Exploration of various approaches for detection of autism spectrum disorder

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ABSTRACT

Autism spectrum disorder (ASD) presents a complex and diverse set of challenges, necessitating innovative and data-driven approaches for effective understanding, diagnosis, and intervention. This review explores recent advancements in methodologies, technologies, and frameworks aimed at addressing ASD and also highlights novel data collection methods, focusing on the integration of wearable internet of things (IoT) sensors for real-time behavioral monitoring and data capture from individuals with ASD. Additionally, the utilization of machine learning (ML), deep learning (DL), and hybrid techniques for data analysis, feature optimization, and prediction of ASD are extensively discussed, showcasing significant progress in early diagnosis and personalized intervention planning. The challenges such as class imbalance, feature selection, and data collection efficiency are identified and addressed using the proposed ASD framework. The review also emphasizes the development of recommendation systems designed to the unique behavioral profiles and needs of individuals with ASD. The findings reveal that integrating these advanced technologies and methodologies can lead to more accurate diagnoses and effective interventions, contributing to the broader field of ASD research.

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1. INTRODUCTION

Autism is a neuro-developmental disorder that profoundly impacts the social growth and development of both children and adults. While a complete cure remains undiscovered, early diagnosis plays a pivotal role in enabling more effective treatment compared to traditional behavioral assessments, which are often time-consuming in identifying and diagnosing autism spectrum disorder (ASD) through clinic-based observations [1]. Although ASD is commonly diagnosed in children around the age of 2, it can also be identified later depending on the complexity and severity of symptoms [2]. Environmental factors and genetic links are significant contributors to ASD, affecting not just the nervous system but also social and cognitive skills [3]. Symptoms vary widely in intensity and presentation, with common indicators including difficulties in social communication, obsessive interests, and repetitive behaviors [3]. Accurate detection of ASD necessitates comprehensive evaluations and assessments conducted by healthcare professionals and psychologists. Early intervention and diagnosis are crucial as they can identify symptoms and improve overall quality of life [4]. However, the diagnostic process for ASD can be time-consuming and challenging, especially when relying solely on behavioral observations in clinical settings. While various clinical approaches exist for early detection, they are not frequently utilized unless there is a high predictive risk of ASD development [5].

Machine learning (ML) offers a promising avenue for training ASD models efficiently with high accuracy [6], as presented in Figure 1. ML techniques streamline ASD risk assessment and the diagnostic process, accelerating access to critical therapies for affected individuals and their families [7]. Classification models in ML can aid in early prediction of autism, preventing long-term effects in both children and adults [8]. Additionally, computational techniques such as internet of things (IoT)-based solutions and deep learning (DL) models have been proposed for ASD detection and healthcare management [9]-[11]. Despite these advancements, challenges persist in acquiring large datasets for model training due to data privacy concerns and regulatory barriers [12]. Security and privacy issues surrounding data transmission also pose additional hurdles in deploying ML models for ASD diagnosis [13], [14]. However, this survey focuses on leveraging wearable internet-of-things (WIoTs) to collect sensory and behavioral data from autism patients efficiently, with minimal latency and energy consumption [15]. WIoTs facilitate wireless connectivity in body area networks, enhancing remote healthcare and real-time monitoring for autism patients [16].

