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ECG based Categorical emotion classification using time-domain features and Machine Learning

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Abstract: Emotions are mental states that result from neurophysiological changes associated with thoughts, feelings, and behavioral responses. Emotions lead to modifications in heart rate variability, which can be identified through electrocardiogram (ECG) signals. In this study, we attempted to analyze the ECG signals to detect categorical emotions using time-domain features and machine-learning algorithms. Initially, the ECG signals of 30 subjects were obtained from the publicly available continuously annotated signals of emotion dataset. Further, the signals were pre-processed and extracted 32-time domain features from ECG signals which were recorded during different emotional states such as amusing, boring, relaxing, and scary. The extracted features were fed to a random forest (RF) classifier to rank the features and to build the three machine learning models such as logistic regression (LR), support vector machine, and RF. We achieved the highest average classification accuracy, sensitivity, specificity, precision, and f1-score of 71.04%, 42.08%, 80.69%, 43.03%, and 42.32%, respectively, with the top 4 features using the LR classifier. We found that the mean of peaks, slope sign change, dynamic range, and mean of first derivative were ranked top and played a significant role in the classification model. Our study shows the effectiveness of utilizing ECG signals for emotion detection in wearable devices.

Keywords: Emotion detection, electrocardiogram, time domain features, machine learning

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1 Introduction

Emotion is influenced by a combination of innate and learned factors, and it plays a significant role in shaping human behavior, cognition, and social interactions [1]. It encompasses a range of affective states, including but not limited to joy, surprise, sadness, anger, fear, and disgust, which are typically accompanied by characteristic behavioral and physiological patterns. Various behavioral techniques, such as body gestures, facial expressions [2], and speech [3], can be employed to detect emotions. Although the behavioral method is comprehensible, it can be intentionally altered to hide genuine emotions. In contrast, physiological signals remain unaffected by subjective awareness, which renders them a dependable indicator of emotions.

Consequently, emotion detection through physiological signals can offer more precise and reliable information concerning emotional expressions [4]. The autonomic nervous system links the mind and cardiovascular systems, enabling them to mutually affect each other's actions. Consequently, emotional encounters lead to modifications in heart rate variability, which can be identified through Electrocardiogram (ECG) signals. Hence, ECGs are extensively employed in emotion recognition due to their high quality and rich information on human emotions embedded within the signals [5]. To understand emotional states, researchers have used various features derived from analyzing the ECG signals [6-9]. These features include time, frequency, and time-frequency domain characteristics. Previous studies have employed different types of classifiers such as linear, non-linear, ensemble, and deep learning-based methods to accurately classify emotional states. In this study, we aim to develop a simple emotion recognition system using the time domain features extracted ECG signals and machine learning algorithms.

2 Methods and Materials

The process pipeline followed in the study is shown in Figure 1.

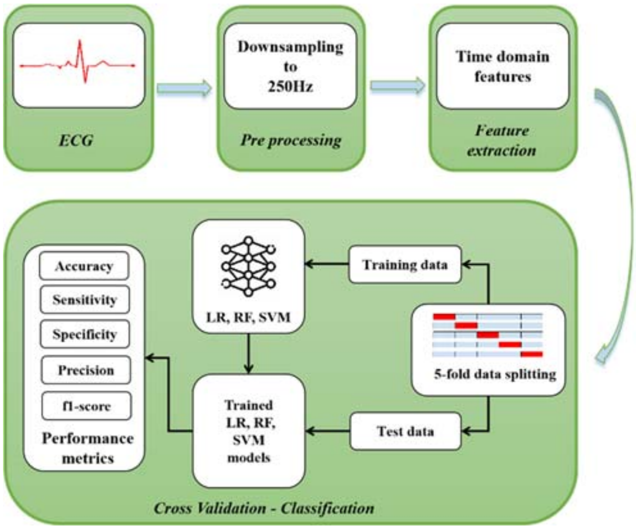

Figure 1: Process pipeline of the study.

