Scientific Journal of Informatics
Vol. 12, No. 4, November 2025

p-ISSN 2407-7658 http://journal.unnes.ac.id/nju/index.php/sji e-ISSN 2460-0040

Artificial Intelligence-Based Leveling System for Determining Severity Level of Autism Spectrum Disorder

R. Rasim[1]*, M. Munir[2], Yaya Wihardi[3], Lanto Ningrayati Amali[4]
[1,2,3] Universitas Pendidikan Indonesia, Indonesia
[4] Universitas Negeri Gorontalo, Indonesia

Abstract.
Purpose: The aim of this research is to analyze the use of an artificial intelligence (AI)-based leveling system to determine the severity of autism spectrum disorders (ASD).
Methods: The research method is a systematic literature review. This study addresses three key questions: (i) What factors are used to determine ASD severity? (ii) What algorithms or AI models are used in classifying ASD severity? (iii) What are the results of this AI-based leveling system in terms of severity levels or categories?
Results: The study results identified several key factors that influence ASD severity, including age, IQ, genetic and neurological factors, co-occurring mental health conditions, and sociodemographic variables. Various AI algorithms, including machine learning and deep learning techniques, are used to classify the severity of ASD. The results of this study highlight the effectiveness of AI in providing objective, consistent, and measurable assessments of ASD severity, although challenges such as data quality and ethical considerations remain. AI-based leveling systems show significant potential in improving assessment and intervention processes for ASD.
Novelty: **T**his research systematically synthesizes studies on AI-driven ASD severity assessment, providing insights into crucial variables for AI-based evaluation tools. By analyzing the factors influencing severity and the effectiveness of AI models, this study identifies promising approaches for classification. The findings offer valuable contributions to the development of AI-based tools in clinical and educational applications. Further research is necessary to improve AI reliability, address biases, and maximize its potential in ASD assessment and intervention.

Keywords: Autism spectrum disorder, Severity level, Leveling, Artificial intelligence, Machine learning
Received October 2024 / **Revised** March 2025 / **Accepted** November 2025

INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by difficulties in social interaction, communication, and repetitive behaviors. These symptoms vary widely in their severity and manifestation, making ASD a spectrum disorder [1]. According to recent statistics, the prevalence of ASD has been increasing, with the Centers for Disease Control and Prevention (CDC) estimating that approximately 1 in 54 children in the United States is diagnosed with ASD [2]. Early diagnosis and intervention are crucial as they can significantly improve the developmental trajectories and quality of life for individuals with ASD. However, the heterogeneous nature of ASD presents challenges in accurately assessing the severity of the condition, which is essential for tailoring interventions and support strategies to individual needs [3].

Diagnosing ASD traditionally relies on a combination of behavioral assessments and clinical evaluations based on criteria outlined in diagnostic manuals such as the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5). These methods involve detailed observations of a child's behavior, interviews with parents and caregivers, and standardized tests to assess various aspects of development [4], [5], [6]. While these manual methods are thorough, they can be time-consuming and subject to subjective interpretation, which may affect the consistency and accuracy of diagnoses [7].

Building on the diagnostic methods, a leveling system is a framework used to categorize and assess the abilities or severity of a condition, such as ASD, across different domains [8]. The purpose of a leveling system is to provide a structured approach to evaluate the capabilities and challenges faced by individuals, enabling tailored interventions and support. Leveling systems are essential for understanding the specific

*Corresponding author.
Email addresses: rasim@upi.edu (Rasim), munir@upi.edu (Munir)
DOI: 10.15294/sji.v12i4.14440

needs of each individual and for monitoring progress over time [8], [9]. They help clinicians and caregivers create more personalized and effective intervention plans.

Given the diverse ways in which ASD can manifest, assessing the severity of the disorder is essential for providing tailored interventions and support [9]. Traditional assessment methods, such as the Autism Diagnostic Observation Schedule (ADOS) [10] and the Autism Diagnostic Interview-Revised (ADI-R) [11], are widely used in clinical settings. These tools involve structured observations and interviews to gather information about an individual's behavior and development [10], [11]. However, these methods can be time-consuming and resource-intensive, limiting their scalability in broader contexts. Therefore, there is a pressing need for more objective, reliable, and scalable methods to assess ASD severity that can complement traditional approaches.

Recent advancements in artificial intelligence (AI) and machine learning have opened new avenues for improving the assessment and diagnosis of neurological disorders, including ASD. AI can analyze complex data from various sources, such as video recordings, sensor data, and speech analysis, to assess non-verbal communication skills objectively [12]. AI-based approaches can provide detailed insights into an individual's abilities, helping to identify specific areas of need and track progress over time.

