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Optimal Classification of Emotions from Electroencephalography (EEG) Signals

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ABSTRACT

It is incredibly challenging to build an intelligent algorithm for emotion recognition that can deliver high accuracy because electroencephalography (EEG) signals are not stationary, nonlinear, and noisy. First, decomposing the preprocessed EEG signals of the SEED dataset into five frequency bands: delta, theta, alpha, beta, and gamma, and then calculated their energy and entropy from the extracted features. Then Principal Component Analysis (PCA) method for feature reduction was performed. It is important to note that different types of wavelets transform (db6, db5, etc.) were tested, and hyperparameter tuning of classification models was done to obtain optimal accuracy. The next step is classifying the emotions into three states: -1(negative), 0(neutral), and +1(positive), and tested the dataset on two types of classification models, namely Random Forest and Support vector machine (SVM). SVM gives better performance compared to Random Forest with an accuracy of 80.74%.

1. Introduction

A new generation of intelligent systems uses emotion recognition models to improve human-machine interaction. It is essential for the systems to be able to adapt their behavior and responses according to the emotions of the humans, therefore making the interaction more natural and natural-looking.

Electroencephalography (EEG) is a widely used non-invasive method of capturing brain waves using electrodes on the scalp. EEG primarily records electrical activity in the cerebral cortex, which has a columnar organization of neurons and is close to the skull, making it ideal for recording. EEG recordings are suitable for capturing oscillatory brain activity or brain waves at different frequencies. These waves, which can arise from the synchronization of many neurons, have distinct frequency ranges and spatial distributions, and are frequently linked to diverse brain functioning states. However, EEG signals generally have a low spatial resolution and high temporal resolution. There are several layers of tissues - such as meninges, cerebrospinal fluid, skull, and scalp - which interfere with the signal transmission between the signal source of brain activity in the cortex region and the sensor placed on the scalp, leading to poor spatial resolution of EEG. In addition, artifacts such as - muscle motion and electrical equipment can bias EEG readings. Some of the significant artifacts in

EEG readings are caused by the user's psychological states (boredom, displeasure, distraction, and tension), eye movements, eye blinks, eyebrow movements, talking, chewing, and head movements.

The EEG signal is linked to a person's degree of consciousness. The EEG signal shifts to a higher dominant frequency with lower amplitude as activity rises. The EEG signal shifts to a lower dominant frequency with higher amplitude as activity falls. Table 1 shows different EEG rhythms and their frequency ranges.

Table 1. Different EEG Bands

EEG Frequency Band	Frequency Range	Location	Signal Condition
Delta	0.5Hz – 4Hz	Frontal lobe	Most apparent in deep sleep state, usually dreamless, stages of sleep, allowing the brain to restore itself.
Theta	4Hz – 8Hz	Temporal dan parietal	Appears in relaxed state, drowsiness, idling, light sleep, and meditation (daydreamers).
Alpha	8Hz – 12Hz	Occipital region	Our default state when our mind is idle – we're physically and mentally relaxed (yogis rejoice).
Beta	13Hz – 30Hz	Frontal and parietal	Involved with logical thinking, accomplishing tasks, being alert, active, and when we're socializing with others (enthusiastic).
Gamma	>30Hz	Parietal	Appears when we're at peak perception, subjective awareness and expanded levels of consciousness.

EEG-based brain computer interface (BCI) devices' usability in this contemporary world is vast. Namely, daily detection of emotions will play a pivotal role in optimizing performance at workplaces like monitoring healthcare facilities, gaming, and entertainment sectors. The remainder of the paper is organized as follows. Section 2 deals with the literature survey. Section 3 describes the methodology of the proposed solution, which includes detailed description on dataset selection, dataset pre-processing, feature extraction, feature reduction and classification models. Section 4 analyses the experimental results and provides discussion. Section 5 deals with applications. Section 6 summarizes this work.

