Emotion Detection for Children on the Autism Spectrum using BCI and Web Technology

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***Abstract*—Brain-computer interface (BCI) technology is getting popular to detect emotions of Autism Spectrum Disorder (ASD) affected children nowadays. Understanding the emotional state of the ASD affected children is very challenging due to their inconsistent behaviour. In this paper, we have introduced a location-guided web-based system to monitor and detect emotions of ASD-affected children employing BCI technology. We have collected raw brainwave data of 30 subjects during three instances: positively excited, neutral, and negatively excited. We have created a 30-sec interval sample to generate the dataset. We have extracted features from the data and applied data pre-processing techniques to find the informative features and remove the outliers. Then, we have built an ensemble model that achieved 93% F1-score and uses majority weighted voting to predict the emotional state of the ASD affected children. Finally, we have deployed the ensemble model into a web application so that guardians can find the emotional state of their child. The brainwave data and location of the child are collected by the headgear and uploaded to the cloud. We have integrated a headgear that can be easily worn by the child. The main objective of this work is to design and develop a location-guided web application so that guardians can access the emotional state along with the location of the child using the web. Our source code including feature extraction, model development and evaluation is available at https://github.com/akibzaman/ASD-children-emotion-prediction.**

***Index Terms*—Autism Spectrum Disorder (ASD), Brain-Computer Interface (BCI), Brainwave Data, Ensemble Learning, Web Application**

I. Introduction

Autism Spectrum Disorder (ASD), commonly referred to as autism, is related to difficulties in identification and verbal expression of feelings [1]. According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-V) [2], autism is defined as a neurodevelopment disorder with qualitative impairments in social interactions and communication in association with restricted, repetitive, and stereotyped behaviours, interests, and activities [3]. Clinical assessments were done to understand the characteristics and IQ level of the total ASD population where 55% of them had an intellectual disability ($IQ < 70$), 16% were moderate to severe intellectual disability ($IQ < 50$), 28% had average intelligence ($115 > IQ > 85$) and 3% were of above-average intelligence ($IQ > 115$) [4]. Maskey et al. [5] revealed that almost 53% of ASD-affected children are prone to remain in coexisting conditions along with emotional and behavioural issues such as sleep deficiency, toileting and eating problems, hyperactivity, self-injury, and sensory difficulties. Moreover, anxiety, tantrums, and aggression towards others were frequent regardless of age, ability, or schooling.

Children with ASD experience a range of emotions, including happiness, anger, and excitement. However, they significantly struggle to distinguish between their own emotions and express them correctly through facial expressions, body language, or tone of voice which have been highlighted in several studies. Stewart et al. [6] showed that depression is common in autism which is a reason for the reduction of adaptive functionality and capacity for self-care. The prolonged unexpressed sadness or depression results in a decrease in self-care. Additionally, Yeasmin et al. [7] indicated that individuals with ASD have less differentiated knowledge about their own emotional world and conceptually differentiate less between discrete emotions compared to Typically Developed (TD) individuals. Similarly, Mates et al. [8] showed symptoms like mood and speech disorders in the case of autistic children which makes it very difficult for them to communicate with others. Thus, Parents or caretakers of ASD children face several difficulties raising their children. Amanda et al. [9] conducted an interview-based research accumulating data from the parents of autistic children. It was evident from the result of the study that autistic children suffer from unstable behavioural patterns which makes it very difficult to understand the emotional state of an autistic child. To explore the mindsets of parents, Pattinni et al. [10] conducted a comparative study of the parents of TD and ASD children. The study showed that parents of the ASD children remain in constant anxiety about the state of their children and project increased social isolation due to uncertainty of the children's behaviour compared to the parents of TD children.

Several studies explored the feasibility of detecting emotions in ASD children using facial images [11]–[13]. However, facial recognition can be misleading due to the inconsistency of facial expressions demonstrated by ASD-affected children. Furthermore, addressing the limitation of facial expression based emotion detection, gait-based [14] and voice-based [15] emotion detection techniques have been utilised and proved to be useful. On contrary, non-invasive brainwave acquisition techniques such as electroencephalogram (EEG) has demonstrated promising results in several applications such as detection of emotions in general mass [16] and special category of people including people with a medical condition [17], soldiers in an operational environment [18], etc. and likely be a good alternative yet to explored significantly. Moreover, the prediction result needs to be visualised to the parents through an intuitive web or mobile application to facilitate the monitoring process of parents or therapist of the ASD child. A live location tracking can also be an useful feature to reduce the constant stress of the parents of ASD children.

