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Detection of Challenging Behaviours of Children with Autism Using Wearable Sensors during Interactions with Social Robots

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***Abstract*— Autism spectrum disorder is a neurodevelopmental disorder that is characterized by patterns of behaviours and difficulties with social communication and interaction. Children on the spectrum exhibit atypical, restricted, repetitive, and challenging behaviours. In this study, we investigate the feasibility of integrating wearable sensors and machine learning techniques to detect the occurrence of challenging behaviours in real-time. A session of a child with autism interacting with different stimuli groups that included social robots was annotated with observed challenging behaviors. The child wore a wearable device that captured different motion and physiological signals. Different features and machine learning configurations were investigated to identify the most effective combination. Our results showed that physiological signals in addition to typical kinetic measures led to more accurate predictions. The best features and learning model combination achieved an accuracy of 97%. The findings of this work motivate research toward methods of early detection of challenging behaviours, which may enable the timely intervention by caregivers and possibly by social robots.**

I. Introduction

Children on the spectrum exhibit challenging behaviours and aggression at higher rates compared to their neurotypical peers [1] [2]. Challenging behaviours take different forms at varying intensities depending on the degree and manifestation of Autism Spectrum Disorders (ASD) [3] [4]. For example, a challenging behaviour could manifest as sensory stimming behaviours, head banging, hand flapping, kicking others, throwing of nearby objects, hand biting, and screaming.

Therapy techniques, such as positive behaviour support, were reported to help in increasing positive interactions while decreasing negative reactions and interfering behaviours among children with autism [5] [6]. There is a growing interest in the integration of technologies in the diagnosis and therapy of children with autism [7] [8]. Children on the spectrum were found to be engaged with technologies such as social robots, which were reported to result in positive outcomes [9]. However, some studies reported instances of aggression toward robots during therapy sessions [10] [11]. Such challenging behaviours could potentially lead to injuries [12]. To mitigate this problem, hardware approaches were used but were found to be limited in terms of applicability and effectiveness [13] [14]. Alternatively, some approaches resorted to using machine learning predictive models to detect occurrences of challenging behaviours and aggression [15] [16].

To employ machine learning models for challenging behaviour prediction, several behaviour characteristics need to be investigated, such as physiological signals. Different physiological data such as movement, heart rate, temperature, and electrodermal activity can be measured through the use of wearable sensors. The physiological arousal of children with autism was found to influence challenging behaviours due to the relation between hyperarousal and sensory reaction [17]. Jansen et al. [18] reported that individuals with ASD experienced lower heart rate compared to neurotypical adults during public speaking. Another study found unusual skin conductance readings in children with autism compared to control group [19]. A strategy that relies on a low arousal approach was proposed to manage challenging behaviours [17]. To date, limited work has been done that utilized wearable devices to detect challenging behaviours during child and robot interaction [20].

In this study, we investigate the potential of using a wrist wearable device coupled with machine learning techniques to identify the occurrence of challenging behaviours during child-robot interaction (Fig. 1). Furthermore, different machine learning models with various wearable data configurations were tested. The following are the contributions of this work:

1) Development of an effective annotation technique to distinguish challenging behaviours.
2) Investigation of the influence of different physiological signals in the prediction of challenging behaviours.
3) Demonstration of the feasibility of an automatic and real-time detection of challenging behaviours using machine learning techniques.
4) Demonstration of an assistive annotation tool to monitor the physiological signs, videos, and to visualize the predictions of the developed machine learning algorithms.

This paper is organized as follows. Section II presents the related work. Section III describes the methodology.