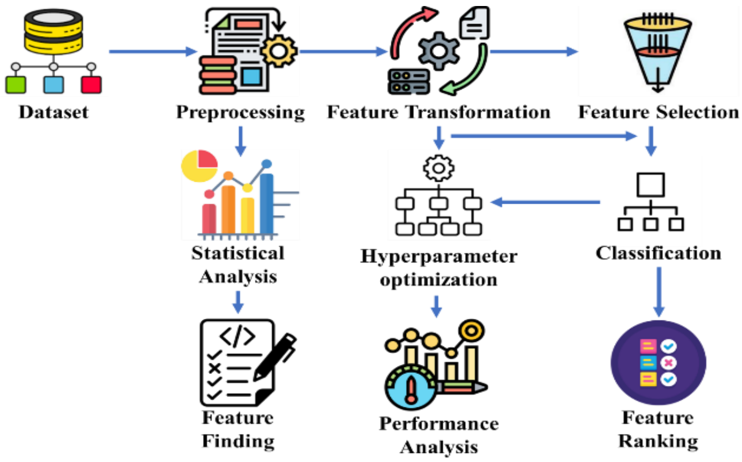

Figure 1. ML ASD detection and prediction

To address limitations in current ML and DL methodologies related to feature selection, dataset size, and accuracy across different neurological disorders, this survey tries to identify the gaps, issues and challenges of the current existing approaches. Moreover, this work proposes an ensemble learning approach with effective feature selection technique. The goal is to develop a robust feature-based classifier using ML to improve classification accuracy in categorizing patients as either having or not having ASD, across different age groups. Ultimately, the aim is to create an efficient recommender system for categorizing autism patients (children, adolescents, and adults) based on novel features extracted from wearable IoT devices. The contribution of this survey is as follows:

- The survey critically examines current ML and DL methodologies, highlighting their limitations in feature selection, dataset size, and accuracy across various neurological disorders, including ASD.
- This survey examines ensemble learning approaches combined with effective feature selection techniques to address the identified gaps and challenges in existing methodologies.
- This survey aims to develop a framework using ML, specifically designed for categorizing patients with ASD across different age groups. This classifier is designed to enhance classification accuracy in distinguishing between individuals with and without ASD.
- Moreover, the ultimate goal of the work is to create an efficient recommender system. This system will utilize novel features extracted from wearable IoT devices, enabling accurate categorization of autism patients, including children, adolescents, and adults.

Overall, the contribution lies in bridging the existing gaps in ML and DL methodologies related to ASD diagnosis, leading to the development of a more accurate and efficient classification system for autism patients across various age groups. Hence, in the next section, a survey has been conducted on various approaches for ASD detection.

2. LITERATURE SURVEY

In the literature survey section, we have structured our investigation into four distinct areas pertaining to ASD. The first section delves into existing methodologies aimed at collecting data efficiently, particularly focusing on efficient approaches designed for ASD-related studies. Moving forward, the survey analyses ML and DL approaches employed in the detection and classification of ASD. Further, the literature survey delves into recommendation approaches designed specifically for ASD. Finally, the complete findings from the study are discussed.

2.1. Efficient data collection approaches

In recent research work, a diverse array of innovative methodologies is proposed to collect data from individuals which are efficient. To implement a power-saving routing system for tracking the well-being and behavior of cattle, [17] laid out an evolutionary method for choosing the best clustered groups in wireless body-area-networks (WBANs). With the assistance of ant-lion-optimizer (ALO), the suggested method took user choices regarding cluster densities into account while choosing the best clustered groups for various food sizes, all while utilizing sensors with varying communication ranges. This study used a randomly generated waypoint movement approach (simulation) and examined nodes. Recent methods including moth-flame optimization (MFO), grasshopper optimization (GO) and ant-colony optimization (ACO) were compared alongside the suggested ALO. The study's findings demonstrated the usefulness of the suggested approach, achieving better routing. Zeb *et al.* [18], suggested dynamic time-scheduling media-access-control (DT-MAC) as an improved variant based on the popular method mobility-aware timeout MAC (MT-MAC) approach for the purpose of maintaining communication reliability. The system's stability was ensured by considering a node handover method between virtual clustering groups. Prominent methods, like MT-MAC, were subsequently tested against DT-MAC. This study used a simulated framework that included 50 nodes, a 150×150 m area, and a 2-second pause for its parameters. The findings from the experiments demonstrated that DT-MAC improved the MT-MAC's packet transmission by approximately 13%-17% and responses by approximately 15% with a rise in small delay of approximately 3%.

