



Review Article

A Meta-Review of Computational Intelligence Techniques for Early Autism Disorder Diagnosis

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Abstract: Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition affecting social communication and behavior, with global prevalence rising to 1-1.6%. This review evaluates Machine Learning (ML), Deep Learning (DL), and hybrid models for ASD diagnosis using structural and functional MRI data from the ABIDE (Autism Brain Imaging Data Exchange) database. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines, we systematically analyzed 512 articles from Google Scholar, PubMed, and ScienceDirect (2020-2024), ultimately selecting 65 studies meeting inclusion criteria. The review revealed that hybrid models dominate the field (66% of studies), outperforming standalone ML (8%) and DL (26%) approaches. Pooled mean accuracies were 76.80% (ML), 80.10% (DL), and 82% (hybrid models), with five hybrid models and one DL model exceeding 95% accuracy. Notably, Convolutional neural network (CNN) based hybrid architectures showed superior performance in classifying ASD vs. neurotypical subjects across Magnetic Resonance Imaging (MRI) (8% of studies), functional MRI (fMRI) (32%), and resting state-fMRI (rs-fMRI) (49%) modalities. Key findings demonstrate that integrating CNN with other algorithms (e.g., Support Vector Machine (SVM), Graph Convolutional Networks (GCN), or attention mechanisms) yields the most reliable discrimination of ASD, combining the feature extraction strengths of DL with the interpretability of traditional ML. These advanced models show particular promise for early diagnosis, with low prediction risk. This work also highlights hybrid models as the current state-of-the-art for neuroimaging-based ASD classification, though standardization challenges remain regarding dataset heterogeneity and model interpretability.



Keywords: Brain disorder; ASD; rs-fMRI; Medical imaging analysis; Health risks

1. Introduction

According to the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), ASD is a multifaceted or complex brain disorder that affects the functionality of the brain. It is considered a lifelong evolving disability that damages social communication, social interaction, restricted, repetitive behavior, stereotyped patterns of behavior, interests, and activities [1]. According to the median estimate, the prevalence of ASD among children is 1/100 worldwide and in the United States is 1:31 among children aged 8 years [2-4]. ASD is frequently diagnosed in early childhood from 18-24 months and over the years. Globally, the cases of ASD increased by 0.62%-1.0% from 2012 to 2021 [5]. There are many issues faced by ASD patients as compared to non-ASD subjects. A 20% rate of depression was found in ASD subjects and 7% was found in non-ASD subjects. An 11% rate of anxiety was found in ASD subjects and 5% was found in non-ASD subjects. A 13% rate of sleep difficulties was found in ASD subjects and 5% was found in non-ASD subjects. A 21% rate of epilepsy with co-occurring intellectual disability was found in ASD subjects and 0.8% was found in non-ASD subjects [6]. Many reasons or causes play a role in having ASD disorder. Scientists do not know the exact reasons or cause of ASD, but evidence suggests that ASD happens due to genes and environment. The risk of ASD is higher due to specific genetic conditions, such as Fragile X syndrome or tuberous sclerosis. Researchers focus on how genes interact with each other and with environmental factors, such as the medical condition of the family, complications during the birth or pregnancy, parental age, and demographic variables [7]. Ongoing research is continuously conducted to understand the etiologic mechanism of ASD disorder but presently no single unifying cause or reason has been identified. The neuroimaging studies are limited but these studies revealed the cerebellar architecture, limbic system abnormalities, connectivity, and frontal and temporal lobe differences of the ASD subjects [8]. In recent years, doctors have investigated brain disorders by checking the vision, hearing, balance, and brain images such as computerized tomography (CT) scans, MRI scans, fMRI scans, and Positron Emission Tomography (PET) scans and Single Photon Emission Computed Tomography (SPECT) scans. To check brain activation, doctors studied regional Cerebral Blood Flow (rCBF), blood oxygen levels, and neuroreceptor density [9]. The fMRI brain images were used to investigate the severity of brain disorder using brain activations from patients and healthy control subjects [10]. The fMRI is a great way to collect brain activation data voxel-wise and region-wise from subjects during rest and while performing tasks [11]. The rs-fMRI is similar to the fMRI but the subjects do not perform any task during the experiment. A person simply lies in a scanner for five to ten minutes with eyes closed or open while the data are collected. The rs-fMRI scans are very useful to find the functional relationship between the brain areas and also useful for the clinical field and mental status investigation of the population [12]. The rs-fMRI scans are suitable to observe the treatment response of PTSD patients [13]. The fMRI techniques focus on finding the relationship between individual voxels and cerebral factors. In this study, we performed a systematic review and meta-analysis to compare the performance of Machine learning, deep learning, and hybrid approaches for the diagnosis of ASD disorder of recent studies from 2020–2024. We focus on neuroimaging sources such as MRI, fMRI, and rs-fMRI in this meta-analysis study to observe the most useful sources for the diagnosis processes of ASD subjects. We also observe the most suitable, reliable, worthy, and consistent approach to declare a particular person as an ASD subject.

1.1. Research problem

ASD classification is a complex and evolving area of research. There are different main challenges such as the heterogeneity of ASD, diagnostic criteria and methods, machine learning applications, data sources and quality, and multi-class classification. Heterogeneity: ASD presents an extensive range of severity levels and symptoms that create difficulty in the classification process. The variability in behavior and intellectual outline requires a sophisticated model to capture ASD [14]. Diagnostic criteria and methods: changes in diagnostic criteria over time impact the consistency and reliability of the ASD diagnosis process [15]. Machine Learning Applications: Several studies have applied machine learning models to classify ASD brain disorders. Those studies aim to improve the accuracy rate by increasing the dataset and identifying patterns that may not be evident through traditional methods [16], [17]. Data sources and quality: High quality and comprehensive datasets play a vital role in developing a reliable classification model. The ABIDE is a valuable source of ASD-related data collection but the data still face issues such as data standardization and completeness [18]. Multi-class classification: several studies investigate different techniques for the classification of different types of ASD. The aim is to build a model to distinguish between the different types of ASD brain disease and provide more personalized and precise diagnostic categories for ASD [19].

1.2. Research question

- Are machine learning approaches the most efficient way for ASD Classification?
- Are deep learning approaches the most efficient way for ASD Classification?
- Are hybrid approaches the most efficient way for ASD Classification?

2. Methodology

2.1. Review approach

This current meta review was conducted to provide an understanding of the role of ML, DL, and hybrid approaches in the diagnosis of ASD. A review is a systematic approach that allows researchers to examine emerging evidence from available studies on a specific topic and identify knowledge gaps in a given field [20]. This review follows the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews) guidelines, published in 2018 [21].

2.2. Search strategy

2.2.1. Data Source and Search Sources

In this review study, we focus only on the ABIDE database. We searched articles that were published from January 2020 to 2024. The ABIDE is a valuable source of ASD-related data collection that includes MRI, fMRI, rs-fMRI scans and has two types ABIDE-I and ABIDE-II [22]. We conducted a systematic search from three well-known sources: PubMed, Google Scholar, and ScienceDirect.

