

RESEARCH



RQA-based identification of emotions from electrocardiogram signals for emotion regulation in children with autism spectrum disorder

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Abstract

Children with Autism Spectrum Disorder (ASD) have difficulties in expressing and regulating their emotions resulting in meltdowns and outbursts that make it difficult for parents, medical practitioners and caretakers. This research aims to recognize the unexpressed positive and negative emotional states of children with ASD using electrocardiogram (ECG) signals. Emotional ECG data is obtained from 25 children with ASD using a personalized emotion elicitation protocol, catered to the emotional need of the child. Emotional data was also obtained from 25 typically developed children using a generic protocol. The ECG data was pre-processed and features were extracted using Recurrent Quantification Analysis (RQA) algorithms. The influence of the various features on emotion recognition is analysed. Classification results indicate 97.9% and 87.9% respectively in identifying the positive and negative emotional states in children with ASD. The better correlation of RQA based ECG features with emotions for children with ASD paves way for RQA and similar nonlinear methods to be explored further for better identification of emotional states.

Keywords: Emotion recognition, Psychophysiology, Autism Spectrum Disorder, Recurrent quantification analysis, Positive and negative valence

Introduction

Autism Spectrum Disorder (ASD) is a complex Neuro developmental condition that impacts an individual's social interactions, communication abilities, behaviour, and daily functioning [1]. ASD is described as a "spectrum" disorder as it encompasses a wide range of symptoms and challenges. It includes various conditions and subtypes, and individuals with ASD can exhibit varying degrees of severity and a diverse array of strengths and weaknesses. Common features and traits associated with ASD may involve, impaired social interaction, communication challenges, repetitive behaviours, narrow interests, sensory sensitivities, heightened or reduced sensitivity to sensory stimuli,

rigidity and adherence to routine, altered activity levels [2].

Children with ASD frequently encounter considerable difficulties in conveying what is in their minds often resulting in tantrums and Sudden emotional Outbursts that occur due to discomfort, inflexibility, sensory or neurological issues [3]. One of the most disruptive aspects of ASD is causing self-injury, hitting others, aggressiveness and meltdowns [1]. The problem lies in the fact that, during emotional outbursts, the caregiver or parent is often unaware of the child's underlying emotional state. This research aims to develop a device that would help the caretaker or parent to understand the hidden, unexpressed underlying emotional state of children.

Emotions are an indispensable component of everyday life and influence our thoughts, perceptions, actions, behaviours and quality of life [4]. They are being learnt by researchers from diverse disciplines such as psychology,

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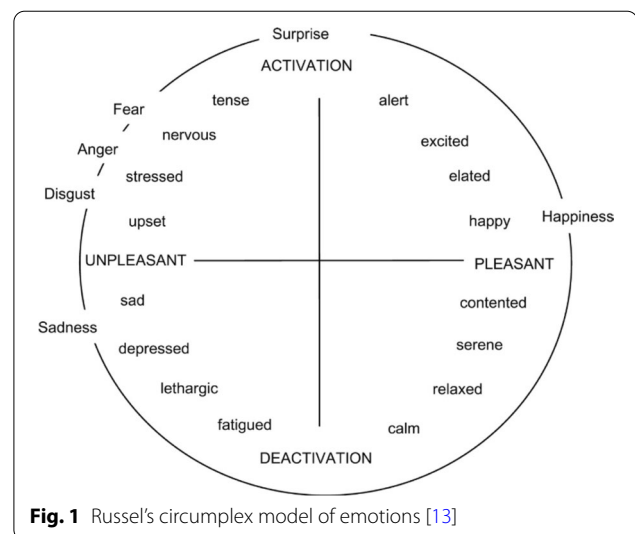
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psychiatry, neuroscience, education, anthropology, artificial intelligence, affective computing, medicine, business, marketing etc., Different aspects such as the cognitive, developmental and behavioural process of emotions, perception and regulation, emotional expression, neural correlates, linkage with mental health disorders, neurochemical process, cultural and social linkage of emotions, recognition of emotions from behavioural, psychological and physiological cues are being researched to understand and define emotions. Though there is not an universally accepted definition available for emotion, they are defined as complex manifestations of physical and psychological states [5–9]. For systematic and better understanding of the basic and complex emotional states, different theoretical models of emotions commonly categorized as discrete and dimensional models are proposed by researchers.

In discrete models, the complex landscape of human emotions are simplified by classifying them into well-defined categories of emotions, each having its own specific features or criteria. The model proposed by Paul Ekman, [7, 10] illustrates the presence of six universal, basic emotions namely happiness, sadness, anger, fear, surprise, and disgust. His research associates distinct facial expressions with emotions across nationalities, culture and people groups [11]. Though Paul Ekman's model is used widely, researchers have also proposed other discrete models such as the Differential Emotions Theory (DET) with ten basic emotions, three wheel model which has primary, secondary and territory emotions [12].

Dimensional model of emotions can represent a wider range of emotions by describing them using two or three fundamental features. Russel's circumplex model views emotions in a two-dimensional bipolar scale namely valence and arousal as indicated in Fig. 1. Valence distinguishes whether an emotion is pleasant or unpleasant, while arousal indicates the intensity or activation level of the emotional experience, spanning from calm and relaxed states to highly intense emotions such as excitement or fear. The Valence Arousal Dominance (VAD) model consists of three dimensions – Valence, Arousal and Dominance. Dominance indicates the level of control of the emotional state ranging from submissive to dominant [5, 13, 14]. The theoretical model of emotions helps researchers to understand the mechanisms involved in the generation, expression and perception of emotions which in turns aids in the design of emotion elicitation protocol and extraction of emotional features for further processing and analysis.

Researchers on affective computing and artificial intelligence have worked on identifying the emotional valence states for typically developed children and adults



using behavioural and physiological measures [15–17]. Physiological measures are considered reliable as they overcome the issues caused due to social masking in the various behavioural modalities [18]. Several databases of physiological signals are available for research on typically developed children and adults. Various techniques are employed and accuracies as much as 95% has been reported in classifying valence and arousal states. Researchers have also worked on classifying multiple emotional states and achieved above 90% accuracy in classifying the emotional states [19, 20].

In case of children and adults with ASD, behavioural techniques are not particularly reliable, as these individuals cannot reliably communicate their feelings which are dependent on various sensory disorders. The neural mechanisms are highly subjective and differs considerably in the ASD continuum. Physiological signals-based analysis of emotion recognition has been worked on by a few researchers and accuracies up to 81% has been achieved in categorizing the two emotional states in children with ASD [21]. Physiological data in children with ASD is challenging because of the neurological biases and variations in the physiological data. Children with ASD are reported to have significantly lower amplitudes of respiratory sinus arrhythmia and faster heart rates and abnormally high sympathetic activity compared to typically developed children [22]. Obtaining emotional physiological data from children with ASD and correlating the emotions to the varying complex and subjective nature of physiological data is exigent.

Researchers have developed various protocols to induce the emotional state in typically children and children with ASD though they do not mimic non laboratory real time

events [3, 23]. Arousal of emotional states in children with ASD depends on the heterogeneous condition and sensitivity to stimuli by the child [23]. Few researchers have worked on subject dependant protocols for acquiring the emotional physiological data from children with ASD [21]. Not only is the data heterogenous but is also prone to noises and artifacts which needs to be carefully removed. The reduced accuracy is due to these complexities in the physiological data that are observed in children with ASD. Though physiological signals such as Electro Encephalogram (EEG), Electrooculogram (EOG), Electromyogram (EMG) and Electrocardiogram (ECG) are used to identify the underlying and unexpressed emotional states, ECG is preferred as it is easily adaptable to wearable devices and the algorithm can be integrated to develop an emotion recognition system that can be used in daily life [20, 24–29].