A distributed-energy-efficient two-hop-based clustering and routing (DECR) approach was suggested in [19] for use with WIoT-enabled WBAN. During the cluster's creation stage of DECR, every node received a two-hop range of data from its neighboring nodes. When optimizing transmission and selecting cluster-heads (CHs), they used an altered variant of the grey-wolf-optimization method. The DECR conducted a simulation which into account node sizes ranging from 50 to 200, regions measuring 100×100 m and 200×200 m, and a randomized waypoint movement framework. Several performance parameters, including energy consumption, node lifetime, overhead, end-to-end delay (EED) and packet delivery ratio (PDR), were surpassed in comparison with existing routing and clustering approaches according to the simulation findings. For 100×100 m and 200×200 m, the DECR attained a PDR of 96% and 93%, respectively. Using ML, [20] suggested an IoT system that would allow children with speech impairments to use a variety of sensors attached to their bodies to communicate. They collected sensors time series information, extracted characteristics from both the temporal domains along with frequency domains, and tested multiple classifiers to see which ones could best identify the hand motions used by kids with ASD. When it came time to identify the movements used by kids with ASD, the findings demonstrated an accurate recognition rate of 96% when using K-nearest neighbor (KNN), random-forest (RF), decision-tree (DT), and artificial-neural-network (ANN) classification approaches. Amit *et al.* [21], collected data from a total of 1,187,397 children, 610,588 (or 51.4% of the total) were boys and 48.6% were girls. Prediction age was a significant factor in the ASD diagnosis approach efficiency, which began to show signs of improvement at twelve months of age. Between 18 and 24 months of age, a framework that included a small set of demographic data along with long-term evaluations of milestones in growth produced an area-under the receiver-operating-characteristic (AUC-ROC) curve of 83. Although research using an identical structure found that M-CHAT had a combined effectiveness of 0.40 of sensitivity and 0.95 of specificity, the top functioning predictive models outperformed it.

2.2. Machine learning and deep learning approaches

In recent studies, significant improvements have been made in the realm of ASD detection and classification, utilizing advanced techniques ranging from ML to DL and hybrid approaches. Subah *et al.* [22], an approach for the identification of ASD based on functionally connected aspects of resting-state f-MRI (functional-magnetic-resonance-imaging) data was suggested. To carry out the identification process, a deep neural-network (DNN) classifier was employed. The autism-brain imaging-data-exchange (ABIDE) dataset [23], [24] was used for the evaluation. While current methods had an average accuracy of 67% to 85%, the suggested approach achieved an average accuracy of 0.88. Makhnytkina *et al.* [25], the outcomes of an automated ML-based conversation categorization of typically developing and atypically developing ASD in Russian-speaking children was presented. To evaluate variations among the speech's semantic features, the Mann-Whitney U-Test was employed. ML techniques like RF, AdaBoost (AB), and gradient-boosting (GB) were employed to construct classification algorithms based on these traits. There was an 88% success rate in classifying the speech patterns of boys diagnosed with different ASDs. Three artificial-intelligence (AI) methods DL, ML along with a hybrid method that combined the two were created for the purpose of initial ASD detection in [26]. They made use of a dataset that included 547 images split evenly between two categories. In the initial approach, neural networks (both ANNs and feed-forward neural-networks (FFNNs)) were used to classify features. The approach used was a combination of gray-level co-occurrence matrix (GLCM) and local-binary-pattern (LBP) methods. For ANNs and FFNNs, this method attained an outstanding 0.998 of accuracy. The second method relied on deep mapping of features extraction to employ a pre-trained convolutional-neural-network (CNN) approach, like GoogleNet and ResNet-18. Models trained using ResNet-18 and GoogleNet both performed admirably, with 0.976 and 0.936 accuracy, respectively. Thirdly, there was a hybrid approach that combined DL (using GoogleNet and ResNet-18) with ML (using support-vector-machine (SVM)), which was known as ResNet-19+SVM and GoogleNet+SVM. The first section employed CNNs to derive deep mappings of features, and the subsequent section utilized SVMs for feature classification. With accuracies of 0.94.5 for ResNet-18+ SVM and 0.955 for GoogleNet+SVM, this approach demonstrated its great diagnosing capability. The use of computerized ML when combined alongside feature classification algorithms to provide meaningful feature patterns for initial autism screening was highlighted in [27]. Their research utilized open-access datasets that were constructed upon the Q-chat ratings of persons from different ages, including adults, adolescents, children and toddlers [28], [29]. A ML framework was suggested for evaluating the possible nonclinical autism indicators, which were cantered upon automatic optimizing hyperparameter. The suggested system achieved overall accuracy of around 0.95 in all four age categories of autism datasets.

