PIPELINE FOR ASSISTING DIAGNOSIS OF CHILDREN WITH AUTISM SPECTRUM DISORDER VIA AUTOMATED METHOD FOR CLASSIFYING REPETITIVE BEHAVIORS

Jimin Sun

Georgia Institute of Technology

Undergraduate Thesis

May 3, 2022

Dr. HyunJoo Oh – Faculty Advisor

Dr. Jennifer Kim – Second Reader

1. Introduction

We present automated methods to collect and provide motion data via sensors that can be used to assist the clinical decision-making process when diagnosing autism spectrum disorder (ASD) in children. The current limitation of assessment tools for diagnosing ASD in children is the subjectivity of the observer [23]. We present a pipeline for automating the process of data collection when children interact with toys, specifically focusing on the repetitive behavior commonly portrayed among children with ASD. We used data that mimicked repetitive behaviors identified in different studies [11,24,39,41]. Existing research and assessment of diagnosis of ASD in children indicates the need for having an automated and quantifiable approach that can provide more than mere observation [38]. It is important to note, however, that this can only aid existing methods of diagnosing autism, and its clinical relevance is to be further evaluated. It is critical for ASD to be detected at the early stages of the life of children. It has been supported that intervention for children with ASD is more effective in the younger age group and is beneficial for the long-term prognosis of children [35,37]. Therefore, automated technology will potentially help increase the efficiency and objectivity of observation-based diagnostic procedures. We discuss how using simple technologies such as an Arduino board [50], could bring efficiency and objective analysis to the observation procedure in the diagnosis of ASD.

2. Literature Review

2.1 Autism Spectrum Disorder Feature

Repetitive behaviors are one critical feature of ASD; it is one common observed symptom of ASD [8,12,48]. Some examples of repetitive behaviors include hand flapping and persistent engagement with specific parts of an object [41]. Different studies have identified repetitive movements with objects, the behavior of consistent single movement, and repeated movements of arms and hands as criteria for repetitive behaviors in children with ASD [11,24,39]. One study supported the finding that preschool children displayed restricted and repetitive behaviors in a free play session compared to typically developing children [26]. Another study reported that unfamiliar environments may interfere with sensory behaviors of children with ASD; thus, a familiar environment may be more successful in planning interventions [42]. Therefore, creating a naturalistic setting for observation and intervention of children with ASD must be taken into consideration.

2.2 Diagnosis of ASD

Autism Spectrum Disorder (ASD) describes individuals with impaired conditions of social communication and shows repetitive behaviors along with restricted interests and behaviors [35]. ASD in children could be diagnosed as early as 24 months after birth [29]. However, it is mostly the case where there is a lack of early diagnosis of children with ASD, not being diagnosed until school age [13]. It is critical for ASD to be detected at the early stages of the life of children. It has been supported that intervention for children with ASD is more effective in the younger age group and is beneficial for the long-term prognosis of children [33,35]. Not only is early detection beneficial to the children, but it can also provide an opportunity for genetic counseling to parents, discussing potential future child plans, psychological support, and concerns [46].

One process of diagnosing ASD involves clinical judgment where clinicians observe and evaluate the behavior and development of a child using standardized observation tools [28]. One standardized interview considered a gold standard is the Autism Diagnostic Observation

Schedule (ADOS), which assesses factors such as social interaction, communication, and use of materials [32]. However, one caveat of this assessment is the problem of bias, as there can be large variations per observer and the interviews are largely based on the memory and understanding of the caregiver [36]. Behavioral diagnosis of ASD is also one process of diagnosing ASD. The behavioral diagnosis of ASD takes place in a clinical setting where a specialist observes a child interacting with an object [5]. One drawback of this approach is that this setting is not naturalistic; it involves a specialist in a hospital setting. In addition, the motor signature of children is not quantified objectively by a specialist, as the observation is mostly conducted as interpreter-coded surveys. Other methods to observe stereotypical behavior of children with ASD include video-based observations or traditional approaches such as paper-pencil rating scales, which are often not accurate enough or time-consuming [22]. It is also that methods of rating and observing behaviors are inherently subjective and may fail to address variations due to intra-individual variations of observers [23]. In addition, one study reported that pediatricians, who provide primary screening and diagnosis in children with ASD, need sufficient information for accurately diagnosing ASD [40]. This study also identified that the diagnosis of ASD is prone to variation and is not always straightforward. Although multiple assessment instruments are recommended to be used instead of relying on a single tool for capturing ASD, there is a need for incorporating an automated and quantifiable approach to collecting quantitative data [38]. This will significantly help reduce variations and result in more consistent and reliable information that could provide additional analysis to clinicians when diagnosing ASD. Acknowledging the aforementioned limitations of current assessment tools, one study developed a motion-tracking technology, MOVIDEA, that measures motor patterns using video recordings [2]. This paper provided a promising insight to leveraging the objectiveness and reliability of existing motor assessment tools used for ASD diagnosis via using automated technology.

