Abstract

Every 1 out of 58 children has Autism spectrum disorder; even though there is no treatment for ASD, early rehabilitation improves patient condition significantly. Autism has multiple symptoms that every child could experience in different severity. The ASD diagnosis is costly and time-consuming, and it is not widely available in low and middle-income societies. Many technology-based screening methods have developed in past years to overcome these challenges.

One of these methods is the smart toy car that proved effective in autism screening toddlers based on their playing patterns. This research introduces the smart toy car 2.0 that has multiple improvements. The encoders sensors are added to the system, and by its ROS compatible pipeline could easily be integrated with other systems; also, by enhancing its classifier system, we manage to reach 85% accuracy in screening ASD.

Introduction

 ASD (autism spectrum disorder) is neurodevelopmental disorder that cause social communication and interaction problems.[1] since ASD is becoming more prevalent in the last years [2], early screening and intervension can be very effective by reducing the impacts of the disorder. Diagnosing autism is done by observing the severity of the symptoms this precidure and collecting the observation of the parents that should be done by experts it is a difficult and time-consuming process, besides due to lack of experts especially in low and middle-income sociaties many cases remain undiagnosed, to overcome these challenges it becomes essential to develop technology-based screening methods to make screening services widely available.

Many technogy based methods are based on CHAT family quesstionares, multiple mobile apps and web applications developed for this purpose, many of these methods impelement a form of machine learning algorithm to improve the screening accuracy. Though these methods prove effective, they heavily rely on the observation of the behavioral symptoms.

* brain imaging
* EEG methods

Although these methods prove effective, they require costly equipment; besides that putting a child in such an environment may cause many discomforts that could easily affect the test's accuracy, so behavioral studies have significant advantages.

* wearables
* robots

Wearable devices are an effective method for ASD screening, but 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 great for analyzing 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 important indication in ASD's diagnosing. [3] In recent years, many technology-based screening systems have developed, many methods focused on vision-based approaches, behavioral analysis methods that use machine vision to detect and recognize movemnet and motor function patterns. R. Oberleitner and et al. [4] developed a recognition system for detecting abnormal behaviors that can be used in screening, assessment, or rehabilitation. Rasool Taban and et al. [5] use Kinect to detect tip-toe walking patterns in children with autism. Guillermo Sapiro and et al. [6] 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 and et al. [7] 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.

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 in their plays. 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.

* toys

In the last successful studies, a toy car has been designed and implemented to investigate distinctive patterns and symptoms of ASD through recording acceleration signals in three directions.[8] in this research, the smart toy car 2.0 is introduced, …….

System design

In the previous version of the smart toy car, 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. In the second version, a custom board based on ESP8266 was developed, and a MEMS accelerometer was used to collect data, and an android app was developed for the system interface. Though they successfully classified autistic and non-autistic groups with 85% accuracy, some disadvantages make future developments necessary. A custom board makes the R&D process time-consuming; exclusively relying on acceleration data for autism screening increases the system uncertainty caused by the spectral nature of autism. Also, integrating the smart toy car with other systems has multiple technical difficulties due to its complex interface. The new system replaces the custom board with an inexpensive IoT board ESP8266 NodeMCU and a MEMS accelerometer to read sensor data and send them wirelessly through Wi-Fi. Many children with ASD have repetitive and cliche behaviors; these repetitive behaviors also could be observed while they play with toy cars. Obsessively rotating wheels is one of these cliches; for detecting this pattern, a magnetic shaft encoder is added to the toy car's forward and backward shaft to collect the wheel rotations data. The electronics parts are embedded inside the car deliberately to avoid any distraction.

The smart toy car firmware is based on the Arduino ecosystem to make future R&D more effortless. Also, for interfacing with the system, a ROS (Robotic Operating System) package is developed. It makes the integration of the toy car in other systems more straightforward. The modular architecture of the ROS makes it possible to use different programming languages and methods for application development.

A blue toy car

Description automatically generated with medium confidenceDiagram

Description automatically generated

Tests

The data collection process took place in the DOOSTEAUTISM autism center, and the smart toy car was tested on 50 children from 3 to 6 years old, from both autistic and normal groups, and four children with non-autism non-normal conditions tested for better evaluation of the system. The test cases play with the smart toy car for about 3 to 5 minutes in a 3x4 meters room; that child could go to the test room alone or with his/her parents to comfort any stress. The recorded data from each participant consists of time, acceleration in 3 dimensions, forward and backward wheel rotation values 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.

From the total number of test cases, 28 were autistic, and 18 were normal; four children that were neither autistic nor normal had CP and fragile X syndrome. From the 28 autistic cases, 5 of them did not seem interested in playing with the smart toy car and neglected it.

