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Negative Emotion Detection using ECG and HRV Features

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***Abstract*—Emotions cause different physical, behavioural and cognitive changes in the human body. Emotions can be positive and negative. Negative emotion is the experience of negative feelings such as anger, frustration, panic, stress and fear. These negative emotions can cause severe health problems. So there is a need for detection of negative emotions . It will help in improving the health of the human body. As these emotions result in a change of various physiological parameters like heart rate, skin temperature, blood pressure, skin conductance, etc., these signals can be used to detect the emotions of a person. These signals are generated by the body during the functioning of various physiological systems, so they cannot be regulated artificially. Due to this reason, it is a reliable source for the detection of such information. So physiological signal is one of the most important factor in the field of emotion detection. The change in signals represents certain characteristics which are used to estimate the emotions. This work mainly focuses to build a better model of negative emotion detection for Typically Developed group using Machine learning approach with the help of Electrocardiogram (ECG) signal. This study was conducted on DECAF database for typically developed group. The study focused to extract the relevant features from both ECG and HRV signals. Then to identify which is more contributing towards negative emotion detection. A machine learning model was developed for typically developed group db4 as mother wavelets for feature extraction. The significant features of ECG and HRV were then classified separately using the logistic regression, ensemble and support vector machine. Logistic regression classifier achieved maximum accuracy using HRV data for typically developed (TD) group.**

***Index Terms*— ECG, negative emotion detection, DWT, ma- chine learning.**

I. INTRODUCTION

Emotion is a state of thought that arises spontaneously and is accompanied by physiological changes. Emotion is made up of three parts: a subjective component that defines how we feel emotions, a physiological component that describes how our bodies react to emotions, and an expressive component that reflects the human reaction to each emotion. External motivations, thoughts, and changes in interior feelings are all referred to as emotion. Emotion recognition has become a vast field of study in cognitive science, engineering, and psychol- ogy. Emotion detection was used in psychology to comprehend the feelings of persons who were being counselled. It

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is also employed in the medical field to help crippled and elderly persons. Emotions can be positive and negative. The sensation of negative feelings such as anger, frustration, panic, stress and fear is known as negative emotion. Negative emotions might lead to serious health issues. As a result, there is a requirement for negative emotion detection. It will aid in the improvement of human health. The early methods employed were facial expression and voice processing, but the primary difficulty with these approaches is that they may be readily hidden because a person can mimic himself and mask the true feelings. The physiological signals can be utilised to determine a person's emotions since they cause changes in physiological characteristics such as heart rate, skin temperature, blood pressure, and skin conductance. Because these signals are produced by the body during the operation of numerous phys- iological systems, which cannot be intentionally managed. As a result, it is a trustworthy source for detecting and forecasting such information. As a result, one of the most essential factors in the field of emotion detection is physiological signal. Phys- iological detection of emotions can have better performance compared to other techniques since physiological signals are not under the voluntary control of the human. Emotion can be modeled as two dimensional emotion model consisting of valence and arousal, where valence denotes pleasantness or polarity of emotion stimuli whereas arousal represents the strength of emotion.

Since brain and emotions are not mapped for autistic people EEG cannot be used for emotion recognition for such people. Here in this work ECG is employed for detecting the emotions. DWT is used for the feature extraction purpose. These ex- tracted features after selection are used as training data for the classifiers. The significant features of ECG and HRV were then classified separately using the logistic regression, ensemble and support vector machine. This paper consists of 5 sections. Section II describes about the previous works done in the field. It gives a detailed review of works carried out in this field. Section III describes about the proposed system and section IV gives the results and discussion and section V gives the conclusion of the work.