2.3 Machine Learning for ASD Diagnosis

Machine learning is a promising area that can help leverage research in behavioral sciences by improving the diagnostic and intervention process [7]. It can also be utilized to make screening of ASD more efficient, as it can decrease the time spent of conducting diagnostic assessments and making observations [6]. A support vector machine (SVM) is one of the most used and the strongest machine learning classifiers in ASD [1,31]. Logistic regression is another promising machine learning algorithm in ASD diagnosis and screening [16,44]. One study employed SVM to evaluate ADOS to differentiate between children with ASD from children who do not have ASD; SVM was trained based on score sheets [31]. Another study used Autism Spectrum Quotient (AQ) to train machine learning classifiers to predict specific ASD symptoms of individuals [1]. Logistic regression was used in one study to predict influential features of ASD using AQ and individual characteristics [44]. Machine learning was shown to have discriminative power on ASD and ADHD when trained with Social Responsiveness Scale score [16]. SVM is a popular supervised learning algorithm used in many clinical studies [14]. This machine-learning algorithm is also widely used to classify datasets in a nonlinear approach [18]. In addition, logistic regression is another algorithm that shows promising performance in ASD screening [44]. Logistic regression is a popular model due to how it can output a probability (value between 0 and 1) [27]. Therefore, we performed SVM and logistic regression in classifying repetitive behaviors from non-repetitive, normal behaviors. Acknowledging the fact that a single assessment tool or method cannot be relied for diagnosis of ASD, sufficiently trained machine learning classifiers will be able to assist clinical decision-making process. By employing machine learning classifiers, we aim to devise a pipeline for classifying repetitive behaviors from non-repetitive behaviors.

3. Study Procedures and Methods

The goal was to leverage commonly used existing technologies to support the process of the diagnostic process of children with ASD via an efficient data collecting method, specifically focusing on collecting and analyzing repetitive motions of children. The qualitative measurement by the observer could be assisted with the help of a technology that enables automated data collection of the child's movement. Children with ASD portray repetitive and restricted behaviors; therefore, it is expected that this technology, when being seamlessly integrated into clinical and observation environments, could measure, and detect the repetitiveness of a child when playing with a toy [33]. However, it is important to note that the data collected for this research is not sampled from real-world settings; data was collected via the researcher mimicking repetitive motions in references [11,24,39,41]. Table 1 shows behaviors that was referenced for data collection.

Table 1 Repetitive behaviors in existing literature

Features	References
Repetitive movements with objects, repetitive use of objects	[11,41]
Repeated movements of arms from shoulder or elbow, repeated movements of hands from wrist	[24,39]

3.1 Existing ASD Diagnostic Tools with Play

Play provides a naturalistic setting for interventions in children with ASD [20]. Therefore, we recognized that diagnostic tools that integrate playful toys, which children are expected to use and play with it, could be assisted by an automated process with a sensor embedded in the toy. It is necessary to identify which existing ASD diagnostic tools integrate play as an observation criterion. These diagnostic tools are potential sources of integration of the developed pipeline – the sensors could be embedded to an object the children interact with. The diagnostic tools are summarized in Table 2.

This provides insight into how functional play and children interacting toys are readily incorporated in existing assessments. Therefore, if this aspect could be leveraged by an efficient and objective method, an automated pipeline for data collection and analysis could be seamlessly integrated into existing methods. Furthermore, since children are interacting with toy-like objects in the functional play aspect of assessments, classifying repetitive behaviors from non-repetitive behaviors could support the analysis.

Table 2 Diagnostic tools with functional play

Assessment	Assessment Description
ADOS/-2 [32]	Standardized interview with semi-structured observation conducted by a clinician. This diagnostic tool includes different modules – communication, social affect, restricted interest/repetitive behaviors, play - per children's age and language ability [19,30].
Screening Tool for Autism in Toddlers and Young Children (STAT) [43]	This diagnostic tool kit assesses social behaviors including play, imitation, and requestion. It includes toys such as balloons, trucks, and dolls [19]
Autism Detection in ADEC [47]	This diagnostic tool kit has 16 items that assess lack of skills, atypical behavior, play, and social communication [15]. The items are used in a play-like interaction [9].

3.2 Pipeline Design

The designed pipeline is mainly three-fold: data collection, data preprocessing, and machine learning classifier. The comprehensive picture of the designed pipeline is illustrated in Figure 1.

