Received: 20 May 2025 | Revised: 10 September 2025 | Accepted: 15 October 2025 | Published online: 19 December 2025

REVIEW

Journal of Computational and Cognitive Engineering
2025, Vol. 00(00) 1-27
DOI: 10.47852/bonviewJCCE52026197

BON VIEW PUBLISHING

Nonclinical Approaches to Autism Trait Prediction Using Deep Learning: An Extensive Review

Ranjeet Vasant Bidwe[1,*], Sashikala Mishra[1], Simi Bajaj[2], Suraj Sawant[3,*], Kailash Shaw[4] and Ketan Kotecha[1,5]

[1] *Symbiosis Institute of Technology (Pune Campus), Symbiosis International (Deemed University), India*

[2] *School of Computer Data and Mathematical Sciences, Western Sydney University, Australia*

[3] *Department of Computer Science and Engineering, COEP Technological University, India*

[4] *Department of Computer Science and Engineering (AI&ML), Vishwakarma Institute of Technology, India*

[5] *Symbiosis Centre for Applied Artificial Intelligence, Symbiosis International (Deemed University), India*

Abstract: Autism spectrum disorder (ASD) is a neurodevelopmental condition characterized by difficulties in communication and social behavior. Early identification of autistic traits is necessary for timely treatment. However, clinical diagnostic methods remain costly, time-consuming, and inaccessible. AI-guided nonclinical screening techniques such as eye tracking and behavior analysis may offer a promising alternative. This is the first systematic bibliometric analysis attempting to discuss the effectiveness, limitations, and trends of AI-based methods proposed for identifying autistic traits using nonclinical analysis. The current study is an unprecedented bibliometric analysis of 152 Scopus and Web of Science articles (2018–2025). This analysis uses VOSviewer and Gephi to map different relations. Deep learning and hybrid transfer learning yield better results. However, most of the proposed methods possess low specificity. The proposed research establishes eye-gaze analysis as the most commonly employed technique in the present study, while key behavioral cues—facial expressions, attention changes, and verbal patterns—are yet to be studied. The key shortcoming is that no standardized evaluation system exists, with earlier work lacking rigorous benchmarks for specificity, interpretability, and bias mitigation. Furthermore, while transfer learning techniques are widely used due to dataset scarcity, no publicly available video-based datasets exist, restricting the development of multimodal ASD screening models. To fill these gaps, this paper suggests a benchmarking framework that focuses on multifeature evaluation (facial expressions and attention shifts) for better diagnosis. In addition, standardized specificity thresholds support clinical reliability and foster geographically diverse, openly available datasets to obtain fairness and generalizability. This study provides the bibliometric synthesis of nonclinical AI-based ASD screening. It proposes a benchmarking framework with multifeature evaluation, standardized specificity thresholds, and diverse open datasets and maps data modalities to suitable deep learning models. These contributions provide practical guidance and deliver actionable insights to advance scalable, multimodal, and interpretable ASD screening tools for early, noninvasive detection.

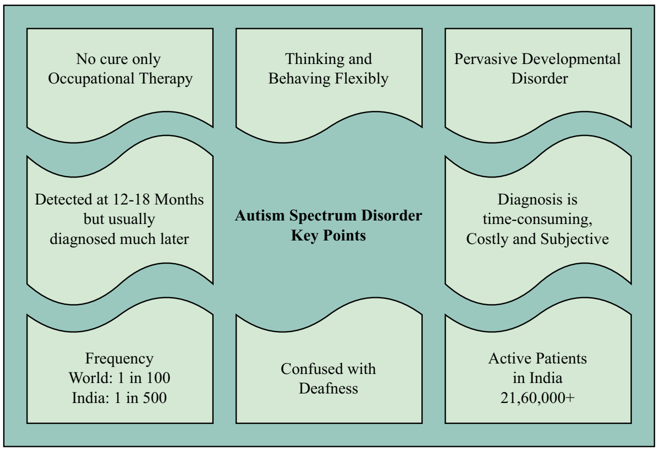
Keywords: autism spectrum disorder (ASD), artificial intelligence, deep neural network (DNN), eye tracking, behavioral analysis, feature extraction and selection, classification

1. Introduction

"Autism spectrum disorder" (ASD) is a disability in children's mental development [1]. Symptoms are generally observed when children are 12–18 months and diagnosed at the age of 2 years. The social behavior of a child with ASD is typical and can be easily identified in a group of children. Depression, anxiety, epilepsy, attention deficit hyperactivity disorder, difficulty sleeping, and self-injury are the significant symptoms observed in India. Children with ASD are unaware of or not interested in activities in their surroundings. They find it troublesome to deal with changes in places, food, people, or the regular placement of their belongings and communicating with others [2]. One common observation in a child with ASD is unusual movements in a crowd of children. In addition, they are extra active in routine day-to-day activities and perform restricted and repetitive exercises. Sometimes ASD is confused with deafness, where a child cannot talk because of deafness. However, doctors or parents perceive it as one of the symptoms of ASD. Figure 1 presents all notable key points regarding ASD. ASD has become an issue of concern worldwide. More than 1% of the children in the world are facing this problem. The overall count of patients has increased by 178% since 2020. One child in 100 children has autistic symptoms in India [3]. One of the major reasons behind the increase in the count is social stigma. In countries like India, many parents hesitate to reveal their child's disability. They feel uncomfortable discussing their child at social gatherings, fearing that other people or children will make fun of them. Another issue commonly observed in India is ignorance regarding this disease. To

***Corresponding author:** Ranjeet Vasant Bidwe, Symbiosis Institute of Technology (Pune Campus), Symbiosis International (Deemed University), India. Email: ranjeet.bidwe@sitpune.edu.in and Suraj Sawant, Department of Computer Science and Engineering, COEP Technological University, India. Email: sts.comp@coeptech.ac.in

Figure 1
ASD: key points to remember



address this issue and create awareness, April 2 is observed annually as World Autism Awareness Day (WAAD), where autism is discussed, which is otherwise overlooked. However, this is not enough; proper education and awareness are required so that people can accept this as any other socially accepted disorder and seek help [1].

2. Methods of Diagnosis

It is essential to understand that although there is no clinical test, such as a blood test, for the diagnosis of ASD, several assessment tools are widely used in clinical practice. Examples include the Modified Checklist for Autism in Toddlers, Autism Diagnostic Observation Schedule, and Autism Diagnostic Interview-Revised [4]. These tools enable clinical diagnosis and extensive clinical investigations, for example, structured interviews with the parent or caretaker, detailed behavioral observation, and neuropsychological assessments. In addition to this, several clinical methods such as fMRI, EEG [5], fNIRS, and MEG [6] provide a great value in research. Their help in mapping neurological patterns is seldom, if ever, done in clinically ASD diagnostic purposes. This research effort puts into perspective nonclinical diagnostic methods that complement the clinical approaches, focusing on indirect observational methods, developmental history, and specific attributes such as eye-gaze patterns. Such a distinction helps in attaining a holistic understanding of diagnostic pathways and underlines the potential of nonclinical methods to serve as supportive tools in early detection.

In addition to behavioral and observation diagnosis, the contribution of genetic testing in the diagnosis of ASD cannot be gainsaid. More recently, genetic testing has been recommended for all children who are diagnosed with ASD because this can explain an underlying molecular or genetic etiology in a sizable proportion. Techniques such as CMA and WES have been very useful in identifying genetic variations related to autism. Identifying the underlying genetic factors will not only facilitate a more specific diagnosis but also lead to individualized treatment and intervention that may benefit affected individuals and their families. Although the current research relates to nonclinical testing methods, incorporating information obtained from genetic testing can yield more valid diagnoses and more information regarding the etiology of ASD. Figure 2 summarizes various approaches used for the identification of autistic traits.

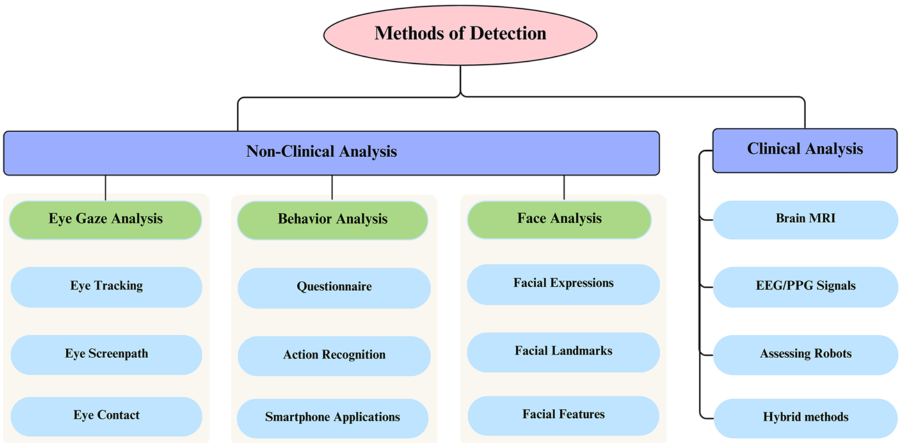
The attributes considered are the child's attentiveness during activities, eye movement or eye position while observing objects, and expressions on the children's faces during activities [7]. Measuring stress may also help in predicting ASD traits, which is also tested [8]. Because doctors are the ones who provide a diagnosis, this may be subjective. Sometimes, this method may provide a misleading diagnosis because there is no specific set of identifiable attributes that can describe the symptoms of ASD as yet. This disorder is called a spectrum disorder because each child may have distinctive behavior, which makes a clear diagnosis a challenging exercise.

Existing proposed approaches that perform nonclinical analysis use eye-gaze analysis, including eye tracking, eye movement, or eye positioning as an attribute for prediction. Children's eye movement is one of the essential attributes in detecting ASD. However, there can be various reasons for not having a fixed or stable eye movement. The main issue with the nonclinical method of diagnosis is that it is very time-consuming and costly because it involves several hours spent with doctors to observe or perform the gait analysis activities. Most parents cannot afford this method.

AI has become very popular in the last decade. It has been proven to be a very efficient method for solving real-time issues [9]. Many bibliometric studies have demonstrated the effectiveness of DNN methods in addressing various complex problems. The adaptive nature of DNN helps in supporting a variety of multimodal input data [10]. A DNN model that works efficiently on images can also be used on video data. We can observe the continuous improvement in the accuracy of the model as we train the model. In addition, transfer learning methods can be very useful when a dataset has limited data inputs.

This paper provides information on bibliometric studies performed on articles that have used AI-based approaches to analyze

Figure 2
Methods for identifying autistic traits



ASD. The articles considered for this study are downloaded from two famous databases, namely, “Scopus” and “Web of Science.”

This study is divided into two sections. First, quantitative analysis includes studying documents and providing information such as country, source, type of publications, year, citation, and keywords. The second part is a qualitative analysis that discusses the types of datasets available for study, the mainframe approach of prediction, the method used, results, and observations from the analysis using the proposed approaches. In addition, it discusses the performance metrics used for prediction. The insights of this analysis are as follows:

1) What are the key trends and findings from the bibliometric study of AI-based approaches for nonclinical ASD screening, particularly in behavioral analysis?
2) How effective are deep neural networks (DNNs) compared to traditional machine learning (ML) models in ASD trait identification, and what are the major challenges related to dataset availability, specificity, and model reliability?
3) How can novel behavioral markers, such as attention and emotional expressions, enhance ASD screening, and what is the need for a multifeatured, multimodal analysis?
4) How can transfer learning and explainable AI improve the performance, interpretability, and reliability of ASD prediction models?
5) What standardized statistical methods are required to validate AI models for ASD screening and ensure consistent, reliable results?

Unlike prior reviews that primarily summarize clinical approaches or reiterate general limitations such as dataset scarcity, this study offers the first bibliometric and qualitative synthesis of non-clinical, AI-driven ASD screening methods. It introduces a bench-marking framework to address specificity, interpretability, and fairness and identifies underexplored behavioral markers (e.g., verbal cues, micro-expressions, and motion-based features). Furthermore, by mapping data modalities (images, videos, and motion sensing) to appropriate deep learning models, this study provides practical guidance for future research and system design.

The organization of this paper is shown in Figure 3 and is presented as follows: Section 3 explains the research strategy and data analysis procedure, Section 4 starts with a quantitative analysis, Section 5 explains the qualitative analysis, Section 6 discusses the performance metrics used by the proposed approaches, Section 7 is a discussion section where the key observations and challenges of this study are discussed, and finally, Section 8 presents the conclusion and future scope of this study.

3. Research Strategy and Data Analysis Procedure

One of the famous evaluation techniques used to assess research needs is bibliometric analysis [11, 12]. In bibliometric analysis, we rigorously analyze academic literature and its scholarly communication. This analysis will help in creating a high research impact, identifying and computing knowledge gaps, resulting in deriving novel ideas in the field of study.

In this study, research documents were retrieved from two widely recognized and authoritative databases—Scopus and Web of Science (WoS). These platforms were selected due to their extensive coverage, reliability, and acceptance in bibliometric studies worldwide.

1) Scopus, introduced by Elsevier in 2004, is the largest peer-reviewed research database, encompassing a broad range of disciplines, conference proceedings, and journals. Its comprehensive citation data and advanced search features make it highly suitable for bibliometric mapping.
2) Web of Science, initially developed by Thomson Reuters and now maintained by Clarivate, offers curated coverage of the Science Citation Index (SCI) and the Social Sciences Citation Index (SSCI). It is recognized for its stringent indexing criteria and is widely used for high-quality citation analysis and trend mapping.

