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Original Article

Time Domain Analysis of Heart Rate Variability Signals in Valence Recognition for Children with Autism Spectrum Disorder (ASD)

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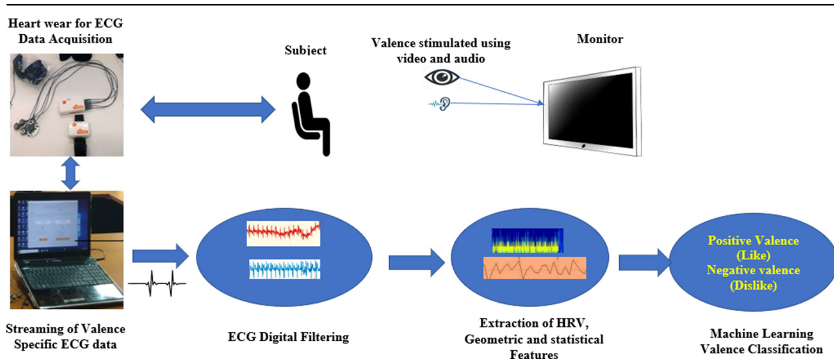
HIGHLIGHTS

- Prediction of the emotional states in children with ASD using ECG signals.
- Customized elicitation protocol using audio and video clips for data acquisition.
- Analysis of geometrical and time domain features of positive and negative emotions.
- KNN and Ensemble classifier were used for the classifying the two emotional states.
- Geometrical features resulted in good accuracy of 84.8% and 74.7% in both states.

GRAPHICAL ABSTRACT



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ABSTRACT

Background: Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that is characterized by various social impairments. Children with ASD have major difficulties in expressing themselves, resulting in stress and meltdowns. Understanding their hidden feelings and needs may help in tackling and avoiding such strenuous behaviors.
Objective: This research aims to aid the parents and caretakers of children with ASD to understand the hidden and unexpressed emotional state by using physiological signals obtained from wearable devices.
Methods: Here, electrocardiogram (ECG) signals pertaining to two valence states ('like' and 'dislike') were recorded from twenty children (10 Control and 10 children with ASD). The heart rate variability (HRV) signals were then obtained from the ECG signals using the Pan-Tompkins's algorithm. The statistical, higher order statistics (HOS) and geometrical features which were statistically significant were trained using the K Nearest Neighbor (KNN) and Ensemble Classifier algorithms.
Results: The findings of our analysis indicate that the integration of major statistical features resulted in an overall average accuracy of 84.8% and 75.3% using HRV data for the control and test population, respectively. Similarly, geometrical features resulted in a maximum average accuracy of 84.8% and 74.2% for control and test population respectively. The decreased HRV in the test population indicates the presence of autonomic dysregulation in children with ASD when compared to their control peers.

1. Introduction

Statistics show an increase in the number of children with ASD in worldwide. The findings from the surveillance conducted in the

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year 2016 by the center for disease control and prevention (CDC) show that the ASD prevalence estimate is 1 in 54 children aged 8 years and ASD is more prevalent in boys than the girls. In India, the International Clinical Epidemiology Network (INCLEN) study shows that the ASD prevalence estimate as 1 in 125 children under about 3 to 6 years of age group and 1 in 85 children of 6 to 9 years [1–4]. These children have difficulties in social interactions, cognitive activities and portray restricted, repeated and stereotyped behaviors [5,6] which hinder them from being socialized with their peers also leading to sudden tantrums, aggressiveness, self-hitting and meltdowns [7]. The other factors such as the inability to express pain, hunger, illness, constipation and fatigue also lead to such explosive outbursts [8]. Many researchers have worked on the various behavioral measures such as facial expression, gestures and speech to understand the psychology of persons with and without special needs [9–11]. However, these methods depend on the external behavior of the person and cannot interpret the true internal state which can be socially masked or unexpressed. Physiological signal based emotion identification by means of bio signals such as ECG, electroencephalogram (EEG), electromyogram (EMG), skin conductance and respiration enables to overcome this difficulty and a large number of works are reported to understand the emotions and other internal states on the control population [12–15]. Very few works have been reported in identifying the emotional and internal states of persons with special needs such as ASD. The findings from the literature show that in few research work they have recorded only single physiological measure [16–18] or combination of more than one physiological measures [5,9,19] in identifying the emotional or the valence states from children with ASD. Also, they have adopted various elicitation stimuli such as audio, audio-visual, various games and activities to elicit their internal states such as valence and arousal [18], happiness, involvement [5], mental stress [20], temper tantrum, outbursts [21], happiness, sadness, fear and disgust [22]. Identifying the changes in inner valence states using physiological measures can help in the early detection of change in internal state. This would enable the therapist or caretaker to provide the needed remedial measures to prevent disruptive behaviors and outbursts. In this work, the positive and negative valence states, also termed as 'like' and 'dislike' states are analyzed using ECG signals.

Different studies on internal states using ECG signals indicate that the cardiac impulses from the heart such as heart rate (HR), heart rate variability (HRV), respiratory sinus arrhythmia (RSA), blood volume pulse (BVP), cardiac production, and peripheral vascular resistance are used as an indicator to detect the change in the internal states [22]. The primary fiduciary points in the ECG such as the P, QRS and T waveforms with a particular length, reflect the depolarization and repolarization of the heart muscles. From the study done by Andrassy et al., shows that the duration of the QT wave was prolonged during the stress but without any significant changes in the R-R interval [23]. The features such as root mean square voltage (RMS) of QRS complex, QRS duration and its low amplitude in terminal complex were considered by Folino et al. and it was found that, there was an increase in the energy of the QRS complex with indicative reduction in the duration during the mental tasks [24]. T wave form was also used by researchers in studies related to stress analysis [25,26]. The emotional or valence information embedded in the physiological signal can be extracted using statistical, linear and nonlinear features in the time, frequency or time-frequency domains using different algorithms [13,27–32]. The discrete wavelet transform (DWT) using a mother wavelet such as Daubechies (db6, db7), symlet (sym8) and coiflet (coif 5) was performed on HRV to extract the statistical features in low frequency (LF) ranges from 0.03-0.12 Hz and high frequency (HF) spectral bands (0.12-0.488 Hz) to identify the five emotions such as sadness, happiness, disgust, fear and neutral using the KNN and linear discriminant analysis (LDA) [33]. Also, the characteristics of the low and high frequency component changes during the positive and negative emotions [28]. In one study, the time-frequency and nonlinear analysis was done using HRV in persons with major depressive disorder (MDD) using the Fast Fourier transform (FFT) with window size of 128 samples which is incorporated using Kubios algorithm and was found that HRV decreases in MDD when compared to that of the controls [34]. In comparison to the HF and LF components, the intrinsic mode functions (IMFs) which are the local oscillatory components Carry useful emotional information. These IMFs are extracted using Empirical Mode Decomposition (EMD) and Hilbert Huang Transform (HHT) methods. It was observed that IMFs in the frequency range 10–40 Hz has information about joy, less than 10 Hz of sadness, 40–100 Hz has fear and more than 100 Hz carries anger information [35]. In a study done by Moskowitz et al., HR was used for the arousal measurement and RSA to assess the anxiety and problem behavior such as screaming, pushing others, running, loud vocalization and elopement in children with ASD. Increased HR and low RSA were noticed during high anxiety relative to low anxiety level [7]. The report by Bal et al., shows an increased HR and lower RSA amplitude in children with ASD indicating a slow understanding of the emotions [36–39]. Bazelmans et al. found that there was a proven link between HRV and receptive language skills in children with ASD [40]. Lory et al.'s findings suggest that there was Autonomous Nervous System (ANS) dysregulation and decreased HRV in ASD compared to controls [41].