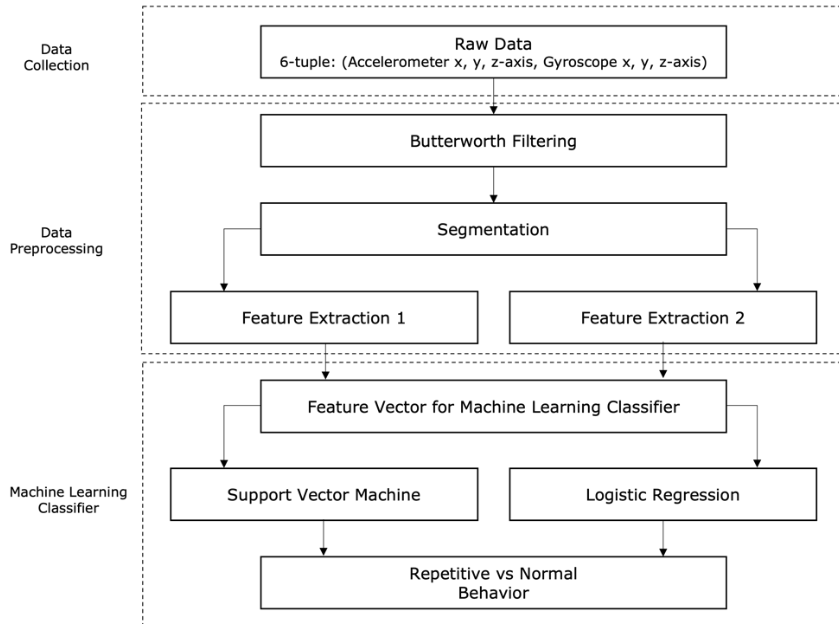

Figure 1 Block diagram of the designed pipeline

3.2.1 Data Collection via Sensors

As the main component of the technology, we used an ESP32 microcontroller to collect activity data. Arduino IDE was used as the main software. Since the objective of the automated data collection process was to target the motion, especially focusing on the repetitive behavior of children, an accelerometer and gyroscope sensor were connected to the Photon. The sensor used for the motion detection was Adafruit LSM6DSOX + LIS3MDL – Precision 9 DoF IMU [51]. Data on linear acceleration and angular velocity could be collected via sensors. Both accelerometer and gyroscope data were collected with respect to three axes (x, y, z-axis). The range of data collected was 2g and 250 degrees per second (DPS) for the accelerometer and gyroscope, respectively. Each data point was sampled per 0.08 seconds, or 12.5 Hz. Considering the portable size of the breadboard with sensors attached (3 ¼” x 2”), the system can be readily embedded into a plush toy. Figure 2 shows the designed sensor for data collection.

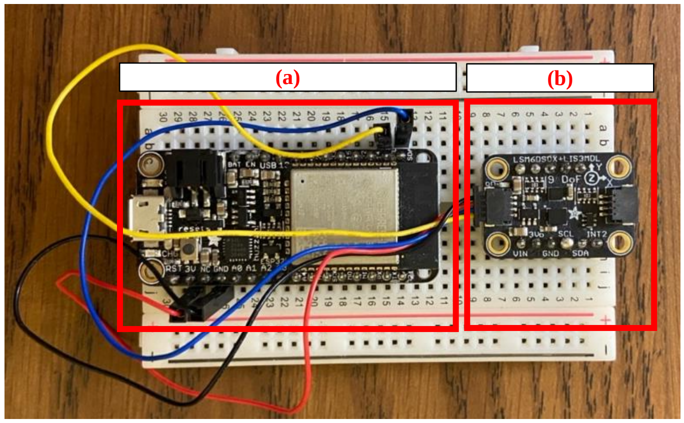

Figure 2 Embedded circuit for data collection:

(a) ESP32 Feather, (b)Adafruit LSM6DSOX - accelerometer + gyroscope

Table 3 Features extracted per category

Category	Features
Statistical Features	average, standard deviation, variance, root mean square, zero-crossing rate, absolute difference, skewness, kurtosis, energy
Fast Fourier Transform Features	average, standard deviation, variance, average absolute difference, skewness, kurtosis, energy

3.2.2 Data Preprocessing

Before collected motion data could be input into a machine learning classifier, features were extracted to get meaningful patterns. There were four steps in extracting features. The collected data was applied Butterworth filtering to eliminate noise and the effect of gravity on the earth [34]. This filtering is expected to remove components except for human activity [49]. The third order and frequency of 0.1 were used for Butterworth filtering. Considering the continuous nature of the collected data, windowing was applied to segment data into “chunks”. A window size of 100 data points was used, and a 50% overlap existed among the windows [10]. The overlap is applied to minimize the loss of information when the time series data is segmented into chunks; the overlap provides consistent data throughout the window. There were two categories of features collected: statistical features and Fast Fourier Transform features. Table 3 depicts the specific features extracted per category. Fast Fourier Transform features were calculated after Fast Fourier Transform was applied to Butterworth-filtered and windowed data. Fast Fourier Transform is an efficient way to calculate a discrete version of Fourier transform, which identifies frequency domains from time domains [3]. Since it is important to understand the frequency of repetitive motion data, Fast Fourier Transform was applied.