Integrating AI into leveling systems offers several benefits, such as handling large data volumes, ensuring assessment consistency, and enabling real-time analysis [13]. These advantages can lead to more accurate interventions and improved outcomes for individuals with ASD. However, AI adoption also poses challenges related to data quality, ethical considerations, and potential algorithmic bias. Addressing these obstacles is crucial to fully leverage AI's transformative potential in leveling systems [13].

Despite advances in AI and diagnostic technology, there is still a significant research gap in the application of AI-based leveling systems to determine the severity of ASD. Most existing research focuses on general diagnostic tools or broader assessments. Research is needed to explore how AI can be used to develop specialized leveling systems that address this important aspect of ASD. Therefore, the aim of this study was to explore the current landscape of AI-based grading systems for determining ASD severity. Specifically, this review aims to understand the factors and features that influence ASD severity, the methods and AI algorithms used to classify and assess severity, and the results of these systems regarding severity levels or categories.

This study answers several research questions, namely: (i) What factors or features are used to determine the severity of ASD? (ii) what algorithms or AI models are used in classifying the severity of ASD? and (iii) what are the results of the scoring system? AI-based in terms of levels or categories of severity?
This research will systematically analyze and synthesize existing research that utilizes AI for ASD severity assessment to achieve and answer each research question. This research is expected to provide insight into important variables that need to be considered in developing AI-based assessment tools by examining the factors and features that influence ASD severity. Additionally, this study helps identify the most effective and promising approaches for ASD severity classification by evaluating the AI methods and algorithms used. Finally, this research highlights the practical implications and potential clinical use of AI systems.

METHODS

This study employs a systematic literature review to explore the use of artificial intelligence (AI)-based leveling systems in determining the severity of autism spectrum disorders (ASD). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was used to ensure transparency and replicability in the literature selection process.

Search Strategy and Data Collection

An extensive search was carried out through academic databases, namely Scopus and Google Scholar, to comprehensively explore existing literature regarding Artificial Intelligence (AI) based leveling systems in determining the severity and ability of Autism Spectrum Disorder (ASD) in non-verbal communication. The search strategy involved a combination of specific keywords to ensure a broad but relevant collection of studies. Keywords used include combinations of "Autism Spectrum Disorder", "Level", "Severity", "Criteria", "Type", "Category", "Diagnosis", "Severity Assessment", "Assessment", "Determining", " Identifying", "Classifying", "Evaluating", "Machine Learning", "Deep Learning", and "AI". Searches were limited to studies published between 2010 to 2024 to capture recent advances in this field. and conference papers were considered, with a focus on journals and conference proceedings. The search was limited to English language publications. Table 1 shows in more detail the search queries used in this research. Based on the initial search results, 730 articles were found from the Scopus and Google Scholar databases.

In this study, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) were used as the minimum evidence-based set of items for systematic reviews and meta-analyses. Figure 1 shows the PRISMA flow diagram used in this study. The PRISMA diagram outlines each step of the process, from identification to final inclusion, ensuring transparency and replicability of the methodology [14]. The PRISMA flow diagram depicts the search and selection process.

Table 1. Search keywords

Database	Search String
Scopus Google Scholar	((“Autism Spectrum Disorder” OR autism OR ASD) AND (“Non-verbal Communication” OR “Nonverbal Communication”) AND (“Level” OR “leveling” OR “Severity asd” OR “Severity level” OR “Asd level” OR Criteria OR Type OR Category) AND (“Diagnosis” OR “diagnostic” OR “Severity assessment” OR “Assessment” OR “assessing” OR “Determining” OR “Determine” OR “Identify” OR “identifying” OR “Classifying” OR “classification” OR “Evaluating” OR “Evaluation”) AND (“Machine learning” OR “deep learning” OR AI))