In this study, we design and develop a monitoring system for ASD children by predicting their emotional state using brainwave data and visualise them to the parents through a web application. We also implemented the live location tracking feature in the developed system to improve the quality of monitoring. First, we collect raw brainwave data of 30 subjects during three instances: positively excited, neutral, and negatively excited. We extract the features from the brainwave and remove the outliers and create a 30-sec interval sample to generate the final dataset. Then, we discard irrelevant features by using feature selection methods following the ANOVA test and selecting features with $p < 0.05$. We then developed a novel weighted voting ensemble model to predict the emotional state which performed better than the conventional models on the extracted dataset with a best F1-score of 0.93. The model is then deployed in a web application that can be accessed from both mobile and computer. We integrate a headgear that can be easily worn by the child. The brainwave data and location of the child are collected by the headgear and uploaded to the user account in a cloud database. Guardians can observe the emotional state along with the live-location of the child using the web application. Moreover, multiple children can be added to a single guardian and can be monitored simultaneously using the developed system. In summary, the salient contributions of this research are as follows:

- We have designed and developed a web-based monitoring system with the integration of live location tracking and emotional state prediction.
- We have trained a weighted majority voting-based ensemble model using brainwave data to classify the emotions of ASD affected children.
- We have evaluated the effectiveness and efficiency of the developed system using real-life usecases.

The rest of the paper is arranged as follows: Section 2 discusses the concerns regarding similar existing works. Requirement Elicitation of the monitoring system is described in section 3. The design and development of the prototype are discussed in Section 4. Section 5 describes the Evaluation of the developed Prototype of the associated mobile application. Finally, Section 6 summarises the contribution and the future scopes.

II. Literature Review

Several studies are conducted to understand and manage ASD-affected children's emotional states. CaptureMyEmotion [19] uses a wrist-worn sensor called the Q sensor from Affectiva[1]. The Q Sensor measures changes in skin temperature, motion, and skin conductivity, can indicate the wearer's emotional state, can transmit the data in real-time to a mobile phone, and can also be worn for a long period to obtain a reliable baseline. However, the feelings of the ASD children are rated along the valence-arousal dimensions and self-rating which can be highly inaccurate for most of the ASD children. To address this issue, automatic detection of the facial expression is used in several recent works. Pooja Rani [11] used conventional Machine Learning (ML) techniques on image data to classify the emotional state of an ASD-affected child from facial expressions into four basic states: happy, sad, angry, and neutral. A support vector machine (SVM) model with an accuracy of 90% performed the best to predict the emotional state. Similarly, Lavanya et al. [12] provided a comparative performance analysis of automated facial expression recognition from thermal and visual facial videos and their fusion for ASD-affected people. The Least Square Support Vector Machines (LSSVM) demonstrated the best result with an accuracy of 85%. Sivasangari et al. [13] integrated facial recognition to identify the emotional states of autistic people (Joy, Sad, Anger, Fear, Distress, Surprise) and use the emotional states to alert caretakers in case of emergency. The proposed method demonstrated an average F1-score of 53 % yielding an average precision of 21% and an average recall of 89%. One of the major drawbacks of the system was the emotion regulation using facial expression requires eye to eye contact which is difficult to be collected in the case of ASD children [14]. Moreover, many ASD people do not show a specific facial expression to express a distinct state of emotion which reduces the reliability of the dataset [19]. Notably, Manfredonia et al. [20] demonstrated that there exists a significant difference between the facial expressions of ASD and TD children. Using Facial FACET program, the study revealed that ASD children are less capable of expressing their variety emotional states such as: joyful, afraid, angry, sad, etc. unlike the TD children.

Nursuriati Jamil et al. [14] worked out another technique involving gait-based emotion detection among ASD children and conducted a preliminary investigation about the emotional states, gait parameters, and methods of gait data acquisition. The study indicated that emotion detection based on only facial expression is associated with the very poor performance of a person's identification whereas gait can be observed from a far. Though this technique can solve the limitations of image processing, the method is not very suitable for autistic children, as they tend to remove the required markers or run out of the camera fields.

In contrary, feature extraction from voice is utilised to assess the emotion of ASD people in few studies. Sukumaran et al.

