*Type of the Paper (Article, Review, Communication, etc.)*

**An Intelligent Toy Car for Autism Screening using Multi-Modal Features**

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**Early screening, which can lead to early diagnosis and intervention of children with autism (ASD), can significantly improve the life quality of children with autism. Unfortunately, the observational process of ASD diagnosis and the lack of experts make the technology-based ASD screening methods more demanding. On the other hand, early ASD screening based on behavioral patterns is one of the most reliable methods that could be done by analyzing children's playing patterns. Thus, in this paper we present an extension of our initial intelligent toy car functionalities by adding shaft encoders to detect attention to details and interest in rotating objects in children with ASD. Using the two modalities to detect different ASD symptoms improved our screening accuracy by more than 10%.**

**Keywords: autism spectrum disorder (ASD), intelligent toy, machine learning, IoT**

**1. Introduction**

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that causes social communication and interaction problems(1). Unfortunately, ASD has become more prevalent in the last two decades(2). On the other hand, studies show that early diagnosis resulting in early intervention can effectively reduce the disorder's impacts. However, diagnosing autism requires experts to observe children and interview parents to determine the severity of the symptoms during multiple time-consuming and challenging sessions. Furthermore, many cases remain undiagnosed due to the lack of widespread experts, especially in low and middle-income societies. Consequently, it becomes essential to develop technology-based screening methods to make screening services cheap and widely available to overcome these challenges.

A very straightforward approach to employ technology was to automate CHAT family questionnaires (3), and make them online through mobile apps or web applications(4). Furthermore, these methods employ machine learning algorithms to improve the screening accuracy(5). Although these methods are proved to be credible, however, they relied on licensed clinicians and observers to correctly answer the questions(3, 6).

To overcome the shortcomings of the questionnaire-based systems, many researchers have focused on biological markers of ASD(7) using brain imaging techniques such as fMRI(8) or EEG (9). Amid all evidence which confirm the effectiveness of the mentioned approaches, the required equipment makes them less accessible. Additionally, putting a child in an fMRI or putting on an EEG cap may cause many discomforts limiting the usage of these procedures.

There are other technology-based approaches, such as wearable devices like smart glasses or sensors (10, 11), which are more convenient options than fMRI or EEG. Despite the lower cost of these systems compared to fMRI and EEG, they still need to be conducted at dedicated centers. There are many studies focused on intelligent observation of behaviors to overcome the challenges of biometric and wearable methods. For instance, Moghaddas et al. (12) developed a vision-based method for ASD screening based on the interaction between children with ASD and a parrot-like robot. Although this approach tackles some of the mentioned difficulties in wearable methods, it still depends on dedicated centers to conduct this screening approach.

That is why home-based IoT devices such as the intelligent toy car(13) were designed to perform screening in children's natural settings at a very low cost. Along with this trend, in this study, we improved the intelligent toy car by incorporating two shaft encoders on the wheels of the car. We wanted to investigate if children with autism focus on the rotation of the wheels instead of the whole car more than Typically Developed (TD) children. This new modality, combined with its initial modality, which was based on capturing the acceleration features in playing with the car, helped improve screening accuracy by more than 10%. In other words, our contribution is in introducing a new modality and incorporating it with another modality to better screen children with ASD. These modalities can be incorporated into other screening methods to increase the accuracy of such screening methods.

**2. Related work**

While questionnaires such as M-Chat have become an integral part of the assessment process for ASD, their accuracy is limited due to the subjective nature of responses from parents or caregivers. Consequently, The American Academy of Pediatrics advocates for a more comprehensive evaluation, including developmental, behavioral, and cognitive assessments to conclusively diagnose ASD (14). Thabtah et al. showed that the questionnaire-based approaches are proficient in accurately detecting characteristics of autism compared to traditional methods (15).

The main disadvantage of the traditional screening/diagnosis tools is in their need for experts to run them. Furthermore, the questionnaire-based or observation-based methods rely on the person handling them. Thus, they suffer from inaccuracy and bias in answering questions or in observations. To address these challenges, several studies focused on developing methods to observe ASD symptoms automatically using biomarkers or behavioral markers.