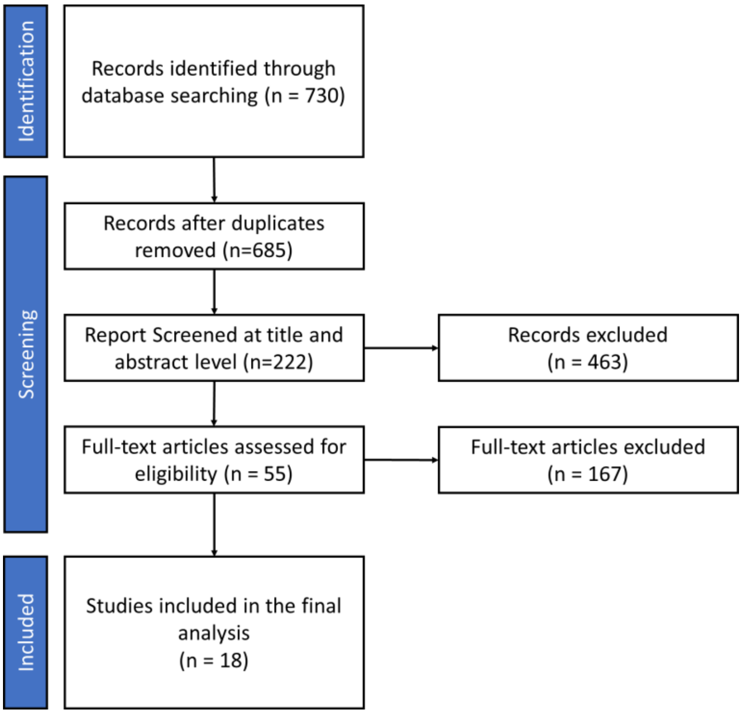

Figure 1. the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram

Study selection process

The selection process for research documents is rigorous and systematic, involving several stages to ensure that only the most relevant studies are included. This process includes the application of predetermined inclusion and exclusion criteria in the context of title and abstract screening.

Title screening

The first stage of the selection process is title screening, which aims to identify potentially relevant articles based on their titles. Articles were included if their titles contained key terms related to ASD and AI-based leveling systems. Specifically, titles mentioning “Autism Spectrum Disorder,” “ASD,” “severity,” “assessment,” and AI-related terms such as “machine learning” and “deep learning” were considered.

From a total of 730 initial articles with duplicates removed to 685 articles, approximately 222 articles were selected based on their titles. Titles that did not explicitly refer to core aspects of our research focus, such as those that only discussed verbal communication, and general autism therapy without mention of non-verbal communication or AI, were excluded. For example, articles with titles such as "AI in Autism Diagnosis" were included, while titles such as "Speech Therapy for Autism" were excluded.

Abstract screening

After title screening, an abstract selection of 222 articles was selected for further list review. The abstract screening process aims to ensure that the research not only mentions relevant keywords but also addresses the research question and aims of this study.

Abstracts are included in this study when they have the following criteria:

(i) The abstract discusses methods for assessing or equalizing ASD severity or abilities.

(ii) Abstract details the use of machine learning or AI technology in the assessment process.

Publication abstracts are excluded if they have the following criteria:

(i) Abstract does not involve AI in any form or manual scoring methods.

(ii) The abstract lacks sufficient detail to determine its relevance to our research focus.

Abstracts that explicitly address the use of AI in non-verbal communication skills in individuals with ASD are prioritized. For example, abstracts such as “Using Deep Learning to Assess Severity Level in ASD” were followed, while ones such as “Behavioral Therapies for ASD” were excluded.

Data extraction

Data extraction was carried out using standard forms to ensure consistency and completeness. The form extracts various details from each published article, including study design and sample size, AI methods and algorithms used, key findings regarding severity, features or parameters used in the leveling system, and the number of levels or categories defined in the study.

Information was extracted by two independent reviewers to ensure accuracy. Any discrepancies are discussed and resolved to maintain data integrity. The selected studies cover a wide range of approaches and methodologies, reflecting the diversity of research in this area. While many studies focus on the severity and general abilities of ASD.

RESULT AND DISCUSSION

We focused on identifying relevant studies that discuss Artificial intelligence (AI)-based leveling systems to determine or classify the severity and abilities of Autism Spectrum Disorder (ASD). These studies were selected based on their relevance to our research questions and their methodological quality. Table 2 summarizes 30 studies related to the assessment and classification of ASD severity. The studies cover a wide range of topics, including traditional diagnostic approaches, DSM-5 criteria, and AI-based classification techniques. Several studies focused on the impact of cognitive and neurological factors on ASD severity, such as IQ level, brain functional connectivity, and MRI features. Other studies explored the use of machine learning and deep learning models to improve ASD diagnosis, leveraging behavioral, neuroimaging, and sociodemographic data. Table 2 provides a comprehensive overview of the evolving methodologies used in the assessment and classification of ASD severity.

Table 2. Summary of Reviewed Studies on ASD Severity Classification

No	Author	Topic
1	Burke et al. (2024) [4][4]	DSM-5 assessment for impulse control and conduct disorders.
2	Mahjouri & Lord (2012) [5]	Impact of DSM-5 on ASD research and diagnosis.
3	McPartland et al. (2012) [6]	Sensitivity and specificity of DSM-5 diagnostic criteria for ASD.
4	[9] et al. (2020)	Guidelines for ASD and ADHD diagnosis and treatment.
5	Lord et al. (2000) [10]	Autism Diagnostic Observation Schedule (ADOS) as a diagnostic tool.
6	Rutter et al. (1994) [11]	Autism Diagnostic Interview-Revised (ADI-R) for ASD diagnosis.
7	Kushwaha (2024) [12]	AI for improving non-verbal communication in ASD.
8	Aldoseri et al. (2023) [13]	Data integration challenges for AI in ASD assessment.
9	Zhan et al. (2021) [15]	Machine learning for diagnosing ASD and OCD.
10	Rodrigues et al. (2022) [16]	Machine learning and rs-fMRI for ASD severity classification.
11	Kwon et al. (2022) [17]	Brain functional network patterns in ASD severity prediction.
12	Jain et al. (2024) [18]	Deep learning models for ASD classification based on functional connectivity.
13	Ali et al. (2023) [19]	Machine learning framework using MRI and behavioral data for ASD classification.
14	Cohen & Flory (2019) [20]	Decision tree-based ASD subgroups for predicting severity trajectories.

