Recognition of aggressive behaviors of children toward a social robot

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***Abstract*— Social robots are being considered to be a part of the therapy of children with autism. During the interaction, some aggressive behaviors could lead to harmful scenarios. The ability of a social robot to detect such behaviors and react to intervene or notify the therapist would improve the outcomes of therapy and prevent any potential harm toward another person or to the robot. In this study, we investigate the feasibility of the Multi-layer Perceptron (MLP) artificial neural network in classifying 6 interaction behaviors between a child and a small social robot. The behaviors were hit, shake, throw, pickup, drop, and no interaction or idle. Due to the ease of acquiring data from adult participants, model was developed based on adults' data and evaluated with children's data. The developed model was able to achieve promising results based on the accuracy (i.e. 80%), classification report (i.e. overall F1-score = 80%), and confusion matrix. The findings highlight the potential of neural networks to characterize children interactions with social robots to improve safety in therapy.**

I. INTRODUCTION

Autism Spectrum Disorders (ASD) is a condition that is diagnosed during childhood and causes impairments in social interaction, communication, and characterized by the exhibition of restricted interests or behaviors [1]. Furthermore, people affected by ASD may exhibit many forms of challenging behaviors, for example, aggression against others, withdrawal, tantrums, property destruction, and meltdowns [2]. The manifestation of challenging behaviors among children on the spectrum varies due to the diverse nature of ASD. There are many contributing factors toward the exhibition of challenging behaviors, such as frustration and new environments rich in sensory stimuli [3]. The reported occurrence rates of challenging behaviors among children with ASD are high (e.g. aggression rate greater than 50% [4]). Early intervention seems to be effective in the mitigation of such behaviors [5].

Recent advancements in technology are providing added tools for improved therapeutic sessions (e.g. independent learning, hands-on learning, and skill training [6]). Furthermore, previous studies demonstrated that children on the spectrum have a strong interest in technology, such as computer applications and virtual environments [7], [8]. Social robots have also been reported to help in improving the outcomes of therapy, such as improving communication, motor and social skills, eye contact, and joint attention [9],[10], [11], [12].

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Social robots are meant to elicit behaviors that may or may not trigger negative or unwanted reactions. The challenging behaviors that exist within ASD pose a risk to the children themselves or to others around them (e.g. throwing objects at others, kicking objects, hitting oneself, and banging on objects [2]). Previous studies showed that children might exhibit some aggression toward the robots [13], [14], [15]. In case of small robots, children might carry the robot and mishandle it. They might even throw the robot and hit others and cause potential harm. For example, hitting others with a small robot on the head might cause superficial injuries or subconcussions [16]. The existence of such behaviors demand for safer robotic designs [17],[18],[19]. To date, limited studies have been conducted to predict the unwanted physical interactions between a child and a robot, especially in relation to potentially harmful behaviors [20], [14], [21].

Unwanted physical interactions between a robot and a child take on different forms, such as hitting, throwing, and shaking. The ability of a robot to classify unwanted physical interactions serves many purposes. This can help in preventing potential harm, to monitor interaction, and to use the robot as a teaching tool. Furthermore, it can be used by the robot to help the child to stop the undesired behavior and prevent any progression [15]. For example, a child shaking or hitting a robot could be a precursor for a meltdown episode.

In this study, we investigate the potential of using an artificial neural network to develop a model that is capable of classifying the unwanted physical interactions between a child and a small social robot (Fig. 1). We have considered six different interaction behaviors, namely: hitting, shaking, dropping, throwing, picking, and being idle (i.e. no active interaction). This paper is organized as follows. Section 2 describes related work. Section 3 describes materials and methods. Section 4 includes results and discussion. Finally, Section 5 concludes the paper.

