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Advancing Emotion Recognition via EEG Signals: A Deep Learning Approach with Ensemble Model

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Abstract: Human emotion is the mind's reaction to external stimuli. Since human emotions are dynamic and hard to predict in the real world, studies focusing on this area have gained a lot of importance. Emotion recognition using EEG(electroencephalogram) signals has recently seen prevalent use of many deep learning and machine learning techniques.In this paper, we have used a real time dataset which includes 15 subjects (7 Males and 8 Females) and their EEG signals are recorded using video stimuli. The real time data is preprocessed and features are extracted from the preprocessed data using different feature extraction methods. The accuracy and loss of model are calculated and compared with raw and preprocessed data. The proposed model - EEGEM (Electroencephalogram Ensemble Model) is compared with other machine and deep learning techniques. EEGEM is a ensemble model with the combination of LSTM and CNN together to achieve the desired output. The accuracy achieved using this model is 95.56% and it has outperformed other existing models.

Keywords: *EEG Signal, Emotion, CNN, LSTM, Ensemble Learning, Feature Extraction*

1. Introduction

In communicating with others and making decisions, human emotions are crucial. Medical professionals may utilise a patient's identified emotions as a sign of some functional diseases, including severe depression. The primary source of human emotions is deduced from facial expressions. However, it is well established that some people have the ability to conceal their true feelings by making deceptive facial expressions [1]. Therefore, researchers stick to using alternative information sources that are trustworthy and resistant to fraud. Electroencephalogram (EEG) signals, which record the electric field of the human brain is better alternative to identify the emotion. Since human responses are connected to brain processes, the EEG data can be used as a source of emotions[2].

Recognizing emotions requires constant expression over an extended period of time. To put it another way, contextual temporal dependencies are present in emotion-related signals. Multiple electrode placements' spatial relationships can demonstrate that human emotional activities are not isolating. However, the majority of currently used EEG-based emotion identification techniques only take into account either spatial or temporal dependency[3]. The proposed model uses tempospatial features to detect emotions. Hence, the accuracy of the system is really close to the actual emotions of the humans[4].

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EEG signals are recordings of electrical activity in the brain that are normally collected by scalp electrodes. EEG signals can provide useful insights into human emotions and are frequently employed in deep learning studies for emotion recognition.The reasons for choosing EEG signals for emotion identification are EEG signals are a precise indicator of brain activity, they are an effective tool for researching emotions[5]. It can be challenging to distinguish the effects of emotions from other inputs like facial expressions or physiological measurements like heart rate because these can be influenced by other forces. Due to the extremely high temporal resolution of EEG signals, they can record changes in neurological activity that take place very quickly. This is crucial for understanding sentiments, which can be quickly changing and dynamic. A non-invasive way to measure brain activity is with an EEG. This makes it secure and unnecessary for invasive procedures, which makes it perfect for researching emotions in a variety of groups. EEG signals may be captured in a range of environments[6], including both the lab and the real world. This enables the study of emotions in a variety of settings, such as social interactions and naturalistic settings. EEG data give an accurate representation of brain activity with high spatiotemporal precision, are noninvasive, and can be captured in a variety of circumstances, making them an important tool for emotion recognition[7] using deep learning.

The major contributions of the proposed work are summarized as follows:

- The proposal involves collecting a real time dataset of EEG signals from the 15 subjects who are allowed to watch different emotional videos which last for 1 minutes. The dataset obtained from the EEG recorder is converted into a .csv file.

- The proposed model prepossesses the real time dataset which involves various feature extraction methods such as PCA, LDA. The important features are extracted from the raw data of EEG signals.
- The proposed work EEGEM captures different emotions accurately than other existing classifiers.

Human emotions are complex reactions the mind produces in response to stimuli from the outside world. Studies in this field have become significantly more important because of how dynamic and elusive they are in practical settings. Notably, the use of (EEG) signals for emotion recognition has become more popular, mostly using cutting-edge deep learning and machine learning approaches. In this paper, we set out on a quest to realize the emotion identification potential of EEG signals. Our study makes use of a real-time dataset compiled from 15 participants, with a balanced representation of 7 men and 8 women. EEG data from these people are rigorously captured while they respond to video stimuli that are representative of real-world circumstances.