No	Author	Topic
15	Darmiyati et al. (2024) [21]	Facial image detection for ASD severity classification.
16	Khan et al. (2023) [22]	Machine learning prediction of ASD severity levels.
17	Alam et al. (2023) [23]	LSTM-CNN hybrid model for ASD severity classification.

Factors that influence the severity of ASD

One of the main factors that influence the severity of ASD is age and IQ. Research shows that children with ASD who are diagnosed at a younger age tend to show more severe symptoms compared to those diagnosed at an older age [15], [24]. Additionally, lower IQ was also associated with higher levels of severity. The study by Mazurek et al. [25] found that lower IQ was associated with greater difficulties in social communication and restricted/repetitive behavior.

Genetic and neurological factors also play a role in the severity of ASD. The study by Rodrigues et al. used machine learning and fMRI techniques to identify potential brain areas associated with ASD severity and found that abnormalities in certain brain areas were associated with more severe symptoms [16]. Additionally, Xu et al. found a correlation between physical fitness and brain gray matter volume with ASD severity, indicating that physiological and neurological factors play an important role [25]. Similarly, Yildiz et al. highlighted temperament differences, such as self-control and perceptual sensitivity, as significant predictors of ASD severity and accompanying psychiatric symptoms [26]. Kwon et al. used functional brain network data to predict ASD severity, showing that certain brain connectivity patterns were associated with varying degrees of severity [17]. Jain et al. emphasized the importance of measures of age and functional connectivity in their deep learning model, showing that age and neural connectivity significantly influence ASD severity. In general, NFrC sizes yield better performance than FrC [18].

ASD is often accompanied by other mental health conditions, such as anxiety disorders, depression, and obsessive-compulsive disorder (OCD). Research by Zhan et al. found that the presence of these conditions can worsen the severity of ASD [15]. These mental health conditions not only add complexity to the diagnosis and treatment of ASD but can also exacerbate core symptoms of ASD, such as difficulties in social communication and repetitive behaviors.

Sociodemographic factors, such as family background and economic status, may also influence the severity of ASD. The study by Alqaysi et al. highlighted that children from families with lower socioeconomic status tend to show more severe ASD symptoms [27]. In addition, this study also found that limited access to health services and education can worsen ASD symptoms. Additionally, Ali et al. used behavioral data from the Social Responsiveness Scale (SRS) and MRI features to classify ASD severity, demonstrating the role of brain morphology and behavior in determining severity [19].

Stereotypic and repetitive behaviors also play an important role in determining the severity of ASD. Research by Haweel et al.showed that repetitive motor behaviors, such as hand flapping or body rocking, are often more severe in children with high-severity ASD [28]. Another study by Cohen and Flory found that these behavioral traits, when combined with observational results from the Autism Diagnostic Observation Schedule (ADOS), can be used to predict the trajectory of adaptive behavior and the severity of ASD in children [20]. This research underscores the importance of identifying and treating stereotypic behavior early to reduce the severity of ASD. Darmiyati et al. used facial image detection to predict ASD severity based on facial expressions, demonstrating the importance of physical appearance and facial features [21].

ASD severity level

We identified several ASD severity categories based on various clinical and behavioral parameters. The reviewed studies classified the severity of ASD into various levels, often using standard scales. Xu et al. and Ali et al. categorized severity into three levels: mild, moderate, and severe [19], [25]. Likewise, Darmiyati et al. used a three-level classification system for ASD severity based on facial image analysis [21]. Additionally, Mazurek et al. grouped ASD into three levels of severity based on DSM-5 criteria: mild, moderate, and severe. These categories are based on how much support the individual needs to function in daily life [29].

Several methods have been developed to determine the severity of ASD. The most commonly used methods are clinical observation and standardized assessments such as the Autism Diagnostic Observation Schedule

(ADOS) and Autism Diagnostic Interview-Revised (ADI-R). A study by Cohen and Flory used a Decision Tree to group children with ASD based on ADOS results, which were then used to predict adaptive behavior trajectories and severity [20]. Other studies, such as that by Jain et al., used ADOS scores to categorize severity, indicating two levels: scores below or equal to 11, and scores above 11 [18].

