# Autism Screening Using an Intelligent Toy Car

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**Abstract.** The number of cases reported with Autism Spectrum disorder (ASD), as a developmental disorder, has increased sharply in recent decades. Early diagnosis of ASD in children is essential for proper treatment and intervention. The difficulties in early detection of autism encouraged the authors to design a novel intelligent toy car for autism screening. The toy car is equipped with an accelerometer, which records a subject's usage behavior in terms of accelerations in three dimensions. A set of features, consisting of forty-four movement characteristics, has been extracted which can be used to discriminate between children with autism and normal children. The intelligent toy car has been tested on 25 children with autism and 25 normal children as the test and control groups respectively. Support Vector Machine (SVM) is used to distinguish between the children with autism and other children. The system has 85% correct classification rate, 93% sensitivity and 76% specificity. The results are the same for boys and girls indicating the possible widespread use of this system among all children.

**Keywords:** Autism spectrum disorder (ASD) · Motor movement · Intelligent toy · Machine learning

## 1 Introduction

Autism Spectrum Disorders [1] (ASDs) are developmental disorders, with signs in early ages of an individual's life. They have a great number of symptoms, which may differ in each individual. One of the most important issues and symptoms in people with autism is their difficulty and lack of social activities and interaction with others. As an example, inability to make eye contact is a well-known symptom of ASDs [2]. In addition, a great percentage of individuals with ASD have restricted areas of interests and show stereotypical and repetitive behavior [2–4].

Despite the severe impacts that this disorder can have on the life of an individual, treatment at early stages of his/her life can be very effective. In other word, it can reduce, the impacts of the disorder severely [4–8]. Consequently, it is essential to detect ASDs at early ages of the life of children with autism for efficient treatment. Nevertheless, in many countries and especially in developing ones, the small number of experts available


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to diagnose autism prevents early diagnosis and treatment. Furthermore, the lack of general knowledge about autism and possible negligence of parents makes it harder to detect autism at its early stages in children with autism. On the other hand, recent evidences show a significant increase in autism especially in countries such as the US in which the ratio of autism in 70s and 80s was 1 in 10000 while it was 1 in 68 in 2010. Therefore, there is a great need to design and develop automatic methods for autism screening, which do not require an expert's full diagnosis. Such systems can play the role of early warning systems to warn parents and caregivers for further screening and evaluation.

That is why there has been much research focused on developing methods that can assist in the initial screening of autism. For instance, there have been many studies applying different biomarkers to detect children with autism. A few of them apply genetic science for autism detection [9–12]. Shen et al. [9] reported evidence suggesting that genetic factors have a great contribution in the development of ASDs. They propose a clinical genetic test, which includes Karyotype, fragile X testing, and CMA all together. In 2009, Wang et al. [10] published their findings on the relation of susceptibility to ASDs and strong association signals detected on specific genes. Vorstman et al. [11] explain the abnormalities in genetic structures in autistic and schizophrenic patients. Veenstra-VanderWeele et al. [12] work, is a comprehensive article on the effects of genetic abnormalities in ASDs. In another study [13], Momeni et al. showed blood-based biomarkers can be used to detect ASDs. They diagnose ASDs by profiling the blood plasma of the subjects. They reported that the peptide pattern of children with autism is significantly different from non-autistic ones. They also investigated the relation between the symptoms of ASDs and different peptide patterns. In their study, an experiment that can profile the peptide using only 3-ml of blood is proposed. Results of the analysis of the blood samples of 28 children with autism and 30 non-autistic ones between 3–12 years old demonstrated 86% sensitivity and 77% specificity.