II. RELATED WORK

The research in human activity recognition relies on different sensors, technologies and wearable devices to acquire data [22], [23], [24]. Human activity recognition is being considered in the healthcare domain, for example, detecting falls among the elderly [25], [26]. Previous studies on fall detection considered wearable devices, ambient devices, and vision based devices [27]. Different sensors were used, such as accelerators, cameras, microphones, and gyroscopes [28]. Furthermore, different classification of falls were investigated (e.g. falls from sleeping or from walking) [27]. A recent study has considered using a wearable device on a belt to detect falls [29]. The device contains an accelerometer that

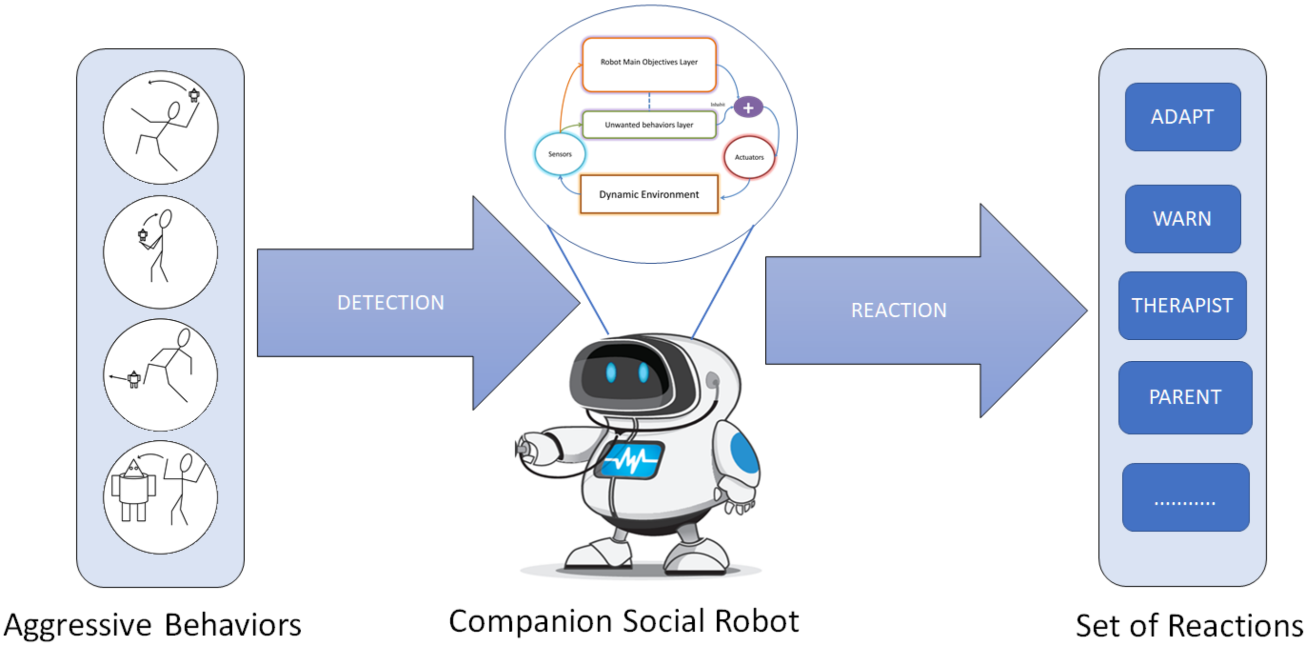

Fig. 1. Overview of the proposed model to detect unwanted physical interactions between a child and a small social robot.

acquires signals at a sampling frequency of 25 Hz. Their method was able to achieve an accuracy of 99.4% using a non-linear classifier and Kalman filter.

The detection of problematic behaviors in the population with special needs is another area in the healthcare domain that considers activity recognition techniques. One study used on-body accelerometers to classify problematic behaviors [30]. Simulated data generated by trained clinic staff were used in the system development and in the validation. The system was able to classify challenging behaviors of a child with autism obtained from a realistic session with an accuracy of 69.7%.

Activity recognition is also gaining attention in the area of robotics, especially when a robot operates in close proximity with humans. In robot-assisted living, one study introduced a wearable system that relies on the fusion of multi-sensors to recognize human daily activities [31]. The sensor system consisted of two nodes (i.e. on the waist and on the foot) that measure angular velocity, magnetic data, acceleration, and temperature. The system was able to produce promising results using a combination of neural networks and hidden Markov models. More recently, human activity recognition is being considered in new interactive applications, such as that found in robot games [32], [33].