That is why machine learning-based methods have been heavily approached in the past decade. Kohli Kar et al. (16) conducted a scoping review to examine the role of intelligent technologies in the early detection of ASD. Their findings suggest that intelligent technologies can be used to detect ASD at an early stage with high accuracy. Belen, R. A. J. et al. (17) (18) conducted a systematic review evaluating a total of 33 studies that used computer vision techniques to screen children with ASD. Their summarization shows that computer vision techniques had been used to measure facial expressions, body language, and social interactions in children with ASD. The authors concluded that computer vision has the potential to effectively analyze behavioral markers.

It should be reminded that many of the above technology-based ASD screening, such as the robot-based , fMRI, and EEG, are costly, need skilled operators to run them, and are not widely available. Furthermore, each approach would evaluate one or a few aspect(s) of autism symptoms. Thus, having other technology-based methods that evaluate ASD from another point of view would be beneficial for better screening of ASD.

Toys can be equipped with sensors and be used to collect data for online or offline analysis. Different sensors can capture different data such as playing patterns that can be used for classification. For instance, Lanini M. and et al. combined accelerometer, gyroscope, and magnetometers data(19). Also, Moradi et al. introduced a platform for autism screening based on acceleration data of a toy car that, in their first version, a Wiimote controller was used as a sensor hub. A Matlab program was developed to interact with the system to collect accelerometer data in x, y, and z axes to investigate distinctive playing patterns. They trained an SVM classifier with 85% accuracy(13). Also, Laura Boccanfuso et al (20), used accelerometer data of a Sphero robot for ASD screening. They analyzed accelerometer data as a modality to study the child responses to different robot behaviors. Beibin Li et al (21), used accelerometer and gyroscope sensor data in Sphero, a commercially available robot, in order to classify behaviors in children with autism. They managed to differentiate kick, drop, hold, and no interaction parts of child-robot behavior with an accuracy of 48.82%.

A summary of the screening/diagnosis approaches listed in the above papers have been presented in Table 1. In this table, we aimed to bring a sample of each approach highlighting their accuracy, sensitivity, and specificity. There are cases that have not reported these measures. Furthermore, we have listed their drawbacks in the last column of the table. In the drawbacks, biased opinion means that answers depend either on the expertise of examiners or on the understanding, punctuality, or intentions of parents who answer the questions. It should be noted that most of these methods are in their initial stages and need further study to prove their usability and reliability. The approaches proposed by Khozaei et al. [22] and Moradi et al. [13] can be used in natural setting which involves noise and unwanted data. Thus, they need extra caution to process data accurately.

Table 1. comparison between different ASD screening methods and their accuracy, sensitivity, and specificity

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Study** | **Type** | **Accuracy** | **Sensitivity** | **Specificity** | **Drawbacks** |
| Thabtah et al. (3) | Questionnaire (M-CHAT & M-CHAT-RF) | - | 95-97% | 99% | need for experts, biased opinion |
| Shokoohi-Yekta et al. (5) | Questionnaire (Expert System) | 92.40% | - | - | biased opinion |
| Sanchez-Garcia et al. (22) | Questionnaire (meta-analysis) | - | 72% | 98% | need for experts, biased opinion |
| Bosl et al. (9) | EEG | - | 94% | 92% | cost, accessibility, difficult for kids |
| Rakić et al. (23) | fMRI | 85% | 81% | 89% | cost, accessibility, difficult for kids |
| Kang et al. (24) | EEG + eye-tracking | 85.50% | - | - | cost, accessibility, difficult for kids |
| Khozaei et al. (25) | Audio/ voice analysis (crying) | - | 78.5% | 100% | Noisy data |
| Rad et al. (10) | wearable motion sensors | - | - | - | accessibility, difficult for kids, distraction |
| Coronato et al. (26) | wearable motion sensors | - | - | - | accessibility, difficult for kids, distraction |
| Nag et al. (11) | wearable sensor + gaze analysis | 84% | - | - | accessibility, difficult for kids, distraction |
| Taban et al. (27) | computer vision (walking pattern) | 72% | 66.50% | 75% | Accessibility |
| Sapiro et al. (28) | computer vision-based app (movements pattern, eye tracking) | - | - | - | Cost, accessibility, reliability |
| Campbell et al. (29) | computer vision-based app (facial mark analysis) | - | 96% | 38% | accessibility, reliability |
| Moradi et al. (13) | smart toy car | 85% | 93% | 76% | Noisy data |