Table 1. Comparison of different Existing System

Title	***Input***	***Output***	***Method/Algorithm***	***Performance Metric/ accuracy***	***Content***	***Dataset***
Recognizing Emotions Evoked by Music using CNN-LSTM Networks on EEG signals(2020)	EEG Signals	Negative Positive Neutral	CNN-LSTM	Accuracy-94% Kappa coefficient-93%	Two-stage classification Three-stage classification	Realtime dataset (16 subjects)
An Investigation of Deep Learning Models for EEG-Based Emotion Recognition(2020)	E EG Signal	Different Emotions	DNN CNN LSTM CNN-LSTM	Emotion recognition - 90.12% Accuracy - 94.17%	End-to-end model which includes feature extraction methods also	DEAP Dataset
EEG emotion recognition using fusion model of graph convolutional neural networks and LSTM. (2021)	EEG Signal	Emotion Recognition	GCNN-LSTM	Accuracy Valence - 90.45% Arousal - 90.60%	Multip le GCNNs are applied to extract graph domain feature	DEAP Datasets
EEG-based emotion recognition using 4D convolutional recurrent	EEG Signal	Emotion Recognition	4 D convolutional recurrent neural network	For	CNN is used to learn frequency and spatial information.	SEED and DEAP datasets

neural network(2020)			CRNN	SEED - 94.74% DEAP - 94.22%	LSTM is used to extract temporal dependence	
CNN and LSTM based ensemble learning for human emotion recognition using EEG recordings(2023)	EEG Signal	Negative Positive Neutral	Hybrid Model CNN - LSTM	Accuracy - 97.16%	An ensemble model combines the predictions of all three models.	SEED and DEAP datasets
Deep Learning-Based Approach for Emotion Recognition Using Electroencephalography (EEG) Signals Using Bi-Directional Long Short-Term Memory (Bi-LSTM)(2022)	EEG Signal	Valence Arousal Liking	Bi-LSTM	Valence - 99.45% Arousal - 96.87% Liking - 99.68%	The statistical features, wavelet features, and Hurst exponent were extracted from the dataset.	DEAP Datasets

Real-time EEG data is meticulously preprocessed to improve data quality and dependability in order to provide a solid basis. The preprocessed data is then used to extract useful and instructive features using a variety of diverse feature extraction methods. The core of this investigation is the thorough assessment of the Electroencephalogram Ensemble Model (EEGEM) that we put out. This model combines the strengths of the Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) deep learning architectures. EEGEM effectively captures complex correlations and patterns in the EEG data by smoothly integrating these networks, which eventually results in predictions that are more accurate.

The rigorous computation and comparison of accuracy and loss measures is one of our study's key findings. In order to understand how preprocessing affects model performance, these measures are methodically examined in the context of both raw and preprocessed data. In order to confirm EEGEM superiority,

We evaluate it against other well-known machine and deep learning approaches. Our efforts have resulted in a remarkable accomplishment: an accuracy rate of 95.56% utilizing the EEGEM model. This degree of precision speaks eloquently about the capacity of our algorithm to precisely identify emotions, outperforming the performance of existing models. This not only confirms the efficacy of the suggested EEGEM technique but also establishes a new standard for emotion research.

This paper is structured as follows: Section II presents an overview of prior and closely related research endeavors. The intricacies of the proposed model are elaborated upon in Section III. The ensuing discussion of outcomes is presented in Section IV, while Section V concludes the paper by highlighting future avenues of exploration.

2. Related Work

There are three basic categories of EEG characteristics used in emotion classification: time domain features, frequency domain features, and time-frequency features.

EEG feature extraction from every frequency band is the second stage. EEG characteristics that are often employed include differential asymmetry [8], differentiable entropy (DE), Power spectral density (PSD), approximation entropy [9], sample entropy [10], and rational asymmetry [11]. Due to the volatility of EEG signals, it is impossible to use the time domain information or the frequency domain details separately. As a result, more and more research combines the time and frequency domain information to represent the nature of EEG signals. Time-frequency features are characteristics that result from the fusion of time and frequency domains. Short-time Fourier transform (STFT), wavelet transform (WT), and other common feature extraction techniques are examples.