[1] www.affectiva.com

[15] carried out study on emotion recognition in ASD-affected individuals using their speech, analysing seven primary emotions. By gathering and pre-processing dataset, different features were retrieved, and then a multi-layer perceptron (MLP) was used to identify the emotional states yielding an accuracy of 81.52%. Recently, non-invasive techniques are used to detect emotions. Aslam et al. [21] developed an EEG-based non-invasive neurofeedback SoC for emotion classification for ASD-affected children. A 4-layers deep neural network classifier is integrated on-sensor to classify emotional states (happy, sad, relaxed, angry) with an accuracy of approximately 85%.

III. Data Collection & Pre-processing

We have used Electroencephalography (EEG), a non-invasive method of brainwave data collection on 30 ASD children during the data collection procedure. We have conducted the procedure in the participant's residence for the convenience of the participants. Before the procedure, the written consent of the guardians of the autistic children is taken. After taking the consent of the parents following steps are conducted on each individual participants:

1) Guardian of the autistic child was requested to accompany the child during the procedure. The child along with its guardian was taken to an isolated room.
2) At first, the EEG headset (Neurosky Mindwave mobile 2) inside the headgear was attached to the head of the children and the electrodes were set at the forehead and earlobe. The connection of the headset with the associated mobile application EEGID was checked.
3) Then, the data collection begins in three-phase:
   - Phase 1: One of the therapists (expert in autism) talk generally with the child for 4-5 minutes. The brainwave data collected during this time period is labeled as *Neutral (N)* data.
   - Phase 2: The therapist uses it to make the child laugh and generate positively hyped emotions in the child. As ASD-affected children get excited listening to their favorite music and rhymes, their favorite music is played to see their level of excitement. After that, the sound of a rattle and other playing objects like balloons and bubbles are presented in front of them. During this phase, the therapist plays peekaboo and tickles them to make them happy and positively excited. We continue this procedure for 5-10 minutes. The brainwave data collected in this time period is labeled as *Positively Excited (PE)* data.
   - Phase 3: After that, the accompanied parent of the child leaves the room and another therapist (expert in autism) enters the room and acts less friendly with the child for 3-4 minutes. The playing objects that were presented in phase 2 are taken away to create a controlled uncomfortable situation. The brainwave data collected in this time period is labeled as *Negatively Excited (NE)* data.

The same steps are repeated for all of the participants of the data collection study and the data are collected at an interval of 5 seconds. Demographics of the autistic children who participated in the data collection study are summarised in Table I. The average age of the participants is 10 years with a minimum of 5 years to a maximum of 13 years.

TABLE I: Statistics of collected dataset.

Category	Size/Method
Sampling technique	Snowball Sampling
Number of participants	30 ASD Children
Gender	Male=18 and Female=12
Age range	Min = 5 years, Max = 13 years, Avg = 9.7 years
Data collected per participant	Min = 12.5 min, Max = 18 min, Avg = 15.75 min
Interval of EEG acquisition	5 seconds
Number of Extracted features	14
Total Size of Dataset	197 MB

A total of 14 features including timestamp, poorsignal, EEGRawValue, EEGRawValueVolts, attention, meditation, blinkStrength, delta, theta, alphaLow, alphaHigh, betaLow, betaHigh, gammaLow, and gammaMid are extracted from an individual sample. We collect data with three different labels (*PE*, *N* and *NE*) from each participant considering a data collection interval of 5 sec. To clean the individual dataset of each participant, at first, we remove the noises in the samples by deleting the samples with a value more than 0 in the feature *poorsignal*. Then, we replace the samples with a null value in any of the features with the mean value of that feature. We perform an outlier analysis to further clean the dataset using the Interquartile range (IQR) method [22] on each of the features. However, a 5-sec interval is very negligible to changing an emotional state. Thus, we calculate the mean of consecutive 6 samples in the clean datasets and record it as a single sample to cover a 30-sec interval. Thus for each individual, we get three preprocessed datasets: a) positively excited b) neutral and c) negatively excited. A dataset of size 978 × 14 is formed from the data collection study by combining the datasets of all of the participants. To find relevant features, we apply the ANOVA test [23] to the extracted features. We consider the features significant for building our model where $p < 0.05$ and unnecessary features are trimmed from the dataset. We handle the imbalanced dataset using the oversampling technique. Neutral and Negatively Excited labelled samples are oversampled from 23.34% to 33.33% and 15.34% to 33.33 % respectively.