In a few studies, Electroencephalography (EEG) was utilized as a distinctive biomarker for autism diagnosis [14–16]. Sheikhani et al. [14] used Quantitative EEG (QEEG) signals of 17 children with autism and 11 non-autistic ones between 6 to 11 years old. By using statistical approaches, their best distinction level is 96.4%. Kamel et al. [15] used average Fast Fourier Transform (FFT) and Related Fisher Linear Discriminant (RFLD) of EEG signals to detect autism. Their data sample consists of 15 children from 10 to 11 years old. The average correct rate is 92%. William Bosl et al. [16] suggest that as a neuro-developmental disorder, ASDs must show brain abnormalities before the behavior symptoms appear. They designed a method, which analyzes the EEG signals of individuals and finds their abnormalities as a biomarker to diagnose the high risk of ASD. The participants' ages were between 6 to 24 months, 46 infants with high risk of ASDs and 33 infants in control group. Their results were achieved for children between 9–12 months old with 80% accuracy of detection. Other notable studies apply computer science and machine learning for automatic ASD detection [17–20]. For instance, there are researchers used image and vision processing technologies to detects ASD. Perego et al. [17] applied action detection methods to autism diagnosis. They analyzed upper limb movements like reach-and-throw, considering the fact that these movements are milestones in child development. They use infrared cameras and markers on designated parts of a subject's body to record movements. Their selected features include time spent for each part to perform the whole action and amount of adjustment movements. Finally Support Vector Machine (SVM) [21] was used to classify subjects based on their movements. Subjects include 10 normal children with average age of 41.6 ($\pm$9.23) months and 10 children with autism with average age of 41.44 ($\pm$16.07) months. Min and Tewfik [18] developed a method to automatically recognize autism by detecting repetitive and self-injurious behaviors. Using wearable sensors to record the body movement, they analyzed the recorded data of 4 children. They used Linear Prediction Coding (LPC) to classify repetitive movements. The recall rate of detecting self-injurious behaviors, flapping and rocking are 95.5%, 93.5%, and 95.5% respectively. Xu et al. [19] tried to screen autism in natural conditions by analyzing differences of vocal patterns between autistic, language delayed and normal developing children by applying a novel system, named LENA (Language ENvironment Analysis). Their subjects were between 8 months to 48 months old, 106 children in typically developed group, 49 children in language-delayed group and 77 children in autistic group. Recorded data was collected from 2006 to 2009 and the achieved accuracy is 85% to 90%. Kannappan et al. [20] used a Fuzzy Cognitive Map (FCM) to detects and predict the ASDs. FCM combines the advantages of fuzzy logic and neural networks. Their main goal was to propose a method of predicting the severity of autism with the help of non-linear Hebbian unsupervised learning algorithm and FCM.

All of the aforementioned diagnosis methods require extensive knowledge of autism symptoms, which necessitate parents to consult experts. In the absence of such measures, the detection of autism is delayed for at least few years. Furthermore, many of these approaches need high cost and complicated devices and tools which are not widely available. Finally, a few of these studies, such as LENA, have not been officially supported or widely referenced.

In this paper, we present an automatic method to detect children with autism with high probability of having ASDs in a natural environment without the presence of any expert. If the results of detection show a great chance of being autistic, parents are notified to consult a specialist for more thorough checking. Since children with autism, especially those under 6 years old, tend to spend a great amount of time playing with toys, it is more likely for an autistic child to show distinctive patterns and symptoms of ASD playing with a toy. From all ASD symptoms, the repetitive and stereotypical movements in long durations are most probable to show themselves in using a toy. It worth mentioning that the number of autistic males is 5 to 6 times more than autistic females [3, 22]. That is why an off-the-shelf toy car is used to have better chance of being used by children with autism. We developed an intelligent toy car through which a child is monitored and his/her pattern of toy movement is analyzed.

## 2 Subjects and Methods

The children with autism in CTAD were diagnosed using DSM-IV criteria [1] and confirmed by two independent experts. Furthermore, GARS test and ADI-R questionnaire were used in the diagnosis procedure, which is accepted in Europe and USA/ Canada [23, 24].

The control group was chosen from a kindergarten, located near CTAD in Tehran, Iran. All children in the control group had developed normally and did not have any developmental or mental disorders. They were tested between May 2012 and December 2012.

Data pertaining to 6 children with autism and 7 normal children are omitted because of the short test time or interruptions at the middle of the test and unreliable recorded data. As shown in Table 1, the ratio of the number of males to the number of females and ages of participants in two groups do not have any significant differences.

**Table 1.** Details of participants

| Gender | | ASD | Controls |
|---|---|---|---|
| Male | Number | 21 | 16 |
| | Mean (s.d.) | 4.763 (1.037) | 5.250 (0.774) |
| | Median (range) | 4.75 (3.5–7) | 5.25 (4–6) |
| Female | Number | 4 | 9 |
| | Mean (s.d.) | 4.800 (1.254) | 4.56 (0.347) |
| | Median (range) | 4.5 (4–7) | 4.5 (4–5) |
| Total | Number | 25 | 25 |
| | Mean (s.d.) | 4.77 (1.03) | 5.02 (0.73) |

## 3 The Intelligent Toy Car Design

In the first version of the car, a Wii remote [25] was embedded in the toy car to record the movements. The Wii remote, or Wiimote in short, has a 3-axis Micro Electro Mechanical System (MEMS) ADXL330 accelerometer, which measures the instantaneous acceleration with a minimum full-scale range of ±3.6 g [26]. As previous studies show that children with autism are more interested in playing with toys that have blinking lights, moving parts, or sound [27], a set of flashing LEDs are embedded on the roof of the toy car to make it more attractive for children with autism (Fig. 1(b)).