In this research, ECG data is used to recognize the positive and negative valence states namely "like" and "dislike" states from controls and children with ASD. The valence specific time domain features were derived from both the normalized ECG signal and the HRV signals that were derived from the ECG data. The features were then analyzed using two classifiers namely K-Nearest Neighbor (KNN) and Ensemble Learning. The performance of the features and methods is also discussed in detail.

2. Methodology

The development of an algorithm using ECG signals to identify the internal states begins with the acquisition of ECG data corresponding internal states, preprocessing the acquired data to remove noises, extraction of features and classification of internal states using machine learning algorithm as depicted in Fig. 1.

2.1. Acquisition of ECG data

a) *Participants*

The raw ECG signals corresponding to the positive and negative valence states were acquired from target group of 10 control (5 male and 5 female) with mean age of (M= 9 Years) and standard deviation of (SD= $\pm$1.897) and 10 children with ASD (7 Male and 3 Female) with mean age of (M= 8.6 Years) and standard deviation (SD= $\pm$1.562) under the age group of five to eleven years. The children with ASD were recruited from National Institute for Persons with multiple Disabilities (NIEPMD), after the assessment done by the psychologists and doctors to find the severity level of autism. The Indian Scale for Autism Assessment (ISAA) that includes metrics such as Social Relationship, and Reciprocity, Emotional responsiveness, Speech -language and Communication, Behavioral Pattern, Sensory Aspects, and Cognitive component was used to find the severity level. Children with Mild and Moderate level autism whose ISAA score ranged from 70 to 150 were chosen for further analysis. The control population were recruited from the neighboring schools.

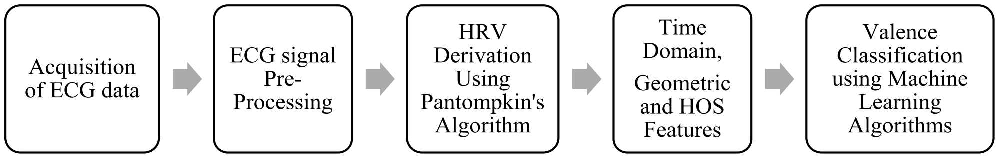


Fig. 1. Methodology.

Start Session	Session 1	Break	Session 2	Break	Session 3	End Session
Baseline ECG data(2minutes)	10 Like and 10 Dislike cues	10 Minutes	10 Like and 10 Dislike cues	10 Minutes	10 Like and 10 Dislike cues	Baseline ECG data(2minutes)

Fig. 2. Emotion Elicitation protocol using audio- and audio-visual cues.

b) *Emotion Elicitation Protocol*

The children with ASD have varied sensory issues and are highly subjective in nature, hence a personalized protocol was developed for inducing the valence states after obtaining ethical approval from ethics committee of NIEPMD. The personalized protocol was designed by studying the patterns of the child and interviewing with teachers, parents and caretakers and developed using audio and audio-visual cues that included cartoons, film songs, rhymes, moral stories, news, sports, advertisements, sounds of alarm and thunderstorm. Fig. 2 depicts the valence elicitation protocol, it had three sessions with 10 minutes of break in between each session.

c) *Experimental Procedure*

The valence specific ECG data was acquired at the sampling rate of 512 Hz using a wearable Heart Wear ECG device. This device is a small, portable and a non-invasive instrument which has five wire and 4 lead system, that acquires the ECG signal using lead II type of ECG measurements. It uses a MSP 430 microcontroller as central processing unit (CPU) with a clock frequency of 24 MHz, bluetooth enabled radio RN42, an integrated 8 GB micro secure digital (SD) card and a rechargeable lithium-ion (LI-ION) battery of 450 mAH that lasts for more than eight hours. An adhesive patch electrode (Ag-Agcl) was placed on the right arm, (RA), left arm (LA), right leg (RL) and with left leg (LL) acting as the reference electrode and the device was held firmly using a chest belt. After obtaining the needed consent and design of protocol, pre-trials were done on two or three days prior to the data collection experiment to familiarize the child with the wearable device and the place where the experimental procedure will be done. The child was assisted with their parents throughout the experiment as shown in Fig. 3(b). The trial sessions were done in a closed room with a smart43-inch LED TV for displaying the cues. A laptop was used for acquiring the ECG signals remotely using the Heart Wear wearable device as depicted in Fig. 3(a). The recording of ECG was started after stable ECG was observed. The baseline data was initially captured for 2 minutes indicating the normal state of the child. The recording as per the protocol lasted for 1.5 hours during which the parents filled in the self-assessment questionnaire. The break time between sessions was varied and allowed the child to recover from the previous session. The obtained data was then split up into the corresponding valence states as per the feedback received from the parent. The feedback form as shown in Table 1 has the ratings from 1 to 5 ('Strongly Dislike', 'Dislike', 'Neutral', 'Like' and 'Strongly Like') for the audio- and audio-visual clips presented to the children. The parents rated the emotions felt by their child as the child viewed the emotional cues.

