A Machine Learning-Based Monitoring System for Attention and Stress Detection for Children with Autism Spectrum Disorders

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The majority of children with Autism Spectrum Disorders (ASD) have faced difficulties in sensory processing, which affect their ability of effective attention and stress management. Children with ASD also have unique patterns of sensory processing when responding to the stimuli in the environment. In this study, a real-time monitoring system has been designed and developed for attention and stress detection. Comprehensive sensory information, including environmental, physiological, and sensory profile data can be collected by the system using sensors, smart devices, and a standard sensory profiling questionnaire. Data acquisition with 35 ASD children using the system prototype was successfully conducted. With the acquired data set, different machine learning models were trained to predict attentional and stress level. Among all the investigated models, Gradient Boosting Decision Tree and Random Forest obtained the best prediction accuracies of 86.67% and 99.05% on attention and stress detection respectively. The two models were then implemented into the system for automatic detection. Future work could be focusing on exploring more supportive features to improve the prediction accuracy for attention detection. Such an easily-accessed monitoring system tailored for children with ASD could be widely-used in daily life to assist ASD users with their attention and stress management.

CCS CONCEPTS • Human-centered computing~Accessibility~Accessibility technologies • Applied computing~Life and medical sciences~Health informatics • Social and professional topics~User characteristics~People with disabilities

Additional Keywords and Phrases: Autism Spectrum Disorders, assistive technology, machine learning, electronic sensors, attention, stress

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1 INTRODUCTION

Autism Spectrum Disorder (ASD) refers to a group of complex and heterogeneous neurodevelopmental disorders. Sensory processing impairments are one of the most common issues observed in individuals with ASD. Evidence from previous studies revealed that as many as 90% of ASD individuals may have experienced sensory processing difficulties in audition, vision, touch, taste and smell [14, 16]. Sensory processing impairments in ASD involve hyper-or hypo-sensitiveness to sensory input [1]. ASD individuals who are hypo-sensitive may fail to notice sensory stimuli which typically developing people can easily detect, resulting in behavioural outcomes such as not listening when being spoken to or having difficulty paying attention. Conversely, those who are hyper-sensitive are likely to experience distress to sensory stimuli. Therefore, individuals with ASD usually have problems with effective attention and stress management due to their sensory processing issues. Monitoring ASD people's sensory environments and detecting their responses, such as attention and stress, appear to be highly helpful for their self-management in daily life. Despite the overwhelming prevalence of sensory processing issues in ASD, less attention was paid to sensory-associated issues compared to other developmental problems in ASD [16]. One possible barrier in addressing the issue would be that the issue is complex and idiosyncratic in individuals with ASD, which are associated with various influences and would require highly-customised solutions.

Recent developments in sensor applications and artificial intelligence have encouraged a number of studies to use technologies or machine learning to capture and model individuals' sensation in different environments, which can further inform the design of technology-based approaches to facilitate the living of people with ASD. Tomczak et al. [17] developed a stress monitoring system for individuals with ASD using low power wearable sensors. They used a heuristic rule-based model to construct the detection module. Heart rate, skin conductivity, body temperature and hand movements were the key parameters to identify the stress response of the individual. Coronato et al. [6] developed a situation-aware system using wearable accelerometers to detect motor anomalies. The employment of a neural network model achieved an accuracy near to 92% on anomalous gestures of a person with ASD. Rad and Furlanello [15] proposed a similar motor detection system using deep learning. However, none of abovementioned studies explored the impact of environmental factors on the disorders. On the other hand, some studies put more emphasis on environmental influences and sensory preference of individuals with ASD. Mauro et al. [13] proposed a personalised recommendation system to predict points of interest for people with ASD based on a Top-N model. This system used a self-defined sensory profiling questionnaire to acquire information about sensory aversion and preference of people with ASD on environments, generating suggestions on places that are expected to be comfortable for the users. Khullar et al. [12] designed an Internet of Things (IoT) system to detect the environmental information and process the information using fuzzy logic algorithms. The system is also able to generate alerts to caregivers of children with ASD and provide video feedback to calm down children with ASD.