Convolutional neural networks (CNNs) have made significant advancements in the processing of images, videos, and sounds due to their capacity to learn small stationary structures and develop them into multi-scale hierarchical patterns [12]. However, CNN's benefits also place restrictions on its capacity to analyze data that can be organized using graphs but is irregular or from non-Euclidean domains. By fusing spectrum theory and convolutional neural networks, graph convolutional neural network (GCNN) extends the capabilities[13] of the conventional convolutional neural network (CNN). The graph convolutional neural network has an advantage over the standard convolutional neural network when it comes to extracting discriminative features from signals in the discrete spatial domain.

The description of convolution operation is crucial because GCNN uses convolution operations to the altered graph. The convolution process may be defined by the result of two Fourier transforms once the Fourier transform is added to the graph and the convolution theory is adopted[14]. An efficient strategy to examine the link between various graph nodes and explain their underlying relationships is to use a graph convolutional neural network, which is what done in the EEG classification of emotions [15].Song et al. [16] introduced a dynamic CNN for emotion identification, and they successfully deployed the dynamic graph convolutional neural network to the SEED and DREAMER data set. A wide learning system was introduced by Wang et al(2018). [17], who also suggested a model that combines a broad learning system with a dynamic convolutional neural network. To test how well the model worked at recognising emotions, they also used the SEED and DREAMER. In order to extract the characteristics from graph-structured data, Zhu et al.(2020) used a graph convolutional neural network for image processing. In order to validate their Cayley Nets and get satisfactory results, [18] suggested a Cayley Nets based on graph convolutional neural networks.

Recurrent Neural Networks (RNNs) are often employed in machine learning for natural language processing because they are effective at handling time series data. RNN uses its unique network structure to memorise earlier data and use it to impact the output of later nodes. A cyclic connection, a basic feature of RNN design, gives RNN the ability to update current states depending on past states and current input data. However, when the corresponding input is huge, an RNN made up of sigma cells or tanh units is unable to learn the necessary information from the input data. The issue of long-term dependencies may be effectively dealt with by LSTM by including gate operations into the layout of cells [19].Although the aforementioned identification techniques made considerable strides in a few areas, the classification efficiency is still rather poor. Successful uses of ensemble learning have sparked fresh concepts for emotion identification using EEG. In order to increase the accuracy [20] of emotion categorization, we thus work to create a unique approach for emotion recognition based on deep learning using EEG signals.

Table 2. Video Stimuli List

Abbreviation	***Definition***	***Video***
NE1	First Negative Emotion Induction	Clip from Titanic - ship sink scene
PE1	First Positive Emotion Induction	Clip from Toy Story 3
NE2	Second Negative Emotion Induction	Clip from The Lion King
PE2	Second Positive Emotion Induction	Clip from The Avengers
NE3	Third Negative Emotion Induction	Clip from Schindler’s List
PE3	Third Positive Emotion Induction	Clip from Back to the Future
NE4	Fourth Negative Emotion Induction	Clip from Hachi: A Dog’s Tale
PE4	Fourth Positive Emotion Induction	Clip from The Sound of Music

3. Methodology

3.1. Real Time Data Collection

To identify emotions from the EEG output, a dataset of three positive, neutral, and negative emotions was developed. All participants were requested to sign their consent form before capturing the signal (their medical history, lifestyle details are

also collected). The data is collected from 15 people (8 female and 7 male) of age group between 30 to 40[21]. To capture the EEG signal, the subjects are allowed to watch the different emotional videos to stimulate the different emotions as shown in the Figure.1.In order to make sure that the subjects weren't tired, all EEG data were captured between 10 and 12 a.m at less than 30°C[22].

Fig. 1. The process of capturing EEG Signal

Participants' positive and negative emotions are stimulated using

video stimulation. In order to avoid any emotion transferring between the video segments, each video track is played for one minute and then stopped for a brief interval[23]. It is also regarded as the process' neutral state. The theme and mood of the movie affect everyone in a general and physiological way through various mental and emotional mechanisms, and the Table has a list of the videos that were shown.2. However, this effect's strength and severity vary depending on the subject's habits, mental history, and neuronal health. The sorrowful subject has been chosen for inducing negative emotions [24].