IV. Building Models

We evaluate the performance of five single model classifiers along with two ensemble models to find out the best performing model for the emotional states prediction of ASD children. At first, we split the dataset into train and test datasets by using an 80/20 split. We apply the datasets on two of the conventional models: Gaussian Naïve Bayes (GNB) and K-Nearest Neighbours (KNN), one of the conventional Ensemble Models:

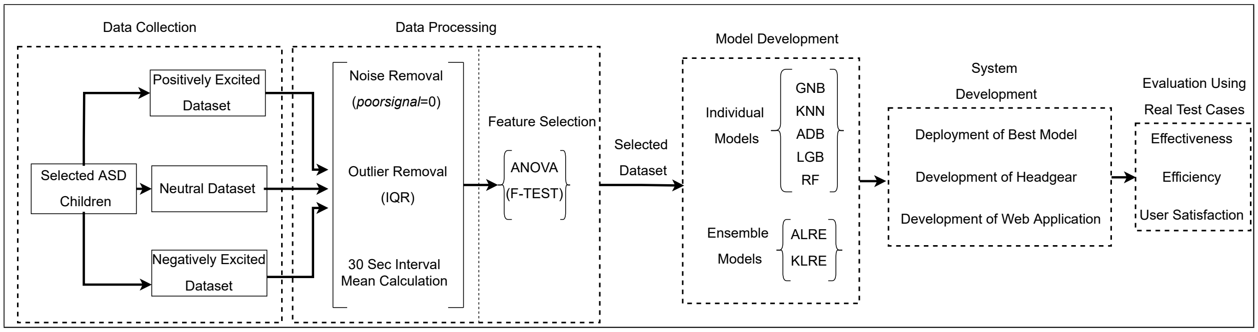


Fig. 1: Research Methodology.

Random Forest (RF) and two of the boosting models: Adaptive Gradient Boosting (ADB) and Light Gradient Boosting (LGB).

We use 3 neighbours in the case of KNN along with the Ball tree algorithm and leaf size of 5. We use the Bayesian optimization hyperparameter tuning technique [24] to select different parameters of RF, ADB, XGB and LGB which provides the advantage of better overall performance and non-requirement of certain values of parameters like Random Search and Grid search [25]. The developed ADB model has a learning rate of 0.5 with 100 estimators. In the case of RF, we use a number of trees as 200 which helps to avoid over-confidence with a minimum leaf size of 1 and minimum sample split of 9. For the LGB model, we use the gradient boosted decision tree (lgbm gbdt) to avoid excessive computational complexity of dart gradient boosting (Lgbm dart). Additionally, the learning rate is taken at 0.8 from the hyperparameter tuning along with 100 estimators, the Number of leaves is taken at 100 with a minimum of 2 data in each leaf and the bagging fraction is set at 0.65 i.e. 65% of rows are used per tree building iteration. Additionally, the objective was set as multiclass with a balanced weight for each class.

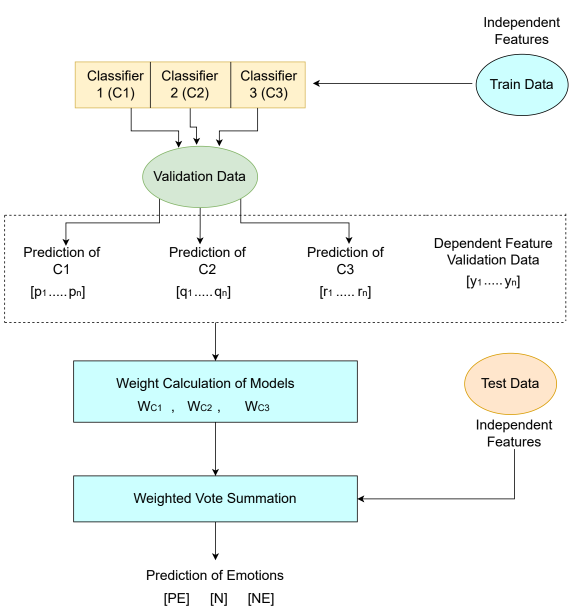


Fig. 2: Architecture of the developed ensemble model.

TABLE II: Comparison of models using the test datasets.