2. Literature Review

P. Santhiya and S. Chitrakala reviewed recent methodologies and dissected the nuances and challenges in using EEG signals for emotion recognition [1]. Using the Pretest-posttest methodology, Yadav GS et al. evaluated overall mood, stress levels, state of depression, sleep quality, and anger between four weeks of meditation and brainwave entertainment [2]. M. Sreeshakthy et al. extracted emotion-related features and then classified those emotions using Neural Network (NN), SVM, K-Nearest Neighbour (KNN), and Linear Discriminant Analysis (LDA). Lastly, emotions are classified into different groups based on their arousal (positive and negative) and valence (calm and excited) [3]. To study the impact of classical music and visuals on evoked emotions, Noppadon Jatupaiboon et al. employed power spectral density (PSD) as a feature and SVM as a classifier [4].

The work of Prof. H. Shao et al. enhanced the detection of emotion in EEG by using CNN (Convolutional Neural Networks). Furthermore, a new method of convolution kernel adjustment exists to adapt the CNN to EEG signals [5]. T. H. Priya et al applied EEG sub-band power ratios as features to classify baseline (relax) and stress. In addition, an SVM classifier with different kernel function parameters was subjected to a KNN classifier with a different number of neighbors with holdout and a 10-fold cross-validation technique [6]. Various feature extraction and feature classification algorithms were proposed by Manjula K, and M.B. Anandaraju. Additionally, they

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discussed the technology and methods utilized in the processing of EEG signals throughout every phase. As a result of this comparative study, an algorithm for further classification of signals has been selected that is suitable [7].

A novel approach to emotion recognition was suggested by Ante Topic and Mladen Russo in a paper examining the development of feature maps for EEG signal properties derived from topographic and holographic representations [8]. A feature fusion framework for emotion analysis has been developed, using convolutional neural networks with correlation coefficients, synchronization likelihood matrices of EEG signals, a fusion framework as a feature extraction tool, and a stacking technique for ensemble learning to improve the model. K. Guo et al investigated the use of convolutional neural networks with correlation coefficients for emotion analysis and ensemble learning for improving computational efficiency [9]. Using a multiband feature matrix (MFM) and a capsule network (CapsNet), an architecture for deep learning has been designed by H. Chao et al. [10].

Therefore, a detailed literature survey on ten recently published research papers related to our study was done. The majority of the studies proposed different feature extraction and emotion classification methodologies. In contrast, few research works focused on proposing a novel paradigm for classifying emotions from EEG signals. Lastly, only three studies worked on real-time applications.

From the above literature survey, the following inferences are listed below.

a. Although other methods for emotion recognition exist, such as speech, facial expressions, muscle activity, and so on, EEG signals are the most accurate because they cannot be altered or replicated to generate a false emotional state.
b. A huge dataset with high quality signal results in more accuracy.
c. PCA works on dimensionality reduction without any loss of information.
d. SVM and Random Forest gives generalized model with high performance.

3. Methodology

The process of classification of emotions by decomposing EEG signals into the delta, theta, alpha, beta, and gamma frequency ranges consists of several phases, as shown in Fig. 1.

