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**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. The observational process of ASD diagnosis and the lack of experts make the technology-based ASD screening methods more demanding. 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. 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 methods to find ASD symptoms[9].

Amid all evidence which confirm the effectiveness of 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 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. Particularly, with the recent studies that provides the statistical significance of technology-based ASD screening tools like García Sanchez et al which conduct a meta-analysis on diagnosing accuracy, these methods were proven to be reliable. According to García Sanchez et al study, Their pooled sensitivity was 0.72, and the specificity was 0.98 which showed consistent statistically significant results and therefore are adequate to detect autism at 14–36 months[14]. Several of these methods trying 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 (positive predicted value) 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%[15]. 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%[16].

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 intelligence approaches and collecting accelerometer data by a wearable sensor unit[17]

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]. However, wearable devices performed promisingly, 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 the accuracy of regarding procedure.

One of the major symptoms of ASD is repetitive and stereotypical behaviors that are considered an essential indication in ASD's diagnosing[18]. In recent years, many technology-based screening systems have been developed with a focus of 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.[19] developed a recognition system for detecting abnormal behaviors that can be used in screening, assessment, or rehabilitation. Additionally, Rasool Taban et al.[20] 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. Another research is Guillermo Sapiro et al.[21] 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 the subject attention. For example, 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[22].

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 for regarding approach. Embedding different sensors data to capture playing patterns, these toys classify different playing patterns. For instance, Lanini M. and et al. combined accelerometer, gyroscope, and magnetometers data[23]. 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]. Also, Laura Boccanfuso et al, 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 an exact stimuli[24].

Accelerometer and gyroscope data have been used for human behavior classification over past years. Consequently, processing these kinds of data for a specific use case like ASD screening or human-robot interaction were studied several times. For instance, Beibin Li et al, use accelerometer and gyroscope sensor data in commercially available robot Sphero in order to classify for category of 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% for children with ASD[25]. Although robot-based ASD studies confirmed the value of robots in evaluating social interactions, their cost and dependency to skilled operators consider to be major drawbacks.

In addition to the ASD screening studies listed above, several studies focused on measuring the severity of ASD in children. For instance, Sara Ali et al. proposed a method to assess ASD levels using the hidden Markov model. They experimented on 12 children, 8 in the test group and 4 in the control group; after analyzing joint attention and imitation factors, their model accurately predicted the ASD level with 76% accuracy[26]

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, also by 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, obsessive attention to detail and repetitive behave, in children with ASD. In order to collect playing pattern data using accelerometer sensor, a Wii remote controller which had an accelerometer, was embedded in the first revision of the intelligent toy car. Due to closed-source form factor of Wii controller, in our new design, the intelligent toy car 2.0 (Fig. 1(a)), the Wii controller has replaced with an inexpensive IoT board called ESP8266 NodeMCU. ESP8266 board reads sensor data and sends them wirelessly through Wi-Fi via UDP protocol to ensure maximum data collection rate. Also, a cheap MEMS accelerometer ADXL345 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.

|  |  |
| --- | --- |
|  | 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 Dooste-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 different groups: children with ASD, typically developed children, and children with other disorders (like: CP and fragile X syndrome). Details of the participants were 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, 27], 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 along x, y, z axis, front and rear wheel rotation counts which saved in a database with a unique ID to preserve user anonymity and privacy, also, 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. ASD group has 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 other 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 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 which is similar to the previous work done in[13]. Also, two other futures are extracted using Short Term Fourier Transform[28] from acceleration signals that representing the rolling and pitching of the car while playing with the wheels. 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 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 items and items' rotation. The playing on the ground section, which movement patterns can be extracted in this state, describes those portions of playing where the intelligent toy car is moved that creating changes in both acceleration and shaft encoder signals. Finally, the playing in the air section is when the intelligent toy car is moved in the air, and the acceleration values change while its 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 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. Classifier’s 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 K-fold cross-validation method[29] 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. However, in 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[29].

**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[29]. 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 which supports our assumptions.

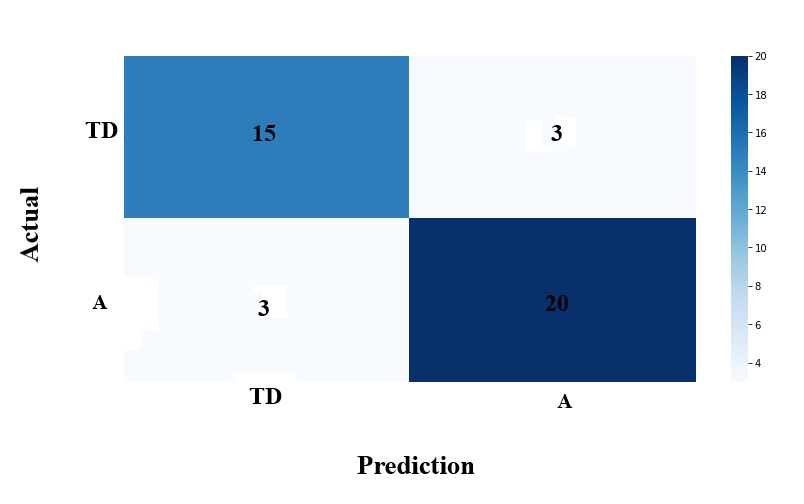
**7. Results**

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 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**  **(recall)** | **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** |



**Figure 2**. The confusion matrix of classifier number 4 (A: children with autism, TD: typically developed children)

**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 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.

The novelty of this research is its multi-modality structure that 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 ASD symptoms analyzing. The advantage of this system over other screening methods is its low cost and limited need for experts which make It a prominent option for initial ASD screening at homes, daycares, or clinics.

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.

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