The inclusion of both databases ensures the completeness and reliability of the dataset, reduces potential bias from relying on a single source, and provides robust citation metadata required for tools such as VOSviewer and Gephi. These qualities make Scopus and WoS not only “famous” but also the most credible and comprehensive sources for conducting bibliometric analyses in scientific research.

Figure 4 presents the search strategy and Table 1 presents the keywords used for identifying relevant documents from the databases. The fundamental keywords for retrieving documents were “autism spectrum disorder” and “ASD.” Additional keywords were identified from abstracts and prior literature trends. Specifically, “deep neural network” and “transfer learning” were included because these techniques are highly prevalent in recent nonclinical ASD detection studies. In particular, transfer learning was considered essential due to the scarcity of large-scale, domain-specific datasets in autism research, which has led researchers to adapt pre-trained models (e.g., VGG, ResNet, and EfficientNet) for tasks such as gaze analysis, facial expression recognition, and behavioral feature extraction. By contrast, domain-specific terms such as “MRI” and “ABIDE” were excluded because the focus of this study was limited to nonclinical approaches. The detailed queries used in Scopus and Web of Science are presented below.

1) Query in Scopus:

(TITLE (ASD) OR TITLE (autism) OR TITLE (“Autism spectrum disorder”) AND TITLE-ABS-KEY (“Deep Neural Network”) AND NOT ALL (MRI)) AND PUBYEAR > 2011.

2) Query in WoS:

(“ASD” (Title) OR “Autism Spectrum Disorder” (Title), AND “Deep Neural Networks” (All Fields) AND “DNN” (Abstract) AND “DNN” (Keyword Plus) NOT “MRI” (All Fields) NOT “ABIDE” (All Fields) AND 01-01-2012 to 31-10-2022 (Publication Date)).

When the above queries were given for the search, 114 and 89 documents were retrieved from the databases “Scopus” and “Web of Science,” respectively. After removing duplicates, the final 152 papers were selected for further analysis. Metadata was extracted for these selected 152 documents, which have detailed information such as the

Figure 3
Organization of this paper

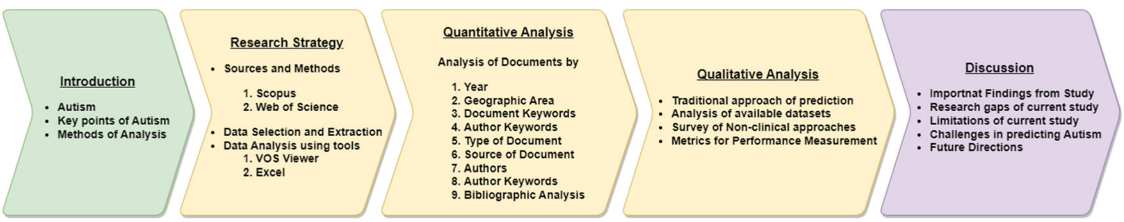


Figure 4
Search strategy for extracting documents

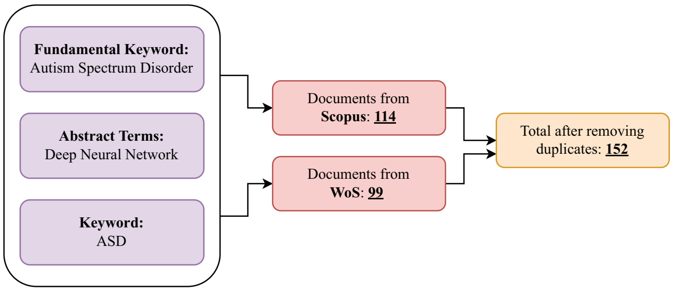


Table 1
List of keywords used in the query

Fundamental keyword	ASD, "autism spectrum disorder"
Primary keyword using "AND"	Deep neural networks
Secondary keywords using "OR"	"Neural network," "transfer learning"
Secondary keywords using "NOT"	"MRI," "ABIDE"

name of the paper, the author's name, the country and organization, the keywords used, the abstract, the year of publication, the publication type, the details of the publisher, the number of citations, and the details of the funding agency, if any. These details were retrieved on March 1, 2025, and were used for further analysis.

The objective behind graphs is to analyze and understand the information studied easily and make it more interactive. These graphs were drawn using the software tools "VOSviewer" [13], "Gephi" [14], and "BibExel" [15]. These tools help in representing multidimensional data in graphical visualization. We can form different types of networks of authors, author keywords, sources of publication, country of publication, citations, co-citations, bibliographic couplings, etc. These tools are freely available for educational purposes. The following quantitative analysis is conducted in this paper:

1) Year-wise analysis of documents
2) Analysis of citations received
3) Analysis of top keywords
4) Analysis of the type of document
5) Analysis by geographical area
6) Co-occurrence analysis for author keywords
7) Citation analysis of the documents
8) Citation analysis of the source of publication
9) Analysis of the author by citations
10) Bibliographic coupling of the documents.

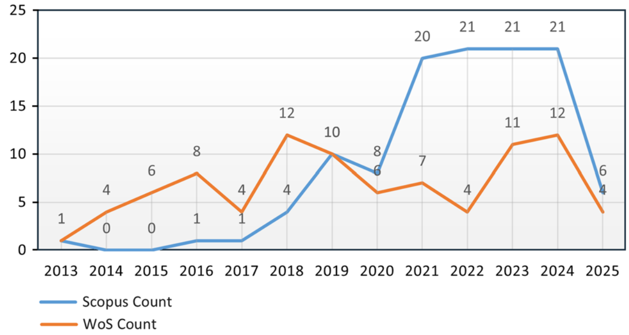
In this study, the quantitative analyses were carried out with the primary goal of providing a comprehensive overview of the research landscape on nonclinical AI-based ASD detection. Specifically, these analyses aim to (i) trace the publication trends over time to understand the growth of interest in this domain, (ii) map collaborative networks among authors, institutions, and countries to highlight influential contributors and partnerships, (iii) analyze keyword co-occurrence and thematic clusters to uncover prevailing research themes, (iv) examine methodological preferences, such as the use of deep learning, transfer learning, and eye-gaze analysis, and (v) identify research gaps and future opportunities by correlating quantitative patterns with observed shortcomings such as dataset scarcity and lack of standardization. By aligning these objectives, quantitative analysis provides both a statistical foundation and meaningful insights that strengthen the bibliometric mapping of nonclinical approaches for ASD detection.

4. Quantitative Analysis

4.1. Year-wise analysis of documents

The prediction and analysis of ASD are always challenging. Several studies have been published regarding prediction. Let us analyze all studies published over the last 4–5 decades. We can find that several multidisciplinary studies have been published in medicine, neurology, psychology, and engineering. In this analysis, we have considered documents published in the engineering domain that perform behavioral analysis. Approximately 114 documents in Scopus and 89 in WoS have been published in the last decade. Since 2018, most of the documents have been published, which indicates that substantial work is ongoing in this field of study. Figure 5 gives the detailed statistics of the same.

Figure 5
Publication by year from Scopus and WoS



4.2. Analysis of citations received

The citations received for the documents represent the importance and relative significance of the solutions or approaches proposed for the topic. Table 2 provides the detailed statistics of the citations received for the documents published in Scopus and WoS libraries. It has been observed that since 2018, more citations have been received for the documents. Tables 3 and 4 provide a list of the top 5 documents as per the count of citations received.

Figure 6 shows the alluvial diagram. The representation of the variations in flow over time and phases is known as an alluvial diagram or alluvial plot. This type of diagram is generally used to visualize the flow of complex data attributes, which is essential for understanding data. In this diagram, multiple vertical axes are allocated to the different variables. In addition, data values are presented in blocks on each axis.

Figure 6 provides a correlation between authors, publication year, and citation count of the top 20 highly cited documents downloaded from the Scopus database. This figure is created using rawgraphs.io. It shows the flow of the data from the author to the number of citations through the year of publication. The first vertical axis, named "Author," represents author names; the second axis, named "Year," represents the year of publication; and the third axis, named "Cited by," represents the number of citations received. The authors on the first axis are written in descending order based on the received citations. The connection is initiated from the first axis (author) of the author names. Then, it passes through a second axis (year) representing the year of publication. The same connection is continued to the last axis (cited by) to the block of its respective citation count, e.g., connection initiated for the paper authored by Jiang M and Zhao Q (axis "Authors") connected to block 2017 (axis "Year") and continued to block 92 (axis "Cited by"). This diagram provides the details of the papers published each year and the number of citations that they received. According to the analysis, most publications were published in 2019, but papers published in 2018 had a high impact because they received the largest number of citations. In

Table 2
Year-wise citations

Year	<2018	2018	2019	2020	2021	2022	2023	2024	2025	Total
Scopus citation	9	12	40	69	148	247	352	525	129	1531
Web of Science citation	51	37	47	54	59	76	82	54	18	478

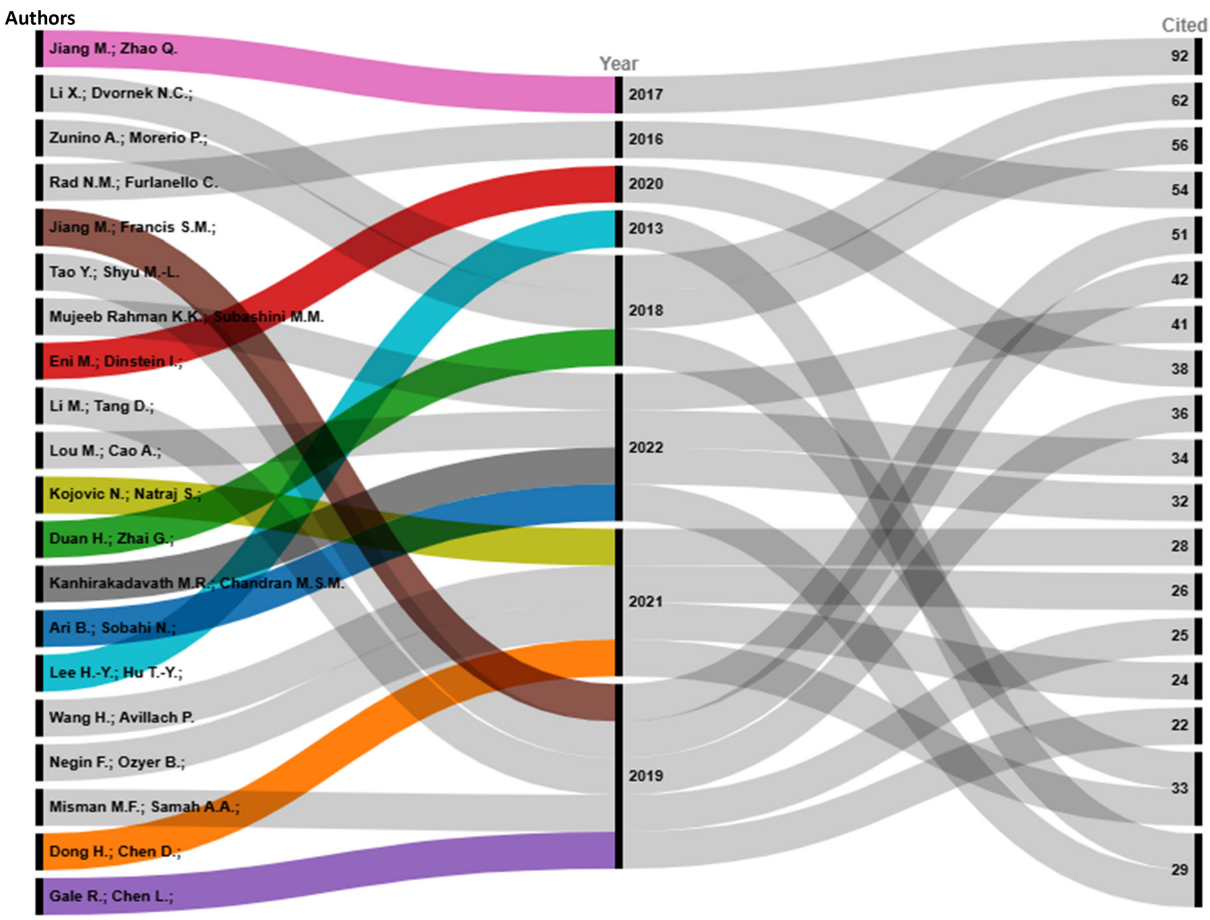
Table 3
Top 5 publications in Scopus (as per citations)

References and years	<2019	2020	2021	2022	2023	2024	2025	Total
[16] 2017	15	11	18	21	22	27	4	118
[17] 2018	3	9	10	12	16	14	4	68
[18] 2018	5	12	15	15	10	7	1	65
[19] 2018	0	5	8	12	14	22	4	65
[20] 2016	14	8	7	14	8	6	1	58

Table 4
Top 5 publications in WoS (as per citations)

References and Years	<2019	2020	2021	2022	2023	2024	2025	Total
[21] 2014	37	7	7	5	6	7	0	69
[22] 2015	29	10	9	7	7	5	0	65
[23] 2020	0	3	13	12	9	8	1	45
[24] 2016	13	4	8	9	6	2	0	42
[25] 2018	10	6	7	9	1	5	1	39

Figure 6
Alluvial diagram of the top 20 documents with the highest number of citations

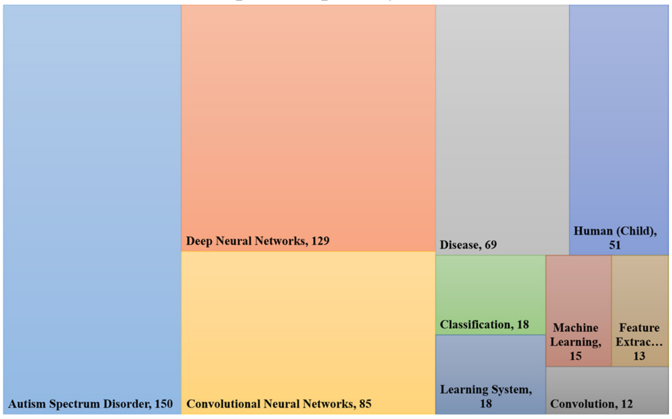


addition, it concludes that more focus is on prediction using nonclinical analysis.

