Machine Learning Driven P300 Signal Classification for Enhanced BCI Intent Recognition

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Abstract

Intent-based brain-computer interfaces (BCIs) represent a promising technology for enabling direct communication between the brain and external de vices, particularly benefiting individuals with severe motor impairments. The P300 speller paradigm is a key application that detects the P300 event-related potential for character selection. Despite advancements, achieving high accuracy in P300 signal classification remains a challenge due to the inherent complexity and variability of electroencephalography (EEG) signals. The primary aim of this project is to enhance the accuracy of P300 signal classification in intent-based brain-computer interfaces (BCIs) using advanced machine learning techniques. By leveraging a combination of traditional machine learning models and state of-the-art neural network architectures, such as EEG-Net and LMDA-Net, the project aims to improve the reliability and performance of BCIs for more effective communication and control applications.

Introduction

A brain-computer interface (BCI) is a transformative technology that enables direct communication between the brain and external devices, bypassing peripheral nerves and muscles. This technology is especially crucial for patients with severe motor disabilities, as it can restore autonomy and communication capabilities. The primary challenge in BCI research is achieving reliable control through accurate measurement and interpretation of brain activity, which is inherently complex, noisy, and variable, particularly with noninvasive EEG recordings. Mis interpretations of these signals can lead to erroneous decisions that do not align with the user's intentions. To address this, hybrid BCI approaches have been developed, leveraging secondary signals to enhance primary classifier decisions and improve overall BCI performance. Error-related brain signals, such as error-related negativity (ERN) and feedback-related negativity (FRN), have shown potential in detecting errors in real-time. Specifically, the P300-Speller paradigm has been utilized to discriminate between correct and incorrect trials, aiming for automatic error detection to enhance BCI accuracy. Previous studies have demonstrated that incorporating error detection can significantly improve BCI performance . Through our experiments, we assessed the accuracy and AUC of these models to determine their effectiveness and computational efficiency in achieving our final goal of improved intent recognition in EEG-based brain-computer interface paradigms.

