

# Detection of autism spectrum disorder using multilayer perceptron classifier

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## ABSTRACT

Autism spectrum disorder (ASD) is a neurodevelopmental condition marked by distinctive challenges in both verbal and nonverbal communication, social interaction, and repetitive behaviors. However, the diagnosis of ASD usually occurs within a clinical setting, conducted by licensed professionals, and often involves lengthy and costly procedures. On the other hand, machine learning holds significant promise for improving diagnostic and intervention research within the behavioral sciences, particularly in research concerning ASD disease. Hence, a deep investigation of a machine learning algorithm for ASD detection is crucial. Therefore, this paper presented a new system for differentiating the ASD samples from non-ASD (i.e., healthy) samples. The samples of ASD have been compiled from toddlers. The multilayer perceptron (MLP) algorithm is used to classify ASD samples from non-ASD samples. The proposed MLP classifier is implemented based on different numbers of neurons (i.e., nodes). In other words, the proposed MLP classifier started with 10 neurons and finished with 50 neurons with an increment step of 5 neurons. The outcomes demonstrate that the MLP classifier acquired different results concerning the number of neurons. The MLP obtained the best performance, reaching an accuracy rate of 100% in identifying ASD cases.

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## 1. INTRODUCTION

Autism spectrum disorder (ASD) is a neurological condition that affects brain development and is associated with difficulties in language use, limited social engagement, impaired communication abilities, patterns of repeated behavior, and delays in motor coordination [1]. Typically, diagnosis can be made using existing protocols from the age of three onwards [2]. ASD affects various brain regions and is also influenced by genetic factors such as gene interactions or polymorphisms [3]. Globally, one in 70 children is affected by autism, with a prevalence rate of 168 out of 10,000 children estimated in the United States in 2018, one of the highest worldwide [4]. Furthermore, ASD is more commonly diagnosed in boys than in girls, with approximately 3.63% of boys aged 3 to 17 having the disorder, compared to about 1.25% of girls in the United States [5]. Diagnosing ASD poses challenges due to the absence of pathophysiological markers, relying solely on psychological criteria. Psychological assessments enable the identification of specific

behaviors and social interaction levels, aiding in early detection. Behavioral evaluations encompass a range of tools and questionnaires that help physicians pinpoint developmental delays (DD) in children. These evaluations may include clinical observations, medical history assessments, autism diagnostic guidelines, as well as assessments of growth and intelligence [6].

The symptoms of ASD exhibit a broad spectrum, which prompts suspicions of autism in individuals due to the persistent presence of diverse symptoms [7]. Presently, the diagnosis of ASD relies on several factors, including i) parental interviews, ii) utilization of scales (e.g., autism diagnostic observation schedule (ADOS), autism observations in infants (AOSI), social-communication rating scale (SOC-RS), and early social communication scales (ESCS)), and iii) clinical observations [8]. This diagnostic process, being highly subjective, may vary depending on factors such as the physician's experience, patient behavior, parental knowledge, and responses on the scales [9]. Consequently, the diagnostic journey may be prolonged, influenced by both the physician and parental factors, and may carry the risk of misdiagnosis due to these discrepancies [10]. This indicates the ongoing necessity for scientific advancements and support in ASD diagnosis. While clinical findings or biomarkers are sought for early ASD detection, it's acknowledged that relying solely on clinical biomarkers may not suffice for early diagnosis.

On the other side, the machine learning domain has demonstrated its efficacy in terms of detection and prediction subjects in various applications by using different types of methods and approaches. For instance, machine learning methods have been applied in emotion recognition [11], [12], cellular network [13], voice pathology detection [14]–[17], license plate identification [18], diabetes prediction [19], crime activity detection [20], and intrusion detection [21]. In addition, the models of machine learning have been used in the ASD recognition [22]–[24]. However, these techniques need further investigation and examination in the detection of ASD in terms of using hyperparameter methods, such as using different numbers of neurons or nodes. Therefore, the primary contributions of this study can be summarized as follows:

- This paper proposes a new method for detecting ASD disease based on a multilayer perceptron (MLP) classifier.
- The proposed MLP model is trained and assessed based on ASD database using different numbers of neurons (i.e., nodes).
- The method is evaluated utilizing several performance measurements such as accuracy, precision, recall, F1-score, specificity, and G-mean.
- The proposed MLP achieves high results for detecting ASD disease, outperforming many of its comparative in terms of detection accuracy.

