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Real Time Emotion Recognition with AD8232 ECG Sensor for Classwise Performance Evaluation of Machine Learning Methods

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A B S T R A C T

Emotions are the accelerators of human intellect and innovation and creativity, so the ability to recognize emotions is in high demand. Real-time hardware has hurdles of Noise and hardware factors as compared to simulations. An electrocardiogram (ECG) sensor (AD8232), a temperature sensor (LM35), and a signal processing circuit is hardware of the proposed real-time emotion identification. The RR intervals are calculated from the ECG data. Emotions prediction using machine learning makes use of RR intervals and body temperature as features. One of the four emotions (namely 1. Happy 2. Stressed 3. Neutral 4. Sad.) is visualized at the serial port of the processor by using WESAD benchmark dataset and the HRV, serial, and pickle libraries.This article's innovation factors are (1) Use of ECG for emotion detection rather than disease detection with Emotion induction method, RR interval capturing and design of RR interval GUI for real time capture of temperature and ECG (2) Display of current emotion on Arduino serial port. (3) Measurement of Class performance using F1 score, macro average, and weighted average instead of general term accuracy. (4) Use of the probability based Navies Bayes as compared to traditional KNN, SVM, Random Forest nethods (5) Class wise performance for example Navies Bayes' specificity or accuracy is lower than SVM's (0.96), but its recall or sensitivity is higher (0.97) vs. (0.94) for stress.In this article, we presented performance parameters in terms of interactive computations, tabular form and graphical display.

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1. INTRODUCTION

Emotions have a major impact on many aspects of human life and actions [1]. The strategies and desired outcomes of organizations are linked to people's emotions [2]. Hence, emotion detection research is in demand. The subjects respond with different levels of emotions to the same set of stimuli [3]. Thus, challenging aspect of emotion recognition is behavioral uncertainty. Emotions can be detected using various signal processing algorithms. Table 1 shows variety of modalities for emotion like facial expressions, biomedical sensors [4]. The speech-based and facial expression emotion identification methods may be representing different emotions than the actual [5]. Emotion recognition using biosensors linked to the subject's body is proportional to emotions and behavioral patterns [6-9]. Wearable technology [6, 9] is now developed from labs to doorsteps. Biological signals (like electrocardiogram (ECG)) which were used for clinical diagnosis [10] can be utilized to detect emotions [11].

Emotions identified with Wearables have the benefit that emotions cannot be suppressed nor be hidden in physiological parameter traits. Real-time emotions can be predicted using a physiological benchmark database [12, 13] and machine learning techniques. The reason to use Machine learning algorithms instead of deep learning is twofold. First reason is, while multiple ECG classifiers are available for disease identification, Support Vector Machine (SVM), K Nearest Neighbor (KNN), and Random Forest [14-19] are employed for emotion categorization with real-time ECG. Second reason is real

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TABLE 1. Modalities of Emotion Recognition and drawbacks

Sr No.	Modality used	Drawback
1	Speech-based emotion identification	speaker's emotion may be hidden or not expressed accurately and is available only for the time till the speaker speaks. The accuracy is low ranging from 44% to 83.5%[5]
2	Facial expressions-based method	it may possibly miscommunicate the level, depth, and underpinned message of emotions[7].

time ECG signals are to be classified hence hardware AD8232 is also to be evaluated with structured limited benchmark dataset WESAD instead of just concentrating on simulation approach. The proposed research aims to develop real-time affective computing with ECG biosensors and Navies bayes machine learning algorithms to classify emotions.

In this article, we propose a comparative approach to ECG based emotion detection using Navies Bays and SVM. The Navies bayes is chosen because it is based on probability rules, and in emotion recognition probability of getting one of the emotions: 1 Happy, 2 Stressful. 3rd: Angry, 4th: Sad.) can be predicted with proposed experimentation. SVM is chosen because for emotion classification with ECG signals it has been proved the best classifier in the literature validated these experiments with performance matrices F1 score, accuracy, etc. (see Table 2).

