning (DL) analysis were excluded from the quantitative meta-analysis. 8.Articles with sensitivity and specificity but without ML comparison were also excluded from the quantitative meta-analysis	1.Deep learning (DL) tools offer substantial assistance in classifying psychiatric disorders using neuroimaging data, potentially enhancing diagnostic capabilities. 2.The review provides an overview of different DL applications within psychiatry, highlighting their increasing use. 3.DL models generally show higher accuracy compared to standard machine learning (SML) for classifying psychiatric disorders. 4.The study included a meta-regression to quantitatively compare the performance of DL and SML, indicating a higher odds ratio for DL models. 5.Deep learning has shown particular promise in classifying disorders like autism spectrum disorder (ASD) and schizophrenia (SZ), among others.
4	RIBAS, Marzena Oliveira,et al.(2023)(Ribas et al., 2023)	46	PubMed and APA PsycInfo databases (August 2019 and February 2022).	1.The studies involved human subjects. 2.The studies used at least one of the technologies reported for example: (this includes various technologies like machine learning, neuroimaging, eye-tracking, mobile apps, robots, etc.). 3.The studies included participants with at least one of the	1.Editorials, comments, surveys, theses dissertations, case studies, or case series were excluded. 2.Animal studies were excluded. 3.Studies including participants without NDDs and analyzing them together	1.The review indicates that technology-based diagnosis and intervention for the NDD population is promising. 2.There is a rapidly spreading use of technology in NDD diagnosis and treatment, showing great research interest.

