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# AI FOR MELTDOWN DETECTION IN AUTISM USING WEARABLE SENSORS.

BY

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# ABSTRACT

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Title: AI for meltdown detection in autism using wearable sensors.

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Autism spectrum disorder is a neurodevelopmental disorder that is associated with many symptoms, such as impairments in social skills, communication, and abnormal behaviors. Children on the spectrum exhibit atypical, restricted, repetitive, and challenging behaviours. The occurrence of such behaviours poses challenges to caregivers and therapists during therapy sessions. In this study, we investigate the feasibility of integrating wearable sensors and machine learning techniques to detect the occurrence of challenging behaviours among children with autism in real-time. Children wore a wearable device, which collected physiological data in five sessions. The video recordings of the sessions were analyzed to identify the instances of challenging behaviours. Four machine learning techniques were used to leverage various features extracted from the wearable sensors to automatically detect challenging behaviors. The best prediction performance was observed when the XGBoost algorithm was used with all gathered features (i.e., accuracy of 99%). Physiological features were found to be more effective than kinetic ones for the prediction task. Among various physiological features, the heart rate was the main contributing feature in the detection of challenging behaviours. Furthermore, experiments revealed that changes in the HRV parameter (i.e., RMSSD) correlated to the instances of challenging behaviours. The findings of this work motivate research towards methods of early detection of challenging behaviours which enable timely intervention by caregivers and parents.

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# CHAPTER 1: INTRODUCTION

Autism spectrum Disorder (ASD) is a heterogeneous and complicated neurodevelopmental disorder. it usually accompanies with difficulties in social communications, restricted or repetitive behaviors, and difficulties in verbal/nonverbal interactions. It's reported that 1 in 88 individuals have ASD [1]. Children on the spectrum experience a set of challenging behaviors that might lead to a meltdown event and even can cause self-damaging behaviors if the child still be stimulated [2]. Challenging behaviors include hand flapping, body rocking, and head banging [3][4]. Early intervention can help in managing such behaviors [5][6]. Software solutions based on machine learning techniques will be applied in this work to anticipate such behaviors and to provide reactions through therapist-child sessions. To employ machine learning models for challenging behaviors detection, several behavioral characteristics need to be measured, such as physical movements and social interactions. There are three traditional methods for measuring such behaviors [7]: (1) paper-and-pencil evaluation, (2) direct observation of behaviors, and (3) video camera-based method. Paper-and-pencil evaluation is based on making live interview which suffers from the subjectivity in evaluation. Also, the detection of intensity and duration of the challenging behaviors isn't accurate in this method [8]. The direct observation procedure is also unreliable, as the therapists can't capture the high-speed movements and document all the challenging behaviors instantaneously by using this method. Second, detecting the start and end points of the challenging behaviors is difficult. Third, the therapists are not able to record concurrently all the environmental conditions and the challenging behaviors. In the video-based method, therapists depend on video capturing, offline annotation, and analysis of the challenging behaviors. This observational approach is much more accurate than the two previous methods. However, it's time consuming and can't be adopted as a practical clinical tool [9]. In light of the increased frequency of autism in children and the lack of reliable methods for measuring challenging behaviors, it is critical to develop efficient and automatic methods to detect accurately such behaviors in real-time. Therefore, constructing a time-efficient tool and quantification system would benefit ASD researchers, families, caregivers, and therapists [10]. Furthermore, such a tool will help evaluate the adaptation of individuals with autism to the different life contexts within an ecological approach. In other words, it would lead to mitigating the frequency of the meltdown events that are predicted by the sudden rise in atypical behaviors [10]. In addition, any automated quantification of atypical behaviors would certainly assist parents or caregivers in removing the stimuli that might cause developing the challenging behaviors by involving children in certain educational activities or social interactions. Releasing such stimuli would decrease the intensity and frequency of the undesired behaviors. Consequently, alleviate their severity on the child and the surrounding individuals [11][12]. A real-time implementation of challenging behaviors detection system would be advantageous for therapists to evaluate the efficiency of the required interventions. A wristband wearable sensor (Empatica E4, Milano, Italy) was used in our experiments to measure the different physical activities and the corresponding physiological signals of the body during the experiments via embedded accelerometer, Electrodermal Activity, Temperature, Heart Rate, and Blood Volume Pulse sensors. Manual annotation was carried out for the participants behaviors. The behaviors were annotated as either 'Challenging' or 'Non-challenging'. A challenging behavior is considered to be any action that is interfering, repetitive, stimming, and might inflict harm on oneself or others. Challenging behaviors also included head banging, arm flapping, ear pulling, kicking, and scratching. Despite considerable research in this orientation, several challenges for automatic detection of challenging behaviors using wearable sensors are still unsolved, particularly in real-time approaches. One of the critical challenges for accurate and reliable detection of challenging behaviors is to extract robust and efficient features from the vital signals obtained from the wearable sensors. Therefore, four-time domain features were extracted from the raw data acquired from the wearable device to be fed into the machine learning-based models. Another challenging point toward developing a real-time detection system is due to personalization factors attached with inter and intra-subject variability [13]. Intra-subject difference is basically mapped with variability in the shape, frequency, duration, and intensity of challenging behaviors in each subject with ASD. On the other hand, inter-subject variability identified by the identical variability through different subjects [10]. These two types of variances within and across individuals with ASD triggers the imperative of developing an adaptive algorithm which is able to adjust to new behavioral patterns. To this end, here we present two complementary studies with four main contributions:

1. Integration of machine learning techniques and wearable sensors to detect challenging behaviours

2. Investigating the influence of different physiological signals in the prediction of challenging behaviours.

3. Demonstrating the feasibility of automatic and real time detection of challenging behaviours using machine learning techniques.

4. Developing an assistive annotation tool to monitor the physiological signs, videos, and to visualize the predictions of the developed machine learning algorithms.

# CHAPTER 2: BACKGROUND

This chapter presents a theoretical background about the essential topics included in this search. This chapter begins with a general description of autism disorder, its prevalence rates, and its discriminating symptoms. Then, it describes the challenging behaviors experienced by individuals with autism. Finally, the chapter provides previous studies on the various applications of challenging behaviors detection and the applied methods.