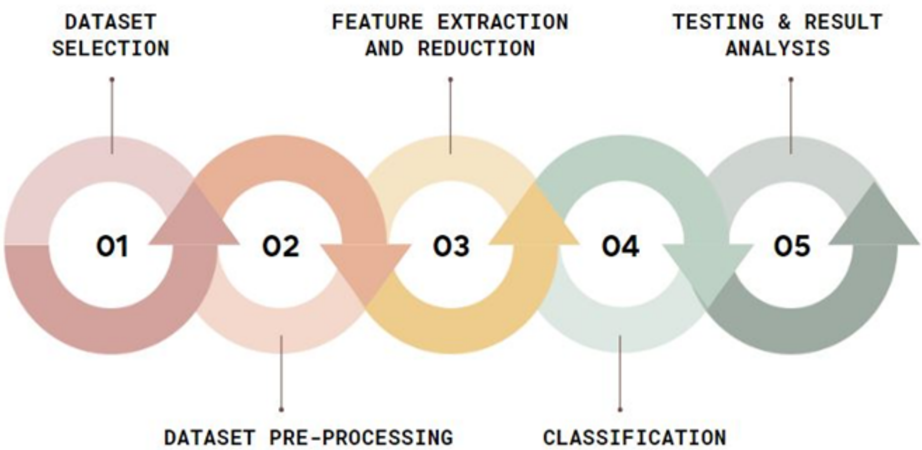

Fig. 1. Block diagram of various phases of the methodology

4.1. Dataset Selection

The selection of an appropriate dataset suitable for our problem statement is the methodology's first and most crucial phase. Many esteemed universities publish many EEG datasets (like DEAP,

SEED, DREAMER, AMIGOS, INTERFACE, IMAGINES EMOTION, etc.). The SEED Dataset was chosen for this research.

SJTU SEED Dataset: This dataset contains the EEG signals of 15 people (7 males and 8 females; MEAN: 23.27, Standard Deviation: 2.37) (SEED). The individuals watched fifteen Chinese film clips, and these clips can be broadly grouped under three emotion labels: negative, positive, and neutral. The EEG data were collected using 62 electrodes, as shown in Fig. 2. In addition, five video snippets were used to depict each emotion. Each subject performed experiments three times, each separated by a week.

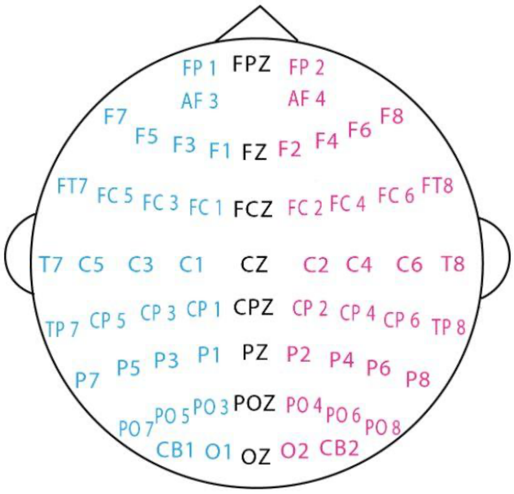

Fig. 2. EEG cap (international 10-20 system for 62 channels)

4.2. Dataset Pre-Processing

Dataset pre-processing is the second phase of the methodology. For each trial, which lasted about four minutes, the EEG data were down-sampled to 200 Hz and processed through a band-pass filter ranging from 0 to 75 Hz. A total of 45.mat files make up the dataset. There are 16 arrays in each subject file. In the first 15 arrays, the segmented pre-processed EEG data are shown, while the last array has emotion labels (0 for neutral, +1 for positive, and -1 for negative).

4.3. Feature Extraction

The feature extraction process can be divided into two steps (as shown in Fig. 3): Wavelet transforms filter bank and calculates energy and entropy.

3.5.1. Wavelet Transform Filter Banks

Wavelet Filter Bank technique was used to divide the EEG pre-processed signals into five frequency sub-bands: alpha, beta, gamma, delta, and theta. It's called a frequency bank because the frequencies are applied consecutively. Next, the frequency band is divided into two lower-level filter halves. They are detailed (high pass) and approximation coefficient (low pass). Finally, the approximation coefficient is passed through the filter to get the frequency range. This process is repeated on each channel until the appropriate frequency bands is obtained. As much as 62 channels was obtained in total, and for each channel, Entropy and Energy are calculated, which individually give five features each.

3.5.2. Calculation of Energy and Entropy

Entropy: Entropy metrics quantify the EEG signal uncertainty, which correlates to the number of possible configurations or probability. Energy: The wavelet energy reflects the distribution of central lines, wrinkles, and different resolution ridges. At the end of Feature Extraction, 620 features were obtained.

