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Detection of Emotion from EEG Signal Using Deep Learning: Bi-LSTM and GRU

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Abstract—**Emotion states are linked to a wide range of human feelings, thoughts, and actions. They affect our ability to act properly in situations like making decisions, perceiving things, and being smart. So, research on recognizing emotions through emotional signs makes Brain Computer Interface (BCI) systems a better subject for clinical uses and social interactions between people. Electroencephalogram (EEG) signal is an electrophysiological method for brain signal recording. Human emotion arises from the brain, so the detection of emotion can be done by using EEG signals to decide human psychological change during the different emotional states. The aim of this study is to classify human emotion named arousal, valence, dominance and liking. The classification has been done for both binary and multiclass classification from EEG signals. Publicly available "DEAP" dataset is engaged in this work, and EEG recording from 13 channels was used. Fast Fourier Transform (FFT) has been used to separate frequency bands from the EEG signal, and then Power Spectrum Density (PSD) features have been extracted. Two deep learning methods, Bidirectional Long Short-Term Memory (Bi-LSTM) and Gated Recurrent Unit (GRU) have been used for the classification of emotion. We found that the GRU+Bi-LSTM model gives the best result for the binary classification with 96.53% accuracy and Bi-LSTM can predict best accuracy of 92.36% for multiclass classification.**

Keywords—*arousal, Bi-LSTM, dominance, GRU, liking, valence.*

I. INTRODUCTION

Human emotions are intricate psychological and physiological phenomena that influence our attitudes, feelings, and actions. EEG (electroencephalogram) signals, that capture the electrical activity of the brain, are strongly tied to human emotions[1]. The neurological mechanisms underpinning emotional experiences can be better understood with the help of EEG recordings. Different emotional states are linked to particular patterns of brainwave activity, like alpha, beta, delta, gamma, and theta waves. The brain activation and connection associated with different emotions can be reflected in changes in EEG signals, which can provide important information for emotional identification and categorization. This complex connections between brain function and emotions by analyzing EEG signals in combination with deep learning techniques [2].

Valence, liking, arousal, and dominance are four distinct types of emotions that capture different dimensions of the human emotional experience. The positive or negative aspect of an emotional state, indicating the degree of happiness or unhappiness, is referred to as valence[3]. Liking indicates the degree of attraction or aversion as well as the subjective sensation of pleasure or satisfaction linked to an emotion. Arousal refers to the degree of excitement or activation level of a mental state[4]. The perception of control or power in a certain circumstance or emotional state is reflected by dominance. Understanding and correctly identifying these four emotional categories can help researchers in the disciplines of psychology, computational psychology, and human-robot interaction gain significant insights on people's emotional states, preferences, degrees of engagement, and psychological dynamics.

The identification of emotions is crucial for the diagnosis and management of mental illness. It helps in the early recognition and detection of mental health diseases like anxiety disorders, mood disorders, and other conditions by precisely recognizing and analyzing emotional states.

Emotion detection is crucial in the fields of effective computation and human-computer interaction as well as interaction with robots. It enables the creation of interfaces and systems that can recognize and react to human emotions. Emotion recognition can improve user experiences, personalization, and adaptive interactions in technology interfaces like chatbots, virtual assistants, and video games[5]. This enhances the quality as well as effectiveness of interactions between people and computers by resulting in more engaging and gratifying user experiences. In general, emotion detection in the field of entertainment creates opportunities for tailored experiences, authentic player-character interactions, improved virtual reality experiences[6], enhanced multiplayer interactions, and well-informed game design.

The main objectives of these research work are to detect prominent emotion by binary classification technique and to predict the emotion strength level for individual emotion classes by multiclass classification technique.

Previous research frequently used classic machine learning techniques like support vector machines (SVM) [7] or random forests, which might have difficulties capturing the complex patterns inherent in EEG signals. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [8], which have shown promise in capturing complicated patterns and hierarchies in EEG data. New algorithms like Bi-LSTM and GRU can improve accuracy in this case.