Further, Alkahtani *et al.* [30] employed several types of deep CNN transfer learning (TL) techniques to identify autistic children using face landmark detection. To increase the CNN algorithm's accuracy in predictions, an experiment was carried out to find the optimal optimization and hyperparameter configurations. Several ML tools were utilized, including hybrid visual geometry group-19 (VGG19), MobileNetV2, logistic-regression (LR), multi-layer perceptron (MLP), KNN, DT, SVM, and GB. In order to test the DL approaches, researchers used a Kaggle baseline dataset that included 2,940 pictures of children with ASD and those without ASD [31]. A 92% success rate upon the test dataset was attained by the MobileNetV2 approach. Based on the findings from the suggested study, MobileNetV2 TL algorithms outperformed previous versions in current platforms. To take advantage of ML's capabilities while keeping the evaluation tool's medical significance, they provided guidance towards the creation of ML-based testing and diagnosing procedures [32]. Sundas *et al.* [33], presented a comprehensive overview of ASD approaches in the context of IoT devices. The main purpose of the study was to recognize important developments in medical research that was dependent on IoT. By locally constructing two ML classifiers, i.e., SVM and LR for the classification of ASD variables and identifying instances of ASD in kids and adults alike, the federated-learning (FL) approach was used for ASD detection in [34]. The researchers used two publicly available datasets on autism: one for children [35], [36] and another for adults [37], [38] in their analysis. In order to find out which method is most successful in detecting ASD in both kids and adults, the outputs of the aforementioned classifications were sent to a centralized server using FL, whereby an additional classification approach was trained. They extracted features from four separate ASD individual datasets, every single of which had over 600 entries of affected kids and adults, sourced from various repositories. With an accuracy of 0.98 in kids and 0.81 in adults, the suggested approach accurately predicted ASD. The study conducted in [39] aimed to assess the effectiveness of a group of individual classification algorithms in comparison to various numerous classification algorithms in the context of examining and anticipating ASD traits (ASDT). The dataset was derived from 3,000 exercises and 300 hours of collected information, involving a total of 61 ASD children. This dataset is commonly referred to as the DREAM dataset [40]. The findings of the study indicate that boosting and bagging ensemble learning techniques exhibit strong performance in forecasting ASDT, particularly when utilized within a multi-stage development framework.