2. LITERATURE REVIEW

Biosensors [10] such as optical sensors, Electrochemical biosensors, and Oxygen sensors are available and can further be utilized in Gephi software for use of ECG for disease prediction. An emotion recognition system [20] is designed with IoT and machine learning techniques with temperature and heart rate parameters [20] to recognize human emotions. A wearable emotion recognition device was used in [9, 11, 21] auto capture the data from a heart rate [21] and other biosignals. Another study approach [4, 21] looked at the solution of emotion detection as emotion extraction using skin conductance, skin temperature, ECG, EMG, and EEG data. Schmidt et al. [12] proposed a WESAD a publicly available dataset for stress detection. Haag, et al. [21] uses a way to teach computers to identify emotions by feeding them signals from a variety of biosensors. The literatures [21, 22] demonstrates EEG signal processing

TABLE 2. SVM KNN, Random forest are the Popular Methods for emotion Recognition with ECG

Sr No.	ECG features	Emotions recognized	Machine learning techniques used	Remark/factor
1	Heart rate HRV) [14]	Emotions: Happy exciting Calm Tense	K-NN [14]	90.51667%
			PSO-SVM	
			Random forest	81.707%
2	Weighted Mean Filter to improve the Baseline Reduction	Relax, Joy, fear idenficaton[1]	SVW, CART, KNN	92%
3	ECG values converted with DCT and sampled frequency domain	The optimal number of features 75, Emotions Happy, calm, relax, and Tense [23]	PSO-SVM Random forest K-NN, SVM, Random Forest [24]	Recognition_ rate (Avg) 90%, 51. 667%, 81.707%, 82.483%
4	Respiration Inhale-Exhale Temperature	Happy, Sad, Fear	[18]	75%
5	Time and frequency-based ECG signal processing [15]	Unhappiness, pleasure, and pride	SVW, CART, KNN [15, 19]	
6	ECG feature extraction with signal processing techniques like analysis with the article is providing ECG classification [16]	ECG classification only no emotion classified	filtering, differentiation transform, and principal component	99.71 predictivity
7	demonstrates emotion recognition with DCT and IIR signal processing. [17]		SVM, KNN, particle swarm optimization method	0.889
8	demonstrates emotions classified with using a Convolutional neural self supervised network for unlabelled ECG data. [25]	Three databases named AMIGOS, DREAMER, and WESAD	Neural Network	0.966

[1] https://docs.arduino.cc/resources/datasheets/A000066-datasheet.pdf

techniques based on SVM and Time-frequency domain respectively. Butkevičiūtė et al. [22] proposed the detection of pulse variations and provides a precise output that indicates the emotional conditions with ECG electrodes. Our proposed research is also using the AD8232 for ECG capturing [22, 26].

Shin et al. [27] proposed an actual time interface with human-targeted emotion which mixes the ratio of ECG and EEG signals. Goshvarpour et al. [13] proposed a method of Matching Pursuit (MP) algorithm for emotions. Bulagang et al. [28] proposed a method of ECG and EDG/ GSR as input traits to categorize feelings. Hui et al. [6] proposed a method of emotion detection with contactless approaches and touch and skin-penetrating electrodes. Hasnul et al. [25] proposed a method that specializes in emotion recognition research based on electrocardiograms (ECGs) as an unimodal and multimodal method Xianhai [29] proposed a technique related to the emotional sample reputation method as a standard neural network classifier to examine ECG statistics with wavelet coefficients. Fernández [8], Zenonos et al. [30], Patil et al. [31] proposed methods to discover the possibility of gadgets for mood reputation for work environments [8, 24] is showing a machine learning approach for predictivity of ECG classification. Some articles consider ECG signal correlation and time-frequency domain statistical characteristics [19, 32]. Data [33] modified weighted mean filter to improve the baseline eduction approach for emotion recognition in the aticle [3].

3. MATERIAL AND DATA

3. 1. Material As shown in Figure 1, The proposed framework consists of hardware of microcontroller, An ECG measuring sensor (AD 8232), pulse sensor, temperature sensor (LM35) and software elements of machine learning algorithms, driver programs, and performance measurement programs written in python.