	Per Class F1-Score			Overall Metrics			
	PE	N	NE	ACC	MP	MR	MF1
GNB	0.33	0.72	0.69	0.60	0.63	0.61	0.57
KNN	0.78	0.96	0.70	0.73	0.71	0.72	0.71
ADB	0.73	0.92	0.74	0.79	0.77	0.83	0.79
LGB	0.85	0.92	0.77	0.83	0.82	0.82	0.82
RF	0.80	0.93	0.78	0.84	0.85	0.84	0.84
KLRE	0.83	**0.99**	0.84	0.90	0.90	0.89	0.89
ALRE	**0.88**	0.98	**0.91**	**0.93**	**0.94**	**0.93**	**0.93**

Alongside these individual models, we develop two ensemble models by fusing the prediction of three individual prediction models at a time: a) ensemble of KNN, LGB and RF (KLRE) and b) ensemble of ADB, LGB and RF (ALRE). The general architecture of the ensemble model utilise a weighted majority voting-based architecture which is highlighted in Figure 2. Firstly, we split the dataset into three segments named: Train (80%), test (10%) and validation (10%) dataset. Then, we use the independent features of Train dataset to train the individual classifiers and use the independent features of the validation dataset to predict the dependent features of the validation dataset. We compare the prediction on the validation dataset with the actual classes of emotions. Then, the weights of the classifiers are calculated by offering a reward for the right prediction and normalising the weight of each classifier using the cumulative sum of the weights of all three classifiers. Then based on these weights, we combine the output of the training dataset by considering the weights generated by the validation dataset.

Being a multi-class classification problem, the performance of the models is compared using the accuracy (ACC), macro-averaged recall (MR), macro-averaged precision (MP) and macro-averaged F1-score (MF1) on the test datasets. Table II shows the per-class F1 score and overall metrics of the models. Among the individual models, RF performed best with an MF1 score of 0.74. In counterpart, GNB demonstrates the lowest performance with an MF1 of 0.57. ADB and LGB also demonstrate a moderate performance with MF1 scores of 0.74 and 0.71 respectively. However, both of the ensemble models perform better than the individual models. Notably, ALRE achieves the highest performance with an ACC and MF1 score of 0.93 and 0.91 respectively. KLRE achieves a near similar

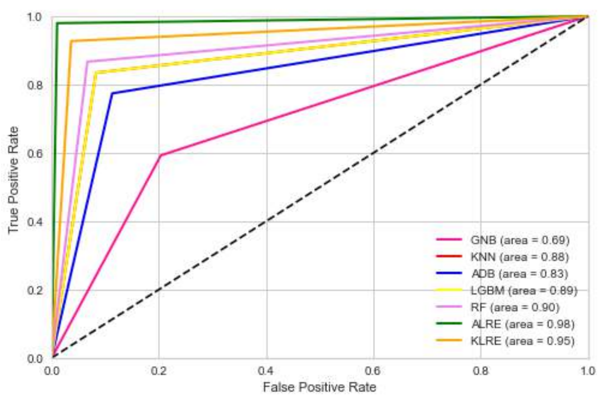


Fig. 3: Comparison of AUC-ROC of the models.

result with ACC and MF1 scores of 0.90 and 0.89 respectively. Additionally, we calculate the area under the curve for receiver operating characteristics (AUC-ROC) for all the models which are highlighted in Figure 3. We observe a better performance of the ensemble models compared to the individual models. Notably, the ALRE model (0.97) demonstrates a better performance than the KLRE model (0.95).

V. Development of the System

Using the best performing model as the backbone, we develop the monitoring system which consists of two major modules: a) Headgear to collect the raw brainwave and location data from a ASD child and b) An associated web application to visualize the information to parents/caretakers.

A. Headgear

The headgear (see Figure 4) consists of two subsystems: the Brainwave acquisition subsystem (BAS) and the Location tracking subsystem (LTS). In BAS, we place a Neurosky Mindwave Mobile 2 EEG headset inside the headgear to acquire the raw brainwave data. The raw data is captured using a third-party mobile application named “EEGID” through the integrated Bluetooth chip in the headset. The collected data is continuously stored in a cloud Firebase database. In LTS, we use an ESP8266 Node MCU as a processing unit and a GPS module (Ublox Neo6-M). We use the Firebase database as cloud storage with a real-time capability to store the user information along with the emotional state predicted by the deployed model and location data fetched from LTS. Figure 5 illustrates the architecture of the developed system.

