# Epileptic Seizure Analysis Using Scalp EEG Signals with Deep Learning

**Ms.B.Madhavi Devi**
**Assistant Professor**
**Madhavidevi.b@iare.ac.in**

Rayedi Srilekha
Btech IV year
Computer Science and Engineering
Institute of Aeronautical Engineering
19951A05K6@iare.ac.in

Gattineni Harshitha
Btech IV year
Computer Science and Engineering
Institute of Aeronautical Engineering
19951A05J2@iare.ac.in

Burri Sushma
Btech IV year
Computer Science and Engineering
Institute of Aeronautical Engineering
19951A05L8@iare.ac.in

***Abstract*—** Over the past few years, there has been a rising interest in utilizing Electroencephalogram (EEG) signals. for emotion detection, with potential applications in fields such as affective computing and medicine. Depression, which is a widespread mental health condition, has been found to cause distinct spatial responses to neurophysiological signals in patients, when exposed to positive and negative stimuli, are different from those in healthy individuals. .Our analysis focuses on key aspects involved in emotion recognition, including themes, extracted features, classifiers, and more, and compares existing research in the field.
To better illustrate the activation process of emotions, we introduce an emotion activation curve. Our algorithm extracts features from EEG signals, employs machine learning techniques to classify emotions, and uses different portions of the experiment to train a proposed model, which is then evaluated for its impact on emotion detection results. Our project's primary objective is to recognize emotions using brain signals by utilizing a novel adaptive channel selection method that can differentiate how brain activity behaves in different individuals and emotional states.
The outcomes of our study indicate a substantial improvement in accurately classifying positive or negative emotions in depressed patients using the proposed method.

**Keywords**— Epilepsy, Seizure detection using EEG, Deep learning, CNN, and Classification.

## I. INTRODUCTION

Depression is a prevalent and debilitating mood disorder characterized by persistent feelings of sadness and anger that impede daily functioning. By 2030, it is predicted to become the most common health condition worldwide, surpassing all other diseases, according to the World Health Organization. Depressive disorders are pathological processes that produce a broad range of symptoms and diminish both physical and mental performance. Depression can lead to cognitive decline, heightened risk of Alzheimer's disease and suicide, and is frequently linked to cognitive impairment. Early detection is essential for effective treatment. The EEG is a low-cost and non-intrusive method that provides excellent temporal resolution, making it a commonly used tool in neurology and rehabilitation approaches..

In depression research, considerable focus is placed on experimental paradigms, sentiment feature extraction, feature selection, machine learning, and datasets for testing and training,with a focus on the selection and feature extraction of spatial data. This research area was chosen because several studies have shown that when exposed to stimuli, depressed individuals exhibit spatially distinct responses compared to healthy individuals.
There have been numerous studies conducted on depression, examining both task-based and resting-state conditions. Electroencephalogram (EEG) signals, like many other physiological signals, are non-stationary and non-linear. To analyze these signals, researchers often utilize a variety of linear and nonlinear functions, including power spectral density, Lempel-Ziv complexity, dispersion, mobility, fluctuations, Higuchi fractal, and approximation entropy. However, the selection of the most effective features for hypothesis analysis is critical.

## II. RELATED WORK

### *A.Classify EEG signals to predict epileptic seizures.*

This focused on predicting epileptic seizures through the classification of EEG signals. While surgery can treat epilepsy in some cases, generalized seizures are often more than 30% of cases are unresponsive to medication treatment. To enhance the signal-to-noise ratio, regression-based techniques were utilizedThe suggested approach underwent training and testing using the CHB-MIT scalp EEG dataset, resulting in an accuracy of 94%, a sensitivity of 93.8%, and a specificity of 91.2%. This technique displayed superior sensitivity and specificity in comparison to current methods.

### *B.Sudy suggests an intelligent health monitoring technique that utilizes deep learning-based spectral analysis of EEG signals to automatically predict epileptic seizures.*

Epilepsy is a common neurological disorder that can cause spontaneous seizures, and early seizure prediction is crucial for effective management. The proposed approach involves filtering, segmentation, and spectral domain transformation of EEG signals. According to the CNN model's findings, by utilizing two distinct spectral band combinations, the approach can achieve peak accuracies of 98.3% and 97.4% for binary classifications of preictal and interictal ictal states. Consequently, the combination of CNN architecture and spectral analysis of EEG signals offers a dependable method and feasible technique for predicting epileptic seizures in real-time., potentially enhancing patient care and quality of life.