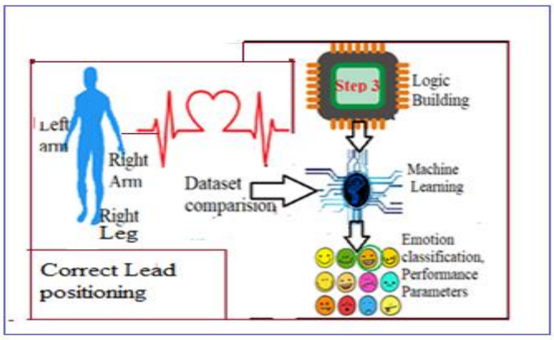


Figure 1. Conceptualization of proposed system arrangement

3. 2. Dataset The Wearable Emotion and Stress Affect Dataset (WESAD) in CSV format is used [12]. Dataset is split between 70 percent training and 30 percent testing. The dataset contains, self reports and collection of 1Hz heartbeat data from the Raspbian device on the chest. and temperature data sampled at 4Hz collected using the wristband device. physiological data from 15 subjects collected during the lab research. Figure 2 shows logical flowchart for RR interval extraction on hardware for duration of 2 minutes interval.

3. 3. Choice and Positioning of Biosensors In the market, 3,4,5,6, and 12 leads ECG models are available. AD8232 is a portable, low-cost, 3 lead ECG with 80 dB CMRR. AD8232 is having inbuild well designed signal conditioning modules[1] and has capability of extraction, amplification, and filtration of cardiac bio signal potentials in the noisy condition. The low-pass signal processing circuits built in the AD 8232 remove powerline interface noise[3]. The ECG sensor detects heartbeat rhythm and pace [26].

Three electrical leads namely, Right Arm [RA] and Right Arm [LA] Right ankle measure the ECG. LM35 is attached to a finger or wrist. From Captured ECG signals, noise is removed with low pass filter and power line inference by thresholding, The output of Sensor and Graphical User Interface is shown in Figures 3 and 4. To capture real time emotions, WESAD [12] serves as the reference dataset.

3. 4. Method Ten volentures of age group 20 to 22 are chosen in such a way that they do not have any mental illness or heart disease.The video induction method of 12 minute duration for emotion induction is used.

The real time ECG data capturing is done for 2 minute per sample. For each volunteers, 6 samples of 2 minutesares collected. Thus for ten volunterees 60

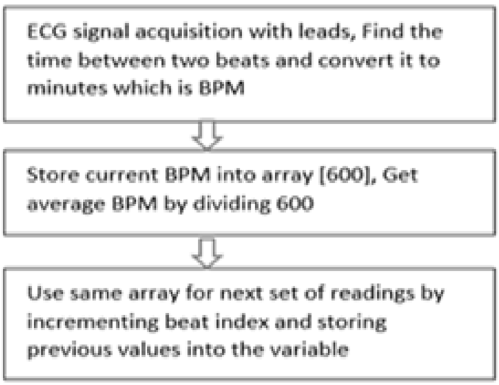


Figure 2. AD 8232 based RR interval determination (600 is array size, in which current peaks are stored and refreshed)

[1] https://www.analog.com/media/en/technical-documentation/data-sheets/ad8232.pdf

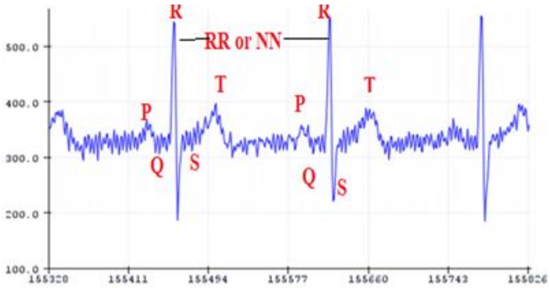


Figure 3. The output waveform of the proposed system wave showing real-time showing QRS complex, RR interval

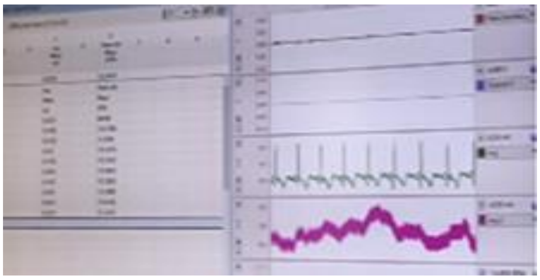


Figure 4. The GUI design for captured heartbeat

samples of each 2 minute duration are collected.Hence we have 600 samples, From these collected samples. We have processed data in real time. For real time implementation Arduino processor[1] with an Analog to Digital Converter resolution of 10 bits is used. The recorded ECG range will range from 0 to 1023 and the real time graphs are available at serial port.