2.3. Recommendation systems for autism approaches

In recent research works focused on ASD, innovative approaches have been developed to automate processes, improve recommendation systems, and enhance treatment personalization using advanced ML techniques. Balaji and Raja [41], the aim was intended to automating the method by identifying the attributes that were most significant utilizing K-means-clustering (KMC) and classification approaches. In order to find the most effective classification approach to use with the binary datasets, they examined ASD databases of children and took mistaken classification into account. The ABIDE dataset was utilized in their research. Their method was 98.81% accurate, according to the results. Hao and Hu [42], presented an approach for enhanced neural-network matrix-factorization (NeuMF) that was derived from collaborative-filtering approach. By incorporating temporal information and utilizing the KMC technique, the approach was further enhanced. Using Python's Scrapy, researchers in this work crawled 289,333 entries from massive open online course (MOOC) databases [43]. They used a number of assessment indices, including mean-absolute-error (MAE) and root-mean square-error (RMSE) to measure how well the suggested approach worked. Compared to the approaches using collaborative filtering and CNN factorization, the enhanced NeuMF approach achieved improved outcomes with RMSE of 1.251 and MAE of 0.625. Kohli *et al.* [44] used two ML techniques to determine the best course of applied-behavior-analysis (ABA) therapy for 29 individuals diagnosed with ASD. On average, the ABA therapy suggestions made by clinicians were 81-40% accurate, while the collaborative filtration and individual matching approaches achieved a normalized-discounted cumulative-gain (NDCG) of 79-81%. Mauro *et al.* [45], presented an approach for extracting sensory analysis from points-of-interest (PoI) evaluations and integrating it into recommendation systems in order to forecast product evaluations by taking consumer preferences. Two datasets, one generated from TripAdvisor reviews alongside another gathered from a crowdsourcing initiative, were utilized for the purpose of testing [46], [47]. Using TripAdvisor information allowed the approaches to achieve the best accuracy and rating ability, according to the findings.

A recommendation system for sensory management was created and evaluated in [48] to assist students with ASD in coping with their unique sensory reactions in the classroom. The system's unique sensory control system used a fuzzy logic component that alerted caregivers and instructors to kid's emotions and potentially dangerous environmental conditions; this was additional innovative feature. Their analysis was based on the dataset provided in [49]. Based on the assessment's findings, it seemed that the tool was easy to utilize and improved the kids' efficiency. For more accurate ASD forecasting, in [50], they built a recommender system using multi-classifiers. To test how well the classifiers worked, they used a number of different ML techniques. To assess their performance, they utilized a dataset provided in [51] that was based on questionnaires. When compared with different methods using recall, F-score, precision and accuracy as assessment measures, they demonstrated that DT and RF performed better. This study's biggest shortcoming was its perfect accuracy, that was attained by using a dataset with a comparable percentage of individuals with and without ASD. This was because they have not addressed the class imbalance issue.

2.4. Findings

The literature survey reveals significant advancements and diverse methodologies in the study of ASD. Researchers have explored various datasets, features, and evaluation metrics to develop innovative approaches for ASD detection and intervention. Each study contributes to a deeper understanding of ASD, employing unique datasets and methodologies to address specific aspects of the disorder. The complete findings from the above literature survey have been formulated in Table 1 in Appendix.

3. GAPS, ISSUES, AND CHALLENGES

The gaps, issues and challenges identified from the above literature survey is as follows:

- Sensor placement optimization: there's a need for research into optimal sensor placement to ensure accurate and comprehensive data collection, especially in scenarios involving ASD individuals where delicate behavioral indications are crucial.
- Data synchronization: challenges may arise in synchronizing data from multiple sensors to create a cohesive and meaningful picture of an individual's behavior, necessitating advancements in data fusion techniques.
- Feature selection and extraction: developing robust algorithms for feature selection and extraction from behavior data is essential to identify meaningful patterns and characteristics indicative of ASD or other conditions.
- Data preprocessing: addressing challenges related to noise, outliers, and missing data through effective preprocessing techniques is crucial for accurate analysis and model development.
- Interpretability vs. complexity: balancing the interpretability of behavioral features with the complexity of models, especially in DL approaches, remains a challenge for researchers.
- Imbalanced datasets: many studies face the challenge of imbalanced datasets, particularly in ASD detection, where the number of affected individuals may be significantly lower than non-affected ones, leading to biased model performance.
- Impact on model performance: class imbalance can skew evaluation metrics such as accuracy, precision, recall, and F1-score, necessitating techniques like resampling, cost-sensitive learning, or ensemble methods to mitigate these effects.