II. Related Work

Zi Cheng et al. [2] used various combination of features extracted from ECG signal and its derived HRV to detect negative emotion. Emotions were evoked by using 15 stan- dardized film clips. HRV was derived using an automatic R peak detection algorithm. They extracted a total of 28 features, including seven linear-derived features, ten nonlinear- derived features, four time-domain features (TD) and six time- frequency domain features (T-F D). 5 classifiers including SVM, Random Forest (RF), k-Nearest Neighbor (kNN), De- cision Tree (DT) and Gradient Boost Decision Tree (GBDT) were also compared. Among all these combinations, the best result was achieved by using only 6 time-frequency domain features coming from wavelet with SVM, which showed the highest accuracy of 79.51% and the lowest time cost of 0.13 ms.Han-Wen Guo et al. et al. [3] used 3-10 minute video excerpts for eliciting emotions such as wrath, fear, sadness, happiness, and relaxation. They used time-domain, frequency- domain, Poincare, and statistic analysis to extract heart rate variability (HRV) components from an ECG signal. Time- domain analysis extracts characteristics such as mean, co ficient of variation, standard deviation of RR interval, a standard deviation of successive differences of RR interva FFT extracted parameters such as low frequency, high frequency, and LH ratio were used to perform spectral analysis of HRV data. Statistics analysis elements include kurto coefficient, skewness, and entropy. The length SD2 along t line of identity and the breadth across this line are Poinca properties of point clouds (SD2). PCA was the data reducti technique used which selected 5 features as relevant featur Then these relevant features were used to classify differe emotion states by support vectors machine (SVM). Usi 13 HRV features the classification accuracy for 2 emotio (negative and positive) was 70.3% and that for 5 emotio was 52%. After feature selection accuracy for 2 emotions wa 71.4% and that for 5 emotions was 56.9%.

M. S. Goodwin et al. [4] investigated whether previous physiological and motion data collected by a wrist-worn biosensor can predict hostility toward others in children with ASD. They recorded peripheral physiological and motion signals from a biosensor worn by 20 youth with ASD and developed prediction models based on ridge-regularized lo- gistic regression. Time series feature extraction and logistic regression classifier was used. B. Anandhi et al. [5] analyzed the QRS complex derived ECG signal for emotion recognition. A personalized emotion elicitation protocol was developed for children with ASD. Emotion evocation was with the help of audio-visual stimuli. They conducted the study for 10 children with ASD. Various digital filters were used for the removal of noise and quality improvement. Different linear and nonlinear features were extracted from this complex and one-way ANOVA was used for the analysis of these features. Finally, the authors used k-nearest neighbor and ensemble classifier for the classification of emotions. They were able to achieve an accuracy of 70.5% for children with ASD.

DECAF[1] is a database containing the physiological re- sponse to different emotions elicited in 30 subjects using 36 movie clips and 40 one minute music video segment. They had collected different signals such as MEG, horizon- tal electrooculogram hEOG, ECG, trapezium electromyogram.,(tEMG) and near-infrared facial videos which were recorded synchronously.

III. METHODOLOGY

The work focuses to extract the relevant features from both ECG and HRV signals. Then to identify which is more contributing towards negative emotion detection. A machine learning model was developed for typically developed group db4 as mother wavelets for feature extraction. The significant features of ECG and HRV were then classified separately using the logistic regression, ensemble, support vector ma- chine and k-nearest neighbor. ECG data for various emotions are collected from DECAF [1]. In this work ECG signal corresponding to two different emotions happy and sad are considered. The block diagram is shown in Fig. 1.

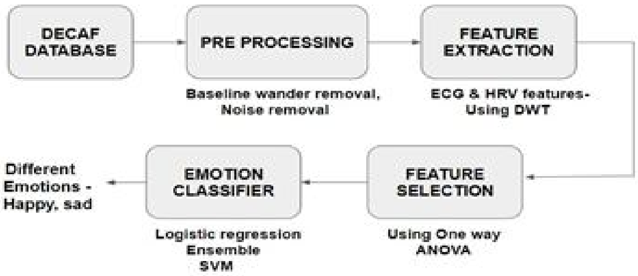


Fig. 1. Block Diagram of Negative Emotion Detection System

A. ECG Data

ECG data was taken from DECAF database[1]. It is a mul- timodal database containing physiological response to various emotions. The emotions are elicited using 24 one minute movie segments and 40 one minute music segments. The experiment was carried out for 30 healthy subjects. In this work only ECG signal response to the one minute movie segment for emotions happy and sad was analysed.