4. RESULTS

4. 1. Platform Used For machine learning part Python HRV, serial, pickle libraries, and WESAD benchmark dataset are used for data acqisition. Ardunio output is seen and transferred to machine learning from serial port. The possible ECG Featureextaction methods are listed in Table 3.

4. 2. PQRST Waveform and RR interval ECG waveform typically forms the typical shape called as the PQRST[2]. The visualization of the waveformis in Table 4. A peak detection method is used as a first step. This method iscomparing each time series data and storing the largest number as a latest peak. The difference between newer peak and the previous peak in time domain is called as RR interval. The current peak value is compared a newest peak value [34] and is selected as R feature to calculate:

Heart Rate =[(60000)]/(R-R interval) (1)

4. 3. ECG based Emotion Classification with Machine Learning For ECG based disease classification, variety of ECG classifiers like Neural network, particle swarm algorithms are available. For emotion detection with ECG classifiers SVM, KNN, Random forest are popular methods (Table 1).

We have proposed navies bays classifier for solving the emotion classification multiclass problem because The navies bays classifier is probablity based. From Litturature, we know that, SVM [27] is the best candidate with better accuracy hence we are proposing SVM to compare with navies bays classifier.

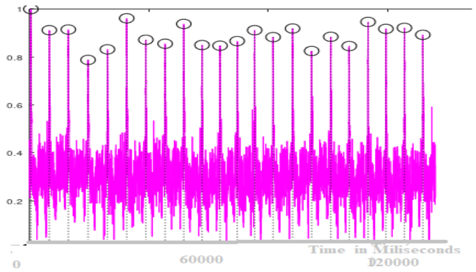
TABLE 3. List of important ECG features, Out of these features, RR interval is selected as feature

Summary of ECG features: A: Time Domain, B.Freqency Domain and Poincare plots		
A.Time domain Features of ECG		
1	HR - M	Mean of heart rate
2	SDR_R	Standard deviation of interbeat (msec) Interval, $SDR_R = \sqrt[2]{\frac{1}{N-1} * \sum_{K=1}^{N}(R_{Rk} - R_R)} \wedge 2$
3	RM_ square _SD	- $SDNN = \sqrt[2]{succesive\ \ NN\ interval\ difference}$ (msec)
4	RR(50)	- (Number of NN interval pairs)> 50 milliseconds
5	PrR_R(50)	- (The % of numbers of pairs of NN) > 50
	$MeanR_R$	$MeanR_R = \frac{1}{N} * \sum_{K=1}^{N}(RR_k)$
B.Frequency domain Features of ECG(R paeak detection)(Power spectral Density)		
1	Power_SD range less than 0.04 Hz,	power distribution across frequency of area/energy
C.Poincare plot		
Poincare plot is the roatational transformation for the X axis is the RR interval with t points, and the Y axis repersents the t+1 points interval		

[1] https://docs.arduino.cc/resources/datasheets/A000066-datasheet.pdf

[2] https://www.svms.org/anns.html

TABLE 4. Visualization of the PQRST points,and significance (we have captured the peaks of PQRST for getting RRinterval)

Points on the ECG	**Source/ Remark**	**Duration/ Remark**	Visualization of PQRST and Selected feature is R RR or NN Interval
p	Depolarization is source of the P wave . stimulation of the both sides of atriais	Duration P < 0.12 sec	
QRS-complex	concurrent movement of the both ventricles	QRS duration is less than 0.10 sec	
ST SEGMENT	QRS complex and T wave are in concave upward direction	Patterns of downward direction or horizontal of ST segment describe depression.	