In the first version of the car, the acceleration data collected by the Wiimote is sent over to a computer using Bluetooth connection. The data is collected and can be viewed in a Graphical User Interface (GUI) designed for this purpose (Fig. 1(c)) or stored for further processing in a file (Fig. 1(d)). In the new version of the car the Wiimote, which was bulky and limited, was replaced by an ESP8266 board equipped with ADXL345 accelerometer. The use of ESP8266, which is an Internet Of Things (IOT) module, gives the ability of using various communications methods. The circuit is capable of high speed data sampling with a Node MCU and a WiFi-module (Fig. 2(b)). Data collected by this circuit was sent over a WiFi connection to an Android phone (Fig. 2(a)). The

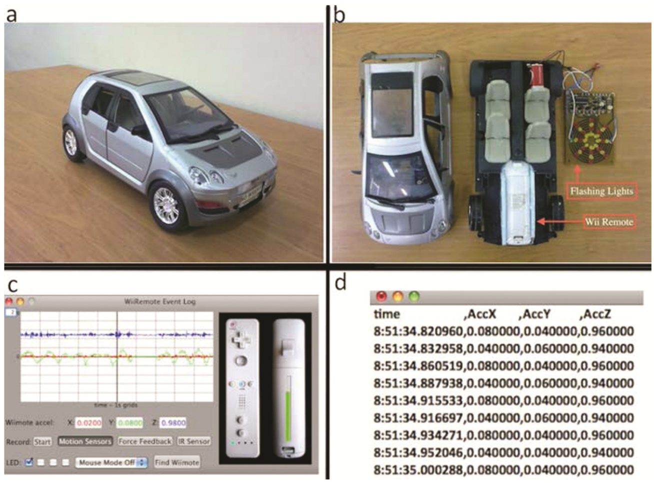


**Fig. 1.** (a) and (b) show the toy car with the embedded Wii Remote and flashing light. (c) A view of User Interface of the Acceleration recorder application. (d) A sample of the saved data from a participant's actions.

data which is collected and can be viewed in a GUI on an Android phone trough an application which has been developed. The data would be sent to a server for further processing and analysis. The collected data would be used to improve classification rate.

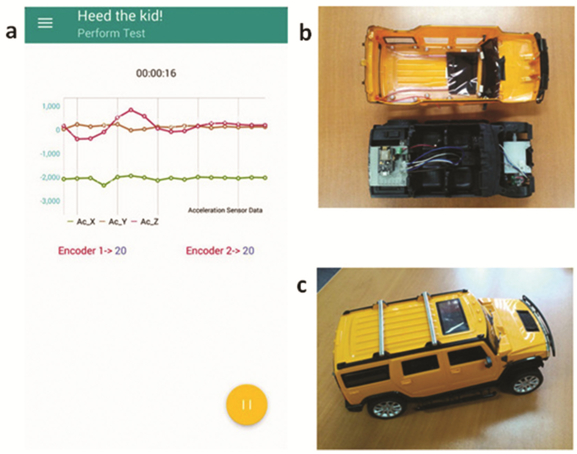


**Fig. 2.** (a) The new version of toy car's Android application. (b) The toy car with the embedded circuit, consists of ESP 8266 IOT module. (c) The second version of intelligent toy car.

# 4 Procedure

The toy car is given to each participant to play with. The participants were tested in approximately $3 \times 3$ meters rooms, in which only the system operator and the subject were present. The test and data recordings were continued as long as the subjects show interest in playing. In practice, on average the subjects played five minutes with the toy car.

The recorded data in the computer, from each subject, includes instantaneous accelerations in the three dimensions (Fig. 1(c)) and the time, which are stored in a file for further processing (Fig. 1(d)). A typical data file includes 5000 samples of a subject's interaction with the toy car composed of the time and the accelerations in the three dimensions.

