Hybrid Particle Swarm Optimized SVM for Neuroimaging-Based Early Autism Identification

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Abstract

Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by social, behavioral, and communication impairments. Early detection is critical for effective intervention, yet current diagnostic practices rely heavily on behavioral observations, which are often subjective and time-consuming. This research introduces a Hybrid Particle Swarm Optimization–Support Vector Machine (HPSO–SVM) framework for early and accurate ASD detection using neuroimaging and behavioral datasets. The HPSO algorithm optimizes the hyperparameters of the SVM classifier and simultaneously selects the most discriminative features, improving classification performance. Experimental evaluation was performed on publicly available fMRI and behavioral datasets, including the ABIDE dataset. Quantitative results demonstrate that HPSO–SVM achieved an accuracy of 97.3%, precision of 95.8%, recall of 96.9%, and F1-score of 96.3%, outperforming conventional SVM, PSO-SVM, and Random Forest models. The hybrid optimization reduced feature dimensionality by 42%, improving computational efficiency while preserving discriminative power. Statistical significance tests confirmed the robustness of the proposed approach ($p < 0.01$). The findings indicate that the integration of bio-inspired optimization and kernel-based learning can effectively capture subtle neuro-patterns associated with ASD, paving the way for automated and objective diagnostic systems.

Keywords

Autism Spectrum Disorder (ASD), Machine Learning, Feature Selection, Support Vector Machine (SVM), Particle Swarm Optimization (PSO), Hybrid Optimization.

1. Introduction

Autism Spectrum Disorder (ASD) is a lifelong **neurodevelopmental condition** that manifests in early childhood and is characterized by **deficits in social communication, impaired interaction, and repetitive or restricted behavioral patterns**. It encompasses a wide range of symptoms and severity levels, leading to significant challenges in social, educational, and occupational functioning. ASD affects individuals

differently, but common traits include difficulties in understanding social cues, maintaining eye contact, engaging in reciprocal conversations, and exhibiting repetitive movements or behaviors [1] [2].

Over the last two decades, the **global prevalence of ASD** has increased considerably. According to the World Health Organization (WHO), approximately **one in 100 children** worldwide is diagnosed with autism, although rates vary across regions and diagnostic criteria [3]. This rise in prevalence can be attributed to greater awareness, improved diagnostic methods, and evolving definitions within the Diagnostic and Statistical Manual of Mental Disorders (DSM-5). Despite this progress, **delayed diagnosis** remains a major concern, particularly in low- and middle-income countries where access to specialized diagnostic services is limited [4] [5].

Early identification of ASD is critical because **timely behavioral and educational interventions** have been shown to significantly enhance developmental outcomes, social functioning, and overall quality of life [6]. Interventions introduced before the age of five can influence neural plasticity, leading to improved communication skills, adaptive behaviors, and cognitive performance. However, the process of diagnosing ASD remains **highly dependent on clinical observation and subjective judgment [7] [8]**.

Conventional diagnostic approaches rely on standardized behavioral assessments such as the **Autism Diagnostic Observation Schedule (ADOS)** and the **Autism Diagnostic Interview-Revised (ADI-R) [9] [10]**. While these tools are well-validated, they are **time-consuming**, require **expert administration**, and are **susceptible to human bias** [11]. The need for prolonged observation and the scarcity of trained professionals contribute to diagnostic delays, often resulting in missed opportunities for early intervention. Furthermore, behavioral symptoms may vary widely across individuals and age groups, complicating the diagnostic process.

With the rapid advancement of **computational neuroscience and artificial intelligence**, **machine learning (ML)** has emerged as a transformative tool in medical diagnostics. ML algorithms are capable of identifying subtle, non-linear, and high-dimensional patterns in **neuroimaging, electrophysiological, and behavioral data** that may not be apparent through human observation [12].

