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A comprehensive analysis towards exploring the promises of AI-related approaches in autism research

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ABSTRACT

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that presents challenges in communication, social interaction, repetitive behaviour, and limited interests. Detecting ASD at an early stage is crucial for timely interventions and an improved quality of life. In recent times, Artificial Intelligence (AI) has been increasingly used in ASD research. The rise in ASD diagnoses is due to the growing number of ASD cases and the recognition of the importance of early detection, which leads to better symptom management. This study explores the potential of AI in identifying early indicators of autism, aligning with the United Nations Sustainable Development Goals (SDGs) of Good Health and Well-being (Goal 3) and Peace, Justice, and Strong Institutions (Goal 16). The paper aims to provide a comprehensive overview of the current state-of-the-art AI-based autism classification by reviewing recent publications from the last decade. It covers various modalities such as Eye gaze, Facial Expression, Motor skill, MRI/fMRI, and EEG, and multi-modal approaches primarily grouped into behavioural and biological markers. The paper presents a timeline spanning from the history of ASD to recent developments in the field of AI. Additionally, the paper provides a category-wise detailed analysis of the AI-based application in ASD with a diagrammatic summarization to convey a holistic summary of different modalities. It also reports on the successes and challenges of applying AI for ASD detection while providing publicly available datasets. The paper paves the way for future scope and directions, providing a complete and systematic overview for researchers in the field of ASD.

1. Introduction

Autism is a developmental condition that affects communication, social interaction, and behaviour and can be observed within the first three years of life [1]. It is a spectrum disorder that affects individuals differently and currently has no cure. However, interventions and therapies such as Applied behaviour Analysis (ABA), speech and language therapy, occupational therapy, and social skills training can help improve its symptoms [2]. Autism is linked to various SDGs. Goals include reducing premature mortality caused by non-communicable diseases, equal access to education, inclusive employment, social and economic inclusion, accessible spaces, representation, and collaboration to address their specific needs [3]. Effective treatments are tailored to the individual's needs. New approaches to learning, such as representation learning, are being utilized to gain insights from data and improve treatment options [4]. When detecting developmental abnormalities like ASD, observing a child's natural behaviour and communication is essential. Different types of data can be collected and analyse for ASD research, such as behavioural, neuroimaging, genetic, and environmental data. These data sources can provide information on social interactions, communication skills, brain abnormalities, genetic mutations, and environmental factors that may contribute to ASD development [5].

The integration of AI in autism research and treatment has revolutionized the field, offering substantial advancements in diagnosis, assessment, and interventions for individuals with ASD. AI encompasses a spectrum of technologies, enabling machines to perform tasks traditionally requiring human-like intelligence, including pattern recognition, language comprehension, and decision-making [6]. Machine Learning (ML), a fundamental component of AI, leverages sophisticated algorithms to glean valuable insights from extensive datasets, aiding in early detection, diagnosis, and treatment of autism by identifying intricate patterns and correlations. Common ML techniques encompass supervised learning, which trains models on labelled data for predictive modelling. Unsupervised learning, uncovering hidden structures within data. Semi-supervised learning, useful with limited labelled data and reinforcement learning, applies to adaptive interventions. Noteworthy ML algorithms in autism research include Support Vector Machine (SVM) for classification tasks, K-Nearest Neighbours (KNN) for pattern

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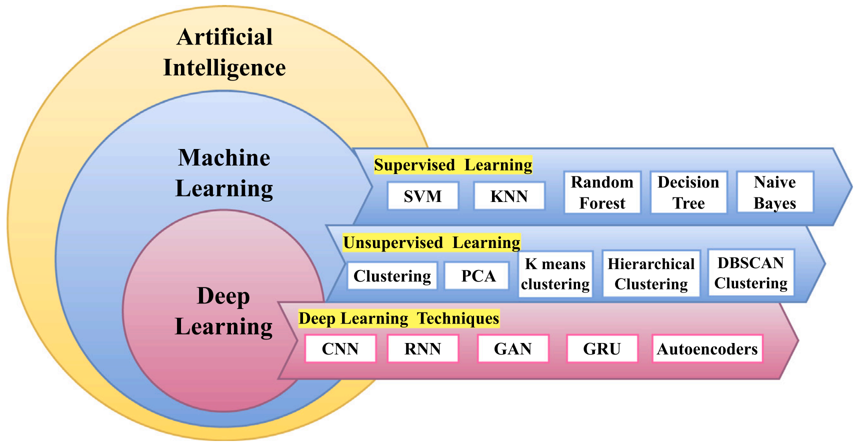

Fig. 1. Comprehensive overview: AI, ML, and DL.

recognition, and Decision Trees for structured data analysis [7]. Deep Learning (DL), a subset of ML, employs Artificial Neural Network (ANN) inspired by the human brain's architecture, excelling in tasks like image recognition, speech analysis, and natural language processing, all of which contribute to autism understanding and treatment [8]. Techniques like Convolutional Neural Network (CNN) for image analysis, Recurrent Neural Network (RNN) and Long Short-term Memory (LSTM) for time-series data, and transformer models for language understanding are valuable in autism research. The Interrelation of AI, ML, and DL is illustrated in Fig. 1. Implementing AI in clinical settings enhances objectivity, reducing potential biases in analysis. AI-based systems rigorously analyse data, significantly improving the reliability of autism diagnoses by mitigating human-influenced errors. For instance, AI algorithms excel at neuroimaging data and video analysis, eliminating subjectivity's impact and augmenting diagnostic accuracy. Moreover, these AI models can continually learn and adapt, potentially refining over time, enabling personalized treatment strategies for autistic individuals.

The rapid growth of AI, particularly in healthcare, holds immense significance. In our comprehensive review of AI applications in ASD research, we have delved into both behavioural and biological markers. Specifically, we have examined markers such as eye gaze, facial expression, and motor skills as behavioural indicators. In addition, we have scrutinized Magnetic Resonance Imaging (MRI)/Functional Magnetic Resonance Imaging (fMRI) and Electroencephalogram (EEG) as biological markers. Furthermore, we have highlighted the emerging trend of employing a multimodal approach, where researchers integrate both types of markers to achieve more precise classification.

Some studies have explored the potential of AI in ASD diagnosis and its correlation with genetic contributions, underlining the necessity of a collaborative approach [9]. Others have leveraged neuroimaging data not only for diagnosis but also for rehabilitation, recognizing the intricate nature of the brain [10]. Furthermore, innovative methodologies have been developed, using functional brain network structures for more accurate autism diagnosis [11]. The utilization of EEG data in ASD classification has revealed potential biomarkers [12]. Moreover, the integration of synthetic data generation with GraphRNN has shown promise in enhancing classification accuracy in autism research [13]. Additionally, investigations into the impact of maternal immune activation on ASD-related neurodevelopmental abnormalities hold great promise in shedding light on the disorder's pathogenesis [14].

Contribution

- The following paper offers a thorough overview of the historical development and current usage of the term "autism". It discusses how the understanding of autism has changed over time, including shifts in meaning and expansions in concepts. The paper also explores the relationship between the historical context and the current use of AI/ML in autism research, focusing on classification tasks.
- Autism Research and the Multimodal Approach: While most studies focus on behavioural or biological modalities, this work takes a holistic approach. It integrates multiple modalities, including behavioural and biological markers, to provide a more comprehensive understanding of autism spectrum disorders. By doing so, it opens up new avenues for research and application, offering a broader perspective on the condition.
- This paper provides a thorough explanation of the AI-based classification techniques used in various modalities. It discusses the specific algorithms, models, and techniques for achieving reliable and precise classification outcomes. By presenting a comprehensive analysis of the classification process, this work serves as a valuable resource for researchers and practitioners in the field.
- This paper also identified some publically accessible datasets on different modalities.
- This paper discusses the successes, challenges, limitations, and future trajectories of autism research and AI/ML. It explores and suggests potential future directions for researchers.

This diverse research landscape underscores the vast potential of AI in healthcare, allowing us to gain deeper insights into diseases and develop more effective treatment strategies. Our work stands out by encompassing a wide range of modalities and exploring applications of AI in healthcare.

1.1. Data and statistics

One of the most significant observational studies on autism is conducted through the Center for Disease Control (CDC) surveillance system, incorporated into the Autism and Developmental Disabilities Monitoring Network (ADDM). This network actively monitors ASD cases, as seen in Fig. 2, which illustrates the annual prevalence rate of autism.

According to the World Health Organization (WHO), 1 in 160 children worldwide are diagnosed with autism. Recent research from the ADDM Network, tracking 11 areas across the United States, estimates that approximately 1 in 44 children were diagnosed with ASD in 2018. This is a higher figure than the previous report's predictions, which estimated that 1 in 54 8-year-old children had an ASD diagnosis in 2016 [15].

While the cause of ASD is not known, research suggests that there may be genetic and environmental factors. Some people believe that childhood vaccines may cause this condition, but there is no scientific evidence to support this theory [16].

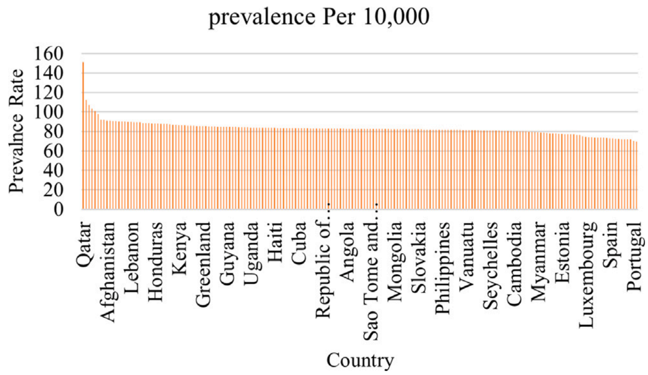

Fig. 2. Global prevalence rate of autism.

1.2. History of autism: Timeline

The history of autism is complex and has evolved. The term "autism" was first coined by psychiatrist Paul Bleuler in 1911 [17] to describe a series of symptoms he observed in some of his patients with schizophrenia. It was not until the 1940s and 1950s that autism was recognized as a distinct condition. Psychiatrist Leo Kanner [18] published a case series in 1943, describing 11 children with a condition he called "early infantile autism" characterized by a lack of social interaction and communication. At around the same time, psychiatrist Hans Asperger described a similar condition in a group of children he called "autistic psychopathy" now known as Asperger syndrome.

Since then, our understanding of autism has continued to develop. The Diagnostic and Statistical Manual of Mental Disorders (DSM) included autism as a separate diagnosis for the first time in 1980. In 2013, the DSM-5 [19] combined autism, Asperger syndrome, and related conditions into a single diagnosis called ASD. In the 1990s and 2000s, research into the causes of autism increased, leading to the discovery of a genetic basis for the disorder and the identification of several risk factors, such as prenatal exposure to certain environmental toxins and prenatal stress. With the help of advances in technology and ML, it has become possible to study autism more precisely and quantitatively, leading to a better understanding of the disorder and the development of new and more effective interventions [4]. Fig. 3 illustrates the timeline of autism research up until the present.

1.3. Organization

The paper is divided into several sections. In the first Section 1, Introduction, we provide an overview of autism and AI and discuss their contributions. The Section 2, Search Strategy, details the search strategy and selection criteria. In Section 3 Related Work: we provide a comprehensive review of the relevant literature related to ASD and the use of AI in its assessment. The review covers both behavioural and biological markers. Section 4, General Flow of AI outlines the general flow of AI for predicting ASD across various modalities. In Section 5, Challenges in AI, we discuss the challenges associated with diagnosing and rehabilitating ASD through AI techniques. Next, in Section 6, Available Datasets, we introduce publicly available datasets and briefly describe each of them. In Section 7, Discussion: we discuss the study's findings and their implications for future research. Section 8, Limitations focus on the study's limitations, and the paper concludes in Section 9, Conclusion. Please refer to the roadmap in Fig. 4 for a visual representation of this structure.

2. Search strategy

In our systematic review focusing on the application of AI approaches in ASD diagnosis, we employed a comprehensive search strategy to ensure the inclusion of relevant literature. We searched prominent databases, including Scopus, PubMed, IEEEXplore, Wiley, and Springer, utilizing targeted keywords related to ASD and AI. The specific terms used encompassed terms like "Autism", "ASD", "Participants", "MRI/fMRI", "EEG", "Eye-tracking", "Facial", "DL", and "ML".

2.1. Inclusion and exclusion criteria

Our inclusion criteria were as follows:

1. Participants with ASD were included.
2. Studies focusing on DL techniques were considered.
3. Outcomes related to DL in autism research were required.
4. English language restrictions were applied.
5. Studies published up to the search date were considered.
6. Materials such as reviews, meta-analyses, keynotes, narratives, editorials, and magazines were not considered for inclusion.