## 4.1 Feature Extraction

The raw data, i.e. the accelerations in the three dimensions and the time, contain important features of the movement that can be helpful in detecting repetitive and stereotypical motor movements. A set of these features can form a feature vector representing the movement features and can be used to distinguish children with autism from normal ones. This feature vector can be used instead of the large and varying size raw data. Determining a suitable feature set for a special application for classification, such as classifying the children with autism, requires an insight into the application's field [21]. Here, the extracted feature vector must contain important properties of movement, which would be helpful in detecting repetitive and stereotypical movements. Based on the knowledge about autism, the features considered for classifying children with autism are categorized in the following six main groups: (1) the play time to measure the perseverance of a participant in doing a repetitive movements, (2) the correlation of accelerations between each two axes, (3) the mean and variance of each acceleration direction to measure the variability of movements, (4) the dominant frequencies of each acceleration direction and their power to measure the main characteristics of movements [28], (5) the total acceleration signals' energy [29] in each acceleration direction, and (6) the number of jolts, in the forward direction, that the toy experiences during a test. The fifth feature group is selected based on our observations that most children with autism like to play in a spatially limited space and with less energetic activities compared to children in the control group. The last selected feature is proposed because our numerous observations showed that children from the control group have a tendency to jolt the toy car, children with autism did not show such interest. The reason of this difference may be attributed to the cognitive deficit in children with autism [30] resulting in their inability to predict the consequences of their interactions with objects. The number of jolts is extracted using Short Term Fourier Transform (STFT) [31] approach.

## 4.2 Constructing a Classifier

Recognizing distinctive movement patterns between autistic and normal groups is possible after extracting the feature vector from each sample. The samples are divided into train and test groups. The train group, consisting of 80% of all the samples, is used to train the classifier and determine the proper threshold for an accurate classifier. In the next step the data from the test group, i.e. the remaining 20% of the samples, is used to measure the accuracy of the designed classifier.

A Support Vector Machine (SVM) classifier, with soft margin and polynomial kernel, is used for the classification purpose [32]. The classic version of SVM is a linear classifier, which divides the subjects into two separate groups. The goal is to determine a hyperplane that can classify all the training samples. However, as can be seen in Fig. 3(d), such a hyperplane may not be unique [32]. The main goal in SVM classifier is to find the best hyperplane, which has the maximum distance from each class of subjects reducing the error probability [21, 32]. In general, the two classes are not linearly separable or samples belong to more than two groups. Consequently, the multi class non-linear version of SVM classifier is used.

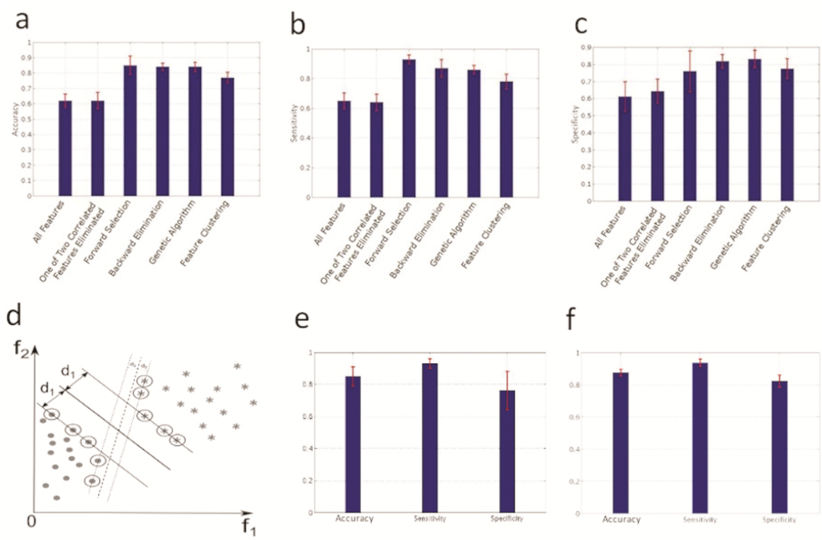


**Fig. 3.** (a), (b) and (c) The best accuracy, sensitivity, and specificity achieved by classifier with different feature selection methods respectively. (d) An example of two linearly separable groups of samples by two different hyperplanes. (e) The best accuracy, sensitivity and specificity achieved by all samples, i.e. males and females together. (f) The best result achieved by male.

### 4.3 Validation the Classifier

As a typical approach in improving the classification, K-fold cross validation is used to improve the reliability of the results and generalize them to an independent data [33]. K-fold cross validation method divides all samples into K separate folds (In this study K = 5). Each time the classifier algorithm is executed, it uses one-fold of samples in the testing phase and the remaining folds are used in the training phase. This process is performed K times using different folds. By averaging all achieved results, the Correct

Classification Rate (CCR), True Positive rate (TP rate or sensitivity) and True Negative rate (TN rate or specificity) are calculated.