B. Pre-Processing

Pre-processing is done to improve the quality of signals by removing noises. These noises include power line interference, baseline wandering and high-frequency noises [6]. This helps to improve the quality of the negative emotion detection method. Baseline wander is a low-frequency noise that arises from breathing, electrodes attached to the body, or subject movement. It occurs in the frequency range of 0.5 to 0.6Hz. Baseline wander can cause the amplitude of the QRS complex to increase significantly. The wavelet-based approach is best for removing ECG signals. The DWT-based method makes use of high-level decomposition to eliminate low-frequency components corresponding to the baseline variation. DWT was performed using Daubechies (db8) as the mother wavelet because of the similarity of wavelet function with the shape of ECG signal[7]. Then high-frequency noises occurring due to power line noises were removed using 6th order low pass Butterworth filter with a cut of frequency of 50 Hz since in India the power line frequency is at 50 Hz. After noise removal heart rate variability (HRV) was derived. It refers to the variation of the time interval between successive heartbeat. Fig. 2 and Fig. 3 represents raw and corresponding pre-processed signals of happy emotion. Fig. 4 and Fig. 5 represents raw and corresponding pre-processed signals of sad emotion.

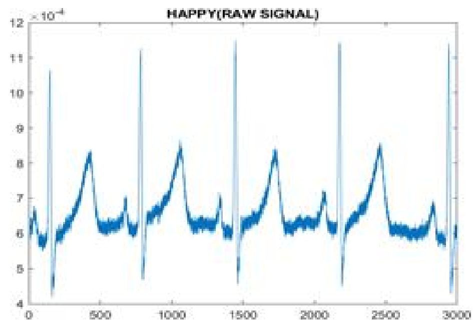


Fig. 2. Raw ECG signal containing happiness of TD group

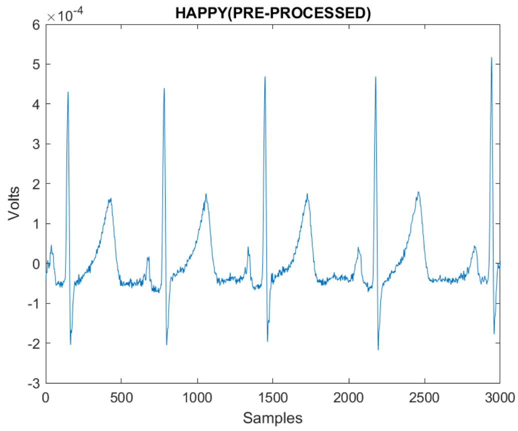
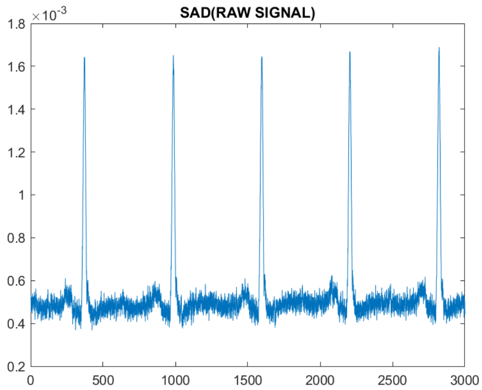


Fig. 3. Pre-processed ECG signal containing happiness of TD group

C. Feature extraction

Here features are extracted from ECG and HRV. Different features are extracted to get the emotional content in the signal. Feature extraction helps to reduce the redundant data present in the signal. Thereby it helps to get useful information from the signals. Different feature extractions techniques are used in the literature [8]. DWT (Discrete Wavelet Transform) was used to extract the features here.

DWT makes use of the mother wavelet which is a single prototype function used to decompose the input signal. Decomposition depends on the scaling and shifting derive frequency sub-bands of the input signal.