- Generalizability: models trained on imbalanced data may struggle to generalize well to real-world scenarios, highlighting the importance of addressing class imbalance for robust and reliable predictions.
- Advanced sensor technologies: invest in research and development of advanced sensor technologies that offer improved accuracy, sensitivity, and data synchronization capabilities for behavior information collection.
- Algorithmic advancements: continuously refine algorithms for feature optimization, data preprocessing, and class imbalance handling, leveraging techniques such as feature engineering, anomaly detection, and ensemble learning.
- Collaborative research: foster interdisciplinary collaboration between experts in psychology, data science, and healthcare to leverage domain knowledge for more effective data collection, analysis, and model development.

By addressing these gaps, issues, and challenges and implementing the recommended strategies, researchers can contribute to more accurate, reliable, and ethically sound approaches in utilizing sensor and behavior information for assisting individuals, particularly those with ASD, in diverse healthcare and support settings. To address all the above issues, a novel approach is presented in the next section.

4. PROPOSED APPROACH

This section introduces a novel framework designed specifically for ASD. The framework encompasses several key steps aimed at leveraging technology to improve assistance and support for individuals with ASD. The complete flow of the framework is presented in Figure 2. The first step involves the collection of data directly from ASD individuals through the utilization of WIoT sensors. These sensors are strategically placed to capture a wide range of behavioral data and interactions in real-time, providing a comprehensive view of the individual's activities and responses. Once the data is collected, the next phase involves extracting behavioral patterns and insights from the dataset. This process entails identifying relevant behavior data points that are indicative of ASD-related characteristics or tendencies. This step is crucial as it forms the basis for subsequent analysis and decision-making within the framework. Following the extraction of behavior data, the framework focuses on feature selection and optimization. This involves identifying the most relevant and informative features from the behaviors data that contribute significantly to ASD prediction. Advanced techniques such as feature engineering and dimensionality reduction may be employed to enhance the quality and efficiency of feature selection. With optimized features in hand, the framework will incorporate using ML or DL approaches to predict whether an individual has ASD or not. These predictive models leverage the selected features to make accurate and reliable assessments regarding ASD diagnosis, contributing to early detection and intervention efforts. Finally, based on the ASD prediction results, the framework integrates a recommendation system designed to assist ASD individuals. This recommendation system utilizes the insights gained from behavioral data analysis and ASD prediction to offer personalized recommendations, interventions, or support strategies. These recommendations may span various domains such as therapy, education, social interactions, and daily living activities, aiming to improve overall quality of life and well-being for individuals with ASD. Overall, this novel ASD framework represents an integrated and technology-driven approach for addressing the unique challenges faced by ASD individuals, offering personalized assistance and support through data-driven insights, predictive modelling, and designed recommendations.