### 4.4 Feature Selection

Although the features were introduced based on possible relation to the movement characteristics of children with autism, however, there are many overlapping features or there are features that did not show their importance in our study. There could be two reasons for the latter case: (a) the ratio of the number of features, i.e. forty-four features, to the number of participants is large which makes it too large for the algorithm to find an optimal classifier for these features, (b) these features are not capable of separating children with autism from normal ones. Consequently, it is necessary to find the best subset of features that can provide maximum separation between the autistic and normal groups. In this study, several methods are evaluated to reduce the number of features in the feature vector, i.e.: (1) eliminating one of the two correlated features of the feature vector, (2) using forward selection to determine the most important features, (3) using backward elimination on the feature vector to remove the least important features, (4) using Genetic Algorithm to find an optimum set of features (5) clustering all features and selecting a representative feature from each cluster. The results of feature selection, using different methods, are demonstrated in Table 2 and Fig. 3(a), (b) and (c).

**Table 2.** The result of the classifiers with different feature conditioning methods.

| Method | Accuracy (s.d.) | Sensitivity (s.d.) | Specificity (s.d.) | # of features |
|---|---|---|---|---|
| Complete feature set | 0.624 (0.043) | 0.651 (0.054) | 0.612 (0.087) | 44 |
| Correlated feature elimination | 0.616 (0.053) | 0.637 (0.058) | 0.643 (0.071) | 31 |
| Forward selection | 0.85 (0.06) | 0.93 (0.03) | 0.76 (0.12) | 5 |
| Backward elimination | 0.84 (0.024) | 0.87 (0.016) | 0.82 (0.04) | 8 |
| Genetic algorithm | 0.842 (0.030) | 0.864 (0.037) | 0.832 (0.051) | 18 |
| Feature clustering | 0.768 (0.035) | 0.779 (0.048) | 0.776 (0.058) | 10 |

It must be noted that since this intelligent toy is planned to be used as an early warning system, and the costs of not detecting children with autism is more than false detection of normal children, we have aimed to maximize the Sensitivity while the Correct Classification Rate (CCR) and Specificity are maintained at acceptable values. However, it has been suggested to maximize specificity to avoid alarming parents and making them nervous about their children. In such a case, the training can be aimed at maximizing specificity.

## 5 Results

In Table 2 the results of classification with different feature sets, which were selected by various feature selection methods, are shown. As can be seen in Table 2, the accuracy ($0.85 \pm 0.06$) and sensitivity ($0.93 \pm 0.03$) belong to the feature set provided by forward selection method, which includes features like the number of jolts in forward direction, dominant frequency in X direction as well as Y direction and total energy of acceleration signals in Y and Z directions. But the best specificity (0.83) is achieved by the feature set that belongs to the genetic algorithm. Note that the achieved feature set by forward selection method was used to examine only male samples. Figure 3(e) and (f) show that no significant difference between the results of the two classifications, i.e. classification of males and females, exists. Thus, the independence of the results from the gender of the samples can be deducted.

## 6 Discussion

The design and successful use of the intelligent toy car suggests that using technology can ease the screening of children with autism and reduce the cost. On the other hand, it is needed to do further tests and increase the accuracy of such systems to increase the confidence in using technology for autism screening. One way to increase the accuracy of such system is to consider further autism symptoms and try to recognize them using technology. Consequently, we have added two shaft encoders on each of the car's shaft. By adding the shaft encoders, we expected that the discrimination rate can be improved since further symptoms can be evaluated and used for separating children with autism from other children. We have a proof of concept that children with autism play with car's wheels much more than normal children. The output of these two encoders and the accelerometer would be fused together to improve the classification rate. To ease the use of the system, an Android application has been developed that connects to the car and records the data. The data is sent to a server for further processing. Collecting data over internet allows us to improve the classification rate by receiving further data. The application provides simple statistical usage data for parents and would report possible existence of autism to parents.

Finally, it should be mentioned that we like to call this system as an early warning system rather than a screening system. The final screening should be performed by an expert after a warning is given to parents or caregivers.

## 7 Conclusion

In this paper the design of a novel automated ASD early warning system based on off-the-shelf equipment is discussed. Due to the importance of determining the best features capable of classifying children with autism, different approaches were used to choose most efficient subset of features that result in maximum specificity, sensitivity and correct classification rate. The 44 features suggested initially gave 65.1% sensitivity, 61.2% specificity and 62.4% CCR. After using the presented feature selection methods

(Elimination of correlated features, forward selection, backward elimination, genetic algorithm, and feature clustering) sensitivity, specificity, and CCR were increased respectively to 93%, 76%, and 85%. The result of the classifier for only male samples shows the independency of the result from the gender of participants.

The current ongoing study is focused on fusing the data from shaft encoders, implemented on the car, with the accelerometer data to increase the accuracy of discrimination. Finally, the system would be implemented as part of a screening room in which multiple technologies would be used to provide better and more reliable screening.

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