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ORIGINAL RESEARCH

Recognition of positive and negative valence states in children with autism spectrum disorder (ASD) using discrete wavelet transform (DWT) analysis of electrocardiogram signals (ECG)

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Abstract

Children with autism spectrum disorder (ASD) are deficit in communication, social skills, empathy, emotional responsiveness and have significant behavioral pattern. They have difficulty in understanding other feelings and their own emotions. This leads to the sudden emotional outburst and aggressive behavior in these children. Parents, caretakers and doctors find it very difficult to prevent such extreme behaviors. Learning the positive and negative valence leads in determining the early indications before the onset of emotional outbursts in children with ASD. The present study measures the psycho physiological electrocardiogram (ECG) signal from the typically developed (TD) children and children with ASD in the age group of 5–11 years. Personalized protocol was developed for every child with ASD to induce positive and negative valence and ECG data was collected using wearable Shimmer ECG device. The heart rate variability (HRV) and the QRS amplitude were derived from ECG signal using Pan–Tompkins algorithm and eleven features were extracted using DWT (*db2*, *db4* and *db8*) mother wavelet. The significant features of ECG, HRV and QRS amplitude were classified using the K nearest neighbor (KNN), support vector machine (SVM) and ensemble classifier. Ensemble and KNN classifier achieved maximum accuracy of 81% and 76.2% for children with ASD and Ensemble and SVM classifiers obtained maximum accuracy of 87.4% and 83.8% for TD children using HRV data.

Keywords Autism spectrum disorder (ASD) · Heart rate variability (HRV) · Pan–Tompkins algorithm · K nearest neighbor (KNN)

1 Introduction

Autism spectrum disorder (ASD) is a spectrum of neurodevelopment disabilities which can be identified during the developmental stages or first 3 years of life (Lord et al. 2000). Centre for Disease Control and Prediction (CDC) has estimated that 1 in 160 children are diagnosed with ASD in 2012 (Elsabbagh et al. 2012). There are more than 2 million children in India with ASD who are between the ages 2–15 (Krishnamurthy 2008). In 2018, the Centers for Disease Control's Autism and Developmental Disabilities Monitoring (ADDM), United State reported that 1 in 59 children (1 in 37 boys and 1 in 131 girls) have been identified with an ASD indicating an exponential increase in the prevalence of autism every year. ASD is caused by a combination of genetic and environmental factors that affects the functioning of the brain leading to severe developmental problems such as social reciprocity, communication skills, restricted and repetitive behavior (APA 2000). Generally, the children are found to have problems related to communication, social interaction, social awareness, behavior and exclusions. Their emotions are often misunderstood and are not cared by anyone leading to loneliness and depression (Raouzaiou et al. 2003). They show less attention to social stimuli, smile, eye contacts etc., and do not have the ability to express their own needs such as pain, hunger, thirst or emotions to their parents or caretakers. They lack in theory of mind makes them to neither understand what they themselves or say or feel (Baron-cohen and Leslie 1985). They show many forms of repetitive stereotyped behaviors and

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have difficulties in organization and sequencing of tasks. Children get into enormous anxiety and stress when their routines are altered or changed resulting in tantrums, outbursts and frustration. These extreme behaviors coupled with a lack of verbal communication makes it difficult to the family members, care takers, teachers and therapists to handle the children and calm them down. A device which can identify changes in the internal emotional states of children and alert the parent or caretaker on time before the onset of an outburst can help in preventing such extreme behaviors.

Recent advancements in human computer interaction (HCI) and similar technologies help in identifying the internal state of persons such as stress, emotions, drowsiness and the like. Researchers are working on various applications to assist patients with stress syndromes, Parkinson's disease etc., by identifying their internal emotional states. Behavioral modalities such as gestures, facial expressions or speech (Dawson et al. 2004; Kessous et al. 2010; Neuhaus et al. 2014; Oberman et al. 2009; Ram and Ponnusamy 2017), physiological metrics such as electroencephalogram (EEG) (Becker et al. 2017; Katsigiannis and Ramzan 2017; Murugappan et al. 2009), electrocardiogram (ECG) (Agrafioti et al. 2012; Goshvarpour et al. 2017; Jerritta et al. 2013; Selvaraj et al. 2014; Zong and Chetouani 2009), galvanic skin response (GSR), respiration (RSP), electromyogram (EMG) (Cheng and Liu 2008; Maaoui and Pruski 2010; Oberman et al. 2009), skin conductance (SC), skin temperature (SKT) and phonocardiogram (PCG) (Selvaraj et al. 2014) are used to identify the emotional states. However, unexpressed and socially masked emotions can only be identified using the physiological signals which are a measure of the involuntary activity of the central nervous system (CNS) and autonomous nervous system (ANS) (Neuhaus et al. 2014).

In the last few decades many research works have been carried out on the emotion recognition using the physiological signals either using only one physiological signal or a combination of other physiological signals for healthy people. Very few research works are reported on persons with disabilities such as ASD or Parkinson's where EEG signal used to recognize emotions such as happiness, sadness, fear, anger, surprise and disgust (Yuvaraj and Murugappan 2016; Yuvaraj et al. 2014a, b). Research on persons with ASD was focused on children with high functioning autism (HFA) (Deschamps et al. 2015; Krupa et al. 2016; Kushki et al. 2015; Kuusikko et al. 2009; Lin et al. 2015; Messinger 2013; Oberman et al. 2009; Palma et al. 2017; Raike et al. 2008; Zantinge et al. 2017b; Sasikumar et al. 2015; Torrado and Gomez 2017).

