Machine learning-based emotions recognition model using peripheral signals

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ABSTRACT

This work proposes a system for emotion recognition using four peripheral signals electromyography, galvanic skin response, blood volume pulse, and respiration. Peripheral signals cannot be modified, unlike other expression like voice and facial expression. The proposed method is applied to the DEAP datasets to verify the accuracy of emotion recognition. The proposed model focuses on accuracy and F1-score. DEAP dataset has more signals but only thirty-seven features from four peripheral signals were extracted for each trail and each video. On the DEAP datasets, the implementation found that the classification accuracy for arousal, valence, liking, and dominance was, respectively, 80%, 75%, 71%, and 78%. For two classes of problems, the corresponding F1-scores for arousal, valence, liking, and dominance are 0.50, 0.49, 0.47, and 0.47. The proposed model was implemented in MATLAB R2017a.

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1. INTRODUCTION

Technology for recognizing and comprehending human emotions is referred to as emotion recognition techniques. These methods can be generally divided into categories like facial expression analysis, voice and speech analysis, text and natural language processing, physiological sensors, and gesture and body language analysis. The analysis of face characteristics and expressions using computer vision and machine learning techniques is referred to as facial expression analysis. Based on variations in facial muscle movements, it may identify emotions including happiness, sorrow, rage, fear, disgust, and surprise. An individual's emotional state can be inferred by examining their speech, tone, pitch, pace, and other acoustic features. Voice and speech emotion detection is the term used to describe this technique. For this voice and speech analysis, machine learning models and speech processing methods are commonly used [1].

In several fields, such as psychology, neurology, healthcare, and human-computer interaction, these physiological signals help research and monitor emotional reactions in humans. In dynamic, complicated environments, it can be difficult to distinguish between different emotions based on physiological cues. Researchers in affective computing and emotion recognition use a mix of physiological signals and sophisticated machine learning approaches to solve these problems. Continuous research is also developing more robust and accurate emotion recognition models based on physiological signals, while taking ethical and privacy considerations into account [2]-[5].

The objective of this work is to improve the accuracy of emotions like valence, liking, arousal, and dominance using four physiological signals from the peripheral nervous system (DEAP dataset):

electromyography (EMG), blood volume pulse (BVP), respiration (RSP), and galvanic skin response (GSR). Human emotional states may be identified from electroencephalography (EEG)-based brain-computer interface research by empowering researchers to apply machine learning techniques. We have studied related various papers that employ deep learning and Machine learning methods for classifying human emotions based on EEG data and compare them with the proposed work. Therefore, this study's main contribution finds the answers to the following questions.

– Why ese DEAP datasets?
– Which feature extraction techniques are there?
– Which feature selection and reduction techniques are there?
– Which feature is used for extraction from DEAP data sets?
– Which deep learning and machine learning methods are currently being applied to EEG-based BCI to categorize human emotional states?

Different EEG datasets are available for emotion recognition only a few of them illustrate like DEAP, DREAMER [6], SEED, AMIGOS [7], SAFE, GAMEEMO, and MAHNOB-HCI tagging. These datasets are research-worthy and have been applied to several studies on emotion identification. According to the research in this study, Figure 1 illustrates the proportion of EEG datasets used for emotion recognition. The two most often used programs are DEEP and SEED, with 19% and 51% of participants, respectively. A smaller percentage of research (17%) used their datasets, which are frequently not publicly available [8]. A publicly accessible dataset called DREAMER showed up in this evaluation with a participation rate of 7%. In our research sample, the MAHNOB-HCI, GAMEEMO, and AMIGOS were present, with a respective participation rate of 2%.