The rest of this paper is organized as follows: section 2 presents the previous studies of ASD recognition utilizing models of machine learning and deep learning. Section 3 presents the proposed method, which consists of two subsections. The first subsection refers to the ASD database for toddlers, which is used to train and assess the MLP model. Meanwhile, the second subsection refers to the proposed MLP classifier that is used to recognize the ASD samples from the non-ASD samples. Section 4 provides and discusses the experimental results of the proposed MLP algorithm. Lastly, the conclusion of this study is provided in section 5.

## 2. RELATED WORK

The use of machine learning approaches to identify ASD disease has been widely studied and investigated. In other words, the previous research studies have analyzed different ASD databases, used various classifiers, and assessed the model using accuracy and other measurements. Hence, many researchers and scholars have attained huge attention to this field of systems. Jayanthi *et al.* [25] proposed an assistive technology aimed at monitoring stress levels in individuals affected by ASD disease. ASD often affects linguistic and motor skills, and stress can exacerbate both physical and mental health issues in these individuals. Reduced heart rate variability (HRV) is observed in those with ASD, which is considered a significant factor. Accordingly, parameters such as body movements, body temperature, and heart rate are monitored. The hardware module integrated various sensors like pulse sensor, temperature sensor, and accelerometers, adaptable to personalized wearables for users. In this study, the collected data is transmitted to a nonrelational database and then processed using machine learning models like random forest (RF) classifiers and linear regression.

Shrivastava *et al.* [26] has applied various machine learning classifiers to distinguish between data representing ASD and typically developed (TD) individuals. Various ASD datasets encompassing all age groups (toddlers, children, adolescents, and adults) were employed for this purpose. Categorical data were converted into numerical data using one-hot encoding during preprocessing. To address missing values and normalize data, the authors have utilized k-nearest neighbors (KNN) imputer in conjunction with

MinMaxScaler feature transformation. Classification of ASD and TD data was performed using support vector machine (SVM), KNN, artificial neural network (ANN), and RF classifiers. The RF classifier exhibited the highest accuracy result, where it is achieved 100% accuracy across different training and testing data splits for all age groups, without occurring overfitting issues.

Another study has been presented for the detection of ASD disease [27]. In this study, the federated learning (FL) approach is utilized and investigated for the purpose of ASD detection. Furthermore, there were machine learning classifiers, which are logistic regression (LR), and SVM that were trained to classify ASD factors and detect ASD in both adults and children. Leveraging FL, the results from these models were transmitted to a central server, where a meta-approach was trained to determine the most accurate approach for ASD detection across different age groups. Four diverse ASD patient databases, each comprising over 600 samples of affected adults and children, were sourced from various repositories for feature extraction. The model demonstrated that the SVM algorithm obtained the highest performance, where it has been achieved a detection accuracy of 99% for ASD in children and 81% for ASD in adults.

The ASD disease has been analyzed and studied based on various techniques of machine learning [28]. This study has delved into the prediction of ASD and compared various aspects, including application kind, simulation method, method comparison, and data type. Its main objective is to offer developers a centralized framework engaged in ASD prediction. The proposed algorithms were examined by using different measurements which are precision, accuracy, and recall. The samples were gathered from the autism brain imaging data exchange (ABIDE) dataset. The RF algorithm emerged as the most effective, outperforming other traditional algorithms. The RF algorithm has attained a detection accuracy of 89.23%. However, the obtained accuracies of naïve Bayes (NB), SVM, and MLP were 85.43%, 80.43%, and 81.84%, respectively.