2.2. Search process

We initiated our search by conducting a systematic query across designated databases, yielding an initial set of 2100 records. Following removing duplicate entries (1380 records) and excluding records for reasons unrelated to duplication (280 records), we were left with 440 records for further evaluation. These 440 records underwent a rigorous screening process, during which titles and abstracts were assessed against predetermined inclusion and exclusion criteria. This

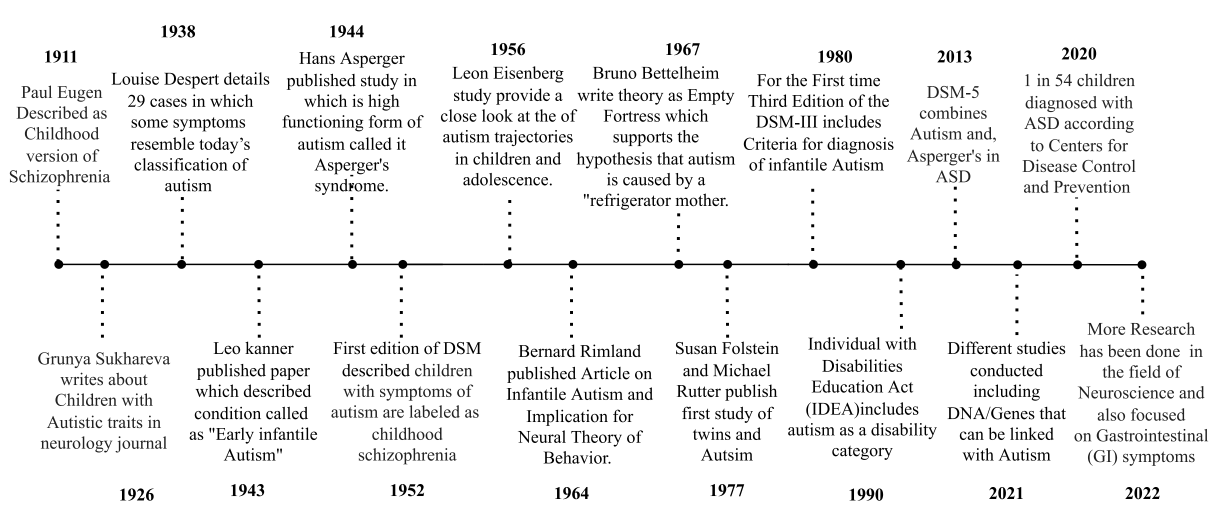

Fig. 3. History of autism: Timeline.

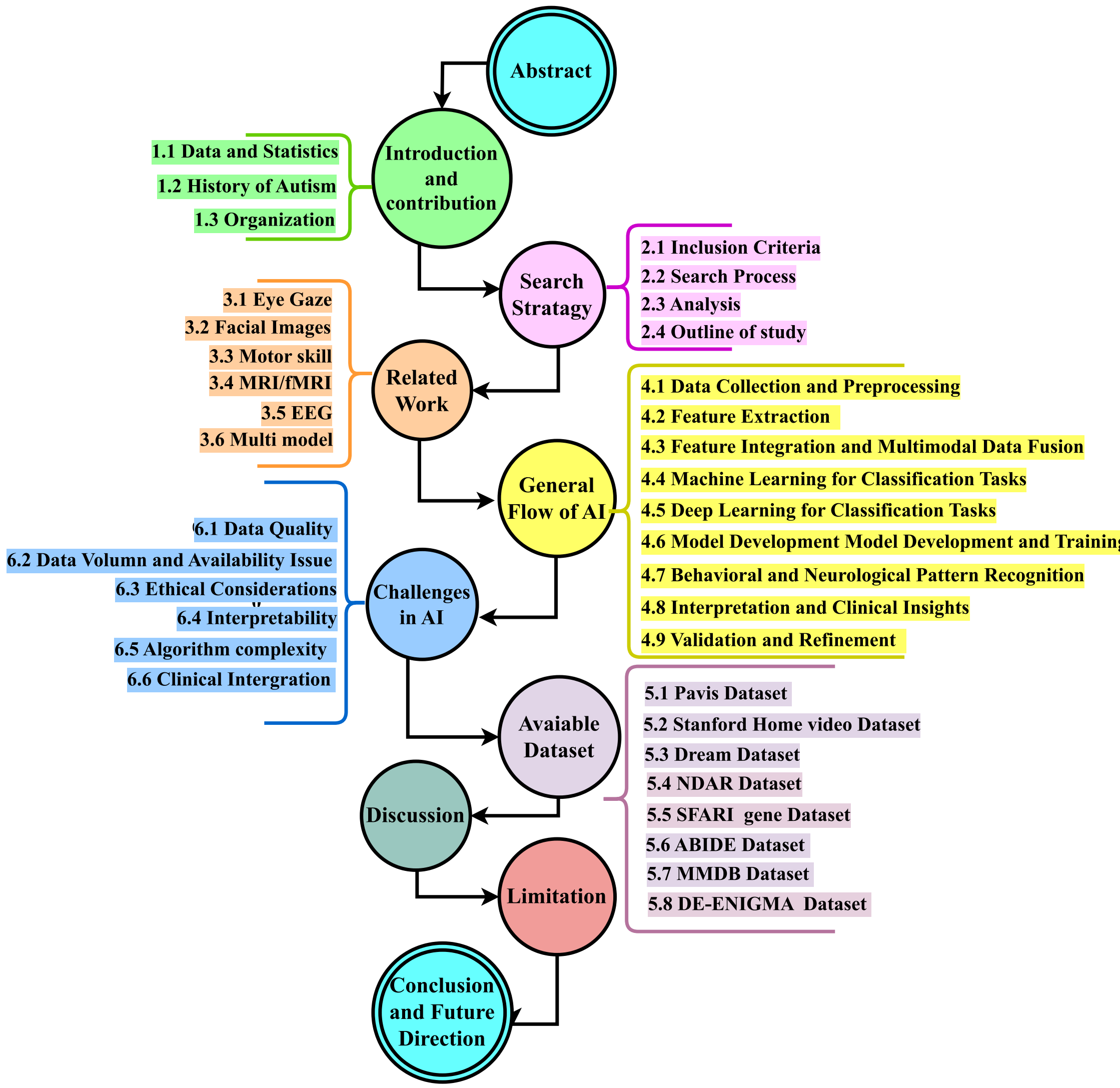

Fig. 4. A visual roadmap to understand the organization of the study.

excluded 298 papers, leaving 142 reports eligible for full-text retrieval and assessment. The 142 identified reports underwent a comprehensive full-text evaluation following the inclusion and exclusion criteria. This process yielded 84 reports that were considered eligible for subsequent evaluation. Our eligibility criteria were centred on studies involving the diagnosis of ASD through AI methodologies, particularly those incorporating DL or ML approaches. These studies encompassed a range of diagnostic modalities, including MRI/fMRI, EEG, eye-gaze, facial expression, and motor skill assessments. Subsequently, reports that did not meet the required criteria were excluded based on the following reasons: Lack of discernible outcomes (n = 4), Irrelevance to ASD diagnosis and AI approaches (n = 7), and Absence of comprehensive information (n = 13).

After screening, we pinpointed 60 studies that aligned with our inclusion criteria and were consequently incorporated into our review. The details of the selected studies, along with their corresponding database information, can be visually observed in Fig. 5, which presents a PRISMA diagram [20] outlining the entire procedure. These chosen studies underwent thorough data extraction and in-depth analysis, allowing us to amalgamate crucial insights about the application of AI methodologies in the realm of ASD diagnosis.

2.3. Analysis

The specific application of each measurable marker in ASD research is thoroughly examined in subsequent subsections. The total number of published studies in this field is visually depicted in Fig. 6 illustrating the year-wise distribution of studies on AI in ASD research up to 2023. It is worth noting that, as of now, some studies from 2023 may not yet be included in the database. Hence, the count for that year may be underrepresented.

The studies we extracted provided data on various factors, categorized into a structured table. This table offered insights into the utilization of AI methodologies for ASD diagnosis. The structured table encompassed categories such as:

1. behavioural and biological markers quantified,
2. Specific AI/MLDL methods,
3. Participant size ASD and Typically Developing (TD),
4. Dataset used,
5. Age range of participants,
6. Deployment focus,
7. Input data and devices,

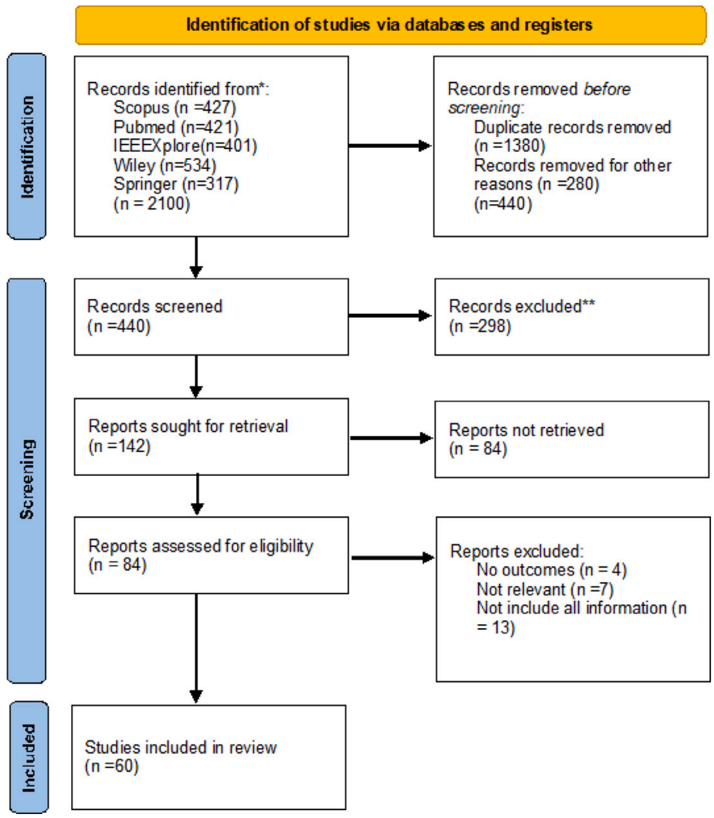

Fig. 5. PRISMA flow diagram for study selection.

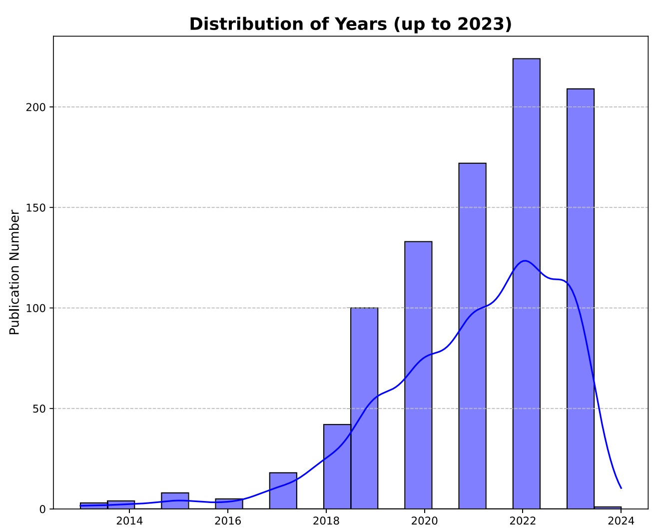

Fig. 6. Year-wise distribution of ASD studies utilizing AI methodologies.

8. Study advantages, and
9. Limitations.

2.4. Outline of study selection

The survey results underscore the substantial impact of AI methodologies on autism research. AI has demonstrated effectiveness in capturing and quantifying diverse forms of data, ranging from eye gaze patterns, facial expressions, and motor skills to functional MRI and magnetic resonance imaging, EEG, and employing multi-modal data approaches.

This review provides a comprehensive analysis of the efficacy of employing AI techniques in three key areas: (1) Identifying behavioural and biological markers for diagnosing and characterizing ASD, (2) Developing assistive technologies to support ASD patients in recognizing and expressing emotions, and (3) Enhancing existing clinical protocols with AI-driven systems for ASD therapy and automated behaviour analysis.

3. Related work: Overview of behavioural/biological markers used in papers

Understanding ASD necessitates a holistic approach that encompasses various modalities of data analysis. The convergence of ML and DL techniques with these diverse data sources has opened new avenues for unravelling the intricate facets of ASD. This section delves into the literature on different modalities commonly employed in ASD research, including eye gaze data (refer Table 1), facial expressions (refer Table 2), motor skills (refer Table 3), MRI/fMRI (refer Table 4), EEG (refer Table 5), and the integration of multimodal data (refer Table 6).

The shown Fig. 7 represents a word cloud created from various academic papers, displaying the most frequently used terms and highlighting the core vocabulary. The bold and larger words indicate a higher frequency of occurrence, which helps understand critical concepts and ideas. The thematic groupings of words form clusters that aid in comprehending the interconnectedness. For researchers, the word cloud is a valuable tool to identify potential areas of interest and gaps in understanding. It provides a powerful visual summary, helping researchers to quickly and efficiently comprehend the most important concepts and ideas in a particular field. The word cloud shows that autism, machine learning, deep learning, EEG, classification, eyes, and ASD are the most commonly used keywords in the selected papers.