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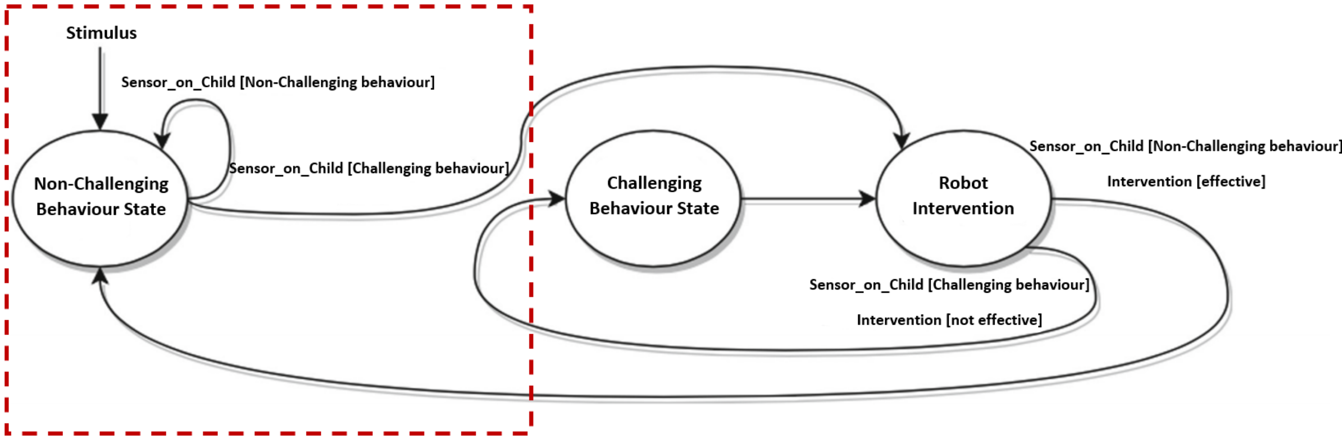

Fig. 1. The intervention framework with wearable sensors and social robots. The wearable sensor detects the occurrence of physiological arousal and notifies the social robot to intervene. The highlighted area represents the focus of this study (Adapted from [20]).

Section IV presents the results while Section V provides the discussion. Section VI concludes the study.

II. Related Work

The application of wearables and machine learning in autism varies. One study investigated different emotions during meltdown in order to construct an emotion recognition system using several machine learning techniques [21]. The best trained model (i.e., Random Forest Classifier) achieved promising results (i.e., 91.27%) using feature selection techniques. For aggressive behaviour classification among children with autism, a movement detection method using wearable sensors was also investigated [22]. The study considered simulating aggressive behaviours by an expert to generate data. Their best machine learning model achieved an accuracy of 69.7% when tested with data acquired from a session with a child with autism.

The detection of stereotypical motor movements of children with autism and their impact on learning and social interactions were investigated in another study [23]. Deep learning techniques have been considered to enhance the automatic detection of stereotypical movements using multi-axis inertial measurement units. Another study investigated the potential of sensory processing in assisting in the diagnosis and classification of ASD [24]. The study used a wristband wearable to measure the changes in electrodermal activity during virtual environmental settings displaying different stimuli. The experiments included children with autism and neurotypical children. Their method showed promising results in identifying autism sensory dysfunction during the visual stimuli condition (i.e., 84.6% identification) .

Real-time stress and anxiety level monitoring were considered using wearables [25]. Physiological data signals obtained from 38 participants were used to train Logistic Regression (LR) and Support Vector Machine (SVM) models. The model based on SVM achieved the best results (i.e., 93% accuracy). Another study considered using physiological measurements namely electrocardiogram, respiration, skin conductance, and temperature to categorize evoke valence (i.e., positive or negative) and arousal intensities (i.e., low and high) [26]. A machine learning model based on an ensemble of classifiers was trained with data obtained from 15 children. The average accuracies of the trained models were all around 80%.

III. Methodology

A. Participants

A ten year old male child with autism took part in this study. The participant is a student at a local center for special needs in Doha, Qatar. The center obtained the necessary parental consent to conduct the study. During the session, the child was with his caregiver and a teacher. The procedures for this work did not include invasive or potentially hazardous methods and were in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki).

B. Stimuli

The experiments considered different toys and two social robots as stimuli (Fig. 2a). The toys were a green ball made of rubber, cymbals, a plastic train with multiple colors, a humanoid robotic toy, and a truck made of wood with blocks that have letters on them. A humanoid robot (Nao, SoftBank Robotics, France) and a robotic seal (PARO Robots, USA) were the two social robots considered. More details about the stimuli can be found in an earlier work [10].

C. Wearable Device

The wearable sensor (Empatica E4 wristband) was used in the experiment (Fig. 2b). The wristband contains an internal memory that allows up to 36 hours of recording with a real-time internal clock. The wristband has multiple sensors.

This study used the data readings obtained from the wearable device worn by the child during the experiment. The signals readings recorded were as follows:

1) Acceleration (ACC): Measured the amount of acceleration that the child was exhibiting in the X, Y and Z axes.

Fig. 2. An overview of the adopted methodology in this study. a) The two social robots (i.e., Nao and Paro) that were used in this study as part of the stimuli group [10]. b) The wrist wearable device Empatica E4. c) A snapshot of the developed observation and annotation assistive tool during the session with the child when he was exhibiting challenging behaviours during the session with social robots. The tool displays the recorded video, wearable signals acquired from the child, and a summary of the machine learning predictions in real time (See supplementary material).