2.1 Dataset

The considered ECG signals were obtained from the publicly available Continuously Annotated Signals of Emotion (CASE) dataset, which includes various physiological signals recorded from 30 subjects (15 male and 15 female) while watching audio-video movie clips [10]. The male and female subjects had an average age of 28.6 ± 4.8 years and 25.7 ± 3.1 years, respectively. The videos were designed to elicit four emotions: amusing, boring, relaxed, and scary (two videos for each emotion). The videos had varying durations, ranging from 101 to 197 seconds.

2.2 Pre-processing and feature extraction

The ECG signals were acquired at a rate of 1000 Hz but were downsampled to 250 Hz. The length of the ECG signals for each emotion was not uniform, so we segmented them to the length of the shortest video recording (29,666 samples) to avoid any potential biases in our analysis [11]. We then extracted 32 time-domain features from ECG signals corresponding to each emotion listed in Table 1. The extracted features were normalized to the scale of 0 to 1 using a Min-Max scaler.

2.3 Feature ranking and classification

The extracted features were fed to the RF classification model to rank the features according to their importance scores. The ranked features were cumulatively fed to all three LR, SVM, and RF classifiers [11, 12] cumulative (starting from n = top 1 to 32) to classify the four emotions. The data were balanced during the training and test splits (same number of observations for each class) across the folds.

Table 1: List of the features extracted from the ECG signal.

Time domain features (32)
Mean, Median, Area, Standard Deviation, Maximum peak value, Minimum peak value, Dynamic Range, mean of first derivative, mean of second derivative, standard deviation of first derivative, standard deviation of second derivative, skewness, kurtosis, median absolute deviation, mean absolute value, Hjorth mobility, Integral absolute value, Hjorth complexity, Percentile, Variance, Waveform length, mean of peaks, Root Mean Square (RMS), Difference absolute standard deviation value (DASDV), Difference absolute mean value (DAMV), Mean Absolute Slope Value (MASV), Mean Firing Velocity(MFV), Slope sign changes (SSC), Maximum fractal length (MFL), Higuchi's fractal dimension (HFD), Fractal dimension, No of peaks

2.4 Validation

We used 5-fold stratified cross-validation to evaluate the performance of the models. Finally, the performance metrics such as accuracy (ACC), sensitivity (SEN), specificity (SPEC), precision (PRE), and f1-score (F1) were calculated [13].

Table 2: Validation metrics and their formula.

Metric	Formula
Accuracy	(TP+TN)/(TP+TN+FP+FN)
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)
Precision	TP/(TP+FP)
f1-score	TP/ (TP+ (0.5*(FN+FP)))

TP-True Positive, TN-True Negative, FP-False Positive, FN-False Negative

3 Results

The performance of machine learning models for the different number of features ranked through RF is shown in Figure 2. It can be observed that the classification performance was low with a lower and large number of features. This observation is consistent between the classifiers. We achieved high classification accuracy with 3-4 features in all the classifiers. The highest 5-fold average classification accuracy of 71.04% was achieved by the LR classifier, followed by SVM (70%) and RF (69.79%). It can be noted that the RF model achieved the highest classification accuracy with the top 4 features and, in the case of LR and SVM, its top 3 features.

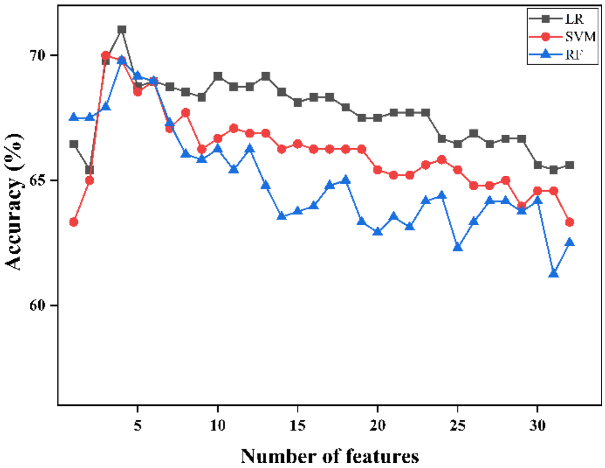

Figure 2: Performance of LR, SVM, RF classifier for different set of top-features.