Alves *et al.* [29] has been introduced an approach for automatically diagnosing ASD disease using functional brain imaging data obtained from a cohort of 500 subjects, among whom 242 have been diagnosed with ASD disease, utilizing bootstrap analysis of stable cluster maps to identify regions of interest. This method has been exhibited a high accuracy in differentiating among the control group and ASD patients. In other words, it has achieved superior performance with an area under the curve (AUC) approaching 1.0. The analysis revealed a reduced connectivity between the left ventral posterior cingulate cortex and a region in the cerebellum among individuals with this neurodevelopmental disorder. Additionally, functional brain networks in ASD patients exhibited greater segregation, reduced information dissemination across the network, and diminished connectivity compared to control subjects. In this work, among all techniques used for the detection of ASD, the RF, and LR algorithms attained the best detection accuracy, where both have been achieved 100%.

A multimodal system relay on machine learning for early screening of ASD is presented [30]. In the study, there were 125 toddlers participated, comprising individuals diagnosed with ASD disease. In other words, the number of ASD patients was 61 samples, the number of DD was 31, and the number of typically developmental (TD) was 33 children. The response to name (RTN) procedures was administered separately by both the assessor and the caretaker. In addition, the data related to behavior were captured using 8-definition tripod-mounted cameras and analyzed using a multimodal machine learning system (MMLS). Besides, the response period, score of response, and time of response were precisely measured to assess RTN. The findings indicated a total accuracy of 0.92 for RTN scores generated by computers. Toddlers with ASD indicated notable distinctions in the response period, score of response, and time of response compared to those with DD and TD in both assessor and caretaker processes. The AUC was 0.81 for computer-generated outcomes, and the human-rated outcomes were 0.91. Meanwhile, the accuracy rates for identifying ASD based on human-rated results and computer-generated results were 82.9% and 74.8%, respectively.

### 3. PROPOSED METHOD

The proposed method aims to distinguish the ASD samples from the healthy ones. In the proposed method, there are two phases, the first one refers to the ASD database, which contains the extracted features from the ASD samples and healthy samples. In addition, the extracted attributes will be provided to the model. The second phase refers to the classification part, where the MLP algorithm performs to classify the samples of individuals who suffer from ASD disease from the healthy ones. The algorithms have been deeply investigated based on different numbers of neurons, starting at 10 neurons and finishing at 50 neurons with an increment step of 5 neurons. The performance of the proposed model has been assessed based on widely known measurements. Figure 1 shows the flowchart of the proposed method for the classification of ASD. In addition, these two stages of the proposed method will be explained further in the following subsections, respectively.

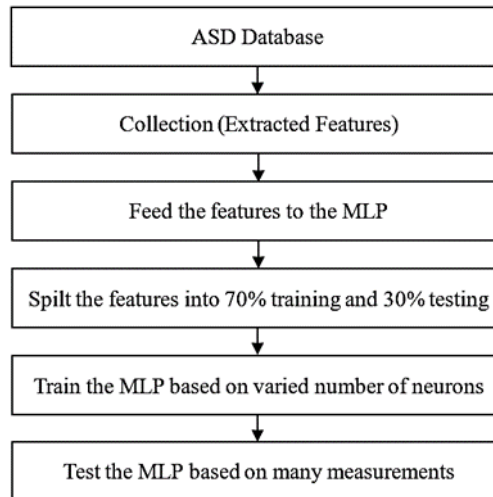


Figure 1. The flowchart of the proposed method

### 3.1. Autism spectrum disorder database

The samples or features of the ASD database are typically utilized to train and assess the models of machine learning. In this study, we have collected the ASD database from Kaggle respiratory [31]. This database has been created by the Department of Digital Technology, New Zealand. The samples in this database have been gathered by using a mobile app named ASDTests.

Furthermore, this database is related to autism screening of toddlers, and it comprises influential features to be utilized for additional analysis, particularly in determining autistic traits and improving the identification of ASD cases. In this database, there are 10 behavioral features (Q-Chat-10) that have been recorded, as well as other attributes that can be used for detecting the ASD cases. There are two classes in this database. The first one was labelled as “yes” (i.e., it refers to the participants having ASD disease) and the second one was labelled as “no” (i.e., non-ASD disease). The database comprises a total of 1,054 samples, where 728 samples were labelled as “yes”, and 326 samples were labelled as “no”. In the proposed method, the database has been separated into 70% and 30% for the training and assessment procedures, respectively. Therefore, the training step includes 737 samples, and the testing step contains 317 samples. In addition, Table 1 shows the number of samples used in the proposed model for the ASD detection.