For social robots that interact with children with ASD, some studies aimed at characterizing interactions [34], [14]. An earlier study used a ball-like mobile robot (i.e. Roball [20]) embedded with sensors to detect the direct interaction instances with the robot. The study considered four interaction cases with the robot, namely robot being alone, robot receiving an interaction, robot being carried, and robot being spun. The study demonstrated the possibility of using the sensor data to make the robot more adaptable. Another study considered different interactions with a smaller ball-like robot (i.e. Sphero), such as holding, kicking, and picking up [21]. Adult participants were asked to perform the behaviors. A set of features were extracted from the data of the embedded tri-axis accelerometer and gyroscope and then tested with different supervised learning algorithms. The best classifier (i.e. random forest algorithm) trained on data obtained from the adult participants achieved an accuracy of around 49% when evaluated with data generated from children participants.

III. Materials and Methods

A. Experimental Setup

1) Robot System Design: The progress in technology is enabling smaller robots to be more intelligent and more compact. Furthermore, smaller social robots are considered to be more affordable and suitable to be used by average home users. These robots have usually characteristics very similar to non robotic toys. The toys considered in this study were selected by considering this aspect. Three different shapes of toys were used, namely a stuffed robot (LATTJO soft toy, IKEA, Sweden), a stuffed panda (KRAMIG Soft toy, IKEA, Sweden), and a toy truck (Fig. 2). The dimensions of these toys (i.e. less than (38.0 x 29.0 x 9.0 cm^3)) and their masses (i.e. less than 0.75 kg) were on the range that enable ease of interaction (e.g. carrying) for children.

The differences in sizes, in shapes, and in materials of the selected toys should cover common variations among different small social robots. Additionally, the selected toys varied in terms of their softness. For example, the stuffed robot is considered the softest while the truck is considered the hardest. Both of the stuffed toys (i.e. the robot and the

Fig. 2. The toys that have been considered as dummy robotic forms. From left to right, a stuffed panda, a soft toy robot, and a toy truck.

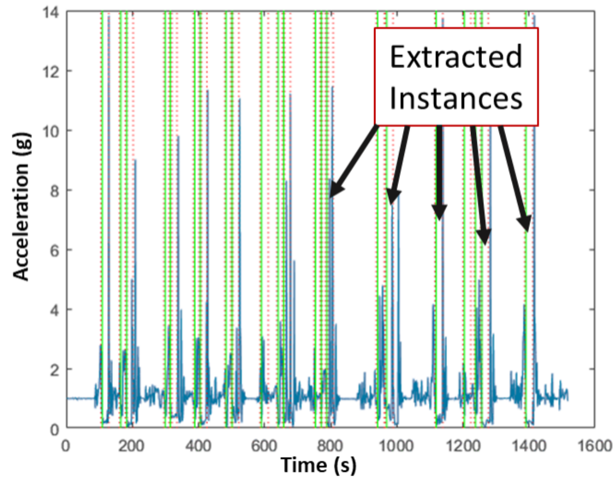

Fig. 4. A sample of the extracted features for the acceleration signal.

panda) were modified with zippered pockets to allow the insertion of the data acquisition and computing system.

2) Data Collection System: The data collection system was based on the Raspberry Pi (Pi 3 Model B+, Raspberry Pi Foundation, UK). The operating system used was the Raspbian (v4.14, Debian Project) installed on a micro SD card (32 GB, EVOplus, SAMSUNG). An add-on board (Sense Hat, Raspberry Pi Foundation, UK) was mounted on the 40-pin GPIO header of the Raspberry Pi (Fig. 3). The built-in accelerometer (LSM9DS1, STMicroelectronics, Switzerland) was used to acquire the data. It can capture acceleration changes for up to 16 g, which is adequate to capture the behaviors considered in this study [35]. The accelerometer data (i.e. acceleration in X, Y, and Z directions) was acquired at a rate of around 30 Hz. This rate was high enough to capture the characteristics of the behaviors being investigated (i.e. greater than 20 Hz) [36]. A Python script was used to read the data of the accelerometer and then store them as comma separated values (CSV) files.