Participants' positive and negative emotions are stimulated by watching the videos on the monitor. To avoid any emotion from transferring[26] from one video to the next, each video clip is played for one minute and then stopped for a brief 15-second break. It is regarded as a neutral state throughout the processing procedure. The subjects are given headphones to listen to the sound from the videos to get the better effect of the same.The capturing of the EEG signal from every subject takes 760 seconds. Everybody is physiologically and generally affected by the video's theme[27] and mood in different ways through various mental and emotional mechanisms.

3.2. Preprocessing

The data array we used in this study was preprocessed, with the EEG data captured, the sampling frequency increased to 128Hz, and the signal subsequently filtered to a frequency range of 4 to 45Hz using a band-pass filter. The EEG information is then averaged to the same reference[28]. This technique concatenates the proper epochs of each emotion into a single prolonged signal. The next step is to build rectangular windows with a predetermined duration and overlap so that the total number of epochs gathered for each category of emotion is equal. The reference length for each trail is 65 seconds, of which 5 seconds are used for setup and the remaining 60 seconds are taken while watching the film. Therefore, in every separate trail, there are 65s*128Hz=8320 sampling points for each channel.

To represent this dataset in terms of its dimensions, we established the data dimension as 40 epochs multiplied by 14 channels, and further multiplied by 8320 time points. To differentiate it from the subsequently mentioned feature extraction data[30], we refer to this dataset as the "RAW" data array, signifying its size of 40x14x8320.

3.3. Cleaning Data

The preprocessing process involves cleaning and filtering of data. The irrelevant data are removed and important data are enhanced using various preprocessing methods. A notch filter is a type of electronic filter that is designed to attenuate or reject a narrow range of frequencies, typically cantered around a specific frequency, while allowing other frequencies to pass through. It is commonly used in electroencephalography (EEG) signal processing to remove interference or noise from EEG signals that may be caused by power line interference (50 or 60 Hz), muscle activity (such as eye blinks or jaw clenching), or other unwanted frequencies. A Butterworth filter is a type of infinite impulse response (IIR) filter that can be used for filtering EEG signals. It is a popular choice due to its simplicity and its ability to provide a relatively flat frequency response in the passband, making it suitable for preserving the shape of the EEG signal while attenuating unwanted frequencies.

Normalization of EEG signals is an important preprocessing step in emotion recognition research to ensure that EEG data is in a standardized format and ready for analysis. EEG signals are recorded from the scalp and are prone to variability due to factors such as electrode placement, scalp conductivity, and individual differences in brain anatomy and physiology. Normalization techniques are used to minimize these variations and facilitate accurate comparison and analysis of EEG data related to emotion recognition. The proposed model used 10 fold validation process to improve the accuracy of the learning model[31]. By diving the data into several subset or folds, it enables us to assess the performance of an emotion recognition algorithm on a dataset in the context of emotion recognition using EEG signals. The dataset is randomly divided into ten folds of roughly equal size.

EEG data from various people in diverse emotional states are present in each fold. The dataset is divided into nine folds as the training set and the remaining fold as the testing set for each iteration of the cross-validation process.

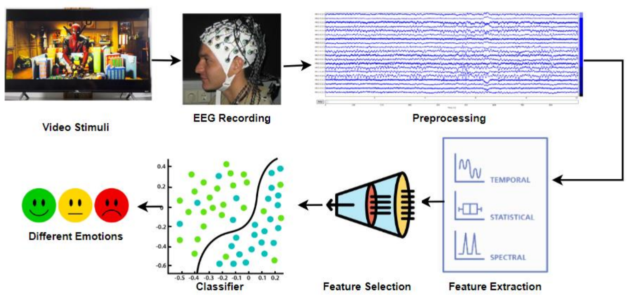

Fig. 2. Workflow of the EEGEM Model

The preprocessed data is given as input to the input layer of the CNN block which processes the data. The data passes through four layers of CNN is explained in Figure.4. The output of the CNN layer is given as a input to the LSTM layer. The extracted features from the previous layers are fed into the LSTM block. The classification of the different emotion are recoginised [37].