In this regard, Acharya et al. (2021) [9]did the multiclass classification only. They applied two different deep learning algorithm named LSTM and CNN individually. They classified four types of emotion on the basis of 0-9 rating according to DEAP dataset. The accuracy gained an average value 84.02% while applying LSTM and 84.78% by applying CNN for arousal, valence, dominance and liking respectively.

Alhagry et al.(2017)[10] proposed LSTM based emotion detection model for binary classification. The average accuracy gained 86.36% for arousal, valence, liking. They did not take dominance in account. They also did not work for multiclass classification. Chao et al.(2019) [11] used a CNN model named CapsNet for binary classification of arousal, valence and dominance which gave average 67.42% accuracy. Ozdemir et al. (2019) [12] used BiLSTM classifier that gave average 95.98% accuracy for arousal, valence and dominance. These knowledge gaps highlight the need for a more comprehensive method of emotion recognition that takes into account all four aspects of valence, liking, arousal, and dominance.

The four bands (delta, theta, beta and alpha) are all taken into account in our study to overcome different constraint of previous researches. We acknowledged that various frequency bands contain distinctive details regarding emotional states, and combining the data from several bands can give a more complete and accurate portrayal of emotions. Using deep learning methods can improve accuracy and results in a more reliable emotion detection system by capturing the interaction between various frequency components and utilizing the complimentary nature of the bands.

II. METHODOLOGY

This work starts with publicly available pre-processed EEG dataset named DEAP Dataset. After that feature extraction have done by using FFT. PSD have used as the main feature. Two deep learning-based algorithm has been applied for classification of four types of emotion. This chapter will also focus primarily on the research design employed to achieve the specific aims of the study.

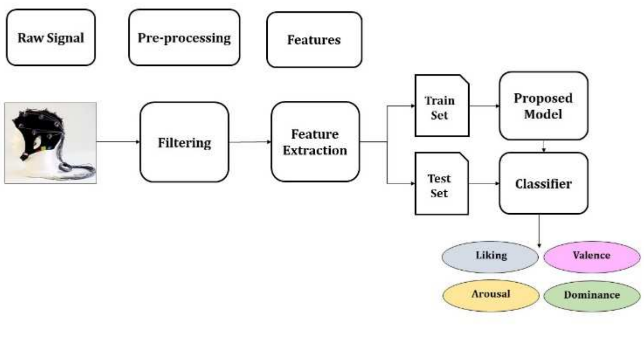

Fig.1 Flow chart for proposed work.

Fig.1 shows the flow diagram of our study which includes EEG data acquisition, pre-processing, feature extraction, classification. In feature extraction, the Fourier transform is applied to the epoch, and the power spectrum is computed.

A. Dataset

The DEAP dataset we have worked on, included 32 participants' EEG and peripheral physiological data were monitored while they watched 40 one-minute-long music video snippets. Participants assigned ratings to each video based on its arousal, valence, like/dislike, dominance, and familiarity levels. The results of an online self-evaluation in which 14–16 volunteers scored each of 120 one-minute music video excerpts on the basis of arousal, valence, liking and dominance[13]. A conventional mouse was used to score each trial's value, arousal, dominance, and likeability on a continuous 9-point scale. Among 32 channels, 14 channels have been used. Data has dimensions of 40 × 40 × 8064. Each video had 40 channels and had 8064 EEG signal data points, for a total of 322560. The labels were in the shape of 40 × 4, where 4 stands for valence, arousal, dominance, and liking. NumPy arrays were utilized and loaded .dat files with latin encoding and the cPickle library[14].