This research focuses on identifying two internal states corresponding to the positive and negative valence ('Like' and 'Dislike') of children with ASD and typically developed (TD) children. The methodology and results of the algorithm developed using three types of wavelets (*db2, db4* and *db8*) for ECG, HRV and QRS amplitude are discussed in detail.

2 Materials and methods

The methodology of the internal state recognition system is as depicted in Fig. 1. ECG data is acquired from the TD children and children with ASD using a wearable Shimmer ECG device when subjected to view the audio and audio-visual cues pertaining to 'Like' and 'Dislike' states. The artifacts and noises in the acquired signals were removed by pre-processing the raw ECG signal using various digital filters. Statistical, linear and nonlinear features were extracted from the filtered ECG, HRV and QRS signal using discrete wavelet transform. The features were then classified using three machine learning algorithms namely SVM, KNN and ensemble classifiers.

2.1 ECG data acquisition

2.1.1 Design of emotion elicitation protocol

As the characteristics of children with ASD are highly subjective, a protocol to elicit the positive and negative valence states was specifically designed for each child. This was done by observing the child in their school environment for a week and interviewing with the parents and teachers to understand their various 'Like' and 'Dislike' of the child. Audio and video clips, food, toys and similar items pertaining to the 'Like' and 'Dislike' states were learnt for each child with ASD and a protocol was designed as in Fig. 2.

The experimental protocol for each child had three trials with ten minutes of break in-between each trial which lasted for 30 to 40 min. 150 (audio and visual stimulus) including advertisements, film songs, cartoons, rhymes,

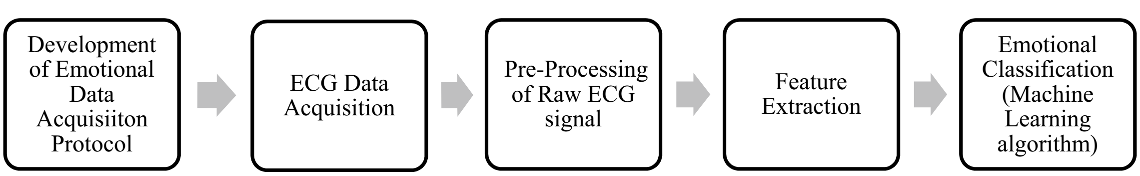

Fig. 1 Methodology

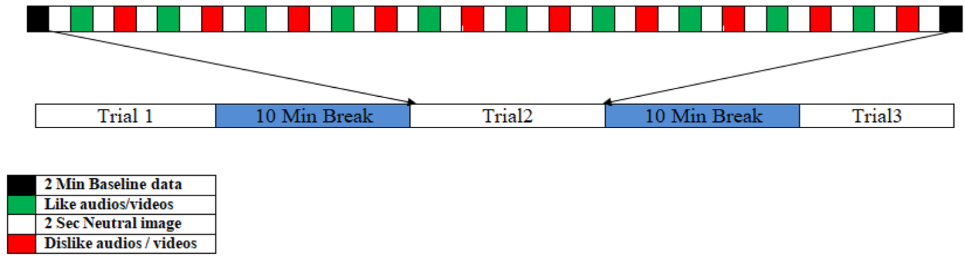

Fig. 2 Protocol to induce 'Like' and 'Dislike' states

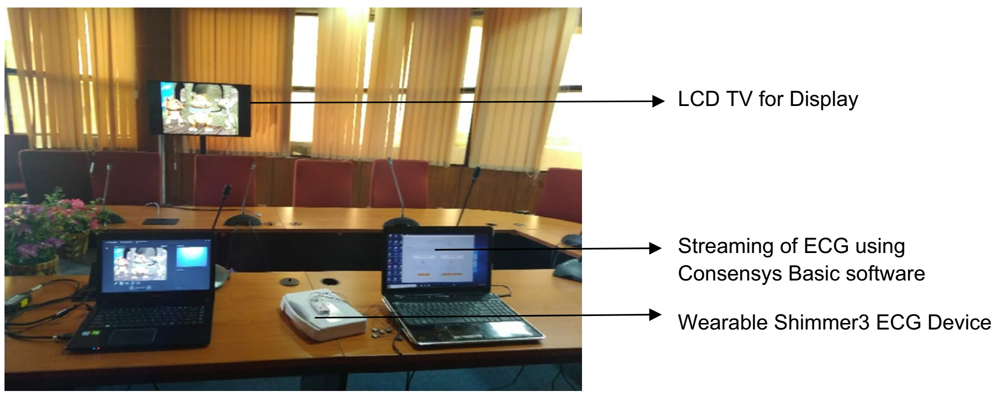

Fig. 3 Experimental setup

news, sports, thunderstorm, sound of crackers, cooker, mixer grinder, vehicles and beach scene were selected depending on the behavioral pattern of the child. Each clip lasted from 16 s to 1 min representing positive and negative valence ('Like' and 'Dislike'). Each trial also started with a baseline period of two minutes and had ten 'Like' and 'Dislike' cues. A time gap of two seconds was allowed between two audio-visual cues.