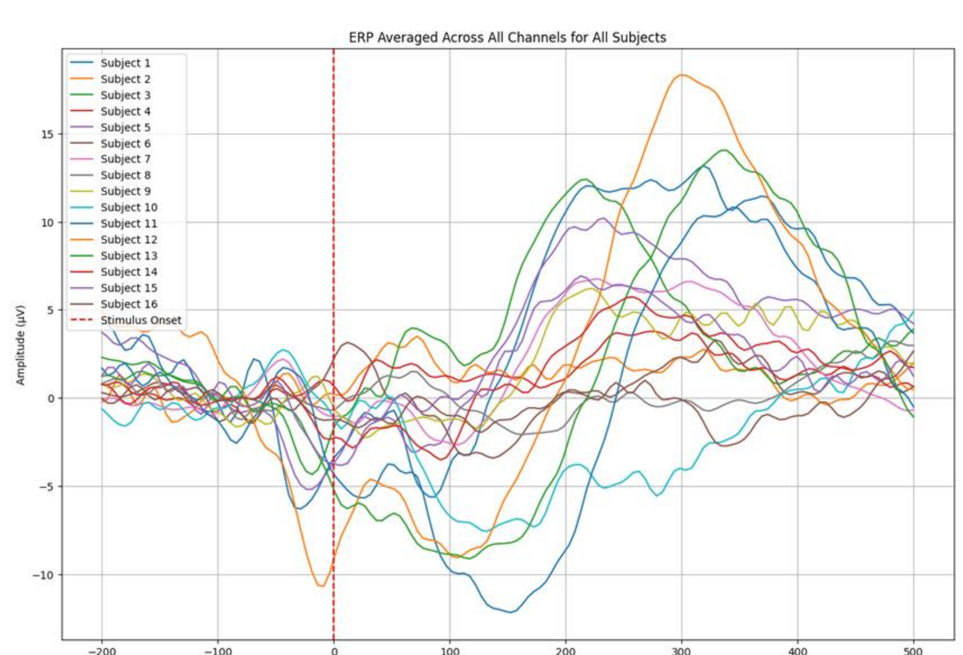

Figure 1. ERP of all 16 subjects

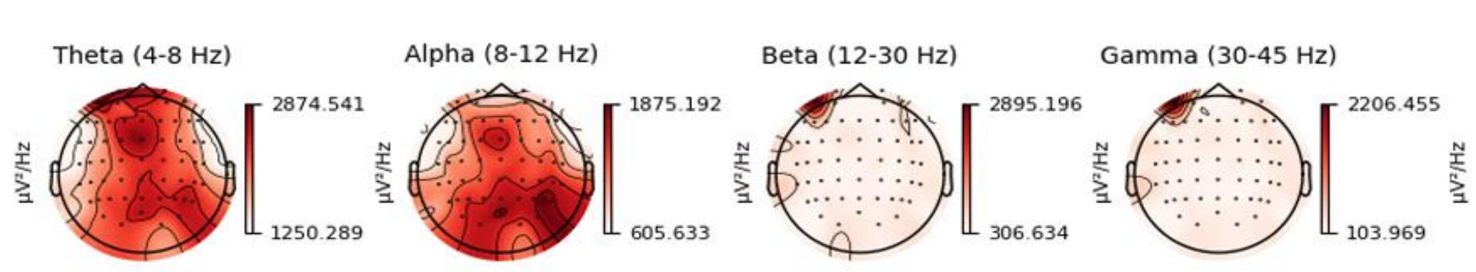

Figure 2. Feature Topomap Showing Spatial Distribution of Theta, Alpha, Beta, and Gamma Bands.

Dataset

The dataset used in this project is derived from an experimental study on the "P300-Speller" paradigm, where 26 healthy participants (13 males, mean age = 28.8±5.4 years) were involved in spelling tasks by focusing on visual stimuli. Each participant underwent five copy spelling sessions, with sessions consisting of either twelve 5-letter words or, in the case of the final session, twenty 5-letter words. Brain activity was recorded using 56 passive Ag/AgCl EEG sensors, following the extended 10-20 system, with signals sampled at 600 Hz and later down-sampled to 200 Hz. The subjects' attentional effort was assessed under two conditions: a fast mode with items flashed 4 times and a slower mode with items flashed 8 times. Eye movements were monitored using EOG derivation. The dataset provides the necessary EEG data to analyze and detect errors in the spelling task by examining the brain signals post-feedback, aimed at improving the accuracy and reliability of brain-computer interfaces through advanced error detection algorithms.

Models

1. Random Forest

We utilized the Random Forest algorithm as a baseline due to its simplicity and effectiveness in handling high-dimensional data, such as EEG signals. The model was implemented using the Random Forest Classifier from the scikit-learn library, with parameters tuned through cross-validation to optimize performance.

2. StackNet

We implemented a StackNet comprising several base classifiers, including LDA, SVM, Logistic Regression, LightGBM, Gaussian Process Classifier, XG Boost, and Random Forest, with Logistic Regression as the meta-classifier. This configuration allowed us to combine the strengths of different classifiers, achieving robust and reliable predictions for EEG data classification.

- Base Classifiers: The first layer consists of multiple diverse classifiers that 4 independently learn from the training data. These base classifiers include: Linear Discriminant Analysis (LDA), Support Vector Classifier (SVC), Lo gistic Regression, LightGBM Classifier (LGBMClassifier), Gaussian Process Classifier, XGBoost Classifier (XGBClassifier)
- Meta-Classifier: Logistic Regression: This model is trained on the predic tions of the base classifiers. It learns to combine their outputs to make the f inal decision.
- StackingCVClassifier: This classifier combines the base classifiers and the meta-classifier into a single model. It uses cross-validation (with 3 folds) to ensure robustness and generalization

3. EEGNet

EEGNet is a compact convolutional neural network designed specifically for EEG-based BCIs. It begins with an initial convolutional layer that captures ba sic features, followed by Batch Normalization to stabilize training. The network features two primary convolutional blocks: the first block utilizes 32 filters, incor porating dropout for regularization and average pooling , while the second block applies additional convolutional filters and pooling. The final stage flattens the feature maps and uses a Linear layer to perform classification

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==========================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================
EEGNet                                   [32, 2]                   --
├─Sequential: 1-1                        [32, 16, 56, 140]         --
│    └─Conv2d: 2-1                       [32, 16, 56, 140]         832
│    └─BatchNorm2d: 2-2                  [32, 16, 56, 140]         32
├─Sequential: 1-2                        [32, 32, 1, 35]           --
│    └─Conv2d: 2-3                       [32, 32, 1, 140]          1,792
│    └─BatchNorm2d: 2-4                  [32, 32, 1, 140]          64
│    └─ELU: 2-5                          [32, 32, 1, 140]          --
│    └─AvgPool2d: 2-6                    [32, 32, 1, 35]           --
│    └─Dropout: 2-7                      [32, 32, 1, 35]           --
├─Sequential: 1-3                        [32, 32, 1, 4]            --
│    └─Conv2d: 2-8                       [32, 32, 1, 35]           15,360
│    └─BatchNorm2d: 2-9                  [32, 32, 1, 35]           64
│    └─ELU: 2-10                         [32, 32, 1, 35]           --
│    └─AvgPool2d: 2-11                   [32, 32, 1, 4]            --
│    └─Dropout: 2-12                     [32, 32, 1, 4]            --
├─Sequential: 1-4                        [32, 2]                   --
│    └─Flatten: 2-13                     [32, 128]                 --
│    └─Linear: 2-14                      [32, 2]                   258
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Figure 3. EEGNet Architecture

