# Emotion Detection Using EEG Signals: Advances in Deep Learning and Hybrid Models

## Abstract

Emotion detection using EEG signals has emerged as a promising approach in mental health diagnostics, human-computer interaction (HCI), and neurofeedback systems. EEG signals provide a direct, accurate means of decoding emotional states, overcoming limitations seen in traditional methods like facial expression or speech analysis. This study presents a hybrid deep learning model combining an Autoencoder for feature extraction with a CNN-BiLSTM architecture for emotion classification. Using the EEG dataset from Kaggle, the model achieved 98% accuracy in classifying emotions (positive, neutral, and negative). This paper reviews recent advances in deep learning for emotion detection and positions the proposed model as a competitive and effective solution.

## 1. Introduction

Emotion recognition is crucial for several applications, including mental health monitoring, human-computer interaction, and affective computing. EEG signals offer a non-invasive way to capture brain activity, allowing for the classification of emotional states with higher precision than traditional methods such as facial expression or speech analysis.

### Motivation

Recent studies have demonstrated the benefits of using deep learning architectures, particularly hybrid models, for emotion detection via EEG signals. Kulkarni et al. (2024) demonstrated the effectiveness of Bi-LSTM and IRNN models in classifying emotions like happiness and anger using the DEAP dataset. Ahmadzadeh et al. (2024) introduced a modified Convolutional Fuzzy Neural Network (CFNN), improving classification accuracy for key emotional dimensions like valence and arousal. However, there is still room for improvement in capturing both the spatial and temporal dynamics of EEG signals for more accurate emotion classification.

This paper proposes a hybrid deep learning model that combines an Autoencoder for dimensionality reduction and feature extraction with a CNN-BiLSTM model for emotion classification. The model's performance is evaluated on the EEG brainwave dataset from Kaggle.

## 2. Literature Review

| **#** | **Paper** | **Key Insight** | **Citations** |
| --- | --- | --- | --- |
| 1 | [Emotion detection using EEG: hybrid classification approach (Kulkarni et al., 2024)](https://typeset.io/papers/emotion-detection-using-eeg-hybrid-classification-approach-2mhn5gto4f) | Utilizes Bi-LSTM and IRNN models for emotion classification | - |
| 2 | [Detecting emotions through EEG signals based on modified convolutional fuzzy neural network (Ahmadzadeh et al., 2024)](https://typeset.io/papers/detecting-emotions-through-eeg-signals-based-on-modified-tlxdywy1wr) | Improved CFNN model for higher valence and arousal accuracy | - |
| 3 | [An Efficient EEG Signal Analysis for Emotion Recognition Using FPGA (Ezilarasan & Leung, 2024)](https://typeset.io/papers/an-efficient-eeg-signal-analysis-for-emotion-recognition-150d199ah3) | CNN-LSTM with ResNet-152 for FPGA-based emotion detection | - |
| 4 | [Detection of Emotion from EEG Signal Using Deep Learning: Bi-LSTM and GRU (Maliha et al., 2024)](https://typeset.io/papers/detection-of-emotion-from-eeg-signal-using-deep-learning-bi-4ritiwc45s) | Bi-LSTM and GRU models for emotion classification | - |

## 3. Methodology

### 3.1 Dataset

The dataset used for this research is the EEG Brainwave Dataset: Feeling Emotions from Kaggle. The dataset contains EEG recordings that capture brainwave patterns linked to three emotional states: positive, neutral, and negative. Each sample represents a series of EEG signals recorded across multiple sensors.

* **Dataset Size**: 427 samples
* **Emotion Labels**: Positive, Neutral, Negative
* **EEG Channels**: Multiple channels capturing brainwave activity

### 3.2 Data Preprocessing

The following preprocessing steps were applied:

* **Normalization**: EEG features were normalized using StandardScaler.
* **Reshaping**: 1D EEG signals were reshaped into 2D grids for convolutional layers.

### 3.3 Autoencoder for Feature Extraction

An autoencoder was used to reduce the high-dimensional EEG data:

* **Encoder**: Composed of convolutional layers for feature extraction.
* **Decoder**: Reconstructs original data to ensure essential features are retained.

### 3.4 CNN-BiLSTM Model for Emotion Classification

The CNN-BiLSTM model combines CNN layers for spatial features and BiLSTM for temporal dependencies. The final classification is performed using a softmax-activated dense layer.

## 4. Training and Evaluation

### 4.1 Autoencoder Training

Autoencoder was trained to minimize MSE loss. The encoder was used for feature extraction.

### 4.2 CNN-BiLSTM Training

The CNN-BiLSTM model was trained for 50 epochs with early stopping and class weights to handle imbalance.

### 4.3 Classification Report and Confusion Matrix

The model's performance was evaluated using precision, recall, and F1-score metrics, along with a 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 |
| **Macro Avg** | 0.98 | 0.98 | 0.98 | 427 |
| **Weighted Avg** | 0.98 | 0.98 | 0.98 | 427 |

### Confusion Matrix

|  | **Positive** | **Negative** | **Neutral** |
| --- | --- | --- | --- |
| Positive | 139 | 1 | 3 |
| Negative | 0 | 146 | 2 |
| Neutral | 2 | 1 | 133 |

## 5. Results

The hybrid model achieved excellent results with an accuracy of 98%. The confusion matrix shows minimal misclassification, reflecting the model's robustness.

## 6. Discussion

The Autoencoder + CNN-BiLSTM model efficiently captures spatial and temporal patterns in EEG signals, leading to high emotion classification accuracy.

## 7. Conclusion

This study presents a novel hybrid model that combines autoencoder-based feature extraction with CNN-BiLSTM for EEG-based emotion detection, achieving excellent results. Future work could focus on expanding the dataset and exploring more advanced architectures.

## 8. Future Work

Future research could focus on detecting more nuanced emotions and incorporating transformer-based models for capturing intricate temporal patterns.

### References

Kulkarni, S., et al. (2024). Emotion detection using EEG: hybrid classification approach. Retrieved from <https://typeset.io/papers/emotion-detection-using-eeg-hybrid-classification-approach-2mhn5gto4f>

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