*C.A deep learning approach for predicting epileptic seizures using scalp EEG signals.*

Early detection of seizures is crucial in managing epilepsy, a prevalent neurological disorder that can cause severe brain damage, stroke, and brain tumors. Seizure prediction systems aim to detect preictal brain states that occur before seizure events. However, developing a seizure prediction model that works accurately across multiple subjects is challenging due to the high inter-individual variability of EEG data. To tackle this challenge, the proposed model utilizes model interpretation to understand classifier behavior for seizure prediction tasks and incorporates MFCC functional maps to identify predictive biomarkers associated with interictal and preictal brain states. The model achieved an average accuracy of 96% across all 24 subjects in the dataset. This research has significant implications for epilepsy management and highlights the potential of deep learning models to predict seizures independent of the patient using scalp EEG signals..

*D. Machine learning approach utilized to predict epileptic seizures using Electroencephalogram (EEG) signals.*

The objective was to detect seizures in patients with accuracy and promptness by analyzing the electrical activity of the brain can vary across different recording regions and physiological conditions.. The authors analyzed 100 EEG recordings taken using a single-channel surface electrode, each consisting of 23.6-second segments collected at a sampling rate of 173.61 Hz. In order to create a dependable classifier, a t-test and SFFS were used in sequence to select and determine the necessary and sufficient features. The selected features were then input into SVM and ANN classifiers resulting in accuracy rates of 100% and 99.5%, respectively. The study's findings could help neurophysiologists devise an effective approach for detecting epileptic seizures.

## III.METHODOLOGY

*A. Data Sets*

The first step is to collect data. In this study, data was gathered from two individuals (one male and one female) in three-minute increments under positive, neutral, and negative conditions. A Muse EEG headband, which utilized dry electrodes, recorded EEG placements at TP9, AF7, AF8, and TP10. In addition, six minutes of resting data and a stimulus used to elicit emotions were recorded.

*B. Selecting and loading data*

Data selection is the process of picking out data from the EEG emotion dataset in order to predict the emotions of patients suffering from depression. Our statistical extraction method was employed to extract EEG brainwave data from this dataset. Two participants, a male and a female, were recorded for three-minute intervals under positive, neutral, and negative emotional states using a Muse EEG headgear and dry electrodes placed at TP9, AF7, AF8, and TP10. Along with this, six minutes of resting neutral data were collected, along with stimuli utilized to elicit emotions.

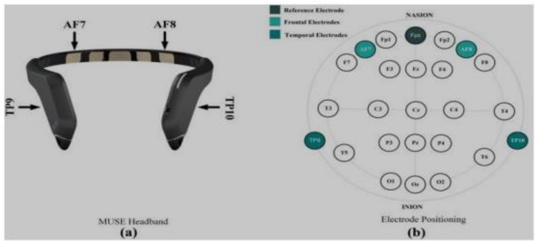


Fig 2.1 a: Muse band which can record EEG placements

2.1 b: Electrode positioning

*C. Data Preprocessing*

Data preprocessing involves eliminating redundant data from a data record, and it comprises of two primary phases:

1. Removal of missing data
2. Encoding of categorical data

The first step is to remove null values, including missing values, using the imputer library. In the subsequent stage, categorical data is encoded, which pertains to variables that possess a limited set of label values. Since most machine learning algorithms require numerical input and output variables, techniques like integer and one-hot encoding are utilized to transform categorical data into numerical data

Data preprocessing involves the elimination of extraneous data from a dataset, which can encompass activities like discarding missing values and encoding categorical data.

In order to eliminate null values, the imputer library is used during this procedure. Categorical data, which refers to variables with a limited number of label values, is transformed into integer data through hot encoding and integers to prepare it for use in machine learning algorithms.

Preprocessing is necessary to make sure that data is in the proper order for machine learning projects, and it involves converting raw and unclean data into clean data that is suitable for analysis.