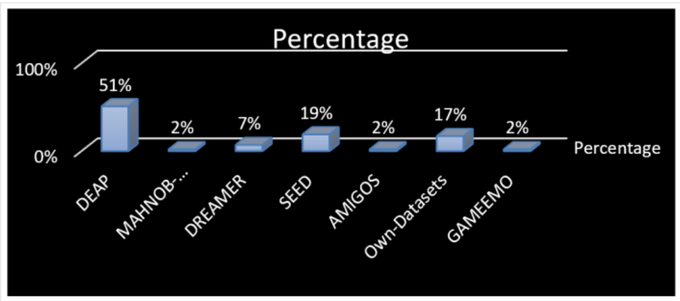

Figure 1. Usage of datasets

A review of the works of literature provides a summary of the major discoveries, approaches, difficulties, and new developments in the subject of physiologically based human emotion identification. Human behavior requires a knowledge of emotions, which has benefits in areas like healthcare and human-computer interaction [9]. The study on human emotion identification using various physiological signals, such as electrocardiography, electroencephalography, galvanic skin response, respiration, and skin temperature, is thoroughly examined in this literature overview.

Martinez *et al.* [10] presented the emotions depth physiological models using two physiological signals with convolutional neural network (CNN). Oh *et al.* [11] introduced the creation of CNN architectures that use many physiological signals to classify emotions into six optimal categories. Chacon *et al.* [12] categorize human emotions using the DEAP dataset without the need for any sensors that measure biosignals. Hereafter collect the movement signals, filter them, extract the main components, reconstitute the heart rate (HR) signal, and then employ the HR signal in the emotion classification process using the Lucas-Kanade method for optical flow. Salari *et al.* [13] focused entire classification of emotions using neural network models and two neural network-based models i.e., the deep neural network and the CNN both used to classify dominance and liking into two yes/no (high and low) categories and valence and arousal into three (high, normal, and low) categories respectively. Lee *et al.* [14] defined CNN-based emotion recognition with specific statistical photoplethysmogram (PPG) features. PPG signal is easy with a variety of instruments and recording. This signal is not as complicated as recording other physiological data. The experimental results were discussed clearly. Xu and Plataniotis [15] presented the use of semi-supervised deep learning algorithms with EEG in the categorization of emotional states. Fu *et al.* [16] proposed multimodal physiological signals and transfer learning for emotion recognition. The algorithms-based results regarding accuracy and F1-score were discussed. Han *et al.* [17] proposed physiological signals from photoplethysmography (PPG) and electromyography (EMG) to create a real-time emotion identification system. Ham *et al.* [18] proposed a multimodal biosignal data-based internet of things-based negative emotion recognition system using five EEG signals and three physiological signals recorded by a smart band. Wang *et al.* [19] discussed a systematic detailed survey with different public data sets like DEAP, SEED, and MPED. Dessai and Virani [20] proposed an emotion characterization model based on GSR, continuous wavelet transform (CWT), and ECG signals using various CNN modeling. Alsubai [21] proposed a study using the discriminative representation of features, deep normalized attention-based residual convolutional neural network (DNA-RCNN) extracts the relevant characteristics. With the suggested attention modules resulting in consistent performance, the proposed neural network additionally investigates attractive aspects. Pidgeon *et al.* [22] proposed a study based on GSR, RSP, and BVP parameters used from DEAP data sets to categorize the emotions, and the algorithms-based results regarding accuracy and F1-score were discussed.

2. METHOD OR FRAMEWORK FOR EMOTION CLASSIFICATION

The effectiveness of emotion recognition can be increased by using the appropriate technique. Figure 2 illustrates the proposed emotion recognition model and how various steps are interconnected.

