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Convolutional neural network-based emotion recognition using recursive feature elimination

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Abstract

Emotion detection plays a crucial role in fields such as biomedical applications, smart environments, brain-computer interfaces, communication, security, and safe driving. In this paper, we present a novel approach for detecting emotions using electroencephalogram signals. The method employs convolutional neural network (CNN) as the classifier, which is chosen from a variety of intelligent algorithms. Discrete wavelet transform is used to decompose the signals into four frequency bands including theta, alpha, beta, and gamma. These bands are then utilized for feature extraction. Out of a total of 1920 features, the recursive feature elimination algorithm based on random forest model combining with 5-fold cross-validation and the K-nearest neighbors model, selects the 720 most relevant features. The proposed algorithm is further validated on the selected feature subset using 5-fold cross-validation with CNN on the validation set. The results demonstrate the potential of this algorithm for emotion recognition.

Keywords: EEG signals; Deep learning; Machine learning; Discrete wavelet transform; DEAP dataset

1. Introduction

Human emotions are physiological and non-physiological states influenced by various feelings, thoughts, and behaviors. They are essential for daily life and serve as important indicators of human cognition, affecting behavior, communication, and social relationships [1]. Emotion recognition is applied in a range of areas such as brain-computer interfaces, human-robot interaction, healthcare, and security, entertainment, monitoring, and marketing [2]. Recently, advancements in Artificial Intelligence (AI) have enabled emotion AI systems to employ either non-physiological methods, such as facial expressions and speech signals, or physiological methods like Electroencephalogram (EEG) signals. While non-physiological techniques can be less reliable due to their vulnerability to manipulation, EEG signals are preferred in affective computing for being secure, cost-effective, non-invasive, user-friendly, and portable [3].

An EEG signal measures the brain's electrical activity through small metal electrodes placed on the scalp. EEG is a reliable technique for recording brain signals related to different mental states from the surface of the scalp. EEG signals are categorized by the frequency of brain waves, which typically range between 1 and 100 Hz. These brain waves are divided into five frequency bands: delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (31-50 Hz) [4]. The number of electrodes used in EEG recording depends on the device. Some devices, like those with 14 channels, provide lower spatial resolution, while others with 128 or 256 channels offer higher spatial resolution [5].

In the emotion recognition process using EEG signals, feature extraction plays a pivotal role in emotion classification. The quality of feature extraction directly impacts the accuracy of the classification. Traditional EEG emotion research primarily involves manual extraction of emotion-related EEG features, such as power spectra of specific frequency bands and energy ratios of different bands. Although this method is straightforward and easy to implement, the extracted features often have low complexity and poor generalization ability, limiting classification accuracy. In recent

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years, numerous studies have introduced various novel EEG signal feature extraction methods. The most commonly employed techniques include Short-Time Fourier Transform (STFT) [6], Power Spectral Density (PSD) [7], Continuous Wavelet Transform (CWT) [8] and Discrete Wavelet Transform (DWT) [1]. DWT was employed to decompose the signals, highlighting its effectiveness in extracting time-frequency information from non-stationary EEG signals. DWT is indeed a vital technique for obtaining time-frequency details from these types of signals. Typically, the lower-frequency components change slowly, while the higher-frequency components exhibit rapid fluctuations. As a result, DWT is particularly well-suited for analyzing discrete EEG signals. Recently, DWT combined with wavelet-based atomic functions has been successfully utilized for EEG signal decomposition in seizure detection applications [9]. Furthermore, authors in [10] employed wavelet-based atomic functions for signal preprocessing, effectively eliminating noise and baseline wander from raw ECG signals.

EEG signal-based emotion recognition has recently gained popularity through the use of machine learning (ML) and deep learning (DL) methods. These ML methods are generally easy to explain and understand, and they can achieve good results; however, they often necessitate complex feature extraction engineering, which makes end-to-end training impractical. In contrast, DL methods utilize multi-layer networks for emotion recognition, enabling end-to-end training without the need for elaborate feature engineering, and they usually offer higher accuracy compared to traditional ML techniques.

In the study [11], the researchers introduced an ensemble learning approach using particle swarm optimization (PSO) to identify emotions from EEG data. They extracted both linear and nonlinear features from the Database for Emotion Analysis using Physiological (DEAP) and the SJTU Emotion EEG Dataset (SEED). PSO was employed for feature selection, and Naive Bayes, SVM, and KNN were used for classification. In another study by [12], sample entropy and wavelet entropy were combined with a SVM and k-fold CV. The study [13] employed quantum principles to generate distinct solutions using a quantum SVM, applied to the DEAP dataset for binary classification. The data were extracted using PSD and subsequently reduced using principal component analysis.