## Autism

Autism is a neurodevelopmental disorder characterized by lifelong challenges and difficulties in communication, social interaction, and the verbal/nonverbal behaviors (American Psychiatric Association [14]). Autism spectrum Disorder (ASD) is a condition that impairs neurodevelopment and diagnosed in early infants. Furthermore, compared to neurotypical children, children with ASD are exposed to experience a variety of behavioral challenges on regular basis [15][14]. The prevalence rate of ASD among children constitutes a growing source of concern worldwide. For example, The Centers for Disease Control Prevention (CDC) estimates that one out of every 59 children in the United States has ASD (Autism and Developmental Disabilities Monitoring Network [16]). However, based on the results of a recent parent survey; that found a prevalence rate of one in 45, this might be an underestimate (Zablotsky et al. [17]). Due to the high prevalence rate and the diverse nature of ASD, the manifestation of challenging behaviors among children on the spectrum may change significantly in their intensity and frequency. Consequently, determining such differences was a critical approach for many researchers.

## Challenging Behaviors

The dispositions and manifestations of ASD in children on the spectrum are quite distinct and complicated. Autism affects such individuals and creates many deficiencies and obstacles in their communication abilities, social interactions, behaviors, sensory input perception, and social life [15]. Self-stimulatory behaviors, perfectionist tendencies, meltdowns, and delayed echolalia are also exhibited [18]. Children with ASD have more extreme and aggressive behaviors than their neurotypical counterparts due to the nature of the disorder. Those with perfectionist inclinations and emotional regulation issues, for example, are more likely to engage in depression, anxiety, and aggressive behavior. Frustration is another component that contributes to the expression of more challenging behaviors. When children with ASD are exposed to new unexpected, stressful, and loud situations, such as those seen in hospitals, they may become frustrated [18][19]. Furthermore, such situations are rich in stimuli that may overwhelm their bodies' senses, making addressing their needs even more difficult as a result of the increasing conflict with the new environmental alterations. Withdrawal, repeated and stereotyped routines, violence against others, self-injury, tantrums, meltdowns, and property damage are all examples of challenging behaviors. Not only such acts harm the children, but they might also injure everyone around them, including other children, nurses, patients, caregivers, parents, and family members [20].

## Applications of Machine Learning in ASD

Machine learning can be categorized into two sections, supervised and unsupervised learning. Supervised machine learning includes algorithms that predict an output feature (the dependent variable) based on input features (i.e., the independent variables). The output feature can be continuous or categorical. Unlike unsupervised learning (i.e., clustering), supervised learning contains datasets where the target variable is given to the model at training time to map the input data with the target feature. To build a successful supervised learning model, the model must be able to (a) predict the target feature accurately for a training dataset with an acceptable degree of accuracy and (b) be generalized to new input data other than those given to training the model. To enhance the ability of a model to make forecasting on unseen data, the cross-validation method is often applied. This technique allows the model to be tested on a subset of data after removing it during the training phase. A K-fold cross-validation method splits the training data into K-categories then trains the model on all but one of the categories and tests on the rest. The procedure is repeated until the model has been trained on all the given data. The performance scores are averaged across all the rounds. The success of the supervised machine learning model is commonly measured according to the accuracy metric (i.e., the ability to correctly classify the unseen datapoints into distinct classes). Furthermore, sensitivity (i.e., the ability to correctly determine true positives) and specificity (i.e., the ability to correctly determine true negatives) are also used as evaluation metrics. Another metric to measure the success of the supervised machine learning model is AUC or area under the receiver operating character curve (ROC). The ROC metric provides a plot of specificity versus sensitivity. And the area under the curve represents how well a model can distinguish between positive and negative categories.

## Supervised Machine learning and wearable sensors in ASD Diagnoses

The supervised learning experiments, conducted by the related studies, applied several classification algorithms to detect behavioral patterns in different datasets. Such algorithms is SVM which has been utilized in attempts to enhance the accuracy of diagnoses and give valuable insight into how various characteristics (such as eye movement data, standardized assessments, neuroimaging data) can assist in differentiating between patients with and without ASD. Bone et al. [21]. trained and cross-validated using SVM classifier to distinguish ASD from other developmental disorders based on data collected from two well-known standardized assessments, the Social responsive Scale (SRS; Constantino and Gruber [22]) and the Autism Diagnostic Interview, Revised (ADI-R; Le Couteur et al. [23]). The participants were categorized into two categories: 10 years old or older individuals and under 10 years of age individuals. The data sample contained 1264 individuals with ASD and 462 individuals with a developmental disorder other than ASD. A classification specificity and sensitivity were reported as 59.0% and 89.2% respectively for individuals 10 years of age or older, and 53.4% and 86.7% respectively for individuals under 10 years old. Jarraya et al, [24]. investigated different emotions during meltdown in order to construct an emotion recognition system using several machine learning techniques. 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 [25]. 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.

Goodwin et al [26], investigated the detection of stereotypical motor movements in children with autism using three-axis accelerometers worn on different parts of the body (i.e., wrists and torso). The data were collected from six individuals with autism. The recognition performance of two employed classifiers (i.e., decision tree and support vector machines) achieved accuracies ranging from 81.2% to 99.1%. Rad et al [27], used the same datasets published by Goodwin et al [26], to implement a convolutional neural network and long short-term memory algorithms. Their results showed that applying deep learning techniques on the acceleration data would improve the detection of stereotypical motor movements in real-time conditions. Another study explored techniques to detect common motor movements for children diagnosed with autism [28]. The study investigated the impact of these motor movements on learning and social interactions using deep learning approaches. Another study investigated the potential of sensory processing in assisting in the diagnosis and classification of ASD [29]. 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 without. Their method showed promising results (i.e., 84.6%) in identifying autism sensory dysfunction during the visual stimuli condition. Another study considered using physiological measurements namely electrocardiograms, respiration, skin conductance, and temperature to categorize evoke valence (i.e., positive or negative) and arousal intensities (i.e., low and high) [30]. 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%. Other studies investigated the possibility of integrating wearable sensors and machine learning techniques to interpret the physiological and kinematic properties of the human body to predict or detect specific affective patterns of emotions or behaviours[31] [30][32]. Some of the sensors and modalities considered were photoplethysmogram, electrodermal activity or galvanic skin response, heart rate, temperature, acceleration, and skin conductance level. There is a growing interest in incorporating wearable sensors in autism therapy. For example, Fazana et al, presented a framework that incorporates a set of existing programs for augmentative and alternative communication with wearable sensors to improve the communication skills, enhance behaviours, and promote health monitoring of children with autism [33]. Pollreisz et al [34], established an emotion recognition system using Empatica E4 watch to collect electrodermal activity, heart rate, and temperature values from ten young adults. The reported success rate for emotions recognition was 65% using a decision tree algorithm. Heart rate variability parameters were also considered (Table 4.1). Lee et al [35], measured both the heart rate variability and galvanic skin response to identify emotions using neural networks. They analyzed the data collected from participants in the frequency and time domains. They found that changes in some of the HRV parameters (i.e., RMSSD and SDNN) might lead to elevated activity in the sympathetic nervous system, which could be inlpterpreted as a sign of fear. Their reported accuracy of the best trained model was 80.2%.