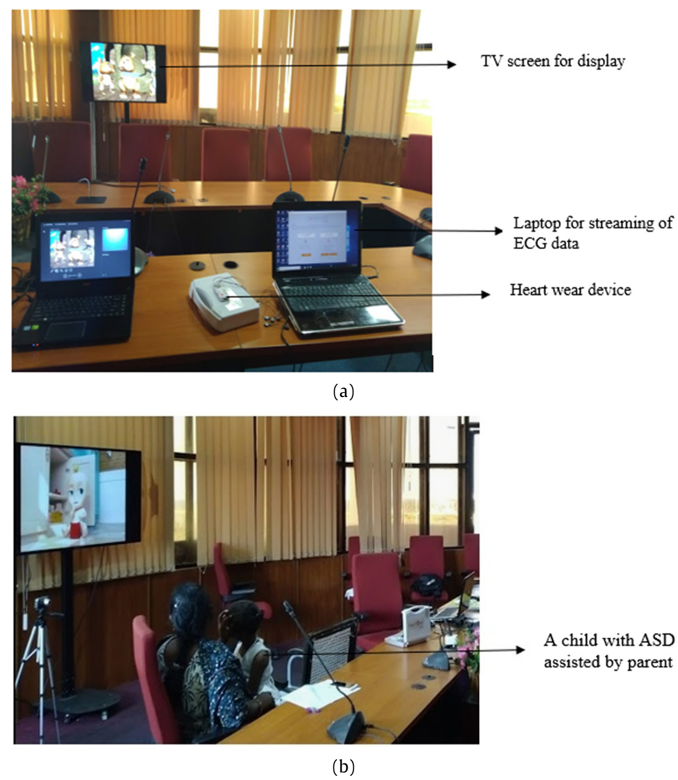


Fig. 3. (a) ECG data acquisition experimental setup in a closed room. (b) A child with ASD viewing the cues assisted by parent.

Table 1
Emotional Assessment Questionnaire to the Parents.

Audio and Video Clipping No	Scale of Like and Dislike				
	Strongly Like 5	Like 4	Neutral 3	Dislike 2	Strongly Dislike 1
1					
2					
3					
4					

2.2. ECG signal pre-processing

The acquired ECG signals from the both the test and control population are subjected to different noises such as muscle artefacts, coughing, baseline wandering, powerline interference and movement artefacts. Baseline drift is an unnecessary low-frequency noise in the frequency range 0.05 and 1 Hz that interferes with the signal, in particular the ST section and the R peak detection [42]. [43]. Baseline wandering was eliminated by removing the residual coefficients using the discrete wavelet transform (DWT) with Daubechies-4 (*db4*) as the mother wavelet in the 8th level of decomposition [44,45]. The powerline interference and other spurious noises due to excessive body movements in the children leads to high frequency noises which was removed using the 6th order low pass (LP) butter worth filter with a higher cut off frequency of 45 Hz [46,47]. The normalization of the ECG signal is done to limit the dynamic range of amplitude from -1 mV to 1 mV, in order to understand the change in amplitude after every signal acquisition [48]. Finally, the QRS complex and R peak index are realized using the Pan-Tompkins Algorithm [49].

2.3. Feature extraction

HRV data does not perceivably vary between the 'like' and 'dislike' state of any child. Hence, appropriate valence relevant features should be derived from the HRV data to determine the variations in HRV data corresponding to the two valence states. In this work, the statistical, higher order statistical (HOS) and Geometrical features were derived from the ECG and HRV data to identify the unseen variations corresponding to the valence states. Six statistical features for the recognition of emotions, namely Mean, Median, Standard Deviation, Mean Absolute Value of the First Signal Difference (Mean I), Mean Absolute Value of the Normalized First Signal Difference (Mean II), Mean Absolute Value of the Second Signal Difference (Mean III) And Mean Absolute Value of the Normalized Second Signal Difference (Mean IV) [50], Nine Higher order statistical (HOS) features namely Skewness, Interquartile Range (IQR), 25th, 50th and 75th quartile percentile (Q1, Q2 and Q3), Mode, Minimum, Maximum and Variance were derived from the normalized ECG signal and the HRV data.

In addition, four Geometrical features were derived from the ECG data to identify the valence states. They include mean value of all R-R intervals (RR mean), Standard Deviation of all R-R intervals (SDNN), Square Root of the Mean Squared Difference of Successive R-Interval (RMSSD), (pNN50) percentage difference of more than 50 msec between adjacent RR intervals.

2.4. Classification of positive and negative valence

All the extracted features were statistically validated using the **Student's-*t* test** with SPSS 16.0 package. The features that were significant with whose *p*-value was less than 0.05 in the **Student's-*t* test** analysis are considered for classification of positive and negative valence using the KNN and the Ensemble classifiers.

The average percentage accuracy was obtained from the predicted class as given below,

$$\%Accuracy_{Valence} = \frac{Number\ of\ samples\ correctly\ classified_{Valence}}{Total\ number\ of\ samples\ tested_{Valence}} \times 100 \tag{1}$$

In this work, 70% of the data was used for training the classifier and 30% was used for testing. The *Number of samples correctly classified$_{Valence}$* was obtained from the confusion matrix for both 'Like' and 'Dislike' states.

3. Results

The elimination of baseline wandering and other high frequency noises was effectively done using the Daubechies db4 mother wavelet-based algorithm, ECG signal normalization and 6th order Butterworth low pass filter respectively is shown in Fig. 4(a) through 4(d). Fig. 5 shows the number of R peaks detected and the HRV derived from the successive RR peaks.

Table 2
Test for normality of the statistical features of ECG and HRV using Shapiro Wilk test.

	Emotional Features	ECG p-value Control	ECG p-value Test	HRV p-value Control	HRV p-value Test
		Shapiro Wilk test-Significant Value			
Statistical features	Mean	**0.000**	**0.000**	**0.051**	**0.000**
	Median	**0.027**	**0.000**	**0.200**	**0.000**
	Standard Deviation	**0.001**	**0.000**	**0.005**	**0.000**
	Mean I	**0.001**	**0.021**	**0.000**	**0.000**
	Mean II	**0.000**	**0.013**	**0.000**	**0.016**
	Mean III	**0.000**	**0.003**	**0.000**	**0.077**
	Mean IV	**0.000**	**0.012**	**0.000**	**0.064**
	Q1	**0.000**	**0.034**	**0.000**	**0.000**
	Q2	**0.027**	**0.000**	**0. 200**	**0.000**
	Q3	**0.000**	**0.000**	**0.000**	**0.000**
	IQR	**0.000**	**0.000**	**0.095**	**0.000**
	Harmonic Mean	**0.000**	**0.000**	**0.000**	**0.000**
	Trim Mean	**0.000**	**0.000**	**0.003**	**0.000**
	Nan Mean	**0.000**	**0.000**	**0.000**	**0.000**
	Mode	**0.000**	**0.000**	**0.000**	**0.000**
	Minimum	**0.000**	**0.000**	**0.000**	**0.000**
	Maximum	**0.002**	**0.000**	**0.000**	**0.000**
	variance	**0.000**	**0.000**	**0.000**	**0.000**
HOS	Skewness	**0.000**	**0.006**	**0.000**	**0.006**
	Kurtosis	**0.000**	**0.000**	**0.000**	**0.000**

Table 3
Test for normality of the Geometrical features of ECG using Shapiro Wilk to test the Normality of the data.