In our research, the intelligent toy car 2.0 is introduced. It extends the previous version's functionality by adding shaft encoders to the wheels to measure the wheels’ rotation data for screening ASD. Our contribution in this study is in 1) introducing a new modality and 2) suggesting new features for ASD screening. It should be noted that our approach can be a complement to other screening methods to increase the overall accuracy of ASD screening.

**3. System design**

The intelligent toy car (Fig. 1(a)) is designed to capture two major symptoms, i.e. the obsessive attention to detail and the repetitive behaviors. In order to collect playing pattern data using accelerometer sensor a cheap IoT board called ESP8266 NodeMCU is used. ESP8266 board reads sensor data and sends them wirelessly to an application through Wi-Fi via UDP protocol to ensure maximum data collection rate. A MEMS accelerometer, i.e. an ADXL345, is used to capture acceleration data. Two magnetic shaft encoders, based on Hall effect, are installed the car’s front and back wheels. The whole system runs on a battery and the electronic parts are embedded inside the car deliberately to avoid any distraction. The diagram of the system is shown in Fig. 1(b).

The intelligent toy car firmware is based on the Arduino ecosystem to make future R&D more effortless. Also, an ROS (Robotic Operating System) package is developed for interfacing with the system. It makes integrating the intelligent toy car into other screening systems more straightforward.

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| (**a**) |
| Diagram  Description automatically generated  (**b**) |

**Figure 1**. (a) the intelligent toy car and (b) the schematic of the system

**4. Experiments**

The data collection process took place in an autism center in Tehran, Iran. The intelligent toy car was tested on 50 children ranging from 3 to 6 years old in three different groups: children with ASD, Typically Developed children (TD), and children with other disorders (like: CP and fragile X syndrome). Details of the participants are shown in Table 2. Since it has been shown that the play complexity and toy engagement of children with ASD in both genders for the car-like toys are almost similar (13, 30), we did not normalize the number of cases based on their gender. The subjects played with the intelligent toy car for about 3 to 5 minutes in a 3x4 meters room. The children could play in the test room alone or with their parents or therapists. The recorded data consists of the play time, acceleration along x, y, z axes, and front and rear wheel rotation counts. These data were saved in a database with each participant’s unique ID, without including name or other personal information, to preserve user anonymity and privacy.

Furthermore, the parents' consent was taken for all the participants and a child psychologist from autism center oversaw the process. The ASD group consisted of 28 children. Five ASD children did not seem interested in playing with the intelligent toy car and neglected it completely. All TD children were very interested in playing with the car. Children with fragile X syndrome and CP also played with the car but with less enthusiasm. Generally, the TD children play was more energic and they moved the car in a greater area compared to the other two groups.

Table 2. Details of the participants

|  |  |  |  |
| --- | --- | --- | --- |
|  | **ASD** | **TD** | **Others (CP and Fragile X)** |
| Number | 28 | 18 | 4 |
| Mean age | 4.63 | 4.61 | 5.5 |
| Median age | 4.0 | 4.0 | 5.5 |

**5. Feature extraction**

As mentioned earlier, the intelligent toy car is designed to capture movement behaviors and interest in rotating objects, which all are symptoms of children with ASD. In this study we analyzed movement patterns using features extracted from the acceleration data (13). The shaft encoders' data are added to the model to determine interest in rotating objects and their rotations. Two steps are taken to analyze the data: a) acceleration feature extraction representing the pattern of the car movement which is similar to the previous work done in (13). b) wheel rotation feature extraction representing children’s interest in the wheels’ rotation. To analyze the rotation of the wheels, two other futures are extracted using Short Term Fourier Transform(31) from acceleration data that represent the rolling and pitching of the car while playing with the wheels.