4.3. Analysis of top keywords

Figure 7 shows a treemap representing the top 10 author key-words of documents downloaded from Scopus. "Autism spectrum disorder" is the most common keyword, i.e., 150 times.

Figure 7
Top 10 Scopus keywords



"Deep neural network" occurred 129 times, and it ranked second. "Human," especially a child, is the keyword that occurs most of the time, which shows that a majority of work is carried out on children. In addition, it is mostly completed using CNN, so "convolutional neural network" is one of the most common keywords. "Disease," "autism," and "classification" are the other most occurring keywords. "Transfer learning" is the keyword that occurs less frequently, showing that there is a scope for working with transfer learning models in this domain. The later section will present the co-occurrence analysis for all key-words.

4.4. Analysis of the type of documents

Figures 8 and 9 show an analysis of the types of documents published in the field of study. Approximately 55% of papers are conference papers, and 44% are journal articles published in Scopus. In WoS, approximately 51% are conference papers, and 47% are journal

Figure 8
Document type published in Scopus

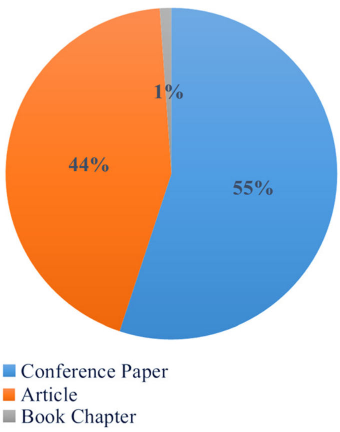
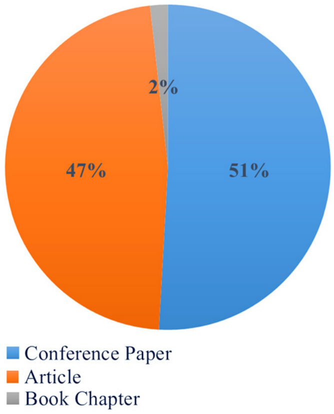


Figure 9
Document type published in WoS



articles. The remaining published documents are book chap-ters. Few literature surveys have been found on the topic, and no bibliometric analysis has been published yet.

Table 5 shows detailed information on the type of documents published in predicting ASD using DNN. A total of 114 and 89 papers were published in Scopus-indexed and WoS-indexed events, respec-tively. Out of 203 documents published, approximately 107 docu-ments are conference papers. A total of 93 are journal articles.

Table 5
Publication counts by document type

Type of publication	Scopus	Web of Science	Total
Conference paper	58	49	**107**
Article/journal	54	39	**93**
Book chapter	2	1	**3**
	114	**89**	**203**

4.5. Analysis by geographical area

An analysis by geographical area will provide detailed infor-mation on countries actively working in that area to conduct research in a particular domain. It shows the severity of the research problem statement and the need for a solution to that problem. Figures 10 and 11 are bar graphs providing information for documents published country-wise. The USA and India are the leading countries in pub-lishing documents. The USA has published most of the documents in WoS, with a total of 18. India ranked second in the WoS publication list. India has published 14 documents. India has published the greatest number of documents, i.e., 40, in Scopus. The USA has published 17

Figure 10
Scopus country-wise publications

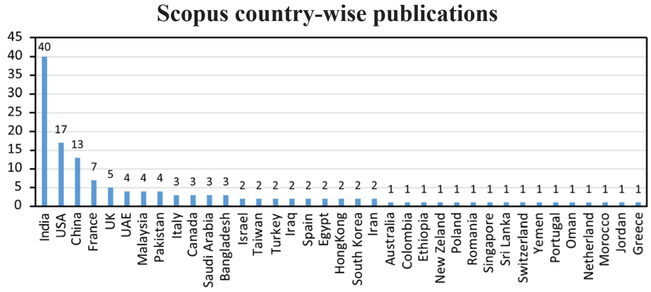
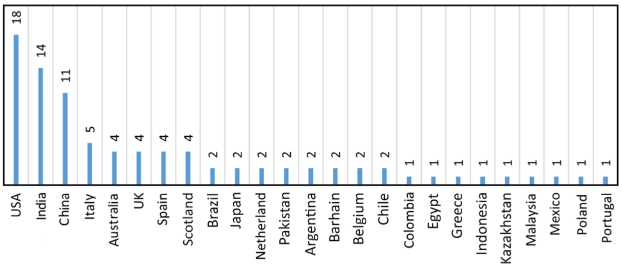


Figure 11
WoS country-wise publications



documents, ranking second. The "National Natural Science Foundation of China," "National Science Foundation," "Natural Sciences and Engineering Research Council of Canada," "United States Department of Health Human Services," "Wuhan University of Science and Technology," "Institute of Automation Chinese Academy of Sci-ences," and "National Institute of Health (NIH) USA" are the funding agencies who have supported these publications.

4.6. Co-occurrence analysis for author keywords

Figure 12 shows the co-occurrence analysis of the author key-words selected from the documents downloaded from Scopus and WoS. "Autism spectrum disorder" is the most frequently used key-word. Other keywords are deep learning, autism, CNN, video atten-tion, transfer learning, etc.

Table 6 gives detailed information regarding keywords, their number of links, and total link strength (TLS) values. Link strength and TLS are weighted attributes. Link attribute is a measure of co-authorship of a given author with other authors, and TLS represents the total strength of co-authorship links between the respective re-searchers and other researchers. "Autism spectrum disorder" has the

Table 6
Author keywords: occurrence, number of links, and TLS

Keyword	Occurrence	Number of links	Total link strength (TLS)
Autism spectrum disorder	39	135	182
Deep neural network	23	52	114
Deep learning	19	58	79
Autism	18	74	93
Convolutional neural network/s (CNN)	13	49	70
Machine learning	8	31	38
ASD	8	34	38
Classification	6	20	24
Visual attention	5	20	23
Transfer learning	4	18	21

largest number of links, i.e., 135, which means that this keyword is used 135 times in the documents in the domain, and a TLS value of 182 means that 182 co-authors have used this keyword in their documents. Figure 13 shows the co-occurrence analysis for all keywords.

4.7. Citation analysis of documents

The citations of the paper represent the impact of the work in the respective domain. Co-citation analysis will result in finding the most influential publication. A detailed analysis of the citations of the

Figure 12
Co-occurrence analysis for author keywords

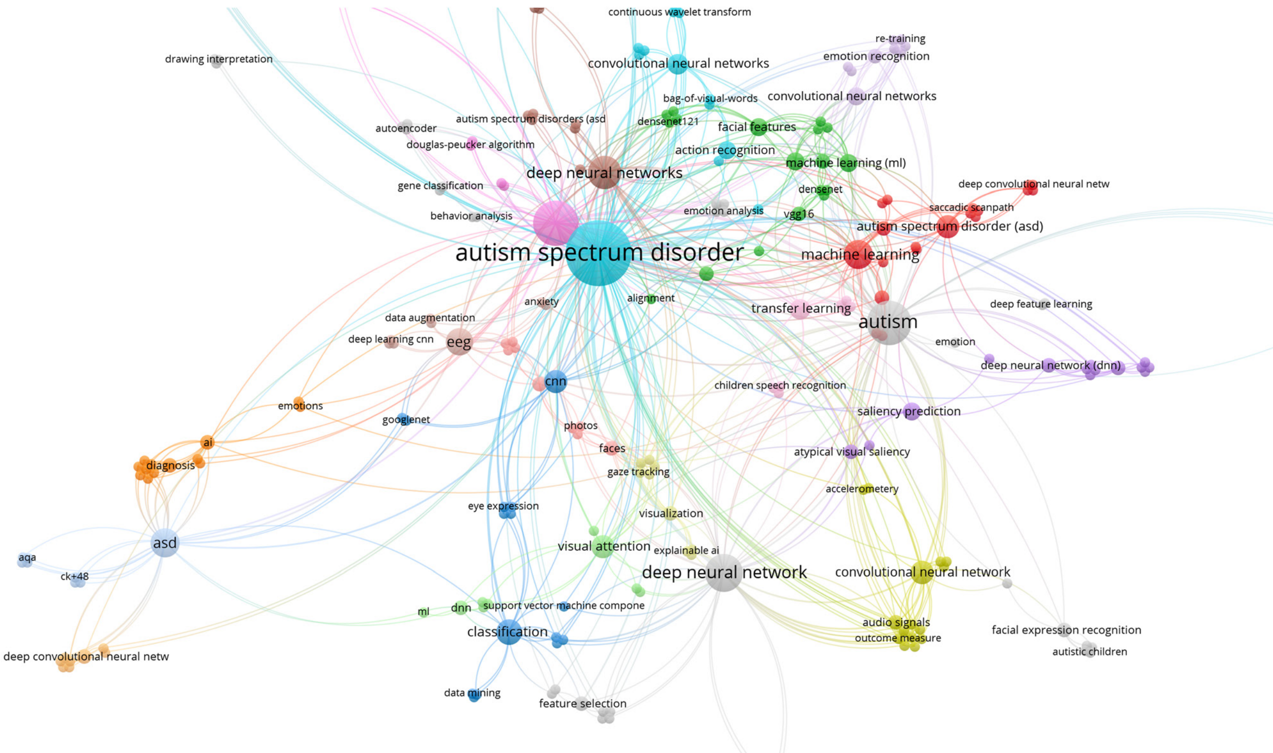
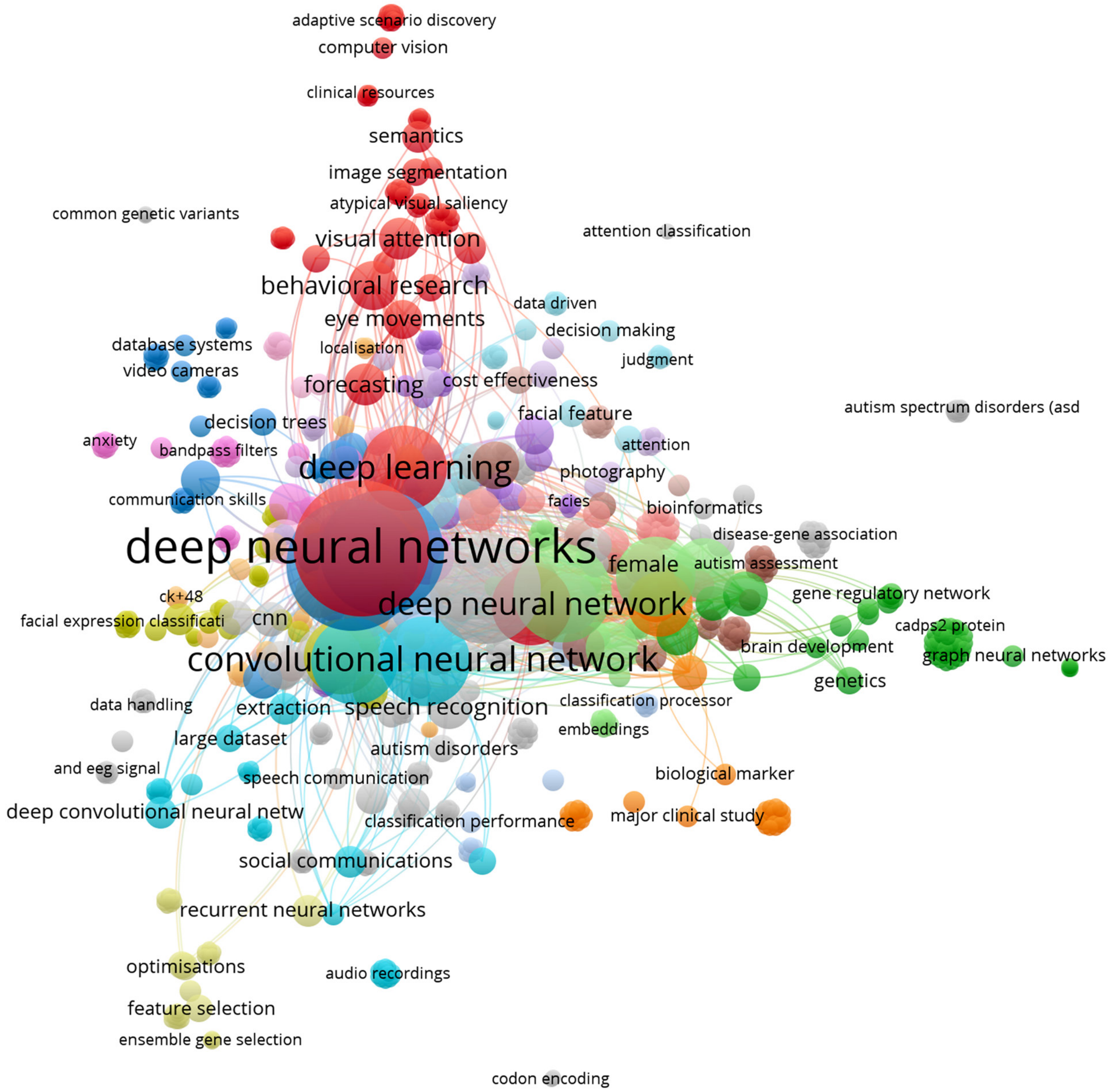