Emotional features are derived from ECG signals using various time domain, frequency domain, time–frequency domain and non-linear methods [17–19, 22, 30–32]. Individuals with ASD often exhibit atypical dynamics such as prolonged high arousal, abrupt shifts, or repetitive loops of affective states. While most of the traditional features such as the statistical features and ECG signal specific features such as Mean Heart Rate (HR), Mean RR, SDNN, LF/HF ratio etc., capture emotion related static information from ECG, RQA captures the dynamic properties during the emotional variation. The feature recurrence reflects the re-emergence of similar affective states, determinism and Longest Diagonal Line indicate predictability in transitions, laminarity and trapping time reveals the entrapment in particular affective regimes [33].

While other nonlinear tools only capture the complexity, RQA aligns directly with the theoretical models of emotion making it more suitable for identification of the valence states. Recent research works have also demonstrated the significance Recurrent Quantification Analysis (RQA) in capturing the minor variations, movements and transitions of physiological signals and has been found successful in capturing ECG abnormalities, drowsiness stages etc. [33–37].

This research work presents the recognition of emotions from children with ASD using electrocardiogram signals. It elaborates the methods

used for acquiring positive and negative emotional ECG data from children with ASD, pre-processing and analysis of the acquired data using RQA, that is suitable for complex, dynamic, nonlinear, nonstationary and noisy data [36]. The influence of the RQA features on the emotional states of typically developed children and children with ASD are elaborated and discussed in detail. Results indicate a maximum accuracy of 95.8 and 82.6% in classifying the positive and negative emotional states of typically developed children, and 97.9 and 87.9% for children with ASD.

Methodology

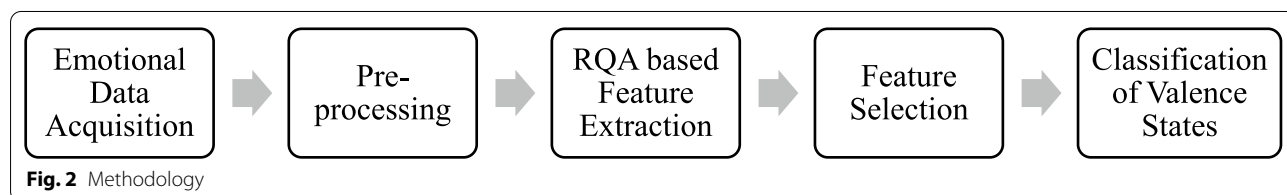
The methodology used in this research work is as illustrated in Fig. 2. The ECG data corresponding to positive and negative valence was obtained from of 25 typically developed and 25 children with ASD by means of a personalized protocol using audio visual signals. The data obtained was preprocessed to remove the influence of noises and artefacts. Features were extracted using RQA based algorithms and classified using various classifiers.

Emotional data acquisition

To evoke positive and negative emotional states, a protocol for data acquisition was meticulously crafted for both typically developed children and children with ASD, ensuring a consistent time frame while tailoring the stimuli to each child’s preferences. The protocol used for eliciting the emotions is as presented in Fig. 3.

The elicitation of positive and negative valence was done including audio clips and images. A cool off time of 1 min was given before the session and a neutral video was played for 2 min to calm the child. Each trial consists of either positive or negative stimuli with breaks. Trial 1 and Trial 3 induced positive valence whereas Trail 2 and Trial 4 induced negative valence. Two sessions were conducted for each child with each one lasting for about 12 min. The break between sessions varied from child to child. In some cases, there was a break during sessions depending on the valence felt of the child.

The choice of stimuli—audio clips, images and videos for the child was determined through trials and interviews with parents, caretakers etc., who helped in identifying images, audio clips and audio-visual stimuli that induce positive and negative emotional states. The



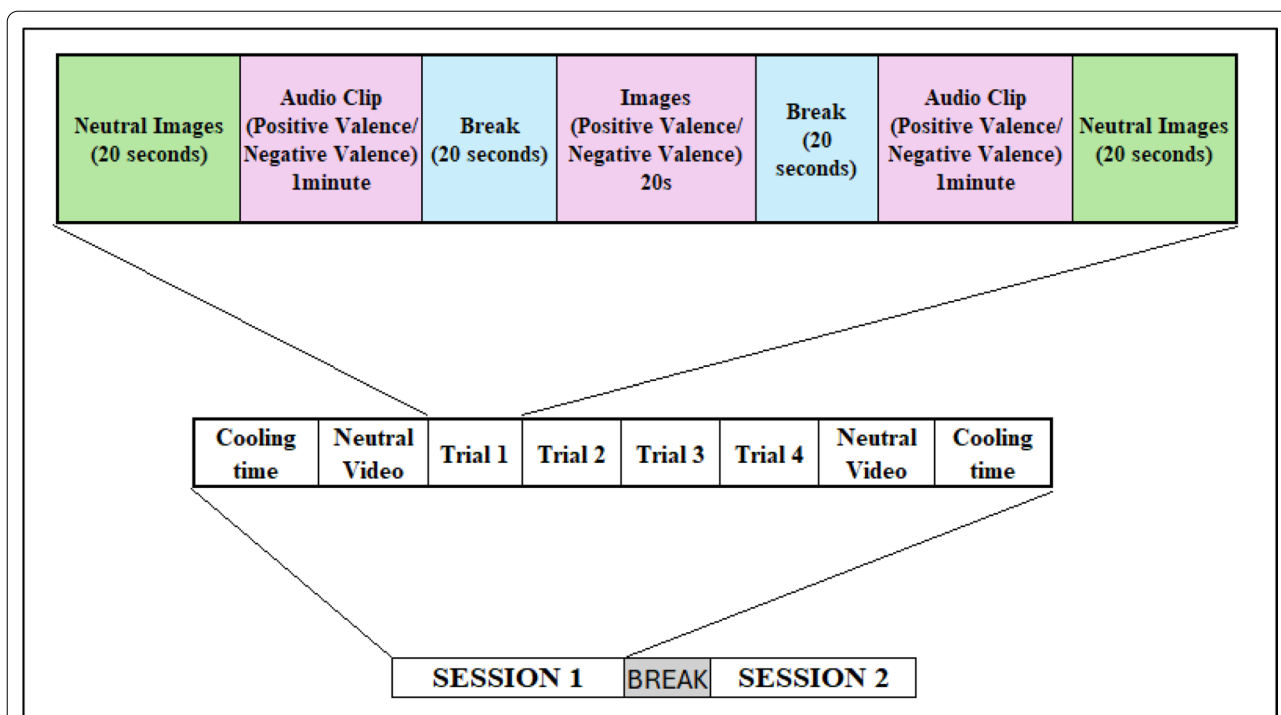


Fig. 3 Emotion elicitation protocol

body language of the child was also observed to identify stimuli where certain actions like jumping indicates their fondness towards the stimuli and aggression, inattention, moving away etc., indicated dislike. As indicated in Fig. 3, the type of stimuli (audio, visual or audio visual) and the duration for which the stimuli were presented to the child was kept the same for all the children. However, stimuli that induced the emotions (the images, audio and audio-visual clip) varied for each child based on the selection of stimuli done along with the parents.

The personalization framework used for identification of emotional stimuli is as presented in Fig. 4. Twenty to Thirty Audio clips, visual pictures and audio-visual clips each were selected from standard databases such as International Affective Picture System (IAPS),

International Affective Digital Sounds (IADS) and various other sources on the internet based on the interviews made with parents /teachers/ caretakers and observations done in the classroom [38–42]. Later all the clips and pictures were displayed to the parents who helped in selecting a minimum of 10 positive audio clips, 10 negative audio clips, 10 positive images, 10 negative images, 10 positive video clips, 10 negative video clips and 10 neutral images. The selected stimuli were then presented to the children during the experiment as per the protocol in Fig. 3.