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4.4. Feature Reduction

PCA is a dimensionality reduction technique where all the correlated features of the dataset are converted to a set of uncorrelated training features. The output is known as the principle component. During this analysis, four main steps were followed (as shown in Fig. 3):

a. Mean Normalization of Features: The main objective of this step is to convert the values of numeric columns to a similar scale. Also, this step ensures that there is no distortion of the range of values and no information is lost.
b. Calculating Covariance Vector: The covariance gives the degree to which two variables are correlated.
c. Calculating Eigenvectors: In this step, transformation is applied to the features. Some vectors remain in the same place after the change is done. Eigenvectors are the names given to these vectors. These Eigenvectors following the transformation are scaled by the factor known as Eigenvalues.
d. Get Reduced Features or Principal Components: The output principal components or reduced features are obtained.

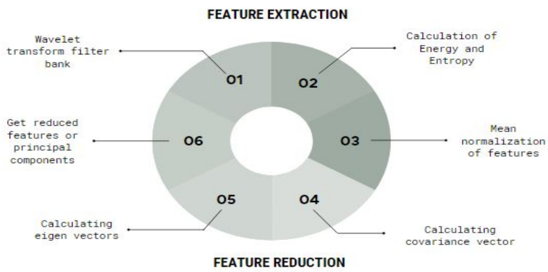

Fig. 3. Feature extraction and feature reduction steps

4.5. Classification

To classify the emotional states (-1, 0, +1), Random Forest and SVM machine learning models were used.

3.5.3. Random Forest

Random forest is one of the supervised machine learning approaches that use a homogeneous ensemble algorithm. It's a collection of decision trees; each classifies each observation separately. In this model, 150 decision trees were used. After that, the algorithm employs majority voting to determine which class the observation belongs to as shown in Fig. 4. Compared to other models, it is more resistant to overfitting since many highly uncorrelated models (trees) working together outperform any of the individual constituent decision trees.

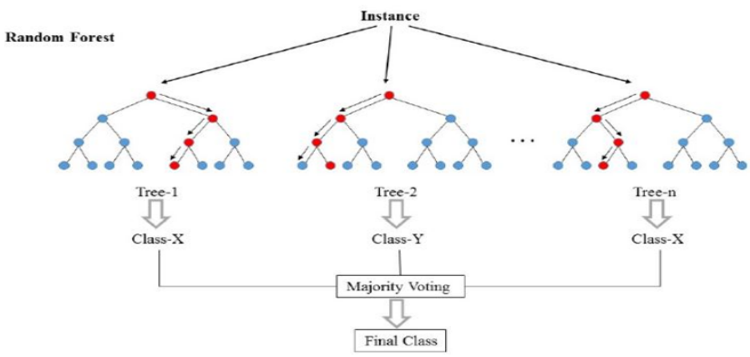

Fig. 4. Random Forest

The following modeling steps were performed:

a. Split the pre-processed data into train and test in 80:20 ratio.
b. Train the Random Forest model.
c. Perform randomized search to check which hyperparameters perform the best.
d. Test the Random Forest model.
e. Finally, obtain the Classification report (Accuracy, Precision, Recall, and F1 Score) and Confusion Matrix.

3.5.4. Support Vector Machine (SVM)

As part of the supervised machine learning techniques, Support Vector Machines (SVMs) are also used. Data points are represented by points in n-dimensional space (n being the number of features), with each feature's value being the SVM algorithm’s value. SVM divides observations into classes by building a hyperplane in the feature space with the shortest distance between it and the data points as shown in Fig. 5. When there is a linear relationship in data, SVM employs a linear kernel to determine an ideal hyperplane that divides the data into two parts. It can be achieved by maximizing the distance between the hyperplane and the nearest training points, called support vectors. If the data is not linear, it is classified using a polynomial and radial bias function kernel functions hyperplane.