It should be noted that the whole children's play with the car can be divided into four states: 1) not playing, 2) playing only with wheels, 3) playing on the floor, and 4) playing in the air.

In the not playing state, the intelligent toy car is almost stationary and has no movements. Thus, both encoders and acceleration signals are almost zero. The playing only with wheels state is when the intelligent toy car is almost motionless while its wheels are rotating. In this case, the shaft encoders show changes while there is no significant change in the acceleration values. This state exactly represents the interest in rotating objects and objects' rotation. In the playing on the floor state, in which movement patterns can be extracted, the car is moved and both acceleration and shaft encoder values change. Finally, the playing in the air state is when the car is moved in the air, and the acceleration values change while the wheels are not rotating. Thus, the encoders' signals show almost zero rotation. Based on the above state analysis, and side by side with the original features proposed in (13), the following extra features (Table 3) were designed and extracted. In these features, the interactive playtime means the summation of time spent in states 2 to 4.

Table 3. details of features

|  |  |  |
| --- | --- | --- |
| **#** | **Features** | **Description** |
| 1 | not playing ratio | the ratio of not playing to the total playtime |
| 2 | playing only with wheels ratio | The ratio of playing only with wheels to the total playtime |
| 3 | playing on the ground ratio | the ratio of playing on the ground to the total playtime |
| 4 | playing in the air ratio | the ratio of playing in the air to the total playtime |
| 5 | interactive playing only with wheels ratio | the ratio of playing with wheels to the interactive playtime |
| 6 | interactive playing on the ground ratio | the ratio of playing on the floor to the interactive playtime |
| 7 | interactive playing in the air ratio | the ratio of playing in the air to the interactive playtime |
| 8 | total wheels turn rate | total number of wheels turns during the total playtime |
| 9 | tilt about X-axis | number of fast movements about X-axis |
| 10 | tilt about Y-axis | number of fast movements about the Y-axis |

**6. Classifier’s Structure**

To train classifiers, the collection of 46 subjects' data was divided into two groups: the training set with 80% of samples and the test set with 20% of remaining samples. The K-fold cross-validation method (32) separates test and training sets in k=5 different ways to generalize the result and make it more reliable. The average accuracy, sensitivity, specificity, and precision of the training are reported. Although in the previous study (13) the SVM classifier was selected as the best classifier for this task, we studied other methods like random forest and MLP with data augmentation strategies too (Table 4). Nonetheless, at the end, SVM was the most promising classifier for the collected data. Moreover, by performing several tests on three kinds of SVM, SVM with a linear kernel is selected for its considerably better performance on our data(32).

**7. Feature Selection**

Since the size of the training set is small compared to the size of the feature vector, feature reduction is necessary before applying machine learning methods. Addressing the mentioned problem, we applied two consecutive backward elimination on all the features. In the first step to reduce the number of features, the correlation between features in each modality was examined. Then, the best features were selected from each highly correlated feature set using the backward elimination method (32). This method effectively reduces the size of the feature vector by about 30%. After reducing the number of features in each modality, the best features among all modalities were selected by the backward elimination method in another round of feature selection.

Then, in the final step, the selected features from the two modalities were combined in an early fusion to select and train the best classifier. The best result was obtained by integrating five acceleration features and two shaft encoder features.