B. Associated Web-Application

We develop an associated web-based application to intuitively visualise the emotional state and location of the children wearing the headgear to the users (parents/therapists/caretakers). The web application is developed using the Django platform and Firebase Cloud database which provides cross-platform compatibility to the users. Users (parents/therapists/caretakers) can start using the app by signing up or logging in to their account by giving the necessary

Fig. 4: Prototype of the system.

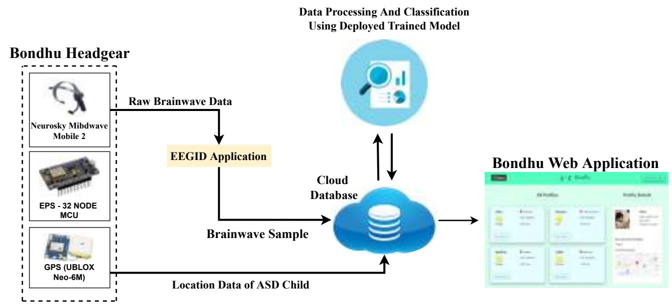


Fig. 5: System architecture.

information and password. After successful login, the user can overview the connected children with his/her account on a Homepage as shown in Figure 6a. The Homepage shows a summary of the connected children including the current emotional state of the child and location. To simplify the state by removing technical jargon to the users, we use “Happy” to represent Positively Excited and “Sad” to represent negatively excited state. The user can see details of any child by hovering on the designated button and the details are displayed on the right side including personal information, predicted emotional state and location on the map. Users can also landmark a location with a customised name, for example, garden, backyard etc. Additionally, users can also observe the historical data of any child by pressing the “*See History*” button. The History page (see Figure 6b) provides users with an option of displaying daily, weekly or monthly statistical data of the child. Users can observe the preferred locations of the child and can also preview a summary of the emotional condition of the children. Notably, all these data can be downloaded and can be used by the therapists of the children to facilitate better medical suggestions.

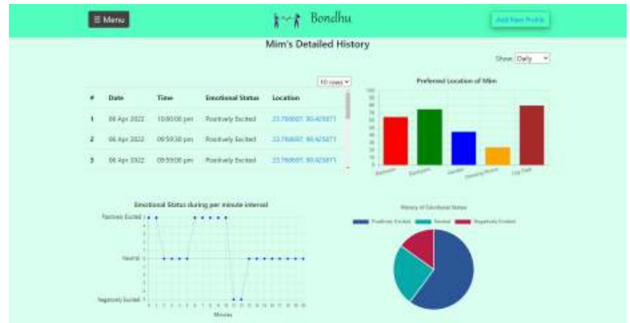
VI. Evaluation

We conduct an evaluation study on the developed system using new users to assess the usability parameters defined by ISO (1998), which include effectiveness and efficiency.

A. Participants’ Profile

In order to evaluate the prototype, a total of 25 ASD children and their parents are invited who were not present in the initial data collection process to develop the model. Among them, 20 of the children (13 male and 7 female) along with a companion (father/mother/caretaker) agree to participate in

(a) Homepage



(b) Visualisation of historical data

Fig. 6: Snippets of the developed location guided web application.

the study. The age range of the children is from 6 to 12 years with an average age of 9 years. Their parents are educated (minimum bachelor's degree holders) and modestly familiar with mobile and web applications. However, none of them have any previous experience with using an EEG headset. Four therapists who have provided medical treatments to the participating children previously are present in the test session. Among the therapists, three of them are Child and Medicine Specialists and one of them is a neurologist.

B. Study Procedure

We conduct the evaluation study by selecting the parent-child duo and the therapist of that child. A few pictures of the evaluation process are shown in the given figure 7. One test session was conducted for each parent-child pair by using the following steps:

1) At first, the parent was given guidelines about the aim of this study, simulated situations during the study, and his/her roles. The parent was reassured that the purpose of this study is to collect brain data from their child in a controlled environment and the simulated situations are designed only to collect required data from the children. It was also mentioned that few steps during the study might create a temporarily uncomfortable scenario for the child but will not create any temporary or permanent negative impact on the child. Moreover, he/she was told to behave normally while accompanying their child and observe the result in the developed application in presence of their child's therapist.
2) As therapists deal with the child regularly, they can understand the emotional side of the child. So the presence of the therapist had the goal of collecting ground truth data to utilise in the evaluation of the prediction performance of the deployed model. All information related to the child's medical condition was collected and approved by the therapist that he/she was fit for this testing session. Moreover, a written consent form was also signed by the parent.
3) The parent was instructed about how to operate the developed application to check the current emotional state of the child and his/her location.
4) After briefing about the whole procedure, the parent was asked to perform the following task on the developed web application:
   - Task 0: Setting up the headgear
   - Task 1: Setting the profile of the child.
   - Task 2: Checking emotional status and current location of the child.
   - Task 3: Checking historical statistics of the child.