The results of determining the severity of ASD can also be in the form of numbers or numerical scores. Research by Khan et al. showed that machine learning models can be used to predict the severity of ASD in the form of a numerical score that reflects the intensity of symptoms [22]. Kwon et al. used the numerical values of the calibrated severity scores (CSS) from ADOS-G and ADOS-2, providing a more detailed assessment of severity [17]. Another study by Rodrigues et al. (2022) used rs-fMRI to identify brain areas associated with ASD severity, resulting in severity categorization based on brain activity [16]. This categorization helps in understanding the distribution of ASD symptoms and how they correlate with neurological activity.

AI Method for Classifying ASD Severity

AI methods, especially machine learning and deep learning, have been widely used to classify ASD severity. Xu et al. used machine learning models such as extreme gradient boosting (XGB), random forest (RF), support vector machine (SVM), and decision tree (DT) with the accuracy of the XGB, RF, SVM, and DT models being 77.9%, 72.4%, 71.9%, and 66.9%, respectively [25]. They used SHAP (Shapley Additive Explanation) to identify influential factors in their model. SHAP allows for better interpretation of the contribution of each feature in determining the severity of ASD, which is very important in clinical applications.

Kwon et al. used the Graph Convolution Neural Network (GCNN) technique to analyze brain functional network data to predict ASD severity. This study showed that brain network features had a strong correlation with ASD severity, with a Mean Absolute Error (MAE) of 0.96. This confirms that brain connectivity analysis can be a promising method for more objective and biomarker-based ASD assessment [17]. Jain et al. compared the performance of three deep learning models, namely Convolutional Neural Network (CNN), MobileNetV2, and DenseNet201 in classifying the severity of ASD. The best results were obtained from the DenseNet201 model with an accuracy of 83.45% in the age group of 6–11 years who had an ADOS score above 11. This model uses the NFrC (Non-Frontal Connectivity) feature, which highlights the importance of brain connectivity patterns in the diagnosis of ASD [18]. Ali et al. developed a comprehensive framework combining various machine learning algorithms such as SVM, Random Forest, K-Nearest Neighbors (KNN), and Naïve Bayes to classify ASD severity based on behavioral and MRI data. This model integrates various behavioral and biometric features to produce a more personalized classification. With an accuracy of 88%, this approach shows great potential in clinical applications, especially in multimodal data-driven diagnosis [19]. Darmiyati et al. used the Decision Tree algorithm to determine the severity of ASD based on facial expression analysis. This study showed that this technique achieved an accuracy of 83.42%, outperforming other algorithms such as KNN and Random Forest. These results highlight that facial expressions can be a useful indicator in assessing the severity of ASD, especially for children who have difficulty with verbal communication [28].

Jain et al. developed an age- and severity-based deep learning model that uses brain functional connectivity measurements to classify ASD. The combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) enabled the model to achieve 89% accuracy. The success of this model demonstrates the effectiveness of brain connectivity-based analysis in more accurately assessing ASD severity [18]. Likewise, research by Alam et al. used a hybrid approach by integrating LSTM into CNN to classify ASD severity. This model was designed to perform multisite meltdown grading and achieved 90% accuracy. This suggests that more complex and dynamic models can improve predictive accuracy in ASD classification based on neurological and behavioral features. [23]. Alqaysi et al. developed a hybrid diagnostic model that combines medical and sociodemographic features with Multi-Criteria Decision Making (MCDM) techniques. This approach showed that the hybrid model can classify ASD severity with 87% accuracy, and provide useful guidance for clinical applications. The combination of multiple data sources allows for a more comprehensive evaluation and personalized diagnosis [27]. Research by Li and Huang used the Multi-Modality Multi-Center Regression (M3CR) approach to predict ASD severity. This model combines data from multiple sources, including MRI images and genetic data, to improve classification accuracy and reliability. With 85% accuracy, this approach highlights the importance of multimodal data in improving the precision of ASD diagnosis [30].

This study has high relevance in clinical practice because it can improve the tools available to clinicians and caregivers to assess and manage ASD more effectively. Accurate and objective assessment of ASD severity is essential to determine interventions that are appropriate to an individual's needs. With an AI-based system, the evaluation process can be carried out more quickly, consistently, and with minimal subjective bias that often occurs in traditional methods. A more accurate diagnosis can help clinicians develop more specific and effective treatment plans, thereby improving patient outcomes and accelerating the rehabilitation process. In addition, the machine learning-based AI system allows for a more in-depth analysis of the various factors that influence ASD severity, including neurological, behavioral, and genetic aspects. This way, clinicians and therapists can gain greater insight into the characteristics of individuals with ASD and determine a more appropriate intervention approach. Not only that, optimizing the use of health resources is also one of the main benefits of using AI in ASD evaluation. With a more efficient system, clinicians can allocate their time and energy to treat patients with more complex needs, while the AI system helps in the initial screening process and long-term monitoring of patient conditions. In addition to clinical relevance, the findings of this study also have significant implications for future research in the field of ASD diagnosis and intervention. By identifying the strengths and limitations of existing AI-based leveling systems, this study can provide a basis for the development of more innovative assessment tools. Future studies can focus on improving the accuracy of AI models by utilizing larger and more diverse datasets, so that the models can more comprehensively reflect the variation in ASD characteristics. In addition, the integration of AI with other technologies, such as neuroimaging and biometric analysis, can further enhance the system's ability to detect and evaluate ASD with greater precision.