Preprocessing of EEG signals is crucial to remove noise, and this can be achieved through techniques such as converting the multichannel EEG signal to surrogate channels or applying a bandpass filter. Averaging or applying Common Spatial Pattern (CSP) filtering can also be used to obtain alternate channels. Using Butterworth filters, wavelet transforms, and Fourier transforms has been shown to improve the signal-to-noise ratio (SNR) of seizure prediction EEG signals. Joint spatial filtering (CSP) can also help improve SNR and reduce computational cost by reducing the number of channels.

The process of dividing available data into two parts for cross-validation purposes is referred to as data partitioning. Dividing the data into a training set and a test set is a critical phase in evaluating a data mining model, as it permits one part of the data to be employed for creating predictive models, while the other is employed for evaluating the model's performance. Typically, the majority of the data is employed for training, while a smaller portion is kept aside for testing purposes.

The above-provided flowchart outlines the different stages of data utilization, beginning with the collection of a dataset based on specific requirements and continuing with data preprocessing, feature scaling, and data partitioning.

*D. Feature Selection*

In order to develop epilepsy detection models from standard epilepsy data and epilepsy detection from actually obtained EEG signal data, feature extraction is a crucial stage in the epileptic seizure detection process. Improvement of feature extraction is crucial because the efficiency of feature extraction and the precision of epilepsy detection are directly related.

Divide the dataset into training and testing subsets.

In order to enable cross-validation, the available data is frequently partitioned into two segments, wherein one segment is utilized for creating a predictive model and the other is set aside for assessing the model's effectiveness.The process of dividing a dataset into these training and testing sets is essential when assessing data mining models. Typically, a larger portion of the data is assigned for training, while a smaller portion is allocated for testing. The technique of dividing data into training and testing sets is widely employed to gauge the effectiveness of machine learning algorithms in predicting outcomes on previously unseen data, which was not part of the model training.

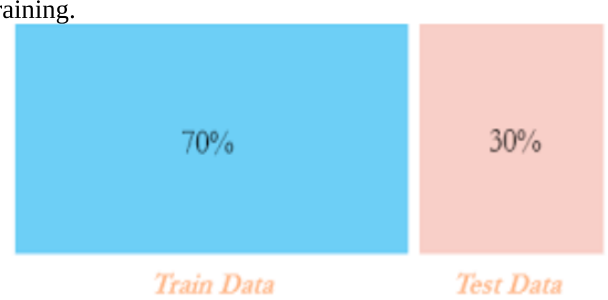


Fig 2.2: Dataset split into training and testing data

*E. Classification*

Classification is the process associated with classification, the process of recognizing, distinguishing and understanding ideas and objects. The project employs KNN and LSTM classification algorithms for data classification. K-Nearest Neighbor is a basic supervised learning technique and one of the simplest machine learning algorithms.

The K-NN algorithm functions on the principle that similarities exist between new and existing cases or data, and it assigns the new cases to the category that is most similar to the existing categories. The method involves classifying new data points based on their resemblance to previously observed data.Therefore, the K-NN algorithm can efficiently and accurately categorize new data into the appropriate category.

Long Short-Term Memory (LSTM) is a form of artificial recurrent neural network architecture employed in deep learning. Unlike conventional feedforward neural networks, LSTMs possess feedback connections that enable them to process both individual data points (such as images) and complete data sequences. LSTMs contain special cells called "memory cells" that allow them to store and retrieve information over extended periods of time. The LSTM architecture is capable of processing sequential data and retaining its hidden state over time, making it ideal for tasks such as speech recognition and language translation.

Statistical moments are extracted from all 23 channels as hand-crafted features, include mean, standard deviation and skewness.

The following are the formulae of the same:

$$\beta = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^3$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N}(x_i)$$

The variable xi denotes the chosen window of the EEG signal, while N represents the total count of samples.