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==========================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================
LMDA                                     [32, 2]                   56
├─Sequential: 1-1                        [32, 24, 56, 136]         --
│    └─Conv2d: 2-1                       [32, 24, 56, 140]         24
│    └─BatchNorm2d: 2-2                  [32, 24, 56, 140]         48
│    └─Conv2d: 2-3                       [32, 24, 56, 136]         120
│    └─BatchNorm2d: 2-4                  [32, 24, 56, 136]         48
│    └─GELU: 2-5                         [32, 24, 56, 136]         --
├─EEGDepthAttention: 1-2                 [32, 24, 56, 136]         --
│    └─AdaptiveAvgPool2d: 2-6            [32, 24, 1, 136]          --
│    └─Conv2d: 2-7                       [32, 1, 24, 136]          8
│    └─Softmax: 2-8                      [32, 1, 24, 136]          --
├─Sequential: 1-3                        [32, 9, 1, 136]           --
│    └─Conv2d: 2-9                       [32, 9, 56, 136]          216
│    └─BatchNorm2d: 2-10                 [32, 9, 56, 136]          18
│    └─Conv2d: 2-11                      [32, 9, 1, 136]           504
│    └─BatchNorm2d: 2-12                 [32, 9, 1, 136]           18
│    └─GELU: 2-13                        [32, 9, 1, 136]           --
├─Sequential: 1-4                        [32, 9, 1, 27]            --
│    └─AvgPool3d: 2-14                   [32, 9, 1, 27]            --
│    └─Dropout: 2-15                     [32, 9, 1, 27]            --
├─Linear: 1-5                            [32, 2]                   488
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Figure 4. LMDA-Net Architecture

4. LMDA-Net (Baseline model)

The LMDA-Net consists of a benchmark network and two attention modules: the channel attention module and the depth attention module. The channel attention module aims to improve the information screening ability in the spatial dimension of EEG signals and the depth attention module further refines the information of high-dimensional EEG features in depth dimension. The channel attention module and the depth attention module can be integrated with any convolutional neural networks.

LMDA-Net with Temporal Attention :

We enhanced our Lightweight Multi-Dimensional Attention Network (LMDA Net) by incorporating a temporal attention layer. The objective was to improve the model's ability to focus on significant temporal features of EEG signals, thereby enhancing the accuracy and robustness of EEG-based Brain-Computer Interface (BCI) intent recognition.

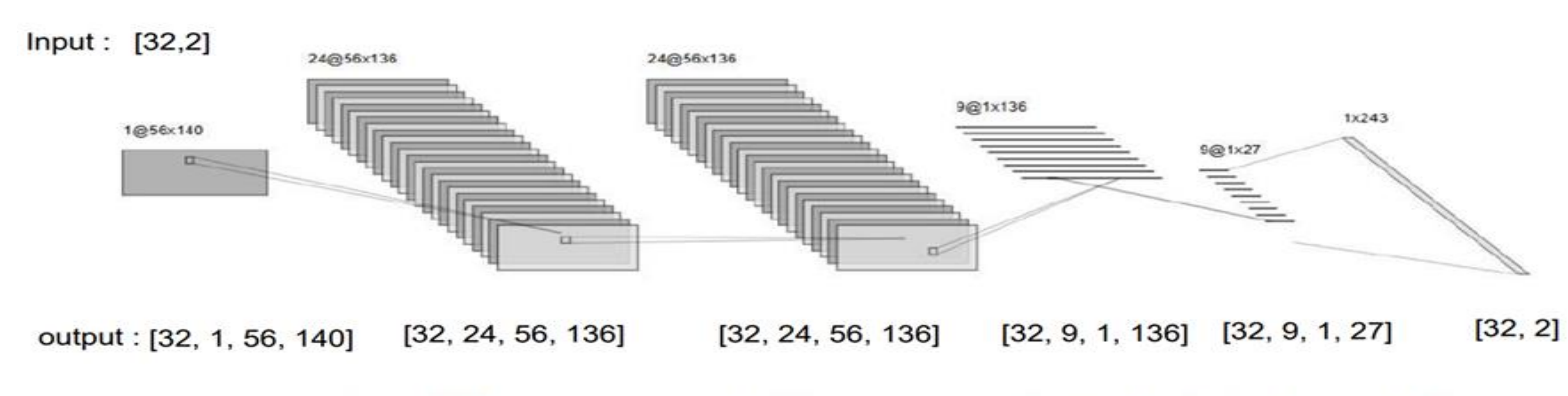

Figure 5. LMDA-Net with Temporal Attention layer Architecture

Results

LMDA-Net demonstrated the highest AUC of 0.81, indicating its strong dis criminatory power in distinguishing between classes in EEG data. Following closely, EEGNet achieved an AUC of 0.79, showcasing its effectiveness as a com pact convolutional neural network tailored for EEG signals. Stack-Net and Random Forest, also showed competitive performance with AUCs of 0.76 and 0.73 respectively.

