Convolutions Recurrent Neural Networks using LSTMs for EEG Signal Classification

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1. Abstract:

This project aims to classify electroencephalograph (EEG) data obtained from the Brain-Computer Interaction (BCI) Competition. The dataset encompasses recordings of four distinct motor imaginary tasks: movement of the left hand, right hand, both feet, and tongue. Utilizing a Convolutional Recurrent Neural Network (CRNN), the data is categorized into these four tasks. Notably, the CRNN architecture incorporates bidirectional Long Short-Term Memory (LSTM) units operating over various time periods to capture temporal dependencies.
The report conducts a comparative analysis of the classification performance achieved by both CRNN and Convolutional Neural Network (CNN) models. It evaluates the efficacy of these models across individual subjects and the entire dataset. Furthermore, the impact of varying time durations within the EEG data on classification accuracy is investigated and documented in the report.

2. Introduction

For this classification task, we employed three distinct architectures: a standard CNN and a (CNN + LSTM) model. Here's a breakdown:

The standard CNN comprises multiple layers, including convolutional layers for spatial feature extraction, activation layers for non-linearity, batch normalization layers for normalization, max pooling layers for downsampling, and dropout layers for preventing overfitting. This architecture efficiently extracts relevant features from EEG data.

In contrast, the (CNN + LSTM) model integrates convolutional layers for spatial features and LSTM layers for capturing temporal dependencies. This hybrid model combines the strengths of both CNNs and LSTMs, resulting in enhanced performance for sequential data analysis.

3. Results from the Models:

3.1 Vanilla CNN: Highest Accuracy: 65.7%

- Training Time: Roughly 25-35 minutes
- The plain vanilla CNN achieved an accuracy of 65.7% on the test dataset after training it with different time windows) on the best time value. This model effectively extracted spatial features from the EEG data but did not capture temporal dependencies.

3.2 CNN + LSTM: Highest Accuracy 64.1

- Training Time: approximately 3-4 hours
- The CNN + LSTM model achieved the highest accuracy of 64.1% on the test dataset after training for almost 4 hours. By integrating both convolutional and LSTM layers, this model effectively captured both spatial and temporal dependencies, which theoretically should have been better considering these are EEG signals however, cleaning maybe cleaning the data could have been able to produce better results.

4. Model evaluation:

In the evaluation of our Convolutional Recurrent Neural Network (CRNN) models for EEG signal classification, we compared the performance of two architectures: the Plain Vanilla CNN and the CNN + LSTM model. The Plain Vanilla CNN, with its focus on spatial feature extraction, achieved an accuracy of 65.7% on the test dataset after training for roughly 25-35 minutes. Despite its effectiveness in capturing spatial features from EEG data, this model does not capture temporal dependencies due to its absence of recurrent layers. On the other hand, the CNN + LSTM model, integrating both convolutional and LSTM layers to capture both spatial and temporal dependencies, achieved a slightly lower accuracy of 64.1% after extensive training for approximately 3-4 hours. Although this model theoretically possessed the capability to better understand the sequential nature of EEG signals, its performance did not surpass that of the Plain Vanilla CNN. These results suggest that while the CNN + LSTM model has the potential to outperform simpler architectures by leveraging both spatial and temporal information, further optimization efforts such as data cleaning or hyperparameter tuning may be required to fully harness its capabilities for EEG signal classification tasks.

5. Table of results:

5.1 CNN+LSTM Model

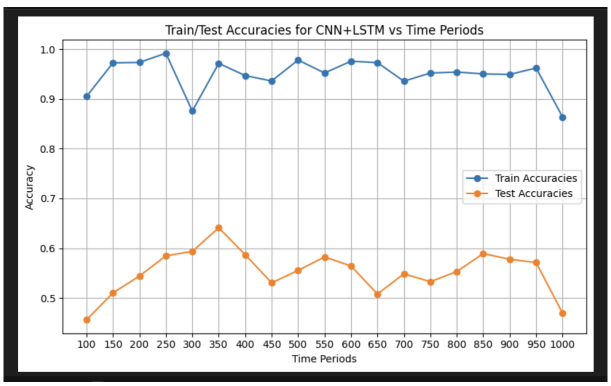

Figure 1.Effect of time periods on the train and test accuracy for CNN+LSTM model