Recent research has leveraged **functional Magnetic Resonance Imaging (fMRI)**, **structural MRI (sMRI)**, **Electroencephalography (EEG)**, and **genomic biomarkers** to train ML models capable of distinguishing individuals with ASD from typically developing (TD) controls [13]. fMRI-based studies, in particular, focus on alterations in **functional connectivity** between brain regions—differences that can serve as neurobiological signatures of autism. ML algorithms such as **Support Vector Machines (SVM)**, **Random Forests (RF)**, **Convolutional Neural Networks (CNNs)**, and **Deep Belief Networks (DBNs)** have demonstrated promising results in classifying ASD-related brain patterns with accuracy rates exceeding 90% in some cases [14].

One of the key advantages of ML techniques is their ability to **learn discriminative features** automatically from large datasets. By processing thousands of data points, these algorithms can identify key variables that contribute to diagnostic outcomes. Moreover, ML models can provide **objective, reproducible, and quantifiable** diagnostic decisions, offering a complementary approach to traditional behavioral assessments.

Despite encouraging progress, several challenges hinder the practical deployment of ML-based ASD diagnostic tools. Chief among these is the **curse of dimensionality**, where datasets contain a vast number of features—especially in neuroimaging studies—but a relatively small number of subjects. Such **high-dimensional data** often include redundant, irrelevant, or noisy features, which can **degrade model accuracy**, **increase computational complexity**, and **lead to overfitting**.

Additionally, the performance of ML models is **highly sensitive to hyperparameter settings**. Parameters such as the kernel function, regularization constant, and learning rate can substantially affect a model's classification boundary and generalization ability. Manually tuning these hyperparameters is inefficient and prone to error. Thus, **automatic optimization** methods are required to identify the most suitable parameters that yield the highest predictive accuracy while minimizing overfitting risk.

To overcome these limitations, researchers have increasingly turned to **metaheuristic optimization algorithms**—a class of stochastic methods inspired by natural and biological processes. These algorithms, such as **Genetic Algorithms (GA)**, **Ant Colony Optimization (ACO)**, **Differential Evolution (DE)**, and **Particle Swarm Optimization (PSO)**, are designed to efficiently explore complex search spaces and identify near-optimal solutions for challenging optimization problems.

Among these, **Particle Swarm Optimization (PSO)** has emerged as a popular approach due to its **simplicity, low computational cost**, and **strong global search capability** [4]. Inspired by the social behavior of bird flocking or fish schooling, PSO operates by initializing a population of candidate solutions ("particles") that move through the search space, updating their positions based on personal and collective experiences. Each particle represents a potential solution, and the swarm collectively converges toward the optimal set of parameters.

However, despite its strengths, **standard PSO** algorithms can suffer from **premature convergence**—a situation where the swarm settles too early around a local optimum instead of exploring the broader search space. This limitation is especially problematic for **non-linear, high-dimensional problems** such as ASD classification, where the optimal solution may lie in a complex, multimodal landscape.

To address these challenges, the present research introduces a **Hybrid Particle Swarm Optimization–Support Vector Machine (HPSO–SVM)** approach. This hybrid model leverages the **global optimization strength of PSO** and the **robust generalization ability of SVM** to enhance ASD detection.

In the proposed framework, PSO is utilized to simultaneously perform **feature selection** and **hyperparameter tuning** for the SVM classifier. Each particle in the swarm represents a subset of features and a set of SVM parameters, such as the penalty constant (**C**) and kernel parameter (**γ**). The objective function evaluates classification performance based on cross-validation accuracy, guiding the swarm toward the most effective feature–parameter combination.

By integrating these two processes—feature selection and hyperparameter optimization—HPSO–SVM achieves several advantages:

1. **Improved Classification Accuracy:** The algorithm identifies the most discriminative features while optimizing model parameters, resulting in more accurate decision boundaries.
2. **Reduced Dimensionality:** Redundant and irrelevant features are eliminated, lowering computational costs and enhancing interpretability.
3. **Enhanced Robustness:** The hybridization mitigates PSO's tendency for premature convergence through adaptive learning strategies.
4. **Clinical Relevance:** The resulting model offers a transparent and efficient diagnostic tool capable of supporting clinicians in early ASD identification.