	Emotional Features	p-value control	p-value test
Geometric Features (Normalized ECG signal)	Mean RR	**0.040**	**0.000**
	RMSSD	**0.200**	**0.000**
	nn50	**0.000**	**0.000**
	pNN50	**0.000**	**0.000**
	SDNN	**0.000**	**0.000**
	SDRR	**0.000**	**0.000**

The statistical features, corresponding to the internal states were extracted from the pre-processed normalized ECG signal and HRV data, geometric features from normalized ECG data for further analysis.

The statistical features derived from the ECG and HRV and the geometrical features of ECG were tested for its normality using the Shapiro Wilk test and 95% of significance was considered and the significant values obtained for the features are tabulated below in Table 2 and 3. It is inferred from the table that all the features shown significance whose *p*-values were less than 0.05 and was proven for its normality.

The significance of all the statistical features of normalized ECG signal and HRV data and six geometric indices obtained from the normalized ECG signal was studied using **student's t test** and their *p*-values are tabulated in Table 5. From Table 4, the highlighted values indicate the significant features that has *p*-value <0.05 and it is observed that nine out of the total eighteen statistical features showed significance for control and test population.

Mean, Mean I, Mean II, Mean III, Mean IV, Q1 Q3, IQR and Nan mean showed significance in identifying the valence states for the control population using the normalized ECG signal and features such as standard deviation, Mean I, Q1, Q3, IQR, Nan mean, Mode, Maximum and Variance were significant for the test population.

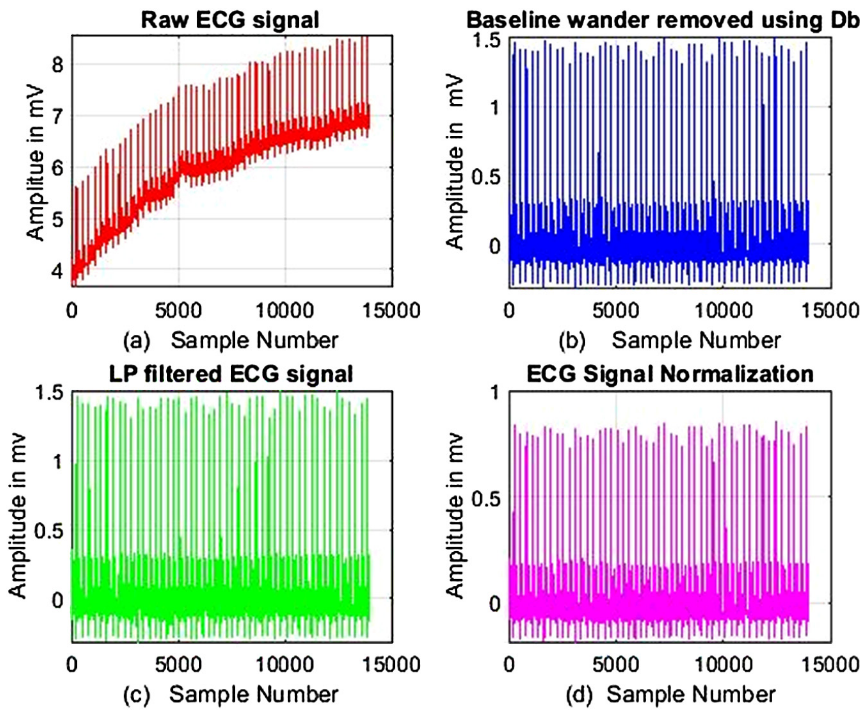


Fig. 4. *a*) Raw ECG signal *b*) Baseline wander removed using (DWT) db4 mother wavelet *c*) Lowpass filtered ECG signal 4d4) ECG signal normalization.

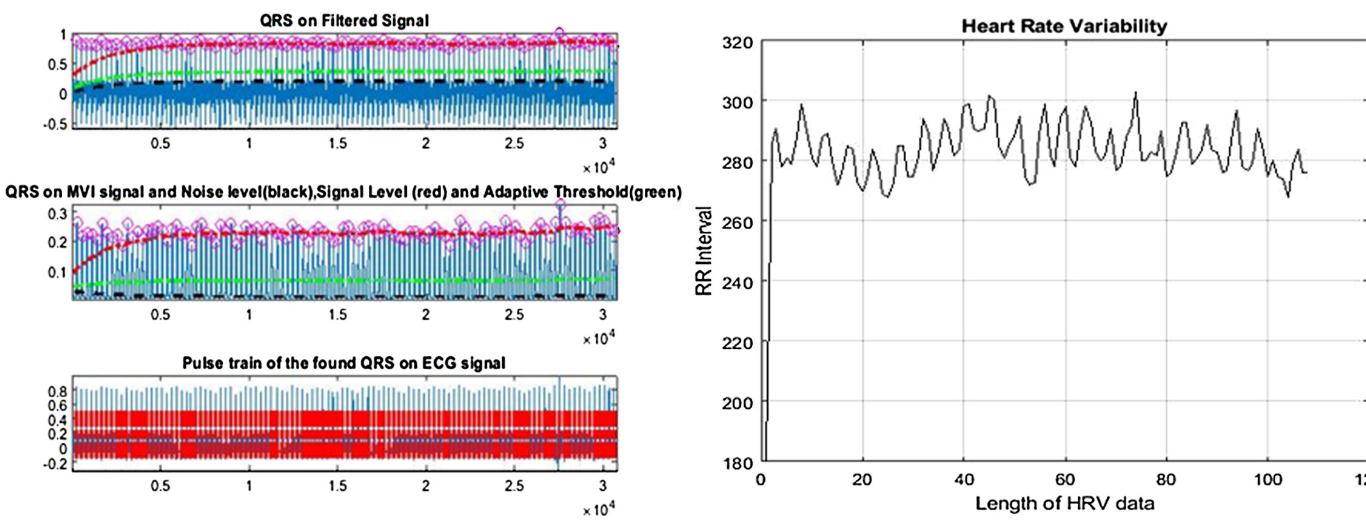


Fig. 5. QRS detection using the Pan-Tompkins Algorithm and HRV data.