4. Feature Extraction and Classification

Once the data is clean from unwanted information, it is ready for feature extraction. In order to get meaningfully represent raw EEG signals that capture significant patterns associated with emotional states, feature extraction is of utmost relevance in EEG-based emotion identification. Since EEG signals are intricate and multidimensional, direct analysis is difficult and expensive to compute. The dimensionality is reduced and the emotional information is distilled by extracting discriminative features like spectral power, event-related potentials (ERPs), or statistical measurements[32], enabling more effective and efficient emotion detection algorithms. Additionally, with the right feature extraction, the model is better able to capture the distinct neurophysiological patterns that characterize various emotions, increasing classification accuracy overall and enabling the creation of robust and understandable emotion recognition systems for a variety of applications, such as mental health, human-computer interaction, and affective computing.

4.1. Feature Extraction Methods

cross-validation techniques should be employed to ensure the robustness and generalizability of the emotion recognition model.

One more feature extraction method (LDA) is also applied on the real time data[34]. Due to its capacity to minimize dimensions, execute discriminative feature extraction, attain statistical optimality, give interpretability, be resilient to noise, and offer computing efficiency, LDA is frequently employed for the extraction of features in EEG-based emotion detection. The precise needs of the emotion identification task and the properties of the EEG data being utilized, determine the feature extraction approach to be used. The workflow of the EEGEM system is step by step explained in Figure.2.

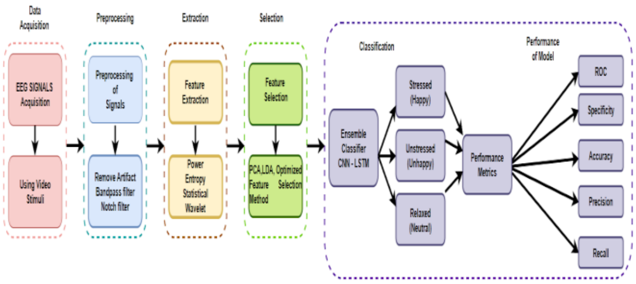

Fig. 3. Block diagram of Proposed System

4.2. Classification

The LSTM is better at understanding long-term dependant relationships in sequence data than the CNN is at capturing spatially localized data properties. As a result, it has been demonstrated that a hybrid CNN and LSTM model is effective at detecting natural signals. The CNN-LSTM hybrid network model based on the CNN and LSTM serial was created as a result of this research. The preprocessed data is fed into the CNN block in our proposed model, where it passes through three levels of CNN. The CNN layers are used to extract the pertinent features from the data. The dataset is used to extract the temporal and spatial feature attributes. To the following layer are transmitted the significant features that were extracted. The LSTM is the following layer, which may remember the previous output and make decisions based on it. The fully connected dense layer is Fig.3.then connected to the output of the LSTM layer. The result is classified by the softmax function. Utilizing the DNN, Stacked LSTM, BiLSTM, CNN, LSTM, and CNN-LSTM in the trials, we modified the model's structural design and optimized the parameter[35].

In this model, 10-fold cross-validation is an effective method for training and assessing deep learning models that use EEG data to identify emotions. The procedure entails dividing the dataset into ten equal-sized subsets, or "folds," and then training the model on nine of the folds while validating the model on the remaining fold. This method is performed ten times, with each fold used for validation once. We can acquire a more accurate estimate of the model's performance by utilising this strategy because it is tested on several validation sets. Furthermore, 10-fold cross- validation [36] helps to prevent overfitting because the model is trained on multiple data combinations and the average performance is used to assess generalization ability.

The Adam optimizer is an adaptive learning rate optimisation technique designed for training deep neural networks on huge datasets. During training, it updates the model's weights using a combination of momentum and adaptive learning rates. This enables it to converge faster than other optimisation techniques, such as stochastic gradient descent (SGD), and requires less hyperparameter tuning. When creating a CNN+LSTM model, you can often specify the Adam optimizer as the optimize r, along with the loss function and any relevant metrics. The process of data collection, preprocessing, extraction, classification and performance is depicted in Figure.3.

The preprocessed data is given as input to the input layer of the CNN block which processes the data. The data passes through four layers of CNN is explained in Figure.4. The output of the CNN layer is given as a input to the LSTM layer. The extracted features from the previous layers are fed into the LSTM block. The classification of the different emotion are recogonised [37].