Children with ASD for data collection were recruited from National Institute of Physical Medicine and Rehabilitation (NIPMR), Kallettumkara, Kerala, India. Ethical approval for data collection was also obtained from

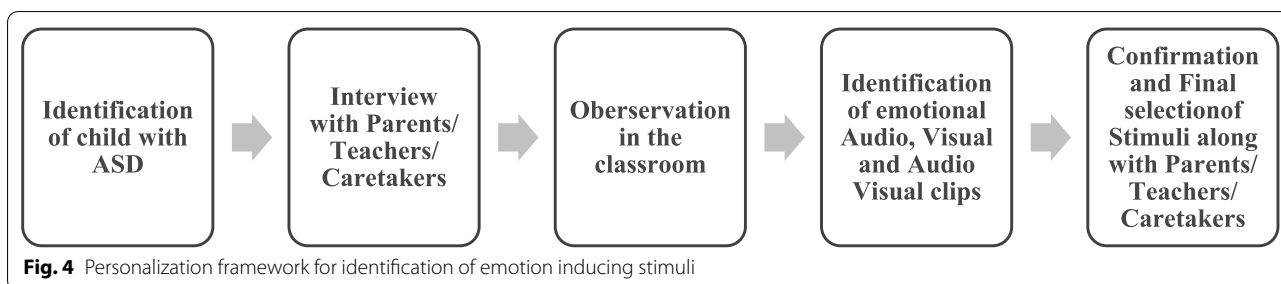


Fig. 4 Personalization framework for identification of emotion inducing stimuli

NIPMR. There were 15 females and 10 male children with mild to moderate Autism based on ISAA Score as indicated in Table 1. Similarly, 25 typically developed children within the same age range and with an average age of 11.5 years were selected from nearby schools.

Consent was obtained and data was collected using the wearable Shimmer Holter device, as shown in Fig. 5 that is designed for continuous monitoring of a person's heart activity. A couple of trials were run on children so that they are comfortable wearing the device. The parent or caretaker who is well acquainted with the child

Table 1 ISAA score of children with ASD

ISAA score	Less than 70	70 to 106	107 to 153	Greater than 153
Autism classification	No autism	Mild autism	Moderate autism	Severe autism
Percentage disability	40%	40–60%	70–90%	100%
Children in the experiment	NA	12 (6 female, 6 male)	13 (9 female, 4 male)	NA

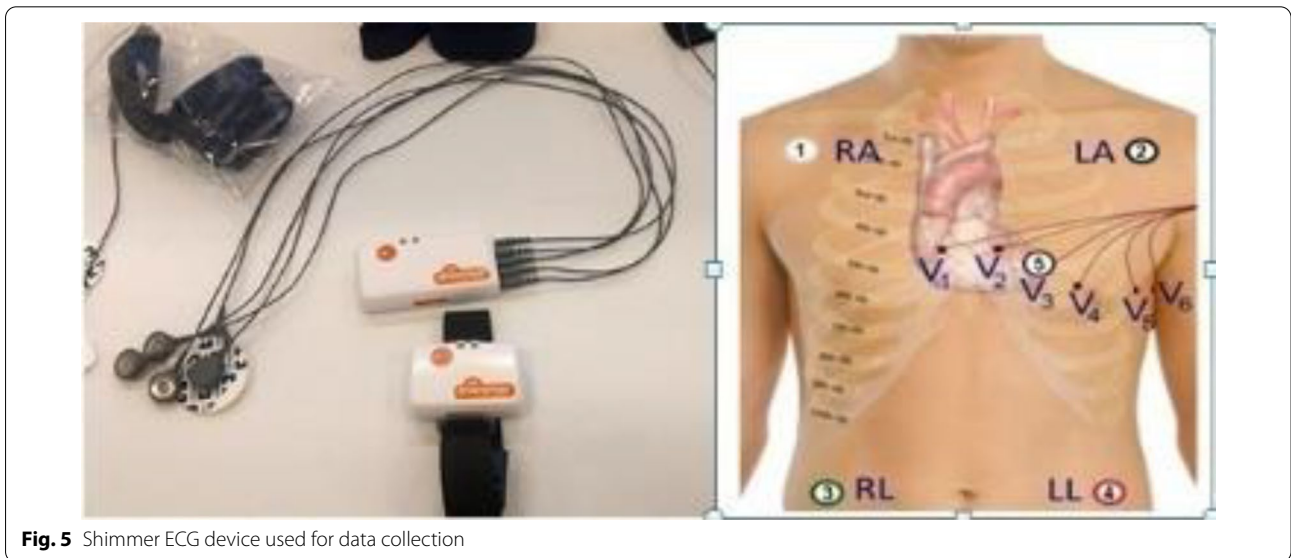


Fig. 5 Shimmer ECG device used for data collection



Fig. 6 Data collection process

accompanied all through the data collection process, as in Fig. 6, and provided feedback of the emotions felt by the child.

Data preprocessing

ECG data contain Baseline wander, Power line interference (50 Hz noise) and Electrode motion Artifacts. Baseline drift is a slow gradual shift in the baseline of the ECG signal caused by factors like breathing, body movement or changes in electrode-skin contact. Power line interference is due to the electromagnetic fields of the powerlines and matches with the power supply frequency of 50 Hz. Electrode motion artifacts occur when electrodes are not properly secured or if there’s movement during the recording. A wavelet-based algorithm was used to remove the baseline wander [43]. Powerline Interference and electrode motion artifacts were removed using notch and low pass filters.

RQA based feature extraction

RQA (Recurrence Quantification Analysis) is a nonlinear analytical method used to explore dynamical systems and extract features. Developed by Eckmann and colleagues, this tool visualizes the phase space of a system (with M dimensions) through a two-dimensional representation of its repetitions. In this representation, any state at time (i) and a different time (j) is depicted in a square matrix. It assesses the fine-scale structures within recurrence plots, revealing the number and duration of a dynamical system’s recurrences and quantify system dynamics.

The extracted measures from the RP are as indicated from Eqs. (1) through (6),

DET (Determinism): This is measured as the percentage of points that form diagonal lines in the recurrence plot of minimal length. It indicates the system’s predictability.

$$DET = \frac{\sum_{l=lmin}^N l P(l)}{\sum_{i,j}^N R(i,j)} \tag{1}$$

where P(l) is the frequency distribution of the lengths l of the diagonal lines (i.e., it counts how many instances have length l). This measure is called determinism and is related with the predictability of the dynamical system, because white noise has a recurrence plot with almost only single dots and very few diagonal lines, whereas a deterministic process has a recurrence plot with very few single dots but many long diagonal lines.

LAM (laminarity): diagonal laminarity is the percentage of points that forms vertical lines. It indicates the probability that a state will not change for the next time. Marwan et al. and Schinkel et al. provide further

mathematical detail for RPs and RQA features [44, 45]. Laminarity is related with the amount of laminar phases in the system

$$LAM = \frac{\sum_{v=vmin}^N v P(v)}{\sum_{v=1}^N v P(v)} \tag{2}$$

where P(v) is the frequency distribution of the lengths v of the vertical lines, which have at least a length of vmin.

LMAX: The length of the longest diagonal line

$$Lmax = \max(Li : i = 1,2, \dots N) \tag{3}$$

TT is related with the laminarity time of the system, i.e. how long the system remains in a specific state.

$$TT = \frac{\sum_{v=vmin}^N v P(v)}{\sum_{v=vmin}^N P(v)} \tag{4}$$

ENT (Entropy): Entropy of the diagonal line lengths(Shannon)

$$ENT = - \sum_{l=lmin}^N P(l) * \ln P(l) \tag{5}$$

RR (Recurrence Rate): Recurrence rate corresponds with the probability that a specific state will recur.

$$RR = - \frac{1}{N * N} \sum_{i,j=1}^N R(i,j) \tag{6}$$

Feature reduction and classification

Statistical analysis using ANOVA was done to identify the features that are suitable for further analysis, It uses a descriptive analysis to compare the means of two samples and helps in identifying significant features which were then classified using Simple Tree classifier, Linear Discriminant Classifier, Quadratic discriminant Classifier, Support Vector Machines, K-Nearest Neighbor and Ensemble Classifiers.

