Stress Detection from EEG Signals Using a Hybrid CNN-BLSTM Model

1 Introduction

In today's fast-paced world, stress is a common issue affecting both mental and physical health. Electroencephalography (EEG) signals, which capture brain activity, can be utilized to detect stress levels. This paper implements a stress detection model based on the methodology described in the study *"A Novel Technique for Stress Detection from EEG Signal Using Hybrid Deep Learning Model"* [1]. The model uses Discrete Wavelet Transform (DWT) for feature extraction and a hybrid Convolutional Neural Network - Bidirectional Long Short-Term Memory (CNN–BLSTM) architecture for classification.

2 Dataset Description

The EEG dataset used in this implementation is sourced from PhysioNet, containing EEG recordings from 36 subjects who performed mental arithmetic tasks [2]. The dataset includes 19 EEG channels recorded at a sampling rate of 500 Hz. Each subject's data consists of 31,000 samples per channel for stress-inducing tasks, and a similar length of baseline (relaxed) recordings is also available. In line with the original study, we applied Discrete Wavelet Transform (DWT) to denoise the signals and to extract five frequency bands.

3 Implementation Details

The EEG signals were preprocessed and transformed using the DWT (Daubechies wavelet, level 4). Feature extraction was automated using a two-layer CNN with 95 and 47 filters, respectively, followed by a max-pooling layer. The BLSTM layer with 64 units was applied for classification, allowing information flow in both forward and backward directions. A dropout rate of 0.5 was used to prevent overfitting. The model was trained with the following parameters:

- Optimizer: Adam
- Loss function: Binary Crossentropy
- Epochs: 100
- Batch size: 20

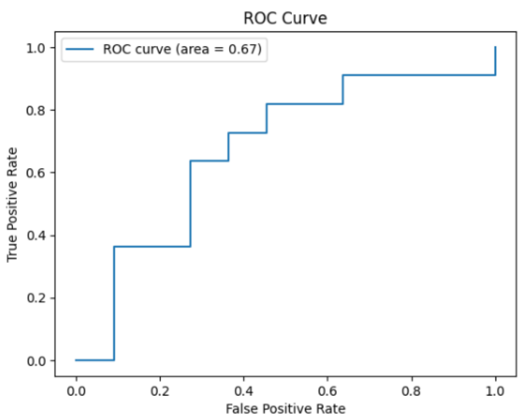
The code was implemented in Python using TensorFlow and Keras. The dataset was split into 70% for training and 30% for testing, and further divided into training and validation sets in a 70:30 ratio.

4 Results

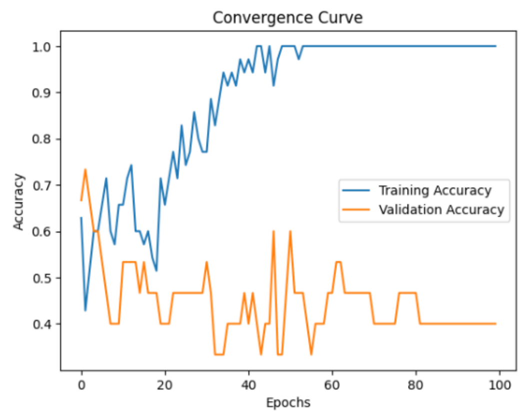
Table 1 and Figure 1 summarize the model's performance on the test data. The hybrid CNN-BLSTM model achieved an accuracy of 68.18% on the test set, with an area under the ROC curve (AUC) of 0.67, indicating a moderate level of discrimination between stress and relaxed states. The convergence curve shows the training and validation accuracy across epochs, highlighting some overfitting as the training accuracy reached near 100% while validation accuracy remained unstable.

Table 1: Performance Metrics on Test Data

Metric	Value
Test Accuracy	68.18%
AUC	0.67
Precision	0.67
Recall	0.73
F1 Score	0.70



(a) ROC Curve (AUC = 0.67)



(b) Convergence Curve: Training vs Validation Accuracy

Figure 1: Performance Analysis of CNN-BLSTM Model

5 Discussion

Compared to the original paper's results, which reported a 99.20% classification accuracy, our implementation yielded a significantly lower accuracy of 68.18%. The discrepancy could stem from various factors, such as differences in dataset processing, model hyperparameters, or regularization techniques. The original study applied tenfold cross-validation and may have benefited from a larger data sample or additional pre-processing techniques.

6 Conclusion

This implementation of a CNN-BLSTM model for EEG-based stress detection demonstrates moderate success in discriminating between stress and relaxed states but falls short of the reported results from the reference paper. Future work could involve refining the model's parameters, improving the preprocessing pipeline, and experimenting with cross-validation to enhance performance.

References

[1] L. Malviya and S. Mal, "A Novel Technique for Stress Detection from EEG Signal Using Hybrid Deep Learning Model," *Neural Computing and Applications*, vol. 34, pp. 19819–19830, 2022.

[2] I. Zyma, S. Tukaev, I. Seleznov, et al., "Electroencephalograms During Mental Arithmetic Task Performance," *PhysioNet*, 2019. [Online]. Available: https://physionet.org/content/eegmat/1.0.0/