Table 1. The ASD database

Classes	Number of cases	Training	Testing
ASD	728	737	317
Non-ASD	326		
Total	1054		

### 3.2. Classification

The proposed method uses the MLP algorithm for the classification part to classify the ASD samples from non-ASD samples. The MLP is a type of ANN that has been widely used for classification tasks, including medical diagnosis, such as thyroid disease detection [32]. This study employed an MLP classifier to distinguish among individuals with ASD and those without, with classes labelled as “yes” for ASD-positive cases and “no” for non-ASD cases. The MLP classifier consists of an input layer, one or more hidden layers, and an output layer. Each layer comprises multiple neurons, and connections between neurons are weighted. The MLP learns from training data by adjusting these weights to minimize classification errors and improve its performance in the classification between subjects.

In the MLP algorithm, there are three main layers, namely input, hidden, and output. The input layer comprises neurons which are representing the features of the input data (i.e., the features of the ASD database). In the hidden layer, the MLPs can include one or more of such layers, each encompassing numerous neurons. These hidden layers allow the network to acquire intricate relationships within the data. In the proposed model using the MLP algorithm, the number of hidden nodes used for training the MLP

classifier varies. In other words, the hidden nodes (i.e., neurons) in the proposed MLP algorithm are set to start from 10 and finish at 50 hidden nodes with an increment by 5 hidden nodes. Meanwhile, the output layer gives the final classification results. In binary classification tasks, the model usually has a single output neuron, whereas in multi-class classification, it employs multiple output neurons corresponding to each class.

In the training process of the MLP algorithm, and during forward propagation, input data is provided into the network. The weighted sum of inputs and biases is calculated at each neuron, followed by the application of activation functions. This process generates predictions. After predictions are made, the algorithm computes the error among forecasted and real outputs. Using gradient descent optimization, it fine-tunes the weights and biases backward through the network to minimize this error. This iterative process is recognized as backpropagation. In the MLP classifier, each neuron typically applies an activation function to present nonlinearity into the model. Familiar activation functions like sigmoid, rectified linear unit (ReLU), and others. In the proposed model, the logistic sigmoid function has been used as an activation function. The main process for the classification part in the MLP algorithm involves forward propagation, where input features are processed through the network to produce output predictions. Furthermore, the MLP algorithm is trained based on (1) and (2).

$$S = X \cdot W + b \quad (1)$$

Where  $A = \text{activation}(S)$ .

$$\tilde{S} = A \cdot \tilde{W} + \tilde{b} \quad (2)$$

Where  $\hat{Y} = \text{softmax}(\tilde{S})$ .

In (1) and (2),  $X$  represents the input data (i.e., features),  $W$  and  $\tilde{W}$  denote the weight values of the 1st and 2nd layers, respectively. In addition,  $b$  and  $\tilde{b}$  represent the bias vectors of the 1st and 2nd layers, respectively.  $S$  and  $\tilde{S}$  represent the weighted sums of inputs in the hidden and output layers, respectively.  $A$  is the activation of the hidden layer. Lastly,  $\hat{Y}$  is the output of the network, representing the predicted probabilities for each class after applying the softmax function.

#### 4. RESULTS AND DISCUSSION

The primary aim of this method is to recognize the ASD disease features utilizing a machine learning approach. Data samples for autism screening data for toddlers encompassing both ASD instances and non-ASD (i.e., normal) were sourced from the Kaggle repository. Within this database, there are ten behavioral features of each participant that have been recorded. Besides, there are two classes that have been labeled as Yes (i.e., ASD class) and No (i.e., non-ASD class). The dataset was partitioned into 70% for training and 30% for assessment purposes.

The features characterizing each class were utilized as inputs for the machine learning model. Specifically, the MLP classifier was employed for the ASD detection. The MLP classifier consists of different neurons (i.e., nodes). In the proposed model, the MLP classifier has a different number of neurons, where the MLP classifier starts with 10 neurons and finishes at 50 neurons with an increment step of 5 neurons. Thus, the total number of experiments is 9.

