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Early Stage Detection of Autism Spectrum Disorder

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Abstract
Autism Spectrum Disorder (ASD) is a developmental condition impacting communication, behavior, and social interaction, and it affects approximately 2% of children in the U.S. Early identification and intervention are critical to improving long-term outcomes for children with ASD, yet delays in diagnosis remain a significant barrier. Current screening tools, such as the Modified Checklist for Autism in Toddlers, revised with Follow-Up (M-CHAT-R/F), are widely used and effective in identifying potential ASD cases. However, these tools often exhibit limitations in specificity, leading to a high rate of false positives and a lower positive predictive value. This poses challenges for healthcare systems and families, as unnecessary follow-ups and evaluations can strain resources and cause undue stress.To address these limitations, a machine learning-based framework has been proposed to enhance the accuracy of early ASD detection. By leveraging advanced computational techniques, the framework evaluates the performance of eight different algorithms, including AdaBoost, Random Forest, and Support Vector Machines (SVM). A voting classifier, which combines predictions from multiple models, is also employed to improve the robustness and reliability of probability assessments. In addition to traditional machine learning methods, the study explores the potential of image-based approaches, such as Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs). These techniques could provide valuable insights when integrated with behavioral data, offering a more comprehensive diagnostic tool. Furthermore, advancements in motion analysis and the use of biomarkers are discussed as complementary strategies to refine the screening process. However, while these technologies show promise, further research and validation are needed to ensure their effectiveness and applicability across diverse populations.

Keywords: *Early Identification, Early Intervention, Diagnostic Delay, Screening Tools,False Positives, Specificity, Positive Predictive Value, Machine Learning, Image-Based Diagnosis, CNN, Deep Neural Networks (DNNs), Behavioral Data Integration, Diagnostic Accuracy, Screening Process ,Predictive Modeling, Early Childhood Development.*

1. Introduction
Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by challenges in social interaction, communication, and restricted or repetitive patterns of behavior. It is referred to as a "spectrum" disorder because the severity and combination of symptoms can vary

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widely from one individual to another. People with ASD may experience difficulties in understanding social cues, maintaining eye contact, or engaging in typical conversations, which often affects their ability to form relationships and participate fully in daily life. The causes of autism are not yet fully understood, but research indicates that both genetic and environmental factors play significant roles. Certain gene mutations and hereditary traits have been linked to the development of ASD, while prenatal factors such as advanced parental age, low birth weight, and exposure to certain environmental toxins may also contribute. However, no single cause has been identified, and autism is believed to arise from a combination of influences rather than any one determinant Symptoms of autism generally appear in early childhood, often before the age of three. While some children show signs as early as infancy, others may develop typically before suddenly regressing. Common indicators include delayed speech development, difficulty with social play, insistence on routines, and intense interest in specific topics or objects. It's important to note that the presentation of symptoms can vary significantly, with some individuals displaying profound impairments while others may have only mild challenges and high intellectual abilities. Early diagnosis and intervention are critical in supporting the development of individuals with ASD. Therapies such as speech and language therapy, behavioral interventions like Applied Behavior Analysis (ABA), and occupational therapy can greatly enhance communication, social, and life skills. Educational support and tailored learning environments are also essential to help children with autism reach their full potential. The earlier these supports are introduced, the more effective they tend to be in improving long-term outcomes. In recent years, public awareness and understanding of autism have improved, leading to greater acceptance and advocacy. However, stigma and misconceptions still persist. It is essential to recognize the strengths and unique perspectives that individuals with autism bring to society. Promoting inclusivity, providing accessible services, and embracing neurodiversity are crucial steps in ensuring that people with ASD can lead fulfilling, meaningful lives within their communities. [1]

1.1.Methods

(1) Developmental Screening: This is an early-stage method where pediatricians use questionnaires or checklists to identify developmental delays in children, typically around 18 to 24 months.(2)Diagnostic Evaluation:If screening shows concerns, a comprehensive diagnostic evaluation is conducted by specialists such as developmental pediatricians, neurologists, or psychologists. This involves detailed observation, parent interviews, and cognitive and behavioral assessments. (3) Autism Diagnostic Observation Schedule (ADOS):This is a standardized, play-based assessment tool used to observe social and communication behaviors associated with ASD. It is considered a gold standard in diagnosis.(4)Autism Diagnostic Interview-Revised (ADI-R):This is a structured interview conducted with parents or caregivers that focuses on the individual's early developmental history, communication skills, and social behaviors.(5)Cognitive and Language Testing:Tools such as the Wechsler Intelligence Scale for Children (WISC) or the Peabody Picture Vocabulary Test (PPVT) assess intellectual and language abilities to better understand an individual's developmental profile and aid in diagnosis. plays a vital role in ensuring a responsive, secure, and scalable fraud detection system. [2]