5. Discussion and Results

The Receiver Operating Characteristic (ROC) curve is a helpful performance indicator for assessing the performance of a binary classifier, such as the EEGEM model, for emotion recognition using EEG signals. At various classification thresholds, the ROC curve is a plot of the true positive rate (sensitivity) compared to the false positive rate (1-specificity) for emotions using EEG signals. The ROC graph is represented in Figure.7.

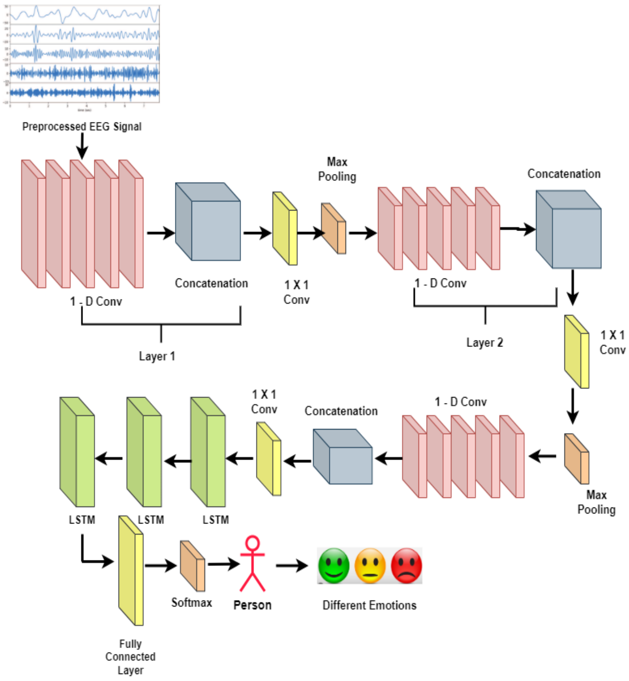

Fig. 4. Architecture of EEGEM Model

Table 2. Comparison of Different Feature Extraction

	LDA	*PCA*
Accuracy	74.23	82.63
Loss	3.02	0.54

Table 4. gives a summary of the loss rates for different models on unprocessed and processed datasets. DNN, Stacked LSTM, BiLSTM, LSTM, CNN, and CNN+LSTM are among the models. Each model-data combination's associated loss values are displayed. In the majority of models, the Preprocessed data consistently results in lower loss values than the Raw data. This shows that preprocessing has an advantage in lowering loss. For both raw and preprocessed data, the CNN+LSTM model combination consistently produces the lowest loss values. These results show how convolutional and recurrent neural networks can be used to minimize loss and improve model performance in Figure.9. Thus the paper compares the existing models with the proposed model with real time data.

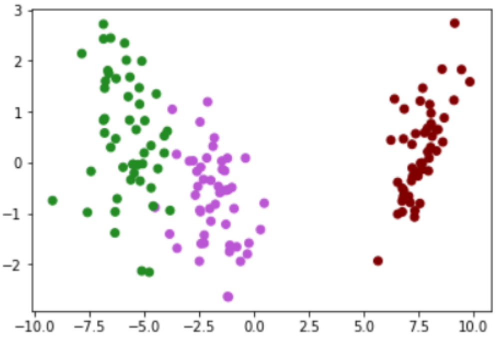

Fig. 5. The representation of the feature (LDA)

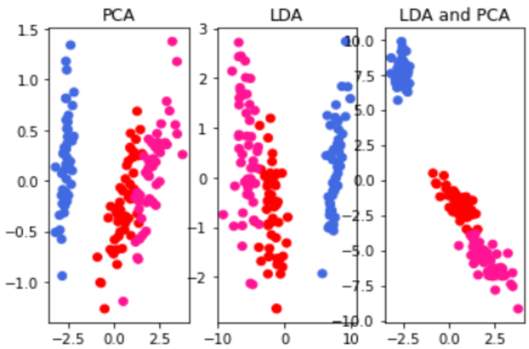

Fig. 6. The representation of the feature(LDA + PCA)