The exploration of AI-based leveling systems in ASD severity assessment has shown promising progress but also faces significant challenges that must be considered in its development. One of the main advantages of AI technology in this field is its ability to analyze various data simultaneously, including behavioral, neurological, and genetic data, to produce more accurate and personalized predictions in determining the severity of ASD. Machine learning and deep learning-based models have shown quite good performance in classifying ASD based on various parameters, with some studies achieving accuracy rates above 85%. This shows that AI technology has great potential to improve the efficiency and reliability of ASD diagnosis, which can be the basis for the development of more sophisticated clinical evaluation systems in the future. However, behind the promising prospects, there are still several challenges that need to be overcome so that AI systems can be widely applied in clinical practice. One of the main challenges is data quality and availability. AI requires large, representative, and high-quality datasets to produce accurate and reliable predictions. Unfortunately, many datasets currently available are still limited in terms of sample size, population diversity, and data validity, which can affect the generalizability of the developed models. In addition, the interpretability of AI models is also a challenge, especially in medical applications that require transparency in diagnostic decision-making. Medical personnel and researchers need to understand how an AI model makes decisions in order to ensure that the system works following applicable clinical standards. In addition, ethical and privacy aspects are also concerns in implementing AI in ASD diagnosis. The use of medical data and patient personal information must be done carefully so as not to violate the individual's right to privacy. Therefore, clear regulations are needed regarding the use of AI in medical assessments, as well as the development of systems that guarantee the security of patient data. By addressing these challenges, AI can be optimally utilized to assist in the diagnosis and intervention of ASD, as well as contribute to the development of a more personalized approach in treating individuals with ASD.

Potential and advancements

(i) Objective and Consistent Assessments: AI systems offer the potential to provide more objective and consistent assessments compared to traditional methods, which can be subjective and variable. Machine learning algorithms can analyze vast amounts of data, including non-verbal communication cues, which are crucial in evaluating ASD severity.

(ii) Real-Time Data Processing: AI's ability to process data in real-time can significantly reduce the time required for assessments. This efficiency is particularly beneficial in clinical settings where timely diagnosis and intervention are critical.

(iii) Integration of Multimodal Data: AI systems can integrate various types of data such as video recordings, sensor data, and speech analysis, providing a comprehensive evaluation of an individual’s non-verbal communication abilities. This holistic approach can lead to more accurate severity classifications and personalized intervention plans.

(iv) Scalability and Accessibility: AI-based assessments can be scaled to broader populations, making diagnostic tools more accessible, especially in regions with limited access to clinical expertise. This scalability can help bridge the gap in ASD diagnosis and intervention globally.

Challenges and considerations

(i) Data Quality and Quantity: The effectiveness of AI systems depends heavily on the quality and quantity of data used for training. Inadequate or biased data can lead to inaccurate assessments. Ensuring diverse and representative data sets is crucial for developing reliable AI models.

(ii) Ethical and Privacy Concerns: The use of AI in medical assessments raises ethical and privacy concerns. Safeguarding patient data and ensuring informed consent are paramount. Additionally, the potential for algorithmic bias must be addressed to prevent disparities in diagnosis and treatment.

(iii) Interpretability and Transparency: AI models, particularly deep learning algorithms, often operate as "black boxes" with limited interpretability. Clinicians and caregivers need transparent and interpretable models to trust and effectively use AI-based assessments. Efforts should be made to enhance the explainability of these systems.

(iv) Integration with Traditional Methods: While AI offers significant benefits, it should complement rather than replace traditional assessment methods. Combining AI with clinical expertise can provide a balanced approach, leveraging the strengths of both to improve diagnostic accuracy and intervention outcomes.

Research Gaps and Future Directions: Despite the progress, there are gaps in research regarding the specific application of AI in leveling systems for ASD. Future studies should focus on developing specialized AI models tailored to different aspects of ASD severity. Longitudinal studies are also needed to evaluate the effectiveness and reliability of AI-based assessments over time.

