Predicting Neurological Outcome After Cardiac Arrest Using a Pretrained Model with Electroencephalography Augmentation

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Abstract

As part of the George B. Moody PhysioNet Challenge 2023, we developed a machine learning approach that uses electroencephalogram (EEG) to predict the neurological recovery of patients following cardiac arrest. The limited size of EEG datasets presents challenges. Our team, ComaToss, developed a novel approach that combines pretrained models and data augmentation (DA) to address the challenge of limited EEG. We employed a deep learning model, ConvNeXt for feature extraction of EEG. Pretrained models improved performance, with ConvNeXt achieving the best results. Furthermore, our DA methods, including temporal reversal, polarity inversion, and CutMix, enhanced model robustness. The combination of polarity inversion and CutMix outperformed other methods. Our model received a Challenge score of 0.79 (ranked 2th out of 36 teams) on the hidden test set. Proposed methods show promise in mitigating the limitations associated with limited EEG datasets, potentially improving the accuracy and reliability of prognostic assessments.

1. Introduction

Electroencephalography (EEG) for brain monitoring aims to reduce the subjectivity of neurological prognosis after cardiac arrest [1]. Machine learning (ML)-based EEG analysis can assess EEG patterns, exploit data dynamics, and automate the analysis of continuous EEG data, thereby increasing the accessibility of brain monitoring, especially in underserved regions where neurological experts are scarce. However, most studies rely on small datasets, often less than 100 patients from single hospitals, which is a significant barrier to high-quality ML applications [2].

The use of pretrained models, derived from deep learning frameworks and trained on large and diverse datasets, has shown promise in the field of EEG analysis [3]. By fine-tuning these pretrained models on EEG-specific data, it becomes possible to effectively leverage EEG data with the wealth of features and representations learned from unrelated domains. This knowledge transfer not only improves the efficiency of feature extraction, but also contributes to increased classification accuracy, especially when dealing with limited EEG datasets.

Data augmentation (DA) involves creating additional samples by applying transformations to the existing dataset [4]. This approach shows potential for enhancing the accuracy and stability of classification, particularly in the context of EEG data. These augmented samples enrich the training dataset, increasing its diversity and capturing variations in EEG patterns. This enrichment allows for a more robust and generalised model, reducing the risk of overfitting and increasing the reliability of EEG-based classification.

In this study, we propose a strategy that integrates two key components, pretrained models and DA. Our aim is to demonstrate their effectiveness in overcoming the challenges posed by limited EEG datasets, ultimately leading to more accurate and reliable prognostic assessments in the field of neurological recovery.

2. Methods

In this section, we provide a comprehensive overview of the dataset used in our study and the preprocessing steps applied to the EEG signals. Additionally, we delve into the architecture of our deep learning model, including the utilization of pretrained models and data augmentation techniques. Finally, we outline the experimental settings employed for evaluating the model's performance.

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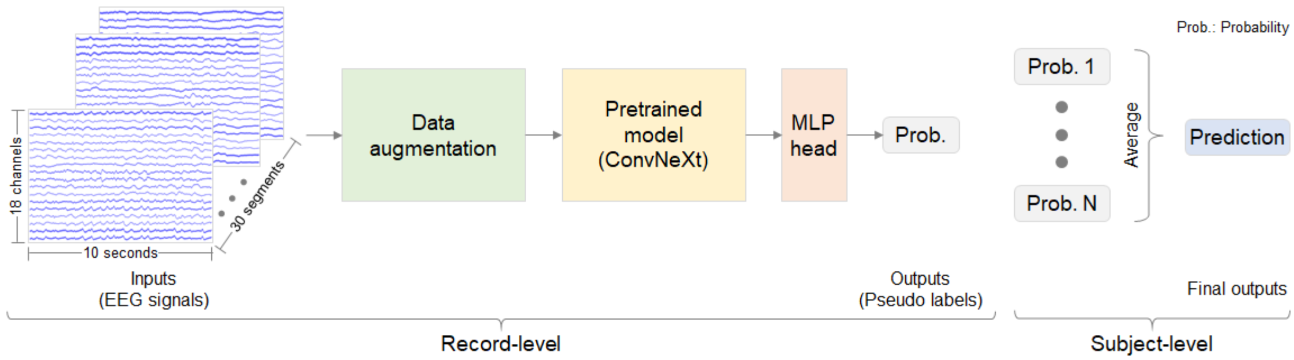

Figure 1. The proposed model architecture for predicting neurological outcomes. The framework comprises two stages: record-level and subject-level. At the record-level, EEG signals processed through data augmentation and a pretrained model to extract features. These extracted features are subsequently used to calculate probability values via a multi-layer perceptron (MLP) head. At the subject-level, the probability values from each record are averaged.

