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EEG-BASED EMOTION RECOGNITION USING ENSEMBLE LEARNING MODEL

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Abstract: Throughout history, emotion recognition has played a pivotal role across various fields. Due to technology limitation, emotions were traditionally evaluated through interviews or questionnaires, methods prone to subjectivity even among psychologists. Hence, development of automated emotion recognition system is necessary. In recent years, prodigious process has been made in this area, with EEG-based emotion recognition becoming increasingly popular. However, the models that used to classify the EEG-based emotion data are still not powerful enough. In this paper, we propose an efficient model for emotion classification, utilizing EEG data from DEAP dataset. The neural signals are first decomposed into the Gamma, Alpha, Beta, and Theta bands according to their respective frequencies, and preprocessed using Welch method. A hybrid model, combining Long Short-Term Memory (LSTM), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Linear Discriminant Analysis (LDA), is employed for classification. This hybrid model distinguishes among three emotional states: positive, negative, and neutral. Compared to existing work, our ensemble learning model achieves a higher accuracy, performs with 95.99% and 95.68% for arousal and valence. Furthermore, our method successfully mitigates the weaknesses of these individual base models, bringing in a more robust emotion recognition framework.
Keywords: EEG; Emotion recognition; Ensemble model; Machine learning; Long-Short Term Memory

1 INTRODUCTION

Emotions play a pivotal role in shaping human behavior and cognition, largely governed by the brain neural activities. Thus, understanding the connection between emotions and brain signals has gained increasing attention[1-4].This research area has found applications in various fields, such as human-computer interaction (HCI) systems[5-9], and medical domains, including the diagnosis of conditions like autism spectrum disorder (ASD) and depression[10-14]. Among the many approaches to studying emotions, EEG-based emotion recognition has emerged as a focal point for researchers. Investigating this relationship is vital for advancements in Artificial Intelligence and Ambient Intelligence[15-16]. The rapid evolution of brain-device interface technology highlights the importance of this area[17-21].

A crucial step in EEG-based emotion recognition is feature extraction. Yoon and Chung[22] employed Fast Fourier Transform (FFT) to extract features from EEG signals in the DEAP dataset. While FFT is useful for frequency analysis, it may overlook important time-domain information. Bhardwaj et al.[23] used Independent Component Analysis (ICA) to decompose EEG signals into five bands, but ICA can be sensitive to noise, which may affect signal accuracy. Alhagy et al.[24] focused on specific frequency bands (theta, alpha, beta) for feature extraction, but limiting the analysis to only a few bands might omit valuable data from other frequencies. Bazgir et al.[25] applied the Average Mean Reference (AMR) method for noise reduction, though it could also remove some signal information along with the noise. Atkinson and Campos[26] used Maximum-Relevance (mRMR) for feature selection, enhancing relevant features but potentially excluding others that might still be useful. Liu et al.[27] extracted features from multiple domains, offering comprehensive analysis but adding computational complexity. Naser and Saha[28] employed advanced techniques like DT-CWPT and SVD for feature selection, though these methods may be computationally intensive. Bhagwat and Paithane[29] utilized Wavelet Transform, which is effective but can be limited by the choice of wavelet function.

Once features are extracted, classification plays a crucial role in emotion recognition. In their work, Bhardwaj et al.[23] used SVM and LDA classifiers on preprocessed data, achieving moderate accuracies. Liu et al.[27] opted for KNN and Random Forest classifiers, refining their models to achieve good results, though they required adjustments for broader applications. Naser and Saha[28] employed SVM as their classifier, which, while effective for feature selection, did not provide the complexity needed for higher accuracy. Alhagy et al.[24] employed a Long Short-Term Memory (LSTM) network with multiple layers, including Dropout and Dense layers, to classify the EEG data into arousal, valence, and liking classes. Despite their relatively high accuracies of around 85%, improvements were still necessary for better generalization. Bazgir et al.[25] used SVM, KNN, and Artificial Neural Network (ANN) models, with SVM incorporating a Radial Basis Function (RBF) kernel and KNN using different nearest neighbors, resulting in accuracies exceeding 90%. However, further refinement was required in certain channels. Iyer et al.[30] introduced a hybrid approach combining Convolutional Neural Networks (CNNs) and LSTMs, achieving a remarkable 97.16% accuracy. Nevertheless, their model was computationally expensive, especially when applied to small datasets.