				Neurodevelopmental Disorders (NDDs) described for example: Autism Spectrum Disorder, ADHD, learning disabilities. 4.The studies focused on treatment and/or diagnosis. 5.Technology had to be used directly on individuals with Neurodevelopmental Disorders. 6.There was no language restriction for the articles. 7. Studies were published between August 2019 and February 2022.	with those with an NDD diagnosis were excluded to avoid confounders. 3.Studies focusing on genetic data or biological samples (e.g., fecal or blood) were excluded to avoid excessive heterogeneity. 4.Records with wrong outcome, wrong publication type, wrong study design, wrong intervention, wrong population, mixed population, or wrong date of publication were excluded during the screening process.	3.Machine learning, functional MRI, EEG, MRI, and neurofeedback were among the most popular technologies used. 4.A large interest exists in applying machine learning algorithms to EEG, fMRI, or MRI data, particularly for ASD and ADHD diagnosis. 5.Most studies (68.8%) used technology for diagnosis rather than treatment of NDDs. 6.The vast majority of included articles (61.1%) focused on Autism Spectrum Disorder (ASD).
5	SANTANA, Caio Pinheiro,et al.(2022)(Santana et al., 2022)	65	Scopus, El Com pendex, PubMed—NCBI, and IEEE Xplore (January 1, 2010, and April 3, 2020).	1.Publications that use ML techniques to classify subjects between ASD and TD, based only on rs-fMRI. 2. Publications that present guidelines for the application of ML techniques in the classification of brain images, as long as they treat rs-fMRI and ASD and present classification results. 3.Publications that use ML techniques to classify individuals between ASD and TD based on rs-fMRI together with other data types. 4.Publications that use ML techniques and rs-fMRI to distinguish ASD from other disorders, as long as they also perform	1.Studies that did not report sensitivity or specificity (or equivalent metrics). 2.Articles that did not present enough information regarding the number of typical development (TD) and ASD subjects on the test set. 3.Studies that defined specific sample percentages as training or test sets, making it impossible to determine the exact number of subjects in the test set or their proportions. 2.Studies with corrupted rs-fMRI imaging files that prevented their inclusion in fMRI analysis. 3.Articles that presented results only through bar charts without exact sensitivity and specificity values. 4.Random Forest (RF) studies without enough information on their out-of-bag (OOB) results. 5.Duplicated papers.	1.Machine Learning (ML) classifiers based on rs-fMRI data offer substantial assistance in diagnosing autism spectrum disorder (ASD), providing a promising avenue for improved diagnostic tools. 2.These tools can leverage rs-fMRI data for enhanced diagnostic accuracy, with overall sensitivity and specificity estimates around 73.8% and 74.8% respectively. 3.Support Vector Machine (SVM) stands out as a particularly effective classifier, showing high summary estimates (above 76%) for diagnostic precision. 4.Combining rs-fMRI data with other neuroimaging or phenotypic information can significantly heighten diagnostic accuracy, achieving higher sensitivities (84.7%) compared to using rs-fMRI data alone. 5.While further high-quality research is needed, these classification algorithms hold potential to extend their use into clinical settings, facilitating more efficient and reliable ASD diagnoses.
6	SHARMA, Chandra Mani et al.(2024)(Sharma & Chariar, 2024)	4	Scopus (January 1, 2012, to June 9, 2023).	1.The language is English. Heliyon 10 (2024) e32548 C.M. Sharma and V.M. Chariar 2.The type of article is a journal article (research or review). 3.The time range is from January 1, 2012, to June 9, 2023.	1.Excluded those records that were out of the predefined range. 2.Excluded records in languages other than English. 3.Excluded conference papers, book chapters, books, notes, etc.	1.The systematic review and meta-analysis summarized the available evidence on using ML classifiers based on rs-fMRI data for ASD diagnosis. 2.Overall, the results indicated a summary sensitivity of 73.8% and specificity of 74.8% for ASD diagnosis using rs-fMRI and ML classifiers. 3.Support Vector Machine (SVM) was the most used classifier, showing high summary estimates (above 76%) for diagnostic precision. 4.Complementing rs-fMRI data with other neuroimaging or phenotypic information can significantly heighten diagnostic accuracy, achieving higher sensitivities (84.7%) compared to using rs-fMRI data alone (72.8%).
7	WOLFERS, Thomas, et al.(2019)(Wolfers et al., 2019)	24	PUBMED (last 10 years; search concluded on April 10, 2019)	1.Human studies. 2.For Pattern Classification studies: - Prediction of ASD clinical diagnostic status either cross-sectionally or longitudinally based on biology, cognition, and/or behavior. -Report of out-of-sample predictions. -Case-control study design. -Report of performance measures. 3.For Stratification studies: -Aimed to identify meaningful clusters within ASD based on biological, cognitive, behavioral, or symptom measures. -Application of automatic stratification approach to ASD.	1.Studies that were review articles. 2.Studies that did not use pattern classification/machine learning for diagnosis prediction or unsupervised stratification/clustering approaches to identify subgroups within ASD. 3.Studies that did not report out-of-sample predictive performance for classification, or for stratification, did not aim to find meaningful subgroups within the ASD phenotype.	1.Pattern classification and stratification approaches have increasingly been used in ASD research over the last ten years with the goal of translation towards clinical applicability. 2.Large variance was observed across pattern classification studies in terms of predictive performance, ranging from approximately 60% to 98% accuracy. 3.Stratification studies were less prevalent, with only two studies reporting replications and just a few showing external validation. 4.While some identified strata based on cognition and intelligence reappear across studies, biology as a stratification marker is clearly underexplored.

						5.Mapping biological differences at the level of the individual with ASD is a major challenge for the field now. 6.In summary, pattern classification approaches show promise but clinical applicability has not been reached, and stratification approaches have not yet robustly detected subgroups for ASD and/or shown how well they map onto underlying biology. 7.Increasingly larger samples might allow for the training of more complex algorithms. 8.Pattern classification is more focused on predicting the course of individuals at risk for ASD rather than the diagnosis itself. 9.Stratification methods are gaining more importance in comparison with pattern classification.