4. 4. Support Vector Machine The SVM approach is used to categorize emotions into four categories: neutral, stress, happy, and sad. The SVM method's goal is to find or decision boundary for categorizing n-dimensional space so that additional data points can be easily classified in the future.

A scatterplot is graph showing the relationship between two variables in the dataset.

Figure 5 shows a output of the SVM Scatterplot with heart rate on X axis and temperature on Yaxis.The prelimanary observation shows that neutal and haapy are well classified in the scatterplot. Neutral to happy. Stress and sad emotions seem to be in close vicinity.

The Table 5 shows values of ranges observed in scatterplot.

The very first step posted by us for ECG Machine learning emotion classifier approach is to make the subjects calm down to a neutral state, and then use 12 minutes of video induction method.

Figure 6 shows the output of neutral emotion labels from the serial monitor of the processor by applying the SVM algorithm to ECG and temperature features. The output label neutral (Base) state is captured when the subjects are instructed to be in the relaxed postion.

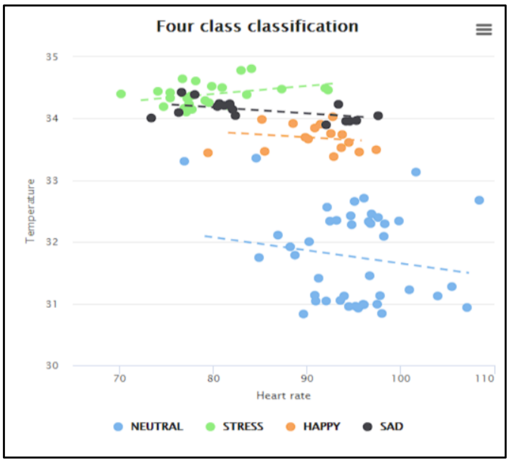


Figure 5. SVM scatterplot :four classes of emotions

TABLE 5. The SVM scatter plot Analysis

Emotion class	**Indicated by (dot) colour**	**SVM**	
		Heart rate Range	**Temp. Range**
Neutral	Blue	85 - 110 BPM	30 - 33°C
Stress	Green	70 - 100 BPM	34°C
Happy	Orange	80 - 100 BPM	33 - 34°C.
Sad	Black	75 – 100 BPM	34 - 34.5°C

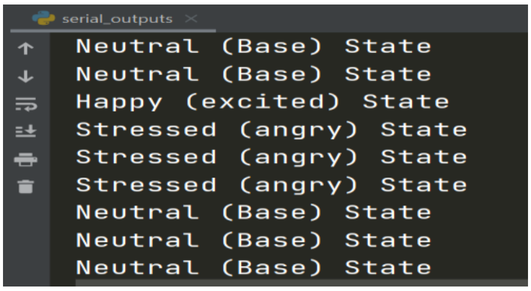


Figure 6. Labeled Neutral Emotions at output at intial instances

Navies Bayes

A naive Bayes classifier is based on the Bayes theorem and is a type of supervised learning. It suggests that the existence (or lack) of one feature of a class is not related to the existence (or lack) of any other feature. For real-time emotion recognition with ECG, the navies bays classifier used is probability-based prediction. As the emotions are totally random events. prediction with probability-based method is a suitable method.

The formula for Bayes' theorem is given as:

$$P(P|Q) = P(Q|P) \times P(P) / P(Q) \quad (2)$$

Performance Parameters Comparison for SVM and Navies Bayes Emotion Classiifies

Machine learning performance working in order to get predictions of the output is evaluated by numbers called its Performance Parameters. While definning these parameters ,True Pos abbreviation is used for True Positive and False Neg False abbreviation is used for False Negative. Some of the calculations of persormance parameters are done for understanding purpose as listed below.

a) Hamming Loss The proposed method is related to multiclass emotion classification, So calculation of accuracy will not truly support accuracy of model predictions. Hence, here Hamming loss term (with range 0 to1) is useful.
Lesser value of hamming loss indicates a better classifier.