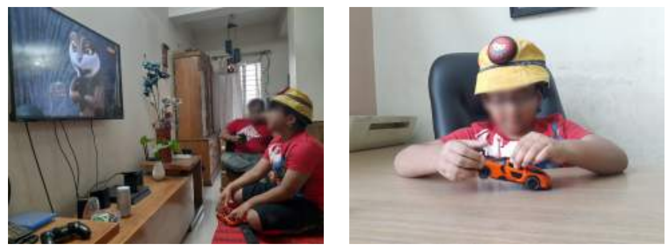


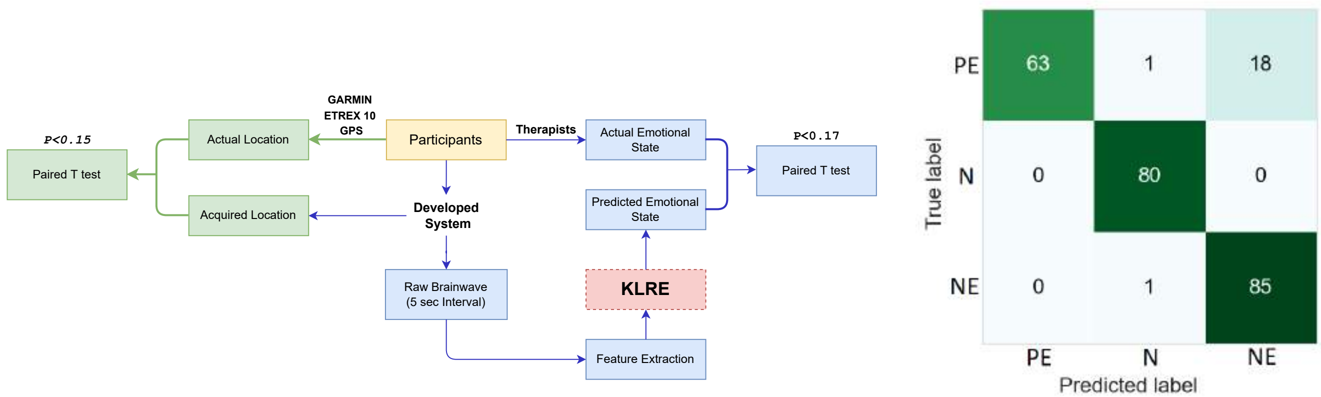
Fig. 7: Evaluation process with parent and child.

C. Results

We use the data collected during the evaluation study to measure the effectiveness and efficiency of the developed system.

1) Effectiveness: In this study, we consider three variables to measure the effectiveness: a) Accuracy of the prediction of the emotional status; b) Correctness of the Location Data and c) Correctness of the data stored and retrieved from the database. Our framework for validating the effectiveness of the developed system is highlighted in Figure 8a.

Accuracy of the prediction of the emotional state: We conduct necessary preprocessing and extracted the features as discussed in Section 3 on the collected dataset of each individual participant. Then, the deployed model (ALRE) in the web application predicts the emotional status of the children. Among a total of 268 instances of prediction, the developed model correctly predict in 228 instances with a macro-averaged accuracy of 92%. Figure 8b highlights the confusion matrix on the accumulation of all the predictions



(a) Effectiveness Evaluation framework.

(b) Confusion matrix of test dataset.

Fig. 8: Evaluation study to measure effectiveness of the developed system.

of 20 participants. Moreover, we compared the actual level and the predicted level of emotional state using *Chi-Square test* [26], since both of the levels are categorical in nature. Then, we obtained that the *p-value was* < 0.17, which also established that our hypothesis accepts the null hypothesis (i.e., rejects the alternate hypothesis) i.e. we can claim that our predicted and actual level of emotional state have no statistical difference.