Yap et al [36], investigated the impact of listening to music on the heart rate and anxiety levels of children with autism to identify which music genre could calm the children. They devised a mobile application that was connected wirelessly to a pulse sensor to measure the heart rate. The goal of their application was to improve communication and learning skills, supporting emotion regulation, and monitoring heart rate while listening to music. Lydon et al [37], focused on investigating the correlation between heart rate and challenging behaviours experienced by children with autism. They analyzed the heart rate data before, during, and after the instances of challenging behaviours in three children with ASD. They found that such behaviours might increase arousal for some children with autism. The prediction of challenging behaviours has also been proposed by J. Nuske et [38]. They investigated the possibility of applying heart rate to predict such behaviours in children with autism based on statistical analysis for the acquired data. Forty-one children diagnosed with autism were involved in their experiments. The participants wore an electrocardiograph monitor and low-level stress was stimulated. considering the intrusive nature of the device and to avoid pulling the ECG electrodes, vests with pockets were used to house the device while placing the electrodes on the backs of the children. Their results showed that physiological stress could be an early sign for the occurrence of challenging behaviours.

# CHAPTER 3: DETECTION OF CHALLENGING BEHAVIOURS: A PILOT STUDY

## Introduction

Children on the spectrum exhibit challenging behaviours and aggression at higher rates compared to their neurotypical peers [39][40]. Challenging behaviours take different forms at varying intensities depending on the degree and manifestation of ASD [41][42]. 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, such as wearable devices and robots, in healthcare applications such as health monitoring, surgery, and in the diagnosis and therapy of children with autism [43][44][45][46]. Children on the spectrum are found to be fascinated with technologies such as social robots, which are reportedly leading to positive outcomes [47][48]. However, some studies reported instances of aggression toward robots during therapy sessions [49]. Such challenging behaviours could potentially lead to injuries [50]. To mitigate potential harm, hardware approaches in social robotics were investigated, but found to be limited in terms of applicability and effectiveness [51][52][53][54][55]. Alternatively, some approaches resorted to using machine learning predictive models to detect the occurrences of challenging behaviours and aggression using embedded sensors within a social robot and wearable devices [56][57][58][59][60].

To employ machine learning models for challenging behaviour prediction, several behaviour characteristics need to be investigated, such as physiological signals and physical movements. 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 is found to influence challenging behaviours due to the relation between hyperarousal and sensory reaction [61]. Jansen et al. [62] 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 [63]. A strategy that relies on a low arousal approach was proposed to manage challenging behaviours [61]. To date, limited work has been done incorporating wearable devices to detect challenging behaviours during child and robot interaction.

### Contributions

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. 3.1). Furthermore, different machine learning models with various wearable data configurations are tested. The following are the contributions of this study:

1. Defining an effective annotation to distinguish challenging behaviours.
2. Investigating the influence of different physiological signals in the prediction of challenging behaviours.
3. Demonstrating the feasibility of automatic and real time detection of challenging

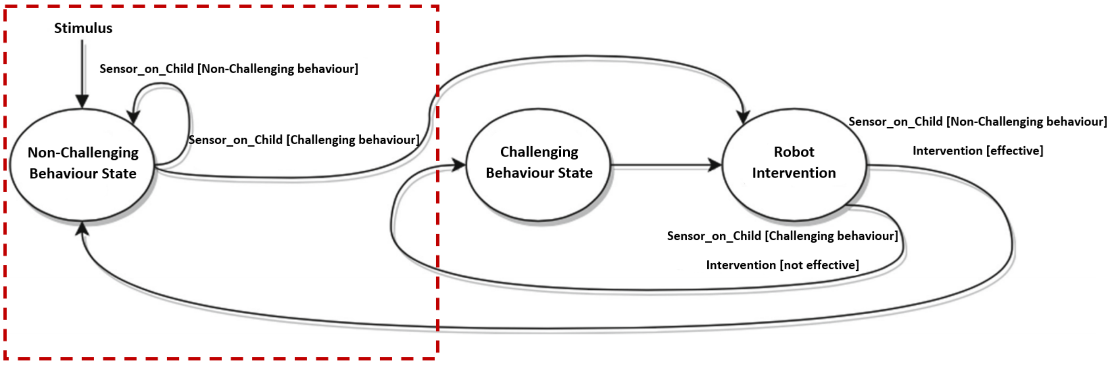


Figure 3.1: The intervention framework with wearable sensors and social robots. The wearable sensor detects the occurrence of physiological arousal and notifies the social robot to intervene. The highlighted area represents the focus of this study (Adapted from [64]).

behaviours using machine learning techniques.

4. Development of an assistive annotation tool to monitor the physiological signs, videos, and to visualize the predictions of the developed machine learning algorithms.

## Methodology

### *Participants*

A ten years 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).

### *Stimuli*

The experiments considered different toys and two social robots as stimuli (Fig. 3.2a). The toys were a green ball made of rubber, cymbals, a plastic train with multiply 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 seal robot (PARO Robots, USA) were the two social robots considered. More details about the stimuli can be found in an earlier work [65].

### *Wearable Device*

The wearable sensor (Emaptica E4 wristband) was used in the experiment (Fig. 3.2b). The E4 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 with autism. 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.

2. Electrodermal Activity (EDA): Measured the variation of skin conductance and the electrical properties of the skin.

3. Inter-Beat 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.

### *Algorithms*

In this study, 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 biological 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 algorithms, 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. Classification tree is when the target can take a discrete value. If not, the model is called a regression tree.

### *Procedures*

#### *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


Figure 3.2: 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 [65]. 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).

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 vital signals changes as the child interacts with the stimuli (Fig. 3.2c). 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 their therapy sessions and recognition systems.

*Machine Learning Model Development*

The annotated data was preprocessed to ensure consistency between the different signal types. The sensors inside the wearable device acquire the data at different frequencies. Hence, frequency matching at 32 Hz was performed to ensure the frequencies of all the signals were the same. Elimination of outliers due to 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 compared to the raw features. Hence, only the time-domain extracted features were considered in this study.