2. Dataset Preparation

2.1.Data Sources and Features

In the early stages of autism spectrum disorder (ASD), data sources primarily include behavioral observations, parental reports, clinical assessments, and developmental screening tools. Healthcare professionals often rely on standardized tools like the Modified Checklist for Autism in Toddlers (M-CHAT), along with detailed interviews and questionnaires filled out by caregivers. Video recordings of children's behavior, medical history, and observational data from speech therapists or pediatricians also serve as critical sources. In recent years, digital tools such as eye-tracking technology, wearable sensors, and smartphone-based apps have started contributing to data collection by capturing

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subtle behavioral cues that might be overlooked in traditional settings. The key features extracted from these data sources include atypical patterns in social interaction, communication delays, repetitive behaviors, and sensory sensitivities. For example, limited eye contact, delayed speech development, lack of response to name, or repetitive hand movements are often early indicators. Motor development patterns, facial expressions, and vocalizations are also examined closely. By analyzing these features through structured checklists or machine learning models, clinicians aim to detect ASD traits as early as possible, ideally before the age of three, to enable early intervention and improved outcomes. [3]

2.2.Preprocessing and Transformation

Preprocessing in the context of early-stage autism spectrum disorder (ASD) involves preparing collected data for accurate analysis and diagnosis. This includes cleaning the data by handling missing values, removing inconsistencies, and standardizing formats across different data sources such as parental reports, video recordings, and sensor data. For behavioral videos, preprocessing might involve frame extraction, face or gesture detection, and noise reduction. For audio data, this could mean filtering background noise and segmenting speech patterns. Textual responses or survey results may be tokenized and normalized to ensure consistency across datasets. Transformation steps aim to convert the preprocessed data into meaningful features suitable for analysis or input into diagnostic models. For instance, video data may be transformed into quantifiable facial expression metrics, gaze direction, or body movement patterns. Audio data might be converted into pitch, tone, or frequency features, while questionnaire data can be encoded numerically. In machine learning-based systems, these transformed features are often scaled or reduced in dimensionality using techniques like PCA (Principal Component Analysis) to enhance the model's performance in detecting early signs of ASD. [4]

3. Model Development and Training

3.1.Model Selection

Algorithm to analyze complex and often multimodal data such as behavioral cues, speech patterns, and physiological signals. Since the data in early ASD diagnosis is typically limited and sensitive, models like decision trees, support vector machines (SVM), and random forests are often preferred for their interpretability and ability to handle small datasets effectively. Logistic regression is also commonly used for binary classification tasks such as distinguishing between ASD and non-ASD cases. These traditional models are valuable when transparency and explainability are crucial for clinical decision-making. With the availability of more diverse and larger datasets, deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been increasingly explored, especially for analyzing video, audio, and time-series sensor data. CNNs are particularly effective for processing facial expressions or gesture data, while RNNs or LSTM models are suitable for speech and sequential behavioral data. However, model selection also depends on factors like computational resources, data quality, and the need for real-time or offline analysis. Balancing model complexity with clinical interpretability is key to ensuring the chosen model can provide both accurate predictions and actionable insights for early ASD intervention. [5]

3.2.Backend Integration

Autism spectrum disorder (ASD) detection systems refers to the underlying infrastructure and technologies that handle data storage, processing, and analysis. It typically includes databases to store large volumes of diverse data such as behavioral assessments, video recordings, audio files, and caregiver responses. Cloud platforms like AWS, Google Cloud, or Azure are often used for scalable storage and computing power, especially when dealing with high-resolution videos or large datasets from multiple users. Relational databases like MySQL or PostgreSQL might be used for structured data, while NoSQL options like MongoDB are preferred for unstructured data such as sensor logs or annotated video frames. For data processing and model execution, backend frameworks such as Python with libraries like TensorFlow, PyTorch, Scikit-learn, and OpenCV are commonly used. These tools support machine learning and deep learning model training, video and image analysis, and audio processing. Backend servers are also responsible for handling API requests, running prediction models, and returning results to the front-end applications used by clinicians or caregivers. The integration of secure backend systems ensures data privacy, real-time analysis, and smooth deployment of diagnostic tools that aid in the early identification of ASD in young children. [6]