It can be found that previous studies have used a range of methods, including sensors, IoT, machine learning techniques or sensory profiling questionnaire to measure sensory responses and associated behavioural outputs, suggesting the feasibility of combining several off-the-shelf technologies to obtain comprehensive information for the development of a real-time monitoring system for children with ASD. However, there is a lack of studies that conducted the comprehensive collection of sensory profile, physiological and environmental data in a monitoring system. Novelty of this study is to use a validated sensory profiling questionnaire, and various wearable and mobile devices to build a real-time monitoring system for sensory information collection. Machine learning models are used for attention and stress detection. This system is tailored for children with ASD aged between three to ten years old.

2 MATERIAL AND METHOD

2.1 Monitoring system development

The monitoring system prototype consists of a sensor network and a software application that allows to manage data from sensors. The physiological measures include skin conductivity, heart rate and hand movements, which can be easily measured using available devices. Some studies have used electroencephalography (EEG) sensors to infer attentional level in ASD [18]. However, as this study conducted the data collection in a real school setting where the acceptance of EEG headband by children and parents was low at the parental consent stage, EEG sensor was not involved in this system. Instead, the study designed three attentional tasks suitable for children with ASD under the guidance of ASD specialists to measure the attentional level. Environmental influences such as temperature, humidity, light exposure and noise associated with attention and stress can be measured by the system as well. Only acquiring environmental and physiological data, however, is not adequate for identifying attention and stress level in ASD because different children with ASD can respond very differently to sensory inputs. Therefore, a standard Sensory Profile of Children Three to Ten Years Caregiver Questionnaire [8] is integrated in this system which should be completed by the caregiver in order to provide initial information about the child's sensory preferences and limitations for further detection model development.

2.1.1 Sensor network

The sensor devices used to measure environmental and physiological data include iPhone [2], Apple Watch [4] and Arduino UNO [5]. iPhones are equipped with various built-in sensors, such as microphone, ambient light sensor, magnetic sensor, and accelerometer motion sensor. The system in this study mainly uses the iPhone to collect data on the sound and air pressure of the environment. Apple Watch is applied to the user's wrist to collect three-axis accelerometer signals and heart rate. The Arduino UNO is built with temperature and humidity sensor, light sensor and Galvanic Skin Response (GSR) sensor. The Bluetooth module on the Arduino board reads the sensor readings and enables the transmission of measurements in real-time. Table 1 presents the sensors and microcontrollers used in the sensor network and the purpose of each component. Figure 1 demonstrates the circuit connection of the Arduino board.

Table 1: Sensors and Microcontrollers

Sensor/ Microcontroller	Unit	Purpose
Light sensor (photoresistor)	Lux (lx)	To measure brightness level.
Microphone	Decibel (dB)	To measure noise level.
Temperature and humidity sensor	Celsius (°C) for temperature, percentage (%) for humidity	To measure temperature and humidity level.
Three-axis accelerometer	Sensor value	To identify the hand movements.

Sensor/ Microcontroller	Unit	Purpose
Heart rate sensor	Beats per minute (bpm)	To measure heart rate.
GSR sensor	Sensor value	To detect skin conductivity.
Barometer	Kilopascal (kPa)	To measure air pressure.
Arduino UNO	/	To fetch and transmit signal from sensors.