There are 40 files under each subject, one for each video with 14 channels and a labelling file for each subject. For each patient's individual movie, the data have been read row by row, with $(C_N \times L_N \times f_N \times S_N)$ data sample

Here, C_N= number of channels = 14
L_N= number of labels
= 4 (valence, liking, arousal, dominance)
f= sampling frequency = 128 Hz
S_N= number of subjects

Each file has 63 seconds of recordings; therefore, the total number of rows is (63×128) or 8064. We have obtained samples during the last 30 seconds, which translates to (30×128) or 3840 rows for our proposed model, as the feeling for a video becomes more visible and active in the closing period and a person may decide his reaction to that video more precisely.

B. Feature extraction

Fast Fourier Transform (FFT) and power spectrum density (PSD) are chosen in EEG feature extraction. EEG data are effectively converted from the time domain to the frequency domain by FFT, allowing for the identification of particular frequency bands linked to various emotions. PSD measures the power distribution across frequency bands and gives important information on the distribution and intensity of brain activity related to processing emotions. Through the extraction of discriminative features linked to brain oscillations, these techniques aid in the classification of emotions by making it easier to identify patterns linked to various emotional states.

C. Classifier

A set of input data is used by the classifier to identify patterns or relationships that can be used to forecast the class or category of new, unforeseen instances. Bi-LSTM and GRU classifiers have been used for the aim of our thesis. Bi-LSTM (Bidirectional Long Short-Term Memory) and GRU (Gated Recurrent Unit) are specific types of recurrent neural network

(RNN) architectures commonly used for sequence modelling and classification tasks.

BiLSTM

In the input sequence, Bi-LSTM takes into account data from both past and future time steps. It comprises of two independent LSTM networks, one processing the sequence ahead and the other backward [15].

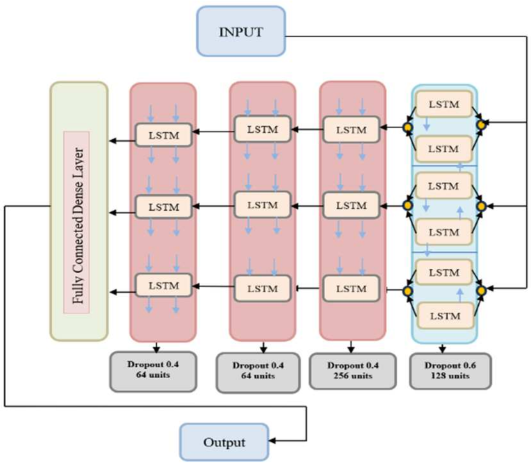

Fig.2 Bi-LSTM architecture of our work.

In Fig.2 it describes the layers of our model where five hidden layers and one output layer has been used. With each hidden layer, there is a dropout layer. Hidden layers and dropout layers are parts used to construct the network architecture in the context of neural networks.

The five hidden layers used in our work are a Bi-LSTM layer of 128 units with a 0.6 dropout layer, two LSTM layers, three LSTM layers (one layer of 128 units with 0.4 dropout layer, one layer of 64 units with 0.4 dropout layer, another layer of 32 units with 0.4 dropout layer, and a dense layer of 16 units with 'ReLU' activation function has been used). Final output dense layer with 'SoftMax' activation function was employed.

GRU+BiLSTM

Another RNN architecture with a topology that is similar to but simpler than LSTM is the GRU. In contrast to LSTM, GRU integrates the memory and gating methods into a single unit, which lowers the number of parameters.

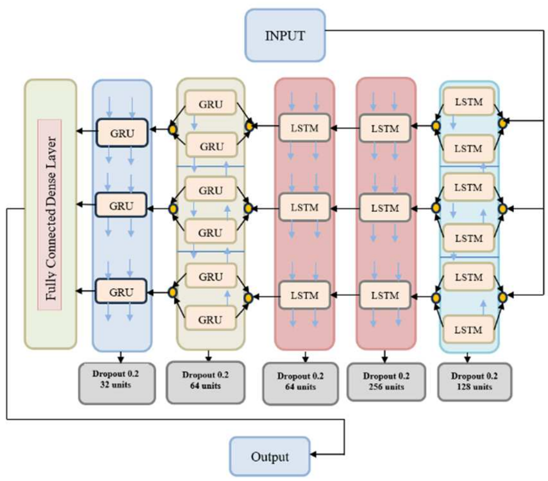

Fig.3 GRU+Bi-LSTM architecture of our work.