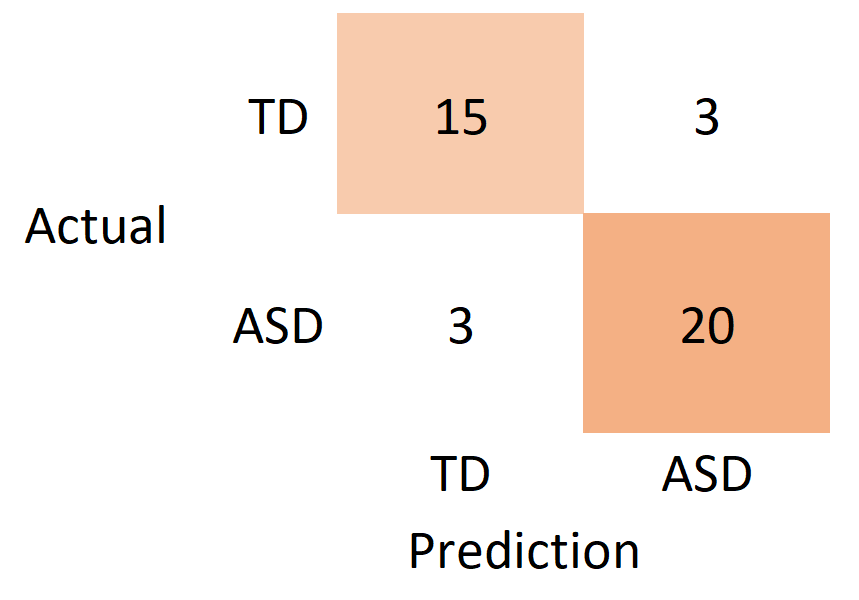
**7. Results**

The classification result based on previous studies is used as a baseline to examine the performance of adding shaft encoder features in the model. The same SVM method, presented in (13), is applied on the selected acceleration features to classify the new data. The best accuracy based on the original acceleration features (baseline features) is 71.11%, as shown in Table 4. It should be mentioned that this accuracy is lower than what reported in (13) since the data is different and the setup collecting data was different too. Furthermore, we implemented the original method in (13) from scratch which may differ in the way that it was optimized before. Adding shaft encoder’s features to the original acceleration features, increased the accuracy to 78.61%. The accuracy is increased from 71.11% to 75.83% by adding the new acceleration feature, i.e. the role and pitch of the car. Finally, by adding both shaft encoders' features and the new acceleration feature, the accuracy reached 85.56% (Table 4).

The selected features from the shaft encoders' features are the playing only with wheels ratio, not playing ratio, and total wheels turn rate. The most effective acceleration features are the jolt in the Y direction, tilt about Y-axis, the energy of the signal in the X direction, correlation of the acceleration signals between X and Y directions, the fourth-highest frequency in the X direction, the fifth-highest frequency in the Z direction, and the relative amplitude of the highest frequency in the Y direction.

*Table 4. The best accuracy, sensitivity, specificity, and precision gained by adding new features to the baseline classification.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **#** | **Classifier** | **Accuracy** | **Sensitivity** | **Specificity** | **Precision** |
| 1 | MLPwith all features | 71.11 | 78.01 | 76.33 | 73.57 |
| 2 | RadomForestwith all features | 80.83 | 85.48 | 83.67 | 78 |
| 3 | SVM with Baseline features | 71.11 | 67.14 | 73.00 | 80.00 |
| 4 | SVM with Baseline features and encoder features | 78.61 | 75.00 | 68.00 | 87.50 |
| 5 | SVM with Baseline and new acceleration features | 75.83 | 65.48 | 77.00 | 64.00 |
| 6 | SVM with Baseline, shaft encoder, and new acceleration feature | **85.56** | **81.67** | **81.00** | **87.67** |



**Figure 2**. The confusion matrix of the 6th classifier (from table 4)

**8. Discussion**

As shown in Table 4, the performance of the new proposed multi-modal approach is better than the previously suggested single modal approach. The added shaft encoder features and the new acceleration feature have improved not only the accuracy, but also other main metrics such as recall and precision. It is obvious that the classifier is more reliable in both situations whether predicting normal or ASD subjects. The confusion matrix of the classifier represents the same result (Fig2). True positive (ASD) and true negative (TD) values are considerably higher than the false negative and false positive values. It should be noted that the sensitivity and specificity of random forest method is better than SVM despite its lower overall accuracy.