2.1.2 Experimental setup

The experiment was conducted in a closed room with the audio-visual system as shown in Fig. 3. The audio and visual cues were displayed in a 43-inch LCD TV screen with inbuilt speaker system. The instrument used for recording was a small and portable wearable shimmer 3 ECG system with MSP430 microcontroller (24 MHz) with Bluetooth radio RN-42 and a rechargeable 450 mAH lithium battery. It consists of a 5 wire, 4 lead electrodes to measure the lead II type of ECG measurements (right arm, left arm, right leg and left leg acting as the reference electrode with adhesive child patch electrode along with chest belt as shown in Fig. 4 and supporting consensys basic software for streaming the electrocardiogram signals (ECG)at the sampling rate of 512 Hz.

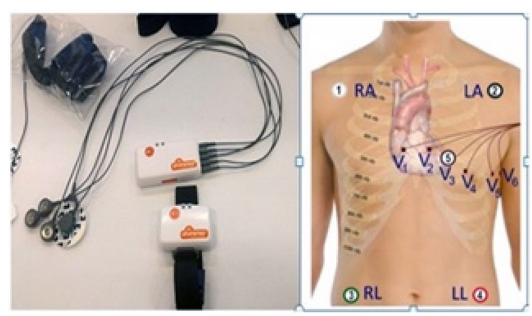

Fig. 4 Wearable Shimmer 3ECG device

2.1.3 Subjects

Six TD children with mean age 8 years (range 7–11 years, SD = 2.8) and Six children with ASD with mean age of 8 years (range 7–11 years, SD = 1.8) of mild and moderate autism (Indian Scale of Assessment of Autism (ISAA) scores ranging from 70 to 150) were recruited with National Institute approval from NIEPMD and obtained consent from the parents.

2.1.4 Experimental procedure

The experimental procedure was initially briefed to the parents and children. After obtaining the needed consent, trial experiments were conducted for two or three days prior to the actual data collection to make the child feel comfortable and acquaint him to the device and process. During the data collection experiment, the participants were seated comfortably in a chair accompanied by their parents or caretakers. The electrodes of the wearable shimmer3ECG device were connected to them using a chest belt. The children were given their own time to settle down and pre-trials were taken two to three times to calm the children. ECG signals were acquired from the children with ASD and TD children as they watched the emotional cues. The parents simultaneously responded to a questionnaire by rating the emotion felt by their child at that point of time. Three trials were conducted for each child. In the case of children with ASD, the entire experiment was carried over two or three different days depending on the mood of the child.

2.2 Pre-processing of emotional ECG data

The acquired raw ECG signal was corrupted with lot of artifacts due to movements, respiration and behavioral activities such as hand flapping, spinning and head rolling. The baseline wandering occurring in the frequency of 0.5–1 Hz was removed using the discrete wavelet transform (DWT) using Daubechies (*db4*) as the mother wavelet at 8th level of decomposition (Behzad and Tinati 2005; Palanisamy and Yaacob 2012). Other high frequency noise signals were removed using6th order low pass (LP) Butterworth filter with a cut of frequency of 20 Hz (Parastesh Karegar et al. 2017). The HRV and QRS amplitude was derived using Pan Tompkins's algorithm (Lee and Jeong 1996)

2.3 ECG feature extraction

As the Daubechies wavelet represents the characteristics of the ECG signal, it was used to extract the statistical, linear and nonlinear features from ECG signal, HRV and QRS amplitude (Imah et al. 2011). Three scaled version of Daubechies namely *db2*, *db4* and *db8* were used in this analysis. The mother wavelet function $\psi_{a,b}(t)$ is given as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left[\frac{t-b}{a}\right]a, b\epsilon R, a > 0, \tag{1}$$

where a, b ϵ R, a > 0, and R is the wavelet space. Parameters 'a' and 'b' are the scaling factor and the shifting factor, respectively, since choosing a prototype function as the mother wavelet should always satisfy the admissibility condition (Eq. 2),

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty \tag{2}$$

where Ψ (ω) is the Fourier transform of Ψ a, b(t).

The six well known statistical features used widely in emotion recognition, higher order statistical features and non-linear features as indicated in Eq. 3 through 13 was used for analysis (Picard et al. 2001; Jerritta et al. 2013).

Means of raw signal

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N} X_n \tag{3}$$

Median of raw signal

$$Median(M_m) = (N+1)/2 \tag{4}$$

Standard deviation of raw signal

$$\sigma_x = \frac{1}{N-1}\sum_{n=1}^{N} (X_{n-}\mu_x)^2 \tag{5}$$

Mean of absolute values of first differences of raw signal

$$Mean\,I = \delta_x = \frac{1}{N-1}\sum_{n=1}^{N-1} \left|X_{n+1} - X_n\right| \tag{6}$$

Mean of absolute values of first differences of raw normalized signal

$$Mean\,II = \hat{\delta}_x = \frac{1}{N-1}\sum_{n=1}^{N-1} \left|\hat{X}_{n+1} - \hat{X}_n\right| \tag{7}$$

Mean of absolute values of second differences of raw signal

$$Mean\,III = \gamma_x = \frac{1}{N-2}\sum_{n=1}^{N-2} \left|X_{n+2} - X_n\right| \tag{8}$$