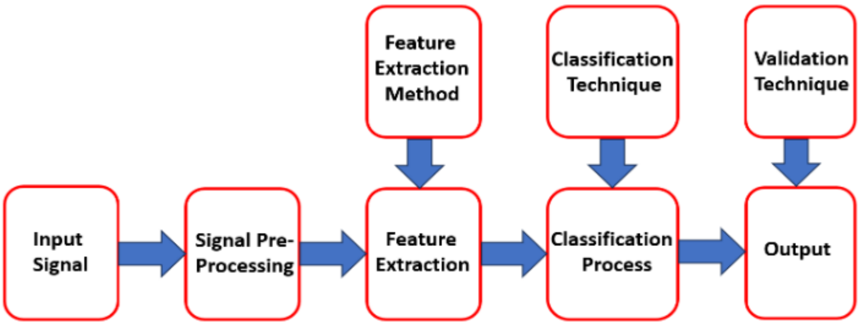

Figure 2. Proposed emotion recognition model

2.1. Input signal or signal processing

DEAP data sets are used as an input signal. In the DEAP pre-processed dataset files were utilized in this work. It includes 8 additional peripheral physiological signals in addition to the 32-channel [23]. In pre-processing out of 8 signals, we extracted only four peripheral physiological signals (EMG, GSR, BVP, and RSP). The DEAP dataset comprises 32 people with good health (namely from s01 to s32), half of them are female, between the ages of 19 and 37, and eight signals from the peripheral nervous system (electrooculography (EOG), GSR, BVP, RSP, EMG, and skin temperature (SKT)). Each participant saw forty-one-minute movies that were sensibly chosen to induce various emotional states while the EEG and physiological data were being captured. In the DEAP dataset of 40 trials of movies, each participant in DEAP assessed each video clip on a scale of 1 to 9 for arousal and valence. Table 1 shows the complete details of DEAP datasets. When identifying emotions, one label for classification that may be applied is the discrete rating value. Data was gathered with a 512 Hz sample rate, and pre-processing was carried out. The signals were captured at 128 Hz down-tempo. The DEAP dataset has 1280 trials (32 channels 40 video)) in total (40 trials for each person) [23].

Table 1. Parameter of DEAP dataset

Parameter	Details
No. of participants	16 male, 16 female
Number of channels	32 EEG, 8 peripheral physiological signals
Type of signals	EEG, EOG, EMG, GSR, RESP, BVP, HST
Channel names for peripheral physiological signals	hEOG, vEOG, zEMG, tEMG, GSR, RESP, BVP, HST
Number of videos (for each participant)	40
Sample rate frequency (after pre-processing)	128 Hz
The number of labels for the dataset	4
Label name	Valence, liking, arousal, dominance
Each label’s rating values	1 to 9
Quantity of information for every label	1,280
Numerical values for each subject	40 videos × 32 channels × 8064 data (numeric data)

This study employed four distinct forms from the DEAP dataset of peripheral physiological signals (EMG, BVP, RSP, and GSR) to determine emotions. The size of extracted features is 32×40 and every cell has much more information like features numerical value and name of EMG, GSR, BVP, and RSP signals along with feedback rating. Valence, liking, arousal, and dominance are used to calculate the accuracy of emotion recognition. All features are stored in .mat file extension with a dimension of 32×40. The pleasantness or unpleasantness of an emotional event or mood is represented by the valence. Liking, also known as “hedonic tone,” is closely connected to valence but highlights how much a person loves or likes a specific emotional state. A person’s subjective assessment of how much they like or hate an emotional event is called liking. The degree of arousal is a measure of how active or intense an emotional experience is. On a scale from low arousal (calm or relaxed) to high arousal (excited or disturbed), it is often characterized. The degree of control or influence that a person feels they have over their emotional state is referred to as dominance. It defines how a person reacts to a specific feeling and how dominating or submissive they feel.

2.2. Feature extraction

It is possible to discard data that is unimportant to the objective, perform calculations more quickly, escape the dimensionality curse, and enhance the model’s generalizability. Feature extraction is frequently necessary before the entry of signals into several conventional classification models. In this study, the fisher discriminant approach is used which is a dimensionality reduction algorithm. The dimension of the data is reduced using this approach. The procedure of selecting a collection of features from the whole set of features is referred to as feature selection. In addition to selecting the characteristics, they also reduce the dimension of the data. Fisher's algorithm also helps to achieve the main goal of lowering the number of variables. When analyzing physiological or multimodal data, the machine learning approach known as ridge regression is frequently utilized for emotion identification. Ridge regression may be used for classification tasks, which is frequently the case in emotion recognition, even though it is more frequently related to regression issues.