Widely-used DL algorithms, such as Convolution neural network (CNN) [14, 15] and Recurrent Neural Network (RNN) [16] and Long-short term memory (LSTM) [17, 18], have demonstrated effectiveness in detecting emotions from EEG signals. In the study [7], a spatial-temporal information learning network (STILN) was proposed for EEG-based emotion recognition. Power topographic maps were generated based on PSD features and used to evaluate the performance of the STILN. In [19] employed temporal domain features with the EEGFuseNet model and leave-one-out cross-validation.

In this paper, we propose a comprehensive approach that includes band decomposition using the DWT algorithm, followed by feature extraction. By utilizing both ML and DL models, our goal is to achieve high accuracy in classifying valence and arousal. To further improve model performance and reliability, we apply feature selection through RFE combined with ML models, and validate our method using 5-fold cross-validation (CV). The main contributions of our work are as follows:

Using DWT to decompose signals into four distinct bands: theta, alpha, beta, and gamma, capturing comprehensive frequency components.

Applying feature selection based on recursive feature elimination (RFE) to individual bands with ML models, identifying and selecting the most important features, thereby reducing dimensionality and enhancing model performance.

Optimization of models using grid search with 5-fold cross-validation Implementing both ML and DL models and performing a comparative analysis to identify the best-performing model for classifying valence and arousal.

The remaining part of the paper is organized as follows: Section 2 presents the materials and methods, and Section 3 describes the results and discussions. Finally, Section 4 summarizes the research.

2. Material and methods

2.1. DEAP dataset

The DEAP dataset, which is publicly accessible, includes 32-channel EEG data along with other physiological signals. To induce emotions, participants watched 40 one-minute music videos. After viewing each video, participants rated it on a 9-point scale for valence, arousal, and dominance. The dataset was collected from 16 male and 16 female participants, with an average age of 26.9 years. In this study, only the EEG channels from the preprocessed version of the dataset are used. The preprocessing involved downsampling to 128 Hz, removing electrooculogram (EOG) artifacts, applying a bandpass filter from 4 to 45 Hz, using common average referencing, and segmenting the signals into 60-second trials with a 3-second baseline. As a result, the EEG dataset for each individual is structured as $40 \times 32 \times 8064$ (video/trial $\times$ channel $\times$ samples). The corresponding labels for the data samples are organized in a 40×4 format, representing the video/trial and the four emotional labels (valence, arousal, dominance, liking) [20].

The 2-dimensional Valence-Arousal model by Russell [21] represents emotional degrees of pleasantness and arousal and is used for experiments on the DEAP database, with emotional intensities assessed using the self-assessment manikin scale. Each dimension is rated on a scale from 1 to 9. This model divides emotions into four distinct zones shown in **Figure 1**, where the valence dimension is classified as either negative or positive, and the arousal dimension as high or low, using a threshold of 4.5. Values above 4.5 are considered high/positive, while values 4.5 or below are considered low/negative.