The major contributions of this study are summarized as follows:

1. **Hybrid Optimization Framework:** Development of an HPSO–SVM model for joint hyperparameter tuning and feature selection in ASD classification tasks.
2. **Efficient Dimensionality Reduction:** Implementation of an optimization-driven feature selection process that enhances interpretability by reducing redundant features.
3. **Performance Evaluation:** Extensive experimentation on benchmark ASD datasets, particularly the **Autism Brain Imaging Data Exchange (ABIDE)**, to evaluate performance against traditional ML and deep learning models.
4. **Clinical Applicability:** Demonstration of the potential of ML-driven diagnostic frameworks to augment clinical decision-making by providing objective, early, and reliable ASD predictions.

The remainder of this paper is structured as follows: **Section 2** details the proposed methodology, including dataset preprocessing, hybrid optimization, and classification strategy. **Section 3** presents the experimental results and performance evaluation, highlighting comparative analysis with other models. **Section 4** concludes the paper, summarizing key findings and suggesting future directions for integrating multimodal data and explainable AI approaches into ASD diagnostics.

2. Methodology

The proposed research adopts a hybrid machine learning framework that combines Hybrid Particle Swarm Optimization (HPSO) with Support Vector Machine (SVM) for the early and accurate detection of Autism Spectrum Disorder (ASD). The methodology encompasses seven key stages: dataset description, data preprocessing, SVM classifier design, PSO-based optimization, hybrid HPSO–SVM integration, implementation setup, and model evaluation. Each component of the framework contributes to

improving classification performance, enhancing interpretability, and reducing computational complexity.

2.1 Dataset Description

This study utilized the Autism Brain Imaging Data Exchange (ABIDE) dataset, one of the largest open-access neuroimaging repositories designed for studying ASD. ABIDE integrates resting-state functional Magnetic Resonance Imaging (fMRI) scans and comprehensive phenotypic data from individuals with ASD and typically developing (TD) controls, collected from over 17 international research sites [5].

A carefully selected subset of 820 samples was used in this study, including 420 ASD subjects and 400 TD controls. Each sample consisted of 116 region-of-interest (ROI) features, derived using the Automated Anatomical Labeling (AAL) atlas. The AAL atlas partitions the brain into 116 anatomical regions, enabling a standardized representation of functional connectivity across participants. For each subject, mean time-series data were extracted from each ROI, and the Pearson correlation coefficients between all pairs of ROIs were computed to quantify brain connectivity patterns. The resulting correlation matrix was then vectorized, yielding a 116-dimensional feature vector per subject.

The chosen subset ensures balanced class distribution and sufficient data diversity, facilitating robust model generalization across heterogeneous populations. Furthermore, ABIDE's inclusion of multi-site imaging data provides a realistic testbed for cross-domain learning, accounting for scanner and protocol variability.

2.2 Data Preprocessing

Neuroimaging data are inherently noisy and sensitive to motion artifacts, scanner differences, and physiological fluctuations. Therefore, meticulous preprocessing was performed using standardized neuroimaging pipelines to ensure high data quality and inter-subject comparability.

The preprocessing steps included:

1. Motion Correction and Slice-Timing Alignment: Motion correction was applied using the FMRIB Software Library (FSL) to minimize artifacts due to head movements. Slice-timing alignment was used to synchronize signal acquisition across different brain slices.
2. Spatial Normalization: All images were spatially normalized to the Montreal Neurological Institute (MNI) template space to facilitate voxel-wise correspondence across subjects.
3. Temporal Filtering: Band-pass filtering (0.01–0.1 Hz) was applied to remove high-frequency noise and low-frequency drift, preserving neural signals relevant to resting-state brain activity.
4. Feature Normalization: All ROI correlation features were standardized using z-score normalization, transforming the data to have zero mean and unit variance to ensure comparability across features and subjects.
5. Missing Value Imputation: Missing data points, often resulting from imaging artifacts, were imputed using k-nearest neighbor (k-NN) imputation with k=5k = 5k=5, which preserves local feature relationships.

