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

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

**Bijan Mehralizadeh 1, Bahar Baradaran 2, Shahab Nikkhoo,3, Pegah Soleiman2, and Hadi Moradi 2,\***

|  |
| --- |
| **Citation:** Lastname, F.; Lastname, F.; Lastname, F. Title. *Sustainability* **2021**, *13*, x. https://doi.org/10.3390/xxxxx  Academic Editor: Firstname Lastname  Received: date  Accepted: date  Published: date  **Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.    **Copyright:** © 2021 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/). |

1 School of Mechanical Engineering, Tehran, Iran ; b.mehr@ut.ac.ir

2 School of ECE, University of Tehran, Tehran, Iran; moradih.ut.ac.ir

3 School of EECS, University of Riverside , California, USA; snikk002@ucr.edu

**\*** Correspondence: moradih@ut.ac.ir; Tel.:+98-21-82084960,

**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. The observational process of ASD diagnosis and the lack of experts make the technology-based ASD screening methods more necessary. Early ASD screening based on behaviors is one of the most reliable methods that could be done by analyzing children's playing patterns. This paper presents an extension of our initial intelligent toy car functionalities by adding shaft encoders to detect attention to detail 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 is becoming 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. Diagnosing autism requires experts to observe children and interview parents to determine the severity of the symptoms. Unfortunately, this is a time-consuming and challenging process. 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.

Many technology-based methods originated from the CHAT family(3) questionnaires, in paper-based format, mobile apps, or web applications(4). These methods employ machine learning algorithms to improve the screening accuracy(5). Although these methods are proved effective, they rely on licensed clinicians and observers, making them time-consuming and exhausting(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 like fMRI(8) or EEG methods to find ASD symptoms(9).

Although these methods were proved effective, they require costly equipment. Furthermore, putting a child in an fMRI or putting on an EEG cap may cause many discomforts limiting the usage of these approaches. On the other hand, wearable devices like smart glasses or sensors are used for ASD screening(10, 11). Despite the lower cost of these systems compared to fMRI and EEG, they still need to be conducted at dedicated centers. Intelligent observation of behaviors is a method to overcome the challenges of biometric and wearable methods. For instance, Moghaddas et al. developed a vision-based method to screen children with ASD based on the interaction between children with ASD and a parrot-like robot(12). Although this approach reduces mentioned difficulties in wearable methods, it still depends on dedicated centers to conduct the screening.

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 our intelligent toy car by incorporating two shaft encoders on the wheels of our car to investigate if children with autism focus on 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 incorporating two modalities to better screen ASD.

**2. Related work**

There have been several studies focused on using technology for ASD screening. These methods try to observe the ASD symptoms automatically using biomarkers or behavioral markers.

For example, William J. Bosl et al. focused on early screening of ASD by a data-driven method based on the EEG's data. They collected EEG measurements of 99 infants with an older sibling that received an ASD diagnosis and 89 low-risk controls. They screen ASD in children as early as three months of age with 95% sensitivity and PPV at some ages. They suggest EEG signals might be a valuable biomarker for ASD screening(9). Also, MladenRakić et al. presented a method to improve ASD detection by combining structural and functional MRI data. They applied machine learning techniques on imaging data of 817 cases and successfully classified them with an accuracy of 85%(14). Integrating biomarkers with other modalities has also proved effective; Jiannan Kang et al. identified ASD in children from 3 to 6 by inputting a combination of EEG and eye-tracking features collected with power spectrum analysis and areas of interest methods to an SVM classifier. They tested on a total number of 97 children and reached the maximum accuracy of 85%(15).

Stereotypical Motor Movements (SMM) is one of the ASD symptoms that multiple methods have been developed to detect. Rad, N. M et al. proposed a Convolutional Neural Network that uses accelerometer sensor data worn on multiple body points to detect SMM. They applied feature learning and transfer learning approaches to improve their deep neural network performance(10).

Detecting and analyzing gaze is also a method in ASD screening; Anish Nag et al. compared the gaze data of 16 children with ASD, and 17 typically developed children were collected using google glass and gaze tracker. Although smart glasses perform promisingly, they do not outperform other automatic classifiers significantly(11).