3.2.3 Machine Learning Classifier

There were two machine learning classifiers trained for the experiment. SVM and logistic regression was used to classify repetitive behaviors from normal behaviors. The data collected for training and testing the two machine learning classifiers were devised by closely observing and following features identified in the documentation describing observed repetitive behaviors. Thus, the developed pipeline particularly focuses on repetitive motions using arms and hands. Repetitive movements, hand waving, and repeated and patterned interaction with an object were carefully followed to create sample data for the experiment [11,21,24,39].

4. Results

Once the sensor using Arduino was attached to a plush toy, three categories of movement was classified using deep learning models. Data formatted as a 6-tuple of (Accelerometer X-axis, Accelerometer Y-axis, Accelerometer Z-axis, Gyroscope X-axis, Gyroscope Y-axis, Gyroscope Z-axis) was produced from the sensors. As aforementioned, to train and evaluate two machine learning classifiers, sample data was created. Each data was collected for about five minutes interacting with the sensor system while the researcher was mimicking repetitive motions. There were ten and two data for train and test split, respectively. Notice here, that because the main contribution of this research is building the technical pipeline, the sample data was collected to demonstrate preliminary results. From mimicked sample data, we collected 3,000 data points (4-minute motion data). Then, data preprocessing steps were applied to produce a final feature vector. SVM and logistic regression were trained to classify binary classes of repetitive motion and normal motion. Table 4, 5 summarizes hyperparameters used to train SVM and logistic regression with different hyperparameters.

Metrics used for evaluating the performance of SVM and logistic regression were accuracy, precision, and recall. Accuracy calculates the correct predictions over all the predictions made – SVM trained with linear kernel and regularization strength of 0.5 had the highest accuracy. Precision calculates the number of correctly predicted positive classes over all predicted positive classes – SVM trained with polynomial kernel and regularization strength of 1 had the highest precision value. Recall calculates the number of correctly predicted positive classes over total positive classes – logistic regression trained with coordinate descent algorithm and regularization strength of 1 had the highest recall value.

Table 4 Performance of SVM

Hyperparameters		Metrics		
Kernel	Regularization strength	Accuracy	Precision	Recall
linear	1	0.656	0.669	0.617
	0.5	0.685	0.681	0.695
polynomial	1	0.510	0.875	0.0234
	0.5	0.507	0.833	0.0168

Table 5 Performance of logistic regression

Hyperparameters		Metrics		
Optimization algorithm	Regularization strength	Accuracy	Precision	Recall
Limited memory BFGS algorithm	1	0.643	0.650	0.617
	1.5	0.662	0.666	0.654
Coordinate descent algorithm	1	0.678	0.666	0.715
	1.5	0.661	0.650	0.698

Moving forward, the trained models – selected with the best hyperparameters – should be tested with real data. However, because of limited access to real-time data of typically developing children and children with ASD, the model was tested with devised sample data with characteristics reflecting repetitive behaviors and normal data collected from how the sensor, when embedded into a plush toy, is expected to play with.

5. Discussion

The results of the trained machine learning classifier showed reasonable performance in identifying repetitive movements from normal range movements. Although the experiment result itself is not a strong classifier, SVM trained with linear kernel and regularization strength of 0.5 and logistic regression trained with coordinate descent algorithm with regularization strength of 1 achieved roughly 70% accuracy. Insufficient training data or lack of exploration of parameters might be contributing factors to the lack of accuracy. Investigating more feature extraction methods such as enveloped power spectrum, linear discriminant analysis, and using Haar-Like filtering could potentially contribute to increasing the accuracy and robustness of the machine learning classifier [4,25]. At this stage of experiment, the classification results alone will not be able to make some judgments on whether a child is autistic or not but can provide an objective viewpoint of the motion data focusing on repetitive behaviors. It is important to note that repetitive behaviors are a common observation featured among autistic children; it is not an indicator of autism. Further research on tuning parameters of machine learning classifiers is needed to leverage the classifiers to be adapted to the real world.

Another area of further research is providing the interpretability of the results. Due to machine learning's black box nature, it is often hard to understand the decision-making process of the algorithm [45]. It is difficult to build trust with the clinicians due to lack of interpretable results [17]. Therefore, it is crucial to the interpretability of the machine learning classifiers to build a trustworthy algorithm that could be used in the real-world diagnostic process.