Seventy percent of the data was used for training and thirty for testing. Ten-fold cross validation was employed to eliminate the effect of biases and over fitting. The performance of the classifiers was evaluated using Accuracy that is computed using the Eq. (7),

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

where True Positives (TP) represent samples accurately identified as the target emotion, while True Negatives (TN) denote samples correctly classified as not the target emotion. False Positives (FP) indicate samples incorrectly

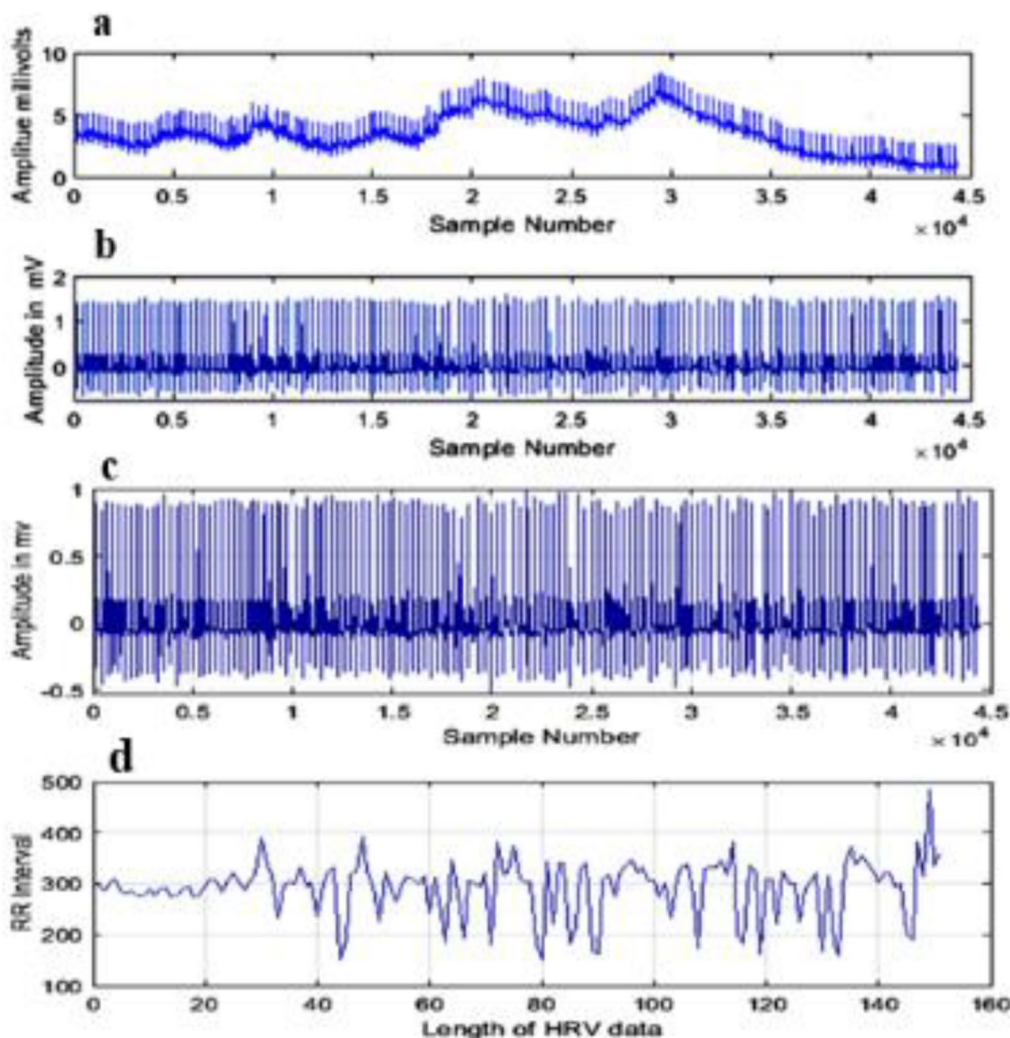


Fig. 7 Preprocessing of ECG signals **a** Raw ECG Signals **b** ECG signals after removal of Baseline Wander **c** ECG Signals after removal of powerline interference and high frequency noises

categorized as the target emotion, and False Negatives (FN) represent samples mistakenly labeled as not the target emotion.

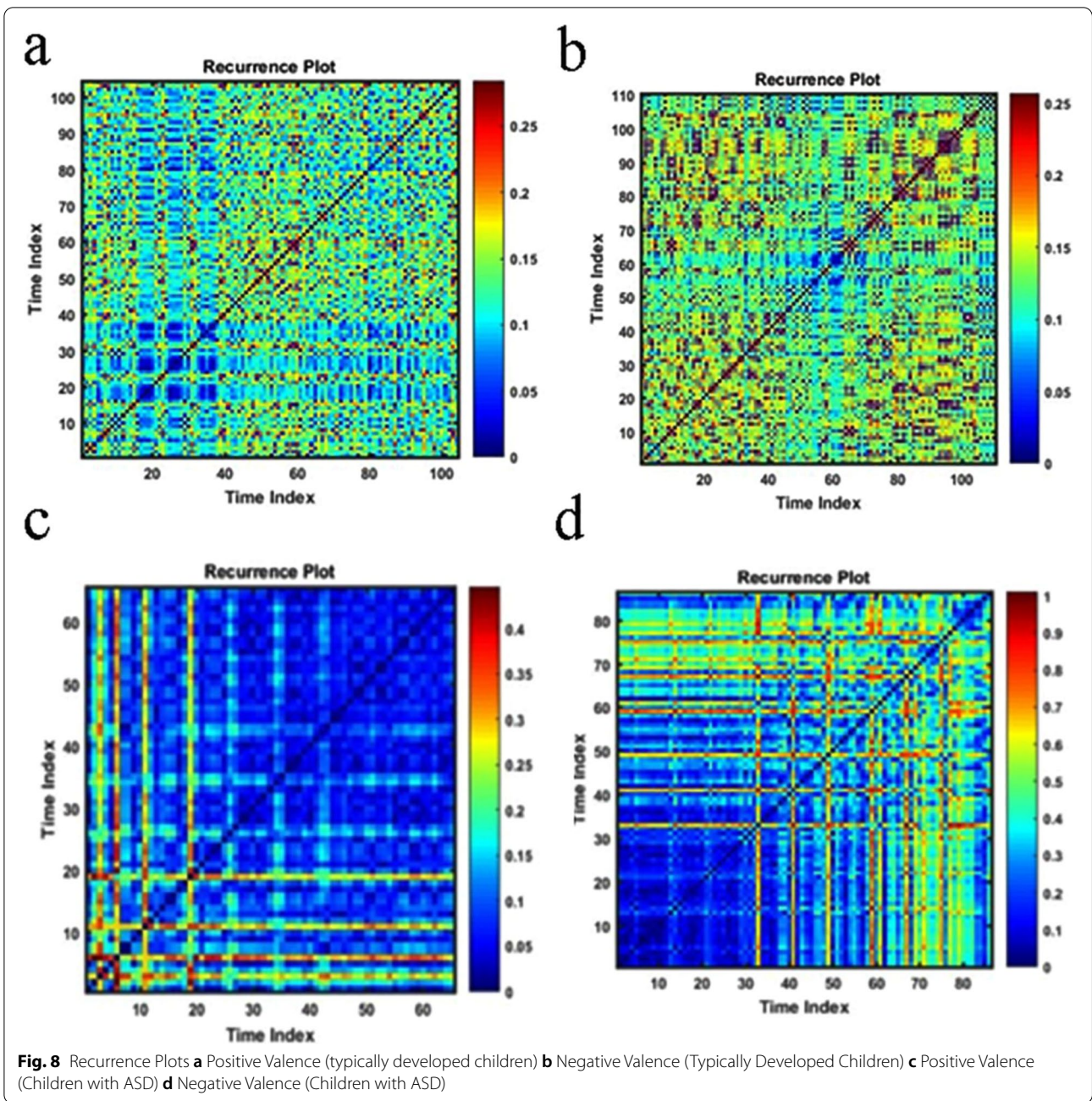
Results

The raw ECG data obtained from children are prone to noises due to baseline wander, powerline interference and other artefacts. Figure 7 illustrates the removal of baseline wander and high frequency noises from the ECG data.