Figure 13
Co-occurrence analysis for all keywords

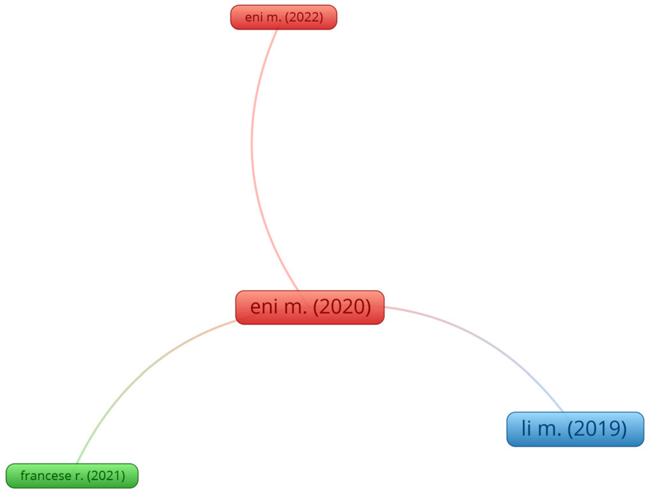


documents is shown in Table 7. The paper written by Jiang et al. [19] received the most citations, i.e., 118. Zakari et al. [21] received 69, and Zunino et al. [17] received 68. These citations are from the most recently published documents. This concludes that a significant amount of work is ongoing in the field and requires more attention to provide a solution to the problem. After analysis, it was found that four documents by Eni et al. [26], Li et al. [27], Eni et al. [28], and Francese et al. [29] have cited papers from the above list for analysis. Figure 14 shows a graph of the citation analysis generated by the software VOSviewer. It represents nodes generated by the authors (different colors for each author) and links between these papers. If papers from different authors have cited each other, then the link connecting them will have a mixed color. Eni et al. have published two papers in the same domain, and their latest paper [28] has cited their previous paper [26], which is shown in red color. The link between papers written by Francese et al. [29] and Eni et al. [26] and that between papers written by Li et al. [27] and Eni et al. [26] have mixed colors.

Table 7
Top 10 cited documents

Document	Citation
Jiang and Zhao [16]	118
Zakari et al. [21]	69
Zunino et al. [17]	68
Li et al. [18]	65
Jiang et al. [19]	65
Barakova et al. [22]	65
Rad and Furlanello [20]	58
Li et al. [23]	45
Tao and Shyu [30]	42
Eni et al. [26]	38

Figure 14
Citation analysis document



4.8. Citation analysis of the source of publication

Figure 15 shows a co-occurrence analysis of publication sources. Conferences and journals have their own set of domains of the documents that they publish. Sometimes it becomes difficult to find a publication source to publish the research. This section will help new researchers find the source to publish their articles. Figure 15 presents the potential relationship between four publication sources: "IEEE Access," "Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)," the "International Conference on Information Visualization," and "Computer Speech and Language," which are represented using nodes with different colors. Mixed-color links connecting various nodes denote that papers from the source have cited each other.

Table 8 shows the top 5 publication sources by Scopus. "Neurocomputing" is the top source, with 4 published documents and 58 citations. "IEEE Access" is another journal source with 3 documents and 51 citations. Approximately 50% of the documents are published at conferences. "Lecture Notes in Computer Science, Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics," "Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)," and "ACM Conference Proceedings" are the top conference sources where three documents are published each with a good number of citations. Table 9 shows the top 5 publication sources by WoS. "Lecture Notes in Computer Science" has published the largest number of documents, i.e., 9.

Figure 15
Citation analysis of the source of publication

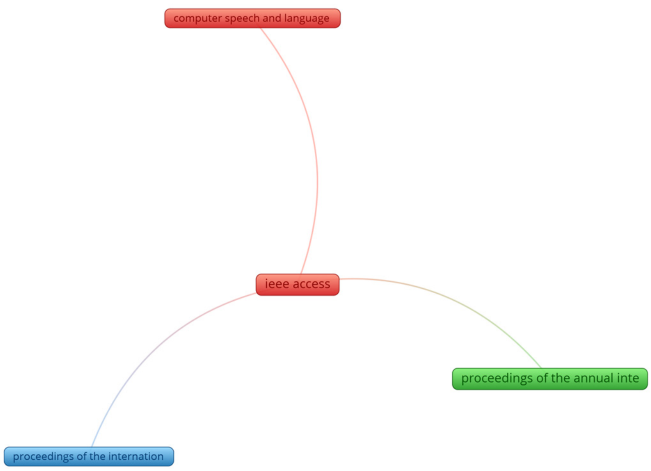


Table 8
Citation analysis by a source according to the number of documents: Scopus

Source	Number of documents	Citations
"Neurocomputing"	4	58
"Lecture Notes in Computer Science, Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics"	3	12
"IEEE Access"	3	51
"Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS)"	3	51
"ACM Conference Proceedings"	3	12

4.9. Analysis of the author by citations

Figure 16 and Table 10 provide the details of the authors who have contributed to the domain by having the greatest number of citations to their documents. This analysis is performed on all extracted documents from Scopus and WoS. Li X has published 4 documents; currently, 65 citations are present. Jiang M has published 3 documents, and 152 documents have been cited. Jayanthi A K is an Indian author who has published 3 documents. Even our team is actively working in the same area and has published 3 documents by Bidwe et al. [31], Vasant Bidwe et al. [32], and Bidwe et al. [33] to date. Figure 16 presents all authors who have contributed to that domain with nodes of different colors. The color of the link between two different nodes denotes whether the authors belonging to that node have cited each other. A mixed-color link means that both authors have cited each other in one or another paper published by them.

4.10. Bibliographic coupling of documents

Bibliographic coupling explains that if two articles share references, they also discuss similar technical contents. This analysis

Table 9
Citation analysis by a source according to the number of citations: WoS

Source	Number of documents	Citations
"Lecture Notes in Computer Science"	9	62
"Advances in Intelligent Systems and Computing"	4	3
"International Journal of Advanced Computer Science and Applications"	3	1
"Universal Access in Human-Computer Interaction Access to Learning Health and Well Being UAHCI 2015"	3	15
"Universal Access in Human-Computer Interaction Access to Learning Health and Well Being UAHCI 2018"	3	6

Figure 16
Citation analysis by author

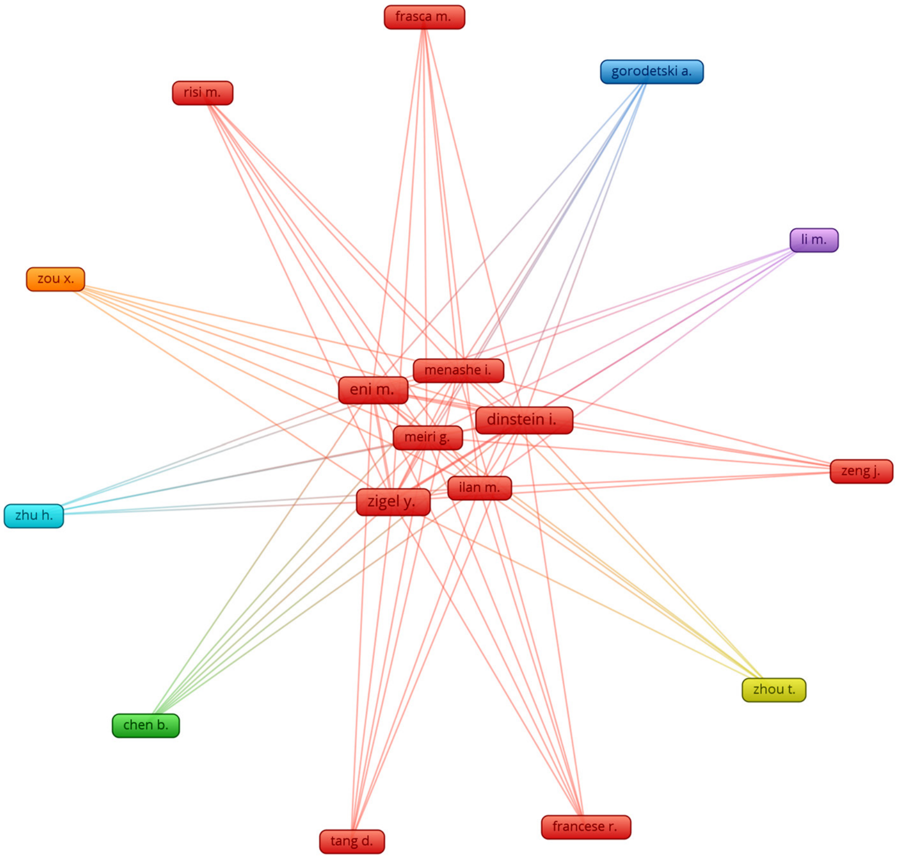


Table 10
Citation count by author

Author	Citation
Jiang and Zhao [16]	118
Zunino et al. [17]	68
Li et al. [18]	65
Jiang et al. [19]	65
Rad and Furlanello [20]	58
Tao and Shyu [30]	42
Eni et al. [26]	38
Li et al. [27]	36
Duan et al. [34]	33
Lee et al. [35]	29

dictates that if two papers cite the third paper, there is a high probability that all three papers discuss the same subject matter. The size of the node is decided according to the paper's citation count. A link will be created between nodes if the paper is cited in another paper. The mixed-color link denotes that papers have cited each other. Figure 17 and Table 11 provide a detailed analysis of the bibliographic coupling of all publications from Scopus and WoS. Jiang M is the author with the highest TLS value (45) with 19 links. The study was performed on all available documents in the domain.

5. Qualitative Analysis

For qualitative analysis, articles are searched and downloaded from "Scopus" and "Web of Science" using the query explained in the above section named "Research Strategy and Data Analysis Procedure." Downloaded articles are sorted based on the date of publication. There are three main types of data available for analysis. The first type of data is images. The second type is videos, and the third type is the use of a questionnaire.

The proposed approaches for clinical analysis of diagnosing ASD [36–39] have used three very famous open-source datasets of MRI images named ABIDE-I, ABIDE-II, and ABIDE preprocessed [40, 41]. Autism Brain Imaging Data Exchange (ABIDE) is an initiative by "International Neuroimaging Data-Sharing Initiative." These datasets contain more than 1000 "Resting-State functional Magnetic Resonance Imaging" (R-fMRI) images from more than 500 individ-uals with ASD and more than 500 typically developed individuals aged 5–64 years. For nonclinical analysis, Kaggle has published an open-source dataset containing children's pictures. This dataset can be used for eye-gaze analysis, which can be further extended to the prediction of ASD. The same type of dataset is also released by Duan et al. [42]. The video dataset can be used for behavioral analysis. Most of the videos used for the analysis are recorded by the authors and used for experimental purposes. Videos are recorded either at home, in a hospital, or in a rehabilitation center. Because they do not want to reveal the identity of the children with ASD, the datasets are not made open source.

The survey-based analysis for the diagnosis of ASD will include answering a standard questionnaire. ASDetect [43, 44] by the "Olga Tennison Autism Research Centre" and the "American Autism

Figure 17
Bibliometric coupling of documents

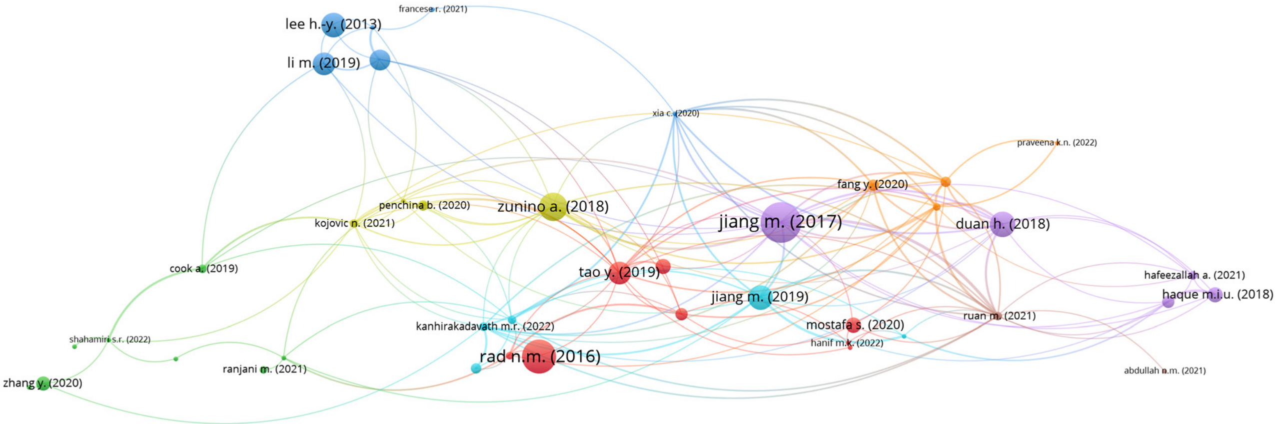
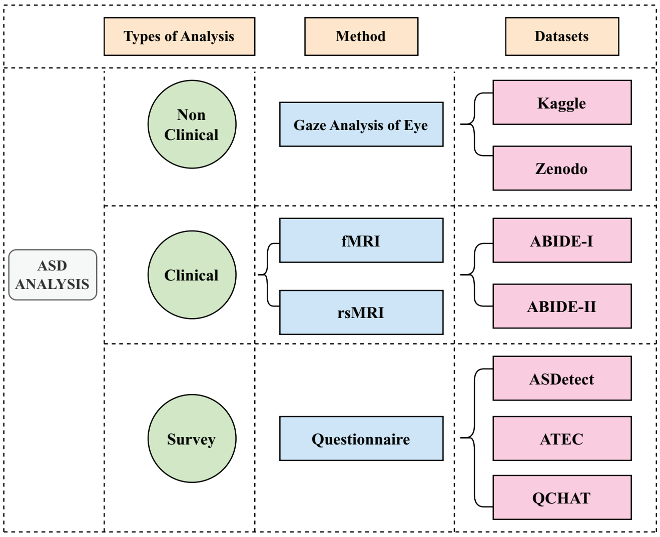


Table 11
Bibliometric analysis of documents

Document	Citation	TLS	Number of links
Jiang and Zhao [16]	118	45	19
Zunino et al. [17]	68	30	15
Li et al. [18]	65	23	6
Jiang et al. [19]	65	3	12
Rad and Furlanello [20]	58	2	2
Duan et al. [34]	24	27	13
Li et al. [27]	19	7	6
Tao and Shyu [30]	19	12	18
Eni et al. [26]	16	16	8
Lee et al. [35]	21	24	3

Figure 18
ASD analysis: types of analysis, methods, and datasets available



Research Institute" have released the "Autism Treatment Evaluation Checklist" (ATEC) [45]. QCHAT and QCHAT-10 [46, 47], ADOS-2 [48], ADI-R, CARS, and AQ-10 [49] are famous questionnaires that are freely available for assessing autistic traits in a child. The ASDetect app has a questionnaire that will help in the preliminary diagnosis of autism. This app claimed an accuracy of 81%–83%. We can use them for the preliminary assessment of children from ages 3 to 12. Figure 18 summarizes the details of the types of analysis (clinical, non-clinical, and survey), methods used by them (eye-gaze analysis, MRI, and questionnaire), and various open-source datasets available for ASD analysis.