## Results

Three classifiers were evaluated in 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 3.1).

With ACC alone, all 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 wearble 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. 3.3a), the use of physiological features led to better classification performance than kinetic ones. 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. 3.3b).

Table 3.1: 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 |

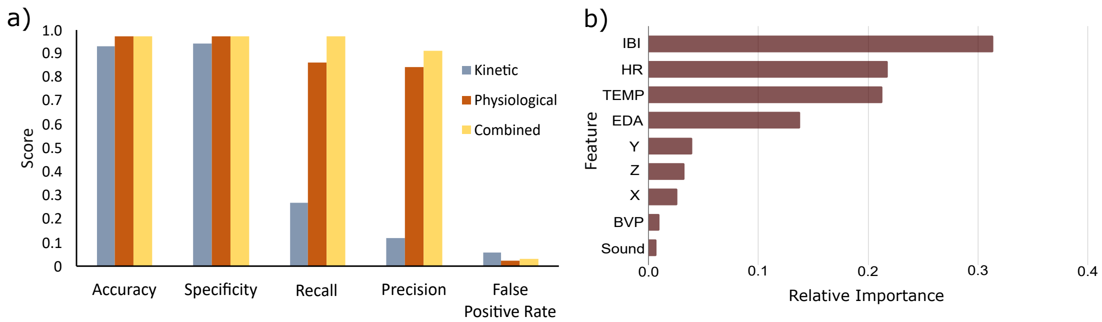


Figure 3.3: The outcomes of the experiments conducted in this studies. a) The evaluation metrics' results for the three tested categories on the best performing classifier (i.e., MLP). b) The feature importance scores for each of the investigated features.

## Discussion

Understanding the interactions during the session is essential to better interpret the occurrence of the challenging behaviours through 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 subject was most attracted to the colourful plastic train, which produced soap bubbles. This triggered a state of excitement in his facial expressions and physical movements such as jumping and arm waving. After 13 mins 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 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 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 inter beat interval signals (Fig. 3.2c). 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 of both improved the overall performance of the machine learning model as supported by the results.

Parents or caregivers need to observe the children directly to be aware of challenging behaviours. Continuous observation might pose as a challenge to many busy caregivers. Hence, having a technology that 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 human professionals and experts, machine learning models lack the means to explain the reasons behind their predictions. This limitation might be hindrance to the adoption of such technologies in sensitive applications such as detecting challenging behaviours among special needs population. 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, interpretability techniques attempt to provide some reasoning behind models' predictions [66]. 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 or about to undergo a challenging behaviour or meltdown event based on reading the physiological data. For example, by telling the parents that your child vitals (e.g. IBI or HR) are not within the normal range. We believe that future studies should focus on incorporating interpretability 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, 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 establishment 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. 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.

## Conclusion

The occurrence of challenging behaviours among children with autism interferes negatively in all aspects of daily functioning including therapy sessions. Technology can be used to detect such behaviours and improve therapy. In this study, we have investigated the feasibility of detecting challenging behaviours using wearable sensor and machine learning techniques. An annotation was proposed and 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 will help in addressing challenging behaviours among children with autism more efficiently. A detection system built using wearable sensors would notify the parents or caregivers to intervene early and prevent the progression of unwanted behaviours. Incorporating social companion robots would also assist in mediating and reacting accordingly to mitigate the intensity and frequency of challenging behaviours.

# CHAPTER 4: HR AS A PREDICTOR OF CHALLENGING BEHAVIOURS

## Introduction

Autism Spectrum Disorders (ASD) is a developmental and neurological disorder that causes impairments characterized by difficulties in social communication and restricted behaviours [14]. Children with ASD exhibit challenging behaviours frequently at varying intensities and in different forms, such as meltdowns, tantrums, property destruction, and aggression [39][67][41]. The prevalence rate of challenging behaviours and aggression among children with ASD is high [68][69][70]. Being frustrated and the presence of new stimuli are some of the contributing factors that increase the occurrence of challenging behaviours [71].

Early intervention can help in managing challenging behaviours [5][6]. The advances in technology are being integrated in the screening of ASD and in therapy sessions to improve the outcomes [72]. Social robots are examples of adopted technologies in therapy that reported positive outcomes (e.g. improved communication, motor, and social skills) among children with autism [73].

Physiological changes of the human body can provide indicators about the current state using wearable devices and machine learning techniques. A previous study found that challenging behaviours are influenced by the physiological arousal of children with autism [61]. Another study reported a difference in the heart rate between adults with ASD and normal adults during public speaking [62]. Research that detects challenging behaviours among children with autism during interactions with social robots is still limited [64].

Table 4.1: Some of the common heart rate variability (HRV) parameters that were previously considered in autism research [74]

| Parameters | Units | Domain | Description |
|---|---|---|---|
| RMSSD | ms | Time | Square root of the mean squared differences between successive RR intervals |
| SDNN | ms | Time | Standard deviation of NN intervals |
| LF | Hz | Frequency | Peak in low frequency range (0.04 to 0.15 Hz) |
| HF | Hz | Frequency | Peak in high frequency range (0.15 to 0.4 Hz) |

## Contributions

In this study, we conduct experiments using data acquired from five children with ASD and machine learning techniques to detect challenging behaviours during interaction sessions with toys and social robots. The contributions of this study are summarized as follows:

1. Integration of machine learning techniques and wearable sensors to detect challenging behaviours.
2. Evaluation of physiological and kinetic features in identifying challenging behaviors.
3. Analysis on the HR and HRV roles in supporting the detection.

## Materials and Methods

### *Participants*

Five male children with autism, ages ranging between 7 and 10 years old, participated in this study. The participants attended a local center for special needs in Doha, Qatar. Parental consent was obtained by the center. The sessions were conducted with each child individually with the supervision and assistance of a teacher or their caregiver. 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).

### *Stimuli*

Social robots and regular children's toys were used as stimuli in this study. The social robots were the humanoid Nao robot (Nao, SoftBank Robotics, Japan) and a white furred robotic seal (PARO Robots, USA). These social robots are shown in (Fig. 4.1b). The toys consisted of a squishy green rubber ball, multi-color train, brass cymbals, and wooden letter blocks that are placed on a toy truck. Further details regarding the stimuli used can be found in [65].