Ridge regression is a machine learning model used in this work to be utilized in the context of emotion identification. It may be used for multiclass tasks like identifying different emotions like happiness, sadness, and rage as well as for binary emotion classification tasks like categorizing emotions as positive or negative. 32 participants participated in 40 video trials (1,280×5×8,064) with 5 channels, 63 seconds of signal sampling at 128 Hz (8,064 values), and data arrays with these dimensions (samples×channels×timesteps) were acquired. The data array's EEG, EOG, and temp channels were removed. For the four remaining channels (GSR, BVP, RSP, and EMG), the range [0,1] was used. Table 2 presented the parameters that are extracted or used in this study and these characteristics were taken out of every channel for every participant. Some feature definitions are explained below with mathematical formulations. This study used time-domain statistical characteristics [1], [24].

Table 2. Feature of peripheral physiological signals

Peripheral physiological signals	Number of channels	No. of features	Name of features
EMG	02	05	Mean, std, kurtosis, skewness, EMG_power
GSR	01	07	nbPeaks, ampPeaks, riseTime, meanGSR, stdGSR, firstQuartileGSR, thirdQuartileGSR
BVP	01	13	mean, HRV, meanIBI, MSE, sp0001, sp0102, sp0203, sp0304, sp_energyRatio, tachogram_LF, tachogram_MF, tachogram_HF, tachogram_energy_ratio
RSP	01	12	mean, std, kurtosis, skewness, sp0001, sp0102, sp0203, sp030, sp0407, sp0710, sp1025, main_freq

Mean can be calculated by dividing the total number in the dataset by its size as presented in (1), which is a mathematical representation of the usual value of a set of data.

$$\mu = \frac{1}{M}\sum_{i=1}^{M} P_i \tag{1}$$

where *M* represents data sample numbers and Pi for the signal. Standard deviation is a statistical metric used to assess the degree of variation or dispersion in a collection of data is the standard deviation, written as σ (sigma) as presented in (2). Calculating the standard deviation in the context of EEG signals gives information about the variability of the signal’s amplitude at certain electrode sites or during specified time frames. It can be represented by σ.

$$\sigma = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(PI - \mu)^2} \tag{2}$$

In Table 3 kurtosis assesses probability distributions or a dataset's shape and peakiness. It reveals the distribution's tails and whether or not it has a higher or lower peak than a normal distribution. Kurtosis can be computed in the context of EEG signals to examine the properties of the EEG signal's amplitude distribution. Skewness is used under time domain features. Skewness calculates the variance in distribution between each variable's mean and median across epochs. The strength of the EMG signal is expressed as a useful characteristic by the variance of EMG. The power of the EMG signal is measured by this characteristic. From the GSR peripheral physiologic signals the quantity of GSR peaks per second, average peak amplitude, average peak rises a period average GSR value, and average variation of GSR were calculated. From BVP, HR variability and other features were extracted.

Each label's rating values are 1 to 9, label names are valence, liking, arousal, and dominance, and vales for (1,1) are shown in Table 4. In DEAP data sets, a 32×40 matrix is described, and attention is directed to elucidating the value at coordinate (1,1) within the matrix. This elucidation implies a systematic approach or method by which other coordinates' values can similarly be explicated. Tables 3 and 4 show the process detailed for discerning the value at (1,1) to serve as the same process for extrapolating values at other coordinates (32×40) within the matrix, suggesting a structured and replicable method for comprehending the matrix's entirety i.e.,1,280 times data recorded for rotal matrix.

Table 3. Feature value of EMG, GSR, BVP and RSP signals

EMG			GSR		BVP		RSP	
Number of channel/ features	CH1	CH2	Number of channel/ features	CH1	Number of channel/features	CH1	Number of channel/ features	CH1
Mean	19.525	-15.43	nbPeaks	1280	Mean	-209.861	Mean	441.8729
std	31.584	42.292	ampPeaks	2767.21	HRV	0.048769	Std	965.254
Kurtosis	2.640	3.0157	Risetime	1.6054	meanIBI'	0.927537	Kurtosis	2.319364
Skewness	0.4810	0.0472	meanGSR	1716.50	MSE	0.336773	Skewness	-0.27688
EMG_power	4.290	5.446	stdGSR	2773.24	sp0001	0.627964	sp0001	14.80007
			firstQuartileGSR	-639.26	sp0102	0.931832	sp0102	13.75895
			thirdQuartileGSR	4459.4	sp0203	1.206461	sp0203	13.63244
					sp0304	1.305362	sp0304	15.47105
					sp_energyRatio	-0.36338	sp0407	14.85189
					tachogram_LF	-3.0415	sp0710	13.75848
					tachogram_MF	-5.50895	sp1025	13.25037
					tachogram_HF	-7.36337	main_freq	0.5
					tachogram_energy _ratio	3.272883		