The Recurrence plot obtained from the ECG data for positive and negative valence of typically developed children and children with ASD is as indicated in Fig. 8. The consistent patterns observed in the plots indicate the quasiperiodic nature of the ECG data. It can be

seen that the negative valence for both typically developed children and children with ASD indicate variation compared to positive valence and can be captured by the RQA based features.

The average value of the features extracted from the ECG signals of Typically developed children and children with ASD for the two states is as indicated in Table 2. For most of the metrics the features indicate more chaotic behavior in the data in children with ASD compared to the typically developed children. The transient nature of emotions is reflected in the higher values of LAM. There is also a huge difference in the TT values between the two types of children, indicating the fast transition rate in the ECG data in children with ASD. The quasi-periodic nature of ECG data with no



abnormalities is reflected in the ENT value, which is in generic low for both the cases.

While values of LMAX and TT provide significant difference between the two valence states for both typically developed children and children with ASD, features such as DET and LMAX do not distinguish between the valence states for typically developed children. There is marginal difference in these features among the valence

states for children with ASD. The features of individuals also show similar differences in the values.

The statistical analysis described in Table 3 indicates the P-values, effect sizes and confidence intervals computed for the features with respect to the positive and negative valence states using one way ANOVA. It can be observed that the features can be observed that the features LMAX, ENT, LAM and TT show significance. The corresponding effect sizes is small, indicating very little distinction of these features between the two classes. TT

Table 2 RQA based features extracted from the ECG data of typically developed children and children with ASD

Features	Totally developed		Children with ASD	
	Positive valence	Negative valence	Positive valence	Negative valence
DET	99.98	99.96	83.64	76.69
LMAX	177	124	51.33	43.87
ENT	7.23	6.94	3.67	3.60
LAM	99.97	99.96	87.31	85.73
TT	83.69	63.5	20.99	16.47

has very small effect size indicating that the distinction between the features may not be practically important. Partial overlap in the confidence intervals is observed in LMAX, ENT and LAM. The feature DET doesn't show statistical significance nor has an substantial effect size limiting its utility in identifying the emotional states. The features LMAX, ENT, LAM and TT were considered for further processing.

It can be observed from Table 4 that positive valence shows higher accuracy compared to negative valence for both typically developed children and children with ASD

Table 3 Statistical analysis of the features DET, LMAX, ENT, LAM and TT with respect to positive and negative valence

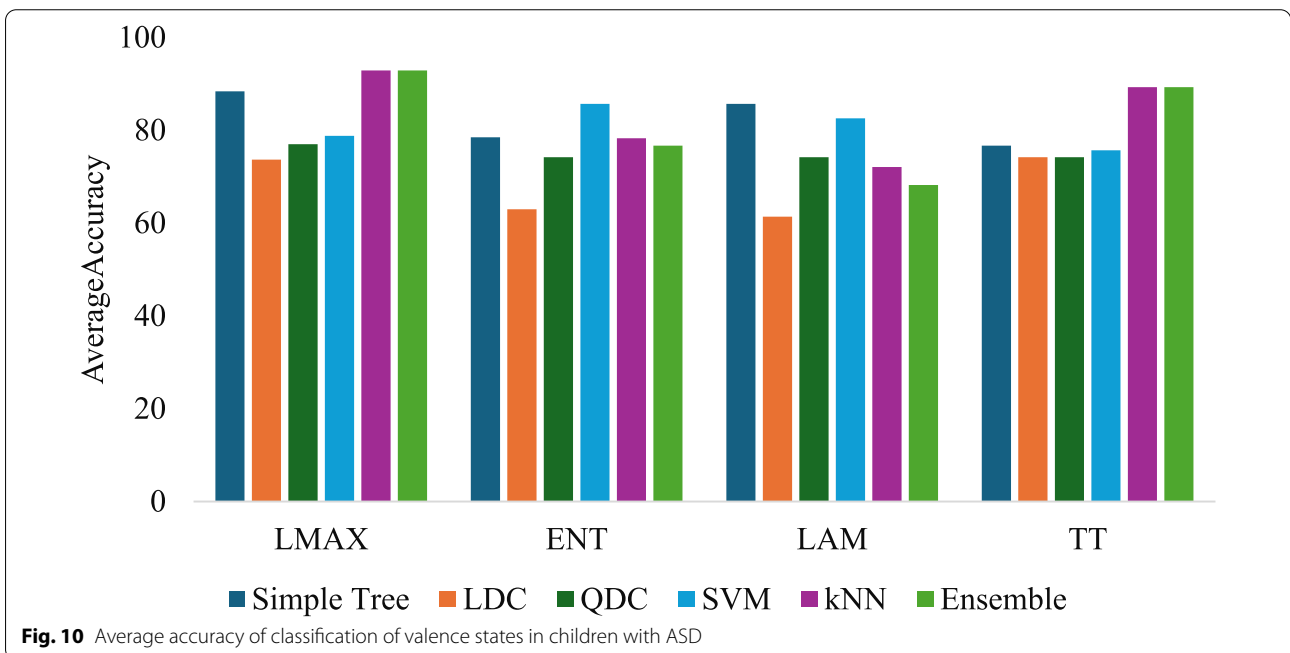
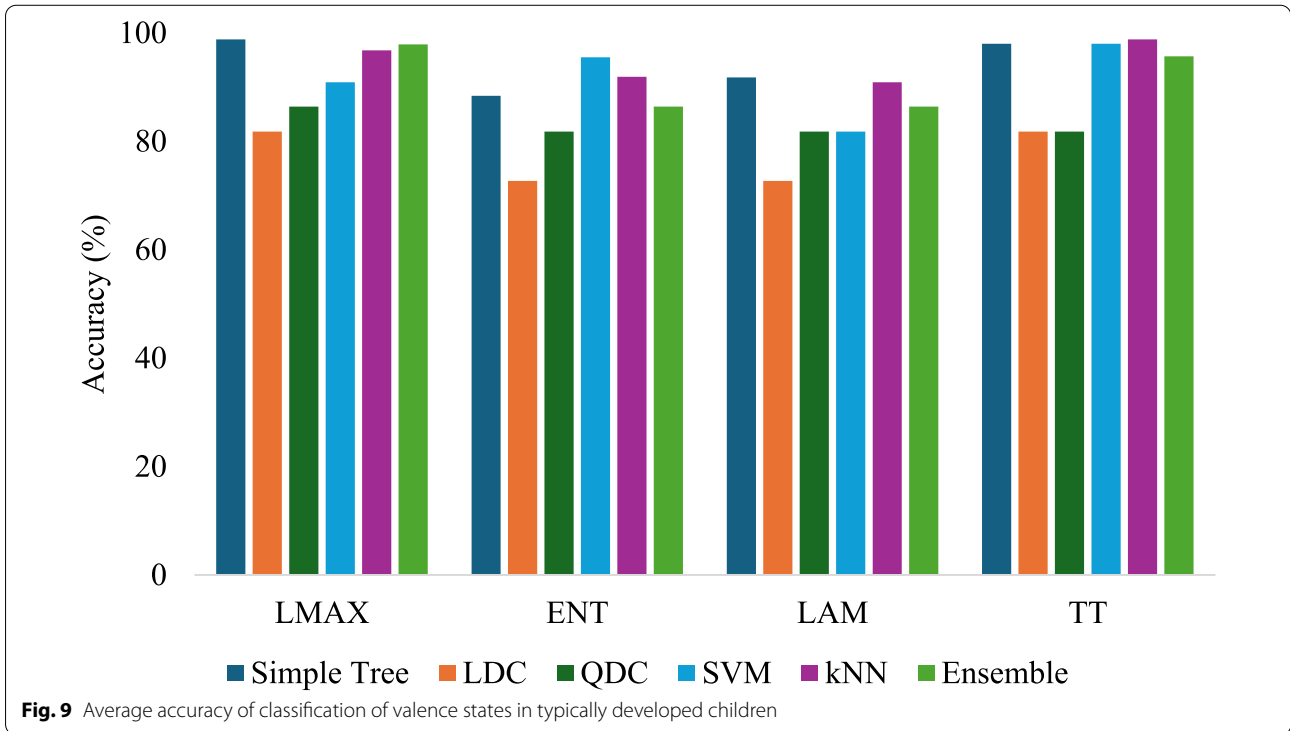
Features		DET	LMAX	ENT	LAM	TT
P value		0.78	0.037	0.024	0.04	0.015
Effect size		0.0334	0.013	0.014	0.047	0.0001
Confidence Interval (95%)	Positive Valence	97.04±2.75	161.03±27.56	6.29±0.65	97.52±2.20	70.24±15.6
	Negative Valence	91.74±5.52	134.33±30.53	5.58±0.82	92.03±5.3	58.71±17.53sn

