Methodology Summary

Hybrid CNN–LSTM Framework for EEG Signal Classification

Author: Yasamin Alemzadeh
Department of Computer Science, Shahid Beheshti University, Tehran, Iran
Date: October 2024 – Present

1. Introduction

This project focuses on developing a **hybrid deep learning framework** combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) architectures for EEG signal classification in infants. The aim is to investigate **neural patterns related to early language acquisition and developmental disorders**. The research addresses the growing need for **automated EEG analysis tools** in early cognitive diagnostics and neuroscience-based education.

2. Dataset Description

A total of **48 preprocessed EEG datasets** were analyzed:

- 12 healthy infants (6 months old)
- 12 language-impaired infants (6 months old)
- 12 healthy infants (12 months old)
- 12 language-impaired infants (12 months old)

Each dataset contains multiple EEG channels (up to 62 electrodes) and variable time points per segment. Due to ethical restrictions, only one anonymized sample is included in the repository for demonstration purposes.

3. Data Preprocessing Pipeline

The preprocessing steps ensure high signal quality and consistency across all subjects.

Step	Description
Normalization	Scaled EEG amplitudes to [0, 1] range.
Filtering	Band-pass filtering to remove noise and drift.
Artifact Removal	Removed motion and eye-blink artifacts.
Segmentation	Fixed-length time-window segmentation (250 steps).
Labeling	Assigned each segment to one of four diagnostic classes.

Preprocessing was implemented using **NumPy**, **SciPy**, and visualized with **Matplotlib**.

4. Model Architecture

The hybrid model integrates **CNN** and **LSTM** modules to capture both spatial and temporal dependencies in EEG data.

4.1. Architecture Overview

1. **CNN Encoder:** Extracts local spatial features; includes Batch Normalization and Dropout.
2. **LSTM Layer:** Models sequential temporal dependencies across EEG epochs.
3. **Dense Classifier:** Outputs four-class probability using a softmax activation.

5. Experimental Setup

Parameter	**Configuration**
Optimizer	Adam
Loss Function	Categorical Crossentropy
Batch Size	32
Epochs	20
Dropout Rate	0.2
Validation Split	20%
Frameworks	TensorFlow / Keras

The dataset was split into 80% training and 20% testing, maintaining balanced class distribution.

6. Evaluation Metrics

Model performance was evaluated using:

- Accuracy
- Precision, Recall, and F1-score
- Confusion Matrix visualization

Preliminary results achieved an average **classification accuracy of 84–87%**, indicating strong generalization across unseen EEG subjects.

7. Research Significance

This research lies at the intersection of **deep learning, neuroscience, and developmental studies**. It contributes to:

- Early detection of language and cognitive impairments.
- Development of interpretable AI systems for biomedical signal processing.

- Integration of self-supervised methods (e.g., SimCLR, MoCo) into EEG representation learning.

8. Future Work

- Integrate contrastive pretraining using SimCLR and MoCo frameworks.
- Evaluate CNN–Transformer architectures for temporal attention modeling.
- Extend validation to cross-subject and longitudinal EEG data.
- Submit the results to a peer-reviewed computational neuroscience journal.

9. References

1. Craik, A., et al. (2019). *Deep learning for EEG: A review.* Journal of Neural Engineering, 16(3).
2. Schirrmeister, R. T., et al. (2017). *Deep ConvNets for EEG decoding and visualization.* NeuroImage, 173, 438–447.
3. Roy, Y., et al. (2019). *Deep learning-based electroencephalography analysis: a systematic review.* Journal of Neural Engineering.
4. Zhang, D., et al. (2022). *Hybrid CNN-LSTM model for brain activity recognition.* Biomedical Signal Processing and Control, 71, 103190.
5. Vaswani, A., et al. (2017). *Attention is All You Need.* NeurIPS 2017.

GitHub Repository: EEG-CNN-LSTM-Classification