Table 4. Feedback values/rating of emotions

Label	Valence	Arousal	Dominance	Liking
Rating	7.71	7.6	6.9	7.83

2.3. Classification

Different input signals are classified by the classifier, which then outputs the appropriate emotion category. The quality of the classifier determines how well emotions are recognized. Deep learning approaches and traditional machine learning methods are two groups into which the current classification techniques are subdivided. The features are provided to the classifier for classification once the optimum feature for classification accuracy has been chosen. A classifier may demarcate between two or more categories before assigning a label based on the features it has selected. It is possible to think of the border as a unique hyperplane that is part of a multidimensional feature space. In other words, the greater the distance from all categories, the better the hyperplane, and the better the classifier. These characteristics are further categorized by combining related features into a single category using discriminant analysis and creating a confusion chart using the real labels in each group and the expected labels in each class after classifying sample Data with dialinear /linear /quadratic /diagquadratic discriminant analysis. A discriminant analysis classifier, which is a gaussian mixture model for data production, is included within a classification discriminant object. Using the predicted approach, a classification discriminant object may anticipate outcomes for fresh data. The object has access to the training data and can calculate resubstituting predictions.

2.4. Output or validation

In machine learning and statistical model evaluation, LOOCV methodology is a specialized and thorough cross-validation method. It is a technique for determining a predictive model's performance by using all but one data point for training and the only remaining data point for testing. Each data point in the dataset is then given the same treatment once again. A specific instance of K-fold cross-validation, where K is the total number of data points in the dataset, is used. LOOCV is operated in the following steps.

- It is temporarily held out as the "test" data point for each data point in the dataset.
- The remaining data points often referred to as the "training" data are used to train the model.
- Testing the model on the lone held-out data point allows for an evaluation of its performance.
- The model is trained and tested N times, leaving out one data point each time, if there are N data points in the dataset. This process is performed for each data point in the dataset.

2.5. Performance metric

The most often used performance indicators in machine learning are recall, precision, accuracy, and standard deviation. F1-score is dependent on recall and accuracy in (6). In physiological signals, emotion identification, and other classification tasks, accuracy in (3) is a frequent performance parameter [24], [25]. To quantify accuracy, a system often needs both the projected labels for a dataset and the true labels (ground truth). The performance formulae are given below.

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{4}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{5}$$

$$F1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision+Recall}} \tag{6}$$

Where true positive (TP) is the model that accurately classifies data as positive. True negative (TN) data is information that the model correctly classifies as negative. FP is the model that misclassifies data from the negative category as positive. FN is included when the model misclassifies data from the positive category as negative [24], [25]. They all depend on how a model that has been trained to distinguish between a certain category of interest (positive category) and the rest of the data (negative category) works.

3. RESULTS AND DISCUSSION

In this section, the analysis and identification of emotions have two objectives. The two-dimensional emotion model is cross-validated using LOOCV, and then through the use of machine learning, different emotions are assessed and predicted from peripheral signals. A multi-task categorization challenge is the recognition of emotions. The tests use the benchmark DEAP dataset, which contains multi-channel EEG data along with peripheral signals as well as valence and arousal data. 32 EEG signals and 8 peripheral signals are used in the DEAP dataset. All tests are conducted on MATLAB 2017a, using 8 GB RAM and a 64-bit Intel I5 CPU. Before the analysis of the current results, previous studies like [12], [14], [16], [17], [22], [23] have been reviewed based on different physiological signals, accuracy and F1-score.