In the case of HOS features, the skewness and Kurtosis did not show any significance for controls. However, in test population skewness was statistically significant with a p value of 0.000. Similar analysis was done using the HRV data for both the control and test population. It is very evident from the p-score values of the statistical and HOS features that features such as Mean, Median, Standard deviation, Mean II, Mean IV, Q1, Q2, Q3, Harmonic mean, Trimean, Nan mean, Mode, Minimum, Maximum, Variance, Skewness and Kurtosis were statistically significant for the control population.

Considering the statistical significance of all the cases, twenty features were considered for classification of valence states.

The statistical analysis of the geometrical features in Table 4 indicates that three features namely nn50, pNN50 and SDNN were statistically significant for the control population and two features namely Mean RR and RMSSD were significant for test population. All these five features were considered for classification of valence states.

All the statistically significant features of normalized ECG and HRV data were trained and tested individually using KNN and Ensemble classifiers to find the Like and Dislike states for both control and test population and the results are specified in Table 5. It is well evident from the results that features such as Mode and Minimum derived from the normalized ECG signal achieved maximum average accuracy of 72% using both KNN and Ensemble classifier in control whereas Mean I achieved maximum average accuracy of 70.5% using both the classifiers in the test population. Similarly, the HOS feature skewness achieved a maximum average accuracy of 70.5% for control using Ensemble classifier and 67% for test population in both the KNN and the Ensemble classifiers. The valence features such as Mean, Mean I and Nan mean derived from the HRV data achieves maximum average accuracy of 88.2%

Table 4
Statistical significance of statistical features of ECG and derived HRV data from Control and of Test Population.

	Emotional Features	ECG p-value Control	ECG p-value Test	HRV p-value Control	HRV p-value Test
Statistical features	Mean	**0.025**	0.269	**0.040**	0.810
	Median	0.491	0.442	**0.033**	0.787
	Standard Deviation	0.562	**0.001**	**0.000**	0.411
	Mean I	**0.007**	**0.037**	0.618	0.552
	Mean II	**0.004**	0.762	**0.000**	0.919
	Mean III	**0.000**	0.462	0.672	0.432
	Mean IV	**0.000**	0.113	**0.001**	0.849
	Q1	**0.001**	**0.001**	**0.022**	0.906
	Q2	0.491	0.442	**0.033**	0.787
	Q3	**0.002**	**0.000**	**0.030**	0.786
	IQR	**0.000**	**0.000**	0.108	0.945
	Harmonic Mean	0.203	0.169	**0.027**	0.666
	Trim Mean	0.573	0.078	**0.030**	0.772
	Nan Mean	**0.025**	**0.026**	**0.040**	0.810
	Mode	0.101	**0.000**	**0.015**	0.500
	Minimum	0.203	0.076	**0.000**	0.206
	Maximum	0.101	**0.000**	**0.017**	0.430
	variance	0.430	**0.002**	**0.008**	0.504
HOS	Skewness	0.523	**0.000**	**0.000**	0.308
	Kurtosis	0.118	0.183	**0.000**	0.192

Table 5
Statistical significance of geometric features derived from normalized ECG signal of Control and of Test Population.

	Emotional Features	p-value control	p-value test
Geometric Features (Normalized ECG signal)	Mean RR	0.189	**0.026**
	RMSSD	0.192	**0.048**
	nn50	**0.000**	0.16
	pNN50	**0.009**	0.259
	SDNN	**0.000**	0.208
	SDRR	0.324	0.604

in control population using both the KNN and Ensemble classifiers whereas Mean IV attains maximum average accuracy of 73% in test population using KNN classifier.

The HOS feature skewness also retrieves the valence information with a good classification rates of 87.6% and 67.4% in control and test population using both the classifiers. From Table 4 it is also evident that the combination of the significant statistical features and the HOS features proved to give the highest classification average accuracy of 72.5% for Control and 69% test population using Ensemble and KNN Classifiers respectively for the normalized ECG signal. The same analysis on HRV data captured valence information better compared to the normalized ECG signal by achieving an overall maximum accuracy of 84.8% and 75.3% using Ensemble classifier for both the control and test population respectively.

Similarly, the Geometric indices derived from the RR interval of normalized ECG signal were classified using the KNN and Ensemble classifiers and the resulting accuracies are tabulated in Table 6. The statistically significant feature RMSSD achieves a maximum average accuracy of 84.8% in control population and not in children with ASD. On the other hand, SDNN achieves maximum average accuracy of 74.2% in test population and not in control.

The overall performance of the statistical and HOS features derived from the normalized ECG signal and the HRV data using the KNN and ensemble learning is shown in Fig. 6. The feature Mean I derived using the normalized ECG signal results in same classification rates of 70.5% in both the KNN and ensemble classifier in the test population, whereas the ensemble classifier performs better by achieving a maximum average accuracy of 68% only in control population. Similarly, HOS feature skewness performs better in ensemble classifier in obtaining 70.5% in control population. The other features such as Mean IV, Mode and Minimum achieve the same classification rates of 70%, 72% and 72% using both the KNN and Ensemble classifiers. The performance of KNN classifier is shown in the figure with accuracy.

The similar analysis of the performance of the classifiers was done using the statistical features of HRV data obtained from the two target groups (control and test population) is shown in Fig. 7. It can be inferred from the bar graph that the statistical features such as Mean I, Mean IV, Mode achieve better classification accuracy in both the control population using the KNN classifier, whereas ensemble classifier achieves better accuracy than the KNN classifier by achieving a maximum average accuracy of 71.9% in test population

The geometrical features derived from the normalized ECG signal have found to perform better in case of the Control when compared to the Test population using both KNN and Ensemble classifier is shown in Fig. 8a. It shows that RMSSD has captured the valence states better for the control whereas SDNN for the test population. The analysis shown in Fig. 8b indicates that when the positive valence ('Like') is elicited, the Mean RR, RMSSD, PNN50 values decreases in children with ASD when compared to the controls. Also, the Mean Heart Rate decreases and HRV increases which indicates there is an increase in Parasympathetic Nervous System (PNS) activity than Sympathetic Nervous System (SNS) activity. During the negative valence ('Dislike') the Mean RR, RMSSD, PNN50 and Mean HR increases and HRV decreases in children with ASD than their peers which is a sign of increased SNS activity and reduced PNS activity. Whereas, while analyzing NN50 and SDNN, the values decrease in children with ASD during the positive valence states than the controls whereas it increases during the negative valence states in children with ASD than the controls.