Correctness of the location data: After setting up the GPS device, we extract the visualized location data of the participants. We use a GARMIN ETREX 10 handheld GPS to acquire the original latitude and longitude of the connected child. Then, We compare the reported location of the developed system with the actual location data. We find the mean difference (MD) in coordinate was 0.162 in latitude and 0.321 in longitude. Then, we conducted *Paired t* tests [27] to check if the means of the acquired sets of location data and actual location data are significantly different by using IBM SPSS. The results showed that the *p-value was* < 0.15 which is not statistically significant. The result of the *Paired t* test indicated that our hypothesis accepts the null hypothesis (i.e., rejects the alternate hypothesis), which claims that there is no difference between actual and acquired location data.

Correctness of the data stored and retrieved from the database: We measure the correctness of data stored and retrieved using the collected data from the three sub-tasks given to the parents.

1) In every test session, the profile setup (Task 1) was done correctly and the information was stored in the database.
2) Location coordinates were saved in the database and retrieved correctly to locate in the map for all the instances during the evaluation.
3) History is saved correctly in the database and retrieved to visualise graphically (Task 4) in the UI for all the test cases.

2) Efficiency: In this study, we use four variables to measure the efficiency of the developed system:

- Time required to predict the emotional status
- Number of clicks required to complete a task
- Time required to complete a task
- Number of help asked from the researchers during a task

Number of clicks required to complete a task: The number of clicks is calculated for tasks 1 and 3 where the minimum number of clicks was 2 and 5. The minimum and maximum clicks for task 1 were 2 and 4 respectively with an average of 2.48 times to complete the task. In the 2nd task, the average click was 4.32. In the case of task 3, the average was 6.90 times with a minimum click of 5 and a maximum click of 9. So, on average, parents took 0.48 and 1.9 more clicks than the minimum or optimal click for tasks 1 and 3. As Task 3 is fairly new to the users, it took more clicks than the Task 1 and Task 2.

Time required to complete a task: The minimum time for completing Task 1 is 18 seconds whereas the maximum time is 26 seconds with an average of 20.4 seconds. For the Task 2, the minimum time was 29 seconds and the maximum time was 41 seconds with an average of 35.4 seconds. The average time of the Task 3 is 50.5 seconds where the minimum time is 39 seconds and the maximum is 62 seconds.

Time required to predict the emotional status: The minimum time for setting up the entire device took 58 seconds whereas the maximum time was 73 seconds with an average of 64.3 seconds. After setting up the device, the data was taken for 5 minutes. After collecting the data, the prediction of the emotional status was on average 49 sec.

Number of help asked from the researchers during a task: In this study process, at first, the parents were briefed about the whole process clearly. Ideally, participants are anticipated to ask for no help in case of an efficient system. Our study results show that on average, the participants asked 0.02, 0.12, and 0.17 more times than the optimal value (i.e. 0) to complete Task1, Task2, and Task3, respectively. This result proves that the instruction of usage of the prototype and the UI of the app is clear enough so that the number of asking for help was low.

VII. Discussion and Conclusion

In this study, we develop a monitoring system to actively predict the emotional status and track the live location of an ASD child. We collect brainwave data from ASD children and utilize the data to predict the emotional status of the children. Notably, we develop two novel ensemble models KLRE and ALRE, and compare the performance of the models with other models. Both of the developed ensemble models worked better than the individual models with a score of 0.89 in accuracy and 0.90 in F1-score in the case of KLRE and with a score of 0.93 in accuracy and 0.93 in F1-score in case of ALRE. We deploy the best-performing model (ALRE) and use it as the backbone to further develop a web application for visualizing the result of the prediction and live-location to the parents or caretakers. We develop the monitoring system with two major modules where the headgear module collects raw brainwave data and location data from the ASD children and the associated web application visualizes the predicted current emotional status along with live-location of the ASD child to the parents/caretakers. We also conduct a lightweight evaluation study to measure the effectiveness and efficiency of the developed system using 20 new test cases. Notably, we find the developed system is effective with an average accuracy of 92% in predicting the emotional status of the child and an error of 2.875% in fetching the accurate location data. To the best of the authors' knowledge, the proposed design is the first of its kind in monitoring ASD Children with the integration of live location tracking. The developed ensemble model performs better compared to the state-of-the-art prediction models to predict the emotional states of ASD children. Furthermore, unlike the prevailing systems, the developed system provides the live-location of the children and stores the history of their emotional states. In future, we. would like to apply deep learning technique and also improve the GUI of the proposed system.

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