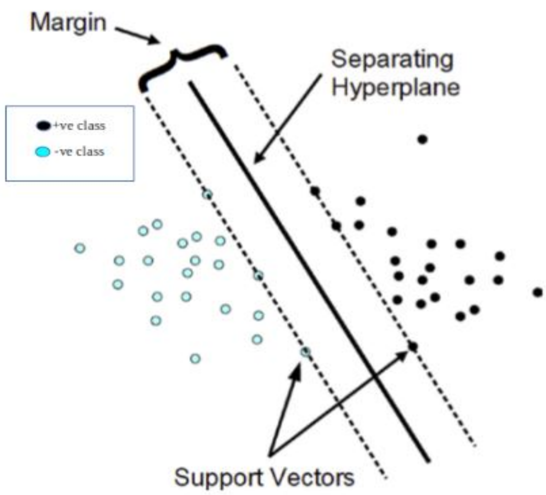

Fig. 5. Support vector machine (SVM)

Following modelling steps were carried out:

a. Split the pre-processed data into train and test by ratio of 80:20.
b. Train the SVM model.
c. Perform grid search to check which hyperparameters perform the best.
d. Test the SVM model.
e. Finally, obtain the Classification report (Accuracy, Precision, Recall, and F1 Score) and Confusion Matrix.

4.6. Testing and Result Analysis

Comparison of various parameters like accuracy, precision, recall, F1-score, and confusion matrices of two classification models is made as explained in detail in the next section.

4. Results and Discussion

4.1. Result

After successfully running our machine learning models, emotions were classified into three states: -1 (negative), 0 (neutral) and +1 (positive). On performing a brief comparative study on the

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classification reports (shown in Fig. 6 and Fig. 8) and confusion matrices (shown in Fig. 7 and Fig. 9), it can be concluded that the SVM model, which has an accuracy of 80.741%, gives better performance than Random Forest model which has an accuracy of 67.41%.

4.2. Statement of results

The confusion matrix was used to calculate the model's efficiency. Our classification captured essential parameters like accuracy, precision, recall, and F1 score.

To assess the effectiveness of a classification model, a confusion matrix of NxN dimensions can be used, where N denotes the number of targeted classes. In our case, N is 3. The matrix compares the actual true values to the machine learning model's predicted values. The rows of the confusion matrix indicate the existing true label, while the columns represent the expected or the predicted label. The principal diagonal values of the matrix indicate the True Positive (TP) values.

Accuracy: The average per-class efficiency of the classifier is used to determine the system's accuracy.

Precision: It's obtained by accumulating all True Positives (TP) and False Positives (FP) in the system overall classes and estimating the degree of agreement between the actual class labels and the classifier's labels.

Recall: The total of all True Positive (TP) and False Negative (FN) values in the system overall classes determine the classifier's ability to identify class labels.

F1 Score: It's the harmonic mean of recall and precision. It's a measure of a model's accuracy on a particular dataset.

4.3. Explanatory text

The evaluation metrics for Random Forest (Fig. 6 and Fig. 7) is given below. It can be observed from the classification report (Fig. 6) that Random Forest model gives an accuracy of 67.41%. From the confusion matrix (Fig. 7), it can be said that the accuracy is not optimal as the TPs and TNs are not high in number.

Accuracy on the testing set is: 67.41%

	precision	recall	f1-score	support
-1	0.64	0.62	0.63	47
0	0.63	0.72	0.67	40
1	0.75	0.69	0.72	48
accuracy			0.67	135
macro avg	0.67	0.68	0.67	135
weighted avg	0.68	0.67	0.67	135