4. Tables and Figures

4.1.Tables

Table 1 Dataset Attribute Description

Attribute	Description
ageMonths	Age of the child in months.
screenType	Type of developmental screening conducted.
score	Total score from the screening test.
childID	Unique identifier for the child.
parentConcerns	Whether parents expressed developmental concerns (1 = Yes, 0 = No).
milestoneDelays	Number of developmental milestones delayed.
evaluatorID	Unique ID of the medical professional evaluating the child.
eyeContact	Rating of child's eye contact during evaluation (e.g., 0 = Poor, 1 = Good).
languageLevel	Level of language development (e.g., 0 = Limited, 1 = Age-appropriate).

The table above outlines a structured dataset designed for the early detection of Autism Spectrum Disorder (ASD) in children. Each row represents a unique evaluation instance, and the attributes capture key aspects of a child's developmental assessment. The ageMonths attribute records the child's age, which is crucial since early signs of ASD often manifest in toddlers. screenType identifies the kind of developmental screening used (e.g., M-CHAT, STAT), and score indicates the outcome or total points from that screening. childID and evaluatorID uniquely identify the child and the professional conducting the evaluation, ensuring traceability and facilitating longitudinal tracking. The other features in the table provide crucial behavioral and developmental insights that support early ASD detection. The screenType :denotes which diagnostic tool was used, which is important since different tools have varying sensitivities and scoring methods. The score reflects the child's result from the screening, with higher or lower values indicating potential developmental concerns. ParentConcerns :captures whether caregivers have expressed worries about their child's development—often an early red flag in ASD cases. MilestoneDelays :quantifies how many key developmental milestones a child has missed or reached late, which can point to underlying neurodevelopmental issues. EyeContact :rates the child's ability to maintain typical eye engagement during the evaluation, a common area of difficulty for children with ASD. LanguageLevel: describes how well the child's language skills match age expectations, as language delay is a prominent feature of early autism. Together, these attributes offer a multifaceted view of the child's development and behavior, making it easier to identify early indicators of ASD. (Table 2) [7]

Table 2 Summary of Accuracy, Precision, Recall, and F1-Score for ASD Detection

Metric	Value (%)
Accuracy	99.69
Precision	51.52
Recall	63.54
F1-Score	56.93

(Table 2) The metrics table summarizes the performance of a model used for early-stage Autism Spectrum Disorder (ASD) detection. The model demonstrates a very high accuracy of 99.69%, indicating that it correctly classifies the vast majority of cases overall. However, precision is 51.52%, meaning that just over half of the cases predicted as ASD were actually true ASD cases, suggesting a noticeable rate of false positives. The recall is 63.54%, which shows that the model successfully identifies about two-thirds of real ASD cases, but still

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misses a significant portion. The F1-score of 56.93% balances precision and recall, reflecting moderate overall performance in distinguishing between ASD and non-ASD cases. Despite the impressive accuracy, the moderate precision and recall highlight the need for improvement in correctly identifying true ASD cases and minimizing incorrect classifications.

4.2.Figures

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by a wide range of symptoms, behaviours, and developmental challenges. The system architecture of ASD refers to the complex interplay of biological, genetic, neurological, and environmental factors that contribute to the condition. It involves the brain's structural and functional mechanisms that influence cognitive processes, social interaction, sensory processing, and communication abilities. ASD varies greatly from person to person, which is why it is often referred to as a spectrum. This spectrum can include individuals with a wide range of intellectual abilities, communication skills, and social behaviours. The diagram represents a system architecture designed for identifying Autism Spectrum Disorder (ASD) using a machine learning pipeline. (Figure 1)