Figure 19 shows the traditional method of predicting ASD. The traditional method includes several stages. First, we need to find data for analysis; then, the data will be preprocessed and forwarded to an efficient AI model. Input data may be images, videos, or a set of questions. In preprocessing the data, videos will be converted into images. Images may be rescaled and reshaped to some size, or data augmentation methods can be applied to increase the size of the dataset.

In deep learning models, various types of layers collaborate to process input data and produce meaningful predictions. Figure 20 illustrates the data flow across each layer and the corresponding outputs.

Convolutional layers play a crucial role in feature extraction by applying filters to the input data. These filters detect patterns such as edges, textures, and shapes and preserve spatial relationships in the data. Following this, pooling layers, such as max-pooling or average-pooling, reduce the spatial dimensions of the feature maps generated by the convolutional layers. This process retains the most important information, enhances computational efficiency, and helps in minimizing overfitting.

Flatten layers convert multidimensional feature maps into a one-dimensional vector, preparing the data for processing by dense (fully connected) layers. These dense layers perform feature selection and classification by learning complex relationships between the extracted features and the target output through weighted connections.

The mathematical representations of these layers showcase how each processes a given input image, contributing to the model's ability to produce an accurate final output. This layered approach highlights the distinct and complementary roles of each component in the deep learning pipeline.

Consider an image with spatial coordinates of (a,b), and its input feature is represented as I. Assume $\mathcal{K}$ as the convolutional kernel with spatial coordinates of (x,y) and a size of $\mathcal{K}_\hbar * \mathcal{K}_\mathcal{W}$, where $\hbar$ is the height and $\mathcal{W}$ is the width of the image. The function of a convolutional layer is represented mathematically by Equation (1).

$$\mathcal{F}_{Convolution}(a,b) = (\mathcal{K}*\mathcal{I})(a,b) = \sum_{x=1}^{\mathcal{K}_\hbar}\sum_{y=1}^{\mathcal{K}_w} \mathcal{K}(x,y).\ I(a+x,b+y). \quad (1)$$

The output of the pooling function can be represented as Equation (2), where $\mathcal{P}$ represents the pooling function used in the

Figure 19
Traditional approach to the prediction of ASD

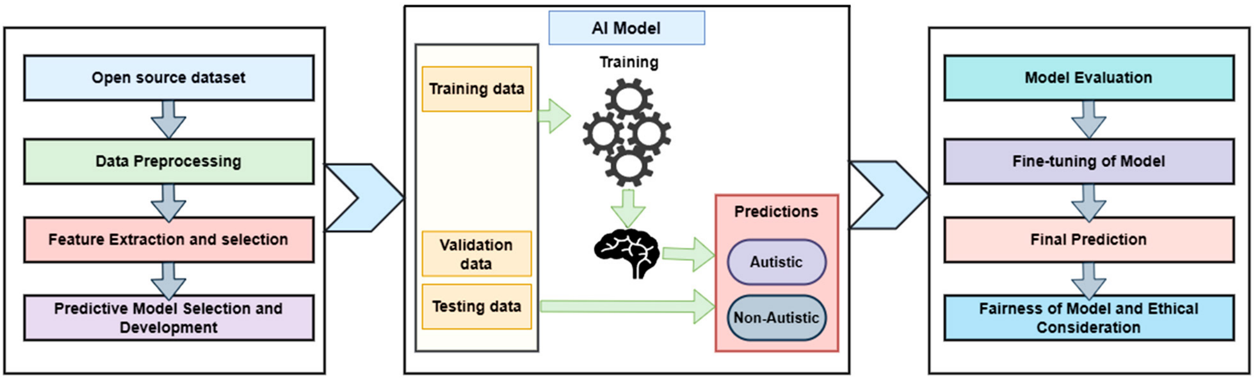
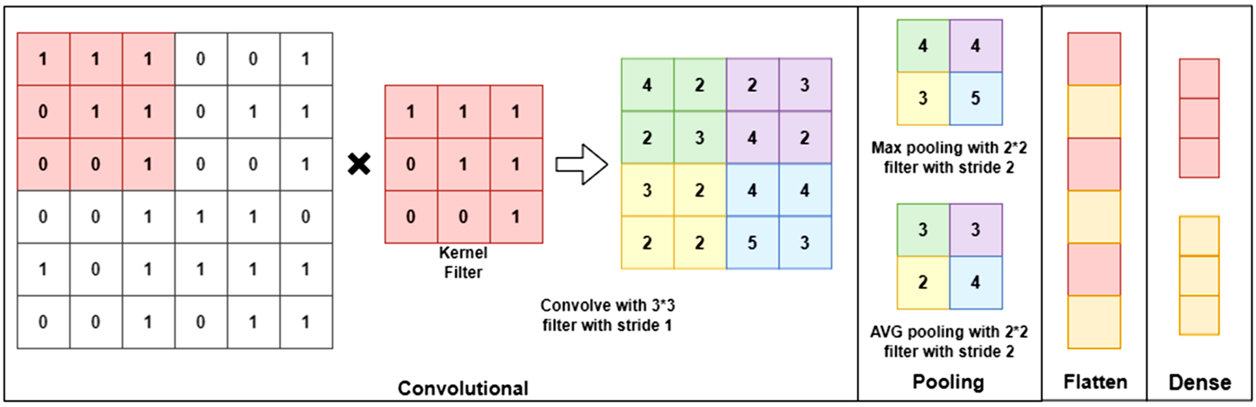


Figure 20
Traditional approach to the prediction of ASD



analysis; mostly, it is max pooling, and the other available option is average pooling. In addition, $\mathcal{S}$ represents the size of the pooling stride used in the analysis.

$$\mathcal{F}_{Pooling}(a,b) = \mathcal{P}(I\,[a.\mathcal{S}:(a+1).\mathcal{S}, b.\mathcal{S}:(b+1).\mathcal{S}]). \tag{2}$$

The flatten layer, represented by Equation (3), later reshapes the input image I of size $\hbar * \mathcal{W} * \mathrm{C}$ to a one-dimensional array represented by Đ, and the height of the image is represented as $\hbar$, width by $\mathcal{W}$, and the number of channels by C.

$$\mathcal{F}_{Flatten} = r(I) = \text{Đ}. \tag{3}$$

Later feature classification by the dense layer can be mathematically represented as follows. It uses a specialized weight matrix of learned parameters, which are represented by $\mathcal{W}$. Đ represents the one-dimensional vector, and later, a bias value of β is added to add nonlinearity. The dense layer function is represented by Equation (4).

$$\mathcal{F}_{Dense} = \alpha(\mathcal{W}.\text{Đ} + \beta) = \mu. \tag{4}$$

α is the activation function used in the above analysis. There are various activation functions used to represent the output differently. SoftMax is the efficient choice of the activation function used in the CNN model. Assume that μ is the output produced by the dense layer and t represents the number of classes. The overall softmax function can be represented by Equation (5).

$$\mathcal{F}_{Softmax} = \frac{\exp(\mu_t)}{\sum_{j-1}^{t} \exp(\mu_j)}. \tag{5}$$

The overall output of CNN can be mathematically represented as Equation (6).

$$o_{CNN} = \mathcal{F}_{Softmax}(\mathcal{F}_{Dense}\,(\mathcal{W}_2.\alpha(\mathcal{W}_1.\text{Đ} + \beta_1) + \beta_2)). \tag{6}$$

The majority of the approaches proposed in this study are leveraging transfer learning methods, which are inspired by the architecture and functionality of convolutional neural networks (CNNs). Transfer learning is a powerful technique in deep learning where a pre-trained model originally developed for a large and general dataset is fine-tuned for a specific task or domain with a smaller, more specialized dataset. By utilizing the knowledge already learned by the pre-trained model, transfer learning reduces the computational effort, training time, and amount of data required to achieve high performance, making it a popular choice for solving complex problems in areas such as image classification and object detection.

In these approaches, the predefined CNN-based transfer learning models incorporate the fundamental layers described earlier—convolutional layers, pooling layers, flatten layers, and dense layers—to perform feature extraction and subsequent classification.

Data are typically preprocessed before inputting images into these transfer learning models to ensure compatibility and optimal performance. Common preprocessing steps include resizing images to match the input size expected by the pre-trained model, normalizing pixel values to a standard range (e.g., 0 to 1), and applying data augmentation techniques such as rotation, flipping, or cropping to expand the dataset and improve the model's robustness artificially. The input image I of size $\hbar * \mathcal{W} * C$ is normalized using the mean μ and standard deviation of σ, represented by Equation (7).

$$I_{processed} = Preprocess(I) = \frac{I-\mu}{\sigma}. \tag{7}$$

Then, this processed image is further given to a pre-trained network represented by $\emptyset(I_{images}\ ;\ \theta_{pretrained\_models})$ of a transfer learning model for training. The model extracts the feature $\mathscr{F}$ during training and contributes to developing a feature vector $\mathscr{R}^{\partial}$; it is represented by Equation (8).

$$\mathcal{F} = \emptyset(I_{processed}\,; \theta_{pretrained\_models}), \tag{8}$$

$$\mathcal{F} \in \mathcal{R}^{\partial}. \tag{9}$$

During the training phase, the model evaluates its loss value ∇, which represents the difference between the predicted labels $\widehat{\vartheta}_{i,j}$ and actual labels $\vartheta_{i,j}$ for all available $I_{processed}$. This loss value serves as feedback for the model, triggering the backpropagation process. In backpropagation, the gradients of the loss function with respect to the model's parameters are calculated, and the weights of the network are updated in the opposite direction of the gradients to minimize the loss. The evaluated loss value is represented by Equation (10).

$$\nabla = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{2}\vartheta_{i,j}.\log\widehat{\vartheta}_{i,j}. \tag{10}$$

The model then iterates through multiple epochs to refine its learning. With each iteration, the model updates its weights and biases to better capture the relationships between the input features and the target labels. This iterative process gradually improves the model's performance, leading to more accurate feature extraction and better classification results. Transfer learning, combined with these iterative training techniques, enables the model to adapt effectively to the specific task and leverages the strengths of the pre-trained CNN-based architecture. In addition, these transfer models can be fine-tuned further using learning from training data, represented by $\theta_{finetuned\_pretrained\_models}$ and represented by Equation (11). Furthermore, a new set of features $\widehat{\mathscr{F}}$ can be extracted, represented by Equation (12).

$$\theta_{finetuned\_pretrained\_models} = \theta_{pretrained\_models} - \theta.\nabla_{train}, \tag{11}$$

$$\hat{\mathcal{F}} = \emptyset(I_{processed}\,; \theta_{finetuned\_pretrained\_models}). \tag{12}$$

Table 12 provides a detailed list of documents that are extracted from databases. The table provides information on the method of diagnosis and the dataset used for nonclinical analysis. In addition, it provides information on the results of the proposed model and observations noted from the paper. All papers have used machine learning or DNN-based approaches to predict ASD. The articles that use the ABIDE dataset for analysis have preferred ML-based classifiers to classify MRI images of autistic children with those of typically developing children. Many approaches have used special hardware devices to record the eye's screen path when children are asked to watch some videos or images. Typically developing children focus more on the central part of the images. In contrast, children with autism were found to pay less attention to the central part and were trying to explore other things in the picture or the surroundings. Recording the screen path and using it for analysis is one of the ways of performing eye-gaze analysis. The other way of doing gaze analysis is by recording eye position and performing analysis. The recorded videos will mainly be used for observing attributes such as facial expressions, head poses, and head trajectory of autistic and typically developing children. These recorded gaze patterns or performed gaze analyses will help in identifying specific behavior changes in children. These appearance-based attributes will also help in doing gaze analysis and can be used as a prediction method. Questionnaire apps such as ASDetect or ATEC can be used easily at home for the preliminary analysis at the individual level. Few methods explore genes to identify autistic traits [50], and few have explored EEG signals recently [51–53]. Several other studies by Kollias et al. [54], Iwauchi et al. [55], Taha Ahmed and Jadhav [56], and Moridian et al. [57] have also helped in getting more detailed information.