2.1. Dataset and preprocessing

The data employed in this study is sourced from the training dataset of the PhysioNet Challenge (PNC) 2023 [5], which serves as a pivotal resource for investigating and advancing the field of cardiac arrest research. This dataset was meticulously curated from the international cardiac arrest research consortium (I-CARE) database [6, 7]. The I-CARE database is a comprehensive repository comprising an array of physiological signals and critical clinical information, including patient age and gender, drawn from a diverse cohort of 607 individuals across seven different hospitals.

This dataset specifically comprises EEG signals collected over a maximum duration of 72 hours from comatose patients following cardiac arrest, along with associated neurological outcomes. These outcomes are categorized into two primary groups: good outcomes and poor outcomes. Good outcomes are defined by a cerebral performance category (CPC) score of 1 or 2, indicating either minor or moderate neurological impairment. Conversely, poor outcomes are characterized by CPC scores ranging from 3 to 5, indicating significant neurological impairment, extended coma, or, in the most severe cases, mortality. This comprehensive and diverse dataset forms the basis for the rigorous analysis and modeling conducted in our research, allowing us to investigate and enhance our understanding of predicting neurological outcomes in the context of cardiac arrest scenarios.

The preprocessing of the EEG signal is conducted in the following sequential manner: First, records with a duration of less than 5 minutes for each participant are excluded. Subsequently, we address the channel configuration of the raw EEG data. Initially, it comprises 19 channels, but we perform a transformation using the longitudinal bipolar referencing technique, resulting in a reduction to 18 channels. Next, a Butterworth bandpass filter with a specified frequency range of 0.5 to 35 Hz is systematically applied, followed by resampling to a sampling rate of 64 Hz. This step isolates the relevant frequency components within the EEG signals while effectively mitigating unwanted noise, thereby improving the signal-to-noise ratio. Finally, we segment the preprocessed EEG signals into intervals of 10 seconds each. Moreover, segments where the mean and variance values across all channels are equal to 0 are removed, resulting in a total of 35,097 records used for training. Subsequently, each segment undergoes z-score-based normalization to ensure uniformity in the dataset.

2.2. Deep learning model

The comprehensive structure of our model is illustrated in Figure 1. This predictive process entails a two-step approach designed to exploit the information inherent in each EEG record. In the initial stage, we train each record with pseudo-labels representing the subject's outcome. EEG signals undergo preprocessing involving data augmentation and feature extraction using a pretrained model. The extracted features are then utilized to compute probability values through a multi-layer perceptron (MLP) head. Subsequently, we calculate probability values for each record using a sigmoid activation function. These individual probabilities are then aggregated and averaged to formulate a prediction about the subject's overall outcome. This two-step approach enables us to distill meaningful insights from the EEG data and significantly contributes to the accuracy of our predictions.

To extract pertinent features related to neurological outcomes from EEG signals, we harnessed the power of the ConvNeXt model [8]. The ConvNeXt model, renowned for its superior ability to discern subtle features and intricate patterns in images, outperforms traditional convolutional neural network (CNN)-based models. Our proposed model was initialized with the pre-trained weights of a ConvNeXt model trained on the ImageNet dataset and subsequently underwent transfer learning. The EEG features extracted by the ConvNeXt model are then processed through a MLP head to predict the pseudo-labels.

To enhance the diversity of EEG signals while preserving specific patterns, we implemented DA methods commonly utilized in audio processing. These methods include reversing the signal sequence (Temporal reversal, TR), inverting signal polarity (Polarity inversion, PI), and combining two signals (CutMix, CM) [9]. During the training process, each augmentation method is sequentially applied with a probability of 0.3, effectively introducing variations into the data. Importantly, these augmentation techniques are not employed during the validation and testing phases, ensuring that the model generalizes well to unseen data while still benefiting from the augmented training dataset.

2.3. Experimental settings

To assess the performance of pretrained models, we conducted a comparative analysis involving two additional CNN models, namely ResNet-50d [10], EfficientNet-v2 [11], in addition to ConvNeXt. These three CNN models have comparable parameter counts, measuring at 25.6 million, 21.5 million, and 28.6 million, respectively. We conducted a comparison of transfer learning results both before applying pre-trained weights and after applying pre-trained weights in our evaluation.

The optimization process was conducted using the Adam optimizer with a learning rate set to 0.0001. Our model underwent training for a total of 20 epochs, employing a batch size of 16 for each training iteration. To ensure the robustness of our results and validate the model's generalization ability, we performed 5-fold cross-validation on the dataset. This cross-validation was meticulously stratified based on labels and the ratio of data originating from different hospitals, thereby ensuring a rigorous assessment of our model's performance across diverse data subsets.

3. Results

In this section, we present the outcomes of our experiments, focusing on the impact of pretrained models and data augmentation techniques on model performance. Additionally, we provide an overview of our team's performance during the official phase of the PNC 2023 challenge.