2.2.2. Search terms

Keyword search strategies were adopted in this review paper for PubMed, Google Scholar, and ScienceDirect sources. The search items were named intervention terms and used to identify the articles. The detailed text plot of these terms is given in Figure 1. The interventions are related to ASD disorder, classification or diagnosis of ASD disorder, ML, DL, and hybrid approaches.

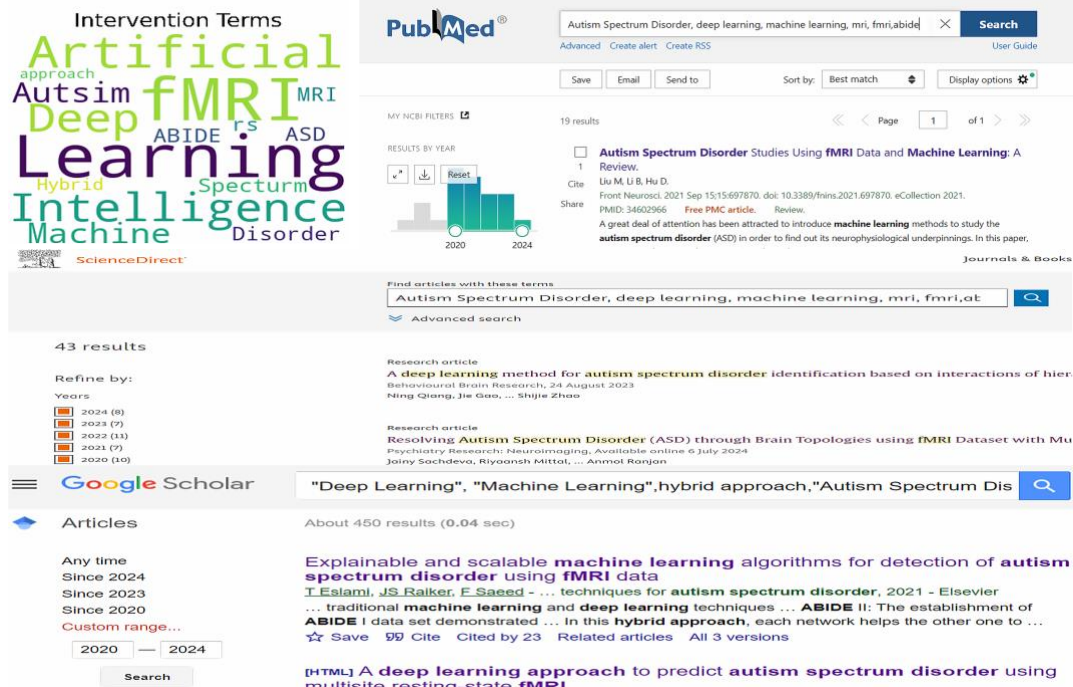


Figure 1: Searching Terms of ASD papers in PubMed, Google Scholar, and ScienceDirect sources.

2.3. Inclusion and exclusion criteria of this study

The inclusion and exclusion criteria used in this study are given in Table 1.

Table 1: Inclusion and Exclusion criteria for articles.

Inclusion criteria	Exclusion criteria
- Use ABIDE database - MRI, fMRI, and rs-fMRI neuroimaging - Participants of ASDs and HCs - Focus on articles from 2020 to 2024 - No restrictions on country - No restrictions for machine learning, deep learning, and hybrid models - English language	- Any participant other than ASDs and HCs - Functional connectivity - Any language other than English - Newspapers, magazines, proposals, thesis, meta-analysis, books, no access to articles, and posters - Models that obtained <70% accuracy rate - Nonhuman subjects

Note: HCs= Healthy control subjects and ASDs= autism spectrum disorder subjects.

2.4. Data extraction

Data were extracted from articles using built forms that include the following information: title of paper, name of First Author, Year of Publication, and Country. Other information such as: sample size of ASDs, HCs, or other types, neuroimaging modality (MRI, fMRI, rs-fMRI), classification methods (ML, DL, or hybrid approach), and performance metrics (accuracy rate).

2.5. Statistical analysis

Microsoft Excel and R-language with R-Studio were used on Windows 10 to perform all analyses of this review paper. The laptop machine has the following specifications such as: 16 GB RAM, 128 GB disk

space, and a 2 GB NVIDIA graphics card. The different methods used include the calculation of pooled estimates of accuracy, assessment of similarity, and evaluation of publication bias through Egger's test.

3. Results

3.1. Search outcomes

In this review, we extracted 512 research articles using Google Scholar: 450, ScienceDirect: 43 and PubMed: 19. From Google Scholar database, Books: 12, Not related: 50, No ABIDE data use: 25, No access available: 111, Only abstract: 4, No predictive models are used: 21, No ABIDE+ No ASD used: 2, No English Language used: 4, Repeated articles: 6, Thesis related: 21, Meta-analysis related: 35, Only Region of interest (ROI) used: 15, fMRI data not used: 25, ASD+ other types: 49, ABIDE+ other data: 11, and <70% accuracy: 6 were excluded in screening or selection process. From ScienceDirect database, Books: 2, Not related: 4, NO access: 7, Meta-analysis related: 5, fMRI data not used: 2, ASD+ other types use: 10, ABIDE+other data: 3, Repeat: 1, and <70% accuracy: 3 were excluded in screening or selection process. From PubMed database, NO access: 4, Meta-analysis related: 2, ASD+ other types use: 2, ABIDE+other data: 1, and <70% accuracy: 4 were excluded in screening or selection process. A total of 65 articles from (Google Scholar:53, ScienceDirect: 6, and PubMed: 6) selected for this study and a detailed flow diagram is given in Figure 2.