6. Performance Metrics

This section presents information of performance metrics used by the proposed methods shown in Table 12. AI-based model's efficiency

Table 12
DNN-based approaches and their used methods, datasets, results, and observations

Document and year	Method used	Dataset type: source	Results and observations
[58] 2025	Human action recognition (HAR) algorithms	Videos: 400 ASD and 125 other developmentally delayed children	The proposed model provides outstanding results on the benchmarked Self-Stimulatory Behaviour Dataset (SSBD). It identified developmental delays of various kinds with an accuracy of 78.57%.
[59] 2025	CNN, CNN-2	Videos: self-generated	This proposed method measures the attention of children during activities. MediaPipe is used to extract essential features and measure attention based on them. This model achieved 97.1% of accuracy in predicting attention in categories highly engaged, moderately engaged, and not engaged.
[60] 2025	ML and feature engineering techniques	Self-generated by combining two datasets	The first stage employs ML-based techniques, and the second stage identifies features from verbal, behavioral, and physical responses. Experimentation provides a classification accuracy of 94% in identifying ASD with chi-square extracted features.
[61] 2025	Hybrid 3DCNN and ResNet, with feature extraction models	Videos: self-generated using VR environment, short videos of 1–3 minutes	Action recognition is completed by the 3DCNN and ResNet model, which achieved a maximum accuracy of 85% (±3%), AUC of 80%, and sensitivity of 66%. The generalized linear mixed-effects model (GLMM) is used to analyze VR performance.

Table 12
(Continued)

Document and year	Method used	Dataset type: source	Results and observations
[33] 2025	Hybrid model of ConvNextBase and LightGBM	Images: Kaggle	A novel hybrid model with certain architectural modifications is proposed to identify correct eye positioning. The proposed model gives a prediction accuracy of 95% and a specificity of 98%, with an AUC of 91%.
[50] 2024	Deep convolutional neural network (DCNN) and attention-based YOLOv8 (AutYOLO-ATT)	Images: generated for identifying various emotions	Six different emotions are correctly identified in real time by DCNN and classified by AutYOLOv8 with an accuracy of 97.2%. Other metrics also show the models' good performance.
[62] 2024	Chronological pelican remora optimization algorithm (CPROA), CNN	Images	This approach utilized a CPROA with a CNN classifier, achieving 95.2% accuracy, 95.8% recall, and 96.3% F1 score by optimizing functional connectivity-based feature selection. Both methods highlight the effectiveness of AI in ASD diagnosis, balancing end-to-end deep learning and handcrafted feature engineering for enhanced detection.
[63] 2024	Multitask cascaded convolutional networks (MTCNN), transfer learning, and face alignment algorithms	Images: self-generated	This manuscript highlights the use of face alignment, which is more useful in predicting ASD. The ResNet50V2 model achieved the highest prediction accuracy of 93.97% and an AUC of 96.33%.
[64] 2024	Deep learning techniques	Multimodal audio and video data	This study introduces a multimodal AI model integrating video and audio inputs to automate FOS-II annotation, reducing manual effort in assessing parent-child interactions in autism. Using deep learning for behavior recognition, the model enhances socially assistive robots (SARs) by improving their understanding of autistic children's behaviors. This approach ensures robust performance in uncontrolled home settings, supporting efficient ASD monitoring and digital health advancements.
[53] 2024	Skeleton-based motion tracking (e.g., Kinect, IMU sensors, or pose estimation techniques)	Multiple ASD diagnosis benchmarks	This study presents a physics-informed neural network (PINN) framework for ASD severity recognition by analyzing skeleton-based motion trajectories. The model encodes subject behavior into a higher-dimensional latent space using physics-based and non-physics-based decoders to predict future motion patterns. A classifier utilizes these embeddings for ASD severity classification, achieving state-of-the-art performance on multiple ASD diagnosis benchmarks and demonstrating applicability to fall prediction tasks.
[65] 2024	An interpretable AI framework to measure attention	Images	This study presents an interpretable AI framework for ASD screening based on attention patterns using standard camera photos instead of high-precision eye trackers. The method automates diagnostic reasoning and enhances clinical trustworthiness by associating photos with semantically plausible attention patterns. Evaluations on both in-domain and out-of-domain data show high classification accuracy and generalizability, making it a cost-effective and scalable solution for ASD diagnosis.
[32] 2024	Transfer learning, HOG, and linear SVM	Images: Kaggle, Zenodo, self-generated	This paper works in two different phases. In the first phase, k-fold cross-validation is used, and ConvNextBase outperformed other algorithms with a prediction accuracy of approximately 88%. In the second phase, this paper proposes attention as a novel feature for autism prediction. Autistic traits are identified based on the EAR value.
[66] 2024	Transfer learning	Images: Kaggle	Images are evaluated on DenseNet121, VGG19, and InceptionV3. DenseNet121 outperformed others with an accuracy of approximately 96%.
[67] 2024	CNN with ISO	Images: self-generated	This paper proposes intelligent search optimizations based on CNN, which help in improving classification capabilities. The paper used k-fold cross-validation, which achieved an accuracy of up to 99% across various platforms.

Table 12
(Continued)

Document and year	Method used	Dataset type: source	Results and observations
[68] 2024	CNN	Images: self-generated	The dataset is self-generated, and eye screen paths are noted for further analysis. The CNN-based approach was used for the feature extraction, which achieved an accuracy of 95.59%.
[69] 2024	Transfer learning with fog and IoT	Images: emotion analysis	Autistic traits are identified based on the participants' six different types of emotions. TL models are used for the analysis, where Xception outperformed ResNet and MobileNet with an accuracy of approximately 95% and better sensitivity, specificity, and AUC. Fog and IoT helped in faster real-time detection of data.
[70] 2024	Transfer learning	Images	A novel self-attention measuring system was developed, which improves the performance of ResNet101 and EfficientNetB3 and achieves an accuracy of 96.50%.
[71] 2023	Deep learning	Images: self-generated	Data are generated from 20 children, and various classification algorithms are used for classification. The maximum accuracy received is 73.8%.
[72] 2024	Deep learning	Video	This approach works on analyzing emotions for predicting autistic traits using CNN, and then, deep regression models are used for continuous emotion prediction. Then, clustering algorithms are used to classify participants according to predicted emotions.
[73] 2023	Deep learning and transfer learning	Images: Kaggle	A new algorithm called the control subgradient algorithm is proposed for identifying autistic traits. Then, DenseNet121 with CNN is used to evaluate the performance of the system. This approach uses L1-regularization to improve the results further. This proposed approach achieved an accuracy of up to 98%.
[74] 2023	Hybrid transfer learning	Images: Kaggle	A hybrid model of DQN and SPiralNet is used, and hyperparameters are tuned using a driving training policy optimizer. This proposed model analyses ROI and predicted autistic traits. This model achieved an accuracy and specificity of 90.7% and 93.6%, respectively.
[31] 2023	Transfer learning	Images: Zenodo	InceptionV3 was much more accurate than VGG16, VGG19, and AlexNet, with 87.99% and 84.33% prediction accuracy in a test and validation dataset, respectively. This difference is highly significant in comparison with the other models proposed. In this study, the first Zenodo dataset was used.
[75] 2023	Computer vision	Images: Kaggle, action-based analysis	The first approach was used to judge the behaviors in recorded videos to find the autistic traits. Videos are recorded while performing the daily routine activities and sessions with the therapists. This paper by Abir and Ochim tries to synthesize a new model that can perform eye-gaze analysis, gesture analysis, and emotion recognition using computer vision. The model, in its entirety, has an accuracy of 72%. This paper has made significant findings using a new and novel method.
[76] 2022	Advanced CNN: 1D CNN	Images: Kaggle	In the present work, the hybridized model of MobileNetV2 and VGG19, with the help of ML models, gave an accuracy of 92%. This model uses facial landmarks to detect dangerous behavior in a person with autism.
[77] 2023	Advanced CNN: 1D CNN	Questionnaire: CSV data	As such, the proposed model for ASD thus provided 1D-CNN-based screening accuracies of 99.45% for adult data, 98.66% for child data, and 90% for adolescent data.
[78] 2023	Advanced machine learning models	Questionnaire: CSV data	The KNN model outperformed all other models.
[79] 2023	Hybrid transfer learning models	Images: Kaggle	The VGG16-MobileNet models achieved the best performance: AUC of 99.25%, accuracy of 98.8%, and precision of 99%.
[80] 2023	Hybrid DL models	Images: Eye screen path, Kaggle	Autism screening techniques, such as fair AI, validations of the dataset using SMOTE, feature engineering, and optimization by advanced DL methods, have provided 99.64% accuracy and 98.89% for both CNN-LSTM and GRU-CNN techniques in the hybrid model.

Table 12
(Continued)

Document and year	Method used	Dataset type: source	Results and observations
[81] 2023	Transfer learning	Images: Kaggle	Analyzed the VGG16 and VGG19 models and gave the model an accuracy score of 84%.
[82] 2023	Transfer learning, explainable AI	Images: Kaggle	More focus has been given to pre-processing the data in the proposed model. The analysis is made up of MobileNetV2, ResNet50V2, and Xception. The input images' pre-processing and data augmentation could make up for a maximum accuracy of up to 98.9% with an AUC of 99.9%.
[83] 2022	All proposed techniques	All types of data	This paper discusses various approaches for identifying autistic traits and discusses approaches proposed for identifying them with challenges.
[84] 2023	Advanced deep learning models and transfer learning: EfficientNet family	Images: Kaggle	This proposed model uses EfficientNet and achieved an accuracy of 85%.
[85] 2023	Advanced machine learning models	Images: self-generated	They developed the data using a self-prepared cartoon image dataset and then validated whether it helped in recognizing the symptoms related to autism. The suggested model is based on a logistic regression and attains an accuracy of 0.73, precision of 0.73, and recall of 0.75.
[86] 2023	Advanced deep learning models and transfer learning: MobileNet family	Images: Kaggle	This proposed model can better apply to input images that are almost very small. MobileNetV2 and MobileNetV3-Large can handle small input image sizes and pass a multiclassifier for better classification performance. From the table below, it is pretty evident how much better the training of the face classifier in these groups of datasets is, with an accuracy of 90.5% and an AUC of 96.32%.
[87] 2023	Machine learning models	Images: Kaggle, QCHAT, self-generated	This dataset is collected and then balanced using SMOTE. The techniques applied to that task are DT, NV, KNN, RF, GB, MP, SVM, AB, and LR. By executing a specific feature selection, it has been reported that AB, LR, SVM, and MLP show the best results among the classes used, while they give an accuracy result of 99.85%.
[88] 2023	Transfer learning models	Images: Kaggle	VGG16 got an accuracy of 87.22%, whereas Xception got an accuracy of 91%.
[89] 2023	Transfer learning models	Images: self-generated	VGG16 got an accuracy of 87.22%.
[90] 2023	Transfer learning models	Images: Kaggle	VGG16 got an accuracy of 90.48%.
[91] 2022	DNN + explainable AI	Images: Kaggle	Using explainable AI (XAI) can help in providing a detailed explanation, which may reduce overall diagnosis time.
[92] 2022	ML classifiers	Images: self-generated	The DNN-based model achieved approximately 78% of AUC, whereas the ML-based model reached approximately 67.80%. The model achieved better accuracy when trained on the original dataset and tested on the augmented dataset. The DNN model could achieve AUC of up to 97%.
[93] 2022	Transfer learning models	Images: Kaggle	AUC values received are 92.81%, 96.63%, and 95.06% by MobileNet, Xception, and EfficientNet, respectively. The highest prediction rate is obtained using EfficientNet at 59.33%.
[94] 2022	ML classifiers	Images: Kaggle	KNN and DT classifiers outperformed SVM and NB in the prediction of dimensional reduction techniques. Both models achieved an accuracy near 100%.
[95] 2022	ML classifiers	Survey/review paper	Discussed how computer vision approaches can help in predicting and diagnosing ASD.
[47] 2022	New dataset	Questionnaire: QCHAT	This questionnaire contains 25 questions and can be used for toddlers aged 18–30 months.

