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Emotion recognition from EEG signal data of the brain using bidirectional long short-term memory

Markapudi Sowmya*, Pothuri Surendra Varma and Katarapu Deepika
Department of Computer Science and Engineering, Velagapudi Ramakrishna Siddhartha Engineering College, Vijayawada

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Abstract
This study aimed to develop an emotion recognition model using brain signals. The brain computer interface (BCI) focuses on creating technology that enables direct brain-to-external device connections. There are two forms of BCI: invasive and non-invasive. In BCI, electroencephalography (EEG) is essential. EEG is a non-invasive method that involves applying electrodes to the scalp to capture electrical activity in the brain. EEG data is utilized to decode the user's intended emotions, activities, and thoughts. Emotions are important for human interaction, communication, and overall well-being. Many paralyzed people worldwide are unable to express their emotions or meet their needs, making it difficult to understand them, which leads to feelings of isolation. However, it is possible to detect emotions using BCI. Emotions are reflected in electrical brain activity and can be analyzed using EEG signals. The EEG signals are then decoded to detect a person's respective emotions. The decoding process mainly includes three steps. First, the signals are pre-processed to remove noise, and data is encoded. Second, the relevant features are extracted using the spectral power method. Third, emotions are classified using long short-term memory (LSTM), gated recurrent unit (GRU), and bidirectional long short-term memory (BiLSTM) algorithms. New EEG data is given to the model, and then emotions are displayed. The model developed using BiLSTM achieved an accuracy of 93.97%. A comparison was made with existing classification techniques that have used many three-dimensional (3D) models and the arousal-valence ratio to identify a person's emotion. The model's generalization will improve further by testing it on different types of datasets. The model's generalization improves further by testing it on different types of datasets.

Keywords
EEG data, Brain computer interface, Pre-processing, Classification, Spectral power, BiLSTM, Emotions.

1.Introduction
Emotions play a huge role when a person want to express something [1]. However, some people are not able to express their emotions. Therefore, in such cases, emotion recognition methods are used to detect emotions [2]. Emotion recognition can be done in many ways, using speech [3], facial expressions of the person [4], and heart rate of the person [5]. While using facial expressions to detect the emotions, one can easily fake the emotions. Even using the heart signals to detect emotions, fake emotions are detected sometimes. In addition to the first two methods, there is another way in which signals from the brain are directly used to detect a person's emotions, as explained in the research by Liu et al. [6].

This process falls under the domain of brain computer interface (BCI) [7, 8], utilizing electroencephalography (EEG) [9] signals for emotion detection.

Many research questions require exploration while considering BCI, such as how paralysis affects communication. Longo et al. [10] explained BCI and its relation to paralysis. Can a person who is paralyzed completely does have healthy brain function? Sensors can track specific physiological events within the brain, which correspond to particular types of brain function, and allow for direct communication with the human brain [11]. Using these technologies, researchers have developed BCI, enabling the creation of communication systems independent of the brain's conventional output channels, such as muscles and peripheral nerves. Vansteensel et al. [12] elucidated how BCI aids in communication. Instead, users

*Author for correspondence

actively manipulate the parts of their brain capable of operating computers or communication gadgets.

1.1Brain computer interface

The history of BCI and EEG traces back to the early 20th century when researchers first began studying electrical activity in the brain. In 1924, Hans Berger recorded the first human EEG, laying the foundation for understanding brainwave patterns [13]. BCI development gained momentum in the late 20th century with advances in computing and neuroscience, leading to applications in medicine, communication, and gaming. EEG, as a non-invasive method to measure brain activity, became pivotal in BCI research due to its accessibility and versatility. Over time, BCI and EEG have evolved with technological advancements, fostering interdisciplinary collaborations and innovations that continue to explore the potential of direct brain-computer communication for various practical and therapeutic purposes.

BCI establishes an intimate connection with the human brain and an external entity, such as a machine or a prosthetic limb, as described by Khan et al. [14]. Bridging the gap between the brain and technology, BCIs enable the transfer of information in both directions, allowing individuals to control devices with their thoughts or receive sensory feedback directly into their brains [15]. Using an array of sensors or implants, BCIs detect and interpret electrical signals or neural activity generated by the brain. These signals are translated into commands, data that can be understood by the connected device [16]. This is another application of BCI where data collected is decoded as explained by Song et al. [17]. This novel interface has enormous promise for a wide range of applications, including supporting persons with impairments in recovering movement and independence, increasing human capacities, and opening up new possibilities for scientific inquiry some others are explained by Mak et al. [18].

Marcia et al. explained in their study that there are two types of BCI, invasive BCIs and non-invasive BCIs [19]. Electrodes or sensor arrays are inserted right into brain cells in invasive BCIs [20]. These electrodes record neural activity with high precision and signal quality. Invasive BCIs typically used for research purposes. In cases where high-level control or fine-grained signal detection is required. However, due to the invasive nature of the procedure, they are less commonly used in clinical applications. Non-invasive BCI [21] uses different signals collected from the brain. They are EEG BCIs, functional near-infrared spectroscopy (FNIRS) BCIs [22], and magnetoencephalography (MEG) BCIs [23]. This study focuses on EEG data.