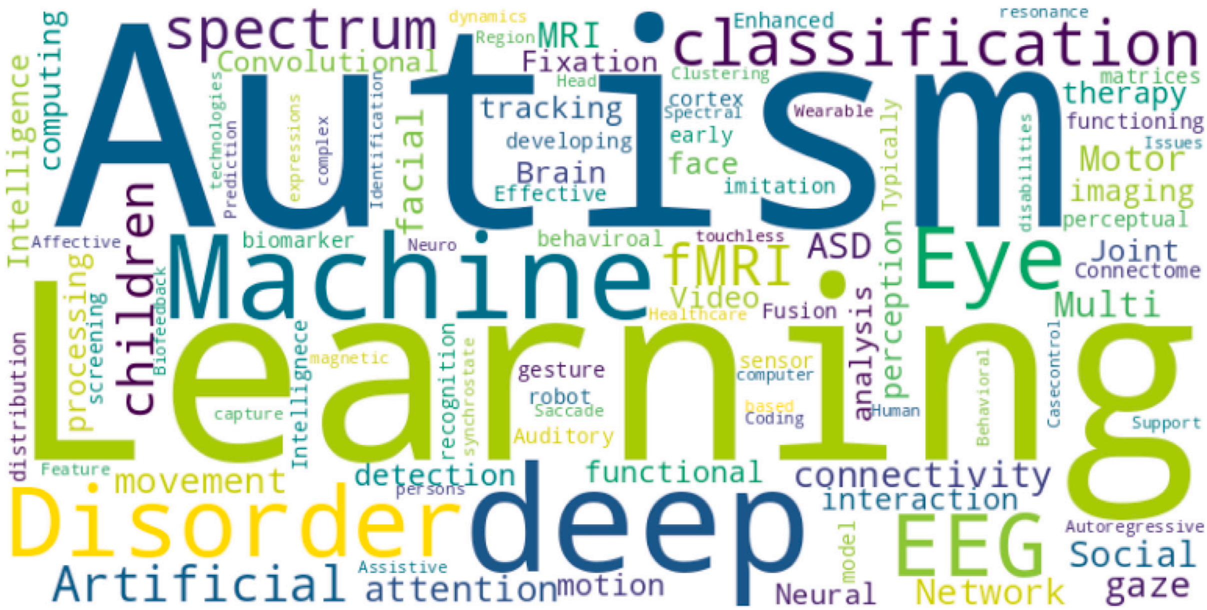

Fig. 7. Visualization of key terminology in analysed papers.

Table 1
Summarizing research article using AI approaches for detecting ASD through eye gaze modality.

Ref	Method	Parti-cipants	Dataset	Age	Focus	Input/Device	Advantages	Limitations
[21]	ML - KNN	16 ASD, 16 TD	Own	2–10 Yrs	Diagnosis using Gaze	Tobii EyeX Controller	Cost-efficient, early detection	Small sample sizes
[22]	DL	20 ASD, 19 TD	[23]	Yrs	Visual Attention preference	Eye gaze tracking Data	Deep neural networks	Small dataset, Not compared against traditional diagnostic methods
[24]	SVM and BOW	20 ASD, 21 TD (Child) 19 ASD, 22 TD (Adult)	[25] [26]		Eye movement for diagnosis	Tobii T60 eye tracker	Early detection and diagnosis of ASD using face scanning patterns.	Small sample size
[27]	OpenFace Toolkit	2 ASD, 2 TD	Own		Behaviour Analysis for Gaze	Camera, Video	Novel interface supports video coding of social attention for ASD	Evaluated the proposed interface with limited variations of videos 180 s long
[28]	DL	50 ASD, 50 TD	Own		Detection of eye contact	Videos	PiCNN method superior eye contact detection performance using computer vision	Dataset imbalanced distribution, evaluation on diverse data is needed
[29]	DL and CNN		MaTHi-Sis		Eye movement analysis for affective states	Video, Camera	Two-stream CNN approach captures eye movements and motion patterns effectively	Imbalanced data, suboptimal optical flow method
[30]	Android Face Detection API	10 ASD, 8 NDD	Own	12–18 Yrs	Attention recognition for assistive tech	Mobile Phone, Video	Engaging educational content delivery for intellectually disabled students.	Challenges with tilting along the y-axis and false alerts with face detection.
[31]		21 ASD, 21 TD	Own	5–17 Yrs	analysing facial expressions	Gaze data and Tobii EyeX Controller	Provides valuable insights into the gaze behaviour and emotion perception of children with ASD	Small sample size
[32]	Bayesian model	15 ASD, 13 TD	Own	8–43 Months	Gaze pattern for saliency analysis	Gaze trajectories, Eye gaze tracking system	Flexible mixture weight distributions, robustness to outliers, and potential for hierarchical analysis of multiple images	Increases computational cost while integrating interpolation of single-frame saccades
[33]	Modified DBSCAN	38 ASD, 179 TD	Own		Identification of fixations and saccades	Eye-tracking Data	MDBSCAN combines advantages of dispersion-based and velocity-based algorithms for fixation identification	MDBSCAN may not always be closest to ground truth, requiring parameter tuning for optimal performance

3.1. Eye gaze

Individuals with autism often experience developmental delays when it comes to following the direction of another person's gaze in social situations. Eye gaze tracking has been utilized in numerous studies on ASD to explore a variety of behaviours and abilities. For instance, eye gaze tracking has been used to examine the social attention patterns of those with ASD and their capacity to identify and

Table 2
Summarizing research article using MLDL approaches for detecting ASD through facial modalities.

Ref	Method	Participants	Dataset	Age	Focus	Input/Device	Advantages	Limitations
[34]	DL, Facial Action Coding System (FACS)	1 ASD, 1 TD	Own		Facial Expression recognition for assistive technology	Video	Unobtrusive facial expression analysis, Enhanced assessment of social skills	Human evaluator bias, Difficulty in detecting subtle movements
[35]	DL, Facial Action Coding System (FACS)	20 ASD, 19 TD	Own	9–14 Years	Facial Expression recognition for quantitative assessment	Motion Capture data, infrared motion camera	Reveals Facial Expression Complexity	Limited Generalization
[36]	DL, CNN	49 ASD, 39 TD	[37] Training: AffectNet and [38] EmotioNet		Facial attributes for ASD classification	Video, iPad	Comprehensive Facial Attribute Analysis, Improved Classification Performance	Limited Data
[39]	DL, CNN	91 ASD, 1035 NDD, 1126 TD	Own		Facial image Analysis for diagnosis	Image, camera	Potential for Assistive Technologies, Robustness to Varied Age Groups	Limited Diversity in Developmental Disorders
[40]	DL	17 ASD	Own	6–13 years	Facial Expression recognition for quantitative assessment	Image sequences	Quantitative and Personalized Assessment,	Small Sample size
[41]	DL, Histogram Oriented Gradients (HOG) feature combined with linear classifier	5 ASD, 5 TD	DISFA [42], SEMAINE [43] and BP4D [44]	65 month	facial expression analysis for diagnosis	Video and Webcam	Non-invasive, Objective Assessment, Emotional behaviour Analysis	Small Sample Size, Limited to Facial Cues
[45]	ML, Histogram Oriented Gradients (HOG) + SVM	20 ASD, 20 TD	Own		Emotional recognition for assistive technology	Video, Google glass and mobile phone	Real-time Emotion Cues, Improving Eye Contact, behavioural Aid	Sensory Overload Concerns, Potential Discomfort
[46]	DL	17 ASD, 10 TD	Own	6-13 years	Facial Expression for quantitative assessment	Image sequences	analyse facial expressions in children, providing accurate evaluations to help improve emotional competence with ASD	sample size
[47]	Ensemble classification (AWS+ Sighthound + Azure)	8 ASD	Own	6–12 years	Facial emotion for mobile game	Mobile phone	Crowdsourced emotion data for improved recognition	Emotion improvement limits due to bias and lack of data.
[48]	Histogram Oriented Gradients (HOG) + SVM	8 ASD, 5 TD	Own		Facial Expression for quantitative assessment	Video, mobile phone	Game-based approach captures natural emotional responses in children's home environment	Limited age groups, Specific prompt categories.

comprehend the emotions of others. Moreover, eye gaze tracking has been employed to study the effects of speech and language therapy interventions on social attention and communication skills in individuals with ASD. Researchers studying ASD have found eye gaze invaluable as it provides a non-invasive and objective measure of social attention and communication abilities [49].

The study of [21] used an ML approach with KNN for diagnosis using the Gaze pattern. In [22,28,29] used DL technique, Jiang and Zhao focus on visual attention preference for diagnosis, they used Deep Neural Network (DNN) based feature learning and SVM based classification. In [28], they introduce the novel Pose-Implicit CNN to eye contact detection during adult–child social interactions in which the adult wears a point-of-view camera that captures an egocentric view of the child's behaviour. By analysing the child's facial regions and inferring their head pose, we can accurately identify the onset and duration of the child's looks to their social partner's eyes. [29] propose a novel technique that combines the concept of spatially targeted optical flow with image processing for affect state recognition concerning a wide variety of learner types, including children with autism and mainstream children, deep Neural Networks on image classification, by adopting a two-stream CNN approach for the recognition task, based on gaze analysis.

The system proposed by [24] uses ML to identify eye movement patterns associated with ASD, along with feature extraction and prediction frameworks.[27] developed a system that visualizes automatic gaze estimation and enables further analysis by experts. [30] presented

Table 3
Summarizing research article using MLDL approaches for detecting ASD through motor skill modality.

Ref	Method	Participants	Dataset	Age	Focus	Input/Device	Advantages	Limitations
[50]	DL, CNN+ LSTM	20 ASD, 20 TD	Publicly available	ASD: 9.8 years TD: 9.5 years	Grasping actions for diagnosis	Video, Vicon VUE video camera	Early autism diagnosis via video analysis, automated and objective	Video quality dependency, limited sensitivity to subtle autism spectrum variations
[51]	Zface to track pitch, yaw, and roll of head movement	21 ASD, 21 TD	Not available publicly	2.5–6.5 years	Head movement analysis	Video, camera	Objective Measurement, Social Response Insight, Potential Diagnostic Cue	Small Sample, Tracking Constraints, Isolated Analysis
[52]	R-CNN		From NODA program of Behaviour Imaging company		Motion pattern for diagnosis	Video, Mobile Phone	Novel motion pattern representation, potential diagnostic aid	Limited data diversity, overfitting risk, resource-intensive process, video quality dependency
[53]		4 ASD	n/a	5–7 years old	Gesture tracking for music therapy	Video, camera	Real-time interaction, customizable mapping for therapy	Latency concerns, small and diverse sample, subjective progress assessment
[54]		10 ASD	n/a	Mean age: 9.6 years old	Body movement for emotional training	Video and motion capture data, Microsoft Kinect v2	Promotes emotional competence in ASC, Transfer of learning to facial expressions	Small sample size, specific age level, imitation deficits impact results, limited long-term assessment
[55]	vision processing, Robot Operating System		n/a		Robot-assisted therapy	Video, Penguin for Autism Behavioural Interventions (PABI)	Robot-assisted approach enables early ASD intervention, features expressive design for interactive engagement	Limited by small sample size, age-specific focus, technical constraints
[56]	Image processing	6 ASD, 6 TD	n/a	ASD: 4.70 ±0.70 TD: 4.26 ±1.05	Head movement analysis for assistive technology	Video, NAO Robot with 2 vertical stereo cameras	Evaluate an adaptive robotic system for joint attention tasks	small sample size, limited interaction time
[57]		5 ASD	n/a	10–12 years old	Movement pattern analysis for game-based therapy	Video, Microsoft Xbox 360 Kinect	touchless motion-based gaming for ASD children, potential learning benefits and positive emotional effects	small sample size and methodological limitations
[58]		15	n/a	10–14 years	Movement pattern analysis to support therapeutic tool	Video,Microsoft Kinect	innovative NUI for sensory integration therapies	small sample size, limited diversity
[59]	ML	44 ASD	Own	12–144 months	ASD prediction	Developmental Quotient (DQ)	facilitates tailored interventions via ML, integrates clinical data, highlights gut-brain axis's role	Limited sample size, gender imbalance, wide age variation

an assistive system that employs haptic feedback to recover attention by tracking it with a mobile camera. Their research with people with varied intellectual disabilities revealed that it could improve learning without intervention.

In the study by Syeda et al. and Campbell et al. [31,32], they conducted a controlled experiment to investigate face-scanning patterns, finding that children with autism tend to spend less time looking at core features of faces (such as the eyes, nose, and mouth), as revealed by the analysis of gaze data. The study summary is presented in Table 1.

3.2. Facial expression

Facial expressions play an important role in social interaction. A smile can convey interest, while a frown can indicate sympathy. However, studies have shown that people with autism struggle to display appropriate facial expressions at the right moment. They may appear expressionless or exhibit inexplicable expressions [68].

Currently, computational analysis of facial expressions is an emerging research topic that could overcome the limitations of human perception. Facial image analysis involves extracting features from facial images to identify potential patterns associated with ASD. DL techniques like CNN have been employed to automatically learn features from facial images. These models can be trained to detect subtle facial expressions and characteristics that might indicate the presence of ASD. Transfer learning from pre-trained models like VGG, ResNet, or custom architectures can be utilized to improve performance. In the work of [34,40,46], they focused on qualitative facial expression recognition; the suggested framework aims to computationally analyse how children with ASD and TD produce facial expressions. Guha et al. [35] focus on Dissimilarities in global and local facial dynamics of children with TD and ASD investigated. Their findings revealed that ASD children's dynamic facial behaviour is less complicated, with the eye region being the primary source of complexity. Li et al. [36] introduced an end-to-end CNN-based approach for ASD classification that utilizes facial attributes. Their results indicate that certain facial features are highly significant and improve classification accuracy by approximately 7%. Shukla et al. [39] also employed DL techniques, specifically CNNs, for facial image analysis in ASD diagnosis.