## III. SYSTEM DIAGRAMS

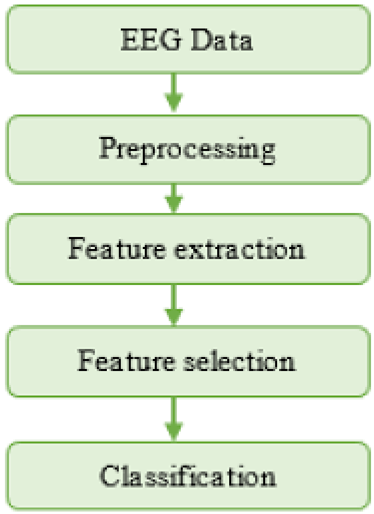


Fig 3.1: Flowchart depicting the process of seizure analysis

The above flowchart shows how data is used at different stages.The first step is data preprocessing that removes unwanted data from the data set. The second step involves data cleaning, while the third step is feature scaling. Feature scaling is used to normalize independent features in the data to a consistent range. If feature scaling is not applied, machine learning algorithms can be biased towards variables with larger values or smaller values, regardless of their units.Then the data is visualised and then splitted. Later it is sent for classification using the ML algorithms like KNN and LSTM. Finally the result is generated.

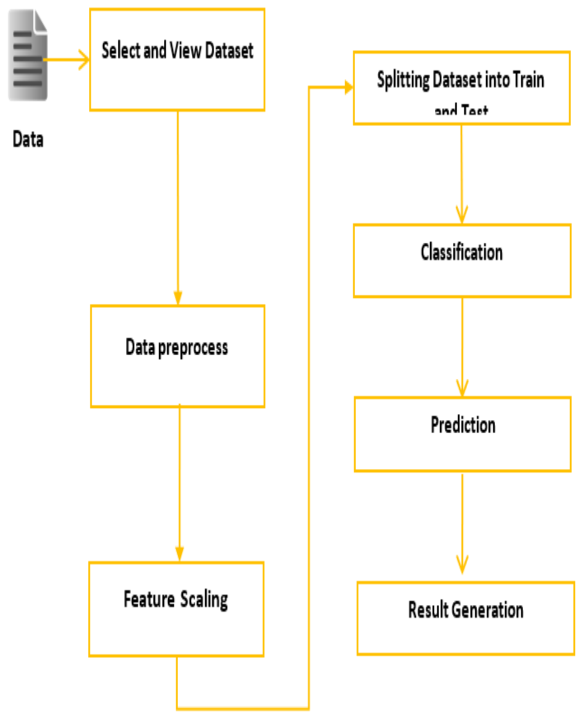


Fig 3.2: Block diagram of seizure analysis

## IV. PROPOSED METHOD

The proposed model shows the main steps of preprocessing phase, feature extraction and classification.This process takes an EEG signal data set and predicts the emotions of depressed patients as positive and negative.
The first process to do this is to preprocess the data set to remove missing and null values from the acquired EEG data set. Classifying different emotions requires recording EEG signals from different subjects and processing them to extract different features.
Traits are employed to generate records for emotion classification, and to improve the precision of classifying emotions as positive or negative in depressed patients, we suggest employing machine learning (KNN) and deep learning (LSTM) algorithms

*A.KNN Algorithm.*

The K-Nearest Neighbor (K-NN) algorithm is a popular supervised learning technique in machine learning, which assumes that similarities exist between new data points and those already present in the dataset. It assigns new data points to categories that are most similar to the existing ones, and stores all available data to classify new data points based on their similarity to the existing ones. Although it can be applied to both regression and classification problems, it is typically used for classification. This nonparametric algorithm does not make assumptions about the underlying data, and it is known as a delayed learning algorithm because it saves the dataset and performs an action during classification. During classification, K-NN algorithm solely utilizes the training dataset to classify new data points into categories that closely resemble the new data.

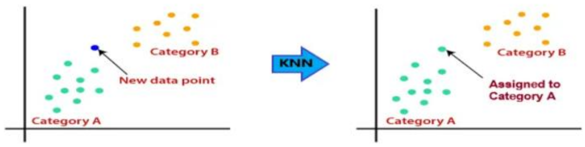


Fig 4.1: Classifying new data based on KNN

*B. LSTM Algorithm*
LSTM, which stands for Long Short-Term Memory, is a type of recurrent neural network (RNN) type that is specialized in processing sequential data, such as speech, time series, and text. Unlike traditional RNNs that rely on a single hidden state spanning time, LSTMs are designed to learn long-term dependencies in sequential data by utilizing memory cells that can store information for extended periods. These memory cells are governed by three gates: input gates, forget gates, and output gates.
The input gate controls the addition of new information to the memory cell, the forget gate governs which data is removed from the memory cell, and the output gate manages the data output from memory cells. This enables LSTMs to select the relevant information to keep or discard as it flows through the network, allowing for long-term dependency learning.
By stacking LSTMs, deep LSTM networks can be formed to learn complex patterns in sequential data. LSTMs can also be combined with other neural network architectures such as Convolutional Neural Networks (CNN) for image and video analysis.