Table 3 indicates the classification results obtained by the three classifiers. It can be noted that the LR achieved the highest classification results of classification accuracy, sensitivity, specificity, precision, and f1-score of 71.04%, 42.08%, 80.69%, 43.03%, and 42.32%, respectively. Figures 3 and 4 indicate the boxplot of the top 4 features for the RF Classifier and the top 3 for LR and SVM classifiers, respectively.

Table 3: Performance of machine learning models.

ML model	ACC	SEN	SPEC	PRE	F1
LR	71.04%	42.08%	80.69%	43.03%	42.32%
SVM	70%	40.00%	80.00%	46.59%	40.53%
RF	69.79%	39.58%	79.86%	39.72%	39.62%

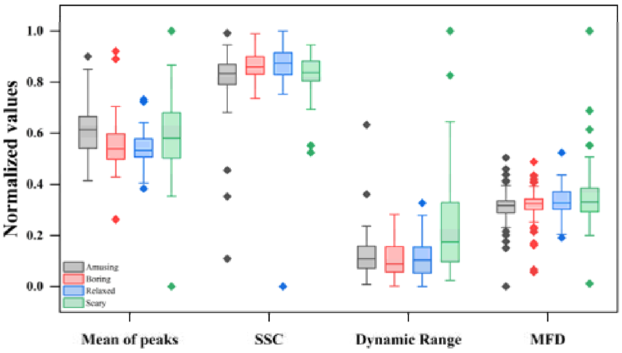

Figure 3: Boxplot of top 4 features that contributed to highest accuracy in RF classifier.

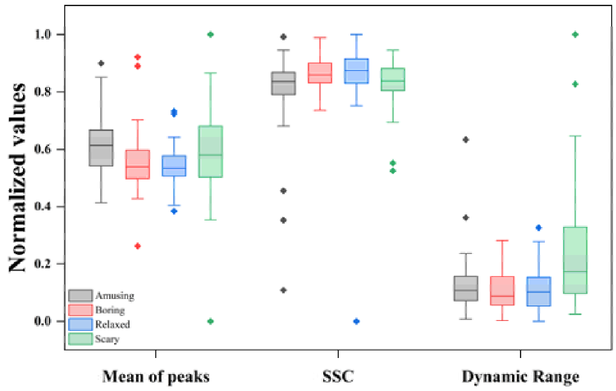

Figure 4: Boxplot of top 3 features that contributed to highest accuracy in LR and SVM classifier.

4 Discussion

In our study, we observed high classification accuracy when using the top-ranked 3-4 features in all classifiers. This high accuracy may be attributed to these features containing the most relevant and discriminative information that can distinguish between different emotional states. Feature selection techniques were used to remove redundant and irrelevant features that may introduce noise and bias to the classification model, thereby improving the performance of the classifiers. Further, we found that the LR classifier demonstrated superior performance to SVM and RF classifiers, as indicated by higher average classification accuracy, sensitivity, specificity, and f1-score. This could be attributed to the fact that LR is a simple yet powerful algorithm well-suited to the dataset considered and easy to implement and interpret. The LR algorithm models the relationship between input features and the output variable using a linear function, enabling it to make predictions quickly and efficiently. In contrast, SVM and RF are more complex algorithms that can be challenging to interpret and require more computational resources. A study by Saurabh et al. [13] reported a classification accuracy of 30.0% for ECG signals using an RF classifier, whereas our study demonstrated superior performance compared to prior research.