In the work of [41], they worked with DL, Histogram oriented features combined with CNN for facial analysis. Voss et al. [45] built an

Table 4
Summarizing research article using MLDL approaches for detecting ASD through MRI/fMRI Modality.

Ref	Method	Participants	Dataset	Age	Focus	Input/Device	Advantages	Limitations
[60]	Mesh Processing	14 ASD, 28 TD	Own	7–39 Years	MRI for diagnosis	MRI scanner	Innovative WM volume evaluation technique for potential ASD diagnosis, age-related insights	Small sample size, limited diversity, lack of extensive clinical validation
[43]	Texture Analysis	34 ASD, 30 TD	ABIDE I Dataset	4–24 Years	MRI for biomarker detection	MRI scanner	Innovative radio mic approach using GLCM texture features for ASD characterization	Small sample size, restricted age ranges, single MRI sequence
[61]	Texture Analysis	539 ASD, 573 TD	ABIDE I Dataset		MRI for biomarker detection	MRI scanner	novel multi-scale texture analysis to identify neuroanatomical differences in ASD and controls	Gender imbalanced, Sensitivity to imaging protocol
[62]	Image Processing	15 ASD, 13 TD	Own		fMRI study for neural bases of complex non-social sound	fMRI scanner	Investigates neural basis of complex sound processing in autism, reveals auditory hierarchical organization	Small sample size, lack of behavioural differences, uncorrected thresholds
[63]	DL, MLP with 2 Hidden LayerL-STM+ SVM	187 ASD, 183 TD	4 Datasets (NYU, USM, OHSU, UCLA) from ABIDE-I fMRI dataset		fMRI for diagnosis	fMRI scanner	Introduces Auto-ASD-Network, a novel DL-SVM fusion, achieving 80% accuracy for autism classification with fMRI	acks clinical validation, and demands significant computational resources.
[64]	DL, SSAE	149 ASD, 161 TD	4 Datasets (LEUVEN, USM, UM, UCLA) from ABIDE Dataset		fMRI for diagnosis detection	rs-fMRI scans	Novel DTL-NN method combines rs-fMRI and transfer learning for improved diagnosis	reliance on healthy FC patterns, potential sample size impact limit broader applicability
[65]	ML/ Constrained Autoregressive Model	31 ASD, 23 TD	San Diego State University cohort of ABIDE-II Dataset		fMRI for diagnosis	Imaging data, GE 3T MR750 scanner	Integrates functional and structural data for comprehensive brain function understanding and improves classification	Limited to direct structural links, impacted by complex interactions
[66]	ML/ SVM	15 ASD, 14 TD	Own Dataset		fMRI for diagnosis detection	fMRI/MRI scans	Leverages data-driven fusion of heterogeneous fMRI experiments for enhanced ASD classification	Limited by small sample size, lack of generalizability, and data fusion complexities.
[67]	ML, independent component Analysis	24 ASD, 27 TD	Own		MRI for Biomarker detection	MRI scans/fMRI scans	Multinetwork Analysis, Identification of Abnormalities	Limited by small sample size, lacks direct behavioural correlations
[44]	Multi-feature-based networks (MFN) and SVM	66 ASD, 66 TD	4 Datasets (NYU, SBL, KUL, ISMMS) from ABIDE Dataset		MRI for Biomarkers detection	MRI scans	Novel method utilizing cortico-cortical similarity-based networks improves ASD classification accuracy	Accuracy may be suboptimal, sample variability due to multicenter data, exclusion of subcortical regions, and generalizability concerns

autonomous facial expression recognition system that runs on Google Glass and provides the wearer with real-time social cues using computer vision techniques. The study summary is presented in Table 2.

3.3. Motorskills

For children with autism, developing their motor skills can be a challenge. Many autistic children struggle with gross motor skills such as running, jumping, and balancing. They may also need help with fine motor skills, such as grasping small objects, manipulating tools, and writing. It is essential to provide these children with appropriate interventions and therapies to help them develop their motor skills. Occupational therapy, physical therapy, and speech therapy can all be effective in addressing motor skill deficits in children with autism. By providing targeted interventions and support, we can help children with autism reach their full potential and achieve greater independence in daily life.

The study by Zunino et al. [50] conducted a study to investigate the use of video gesture analysis as a potential method for detecting ASD. They observed and recorded the behaviours of 20 children with ASD and 20 TD children performing various activities and used machine-learning algorithms to analyse their behaviours. The study's results showed that the algorithms accurately distinguished between the children with ASD and the TD children. The researchers concluded that video gesture analysis could be a valuable tool for detecting ASD. The study by Martin et al. [51] showed the differences in head movement between children with ASD and TD children using objective measures. They used a head-mounted eye tracker to measure the head movements of 38 children with ASD and 38 TD children as they watched a video on a computer screen. The results showed that the ASD group had less varied and less smooth head movements than the TD group. The researchers suggested that these differences may be related to atypical sensory processing in ASD and may have implications for developing interventions and treatments. In the study by Vyas et al. [52], the

Table 5
Summarizing research article using MLDL approaches for detecting ASD through EEG modality.

Ref	Method	Participants	Dataset	Age	Focus	Input/Device	Advantages	Limitations
[69]	(MRMR) feature selection method combined with	49 ASD, 48 TD	Own	3–6 years	Identification of Autism using EEG and Eye gaze tracking	Extracted features from modalities	MRMR feature selection enhances efficiency, Reveals autistic children's atypical face gaze patterns	Sample size diversity and feature extraction complexity
[70]	Hybrid Lightweight Deep Feature Generation (MobileNetV2, ShuffleNet, SqueezeNet)	61 ASD, 61 TD	Own		Automatic autism detection	one-dimensional local binary pattern (1D_LBP) and the generated features	Addresses limitations of previous studies and demonstrates superiority in ASD classification using a large dataset	Real-world implementation and clinical validation are required to assess its effectiveness
[71]	SVM + Multiscale entropy(mMSE)	79 ASD infants	Own	6 to 24 month	EEG signals as a biomarker for early detection of risk for ASD	Extracted feature Vectors	Reveals distinct EEG complexity changes in high-risk infants versus controls	Accuracy drops with age, requiring longitudinal studies for predictive power
[72]	Quantitative electroencephalography (qEEG)	17 ASD, 11 TD	Own	6 to 11 Years	Detection of Abnormalities for Diagnosing ASD	Extracted feature Vectors	Spectrogram and coherence analysis identify distinct abnormalities in alpha and gamma frequency bands	Small sample size and medication influence may affect generalizability
[73]	Neural Network, Fuzzy Synchronization Likelihood (Fuzzy SL)	9 ASD, 9 TD	Own	7 to 13 Years	Investigation of functional connectivity in autism	Selected features	Fuzzy SL for autism functional connectivity, achieves high accuracy, offers potential neurofeedback markers	Small sample size, needs further validation in larger cohorts
[74]	SVM	12 ASD, 12 TD	Own		Presence of autism using the functional brain connectivity	Extraction of brain connectivity features	EEG-based synchronization for high autism detection accuracy using complex networks, discriminant analysis	Small sample, larger diverse studies needed for robust clinical validation.
[75]	Douglas–Peucker with DL	9 ASD and 10 TD	KAU [76]	6–20 years	Enhances ASD detection with EEG recordings through ELM-AE-based data augmentation	EEG signals	Preserves EEG signal integrity by eliminating segmentation, achieving high accuracy	Small dataset, computationally intensive image generation, limited subject diversity
[77]	ROAR for features	88 ASD	Own	Age: 15.34±1.58 years	Evaluation of a CNN for EEG using eXplainable Artificial Intelligence (XAI)	EEG	CNN with XAI for EEG-based facial emotion recognition, featuring a novel ROAR methodology, and evaluating XAI saliency-maps for meaningful feature extraction	Limited sample size, external validation needed
[70]	Hybrid 1D_LBP + STFT	61 ASD, 61 TD	Own	4–13	Autism Detection	EEG signals	novel algorithms incorporating deep lightweight features and ReliefF2 selection, achieving a high accuracy for ASD detection	Applicability to clinical settings and real-world scenarios needs validation and testing
[78]	Convolutional Neural Network based Feature Extractor for BCI Attention Classification (CNN-FEBAC)	15 ASD	Publicly access		Analysing the response and attention patterns of ASD individuals	EEG P300 signals	Proposing a CNN-FEBAC framework achieving 91% accuracy, outperforming previous methods	Limited dataset size and subject-specific model lacks broader applicability

authors developed a method for detecting atypical behaviour in autistic individuals using video data. They used a state-of-the-art pose estimator called 2D Mask R-CNN to estimate children's poses over time in the video. This allowed them to analyse the movements and postures of the children. They then trained a CNN to classify whether a given video clip contained typical (normal) or atypical ASD behaviour. The authors' approach achieved an accuracy of 72% in detecting atypical behaviour, which outperformed conventional video classification approaches. Another study by Margini et al. [53] developed an interactive vision-based system that produces sounds responding to human body movements. A group of clinical psychologists and parents of young patients evaluated the system. The study by Piana et al. [54] estimated a system designed to help children with ASD recognize and express emotions through their full-body movements, as captured by RGB-D sensors. RGB-D sensors

Table 6
MLDL methods for Multimodel approach.

Ref	Method	Parti-cipants	Dataset	Age	Focus	Input/Device	Advantages	Limitations
[79]	DL, ResNet-50 and LSTM	22 ASD and 23 controls for image viewing, 20 ASD and 19 controls for photo taking	Own dataset	–	Attentional and image viewing preference for diagnosis	Photo sequence + Image and Eye fixations	Computational model for ASD using photo-taking task, surpassing human expertise	Limited exploration beyond ASD, data dependency, generalizability validation, and potential complexity in shared space interpretation
[80]	DL, VGG+ SSD	2 ASD, 6 TD	Oxford hand and Ego-hands dataset	Chil-dren: 25 months, Adults: 25 years	Mutual gaze and gesture recognition for diagnosis	Image/Two Logitech BRIO 4K Pro RGB cameras + Microsoft Kinect	The ENIFP protocol provides standardized, ASD assessment through remote accessibility, expanding screening reach	Small sample size, age range limitations, environmental impact, gesture recognition challenges
[81]	DL, Person-alized Perception of Affect Network (PPA-net)	35 ASD	Own dataset - multi-modal data set	3–13 years old	Autism therapy	Synchronized video recordings of facial expressions, head and body movements, pose, and gestures, audio recordings, and autonomic physiology	Personalized DL for autism accommodates various emotional states, matching human experts effectively	Contextual reliance and expert knowledge needed, posing challenges with limited or inconsistent data
[82]	Artificial intelligence	3 ASD	Own dataset	8–13 years old	Head pose, body posture, eye contact, and facial expression for robotics treatment of autism	Robokind Zeno R25 humanoid robot and a Microsoft Kinect	Customized treatment protocol with a social robot mediator improves eye contact, facial expression imitation, and engagement in children with autism.	Small preliminary study, potential challenges in generalizing findings to a wider ASD population.
[83]	PABI Face Detection: HOG + Face recognition: LBPH, Regression trees, Perceptive-N-Point problem	5 ASD	HELEN dataset	5–8 years old	Face recognition, head pose, and eye gaze estimation for assistive technology	Video, Penguin for Autism behavioural Intervention (PABI)	Robot enhances engagement through personalized, standardized, and multimodal interactions in autism therapy.	Small initial study sample, requiring further research to establish long-term efficacy and broader applicability.
[84]	–	6 ASD, 2 TD	Own dataset	4–10 years old	Analysis of joint attention and imitation accuracy	2 NAO robots, Microsoft Kinect, and EEG	study attention and imitation in ASD children via unique multi-robot setup, revealing preferences abilities	Small sample, need more research for validation
[85]	ML for clas-sification	58 ASD, 48 TD	Own dataset	3–6 years	Identifying distinctive neuroimaging features	MRI/fMRI	High accuracy in distinguishing low-functioning ASD preschoolers from controls using T1w MRI and DTI	Small sample, potential biases, need for broader validation.
[86]	Multimodal Fusion	380 ASD	BSNIP-1, FBIRN, COBRE, ABIDE I, MPRC, ABIDE II	3–6 years	Distinguishing SZ and ASD	fMRI and sMRI	High accuracy with combined FNC and GMV, revealing differentiating features	No symptom associations, 3-class classification, limited feature insights
[87]	ANNs		Multi-sensor Data		Continuous Performance Test for Attention ASD	Video and audio, Sensor	Facial and speech emotion features through AI enhances the accuracy of early ASD identification	Individual emotional and expressive differences may affect the accuracy of ASD prediction.
[88]	ML, SVM with a linear kernel	50 children (ASD + TD)	Own	3 to 6 years old	sensorized toy car 2.0 for low-cost multi-modal ASD screening, early detection	MEMS accelerometer	Enhanced accuracy with shaft encoders and acceleration, low-cost, expert-independent for initial screening.	Feature selection dependence, limited depth compared to fMRI/EEG, further research needed for validation and generalization.

can capture colour (RGB) and depth (D) information. In the study, the authors found an increase in the accuracy of the task (i.e., emotion recognition) from the beginning to the end of the training sessions. This suggests that the system was effective in helping children with ASD to improve their ability to recognize and express emotions through their movements. The study by Dickstein-Fischer and Fischer [55] created a robot named Penguin for Autism Behavioural Interventions (PABI) to facilitate interactive therapy for autistic children. PABI is designed to engage with autistic children meaningfully during therapy sessions and is equipped with augmented vision technology, which enhances the robot's natural senses, specifically its visual abilities. Similarly, Bekele et al. [56] created an adaptive robot-mediated intervention architecture (ARIA) to provide individualized therapy for autistic children. ARIA is designed to offer joint attention prompts, which involve sharing attention with others and following their gaze or attention to an object or event. Since children with autism may struggle with joint attention, this can affect their social and communication skills. The study by Bartoli et al. [57] conducted a study exploring the use of motion-based, touchless games for learning in children with autism. Touchless games are interactive games that can be played without physical touches, such as through gestures or body movements. Similarly, Ringland et al. [58] created a therapeutic tool called sensory paint that enables whole-body interactions and can potentially be an effective intervention for children with autism [59]. This study used ML models to find the best predictors of ASD development and specific characteristics in children with ASD. It aimed to improve early diagnosis and tailor interventions using maternal and infant data alongside ADOS-2 scores. The results highlighted factors like gut disturbances, EEG retrievals, sleep problems, age at diagnosis, and weight at birth as significant predictors. The study summary is presented in Table 3.