### *Wearable Device*

A wristband wearable sensor (Empatica E4, Milano, Italy) was used to obtain the data readings from the children during the experiments (Fig. 4.1a). The E4 wearable sensor contains a real-time clock and it is capable of recording physiological data signals to an internal memory (Fig. 4.1c). The physiological signals considered are as follows:

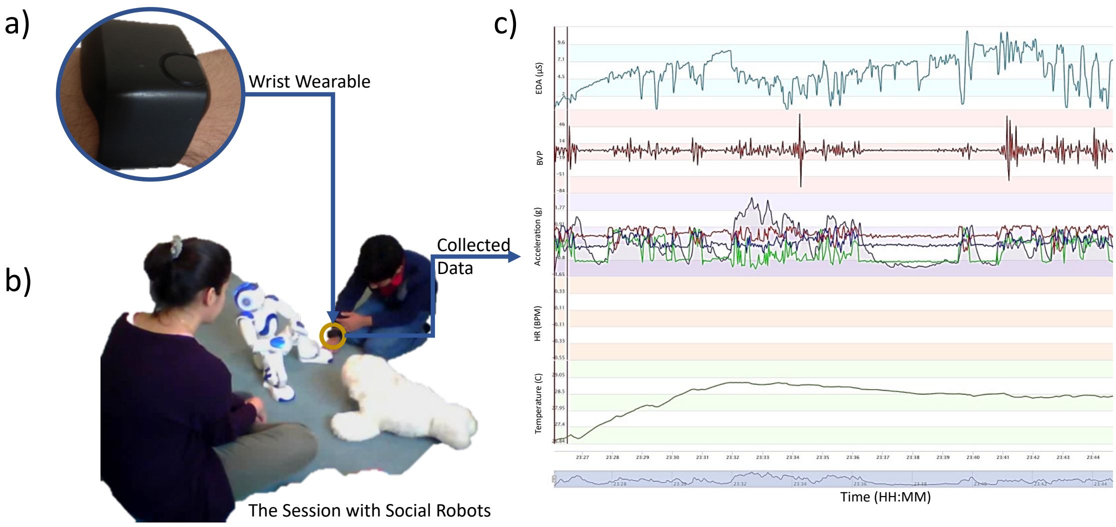


Figure 4.1: An overview of the adopted methodology in this study. a) The Empatica E4 wearable device. b) One of the children interacting with the social robots (See supplementary material). c) A sample of the acquired data using the wearable device.

1. Acceleration (ACC): measures wrist's motion changes in terms of the acceleration changes in the x,y, and z directions.

2. Electrodermal Activity (EDA): determines the change in skin conductance and the skin's electrical properties.

3. Temperature (TEMP): determines the temperature of the skin.

4. Heart Rate (HR): the number of beats per minute.

5. Blood Volume Pulse (BVP): determines the changes in the blood volume.

*Algorithms*

Several machine learning models were applied to detect the challenging behaviours in real time. The implemented algorithms were as follows:

1. Support-Vector Machine (SVM): non-probabilistic binary linear supervised learning model that can solve and classify both linear and non-linear problems.

2. Multilayer Perceptron (MLP): learning technique inspired by the biological brain that consists of layers of artificial neurons that can learn from data.

3. Decision Tree (DT): an algorithm that predicts the output by moving through the different discrete decision options that are represented in a tree-like structure until a conclusion is reached.

4. Extreme Gradient Boosting (XGBoost): an ensemble supervised machine learning technique which utilizes regularized gradient boosted decision trees to improve performance and classification speed.

## *Procedures*

### *Annotation*

Manual annotation was carried out for each of the five children's behaviours. This was done with the help of a free annotation software (BORIS, v. 7.10.2, Torino, Italy). The behaviours were annotated as either 'Challenging' or 'Non-challenging'. A Challenging behaviour is considered to be any action that is interfering, repetitive, stimming, and might inflict harm on oneself or others. Challenging behaviours also included head banging, arm flapping, ear pulling, kicking, and scratching.

### *Data Preprocessing*

To ensure consistency, the data acquired from the wearable device were preprocessed and the sampling frequency of every acquired data signal was set to 64 Hz. This is crucial since the different sensors obtain data at different sampling rates. The preprocessing stage included outliers removal and resampling the training data to ensure that classes are equally balanced. A portion equals to thirty percent of the original dataset was used as the unseen testing set. Initial experiments with the dataset indicated that the extracted features produced better performance when compared to the raw features alone. For this reason, only time-domain extracted features (i.e., mean, standard deviation, min, and max) were considered throughout this study.

## Results

### *Machine Learning Models*

Four machine learning algorithms were evaluated based on the evaluation metrics in addition to the prediction speed (Table 4.2). In the results, challenging behaviors were considered to be the positive class. The models were developed using Python libraries (i.e., Sklearn [75] and XGBoost [76]). The depth of the DT algorithm was set to *dynamic* and the *Gini* function was used for the splitting criteria. SVM used a radial basis function kernal with regularization parameter of 0.1 and a gamma parameter was set to *scale*. As for the MLP, it contained one hidden layer that consisted of 100 neurons with weights adjusted using stochastic gradient descent at 0.0001 *L2* regularization. XGBoost was trained with *logistic* objective, *max depth* of 6, *aplha* equal to 1, *learning rate* of 0.3, and 100 *estimators*.

XGBoost showed better overall performance compared to other classifiers in terms of precision (0.88), recall (0.99), F1-Score (0.93), and accuracy (0.99). Additionally, it has achieved the fastest time (i.e., 0.24 sec) to predict the test samples. The second best performing algorithm was DT followed by MLP. SVM achieved the lowest performance and took the longest time to predict the test samples, which was around 2.5 seconds. Due to its performance, XGBoost has been considered in the upcoming experiments.

### *Features Effects*

To measure the contribution of each sensor to the prediction performance, sensor features were added gradually to the overall feature vector and the results were compared for the individualized models and combined model (Table 4.3). With ACC alone, the classifier performed poorly on all five participants individually and on their combined model. Set 2 considered the effect of adding the HR sensor reading to the feature vector that has led to a large increase in performance for all participants individually and their combined model. As for Set 3, adding BVP had little effect on all the models. Adding TEMP improved the performance of the individual personalized models and their combined model slightly. Finally, adding EDA in Set 5 has led to a further increase in the overall performance for most of the models.