Considering the challenges in both feature extraction and classification, this paper proposes a novel method that combines Welch’s method for feature extraction with an ensemble model for classification. Welch's method effectively captures frequency-domain information while reducing noise, making it well-suited for EEG signal analysis. Our ensemble model ,combining LSTM, SVM, LDA, and KNN, is tested on the DEAP dataset, divided into four frequency bands: theta (4-8Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-64 Hz). This ensemble model, leverages the strengths of each classifier: LSTM excels at handling time-series data, while SVM and LDA are effective for binary classification tasks, and KNN is simple yet powerful for pattern recognition. The ensemble method improves robustness and generalization, making the model adaptable to both simple and complex datasets, providing a more robust approach to EEG-based emotion classification.

This paper is organized as follows: Section II introduces the dataset and the ensemble learning-based emotion recognition framework, along with the improvements made to these methods. Section III discusses the pre-processing, visualization, and decoding results using the DEAP dataset, followed by a comparison of our ensemble model with others. The conclusion is presented in Section IV (Figure 1). The whole process for creating the ensemble model can be divided into five parts, including data acquisition, data preprocessing, feature extraction, Ensemble Learning, and Emotion Prediction.

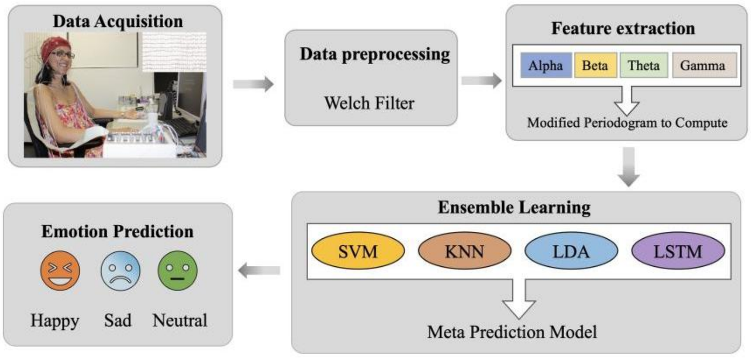

Figure 1 Structure of the Paper

2 METHODS

2.1 Dataset

We used data from the DEAP dataset, which was recorded when 32 participants watched 40 music videos. Each video lasted one minute. The participants were aged between 19 and 32,with 16 males and 16 females. The dataset recorded the emotional changes of each participant while watching these videos and rated the videos according to four aspects: arousal, valence, dominance, and liking. Each file contains data, including 40 trials and 40 channels, and a label array, which contains 4 trials and 4 subjective ratings. The sampling frequency was downsampled to 128Hz. The data was preprocessed according to these labels.

2.2 Ensemble Learning-Based Emotion Recognition Framework

We proposed an EEG-based emotion recognition architecture that employs ensemble learning model as illustrated in Figure 1. The EEG data were sourced from the DEAP dataset, where participants' signals were recorded and preprocessed while they watched short video clips. After preprocessing, features were extracted and periodograms were adjusted for further analysis. The extracted features were then used to train the LDA, SVM, LSTM, and KNN models. Based on the outputs from these models, emotion predictions were generated.

2.1.1 Data preprocessing and feature extraction

EEG signals have four different frequency bands: theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-64 Hz), which are commonly analyzed in the emotion recognition field. We use the Welch method to estimate the power spectrum features based on the preprocessed data.