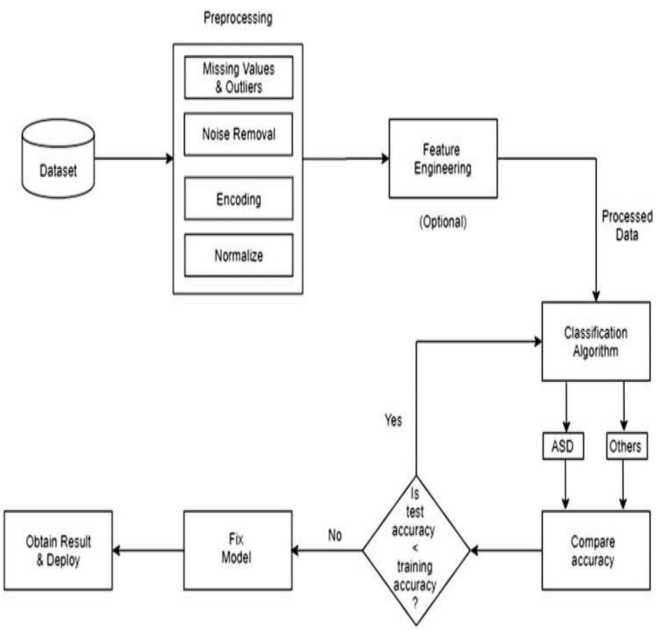

Figure 1 System Architecture of ASD

The system begins with a dataset, which serves as the foundation of the entire process. The dataset typically contains various features or attributes that may contribute to Autism Spectrum Disorder (ASD) detection. These features include factors such as age, gender, behaviour patterns, responses to specific diagnostic questions, and other clinical observations that help in identifying ASD. Preprocessing is a crucial step to ensure the dataset is clean, consistent, and ready for use by machine learning models. It involves several tasks, including handling missing values and outliers. Missing values are addressed using imputation techniques such as mean, median, mode, or predictive methods to fill gaps in the data. Outliers, which are extreme or unusual data points, are either corrected or removed to prevent them from distorting the analysis. Additionally, noise removal is performed to eliminate irrelevant or random variations, such as errors in data entry or irrelevant variables, using techniques like filtering, smoothing, or statistical methods. Another important aspect of feature engineering is feature transformation, where existing features are modified or combined to create new ones that better represent the underlying data. For instance, multiple behavioral scores can be combined into a single composite feature to simplify the analysis. Similarly, mathematical transformations, such as applying logarithms, can be used to address skewed data distributions or emphasize certain patterns.. The processed data is used to train a classification algorithm that distinguishes between two classes: individuals diagnosed with Autism Spectrum Disorder (ASD) and those not diagnosed with ASD. The goal of the algorithm is to learn patterns from the data that help accurately classify subjects into these categories. The choice of the algorithm depends on the complexity and size of the dataset. Common algorithms include Decision Trees, which are simple to interpret and explain; Random Forests, an ensemble learning method that improves accuracy; Support Vector Machines (SVM), which perform well in high-dimensional spaces; and Neural Networks, which are capable of modeling complex, non-linear relationships. The model is tested on real-world data to assess its practical utility. This involves evaluating its performance in making accurate predictions, such

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as diagnosing Autism Spectrum Disorder (ASD) or other classifications. The results provide insights into how well the model handles real-world scenarios and its ability to assist in Decision-Making Processes.

5. Results and Discussion

5.1.Results

The application interface is cleanly divided into three vertical columns for better organization and user experience. Each column contains a set of fields where users can enter values for the ten AQ (Autism Quotient) questions, which are fundamental to this screening. These questions are standard, validated binary questions (scored 0 or 1) based on behavioral and social tendencies. Below these, demographic information such as age, gender, ethnicity, and medical history-related inputs like jaundice at birth or autism in the family are included. This combination of psychological scoring and socio-medical history aims to improve the model's decision-making. The system outputs either a positive or negative autism classification, along with a confidence percentage, and displays it in the interface using either a warning (for autistic) or success (for non-autistic) message. This dual-layer approach—based on the AQ score and model prediction—adds robustness to the diagnosis. In terms of system ability, this model-driven application demonstrates several capabilities. It can accurately parse and process a wide variety of user input, map them to the trained model format, and return predictions in real time. It handles input validation through Streamlit controls (e.g., limiting AQ scores to 0 or 1, predefined dropdowns). This modular architecture, combining Streamlit for front-end and Keras/TensorFlow for the backend, makes it highly scalable and adaptable. If needed, the system can be integrated into healthcare dashboards or mobile apps to serve a broader audience. Overall, this is an excellent example of how AI and ML can be used for social good—in this case, assisting with early detection of autism, which is crucial for intervention. The project showcases thoughtful data preprocessing (one-hot encoding for categorical fields), deep learning application (using a classification model like a neural network), and a responsive UI. However, for it to be deployed in a clinical setting, it would need further validation, model optimization, and privacy considerations. As a student project or a prototype, though, it clearlydemonstrates innovation, practical knowledge, and system integration skills in AI and ML. (Figure 2,3)