1.2Electroencephalography

EEG data is gathered by placing electrodes on the scalp to detect and measure brain electrical activity. Al-nafjan et al. [24] explored the use of EEG data within BCI. Standardized electrode placement systems, such as the worldwide 10-20 or 10-10 system, are commonly used. These systems make electrode placement suggestions based on anatomical landmarks on the scalp. When the electrodes are implanted, they detect the electrical impulses produced by the neurons in the brain. Then to amplify, digitize, and record these impulses, an EEG amplifier is employed. The information results in a temporal series of voltage readings representing the electrical activity at each electrode site.

Extracting emotions from the brain signals is very hard. Zhang et al. [25] and Wei et al. [26] emphasized the necessity of incorporating a significantly large set of features into the BCI model to achieve enhanced accuracy. Mutawa and Hassouneh [27] mentioned some other challenges including complexity and generalizability. In this paper, a model was developed for overcoming challenges and helping paralyzed persons to express their real emotions. The main objective of this paper is to develop an architecture that identifies the inner emotions of a person using EEG signals. The system leverages both software and hardware components, focusing on preprocessing, feature extraction, and classification using neural network models like bidirectional long short-term memory (BiLSTM). The aim is to create a highly accurate model that can classify emotions based on EEG data, with a particular focus on improving the model's generalization.

The rest of the paper is organized as follows: literature review is discussed in Section 2. Section 3 covers the methods used and the dataset for experimentation. Results are illustrated in Section 4. It is illustrated in Section 5. Finally, conclusions are presented in Section 6.

2.Literature review

There are a variety of applications related to our study that vary in terms of methodology and instrumentation. Some also differ in terms of the mechanism employed to forecast emotions. In all applications, two main approaches are used: one involves using valence arousal rating, and the other involves using EEG data. To tackle the problem of long-term dependencies, Wei et al. [28] introduced simple recurrent networks (SRN). SRN was employed in this process to manage temporal dependencies, which involve considering how expressions change over time. The original signal underwent dissection through the dual tree complex wavelet transform (DTCWT). Subsequently, time, frequency, and nonlinear analyses were applied to extract its characteristics. Then ensemble learning is used to classify emotions. The accuracy achieved for this model is 75. They used the EEG dataset in their work.

Pandey and Seeja [29] introduced a study where they presented a subject utilizing EEG data independent of individual variation. Feature extraction using the variational mode decomposition (VMD) approach, deep neural networks are employed to classify an individual's emotions. The classification of emotions was based on dimensions. Emotions are expressed in the dimensional model along several dimensions, including valence, arousal, dominance, and liking/disliking. The individuals are asked to score their feelings on valence and arousal ratings before EEG recording. The accuracy achieved for this model is 62. In their investigation, they used the dataset for emotion analysis using physiological signals (DEAP) dataset.

Li et al. [30] devised a model addressing individual differences by combining a meta-transfer learning (MTL) technique with a multiscale residual network (MSRN). The MSRN served to categorize emotions and illustrate EEG data connectivity aspects. Employing the MTL approach involved training on one dataset and testing on another. The valence ratio was utilized for emotion categorization, yielding an accuracy of 72 for this model. They conducted testing on the sjtu emotion EEG dataset (SEED) dataset and training on the DEAP dataset.

A method of emotion identification based on inter-subject variability was proposed by Peng et al. [31] using time-frequency analysis methods like wavelet transform and spectrogram analysis, a collection of characteristics taken from each epoch of EEG data. A combined feature adaption strategy lessens the domain disparity between the training and testing data. The disparity is reduced by learning a mapping function that changes the training data's characteristics to resemble the testing data. The graph was constructed to model the relationships between the epochs of EEG signals. The label of each epoch is updated based on the labels of its neighboring epochs in the graph. Lastly, emotions are classified. They built their model using the SEED-IV dataset.

Bano et al. [32] developed a system that uses time-domain analysis and statistical measures to extract relevant characteristics from the EEG signals. A support vector machine (SVM) classifier is used to classify the user's emotional states. The experiments conducted in the study show promising results in identifying four different emotional states. The accuracy achieved for this model is 80. Categorical emotions are classified using the SVM model. In this paper, they made use of the EEG dataset.

Tao et al. [33] propose a novel EEG-based emotion identification system that enhances accuracy by utilizing channel-wise attention and self-attention strategies. System three components are feature extraction and methods mentioned. Utilizing publicly accessible data, the authors conducted studies and outperformed cutting-edge techniques with an accuracy of 80.05. The article offers a thorough examination of how each component affects the system's overall effectiveness. The suggested technology may have useful applications in situations seen in the actual world. They used data from the DEAP project.

Salankar et al. [34] proposed and investigated the empirical mode decomposition (EMD) approach and its second-order difference plots (SODP) for categorizing emotions in the quadrants of high and low arousal and dominance. Using SVM, there are two hidden layers, a multilayer perceptron is used to categorize emotions into binary and many classes according to their valence, arousal, dominance, and liking. This model's accuracy score is 80 percent. The DEAP dataset was used by them.