2) Electrodermal Activity (EDA): Measured the variation of skin conductance and the electrical properties of the skin.
3) Interbeat Interval (IBI): Determined the time between the child's individual heart beats.
4) Temperature (TEMP): Measured the temperature of the child.
5) Heart Rate (HR): Determined the number of heart beats per minute of the child.
6) Blood Volume Pulse (BVP): Measured the blood volume changes.

D. Algorithms

Three supervised machine learning algorithms were considered.

Support-Vector Machine (SVM) is among the supervised learning models that can be used in classification and regression. SVMs are based on statistical learning frameworks and are non-probabilistic binary linear classifiers that can solve both linear and non-linear problems. The SVM's training model labels new example to either category while aiming to maximize the gap between them.

Multilayer Perceptron (MLP) is a feedforward class of Artificial Neural Networks (ANN) that uses back propagation, a supervised learning technique, for training. Inspired by the brain, an MLP model consists of at least an input, hidden, and output layer of nodes. Every node except for the output layer is a neuron that employs a nonlinear activation function.

Decision tree (DT) is a very popular ML algorithm, due to its simplicity and ease of visualization. DTs are predictive models that use a tree structure to move from one decision to another until it reaches a target.

E. Procedures

1) Annotation: The video recording of the child was manually annotated using an annotation software (BORIS, v. 7.10.2, Torino, Italy). The annotation categorises the child's valance into 'Challenging' or 'Non-challenging' behaviour. To elaborate, any behaviour that is harmful or has potential to cause injuries to the child or others, or destructive is considered as a challenging behaviour. This includes but not limited to head banging, arm flapping, ear pulling, kicking, scratching. These behaviours may be produced to express various emotions and feelings such as frustration, anxiety, anger, and sadness. Anything that was not labeled as 'Challenging' behaviour was annotated as 'Non-Challenging'.

An assistive tool was developed to monitor the changes in vital signals as the child interacts with the stimuli (Fig. 2c). Additionally, the tool displays the current predictions of the developed machine learning algorithms. The tool can be used to assist annotators, caregivers, and developers in evaluating the therapy sessions and aid in the development of recognition systems.

2) Machine Learning Model Development: The annotated data was preprocessed to ensure the consistency between the different signal types. The sensors in the wearable device acquired the data at different frequencies. Hence, frequency matching at 32 Hz was performed to ensure that the frequencies of all the signals were the same. Elimination of outliers due to the sensors' errors was performed to ensure accurate representation of the signals. Resampling techniques were performed on the training set to ensure both classes were balanced. A portion of the original dataset was left as part of the unseen testing set.

Preliminary tests were conducted using the raw sensors data and time-domain extracted features in the development of machine learning models. The considered time-domain features were maximum, minimum, mean, and standard deviation over a window size of two seconds (i.e., 64 samples). The preliminary results showed that the extracted features performed better when compared to the raw features. Hence, only the time-domain extracted features were considered in this study.

TABLE I

RESULTS FOR THE EXPERIMENTS CONSIDERING THE IMPACT OF ADDING EACH FEATURE TO THE FEATURE SET.

Set	1			2			3			4			5			6		
Feature	ACC			Set 1 + HR			Set 2 + IBI			Set 3 + BVP			Set 4 + EDA			Set 5 + TEMP		
Metric	Prec	Recall	F1	Prec	Recall	F1	Prec	Recall	F1	Prec	Recall	F1	Prec	Recall	F1	Prec	Recall	F1
SVM	0.11	0.36	0.17	0.50	0.66	0.52	0.76	0.83	0.73	0.78	0.76	0.74	0.88	0.77	0.74	0.91	0.78	0.76
MLP	0.14	0.31	0.18	0.61	0.63	0.55	0.71	0.84	0.72	0.72	0.76	0.68	0.84	0.95	0.83	0.90	0.97	0.90
DT	0.15	0.11	0.11	0.84	0.47	0.51	0.70	0.85	0.72	0.77	0.86	0.78	0.74	0.78	0.74	0.74	0.72	0.66