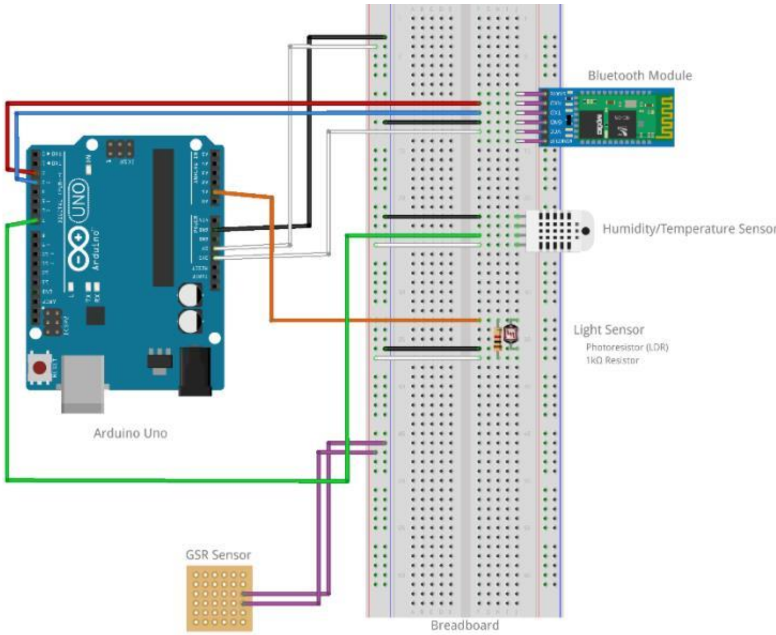

Figure 1: Arduino UNO Circuit Diagram

2.1.2 Software application

An iPhone-based application was developed to connect the Arduino UNO and access the built-in sensors on the phone and Apple Watch. Data from the sensors are displayed in numerical and graphical format which allows the user to view the environmental and physiological changes (Figure 2). The log in and registration module allows a caregiver to enter name, date of birth and gender of the child, and to give parental consent for data collection. Upon successful registration, the caregiver is directed to the Sensory Profile of Children Three to Ten Years Caregiver Questionnaire. The questionnaire is a standard sensory profiling tool developed by Dunn [8] that assesses the sensory processing pattern of a child. With this measure, the study elicits children's sensory preferences or limitations and classify their sensory pattern under four quadrants based on Dunn's model of sensory processing. Table 2 describes the characteristics of individuals under the four quadrants. The caregiver is allowed to manage sensory profile data, such as adding new sensory profile as child grows or deleting existing data from the database. However, the latest sensory profile of a registered child must be remained in the database.

Figure 2: Data visualisation interface

Table 2: Characteristics of four sensory patterns [9]

Sensory pattern	Characteristics
Low registration	Less likely to notice sensory input, may behave as passive or easy going.
Sensory seeking	Prone to add sensory events to daily life, may be very active or keep busy.
Sensory sensitivity	More likely to get distracted by sensory inputs, often show discomfort and sensitivity towards daily events.
Sensory avoiding	Prone to withdraw from overwhelming sensory stimulation, may be very ritualistic and rule-bound.

2.2 Machine learning models for attention and stress detection

2.2.1 Data acquisition and sample

The data acquisition using the monitoring system prototype was performed on 35 children (aged from 3 to 7 years, mean age: 5.3; 29 males, 6 females, gender ratio: 4.83:1). All the children had been formally diagnosed with ASD by a medical professional. Parents' informed consent and children's sensory profile questionnaire answers were obtained in the registration phase. A reading room in a local school, which equipped with air conditioner, study lamps, speakers, video recorder, table and chairs, was used as the data recording room. The participant was required to enter the room accompanied by their parent or caregiver. Environmental influences (i.e., temperature, noise and light intensity) were controlled in the room during the session. Each of these variables has five different settings, namely low level, low-moderate level, moderate level, moderate-high level and high level. Before each session started, one of the variables was adjusted to a desired level and the other two independent variables were controlled to be 'moderate'. Details about controlled variables are provided in Table 3. Each participant was supposed to undergo 15 sessions in total following a pre-defined experimental design. Each session lasted about fifteen minutes. The first five-minute phase was used for getting the participant to adapt to the setting and equip the device. Following the first phase was attentional tasks with on-site healthcare professionals monitoring the performance and managing potential risks. According to the participant consent form, parents or on-site healthcare professionals were able to decide not to continue the session for the child if they spot any uncontrollable feelings from the child. Finally, 31 out of 35 children completed all required sessions. Three children could not complete a session under a certain extreme environmental condition due to anxiety; one child did not complete a session in low noise level setting because he seemed not to hear the instruction of the task and was distracted by the animation on the Apple Watch.