In addition, the final deliverable of this research is the sensor system yet to be implemented in a plush toy. More research and prototyping are needed to embed the sensor system to a plush toy that could readily be used to interact with children.

The limitation of the study is mainly three-fold. First, the data collected to conduct an experiment with the tangible setup and to be ultimately used as an input in the machine learning classifier does not fully reflect the real-world data. This mock data is not sampled from the real world; it is not collected from children's movements. Rather, it was collected from movements that reflected and intentionally targeted repetitive movements. Second, there still needs improvement on hyperparameter tuning regarding developing a more robust machine learning classifier. SVM is one of the most basic and fundamental algorithms for a machine learning classifier. More advanced development of algorithms could be employed. Third, this research lacks real-world application. This research can provide an initial step to the further development of an automated method of assisting clinicians in diagnosing ASD by providing objective numerical data. Future studies could improve upon collecting real-world data, from typically developing children to children with ASD. Also, future studies can explore different movements and interactions according to the different types of toys. Finally, future research could investigate different types of toys may produce various interactions of children and the toy.

6. Conclusion

Autism in children has been diagnosed via different methodologies, including observation by experts. One of the salient behaviors found in children with autism includes repetitive movements, and there is a demand for objective observation of these behaviors in many diagnostic tools. This study presents a prototype composed of ESP 32 microcontroller with a gyroscope and an accelerometer to devise an automated method for collecting motion data via sensors to be used for the diagnosis of autism. This study incorporated mimicked data to apply the developed pipeline.

Although the experimental data still requires further elaboration and improvements, the findings provide an initial step toward the potential adaptation of automated methods in collecting motion data.

Future work is needed to expand upon the study. This study is only a first step in utilizing machine learning algorithms to identify behaviors based on motion data. A finer approach to collecting and processing the data will be required to implement this in clinical settings. This study has the limitation of not having been tested on a real-world dataset. To build a high-sensitivity machine learning algorithm, real-world data should be collected, followed by a more detailed analysis with iterative testing. Ultimately, this research brings together the usage of computer science and healthcare, in providing a more objective and efficient method to support decision-making in autism diagnosis of children.

References

[1] Maitha Rashid Alteneiji, Layla Mohammed Alqaydi, and Muhammad Usman Tariq. 2020. Autism spectrum disorder diagnosis using optimal machine learning methods. *International Journal of Advanced Computer Science and Applications* 11, 9 (2020). DOI:https://doi.org/10.14569/IJACSA.2020.0110929

[2] Walter Baccinelli, Maria Bulgheroni, Valentina Simonetti, Francesca Fulceri, Angela Caruso, Letizia Gila, and Maria Luisa Scattoni. 2020. Movidea: A software package for automatic video analysis of movements in infants at risk for neurodevelopmental disorders. *Brain Sciences* 10, 4 (2020). DOI:https://doi.org/10.3390/brainsci10040203

[3] G. D. Bergland. 1969. A guided tour of the fast Fourier Transform. *IEEE Spectrum* 6, 7 (1969). DOI:https://doi.org/10.1109/MSPEC.1969.5213896

[4] Rasel Ahmed Bhuiyan, Nadeem Ahmed, Md Amiruzzaman, and Md Rashedul Islam. 2020. A robust feature extraction model for human activity characterization using 3-axis accelerometer and gyroscope data. *Sensors (Switzerland)* 20, 23 (2020). DOI:https://doi.org/10.3390/s20236990

[5] Mariasole Bondioli, Stefano Chessa, Antonio Narzisi, Susanna Pelagatti, and Michele Zoncheddu. 2021. Towards motor-based early detection of autism red flags: Enabling technology and exploratory study protocol. *Sensors* 21, 6 (2021). DOI:https://doi.org/10.3390/s21061971

[6] Daniel Bone, Somer L. Bishop, Matthew P. Black, Matthew S. Goodwin, Catherine Lord, and Shrikanth S. Narayanan. 2016. Use of machine learning to improve autism screening and diagnostic instruments: effectiveness, efficiency, and multi-instrument fusion. *Journal of Child Psychology and Psychiatry and Allied Disciplines* 57, 8 (2016). DOI:https://doi.org/10.1111/jcpp.12559

[7] Daniel Bone, Matthew S. Goodwin, Matthew P. Black, Chi Chun Lee, Kartik Audhkhasi, and Shrikanth Narayanan. 2015. Applying Machine Learning to Facilitate Autism Diagnostics: Pitfalls and Promises. *Journal of Autism and Developmental Disorders* 45, 5 (2015). DOI:https://doi.org/10.1007/s10803-014-2268-6