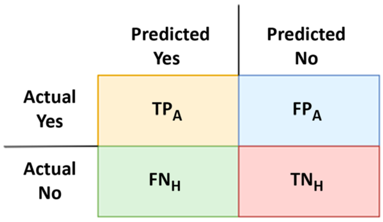
Table 12
(Continued)

Document and year	Method used	Dataset type: source	Results and observations
[96] 2022	Hybrid transfer learning models	Images: self-generated	Accuracies calculated: GoogLeNet = 93.6%, ResNet-18 = 97.6%, GoogLeNet + SVM = 95.5%, ResNet-18 + SVM = 94.5%.
[97] 2022	ML-based analysis	Images: self-generated	ANN provided the best accuracy of 98.94% after data were pre-processed using techniques: PCA, SMOTE.
[98] 2021	ML classifiers	Images: self-recorded	Accuracy calculated: SVM = 92.31%, LDA = 89.74%, DT = 84.62%, RF = 84.62%.
[99] 2021	ML classifiers	Questionnaire: QCHAT	Sequential minimal optimization (SMO) based support vector machine (SVM) classifier outperformed other classifiers and achieved 99.9% and 97.58% accuracy for the adolescent and adult datasets.
[100] 2021	ML classifiers	Images: self-generated	Results are taken on the Q-CHAT dataset. Accuracies received: LR = 97.15%, NB = 94.79%, SVM = 93.84%, KNN = 90.52%, RFC = 81.52%.
[101] 2021	PCA, DNN	Questionnaire: ASD test app	The app contains a basic questionnaire based on behavioral analysis and claims 81%–83% accuracy.
[102] 2021	DNN method with the use of XAI	Images: Kaggle	DNN achieved an accuracy of 79% when using the first seven features from the dataset for prediction. Using XAI helps in achieving good accuracy with detailed explanations for accurate prediction.
[103] 2021	ML classifiers	Images: Kaggle	Accuracy calculated: neural network = 99%, C4.5 Tree = 96%, random forest = 98%.
[104] 2021	ML classifiers	Videos: self-generated/recorded	AUROC and AUPRC scores: 0.98. Sensitivity = 96.0%, specificity = 80.0%, and accuracy = 88.0% by logistic regression classifier. Classifiers provide good sensitivity but not a satisfactory specificity value.
[105] 2022	LSTM	Videos: self-generated/recorded	Classification based on appearance-based features from videos. LSTM with an accuracy of 96.7%.
[23] 2020	LSTM	Videos: self-generated/recorded	LSTM provides an accuracy of 92.6% with TPR = 91.6% and TNR = 93.4%.
[106] 2020	ML classifier	Videos: self-generated/recorded	ML classifier's classification accuracy = 92.5% and MAE of 2.03 on CARS.
[107] 2021	ML-based approach and DNN-based approach	Videos: self-generated/recorded	The DNN-based approach used for behavioral analysis: smile: 70% accuracy, look face: 68% accuracy, look object: 67%, vocalization: 53% accuracy. The ML classifier for diagnosis: 82% accuracy.
[108] 2020	ML classifiers	Videos: self-generated/recorded	Found improvement in accuracy compared to previous versions. LR achieved an accuracy of 89.57, and ADTree attained an accuracy of 87.14%.
[109] 2020	ML classifiers, CNN	Survey/review paper	CNN outperforms other models by an accuracy of 99.53%.
[110] 2019	CNN with temporal pyramid network	Videos: self-generated/recorded	The proposed system has achieved an accuracy of 95.2%.
[111] 2018	ML classifiers	Videos: self-generated/recorded	Results obtained from clinical score sheets may differ from those collected on live data. Achieved maximum accuracy of 76%.
[30] 2019	Hybrid CNN and LSTM	Images: IEEE ICME 2019	The CNN-LSTM model achieved an accuracy of 74.22%.
[42] 2019	New dataset	Images: self-generated	An open-source dataset was made available for the study.
[112] 2019	ANN	Images: self-generated	ANN classifiers achieve more than 90% accuracy.
[113] 2018	DNN classifiers	Images: self-generated	Pictures are captured in the Tobii studio environment. The paper has experimented with attention by autistic and typically developing children during activities. Autistic children are found to be less attentive.
[114] 2018	RNN	Images: self-generated	The model achieved approximately 98% confidence for fitness values of 0.008–0.006, with the best accuracy value of 94%.

can be evaluated using a confusion matrix [115]. The following are the basic terminologies and the confusion matrix used for evaluation. Figure 21 presents the confusion matrix.

TP_A = child with autistic features predicted autistic.
FP_A = child with healthy features predicted autistic.
TN_H = child with autistic features predicted healthy.

Figure 21
Confusion matrix for performance analysis



FN_H = child with healthy features predicted healthy.

Accuracy = how many children were predicted correctly (autistic or healthy) out of the total number of children, represented by Equation (13).

Precision = how many children were predicted to be autistic who are autistic, represented by Equation (14).

Recall/sensitivity/true positive rate (TPR) = how many autistic children were predicted correctly out of the total autistic children predicted, represented by Equation (15).

Specificity = how many healthy children were predicted correctly out of the total healthy predicted, represented by Equation (16).

False positive rate (FPR) = how many healthy children were predicted to be autistic, represented by Equation (17).

$$\textbf{Accuracy} = \frac{TP_A+TN_H}{TP_A+FP_A+FN_H+TN_H}, \tag{13}$$

$$\textbf{Precision} = \frac{TP_A}{TP_A+FP_A}, \tag{14}$$

$$\textbf{Recall} = \textbf{Sensitivity} = TPR_A = \frac{TP_A}{TP_A+FN_H}, \tag{15}$$

$$\textbf{Specificity} = \frac{TN_H}{FP_A+TN_H}, \tag{16}$$

$$FPR_A = 1 - \textbf{Specificity}. \tag{17}$$

The TPR_A and FPR_A values are used to draw the AUC [115]. AUC stands for "area under the ROC curve," whereas ROC stands for "receiver operating characteristic curve." AUC represents and measures aggregate performance across possible epoch values. TPR_A represents the Y-axis, and FPR_A represents the X-axis. In addition, coordinates will be plotted in this space for the value of the decided epochs. Then, a curve will be drawn joining all coordinates and will be called AUC, represented by Equation (18), and the detailed computation of the AUC value is represented by Equation (19), where i is the index of the point in the ROC curve and n is representing the total number of points in the ROC curve.

$$AUC = \int_0^1 TPR_A(FPR_A)d(FPR_A), \tag{18}$$

$$AUC = \sum_{i-1}^{n-1}\left(\left(FPR_{A_{i+1}} - FPR_{A_i}\right)\left(\frac{\left(TPR_{A_{i+1}}+TPR_{A_i}\right)}{2}\right)\right). \tag{19}$$

If a curve is a diagonal straight line ($TPR_A = FPR_A = 0$ for all epochs), it means that the classifier is getting confused and cannot classify the data. The higher the value of AUC is, the better is the classifier's performance. Most of the methods in Table 13 have been evaluated using accuracy, sensitivity, specificity, and AUROC value. The other metric used for the evaluation by a few approaches is the "Childhood Autism Rating Scale," commonly known as CARS [116]. CARS is a clinical rating scale for professional clinicians to evaluate the presence of autistic traits in a child after direct observation. The cutoff CARS score is 28. Values evaluated above the cutoff score can be categorized into "mild to moderate" and "severe" levels of autistic attributes. The next section of this paper discusses detailed observations and challenges observed after qualitative analysis.

7. Discussion

In quantitative analysis, we studied articles in the domain of interest. We conducted a detailed study of articles in two main sections: quantitative analysis, which is an analysis based on authors, organizations, keywords, sources, citations, countries of publication, funding agencies, etc., and qualitative analysis, which is an analysis of various types of input datasets used for prediction, the open-source datasets available for study, the traditional method of prediction, clinical and nonclinical methods of analysis, etc. It was found that many proposed approaches prefer ML-based classifiers for analysis. A few approaches have tried DNN-based classifiers to get better results. For clinical analysis, classifiers are doing satisfactory work. However, for nonclinical analysis, it is difficult to predict ASD based on the symptoms because we may observe different symptoms in every child. Therefore, ASD is called a spectrum disorder. This bibliometric analysis aims to survey available datasets, proposed methods, and their performance. Key observations and challenges to the study are listed below based on the analysis performed.

As part of the qualitative analysis, detailed tabular summaries were prepared to consolidate the findings from the reviewed studies. Table 12 presents DNN-based approaches along with their corresponding datasets, results, and observations, offering a comprehensive view of how deep learning has been applied in ASD prediction since 2018. Table 13 provides a comparative perspective on the sufficiency of clinical versus nonclinical methods, highlighting strengths and limitations in data availability. Table 14 synthesizes the methods used for identifying autistic traits, mapping classical ML, DNNs, transfer learning, and hybrid approaches. While these tables provide depth and

Table 13
Analysis of methods used for the screening of ASD

Category	Techniques used	India (% usage)	Other countries (% usage)	References
Clinical methods	MRI/brain imaging	Limited (<5%)	Moderate (~15%–20%)	[117]
	EEG (electroencephalogram)	Rare (<5%)	Moderate (~10%–15%)	
	Blood biomarkers (genetic testing)	Rare (<5%)	Moderate (~20%)	
	Gut microbiome testing	Minimal (1%–3%)	Emerging (~5%)	
	Stem cell/hyperbaric oxygen therapy	Experimental (<2%)	Experimental (<5%)	
Nonclinical methods	Behavioral analysis (e.g., ADOS, ISAA, and CARS)	High (~75%)	High (~70%–80%)	
	Modified Checklist for Autism (M-CHAT)	Moderate (~40%–50%)	High (~70%)	
	Speech and social interaction observation	High (~70%)	High (~70%–80%)	

Table 14
Methods used for identifying autistic traits

Machine learning (ML)	Deep neural networks (DNNs)	Transfer learning (TL)	Other methods
Support vector machines (SVMs)	Convolution neural network	VGG family	Explainable AI
Random forest classifier (RFC)	Recurrent neural network	MobileNet family	Hybrid models (deep learning or transfer learning models with ensemble learning)
K-nearest neighbors (KNNs)	Long short-term memory	EfficientNet family	Computer vision techniques
Logistic regression (LR)	1D/2D/3D convolution neural network	ResNet family	HOG and linear SVM
Decision trees (DT)	Deep attention neural network (DANN)	Inception family	Object detection techniques
Artificial neural networks (ANNs)	Deep convolutional neural network (DCNN)	Xception	Data augmentation techniques
Logistic regression (LR)	Multitask cascaded convolutional networks (MTCNNs)	AlexNet	SMOTE
Naive Bayes (NB)		NasNet	Special hardware devices
Linear discriminant analysis (LDA)		ConvNextBase	Human action recognition (HAR)
Quadratic discriminant analysis (QDA)		SqueezeNet	Feature engineering techniques
Principal component analysis (PCA)		GoogLeNet	Chronological pelican remora optimization algorithm (CPROA)
Ensemble learning		Hybrid models (various transfer learning models)	Skeleton-based motion tracking (e.g., Kinect, IMU sensors, or pose estimation techniques)

serve as reference material, the synthesis of their insights is discussed in Section 7.1 (Key observations) and Section 7.2 (Challenges to predict ASD), ensuring that essential conclusions are presented in a concise and reader-friendly manner. Later, this section summarizes the research gaps, challenges, and limitations of ASD.

7.1. Key observations from the analysis

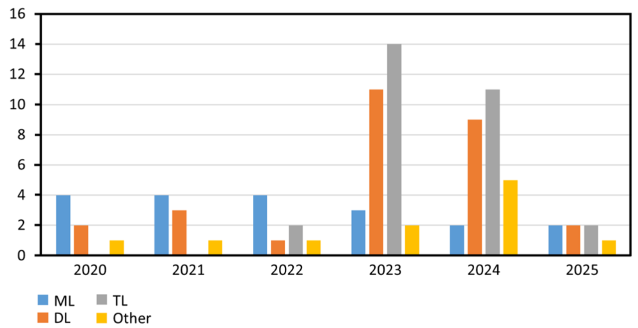
After conducting quantitative and qualitative analyses, the following key observations are listed:

1) The fitness of the mind is as vital as the body. The world is currently dealing with a significant issue of ASD. Patients with ASD have trouble interacting and communicating with others, often referred to as "behavioral illness." Young children often exhibit ASD symptoms, particularly in the first two years, that persist until appropriate therapy is administered.
2) ASD can be treated clinically or nonclinically. There is no specific test for clinical analysis, such as a blood test or any comparable test. Doctors observe differences in the brain MRI and conclude. Usually, this method can be used at the age of 4 or above, which is a very late diagnosis.
3) For a nonclinical diagnosis, children must go to the doctor with their parents for several sessions. In sessions, doctors will have personal interactions with parents and children and ask children to perform some activities. On the basis of the observations from personal interactions and activities performed by the child, the doctor will declare the result. This result may be subjective and misleading. In addition, this method of diagnosis is very time-consuming and costly, which is not affordable to many parents.
4) Clinical and nonclinical methods play a vital role in autism screening and diagnosis, with significant variations in their adoption across India and other countries. In clinical methods, advanced techniques such as MRI/brain imaging and EEG are used moderately (~15%–20% and ~10%–15%, respectively) in other countries. However, their usage remains limited in India, accounting for less than 5% due to infrastructure and accessi-bility challenges. Although emerging globally, blood biomarker analysis and gut microbiome testing are rarely adopted in India, with usage rates below 5%. Stem cell therapy and hyperbaric oxygen therapy are still experimental in both regions. Con-versely, nonclinical methods are more widely adopted in India due to their accessibility and cost-efficiency. Behavioral tools, such as the ISAA and CARS, are utilized in approximately 75% of cases in India, aligning closely with global usage (~70%–80%). The Modified Checklist for Autism (M-CHAT), alt-hough moderately adopted (~40%–50%) in India, enjoys a higher prevalence in other countries (~70%). Speech and social interaction observations show consistently high adoption rates (~70%–80%) across both regions. These patterns highlight significant reliance on nonclinical methods in India, driven by limited access to clinical diagnostic tools. However, the global scenario reflects a more balanced approach that integrates clinical and behavioral assessments. The need for enhanced infra-structure and investment in clinical diagnostic methods is crucial to bridging the gap and improving autism diagnosis outcomes in India. Table 13 below provides a detailed analysis of the data sufficiency test performed for clinical and nonclinical analysis used for the screening of ASD.
5) The majority of the articles propose approaches for clinical analysis. They used an open-source dataset named ABIDE and several ML-based classifiers for classification. SVM, RFC, NB, LR, KNN, and PCA are the favorite choices of researchers for analysis. In addition, many researchers prefer to use deep neu-ral-based approaches. DNNs have become very popular today as an automated and efficient solution to various real-time issues because of their adaptive nature, support for multimodal data, and continuous performance improvement. Researchers preferred CNN, RNN, or LSTM for

the analysis. A couple of researchers have tried using DANN for analysis and 3D-CNN. It was found that DNN-based classifiers work more efficiently than ML-based classifiers. Researchers also received exciting results using transfer learning. TL is widely used because of its advantages, such as generalization, saving training time, and improved accuracy. Ideally, a higher start, a higher slope, and a higher asymptote are the three significant benefits that we get from the successful application of TL. Table 14 summarizes the methods used by the proposed approaches for identifying autistic traits. Many new proposed pre-trained TL methods such as ConvNextBase, GoogLeNet, SqueezeNet, and hybrid models of these methods are being tested and are providing better results. Therefore, the popularity of using TL methods for predicting autistic traits has increased exponentially, which is shown in Figure 22. A few approaches include using the latest computer vision techniques such as HOG and linear SVM, data augmentation, and preprocessing techniques such as SMOTE. A very interesting method used is explainable AI, which helps in describing the analysis of autism prediction.