The classification rate or accuracy for the valence type of emotion category for 32 subjects is 0.675, 0.725, 1, 0.525, 0.725, 1, 0.85, 0.925, 1, 0.775, 0.775, 0.525,0.575, 0.375, 0.7, 0.725, 1, 1, 0.75, 1, 0.775, 0.5, 0.875, 0.5, 0.575, 0.525, 0.975, 0.525, 0.55, 1, 0.65, and 0.775 respectively from s01 to s32. The average accuracy is 0.75 for valence. In the same way, the classification rate or accuracy for the arousal, liking, and dominance type of emotion category for 32 subjects was also recorded, which is shown in Tables 5 and 6. In the last the value of the accuracy is saved in a variable in MATLAB programming for each subject. The variable of the MATLAB file and the last average was done. The F1 score for the valence type of emotion category for 32 subjects is 0.551, 0.68, 0.5, 0.522, 0.5891, 0.5, 0.7058, 0.4805, 0.5, 0.5256, 0.586, 0.386, 0.365, 0.2727, 0.4805, 0.494, 0.5, 0.5, 0.428, 0.5, 0.4366, 0.4301, 0.4666, 0.33333, 0.4813, 0.344, 0.8933, 0.468, 0.4, 0.5, 0.5333, and 0.436. The average F1 score is 0.50 for valence. In the same way, The F1-score for the arousal, liking, and dominance type of emotion category for 32 subjects was also recorded, as shown in Table 6. In the last the value of F1-score is saved in a variable in MATLAB programming for each subject.

The findings of the proposed study are compared with the previous work [12], [14], [16], [17], [22], [23]. Compared to other investigations, this effort produced the best categorization of valence class findings.

According to the experimental findings, the suggested study classified data for arousal, valence, liking, and dominance on the DEAP datasets with an accuracy of 80%, 75%, 71%, and 78%, respectively. Additionally, for the two classes problem, the F1-score values for arousal, valence, liking, and dominance are 0.50, 0.49, 0.47, and 0.47, respectively. It appears that the results demonstrate the effectiveness of the proposed system. Table 5 and Table 6 show the experiment outcomes that, in the context of physiological peripheral data, the projected algorithm obtains a mediocre recognition accuracy level. Four peripherical signals, such as GSR, BVP, RSP, and EMG were used for this study, for a single channel 42 features have been extracted and calculated for four said peripherical signals.

Table 5. Comparison of proposed work

Contribution	Dataset	Physiological response	Arousal acc	Valence acc	Affective rating
Han *et al.* [17]	DEAP	PPG, EMG	75.76	74.32	Arousal, valence
Fu *et al.* [16]	DEAP	EEG, PPG, GSR, RES	63.6	64.4	Arousal, valence
	DEAP	RSP	61.25	64.24	Arousal, valence
Pidgeon *et al.* [22]	DEAP	GSR	62.50	60.18	Arousal, valence
	DEAP	BVP	63.49	61.13	Arousal, valence
Lee *et al.* [14]	DEAP	PPG	80.9	82.1	----
Chacon *et al.* [12]	DEAP	HRV, BPM, pulse	57.0	60.6	-----
Proposed work	DEAP	GSR, BVP, RSP, and EMG	80.00	75.00	Arousal, valence, liking, dominance

Table 6. Comparison of F1-score/accuracy [23] and [16]

Modality	Arousal		Valence		Liking		Dominance	
	Acc	F1S	Acc	F1S	Acc	F1S	Acc	F1S
Koelstral *et al.* [23]	57.0	0.533	62.7	0.608	59.1	0.502	--	--
Fu *et al.* [16]	64.4	0.679	63.6	0.653	--	--	--	--
Proposed method	80.0	0.50	75.0	0.49	71.0	0.49	78.0	0.47

4. CONCLUSION AND FUTURE SCOPE

Due to the robust feature extraction method and effective classifier, several recent machine learning experiments on physiological signals and emotion identification have shown promising results. This work elaborates the emotion recognition using peripheral signals with the combination of ridge regression with Fisher's discernment analysis using 42 different features for each cell of 32×40 size of matrix. Results were calculated based on features recorded 1,280 times. LOOCV technique used for determining a performance predictive model. From the experimental results, evaluate the model concerning accuracy and F1-score. On the DEAP datasets, the proposed study used four peripherical signals, such as GSR, BVP, RSP, and EMG for arousal, valence, liking, and dominance, respectively, and obtained higher classification accuracy of 80%, 75%, 71%, and 78%.