3.4. Magnetic resonance imaging/functional MRI

In studies on ASD, MRI and fMRI are commonly used imaging techniques to examine brain structure and function. MRI generates high-resolution images of the body, including the brain, using magnetic fields and radio waves. This technique helps researchers investigate the size and shape of various brain regions in individuals with ASD. In contrast, fMRI measures blood flow to different brain areas and allows studying brain function. Researchers can infer which brain regions are more active by asking individuals to perform specific tasks or respond to stimuli during the scan. These techniques are essential in helping researchers better understand the brain basis of ASD and in developing new treatments or interventions. For instance, Abdelrahman et al. [60] used MRI scans to create a 3D model of the brain, precisely measuring the volume of white matter in the segmented brain. By using white matter volume as a discriminatory feature in the k-nearest neighbour classification technique, they achieved a 93% accuracy rate. In the work of Chaddad et al. [43,61], the potential of hippocampal texture features as a biomarker for the diagnosis and characterization of ASD was demonstrated using the ABIDE repository. Using fMRI scans, Samson et al. [62] investigated the differences in complex non-social sound processing between individuals with ASD and TD. The results showed that TD individuals had more activity in the anterolateral superior temporal gyrus with increased temporal complexity, while ASD individuals had more activity in Heschl's gyrus.

In the study [63–65], they used a DL technique for fMRI diagnosis; in the work of [63] propose a method called Auto-ASD-Network, the power of deep learning for extracting useful patterns from the data as well as discriminative power of SVM classifier which is a very well known approach in brain disorder classification.[64] developed a novel DTL-NN framework by utilizing healthy FC patterns to facilitate the application of DL models for smaller neuroimaging rs-fMRI studies and demonstrated enhanced ASD classification compared to DNN models. The work of [65,65] employed an ML approach that combined a constrained autoregressive model with an SVM to distinguish individuals with ASD from TD.

In the study, [66], they have used the Multivariate Variate Pattern Analysis approach for task-based and resting-based fMRI recordings to investigate which neural markers distinguish individuals with ASD. Ahmadi et al. [67] demonstrated that individuals with ASD have lower within-network connections on fMRI images compared to TD individuals, using independent component analysis. The study by Zheng et al. [44] employed multi-feature-based networks (MFN) and SVM to classify individuals with ASD and TD. They found that MFN significantly improved classification accuracy by approximately 14% compared to morphological features alone. Their findings suggest that variations in cortico-cortical similarities could be used as potential biomarkers in the diagnostic process. The study summary is presented in Table 4.

3.5. EEG

Brain–computer interface (BCI) is a collaboration between a brain and a device that enables signals from the brain to direct some external activity [89]. Human–computer interface is another term for it. BCI is an emerging research field that has broadened its application to various fields—a test to see what exists in the brains of autistic subjects. This is accomplished by obtaining signals from the brain, reading the signs, and interpreting and analysing the signals. Natural conversation involves using muscles or nerves to convey, exchange, and share ideas and feelings with human intent. This causes a complex process in some brain areas. When neurons are stimulated, an indigenous current is produced. The amount of signals produced during synaptic movement of dendrites in the cerebral cortex of the brain is referred to as EEG [90]. The BCI machine executing Signal Processing and Pattern recognition deduces the signal activity occurring from the brain is denoted to a Brain Machine Interface [91]. The EEG spikes primarily in the frontal, parietal, and temporal brain regions. Although the role of spectral power changes, it is still unclear in the developmental windows of children with autism; it may be associated with cognitive and behavioural dysfunctions [92].

In the work of [69], Identifying children with ASD may benefit from an ML technique that combines EEG and eye-tracking data. The classification of autistic children against typically developing children was done using the minimum redundancy maximum relevance (MRMR) feature selection method combined with SVM classifiers. In other work, [70] used hybrid lightweight deep feature generation for automatic autism detection using an SVM classifier, similarly in [71], Developmental cognitive problems may have an early biomarker that abnormal EEG signals can identify. Modified multiscale entropy (mMSE) was calculated based on resting-state EEG data. In [72], Neurophysiologic diagnostics have been performed using quantitative electroencephalography (qEEG) to detect abnormalities in ASD diagnosis. In the work of [73] presented a methodology for investigating functional connectivity in autism, all wavelet-derived EEG sub-bands and the full-band EEG are used to calculate brain regions. Then, using Analysis of Variance, discriminative Fuzzy SLs across and within various regions and various EEG sub-bands or full-band EEG are developed for separating autistic children from normal control children (ANOVA). The enhanced probabilistic neural network classifier is then utilized to diagnose ASD using the input from the chosen features accurately. In this study [75], an automated detection method for ASD using EEG signals was developed. To reduce the number of EEG samples, the Douglas–Peucker algorithm was applied. Sparse coding was then utilized to construct EEG rhythm-based images, and an image data augmentation technique based on Extreme Learning Machine Autoencoder (ELM-AE) was employed. Finally, pre-trained deep CNN models were used for classification. The proposed method achieved remarkable results, with an accuracy of 98.88%, sensitivity of 100%, and specificity of 96.4%, demonstrating its potential as an effective tool for automated ASD detection based on EEG signals. In another study [77], Researchers used the RemOve-And-Retrain (ROAR) method to test the reliability and accuracy of XAI techniques for EEG-based FER tasks. The study included individuals with and without ASD; XAI methods like LRP were analysed.

LRP showed higher relevances in late-time components for individuals with ASD experiencing negative emotions. ROAR involved removing potentially relevant features and re-validating results. The findings showed significant differences between TD and ASD binary masks in late-time components and XAI methods, indicating unique emotional information encoding between the two groups. The study [70] presents a novel approach for automated autism detection using EEG signals by combining a one-dimensional local binary pattern (1D_LBP) and short-time Fourier transform (STFT). Feature ranking and selection are performed using a two-layered ReliefF algorithm, and the selected features are inputted into various shallow classifiers. The results demonstrate that the proposed model achieves a high accuracy of 96.44% using an SVM classifier. This suggests that the hybrid deep lightweight feature extractor has strong potential for aiding neurologists in autism diagnosis as an adjunct tool in medical centres. In another study by [78], The author proposed CNN-FEBAC, a framework that measures attention in individuals with ASD using CNN technology to analyse EEG signals. With 91% accuracy on the BCIAUT-P300 dataset, CNN-FEBAC surpasses previous methods by extracting significant features and adjusting to individual differences in attention patterns. This advancement will aid in developing diagnostic and therapeutic tools for ASD by providing accurate assessments of attention. EEG data records the electrical activity of the brain and is used to study brain function. ML techniques, such as SVM, RNN, or CNN, can classify EEG patterns associated with ASD. Feature extraction from EEG data is crucial, and techniques like wavelet transform or time–frequency analysis can be employed to capture relevant information. The study summary is presented in Table 5.

3.6. Multimodel approach

In the field of autism research, various studies have been conducted to explore the potential of DL and AI in improving ASD screening, diagnosis, and therapy. For example, Chen and Zhao [79] proposed a framework that combined information from a photo-taking task and an image-viewing task with eye-tracking data. By integrating features extracted from these tasks using CNN and LSTM models, they achieved significant performance improvement of over 30%, resulting in new state-of-the-art results for ASD screening. Similarly, Wang et al. [80] developed a non-invasive system called Expressing Needs with Index Finger Pointing (ENIFP) for ASD diagnosis, which used DL techniques to capture the participant's eye gaze and gestures during the protocol. This system successfully assessed mutual attention and gestures, highlighting the potential of AI in analysing multimodal data for ASD screening. Additionally, Several studies [81–84] have explored the use of computer vision in autism therapy through social robots that adapt their behaviours automatically. By combining multiple aspects such as eye contact, joint attention, imitation, and emotion recognition, these systems provide adaptive and personalized interactions, significantly improving the effectiveness of therapy for children with ASD. Overall, these approaches have shown great potential in advancing autism research, surpassing previous state-of-the-art methods, and improving the accuracy and effectiveness of interventions for individuals with ASD. The study by Kim et al. [85] focused on using ML classifiers to differentiate low-functioning preschoolers with ASD from typically developing controls using T1-weighted MRI and DTI data. The classification achieved an accuracy of 88.8%, sensitivity of 93.0%, and specificity of 83.8%, with specific neuroimaging features identified as key contributors to the classification. In another study by Du et al. [86], the Neuroimaging fusion method was used to classify ASD patients using fMRI and sMRI data from multiple datasets, focusing on distinguishing the disorders. Emotion-based ASD identification using ANN approach by [87], focusing on video and audio data of autistic and non-autistic children to predict ASD through facial and speech emotion features. In the study by [88], the author introduces a novel multimodal ASD screening tool. The upgraded design includes shaft encoders to capture rotational tendencies in children with ASD. Moreover, they have enhanced the feature selection strategy, improving accuracy in multi-modal ASD symptom analysis. The study summary is presented in Table 6.

In summary, this literature section has delved into various modalities utilized within autism research, spanning eye gaze, facial expressions, motor skills, MRI/fMRI, EEG, and multimodal data. A more extensive examination of behavioural and biological markers is available in the discussion Section 7, offering in-depth analyses for each modality. Additionally, the discussion section includes visual representations encompassing behavioural and biological markers across all modalities.

4. General flow of AI

4.1. Data collection and preprocessing:

The research begins with collecting diverse data modalities that capture different aspects of autism-related behaviours and neurological patterns. Eye-tracking systems record gaze trajectories during tasks involving visual stimuli, while facial expression analysis tools extract facial features and emotions from recorded videos. Motor skill assessments capture fine and gross motor abilities, while neuroimaging techniques like MRI/fMRI capture structural and functional brain characteristics. EEG records neural electrical activity, providing insights into brainwave patterns. Collected data undergoes pre-processing to enhance quality and ensure compatibility for subsequent analysis.

4.2. Feature extraction:

Extracting features is crucial to enable AI algorithms to process and comprehend information from various sources. In the context of eye gaze and facial expression data, fixation duration, gaze shifts, and emotional expressions are essential features that provide insights into a person's visual focus and emotional state. AI techniques enhance this by extracting microexpressions, which are subtle and rapid facial muscle movements that convey nuanced emotions not easily discernible by the human eye alone. Similarly, assessments of motor skills yield features such as movement accuracy and coordination metrics, which provide valuable information about a person's physical ability and precision in performing tasks. AI algorithms can also extract biomechanical parameters such as joint angles and forces, providing a deeper understanding of movement mechanics and their impact on performance. Additionally, neuroimaging techniques such as MRI/fMRI yield features including regional brain activity and connectivity patterns, illuminating the functional interactions within the brain. AI techniques expand on this by extracting features related to brain network dynamics, uncovering the strength and changes in connectivity over time. Furthermore, EEG data, recorded by scalp electrodes, is transformed into spectral power and connectivity features, enabling analysis of electrical brain activity and synchronization across regions. AI facilitates the extraction of Event-related potentials (ERPs) and time-locked brain responses to specific stimuli or tasks, offering valuable insights into cognitive processes such as attention and memory. These extraction techniques convert raw data into a format that AI algorithms can effectively analyse. This advancement enables various applications, from emotion recognition to cognitive assessment, significantly enhancing our understanding of human behaviour and brain function.

4.3. Feature integration and multimodal data fusion:

Combining information from different modalities often leads to richer insights. Multimodal data fusion integrates data from sources like eye gaze, facial expressions, motor skills, MRI/fMRI, and EEG. This fusion enhances the understanding of complex interactions between behavioural and neurological aspects of autism. AI techniques like DL can be employed to handle the complexity of multimodal data.

4.4. ML for classification tasks:

ML algorithms are commonly employed in autism research for classification tasks such as predicting specific diagnostic outcomes or classifying autism severity levels based on extracted features. One of the most commonly used ML algorithms in autism research, the Support vector machine, is powerful for binary classification tasks. They work by finding a hyperplane that maximizes the margin between classes. SVMs can also be extended to handle multi-class classification. Random Forest is an ensemble learning method that combines multiple decision trees to make more accurate predictions. It is robust and can effectively handle high-dimensional data. Despite its name, Logistic Regression is used for binary classification tasks and models the probability of a sample belonging to a particular class. KNN classifies data points based on the majority class among their K-nearest neighbours. It is intuitive and easy to implement. Naive Bayes is a probabilistic algorithm based on Bayes' theorem, assuming independence between features. It is useful for text classification tasks. Decision Trees split data based on features to create a tree-like structure for classification. They are interpretable and can handle both categorical and continuous features.