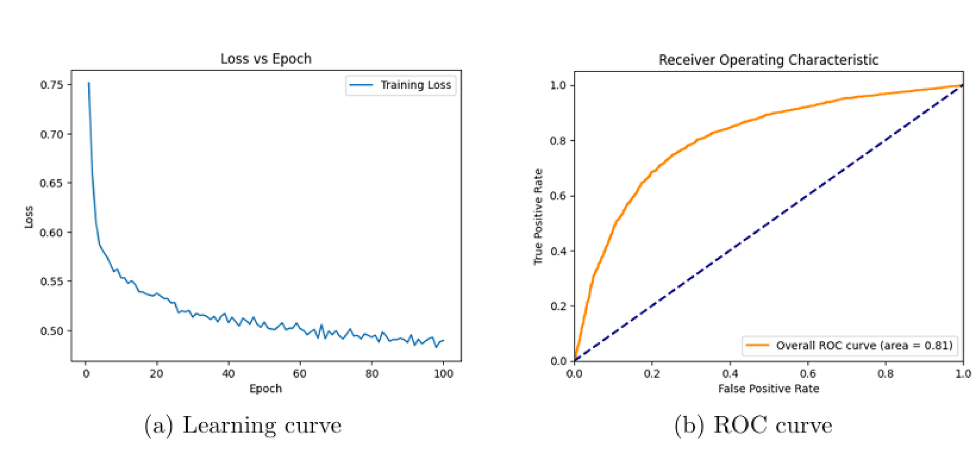

Figure 6. LMDA-Net

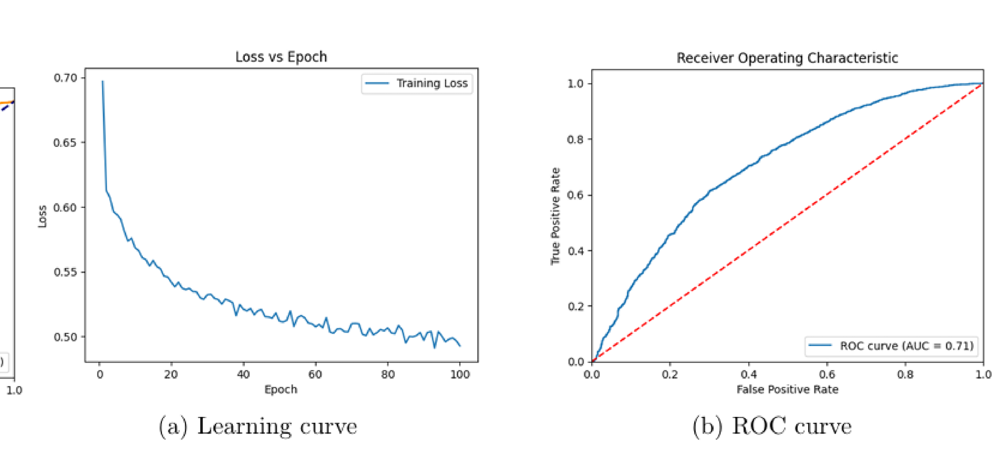

Figure 7. LMDA-Net with Temporal Attention

Inference Time - In our comparison of model inference times, the LMDA-Net exhibited an average inference time of 0.24 seconds. This is notably higher than the inference time for the EEGNet model, which stands at 0.10 seconds. The increased infer ence time for LMDA-Net may be attributed to its more complex architecture and additional layers.

Table 1. Average Inference time (in seconds) over 100 runs

Model	*CPU*	*GPU*
Random Forest	8.2803	-
StackNet	8.2179	-
EEGNet	1.7969	0.101903
LMDANet	4.4328	0.242571

Table 2. Results obtained for different models

Model	*AUC*	*Accuracy*
Random Forest	0.73	73.2%
StackNet	0.76	76%
EEGNet	0.79	75.32%
LMDANet	0.81	80.68%

Note : *Despite the addition of temporal attention layer, the AUC score of the model decreased to 0.71. This unexpected result suggests that the temporal attention mechanism may not have been optimally integrated or may require further tuning to achieve the desired improvement in performance. Experimenting with different configurations and hyperparameters, as well as exploring alternative attention mechanisms.*

References

1. LMDA-Net: *A lightweight multi-dimensional attention network for general EEG-based brain-computer interface paradigms and interpretability https: //arxiv.org/pdf/2303.16407v1.*

2. EEGNet: *A Compact Convolutional Neural Network for EEG-based Brain Computer Interfaces https://arxiv.org/pdf/1611.08024.*