[8] Brian A. Boyd, Stephen G. McDonough, and James W. Bodfish. 2012. Evidence-Based Behavioral Interventions for Repetitive Behaviors in Autism. *Journal of Autism and Developmental Disorders* 42, 6 (June 2012), 1236–1248. DOI:https://doi.org/10.1007/s10803-011-1284-z

[9] Neil Brewer, Robyn L. Young, and Carmen A. Lucas. 2020. Autism Screening in Early Childhood: Discriminating Autism From Other Developmental Concerns. *Frontiers in Neurology 11*. DOI:https://doi.org/10.3389/fneur.2020.594381

[10] Pierluigi Casale, Oriol Pujol, and Petia Radeva. 2011. Human activity recognition from accelerometer data using a wearable device. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. DOI:https://doi.org/10.1007/978-3-642-21257-4_36

[11] Centers for Disease Control and Prevention. Early Warning Signs of Autism Spectrum Disorder. Retrieved April 18, 2022 from https://www.cdc.gov/ncbddd/actearly/autism/curriculum/documents/early-warning-signs-autism_508.pdf

[12] Michael L. Cuccaro, Yujan Shao, Janet Grubber, Michael Slifer, Chantelle M. Wolpert, Shannon L. Donnelly, Ruth K. Abramson, Sarah A. Ravan, Harry H. Wright, G. Robert

DeLong, and Margaret A. Pericak-Vance. 2003. Factor analysis of restricted and repetitive behaviors in autism using the autism diagnostic interview-R. *Child Psychiatry and Human Development* 34, 1 (2003). DOI:https://doi.org/10.1023/A:1025321707947

[13] Amy M. Daniels and David S. Mandell. 2014. Explaining differences in age at autism spectrum disorder diagnosis: A critical review. *Autism 18*. DOI:https://doi.org/10.1177/1362361313480277

[14] Ayşe Demirhan. 2018. PERFORMANCE OF MACHINE LEARNING METHODS IN DETERMINING THE AUTISM SPECTRUM DISORDER CASES. *Mugla Journal of Science and Technology* (2018). DOI:https://doi.org/10.22531/muglajsci.422546

[15] Leigh Dix, Rachael Fallows, and Glynis Murphy. 2015. Effectiveness of the ADEC as a Level 2 screening test for young children with suspected autism spectrum disorders in a clinical setting. *Journal of Intellectual and Developmental Disability* 40, 2 (2015). DOI:https://doi.org/10.3109/13668250.2015.1014323

[16] M. Duda, R. Ma, N. Haber, and D. P. Wall. 2016. Use of machine learning for behavioral distinction of autism and ADHD. *Translational Psychiatry* 6, 2 (2016). DOI:https://doi.org/10.1038/tp.2015.221

[17] Radwa Elshawi, Mouaz H. Al-Mallah, and Sherif Sakr. 2019. On the interpretability of machine learning-based model for predicting hypertension. *BMC Medical Informatics and Decision Making* 19, 1 (2019). DOI:https://doi.org/10.1186/s12911-019-0874-0

[18] Dadang Eman and Andi W.R. Emanuel. 2019. Machine learning classifiers for autism spectrum disorder: A review. In *2019 4th International Conference on Information Technology, Information Systems and Electrical Engineering, ICITISEE 2019*. DOI:https://doi.org/10.1109/ICITISEE48480.2019.9003807

[19] Peter A.J. Fanning, Laura Sparaci, Cheryl Dissanayake, Darren R. Hocking, and Giacomo Vivanti. 2021. Functional play in young children with autism and Williams syndrome: A cross-syndrome comparison. *Child Neuropsychology* 27, 1 (2021). DOI:https://doi.org/10.1080/09297049.2020.1804846

[20] Jenny L Gibson, Emma Pritchard, and Carmen de Lemos. 2021. Play-based interventions to support social and communication development in autistic children aged 2–8 years: A scoping review. *Autism & Developmental Language Impairments* 6, (January 2021), 239694152110158. DOI:https://doi.org/10.1177/23969415211015840

[21] Sylvie Goldman and Paul E Greene. 2012. Stereotypies in autism: a video demonstration of their clinical variability. *Front Integr Neurosci* 6, (2012), 121. DOI:https://doi.org/10.3389/fnint.2012.00121

[22] Nuno Goncalves, Jose L. Rodrigues, Sandra Costa, and Filomena Soares. 2012. Automatic detection of stereotyped hand flapping movements: Two different approaches. In *Proceedings - IEEE International Workshop on Robot and Human Interactive Communication*. DOI:https://doi.org/10.1109/ROMAN.2012.6343784

[23] Matthew S. Goodwin, Stephen S. Intille, Fahd Albinali, and Wayne F. Velicer. 2011. Automated detection of stereotypical motor movements. *Journal of Autism and Developmental Disorders* 41, 6 (2011). DOI:https://doi.org/10.1007/s10803-010-1102-z