4.5. DL for classification tasks:

DL is a type of ML that involves training neural networks to learn hierarchical representations from the data automatically. In autism research, DL models are highly effective for tasks that require working with large, high-dimensional datasets. Here are some common types of DL architectures: CNN is particularly effective for tasks that involve images. They use convolutional layers to automatically extract features from images, making them suitable for facial expression analysis and MRI/fMRI data analysis tasks. RNNs are designed to handle sequences of data. They are helpful for tasks that involve time-series data, such as EEG analysis, where the temporal order of data points is crucial. LSTM Networks is a specialized form of RNNs designed to capture long-term dependencies in sequential data. They are adequate for tasks that have complex temporal patterns. Autoencoders are used for unsupervised learning tasks. They aim to reconstruct the input data and can be applied to anomaly detection or feature extraction tasks. Whereas Transfer Learning is a technique that involves pre-training a neural network on a large dataset and then fine-tuning it on a specific task. It is useful when there is limited labelled data available.

4.6. Model development and training:

AI models, such as ML algorithms and neural networks, are developed to analyse the extracted and integrated features. Supervised learning may involve training models to predict specific diagnostic outcomes or classify autism severity levels based on the features. Unsupervised techniques, like clustering or dimensionality reduction, can identify hidden patterns within the data.

4.7. Behavioural and neurological pattern recognition:

Trained AI models can effectively recognize patterns indicative of autism traits or neurological abnormalities. These models can identify subtle behavioural nuances, aberrant brain connectivity, or atypical neural activations that may serve as biomarkers for ASD.

4.8. Interpretation and clinical insights:

The identified patterns and correlations are then interpreted in the context of existing autism research and clinical knowledge. The insights from AI analysis can provide a deeper understanding of autism-related behaviours, cognitive processes, and underlying neural mechanisms.

4.9. Validation and refinement:

The generated findings are subject to validation using independent datasets or cross-validation techniques to ensure the robustness and generalizability of the AI models. Feedback from clinicians and domain experts helps refine the models and improve their diagnostic and predictive accuracy.

Fig. 8 offers a comprehensive visual representation of the complete workflow, encompassing various stages, starting with the initial data pre-processing and proceeding through subsequent steps to the final prediction or classification task.

5. Challenges in AI

AI is a rapidly growing field with a wide range of potential applications. However, the development and deployment of AI systems also come with some challenges that must be addressed to ensure the safe, fair, and effective deployment of AI in various domains. These challenges include data availability and quality, interpretability and explainability, safety and security, privacy, and data protection. These challenges must be overcome to fully realize AI's potential in various fields (see Table 7).

5.1. Data quality

The data quality used to train AI models significantly affects their accuracy and predictability. Errors, biases, and noise can lead to misinterpretation and incorrect results. To achieve reliable predictions in autism research, where subtle patterns and behaviours are significant, it is crucial to ensure data quality through careful preparation, cleaning, and validation. Eliminating data biases is also necessary to prevent AI models from amplifying discrimination [93].

5.2. Data volume and availability issue

AI algorithms, especially DL models, thrive on large amounts of data to learn effectively and generalize well. However, autism research often suffers from limited and diverse datasets. The need for well-labelled data challenges training accurate and robust AI models. Generating and curating sufficient data that captures the complexity of autism is essential for overcoming this challenge. Collaboration between researchers, clinicians, and data collection initiatives can play a pivotal role in gathering the necessary data [93].

5.3. Ethical considerations

When dealing with medical data, especially related to autism, strict adherence to ethical guidelines and legal regulations is crucial. Patient privacy, data security, and informed consent are of utmost importance. AI algorithms must be designed with privacy safeguards, encryption, and access controls to prevent unauthorized use of sensitive information while balancing data utility and patient confidentiality [98].

5.4. Interpretability

DL algorithms can map complicated, nonlinear functions, making them challenging to understand. This becomes an essential factor to consider in healthcare applications because the capacity to understand the factors that influence outcomes is just as crucial as the capacity to anticipate the outcome correctly. Interpretability is essential to encourage healthcare professionals to make a decision based on the changes proposed by algorithms and to enable their rapid adoption in the clinical setting, where systems are intended to improve the

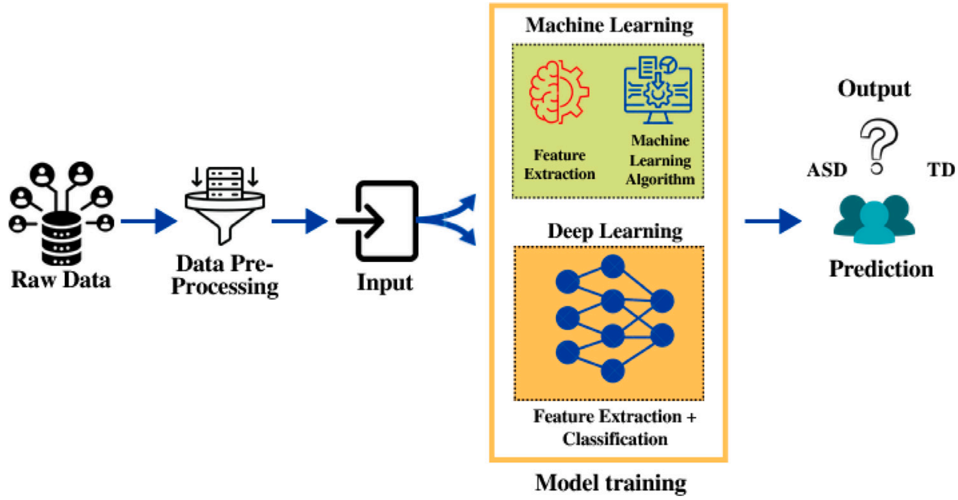

Fig. 8. Methodology for ASD prediction.

Table 7
Challenges in AI-driven Autism Research.

References	Challenges	Description
[93]	Data Quality	The accuracy and reliability of AI models heavily depend on the quality of input data. Noisy, biased, or insufficient data can lead to suboptimal results.
[93]	Data volume and availability	Autism research often deals with limited and heterogeneous datasets, which can hinder the development of robust AI models. The need for well-labelled data poses a significant challenge.
[94]	Ethical Considerations	Processing sensitive medical data raises ethical concerns regarding privacy, consent, and data security. Ensuring compliance with regulations and safeguarding patient information is paramount.
[95]	Interpretability	Many AI algorithms operate as black boxes, making understanding the rationale behind their decisions challenging. This lack of interpretability hinders their adoption in clinical settings.
[96]	Algorithm Complexity	Advanced AI techniques, such as DL, can be computationally intensive and resource-demanding. Implementing and training these models require substantial computational power and expertise.
[97]	Clinical Integration	Bridging the gap between research and clinical practice is challenging. AI solutions must seamlessly integrate into clinical workflows, requiring collaboration between AI researchers and medical professionals.

decision-making capabilities of healthcare professionals. As a result, significant initiatives within the DL community to address the issues of interpretability and explainability can facilitate the adoption of DL techniques in healthcare [95]. To overcome the interpretability issue, XAI aims to offer comprehensible explanations for its actions. While achieving this goal has been challenging, numerous methods have been suggested to enhance the transparency of artificial intelligence, gain the trust of clinicians and achieve favourable clinical results. Understanding DL algorithms can be challenging due to their ability to map complicated, nonlinear functions. This is especially important in healthcare applications, where it is crucial to comprehend the factors that impact outcomes. Interpretability plays a significant role in encouraging healthcare professionals to make decisions based on the recommendations provided by algorithms. It also enables swift adoption in clinical settings, where the goal is to enhance decision-making capabilities. Therefore, the DL community has taken significant steps towards addressing the issues of interpretability and explainability, which could facilitate the adoption of DL techniques in healthcare [95]. eXplainable Artificial Intelligence (XAI) aims to provide transparent and understandable explanations for its actions to overcome the interpretability issue. Although achieving this goal may be challenging, various methods have been proposed to increase the transparency of artificial intelligence, gain the trust of clinicians and achieve favourable clinical outcomes [99].

5.5. Algorithm complexity

Advanced AI techniques often require much computational power, demanding adequate hardware, model creation, and training knowledge. The complexity of AI algorithms can be a barrier in autism research and clinical settings where resources may be few. It is crucial to find approaches to optimize and modify these algorithms so they can operate effectively with the resources at hand [96].

5.6. Clinical integration

Translating DL models from research to clinical practice necessitates a thorough validation process encompassing clinical trials, comparisons with established standards, and rigorous assessments of efficacy and safety. This validation must be complemented by seamless integration with Electronic health records (EHR) and clinical workflows, addressing technical challenges such as data interoperability, security, and real-time processing. Additionally, considerations for scalability, user interface design, and regulatory compliance are paramount. Success in this endeavour hinges on close collaboration between researchers, clinicians, regulatory bodies, and technical experts to ensure the models are accurate but also practical and safe for real-world clinical application [97].

6. Available datasets

The reviewed papers utilized public datasets to examine markers in individuals with autism. The datasets were selected based on the markers and AI methods employed. Table 8 contains the sources for these datasets, ensuring they are compatible with the research objectives.

6.1. Pavis dataset

The dataset includes trials conducted by both autistic and non-autistic children. The primary goal is to complete this two-class classification. Andrea Zunino, Pietro Moreno, and other researchers from

Table 8
Available Datasets for ASD.

Reference	Dataset	Type	Link as on date:22-08-2023
[100]	Pavis Dataset	Video	https://pavis.iit.it/autism-spectrum-disorder-detection-dataset
[101]	Stanford Home Video Project	CSV	https://github.com/qandeelt/Tariq-Wall-2018-PLOS-MEDICINE
[102]	The DREAM Dataset	Eye gaze	https://github.com/dream2020/data
[103]	National Database for Autism Research (NDAR)	Text, numeric, image, time series, etc.	https://healthdata.gov/dataset/National-Database-for-Autism-Research-NDAR-/7ue5-z77y/data
[104]	SFARI Gene Dataset	Genetic and phenotypic data	https://www.sfari.org/resource/autism-cohorts/
[105]	ABIDE	MRI	http://fcon_1000.projects.nitrc.org/indi/abide/abide_I.html
[106]	MMDB	Multi-Model	https://cbs.ic.gatech.edu/mmdb/dataset.php
[107]	DE-ENIGMA	Multi-Model	https://deenigmadb.wordpress.com/

Istituto Italiano di Tecnologia provided this video dataset consisting of video clips of children with ASD and IQ-matched TD children doing reach-to-grasp movements. The children from both groups were asked to grasp a bottle and do four distinct motor actions: placing, pouring, passing to pour, and passing to place. Researchers have attempted to classify whether steps are performed by a normal or an autistic child by solely processing the section of video data showing the grasping gesture, as motivated by recent studies in neuroscience [100].

6.2. Stanford Home Video Project

The Stanford Home Video Project dataset [101] is a collection of family and children's home recordings that aims to examine social interaction and development in the context of ASD. These videos, shot in real-world household environments, provide insightful views into the activities, relationships, and growth patterns of kids with ASD. Researchers have used this dataset to examine early signs of ASD, language development, and numerous social communication topics. Researchers can use the dataset's open accessibility on GitHub to explore the information, identify behavioural trends, and acquire a better knowledge of early development and autism [108].

6.3. Dream dataset

The behavioural data is obtained from 61 children diagnosed with ASD. The information was gathered in a large-scale Robot Enhance Therapy (RET) study. Over 3000 therapy sessions and over 300 h of therapy are included in the dataset. A therapist supervised half of the children while they engaged with the social robot NAO. The other half, the control group, had direct contact with a therapist. Both groups followed the ABA methodology. Three RGB cameras and two RGBD (Kinect) cameras were used to record each session, providing precise information on the children's behaviour during therapy. Body motion, head position and orientation, and eye gaze characteristics are all defined as 3D data in a shared frame of reference in this public release of the dataset. Participants' age, gender, and autism diagnosis (ADOS) factors are also provided in the metadata. We are releasing this information in the hopes of spurring further data-driven research towards better therapy approaches and a better knowledge of ASD in general [102].

6.4. National Database for Autism Research (NDAR)

The NDAR [103] is an NIH-funded research data repository that aims to accelerate progress in ASD research by promoting data sharing, harmonization, and reporting findings. It acts as a data repository and a scientific community platform, with standardized tools and policies for integrating computing resources from scientific research institutions, private foundations, and government organizations funding ASD research. NDAR has collaborated closely with the ASD research community to develop a data dictionary with over 300 clinical, imaging, and genomic research terminologies. Researchers must structure their data following an existing data definition or create a new one accessible to other researchers through NDAR. As the world's largest archive, NDAR makes all forms of data available at every biological and behavioural level. As of November 2013, qualified investigators can access data from nearly 90,000 research participants through the NDAR portal. The public website of NDAR also summarizes the data available, making it a valuable resource for ASD research.