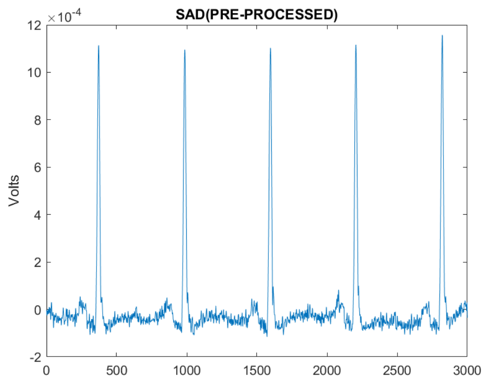


Fig. 4. Raw ECG signal containing sadness of TD group Fig. 5. Pre-processed ECG signal containing sadness of TD group

DWT decomposes the original signal to approximation and detail coefficients with the help of a low pass filter and high pass filter. The output of the low pass filter (LPF) is known as approximation coefficients and the output of the high pass filter (HPF) is known as detailed coefficients. The output of this LPF is again applied to HPF and LPF which forms the second decomposition level. In this study 14 level decomposition is done. This is because the emotional content is present in the low-frequency band and high-frequency band [10]. Detail coefficient from 11th to 14th is used for extracting various features.

Wavelet transform make use of mother wavelets. Different wavelets includes Daubechies (db) wavelet, Haar wavelet, Symlet wavelet, Coiflet wavelet etc. Daubechies are orthogonal wavelets which is characterized by maximum number of van- ishing moments for some predefined support length. The name of these wavelets are represented as dbN. Here N represents the order of these wavelets. Usually N varies from 1 to 8. In this work, analyses were carried out using db4 mother wavelet. ECG and HRV features were extracted for negative emotion detection using two emotions. All the features extracted from ECG and HRV data is listed in Table I.

In addition, time domain features of HRV is also considered which includes mean R-R interval difference(meanRR), Root Mean Square Distance of Successive R-R interval(RMSSD), Number of R peaks in ECG that differ more than 50 mil- lisecond(NN50), percentage of successive RR intervals that differ more than 50 ms (pNN50), standard deviation of RR intervals(SD RR), and Standard Deviation of Heart Rate(SD HR).

TABLE I. FEATURES EXTRACTED FROM ECG AND HRV

Serial no.	Features	Description
1	max	Maximum value of signal in each level
2	min	Minimum value of signal in each level
3	mean	Mean value of signal in each level
4	median	Median value of signal in each level
5	std	Standard deviation of signal in each level
6	mad	Mean absolute deviation of signal in each level
7	range	Range of signal in each level
8	power	Power of signal in each level
9	L1 norm	L1 norm of signal in each level
10	L2 norm	L2 norm of signal in each level
11	Kurtosis	Kurtosis value of signal in each level
12	entropy	Entropy value of signal in each level
13	skewness	Skewness value of signal in each level
14	HF power	Sum of power of levels 11 and 12
15	LF power	Sum of power of levels 13 and 14
16	LF power norm	HF power/(LF power + HF power)
17	HF power norm	LF power/(LF power + HF power)
18	power	HF power + LF power
19	ratio	Ratio of HF power and LF power

D. Feature extraction

Here features are extracted from ECG and HRV. Different features are extracted to get the emotional content in the signal. Feature extraction helps to reduce the redundant data present in the signal. Thereby it helps to get useful information from the signals. Different feature extractions techniques are used in the literature [8]. DWT (Discrete Wavelet Transform) was used to extract the features here.

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E. Feature extraction

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DWT makes use of the mother wavelet which is a single prototype function used to decompose the input signal. Decomposition depends on the scaling and shifting.