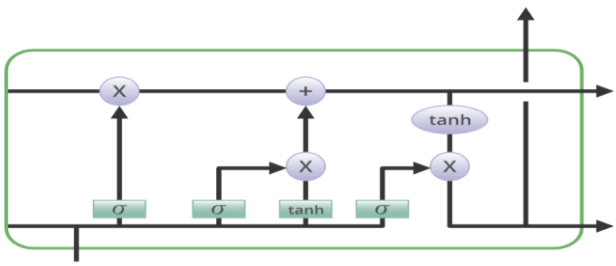


Fig 4.2: Structure of LSTM with chain structure that contains four neural network

*1.Forget Gate*
The forget gate plays a crucial role in discarding unnecessary information from the cell state. This gate receives two inputs, x_t (the input at a given time) and h_t-1 (the output of the previous cell), which are multiplied by a weight matrix and added with a bias. The resulting output is then passed through an activation function that produces a binary output. If the output is 0, the information is disregarded, while if it is 1, the information is retained for future use.

*2. Input Gate*

The task of incorporating relevant information into the cell state is handled by input gates. These gates regulate the input information via a sigmoid function, and the remembered value is further filtered through the inputs h_t-1 and x_t, in a way similar to the forget gate. Next, the tanh function is applied to generate a vector that outputs values ranging from -1 to +1, which contains all feasible values of h_t-1 and x_t. Ultimately, the values in the vector are multiplied by the modified values to produce meaningful information.

*3. Output Gate*

To extract valuable information from the present cell state and represent it as output, output gates are employed. The first step involves applying the tanh function to the cells, generating a vector. Next, the information is modulated by a sigmoid function and filtered using inputs h_t-1 and x_t to preserve only relevant information. The resulting values in the vector and the modulated values are multiplied and forwarded to the subsequent cell as both inputs and outputs.

## V. RESULTS AND DISCUSSIONS

The approach suggested computes a final score by considering the overall classification and prediction, and its efficacy is assessed through multiple metrics such as Accuracy, Precision, Recall, and F-Measure.

Accuracy is a measure of the classifier's power to correctly predict the class labels. It is also used to measure how well a particular predictor can predict the value of a predictor attribute in new data. The formula for accuracy is:

AC = (TP + TN) / (TP + TN + FP + FN)

Precision is calculated by dividing the number of true positive results by the sum of true positive and false positive results. It indicates how well the classifier can accurately identify positive samples. The precision formula is represented as:

Precision = TP / (TP + FP)

Recall, also known as sensitivity in binary classification, is the proportion of correctly identified positive results to the total number of relevant elements. It measures how well the classifier can detect positive samples. The recall formula is:

Recall = TP / (TP + FN)

The F-measure, or F1 score, is a metric of test accuracy that considers both precision and recall, balancing the two values. It is calculated as the weighted harmonic mean of precision and recall. The formula for the F-measure is:

F-measure = 2TP / (2TP + FP + FN)