### *Kinetic vs Physiological*

To understand which category of features are most significant, kinetic, physiological, and a combination of the two were investigated. The evaluation metrics results for the two categories and their combined features are depicted in Figure 4.3. The results showed that kinetic features alone performed poorly with respect to physiological and combined features. Physiological features were found to perform similarly to the combined features. In spite of this, the overall best performance comes from using the combined features.

To further investigate how each individual feature contributes to the performance of the machine learning model, the importance of each individual feature with respect to F-score were plotted using the built-in XGBoost tool [76]. The individual plots for each participant revealed a discrepancy between the importance of each features (Fig. 4.2a). However, HR appears to be the most important factor for the majority of the participants followed by either EDA or TEMP. The combined plot for the generalized model revealed that the most important feature was HR then followed by EDA, TEMP, ACC readings in the Y, Z, and X directions, and finally BVP (Fig. 4.2b).

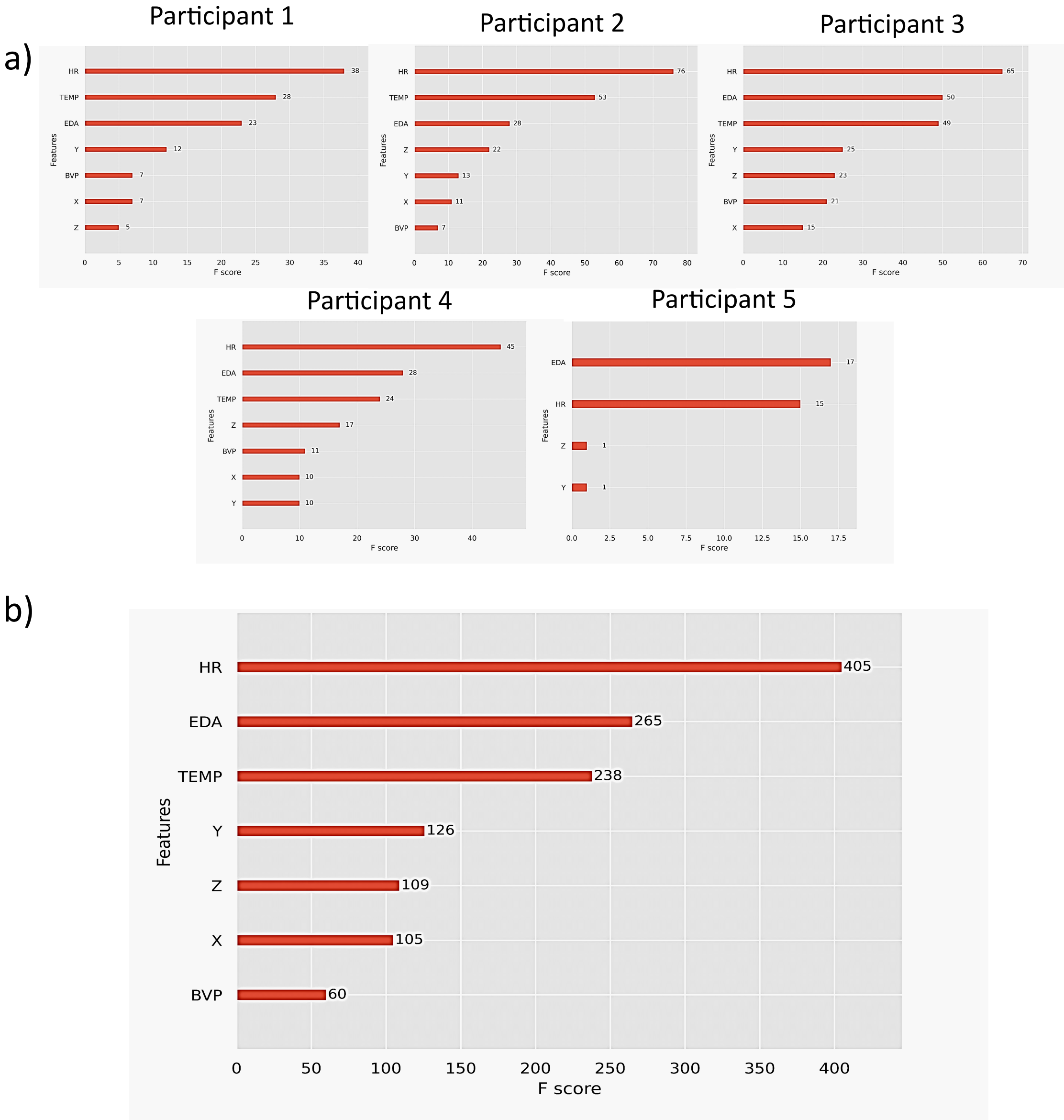


Figure 4.2: The contributing features on the performance of the best prediction algorithm (i.e., XGBoost). a) For each child. b) For the combined model.

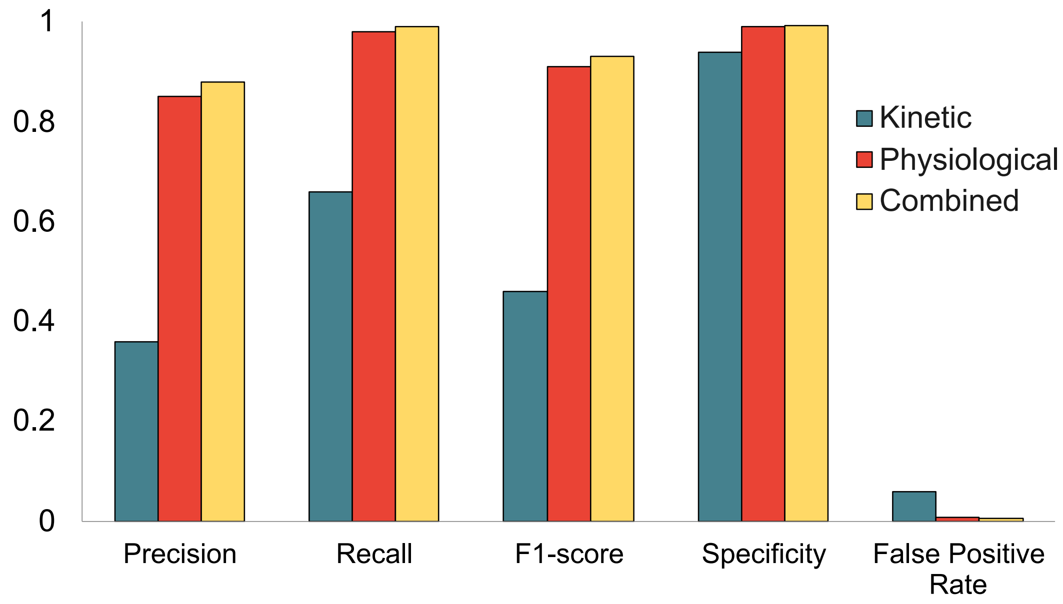


Figure 4.3: The evaluation metrics results for the three categories using the best performing algorithm (i.e., XGBoost).

