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

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

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| **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/). |

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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. 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 behaviors 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 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 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.

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 credible, they relied on licensed clinicians and observers, making them a tedious and exhausting task[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 [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. On the other hand, wearable devices like smart glasses or sensors, which are a more convenient option, are also 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. Addressing the drawbacks of the mentioned systems, multitude of studies focused on intelligent observation of behaviors to overcome the challenges of biometric and wearable methods. For instance, Moghaddas et al. developed a vision-based method for ASD screening 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 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 incorporating two modalities to better screen ASD. These modalities can be incorporated into other screening methods to increase the accuracy of such screening methods.

**2. Related work**

There have been several studies focused on using technology for ASD screening. Sanchez-Garcia et al. performed a study on the diagnostic accuracy of screening tools for autism spectrum disorder (ASD) in toddlers [14]. The authors reviewed several studies and used the Bayesian model to estimate the overall accuracy of ASD screening tools was moderate, their pooled sensitivity was 0.72, and the specificity was 0.98, which showed consistent statistically significant results to screen autism at 14–36 months. They concluded that although the accuracy of ASD screening tools is not perfect, they can be used to identify toddlers at risk for ASD and should be considered as part of a comprehensive assessment process.

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. Addressing 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 used in the past decade. For instance, Kohli Kar et al. conducted a scoping review to examine the role of intelligent technologies in the early detection of ASD. The findings suggest that intelligent technologies can be used to detect ASD at an early stage with high accuracy[15]. Additionally, studies like Belen, R. A. J. et al. examine behavioral data applications in ASD screening. In their systematic review, they reviewed a total of 33 studies that used computer vision techniques to screen children with ASD Results showed that computer vision techniques had been used to measure facial expressions, body language, and social interactions in ASD . The authors concluded that computer vision has the potential to effectively analyze behavioral markers[16]. Acknowledging the reliability of using AI-based methods in ASD screening, Song, D. Y. et al. literature review examines the use of AI in ASD screening, and results indicate AI can improve accuracy and efficiency in the screening and diagnosis of ASD. They studied the application of AI technologies with novel observational data in ASD screening and reported an average accuracy of 88%, average sensitivity of 86%, and an average specificity of 88%[17].

Another trend in using technology-based approaches is based on EEG data. For example, William J. Bosl et al. focused on early screening of ASD by a data-driven method based on an EEG's data. They collected EEG measurements of 99 infants with an older siblings that received an ASD diagnosis and 89 low-risk controls. They screened ASD in children as early as three months of age with 95%. They suggested that 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%[18]. Integrating biomarkers with other modalities has also proved effective; Jiannan Kang et al. identified ASD in children from 3 to 6 years of age 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%[19].

Stereotypical Motor Movements (SMM) is also 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]. In addition, Antonio Coronato et al, developed a method in order to detect stereotyped motion disorders by implementing artificial intelligent approaches and collecting accelerometer data by a wearable sensor unit[20]

Detecting and analyzing gaze is another modality in ASD screening; For instance, Anish Nag et al. compared the gaze data of 16 children with ASD, and 17 typically developed children that were collected using google glass and gaze tracker. Although smart glasses perform promisingly, their method did not outperform other automatic classifiers significantly[11]. On the other hand, although wearable devices performed promisingly, however, 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 and consequently its accuracy.

One of the major symptoms of ASD is repetitive and stereotypical behaviors that are considered an essential indication in ASD's diagnosing[21]. In recent years, many technology-based screening systems have been developed with a focus on adopting vision-based approaches for behavioral analysis. These methods use machine vision to detect and recognize movements and motor function patterns in order to perform ASD screening. For instance, R. Oberleitner et al.[22] developed a recognition system for detecting abnormal behaviors that can be used in screening, assessment, or rehabilitation. Additionally, R. Taban et al.[23] proposed rrecording walking patterns by Kinect and then analyzing them using central pattern generator parameters as their classifier features. They accurately distinguished between tip-toe walking and regular walking pattern. Another research is Guillermo Sapiro et al.[24] that developed a low-cost mobile app which applied machine learning and machine vision methods to detect movement patterns and assess eye tracking patterns.

Vision-based methods also used for studying subjects attention. For example, K. Campbell et al. developed an app that record and analyze the reaction of toddlers to video stimuli that designed to engage children's attention. Their algorithm classifies by automatically detecting and tracking multiple facial landmarks and analyzing their patterns[25].

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. During play, repetitive patterns could be recognized. Studying playing patterns does not have challenges like the discomfort feelings of brain imaging or EEG methods, and unlike wearable devices, they do not affect child attention and are considerably more cost-effective than robots.

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[26]. 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 [27], used accelerometer data for ASD screening as part of their research. Although they focused on child-robot interaction, they analyzed accelerometer data as a modality to study the child responses regarding a stimuli. Beibin Li et al [28], 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%.