Data processing

Feature Vector Extraction

The research aims to classify the data collected from children into two groups: autistic and non-autistic. One of the most frequent symptoms of ASD in children is their focus on specific objects and showing repetitive behaviors. The second symptom is using less energy while working compared to normal children, which was apparent during their play with the car in the test. Some even refused to play, as they were not interested in it. These symptoms can be extracted from signals obtained from the smart toy car. The previous studies used movement patterns extracted from acceleration data for classification. [6] In this research, the same patterns are extracted, and the encoder's data are integrated to increase the model's accuracy. Based on a similar study on movement patterns, four necessary steps should be taken in this regard: 1) preprocessing of the data to reduce noise, 2) extraction of features representing the pattern of the car movement, 3) feature selection to reduce the complexity of the model, 4) classification of the data based on machine learning methods.[6][7] Since even small changes in the signals may considerably affect the result, a simple wavelet filter removes the acceleration sensor noises. In the next step, 55 features are extracted; 44 are for the accelerations [6] and 11 for encoders. Acceleration features are: 1) the mean and the variance in each coordinate axis, 2) the highest frequencies in each direction, and their relative amplitude, which represent repetitive behaviors, 3) the total energy of the signal in each direction, 4) the correlation of acceleration signals between every two axes, 5) the number of jolts extracted from acceleration in the x-axis, in the direction of the car movement, with the use of Short Term Fourier Transform, and 6) the time of the play. [6] Many of these features represent the child's interest and energy during the play. Encoder features can be a better representative of repetitive behaviors. For extracting encoder features, two methods are used. In the first method, two absolute features merely from encoders are extracted. These features are 1) the total number of wheel turns per time, 2) the number of spikes in encoders' derivation per time. In the second method, encoder features are extracted using acceleration signals. The whole children's playtime with the smart toy car can be divided into four sections: Stop, playing only with wheels, Playing on the ground, and Playing in the air. In the Stop section, the smart toy car is almost stationary and has no movements, and both encoders and acceleration signals are almost constant. The Playing only with wheels section is when the test case holds the smart car almost motionless while rotating any wheels. The playing on ground section represents those portions of playing that the test case is only moving the smart car on the ground, and both acceleration and encoders change continuously, and the playing on air section is when the smart toy car is moved in the air, the encoders data is almost constant, and the acceleration is changing. Integrating the jerk of summed acceleration signals with the variation of the encoder's data separates those four mentioned sections from each other. If the jerk is almost zero, then the car is almost stationary and depends on the encoders variation; the smart car could be in the Stop or the Playing only with wheels section, and if the jerk was non-zero, then the car is moving and based on its encoders data it could be moved on the ground or in the air, The percentage of every part to the whole signal is a feature. By defining an active duration for the smart car that consists of Playing only with wheels, playing on the ground, and playing in the air sections, the absolute interaction period of the test case is calculated. The ratio of each section to the length of the absolute interaction period is also a feature. That concludes the total number of features to 7, 4 are the percentages of the mentioned sections to whole signal length and 3 for Playing only with wheels, playing on the ground, and playing in the air sections ratio to the absolute interaction period length.

Feature Selection

Since the training set's size is small compared to the size of the feature vector, feature reduction is necessary before applying machine learning methods. In the first step to reducing the number of features, their correlation is examined. Only one feature in the groups with higher correlation is selected while the others are removed. In the next step, two algorithms in python are used to find the best features: 1) SelectKBest from Sklearn library, which finds K best features for classification (K is the number of features selected by the user), 2) RFE from Sklearn library, which provides a ranking for all of the features, representing their importance in the feature vector. The last step tests selected features based on manual optimization methods to improve classification accuracy. In this step, the first best number of features to classify data is investigated through testing 3 to 8 features. [Adding Fig1 showing accuracy, sensitivity, and specificity for each number of features] As it can be seen in Fig.1, selecting 5 or 6 features has the best results. Then selected features are examined again reasonably, and they can be replaced with some other features if it seems necessary. For example, based on the SelectKBest algorithm, two features have been selected from the energy category. At the same time, there is no feature from the acceleration correlation category as it can be predicted that correlation between accelerations may have a considerable effect on classification. One of the energy features is removed and replaced by one of the correlation features, which improves the classification performance by more than 5 percent. Lastly, by removing features with high correlation, only one feature remains from the highly correlated group randomly while other features are removed. This process is repeated to improve feature selection, and one specific feature is selected every time. [Adding Fig2 showing accuracy, sensitivity, and specificity for each feature selected] For instance, features 1 to 5 representing the five best frequencies in acceleration signal in the X-axis form a high correlation group as shown in Fig.2 between these features, feature number 4 is the best choice to enhance the classification function.

Classification Structure

It is possible to differentiate between children with autism and others by applying machine learning methods. In this regard, the collection of 50 samples is 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. Accuracy, sensitivity, and specificity are three major factors used to examine the classifier's effectiveness. In this research, a Support Vector Machine (SVM) is a suitable machine learning method that has effectively classified this kind of data. By testing three kinds of SVM, SVM with a linear kernel is selected due to its considerably higher accuracy.

Effect of Encoder in Classification

   The data is classified based on acceleration features to compare the effect of adding encoders in the model in the next step. The best accuracy based on the six best acceleration features is achieved 81% by randomly changing the training and test sets and averaging them. In the early fusion method, by adding the best feature of the encoder in the model, which is the number of spikes in encoders' derivation per time, the accuracy increases to 84.6 %. Although it was predicted that encoder features extracted with acceleration signals provide better accuracy, as shown in Fig3, they reduce accuracy to 78%. [Adding Fig3 showing accuracy, sensitivity, and specificity with and without encoder in three conditions]

In the late fusion method

# Results

* remove results from previous sections and add here
* accuracy, specifity, sensivity
  + false positive, false negative
* test case table → figure, visualization

# Discussion

* comparison between encoder features
* reasons why Bijan's encoder does not work (limitation of the work due to sensor dependency)

# Conclusion

* limitation
* suggestion
* outro

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