In the Welch method, we first decompose the signal into several blocks based on their ranges and calculate the periodogram of each block. Then, we estimate the power spectra by averaging the periodograms of the blocks. The formula for the Welch method is shown below:

$$\hat{S}_x \triangleq \frac{1}{K}\sum_{m=0}^{k-1}\left[\frac{1}{L}|FFT(x_n)|^2\right] \tag{1}$$

We decompose the signal into n continuous blocks.x_n represents each block. K is the total number of blocks in the signal. And L represents the total number of points in these signals. Both the 32 channels in the DEAP dataset and the four EEG bands result in 128 power features. After the preprocess, our result in each band is plotted as an image that show in the result part.

2.1.2 Ensemble learning model

Machine learning has become a crucial component in the study of emotions due to its strong capability in model training and solving computational intelligence problems. Among the various techniques available, ensemble models stand out as they enhance model performance through different strategies. Three of the most widely used ensemble learning methods are Boosting, Bagging, and Stacking.

In this paper, we focus on Stacking, also known as stacked generalization, which is considered one of the most effective ensemble modeling techniques. Stacking improves predictions by combining the outputs of multiple base models—in our case, SVM, LSTM, KNN, and LDA—to generate a more accurate final prediction. All sub-models contribute equally, which is why the technique is referred to as "stacking." The diagram illustrates the architecture of our stacking model as shown in Figure 2 (The base models are LSTM, KNN, SVM, and LDA, by putting the labels of these models in to the Ensemble Model, we successfully increasing the accuracy of emotion recognition). We utilize LSTM, SVM, LDA, and KNN as base models, whose predictions are then combined to form the ensemble, which ultimately produces the final prediction.

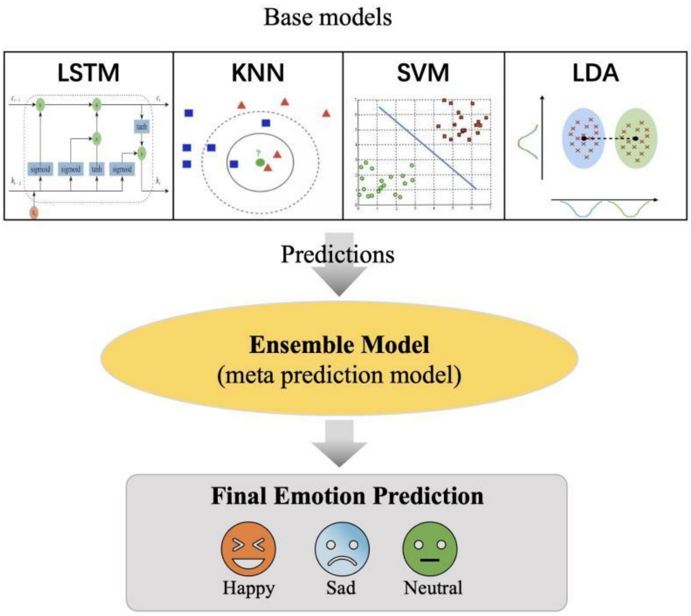

Figure 2 Structure of the Ensemble Model

2.3 Classification Algorithms

2.3.1 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a technique that uses statistics and machine learning to find the linear combination of features that best separates two or more classes of objects. The resulting combination is often used for dimensionality reduction. As a classic linear learning method, LDA projects of the same kind of samples closed to each other and far from other classes in a given training set. The targets for using LDA are to minimize intra-class covariance(make similar projection points as close as possible) and maximize inter-class covariance(keep the Heterogeneous projection points as far as possible). For a given data set $D = \{(x_i, y_i)\}_{i=1}^{m}, y_i \in \{0,1\}$, the objective function is shown as:

$$J = \frac{\|w^T\mu_0 - w^T\mu_1\|_2^2}{w^T\sum_0 w + w^T\sum_1 w} = \frac{w^T(\mu_0-\mu_1)(\mu_0-\mu_1)^T w}{w^T(\Sigma_0+\Sigma_1)w} \tag{2}$$

Where X_i, μ_i, Σ_i represent the collection of the samples that belong to $i \in \{0,1\}$, mean vector, and covariance matrix. If projecting the data onto the line w, the projection of the centers of these two kinds of samples are $w^T\mu_0$ and $w^T\mu_1$.