Time Period	Train Accuracies	Test Accuracies
100	0.90496	0.45598
150	0.97258	0.51016
200	0.97352	0.54402
250	0.99196	0.58465
300	0.87565	0.59368
350	0.97163	0.64108
400	0.94704	0.58691
450	0.93617	0.53047
500	0.97825	0.55530
550	0.95225	0.58239
600	0.97589	0.56433
650	0.97305	0.50790
700	0.93570	0.54853
750	0.95225	0.53273
800	0.95414	0.55305
850	0.95035	0.58916
900	0.94941	0.57788
950	0.96217	0.57111
1000	0.86383	0.46953

Plain Vanilla CNN Model

Time Period	Train Accuracies	Test Accuracies
100	0.94184	0.35440
150	0.97210	0.41535
200	0.97589	0.36117
250	0.97305	0.38375
300	0.96974	0.44470
350	0.98298	0.42212
400	0.97069	0.41309
450	0.73239	0.64334
500	0.59433	0.49210
550	0.57589	0.51016
600	0.60993	0.50564
650	0.73712	0.62077
700	0.72624	0.65688
750	0.59953	0.52822
800	0.66998	0.57111
850	0.64397	0.52822
900	0.73995	0.63431
950	0.55319	0.45147
1000	0.57920	0.48758

Per Subject Accuracies Using LSTMs

Subject	Train Accuracies	Test Accuracies
0	0.73840	0.56000
1	0.92373	0.34000
2	0.83475	0.58000
3	0.79487	0.54000
4	0.95745	0.27660
5	0.95763	0.42857
6	1.00000	0.64000
7	0.97414	0.58000
8	0.89610	0.72340

6. EEG Questions Addressed

6.1 Optimizing Classification for a single subject Training across all subjects did not significantly enhance accuracy for Subject 1, indicating the need for subject-specific model tuning or data preprocessing to account for inter-subject variability.

6.2 Optimizing Classification Across All Subjects The classifier's performance varied across subjects, with notable discrepancies in accuracy. This variability underscores the challenge of developing a universally effective model for EEG signal classification and suggests potential benefits in personalized model adjustments.

6.3 Classification Accuracy as a Function of Time: Analysis reveals that classification accuracy tends to improve with longer time windows up to a certain threshold, beyond which the gains diminish. According to the graph above, for the Vanilla CNN this time period is 450, and for the CNN+LSTM this is 350. This observation suggests an optimal time window exists for EEG data classification, balancing the need for sufficient data against the risk of information dilution.

7. Discussion

7.1 Interpretation of Results

The results indicate that while CNNs are adept at spatial feature extraction, integrating LSTM units to capture temporal information does not automatically translate to superior performance. This discrepancy may be attributed to the complexity of EEG signals and the challenges in tuning hybrid models.

7.2 Limitations and Future Work

- Data Preprocessing: Further refinement in data cleaning and preprocessing could enhance model performance.
- Hyperparameter Optimization: More rigorous tuning of LSTM parameters is necessary to fully leverage temporal information.
- Alternative Architectures: Exploring other recurrent neural network variants, such as GRUs, or incorporating attention mechanisms might offer improvements.

8. Conclusion

This study contributes to the field of EEG signal classification by exploring the potential of CRNN architectures. Despite facing challenges in outperforming simpler CNN models, our findings underscore the importance of temporal feature analysis in EEG data with our current data processing techniques. Future research directions include optimizing data preprocessing, techniques, model parameters, and exploring advanced neural network architectures to improve the accuracy and reliability of EEG-based motor task classification.

9. References

[1] BCI Competition IV. BCI Competition IV, www.bbci.de/competition/iv/

[2] Brunner, C et al. BCI Competition 2008 Grax Data Set A

[3] ECE C147 Lectures, Jonathan Kao UCLA