Mean of absolute values of second differences of normalized signal

$$Mean\,IV = \hat{\gamma}_x = \frac{1}{N-2}\sum_{n=1}^{N-2} \left|\hat{X}_{n+2} - \hat{X}_n\right| \tag{9}$$

Skewness

$$Skewness = \frac{\sum_{n=1}^{N} (X_{n-}\mu_x)^3}{(N-1)\sigma_x^3} \tag{10}$$

Kurtosis

$$Kurtosis = \frac{\sum_{n=1}^{N} (X_{n-}\mu_x)^4}{(N-1)\sigma_x^4} - 3 \tag{11}$$

Hurst

$$Hurst = E\left[\frac{R_n}{S_n}\right] = Cn^H asn \rightarrow \infty \tag{12}$$

Approximate entropy

$$ApEn = \varphi^m(r) - \varphi^{m+1}(r) \tag{13}$$

3 Results and discussion

Baseline wander and high frequency noises were removed from the raw ECG signals using Daubechies *db4* mother wavelet-based algorithm and sixth order Butterworth low pass filter respectively as shown in Fig. 5a through c. HRV data and QRS Amplitude was derived from the filtered ECG is shown in Fig. 5d, e respectively. The features (Eqs. 3–13) corresponding to the internal states were extracted from the pre-processed ECG, HRV and QRS data after applying DWT *(db2, db4 and db8)* for further analysis.

3.1 Statistical validation of features

The statistical significance of all the features derived from ECG signal, HRV and QRS amplitude using the DWT (*db2, db4 and db8*) was studied using analysis of variance (ANOVA) and the p values are tabulated in Table 1. From Table 1, it is evident that the features whose (p value < 0.05) such as mean and median indicate significance for TD children using HRV data for all the three wavelets. Similarly, the feature Mean IV, indicate significance in QRS amplitude across all wavelets for TD children. In the case of children with ASD, entropy and kurtosis showed significance for QRS amplitude for all the wavelets. Skewness showed significance for *db2* and *db8* in HRV data.

Other features such as mean I, mean II and mean III showed significance in some of the cases corresponding to ECG, HRV or QRS amplitude. Table 2 list the various features used in the analysis of this work based on the significance.

3.2 Classification of positive and negative valance

The results of significant features of ECG data, HRV and QRS for db2, *db4* and db8 wavelets are tabulated from Tables 3, 4 and 5 respectively. From Table 3, it is well evident that Mean IV of signal drawn from ECG using DWT (*db2*) captures better valence information resulting in maximum average accuracy of 76.6% and74.3% for TD children and children with ASD respectively. Mean I of signal derived from the HRV data proves to hold more useful information