Further, the experiments of the proposed model were implemented using Python 3.10 on a laptop equipped with an Intel Core i5 processor (2.50 GHz) and 8 GB of RAM. To assess the effectiveness of the proposed model, a range of evaluation measurements including accuracy, precision, recall (i.e., sensitivity), F1-score (i.e., F-measure), specificity, and G-mean were utilized. These measures are calculated employing in (3)-(8) [33], [34]. The experimental results of the proposed method using the MLP classifier for the detection of ASD disease are displayed in Table 2.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (5)$$

$$\text{F1 - score} = \frac{(2 \times \text{Precision} \times \text{Sensitivity})}{(\text{Precision} + \text{Sensitivity})} \quad (6)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (7)$$

$$G - \text{Mean} = \sqrt[2]{\text{Specificity} \times \text{Sensitivity}} \quad (8)$$

Table 2. The experimental results of the MLP algorithm for ASD detection

Neurons	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)	G-mean (%)
10	85.49	82.37	54.90	70.88	54.90	74.10
15	83.91	80.82	50.00	66.66	50.00	70.71
20	93.06	90.71	78.43	87.91	78.43	88.56
25	97.48	96.41	92.15	95.91	92.16	96.00
30	97.79	96.84	93.13	96.44	93.14	96.51
35	93.69	91.48	80.39	89.13	80.39	89.66
40	99.68	99.53	99.01	99.50	99.02	99.51
45	100	100	100	100	100	100
50	100	100	100	100	100	100

According to the experimental results, the MLP classifier has obtained different results based on various numbers of neurons. In other words, when the number of neurons is 10, the proposed MLP classifier has achieved 85.49% accuracy, 82.37% precision, and 54.90% recall. Furthermore, the results of the proposed MLP algorithm for F1-score, specificity, and G-mean were 70.88%, 54.90%, and 74.10%, respectively. The proposed MLP classifier has achieved the best outcomes when the number of neurons reached 45 and 50, whereas the MLP classifier has achieved 100% for each evaluation measurement. Figure 2 displays the best outcomes of the MLP classifier for the detection of ASD disease.