The novelty of this research is in its multi-modality structure that results in the examination of ASD through a wider variety of symptoms. To reach this purpose, shaft encoders were added to the system, that increases the number of features. This is an important factor in screening ASD since ASD subjects may be in different parts of ASD spectrum and evaluating them based on different modalities is very important.

**9. Conclusion**

In this paper, we introduced the intelligent toy car 2.0 in which multi-modal ASD screening is planned. The new design incorporates shaft encoders to capture the tendency of children with ASD in rotating objects. Furthermore, we improved the feature selection strategy to increase the system accuracy by multi-modal ASD symptoms analysis. The advantage of this system over other screening methods is in its low cost and limited need for experts which make it a prominent option for initial ASD screening at homes, daycares, or clinics. Furthermore, it can be part of a multi-modal system to evaluate children with ASD from different aspects to increase the overall accuracy and other measure of the system. We expect that having more modalities observed can help for better screening.

For future work, we have to test the system on a wider population and test it on a variety of cognitive deficits to see if it can differentiate between different cognitive deficits or not. Consequently, at this stage, it can be used as a warning system to alarm the parents and caregivers to perform further evaluation through experts. Furthermore, we have to investigate the effects of size, shape, and color of the car on the results and the usage of ASD children.

**References**

1. Edition F. Diagnostic and statistical manual of mental disorders. Am Psychiatric Assoc. 2013;21(21):591-643.

2. Investigators AaDDMNSYP. Prevalence of autism spectrum disorder among children aged 8 years—autism and developmental disabilities monitoring network, 11 sites, United States, 2010. Morbidity and Mortality Weekly Report: Surveillance Summaries. 2014;63(2):1-21.

3. Thabtah F, Peebles D. Early autism screening: a comprehensive review. International journal of environmental research and public health. 2019;16(18):3502.

4. Brooks BA, Haynes K, Smith J, McFadden T, Robins DL. Implementation of web-based autism screening in an urban clinic. Clinical pediatrics. 2016;55(10):927-34.

5. Shokoohi-Yekta M, Mahmoudi M, Bonab BG, Bagherzadeh AA, Moradi H, Pouretemad HR, et al. Developing Autism Screening Expert System (ASES). Global Journal on Technology. 2013;4(2).

6. Crane L, Chester JW, Goddard L, Henry LA, Hill E. Experiences of autism diagnosis: A survey of over 1000 parents in the United Kingdom. Autism. 2016;20(2):153-62.

7. Hewitson L. Scientific challenges in developing biological markers for autism.

8. Eslami T, Saeed F, editors. Auto-ASD-network: a technique based on deep learning and support vector machines for diagnosing autism spectrum disorder using fMRI data2019 2019.

9. Bosl WJ, Tager-Flusberg H, Nelson CA. EEG analytics for early detection of autism spectrum disorder: a data-driven approach. Scientific reports. 2018;8(1):1-20.

10. Rad NM, Kia SM, Zarbo C, van Laarhoven T, Jurman G, Venuti P, et al. Deep learning for automatic stereotypical motor movement detection using wearable sensors in autism spectrum disorders. Signal Processing. 2018;144:180-91.

11. Nag A, Haber N, Voss C, Tamura S, Daniels J, Ma J, et al. Toward continuous social phenotyping: analyzing gaze patterns in an emotion recognition task for children with autism through wearable smart glasses. Journal of medical Internet research. 2020;22(4):e13810.

12. Moghadas M, Moradi H, editors. Analyzing human-robot interaction using machine vision for autism screening ICRoM 2018: IEEE.

13. Moradi H, Amiri SE, Ghanavi R, Aarabi BN, Pouretemad H-R, editors. Autism screening using an intelligent toy car, UCAmI 2017: Springer.