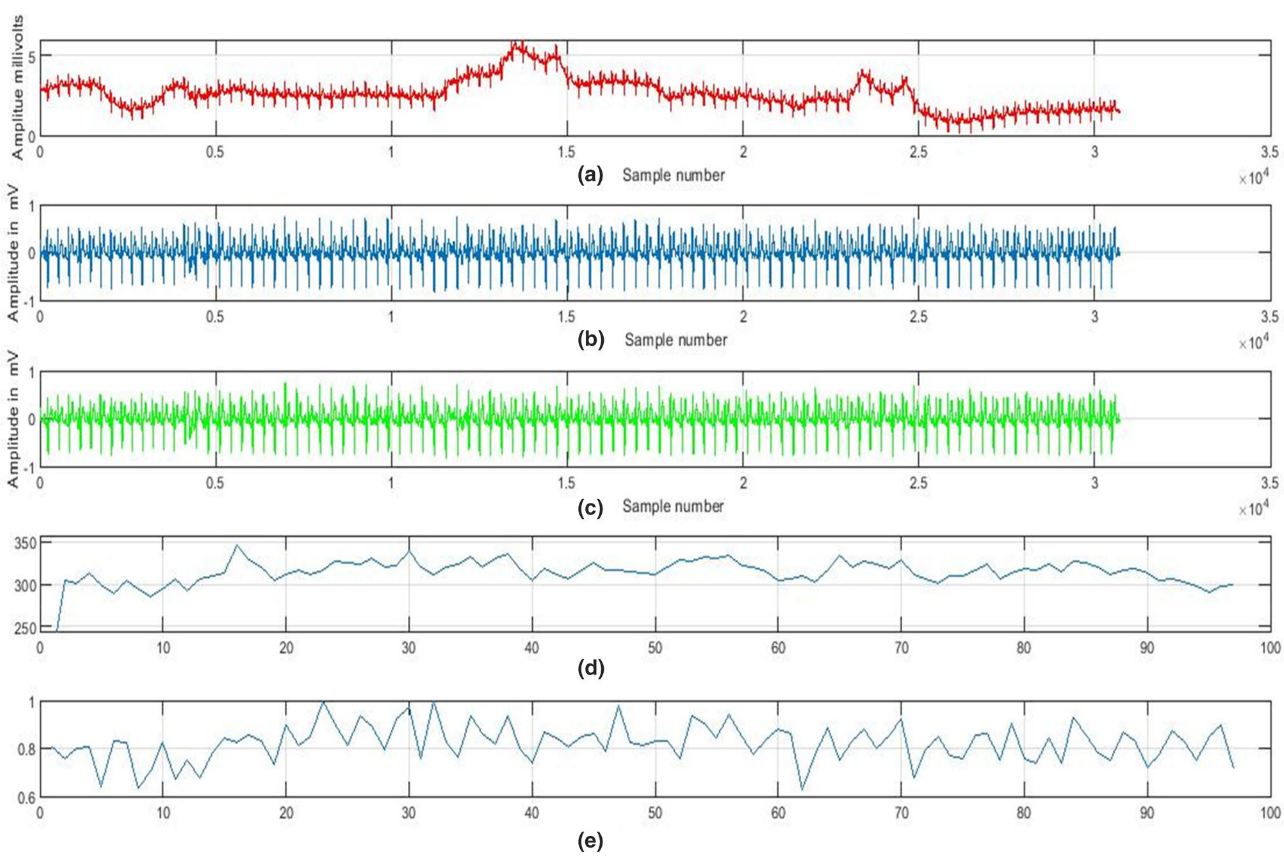

Fig. 5 **a** Raw ECG signal, **b** baseline wander removed signal, **c** lowpass filtered signal, **d** HRV data and **e** QRS amplitude

Table 1 Statistical analysis of features derived from ECG, HRV and QRS of TD children and children with ASD

Emotional features	TD children									Children with ASD								
	ECG			HRV			QRS			ECG			HRV			QRS		
	db2	*db4*	*db8*	*db2*	*db4*	*db8*	*db2*	*db4*	*db8*	*db2*	*db4*	*db8*	*db2*	*db4*	*db8*	*db2*	*db4*	*db8*
Mean	0.222	0.222	0.216	**0.01**	**0.012**	**0.009**	0.095	0.161	0.21	0.283	0.284	0.263	0.168	0.157	0.152	0.375	0.375	0.356
Median	0.335	0.348	0.308	**0**	**0.003**	**0.013**	0.153	0.234	0.341	0.168	0.159	0.164	0.203	0.205	0.238	0.448	0.421	0.359
Standard deviation	0.915	0.916	0.919	0.064	0.071	0.122	0.842	0.484	0.749	0.32	0.32	0.32	0.067	0.06	0.059	0.559	0.709	0.603
Mean I	0.564	0.564	0.554	**0.03**	0.077	0.153	0.579	0.732	0.564	0.346	0.346	0.347	0.104	0.092	0.107	0.116	0.629	0.269
Mean II	0.101	0.1	0.093	0.329	0.591	0.729	0.531	0.155	0.589	0.69	0.689	0.685	0.348	0.393	0.183	**0.049**	0.404	0.073
Mean III	0.595	0.583	0.599	**0.04**	0.08	0.241	0.929	0.595	0.831	0.344	0.344	0.344	0.096	0.085	0.11	0.129	0.488	0.207
Mean IV	**0.045**	**0.044**	**0.042**	0.29	0.245	0.91	0.806	0.167	0.785	0.829	0.833	0.832	0.488	0.329	0.176	0.068	0.327	0.066
Entropy	0.651	0.664	0.606	**0.024**	0.484	**0.045**	0.238	0.141	0.104	0.059	0.06	0.059	0.07	0.676	0.081	**0.021**	**0.019**	**0.025**
Skewness	0.242	0.242	0.25	0.953	0.551	0.955	0.834	0.699	0.865	0.121	0.121	0.129	**0.023**	0.108	**0.014**	0.931	0.34	0.908
Kurtosis	0.384	0.385	0.381	0.654	0.489	0.422	0.88	0.81	0.494	0.592	0.59	0.587	0.217	0.377	**0.008**	**0.017**	**0.04**	**0.014**
Hurst	**0.003**	0.001	**0**	**0.025**	0.256	0.538	**0.04**	0.215	0.133	0.992	0.955	0.629	0.227	0.609	0.354	0.918	0.054	0.713

Bold value indicates the p value of the features whose values are < 0.05

Mean I—mean of absolute value of first difference of signal; Mean II—mean absolute value of normalized first difference of signal; Mean III—mean absolute value of second difference of signal; Mean IV—mean absolute value of normalized second difference of signal

Table 2 Significant features of ECG, HRV and QRS amplitude

ECG	HRV	QRS
Mean IV	Mean	Mean II
Hurst	Median	Entropy
	Mean I	Kurtosis
	Mean III	Hurst
	Entropy	
	Skewness	

when compared with the other significant features by achieving a maximum average accuracy of 87.4% and 74.3% for both TD children and children with ASD in both KNN and Ensemble classifier. In the case of QRS amplitude, mean II and kurtosis obtained from the results in maximum average accuracy of 79.3% and 72.4% for TD children and children with ASD respectively.

In the case of *db4* wavelets, mean IV resulted in maximum average accuracy of 71.2% and 64.8% for both TD children and children with ASD. Mean I of signal drawn from HRV achieves better accuracy of 83.8% for TD children and 74.3% for children with ASD using both the KNN and Ensemble classifiers. In further analysis, the features from the QRS amplitude shows that Kurtosis captures the useful valence information resulting in a maximum average accuracy of 78.4% for TD children and Mean II provides better information of valence in children with ASD.