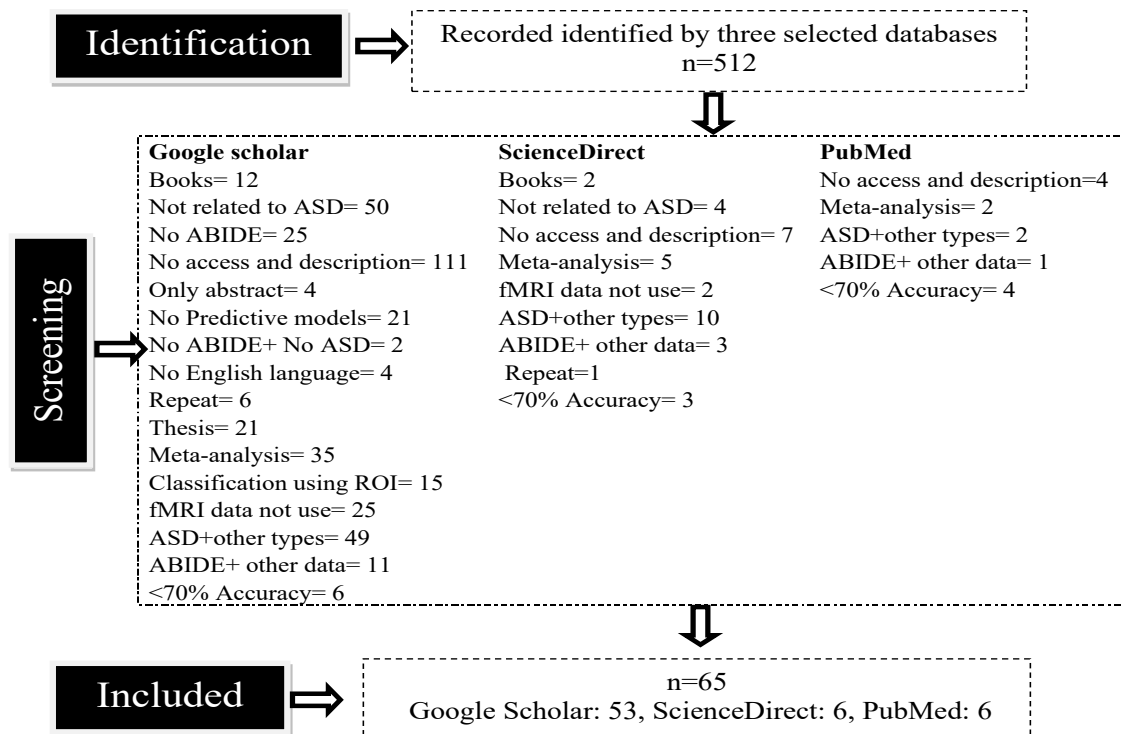


Figure 2: Flow diagram for selected articles.

3.2. Characteristics of included studies

Among the 65 articles, in 5 (8%) articles the ML models were utilized [23-27], in 17 (26%) articles the DL models were utilized [28-44], and in 43 (66%) articles the hybrid models were used to assess the accuracy rate for diagnosis of ASDs from HCs [45-87]. The 3 (6%) articles were included from 2020, 8 (15%) articles from 2021, 9 (17%) articles from 2022, 21 (40%) articles from 2023, and 12 (23%) articles

from 2024 in Google Scholar database. Similarly, 2 (33%) articles were included from 2020, 1 (17%) article from 2021, 2 (33%) articles from 2023, and 1 (17%) article from 2024 in PubMed database. Similarly, 2 (33%) articles were included from 2020, 1 (17%) article from 2022, 2 (33%) articles from 2023, and 1 (17%) article from 2024 in ScienceDirect database. Out of 53 articles from Google Scholar database, 2 (4%) articles used ML models, 12 (23%) used DL models, and 39 (73%) articles used hybrid models. Out of 6 articles from PubMed database, 4 (67%) articles used DL models, and 2 (33%) used hybrid models. Similarly, out of 6 articles from ScienceDirect database, 3 (50%) articles used ML models, 1 (17%) used DL models, and 2 (33%) used hybrid models to assess the accuracy of ASDs diagnosis from HCs given in Figure 3.

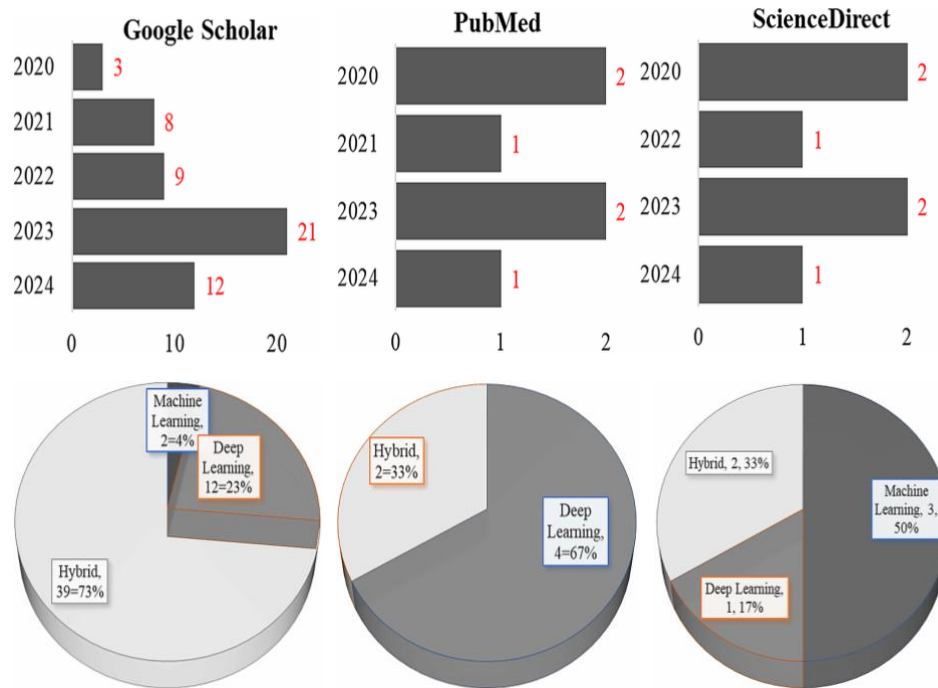


Figure 3: General ratio of selected articles after data extraction from selected sources.

The selected articles were published in 13 different countries. The 36 articles were published in China [24], [27-29], [31], [34], [38], [40], [45-46], [50-51], [53], [58-60], [62], [64-65], [67-74], [76-79], [82-85], [87], 1 article from Greece [26], 1 from Hong Kong [37], 12 from India [23], [42], [44], [48-49], [54-57], [61], [80], [86]. Similarly, 1 article from Iran [33], 2 from Japan [35], [81], 2 from Qatar [43], [47], 2 from Saudi Arabia [41], [52], 1 from Spain [63], 1 from Sweden [32], 1 from Tunisia [66], 2 from Turkey [25, 39], and 3 from the USA [30, 36, 75]. The highest number of articles were published in China as we can observe in Table 2. Similarly, 7 articles belong to 2020, 9 to 2021, 10 from 2022, 25 from 2023, and 14 from 2024. The highest number of papers belonged to 2023, as given in Table 2, used to diagnose ASDs from HCs.

Table 2: Comparison of included studies concerning countries and years.

Country	2020	2021	2022	2023	2024	n	References
China	4	4	9	14	5	36	[24], [27-29], [31], [34], [38], [40], [45-46], [50-51], [53], [58-60], [62], [64-65], [67-74], [76-79], [82-85], [87]
Greece		1				1	[26]
Hong Kong		1				1	[37]
India			1	6	5	12	[23],[42], [44],[48-49], [54-57], [61], [80], [86]
Iran				1		1	[33]
Japan	1	1				2	[35],[81]
Qatar				2		2	[43],[47]
Saudi Arabia		1			1	2	[41],[52]
Spain	1					1	[63]
Sweden				1		1	[32]
Tunisia				1		1	[66]
Turkey	1	1				2	[25],[39]
USA					3	3	[30],[36],[75]
n	7	9	10	25	14	65	

3.3. Similarity exploration

The 36 articles were published in China, where 1 article used the MRI data [34], 11 used fMRI data [27-28], [40], [45], [53], [59-60], [67-68], [73-74], 1 used MRI, rs-fMRI [58], 23 used rs-fMRI dataset in

Table 3: Comparison of data types of included studies with respect to countries.