Although wearable devices are a helpful method for ASD screening, it is always challenging to persuade a young toddler to wear such devices, especially children with special needs; besides, wearing such devices is usually a major distraction that affects the procedure. Robots are an excellent option for evaluating social interactions, but they are costly and usually require operators to handle the process.

One of the major symptoms of ASD is repetitive and stereotypical behaviors that are considered an essential indication in ASD's diagnosing(16). In recent years, many technology-based screening systems have been developed, many methods focused on vision-based approaches, behavioral analysis methods that use machine vision to detect and recognize movements and motor function patterns. R. Oberleitner et al.(17) developed a recognition system for detecting abnormal behaviors that can be used in screening, assessment, or rehabilitation. Rasool Taban et al.(18) record walking patterns by Kinect and then analyze them using central pattern generator parameters as their classifier features. They accurately distinguished between tip-toe walking and regular walking pattern. Guillermo Sapiro and et al.(19) developed a low-cost mobile app that uses machine learning and machine vision methods to detect movement patterns and assess eye tracking patterns.

Vision-based methods also used for studying the subject attention; Kathleen Campbell et al. developed an app that record and analyze the reaction of the toddlers to video stimuli that designed to engage child's attention; their algorithm classifies by automatically detecting and tracking multiple facial landmarks and analyzing their patterns(20).

One of the best ways to study the behavior in children is through their play with toys and pet animals. Since children spend a considerable amount of time playing with toys at a young age, the repetitive patterns could easily be recognized. Studying playing patterns does not have challenges like the discomforting feeling of brain imaging or EEG analyzing methods, and unlike wearable devices, they do not affect child attention and are considerably more cost-effective than robots.

Sensorized toys are valuable tools in ASD screening, embed different sensors inside toys to capture playing patterns, and are classified based on proven effective, i.e., Lanini M. and et al. combined accelerometer, gyroscope, and magnetometers data(21). Also, Moradi et al. introduced a platform for autism screening based on acceleration data of a toy car that, in their first version, a Wii remote controller perform as a sensor hub and a Matlab program developed to interact with the system to collect accelerometer data of x, y, and z axes to investigate distinctive playing patterns and implement an SVM classifier with 85% accuracy(13).

In this research, the intelligent toy car 2.0 is introduced. It extends the previous version's functionality by adding shaft encoders to the wheels, introducing new features, and optimizing the feature selection method. It enables us to study the ASD symptoms with a multi modalities approach and simultaneously analyze the repetitive behaviors and the obsessive attention to the details.

**3. System design**

The intelligent toy car is designed to capture the signs of two major symptoms in children with ASD, i.e., obsessive attention to detail and repetitive behaviors. i.e., Thus, in the first design Intelligent Toy Car 1.0, a Wii Mute handle which includes an accelerometer, was placed in the car. Our new design, the intelligent toy car 2.0 (Fig. 1(a)), has had multiple upgrades with respect to its first design. The new system has an inexpensive IoT board ESP8266 NodeMCU to read sensor data and send them wirelessly through Wi-Fi via UDP protocol to ensure maximum data collection rate. Also, the cheap MEMS accelerometer ADXL345 is placed inside the car, and two magnetic shaft encoders are installed on the front and back axles of the car. The whole system runs on a battery, and all 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 in other systems more straightforward.

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

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

**4. Experiments**

The data collection process took place in the Dosste-Autism center (Autism friends center) in Tehran, Iran. The intelligent toy car was tested on 50 children ranging from 3 to 6 years old in three groups: children with ASD, TD children, and other (CP and fragile X syndrome) shown in Table 1. 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, 22), 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 from each participant consists of time, acceleration in 3 dimensions, front and back wheel rotation counts saved in a database. A unique ID in the database only identified each participant, and to preserve user anonymity and privacy, no personal data was recorded during the procedure.

Furthermore, the parents' consent was taken for all the participants. ASD group has 28 children that five of them did not seem interested in playing with the intelligent toy car and neglected it. All TD children were very interested in playing with the intelligent toy car, and children with fragile X syndrome and CP also played with the intelligent toy car but with less enthusiasm. Generally, the TD children playing was more energic, and they moved the car in the greater area than other groups.