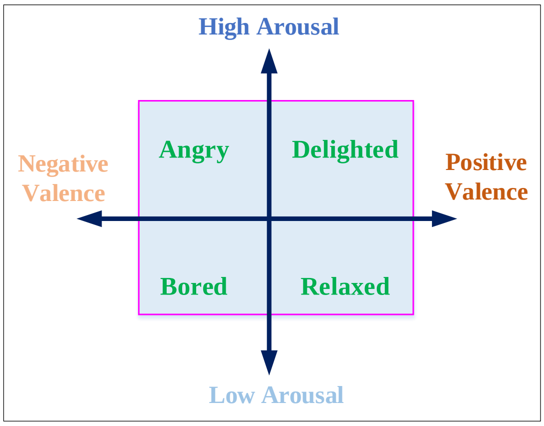

Figure 1 Two-dimensional (arousal-valence) emotion space

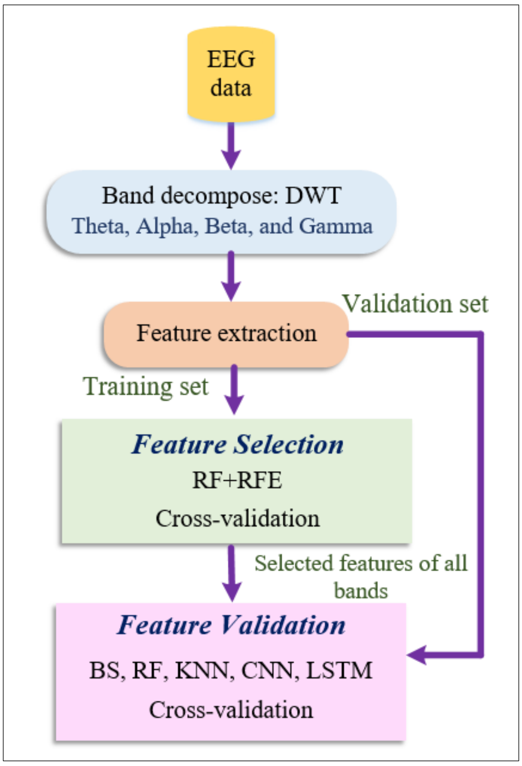

Figure 2 Flowchart of the method

2.2. Methods

The proposed method consists of three main steps shown in **Figure 2** including data preprocessing, feature selection, and feature validation. Initially, EEG signals are processed using DWT to generate four bands, theta, alpha, beta, and gamma, which are then normalized. The RF model, combined with the RFE procedure, is used to select the most relevant subset of features from each band. The maximum number of features across all four bands is chosen as the final feature count for each individual, and these are combined to form the selected features of all bands (SFB). Next, feature validation is carried out using the SFB on the training set to choose optimal model, followed by model validation on the validation set.

2.2.1. Data preprocessing

DWT decomposes a signal into two parts: (1) an average or lowpass component using a scaling function, and (2) a difference or highpass component using a wavelet function. The standard DWT method recursively breaks down the lowpass component using the same scaling and wavelet functions until the desired level of decomposition is reached [5]. Features are extracted from the time-frequency domain using DWT, which is commonly applied to nonstationary signals. For each channel in every EEG sample, DWT is used to obtain the coefficients for the Theta, Alpha, Beta, and Gamma frequency bands. These coefficients are then utilized to compute entropy and energy as follows [22]:

$$\text{Entropy}(x) = -\sum_{t=1}^{n} x(t^2)\log(x(t)^2) \quad (1)$$

$$\text{Energy}(x) = \sum_{t=1}^{n} x(t)^2 \quad (2)$$

Where *x* represents the signal being analyzed and *n* is the coefficient value at time step *t.*

A total of 15 features including second difference, normalized second difference, mean value of EEG amplitude, median of EEG time, Kurtosis, Hjorth mobility [23], Lyapunov exponent [24], approximate entropy, sample entropy [25], fuzzy entropy, Tsallis entropy [26], complexity measure [27], covariance calculation, area calculation, and frequency calculation [28] are extracted from each channel across the different frequency bands. This results in 480 features per band, amounting to a total of 1920 features across all bands.

2.2.2. Feature selection

Recursive Feature Elimination (RFE) is a feature selection algorithm to improve model performance by identifying the most important features. It works by recursively fitting a model and eliminating the least important features, one by one, based on their importance scores. At each iteration, the model is trained, and the least relevant feature is removed, allowing the model to focus on the most significant features.

RFE is implemented on individual bands of features. It starts with 480 features, initializing a set S_n of all features for each band. In the first step, feature importance values are calculated using a RF model. This involves training the model on 5-folds of the dataset, where in each fold CV_j, the RF model is trained on *j*-th fold and the importance values are calculated on the remaining fold CV_j. After that, the features are ranked according to their importance. Next, feature elimination begins by repeatedly removing 20 features with the lowest importance values. The KNN performance is calculated after each elimination. The process continues until only 20 features remain. During each iteration, the subset of remaining features is saved. In total, 24 subsets of features are saved for later use.

As a result, the optimal feature count varies between bands. The final feature count is set by selecting the largest number of features among the four bands, which is then used to form the SFB for the next steps.

2.2.3. Feature validation

In this study, three ML models (RF, KNN, and BS) and two DL models (CNN and LSTM) are utilized. A grid search-based model selection method, combined with a 5-fold CV process, is employed to determine the optimal learning and structural parameters using SFB. Proper hyperparameter tuning for these models is crucial to prevent overfitting issues.