Table 4 Accuracy of classification of valance states

Features	Classifiers	Typically developed children		Children with ASD	
		Positive valence (%)	Negative valence (%)	Positive valence (%)	Negative valence (%)
Longest diagonal line (LMAX)	Simple Tree	98.5	78.5	98.8	78.0
	LDC	85.4	50.0	81.8	65.7
	QDC	80.3	50.0	86.4	67.7
	SVM	95.3	83.5	90.9	66.7
	KNN	90.3	80.4	96.8	88.9
	Ensemble	95.8	82.6	97.9	87.9
Entropy (ENT)	Simple Tree	88.6	64.7	88.4	68.7
	LDC	70.6	56.5	72.7	53.3
	QDC	71.3	64.5	81.8	66.7
	SVM	87.8	64.0	95.5	76.0
	kNN	75.0	56.5	91.9	64.6
	Ensemble	71.3	63.0	86.4	67.0
Laminarity (LAM)	Simple Tree	86.4	85.3	91.8	79.6
	LDC	82.4	77.7	72.7	50.0
	QDC	80.3	60.5	81.8	66.7
	SVM	90.5	90.4	81.8	83.3
	KNN	85.3	67.4	90.9	53.3
	Ensemble	92.6	57.8	86.4	50.0
Trapping Time (TT)	Simple Tree	75.4	85.8	98.0	55.3
	LDC	66.5	56.5	81.8	66.7
	QDC	65.3	66.8	81.8	66.7
	SVM	80.5	79.5	98.0	53.3
	KNN	78.9	77.7	98.8	79.7
	Ensemble	90.3	88.6	95.7	82.8

across all classifiers. Considering the individual features, it can be observed that LMAX and TT performed well in identifying positive valence in children with ASD with highest accuracies of 97.6 and 98.8% respectively. Negative Valence was better captured by LMAX compared

to TT, though the performance metrics for classification of negative valence is less for all the features. Though the feature ENT has lesser accuracy it can be observed that this feature also classified positive valence of children with ASD at 95.5% using the SVM Classifier. The



accuracy of identifying negative valence states was not consistent across all the features and classifiers. It can be observed that Ensemble and KNN captured negative valence in a better way for LMAX and TT features whereas SVM Classifier could do better for the feature LAM. LMAX and TT features capture the temporal structure and stability of the transient emotional expressions and need to be explored further in the development of emotion aware systems.

Figures 9 and 10 compares the average accuracy of the features for the different classifiers for both typically developed children and children with ASD respectively. It can be observed that the accuracy of classifying the states is better for LMAX and TT for both the states though the accuracy for children with ASD is less compared to typically developed children. Ensemble classifier that combines multiple models and is suitable for multi-dimensional chaotic data works better in all cases.

Table 5 F1 Score of the various classifiers

Classifiers	Typically developed children		Children with ASD	
	Positive valence (%)	Negative valence (%)	Positive valence (%)	Negative valence (%)
Simple Tree	82.0	70.0	90.0	83.0
LDA	82.3	85.1	83.3	86.9
QDA	71.0	63.0	70.0	73.0
SVM	84.0	86.9	90.3	86.6
KNN	93.1	91.6	93.3	93.0
Ensemble	84.0	88.8	90.5	86.6

The F1 score of the different classifiers are as presented in Table 5. It can be observed that the KNN Classifier performs better with F1 values ranging from 91.6 to 93.3 indicating a robust balance between precision and recall. SVM also performs better in capturing the nonlinearities of the emotions captured by RQA. It can also be noted that the F1 score of positive valence is higher for children with ASD compared to typically developed children. Similar observation can also be made negative valence in the case of Simple Tree, LDA, QDA and KNN Classifiers. These indicate that the emotional patterns of children ASD are distinct and easier to discriminate compared to typically developed children.

The results of RQA compared with previous research work [46] done by researchers using discrete wavelet transform is as illustrated in Fig. 11. It can be observed that RQA based algorithms perform significantly better for recognizing the negative emotional state of typically developed children, and both the emotional states of children with Autism. The sensitivity of RQA algorithms to transitions help in capturing the nonlinear and sudden dynamics of transient data needs to be explored further to improve the accuracy of classifying the valence states using ECG data.

Discussion

Acquisition of emotional ECG data

The emotional ECG data was obtained in four trials from 25 children with ASD and 25 typically developed children. Each trial had three emotional inducing stimuli and two neutral states. For children with ASD, the emotion inducing stimuli was personalized for each child