Wang et al. propose a method utilizing electrode-frequency distribution maps (EFDMs) derived from short-time Fourier transform for simplifying EEG signal representation [35]. Their approach involves automatic feature extraction from EFDMs and leveraging deep convolutional neural networks (CNN), particularly those with residual block architectures, to enhance emotion classification accuracy. They recommend transfer learning techniques to generalize models across datasets, addressing limitations associated with limited EEG datasets and individual variability in emotions. Experimental evaluations on SEED and DEAP datasets demonstrate notable performance improvements. Additionally, visualization methods like gradient-weighted class activation mapping offer insights into learned features, aiding in understanding EEG-based emotion identification. However, challenges may arise regarding the interpretability of learned features and the scalability of the approach to larger datasets.

Dharia et al. discuss the significance of emotion regulation, particularly for elderly individuals with frontal lobe atrophy, proposing EEG-based emotion identification [36]. They introduce a multimodal deep learning approach integrating EEG and eye movement data, incorporating an attention mechanism layer to fuse features from both modalities. Testing on SEED-IV and SEED-V datasets yields average accuracies of 67.3% and 72.3%, respectively. The study's implications for evaluating emotional regulation in clinical and research contexts, particularly concerning age-related cognitive changes, highlight the potential of multimodal deep-learning models for subject-independent emotion identification. However, challenges may arise in interpreting the combined features and addressing data variability across different age groups and clinical conditions.

Farokhah et al. propose a cooperative strategy for EEG-based emotion identification, integrating CNN, power spectral density-based channel selection, and two-dimensional (2D) EEG scalograms to mitigate cross-subject validation challenges and computational complexity [37]. Experimental findings on the DEAP dataset demonstrate improved emotion detection accuracy, particularly in cross-subject validation settings. The method offers advantages in enhancing emotion recognition accuracy while reducing computational overhead. However, limitations may arise in generalizing the approach across diverse datasets and experimental conditions, necessitating further research for comprehensive validation.

Hwang et al. introduce a method for EEG-based emotion identification, utilizing a multi-task deep neural network to address subject-dependency issues [38]. Their approach categorizes subject-independent emotional labels and prevents model differentiation between subject labels through adversarial learning with three modules: adversarial, subject classification, and emotion classification. By applying a randomization function to confound subject labels, the model is trained to generalize across different subjects. Evaluation of the SEED dataset demonstrates improved performance, with an average accuracy of 75.31% and a low standard deviation of 7.33%. Advantages include enhanced performance in EEG-based emotion identification, while limitations may arise in generalizing the method to diverse datasets and experimental conditions, warranting further investigation.

Dhara et al. present a novel fuzzy ensemble-based deep learning method to address challenges in EEG-based emotion identification [39]. Their approach incorporates the Gompertz function with three deep learning models to a fuzzy rank-based technique. Evaluation of the DEAP and AMIGOS datasets reveals high accuracy in valence and arousal dimensions, surpassing 80% on DEAP and attaining state-of-the-art performance on AMIGOS. The method showcases strong performance in subject-dependent and subject-independent configurations, indicating its utility for EEG-based emotion recognition. However, limitations may include potential overfitting due to the complexity of the ensemble model, and further research is warranted to explore its generalizability to other datasets and experimental settings.

Keelawat et al. introduce a CNN-based methodology for EEG-based emotion identification during music listening, aiming for subject-independent performance [40]. They evaluate various CNN architectures for binary classification tasks related to arousal and valence without explicit feature extraction, utilizing information from electrodes and time steps. Through 10-fold cross-validation, promising accuracy rates of 81.54% for arousal and 86.87% for valence are achieved, indicating the model's capacity to capture EEG signal patterns across individuals. The model exhibits superior generalization compared to previous techniques, as demonstrated by leave-one-subject-out validation, suggesting its potential for subject-independent emotion identification during music listening. However, potential limitations may include the need for further validation across diverse music genres and populations to ensure robustness and generalizability.

Kanuboyina et al. present a deep learning-based technique for automated emotion state categorization using EEG data, addressing previous methodological limitations [41]. They preprocess EEG signals from real-time and DEAP databases to eliminate noise and utilize differential entropy (DE) and power spectral density methods for meaningful information extraction. Feature reduction and emotion state categorization are conducted via principal component analysis and artificial neural networks. Experimental findings reveal superior accuracy compared to standard SVM on both datasets, showcasing the method's effectiveness in EEG-based emotion state categorization. While advantageous for its enhanced performance, potential limitations may include the need for further validation across diverse datasets and experimental conditions to ensure robustness and generalizability.

Hancer and Subasi proposed an EEG-based framework for emotion identification, consisting of preprocessing, feature extraction, feature selection, and classification phases [42]. Utilizing DTCWT for feature extraction and multi-scale principal component analysis with sysmlets-4 filtering for preprocessing, the method employs various statistical criteria for feature dimension reduction and ensemble classifiers for classification. The framework demonstrates promising results in accurately recognizing emotions from EEG data. However, its effectiveness may be influenced by the choice of statistical criteria and ensemble classifiers, necessitating careful selection and validation. Additionally, further research is needed to assess its performance across diverse datasets and experimental conditions to ensure its robustness and generalizability in real-world applications.