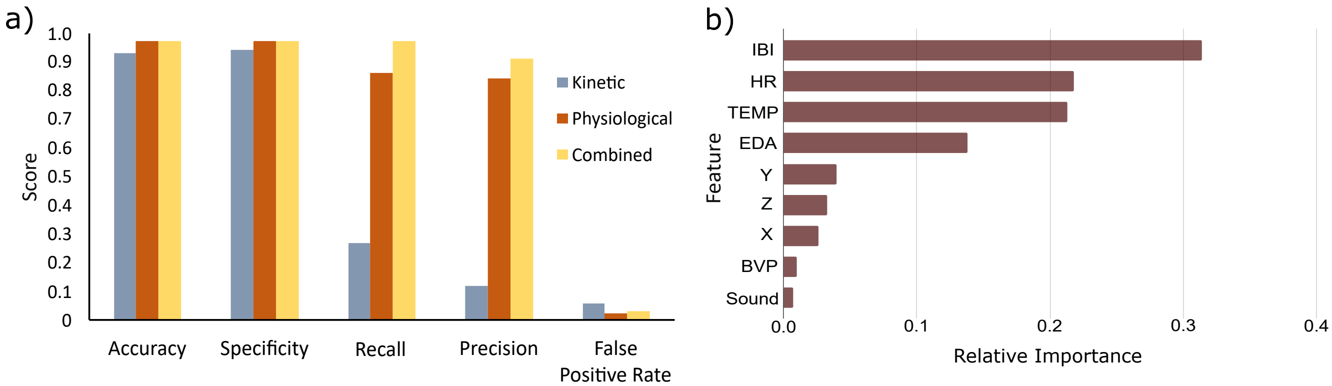

Fig. 3. The outcomes of the experiments conducted in this study. a) The evaluation metrics' results for the three tested categories on the best performing classifier (i.e., MLP). b) The feature importance scores for each of the investigated features.

IV. RESULTS

Three classifiers were evaluated for their performance. Cross validation with 10 folds was used to report the evaluation metrics. Scikit-Learn and keras libraries in Python were used to develop the models. The Decision Tree (DT) algorithm was trained using a dynamic maximum-depth number and a Gini function to measure the quality of splitting the tree. As for the SVM, the adopted kernel was radial basis function (RBF) with a value of 0.1 as a regularization parameter and the gamma parameter was set to scaled. The MLP consisted of one hidden layer with 100 neurons and weights adjusted using stochastic gradient descent at 0.01 regularization. The activation function considered was *Relu* with *Adam* as the solver for weight optimization.

In the first experiment, we investigated the effect of adding each physiological signal (one at a time) to the commonly used kinetic feature vector. In the three employed learning algorithms, the impact and contribution of each signal is shown in Table I. With ACC alone, all the models performed poorly. Adding the HR sensor data to the feature vector (Set 2) led to substantial performance improvements, and further improvements were observed when the IBI signal was added (Set3). When the BVP and EDA features were added, a small overall improvement in the performance of the three models was achieved. The addition of TEMP in (Set 6) led to further improvements albeit only in the MLP and SVM classifiers.

In the second experiment, we sought to establish whether using the physiological signals alone (without kinetic ones) is sufficient for detecting challenging behaviors.
Features from the wearable device were divided into three categories to study their influence on the performance of the machine learning algorithm. The first category *Kinetic* contained the acceleration data only while the second category *Physiological* was comprised of HR, IBI, BVP, EDA, and temperature. The third category contained the combined data. As can be seen by the results depicted in Fig. 3a, the use of physiological features led to better classification performance than kinetic ones. The physiological and combined features performed the best at a rate of 0.97 in terms of accuracy and specificity. Combined features gave the best results for recall (0.97) and precision (0.91) while physiological performed the best in terms of false positive rate (0.025). The importance of each feature was investigated using Scikit-Learn library (i.e., ExtraTreeClassifer). The sound extracted from the recorded video was also included in this test. The IBI feature was reported to be the most influencing feature in the model followed by HR, TEMP, and EDA (Fig. 3b).

V. DISCUSSION

Understanding the interactions during the session was essential to better interpret the occurrence of the challenging behaviours in this study. The child with autism displayed varying levels of interaction with the stimuli groups (i.e. green ball, cymbals, plastic train, humanoid robotic toy, and a wooden truck). The participant was most attracted to the colourful plastic train, which produced bubbles. This triggered a state of excitement in his facial expressions and physical movements such as jumping and arm waving. After 13 minutes of interaction, the child started to experience challenging behaviours (e.g. body rocking and screaming).

During the session with social robots, the child exhibited an increase in the challenging behaviours to some social robots more than others, perhaps due to specific undesirable features of these robots which appeared to scare him. He jumped in refusal to interact with any of the two social robots and continued to scream while exhibiting stimming and repetitive behaviours. In the entire session, there were only a few occurrences of challenging behaviors observed.