[24] Enzo Grossi, Elisa Caminada, Michela Goffredo, Beatrice Vescovo, Tristana Castrignano, Daniele Piscitelli, Giulio Valagussa, Marco Franceschini, and Franco Vanzulli. 2021. Patterns of Restricted and Repetitive Behaviors in Autism Spectrum Disorders: A Cross-Sectional Video Recording Study. Preliminary Report. *Brain Sciences* 11, 6 (May 2021), 678. DOI:https://doi.org/10.3390/brainsci11060678

[25] Yuya Hanai, Jun Nishimura, and Tadahiro Kuroda. 2009. Haar-like filtering for human activity recognition using 3D accelerometer. In *2009 IEEE 13th Digital Signal Processing Workshop and 5th IEEE Signal Processing Education Workshop, DSP/SPE 2009, Proceedings*. DOI:https://doi.org/10.1109/DSP.2009.4786008

[26] Clare Harrop, Helen McConachie, Richard Emsley, Kathy Leadbitter, and Jonathan Green. 2014. Restricted and repetitive behaviors in autism spectrum disorders and typical development: Cross-sectional and longitudinal comparisons. *Journal of Autism and Developmental Disorders* 44, 5 (2014). DOI:https://doi.org/10.1007/s10803-013-1986-5

[27] Denise Howel and D. G. Kleinbaum. 1995. Logistic Regression: A Self Learning Text. *The Statistician* 44, 3 (1995). DOI:https://doi.org/10.2307/2348716

[28] Yvette Hus and Osnat Segal. 2021. Challenges Surrounding the Diagnosis of Autism in Children. *Neuropsychiatr Dis Treat* 17, (2021), 3509–3529. DOI:https://doi.org/10.2147/NDT.S282569

[29] Chris Plauché Johnson, Scott M. Myers, Paul H. Lipkin, J. Daniel Cartwright, Larry W. Desch, John C. Duby, Ellen Roy Elias, Eric B. Levey, Gregory S. Liptak, Nancy A. Murphy, Ann Henderson Tilton, Donald Lollar, Michelle Macias, Merle McPherson, Donna Gore Olson, Bonnie Strickland, Stephanie Mucha Skipper, Jill Ackermann, Mark del Monte, Thomas D. Challman, Susan L. Hyman, Susan E. Levy, S. Andrew Spooner, and Marshalyn Yeargin-Allsopp. 2007. Identification and evaluation of children with autism spectrum disorders. *Pediatrics 120*. DOI:https://doi.org/10.1542/peds.2007-2361

[30] I. Kamp-Becker, K. Albertowski, J. Becker, M. Ghahreman, A. Langmann, T. Mingebach, L. Poustka, L. Weber, H. Schmidt, J. Smidt, T. Stehr, V. Roessner, K. Kucharczyk, N. Wolff, and S. Stroth. 2018. Diagnostic accuracy of the ADOS and ADOS-2 in clinical practice. *European Child and Adolescent Psychiatry* 27, 9 (2018). DOI:https://doi.org/10.1007/s00787-018-1143-y

[31] J. A. Kosmicki, V. Sochat, M. Duda, and D. P. Wall. 2015. Searching for a minimal set of behaviors for autism detection through feature selection-based machine learning. *Translational Psychiatry* 5, 2 (2015). DOI:https://doi.org/10.1038/tp.2015.7

[32] Lord C, Rutter M, DiLavore PC, Risi S, Gotham K, and Bishop SL. 2012. Autism Diagnostic Observation Schedule. 2nd. *Western Psychological Services* (2012).

[33] Catherine Lord, Mayada Elsabbagh, Gillian Baird, and Jeremy Veenstra-Vanderweele. 2018. Autism spectrum disorder. *Lancet* 392, 10146 (2018), 508–520. DOI:https://doi.org/10.1016/S0140-6736(18)31129-2

[34] Abdul Kadar Muhammad Masum, Erfanul Hoque Bahadur, Ahmed Shan-A-Alahi, Md Akib Uz Zaman Chowdhury, Mir Reaz Uddin, and Abdullah al Noman. 2019. Human Activity Recognition Using Accelerometer, Gyroscope and Magnetometer Sensors: Deep Neural Network Approaches. In *2019 10th International Conference on Computing, Communication and Networking Technologies, ICCCNT 2019*. DOI:https://doi.org/10.1109/ICCCNT45670.2019.8944512

[35] Johnny L. Matson, Jonathan Wilkins, and Melissa González. 2008. Early identification and diagnosis in autism spectrum disorders in young children and infants: How early is too early? *Research in Autism Spectrum Disorders* 2, 1 (2008). DOI:https://doi.org/10.1016/j.rasd.2007.03.002