Sharma et al. propose a method for online recognition of human emotions using EEG signals, employing deep learning algorithms and nonlinear higher-order statistics [43]. The approach involves decomposing EEG data into sub-bands and exploring their nonlinear dynamics to precisely detect emotional states. Data reduction is achieved through particle swarm optimization, followed by long short-term memory (LSTM) based deep learning to uncover emotional fluctuations. Experimental results on the DEAP dataset demonstrate accurate and rapid emotion recognition. While the method offers promising advantages in terms of accuracy and speed, potential limitations may include challenges in generalizing across diverse datasets and real-world scenarios, necessitating further validation and refinement.

Liu et al. propose a novel EEG emotion identification framework combining CNN and transformer topologies, aiming for interpretability [44]. The method integrates spatial convolution for channel connections and temporal convolution for information extraction, along with a transformer module for spatiotemporal data fusion. Experimental results underscore the influential role of specific EEG bands in emotion identification, demonstrating superior performance compared to CNN and LSTM based models. Additionally, the model utilizes a customized convolution kernel for efficient high-frequency noise filtering. While offering enhanced interpretability and noise reduction capabilities, potential limitations may include challenges in model interpretability with complex neural architectures and the need for further validation across diverse datasets and real-world contexts to assess generalizability.

Li et al. presented an EEG-based technique for emotion identification that selects and extracts features based on common spatial patterns [45]. An optimized frequency band and channel subsets are identified using a nonparametric test, that improves the accuracy of the emotion identification process. Batch normalization mitigates the influence of individual variances, thereby further enhancing performance. Evaluation using traditional classifiers indicates that the approach effectively distinguishes between emotional states. However, the methodology may require meticulous parameter adjustment. Applicability is limited to dataset characteristics.

After careful investigation of all the methodologies proposed by different authors, it is clear that the DEAP and SEED are the most used datasets by all the authors except some authors. Other authors used valence and arousal ratings, signals of EEG. We preferred the SEED dataset to detect real emotion through signal processing and addressed some challenges by authors. The main challenges are complexity and generalization. We tried to achieve these challenges through the proposed work.

3.Methods

3.1Software and hardware requirements

3.1.1Data collection

Liu et al. from Shanghai Jiao Tong University created an EEG signal dataset called SEED-V for various EEG-based emotional evaluation tasks [46]. The dataset is available for download on the SEED website. This collection utilizes EEG data from EEG signals for a variety of purposes. For preprocessing the raw EEG data bandpass filter is used to eliminate noise and artifacts. The website provides raw EEG data samples and feature-extracted data using the DE feature extraction technique. Both data samples are used and compared with three different models.

3.2Dataset preparation

The dataset comprises raw EEG data, which undergoes data cleaning and data transformation. In the data cleaning phase, mean imputation, a popular and straightforward method for addressing missing values, is employed. By calculating the mean value for each column, we obtain a representative measure of central tendency that can used to fill in the gaps caused by missing data. The data provided by the seed website is already clean and free from artifacts. This approach is employed to ensure that the data contains no missing values, thus enhancing the model's effectiveness with unknown data.

The transformation of the data involves two steps: standardizing the input data using the StandardScaler method from the sklearn library and encoding the labels. The emotions are labeled as 0: 'Disgust', 1: 'Fear', 2: 'Sad', 3: 'Neutral', and 4: 'Happy'. The labeled data is encoded using encoding techniques. StandardScaler is a preprocessing class from the popular Python machine-learning library sci-kit-learn, designed to scale the features of a dataset so that they have a mean of zero and a variance of one. Equation 1 is the standardization formulae where x is the input sample, m, s are the mean and standard deviation of the dataset, and z is the score.

$$z = \frac{(x-m)}{s} \tag{1}$$

The technique of one-hot encoding is utilized to represent categorical or discrete data as binary vectors. Each category is assigned a unique binary pattern, where only one bit is active (1) and all others are inactive (0). Some models, like the BiLSTM model, require the label data to be in encoded form for input. So, encoding the data is a must before giving data to the model. This scheme allows the model to treat each emotion category equally, preventing it from inferring any numerical relationships between emotions.

3.3Feature extraction

This process entails computing power within predefined frequency bands such as theta, alpha, beta, and gamma to capture the intensity of brain activity linked to various emotional states. The frequency range of the respective bands is defined as follows: delta (1, 4), theta (4, 8), alpha (8, 13), beta (13, 30), and gamma (30, 50). The electrical velocities of the channels are then added, and the mean is taken for each band limit. These features encapsulate the underlying neural dynamics, offering valuable insights into the neural mechanisms behind emotions. By quantifying the strength of specific frequency components, spectral power features provide a concise representation of EEG signals, enabling machine learning models to discern and classify emotional states effectively. This approach encapsulates both temporal and frequency aspects of EEG data, making it a crucial tool in understanding and decoding the intricate relationship between brain activity and human emotions.

3.4Classification

Initially, the data is partitioned into training and testing sets, comprising 70% and 30% of the data, respectively. Consequently, the data is segmented into four sections. During training, both the data and labels are utilized. The shapes of the training and testing samples are adjusted to suit the model's requirements. In the case of recurrent neural networks, the typical input shape is (number of samples, number of timesteps, number of features). By reshaping the data to adhere to this shape, we ensure the creation of a Sequential model object.