Country	Scan	n	References
China	MRI	1	[34]
	fMRI	11	[27-28], [40], [45], [53], [59-60], [67-68], [73-74]
	MRI, rs-fMRI	1	[58]
	rs-fMRI	23	[24], [29], [31], [38], [46], [50-51], [62], [64-65], [69-72], [76-79], [82-85], [87]
Greece	MRI, fMRI	1	[26]
Hong Kong	MRI, fMRI	1	[37]
India	MRI	2	[56-57]
	fMRI	4	[42], [48-49], [55]
	MRI, fMRI	1	[54]
	rs-fMRI	5	[23], [44], [61], [80], [86]
Iran	fMRI	1	[33]
Japan	fMRI	2	[35],[81]
Qatar	rs-fMRI	2	[43],[47]
Saudi Arabia	fMRI, MRI	2	[41],[52]
Spain	MRI	1	[63]
Sweden	rs-fMRI	1	[32]
Tunisia	MRI, fMRI	1	[66]
Turkey	MRI, fMRI, rs-fMRI	2	[25],[39]
USA	fMRI, rs-fMRI	3	[30],[36],[75]

Similarly, Greece published one study while using MRI, fMRI both types of datasets [26] and Hong Kong also published 1 study while using MRI, fMRI both types of datasets [37]. Similarly, India published 12 articles, where 2 belong to MRI dataset [56-57], 4 belong to fMRI dataset [42], [48,49], [55], 1 belongs to both MRI, fMRI dataset [54], and 5 belong to rs-fMRI dataset [23, 44, 61, 80, 86]. Similarly, Iran published 1 article using fMRI data [33], Japan published 2 articles with fMRI dataset [35], [81], Qatar also published 2 articles with rs-fMRI dataset [43], [47], and Saudi Arabia also published 2 articles with fMRI, MRI both datasets [41], [52]. Similarly, Spain published 1 article with MRI data [63], Sweden also published 1 article but with rs-fMRI data [32], and Tunisia also published 1 article with both MRI, fMRI datasets [66].

Table 4: Comparison of quantity of ASD and HC subjects in included studies.

Subjects (ASDs/HCs)	No. (%)	Reference	Subjects (ASDs/HCs)	No. (%)	Reference
205/209	1(2%)	[76]	505/530	8(12%)	[40-41], [43], [55], [61-62], [75], [77]
234/236	1(2%)	[84]	511/561	1(2%)	[53]
240/284	1(2%)	[30]	521/593	2(3%)	[66], [78]
306/368	1(2%)	[64]	529/573	1(2%)	[31]
					[26-27],[32-34], [36], [46], [48-49], [51],[56-58], [60], [71-72], [79-80], [83],
317/400	1(2%)	[42]	539/573	22(34%)	[85-86]
389/442	1(2%)	[45]	634/800	1(2%)	[44]
402/423	1(2%)	[82]	79/105	1(2%)	[87]
402/464	1(2%)	[35]	100/100	1(2%)	[25]
		[37, 39,			
403/468	5(8%)	70, 73, 81]	1072/1176	1(2%)	[52]
408/476	1(2%)	[38]	150/150	1(2%)	[23]
41/41	1(2%)	[47]	368/449	1(2%)	[63]
45/47	2(3%)	[29, 69]	403/468	1(2%)	[59]
461/451	1(2%)	[68]	415/574	1(2%)	[24]
481/526	1(2%)	[65]	419/530	1(2%)	[28]
495/554	1(2%)	[50]	419/531	1(2%)	[67]
500/600	1(2%)	[54]			

Turkey published two articles with (MRI, fMRI), rs-fMRI datasets [25], [39], and USA published three articles with fMRI, rs-fMRI datasets [30], [36], [75] presented in Table 3. The number of subjects varied from included studies, 1(2%) article used ASD:205, and HC: 209, 1(2%) article used ASD:234, and HC: 236, 1(2%) article used ASD:240, and HC: 284, and 1(2%) article used ASD:306, and HC: 368 subjects. Similarly, 1(2%) article used ASD:317, and HC: 400, 1(2%) article used ASD:389, and HC: 442, 1(2%) article used ASD:402, and HC: 423, and 1(2%) article used ASD:403, and HC: 464 subjects. The 5(8%) articles used ASD:403, and HC: 468 subjects, 1(2%) article used ASD:408, and HC: 476, 1(2%) article used ASD:41, and HC: 41, 2(3%) articles used ASD:45, and HC: 47 subjects. Similarly, 1(2%) article used ASD:461, and HC: 451, 1(2%) article used ASD:481, and HC: 526, 1(2%) article used ASD:495, and HC: 554, 1(2%) article used ASD:500, and HC: 600, and 8(12%) articles used ASD:505, and HC: 530 subjects. Similarly, 1(2%) article used ASD:511, and HC: 561, 2(3%) articles used ASD:521, and HC: 593, and 1(2%) article used ASD:529, and HC: 573 subjects. Similarly, 22(34%) articles used ASD:539, and HC:

573 subjects, 1(2%) article used ASD:634, and HC: 800, 1(2%) article used ASD:79, and HC: 105, 1(2%) article used ASD:100, and HC: 100, and 1(2%) article used ASD:1072, and HC: 1176 subjects. Similarly, 1(2%) article used ASD:150, and HC: 150, 1(2%) article used ASD:368, and HC: 449, and 1(2%) article used ASD:403, and HC: 468 subjects. Similarly, 1(2%) article used ASD:415, and HC: 574, 1(2%) article used ASD:419, and HC: 530, and 1(2%) article used ASD:419, and HC: 531. The details with references are given in Table 4.

3.4. Accuracies of models

The ML, DL, and hybrid models were compared in the form of accuracy rate of 65 articles. From ML models the 2(3%) articles obtained the accuracy from 70%-75% [25], [27], 1(2%) achieved the accuracy from 75.05%-80% [26], and 2(3%) achieved the accuracy from 80.05%-85% [23], [24]. Similarly, from DL models the 7(11%) articles achieved accuracy from 70%-75% [34], [28], [39], [33], [44], [30], [41], 3(5%) achieved from 75.05%-80% [29], [32], [43], 2(3%) achieved accuracy from 80.05%-85% [31], [42]. Similarly, from the DL models 4(6%) articles achieved 85.05%-90% [35-38], and 1(2%) achieved >95% [40] accuracy rate. Similarly, from hybrid models the 7(11%) articles achieved accuracy from 70%-75% [61], [65], [87], [81], [82], [51], [78], 15(23%) achieved from 75.05%-80% [86], [69], [64], [60], [62], [53], [70], [55], [50], [68], [74], [67], [71], [75], [46], 10(15%) achieved accuracy from 80.05%-85% [63], [48], [73], [59], [79], [58], [52], [76], [84], [77]. Similarly, from the hybrid models 2(3%) articles achieved 85.05%-90% [49], [85], 4(6%) achieved 90.05%-95% accuracy rate [45], [66], [72], [80] and 5(8%) achieved >95% [47], [54], [56], [57], [83] accuracy rate given in Table 5.

Table 5: Accuracy comparison of ML, DL, and hybrid models of included studies.