Random forest: RF is a machine learning model based on decision tree algorithms, commonly used for classification and regression tasks. RF builds a collection of multiple decision trees (a forest), each trained on a random subset of the data. For predictions, the trees vote, and the final output is determined by majority voting (for classification). By aggregating the results from multiple trees, RF reduces the risk of overfitting and improves accuracy compared to a single decision tree.

K-Nearest Neighbors: KNN is a simple machine learning. It operates on the principle that similar instances tend to be close to each other in feature space. When making a prediction for a new data point, KNN identifies the K nearest neighbors from the training dataset based on a distance metric. The algorithm then classifies the data point based on the majority class among the K neighbors. KNN is easy to implement and interpret but can be computationally expensive with large datasets and sensitive to the choice of K and the distance metric used.

Boosting: BS is a machine learning ensemble technique that combines multiple weak learners, typically decision trees, to create a strong predictive model. The process involves sequentially training models, where each new model focuses on correcting the errors made by its predecessor. This is achieved by assigning higher weights to misclassified instances, ensuring that subsequent models pay more attention to difficult cases. Boosting improves accuracy and reduces bias, making it a powerful approach for various classification tasks.

Convolutional Neural Network: CNN is a type of deep learning model. It consists of several key layers: convolutional, pooling, fully connected, and softmax layers. The convolutional and pooling layers are responsible for feature extraction. The convolutional layer performs operations to detect patterns, while the pooling layer reduces the dimensionality by retaining the most significant features. The fully connected layers map these features to the final output, such as classification. Activation functions such as ReLU introduce non-linearity, and the softmax layer generates probabilities for each possible output label, with the highest probability determining the final prediction.

Long Short-Term Memory: LSTM is a type of recurrent neural network (RNN) designed to process and learn from sequential data, such as time series, text, or speech. Unlike traditional RNN, LSTM is capable of learning long-term dependencies by using special units called memory cells, which can maintain information over time. Key components of LSTM include: input gate, which determines what new information to store; memory cell, which stores information overtime; forget gate, which decides what information to discard from the memory; and output gate, which controls the output based on the memory cell's state. The architecture of LSTM allows it to avoid problems like vanishing and exploding gradients, making it highly effective for tasks involving long-term sequences.

The models are trained on the training set to find the optimal configurations and are subsequently validated for performance using the SFB on the validation set. A 5-fold CV process is also applied to ensure reliable simulation outcomes. The validation set is split into 5 folds, where 4 folds are used for training and 1 fold for testing. The models are trained and tested 5 times, rotating the test fold each time so that every fold serves as a test set. The mean and standard deviation of the classification results are calculated to compare performance between the models and existing studies. The model with the highest accuracy using SFB is chosen as the final proposed emotion detection algorithm.

3. Results and discussion

3.1. Feature selection

Table 1 presents the results of feature selection for the four bands. The number of features ranges from a minimum of 20 to a maximum of 180. To ensure consistency, 180 features are selected for each band, resulting in a total of 720 features being chosen as SFB.

Table 1 The number of optimal features for each band

	Theta	**Alpha**	**Beta**	**Gamma**
Valence	160	120	180	60
Arousal	160	100	40	20

3.2. Feature validation

A grid search-based hyperparameter tuning method is used to identify the five optimal models, utilizing a 5-fold CV procedure. For the CNN model, the chosen parameters include three blocks: the first block contains three convolutional layers with a filter size of 5×1 and 16 filters, three ReLU activations, and one max-pooling layer with a filter size of 3×1; the second block consists of one convolutional layer with a filter size of 5×1 and 32 filters, one ReLU activation, and one max-pooling layer with a filter size of 3×1; the third block includes one convolutional layer with a filter size of 5×1 and 64 filters, one ReLU activation, and one max-pooling layer with a filter size of 3x1. Additionally, the KNN model is optimized with a K value of 25 for both valence and arousal classification. The optimal BS model is identified with a learning rate of 0.95, 25 iterations, and a leaf number of 50. For the RF model, the tuning process identified the optimal number of estimators as 95, with a maximum depth of 100, a minimum sample split of 5, and a minimum samples leaf of 3. Finally, LSTM model consists of three LSTM layers with 200, 100, and 50 hidden units, each followed by batch normalization and a dropout layer (dropout rate of 0.2). After the LSTM layers, two fully connected layers are added, one with 32 units and the other with the number of output classes. The training options include a learning rate of 0.001, momentum of 0.95, L2 regularization of 0.1, and a maximum of 200 epochs with a mini-batch size of 100, using the stochastic gradient descent with momentum (SGDM) optimizer.