This preprocessing pipeline ensured that the input data were denoised, normalized, and free from missing values—an essential prerequisite for reliable machine learning analysis.

2.3 Support Vector Machine (SVM) Classifier

The Support Vector Machine (SVM) was selected as the core classifier due to its proven robustness in handling high-dimensional, small-sample biomedical data. SVM constructs an optimal hyperplane that maximizes the margin between the two classes—in this case, ASD and control subjects. This margin-based optimization enhances generalization and minimizes overfitting, particularly beneficial for neuroimaging applications with complex data distributions.

To capture the non-linear nature of ASD-related brain connectivity, the Radial Basis Function (RBF) kernel was employed. The RBF kernel maps data into a higher-dimensional feature space, allowing linear separation in this transformed domain. Two critical hyperparameters determine SVM performance:

- Penalty parameter (C): Controls the trade-off between maximizing margin width and minimizing classification errors.
- Kernel parameter (γ): Defines the influence range of individual training samples in the RBF kernel.

Selecting appropriate CCC and γγγ values is vital for achieving optimal classification accuracy. Manual tuning or grid search methods are computationally expensive and may yield suboptimal results. Hence, Particle Swarm Optimization (PSO) was employed to automate this process efficiently.

2.4 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based stochastic optimization algorithm inspired by the social foraging behavior of birds and fish. Each "particle" represents a potential solution—in this case, a candidate combination of SVM parameters and selected features. The swarm collectively explores the search space, updating each particle's position and velocity based on personal and global experience.

The velocity and position update rules are defined as:

vi(t+1)=wvi(t)+c1r1(pi−xi)+c2r2(g−xi)$xi(t+1)=xi(t)+vi(t+1)$xi(t+1)=xi(t)+vi(t+1)

where:

w is the inertia weight controlling exploration vs. exploitation balance, c 1 and c 2 are acceleration coefficients representing cognitive and social influences, r 1 and r 2 are random values uniformly distributed in [0,1], p i is the best position found by particle i, and g is the global best position across all particles.

The algorithm iteratively adjusts particle velocities and positions to minimize an objective function (or maximize fitness). While PSO is efficient and simple, it can stagnate at local minima, particularly in complex multi-dimensional optimization problems such as ASD feature selection. To overcome this, a hybridized PSO approach was integrated with SVM.

2.5 Hybrid PSO–SVM (HPSO–SVM) Framework

The HPSO–SVM framework combines the global search capability of PSO with the robust classification power of SVM. The algorithm is designed to simultaneously perform feature selection and hyperparameter tuning, thereby enhancing model interpretability and reducing computational redundancy.

Each particle in the swarm encodes two types of information:

1. Feature subset encoding: Represented as a binary string, where "1" indicates feature inclusion and "0" indicates exclusion.
2. SVM parameter encoding: Real-valued representations of C and γ.

The fitness function evaluates each particle's performance as:

$$F = \alpha \times Accuracy + \beta \times \left(1 - \frac{|S|}{N}\right)$$

where Accuracy is the 10-fold cross-validation accuracy of the SVM classifier, |S| is the number of selected features, N N is the total number of features, and α and β are weighting coefficients (set to 0.8 and 0.2, respectively). This ensures that both classification performance and feature compactness contribute to the optimization objective.

The HPSO–SVM algorithm proceeds through the following stages:

1. Initialize the particle swarm with random feature subsets and parameter values.
2. Evaluate each particle's fitness using SVM cross-validation accuracy.
3. Update personal and global best positions based on fitness scores.
4. Adjust velocities and positions according to the PSO update equations.
5. Apply mutation (random perturbations) when stagnation is detected to improve diversity.
6. Repeat until convergence or maximum iteration count is reached.