The model was developed by including a 64-unit BiLSTM layer with a rectified linear unit (ReLU) activation function defined as Equation 2 where i is input. For obtaining all layer's output sequences, the return_sequences option is set to True. Overfitting was mitigated by introducing a dropout layer after the initial BiLSTM layer, randomly deactivating a portion of the input units to 0 during each training update. Subsequently, another BiLSTM layer with 32 units was added, featuring a sigmoid activation function specified as Equation 3. Within the second BiLSTM layer, a dropout layer and a dense layer with five units were added, representing the number of emotion classes. The activation function is SoftMax defined as Equation 4 where x_i is the present input data, x_j is previous data, and it produces a probability distribution across the classes.

$$f(i) = max(0, i) = \begin{cases} i \ if \ i \ is \ positive \\ 0 \ if \ i \ is \ negative \end{cases} \tag{2}$$

$$f(i) = \frac{1}{1+e^{\wedge}-i} \tag{3}$$

$$f(x_i) = \frac{e^{\wedge}(x\_i)}{\sum(e^{\wedge}(x\_j))} \tag{4}$$

3.5Proposed approach

Figure 1 illustrates the proposed procedure for emotion recognition from EEG data. It includes the training process, evaluation of model performance, testing with new sample data, and displaying the predicted emotion. To increase the performance of the model and the optimized output, the EEG data is first taken from the dataset and then goes through data cleaning by managing missing values. The following stage is data preparation, which includes a number of procedures including one-hot encoding and standardization since, as we all know, these are crucial phases in the model-building process. It goes through testing and training following the feature extraction. The model that has been utilized is the BiLSTM model, which produces the best-optimized output when compared to other algorithms. The training procedure explains the model and how it was trained. The entire procedure, including the phases taken into account in the model proposed below, is crucial to creating the optimal model.

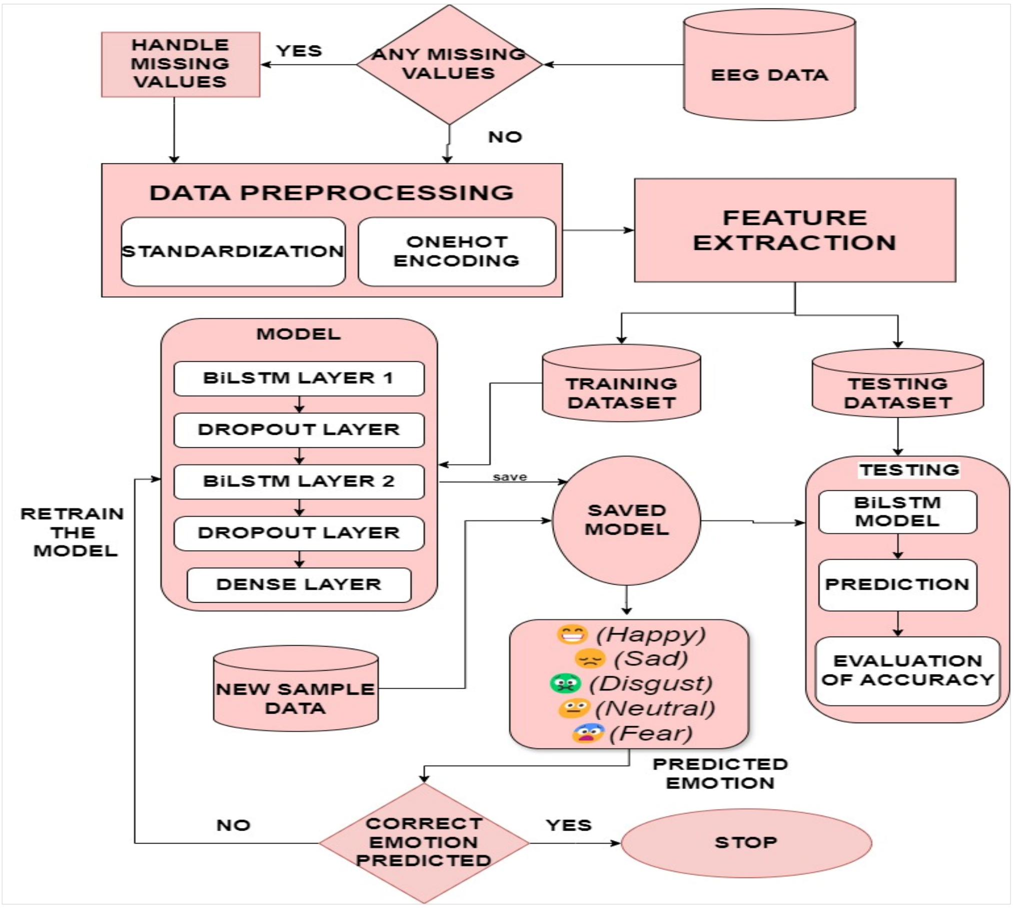


Figure 1 Proposed approach

The model was trained using the training data by calling the fit () method. Adam, short for adaptive moment estimation, was employed as an extension of stochastic gradient descent. It computed adaptive learning rates for each parameter, aiding faster convergence and necessitating less hyperparameter tuning. As the model is multi-class, labels were encoded before the categorical_crossentropy loss function was used. The input data is sent forward throughout the layers of the model as it trains. The model training algorithm is outlined below:

