Frequency and Time Domain EEG Analysis for Prognostication of Postanoxic Comatose Patients

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Abstract

As part of the George B. Moody PhysioNet Challenge 2023, our team (am_vision) presents a novel approach to prognosticate the outcomes of postanoxic comatose patients based on frequency domain and time domain features by using electroencephalogram (EEG) recordings. Frequency domain features include spectral entropy, power distribution, and dominant frequency. In the Time domain, zero crossing rate, energy, and entropy were calculated. We also utilized demographic information: Age, Sex, Return of Spontaneous Circulation (ROSC), Out-of-Hospital Cardiac Arrest (OHCA), Shockable Rhythm, and Targeted Temperature Management (TTM) to train XGBoost regressor and classifier to predict both the Cerebral Performance Category (CPC) score and the Outcome respectively. Our proposed method received a challenge score of 0.485 (ranked 18^{th} out of 36), an outcome accuracy of 0.81 (ranked 4^{th} out of 36), and an outcome F-measure of 0.769 (ranked 5^{th} out of 36) on the test set.

1. Introduction

Comatose following cardiac arrest present a complex and multifaceted clinical challenge. The assessment of their prognosis is crucial for making informed medical decisions regarding life-sustaining therapies. Traditionally, clinicians have relied on various clinical and neurophysiological markers, including somatosensory-evoked potentials (SSEPs), pupillary reflexes, corneal reflexes, motor responses to pain, and serum neuron-specific enolase [1]. However, recent studies have underscored the potential of early EEG as a reliable prognostic tool [2, 3].

Early EEG recordings have revealed intriguing time-dependent patterns associated with patient outcomes. For instance, continuous EEG patterns observed at the 12-hour mark have shown strong associations with favorable patient outcomes, while the presence of isoelectric patterns at 24 hours has been linked to less favorable results. Additionally, specific frequency-dependent patterns have been identified, such as dominant frequency. Notably, the presence of Burst Suppressions, characterized by identical bursts, have consistently shown a robust correlation with poor patient outcomes, irrespective of the timing of assessment [2]. Despite the promise of early EEG, the dynamic and variable nature of EEG recordings presents challenges in interpretation, often necessitating expert analysis. Furthermore, the shortage of neurologists available for such critical tasks underscores the need for advanced algorithms capable of automated analysis and prognostication.

The George B. Moody PhysioNet Challenge 2023 provided a unique platform for teams to develop open-source algorithms capable of leveraging fundamental clinical information, along with EEG and ECG recordings. The primary objective was to predict the extent of neurological recovery in patients who have experienced cardiac arrest and remain in a comatose state [4, 5]. This challenge granted participants access to a comprehensive dataset comprising EEG data and neurological outcomes from comatose patients, generously made available by the International Cardiac Arrest REsearch consortium (I-CARE) [6].

Recent literature have demonstrated the superiority of Deep Learning (DL), particularly convolutional neural networks, over traditional models like Logistic Regression and Random Forest in using EEG for various clinical challenges [7, 8]. However, efforts are made in other research fields to use Tree-Based Machine Learning (ML) models that yield classification results comparable to DL methods combined with better clinical interpretability [9].

In this paper, we detail our approach to assessing the prognosis of postanoxic comatose patients by utilizing EEG data. First, An artifact detection pipeline was adopted to identify certain artifacts. Our teams earlier successes in capturing spectral and temporal features of EEG and other bio-medical signals [10, 11] paved a way to combine time and frequency domain features and apply ML tech-

niques, such as an XGBoost classifier for predicting patient outcomes and an XGBoost regressor to estimate the CPC score.

2. Methods

This proposed methodology includes three main phases: EEG preprocessing, feature extraction, and model training as shown in Figure 1.