Table 1. Details of the participants

|  |  |  |  |
| --- | --- | --- | --- |
|  | **autistic** | **TD** | **Other (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 motion behaviors, focus on details, and interest in rotating items, which all are symptoms of children with ASD. Our previous study used movement patterns extracted from acceleration data for classification(13). The same patterns are extracted in this research, and the encoders' data are added to the model to determine interest in rotating items and their rotations. Two steps are taken to capture all three symptoms together: a) extraction of features representing the pattern of the car movement. This process is similar to the previous work done in (13). Also, two other futures are extracted from acceleration signals representing the rolling and pitching of the car while playing with the wheels. To extract these features, Short Term Fourier Transform(23) is used. b) extraction of features representing focusing on details, interest in items' rotation, and interest in rotating items, i.e., wheels' rotation and rotating wheels. The summation of two shaft encoder signals is used to extract these features.

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

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

Table 2. details of features

|  |  |  |
| --- | --- | --- |
|  | features | description |
| 1 | not playing ratio | the ratio of not playing to total playtime |
| 2 | playing only with wheels ratio | the ratio of playing only with wheels to total playtime |
| 3 | playing on the ground ratio | the ratio of playing on the ground to total playtime |
| 4 | playing in the air ratio | the ratio of playing in the air to total playtime |
| 5 | interactive playing only with wheels ratio | the ratio of playing only with wheels to interactive playtime |
| 6 | interactive playing on the ground ratio | the ratio of playing on the ground to interactive playtime |
| 7 | interactive playing in the air ratio | the ratio of playing in the air to interactive playtime |
| 8 | total wheels turn rate | total number of wheel 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. Classification Structure**

To train classifiers, the collection of 45 subjects' data was divided into two groups: the training set with 80% of samples and the test set with 20% of remaining samples. The training set is used to train the classifier, and the test set is used to measure the classifier's performance. The K-fold cross-validation method(24) 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. In this research, a Support Vector Machine (SVM)(24) is a suitable machine learning method that can effectively classify this kind of data. By testing three kinds of SVM, SVM with a linear kernel is selected for its considerably better performance.

**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. In the first step to reduce the number of features, the Correlation between features in each modality was examined. Then, the best feature was selected from each highly correlated feature set using the backward elimination method(24). 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 were selected by the backward elimination method in another round of feature selection.

Then in the final step, all 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**

Classification result based on previous studies is used as a baseline to examine the performance of adding encoder features in the model. The same SVM method is performed on the selected acceleration features presented in(13) to classify the new data. The best accuracy based on these acceleration features is 71.11%, as shown in Table 3. Adding encoder features increases the accuracy to 78.61%. The accuracy is increased from 71.11% to 75.83% by adding the new acceleration feature.

Moreover, by adding both encoders' features and the new acceleration feature, the accuracy reaches 85.56% (Table 3). Based on this study's optimized feature selection method, the most effective shaft encoders' features are playing only with wheels ratio, not playing ratio, and total wheels turn rate. The most effective acceleration features are 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 3. The best accuracy, sensitivity, specificity, and precision gained by adding new features to the baseline classification.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classifier** | **Accuracy** | **Sensitivity**  **(recal)** | **Specificity** | **precision** |
| 1-Baseline features | 71.11 | 67.14 | 73.00 | 80.00 |
| 2-Baseline and encoder features | 78.61 | 75.00 | 68.00 | 87.50 |
| 3-Baseline and new acceleration feature | 75.83 | 65.48 | 77.00 | 64.00 |
| 4-Baseline, encoder features and new acceleration feature | **85.56** | **81.67** | **81.00** | **87.67** |

|  |  |
| --- | --- |
|  |  |
| (**a**) | (**b**) |

**Figure 2**. (a) Confusion matrix of the classifier number 4. In the diagram, number 1 represents the outistic cases, number 0 represents normal cases.(b) Histogram of the results obtained by the classifier number 4

**8. Discussion**

As shown in Table 3, the performance of the new proposed multi-modal approach is better than the previously suggested single modal approach. Added encoder features and new acceleration feature have improved not only the accuracy, but also other main metrics such as recal and precision. It is obvious that the classifier is reliable in both situations whether predicting normal or autistic cases (0 or 1). The confusion matrix of the classifier represents the same result. (Fig2) True positive (autistic) and true negative (normal) values are considerably higher than the false negative and false positive values. To investigate the significance of data, in the first step the histogram of the output of SVM algorithm has been drawn. The distribution of data near 0 and 1 is higher, which represents the reliability of data. In the second step, the pair t-test has been performed on the output.