To further investigate the importance of heart rate parameters, the heart rate variability (HRV) based on calculating the RMSSD was considered. The RMSSD was derived from the interbeat interval signal of the wearable device using a sampling frequency of 64 Hz. The HRV changes for one of the children during different states were investigated (Fig. 4.5). The HRV values appear to be highest during rest state while lowest during the occurrence of a challenging behaviour (Fig. 4.5c).

A machine learning model was trained that contained an additional feature called HRV. The results showed the importance of HRV for a child that exhibited more challenging behaviours (Fig. 4.4a) is higher compared to a child that exhibited less instances of challenging behaviours (Fig. 4.4b). Furthermore, the contribution of HRV outweighed that of HR in the child exhibiting challenging behaviours and vice verse in the child ex-

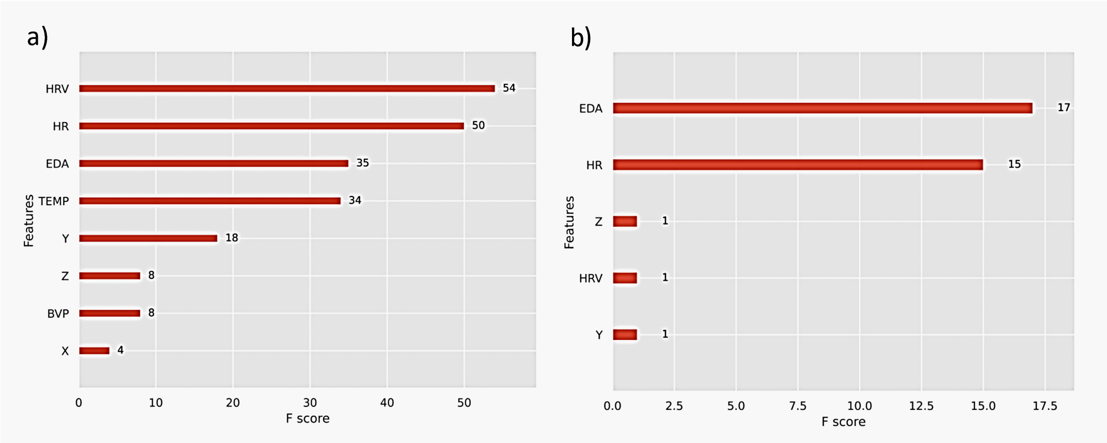


Figure 4.4: The contribution of HRV in the performance of the machine learning model (i.e., XGBoost). a) Represents the feature importance for one of the participants whose challenging behaviours were more frequent and intense. b) The feature importance for another participant who displayed less challenging behaviours.

Table 4.2: The evaluation metrics scores for the four algorithms and their test times (in seconds) needed to evaluate the test samples

| | Precision | Recall | F1-Score | Accuracy | Testing Time |
|---|---|---|---|---|---|
| XGBoost | 0.88 | 0.99 | 0.93 | 0.99 | 0.24 |
| MLP | 0.67 | 0.98 | 0.80 | 0.97 | 0.36 |
| SVM | 0.24 | 0.91 | 0.38 | 0.85 | 2.48 |
| DT | 0.87 | 0.92 | 0.89 | 0.98 | 0.29 |

periencing less challenging behaviours. Hence, the detection of challenging behaviours appears to depend on the changes in HRV.

## Discussion

To properly understand the occurrence of challenging behaviour, it is vital to analyze the interactions of the participants throughout their sessions. The children displayed different levels of activity and interaction with the presented stimuli. The participants

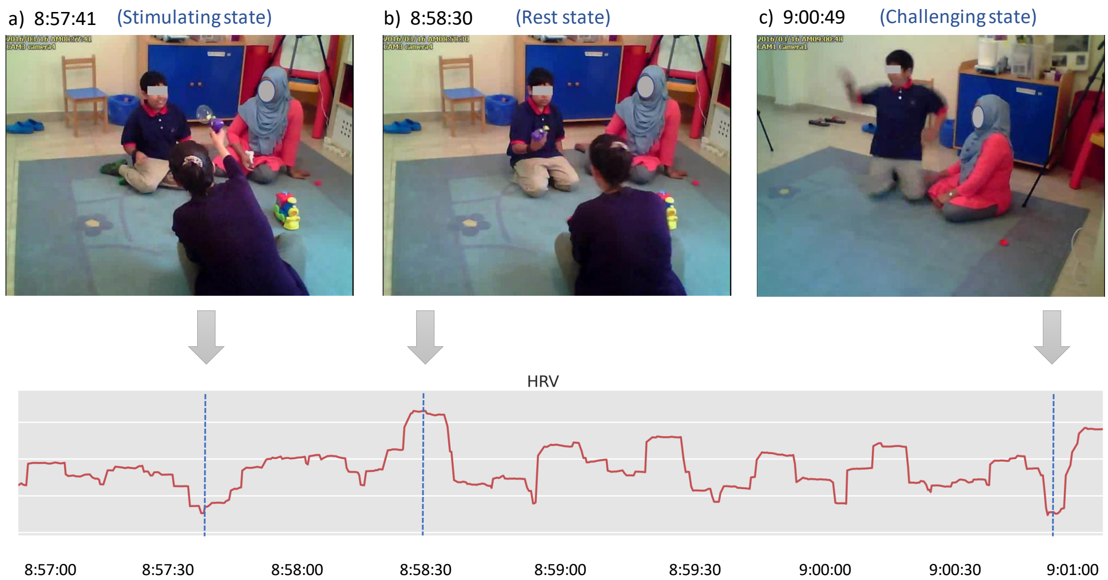


Figure 4.5: The changes in the HRV (i.e., RMSSD) corresponding to different states. a) The child is overwhelmed and stimulated by the bubble gun toy. b) The child is in a rest state. c) The child experiences a challenging behaviour.