Table4 : Summary of specific included original articles

Author, year	Dataset	Architecture model	Accuracy	Sensitivity/ Recall	Specificity	Precision	F1-score/Dice coefficient	AUC	ROC	PPV	NPV
Gürbüz et al.(2021) (Gürbüz & Rekik, 2021)	ABIDE I	MGN-Net	74.23								
Ingalhalikar et al.(2021) (Ingalhalikar et al., 2021)	ABIDE	ANN	71.35	59	81						
Haweel et al.(2021) (Haweel et al., 2021)	NDAR	CNN	78					80			
Al-Hiyali et al.(2021) (Al-Hiyali, Yahya, Faye, & Hussein, 2021)	ABIDE	CNN	89.8								
LIU, Shuaiqi, et al.(2020) (Liu et al., 2020)	e ADHD-200	3D-CNN	69.15								
		4D-CNN	71.30	73.2	69.7						
		CDAE	75.64	76.92	73.08						
HU, Jinlong, et al.(2021) (Hu et al., 2021)	ABIDE I	GAT2	95	96	95	95			95		
HUANG, Zhi-An, et al. (2020) (Huang, Zhu, Yau, & Tan, 2020)	ABIDE	DBN	76	73	74						
		CNN	74	72	73						
		DNN	70	74	63						
		CNNPL	76	77	74	77	77				
		T-CNNPL	77	78	78	79	78				
MUJEEB RAHMAN, K. Ket al.(2022) (Mujeeb Rahman & Monica Subashini, 2022)	QCHAT-10 Toddler	DNN	100	99.86				100			
	QCHAT, Polish Toddlers	DNN	92.82	83.37				97.18			
SHAO, Lizhen, et al.(2021) (Shao, Fu, You, & Fu, 2021)	ADHD	GCN	79.5					84			
		MLP	78.1					85			
USMAN, Opeyemi Lateef et al. (2021)	C-BIRD	Inception-V3	89.08	90.22	92.86		91.52				
		Cascaded CNN	91.21	93.11	92.95		93.03				

(Usman et al., 2021)		ResNet50	94.67	95.79	94.91		95.35				
ZHAO, Kanhao et al.(2022) (Zhao et al., 2022)	ADHD	dGCN	72	71.6	72.2						
Li X,et al. (2021) (X. Li et al., 2021)	Biopoint	BrainNetCNN	75.20			65.60	65.58				
		GAT	77.40			79.40	75.08				
		Graph SAGE	78.60			76.20	75.55				
		PR-GNN	77.10			76.50	75.20				
		BrainGNN	79.80			79.60	75.80				
	HCP	MLP	67.20			62.97	63.49				
		BrainNetCNN	90.60			90.81	90.96				
		GAT	78.60			91.20	77				
		Graph SAGE	89.80			87.80	88.60				
		PR-GNN	91.20			91.14	91.09				
		BrainGNN	94.40			94.40	94.34				
KHOSLA, Meenakshi et al. (2019) (Khosla, Jamison, Kuceyeski, & Sabuncu, 2019)	HO	3D-CNN	67.7								
	CC200		72.8								
	EZ		66.4								
	TT		70								
	CC400		70.5								
	AAL		69.5								
	DOS160		67								
	MA-Ensemble		71.7								
	SP-Ensemble		72.3								
CHEN, Zhihui et al. (2019) (Chen, Ji, & Liang, 2019)	ABIDE I	DFC-CNN	68.80	62.73	74.38	69.08					
		CNN-EW	65.54	62.73	68.13	64.33					
		BrainNetCNN	63.15	59.77	66.25	61.79					
		DAE	65.76	64.77	66.67	64.34					
EL GAZZAR, Ahmed, et al. (2019) (El Gazzar, Cerliani, van Wingen, & Thomas, 2019)	ABIDEII	simple 1-D convolutional network	81	77	83						