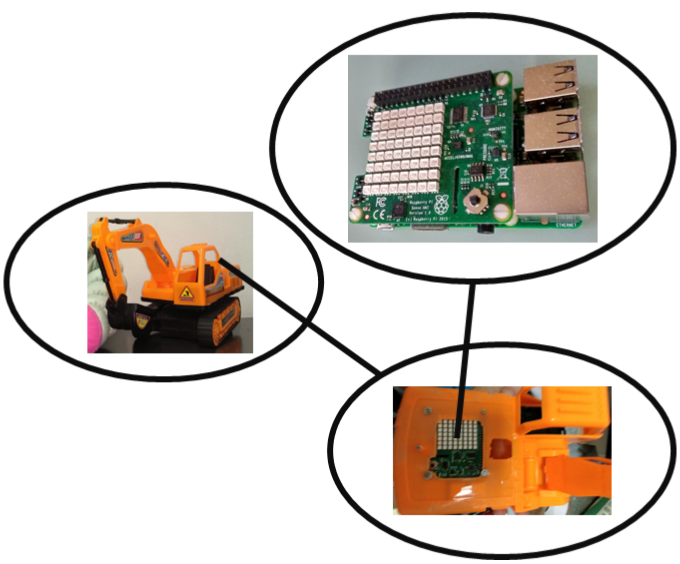

Fig. 3. The data collection system that was based on a SenseHat board mounted on a Raspberry Pi board.

B. Procedures

Acquiring sufficient data from adults is relatively easier than from children [21], [30], hence, the development of the model was based on data acquired from adult participants. The participants that took part in this study were asked to perform five different behaviors with each robot. The participants were given the freedom in performing the required behaviors and to take breaks between experiments. No instructions were given to the participants, especially about how a particular behavior should be performed (e.g. the way to hit or shake the robot). The only instructions were given to let the participants know the start and the end of each experiment. A MATLAB script (v2018, MathWorks, Massachusetts, USA) was used to analyze the data and then extract the instances of each behavior based on thresholds (Fig. 4). These data were then used to train, develop, and test the neural network model.

The data to validate the model were acquired from neurotypical children. Imaginative scenarios were told to the children to make them perform the behaviors of interest. For example, to acquire pickup and shake behaviors, they were told that ”*The robot is asleep and you need to pick it up and then shake it to wake it up*” (Fig. 5). We believe that the characteristics of behaviors (e.g. hitting) considered in this study are similar and comparable between neurotypical children and those with autism. Hence, these data will be used as indicator for the applicability of the developed model to the targeted end-users.

C. Participants

Five healthy adults (one female and four males) aged 24 to 31 years old participated in this study. Their data were used to train and test the model. Additionally, the study

Fig. 5. Samples from the sessions with the children.

acquired data from four neurotypical children (one female and three males). The children's data were used to validate the developed model. The procedures for this work did not include invasive or potentially hazardous methods and were performed in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki).

D. Algorithm

The development of the classification algorithm was based on Scikit-learn, a Python-based machine learning library [37]. This library includes many supervised and unsupervised learning algorithms along with other evaluation tools. Furthermore, it uses high-level language that makes the implementation convenient and flexible. The classification algorithm in this study was based on a supervised learning algorithm, the Multi-layer Perceptron (MLP).

MLP is one of the most widely used form of neural networks. The simplest configuration of this network consists of an *input* and an *output layer*, while a more complex configuration includes also one or more *hidden layers* between the *input* and the *output* layers. Connections between layers follow consecutive order starting from the *input layer* and terminating at the *output layer*. All connections have assigned values called *weights* that are learned during the network training. Each *neuron* has an *activation function* (e.g. sigmoid) that generates an output based on the product of the inputs of the preceding layer and the weights of their connections. More detailed, mathematical description of MLP can be found in [38].

The neurons of the *input layer* of the classification algorithm take the resultant acceleration values as an input vector. A window size of approximately 1 sec (i.e. 25 data points) was considered. This size was expected to provide fast recognition speed while maintaining sufficient accuracy [39]. The magnitude of the resultant acceleration was based on the square root of the sum of the squares of the individual accelerations. The relation is represented as follows:

$$|A| = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{1}$$

where A_x is the magnitude of acceleration in the X direction, A_y is the magnitude of acceleration in the Y direction, and A_z is the magnitude of acceleration in the Z direction. The classification algorithm trains to map the resultant acceleration values into labeled outputs corresponding to different behaviors.