4. Discussion

4.1. Subjective response of children with ASD and controls

In this research, the primary aim is to classify the valence states in children with ASD and TD children. The children with ASD showed more eye contact towards the screen during the positive valence states and showed their likes by jumping and using different body movement. Yet when there was a change from positive to negative valence, the child with ASD made no eye contact at all on the screen and expressed their dislike by crying, screaming, hitting others and running around the room. It was also found that during negative valence, the HR of children with ASD was high relative to TD children. This shows that children with ASD are unable to regulate or control their negative emotions, so the forecasts of their valence states with the help of personalized valence elicitation stimuli can significantly assist in early intervention, and recent technical advancements help to build a system that automatically senses their negative emotional transition and alerts parents or care.

4.2. ANS relativity to valence states

The overall comparison of the mean HRV from the test and control population indicates that the children with ASD have an decreased HRV than the control as shown in Fig. 9b, which is in line with the results of previous research studies [37,51]. The increased HRV during the relaxing states indicates ANS has good arousal control and exhibits better social emotional response to stimuli in controls [52,53]. On the other hand lower HRV is an indicator of imbalance in the ANS leading to higher activation of

Table 6
Classification accuracy for statistical features using KNN and Ensemble Classifiers.

	Emotional Features	Classifiers	Normalized ECG – Accuracy – Control population – Like %	Dislike %	Average %	Test population – Like %	Dislike %	Average %	HRV Data – Accuracy – Control population – Like %	Dislike %	Average %	Test population – Like %	Dislike %	Average %
Statistical Features	Mean	KNN	66	73	69.5	57	75	66	84	90	87.1	62	75	68.5
		Ensemble	68	71	69.5	57	75	66	**84**	**92**	**88.2**	62	74	68
	Standard Deviation	KNN	66	74	70	58	67	62.5	76	85	80.9	64	74	69.1
		Ensemble	66	74	70	58	67	62.5	76	85	80.9	63	72	67.4
	Mean I	KNN	63	72	67.5	**67**	**74**	**70.5**	**84**	**92**	**88.2**	60	76	68
		Ensemble	64	72	68	**67**	**74**	**70.5**	**84**	**92**	**88.2**	61	73	66.9
	Mean II	KNN	65	77	71	56	76	66	84	90	87.1	69	74	71.3
		Ensemble	65	77	71	57	71	64	84	90	87.1	67	75	71.3
	Mean III	KNN	58	81	69.5	63	73	68	81	85	83.1	64	73	68.5
		Ensemble	57	83	70	63	73	68	81	85	83.1	65	71	68
	Mean IV	KNN	63	77	70	53	71	62	79	93	86	**72**	**74**	**73**
		Ensemble	63	77	70	55	70	62.5	79	92	85.6	73	71	71.9
	Q1	KNN	69	74	71.5	57	72	64.5	84	88	86	67	69	68
		Ensemble	69	74	71.5	57	72	64.5	84	88	86	66	67	66.9
	Q3	KNN	67	76	71.5	58	70	64	78	93	85.4	66	78	71.9
		Ensemble	67	76	71.5	59	69	64	75	93	84.3	66	78	71.9
	IQR	KNN	64	74	69	58	70	64	78	88	82.6	61	75	68
		Ensemble	63	71	67	53	70	61.5	76	85	80.9	61	76	68.5
	Nan Mean	KNN	66	73	69.5	57	75	66	**84**	**92**	**88.2**	62	75	68.5
		Ensemble	68	71	69.5	57	75	66	84	90	87.1	62	74	68
	Mode	KNN	**71**	**73**	**72**	57	71	64	84	90	87.1	63	73	68
		Ensemble	**71**	**73**	**72**	55	72	63.5	84	90	87.1	63	73	68
	Min	KNN	**71**	**73**	**72**	57	71	64	78	89	83.1	71	69	69.7
		Ensemble	**71**	**73**	**72**	57	71	64	79	87	82.6	63	81	71.9
	Variance	KNN	66	74	70	58	67	62.5	76	85	80.9	64	74	69.1
		Ensemble	66	74	70	58	67	62.5	76	85	80.9	63	72	67.4
HOS	Skewness	KNN	66	74	70	**64**	**70**	**67**	82	93	87.6	**63**	**72**	**67.4**
		Ensemble	**65**	**76**	**70.5**	**64**	**70**	**67**	83	91	87.1	**63**	**72**	**67.4**
	All significant	KNN	73	68	70.5	**63**	**75**	**69**	70	74	72	61	70	65.5
		Ensemble	**80**	**65**	**72.5**	61	69	65	**69**	**85**	**84.8**	**72**	**79**	**75.3**

Table 7
Classification accuracy for geometric features of normalized ECG signal using KNN and Ensemble Classifiers.

	Emotional Features	Classifiers	Accuracy – Control population – Like %	Dislike %	Average %	Test population – Like %	Dislike %	Average %
Geometric Features	Mean RR	KNN	72	92	82	65	75	70.2
		Ensemble	73	90	81.5	65	75	70.2
	RMSSD	KNN	**85**	**84**	**84.8**	61	67	64
		Ensemble	**85**	**84**	**84.8**	61	67	64
	Nn50	KNN	73	75	74.2	76	36	56.2
		Ensemble	70	82	75.8	30	84	57.3
	pNN50	KNN	76	79	77.5	78	46	61.8
		Ensemble	71	84	77.5	65	61	62.9
	SDNN	KNN	76	92	84.3	**66**	**82**	**74.2**
		Ensemble	76	92	84.3	**69**	**81**	**74.7**

sympathetic nervous system (SNS) and reduced activity of para sympathetic nervous system (PNS) which results in the impairment of social responses to evoked stimuli [52]. Our findings from HRV show that the children with ASD have ANS dysregulation due to the impact of sensory activities.