Algorithm 1: BiLSTM model

Start

Step 1: Split the data into training and testing parts in the ratio of 70:30

Step 2: Reshape the training and testing data for neural network

Step 3: Build BiLSTM Model ()

Recurrent neural network (RNN) with 2 hidden layers, dropout layers, dense output layer

Step 4: Compile the developed model with loss function, evaluation metrics

Step 5: Train the BiLSTM model with the reshaped training data with max_epochs=15 epoch=1

Step 6: Loop until epoch>max_epochs

Loop: For each (x_input, y_target) pair

Forward pass:

Step 6.1: Pass the input x_input to first BiLSTM layer

h1=ReLU(w1*x_input+u1*h_prev1+b1)

Step 6.2: Apply drop out to h1 with dropout rate=0.2

Step 6.3: Apply the second BiLSTM layer with sigmoid activation

h2=Sigmoid(w2*h1+u2*h_prev2+b2)

Step 6.4: Apply drop out to h2 with dropout rate=0.2
Step 6.5: Apply the dense BiLSTM layer with softmax activation
Output=(w_dense*h2+b_dense)
cal_output=Softmax(output)
Step 6.6: Compute the loss between cat_output and y_target
Backpropagation:
Update the model weights and biases using adam optimizer update rule
Calculate training loss, evalution metrics and store them for each pair
End Loop
Increment epoch number by 1
Stop

Algorithm 1 starts with designing the model. Every layer conduct calculation and transmits the results to the following layer. The model has a total of 5 layers with two dropout layers in between them to reduce the overfitting of the model. The first BiLSTM layer has 64 memory units, the third BiLSTM layer has 32 units, and the last layer has five units since the classes are five and it is one hot encoded. The model performs backpropagation using the loss value to determine the gradients of the loss concerning the weights and biases of the model. Hold-out validation is used for the validation process using the test data divided before model design. For every epoch, the validation is performed with the test data and labels. This procedure determines the contribution of each weight and bias to the total error and assists in adjusting them accordingly. We have done the project in 3 models. LSTM and gated recurrent unit (GRU) do not perform well compared to BiLSTM. However, BiLSTM achieved a high accuracy among all the other models.

4.Results

To detect the real emotions of a person from EEG data of the brain, a dataset called SEED-V was used. Data pre-processing techniques were performed to remove noise and avoid incorrect results. Next, the model was trained using the LSTM algorithm of the RNN. The output can be any of the five classes: disgust, happy, fear, sad, and neutral. The accuracy achieved for the model is 82.63%. To further enhance the efficiency of the proposed work, two additional models of RNN were used, both of which demonstrated superior performance compared to the LSTM. GRU achieved an accuracy of 89.76% whereas the BiLSTM model achieved an accuracy of 93.97%. The BiLSTM is the best-performing model among the three. Except for the disgust emotion, all models performed well, and BiLSTM has performed better for all labels, due to its ability to capture information from past and future contexts. The new data is sent as input and checked whether the model correctly predicts the emotion of the data or not, and the resulting emotion is displayed.

4.1Performance evaluation

Three models were developed: initially, the LSTM model, followed by the BiLSTM and GRU models to enhance functionality. BiLSTM outperformed LSTM, achieving higher accuracy. This study evaluates and compares the performance of LSTM, GRU, and BiLSTM. Performance criteria used to evaluate the classification models include accuracy, precision, recall, and F1-score. BiLSTM and LSTM tend to have slightly higher complexity compared to GRU. The training time for GRU is also less due to its fewer gates and parameters. However, considering performance, BiLSTM performed the best (*Table 1*).

Table 1 Evaluation measures for LSTM, GRU, and Bi LSTM

Model	Accuracy	Precision	Recall	F1-score
LSTM	82.63	86.75	82.63	76.63
GRU	89.76	92.14	89.76	88.58
BiLSTM	93.97	94.69	93.98	93.53

4.2Experimental results

The confusion matrix illustrates the counts or percentages of true positive, true negative, false positive, and false negative predictions made by the model for each class. It showcases the effectiveness of a classification model and offers detailed insights into the reasons for the model's errors and predictions. *Figure 2* and *Figure 3* represent the confusion matrix of the LSTM and GRU models when applied to the test data. The proportion of correctly identified labels was higher compared to incorrectly recognized labels. The disgust class exhibited more false predictions for both models. GRU model predicted more samples as sad which were labelled disgust. To address this issue and reduce false negatives, an enhanced model, BiLSTM was trained. Ultimately, the BiLSTM model achieved an impressive accuracy of 93.97%.