The investigation of the kinetic and physiological features' contributions to the prediction performance have shed insights into the instances of challenging behaviours. Specifically, many challenging behaviours involved hand movements. Hence, the accelerometer inside the wrist wearable was able to record these instances that are distinguishable compared to other hand movements. The evaluation metrics results of the best performing classifier supports these finding. However, considering the kinetic features alone did not provide the best outcomes in this study. Although, some of the challenging behaviors are expressed by physical movements, others may not be as such. For example, fear of a social robot may only be captured by a sudden increase of heart rate and interbeat interval signals (Fig. 2c). This is especially more evident in children of young ages where abrupt physical movements are expected. This highlights that some forms of challenging behaviours can only be identified with sensors that measure the physiological signs. Adding the physiological data to kinetic data would increase the accuracy of prediction. Hence, the combined effects improved the overall performance of the machine learning model as shown by the results.

Parents or caregivers need to observe the children directly to be aware of the challenging behaviours. Continuous observation might pose as a challenge. Hence, having a technology that can help in monitoring and detecting challenging behaviors will improve the quality of therapy. This is achieved by constructing real-time systems to detect such behaviours. Such systems will be beneficial to parents, therapists, caregivers, and even researchers. With the help of an automatic detection system, assessments can be made on the adaptation of a child to different environmental conditions and stimuli. Hence, preventive measures can be taken early to reduce the probability of detrimental behaviours. In this study, a tool was developed toward achieving the goal of developing such systems using wearable sensors and social robots for early intervention purposes.

Unlike medical professionals, machine learning models lack the means to explain the reasons behind their predictions. This limitation might be a hindrance to the adoption of such technologies in sensitive applications such as detecting challenging behaviours for individuals with special needs. Parents would use this technology if it could provide some form of an explanation. Hence, the need for interpretation is vital. To undermine such limitation, interpretation techniques attempt to provide some reasoning behind models' predictions [27]. Such techniques can help parents and healthcare providers understand their patients better by omitting any confusion behind a machine learning model's prediction. A detection system would explain why a child is about to undergo a challenging behaviour or meltdown event based on the readings of the physiological data. For example, the system can inform the parents that the child's vitals (e.g. IBI or HR) are not within the normal range. We believe that future studies should focus on incorporating interpretation techniques into their systems.

Collecting comprehensive data to account for the spectrum of children with autism represents a challenge. To account for inter-individual differences, a large amount of data is needed to be collected so a reliable machine learning model can be developed. While the exhibition of challenging behaviors among this population is high, collecting enough data to account for the differences in their characteristics represents a major limitation. Children with autism show heterogeneous profiles in their symptoms and dispositions. Hence, their display of challenging behaviours can vary from one individual to another. Therefore, a focus group can be narrowed down to children with ASD who exhibit sensory stimming behaviours (e.g. kinetic and motor movements). This gives a rise toward the need of personalized machine learning models to consider such distinctive differences among this population and to gather the requisite comprehensive data. The machine learning models developed in this study showed promising results toward the development of personalized detection systems for challenging behaviours.

The investigations in this study were limited to one child with autism. Hence, the findings can not be generalized to other children on the spectrum. Additionally, there is a need to acquire more data to cover a wider range of different challenging behaviours. Future works will consider conducting longer and repeated sessions with different children on the spectrum. The data collection process was limited to using a wrist wearable device. However, children on the spectrum may get irritated by it, try to remove it, or use it to harm themselves [20]. Furthermore, wrist wearable alone may not be able to capture the movements of other body parts (e.g. leg). Future studies should consider the application of other wearable devices embedded within the child's clothing or shoes.

VI. CONCLUSION

The occurrence of challenging behaviours among children with autism interferes in the social and functional activities of daily living, including their therapy sessions. Technology can be used to detect such behaviours and improve therapy. In this study, we investigated the feasibility of detecting challenging behaviours using a wearable sensor and machine learning techniques. An annotation method was proposed and was used to identify instances of challenging behaviours in a recorded session between a child with autism and stimuli group that included social robots. Different features were extracted and investigated with three different machine learning algorithms. Additionally, an assistive tool that displays the session, physiological changes, predictions of the three algorithms was developed and presented. The best developed model showed promising results across all the evaluation metrics.

The findings of this work could help in addressing challenging behaviours among children with autism more efficiently. A detection system using wearable sensors can notify the parents or caregivers to intervene early and prevent the progression of unwanted behaviours. Incorporating social companion robots can also assist in mediating and reacting accordingly to mitigate the intensity and frequency of challenging behaviours.

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