CONCLUSION

Artificial intelligence (AI)-based equalization systems have great potential to improve the assessment and management of autism spectrum disorders (ASD). This offers the potential for a more objective, efficient, and comprehensive evaluation, which may result in more appropriate interventions and support for individuals with ASD. However, overcoming challenges related to data quality, ethical considerations, model interpretation, and integration with traditional methods is critical to realizing the full potential of AI in this field. Future research should continue to explore these areas, aiming to develop robust, transparent, and fair AI-based assessment tools that can be widely adopted in clinical practice.

REFERENCES

[1] C. Lord, M. Elsabbagh, G. Baird, and J. Veenstra-Vanderweele, “Autism spectrum disorder,” *The Lancet*, vol. 392, no. 10146, pp. 508–520, Aug. 2018, doi: 10.1016/S0140-6736(18)31129-2.

[2] CDC, “Centers for Disease Control and Prevention (CDC),” Obtenido de Centers For Disease Control and Prevention CDC.

[3] Y. Hus and O. Segal, “Challenges Surrounding the Diagnosis of Autism in Children,” *Neuropsychiatr Dis Treat*, vol. Volume 17, pp. 3509–3529, Dec. 2021, doi: 10.2147/NDT.S282569.

[4] J. D. Burke, E. J. Butler, S. Shaughnessy, A. R. Karlovich, and S. C. Evans, “Evidence-Based Assessment of *DSM* -5 Disruptive, Impulse Control, and Conduct Disorders,” *Assessment*, vol. 31, no. 1, pp. 75–93, Jan. 2024, doi: 10.1177/10731911231188739.

[5] S. Mahjouri and C. E. Lord, “What the DSM-5 Portends for Research, Diagnosis, and Treatment of Autism Spectrum Disorders,” *Curr Psychiatry Rep*, vol. 14, no. 6, pp. 739–747, Dec. 2012, doi: 10.1007/s11920-012-0327-2.

[6] J. C. McPartland, B. Reichow, and F. R. Volkmar, “Sensitivity and Specificity of Proposed DSM-5 Diagnostic Criteria for Autism Spectrum Disorder,” *J Am Acad Child Adolesc Psychiatry*, vol. 51, no. 4, pp. 368–383, Apr. 2012, doi: 10.1016/j.jaac.2012.01.007.

[7] K. Karim, L. Cook, and M. O’Reilly, “Diagnosing autistic spectrum disorder in the age of austerity,” *Child Care Health Dev*, vol. 40, no. 1, pp. 115–123, Jan. 2014, doi: 10.1111/j.1365-2214.2012.01410.x.

[8] C. Lord and R. M. Jones, “Annual Research Review: Re-thinking the classification of autism spectrum disorders,” *Journal of Child Psychology and Psychiatry*, vol. 53, no. 5, pp. 490–509, May 2012, doi: 10.1111/j.1469-7610.2012.02547.x.