BENGS, Marcel et al. (2020)(Bengs, Gessert, & Schlaefer, 2020)	ABIDE	CNN3D-MS	60				65				
		convGRU-CNN3D	67				71				
		CNN4D	60				68				
PARISOT, Sarah, et. al (2017) (Parisot et al., 2017)	ABIDE	GCN	69.5								
GUPTA, Sukrit, et al. (2020) (Gupta, Rajapakse, Welsch, & Initiative, 2020)	ABIDE	DNN	74.1								
SAIRAM, K., et al.(2019) (Sairam, Naren, Vithya, & Srivathsan, 2019)	ABIDE	RF	63	69	58						
		DNN	70	74	63						
DVORNEK, Nicha C.et al (2018) (Dvornek, Ventola, & Duncan, 2018)	ABIDE	RNN	70.1								
KHOSLA, Meenakshi, et al. (2018) (Khosla, Jamison, Kuceyeski, & Sabuncu, 2018)	ABIDE I	3D CNN	73.3								
	ABIDE II		71.7								
PARISOT, Sarah, et al. (2018) (Parisot et al., 2018)	ABIDE	GCN	70.4								
YIN, Wutao et al. (2021) (Yin, Mostafa, & Wu, 2021)	ABIDE 1	DNN	79.2					82.4			
LIANG, Yin et al. (2021) (Liang, Liu, & Zhang, 2021)	ABIDE	CNN	68	71	65	69	70				
		CNNPL	76	77	75	77	77				
		T- CNNPL	77	78	78	79	78				
Iidaka T et al .(2015) (Iidaka, 2015)	ABIDE	PNN	92	87	89						
JIANG, Hao, et al .(2020) (Jiang, Cao, Xu, Yang, & Zaiane, 2020)	ABIDE	Population GCN	63	62	65			67			
		BrainNetCNN	65	62	66			73			
		t-BNE	65	61	62			71			
		Graph Boosting	64	62	64			72			

		Ordinal Pattern	64	61	63			73			
		Hi-GCN	67	66	68			74			
	ADNI	Eienpooling GCN	75	66	78			71			
		Population GCN	74	65	76			74			
		BrainNetCNN	73	76	74			74			
		t-BNE	72	66	75			72			
		Graph Boosting	73	76	72			73			
		Ordinal Pattern	73	67	77			74			
		Hi-GCN	75	69	77			79			
YANG, Chunde, et al .(2021) (Yang, Wang, Tan, Liu, & Li, 2021)	ABIDE	GNN	72.40								
Eslami, T.et al. (2019) (Eslami & Saeed, 2019)	OHSU	DNN	74	66.6	86.6						
		MLP	64	62.5	61.6						
		MLP-DA	74.3	74.1	70.8						
		MLP-SVM-ATM	78	67.3	84.6						
		Ato-ASD-Network	80	73	83						
	NYU	DNN	64.5	78	46						
		MLP	68.5	44	87						
		MLP-DA	70	65.1	71.5						
		MLP-SVM-ATM	69.7	57.3	79						
		Ato-ASD-Network	70	57.9	79.2						
	USM	DNN	62	20	84						
		MLP	64	100	0						
		MLP-DA	70	70	53.7						
		MLP-SVM-ATM	72.3	85	42						
		Ato-ASD-Network	72.4	87.3	45						
	UCLA	MLP	71.9	76.7	64.8						
		MLP-DA	72.7	77.6	65.2						
			70.6	75.6	63.6						

		MLP-SVM-ATM Ato-ASD-Network	72.2	82.3	59.8						
LI, Hailong et.al(2018) (H. Li, Parikh, & He, 2018)	UM	DNN DTL-NN	62.3 67.2	64.2 68.9	62.3 67.6			0.63 0.67			
	UCLA	DNN DTL-NN	60.7 62.3	55.2 55.9	64.6 68			0.64 0.69			
	USM	DNN DTL-NN	63.6 70.4	66.2 72.5	52.6 67			0.66 0.73			
	LEUVEN	DNN DTL-NN	60 68.3	58.5 65.4	66.5 70.6			0.662 0.74			
PRICE, True, et al. (2014) (Price, Wee, Gao, & Shen, 2014)	ABIDE	Single-Network, Static FC	68	70	67					68	69
		Single-Network, Dynamic FC	83	83	83					83	83
		Multi-Network, Static FC	83	87	80					72	86
		Multi-Network, Dynamic FC	90	87	93					93	88
XING, Xinying et al. (2018) (Xing, Ji, & Yao, 2018)	ABIDE I	FC5net	64.67	63.29	66.88						
		E2Nnet SMP	65.12	64.13	67.73						
		E2Nnet	65.36	64.32	67.60						
		CNN-EW SMP	66.60	66.02	69.94						
		CNN-EW	66.88	66.44	70.40						
HEINSFELD, Anibal Sólon, .et al. (2018) (Heinsfeld et al., 2018)	ABIDE I	DNN	70	74	63						
		RF	63	69	58						
SHERKATGHANAD, Zeinab, .et al (2020) (Sherkatghanad et al., 2020)	ABIDE I	CNN	70.22	77.46	61.82			74.86			
SUBBARAJU, Vigneshwaran, et al.(2017) (Subbaraju, Suresh, Sundaram, & Narasimhan, 2017)		SFM (Spatial Feature based detection Method)	77.3								