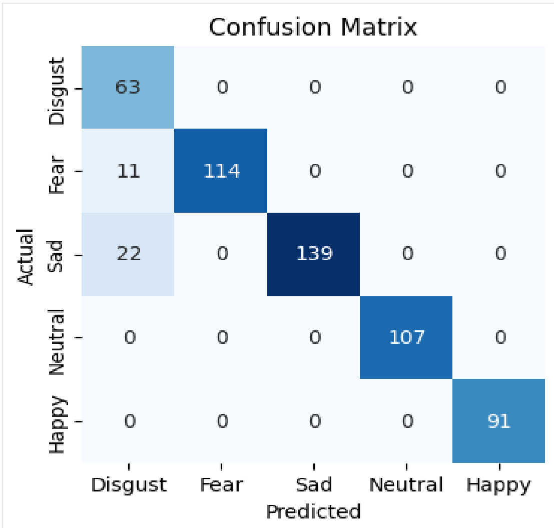


Figure 2 Confusion matrix for LSTM model

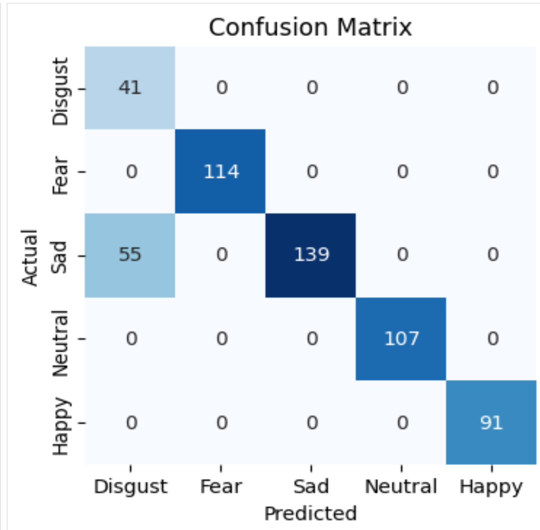
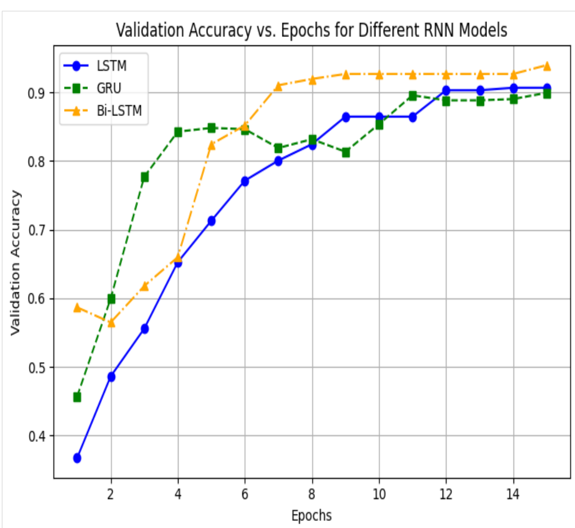


Figure 3 Confusion matrix for GRU model

Figure 4 represents the confusion matrix of the BiLSTM model. Reduction in false predictions for the disgust class, with the majority class sad being predicted for incorrect predictions, likely due to class imbalance. Balancing of class may give good results. *Figure 5* illustrates a graph displaying the accuracy achieved by the three different models across each epoch of the training period. It was observed that the accuracy of all three models gradually increased as the number of epochs increased. A confusion matrix is a table that showcases a machine learning model's performance by comparing predicted outcomes with actual ones. It delineates true positives, true negatives, false positives, and false negatives, offering insights into the model's accuracy and error patterns. By visualizing these metrics, it helps analysts evaluate the model's strengths and weaknesses, guiding improvements for enhanced predictive capabilities.



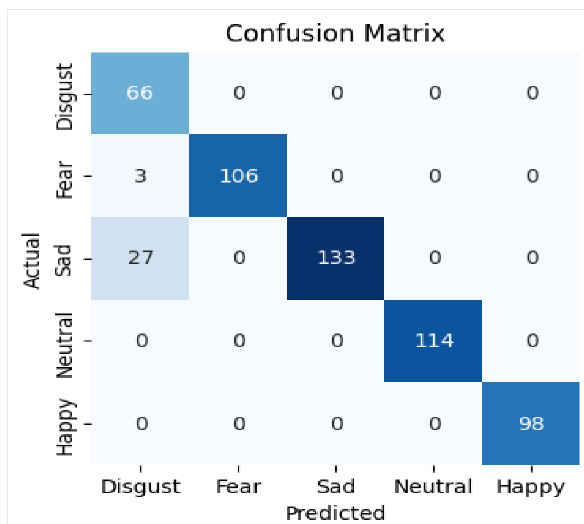


Figure 4 Confusion matrix for BiLSTM model

Figure 5 Comparative analysis graph

5.Discussion

Even though the developed model was based on one particular dataset, the proposed work can fit unseen data also if followed by the same feature extraction method. Methods for addressing missing data and artifacts proposed. Given data with varying numbers of emotions and diverse emotion evaluation tasks, modifications to the model architecture are necessary. Model generalization is one of the limitations of the proposed work. *Table 2* represents the tabular representation of the related works with the proposed work. The accuracy of the model is increased compared to others. The model achieved better accuracy than all previous works because of the dataset with more samples. The feature extraction technique and the recurrent models increased the model's accuracy.