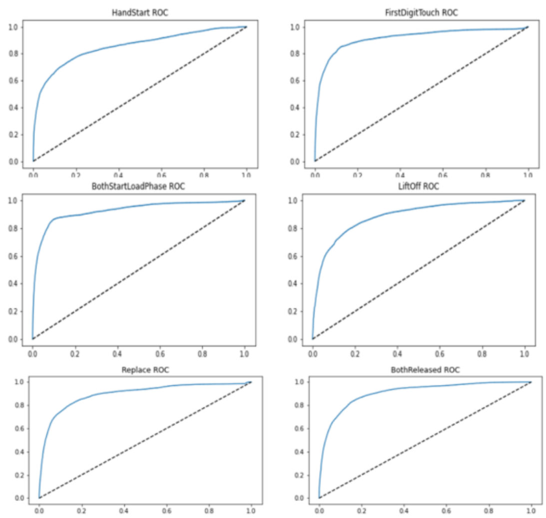

Fig. 7. The ROC representation of the features extracted

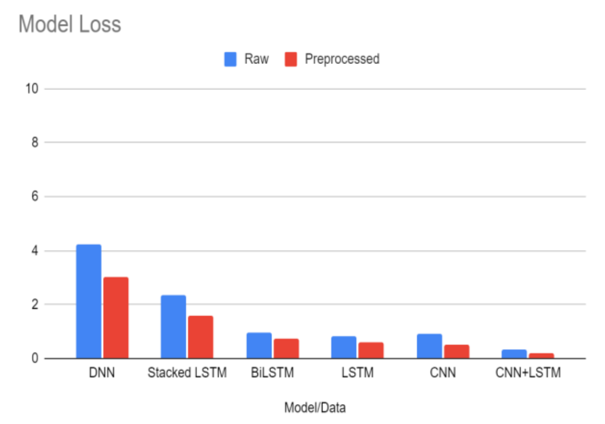

Fig. 8. Model accuracy for raw and preprocesed dataset

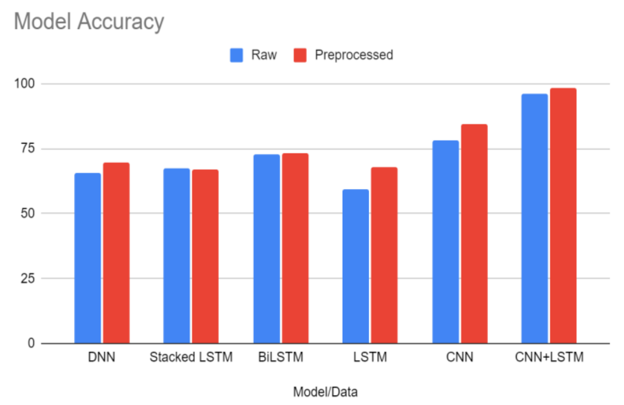

Fig. 9. Model Loss for of different models

Table 2. The Accuracy results of different models

Model	***Raw***	***Preprocessed***
DNN	65.48	69.88
Stacked LSTM	67.45	66.89
BiLSTM	72.81	73.16
LSTM	59.49	67.80
CNN	78.23	84.44
CNN+LSTM	96.11	98.48

6. Conclusion

This study explores the complex area of human emotion recognition, a field whose importance is expanding as a result of the complex and dynamic nature of emotional reactions to environmental cues. Electroencephalogram (EEG) signals used in conjunction with cutting-edge machine learning and deep learning techniques have become a powerful tool for understanding the intricacies of human emotions. This study adds to the empirical understanding of emotion detection by using a real-time dataset made up of EEG signals from 15 people, including both male and female participants, that were captured while being exposed to video stimuli. The quality and reliability of the resulting analysis are improved by meticulously preparing the real-time data using a variety of filters. The use of several

feature extraction approaches to extract prominent characteristics from the preprocessed data is a significant contribution of this work. The effectiveness of the suggested technique is supported by the careful comparison of accuracy and loss measures across models constructed using both raw and preprocessed data. The EEGEM (Electroencephalogram Ensemble Model), which is the focus of this project, stands out as proof of the synthesis of cutting-edge deep learning approaches. EEGEM exhibits its skill in emotion recognition by combining the advantages of Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN). Combining these techniques results in an astounding accuracy rate of 95.56%, demonstrating the model's ability to interpret the complex patterns found in EEG data and correctly anticipate emotions.

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Author contributions

Immanuel RR: Conceptualization, Methodology, Software, Field study, Writing-Original draft preparation, Software, Validation., Field study **Sangeetha:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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