6) It is important to emphasize that the choice of a deep learning model depends strongly on the type of data collected. For image-based data such as facial expression images, eye-region snapshots, or ROI-focused frames, convolutional neural networks (CNNs) and their transfer learning variants (e.g., VGG, ResNet, and EfficientNet) are most effective due to their strong capability in extracting spatial features. For video-based data, where temporal dynamics such as gaze shifts, micro-expressions, or body movements are captured, models such as recurrent neural networks (RNNs), long short-term memory (LSTM), 3D-CNNs, and hybrid CNN–LSTM architectures are better suited because they can process both spatial and temporal dependencies. For motion-sensing data (e.g., gait patterns, skeleton tracking, or IMU sensor recordings), specialized approaches such as skeleton-based deep models, graph convolutional networks (GCNs), and human action recognition (HAR) models are more appropriate because they can learn structured spatiotemporal patterns in sequential motion data. In addition, transfer learning has been widely adopted across all of these modalities, enabling the adaptation of pre-trained models to autism-related datasets where sample sizes are often limited. To support this mapping, Table 12 provides a detailed overview of the methods used, dataset types/sources, and reported results from all relevant studies published since 2018, thereby serving as a reference point for selecting suitable modeling frameworks according to data modality.
7) The nonclinical analysis is completed by performing eye-gaze analysis. One of the most trusted behavioral observations is eye positioning or tracking. Eye tracking is a noninvasive method where the system calculates the precise attention given to the regions of interest (ROI) from the picture based on the eye position. A visual attention model includes an efficient AI model that can be used for eye tracking. The system will evaluate children's attentiveness to the ROI, and an early diagnosis can be made. A special set of hardware devices can be used to save screen paths for eye tracking, and based on the children's at-tentiveness, ASD can be predicted. In addition, nonclinical analysis can be performed by recording videos of children while performing day-to-day activities. A gait analysis may help in predicting ASD.
8) Along with clinical and nonclinical analyses, apps such as "ASDetect" or "ATEC" can help parents perform preliminary analysis at home individually. These are free apps and contain a set of questions that are based on regular activities. Answering those questions will help in predicting symptoms of ASD in their children. You can expect approximately 83% accuracy from these apps. QCHAT is also a similar kind of questionnaire that is widely used by clinical practitioners for analysis. Figure 23 provides briefs regarding research gaps, challenges, and limitations in studying ASD.
9) Few approaches have tried applying explainable AI (XAI) for the analysis. Using XAI can help in achieving good accuracy with detailed explanations for accurate prediction.
10) The research gaps found from current research include the following:
    a. Unavailability of the dataset because parents of autistic children do not wish to reveal their children's identities.
    b. Available datasets have limitations, including a limited number of images and the lack of information such as age, gender, family history, and clinical reports. In addition, available datasets are not balanced (unequal number of male and female participants in dataset preparations).
    c. No open-source video dataset is available. The proposed approaches have been recorded for analysis but have not been released.
    d. Traditional ML classifiers are not proven reliable because they failed to provide a satisfactory specificity value.
    e. Unavoidable attributes of datasets, such as image resolution, video length, and noise, affect the algorithm's performance.
11) The following are the limitations found in existing AI-based approaches used for the prediction of ASD:
    a. The majority of the approaches are better at classification, but they do not perform well in predicting diseases. They failed to provide a good specificity value, which is considered an important performance metric in predicting ASD. This is due to the difficulty of AI-based techniques in extracting accurate or relevant traits or data from existing datasets.
    b. The results produced by the approaches are not bias-free. The main reason is unbalanced sample inputs in available open-source datasets. The other reason is the transparency of the features used for prediction, assessment method, and results validation.
    c. No standard statistical method is available to choose the correct model for prediction and to validate the results produced by the model. K-fold validations can be a way to do this, but they have not been explored by methods proposed for nonclinical analysis.
    d. There are doubts regarding the fairness of the results produced by AI and the many ethical concerns regarding generating datasets and disclosing the identity of the participants.
    e. Because specificity is the most important performance metric, there is no AI technique to take responsibility for producing results correctly.

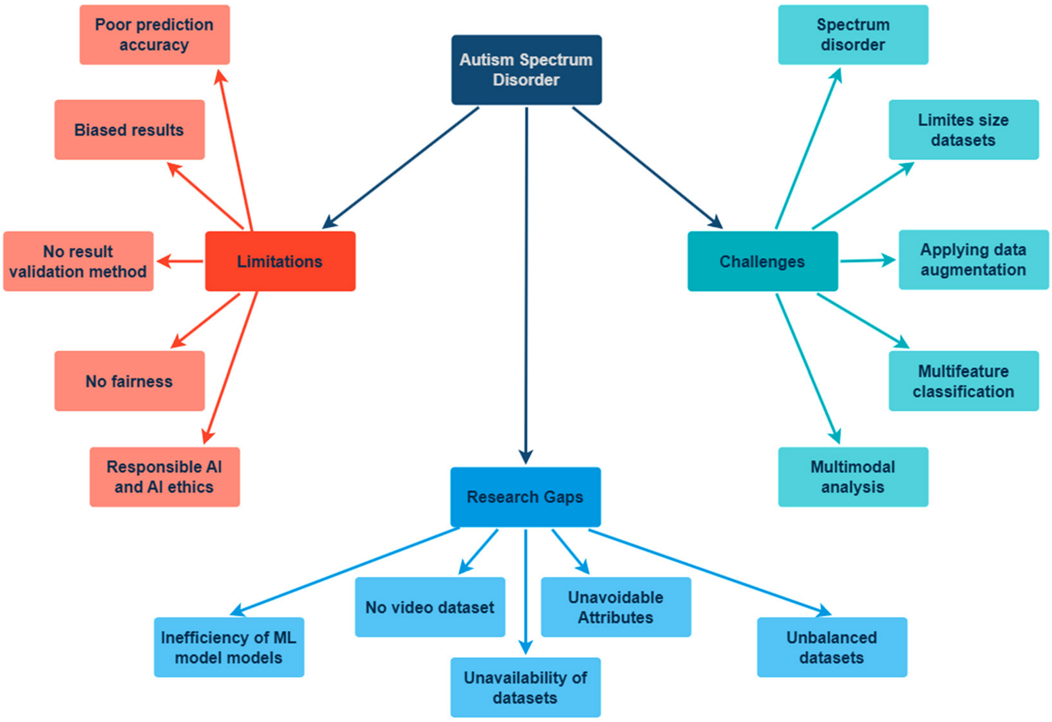
Figure 22
Trend of using TL for the prediction of autism



7.2. Challenges to predict ASD

1) ASD is a spectrum disorder. It has been said that approximately 20–100 various behavioral attributes are observed in patients with ASD.

Figure 23
Research gaps, challenges, and limitations of ASD



Therefore, it becomes challenging to do multifeature classification to diagnose ASD. Clinical analysis can be performed after a certain age, which may be too late for the diagnosis. Nonclinical analyses are subjective, misleading, time-consuming, and costly.

2) As per the recent survey by WHO and Statesman, we found 1 autistic child in every 100 children worldwide and approximately 1 in 500 in India. There are more than 21.6 lakh autistic children present in India. The primary issue in India is the prevalence of parents who attempt to hide their child's im-pairment from others. They feel uncomfortable bringing them to social functions because they worry that other adults or kids will make fun of them. In addition, it is a societal stigma in India that people are unaware of this illness. Therefore, creating awareness of this disease is necessary for further research extension.
3) Unavailability of datasets is the main challenge in the research. As mentioned earlier, the ABIDE group is the only open-source dataset of MRI images, and for behavioral attribute analysis, only two datasets are made available by Kaggle and Zenodo.
4) The number of images in both datasets is presented in Table 15.
5) The size of the available datasets, especially by Kaggle and Zenodo, is very limited, as shown in Table 14. Datasets have pictures of autistic and typically developing children, with fix-ation maps and screen paths. This information can be used to identify various visual traits of children. The available data have a limited number of pictures. Therefore, the size and quality of the dataset can be increased and improved using various data augmentation techniques, but this may affect the dataset's quality. The process of data augmentation artificially adds more images using existing images in the dataset. It makes minor geometric transformations such as rotating existing images at some angle, flipping, translating color schemes, and adding some noise and makes a few more images available in the dataset for the model. This new addition may lead to noticing various attributes of the disease.
6) In addition to the above, the following two more challenges are faced by the researchers:
   a. Performing multifeature classification: it has been said that approximately 20–100 various behavioral changes are observed in patients with ASD. We can observe different behaviors in each child. Therefore, it becomes challenging to do multifeature classification to diagnose ASD. In addition, analyses performed by practitioner doctors are subjective.
   b. Performing multimodal analysis: current research in this domain mainly predicts ASD using single-modality data such as MRI images, facial expression analysis, and eye-tracking signals. However, researchers have not yet explored comprehensive multimodal video datasets that combine video clips, images, and EEG signals for ASD prediction. Incorporating diverse data sources would enable richer behavioral pattern analysis, in-cluding gaze trajectories and attention shifts, leading to more accurate performance. This limitation is further illustrated in the qualitative analysis section, which shows the imbalance in available datasets across modalities and highlights the scarcity of multimodal video-based resources.

Table 15
Number of images available in the datasets

Dataset	Autistic images	Non-Autistic images	Total Images
Kaggle	1327	1327	2654
Zenodo	1270	1270	2540

8. Conclusion and Future Directions

Early diagnosis of ASD is crucial for early intervention and improved quality of life. AI-based methods—particularly deep learning and transfer learning models—have been promising for nonclinical

ASD screening. However, there are significant challenges, particularly in the availability of datasets, model specificity, and interpretability. While hybrid models achieve an accuracy as high as 98%, they do not provide good specificity values. Again, this is an important metric to assess a model, leading to increased false positive rates. Moreover, available datasets are not diverse, with most research utilizing small image-based samples, and there are no publicly accessible video datasets for a multimodal solution. The absence of standardized validation protocols further limits the clinical adoption of AI-based ASD screening.

To address these limitations, future research must prioritize:

1) Developing geographically diverse, publicly available datasets, ensuring multimodal behavior analysis that includes eye gaze, facial expressions, attention patterns, motion cues, and speech features.
2) Enhancing model specificity through optimized hybrid architectures, bias reduction techniques, and rigorous benchmarking frameworks.
3) Integrating explainable AI (XAI) methods to improve transparency so that clinicians and caregivers can interpret AI-based predictions.
4) Creating standardized validation metrics and aligning dataset development with regulatory requirements (e.g., GDPR and HIPAA) to ensure fairness, privacy, and clinical soundness.
5) Designing compact AI models optimized for edge and mobile devices, enabling real-time, accessible ASD screening in low-resource settings.
6) Encouraging interdisciplinary collaborations between AI researchers, pediatricians, and behavioral scientists to validate AI-based methods through large-scale, multisite clinical trials.

As a concrete example, the proposed benchmarking framework could be operationalized by defining minimum specificity thresholds (e.g., ≥85%) as a standard for model acceptance, requiring multimodal evaluation across at least two behavioral data types (e.g., gaze and facial expression datasets), and mandating the integration of explainable AI methods such as layer-wise relevance propagation (LRP) or Grad-CAM to ensure interpretability. This framework would not only guide researchers in method selection but also establish practical criteria for clinical reliability, transparency, and fairness, thereby making AI-based ASD screening tools more suitable for real-world deployment.

By advancing AI-powered, low-cost, and accessible screening methods, this research bridges the gap between AI research and healthcare translation. A viable, AI-assisted multimodal screening framework can assist in reducing diagnostic delays, enabling early intervention initiatives, and alleviating the burden for both individuals and healthcare practitioners. Ultimately, this research opens the door to the real-world translation of AI in ASD screening, fostering inclusivity, early intervention, and improved clinical decision-making.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/shahriarrafi1071/autism-dataset?select=AutismDataset.

Author Contribution Statement

Ranjeet Vasant Bidwe: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Sashikala Mishra:** Conceptualization, Methodology, Software, Validation, Data curation, Writing – review & editing, Supervision, Project administration. **Simi Bajaj:** Conceptualization, Methodology, Software, Validation, Writing – review & editing, Supervision, Project administration. **Suraj Sawant:** Validation, Formal analysis, Investigation, Resources, Writing – review & editing, Supervision, Project administration. **Kailash Shaw:** Validation, Writing – review & editing, Supervision. **Ketan Kotecha:** Validation, Supervision, Project administration.

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How to Cite: Bidwe, R. V., Mishra, S., Bajaj, S., Sawant, S., Shaw, K., & Kotecha, K. (2025). Nonclinical Approaches to Autism Trait Prediction Using Deep Learning: An Extensive Review. *Journal of Computational and Cognitive Engineering*. https://doi.org/10.47852/bonviewJCCE52026197