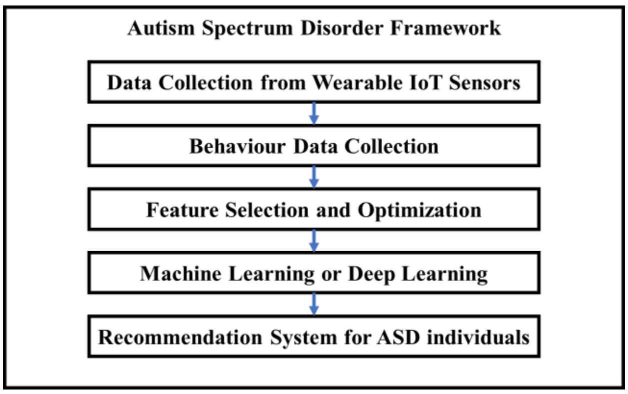

Figure 2. Proposed ASD framework

5. CONCLUSION

The comprehensive exploration of various methodologies, technologies, and frameworks presented in this literature survey underscores the ongoing efforts and advancements in addressing ASD from multiple perspectives. The key findings and insights collected from the surveyed works pave the way for a deeper understanding of effective strategies for data collection, analysis, prediction, and recommendation systems tailored to assist individuals with ASD. One of the notable trends observed is the integration of WIoT sensors for data collection, allowing for real-time monitoring and capture of behavioral patterns and responses. This not only facilitates more accurate and detailed data collection but also enables the development of personalized interventions and support systems based on individualized behavioral profiles. Furthermore, the adoption of ML, DL, and hybrid techniques has demonstrated significant progress in ASD detection, classification, and prediction. These advanced computational approaches, combined with optimized feature selection and model training, contribute to early diagnosis, intervention planning, and personalized recommendation systems aimed at improving outcomes for ASD individuals. The emphasis on addressing challenges such as class imbalance, feature optimization, and data collection efficiency highlights the ongoing efforts to enhance the reliability and effectiveness of ASD-related frameworks and methodologies. Future research directions may focus on refining existing algorithms, incorporating additional data sources or modalities, and evaluating the scalability and generalizability of proposed models and systems. In conclusion, the collective body of work reviewed in this survey underscores the interdisciplinary nature of ASD research, bringing together expertise from fields such as healthcare, data science, engineering, and psychology. By leveraging innovative technologies, advanced analytics, and data-driven insights, researchers can continue to advance our understanding of ASD, develop more accurate diagnostic tools, and create specific interventions and support systems that positively impact the lives of individuals with ASD and their families.

APPENDIX

Table 1. Dataset, feature, and metric findings

Study	Dataset used	Purpose	Dataset size	Features	Evaluation metrics
[17]	Simulation parameters	Energy-efficient routing protocol for livestock health and behavior monitoring	Node size: 50-200, Range: 10 m, Area: 100×100 m to 400×400 m, mobility model: random waypoint	Cluster density, transmission ranges	Effectiveness in energy-efficient protocols, comparative analysis with other techniques
[18]	Simulation parameters	Enhanced version of MT-MAC (DT-MAC) for message delivery	Node size: 50, area: 150×150 m, mobility model: random waypoint with 2 seconds pause	Network integrity, efficient energy utilization	Latency improvement, packet delivery improvement, response time enhancement
[19]	Simulation parameters	DECR	Node size: 50-200, area: 100×100 m to 200×200 m, mobility model: random waypoint	Node connectivity, residual energy, optimal number of clusters	Packet delivery ratio, end-to-end delay, control overhead, energy consumption
[20]	Kaggle dataset (ASD gestures)	Recognition of sign language of speech-impaired children	N/A	Time-domain and frequency-domain features	Recognition accuracy using various classifiers
[21]	Nationwide developmental surveillance data	Predictive models for ASD at different ages and clinical scenarios	N=1,187,397 children, age range: birth to 6 years	Developmental milestone assessments, demographic variables	AUC-ROC curve, sensitivity, specificity
[22]	ABIDE	ASD detection using functional connectivity features of resting-state fMRI data	-	Functional connectivity features	Accuracy, sensitivity, F1-score, AUC score
[25]	Interview data	Automatic classification of dialogues of Russian-speaking children	Boys aged 8-11 years with TD, ASD, and DS	Linguistic characteristics of speech	Classification accuracy using ML methods
[26]	Image dataset (547 images)	Early diagnosis of autism using AI techniques	547 images (219 ASD, 328 TD)	Image-based features, DL models	Accuracy of neural networks, CNN models, Hybrid techniques
[27]	Q-chat scores data	Automated ML for significant feature signatures in autism detection	Diverse age groups (toddlers to adults)	Potential nonclinical markers for autism	Mathew's correlation coefficient, balanced accuracy
[30]	Kaggle dataset (facial landmarks of autistic children)	ASD recognition based on facial landmark detection	2,940 images of autistic and non-autistic children	Facial landmark features, Transfer learning approaches	Model accuracy using CNN and ML classifiers
[34]	Open-source children and adult autism datasets	ASD detection using FL technique and ML classifiers	More than 600 records of children and adults with ASD	Features extraction from ASD datasets	Prediction accuracy for ASD detection in children and adults

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