Fig. 6. Random Forest Classification report

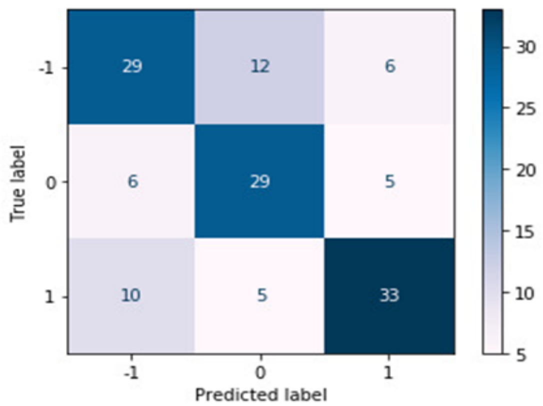

Fig. 7. Random forest confusion matrix

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The evaluation metrics for SVM (Fig. 8 and Fig. 9) is given below. It can be observed from the classification report (Fig. 8) that SVM model gives a higher accuracy of 80.741% comparatively. This is because of higher TPs and TNs than FPs and FNs as seen in the confusion matrix (Fig. 9).

```
Accuracy on the testing set is: 80.741%
              precision    recall  f1-score   support

          -1       0.80      0.74      0.77        47
           0       0.77      0.82      0.80        40
           1       0.85      0.85      0.85        48

    accuracy                           0.81       135
   macro avg       0.81      0.81      0.81       135
weighted avg       0.81      0.81      0.81       135
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Fig. 8. SVM Classification Report

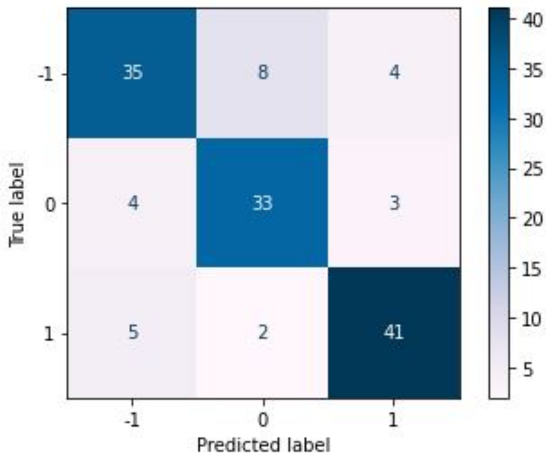

Fig. 9. SVM confusion matrix

4.4. Discussion

Classification using Random Forest demands a significant amount of processing power and resources, as it involves the construction of multiple trees to integrate their output, and hyperparameter tuning is time ordering. In addition, the system fails to determine the importance of each variable. On the other hand, when hyperparameter tuning was applied on SVM model, the performance of the model increased.

5. Applications

In the very near future, emotion recognition will play a role in a wide range of applications, including the following:

a. Decision-making systems: Making decisions based on emotion detection and classification can be an essential tool in the future.
b. Identifying actual feelings and stress levels: It is challenging to analyze one's real emotions while conversing with them. If people knew how the person feels, conversation would be different.
c. Learning human emotions: Robots are usually devoid of human emotions. If it could understand and learn human emotions, there would be a tremendous change in its work and technological advancement.

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d. Crime and Justice Departments: It could be used for lying detection in crime and justice departments
e. Depressive disorders: Therapists can treat patients suffering from depressive disorders as well.

6. Conclusion

Emotions were classified by decomposing pre-processed EEG signals of the SEED dataset into the delta, theta, alpha, beta, and gamma frequency bands, respectively, during feature extraction. Followed by this, the Principal Component Analysis (PCA) method was performed for feature reduction. Lastly, the dataset on two types of classification models, namely Random Forest and Support vector machine, was tested. The random forest model gave an accuracy of about 67.4%, whereas the Support vector machine (SVM) model's accuracy was 80.74%. Hence, it can be concluded that SVM is the most suitable model for classifying emotions from EEG signals. It is important to note that different types of wavelets transform (like db6, db5, etc.) were tested, and hyperparameter tuning of classification models was done to obtain optimal accuracy.

From a technological standpoint, as computer simulation advances, new algorithms with improved performance and shorter operating times, such as pre-processing and deep learning models, will be created over time. Furthermore, while the SVM model in the proposed framework presently works well, models with better learning capabilities and classification accuracy will be replaced in the future. To preserve the framework's competitiveness over time, it must be adjusted and maintained regularly, and more advanced algorithms and technologies should be used to upgrade it constantly. Researchers can strive to improve the model in the future to produce a more standard emotion classification system.

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