Model	Accuracy	No. (%)	Reference
ML	70%-75%	2(3%)	[25,27]
	75.05%-80%	1(2%)	[26]
	80.05%-85%	2(3%)	[23,24]
DL	70%-75%	7(11%)	[34, 28, 39, 33, 44, 30, 41]
	75.05%-80%	3(5%)	[29, 32, 43]
	80.05%-85%	2(3%)	[31, 42]
	85.05%-90%	4(6%)	[35-38]
	>95%	1(2%)	[40]
Hybrid	70%-75%	7(11%)	[61, 65, 87, 81, 82, 51, 78]
	75.05%-80%	15(23%)	[86, 69, 64, 60, 62, 53, 70, 55, 50, 68, 74, 67, 71, 75, 46]
	80.05%-85%	10(15%)	[63, 48, 73, 59, 79, 58, 52, 76, 84, 77]
	85.05%-90%	2(3%)	[49, 85]
	90.05%-95%	4(6%)	[45, 66, 72, 80]
	>95%	5(8%)	[47, 54, 56, 57, 83]

3.5. Types of models

The included studies demonstrate the three types of models, ML, DL, and hybrid models that were used to classify the ASDs from HCs using their fMRI, MRI, and rs-fMRI datasets.

3.5.1. Machine learning

Five machine learning models (logistic regression (LR) and multilayer perceptron (MLP), SVM, and 20 ML pipeline) were used in included studies to diagnose the ASDs from HCs [23], [24], [26], [27], [25]

respectively. Out of 5(100%) included articles, 1(20%) article on ML models used LR and MLP both models, 3(60%) articles used SVM models, and 1(20%) article used 20 ML pipelines for the diagnosis process of ASDs given in Table 6.

Table 6: Quantitative description of ML models of selected articles.

Machine Learning	No. (%)	Reference
LR & MLP	1(20%)	[23]
SVM	3(60%)	[24,26,27]
20 ML pipeline	1(20%)	[25]

3.5.1.1. Forest plot of ML models

The forest plot was used to provide a detailed overview of the accuracy using the study Id, Model name, quantity of ASDs and HCs, Type of Data, and Risk of Prediction. The forest plot was stacked from the largest year to the smallest year. Using the rs-fMRI data the ML models got >80% accuracy rate and achieved the low risk of prediction of ASDs from HCs given in Figure 4. The two models (LR & MLP, SVM) obtained >80% accuracy rate with low risk of prediction and 3 models (SVM, SVM, 20 ML pipeline) achieved <80% accuracy rate with a Moderate risk of prediction.

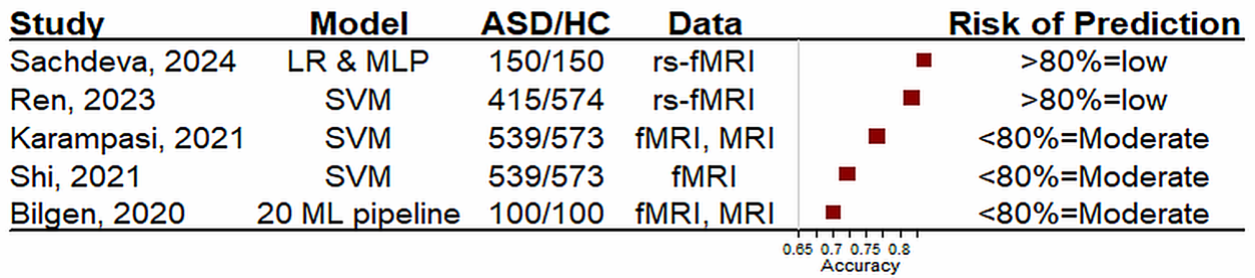


Figure 4: Forest plot of ML models, here dark red color boxes present the accuracy of each model from 2020 to 2024.

3.5.2. Deep learning

The 17 DL models [28-44] were used to diagnose the ASDs from HCs. Out of 17 (100%) DL models, 1 (6%) article used the MLP model [28] 1(6%) used Belief-value with MLP model [29], 5 (29%) used CNN models [30-34], and 1 (6%) Deep neural network (DNN) model was used [35]. Similarly, 2 (11%) GCN models were used [36-37], 1(6%) used GCN based on pooling [38] and 1 (6%) Long Short-Term Memory (LSTM) model was used [39]. Similarly, 1 (6%) Graph attention network (GAT) model was used [40], 1 (6%) Sparse autoencoder (SAE) net model was used [41], and 1 (6%) DenseNet201 model was used [42]. All acronyms with phrases are presented in Appendix A.

Table 7: Quantitative description of DL models of selected articles.

Deep Learning	No. (%)	References
MLP	1(6%)	[28]
Belief-value with MLP	1(6%)	[29]
CNN	5(29%)	[30-34]
DNN	1(6%)	[35]
GCN	2(11%)	[36-37]
GCN based on pooling	1(6%)	[38]

LSTM	1(6%)	[39]
GAT	1(6%)	[40]
SAE net	1(6%)	[41]
DenseNet201	1(6%)	[42]
ASD-DiagNet	1(6%)	[43]
MobileNetV2 and DenseNet201	1(6%)	[44]

As presented in Table 7, 6% ASD-DiagNet model was used and 6% MobileNetV2 and DenseNet201 model were used to diagnose the ASDs from HCs.

3.5.2.1. Forest plot of DL models

The forest plot was also stacked for DL models from the largest year to the smallest year. The GAT2 model achieved higher accuracy >95% and obtained very low risk of prediction. The 6 models (GCN, DenseNet201, GCN pooling, DNN, GCN, CNN) achieved >80% accuracy rate with low risk of prediction. The 10 models (CNN, MLP with belief value, ASD-DiagNet, CNN, MobileNetV2 & DenseNet201, CNN, CNN, LSTM, SAE, and MLP) achieved <80% accuracy rate with Moderate risk of prediction given in Figure 5.

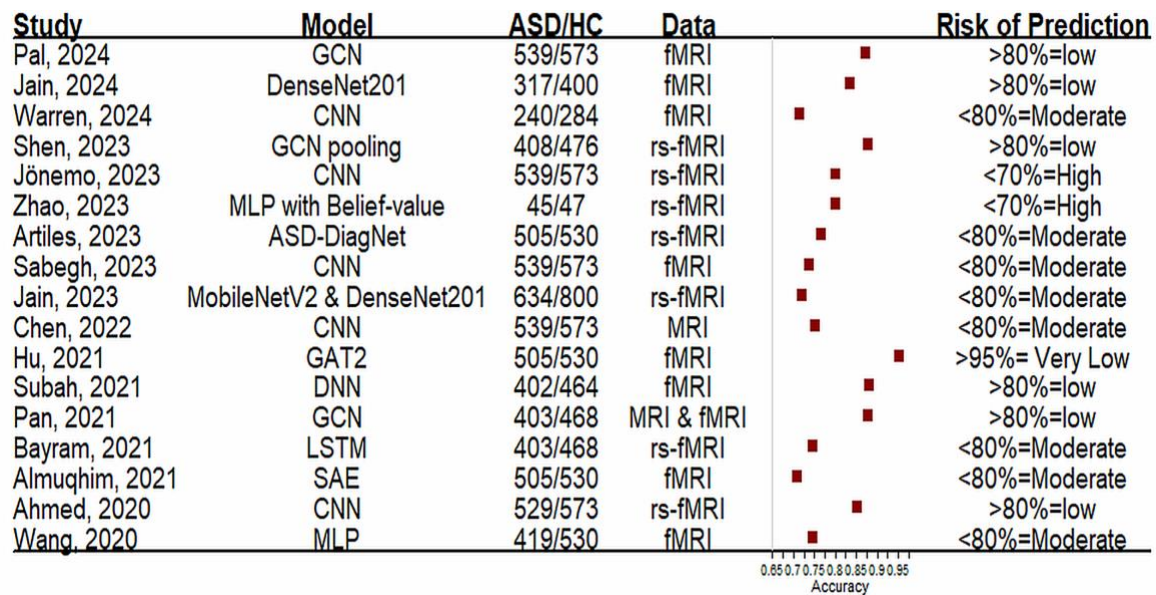


Figure 5: Forest plot of DL models, here dark red color boxes present the accuracy of each model from 2020 to 2024.