2.3.2 Support Vector Machines (SVM)

Support Vector Machines (SVM) are generalized linear classifier used to infer a function or relationship from data through supervised learning. It can find the hyperplane that best separate the data into different classes and maximize the margin between the classes. this hyperplane is defined as follows:

$$\min_{w,b} \frac{1}{2}\|w\|^2, \text{s.t.}, y_i(wx_i + b) \geq 1 \tag{3}$$

Where (x, y) represents the coordinates of these points, w, b denotes the vector and bias.

In this way, data were separated into two parts. SVMs are commonly applied in pattern recognition, classification and regression analysis. This supervised learning algorithm can successfully separate these two classes when a set of data that consist of two different classes is provided.

2.3.3 K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a simple yet effective machine learning algorithm used to recognize and classify unknown objects. It excels at classifying objects with a large sample size. The result of KNN is determined by the class of one or more samples closest to the unknown samples. The ‘k’ in KNN represents the number of the closest neighbors considered when making a classification decision. however, it can be computationally intensive with large datasets, as it requires calculating the distance between the unknown sample and all the existing samples in the dataset.

In order to use KNN model for classifying data, we need to determine the distance between two instance points in a feature space. Given the dataset $x_i = \left(x_i^{(1)}, x_i^{(2)}, \cdots, x_i^{(n)}\right)^T$ and $x_j = \left(x_j^{(1)}, x_j^{(2)}, \cdots, x_j^{(n)}\right)^T$, the formula of the distance L_p is defined as:

$$L_p(x_i, x_j) = \left(\sum_{l=1}^{n} \left|x_i^{(l)} - x_j^{(l)}\right|^p\right)^{\frac{1}{p}} \tag{4}$$

Where x_i and x_j represent the two points in feature space X.

2.3.4 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a method that is created in order to solve the long-term dependence problem in Recurrent Neural Network (RNN). In LSTM model, issue of vanishing/exploding can be overcome. LSTM commonly consists of input gates, forget gates, memory cells and output gates.

$$i_t = \sigma(W_i[x_t, h_{t-1}] + b_i) \tag{5}$$

$$f_t = \sigma(W_f[x_t, h_{t-1}] + b_f) \tag{6}$$

$$o_t = \sigma(W_o[x_t, h_{t-1}] + b_o) \tag{7}$$

Where i_t means the input gate is open or close,f_t represents the state of the forget gate, o_t represents the state of the forget gate. x_t is the value of the data, h_t represents the hidden state of the memory cell, W and b are weights and biases, respectively, and σ means the sigmoid function.

The sigmoid activation function in the input gates decide which information is important and in the output gates choose the information that should be output. The tanh activation function produces new information and process information for output in input and output shapes. Forget gates, only have sigmoid activation functions and decide which information should be removed.

We also need to compute the state of the memory cell. The formula of the cell's state c_t is

$$c_t = f_t c_{t-1} + i_t c_t^{'} \tag{8}$$

$$c_t^{'} = \tanh(W_c[x_t, h_{t-1}] + b_c) \tag{9}$$

$$h_t = o_t \cdot \tanh\,(c_t) \tag{10}$$

Where $c_t^{'}$ is the status of candidate cell and h_t represents the hidden state of the cell.

3 RESULT

In this section, we will first visualize the DEAP dataset data in terms of valence and arousal, and explain the process of label generation. Next, we will use Welch's filter to calculate the power spectrum for each frequency band to facilitate further analysis. Finally, we will present and compare the classification results obtained with individual algorithms and the ensemble learning model, focusing on decoding accuracy.