3.1. Pretrained models

The receiver operating characteristic (ROC) curves and true positive rate (TPR) at a false positive rate (FPR) threshold at 0.05) before and after applying pretrained

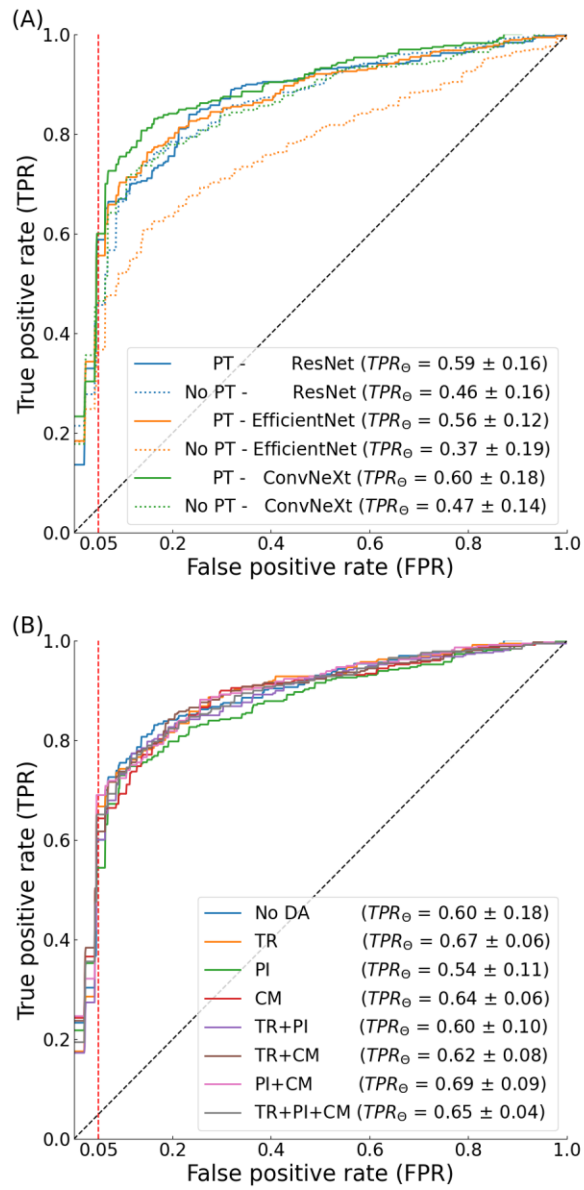

Figure 2. Results of ROC curves and TPR at a FPR of 0.05, using 5-fold cross validation on training data. The red vertical dashed line represents the FPR threshold at 0.05. (A) represents results based on pretrained (PT) models, where the solid line indicates results using PT models, and the dashed line indicates results without using them. (B) represents results based on data augmentation (DA). Temporal reversal (TR), Polarity inversion (PI), and CutMix (CM)

models are presented in Figure 2 (A). The results indicate that, for all CNN models, using pretrained models resulted in better performance than not using them. The ConvNeXt with pretrained models exhibited the highest performance among the models. The pretrained ConvNeXt exhibited the highest performance based on the TPR criterion.

3.2. Data augmentation

The ROC curves and TPR based on DA combinations are presented in Figure 2 (B). When applying each of the three DA methods individually, except for PI, both TR and CM methods showed performance improvements compared to not using DA. When DA was performed with two combinations, TR and PI combination exhibited lower performance compared to applying only TR, while the combination with CM showed better performance. In the case of the three combinations, they showed lower performance than the two combinations. The combination of PI and CM demonstrated the highest performance.

3.3. PhysioNet challenge result

Ultimately, in official scores of the PNC 2023, our team (ComaToss) achieved performance scores of 0.24, 0.59, 0.73, and 0.79 based on the challenge score criteria for 12, 24, 48, and 72 hours, respectively. Each result of training, validation, and ranking of the official phase are presented in Table 1.

Training	Validation	Test	Ranking
0.69 ± 0.09	0.61	0.79	2/36

Table 1. TPR at a FPR of 0.05 (the official Challenge score) for our final selected entry (team ComaToss), including the ranking of our team on the hidden test set. We used 5-fold cross validation on the public training set, repeated scoring on the hidden validation set, and one-time scoring on the hidden test set.

4. Discussion

This study presents a promising approach to improving EEG-based outcome predictions through the integration of pretrained models and DA methods. Pretrained models, particularly ConvNeXt, improved TPR performance. DA, especially when combining techniques like TR, PI, or CM, enhanced model robustness and predictive accuracy. These combined methods have shown potential in elevating the accuracy and reliability of neurological outcome predictions, with significant implications for enhancing clinical decision-making and advancing patient care.

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