E. Evaluation metrics

Several metrics were used to evaluate the developed model, such as the accuracy, classification report, and confusion matrix. Accuracy reported the percentage of correct predictions in relation to the overall predictions performed by the model as in (2). Classification report provided the precision, recall, and F1- Score, and support for the model. Precision provided the percentage of true positives in relation to the total predicted positive as reported in equation 3. Recall indicated the number of true positives in relation to the total number of actual positive as in equation 4. F1 - score provided the harmonic mean of precision and recall as in equation 5. The confusion matrix reported in table 8 provides a breakdown for all the predictions (i.e. correct and incorrect) by each class.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \tag{2}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{3}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{4}$$

$$F1 = 2 \times \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

IV. Results and Discussion

All participants performed the requested behaviors differently from each other. For example, different intensities were demonstrated when shaking or hitting the robots. The data of the behaviors were post-processed and the features were extracted (Fig. 6). The selected window size was large enough to capture the most important features of each behavior. The features of some of the behaviors performed by the participants with the robots appeared to have some similarities in their characteristics. For example, drop behavior was characterized by low acceleration values followed by a large spike and then oscillations. A hit behavior was characterized by a large spike of a short duration. Pickup has some resemblance to hit, but the spikes were longer in duration and smaller in amplitude. Shake behavior was characterized by continuous oscillations at different amplitudes and frequencies. Throw was characterized by a wave of low amplitude (i.e. start of throwing) followed by decline in acceleration and then ending with a large spike, upon impact.

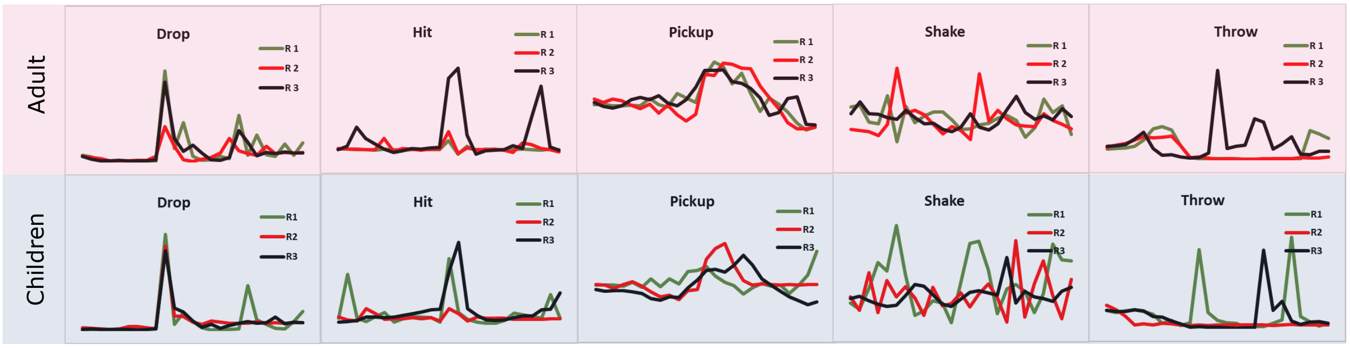

Fig. 6. Samples of the extracted behaviors from the accelerometer signals for adults and children.