6.5. SFARI Gene dataset

The SFARI Gene [109] web portal seamlessly integrates various types of genetic data generated by research studies, encouraging the development of new hypotheses in the process. SFARI Gene uses a systems biology method to incorporate information on autism potential genes from its original Human Gene module to data from various supplementary data modules. The data establishing the association between ASD risk genes and autism is then graded using a set of annotation guidelines created in cooperation with an external advisory group and categorized into specific categories.SFARI Gene's Human Gene module provides a comprehensive collection of genes examined in the context of autism. It includes information on the genes, scholarly article references, and a summary of the evidence tying the genes to ASD. The SFARI Gene Copy Number Variant module is a separate resource that catalogues recurrent single-gene and multi-gene deletions and duplications in the genome and describes their possible link to autism. The Animal Models Module of SFARI Gene offers information about lines of genetically engineered mice that could be used as autism models. The nature of the targeting construct, the background strain, and, most crucially, a complete summary of the phenotypic traits most relevant to autism are all included in this material.

6.6. Autism Brain Imaging Data Exchange (ABIDE)

The Preprocessed Connectomes Project (PCP) has preprocessed neuroimaging data from the ABIDE [105] for public use and sharing. ABIDE is a collaborative effort between 16 international imaging sites, which have collected and openly shared neuroimaging data from 539 individuals with ASD and 573 healthy controls as part of the International Neuroimaging Data Sharing Initiative (INDI). These datasets include structural and resting state functional MRI data and various phenotypic data.

To preprocess data from ABIDE, five teams utilized their preferred technologies. The Connectome Computation System (CCS), the Configurable Pipeline for the Analysis of Connectomes (CPAC), the Data Processing Assistant for Resting-State fMRI (DPARSF), and the NeuroImaging Analysis Kit were employed for functional preprocessing. The CPAC software calculated statistical derivatives for each pipeline and technique to standardize the variance between outputs to solely preprocessing. Three pipelines were used for structural preprocessing and cortical measure calculation: ANTS, CIVET, and FreeSurfer.

6.7. Multimodal Dyadic behaviour dataset

The Multimodal Dyadic Behaviour (MMDB) dataset [106] stands as a distinctive compilation comprising 160 instances of multimodal recordings encompassing video, audio, and physiological data. These recordings are accompanied by annotations that shed light on the social and communicative tendencies of 121 children aged between 15 and 30 months. These invaluable records were collated using a methodology termed the Rapid-ABC sessions. The Rapid-ABC sessions

Table 9
Application of ML/DL to ASD Analysis in Different Modalities.

Modality	Data collection	Pre-processing	Feature extraction	Model architecture	Training & Validation	Interpretation	Clinical applications	Advantages	Disadvantages
Eye gaze	Record gaze patterns	Clean, normalize gaze coordinates	CNNs analyse gaze patterns	CNNs	Train on gaze data, validate	Identify gaze patterns related to ASD	Understand social interaction and sensory aspects	Direct insight into visual attention	Challenges in interpretation, affected by lighting and calibration, limited to controlled settings, may miss spontaneity
Facial Images	Gather facial images	Normalize, resize, align	CNNs learn facial features	CNNs	Train with labelled data, validate	Visualization of influential regions	Assist in diagnosis and severity assessment	Non-invasive, allows visual evaluation of facial expressions	Subjective interpretation, context-dependency, cultural variability, limited to visible cues
Motor Skills	Collect motion capture data	Filter, normalize, segment	RNNs capture motor patterns	RNNs, LSTMs	Train on motor data, validate	Identify motor deviations in ASD	Monitor motor behaviour and intervention progress	Provides precise motor behaviour measurements, captures intricate motor patterns	Challenges include external factors, skill variability, and issues with severe impairments
MRI/fMRI	Acquire structural/ functional	Skull strip, normalize, motion correction	CNNs/3D CNNs for structure	CNNs, RNNs, 3D CNNs	Train on brain images, validate	Discover brain differences in ASD	Uncover structural/ functional brain changes	Offers detailed brain info, pinpoints ASD-related brain differences	Expensive and time-consuming, Motion artefacts, Restricted to tolerant individuals
EEG	Record brain activity	Noise removal, segmentation	RNNs capture temporal patterns	RNNs, LSTMs	Train on EEG sequences, validate	Identify brain patterns related to ASD	Detect ASD-related neural signatures	Offer precise brain activity timing, identify ASD-related brainwave patterns	Limited to spatial resolution, Pre-processing challenges, and variation due to electrode placement

involve a dynamic assessment process spanning 3 to 5 min each. Within this timeframe, a series of five semi-structured play interactions are orchestrated. During these interactions, the examiner adeptly draws social attention, cultivates interactive exchanges, and observes the non-verbal communication nuances of the participating child. This methodology captures the essence of the child's developmental stage and their propensity for interpersonal interactions, making the MMDB dataset an indispensable resource for advancing our understanding of early childhood social and communicative behaviours.

6.8. DE-ENIGMA dataset

The DE-ENIGMA dataset [107] stands as a comprehensive and freely accessible resource for extensive multi-modal research, encompassing diverse data types such as audio, video, and depth information. It has been meticulously compiled to capture the interactions of children on the autism spectrum, thereby serving as a valuable asset for behavioural investigations. The study featured the participation of 128 children diagnosed with autism, each contributing to the dataset. The experimental design entailed the random assignment of children into distinct age groups. Participants were allocated to either a robot-led or a researcher/therapist-led teaching intervention within each group. This intervention was carried out across a series of concise sessions, fostering a dynamic learning environment. The dataset encompasses a remarkable volume, totalling around 13 terabytes of multi-modal data, corresponding to approximately 152 h of recorded interactions. To enhance the dataset's utility, a subset of 50 children's data has undergone meticulous annotation by experts. This annotation encompasses key aspects such as emotional valence, arousal levels, audio characteristics, and body gestures. The availability of this annotated data positions it as a prime resource for future ML research focusing on autism-related inquiries. The DE-ENIGMA dataset thus not only advances our understanding of autistic children's interactions but also provides a robust foundation for developing and refining machine-learning approaches tailored to autism research.

7. Discussion

This paper provides a comprehensive review of the application of AI in predicting ASD using various behavioural and biological markers. It discusses how different modalities impact the accuracy of predictions and traces the historical progression of autism research. The methodology for employing AI in ASD prediction across other modalities is detailed, focusing on the necessary steps for integration into autism research. However, the review highlights persisting challenges, particularly in accurately quantifying real-world data, especially when dealing with image or video streams. The assessment of publicly available datasets related to behaviour analysis is emphasized as a valuable resource for researchers conducting ASD studies involving behaviour and biological analysis. The summarized analysis in Table 9 offers a brief overview of the critical stages and outcomes in the entire process. It dissects the process into essential components such as data collection, pre-processing, feature extraction, model architecture, training, validation, interpretation, clinical applications, and associated advantages and disadvantages for each modality. This table serves as a valuable tool for researchers and clinicians seeking insights into diverse approaches utilized in ASD studies, ranging from analysing eye gaze patterns, facial images, and motor skill assessment to examining brain MRI/fMRI and EEG data. It underscores the potential benefits of these approaches, such as gaining direct insights into visual attention, non-invasive facial image analysis, and precise timing of brain activity. Simultaneously, it acknowledges the limitations and challenges, such as subjectivity in interpretation, reliance on controlled settings, and variations in data quality. This comprehensive summary provides valuable insights for individuals involved in ASD research and healthcare, offering essential information about techniques and their implications. For a more detailed understanding of the model's operation, please refer to Fig. 9. This visual representation guides you through all the modalities, starting from data collection, proceeding through preprocessing, model implementation, and ultimately leading to the prediction phase.

7.1. Behavioural modalities for ASD classification tasks

Behavioural modalities such as eye gaze, facial expression, and motor skills are rich sources of information for identifying ASD. Thanks to advanced ML and DL techniques, researchers have made significant progress in utilizing these modalities to distinguish individuals with ASD from their neurotypical peers. In this section, we will provide an in-depth analysis of how each behavioural modality can be effectively used in classification tasks for ASD.

7.1.1. Eye gaze analysis:

Machine learning and deep learning techniques have revolutionized the analysis of eye gaze data in the context of ASD. This methodology involves extracting various features, such as fixation durations, saccade patterns, and gaze trajectories, which serve as discriminative markers in classification tasks [21,22]. Using labelled datasets, classification models like SVM, random forests, and deep neural networks can be trained to differentiate between individuals with ASD and typically developing individuals [22]. Furthermore, machine learning models can identify context-dependent gaze patterns, providing nuanced insights into social attention differences during specific situations such

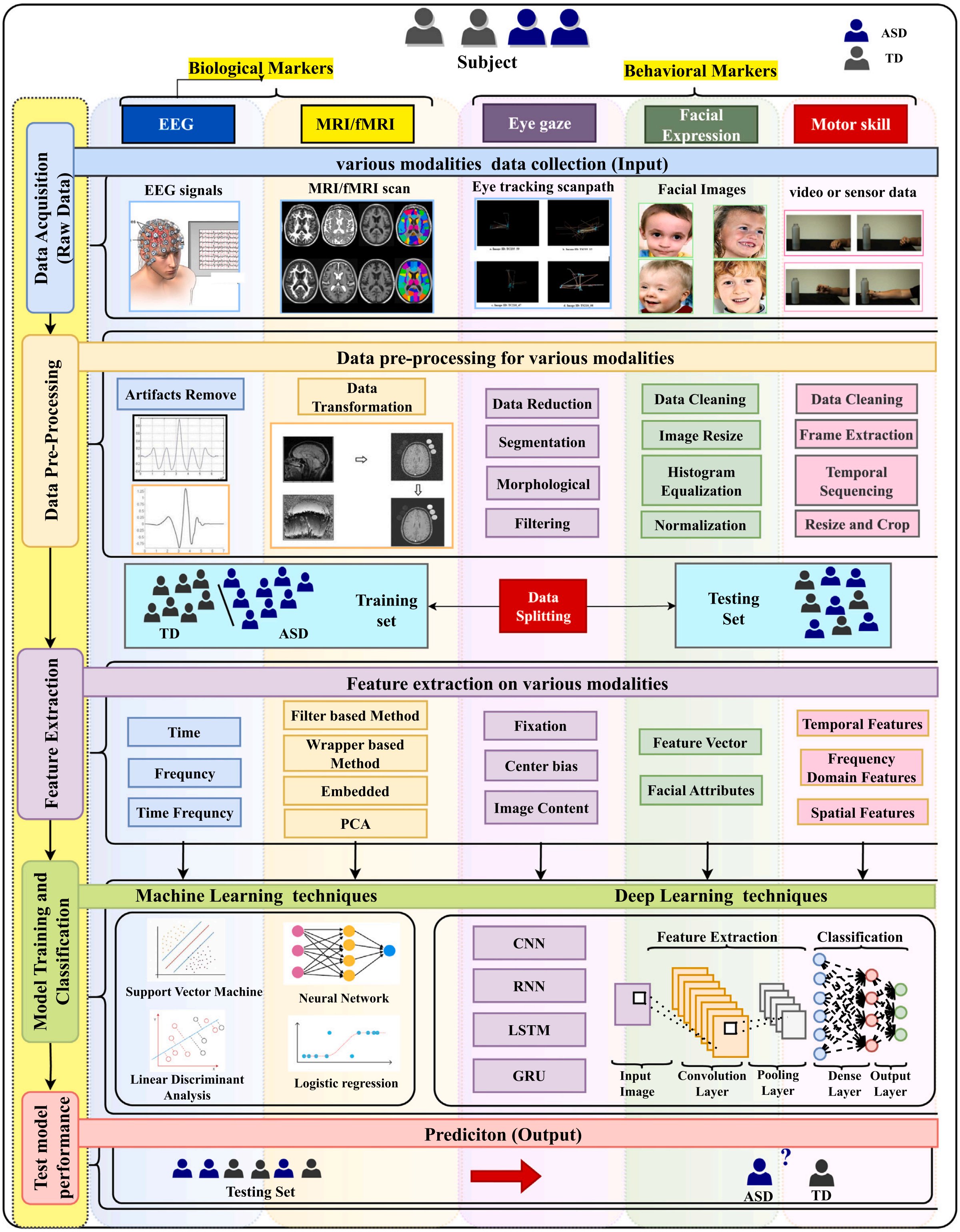

Fig. 9. Overall block diagram for ASD classification using different modalities.

as conversations or viewing emotions. The advantages of using eye gaze data for ASD research are significant. It offers an objective and quantifiable measurement of social attention, reducing potential biases associated with self-reporting or observer-based assessments [24,27]. It also holds the potential for early detection, enabling timely intervention and support. The analysis of eye gaze data further facilitates the creation of individualized interventions tailored to the specific gaze behaviour and needs of individuals with ASD while contributing to a deeper understanding of the condition's underlying mechanisms [28]. However, there are notable limitations to consider. ASD is characterized by significant heterogeneity, and machine learning models may struggle to capture the full diversity of gaze patterns [29]. Ethical and privacy concerns arise from collecting sensitive and personal data through eye gaze. Additionally, generalizing findings across different contexts, cultures, and age groups can be challenging, as various factors influence gaze behaviour [30,31]. Lastly, the quality of eye gaze data, including calibration errors, occlusions, and participant fatigue, can impact the accuracy of machine learning models and their ability to make reliable predictions. Therefore, researchers in this field must be mindful of these limitations and ensure robust and ethical data collection and analysis practices [32,33].