2.1. Preprocessing

Given the substantial volume of EEG data, We reorganized it ensuring consistent channel names across all patient records. To mitigate power line interference, we applied a notch filter at 60Hz. Furthermore, we implemented a bandpass filter (0.1Hz - 30Hz) to retain relevant signal frequencies. In instances where EEG signals had a sampling rate of 256Hz, we used poly-phase filtering technique, resampling them to 128Hz. Signals with a sampling rate of 250Hz were resampled to 125Hz. We identified 19 common channels across all patients (Fp1, F7, T3, T5, O1, Fp2, F8, T4, T6, O2, F3, C3, P3, F4, C4, P4, Fz, Cz, Pz). However, 2 channels Fpz and F9 were inconsistent and we excluded them. Subsequently, we transformed the 19 individual channels into 18 bipolar channels (Fp1-F7, F7-T3, T3-T5, T5-O1, Fp2-F8, F8-T4, T4-T6, T6-O2, Fp1-F3, F3-C3, C3-P3, P3-O1, Fp2-F4, F4-C4, C4-P4, P4-O2, Fz-Cz, Cz-Pz). This decision was underpinned by the advantages of a bipolar montage, which exhibits high sensitivity to physiological changes, making it well-suited for various clinical applications, including diagnostic purposes [12].

Following the initial signal processing techniques, an artifact detection pipeline was implemented, drawing inspiration from a recent literature source that operated on the same dataset [13]. In this pipeline, the EEG data is divided into non-overlapping 5-minute segments. Within each segment, artifacts are identified every 5 seconds based on three primary criteria: amplitude, signal flatness, and StairCase-like patterns. Abnormally large amplitudes exceeding 500μV are flagged. Flat signals, characterized by a standard deviation of less than 0.2μV for more than 2 seconds within a 4-second window, are also detected. Additionally, StairCase-like patterns, often caused by ICU machines like cooling blankets or pumps, are identified using EEG spectrograms. This process involves spectral analysis using multitaper spectral estimation, calculating the power spectral density (PSD) within a frequency range of 0.1Hz to 30Hz. The resulting PSD values are converted to decibels (dB) using a logarithmic scale. Subsequently, a smoothing operation is applied using a Hanning window, followed by convolution with specific templates: (-1., -1., 0, 1., 1., 1., 1.) for detecting increasing staircase-like patterns and (1., 1., 1., 1., 0., -1., -1.) for detecting decreasing staircase-like patterns. The artifact indicator (0/1) and signal quality assessment in the referenced study are based on the number of consecutive 5-second clean epochs. Unlike that, our research focuses on counting the detected artifacts for each 5 s, contributing to the overall artifact count. The best EEG segment with the highest signal quality, determined by the lowest artifact count is selected for subsequent feature extraction. If no clean 5-minute segment is found or if the signal data is less than 5 minutes, the entire signal is excluded from further analysis.

2.2. Frequency domain features

Dominant frequency: It refers to the frequency component within a signal that has the highest magnitude. The dominant frequency is determined using the Fast Fourier Transform (FFT), a mathematical technique that transforms a time-domain signal into frequency domain. The process begins by computing FFT for the signal, resulting in a complex-valued spectrum. The next step involves calculating the magnitude of the FFT result. The index corresponding to the highest magnitude, indicating the dominant frequency component, is identified. The associated frequency value is obtained by mapping this index.

Spectral entropy: Spectral entropy provides insights into the complexity of frequency components present in the signal. First, the FFT is applied to the EEG signal. Next, the magnitudes of the resulting complex FFT values are computed, representing the amplitudes of different frequency components in the EEG signal. Entropy(1) was calculated for normalized magnitudes.

$$Entropy = -\sum_{i=1}^{N} p(x_i) \cdot \log_2(p(x_i)) \tag{1}$$

Here x_i represents different values in the normalized magnitude spectrum, and $p(x_i)$ represents the probability that a specific value occurs in the spectrum.

Power distribution: The process begins with the application of the FFT to the EEG signal. Subsequently, the squared magnitudes of the complex FFT values are computed, representing the power of each frequency component in the EEG signal. To ensure a valid power distribution, the computed power values are normalized by dividing each power value by the sum of all power values, effectively scaling the distribution between 0 and 1. The power distribution for each EEG channel is then obtained.

$$Power\ distribution = \frac{|FFT(signal)|^2}{\sum |FFT(signal)|^2} \tag{2}$$

2.3. Time domain features

Zero Crossing Rate(ZCR): ZCR is a measure of how often a signal changes its sign within a given frame. This