In the future SKT, ECG, PPG, and oximetry of pulse biosignals can be used for emotion recognition with different data sets for better accuracy with different combinations of classifiers along with different and appropriate feature sets. Human-robot interactions, electronic learning, analysis of markets, and several healthcare applications such as the diagnosis of depression, schizophrenia, alzheimer's disease, parkinson's disease, and other conditions all benefit from the usage of emotions. However, because there are not many publicly available datasets, there has not been much study in these disciplines on human emotion detection systems. Therefore, to increase the applicability of research studies on human emotions, our evaluation advises creating and making publicly available datasets. The findings presented in this study show that it is feasible to identify emotions from peripheral physiological data. Subsequent research endeavors will examine enhancing the techniques for extracting features to augment recognition efficacy and investigate sophisticated neural prediction models.

REFERENCES

[1] M. Soleymani, F. Villaro-Dixon, T. Pun, and G. Chanel, "Toolbox for emotional feature extraction from physiological signals (TEAP)," *Frontiers in ICT*, vol. 4, no. Feb, Feb. 2017, doi: 10.3389/fict.2017.00001.
[2] J. Wang and M. Wang, "Review of the emotional feature extraction and classification using EEG signals," *Cognitive Robotics*, vol. 1, pp. 29–40, 2021, doi: 10.1016/j.cogr.2021.04.001.
[3] R. Alhalaseh and S. Alasasfeh, "Machine-learning-based emotion recognition system using EEG signals," *Computers*, vol. 9, no. 4, pp. 1–15, Nov. 2020, doi: 10.3390/computers9040095.