First, we visualize the structure of the DEAP dataset. EEG and peripheral physiological signals were recorded from 32 participants as they watched 40 music videos each. Participants rated each video based on four subjective dimensions: arousal, valence, dominance, and liking. The data was downsampled to 128Hz, preprocessed, and stored in pickled Python formats. Each participant's file contains two arrays: a "data" array (40 trials x 40 channels x 8064 data points) and a "label" array (40 trials x 4 ratings: valence, arousal, dominance, and liking). We combined the data files into two new arrays, resulting in 880 trials for all 32 participants.

Valence represents the degree of positivity or negativity of an emotion, while arousal indicates the intensity of the emotional state. We plot the first 40 trials of one subject, as shown in Figure 3, where the x-axis represents trial numbers and the y-axis shows intensity. The plot reveals that the combinations of valence and arousal can be categorized into four emotional states: High Arousal Positive Valence (Excited, Happy), Low Arousal Positive Valence (Calm, Relaxed), High Arousal Negative Valence (Angry, Nervous), and Low Arousal Negative Valence (Sad, Bored). Based on these distributions, we generate box plots to visualize the four emotional classes under the conditions of valence and arousal as shown in Figure 3.

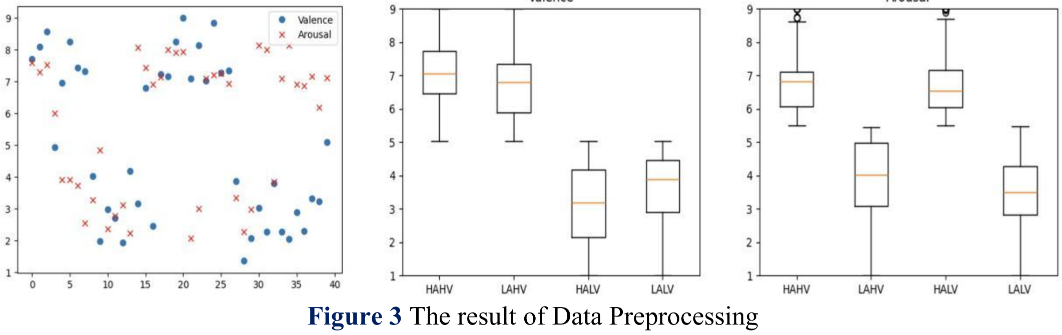

Figure 3 The result of Data Preprocessing

Next, we use Welch's method to extract the band power from each channel, as illustrated in Figure 4. The x-axis represents frequency, while the y-axis denotes power spectral density. The curve shows the distribution of power spectral density across different frequencies. The shaded areas—blue, yellow, green, and red—represent the theta, alpha, beta, and gamma bands, respectively. We observe that the power spectral densities in the theta and alpha bands are generally higher compared to the beta and gamma bands. From the chart, it is evident that the trends in the theta and alpha bands are not straightforward, showing neither a consistent increase nor decrease, with notable fluctuations in density. In contrast, the data in the beta and gamma bands display a more discernible diminishing trend.

During preprocessing, we also generated topomaps for each frequency band at different time points. Each row corresponds to a specific band, while each column represents a different time stamp (Figure 4). The most noticeable changes occur in the Theta and Alpha bands, whereas the Beta and Gamma bands show less variation over time. This observation aligns with the results from Welch's periodogram, where we also see significant fluctuations in the Alpha and Theta bands, and more consistent patterns in the Beta and Gamma bands.