In Fig.3 describes the layers of our GRU+Bi-LSTM model. There are five layers with dropout layer and a fully connected dense layer. There are five hidden layer The five hidden layers are Bi-LSTM layer of 128 units with 0.2 dropout layer, 2 LSTM layers; one of 256 units with 0.2 dropout layer and another of 256 units with 0.2 dropout layer, Bi-GRU layer of 128 units with 0.2 dropout layer, GRU layer of 128 units with 0.2 dropout layer and a dense layer of 16 units with ‘ReLU’ activation function has been used. Eventually a final output dense layer has been used with ‘SoftMax’ activation function.

III. Performance Evaluation

We have identified not only our model's accuracy and loss curve for identifying overfitting or underfitting problems but also the confusion matrix for every emotion. Accuracy and loss curves, as well as the confusion matrix for precise split of the model's predictions, actual class labels and identification of specific types of mistakes. These assessment components work together to enable model development, allowing for better decision-making and assuring the model's reliability in real-world applications. This section will describe the result analysis about our research.

A. *Binary classification*

We have separated the overall rating of emotion into two classes using a binary classification system, one for prominent emotion and the other for mild emotion for each emotion. Mild emotions are those with a rating of 0 to 4, and significant emotions are those with a rating of 4 or higher. A high level of accuracy was provided by this binary classification. In our studies, we have used Bi-LSTM and GRU as our classifier and GRU+Bi-LSTM performed better than Bi-LSTM. When utilizing Bi-LSTM+GRU for binary classification, we obtained higher accuracy.

Accuracy Curve

The accuracy curve depicts how a machine learning model's accuracy changes as the number of training epochs grows. Each epoch denotes a whole repetition of the training and testing data.

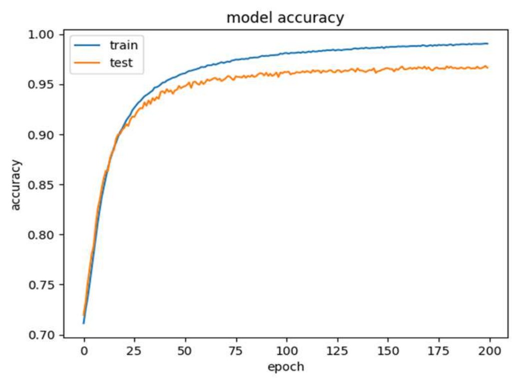

Fig.4 Accuracy curve for valence using Bi-LSTM+GRU.

In Fig.4, the train curve is slightly higher than the test dataset, indicating good accuracy with a minor underfitting issue. The test accuracy curve being slightly below the train accuracy curve points to overfitting and the inability to generalize the complicated unseen data well.

Loss Curve

The model's parameters are iteratively updated to minimize this loss function, which improves model's performance. The loss function is a measure of how well the model is performing on the task it has been trained for.

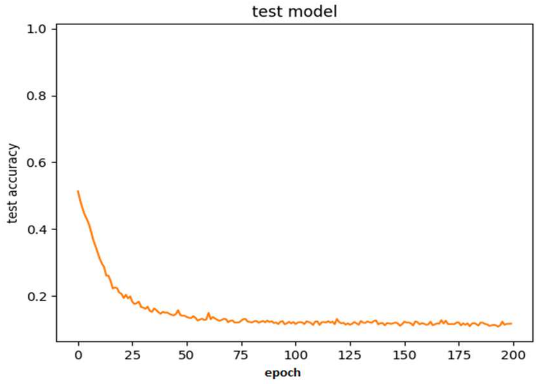

Fig.5 Loss curve for Valence for binary classification using Bi-LSTM+GRU.