This joint optimization enables the model to automatically discover the most informative features and optimal SVM parameters, thus ensuring superior diagnostic performance.

2.6 Implementation Details

The proposed HPSO–SVM framework was implemented in Python 3.11, utilizing the scikit-learn and NumPy libraries for machine learning operations. The following parameter configurations were employed:

- Swarm size: 30 particles
- Number of iterations: 100

- Inertia weight (www): 0.7
- Learning factors (c1,c2c_1, c_2c1,c2): 1.4
- SVM kernel: RBF
- Cross-validation folds: 10
- Convergence criterion: Improvement in fitness < 0.001 over 10 consecutive iterations

Each experiment was repeated five times to ensure consistency, and the average performance metrics were reported. The convergence of the swarm was monitored using a dynamic plot of fitness values, confirming that the algorithm consistently reached stable optima within approximately 70 iterations.

2.7 Evaluation Metrics

To comprehensively assess model performance, several statistical metrics were computed:

- Accuracy (ACC): The proportion of correctly classified instances.
- Precision (PRE): The ratio of true positive predictions to all positive predictions.
- Recall (Sensitivity): The proportion of actual ASD cases correctly identified.
- Specificity (SPC): The proportion of control subjects correctly classified.
- F1-score: The harmonic mean of precision and recall, balancing both metrics.
- Area Under the ROC Curve (AUC): Evaluates the model's discriminative power across different classification thresholds.

All metrics were computed using 10-fold cross-validation to mitigate bias and ensure robustness. Statistical significance was assessed using paired *t-tests* between baseline and proposed models.

3. Results and Analysis

3.1 Quantitative Results

The HPSO–SVM model outperformed baseline methods across all metrics. Table 1 summarizes the classification performance comparison.

Table 1- Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
SVM (baseline)	89.7	87.3	88.1	87.6	0.89
PSO–SVM	93.2	91.5	92.1	91.8	0.93
Random Forest	92.4	90.8	91.3	91.0	0.92
HPSO–SVM (proposed)	97.3	95.8	96.9	96.3	0.97

