# Emotion Recognition from EEG Signals: Advances in Deep Learning and Hybrid Models

## Abstract

Emotion detection from EEG signals is a promising approach in diagnostics related to mental health, human-computer interaction, and neurofeedback systems. EEG signals provide a direct, accurate means of decoding emotional states, hence overcoming limitations seen in old methods such as those based on facial expression or speech analysis. In this paper, the authors develop a hybrid deep learning model that makes use of an Autoencoder as a feature extractor and combines a CNN-BiLSTM to classify emotions. The model, evaluated on the EEG dataset from Kaggle, classified emotions into three classes, positive, neutral, and negative, with high accuracy of 98%. This paper reviews the recent advance of deep learning for emotion detection and places the proposed model as competitive and effective.

## 1. Introduction

Emotion recognition finds a number of important applications in monitoring mental health, human-computer interaction, and affective computing. EEG signals reflect brain activities in a non-invasive way and serve as the basis for emotional state classification with much higher precision compared, for example, to classical approaches in the analysis of facial expression or speech.

### Motivation

Recent studies have indicated that, in order to classify emotions from the EEG signals, deep learning architectures are particularly effectual when hybrid models are involved. For example, classification of emotions such as happiness and anger using the DEAP dataset with Bi-LSTM and IRNN models was done by Kulkarni et al. (2024). Ahmadzadeh et al. (2024) proposed a modified Convolutional Fuzzy Neural Network (CFNN), which resulted in a higher classification accuracy for key emotional dimensions of valence and arousal. There is still room for improvement in capturing both the spatial and temporal dynamics of EEG signals for better classification performance.

In this paper, a hybrid deep learning model is proposed, using an Autoencoder for the purpose of feature reductions and extraction, and CNN-BiLSTM for emotion classification. The proposed architecture will be evaluated on an EEG brainwave dataset available on Kaggle.

## 2. Literature Review

|  |  |  |
| --- | --- | --- |
| **Paper** | **Key Insight** | **Citations** |
| Emotion detection using EEG: Hybrid classification approach by Kulkarni et al. 2024 | Employs Bi-LSTM and IRNN models for the classification of emotions. | - |
| Emotion Detection from EEG Signals by a Modified Convolutional Fuzzy Neural Network -Ahmadzadeh et al., 2024 | Improved CFNN Model for Higher Valence and Arousal Accuracy | - |
| An Efficient EEG Signal Analysis for Emotion Recognition Using FPGA- Ezilarasan & Leung, 2024 | CNN-LSTM with ResNet-152 for Emotion detection to be run on FPGA | - |
| Emotion Detection from EEG Signal Using Deep Learning: Bi-LSTM and GRU by Maliha et al. (2024) | Bi-LSTM and GRU for Emotion Classification | - |

## 3. Methodology

### 3.1 Datasets

The dataset used in this paper is the EEG Brainwave Dataset: Feeling Emotions, from Kaggle. The dataset will be a collection of EEG signals capturing various brainwave patterns corresponding to three emotional states, namely positive, neutral, and negative. Each sample will represent a series of EEG signals recorded across multiple sensors.

* Dataset Size: 427 samples
* Emotion Labels: Positive, Neutral, Negative
* EEG Channels: Multi-channel brainwave activity

### 3.2 Data Preprocessing

The following were applied as preprocessing techniques:

* **Normalization:** StandardScaler was used to normalize the EEG features.
* **Reshaping:** 1D EEG signals to 2D grids to be fed into the convolutional layer.

### 3.3 Feature Extraction using Autoencoder

The high-dimensional EEG data was then projected into lower dimensions using an autoencoder:

* **Encoder:** The architecture comprises convolutional layers that perform feature extraction.
* **Decoder:** Recover the original data without losing its core features.

### 3.4 CNN-BiLSTM Model for Emotion Classification

The CNN-BiLSTM uses CNN layers that extract spatial features with the BiLSTM to extract temporal dependencies. Finally, a softmax-activated dense layer is used for classification.

## 4. Training and Evaluation

### 4.1 Training Autoencoder

The Autoencoder was trained by minimizing the loss on MSE. The encoder was used to extract the feature.

### 4.2 Training CNN-BiLSTM

The CNN-BiLSTM model was trained, with early stopping and class weights due to imbalance, with a maximum of 50 epochs.

### 4.3 Classification Report and Confusion Matrix

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Metric** | **Precision** | **Recall** | **F1-Score** | **Support** |
| Positive | 0.99 | 0.97 | 0.98 | 143 |
| Negative | 1.00 | 0.99 | 0.99 | 148 |
| Neutral | 0.96 | 0.99 | 0.97 | 136 |
| **Accuracy** | **0.98** | - | - | 427 |

## 5. Results

The hybrid model performs with an excellence of 98%. The confusion matrix is also observed to have minimal misclassifications, indicating that the model is robust.

## 6. Discussion

The Autoencoder + CNN-BiLSTM model effectively captures spatial and temporal patterns present in the EEG signals for high accuracy in emotion classification.

## 7. Conclusion

This paper proposes a hybrid model that combines autoencoder-based feature extraction with CNN-BiLSTM for EEG-based emotion detection and exhibits remarkable performance. The work may be further pursued by enlarging the dataset and exploring even deeper models.

## 8. Future Work

Future studies might investigate subtle emotion detection as well as transformer-based models to achieve better temporal pattern capture.

## References

* Kulkarni, S., et al. 2024. Emotion detection using EEG: hybrid classification approach. Accessed on <https://typeset.io/papers/emotion-detection-using-eeg-hybrid-classification-approach-2mhn5gto4f> (retrieved).
* Ahmadzadeh, R., et al. (2024). Emotion detection based on modified convolutional fuzzy neural