Fig.5 displays a loss curve, plotted along the y axis while epochs are plotted along the x axis which decreases as the period increases and gets saturated at a certain epoch. As the model learns to minimize the loss function by adjusting parameters, the loss curve lowers across epochs until it reaches an equilibrium point when additional training is unable to significantly improve performance on the training set.

Confusion Matrices

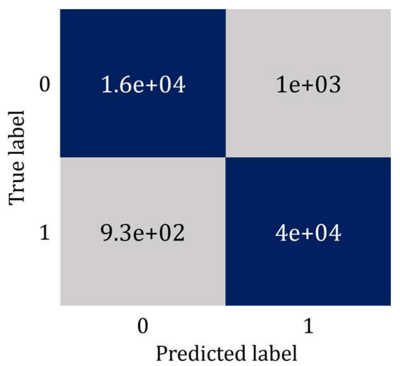

Fig.6 Confusion metrics of valence type emotion using GRU+Bi-LSTM.

This Fig.6 depicts that predicted level is shown on the x axis, and the true value is shown on the y axis. The scale on the right reflects the amount of prediction accuracy. A darker hue indicates that the algorithm can enable more data to detect the level accurately. The darker ones represent the TP (true positive) value. For level 0(minor emotion), $1.6e^4$ data can reliably forecast that level '0'. $1e^3$data will fall into the FP (false positive) value segment. The number of cases that are mistakenly forecasted as positive by a classification model is represented by FP. Then $4e^4$ data predicts true negative, whereas $9.3e^2$data predicts false negative. As more data can predict 1(prominent emotion) accurately, true positive block for 1 is in the darkest shade according to the scale given on the right side.

Although BiLSTM and GRU models are good at identifying temporal relationships in EEG signals, they might not be able to generalize to all the patterns, which could lead to inaccurate predictions. False positives and negatives are a result of class disparities, inconsistent categorization, and variability in emotional reactions. Unbalanced data can lead to biases towards majority classes which contributes inaccurate predictions. False predictions can be reduced by using regularization techniques, optimizing hyperparameters, and fine-tuning the architecture of the model.

B. Multiclass classification

The overall rating in multiclass emotion has been divided into ten classes with ratings ranging from 0 to 9. Accuracy is less than binary in this circumstance because it calculates accuracy for each class rather than overall accuracy. Because we obtained superior accuracy for multiclass classification when using Bi-LSTM rather than Bi-LSTM+GRU, the accuracy curve, loss curve, and confusion matrices will only be given when using Bi-LSTM.

Accuracy Curve

Overfitting is frequently less prominent in multiclass classification than in binary classification because of increasing complexity, larger training datasets, and the presence of several decision boundaries.

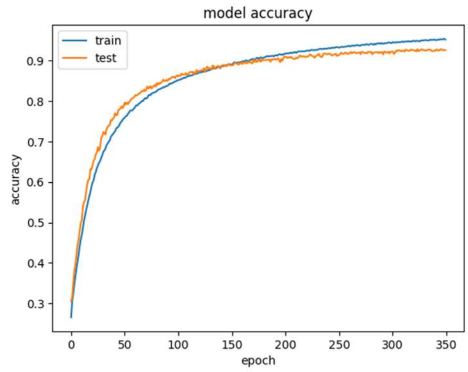

Fig.7 Accuracy curve for valence type emotion using Bi-LSTM.

In Fig.7 the train accuracy curve and the test accuracy curves are quite similar. So, it can be said that there is less overfitting problem than Binary classification problem.