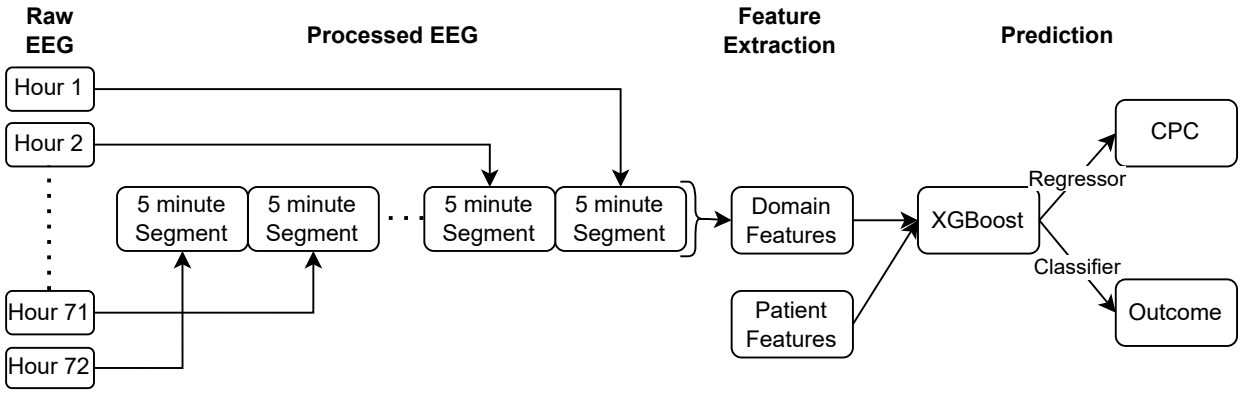

Figure 1. Workflow for predicting patient Outcome and CPC score. It involves selecting the most optimal 5-minute segment from each hour, which is then followed by feature extraction and prediction.

feature provides information about the frequency of rapid changes in the EEG signal. It quantifies the rate at which the signal crosses zero. We calculate the number of zero-crossings and normalize it by dividing it by twice the length of the signal.

$$ZCR = \frac{Number\ of\ Zero\ Crossings}{2 \times Signal\ Length} \tag{3}$$

Energy: Energy is a fundamental time domain feature that reflects the magnitude of signal variations. It is calculated by taking the sum of the squared values of the signal. We calculate the energy by summing the squares of the signal values. The formula for Energy is as follows:

$$Energy = \sum_{i=1}^{N} x_i^2 \tag{4}$$

Here, x_i represents EEG signal values.

Entropy: Entropy is a measure of the randomness or unpredictability of the signal values. First, we create a histogram of the signal values with a specified number of bins (50 bins). Next, we normalize the histogram and calculate the Shannon entropy(1). Here, $p(x_i)$ is the probability of each bin value x_i in the histogram.

2.4. Model Training

After extracting features, the resulting input feature vector dimension for each patient amounted to 116. The domain features were derived from each of the 18 EEG channels, resulting in 108 (18 $\times$ 6) features, and were complemented by an additional 8 demographic features. The choice of XGBoost, a tree-based model, was made for both classification and regression tasks, and further optimization of hyperparameters was carried out. Table 1 shows details regarding the model training parameters.

Parameter	Values
max_depth	3, 5, 7, 9
learning_rate	0.01, 0.1, 0.02
n_estimators	200, 250, 300, 350, 400, 450, 500
base_score	0.3, 0.4, 0.5, 0.6

Table 1. Hyper parameters used for the XGboost model.

3. Results

The challenge scores of our model are presented in Table 2. Further evaluation metrics received on our algorithm are listed in Table 3. Out of 112 teams that participated in the challenge, am_vision secured a rank of 18^{th} (out of 36 teams that were eligible for rankings) with the challenge score of 0.485. Additionally, in the categories of Outcome Accuracy and Outcome F-measure, our team is placed in 4^{th} and 5^{th} positions for the scores of 0.81 and 0.769 respectively, on the hidden test set.

	12 h	24 h	48 h	72 h
training	0.356	0.427	0.741	0.838
validation	0.254	0.388	0.463	0.522
test	0.292	0.401	0.446	0.485
rank (out of 36)	13	16	18	18

Table 2. The challenge scores on the training, validation, and test sets, ranks received at different hours after ROSC.