5 Limitations and future scope

In this study, we analyzed the utilization of ECG signals for emotion detection using time-domain features and machine-learning algorithms. The study only examined four emotional states (amusing, boring, relaxing, and scary), which may not be comprehensive enough to capture human emotions. The study can be further extended to explore the possibility of including the frequency and time-frequency domain features to analyze the signals. Further, advanced machine learning and deep learning algorithms can be incorporated to improve classification accuracy. Moreover, multimodal approaches can be implemented, including other physiological signal modalities.

6 Conclusion

In this study, we extracted 32 time-domain features from the ECG signals to detect the four emotions such as amusing, boring, relaxed, and scary. The features were ranked, and classification models were built using LR, SVM, and RF classifiers. We achieved an average 5-fold classification accuracy of 71.04% using the top 4 features using the LR classifier. The features such as mean of peaks, slope sign changes, dynamic range, and mean of first derivative highly contributed to the classification model. Our study shows the possibility of ECG signals in emotion detection in wearable devices.

Author Statement

Research funding: The author states no funding is involved. Conflict of interest: Authors state no conflict of interest. Informed consent: The data was from a publicly available dataset, and Informed consent was obtained from all individuals included in this study. Ethical approval: The research related to human use complies with all the relevant national regulations and institutional policies, was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the author's institutional review board or equivalent committee.

References

[1] Pal, A., Ghosh, S., Halder, R., Sengupta, S., & Kundu, D. Real Time Facial Emotion Recognition based on Image Processing and Machine Learning. International Journal of Computer Applications, 975, 8887.

[2] H. Prawiro, T.-Y. Pan, and M.-C. Hu, "An empirical study of emotion recognition from thermal video based on deep neural networks," in 2020 IEEE International Conference on Visual Communications and Image Processing (VCIP). IEEE, 2020.

[3] Akçay, M. B., & Oğuz, K. (2020). Speech emotion recognition: Emotional models, databases, features, pre-processing methods, supporting modalities, and classifiers. Speech Communication, 116, 56-76.

[4] Zhongze, Z., Wang, X. F., Li, P., Chen, X., & Shao, L. (2020). Research on emotion recognition based on ECG signals. Journal of Physics, 1678(1), 012091. https://doi.org/10.1088/1742-6596/1678/1/012091

[5] ECG-based Emotion Recognition: Overview of Methods and Applications. (2018, September 1). VDE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/document/8576722/authors#authors

[6] S. Wioleta, "Using physiological signals for emotion recognition," in 2013 6th International Conference on Human System Interactions(HSI). IEEE, 2013, pp. 556–561

[7] E. Di Lascio, S. Gashi, and S. Santini, "Unobtrusive assessment of students' emotional engagement during lectures using electrodermal activity sensors," Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 2, no. 3, pp. 1–21, 2018.

[8] M. Zecca, S. Micera, M. C. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," Critical Reviews™ in Biomedical Engineering, vol. 30, no. 4-6, 2002.

[9] S. Huynh, S. Kim, J. Ko, R. K. Balan, and Y. Lee, "Engagemon: Multimodal engagement sensing for mobile games," Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 2, no. 1, pp. 1–27, 2018

[10] Sharma K, Castellini C, van den Broek EL, Albu-Schaeffer A, Schwenker F. A dataset of continuous affect annotations and physiological signals for emotion analysis. Scientific data. 2019 Oct 9;6(1):1-3.

[11] Sriram Kumar P, Govarthan PK, Ganapathy N, Jac Fredo AR. Electrodermal activity based analysis of emotion recognition using temporal-morphological features and machine learning algorithms. Journal of Mechanics in Medicine and Biology. 2023 Apr 7.

[12] Sriram Kumar P, Govarthan PK, Ganapathy N, Fredo Ar J. A Comparative Analysis Of Eda Decomposition Methods For Improved Emotion Recognition. Journal of Mechanics in Medicine and Biology. 2023 Apr 8.

[13] Hinduja S, Kaur G, Canavan S. Investigation into Recognizing Context Over Time using Physiological Signals. In2021 9th International Conference on Affective Computing and Intelligent Interaction (ACII) 2021 Sep 28 (pp. 1-8). IEEE