Table 3: The value of the controlled variables

Variable	Values (from low to high)	Unit
Temperature	22, 24, 26, 28, 30	°C
Noise	40, 50, 60, 70, 80	dB
Light intensity	275, 325, 375, 425, 475	lx

2.2.2 Feature extraction

Data collected in the 2.2.1 were pre-processed in order to extract features useful for classification and detection. 14 features in Table 4 were extracted as predictors for attention and stress detection. In particular, each sensory pattern in a child's sensory profile was classified into three classes (1 = "typical performance", 2 = "probable difference", 3 = "definite difference"). The watch accelerometer is the mean absolute value, which is obtained from the average of the absolute value of each signal from 3 axes.

Table 4: Extracted data features

Category	Included features
Environmental features	Temperature, volume, humidity, light, pressure
Sensory Profile	Low registration, sensory seeking, sensory sensitivity, sensory avoiding
Physiological features	GSR, heart rate, watch accelerometer
Personal characteristics	Gender, age

2.2.3 Models for attention detection

Four machine learning models were implemented and compared for identification of low attentional level. The investigated models include K Nearest Neighbour (KNN), Random Forest (RF), Support Vector Machine (SVM) and Gradient Boosting Decision Tree (GBDT). These four conventional models have been widely-applied in supervised learning for classification problems. However, there is a challenge which is to classify low attention with some commonly-used biological indicators (e.g., EEG data) being unavailable. This study took attentional task scores, combined with healthcare professional's assessment to label attentional level of the children. Task performance rating between 0.6 and 1 is labelled as a normal level of attention where the children could generally pay attention to the tasks. Rating between 0 and 0.6 is labelled as the opposite of normal level, indicating low attention level.

2.2.4 Models for stress detection

A child's stress in this study was classified into three levels: low stress, medium stress and high stress. ANN, RF and GBDT models were used for stress detection because these three models are capable of handling multiple classes directly [10]. In this study, children relaxing under moderate environmental conditions is classified as low stress, while playing tasks under moderate and extreme environmental conditions (e.g., high noise, high temperature, low brightness) is classified as moderate stress and high stress respectively. Subsequently, real-time data were extracted from corresponding segments and labelled with different stress levels.

In the model training, the pre-processed data were split into the training and testing data set by adopting 80 : 20 as the ratio of training : testing data set. Grid Search was applied for fine-tuning the models. Best combination of hyperparameter values of each model was used before comparison analysis. Since this is a classification problem, prediction accuracy and confusion matrix were used as evaluation metrics in this study. The prediction accuracy is mathematically defined as the ratio of the number of predictions done correctly by the machine learning model to the total number of predictions made:

$$Accuracy = \frac{\text{number of correct predictions}}{\text{total number of predictions made}} \qquad (1)$$

Confusion matrix is a commonly-used tool that provides a better view of classification errors [11]. For two-class problems, the F1-score can be obtained from the confusion matrix to compare the classification performance of different models, which is defined as the harmonic mean of precision and recall:

$$F1 - score = 2 \times \frac{\text{precision}\times\text{recall}}{\text{precision}+\text{recall}} \qquad (2)$$

$$Precision = \frac{\text{true positive}}{\text{true positive}+\text{false positive}} \qquad (3)$$

$$Recall = \frac{\text{true positive}}{\text{true positive}+\text{false negative}} \qquad (4)$$

Considering the machine learning model will be implemented on the iPhone-based monitoring system, the response time of the model is another critical factor worth exploring. All the models were processed on a laptop CPU and the inference time of each model was calculated and compared:

$$Inference\ time = \frac{\text{total time taken to calculate the outputs}}{\text{number of samples}} \qquad (5)$$

