1. Methodology

1.1 Data Collection:

The dataset utilized in this study was obtained from Figshare, comprising EEG recordings from 94 patients diagnosed with Abnormality and 85 healthy control subjects. European Data Format (EDF) files were used to store each recording in order to ensure compatibility with the preprocessing steps that followed.

1.2 Preprocessing:

Preprocessing EEG data is essential in neurophysiological research, especially in depression studies. Its objective is to improve EEG signals by removing artefacts and noise, exposing precise patterns of brain activity. A key technique used here is bandpass filtering.

Data Loading: Using the MNE library in Python, EEG recordings in EDF format were imported. Abnormal subjects' files starting with 'm' and Normal subjects' files starting with 'h' were selectively loaded, ensuring representation across groups.

Bandpass Filtering: Bandpass filtering is used to isolate relevant neural oscillations associated with Abnormality while suppressing unwanted frequency components. We applied a bandpass filter with cutoff frequencies set at 0.5 Hz and 40 Hz to filter out lowfrequency drifts, physiological noise, and high-frequency artifacts. This helped clean the EEG data, ensuring that only the relevant brain signals associated with abnormality were preserved for analysis.

Then the filtered EEG data was converted into pandas DataFrame format, simplifying integration with Python's tools. This made signal manipulation efficient, offering researchers flexibility for analysis and preprocessing.

1.3 Feature Extraction:

Feature extraction involves transforming raw data into representative features for analysis. We used wavelet transformation for this purpose, exploring EEG data to understand conditions like depression.

Wavelet Transformation: Wavelet transformation decomposes EEG signals into different frequency components, revealing time-frequency characteristics inherent in the data. Here, we employ the Daubechies 4 (db4) wavelet, a type of wavelet known for its effectiveness in capturing detailed information across multiple scales.

Coefficient Analysis: In wavelet transformation, we extracted two types of coefficients: approximation (cA) and detail coefficients (cH, cV, cD). The cA coefficients provided us with a general understanding of the neural activity associated with abnormality, whereas detail coefficients concentrated on particular details, such as sudden changes or unusual patterns. We specifically focused on extracting cA coefficients to grasp the broader trends in neural activity linked to abnormality. These coefficients provide an all-encompassing perspective that is essential for comprehending underlying patterns in EEG signals linked to abnormality.

Next, **these extracted features, particularly the cA coefficients, will be turned into images.** These images will serve as input for our model, aiding further analysis and interpretation of the EEG data.

2. Results

Deep Learning Models	Accuracy	ROC & AUC Score
CNN	49.75%	0.50
Bidirectional Lstm+InceptionV3	48.93%	0.63
Lstm+InceptionV3	93.12%	0.99
EfficientNet B6	96.81%	1.00

3. Conclusion

3.1 Convolutional Neural Network (CNN):

The trained CNN model achieved an accuracy of 49.75% on the test set, indicating poor performance.

The ROC curve had an AUC score of 0.50, suggesting that the model's ability to distinguish between classes is not better than random guessing.

3.2 Hybrid of InceptionV3 + Bi-directional LSTM:

The hybrid model combining InceptionV3 with Bi-directional LSTM achieved an accuracy of 48.93% on the test set, indicating poor performance.

However, the ROC curve showed a slightly better performance with an AUC score of 0.63 compared to the CNN model.

3.3 Hybrid of InceptionV3 + LSTM:

The hybrid model combining InceptionV3 with LSTM achieved a significantly higher accuracy of 93.12% on the test set, indicating much better performance compared to the previous models.

The ROC curve demonstrated excellent performance with an AUC score of 0.99, suggesting a high ability to distinguish between classes.

3.4 EfficientNet B6:

The trained EfficientNet B6 model achieved an impressive accuracy of 96.81% on the test set, indicating excellent performance.

The ROC curve showed outstanding performance with an AUC score of 1.00, indicating perfect discrimination between classes.