| 1 | # mean_0_a | mean_1_a | mean_2_a | mean_3_a | mean_4_a | mean_d_0_ |
|---|---|---|---|---|---|---|
| 2 | 4.62E+00 | 3.03E+01 | -3.56E+02 | 1.56E+01 | 2.63E+01 | 1.07E+00 |
| 3 | 2.88E+01 | 3.31E+01 | 3.20E+01 | 2.58E+01 | 2.28E+01 | 6.55E+00 |
| 4 | 8.90E+00 | 2.94E+01 | -4.16E+02 | 1.67E+01 | 2.37E+01 | 7.99E+01 |
| 5 | 1.49E+01 | 3.16E+01 | -1.43E+02 | 1.98E+01 | 2.43E+01 | -5.84E-01 |
| 6 | 2.83E+01 | 3.13E+01 | 4.52E+01 | 2.73E+01 | 2.45E+01 | 3.48E+01 |
| 7 | 3.10E+01 | 3.09E+01 | 2.96E+01 | 2.85E+01 | 2.40E+01 | 1.65E+00 |
| 8 | 1.08E+01 | 2.10E+01 | 4.47E+01 | 4.87E+00 | 2.81E+01 | 2.14E+00 |
| 9 | 1.78E+01 | 2.78E+01 | -1.02E+02 | 1.69E+01 | 2.69E+01 | -3.21E+00 |
| 10 | 1.15E+01 | 2.97E+01 | 3.49E+01 | 1.02E+01 | 2.69E+01 | -3.80E+01 |
| 11 | 8.91E+00 | 2.92E+01 | -3.14E+02 | 6.51E+00 | 3.09E+01 | -1.88E+00 |
| 12 | 5.21E+00 | 2.84E+01 | 1.85E+01 | 3.66E+00 | 2.26E+01 | -1.19E-01 |
| 13 | 1.33E+01 | 3.04E+01 | -1.49E+02 | 1.18E+01 | 2.83E+01 | 3.03E+00 |
| 14 | 3.01E+01 | 3.27E+01 | 2.94E+01 | 2.83E+01 | 2.43E+01 | -6.05E+00 |
| 15 | 1.93E+01 | 3.17E+01 | -4.56E+00 | 2.38E+01 | 3.29E+01 | -3.41E+00 |
| 16 | 2.88E+01 | 3.18E+01 | 3.01E+01 | 2.69E+01 | 2.18E+01 | -3.55E-01 |
| 17 | 1.27E+01 | 2.38E+01 | -1.93E+02 | 1.11E+01 | 2.76E+01 | -3.72E+00 |
| 18 | 4.25E-01 | 3.49E+01 | 5.39E+01 | -1.19E+01 | 2.26E+01 | 1.24E+01 |
| 19 | 2.89E+01 | 3.08E+01 | 2.94E+01 | 2.74E+01 | 2.51E+01 | -7.86E+00 |
| 20 | -1.41E+01 | 2.19E+01 | -9.46E+02 | 8.93E+00 | 2.26E+01 | 2.89E-02 |

y - NumPy array

| | 0 | 1 | 2 |
|---|---|---|---|
| 0 | 1 | 0 | 0 |
| 1 | 0 | 1 | 0 |
| 2 | 0 | 0 | 1 |
| 3 | 0 | 0 | 1 |
| 4 | 0 | 1 | 0 |
| 5 | 0 | 1 | 0 |
| 6 | 0 | 0 | 1 |
| 7 | 1 | 0 | 0 |
| 8 | 0 | 1 | 0 |
| 9 | 1 | 0 | 0 |
| 10 | 0 | 0 | 1 |
| 11 | 1 | 0 | 0 |
| 12 | 0 | 1 | 0 |

Format Resize Background color

Save and Close Close

Fig 5.1: Input data

```
------K-Nearest Neighbor------

------Classification Report------
              precision    recall  f1-score   support

           0       0.98      0.94      0.96       139
           1       0.97      0.94      0.95       157
           2       0.87      0.95      0.91       131

   micro avg       0.94      0.94      0.94       427
   macro avg       0.94      0.94      0.94       427
weighted avg       0.94      0.94      0.94       427
 samples avg       0.94      0.94      0.94       427


------Accuracy------
KNN Accuracy: 0.9414519906323185
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 1, 64)             668928
_________________________________________________________________
dropout (Dropout)            (None, 1, 64)             0
_________________________________________________________________
lstm_1 (LSTM)                (None, 32)                12416
_________________________________________________________________
dropout_1 (Dropout)          (None, 32)                0
_________________________________________________________________
dense (Dense)                (None, 3)                 99
=================================================================
Total params: 681,443
Trainable params: 681,443
Non-trainable params: 0
_________________________________________________________________
Train on 1705 samples, validate on 427 samples
Epoch 1/10
1705/1705 [==============================] - 7s 4ms/sample - loss: 0.8137 - acc: 0.8211 -
val_loss: 0.6246 - val_acc: 0.9110
Epoch 2/10
1705/1705 [==============================] - 2s 1ms/sample - loss: 0.5560 - acc: 0.9320 -
val_loss: 0.4895 - val_acc: 0.9204
Epoch 3/10
1705/1705 [------------------------------] - 2s 880us/sample - loss: 0.4398 - acc: 0.9437
- val_loss: 0.4145 - val_acc: 0.9157
Epoch 4/10
1705/1705 [==============================] - 2s 897us/sample - loss: 0.3519 - acc: 0.9455
- val_loss: 0.3334 - val_acc: 0.9227
Epoch 5/10
1705/1705 [------------------------------] - 1s 786us/sample - loss: 0.2928 - acc: 0.9455
- val_loss: 0.2954 - val_acc: 0.9204
```