2.3 Model deployment for automatic detection

Implementing the machine learning model into the iPhone-based monitoring system is achieved using CoreML [3]. The model that has the best performance is transformed and exported to CoreML model file specified with training parameters to enable on-device training, as shown in Figure 3. After the generated model file is imported into the system code bundle, it is used to implement the automatic attention and stress detection. Real-time data of input features are collected and aggregated to feed into the model. The system then makes predictions on attention and stress level, prompting the user through the data visualisation interface to provide ratings for predictions in order to improve the model.

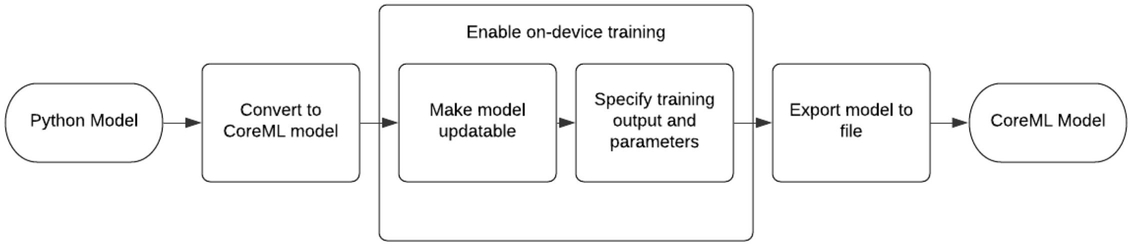

Figure 3. CoreML model generation

3 RESULTS

The prediction accuracy, F1-score and inference time on the testing data set of SVM, RF, KNN, and GBDT models with optimal hyperparameters for attention detection is presented in Table 5.

Table 5: Model performance on attention detection

Model	Accuracy	F1-score	Inference time (ms)
SVM	80.00%	0.8205	0.0074
RF	80.95%	0.8113	0.0613
KNN	81.90%	0.8319	0.0177
GBDT	86.67%	0.8772	0.0036

The results showed that GBDT significantly outperformed the other three models on attention detection with the highest accuracy (86.67%) and F1-score (0.8772). GBDT was also the fastest one among all the models. A second trial was conducted by excluding sensory profile (SP) features in the training. Hyperparameters were tuned and comparison of prediction accuracies with and without SP features is presented in Figure 4.

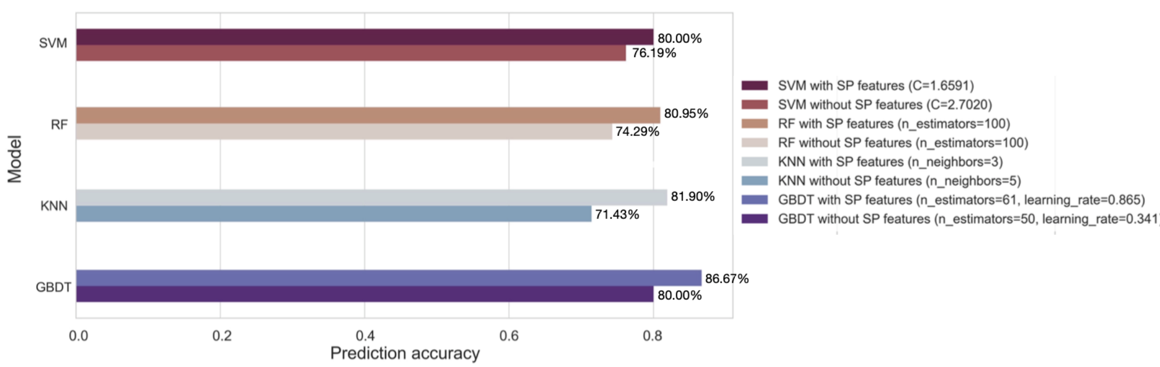

Figure 4. Prediction accuracy on attention with and without SP features

Similar trend was discovered in all four models that the prediction accuracy dropped after the SP features were excluded. Thus, it could be inferred that sensory profile is an indispensable predictive factor which could increase machine learning models' prediction accuracy.