It is evident from Table 5 that the nonlinear feature Hurst derived from ECG signal using DWT (*db8*) resulted in maximum average accuracy of 80.2% for TD children and 72.4% for children with ASD. Median and Mean I drawn from HRV data achieves a maximum average accuracy of 79.3% for TD children whereas Mean I holds good for both TD children and children with ASD. In case of the QRS amplitude, mean II of signal drawn using DWT (*db8*) resulted in maximum average accuracy of 79.3% and 77.1% for TD children and children with ASD respectively.

The overall performances of the classifiers for ECG, HRV and QRS amplitude data using the combination of all significant features is shown from Figs. 6, 7, and 8. Figure 8 indicates that the *db8* features from ECG data achieves maximum average accuracy of 82% for TD children and 78.1% for children with ASD using the Ensemble and SVM classifiers respectively.

HRV signals achieved an overall accuracy of 84.7% and 81% for TD children and children with ASD respectively using *db8* wavelet function as in Fig. 6 and QRS amplitude data achieved a maximum accuracy of 81.1% in both *db4* and *db8* wavelet function for the TD children. A maximum accuracy of 76.2% was achieved for children with ASD using DWT (*db8*) as in Fig. 7.

The analysis in Fig. 9 indicates that HRV data, indicating the variability in heart rate is an effective indicator for

Table 3 Classification of 'Like' and 'Dislike' states using db2 analysis

Data	Emotional features	Classifiers	Accuracy (*Db2*)					
			Typically developed children			Children with ASD		
			Like %	Dislike %	Average %	Like %	Dislike %	Average %
ECG	Mean IV	SVM	75	49	62.2	46	57	51.4
		KNN (1)	70	84	76.6	65	83	74.3
		Ensemble	70	84	76.6	65	83	74.3
	Hurst	SVM	95	16	55.9	29	77	53.3
		KNN (1)	73	69	71.2	63	74	68.6
		Ensemble	68	73	70.3	63	74	68.6
HRV	Mean	SVM	30	91	60.4	63	66	64.8
		KNN (1)	68	91	79.3	58	81	69.5
		Ensemble	68	91	79.3	60	81	70.5
	Median	SVM	79	53	65.8	54	53	53.3
		KNN (1)	82	89	85.6	60	77	68.6
		Ensemble	79	85	82	58	75	66.7
	Mean I	SVM	45	78	61.3	54	66	60
		KNN (1)	80	93	86.5	63	85	74.3
		Ensemble	82	93	87.4	63	85	74.3
	Mean III	SVM	32	93	62.2	67	42	54.3
		KNN (1)	71	93	82	67	77	72.4
		Ensemble	70	93	81.1	67	77	72.4
	Entropy	SVM	39	71	55	75	36	55.5
		KNN (1)	85	20	52.5	45	76	60.2
		Ensemble	23	78	50.5	45	76	60.2
	Skewness	SVM	75	40	57.7	63	40	51.4
		KNN (1)	82	75	78.4	62	72	66.7
		Ensemble	82	75	78.4	63	72	67.6
QRS	Mean II	SVM	63	51	56.8	49	66	57.5
		KNN (1)	59	84	71.2	60	84	72.4
		Ensemble	59	84	71.2	60	84	72.4
	Entropy	SVM	59	56	57.7	53	59	56.3
		KNN (1)	57	60	58.6	63	64	63.2
		Ensemble	57	60	58.6	63	64	63.2
	Kurtosis	SVM	39	65	52.3	12	95	54
		KNN (1)	80	73	76.6	67	75	71.3
		Ensemble	70	89	79.3	67	75	71.3
	Hurst	SVM	64	60	62.2	67	39	52.9
		KNN (1)	75	33	54.1	47	77	62.1
		Ensemble	39	89	64	47	77	62.1

categorizing the like and dislike states of both TD children and children with ASD (Krupa et al. 2016; Quintana et al. 2012). However, the maximum accuracy is only 85%. More features can be explored in HRV to achieve higher classification accuracy for categorizing the valence states.

4 Conclusion

In this study the protocol for inducing the 'like' and 'dislike' states were designed for each child using the audio- and audio-visual stimulus. The raw ECG data was pre-processed