Fig 5.2: Output of KNN Algorithm

LSTM Accuracy: 95.31615925058547

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.99 | 0.92 | 0.95 | 143 |
| 1 | 0.99 | 0.96 | 0.98 | 158 |
| 2 | 0.87 | 0.98 | 0.93 | 126 |
| accuracy | | | 0.95 | 427 |
| macro avg | 0.95 | 0.95 | 0.95 | 427 |
| weighted avg | 0.96 | 0.95 | 0.95 | 427 |

Fig 5.3: Output of LSTM Algorithm

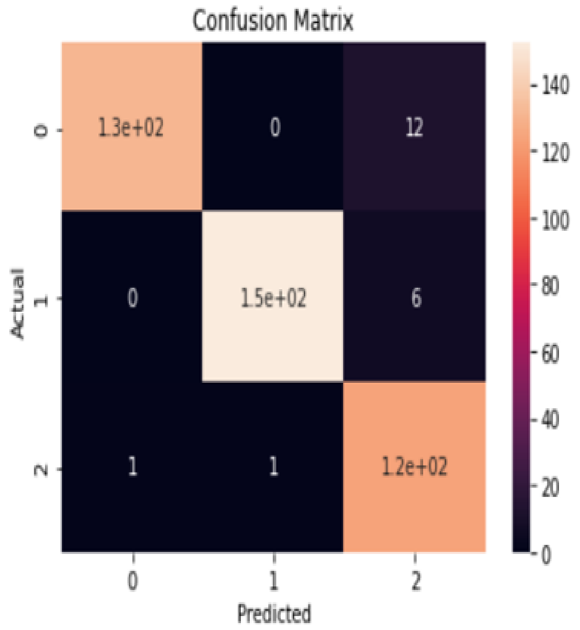


Fig 5.4: Confusion Matrix

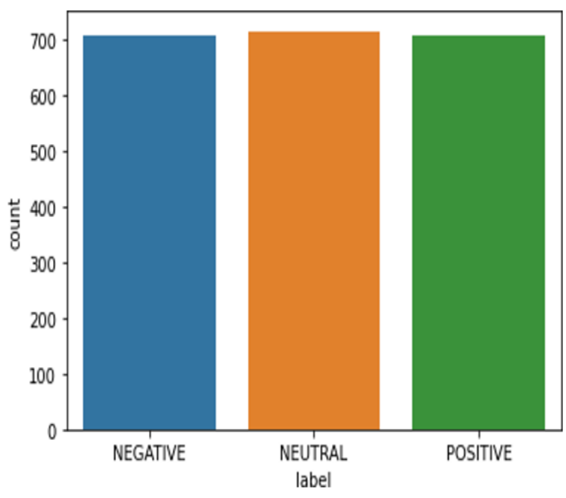


Fig 5.5: Bar graph indicating negative, positive and neutral data

## VI. CONCLUSION

The incidence of depression, a mood disorder, is on the rise. In order to identify individuals suffering from depression, we devised a feature classification method based on EEG data obtained during a face-in-the-crowd task experiment. Our approach involved filtering frequency information, extracting time-related features, and selecting spatial information features. By integrating spatial information into our method, we achieved a considerable improvement in classification accuracy.However, the dataset used has certain limitations that should be taken into account.

The KNN algorithm yielded an accuracy of 94%, while the LSTM algorithm yielded an accuracy of 95%.

## VII. ACKNOWLEDGEMENT

We would like to thank Institute of Aeronautical Engineering for conducting this research project.

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