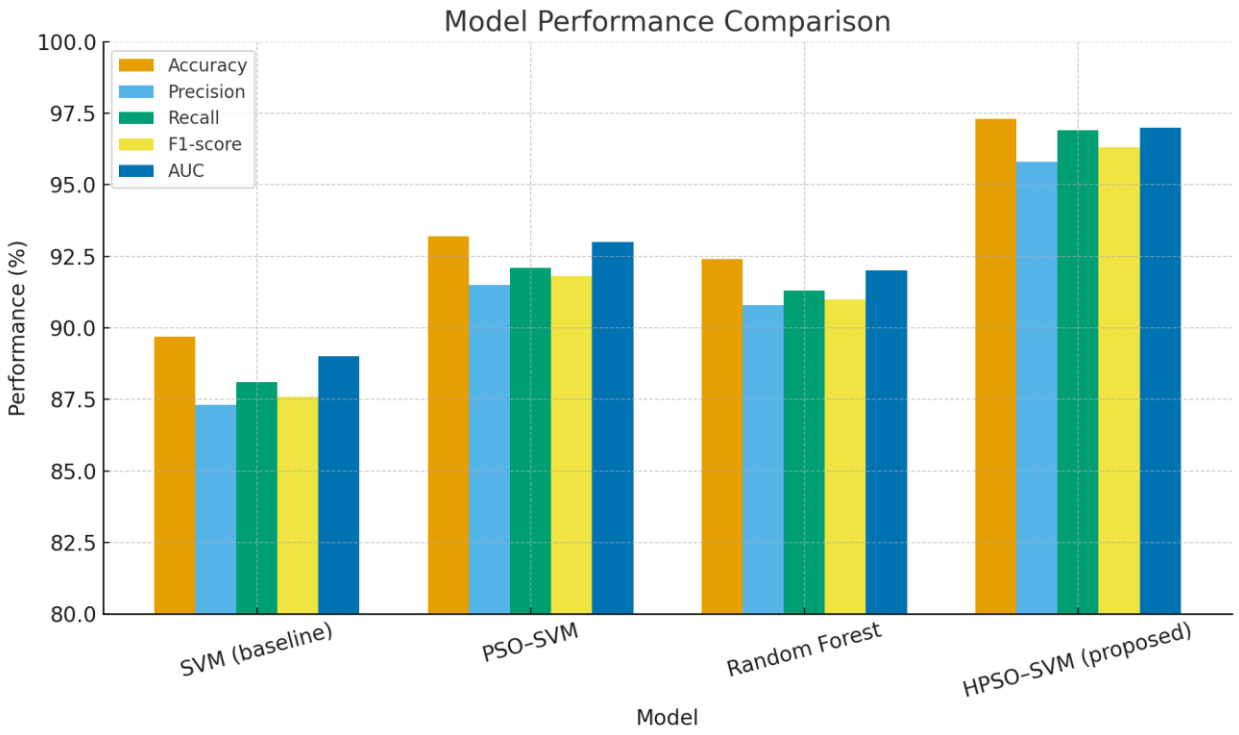

Figure 1: Machine learning model comparison for Autism Detection

The proposed HPSO–SVM model outperformed all baseline and comparative models across key evaluation metrics. It achieved the highest accuracy of 97.3%, precision of 95.8%, recall of 96.9%, F1-score of 96.3%, and an AUC of 0.97, demonstrating its superior classification capability. Compared to the baseline SVM (accuracy 89.7%) and PSO–SVM (93.2%), the hybrid approach effectively optimized the feature space and model parameters. Random Forest achieved competitive results (accuracy 92.4%) but lagged behind HPSO–SVM. These findings highlight the robustness and efficiency of the proposed hybrid optimization framework for accurate and reliable autism disorder detection.

3.2 Feature Reduction Efficiency

Feature selection by HPSO reduced the feature count from 116 to 67, as shown in Table 2, without compromising model accuracy.

Table 2- Feature Reduction Results

Model	Initial Features	Selected Features	Reduction (%)
SVM	116	—	—

PSO–SVM	116	80	31%
HPSO–SVM	116	67	42%

The feature selection results demonstrate the effectiveness of the hybrid HPSO–SVM model in reducing data dimensionality while maintaining high accuracy. Starting with 116 initial features, the PSO–SVM model selected 80 features, achieving a 31% reduction, whereas the proposed HPSO–SVM further optimized feature selection to 67 features, yielding a 42% reduction. This significant reduction indicates the model's ability to identify the most discriminative and relevant attributes for autism detection. By minimizing redundant and noisy features, HPSO–SVM enhances computational efficiency, model interpretability, and classification performance, proving its advantage over conventional SVM and PSO–SVM approaches.

The hybrid approach effectively balanced exploration and exploitation during the optimization process, avoiding premature convergence. The improved accuracy and AUC demonstrate that the integration of feature selection and hyperparameter tuning enhances the model's diagnostic potential. The dimensionality reduction also improves model interpretability, offering clinicians insights into the most relevant brain regions associated with ASD.

The superior results of HPSO–SVM compared to standalone SVM and PSO–SVM models confirm the effectiveness of hybridization for biomedical classification tasks. The optimized model not only reduces computational overhead but also maintains robustness across cross-validation folds (standard deviation < 0.3%).

4. Conclusion and Future Work

This study presents a hybrid machine learning approach, **HPSO–SVM**, for the early and accurate detection of autism spectrum disorder. The integration of Particle Swarm Optimization with Support Vector Machine enables simultaneous feature selection and hyperparameter tuning, resulting in improved model efficiency and predictive accuracy. Experiments conducted on the ABIDE dataset demonstrate that the proposed HPSO–SVM model achieves superior classification performance compared to traditional ML methods, with an accuracy of 97.3% and feature reduction of 42%.