3.5.3. Hybrid models

The 43 hybrid models [45-87] were also used to diagnose the ASDs from HCs. Out of 43 (100%), 1(2%) (CNN+SVM) model was used to diagnose the ASDs from HCs, and 1(2%) CNN+Attention Mechanism (AM) was used in the diagnosis process. Similarly, 1(2%) CNN+K-Nearest Neighbor (KNN) was used, 1(2%) CNN+Low-Estimation Rank Tensor (LERT) was used, 1(2%) CNN+GCN+Recurrent neural network (RNN) was used in the diagnosis process. Similarly, 1(2%) CNN+Denoising AE (DAE)+ Shared weights (SW) was used, 1(2%) CNN+Gated Recurrent units (GRU) was used, and 1(2%) CNN+Grid search optimization (GSO) was used for diagnosis process. Similarly, 1(2%) CNN+prototype learning (PL) was used, and 1(2%) CNN+Multisite anti-interference neural network

(Multi-site AINN) was used for diagnosis process. Similarly, 1(2%) Optimized CNN-Based Automatic (OCNN) was used, 1(2%) Multichannel Tri integrated CNN (MT-CNN) +Attention was used, 1(2%) Deep CNN (DCNN)+Artificial Gannet Optimization enabled (AGOE) was used, and 1(2%) DCNN+Dwarf Mongoose optimized Residual Network (DMORN) was used. Similarly, 1(2%) Hierarchical recurrent variational AE (HRVAE) was used, 1(2%) AE+DNN was used, 1(2%) AE+MLP was used, and 1(2%) Variational AE (VAE)+ MLP was used. Similarly, 2(5%) Stacked AE (SAE)+ MLP were used, 1(2%) DAE+ Deep Canonical Correlation Fusion (DCCF) was used, and 1(2%) Principal Component Analysis (PCA)+ Artificial neural network (ANN) was used. Similarly, 1(2%) Multi-atlas GCN was used, 1(2%) GCN+ Invertible dynamic (ID) was used, 1(2%) GCN+Self Attention (SA) was used, 1(2%) GraphGCN (GGCN) and 1(2%) GCN+Phenotypic Feature Extractor (PFE)+ Recursive Feature Elimination (RFE) was used. Similarly, 1(2%) Graph-RNN (GRNN) was used, 1(2%) Multi-Kernel Learning Fusion with RNN (MK-RNN) +GRU was used, 1(2%) LASSO + hidden Markov model (HMM)+ LSTM was used, and 1(2%) Multi-Atlas Deep Ensemble Network (MA-DEN) was used. Similarly, 1(2%) Adversarial learning (AL)+ node edge graph attention network (NGAN) was used, 1(2%) Heterogeneous graph convolutional attention network (HGCAN) was used, 1(2%) Spatio-Temporal ASD Network (ST-ASD-N) was used, and 1(2%) Student Neural Networks (SNN)+Sequential Feed Forward (SFF) was used.

Table 8: Quantitative description of hybrid models of selected articles.

Hybrid models	No(%)	Reference	Hybrid models	No(%)	Reference
CNN+SVM	1(2%)	[45]	Multi-atlas GCN	1(2%)	[67]
CNN+AM	1(2%)	[46]	GCN+ ID	1(2%)	[68]
CNN+KNN	1(2%)	[47]	GCN+ SA	1(2%)	[69]
CNN+LERT	1(2%)	[48]	GGCN	1(2%)	[70]
CNN+GCN+ RNN	1(2%)	[49]	GCN+PFE+RFE	1(2%)	[71]
CNN + DAE+SW	1(2%)	[50]	Graph-RNN	1(2%)	[72]
CNN+ GRU	1(2%)	[51]	MK-RNN+GRU	1(2%)	[73]
CNN + GSO	1(2%)	[52]	LASSO +HMM+ LSTM	1(2%)	[74]
CNN +PL	1(2%)	[53]	MA-DEN	1(2%)	[75]
CNN+Multi-site AINN	1(2%)	[54]	AL+NGAN	1(2%)	[76]
OCNN	1(2%)	[55]	HGCAN	1(2%)	[77]
MT-CNN +Attention	1(2%)	[56]	ST-ASD-N	1(2%)	[78]
DCNN+AGOE	1(2%)	[57]	SNN+SFF	1(2%)	[79]
DCNN+DMORN	1(2%)	[58]	Siamese network	1(2%)	[80]
HRVAE	1(2%)	[59]	DQ-LN+SpinalNet	1(2%)	[81]
AE+ DNN	1(2%)	[60]	FM-CBS+DR	1(2%)	[82]
AE+MLP	1(2%)	[61]	Ensemble+GSP	1(2%)	[83]
VAE+MLP	1(2%)	[62]	GB+DT	1(2%)	[84]
SAE +MLP	2(5%)	[63-64]	MST+SVM	1(2%)	[85]
DAE+DFFC	1(2%)	[65]	PCA+FFT	1(2%)	[86]
PCA+ANN	1(2%)	[66]	MFBN	1(2%)	[87]

Similarly, 1(2%) Siamese network was used, 1(2%) Deep Q learning network (DQ-LN) +SpinalNet was used, 1(2%) Feature Maps obtained from Combined BS (FM-CBS) +Dual Regression Edges (DR)

was used, and 1(2%) Ensemble+Graph Signal Processing (GSP) was used. Similarly, 1(2%) Gradient Boosting (GB)+Decision Tree (DT) was used, 1(2%) Minimum spanning tree (MST)+SVM was used, 1(2%) PCA+Fast Fourier Transform (FFT) was used, and 1(2%) Multiview FBN fusion (MFBN) was used, given in Table 8.

3.5.3.1. Forest plot of hybrid models

The forest plot was also stacked for hybrid models from the largest year to the smallest year. Panel A presents the results of hybrid models from 2023 to 2024, and panel B presents the results of 2020 to 2023. The 5 models (MT-CNN+Attention, Ensemble+GSP, DCNN+AGO, CNN+KNN, CNN+ Multi Site AINN) achieved >95% accuracy rate for diagnosis of ASDs from HCs with very low risk rate. Similarly, 16 models such as (CNN+SVM, CNN+GSO, AL+NGAN, GB+DT, Siamese network, PCA+ANN, CNN+GCN+RNN, CNN+LERT, MK-RNN+GRU, HRVAE, DCNN+DMORN, HGCAN, Graph-RNN, MST+SVM, SAE+MLP, SNN+SFF) achieved >80% accuracy rate with low prediction risk of ASDs from HCs. Similarly, 21 models (CNN+DAE+SW, Multi-Atlas DEN, SAE+MLP, DGCN, OCN, RFE+GCN+PFC, CNN+AM, MFBN, FMC-BS+DRE, ST-ASDN, SA+GCN, VAE+MLP, ID+GCN, LASSO+HMM+LSTM, Multi-atlas GCN, AE+MLP, DAE+DCCF, CNN+GRU, AE+DNN, CNN+PL, and DQ-LE+SpinalNet) achieved <80% accuracy rate with a moderate prediction risk of ASDs from HCs given in Figure 6.