It should be mentioned that other technology-based ASD screening, such as the robot-based ASD studies, confirmed the value of robots in evaluating social interactions, their cost and dependency to skilled operators are major drawbacks of these methods.

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 to measure another wheel rotation data for screening ASD. Our contribution in this study is both introducing new features (modalities) and further optimizing the feature selection method that enables us to study the ASD symptoms with a multi modal approach. Furthermore, it should be noted that our approach can be a complement to other screening methods to increase the accuracy of the results. **3. System design**

The intelligent toy car is designed to capture the signs of two major symptoms, obsessive attention to detail and repetitive behavior. In order to collect playing pattern data using accelerometer sensor an inexpensive IoT board called ESP8266 NodeMCU is used. ESP8266 board reads sensor data and sends them wirelessly through Wi-Fi via UDP protocol to ensure maximum data collection rate. Also, ADXL345, a cheap MEMS accelerometer, and two magnetic shaft encoders are installed inside the toy car. Each magnetic shaft encoders were placed in the rear position of each car axles. 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.

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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 the Dooste-Autism center (Friend of 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, and children with other disorders (like: CP and fragile X syndrome). Details of the participants are 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, 29], 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 along x, y, z axes, front and rear wheel rotation counts which saved in a database with a unique ID to preserve user anonymity and privacy. No personal data was recorded during the procedure.

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 that five of them 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 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 the other two groups.

Table 1. 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) extraction of features representing the pattern of the car movement which is similar to the previous work done in[13]. To analyze the rotation of the wheels, two other futures are extracted using Short Term Fourier Transform[30] from acceleration data that represent the rolling and pitching of the car while playing with the wheels. b) extraction of features representing interest in the wheels’ rotation. 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 state, 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 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. The playing on the ground state, in which movement patterns can be extracted, describes those portions of playing where the intelligent toy car is moved in which both acceleration and shaft encoder data changes. Finally, the playing in the air state is when the intelligent toy 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 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 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[31] 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 our previous study the SVM classifier architecture adopted for differentiation by acceleration features, we studied other methods like random forest and MLP with data augmentation strategies too (Table 3). However, at the end, the SVM was the most promising classifier for collected data and in this research, it can effectively classify based on previously introduced features and newly proposed ones. 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[31].

**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 feature was selected from each highly correlated feature set using the backward elimination method[31]. 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.

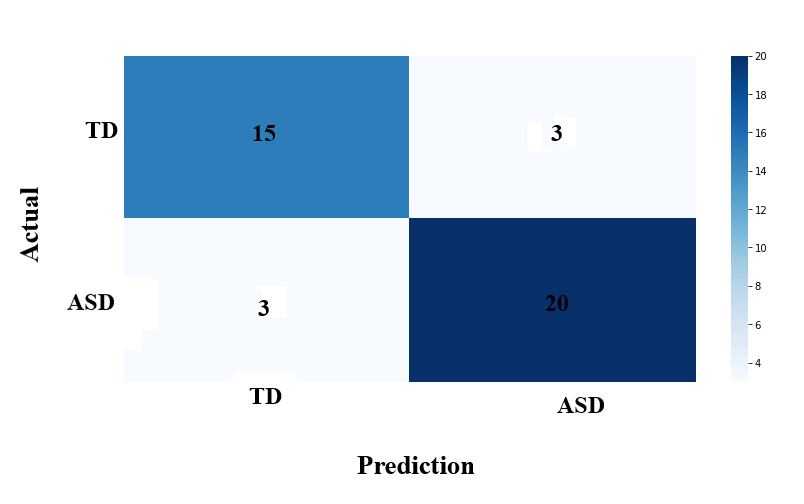
Then, in the final step, all the selected features from the two modalities were combined in an early fusion to select and train the best classifier. The best result was obtained by integrating five acceleration features and two shaft encoder features.

**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 applied on the selected acceleration features presented in[13] to classify the new data. The best accuracy based on the original acceleration features (baseline features) is 71.11%, as shown in Table 3. 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. role and pitch of the car. Finally, by adding both encoders' features and the new acceleration feature, the accuracy reached 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**  **(recall)** | **Specificity** | **precision** |
| **1** | **MLP** with all features | 71.11 | 78.01 | 76.33 | 73.57 |
| **2** | **Radom Forest** with 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 features and new acceleration feature | 75.83 | 65.48 | 77.00 | 64.00 |
| 6 | SVM with Baseline features, encoder features and new acceleration feature | **85.56** | **81.67** | **81.00** | **87.67** |



**Figure 2**. The confusion matrix of the 6th classifier (from table 3)

**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. The added encoder features and 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 autistic cases. The confusion matrix of the classifier represents the same result (Fig2). True positive (A) 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 resulting in the examination of ASD through a wider variety of symptoms. In order to reach this purpose, shaft encoders are added to the system, that 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 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 another aspect.

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. Furthermore, we have to investigate the effects of size, shape, and color of the car on the results and the usage of ASD children.

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 for better screening.

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