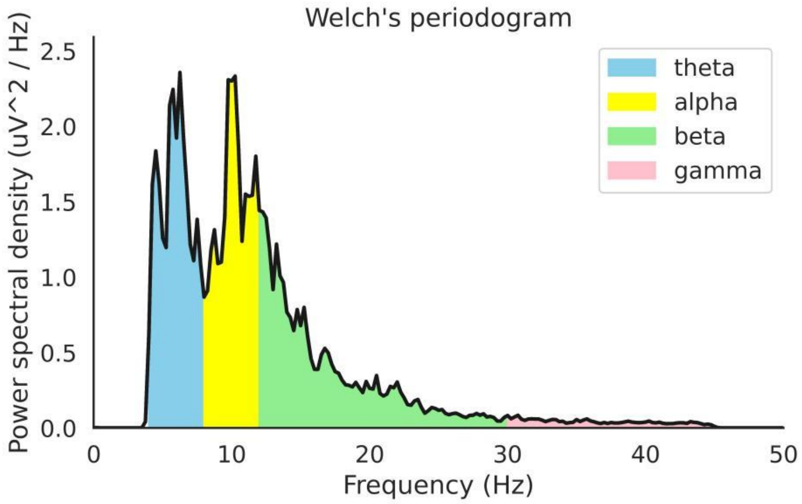

Figure 4 Frequency Distribution across Different Data Bands after Feature Extraction, Distinct Colors are used to Visualize Differences among Bands more Clearly

After the preprocessing, we used individual algorithms (SVM, KNN, LSTM, and LDA) to classify the preprocessed data. The data was shuffled five times with different initializations, with 70% used for training, 10% for evaluation, and the remaining 20% for testing. For SVM, a simple linear kernel was applied. In KNN, the number of neighbors was set to 5. For LDA, the SVD solver was employed. The LSTM model used the standard LSTM formulation, with logistic functions on the gates and hyperbolic tangents for activations. The input size was 10752*32, and the model included two LSTM layers with dropout (rate = 0.5) between them. The Adam optimizer was used, with a learning rate of 0.0001. The classification accuracies for valence and arousal using these methods are shown in the table. For SVM, the highest accuracy for arousal was 61.79%. LDA achieved an optimum accuracy of 60.16%. KNN reached 69.11% accuracy for valence. The LSTM classifier performed the best, with 83.66% accuracy for arousal in the beta band and 84.77% for valence in the theta band and the we also printed the training loss of LSTM (Figure 5). After evaluating all the single algorithm, we applied an ensemble model to further improve classification accuracy. The base models (SVM, KNN, LSTM, and LDA) first produced emotion predictions, which were then used as inputs for the ensemble model. Specifically, we combined the outputs of these four individual models into a new input vector, and fed it into a meta-model, which in this case was a logistic regression model. This meta-model integrated the predictions from the base models to generate the final output.