The **students** *t* **test** was performed to find the group (baseline, like and dislike) difference in both the population is tabulated in Table 8 and Table 9. It can be inferred from Table 8 that, there is no significant differences in the heart rate between TD children and children with ASD during like and dislike, whereas HRV shows significant difference in TD children.

Table 9 infers that the baseline Heart Rate and HRV shows significant differences between both the population

Table 8
Statistical analysis for two class (Like and Dislike) in TD children and children with ASD.

Student's t Test	Heart Rate – TD	Heart Rate – ASD	Heart Rate Variability – TD	Heart Rate Variability – ASD
P-Value (Like and Dislike)	0.481	0.763	**0.000**	0.784

Table 9
Statistical analysis for two class (TD and ASD) using baseline HR and HRV.

Student's t Test	Heart Rate	Heart Rate Variability
P-Value Baseline (ASD and TD)	**0.025**	**0.000**

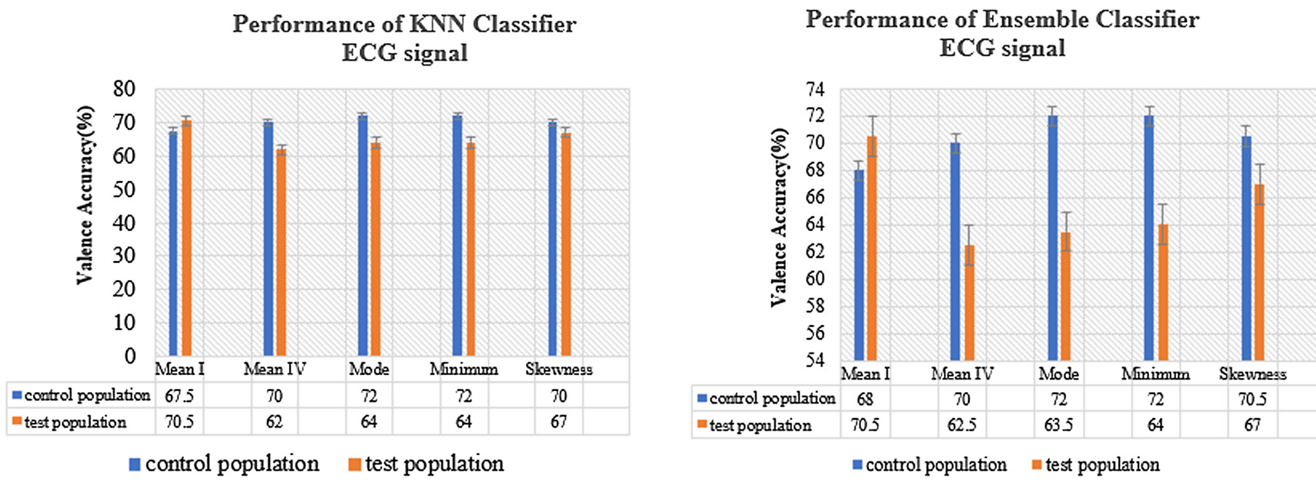


Fig. 6. Performance of KNN and Ensemble classifier using ECG signal from the control and test population.

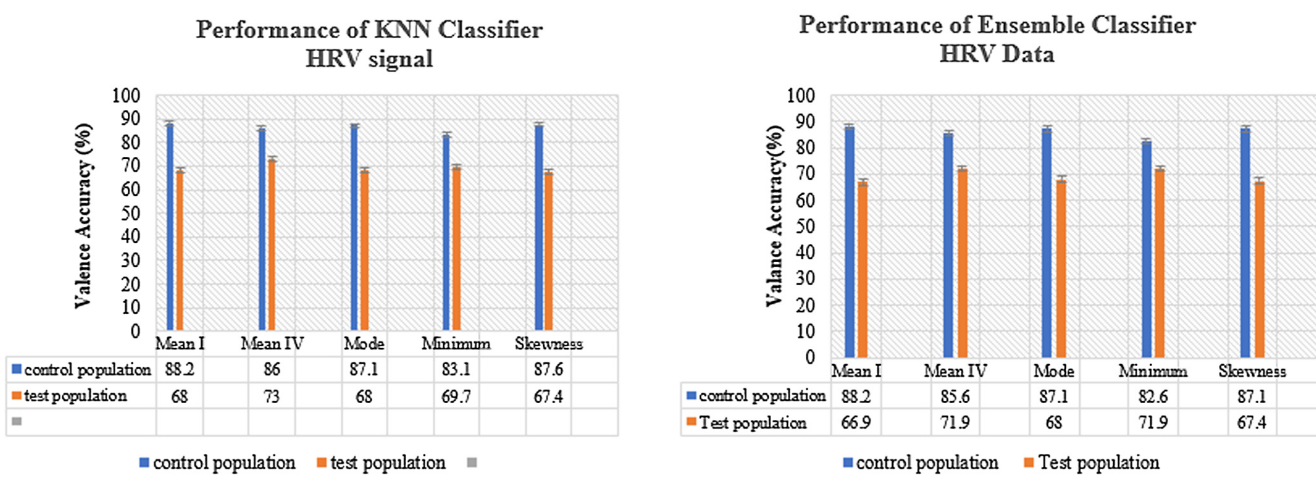


Fig. 7. Performance of KNN and Ensemble classifier using HRV data from the control and test population.

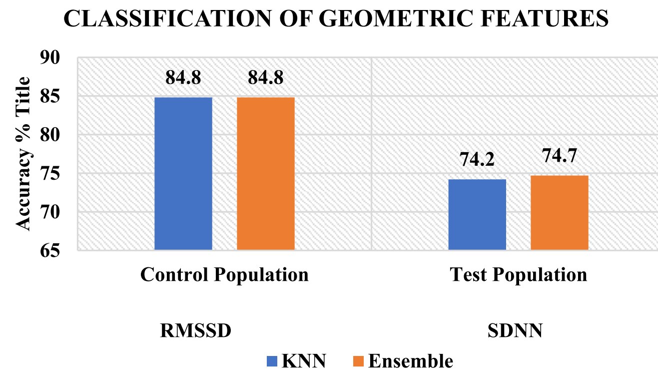
The heart rate of the control children is lower compared to that of the children with ASD for the Valence states ('Like 'and 'Dislike'). The SNS activity increases the Heart Rate and decreases the HRV during dislike state and vice versa during the PNS during like state as shown in Fig. 9 (a). As per the protocol the resting state or the relaxed state (Baseline ECG data) before and after each session was recorded. The analysis of baseline ECG data shows that the Heart Rate of the children with ASD was increased and the HRV was found to be decreased when compared to the control population.