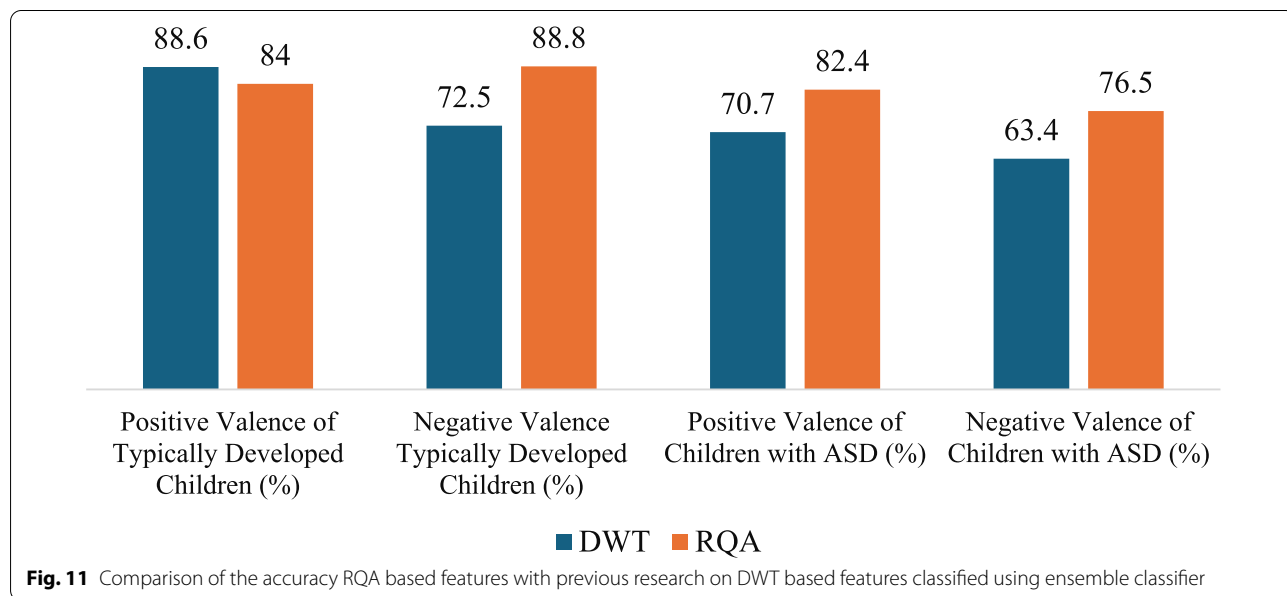


Fig. 11 Comparison of the accuracy RQA based features with previous research on DWT based features classified using ensemble classifier

by interviewing and getting information on the positive and negative experience of children from their parents or caretakers and their teachers. There is no single standard protocol for all the children, mainly due to the subjective and diverse nature of the children with ASD who had varying ranges of sensitivity and ISAA scales. In addition, emotion inducing stimuli was selected from both standard databases for emotion inducing stimuli such as IAPS, IADS etc., and other diverse publicly available databases mostly in regional language that was comfortable for the children. In all cases the parents or caretakers affirmed the selection of the protocol before it was used in the experimental work.

Such construction of personalized protocol was time consuming and challenging, and these protocols also do not ensure the simulation of the expected emotion. There were instances when the children reacted negatively compared to expected valence state. Research indicates that children with ASD are either more reactive to the stimuli or may take a long time to habituate to the stimuli, though the stimuli is developed according to their specific needs of each child [23]. To avoid ambiguity in knowing the emotions induced by the child, the caretaker or parent, who are well acquainted with the child, labelled the emotional data for the children with ASD during the data acquisition process. A generic protocol was used for all the typically developed children.

Care was also taken that the children were not over simulated during the experimental process. Initially the children were provided with trials to get acquainted with the ECG device and the process. The parent or caretaker always accompanied the child during the data collection process. In some cases, the experiment was stopped based on the caretaker or parent's advice and the data collection was scheduled for another day. Sometimes the children were very excited and were moving around leading to high noises and artefacts. It should also be noted that in this research work and in most of the research works specified in the literature the emotions are induced in a controlled laboratory environment which is different from that of real time situations [23].

Feedback obtained from the parents or caretakers during the data collection experiment was used to label the data for development of emotion recognition algorithms. Though they know the child in depth, the effect of subjectivity and potential biases is a key limitation in the current work. In future experiments, multiple observations need to be done by including multiple observers such as occupational therapists, special educators etc., during the data collection process. Ratings may also be obtained from children who can

express their felt emotions. Inter-rater agreement may be calculated to validate the labels and remove any potential biases. Objective cross validation strategies such as concurrent behavioral coding involving independent and trained observers, physiological ground truth validation using multiple physiological signals may be employed for robustness and reproducibility.

Processing of emotional ECG data

The data acquired from children was highly prone to baseline wander and movement artifacts which need to be removed without filtering the emotional content of the data. It was also observed that the basal parameters of children with ASD were subjective and hence need to be normalized. The data acquisition protocol for each child contained four trials, two of which were used to induce positive emotion and two induced negative emotion. The quantity of data used for this research work is sufficient for preliminary analysis indicating the correlation between emotional states and ECG for children with ASD. Future research should involve extensive data collection by increasing the number of children and introducing heterogeneity with varying levels of severity, functional abilities, comorbidities and demographics. This would require hiring researchers and children with ASD from diverse locations, clinical centers, and ASD Support networks. Furthermore, the stimuli used data acquisition for each child should be tailored to meet the emotional requirements of the child which requires careful study of the child and interviewing with parents, caretakers and teachers who also accompany the child during the data acquisition process. Increasing the quantity and heterogeneity of the data will aid in developing a more refined algorithm for recognizing the emotional states though there may be an increased complexity in processing the physiological data.

Emotions are transient and temporary occurring in response to stimulus and situations. The emotional physiological data does not show difference in critical parameters or on inspection though the changes caused due to variation in the emotional states are hidden in the data. Various time domain, frequency domain, time–frequency domain and nonlinear features are extracted from the psychophysiological data to identify the hidden and unexpressed states from physiological data. The features derived from RQA that is known to capture information from chaotic, nonlinear, noisy with subtle variations, is found to capture the emotional information in a significantly better way with the maximum accuracy is about 90%. RQA and similar nonlinear algorithms need to be explored further using larger datasets to identify the hidden emotions with higher efficiency. While this initial analysis is crucial, the importance of the features

extracted need to be analyzed using model explainability techniques to enhance the practical relevance.

Considering the limited sample size and low dimensionality of the features, machine learning classifiers were chosen based on the suitability of the features and evident results in literature. Deep learning models were intentionally not used in this work as they require larger quantity of data for effective generalization. Additionally, the computational complexity of deep learning algorithms is higher and resulting in the need for sophisticated processors to implement the algorithm in real time.

Analysis of physiology based affect recognition systems

Very few research works are presented correlating the physiological signals and internal states of children and patients with ASD. Table 6 compares the results of the presented research work with some of the previous research works. It can be observed that most of the studies had a limited number of samples which is attributed to the heterogeneity condition of children with ASD consisting of a wide range of symptoms, behaviors and sensitivity.

All the studies indicate that physiological signals have high correlation with internal states though some of the researchers have worked on identifying specific states such as agitation, stress etc., by providing appropriate tasks. However, in most cases, the task or stimuli was generalized for all the subjects. In the proposed research work the stimuli to induce emotional states were defined specifically for each child. Higher accuracy of 99 and 92.86% was obtained in the studies by Ref. [49, 50] respectively. These higher accuracies are due to subject specific analysis in Ref. [49] and combination of multiple physiological signals in Ref. [50]. Subject independent analysis presented in this research work indicate an average accuracy of 87.9% for 25 children with ASD. Though

the quantity of data analyzed is limited, these research outlay the significance of developing affect recognition systems by analyzing physiological variations for children with ASD.

Real time implementation

The proposed architecture for implementation of the RQA based valence recognition system is as presented in Fig. 12 and is in line with the methods used in recent research works [53, 54]. The heart rate or ECG data would be sensed from a wearable device that is comfortable and non-intrusive to the child. The data would be transferred to the cloud which would pre-process the data, compute the significant RQA feature and use a lightweight classifier that yields better performance. On device notification to the user and notification via mobile app would be sent to parents, caretakers or medical doctors when an abnormal, continuously negative valence state is observed.

The computational complexity and latency of the device majorly depend on the computation of recurrence matrix, RQA features, and network induced delays. Feature importance analysis using SHAP for the various classifiers (Fig. 13) indicates that LMAX and TT outperform all other features and hence only these may be considered when implementing the algorithm in real time.

Though processing on cloud will significantly reduce the latency, the sampling frequency and window size would be optimized to ensure that the computational complexity, latency, throughput and accuracy obtained is optimal. The data and logs would be stored in the cloud for future access. The mobile app will also facilitate the visualization and analytics of data, event log and history, real time notification, personalized suggestion of remedial measures or therapy from a health care provider, support and care network etc.