Loss Curve

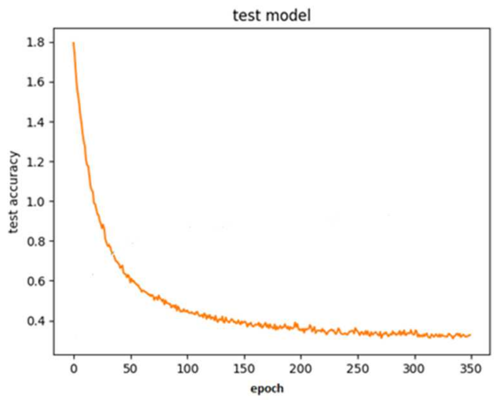

Fig.8 Loss curve for valence type emotion using Bi-LSTM.

In Fig.8 the curve represents the model's loss when working with the testing dataset which has been plotted on the y axis while the epochs have been plotted on the x axis. The loss function in multiclass classification is frequently based on techniques such as categorical cross-entropy, which assesses the dissimilarity between predicted class probabilities and true class labels. In this multiclass classification, the loss and accuracy curves intersect, whereas in binary classification, they do not.

. The dissimilarity between the predicted probability of one class and the true label (0 or 1) is calculated using this loss function. The optimization landscape is easier because there are only two classes, and the loss decreases monotonically as the model improves. As a result, in binary classification, the accuracy curve frequently does not meet with the loss curve.

Confusion Matrices

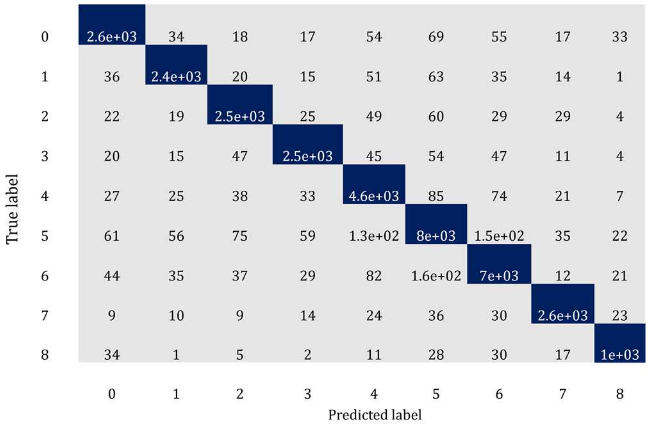

Fig.9 Confusion matrices for valence type emotion using Bi-LSTM+GRU.

In Fig.9 the diagonal of matrices shows the true positive value for each level. For a specific level For the TP value, the False-negative value for a class is the total of the values of the related rows. Here the FP value for a class is the total of the values in the relevant column. The TN value for a class is the sum of the values of all columns and rows except the values of the class for which level the values are being calculated and lastly the TP value, which occurs when the actual and anticipated values are the same. Here the range of number of data to predict the level is given in a scale on the right side of the confusion matrices. Though there are 10 levels from 0 to 9, there are only 9 levels from 0 to 8 that have been shown in the confusion matrices because in test dataset there was no data on the range of 9. In the diagonal of the confusion matrices, the number of data predicting level five accurately is the highest and it is $8e^3$. As a result, the true positive block for level 5 is the darkest in the shade.

BiLSTM and GRU models for multiclass emotion detection have difficulties in distinguishing between different emotional states, subjectivity in emotional reactions, unequal class distribution, and the difficulty of collecting subtle information from EEG signals. These obstacles could lead to incorrect classifications, necessitating careful data processing and model modification for increased accuracy.