7.1.2. Facial expression

Facial expression analysis is a crucial tool in identifying ASD [34]. It involves capturing pictures or videos of individuals, removing noise, resizing images, and standardizing the data [35]. The dataset is then split into training and testing sets, and feature extraction is performed. This process involves analysing facial cues using various ML and DL algorithms, such as SVM and CNN [36,39]. ML models focus on extracting relevant features, while SVM excels in classification tasks by finding optimal hyperplanes. CNNs, on the other hand, are excellent at learning hierarchical features from images. DL models, such as RNNs and LSTM networks, are effective for analysing sequences of facial expressions by capturing temporal dependencies [40,41,45]. Attention mechanisms can also be used to concentrate on specific facial features. This method offers advantages such as non-invasive, objective assessment, quantifiable data for tracking progress, and potential for early detection of ASD [46]. However, there are some limitations to this approach, including context sensitivity of expressions, individual variability in emotional expression, reliance on visible expressions, susceptibility to environmental factors, and ethical considerations regarding privacy and consent when dealing with sensitive data [47]. Overall, facial expression analysis using ML and DL methods holds promise for providing valuable insights into emotional processing differences in individuals with ASD [48].

7.1.3. Motor skills analysis:

Extracting kinematic features from fine and gross motor movements in individuals with ASD is an area where ML and DL algorithms can be very helpful [50]. However, before we can delve into feature extraction, we must first carry out data preprocessing. This crucial step involves cleaning the motor data by removing any noise or outliers, normalizing it, and potentially resampling it to ensure accuracy [51,52]. Once the data is prepared, feature extraction comes into play. In motor skill analysis, feature extraction allows us to identify key attributes that describe the movement patterns. These attributes could include measures of movement speed, such as velocity or acceleration, metrics of accuracy, like trajectory smoothness, and coordination indicators, such as the degree of joint synchronization [53,54]. ML models can then use these extracted features to classify individuals based on their motor skills and ability to perform specific tasks or activities of daily living [55]. On the other hand, DL models can capture complex temporal patterns in motor data, allowing for a more in-depth exploration of motor skill characteristics associated with ASD [56,57]. It is important to note that while this approach offers promising insights, it relies heavily on the data quality and may be influenced by various confounding variables that need to be carefully considered in the analysis [58]. Nonetheless, this methodology represents a potent tool for understanding how ASD manifests in motor behaviour and for tailoring interventions to improve functional abilities in individuals with ASD [59].

7.2. Biological modalities in ASD classification

Integrating biological modalities, such as MRI/fMRI and EEG, with ML and DL techniques has revolutionized the classification of ASD. This multidimensional approach provides a comprehensive understanding of the neurobiological underpinnings of ASD, offering insights that complement behavioural assessments. The combination of MRI/fMRI and EEG with ML/DL techniques has proven to be a powerful tool for classifying ASD, enabling researchers and clinicians to gain a deeper understanding of the complex and heterogeneous nature of the disorder. By leveraging these modalities, researchers and clinicians can more accurately diagnose and treat individuals with ASD, ultimately improving outcomes for those affected by this condition.

7.2.1. MRI/fMRI

MRI and fMRI are frequently used in the classification of ASD [60]. MRI allows for extracting structural features such as regional volumes, cortical thickness, and white matter integrity, which ML algorithms can analyse to identify specific brain regions or circuits with atypical morphology [43]. This analysis provides valuable insights into the structural basis of ASD. fMRI measures blood flow changes in the brain, enabling the analysis of functional connectivity networks. ML models can distinguish differences in connectivity patterns, serving as unique markers for classification [61,62]. Task-based fMRI examines brain activation patterns during specific tasks like social cognition tasks, revealing variations in neural processing related to ASD. Before analysis, it is essential to preprocess the data by taking steps such as motion correction, spatial normalization, and possibly denoising techniques for artefact removal [63,64]. In MRI, feature extraction involves quantifying anatomical properties, whereas in fMRI, it includes measures of functional connectivity, activation patterns, or task-specific responses [65]. The advantages of these approaches include objective assessment, the potential for early detection, and insights into the neurobiological basis of ASD [66]. However, the complexity of data processing, interpretability of findings, heterogeneity in ASD, and the impact of data quality on results present significant challenges. Therefore, careful consideration of these factors is vital to ensure meaningful and reliable insights into ASD using neuroimaging data [44,67].

7.2.2. EEG

EEG data can be transformed into the frequency domain, allowing for the identification of spectral features that may indicate neural abnormalities in individuals with ASD [69]. These features can serve as crucial inputs for classification algorithms [70] Additionally, connectivity analysis offers insights into how different brain regions communicate, providing a deeper understanding of neural functioning [71]. ML algorithms can process EEG data to analyse connectivity patterns, and alterations in functional connectivity can be leveraged as discriminative features for classification [72]. The advantages of using ML and DL in EEG analysis for ASD include the ability to uncover subtle neural abnormalities, high temporal resolution, and the potential for early detection [73]. However, limitations have the need for large and diverse datasets, challenges in the interpretability of complex neural patterns, and the potential influence of confounding variables on EEG signals [74,75]. Careful consideration of these factors is essential for maximizing the utility of ML and DL techniques in EEG-based ASD classification [70,77,78].

7.3. Integration of multimodel approach:

Behavioural markers provide real-time, context-rich data, but they have some limitations, such as subjectivity, context dependence, and potential masking by individuals with ASD. In contrast, biological markers, such as MRI/fMRI and EEG, offer objective, neurobiological insights, but they can be complex to interpret, costly, and less accessible.

A multimodal approach combines both behavioural and biological markers, taking advantage of their strengths and mitigating their limitations [79,80]. By integrating these markers, researchers and clinicians can create a more comprehensive picture of ASD, enabling cross-validation and enhancing the robustness of findings [81].

For example, when behavioural markers highlight atypical social interaction patterns, they can be linked with corresponding neurobiological markers from MRI/fMRI or EEG, showing the underlying neural mechanisms. This can provide a more nuanced understanding of the condition, addressing the limitations of subjectivity and context dependence [82]. Additionally, integrating both markers allows for the early identification of potential neurobiological indicators that may precede behavioural manifestations, enabling earlier intervention and support [83].

Furthermore, a multimodal approach enhances the accuracy and specificity of ASD diagnosis [84]. By incorporating both behavioural and biological markers, diagnostic criteria become more comprehensive and reliable [85]. This not only refines the classification of ASD but also aids in categorizing subtypes based on distinct behavioural and neurobiological profiles, leading to more targeted interventions and personalized support strategies. In summary, a multimodal approach combines the strengths of both behavioural and biological markers while compensating for their limitations. This multidimensional understanding of ASD enables more accurate diagnoses, earlier intervention, and more tailored support strategies, ultimately improving the quality of life for individuals with autism and their families [86]. Collaboration between experts in both behavioural and biological sciences is essential for harnessing the full potential of a multimodal approach in ASD research and clinical practice [87,88].

In summary, the key findings of this investigation include:

1. Early detection and intervention are crucial for improving outcomes in autistic individuals. AI has the potential to assist in this endeavour by leveraging a multimodal approach that combines behavioural and biological markers. This can enhance the accuracy and timeliness of diagnoses, allowing for early intervention strategies tailored to individual needs.
2. AI has the ability to use a diverse range of behavioural and biological markers to predict and diagnose ASD. The accuracy of these predictions can vary depending on the data types and sources used. However, when multiple modalities are integrated, the strengths of each marker type can compensate for the limitations of the other, providing a more comprehensive assessment of ASD.
3. Publicly accessible datasets focusing on behavioural and biological analyses are invaluable resources for researchers exploring ASD. These datasets enable the development and validation of AI algorithms, ensuring that the models are robust and applicable across diverse populations.
4. AI can offer personalized solutions by analysing individual characteristics, such as behaviour and brain activity. This can enhance the development of tailored interventions and support strategies. The integration of multimodal data allows for the creation of individualized profiles, guiding the design of interventions that address specific needs and preferences.
5. AI can simulate the effects of interventions on intricate mental and behavioural models. This can aid researchers in identifying effective strategies and refining them before clinical trials. By simulating the impact of interventions in a controlled virtual environment, researchers can optimize treatment plans and increase their chances of success in real-world applications.
6. This paper offers a comprehensive overview of the current state of autism research. It encompasses historical perspectives, foundational steps, and the latest AI-driven advancements in the study of autism. Integrating a multimodal approach is a pivotal advancement, offering a more nuanced and personalized understanding of ASD. This has the potential to revolutionize interventions and support strategies for individuals with autism and their families.

8. Limitation of the study

This narrative review aims to identify gaps, inconsistencies, and potential opportunities in utilizing AI in ASD research. By evaluating the promising impact of AI, the study seeks to inspire future researchers to explore its possibilities further. However, it is important to acknowledge that the review process may introduce some subjectivity, potentially leading to bias in the selection and interpretation of literature. The review primarily focuses on two modalities: behavioural emotion processing and biological neural activity and connectivity patterns analyse through EEG and MRI/fMRI, aiming to uncover complex aspects of ASD. The study investigates how individuals with autism perceive, understand, and respond to emotions expressed by others using behavioural emotion processing. Simultaneously, EEG and MRI/fMRI are employed to explore neural activity and connectivity patterns in the brain, potentially identifying biomarkers associated with autism. EEG records electrical brain activity non-invasively, while MRI/fMRI generates highly detailed images of brain structure, albeit being more resource-intensive.

While these modalities are significant in the study of autism, it is essential to recognize that other dimensions, such as social interactions, gestures, speech, and genetic factors, can provide valuable insights into the disorder. Therefore, the review encourages future research to explore these alternative modalities to harness the full potential of AI in advancing our understanding of autism. A multi-faceted approach will pave the way for more effective diagnostic and therapeutic interventions.

9. Conclusion and future direction

Over the past few years, the research community has shown deep interest in applying Artificial intelligence techniques in various fields, especially in the medical field, where early diagnosis is crucial to addressing disease-related issues. AI techniques can help to understand complex patterns and identify various factors affecting the disease, which helps in early detection. This study demonstrates the impact of AI on autism and its early detection. AI algorithms use behavioural cues like facial expressions, Eye gaze, and motor skills for pattern recognition. Meanwhile, biological indicators like EEG and MRI/fMRI offer more detailed patterns that provide deeper insights into cognitive and neurological processes. The review is a detailed account of recent work in this area, including all the modalities in which AI is applied. The summary tables group data by different modalities, providing detailed analysis and comparison of recent work. Strengths and limitations are identified, and each modality gives insight into AI usage. A categorical review aims to identify future research gaps that can help the researchers plan the work ahead. After compiling a detailed review, the available datasets and sources facilitate the community to experiment further. Here are specific directions for DL practitioners to harness dataset potential and push field boundaries:

1. Embrace Multimodal Approaches with Fusion Methods: While many studies have predominantly focused on processing RGB data from images or videos, combining information from multiple modalities can enhance performance. Researchers should explore integrating various data types, such as audio, depth, and sensor data, to achieve more comprehensive insights.
2. Standardize Benchmark Datasets for Reliable Evaluation: To establish a solid basis for comparison, researchers must adopt standard benchmark datasets. These datasets will enable consistent evaluation of models' performance. Existing datasets can serve as initial foundations for building and evaluating DL models for specific tasks in computer vision, such as human activity recognition in individuals with ASD.
3. Address Real-World Scenarios and Unconstrained Environments: Instead of limiting studies to clinical settings, there is a pressing need to develop computer vision models that can function effectively in real-world, uncontrolled environments. This entails handling diverse lighting conditions, backgrounds, and contextual variations, making models more robust and applicable in natural settings.
4. Prioritize Longitudinal Studies and Diverse Cohorts: In-depth research demands longitudinal studies or the inclusion of substantial cohorts encompassing individuals both with ASD and TD individuals. Rigorous empirical validation should underpin the

development of DL systems. These studies will help ascertain the models' accuracy, reliability, interpretability, and clinical viability, ensuring they generalize across various demographic groups while maintaining fairness and impartiality.

5. Explore Human Factors, User Experience, and Ethical Aspects: Beyond technical aspects, DL researchers should delve into the human factors, user experience, and ethical dimensions associated with deploying vision-based systems. This exploration will aid in crafting systems that are technically proficient, user-friendly, and ethically sound. This will lead to the development of usable systems that can genuinely complement behavioural observations in clinical settings.

10. List of abbreviations

ASD Autism Spectrum Disorder

ABA Applied Behaviour Analysis

TD Typically Developing

MRI Magnetic Resonance Imaging

fMRI Functional Magnetic Resonance Imaging

EEG Electroencephalogram

SVM Support Vector Machine

CNN Convolutional Neural Network

ABA Applied behaviour Analysis

AI Artificial Intelligence

DL Deep Learning

ML Machine Learning

KNN K-Nearest Neighbours

DNN Deep Neural Network

RNN Recurrent Neural Network

ANN Artificial Neural Network

LSTM Long Short-term Memory

RET Robot Enhance Therapy

EHR Electronic health records

SDGs Sustainable Development Goals

ADDM Autism and Developmental Disabilities Monitoring Network

CDC Center for Disease Control

WHO World Health Organization

XAI eXplainable Artificial Intelligence

DSM Diagnostic and Statistical Manual of Mental Disorders

ERPs Event-related potentials

Declaration of competing interest

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

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