4. Discussion and Conclusions

In our research, we have introduced an approach that encompasses feature extraction from both the time and frequency domains. The model demonstrated good discrimination ability (AUROC) and precision-recall trade-off (AUPRC) on all sets, indicating its capacity to distinguish between poor and good outcomes effectively. The

	Outcome AUROC	Outcome AUPRC	Outcome Accuracy	Outcome F-measure	CPC MSE	CPC MAE
training	0.947	0.969	0.865	0.852	0.466	0.391
validation	0.803	0.88	0.748	0.707	2.579	1.311
test	0.841	0.89	0.81	0.769	2.449	1.282

Table 3. Advanced evaluation metrics for the training, validation, and test sets at 72 hours after ROSC.

accuracy and F-measure values were high on the training set, indicating correct classifications and a balance between precision and recall. The drop in challenge scores on the validation and test sets suggests potential overfitting and challenges in generalization on new data. Notably, in a previous submission, where only demographic data was input to the HistGradient Boost model, it achieved a score of 0.45 on the validation set highlighting the relevance of such information in our modelling. It is important to acknowledge that, in our current approach, we identify only three specific artifacts, whereas EEG data commonly contains various other artifacts, including muscle artifacts, ECG artifacts, and more. Due to time limitations imposed on the algorithm, we couldn't address all artifacts. However, we firmly believe that a more comprehensive approach, encompassing the identification of various artifacts and training a model based on fundamental features, can lead to optimal results, potentially surpassing the need for complex feature extraction techniques.

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References

[1] Wijdicks E, Hijdra A, Young GB, Bassetti CL, Wiebe S. Practice parameter: Prediction of outcome in comatose survivors after cardiopulmonary resuscitation (an evidence-based review). Neurology 2006;67(2):203–210.

[2] Ruijter BJ, Tjepkema-Cloostermans MC, Tromp SC, van den Bergh WM, Foudraine NA, Kornips FHM, et al. Early electroencephalography for outcome prediction of postanoxic coma: A prospective cohort study. Annals of Neurology 2019;86(2):203–214.

[3] Cloostermans MC, van Meulen FB, Eertman C, Hom HW, van Putten MJ. Continuous electroencephalography monitoring for early prediction of neurological outcome in postanoxic patients after cardiac arrest: A prospective cohort study. Critical Care Medicine 2012;40:2867–2875.

[4] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, et al. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation 2000;101(23):e215–e220.

[5] Reyna MA, Amorim E, Sameni R, Weigle J, Elola A, Bahrami Rad A, et al. Predicting neurological recovery from coma after cardiac arrest: The George B. Moody PhysioNet Challenge 2023. Computing in Cardiology 2023; 50:1–4.

[6] Amorim E, Zheng WL, Ghassemi MM, Aghaeeaval M, Kandhare P, Karukonda V, et al. The International Cardiac Arrest Research (I-CARE) Consortium Electroencephalography Database. Critical Care Medicine 10 2023;.

[7] Pham S, Keijzer H, Ruijter B, Seeber A, Scholten E, Drost G, et al. Outcome prediction of postanoxic coma: A comparison of automated electroencephalography analysis methods. Neurocritical care 2022;37:248–258. ISSN 1541-6933.

[8] Hangaragi S, Nizampatnam N, Kaliyaperumal D, Özer T. An evolutionary model for sleep quality analytics using fuzzy system. Proceedings of the Institution of Mechanical Engineers Part H Journal of Engineering in Medicine 2023;.

[9] Rangan ES, Pathinarupothi RK, Anand KJS, Snyder MP. Performance effectiveness of vital parameter combinations for early warning of sepsis—an exhaustive study using machine learning. JAMIA Open 10 2022;5(4):ooac080.

[10] Bodda S, Diwakar S. Exploring EEG spectral and temporal dynamics underlying a hand grasp movement. PLoS ONE 2022;17(6 June).

[11] Padmavilochanan D, Pathinarupothi RK, Menon KU, Kumar H, Guntha R, Ramesh MV, et al. Personalized diabetes monitoring platform leveraging IoMT and AI for non-invasive estimation. Smart Health 2023;30:100428. ISSN 2352-6483.

[12] Ríos-Herrera WA, Olguín-Rodríguez PV, Arzate-Mena JD, Corsi-Cabrera M, Escalona J, Marín-García A, et al. The influence of EEG references on the analysis of spatio-temporal interrelation patterns. Frontiers in Neuroscience 2019;13.

[13] Zheng WL, Amorim E, Jing J, Wu O, Ghassemi M, Lee JW, et al. Predicting neurological outcome from electroencephalogram dynamics in comatose patients after cardiac arrest with deep learning. IEEE Transactions on Biomedical Engineering 2022;69(5):1813–1825.

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