GUO, Xinyu et.al,(2017) (Guo et al., 2017)		DNN	86.36								
DVORNEK, Nicha C.et al (2017) (Dvornek, Ventola, Pelphrey, & Duncan, 2017)	NYU	RNN+LSTM	68.50								
RIAZ, Atif, et al. (2018) (Riaz et al., 2018)	ADHD-200(NYU)	DeepFMRI	73.1	65.5	91.6						
	ADHD-200(NI)	DeepFMRI	67.9	63.6	71.4						
	ADHD-200(Peking)	DeepFMRI	62.7	48.1	79.1						
	ADHD-200(NI)	FCNet	62.7								
	ADHD-200(Peking)	FCNet	60								
WANG, Tianyi et al.(2019) (T. Wang & Kamata, 2019)	ADHD200	3D-CNN	69.01								
WANG, Zijian, et al.(2019) (Z. Wang, Sun, Shen, & Cao, 2019)	ADHD-200	dilated 3D CNN	77	86	82		81				
		ResNetXt	63	60	64		69				
		VGG	64	74	69		68				
		Spars Net	77	83	80		78				
		Alex Net	72	66	69		69				
SEN, Bhaskar, et al.(2018) (Sen, Borle, Greiner, & Brown, 2018)	ADHD	L_EFM_{SF}	67	85	45						
	ABIDE	L_EFM_{SF}	64	68	60						
ANIRUDH, Rushil et al .(2019) (Anirudh & Thiagarajan, 2019)	ABIDE	(G)Bootstrapping graph convolutional neural networks	70.86								
		(Naïve Graph) Bootstrapping graph convolutional neural networks	67.85								
		(Noisy G) Bootstrapping	67.39								

		graph convolutional neural networks									
Aghdam, M. A. et al.(2019) (Aghdam, Sharifi, & Pedram, 2019)	ABIDE I	CNN	69.1	64.12	73.79						
	ABIDE II	CNN	67.65	57.02	78.33						
	ABIDE I & ABIDE II	CNN	70.45	67.91	74.21						
KUANG, Deping, et al.(2014)a (Kuang, Guo, An, Zhao, & He, 2014)	KKI	DBN	61.90								
ZOU, Liang, et al. (2017) (Zou, Zheng, Miao, Mckeown, & Wang, 2017)	ABIDE	single-modality 3D CNN (Amplitude of Low Fre quency Fluctuations (ALFF)density)	66.04								
		single-modality 3D CNN (gray matter (GM) density)	65.86								
		multi-modality 3D CNN (fALFFandGM density)	69.15								
		3D CNN	69.1								
LI, Guannan, et al. (2018) (G. Li, Liu, Sun, Shen, & Wang, 2018)	NYU	DE-MC	76.24								
		MC	62.31								
		DE-MC2	74.32								
Kam et al. (2017) (Kam, Suk, & Lee, 2017)	UM	Single cluster (DRBM)	67.70	67.14	67.68					64.08	72.07
		Multiple cluster (DRBM)	80.82	75.48	85					81.12	81.37
	NYU	Single cluster (DRBM)	68.23	59	74.82					69.71	70.02
		Multiple cluster (DRBM)	75.24	61.33	85.71					82.10	73.73
	UM+NYU	Single cluster (DRBM)	64.39	58.33	69.44					61.40	66.67
		Multiple cluster (DRBM)	67.42	58.33	75					66.04	68.35