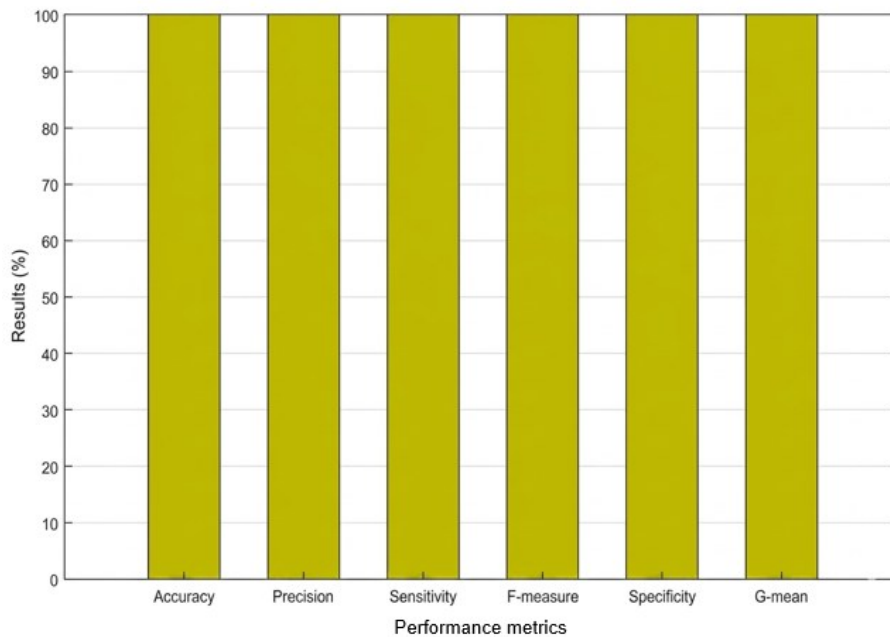


Figure 2. The highest obtained results of the MLP classifier for ASD detection

However, the MLP classifier has been obtained the lowest results when the number of neurons was 15, where the MLP classifier obtained 83.91% accuracy, 80.82% precision, and 50.00% recall. Moreover, the lowest obtained results of the MLP classifier for F1-score, specificity, and G-mean were 66.66%, 50.00%, and 70.71%, respectively. In addition, the proposed method using the MLP classifier has been compared with other methods and techniques for the recognition of ASD illness in terms of accuracy. Table 3 displays the comparison between the proposed MLP classifier and other approaches [35]–[40]. These methods have been used the same dataset, which is ASD data for toddlers. Additionally, these methods have been used with different techniques for the detection of ASD disease. For example, the method in [35], KNN, RF, LR, and

decision tree (DT) algorithms were used, C4.5 tree, RF, and neural network (NN) [36], SVM [37], NB, LR, SVM, and RF [38], adaptive boosting (AB) [39], and linear discriminant analysis (LDA) [40].

Based on the obtained results for each method, the performance of the proposed MLP algorithm has been showed the highest achieved accuracy compared to other methods. This demonstrates the significance of deep investigation of classifiers in the detection of ASD disease, where it has been indicated that the proposed MLP classifier obtained the highest result when the number of neurons reached 45 and 50, respectively. However, there are some limitations of the proposed method that can be considered as future works. These limitations can be listed as follows:

- This method is limited to detecting ASD data for toddlers. Meanwhile, the ASD data for adults is significant.
- The statistical analysis for further analyzing the experimental result is ignored in this method.
- In the proposed method, one dataset and one classifier have been used.

Table 3. Comparison between methods

Methods	Accuracy (%)
The proposed MLP classifier	100
KNN [35]	78.12
RF [35]	90.88
LR [35]	85.38
DT [35]	91.02
C4.5 tree [36]	98
RF [36]	96
NN [36]	99
SVM [37]	98
NB [38]	43.6
LR [38]	68.48
SVM [38]	76.77
RF [38]	92.65
AB [39]	99.25
LDA [40]	93.84

## 5. CONCLUSION

ASD is a condition impacted by genetic and neurological factors, resulting in challenges related to social interaction and communication. However, diagnosing ASD typically involves specialized clinical assessments, which can be time-consuming and expensive. Conversely, machine learning presents a promising avenue for advancing diagnostic and intervention research in behavioral sciences, particularly in the context of ASD. Moreover, most studies that used several algorithms for the ASD recognition have been used fixed parameters, such as a fixed number of hidden nodes. Therefore, investigating a model for ASD recognition based on different numbers of hidden nodes is imperative. This paper presented a novel system designed to distinguish ASD samples from non-ASD (healthy) samples, focusing on data collected from toddlers. The system employed the MLP algorithm for classification, varying the number of neurons in the MLP classifier from 10 to 50 in increments of 5. Performance evaluation of the MLP classifier encompasses multiple metrics such as accuracy, precision, recall, F1-score, specificity, and G-mean. Experimental findings reveal that the proposed MLP classifier achieves varying results based on the number of neurons, with the highest result of 100% for each evaluation measure. This result is achieved when the number of neurons reaches 45 and 50. However, the lowest results of each evaluation measure were achieved when the number of neurons reached 15. The outcomes demonstrate a promising performance of the proposed MLP classifier, surpassing its counterparts in terms of detection accuracy. Future work includes using many databases and classifiers for ASD detection, where the results can be statistically analyzed.

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### AUTHOR CONTRIBUTIONS STATEMENT

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

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### CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

### DATA AVAILABILITY

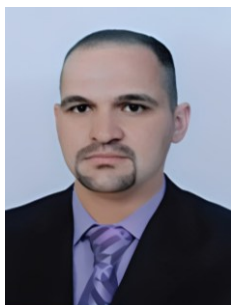
The data that support the findings of this study are openly available in Kaggle Respiratory at <https://www.kaggle.com/code/vaibhavvishal77/autism-spectrum-disorder-asd/input>, reference [33].




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