Table 4 Classification of 'Like' and 'Dislike' states using db4 analysis

Data	Emotional features	Classifiers	Accuracy (*Db4*)					
			Typically developed children			Children with ASD		
			Like %	Dislike %	Average %	Like %	Dislike %	Average %
ECG	Mean IV	SVM	79	36	57.7	52	53	52.5
		KNN (1)	64	76	70.3	63	66	64.8
		Ensemble	64	71	67.6	63	66	64.8
	Hurst	SVM	77	25	51.4	25	91	58.1
		KNN (1)	63	80	71.2	56	74	64.8
		Ensemble	63	80	71.2	56	74	64.8
HRV	Mean	SVM	39	71	55	85	23	53.3
		KNN (1)	80	73	76.6	69	74	71.4
		Ensemble	79	73	75.7	69	74	71.4
	Median	SVM	63	49	55.9	35	70	52.4
		KNN (1)	71	84	77.5	56	81	68.6
		Ensemble	73	80	76.6	56	81	68.6
	Mean I	SVM	32	93	62.2	60	60	60
		KNN (1)	86	85	85.6	62	87	74.3
		Ensemble	82	85	83.8	56	85	70.5
	Mean III	SVM	36	89	62.2	75	19	46.5
		KNN (1)	68	95	81.1	62	75	68.6
		Ensemble	70	89	79.3	62	75	68.6
	Entropy	SVM	23	78	50.5	60	46	53
		KNN (1)	80	27	54.1	35	74	54.5
		Ensemble	20	91	55	86	35	60.5
	Skewness	SVM	63	55	58.6	17	81	49.5
		KNN (1)	64	89	76.7	60	68	63.8
		Ensemble	64	87	75.7	60	68	63.8
QRS	Mean II	SVM	61	47	51.4	56	68	61.9
		KNN (1)	64	71	67.6	62	75	68.6
		Ensemble	64	71	67.6	62	75	68.6
	Entropy	SVM	63	53	57.7	60	53	56.2
		KNN (1)	79	53	65.8	69	60	64.8
		Ensemble	61	76	68.5	75	58	66.7
	Kurtosis	SVM	73	36	55	17	91	54.3
		KNN (1)	66	84	74.8	50	70	60
		Ensemble	66	82	73.9	54	60	57.1
	Hurst	SVM	61	55	57.7	21	89	55.2
		KNN (1)	89	29	59.5	56	66	61.0
		Ensemble	48	82	64.9	56	66	61.0

to remove BW using daubechies *db4* mother wavelet, and high frequency noise was removed using 6th order Butterworth low pass filter. The Statistical, HOS, linear and nonlinear features were extracted using DWT (*db2, db4* and *db8*) of ECG signal, HRV and QRS amplitude. Classification results indicate that the significant features drawn from HRV using *db8* wavelet achieves overall maximum average accuracy of 84.7% and 81.1% respectively for TD children and children with ASD compared to *db2* and *db4*. HRV data is found to be more effective than ECG and QRS amplitude in capturing the valence states in TD children and children with ASD. However, more analysis should be done on HRV data to extract features that can improve the accuracy of classification.

Table 5 Classification of 'Like' and 'Dislike' states using db8 analysis

Data	Emotional features	Classifiers	Accuracy (*Db8*)					
			Typically developed children			Children with ASD		
			Like %	Dislike %	Average %	Like %	Dislike %	Average %
ECG	Mean IV	SVM	95	24	59.5	38	74	56.2
		KNN (1)	63	91	76.6	48	89	68.6
		Ensemble	63	91	76.6	48	87	67.6
	Hurst	SVM	43	75	58.6	60	45	52.4
		KNN (1)	75	85	80.2	63	79	71.4
		Ensemble	75	85	80.2	65	79	72.4
HRV	Mean	SVM	29	84	55.9	56	58	57.1
		KNN (1)	73	78	75.7	56	74	64.8
		Ensemble	73	78	75.7	56	74	64.8
	Median	SVM	20	85	52.9	44	64	54.3
		KNN (1)	71	87	79.3	60	81	70.5
		Ensemble	71	87	79.3	63	81	72.4
	Mean I	SVM	41	67	54.1	71	21	45.7
		KNN (1)	73	85	79.3	69	81	75.2
		Ensemble	73	85	79.3	69	81	75.2
	Mean III	SVM	32	91	61.3	23	60	41.9
		KNN (1)	71	80	75.7	56	83	69.5
		Ensemble	71	80	75.7	60	75	67.6
	Entropy	SVM	36	71	53.2	45	74	59.2
		KNN (1)	88	25	56.8	67	40	53.5
		Ensemble	29	87	57.7	19	84	51.5
	Skewness	SVM	63	47	55	48	64	56.2
		KNN (1)	59	80	69.4	48	83	65.7
		Ensemble	59	80	69.4	48	83	65.7
QRS	Mean II	SVM	48	60	54.1	37	79	58.1
		KNN (1)	73	85	79.3	63	91	77.1
		Ensemble	73	85	79.3	63	91	77.1
	Entropy	SVM	59	55	56.8	52	57	54.3
		KNN (1)	84	51	67.6	69	66	67.6
		Ensemble	84	51	67.6	69	66	67.6
	Kurtosis	SVM	36	84	59.5	65	57	61
		KNN (1)	68	89	78.4	58	77	67.6
		Ensemble	75	78	76.6	58	77	67.6
	Hurst	SVM	80	35	57.7	60	47	53.3
		KNN (1)	80	73	76.6	62	77	69.5
		Ensemble	63	93	77.5	62	77	69.5