Table 5: Over lapping of the articles between the SRs

	Ryan Anthony J et al.(2020) (De Belen et al., 2020)	Sun Jae Moon et al.(2019) (Moon et al., 2019)	Mirjam Quaak et al.(2021) (Quaak et al., 2021)	Marzena Oliveira Ribas et al.(2023) (Ribas et al., 2023)	Caio Pinheiro Santana et al. (2022) (Santana et al., 2022)	Chandra Mani Sharma et al.(2024) (Sharma & Chariar, 2024)	Wolfers, T et al.(2019) (Wolfers et al., 2019)
Gürbüz et al.(2021) (Gürbüz & Rekik, 2021)	No	No	No	Yes	No	No	No
Ingalhalikar et al.(2021) (Ingalhalikar et al., 2021)	No	No	No	Yes	No	Yes	No
Haweel et al.(2021) (Haweel et al., 2021)	No	No	No	Yes	No	No	No
Al-Hiyali et al.(2021) (Al-Hiyali et al., 2021)	No	No	No	Yes	No	No	No
LIU, Shuaiqi, et al.(2020) (Liu et al., 2020)	No	No	No	Yes	No	No	No
HU, Jinlong, et al.(2021) (Hu et al., 2021)	No	No	No	Yes	No	No	No
HUANG, Zhi-An, et al. (2020) (Huang et al., 2020)	No	No	No	Yes	No	No	No
MUJEEB RAHMAN, K. Ket al.(2022) (Mujeeb Rahman & Monica Subashini, 2022)	No	No	No	Yes	No	No	No
SHAO, Lizhen, et al.(2021) (Shao et al., 2021)	No	No	No	Yes	No	No	No
USMAN, Opeyemi Lateef et al. (2021) (Usman et al., 2021)	No	No	No	Yes	No	No	No
ZHAO, Kanhao et al.(2022) (Zhao et al., 2022)	No	No	No	Yes	Yes	No	No
Li X,et al. (2021) (X. Li et al., 2021)	No	No	No	Yes	Yes	No	No
KHOSLA, Meenakshi et al. (2019) (Khosla et al., 2019)	No	No	Yes	No	Yes	No	No
CHEN, Zhihui et al. (2019) (Chen et al., 2019)	No	No	No	No	No	No	No
EL GAZZAR, Ahmed, et al. (2019) (El Gazzar et al., 2019)	No	No	No	No	Yes	No	No
BENGS, Marcel et al. (2020) (Bengs et al., 2020)	No	No	No	No	Yes	No	No
PARISOT, Sarah, et al (2017) (Parisot et al., 2017)	No	No	No	No	Yes	No	No