The novelty of this research is its multi-modality structure resulting in the examination of ASD through a wider variety of symptoms. In order to reach this purpose, encoders are added to the system, which increases the number of features. Since having a smaller learning space enhances the model functionality, feature reduction algorithms are implemented on each modality separately. After applying two-stage feature reduction, including high correlated features elimination and most important features selection, selected features are combined. Ultimately, the data is classified based on the early fusion method, leading to the best result.

**9. Conclusion**

In this paper, we introduced the intelligent toy car 2.0 by which multi-modal ASD screening is planned. The new design incorporates shaft encoders to capture the tendency of children with ASD into details and rotating items. Furthermore, we improved the feature selection strategy to increase the system accuracy by multi-modal analyzing ASD symptoms. The advantage of this system over other screening methods is its low cost and limited need for expertise. It can be used at homes, daycares, or clinics for initial 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 a further evaluation through experts.

Finally, the intelligent toy car can be used besides other screening devices to increase the accuracy by considering other modalities of children with ASD. We expect that having more modalities observed can help to better screening.

**References**

1. American Psychiatric A. Diagnostic and Statistical Manual of Mental Disorders. Fifth Edition ed: American Psychiatric Association; 2013 2013/05/22/.

2. Prevalence of autism spectrum disorder among children aged 8 years - autism and developmental disabilities monitoring network, 11 sites, United States, 2010. MMWR Surveill Summ. 2014;63(2):1-21.

3. Thabtah F, Peebles D. Early Autism Screening: A Comprehensive Review. Int J Environ Res Public Health. 2019;16(18).

4. Brooks BA, Haynes K, Smith J, McFadden T, Robins DL. Implementation of Web-Based Autism Screening in an Urban Clinic. Clinical Pediatrics. 2015;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. 2015;20(2):153-62.

7. Hewitson L. Scientific challenges in developing biological markers for autism. OA Autism. 2013;1(1):7.

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 data. Proceedings of the 10th ACM International Conference on Bioinformatics, Computational Biology and Health Informatics; 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):6828.

10. Mohammadian Rad N, 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. J Med Internet Res. 2020;22(4):e13810.

12. Moghadas M, Moradi H, editors. Analyzing Human-Robot Interaction Using Machine Vision for Autism screening. 2018 6th RSI International Conference on Robotics and Mechatronics (IcRoM); 2018 23-25 Oct. 2018.

13. Moradi H, Amiri SE, Ghanavi R, Aarabi BN, Pouretemad H-R, editors. Autism screening using an intelligent toy car. International Conference on Ubiquitous Computing and Ambient Intelligence; 2017: Springer.

14. 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.

15. 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.

16. Baron-Cohen S. Autism and Asperger syndrome. New York, NY, US: Oxford University Press; 2008. xii, 157-xii, p.

17. Oberleitner R, Abowd G, Suri JS. Behavior Imaging®’s Assessment Technology: A Mobile Infrastructure to Transform Autism Diagnosis and Treatment. In: Casanova MF, El-Baz AS, Suri JS, editors. Imaging the Brain in Autism. New York, NY: Springer New York; 2013. p. 371-80.

18. Taban R, Parsa A, Moradi H, editors. Tip-Toe Walking Detection Using CPG Parameters from Skeleton Data Gathered by Kinect2017; Cham: Springer International Publishing.

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

20. 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.

21. Lanini M, Bondioli M, Narzisi A, Pelagatti S, Chessa S, editors. Sensorized Toys to Identify the Early ‘Red Flags’ of Autistic Spectrum Disorders in Preschoolers2019; Cham: Springer International Publishing.

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

23. 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.

24. 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.