IV. Comparative Study

TABLE I. COMPARATIVE STUDY FOR MULTICLASS CLASSIFICATION

Reference	Method Applied	A%	V%	D%	L%	Avg %
Acharya et al.(2021) [9]	LSTM	85.07	83.83	81.43	85.74	84.02
	CNN	85.48	82.59	83.61	87.42	84.78
Our work	Bi-LSTM	**92.45**	91.75	**92.64**	**92.58**	**92.36**
	GRU + Bi-LSTM	91.73	**91.84**	92.63	92.38	92.15

TABLE II. COMPARATIVE STUDY FOR BINARY CLASSIFICATION

Reference	Method Applied	A%	V%	D%	L%	Avg %
Bazgir et al. (2018) [7]	SVM	91.30	91.10	×	×	91.21
Alhagry et al.(2017)[10]	LSTM	85.65	85.45	×	87.99	86.36
Chao et al. (2019)[11]	CapsNet	68.28	66.73	67.25	×	67.42
Yang et al. (2019)[17]	CNN	90.65	90.01	×	×	90.33
Ozdemir et al.(2019)[12]	CNN	96.09	95.96	95.90	×	95.98
Our work	Bi-LSTM	96.98	94.66	96.21	95.10	95.73
	Bi-LSTM + GRU	**96.55**	**96.63**	**96.81**	**96.13**	**96.53**

Only Acharya et al. (2021) performed multiclass classification in Table I, while others performed only binary classification, with many of those who performed binary classification failing to detect all four emotions in Table II. But in our study, we have included these four types of emotion for binary as well as multiclass classification and improved accuracy compared to the existing works with the help of Bi-LSTM and GRU model which has been clearly visible in Table I and Table II.

. In our study we have first applied Bi-LSTM classification model for both multiclass and binary classification. For multiclass classification our Bi-LSTM model gains For multiclass classification our BiLSTM model gains 92.45%, 91.75%, 92.64%, 92.58% accuracy respectively with an average accuracy 92.36% and GRU+Bi-LSTM gives respectively 91.73%, 91.84%, 92.63%, 92.38% accuracy for arousal(A), valence(V), dominance(D) and liking(L) with an average accuracy 92.15%. For binary classification Bi-LSTM model's average accuracy 95.73%. Our GRU+Bi-LSTM model gives 96.55%, 96.63%, 96.81%, 96.13% for arousal, valence, dominance, liking and 96.53% average accuracy. Our proposed work has gained better accuracy in every case of classification compare to previous works.

V. Conclusions

This work presented deep learning based both multiclass and binary classification of emotion based on EEG signals. "DEAP" dataset is used for emotion detection classification. Our work's main theme was to detect the prominent emotion and the level of the emotion. EEG signals develop the sequence itself which contains information related to emotion. For handling sequential data, Bi-LSTMs and GRUs are especially made to capture these temporal connections between data points. Despite the strength, LSTMs have trouble with very long sequences because of diminishing gradients. Due to the ability to analyze data both forward and backward, Bi-LSTMs is able to capture the emotional patterns' context inside the EEG sequence more efficiently. For the primary concentration on local features, CNNs and SVMs may miss these more extensive contextual linkages.

For the detection of prominent emotion, binary classification has been used, which gives 95.73% accuracy while using Bi-LSTM, and when we were using Bi-LSTM +GRU, it gives 96.53% accuracy. Eventually, for the detection of the level, we used the same model, and this time, Bi-LSTM performed better than Bi-LSTM+GRU. Here Bi-LSTM gives an accuracy of 92.36%, and Bi-LSTM+GRU gives an accuracy of 92.15%. So, it can be said that Bi-LSTM+

GRU performs better than the Bi-LSTM in Binary classification, and Bi-LSTM is preferred to use during multiclass classification. Bi-LSTM and GRU outperform other models due to better long-term dependency modeling (Bi-LSTM) and benefits from bidirectional processing, which takes into account both past and future context, efficient and simpler architectures (GRU), resulting in faster training and a lower risk of overfitting.

There can be different fields for future studies on the basis of our work. PSD is employed as a primary feature in this study. There are at least 70 additional features in PyEEG lab that we did not include in this research. By including more EEG features in our model, further analysis can be done for future research. Though using five frequency bands gives better results, it requires more runtime and makes the algorithm more difficult. Additional research may be conducted on single-band analysis, which will be more reliable and necessitate an intuitive algorithm.

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