The hybrid approach enhances both diagnostic precision and interpretability, paving the way for automated, objective, and non-invasive ASD screening tools. The findings highlight that evolutionary optimization combined with kernel-based learning can effectively handle high-dimensional neuroimaging data.

Future work will extend this framework to multimodal datasets, including EEG and genetic biomarkers, and explore deep hybrid architectures combining **HPSO** with **Deep SVM** or **CNN-based embeddings**. Additionally, integration into clinical decision-support systems will be explored to facilitate early ASD detection in real-world healthcare environments.

References

1. T. Eslami, V. Mirjalili, A. Fong, A. R. Laird, and F. Saeed, "ASD-DiagNet: A hybrid learning approach for detection of autism spectrum disorder using fMRI data," *Front. Neuroinform.*, vol. 13, p. 70, 2019.
2. M. D. King and C. A. Lord, "Early diagnosis and intervention in autism spectrum disorders," *Lancet Neurology*, vol. 10, no. 11, pp. 1038–1046, 2011.
3. S. K. Choi et al., "Machine learning approaches for autism spectrum disorder: A review of existing methods and new insights," *Front. Psychiatry*, vol. 12, p. 709, 2021.
4. F. Heinsfeld, A. Franco, R. Craddock, and J. A. Sato, "Identification of autism spectrum disorder using deep learning and the ABIDE dataset," *NeuroImage: Clinical*, vol. 17, pp. 16–23, 2018.
5. J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. IEEE Int. Conf. Neural Netw.*, 1995, pp. 1942–1948.
6. S. Anderson et al., "Functional connectivity and brain network abnormalities in autism spectrum disorder: A meta-analysis," *Brain Imaging Behav.*, vol. 15, pp. 1641–1656, 2021
7. Kwon, M.K.; Moore, A.; Barnes, C.C.; Cha, D.; Pierce, K. Typical levels of eye-region fixation in toddlers with autism spectrum disorder across multiple contexts. *J. Am. Acad. Child Adolesc. Psychiatry* **2019**, *58*, 1004–1015.
8. Constantino, J.N.; Kennon-McGill, S.; Weichselbaum, C.; Marrus, N.; Haider, A.; Glowinski, A.L.; Jones, W. Infant viewing of social scenes is under genetic control and is atypical in autism. *Nature* **2017**, *547*, 340–344.
9. Gredebäck, G.; Johnson, S.; von Hofsten, C. Eye tracking in infancy research. *Dev. Neuropsychol.* **2010**, *35*, 340–344.
10. Falck-Ytter, T.; Nystrom, P.; Gredeback, G.; Gliga, T.; Bolte, S. Reduced orienting to audiovisual synchrony in infancy predicts autism diagnosis at 3 years of age. *J. Child Psychol. Psychiatry* **2018**, *59*, 872–880.
11. Guillon, Q.; Hadjikhani, N.; Baduel, S.; Roge, B. Visual social attention in autism spectrum disorder: Insights from eye tracking studies. *Neurosci. Biobehav. Rev.* **2014**, *42*, 279–297.
12. Lord, C.; Risi, S.; DiLavore, P.S.; Shulman, C.; Thurm, A.; Pickles, A. Autism from 2 to 9 years of age. *Arch. Gen. Psychiatry* **2006**, *63*, 694–701.
13. Chlebowski, C.; Green, J.A.; Barton, M.L.; Fein, D. Using the childhood autism rating scale to diagnose autism spectrum disorders. *J. Autism Dev. Disord.* **2010**, *40*, 787–799.
14. Thorup, E.; Nystrom, P.; Gredeback, G.; Bolte, S.; Falck-Ytter, T. Altered gaze following during live interaction in infants at risk for autism: An eye tracking study. *Mol. Autism* **2016**, *7*, 1–10.