[36] Patrick McCarty and Richard E. Frye. 2020. Early Detection and Diagnosis of Autism Spectrum Disorder: Why Is It So Difficult? *Seminars in Pediatric Neurology 35*. DOI:https://doi.org/10.1016/j.spen.2020.100831

[37] Jennifer Pinto-Martin and Susan E. Levy. 2004. Early diagnosis of autism spectrum disorders. *Current Treatment Options in Neurology* 6, 5 (2004). DOI:https://doi.org/10.1007/s11940-996-0030-x

[38] Umberto Provenzani, Laura Fusar-Poli, Natascia Brondino, Stefano Damiani, Marco Vercesi, Nicholas Meyer, Matteo Rocchetti, and Pierluigi Politi. 2020. What are we targeting when we treat autism spectrum disorder? A systematic review of 406 clinical trials. *Autism* 24, 2 (February 2020), 274–284. DOI:https://doi.org/10.1177/1362361319854641

[39] Giulia Purpura, Valeria Costanzo, Natasha Chericoni, Maria Puopolo, Maria Luisa Scattoni, Filippo Muratori, and Fabio Apicella. 2017. Bilateral Patterns of Repetitive Movements in 6- to 12-Month-Old Infants with Autism Spectrum Disorders. *Front Psychol* 8, (2017), 1168. DOI:https://doi.org/10.3389/fpsyg.2017.01168

[40] Melinda Randall, Natalia Albein-Urios, Amanda Brignell, Alisha Gulenc, Sabine Hennel, Cathy Coates, Christos Symeonides, Harriet Hiscock, Catherine Marraffa, Natalie Silove, Vivian Bayl, Susan Woolfenden, and Katrina Williams. 2016. Diagnosing autism: Australian paediatric research network surveys. *Journal of Paediatrics and Child Health* 52, 1 (January 2016), 11–17. DOI:https://doi.org/10.1111/jpc.13029

[41] Jennifer Richler, Somer L. Bishop, Jennifer R. Kleinke, and Catherine Lord. 2007. Restricted and repetitive behaviors in young children with autism spectrum disorders. *Journal of Autism and Developmental Disorders* 37, 1 (2007). DOI:https://doi.org/10.1007/s10803-006-0332-6

[42] Roseann C Schaaf, Susan Toth-Cohen, Stephanie L Johnson, Gina Outten, and Teal W Benevides. 2011. The everyday routines of families of children with autism: examining the impact of sensory processing difficulties on the family. *Autism* 15, 3 (May 2011), 373–89. DOI:https://doi.org/10.1177/1362361310386505

[43] Wendy Stone and Opal Ousley. 2008. Screening tool for autism in toddlers and young children (STAT). *Vanderbilt University* (2008).

[44] Fadi Thabtah, Neda Abdelhamid, and David Peebles. 2019. A machine learning autism classification based on logistic regression analysis. *Health Information Science and Systems* 7, 1 (2019). DOI:https://doi.org/10.1007/s13755-019-0073-5

[45] David S. Watson, Jenny Krutzinna, Ian N. Bruce, Christopher E.M. Griffiths, Iain B. McInnes, Michael R. Barnes, and Luciano Floridi. 2019. Clinical applications of machine learning algorithms: Beyond the black box. *BMJ (Online)* 364, (2019). DOI:https://doi.org/10.1136/bmj.l886

[46] Jo Williams and Carol Brayne. 2006. Screening for autism spectrum disorders: What is the evidence? *Autism 10*. DOI:https://doi.org/10.1177/1362361306057876

[47] R.L. Young. 2007. *Autism Detection in Early Childhood (ADEC) Manual*. ACER Press.

[48] Fiona Zandt, Margot Prior, and Michael Kyrios. 2007. Repetitive Behaviour in Children with High Functioning Autism and Obsessive Compulsive Disorder. *Journal of Autism and Developmental Disorders* 37, 2 (February 2007), 251–259. DOI:https://doi.org/10.1007/s10803-006-0158-2

[49] Shangyue Zhu, Junhong Xu, Hanqing Guo, Qiwei Liu, Shaoen Wu, and Honggang Wang. 2018. Indoor human activity recognition based on ambient radar with signal processing and machine learning. In *IEEE International Conference on Communications*. DOI:https://doi.org/10.1109/ICC.2018.8422107

[50] Arduino - Board. Retrieved April 25, 2022 from https://www.arduino.cc/en/reference/board

[51] Adafruit LSM6DSOX + LIS3MDL - Precision 9 DoF IMU - STEMMA QT / Qwiic. Retrieved April 18, 2022 from https://www.adafruit.com/product/4517