GUPTA, Sukrit, et al. (2020) (Gupta et al., 2020)	No	No	No	No	Yes	No	No
SAIRAM, K., et al.(2019) (Sairam et al., 2019)	No	No	No	No	Yes	No	No
DVORNEK, Nicha C.et al (2018) (Dvornek et al., 2018)	No	No	Yes	No	Yes	No	No
KHOSLA, Meenakshi, et al. (2018) (Khosla et al., 2018)	No	No	Yes	No	Yes	No	No
PARISOT, Sarah, et al. (2018) (Parisot et al., 2018)	No	No	Yes	No	No	No	No
YIN, Wutao et al. (2021) (Yin et al., 2021)	No	No	No	Yes	No	No	No
LIANG, Yin et al. (2021) (Liang et al., 2021)	No	No	No	Yes	No	No	No
Iidaka T et al .(2015) (Iidaka, 2015)	No	Yes	No	No	Yes	No	Yes
JIANG, Hao, et al .(2020) (Jiang et al., 2020)	No	No	No	Yes	No	No	No
YANG, Chunde, et al .(2021) (Yang et al., 2021)	No	No	No	Yes	No	No	No
Eslami, T.et al. (2019) (Eslami & Saeed, 2019)	Yes	No	No	No	Yes	No	No
LI, Hailong et .al(2018) (H. Li et al., 2018)	No	No	No	Yes	No	No	No
PRICE, True, et al. (2014) (Price et al., 2014)	No	Yes	No	No	No	No	No
XING, Xinying et al. (2018) (Xing et al., 2018)	No	No	Yes	No	Yes	No	No
HEINSFELD, Anibal Sólon, .et al.(2018) (Heinsfeld et al., 2018)	No	Yes	Yes	No	Yes	No	Yes
SHERKATGHANAD, Zeinab, .et al (2020) (Sherkatghanad et al., 2020)	No	No	No	No	Yes	No	No
SUBBARAJU, Vigneshwaran, et al.(2017) (Subbaraju et al., 2017)	No	No	No	No	No	No	Yes
GUO, Xinyu et.al,(2017) (Guo et al., 2017)	No	No	Yes	No	Yes	No	No
DVORNEK, Nicha C.et al (2017) (Dvornek et al., 2017)	No	No	Yes	No	Yes	No	No
RIAZ, Atif, et al. (2018) (Riaz et al., 2018)	No	No	Yes	No	No	No	No
WANG, Tianyi et al.(2019) (T. Wang & Kamata, 2019)	No	No	Yes	No	No	No	No

WANG, Zijian, et al.(2019) (Z. Wang et al., 2019)	No	No	Yes	No	No	No	No
SEN, Bhaskar, et al.(2018) (Sen et al., 2018)	No	No	Yes	No	No	No	Yes
ANIRUDH, Rushil et al .(2019) (Anirudh & Thiagarajan, 2019)	No	No	No	No	Yes	No	No
Aghdam, M. A. et al.(2019) (Aghdam et al., 2019)	No	No	Yes	No	Yes	No	No
ANIRUDH, Rushil et al .(2019) (Anirudh & Thiagarajan, 2019)	No	No	No	No	No	No	No
ZOU, Liang, et al. (2017) (Zou et al., 2017)	No	No	Yes	No	No	No	No
LI, Guannan, et al. (2018) (G. Li et al., 2018)	Yes	Yes	No	No	Yes	No	No
Kam et al. (2017) (Kam et al., 2017)	No	No	Yes	No	Yes	No	No