14. Hyman SL, Levy SE, Myers SM, Kuo DZ, Apkon S, Davidson LF, et al. Identification, evaluation, and management of children with autism spectrum disorder. Pediatrics. 2020;145(1).

15. Thabtah F, Kamalov F, Rajab K. A new computational intelligence approach to detect autistic features for autism screening. International journal of medical informatics. 2018;117:112-24.

16. Kohli M, Kar AK, Sinha S. The role of intelligent technologies in early detection of autism spectrum disorder (asd): A scoping review. IEEE Access. 2022.

17. Song D-Y, Kim SY, Bong G, Kim JM, Yoo HJ. The use of artificial intelligence in screening and diagnosis of autism spectrum disorder: a literature review. Journal of the Korean Academy of Child and Adolescent Psychiatry. 2019;30(4):145.

18. de Belen RAJ, Bednarz T, Sowmya A, Del Favero D. Computer vision in autism spectrum disorder research: a systematic review of published studies from 2009 to 2019. Translational psychiatry. 2020;10(1):333.

19. Lanini M, Bondioli M, Narzisi A, Pelagatti S, Chessa S, editors. Sensorized toys to identify the early ‘red flags’ of autistic spectrum disorders in preschoolers2018 2018: Springer.

20. Boccanfuso L, Barney E, Foster C, Ahn YA, Chawarska K, Scassellati B, et al., editors. Emotional robot to examine different play patterns and affective responses of children with and without ASD. 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI); 2016: IEEE.

21. Li B, Boccanfuso L, Wang Q, Barney E, Ahn YA, Foster C, et al., editors. Human robot activity classification based on accelerometer and gyroscope. 2016 25th IEEE international symposium on robot and human interactive communication (RO-MAN) Presented at the 2016 25th IEEE international symposium on robot and human interactive communication (RO-MAN); 2016.

22. Sanchez-Garcia AB, Galindo-Villardon P, Nieto-Librero AB, Martin-Rodero H, Robins DL. Toddler screening for autism spectrum disorder: A meta-analysis of diagnostic accuracy. Journal of autism and developmental disorders. 2019;49(5):1837-52.

23. Rakić M, Cabezas M, Kushibar K, Oliver A, Lladó X. Improving the detection of autism spectrum disorder by combining structural and functional MRI information. NeuroImage: Clinical. 2020;25:102181.

24. Kang J, Han X, Song J, Niu Z, Li X. The identification of children with autism spectrum disorder by SVM approach on EEG and eye-tracking data. Computers in biology and medicine. 2020;120:103722.

25. Khozaei A, Moradi H, Hosseini R, Pouretemad H, Eskandari B. Early screening of autism spectrum disorder using cry features. PloS one. 2020;15(12):e0241690.

26. Coronato A, Pietro GD, editors. Detection of motion disorders of patients with autism spectrum disorders. International Workshop on Ambient Assisted Living; 2012: Springer.

27. Taban R, Parsa A, Moradi H, editors. Tip-Toe Walking Detection Using CPG Parameters from Skeleton Data Gathered by Kinect2017 2017: Springer.

28. Sapiro G, Hashemi J, Dawson G. Computer vision and behavioral phenotyping: an autism case study. Current Opinion in Biomedical Engineering. 2019;9:14-20.

29. Campbell K, Carpenter KL, Hashemi J, Espinosa S, Marsan S, Borg JS, et al. Computer vision analysis captures atypical attention in toddlers with autism. Autism. 2019;23(3):619-28.

30. Harrop C, Green J, Hudry K, Consortium P. Play complexity and toy engagement in preschoolers with autism spectrum disorder: Do girls and boys differ? Autism. 2017;21(1):37-50.

31. Virtanen P, Gommers R, Oliphant TE, Haberland M, Reddy T, Cournapeau D, et al. SciPy 1.0: fundamental algorithms for scientific computing in Python. Nature methods. 2020;17(3):261-72.

32. Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: Machine learning in Python. the Journal of machine Learning research. 2011;12:2825-30.