$$\text{Hamming loss} = \frac{\text{wrongly predicted labels}}{\text{(Total labels)}} \tag{3}$$

b) Specivity

$$\text{Specitivity } \frac{\text{True Neg}}{\text{(False pos)+(True neg)}} = 1/3+5=0{,}125 \tag{4}$$

c) Sensitivity or Precision

$$\text{Sensitivity or precision} = \frac{\text{True pos}}{\text{(True pos)+(False Pos)}} \tag{5}$$

e.g. for Stress emotion class with navies bayes is calculated as Precision=201/ (201+34) =0.86

d) Recll e.g., for sad emotion class:

$$\text{Recall} = \frac{\text{True pos}}{\text{(True pos)+(False neg)}} == \frac{128}{128+11} = 0.92 \tag{6}$$

e) F1-Score F1 Score can be described as the harmonic mean of the model's precision and recall.

$$\text{F1Score} = 2 \times \frac{\text{(Precision)}*\text{(Re call)}}{\text{(Precision)+(Recall)}} \tag{7}$$

e.g., for sad emotion class:

$$\text{F1 Score} = 2 * \frac{0.94*0.92}{0.9+0.92} = 0.93 \tag{8}$$

f) Macro-average It is the basic mean of all class:

$$\text{Macro avg} = \frac{\text{F1−Score of all emotion class}}{\text{Total number of emotion class}} \tag{9}$$

$$\text{Macro} - \text{avg} = \frac{1+1+0.93+0.96}{4} = 0.97 \tag{10}$$

g) Weighted-average The weighted-average F1 score is the mean of all per-class F1 scores with respect to each class's support.

$$\text{Weighted}_{\text{avg}} = \frac{\text{(F1−Score)} \times \text{Support}}{\text{Sum of Support}} \tag{11}$$

$$\text{Weighted}_{\text{avg}} = \frac{1*0.446+1*0.133+0.93*0.139+0.96*0.234}{0.961} = 0.97077 \cong 0.98 \tag{12}$$

As per the above calculations and interpretation analysis, for the proposed setup with the SVM and Navies Bayes The performance of proposed system in Table 6, Figure 7 is at par with the previous liturature described in Table 1. The comparisons of SVM and

TABLE 6. Comparision of performance factors for Navies byes and SVM (70 %Training and 30% testing spilt)

Predicted Class	Method	Precision	Recall	F1 score	Support	Remark
Sad	SVM	0.94	0.92	0.93	139	Parameters are defined with definations and calculations in previous section
	Navies Bayes	0.99	0. 73	0.83	139	
Stress	SVM	0.96	0.97	0.96	234	
	Navies Bayes	0.86	1.00	0.92	234	
Neutral	SVM	1.00	1.00	1.00	446	The Scatterplot in Figure also shows all 6 readings classified correctly
	Navies Bayes	1.00	1.00	1.00	446	
Happy	SVM	1.00	1.00	1.00	133	
	Navies Bayes	1.00	0.99	1.00	133	

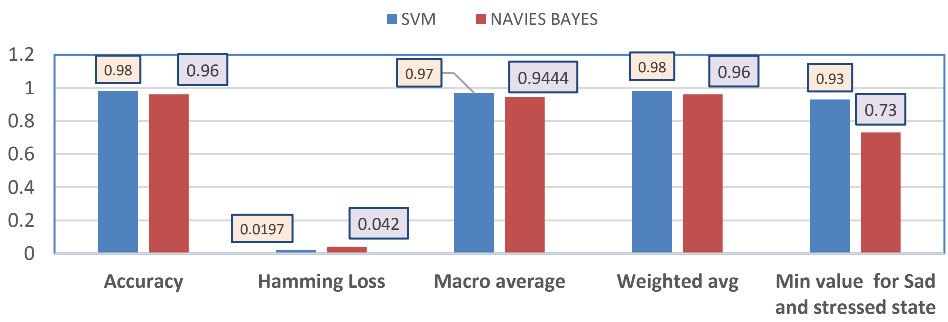


Figure 7. Comparasion of performance factors for Navies and SVM 70 % training and 30 % testing split

Navies Bayes for emotion detection showS SVM has better accuracy of 98 percent and less Hamming Loss of 0.0197 as compared to Navies Bays values of 96 percent and 0,042 Hamming loss values. SVM proved better with less loss and better accuracy.