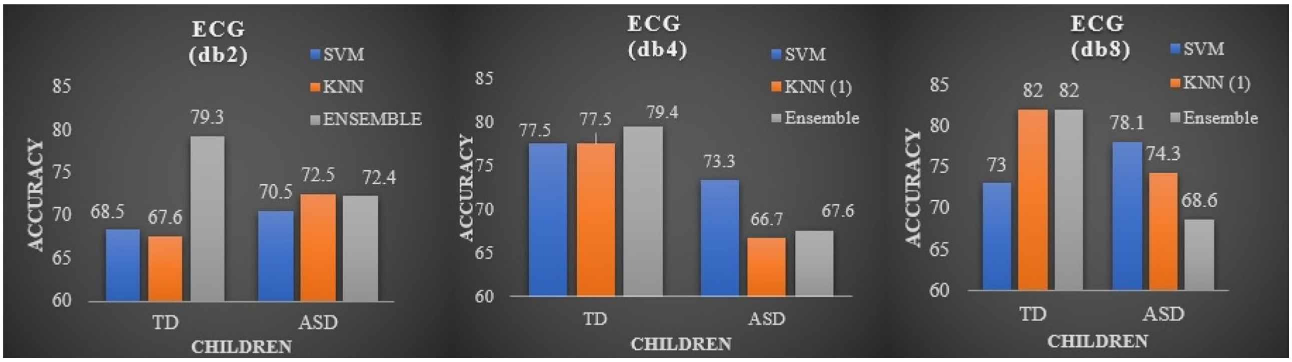

Fig. 6 Overall accuracy of HRV signals

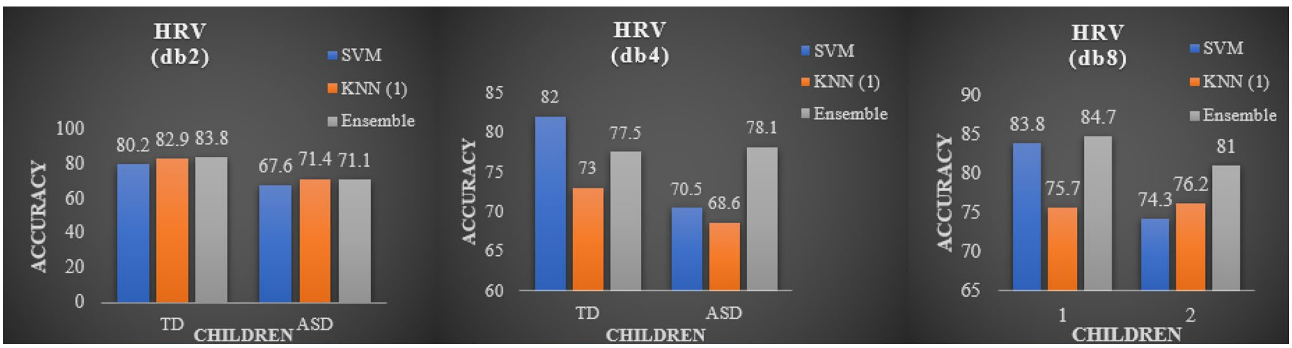

Fig. 7 Overall accuracy of QRS amplitude

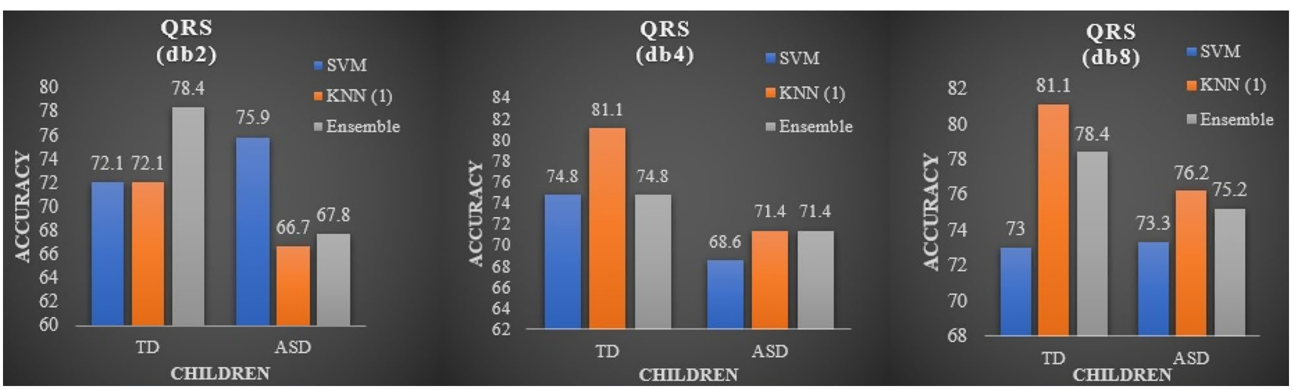

Fig. 8 Overall accuracy of ECG signals

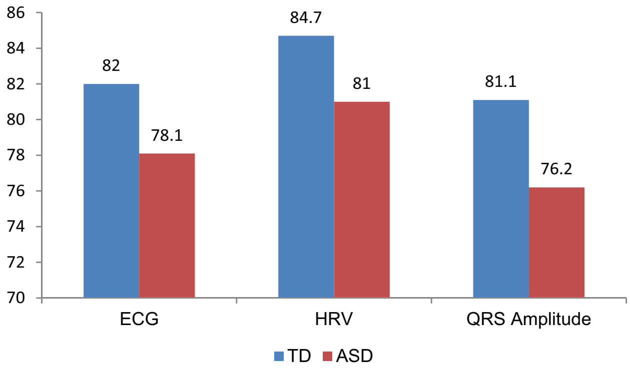

Fig. 9 Comparison of ECG, HRV and QRS

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical consideration Ethical approval was obtained from the Ethics Committee of National Institute for Empowerment of Persons with Multiple Disabilities (NIEPMD), Chennai regarding the protocol and data acquisition procedure prior to performing the experiments. Ethical Approval ID: SE: -0101/2018.

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