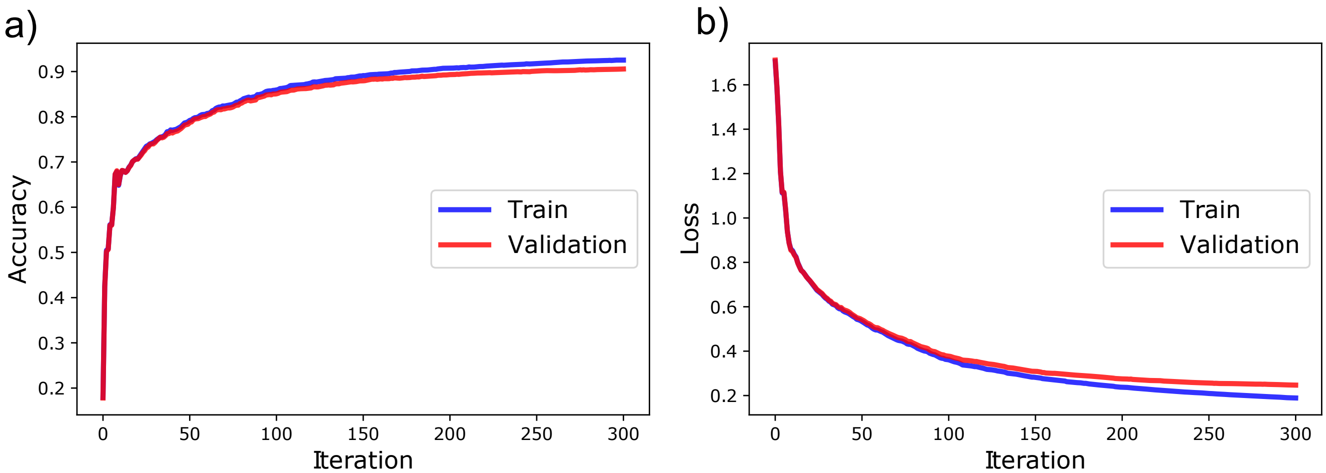

Fig. 7. The training and validation over iterations plots for the developed model a) Accuracy plot. b) Loss plot.

TABLE I
THE CLASSIFICATION REPORT FOR THE EVALUATED UNSEEN ADULT'S DATASET

Behavior	Precision	Recall	F1 - score	Support
Drop	0.91	0.90	0.90	265
Hit	0.84	0.84	0.84	797
Idle	1.00	1.00	1.00	131
Pickup	0.80	0.84	0.82	747
Shake	0.91	0.86	0.88	776
Throw	0.94	0.94	0.94	614
Avg/ Total	0.88	0.88	0.88	3330

A. *Model development*

The extracted features of behaviors were labeled and organized as a dataset to be used in the model training. A total of 1,000 instances for each behavior covering all robots and participants were extracted. For the idle class, 1,000 instances were added, hence, making the total instances to be 6,000. Augmentation (i.e roll by a factor of 25) on the data was performed that should provide more robustness to the model in terms of predicting new data. Additionally, it should help in avoiding the learning of any specific pattern in the data. A standard scaler was used to standardize the features by scaling (i.e. to unit variance) and removing the mean. The data were randomly split into 70% for training and 30% for validation. Different network configurations were tested and evaluated. The configurations for the best trained model (i.e. accuracy of 92%) included a hidden layer consisting of 300 or 150 units, a Rectifier Linear unit (i.e. *ReLu*) as activation function, *alpha = 0.0001* for the regularization penalty term, and Limited-memory Broyden Fletcher Goldfarb Shanno method (i.e. *lbfgs*) as weight optimization solver. The performance of the model improved proportionally with the number of iterations (Fig. 7a). The losses of training and validation were decreasing over iterations and converging closely (Fig. 7b). This indicated a comparable performance and a good fit for the model. Finally, the entire dataset was used to train the finalized model.

TABLE II

CLASSIFICATION REPORT FOR THE EVALUATED CHILDREN'S DATASET

Behavior	Precision	Recall	F1 - score	Support
Drop	0.72	0.98	0.83	49
Hit	0.81	0.67	0.73	195
Pickup	0.44	0.52	0.48	56
Shake	0.87	0.91	0.89	377
Throw	0.78	0.67	0.72	70
Avg/ Total	0.80	0.80	0.80	747

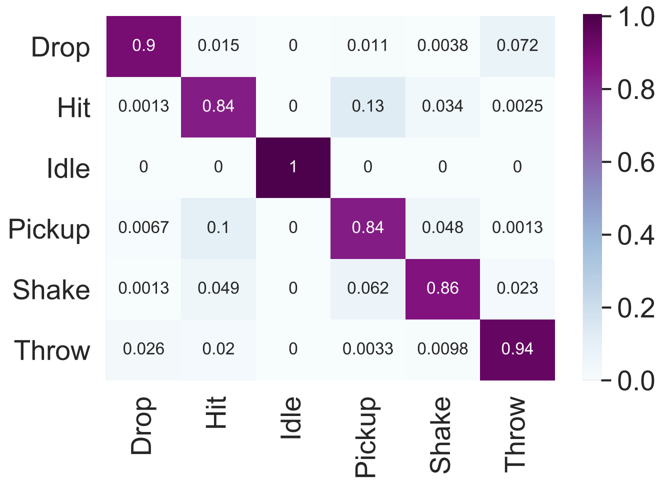

Fig. 8. The confusion matrix for the unseen adult's data.