TABLE II . SIGNIFICANT FEATURES WITH P AND MEAN VALUES FOR ECG

Sl no.	Features	Sig. Value	Mean Value (happy)	Mean Value (sad)
1	mediand11	0.044	$-2.3x10^{-6}$	$9.86x10^{-7}$
2	kurtosisd11	0.034	12.933	14.235
3	ratio	0.01	0.3573	0.4241

TABLE III SIGNIFICANT FEATURES WITH P AND MEAN VALUES FOR HRV

Sl no.	Features	Sig. Value	Mean Value (happy)	Mean Value (sad)
1	meand11	0.028	618.372	692.67
2	L1d14	0.012	$-3.5x10^{7}$	$-5.4x10^{7}$
3	NN50	0.000	70.504	70.90
4	SD HR	0.000	26.808	28.004

F. Classification

The significant features obtained after feature selection is classified using various machine learning algorithms. Every machine learning classifier have two phases. First phase is training phase and followed by a testing phase. 70% of total available data is used for training and model is tested using remaining 30%. Classifiers are used to classify the significant features into emotions happiness and sadness of typically developed group. Here three different machine learning models such as logistic regression, ensemble and SVM are used for negative emotion detection.

IV. RESULTS AND DISCUSSION

The features extracted from ECG signal includes time- frequency domain features and frequency domain features. Time-frequency domain features include maximum value, minimum value, mean value, median value, standarddeviation, mean absolute deviation, range, power, L1 norm, L2 norm, entropy, kurtosis, skewness of 11th to 14th decomposition level detail coefficient. Frequency domain features include high frequency power, low frequency power, total power, low frequency power norm, high frequency power norm

The features extracted from HRV data include time- frequency domain features,time domain features and frequency domain features. Time-domain features include mean R-R interval difference (meanRR), Root Mean Square Distance of Successive R-R interval (RMSSD), Number of R peaks in ECG that differ more than 50 millisecond(NN50), percent- age of successive RR intervals that differ more than 50 ms (pNN50),standard deviation of RR intervals (SD RR), and Standard Deviation of Heart Rate(SD HR). Frequency domain features include high frequency power, low frequency power, total power, low frequency power norm, high frequency power norm and ratio of low frequency power and high frequency power.

Significant features of ECG for typically developed group using db4 analysis includes mediand11, kurtosisd11 and ratio of low frequency power and high frequency power. Significant features of HRV for typically developed group using db4 analysis includes meand11, L1d14, NN50 and SD HR.

Logistic regression, ensemble and SVM classifiers were used for classifying signals to emotion happiness and emotion sadness. The training phase is carried out on 70% percent of the feature data set while the testing phase is the remaining feature set. Confusion matrix of logistic regression classifier obtained for db4 analysis using HRV features for typically developed group is shown in Fig 6. Accuracy gives a measure of correctly classified signals with respect to total number of signals.

The classification results obtained for typically developed group is given in the Table IV and Table V. This analysis indicates that HRV data, indicating the vari- ability in heart rate is an effective indicator for detecting negative emotions. Logistic regression and ensemble classifier was found to have better performance than other classifiers.

Fig. 6. Confusion matrix obtained for Logistic regression using HRV features

TABLE IV. SUMMARY OF RESULTS OBTAINED BY USING ECG FEATURES

Model	Accuracy	Precision	Recall	F-1 score
Logistic Regression	63.3%	60%	64.2%	62%
Ensemble	66.7%	66.7%	66.7%	66.7%
SVM	66.7%	66.7%	66.7%	66.7%

TABLE V. SUMMARY OF RESULTS OBTAINED BY USING HRV FEATURES

Model	Accuracy	Precision	Recall	F-1 score
Logistic Regression	96.7%	93.3%	100%	96.5%
Ensemble	90%	86.7%	92%	87.5%
SVM	86.7%	86.7%	86.7%	86.7%

V. CONCLUSION

Electrocardiogram signals are an effective way for analyzing human emotions. In this work, negative emotion detection for typically developed group using different classification models was done. The study included a comparison between ECG and HRV features. It was found that HRV features are more contributing towards the emotion detection. Logistic regression and Ensemble classifier showed better performance compared to other machine learning algorithms for typically developed group.

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