Figure 1: PRISMA flow diagram of the selected studies

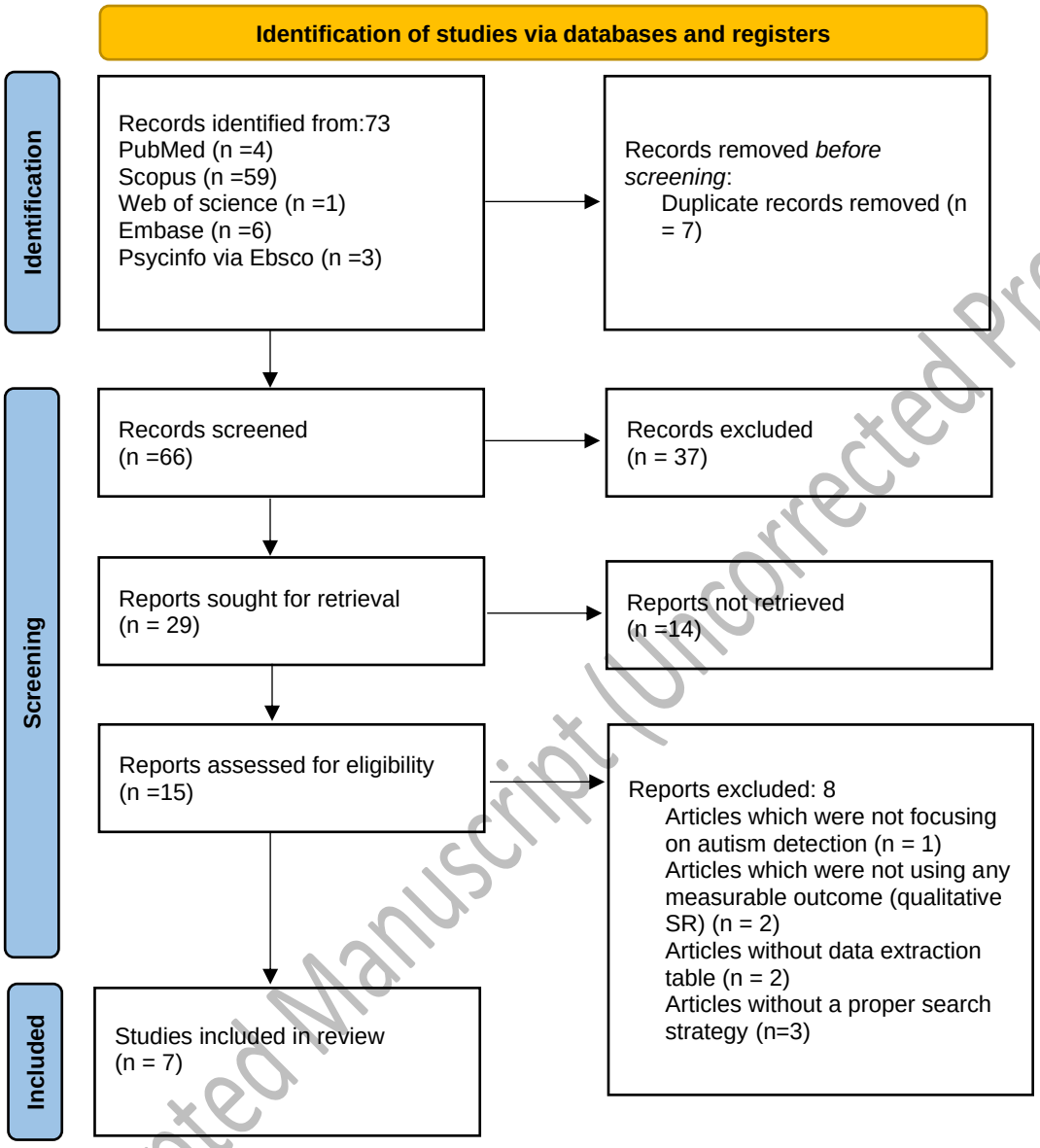

Figure 2: Evaluation of the risk of bias across the included systematic reviews

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	Overall
Ryan Anthony J et al.(2020) (De Belen et al., 2020)	+	+	+	+	X	-	-		X	-	+	-
Sun Jae Moon et al.(2019) (Moon et al., 2019)	+	+	+	+	X	+	-	+	-	+	+	+
Mirjam Quaak et al.(2021) (Quaak et al., 2021)	+	+	+	-	X	-	-	+	-	+	+	-
Marzena Oliveira Ribas et al.(2023) (Ribas et al., 2023)	+	+	+	+	+	+	-		X	+	+	+
Caio Pinheiro Santana et al.(2022) (Santana et al., 2022)	+	+	+	+	X	+	+	+	+	+	+	+
Chandra Mani Sharma et al.(2024) (Sharma & Chariar, 2024)	+	+	+	-	X	-	-		X	+	+	-
Wolfers, T et al.(2019) (Wolfers et al., 2019)	+	+	+	+	X	-	-		X	+	+	-

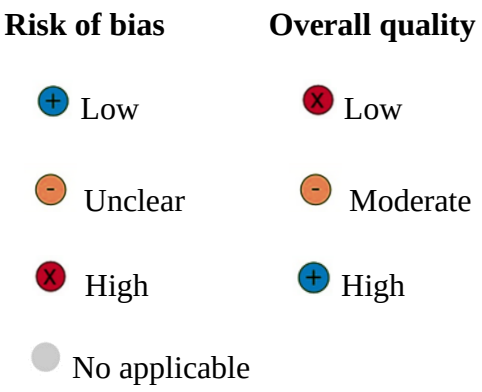

Figure 3: Comprehensive assessment of risk of bias for included systematic reviews, using eleven predefined questions (Q1–Q11) to assess methodological areas