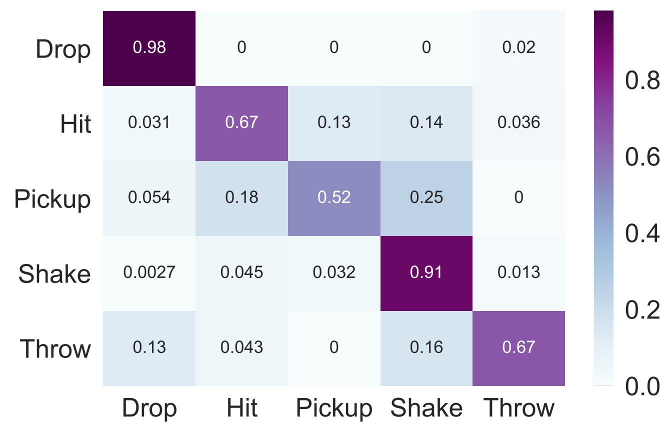

Fig. 9. The confusion matrix for the children's dataset.

An accuracy of 88% was achieved when validating the finalized model with unseen adult data. The confusion matrix and classification report for the model were generated for further analysis (Fig. 8 and Table I). Excluding the idle case, the confusion matrix reported the highest value for the throw case, while the lowest recognition for pickup and hit behaviors. The model has identified incorrectly some pickup instances mainly as hit or as shake instances. Similar observation for the incorrect identification of some instances can be made for shake and hit behaviors. Throw behavior instances were mainly identified incorrectly as drop behavior. These problems in identification could be attributed to some similarities in the features of these behaviors. However, the overall evaluation metrics of the model were promising. For example, the model has achieved an average precision of 88%, a recall of 88%, and an F1- score of 88%. Precision shows the ability of the model not to identify an incorrect instance as correct, while recall shows the ability of the model to find all correct instances. Finally, the F1 score takes the average of recall and precision into consideration.

B. Model evaluation with children's data

The main objective of this study is to develop a model that can characterize the interactions between a child and a small toy robot. Hence, evaluating the developed model with children's data was necessary to investigate its feasibility and applicability to children. There are some similarities between the acceleration characteristics of behaviors that were exhibited by the children and the adult participants, for example, in case of hit, drop, and shake behaviors (Fig. 6). Visual differences in performing some of the behaviors were evident in pickup and throw.

The developed model has achieved an overall accuracy of 80% when evaluated with the children's dataset. The confusion matrix showed that the model was able to identify drop and shake behaviors with the best results (i.e. accuracy $>$ 90%) followed by hit and throw behaviors (i.e. 67%) (Fig. 9). Pickup instances were the lowest to be identified correctly with an accuracy of 52%. One quarter of pickup instances were identified as shake behavior. The majority for the incorrectly classified throw behaviors were identified as either drop or shake. As for hit, they were incorrectly identified as pickup or shake. These misclassifications could be attributed to the differences in the behaviors' intensities as exhibited by different age groups that confuses the classifier. For example, a child's pickup behavior is more gentle and slower as compared to that of an adult, hence, it was identified as a shake behavior. The overall precision, recall, and F1 - score of the model were all promising (i.e. 80%; Table II).

In contrast to a previous study [21], the results showed the possibility of using adult-based generated data to develop a model that can classify some of the children's unwanted interactions with a small robot. Furthermore, it shows the capabilities of using a relatively simple multi-layer perceptron (MLP) in such applications as compared to other more demanding algorithms (e.g. support vector machines and random forests).

V. Conclusion

In this study, a Multi-layer Perceptron (MLP) based neural network was developed and validated for its potential in classifying behaviors between a child and a small robot. The physical interactions considered were hit, shake, throw, drop, and pickup. We believe that these behaviors could potentially be used to identify any unwanted interaction between a child and a robot, which could then act to prevent the occurrence of aggressive behaviors that might lead to harm [16]. The data to develop the model was based on adult participants performing the behaviors while the data used to validate the developed the model was based on the children's interactions. The developed model was able to achieve a high recognition accuracy (i.e. $> 80\%$) when tested with children's data. Furthermore, the confusion matrix and the classification report reported promising results.

The current findings have opened the possibilities for future work on continuous online recognition that is embedded within a social robot. The robot can then be programmed to deliver an appropriate response. These findings can be considered as a contribute toward improved therapy sessions by anticipating some unwanted interactions and then preventing the occurrence or progression of challenging behaviors by the intervention of a human therapist or the social robot itself [15].

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