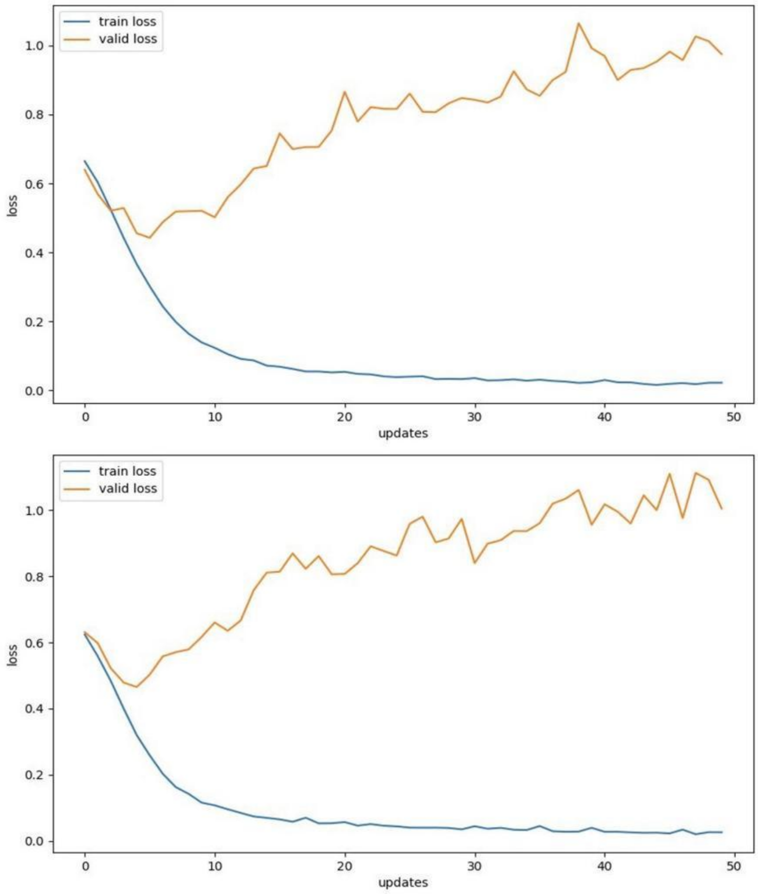

Figure 5 The Picture at the Top is the Train Loss of LSTM for Valence and the Picture at the Bottom is the Train Loss for Arousal

The performance of the ensemble model is shown below in Table 1. Compared to other researchers, our model achieves higher accuracy. The overall accuracy of SVM and LDA in Bhardwaj et al.[23]'s research are 74.13% and 66.50% and lower than the accuracies of our ensemble Model, which are 95.68% and 95.99%.Similarly, our results are also better than the accuracies in Nawaz et al.[7]'s work, which are 77.62% and 78.96% for valence and arousal. Compared to the individual models, the ensemble method also demonstrated superior accuracy. The accuracies of the ensemble model are fully deserved the best among these models since it achieved 95.68% accuracy of valence and 95.99% accuracy of arousal which are the highest accuracies for valence and arousal. By leveraging the strengths of each base model, the ensemble was able to better capture the complexity of the data, leading to improved classification results for both valence and arousal across all frequency bands. This highlights the effectiveness of ensemble learning in emotion recognition tasks, as it mitigates the limitations of single models and provides more robust predictions.

Table 1 The results of the Ensemble Model Compared to Other Base Models

Method	Valence	Arousal
LSTM	84.77	83.66
KNN	69.11	64.23
SVM	60.16	61.79
LDA	58.54	60.16
Ensemble Model	95.68	95.99

4 CONCLUSION

Emotion recognition has gained significant attention in recent years due to its applications in human-computer interaction and mental health analysis.In this study, we aimed to find a method that is both efficient and practical for emotion recognition using EEG signals. The results demonstrate the potential of EEG-based approaches for accurate emotion classification. We first divided the DEAP dataset into four frequency bands—Theta, Alpha, Beta, and Gamma—and used Welch's method for preprocessing. Then, we proposed a hybrid model that integrates SVM, KNN, LDA, and LSTM to classify emotions into positive, negative, and neutral categories. Among the base models, SVM outperformed LDA and KNN, with LSTM achieving the highest accuracy of 90%. Additionally, the average accuracy of LSTM across all trials was noteworthy. The hybrid model further improved classification performance, outperforming individual classifiers and providing a more accurate and robust framework.

One of the key advantages of the hybrid model is its ability to mitigate the limitations of individual algorithms. For instance, SVM can be sensitive to irrelevant data, while LSTM and KNN face challenges related to data complexity. By combining the strengths of each model, the hybrid approach compensates for these weaknesses, resulting in more reliable predictions.

However, despite these promising results, there are several areas for improvement in future work. One potential enhancement involves diversifying the emotion stimuli. Currently, most datasets, including DEAP, rely on pictures or short videos to evoke emotions. Future studies could explore alternative stimuli, such as text or speech, which may elicit more nuanced emotional responses in certain contexts.

Another improvement lies in the feature extraction process. Although Welch's method proved effective for our data, more advanced and sophisticated techniques may lead to better results, particularly with complex datasets.

Finally, the biggest challenge remains applying this technology in real-world scenarios. While EEG-based emotion recognition has made significant strides, it is still in the experimental phase. Real-world applications face hurdles such as inefficient classifiers and noise from external factors, which complicate real-time analysis. Overcoming these obstacles is crucial for transitioning from experimental results to practical, real-world implementations of emotion recognition systems.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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