Table 2 Comparison of prior relevant implementations with the proposed work

Literature	Dataset	Algorithms	Accuracy
Wei et al. [27]	SEED	SRN	75%
Pallavi et al. [28]	DEAP	VMD	62%
Jinyu et al. [29]	DEAP	MTL, MSRN	72%
Peng et al. [30]	SEED-IV	Joint Feature Adaption	65%
Bano et al. [31]	SEED	SVM	80%
Tao et al. [32]	DEAP	Channel Wise Attention	80.05%
Nilima et al. [33]	DEAP	SVM	80%
Proposed Work	SEED-V	BiLSTM	93.97%

5.1Limitations

The proposed algorithm was based on one private dataset provided by the SEED website. The generalization of the model increases by testing it on different types of datasets. This was one of the limitations of the proposed work. In scenarios where an individual experiences mixed emotions, such as encountering something they both hate and fear, they may feel disgusted and fearful at the same time. In such cases, accurately predicting a single emotion becomes challenging. Sometimes, the combination of two emotions may result in different predictions. A complete list of abbreviations is listed in *Appendix I.*

6.Conclusion and future work

This study covered the BCI and RNN algorithms used in emotion recognition. A person's pulse and facial expressions can both reveal their emotions. In this study, a technique utilizing brain signals to categorize and predict emotions was explored. The SEED V dataset was obtained from the SEED website for the experimentation. The data was pre-processed, and significant features were extracted. Due to the cleaned data from different sessions and trials from the SEED website, the model generalized better. The data was standardized and encoded during preprocessing. The model was then constructed by determining the number of hidden, dropout, and dense layers needed. The data was separated into train and test sets, and the model was trained accordingly. Upon examining the model's performance, it displayed a 93.97% accuracy rate. When new data was fed into the model, the projected emotion was revealed. By evaluating and comparing the performance of these models, researchers gain valuable insights into their strengths and weaknesses in capturing emotional signals from EEG data.

In the future, the work can be enhanced by incorporating data on artificially generated emotions created by users, alongside real-time implementations. Additionally, further development of the model is necessary to improve its ability to predict system responses when mixed emotions are present.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability

The SEED-V dataset utilized in this study is publicly accessible and can be found at https://bcmi.sjtu.edu.cn/home/seed/seed-v.html.

Author’s contribution statement

Markapudi Sowmya: Conceptualization, data collection, design, writing – original draft, writing – editing. **Pothuri Surendra Varma:** Supervision, design, data curation, writing – original draft, writing - review. **Katarapu Deepika**: Investigation, design, data collection, writing-original draft, writing- editing.

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Markapudi Sowmya was born in Vatsavai on 8^{th} Aug 2002. She is currently pursuing B. Tech degree in Computer Science and Engineering at Velagapudi Ramakrishna Siddhartha Engineering college. She contributed to the project "Development and Evaluation of a Student Location Monitoring System Based on GSM and GPS Technologies", which was published at 6th International Conference on Innovative Computing and Communication (ICICC-2023), New Delhi, India, 2023.
Email: 208w1a0596@vrsec.ac.in

Dr. Pothuri Surendra Varma is working as Assistant Professor in the Department of Computer Science and Engineering, Velagapudi Ramakrishna Siddhartha Engineering college, Vijayawada, Andhra Pradesh, India. He completed his Ph.D. from National Institute of Technology, Raipur, Chhattisgarh, India, in the year 2023. He has received his M.Tech and B.Tech degrees in Computer Science and Engineering in 2014 and 2011, respectively from engineering colleges affiliated to Jawaharlal Nehru Technological University, Kakinada, Andhra Pradesh, India. His current research interests include Wireless Sensor Networks, Internet of Things, and Machine Learning.
Email: surendravarma@vrsiddhartha.ac.in

Katarapu Deepika was born in Vijayawada on 19^{th} july 2003. She is currently pursuing B. Tech degree in Computer Science and Engineering at Velagapudi Ramakrishna Siddhartha Engineering college. She contributed to the project "Development and Evaluation of a Student Location Monitoring System Based on GSM and GPS Technologies", which was published at 6th International Conference on Innovative Computing and Communication (ICICC-2023), New Delhi, India, 2023.
Email: 208w1a0589@vrsec.ac.in

Appendix I

S. No.	Abbreviation	Description
1	3D	Three-Dimensional
2	2D	Two-Dimensional
3	BCI	Brain Computer Interface
4	BiLSTM	Bidirectional Long Short-Term Memory
5	CNN	Convolutional Neural Networks
6	DE	Differential Entropy
7	DEAP	Dataset for Emotion Analysis Using Physiological Signals
8	DTCWT	Dual Tree Complex Wavelet Transform
9	EEG	Electroencephalography
10	EFDMs	Electrode-Frequency Distribution Maps

11	EMD	Empirical Mode Decomposition
12	FNIRS	Functional Near-Infrared Spectroscopy
13	GRU	Gated Recurrent Unit
14	LSTM	Long Short-Term Memory
15	MEG	Magnetoencephalography
16	MSRN	Multiscale Residual Network
17	MTL	Meta-Transfer Learning
18	ReLU	Rectified Linear Unit
19	RNN	Recurrent Neural Network
20	SEED	SJTU Emotion EEG Dataset
21	SODP	Second-Order Difference Plots
22	SRN	Simple Recurrent Networks
23	SVM	Support Vector Machine
24	VMD	Variational Mode Decomposition