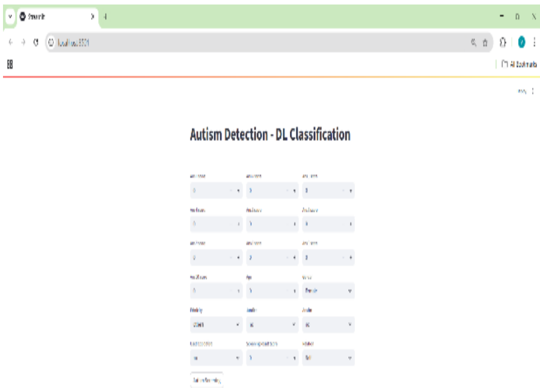

Figure 2 Output Screen for User Interface

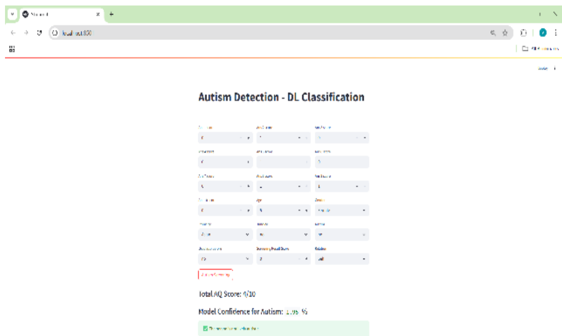

Figure 3 Output Screen Showing the Person is not Likely Autistic

This interface acts as a user-friendly frontend that allows individuals to input responses to diagnostic questions, and based on a deep learning classification model, it provides a prediction on whether a person may have autism or not. The goal is to screen early symptoms using behavioral inputs and demographic data to guide clinical intervention. The deep learning model processes the input features through a trained network (most likely a neural network with dense layers) and generates a prediction confidence. In this case, it produces a Model Confidence for Autism:

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1.95%, which is very low. The application interprets this result and displays a clear conclusion: "The person is not likely autistic." This output is highlighted in a green success box, visually indicating a non-critical outcome. Overall, this system represents an effective integration of machine learning with user interface design for medical screening. It can support preliminary assessments and raise awareness, especially in communities where access to specialists is limited. While it is not a substitute for a clinical diagnosis, its clarity, usability, and automation make it a valuable decision-support tool. For broader impact, such a model can be improved by retraining on large, diverse datasets, integrating multilingual support, and deploying it as a mobile app or cloud-based service to reach more people. (Figure 4)