5. CONCLUSION

In this paper, the successful implementation of human emotion detection and classification from physiological signals is done. Apart from ECGs use for disease dignosis, ECG signal can be used for emotion detection on hardware. We have classified the real time readings of 12 minute video induction into six 2 minute sample time. As per the peak values and disitance among peaks, four different emotion classes based on the ranges of different heart rate and temperature values are categarised. with machine learning algorithms.

5. 1. Strengths of Experimentation

1. Visualization of PQRST waveforms, Peaks, RRinterval, Scatterplot, comparision of output classes for SVM and Navies Bayeson real time data on the hardware is most challanging part which is successfully implemented. Real time body parameters heart rate, and body temperature are the two features are considered for ML algorithms instead of only ECG RR interval consideration.
2. Classwise precision, F1score, micro weights changes were not disscussed till now, But we have presented them in interactive manner of calculations, tabluar form (Table 6) and graphical display.Hence, Thus strength is of this research is the Analysis of the emotion’s classification by emotion classwise consideration of performance matrix
3. Primary contribution of this research is successful implemention of real-time affective computing with RR interval feature on hardware despite of noise and harware parameters, simulation is always easy than Hardware implementation.

5. 2. The Limiation The limitation of this study is the signal acquired are not compared with medical standard equipment beacause ECG in proposed study is not used for dignostic study.

5. 3. Future Scope

1. Additional body parameters such as SpO_2, skin conductance can be used for detecting human emotions.
2. Portable wearable devices can be created with the inclusion of mentioned body parameters to be employed in gaming zones or parental controls for gaming PCs.
3. Comparision of ECG aquisition readings with standard medical equpment before emotion classification.

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Persian Abstract

چکیده

احساسات شتاب دهنده عقل و نوآوری و خلاقیت انسان هستند، بنابراین توانایی تشخیص احساسات بسیار مورد تقاضا است. سخت‌افزار بلادرنگ در مقایسه با شبیه‌سازی‌ها دارای موانعی از نظر نویز و عوامل سخت‌افزاری است. یک سنسور الکتروکاردیوگرام (AD8232) (ECG)، یک سنسور دما (LM35)، و یک مدار پردازش سیگنال سخت افزاری برای شناسایی احساسات بلادرنگ پیشنهادی است. فواصل RR از داده های ECG محاسبه می شود. پیش‌بینی احساسات با استفاده از یادگیری ماشین از فواصل RR و دمای بدن به عنوان ویژگی استفاده می‌کند. یکی از چهار احساس (یعنی ۱. خوشحال ۲. استرس ۳. خنثی ٤. غمگین.) در پورت سریال پردازنده با استفاده از مجموعه داده های معیار WESAD و کتابخانه های HRV، سریال و ترشی تجسم می شود. عوامل نوآوری این مقاله عبارتند از (۱) استفاده از ECG برای تشخیص احساسات به جای تشخیص بیماری با روش القای احساسات، ضبط فاصله RR و طراحی رابط کاربری گرافیکی بازه RR برای ضبط زمان واقعی دما و (2) ECGنمایش احساسات فعلی در پورت سریال آردوینو. (۳) اندازه گیری عملکرد کلاس با استفاده از امتیاز F1، میانگین کلان، و میانگین وزنی به جای دقت اصطلاح عمومی. (٤) استفاده از ناویس بیز مبتنی بر احتمال در مقایسه با روش‌های سنتی KNN، SVM، جنگل تصادفی (٥) عملکرد عاقلانه کلاس برای مثال ویژگی یا دقت Navies Bayes کمتر از (0.96) SVMاست، اما فراخوان یا حساسیت آن بالاتر است. (۰.۹۷) در مقابل (۰.۹٤) برای استرس. در این مقاله، پارامترهای عملکرد را از نظر محاسبات تعاملی، شکل جدولی و نمایش گرافیکی ارائه کردیم.