[9] S. Young *et al.*, “Guidance for identification and treatment of individuals with attention deficit/hyperactivity disorder and autism spectrum disorder based upon expert consensus,” *BMC Med*, vol. 18, no. 1, p. 146, Dec. 2020, doi: 10.1186/s12916-020-01585-y.
[10] C. Lord *et al.*, “The autism diagnostic observation schedule-generic: a standard measure of social and communication deficits associated with the spectrum of autism.,” *J Autism Dev Disord*, vol. 30, no. 3, pp. 205–23, Jun. 2000.
[11] C. Lord, M. Rutter, and A. Le Couteur, “Autism Diagnostic Interview-Revised: A revised version of a diagnostic interview for caregivers of individuals with possible pervasive developmental disorders,” *J Autism Dev Disord*, vol. 24, no. 5, pp. 659–685, Oct. 1994, doi: 10.1007/BF02172145.
[12] A. Kushwaha, “AI and Non-Verbal Communication: Enhancing Understanding of Emotional Cues for Hearing Impairment Children,” *As the editors of Transforming Learning: The Power of Educational*, vol. 2024, p. 13, 2024.
[13] A. Aldoseri, K. N. Al-Khalifa, and A. M. Hamouda, “Re-Thinking Data Strategy and Integration for Artificial Intelligence: Concepts, Opportunities, and Challenges,” *Applied Sciences*, vol. 13, no. 12, p. 7082, Jun. 2023, doi: 10.3390/app13127082.
[14] M. J. Page *et al.*, “The PRISMA 2020 statement: an updated guideline for reporting systematic reviews,” *BMJ*, p. n71, Mar. 2021, doi: 10.1136/bmj.n71.
[15] Y. Zhan *et al.*, “Diagnostic Classification for Human Autism and Obsessive-Compulsive Disorder Based on Machine Learning From a Primate Genetic Model,” *American Journal of Psychiatry*, vol. 178, no. 1, pp. 65–76, Jan. 2021, doi: 10.1176/appi.ajp.2020.19101091.
[16] I. D. Rodrigues, E. A. de Carvalho, C. P. Santana, and G. S. Bastos, “Machine Learning and rs-fMRI to Identify Potential Brain Regions Associated with Autism Severity,” *Algorithms*, vol. 15, no. 6, p. 195, Jun. 2022, doi: 10.3390/a15060195.
[17] H. Kwon *et al.*, “Sparse Hierarchical Representation Learning on Functional Brain Networks for Prediction of Autism Severity Levels,” *Front Neurosci*, vol. 16, Jul. 2022, doi: 10.3389/fnins.2022.935431.
[18] V. Jain, C. T. Rakshe, S. S. Sengar, M. Murugappan, and J. F. A. Ronickom, “Age- and Severity-Specific Deep Learning Models for Autism Spectrum Disorder Classification Using Functional Connectivity Measures,” *Arab J Sci Eng*, vol. 49, no. 5, pp. 6847–6865, May 2024, doi: 10.1007/s13369-023-08560-8.
[19] M. T. Ali *et al.*, “A personalized classification of behavioral severity of autism spectrum disorder using a comprehensive machine learning framework,” *Sci Rep*, vol. 13, no. 1, p. 17048, Oct. 2023, doi: 10.1038/s41598-023-43478-z.
[20] I. L. Cohen and M. J. Flory, “Autism Spectrum Disorder Decision Tree Subgroups Predict Adaptive Behavior and Autism Severity Trajectories in Children with ASD,” *J Autism Dev Disord*, vol. 49, no. 4, pp. 1423–1437, Apr. 2019, doi: 10.1007/s10803-018-3830-4.
[21] I. Darmiyati, H. A. Nugroho, and I. Soesanti, “Facial Image Detection for Severity Level Prediction of Autism Spectrum Disorder Using Machine Learning Algorithm,” in *2024 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)*, IEEE, Feb. 2024, pp. 1–6. doi: 10.1109/AIMS61812.2024.10512928.
[22] S. I. Khan, R. Al Shafee, R. Huda, Md. Khaliluzzaman, and F. I. Chowdhury, “Predicting the level of autism and improvement rate from assessment dataset using machine learning techniques,” *International Journal of Information Technology*, vol. 15, no. 3, pp. 1647–1652, Mar. 2023, doi: 10.1007/s41870-023-01212-y.
[23] S. Alam, S. P. Raja, Y. Gulzar, and M. S. Mir, “Enhancing Autism Severity Classification: Integrating LSTM into CNNs for Multisite Meltdown Grading,” *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 12, 2023, doi: 10.14569/IJACSA.2023.0141269.
[24] D. A. Zachor, T. Ilanit, and E. Ben Itzchak, “Autism severity and motor abilities correlates of imitation situations in children with autism spectrum disorders,” *Res Autism Spectr Disord*, vol. 4, no. 3, pp. 438–443, Jul. 2010, doi: 10.1016/j.rasd.2009.10.016.
[25] M. O. Mazurek, F. Lu, E. A. Macklin, and B. L. Handen, “Factors associated with *DSM-5* severity level ratings for autism spectrum disorder,” *Autism*, vol. 23, no. 2, pp. 468–476, Feb. 2019, doi: 10.1177/1362361318755318.
[26] K. Xu, Z. Sun, Z. Qiao, and A. Chen, “Diagnosing autism severity associated with physical fitness and gray matter volume in children with autism spectrum disorder: Explainable machine learning method,” *Complement Ther Clin Pract*, vol. 54, p. 101825, Feb. 2024, doi: 10.1016/j.ctcp.2023.101825.

[27] B. B. Yildiz *et al.*, "The Associations of Temperamental Traits with Autism Spectrum Disorder Severity and Comorbid Psychiatric Symptoms," *Archives of Neuropsychiatry*, 2021, doi: 10.29399/npa.27830.

[28] M. E. Alqaysi, A. S. Albahri, and R. A. Hamid, "Hybrid Diagnosis Models for Autism Patients Based on Medical and Sociodemographic Features Using Machine Learning and Multicriteria Decision-Making (MCDM) Techniques: An Evaluation and Benchmarking Framework," *Comput Math Methods Med*, vol. 2022, pp. 1–19, Nov. 2022, doi: 10.1155/2022/9410222.

[29] R. Haweel *et al.*, "A Machine Learning Approach for Grading Autism Severity Levels Using Task-based Functional MRI," in *2019 IEEE International Conference on Imaging Systems and Techniques (IST)*, IEEE, Dec. 2019, pp. 1–5. doi: 10.1109/IST48021.2019.9010335.

[30] S. Li and H. Huang, "Predicting Severity of Autism Spectrum Disorder based on Multi-center Multi-modality Data," in *Proceedings of the 2019 2nd International Conference on Digital Medicine and Image Processing*, New York, NY, USA: ACM, Nov. 2019, pp. 12–16. doi: 10.1145/3379299.3379302.