The performance of the five optimal models is validated using SFB as input on the validation set, as shown in **Table 2.**

Table 2 Performance of optimal models on validation set

Method	Valence		Arousal	
	Accuracy	F1-score	Accuracy	F1-score
BS	57.35 ± 6.23	67.58 ± 7.86	58.34 ± 12.36	65.41 ± 15.93
RF	48.21 ± 2.55	55.30 ± 4.75	49.87 ± 3.34	41.78 ± 7.21
KNN	64.13 ± 5.45	76.45 ± 5.98	62.35 ± 11.95	74.98 ± 8.74
CNN	65.59 ± 8.12	79.02 ± 6.78	66.18 ± 3.41	79.51 ± 2.89
LSTM	62.34 ± 5.24	74.56 ± 5.12	63.21 ± 4.72	76.13 ± 3.13

4. Discussions

Feature selection is crucial for reducing high-dimensional data, particularly to decrease computation time and enhance model performance. RFE is highly effective in this context, as it narrows down the feature set to only the most relevant ones. In this case, 720 features are selected from the initial 1920 features extracted across four EEG frequency bands: theta, alpha, beta, and gamma. Each band contributes 180 features from 32 channels, with 140 features originating from 28 channels and 40 features from the remaining 4 channels. Specifically, 28 channels each contribute 5 features, including Sample entropy, Kurtosis, Lyapunov exponent, Normalized second difference, and Approximate entropy, while the other 4 channels contribute 10 features each, including Sample entropy, Kurtosis, Lyapunov exponent, Normalized second difference, Complexity measure, Approximate entropy, Covariance calculation, Area calculation, Frequency calculation, and Hjorth mobility.

The 180 informative features for each band are utilized to assess the classification performance of the five models. The results are illustrated in **Table 2**, where the accuracy and F1-score for both valence and arousal classifications are presented. Among 5 models, the CNN model achieved the highest accuracy for valence 65.59% and arousal 66.18% classifications, along with the best F1-scores 79.02% for valence and 79.51% for arousal. The accuracy and F1-score are similar for both valence and arousal classifications, demonstrating the effectiveness of the CNN model for emotion detection. This indicates that CNN effectively capture and differentiate subtle emotional cues based on the extracted features, leading to more accurate and reliable emotion detection across various emotional states. The CNN's capability to adaptively learn spatial hierarchies from the extracted features further enhances its effectiveness.

The performance comparisons of the proposed algorithm with existing studies are summarized in **Table 3**. The proposed method demonstrates competitive performance in both valence and arousal classifications. It surpasses F1-score when compare F1-score. The notable advantage of the proposed method lies in its superior F1 scores, indicating enhanced precision and recall for emotion detection. Specifically, our proposed method achieves an accuracy of 65.59%

for valence, as well as 66.18% accuracy for arousal. These results outperform the scalogram images combined with CNN [14], which achieved an accuracy of 61.50% for valence and 58.50% for arousal.

Table 3 Comparison of the performance of the proposed method with other studies

Method	**Valence**		**Arousal**	
	Accuracy (%)	**F1-score (%)**	**Accuracy (%)**	**F1-score (%)**
Scalogram images + CNN [14]	61.50	NaN	58.50	NaN
EEGFuseNet [19]	68.31	68.26	67.52	68.00
PSD + STILN [7]	68.31	68.26	67.52	68.00
Our	**65.59**	**79.02**	**66.18**	**79.51**

5. Conclusion

Emotion recognition plays a vital role across various fields, particularly in BCI. Consequently, prompt and accurate emotion recognition is essential for adaptation and response within BCI systems, significantly enhancing human-computer interaction capabilities. Therefore, in this research, we propose a robust algorithm for emotion detection. The proposed approach utilizes a refined feature subset along with CNN classifier. DWT is employed to decompose EEG signals into four frequency bands, from which a total of 1,920 features are extracted. From these, 720 features are selected, representing the most informative subset identified through the RFE method, integrated with a machine learning model and a 5-fold cross-validation procedure. Our proposed algorithm demonstrated promising results, achieving statistically validated performance metrics of 65.59% accuracy and 79.02% F1 score for valence classification, as well as 66.18% accuracy and 79.51% F1 score for arousal detection. These findings indicate that our algorithm is well-suited for practical emotion detection applications.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest is to be disclosed.

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