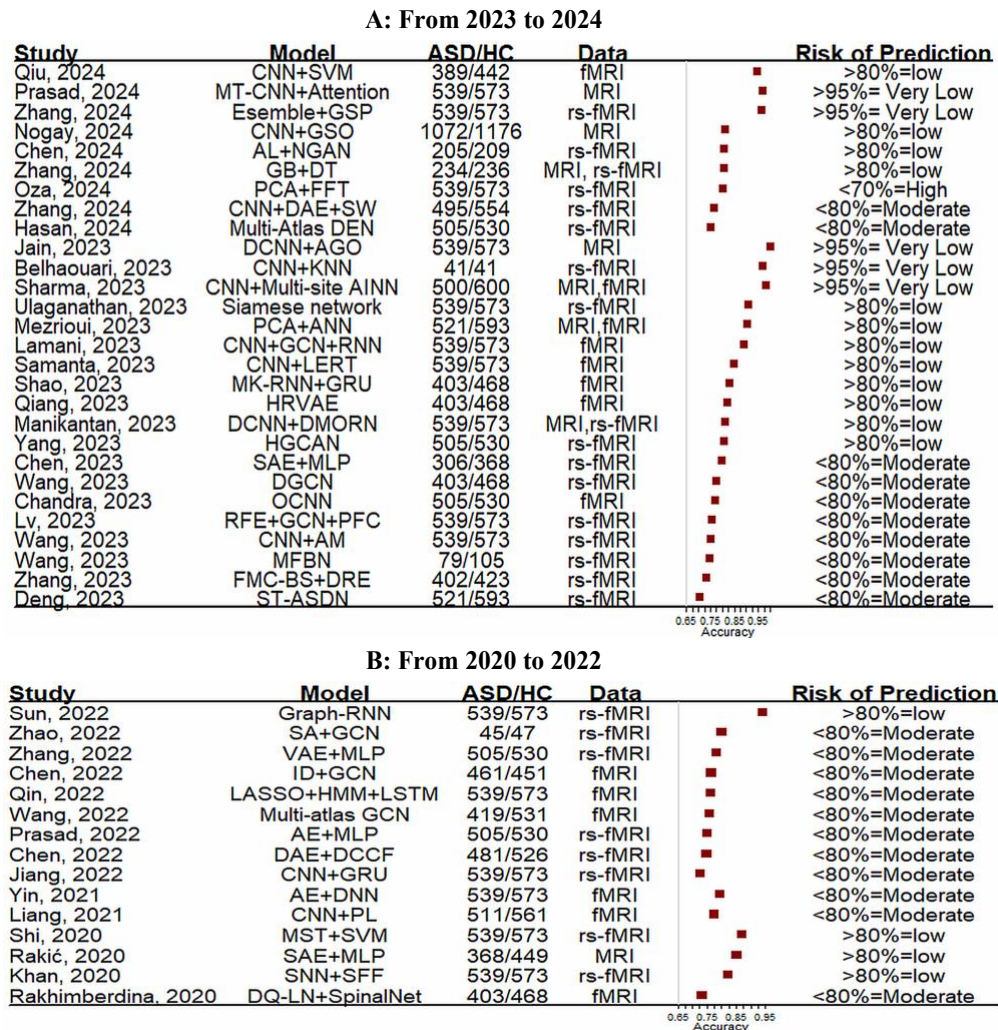


Figure 6: Forest plot of hybrid models, here dark red color boxes present the accuracy of each model.

3.6. Egger's test

The Egger's test was utilized to check the publication bias and small study effects in ML, DL and hybrid models [88]. The ML approach obtained a p-value of 0.834, which suggests that there is no substantial evidence of publication bias or small-study effects in ML models. Similarly, the p-values of DL and hybrid models were 0.001 and 0.001 respectively. The smaller p-values suggest that there is substantial evidence of publication bias or small-study effects in DL and hybrid models given in Table 9.

Table 9: Egger's test of publication bias for ML, DL, and hybrid models of selected articles.

	Intercept	Slope	P-value	Conclusion
ML	-1.235	0.292	0.834	There is no substantial evidence of publication bias or small-study effects in ML.
DL	-16.551	0.521	0.001	There is substantial evidence of publication bias or small-study effects in DL
Hybrid	-16.045	0.520	0.001	There is substantial evidence of publication bias or small-study effects in hybrid.

4. Discussion

In this review, we extracted 512 research articles using Google Scholar: 450, ScienceDirect: 43, and PubMed: 19. After screening and cleaning, a total of 65 articles were included (Google Scholar:53, ScienceDirect: 6, and PubMed: 6) to fulfill the study aims. Among the 65 articles, 5 (8%) articles used ML models, 17 (26%) articles used DL models, and 43 (66%) articles used hybrid models to assess the accuracy rate for diagnosis of ASDs from HCs. The 3 (6%) articles were included from 2020, 8 (15%) from 2021, 9 (17%) from 2022, 21 (40%) articles from 2023, and 12 (23%) articles from 2024 in the Google Scholar database. Similarly, 2 (33%) articles were included from 2020, 1 (17%) from 2021, 2 (33%) from 2023, and 1 (17%) from 2024 in the PubMed database. Similarly, 2 (33%) articles were included from 2020, 1 (17%) from 2022, 2 (33%) from 2023, and 1 (17%) from 2024 in the ScienceDirect database. The 2 articles used ML models, 12 used DL models, and 39 articles used hybrid models in Google Scholar. The 4 articles used DL models, and 2 used hybrid models in PubMed. The 3 articles used ML models, 1 used the DL model, and 2 used hybrid models in ScienceDirect to assess the accuracy of ASDs diagnosis from HCs.

4.1. Similarity and publication bias

This study observed that 5 (8%) studies used the MRI dataset, 21 (32%) used the fMRI dataset, 5 (8%) studies used MRI and fMRI both datasets, 2(3%) studies used MRI, rs-fMRI both datasets and 32 (49%) studies used rs-fMRI dataset to diagnose the ASDs from HCs given in Table 3. The 26 studies used ASD/Hc (205/209, 234/236, 240/284, 306/368, 317/400, 389/442, 402/423, 402/464, 408/476, 41/41, 461/451, 481/526, 495/554, 500/600, 511/561, 529/573, 634/800, 79/105, 100/100, 1072/1176, 150/150, 368/449, 403/468, 415/574, 419/530, and 419/531) respectively [76, 84, 30,64, 42, 45, 82, 35, 38, 47, 68, 65, 50, 54, 53, 31, 44, 87, 25, 52, 23, 63, 59, 24, 28, 67]. Similarly, 5 studies used 403: ASD, 468: HC, 2 studies used 45:ASD, 47:HC, 8 studies used 505:ASD, 530:HC, 2 used 521:ASD, 593:HC, and 22 studies used 539:ASD and 573:HC subjects [81, 29, 69, 40-41, 43, 55, 61-62, 75, 77, 66, 78, 26-27,32-34, 36, 46, 48-49, 51,56-58, 60, 71-72, 79-80, 83, 85-86] respectively. There is no substantial evidence of publication bias or small-study effects in ML models. However, there is substantial evidence of publication bias or small-study effects in DL and hybrid models, as given in Table 9.