Table 4.3: Results for the experiments considering the impact of adding each feature to the feature set for the personalized models of each participant and their combined generalized model.

| Set | 1 | | | 2 | | | 3 | | | 4 | | | 5 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Feature | ACC | | | Set 1 + HR | | | Set 2 + BVP | | | Set 3 + TEMP | | | Set 4 + EDA | | |
| Metric | Prec | Recall | F1 | Prec | Recall | F1 | Prec | Recall | F1 | Prec | Recall | F1 | Prec | Recall | F1 |
| Participant 1 | 0.35 | 0.87 | 0.50 | 0.63 | 1 | 0.78 | 0.62 | 1 | 0.77 | 0.79 | 0.97 | 0.87 | 0.79 | 0.97 | 0.87 |
| Participant 2 | 0.53 | 0.89 | 0.67 | 0.72 | 1 | 0.84 | 0.71 | 0.97 | 0.82 | 0.77 | 0.99 | 0.86 | 0.92 | 1 | 0.96 |
| Participant 3 | 0.51 | 0.75 | 0.61 | 0.69 | 0.90 | 0.78 | 0.69 | 0.89 | 0.78 | 0.96 | 0.99 | 0.97 | 0.96 | 0.99 | 0.98 |
| Participant 4 | 0.37 | 0.72 | 0.49 | 0.75 | 0.98 | 0.85 | 0.75 | 0.98 | 0.85 | 1 | 0.98 | 0.99 | 1 | 0.98 | 0.99 |
| Participant 5 | 0.26 | 0.64 | 0.37 | 0.43 | 0.91 | 0.58 | 0.58 | 0.97 | 0.73 | 0.54 | 1 | 0.70 | 0.57 | 1 | 0.73 |
| All Participants | 0.36 | 0.66 | 0.46 | 0.62 | 0.86 | 0.72 | 0.63 | 0.86 | 0.72 | 0.82 | 0.98 | 0.89 | 0.88 | 0.99 | 0.93 |

showed fascination in the colourful train that produced bubbles, which encouraged their engagement. The fascination and interaction came in various forms that included both facial expressions and physical movements. Most of the participants did not prefer the white robotic seal, which could be due to its animal-like appearance. Hence, that might have led to participants exhibiting challenging behaviours. Furthermore, the robotic humanoid caused confusion and curiosity as some of the sudden movements produced by it led to negative reactions by some of the participants.

In this work, we investigated the detection of challenging behaviours among children with autism using wearable sensors to acquire data and machine learning techniques. While there are many machine learning approaches, not all are suitable to be considered in such application. In addition to prediction accuracy, a system must also make predictions fast enough for timely intervention. In our evaluations, XGBoost algorithm fulfilled these two criteria.

The findings showed that the heart rate (HR) was the most significant contributing feature on the performance of the classifying model for almost all the participants. Our interpretation is that challenging behaviours are usually accompanied by higher stress levels, which lead to an increasing in the HR above the baseline [77]. Studying the contributions of both kinetic and physiological features in behavioural classification helped us to better understand the nature of challenging behaviours. More precisely, it was observed that most challenging behaviours tend to involve some sort of specific hand movements. With this in mind, these hand movements were distinguished from regular hand motion through the help of the accelerometer. Considering HR along with other modalities would offer a valuable decision support during moment-to-moment treatment planning for individuals with autism.

Another experiment was conducted to elucidate the relationship between heart rate variability (HRV) and challenging behaviours. We found that HRV decreased during stress and stimulating episodes while it increased through rest states. With exception to one participant, the HRV analysis for the participants showed a strong correlation between the fluctuations of HRV and the occurrence of challenging behaviours. A possible explanation for these disparate findings is that children with autism may not have a stable system for regulating emotions [38]. The children initially interacted with the social robots with fear at different levels and intensities. This variation in emotions has led to distinct representations of the HRV signal. Hence, HRV can be used as an indicator for the occurrence of challenging behaviours when it is associated with high reactive interactions in children with autism. Nonetheless, further research is required on a larger number of participants to outline the psychological changes during the exhibition of challenging behaviours.

Employing wearable sensors allows for lower costs, non-invasive, and less restraining methods in tracking motor movements and physiological stress for children with autism. Based on the findings, it is promising to derive HRV parameters from the wearable sensors to acquire extra information. Dedicated warning techniques that get activated due to an increase in challenging behaviour episodes would provide a valuable support for children with autism. The benefits of such systems are magnified for non-verbal individuals who have restricted means to express their stress to their parents or caregivers [78]. Hence, parents or caregivers, or even a social robot intervene early to remove the stimuli causing that challenging behaviour [64].

One of the main limitations in this study was the low frequency of the observed challenging behaviours compared to non-challenging ones. While resampling techniques to balance the challenging and non-challenging behaviours can be used during the training phase, collecting more data that contain more instances of challenging behaviours is essential to capture the full spectrum of such behaviours. Another limitation was that collecting data was restricted to utilizing a wrist wearable device within controlled environmental conditions. Children with autism might not tolerate the wrist wearable. Hence, they might attempt to remove it, throw it, or even hurt themselves with it (e.g. in head banging). Future work should investigate different body's locations that are less intrusive to place one or multiple wearable devices that can recognize different patterns of behaviours at the same time. Additionally, acquiring data should be conducted under less controlled conditions and closer to their daily living scenarios to generalize the observed challenging behaviours in children with autism throughout the day.

## Conclusion

The advances in technology can be exploited to help target challenging behaviours among children with ASD. The combination of wearable sensors to detect behaviours and social robots to respond have a great impact on the outcomes of therapy sessions. In this study, we have conducted several investigations using wearable sensors and machine learning techniques to detect challenging behaviours among children with autism. The wearable sensors acquired different physiological and kinetics signals from five children. Annotated video sessions and time extracted features were considered to evaluate the detection models. Four machine learning techniques were evaluated and the best, based on XGBoost, was considered in further tests. Features tests were conducted to evaluate the effects of adding each feature to the existing pool of features. In terms of feature importance, heart rate followed by electrodermal activity and temperature were found to be the most affecting features on the performance of the prediction model. Testing the categories of features revealed that physiological based features provided more useful information to the machine learning model compared to kinetic features, hence, improving its performance considerably. The heart rate variability changes based on RMSSD parameter was also derived and investigated. This parameter was found to correlate with challenging behaviours and to be a major contributor to the prediction performance.

The outcomes of this work pave the way towards the development methods and tools based on machine learning techniques and wearables technologies that can be used to detect challenging behaviours and to be integrated into social robots-aided sessions.

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