It is seen from the Fig. 9(b) that the variations of HRV for the during the relaxed states increased in TD children whereas HRV decreased in children with ASD. During the positive valence and Negative valence increases for the control or Typically developed (TD) children whereas it decreases in case of the children with ASD which is very evident that they have Autonomic Nervous System Dysregulation which the pattern recognition also verifies using the KNN and Ensemble algorithms.

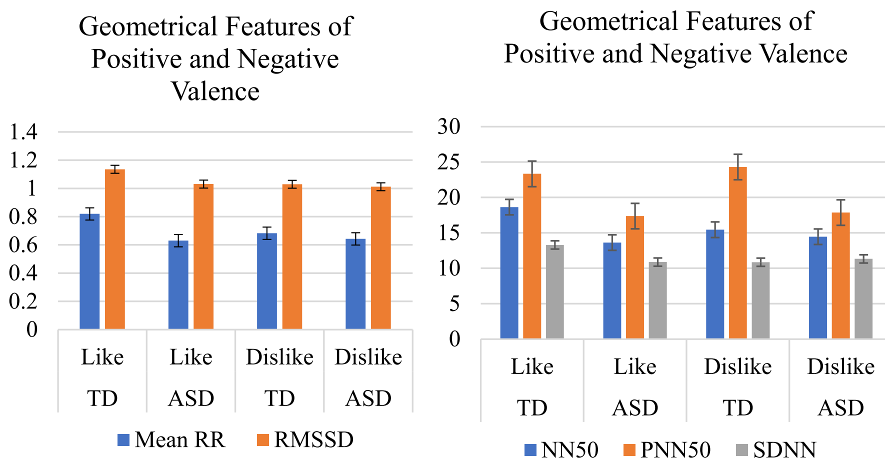
From our findings, it was inferred that as compared to their peers, baseline HRV and an increased HR during the Negative valence states was observed to be low in the case of children with ASD. Also, the RMSSD attribute, which is found to be the reliable valence measure, also reflects that cardiac vagal regulation contributes further to the classification of valence states in both population states which is also verified by the machine learning algorithm. The key difficulties of this research are that the results of the study can be greatly influenced by the varying characteristics, sensory or neurological disorders, various mood changes and inability to self-report the valence experience of the children with ASD. In addition, the size of the population to be improved and the fusion approach of other physiological signals along with ECG improves the accuracy of the system.

5. Conclusion

This research presents the classification of emotional ECG data into two valence states was done using the statistical features, HOS and the Geometric indices derived from the normalized ECG signals of twenty children (10 control and 10 test population) between five and eleven years of age. The findings indicate that the HRV indices have substantial variations between the emotional states of opposite valence ('Like' and 'Dislike'). The overall cumulative average accuracy of 84.8% and 75.3% for control and test population respectively, using Ensemble classifier results, additionally shows that there is diminished HRV in children with ASD when contrasted with their peers which suggests, they have ANS dysregulation due to the effect of tactility. This work was carried out with audio and audio -visual stimuli to induce valence states in children with the mild and moderate level of autism severity. Our future work will include children with severe autism level using even with other modalities such as smell and taste and to achieve better classification accuracy using advanced machine learning algorithms.

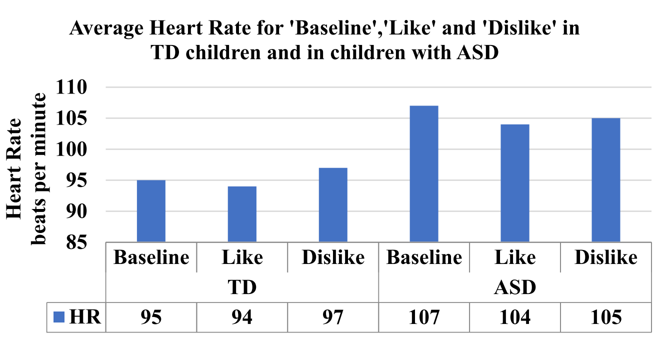


(a)

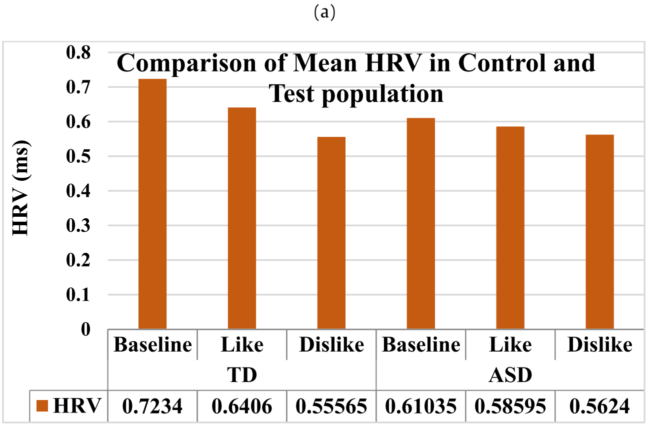


(b)

Fig. 8. (a) Shows the overall highest classification accuracy of geometrical features derived from Normalized ECG of Control and Test population. (b) Shows the comparison of geometrical features in both the population.



(a)



(b)

Fig. 9. (a) Comparison of Heart Rate of TD children Vs Children with ASD for Like and Dislike valence states. (b) Comparison of Mean HRV in control and test population.

Human and animal rights

The authors declare that the work described has been carried out in accordance with the Declaration of Helsinki of the World Medical Association revised in 2013 for experiments involving humans as well as in accordance with the EU Directive 2010/63/EU for animal experiments.

Informed consent and patient details

The authors declare that this report does not contain any personal information that could lead to the identification of the patient(s).

The authors declare that they obtained a written informed consent from the patients and/or volunteers included in the article. The authors also confirm that the personal details of the patients and/or volunteers have been removed.

Disclosure of interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

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Author contributions

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship.

S. Jerritta: Conceptualization, methodology, supervision, investigation, writing review and editing. B. Anandhi: Writing original draft, data processing, validation, algorithm and data collection.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Ethical consideration

Ethical approval was received from the Board of Ethics Committee of the National Institute for Empowerment of Persons with Multiple Disabilities (NIEPMD), Chennai on the protocol and data collection method before the experiments were carried out.

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