4.2. Accuracy and dataset

In this review, we determined that out of 65(100%) studies, 16 (25%) included articles have 70%-75% accuracy rate, 19 (29%) articles have 75.05%-80% accuracy, 14 (22%) articles have 80.05%-85% accuracy rate. Similarly, 6 (9%) articles achieved an 85.05%-90% accuracy rate, 4(6%) included articles achieved a 90.05%-95% accuracy rate, and 6 (9%) articles achieved >95% classification accuracy rate of ASDs from HCs. Only 6 articles using (GAT2, MT-CNN+Attention, Ensemble+GSP, DCNN+AGO, CNN+KNN, CNN+ Multi Site AINN) models achieved >95% accuracy rate, which describes the potential ability of discrimination. The GAT2 is a DL model and (MT-CNN+Attention, Ensemble+GSP, DCNN+AGO, CNN+KNN, CNN+ Multi Site AINN) were hybrid models. Across all included articles, 5 (8%) studies used the MRI dataset, 21 (32%) used the fMRI dataset, 5 (8%) studies used MRI and fMRI both datasets, 2(3%) studies used MRI, rs-fMRI both datasets and 32 (49%) studies used rs-fMRI dataset to diagnose the ASDs from HCs. The top 6 models utilized MRI, fMRI, and rs-fMRI scans to diagnose the ASDs from HCs.

4.3. Performance comparison

The pooled mean value for ML models is 0.768 or 76.80% of 5 studies, the pooled mean value of DL models is 0.801 or 80.10% of 17 studies, and the pooled mean value for hybrid models is 82% with 43 studies. Overall, the performance of hybrid models was better than that of ML and DL approaches. Specifically, the hybrid of the CNN model with other models achieved a higher accuracy rate of classification for ASD subjects using the MRI, fMRI, and rs-fMRI scans. The hybrid models could be used in clinical processes to diagnose ASDs from HCs. This is because 5 hybrid models (MT-CNN+Attention, Ensemble+GSP, DCNN+AGO, CNN+KNN, CNN+ Multi Site AINN) achieved >95% accuracy rate for diagnosis of ASDs from HCs with very low-risk rate.

4.4. Future research and practical implications

- This study revealed the ML, DL, and hybrid approaches to diagnose ASD from HC subjects using the ABIDE (MRI, fMRI, rs-fMRI) datasets.
- This study found that the hybrid of CNN with other models mostly achieved a high accuracy rate; therefore, future studies should focus on hybrid of the CNN with other models.
- Future studies should explore studies that involve the Regions of interest (ROI) based identification of ASDs from HCs using the ABIDE dataset.
- Future studies should include other brain disorders to compare the classification accuracy rate of ASDs and HCs. As well as larger datasets to observe the role of large datasets in the diagnosis of ASDs.
- Clinicians and researchers should further explore the use of hybrid models related to technology in clinical settings and the outcomes of using hybrid models in diagnosing ASDs.

5. Conclusion

This meta review covered recent studies in which ML, DL, and hybrid models were used to classify the ASDs from HCs. The goal of this study was to identify the most reliable approach to classify the ASD subjects using the fMRI, rs-fMRI, and MRI datasets. This study found from recent studies that the hybrid approach is the most reliable and suitable way to diagnose ASDs from HCs using their fMRI, rs-fMRI, and MRI brain scans. The hybrid approach can help in a faster and better way to declare a particular person as an ASD patient with a low risk of prediction. This meta review follows the PRISMA-ScR (Preferred

Reporting Items for systematic reviews and meta-analyses Extension for meta reviews) guidelines, published in 2018. To fulfill the study aims, the three databases (Google Scholar, PubMed, and ScienceDirect) were explored to retrieve the articles. The screening and cleaning approaches were utilized for included studies to enhance the search. Microsoft Excel and RStudio were used to estimate the pooled mean accuracy, similarity, forest plot, and publication bias.

This review only captured recent articles from three selected databases (Google Scholar, PubMed, and ScienceDirect) and other databases are excluded. Similarly, this study only focuses on MRI, fMRI, and rs-fMRI scans, and other types such as CT scans, PET scans, SPECT scans, EEG scans, etc. were excluded. Similarly, the articles were selected that only used the ABIDE datasets and all others were excluded. Moreover, we only focused on articles published from 2020 to 2024. Articles not published in English were excluded. Furthermore, we only included ML, DL, and hybrid models that were used to diagnose the ASDs from HCs with a >70% accuracy rate. All other articles that used the ABIDE data of ASD subjects for functional connectivity processes or to check region severity were excluded.

5. 1 Future research and practical implications

This study revealed the ML, DL, and hybrid approaches to diagnose ASD from HC subjects using the ABIDE (MRI, fMRI, rs-fMRI) datasets. Additionally, it is found that the hybrid of CNN with other models mostly achieved a high accuracy rate; therefore, future studies should focus on hybrid of the CNN with other models.

Future studies should explore studies that involve the Regions of interest (ROI) based identification of ASDs from HCs using the ABIDE dataset. It might include other brain disorders to compare the classification accuracy rate of ASDs and HCs. As well as larger datasets to observe the role of large datasets in the diagnosis of ASDs.

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Appendix A: List of Abbreviations

Acronym	Phrase
ASD	Autism spectrum disorder
ML	Machine learning
DL	Deep learning
ABIDE	Autism Brain Imaging Data Exchange
PRISMA-ScR	Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews
rs-fMRI	Resting state- functional magnetic resonance imaging
CT	Computerized tomography
PET	Positron Emission Tomography
SPECT	Single Photon Emission Computed Tomography
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
CBF	Cerebral Blood Flow
CNN	Convolutional neural network
SVM	Support vector machine
GCN	Graph Convolutional Networks
MLP	Multilayer perceptron
LR	logistic regression
LSTM	Long Short-Term Memory
GAT	Graph attention network
SAE	Sparse autoencoder
PL	Prototype learning
AGOE	Artificial Gannet Optimization enabled
DMORN	Dwarf Mongoose optimized Residual Network
HRVAE	Hierarchical recurrent variational AE
DCCF	Deep Canonical Correlation Fusion
PCA	Principal component analysis
ANN	Artificial neural network
GGCN	GraphGCN
RFE	Recursive Feature Elimination
GRNN	Graph-Recurrent neural network
HMM	Hidden Markov model
NGAN	Node edge graph attention network
HGCAN	Heterogeneous graph convolutional attention network
ST-ASD-N	Spatio-Temporal ASD Network
SNN	Student Neural Networks
SFF	Sequential Feed Forward