[4] Y. Liu and G. Fu, “Emotion recognition by deeply learned multi-channel textual and EEG features,” *Future Generation Computer Systems*, vol. 119, pp. 1–6, Jun. 2021, doi: 10.1016/j.future.2021.01.010.
[5] R. Nawaz, K. H. Cheah, H. Nisar, and V. V. Yap, “Comparison of different feature extraction methods for EEG-based emotion recognition,” *Biocybernetics and Biomedical Engineering*, vol. 40, no. 3, pp. 910–926, Jul. 2020, doi: 10.1016/j.bbe.2020.04.005.
[6] S. Katsigiannis and N. Ramzan, “DREAMER: a database for emotion recognition through EEG and ECG signals from wireless low-cost Off-the-shelf devices,” *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 1, pp. 98–107, Jan. 2018, doi: 10.1109/JBHI.2017.2688239.
[7] J. A. Miranda-Correa, M. K. Abadi, N. Sebe, and I. Patras, “AMIGOS: a dataset for affect, personality and mood research on individuals and groups,” *IEEE Transactions on Affective Computing*, vol. 12, no. 2, pp. 479–493, Apr. 2021, doi: 10.1109/TAFFC.2018.2884461.
[8] E. H. Houssein, A. Hammad, and A. A. Ali, “Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review,” *Neural Computing and Applications*, vol. 34, no. 15, pp. 12527–12557, Aug. 2022, doi: 10.1007/s00521-022-07292-4.
[9] S. K. Khare, V. Blanes-Vidal, E. S. Nadimi, and U. R. Acharya, “Emotion recognition and artificial intelligence: a systematic review (2014–2023) and research recommendations,” *Information Fusion*, vol. 102, p. 102019, Feb. 2024, doi: 10.1016/j.inffus.2023.102019.
[10] H. P. Martinez, Y. Bengio, and G. Yannakakis, “Learning deep physiological models of affect,” *IEEE Computational Intelligence Magazine*, vol. 8, no. 2, pp. 20–33, May 2013, doi: 10.1109/MCI.2013.2247823.
[11] S. Oh, J. Y. Lee, and D. K. Kim, “The design of CNN architectures for optimal six basic emotion classification using multiple physiological signals,” *Sensors (Switzerland)*, vol. 20, no. 3, p. 866, Feb. 2020, doi: 10.3390/s20030866.
[12] L. A. B. Chacon, A. Fedoskin, E. Shcheglakova, S. Neamsup, and A. Rashed, “Emotion analysis using heart rate data,” in *Communications in Computer and Information Science*, vol. 1062, 2019, pp. 147–154. doi: 10.1007/978-3-030-27684-3_19.
[13] S. Salari, A. Ansarian, and H. Atrianfar, “Robust emotion classification using neural network models,” in *2018 6th Iranian Joint Congress on Fuzzy and Intelligent Systems, CFIS 2018*, IEEE, Feb. 2018, pp. 190–194. doi: 10.1109/CFIS.2018.8336626.
[14] M. S. Lee, Y. K. Lee, M. T. Lim, and T. K. Kang, “Emotion recognition using convolutional neural network with selected statistical photoplethysmogram features,” *Applied Sciences (Switzerland)*, vol. 10, no. 10, p. 3501, May 2020, doi: 10.3390/app10103501.
[15] H. Xu and K. N. Plataniotis, “Affective states classification using EEG and semi-supervised deep learning approaches,” in *2016 IEEE 18th International Workshop on Multimedia Signal Processing, MMSP 2016*, IEEE, Sep. 2017, pp. 1–6. doi: 10.1109/MMSP.2016.7813351.
[16] Z. Fu, B. Zhang, X. He, Y. Li, H. Wang, and J. Huang, “Emotion recognition based on multi-modal physiological signals and transfer learning,” *Frontiers in Neuroscience*, vol. 16, Sep. 2022, doi: 10.3389/fnins.2022.1000716.
[17] E. G. Han, T. K. Kang, and M. T. Lim, “Physiological signal-based real-time emotion recognition based on exploiting mutual information with physiologically common features,” *Electronics (Switzerland)*, vol. 12, no. 13, p. 2933, Jul. 2023, doi: 10.3390/electronics12132933.
[18] S. M. Ham, H. M. Lee, J. H. Lim, and J. Seo, “A negative emotion recognition system with the internet of things based multimodal bio signal data,” *Electronics (Switzerland)*, vol. 12, no. 20, p. 4321, Oct. 2023, doi: 10.3390/electronics12204321.
[19] X. Wang, Y. Ren, Z. Luo, W. He, J. Hong, and Y. Huang, “Deep learning-based EEG emotion recognition: current trends and future perspectives,” *Frontiers in Psychology*, vol. 14, Feb. 2023, doi: 10.3389/fpsyg.2023.1126994.
[20] A. Dessai and H. Virani, “Emotion classification based on CWT of ECG and GSR signals using various CNN models,” *Electronics (Switzerland)*, vol. 12, no. 13, p. 2795, Jun. 2023, doi: 10.3390/electronics12132795.
[21] S. Alsubai, “Emotion detection using deep normalized attention-based neural network and modified-random forest,” *Sensors*, vol. 23, no. 1, p. 225, Dec. 2023, doi: 10.3390/s23010225.
[22] M. Pidgeon, N. Kanwal, N. Murray, and M. Asghar, “End-to-end emotion recognition using peripheral physiological signals,” in *35th British HCI Conference Towards a Human-Centred Digital Society, HCI 2022*, 2022. doi: 10.14236/ewic/HCI2022.19.
[23] S. Koelstra *et al.*, “DEAP: a database for emotion analysis; using physiological signals,” *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18–31, Jan. 2012, doi: 10.1109/T-AFFC.2011.15.
[24] A. Hag, D. Handayani, T. Pillai, T. Mantoro, M. H. Kit, and F. Al-Shargie, “EEG mental stress assessment using hybrid multi-domain feature sets of functional connectivity network and time-frequency features,” *Sensors*, vol. 21, no. 18, p. 6300, Sep. 2021, doi: 10.3390/s21186300.
[25] T. Kumar, R. C. Singh, and R. Kumar, “Emotions recognition based on physiological signals using machine learning techniques,” in *Proceedings - International Conference on Technological Advancements in Computational Sciences, ICTACS 2023*, IEEE, Nov. 2023, pp. 823–827. doi: 10.1109/ICTACS59847.2023.10390266.

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