Table 6 Comparison of results with previous research works

References	Number of subjects with ASD	States	Physiological signals used	Accuracy (%)
[47]	3	Normal vs Agitation	Heart Rate, Skin conductance, Gestures, Vocal	79.49
[48]	15	Stress	PPG, EDA, Temperature, Accelerometer	75.40
[49]	5	Challenging and Non challenging Behaviours	EDA, HR, Acceleration, Temperature, BVP	99
[50]	5	Happy, sad, angry, and scared	Eelectrocutaneous signals ECG	92.86
[51]	7	Problematic Behaviour	BVP, EDA, Temperature, Accelerometer Gestures	80.17
[52]	15	High and Low Arousal States	ECG, Skin Conductance, Respiration, Skin Temperature	~80
Current Work	25	Positive and Negative Valence	ECG, HRV	87.9

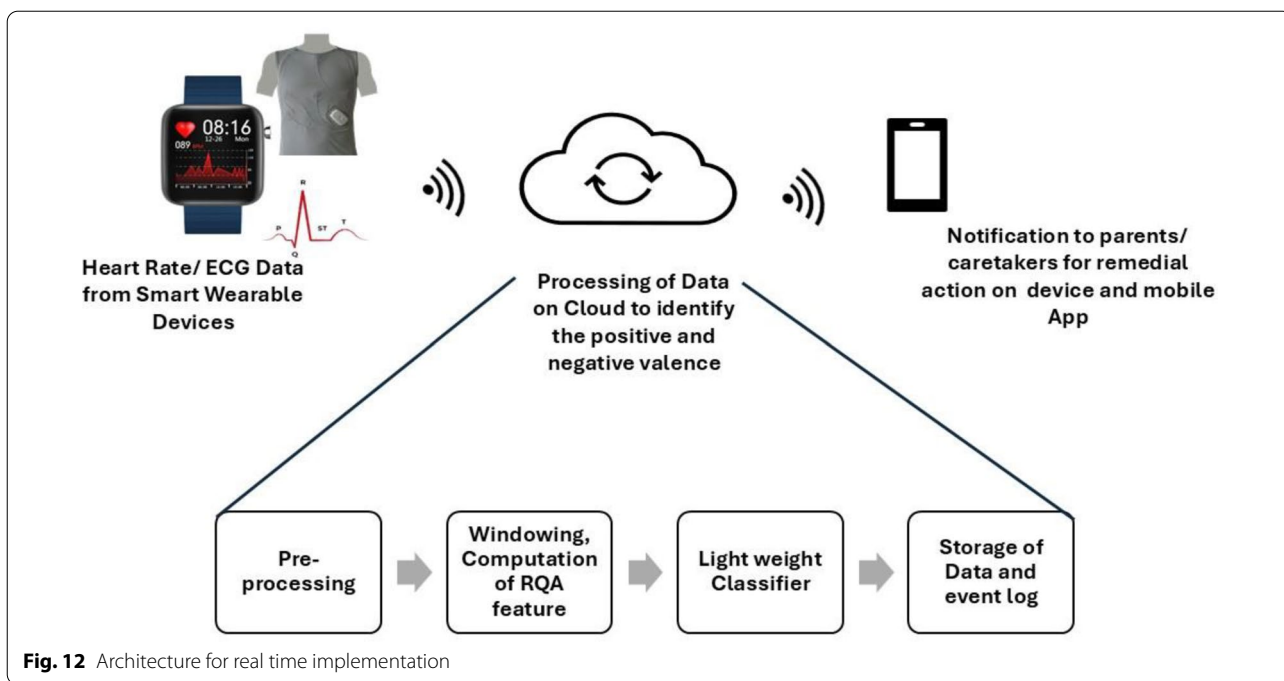


Fig. 12 Architecture for real time implementation

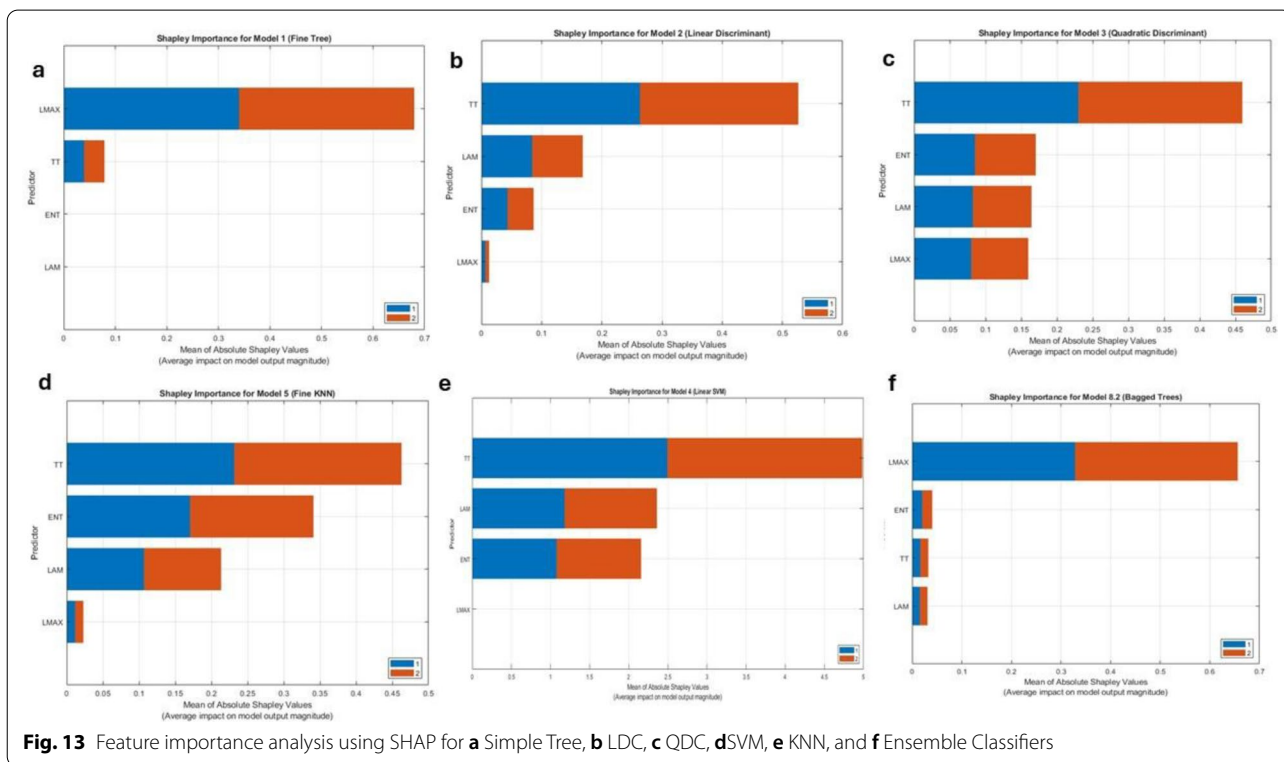


Fig. 13 Feature importance analysis using SHAP for **a** Simple Tree, **b** LDC, **c** QDC, **d**SVM, **e** KNN, and **f** Ensemble Classifiers

Conclusion

This research analyzed Recurrent Quantification Analysis based features for the classification of valence states of children with Autism Spectrum Disorder (ASD) using

ECG signals. The methodology from the acquisition of signals, pre-processing, RQA and features using RQA, classification is discussed in detail. The accuracy of the

different RQA features in categorizing the valence states are presented and results indicate a overall accuracy of 82.4 and 76.5% in classifying the positive and negative valence using RQA based features. It should be noted that this study was done on data from 25 participants. The performance of the algorithm can be improved by increasing the quantity of data and appropriately normalizing the data so that the finer details reflecting the valence states can be captured. Integrating this algorithm into real time wearable systems will require appropriate system integration and optimization the computational overhead, latency etc., for timely prediction of emotions and personalized interventions.

Declarations

Conflict of interests

The authors declare that they have no competing interests.

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