ANN, RF and GBDT were used for stress detection. Model performance on the testing data set shown in Table 6 illustrated that machine learning models had overall better performance on stress detection than attention detection. The prediction accuracies of all three models were over 95%. One reason for this may be that the prediction performance of machine learning models was greatly affected by the supportive features. The current combination of features had critical impact on the stress, while for attention detection there might be a lack of stronger indicators such as EEG features.

Table 6: Model performance on stress detection

Model	Accuracy	Inference time (ms)
RF	99.05%	0.0240
GBDT	98.94%	0.0360
ANN	96.89%	0.0021

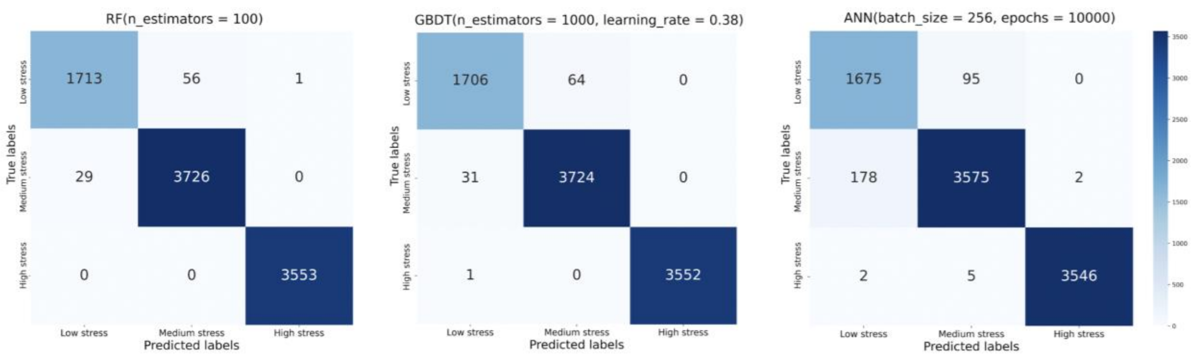

Figure 5. Confusion matrixes

RF and GBDT had similar prediction accuracy and distribution of classification errors (Figure 5). Compared with conventional machine learning models, ANN did not show better performance for predicting stress level in this study. Although the inference speed of ANN is higher than RF and GBDT, it can be found that in this study, all the models can process an input within 0.1 millisecond (ms). The results suggested that two ensemble learning models: GBDT and RF, could be chosen to be implemented into the system for effective attention and stress detection.

4 CONCLUSION AND FUTURE WORKS

This study developed a machine learning-based monitoring system specifically for attention and stress detection in ASD. The system consisting of a sensor network and a software application can successfully capture a range of features from children with ASD. Different machine learning models were evaluated and compared. Among all the investigated models, GBDT and RF yielded the best prediction accuracies of 86.67% and 99.05% on attention and stress detection respectively. These two models were then selected to be deployed into the system using CoreML for automatic attention and stress detection. It is worth pointing out that the prediction accuracy on attention was not as satisfying as the one on stress. More efforts should be taken to explore better prediction features in the future. Notice will be made to the caregivers of ASD users in the system that the attention detection might be more accurate if they would like to use additional sensors such as EEG headband and eye trackers. However, some assistive technologies, such as headband and smart glasses, can be noticeable in daily life, which raised many caregivers' concerns about exposing children's disability to the public [7]. The current monitoring system with commonly-seen devices (e.g., mobile phone, smart watch) is considered to be more acceptable in most settings. At the next stage, this system is expected to notify the caregivers about detected anomalies via message. The system will also be capable of generating suitable strategies to optimise the environmental conditions for children with ASD, assisting the children to better manage their attention and stress.

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