CNN-BLSTM Deep Learning Approach for Stress Detection Using EEG Signals

Abstract

In order to identify stress using EEG signals, this study suggests a hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BLSTM). The model makes use of CNN for feature selection, BLSTM for temporal sequence modeling, and Discrete Wavelet Transform (DWT) for feature extraction from EEG data. This method supports mental health assessment and intervention by accurately classifying stress and relaxation states.

1. Dataset Description

The dataset includes EEG recordings provided in EDF (European Data Format) files, with each subject having two files: a baseline recording ("_1") taken before the mental arithmetic task and a task recording ("_2") taken during the task. Subjects are divided into two groups based on task performance: Group "G" (24 subjects), who performed well with a mean of 21 operations in 4 minutes (SD = 7.4), and Group "B" (12 subjects), who performed poorly with a mean of 7 operations (SD = 3.6).

2. Methodology

2.1 Preprocessing and Feature Extraction

Each EEG channel was subjected to the Discrete Wavelet Transform (DWT), which effectively reduced noise and extracted features by breaking the signals down into several frequency bands (Delta, Theta, Alpha, Beta, and Gamma). A CNN was then fed the wavelet-decomposed signals to choose features automatically.

2.2 Model Architecture

The suggested hybrid model includes a Bidirectional Long Short-Term Memory (BLSTM) layer for temporal modeling after a Convolutional Neural Network (CNN) for spatial feature extraction. The following describes the model architecture:

- **Convolutional Layers:** Two Conv1D layers with Batch Normalization and MaxPooling, followed by a Dropout layer to prevent overfitting.
- **BLSTM Layer:** A BLSTM layer to capture temporal dependencies in EEG sequences.

3. Results and Evaluation

The model's performance was evaluated using several metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. The ROC curve (Fig. 1) demonstrates the model's ability to distinguish between stress and non-stress cases.

Table 1: Performance Metrics for Stress Detection

Metric	Value
Accuracy	73%
AUC (ROC)	0.79
Precision (Stress)	0.73
Recall (Stress)	1.00
F1-Score (Stress)	0.84

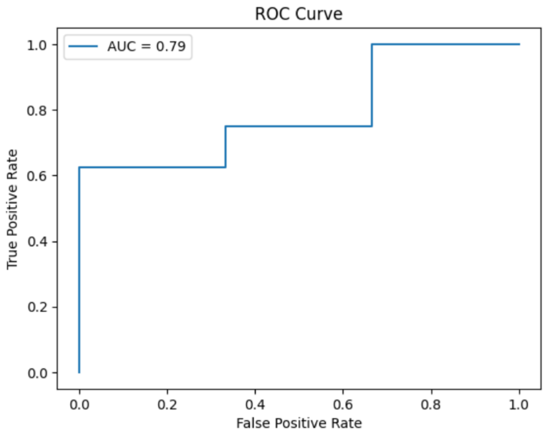

Figure 1: ROC Curve with AUC = 0.79

4. Limitations

The main limitation of this model is its reduced specificity for non-stress cases, as observed in the results. This limitation suggests a potential for false positives, which could lead to over-detection of stress.

5. Conclusion

The efficiency of a CNN-BLSTM hybrid model for stress detection from EEG signals is demonstrated in this work. The model's encouraging results for automated stress classification, with an AUC of 0.79, could help with real-time mental health monitoring.