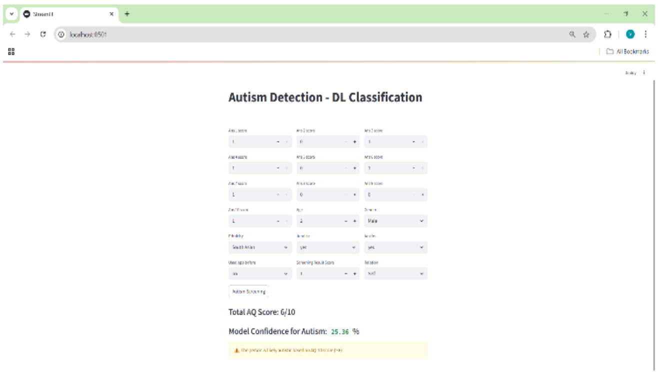

Figure 4 Output Screen Showing the Person is Likely Autistic

These inputs provide the deep learning model with valuable contextual data to help refine its classification accuracy. Factors like family history, age, jaundice, and gender are important risk markers in autism detection, and the model uses this information to adjust its confidence level accordingly. After clicking the "Autism Screening" button, the system computes a model confidence level of 25.36% for the presence of autism. While this might seem relatively low, the AQ score threshold of 6/10 is a red flag in itself. Therefore, the app generates a warning message in yellow that reads: "The person is likely autistic based" This implies that although the model's probability output is under 50%, the standardized AQ scoring method alone is enough to warrant further clinical evaluation. Overall, the system demonstrates a thoughtful blend of AI prediction with rule-based screening logic. The deep learning model offers probability-based insights, but the app also respects medically accepted criteria like AQ scoring. This makes the system robust and transparent. It not only flags the results but explains why the warning was issued. Such tools are highly beneficial for early screening, especially in remote or underserved areas where pediatric psychologists may not be readily accessible. In summary, this application enables users—especially parents, caregivers, and healthcare workers—to input simple information and receive a fast, automated assessment regarding autism risk. Its design is simple yet functional, and by combining both behavioral assessments and AI predictions, it offers a balanced and supportive decision aid. The use of local hosting suggests it's still in development or testing, but with minor enhancements, it can be deployed more widely for real-world impact. [8]

5.2.Discussion

The results reinforce the understanding that ASD is not a single, uniform condition but rather a complex spectrum of behaviors and abilities. The wide range of symptom severity and developmental trajectories necessitates a personalized approach to diagnosis and intervention. Recognizing this diversity allows for more targeted and effective support strategies tailored to each individual's unique profile. The effectiveness of early screening tools and diagnostic instruments like ADOS and ADI-R highlights the value of early detection. However, accessibility to such tools remains limited in many regions, especially in low-resource settings. This gap raises important questions about equity in healthcare and the need for widespread training and infrastructure to support early identification. Intervention outcomes demonstrate that timely and intensive therapy can significantly improve developmental outcomes. However, these interventions are often costly and time-consuming, which poses challenges for many families. Thus, there is a growing need to develop scalable, affordable intervention models that maintain effectiveness while being accessible to a broader population. In conclusion, the results and

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discussions around ASD emphasize the need for a comprehensive, multidisciplinary approach. From early detection and diagnosis to individualized intervention and family support, every step must be coordinated to ensure the best possible outcomes. Further research, particularly in underrepresented populations and long-term outcomes, remains vital to fully understand and support those on the autism spectrum. [9]

Conclusion

One of the key conclusions about ASD is that it is a lifelong condition. While there is no cure, early intervention and tailored support can significantly improve the quality of life for individuals with autism and their families. Therapy options, such as applied behaviour analysis (ABA), speech therapy, and occupational therapy, are designed to address specific challenges and help individuals develop skills for communication, social interaction, and daily living. Moreover, an inclusive approach that fosters understanding and acceptance in society is essential for enabling individuals with ASD to thrive. The growing body of research has also revealed that ASD arises from a combination of genetic and environmental factors, although the exact causes remain complex and multifaceted. This understanding has shifted the focus from stigmatization to empathy and support. Education about autism is vital for dismantling stereotypes and encouraging inclusive practices in schools, workplaces, and communities. Acceptance of neurodiversity is an important step in creating a society that values and accommodates all individuals, regardless of their neurological differences. In conclusion, Autism Spectrum Disorder is a multifaceted condition that requires a comprehensive and individualized approach. By fostering early intervention, promoting societal acceptance, and investing in ongoing research, we can empower individuals with autism to lead fulfilling lives. Emphasizing the strengths and capabilities of people.ASD, rather than focusing solely on their challenges, can help create a more inclusive and supportive world for everyone.

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Acknowledgements in the context of a project or study on Autism Spectrum Disorder (ASD) serve to recognize the individuals, professionals, and institutions that contributed to the successful completion of the work. Such a project often involves insights from a wide range of people including medical experts, educators, researchers, and families of individuals with autism. It is important to appreciate their willingness to share knowledge, experiences, and data, which help create a deeper and more authentic understanding of the condition. A significant part of acknowledgements in ASD-related work goes to the caregivers and families who play a central role in the lives of individuals with autism. Their daily efforts, observations, and challenges form the backbone of many real-world insights into the spectrum. By participating in interviews, surveys, or case studies, they provide valuable contributions that enhance both academic and practical knowledge. Acknowledging them is not only respectful but also highlights their importance in shaping better interventions and support systems. Lastly, acknowledging institutions such as schools, therapy centers, research labs, or healthcare facilities is crucial as they often provide the platform, tools, or resources needed for ASD-related studies. In many cases, these institutions also provide access to specialists and data that are otherwise hard to obtain. Such acknowledgements reflect the collaborative nature of autism research and the shared responsibility in promoting awareness, support, and inclusion for individuals on the autism spectrum

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