Predicting Coma Recovery Outcomes After Cardiac Arrest Using Deep Learning on EEG Data

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Abstract

Cardiac arrest leads to significant brain injury that can result in coma and pose a challenge in predicting the recovery or long-term neurological deficits. Prognosis currently depends on the interpretation of the EEG patterns by experts, which is resource-intensive and inaccessible in many healthcare settings. In this project, we explore a deep learning based approach for coma prognosis using the EEG data, aiming to address these limitations. We utilised the I-CARE dataset that has over 32,712 hours of EEG and ECG recordings. We concentrated on a subgroup of patients to train the ResNet model with frequency band extraction and a majority voting mechanism. The model was able to predict both favorable (CPC 1-2) and bad (CPC 3-5) recovery outcomes with an F1 score of 0.33, despite the limitations of a small dataset. These results show the potential use of the EEG data for coma prognosis and suggest future improvements with larger datasets and additional data types.

Introduction

<u>Clinical problem and its significance:</u>
Cardiac arrest is a serious medical emergency with significant rates of death and morbidity. Survivors of cardiac arrest frequently experience severe neurological abnormalities, such as cognitive dysfunction and coma. Predicting the neurological outcomes following cardiac arrest is a major challenge. Accurate prediction of the long-term neurological outcomes, such as the Cerebral Performance Category (CPC), is important for guiding the treatment strategy and improving patient outcomes. CPC is a commonly used metric to classify brain function following cardiac arrest and ranges from CPC 1 to CPC 5.

- **CPC 1**: Good cerebral performance (good recovery or only mild disability)
- **CPC 2**: Moderate disability (independent but with some neurological impairment).
- **CPC 3**: Severe disability (conscious but dependent on others for daily activities).
- **CPC 4**: Comatose state.
- **CPC 5**: Brain death.

Early and accurate prediction of the CPC score allows the healthcare providers to make evidence-based decisions about continuing care, contacting relatives and stopping life-sustaining therapies.

The timely prediction of the CPC scores is critical for the following reasons:

- **Optimise resource allocation:** Advanced life-support equipment, intensive care unit (ICU) beds, and medical staff are scarce resources. Clinicians can better direct these

resources toward patients who have a better chance of recovering if they identify patients who are likely to have poor outcomes early.
- **Provide clarity to Families:** post-cardiac arrest families usually face emotional and financial strain while waiting for prognostic information. Accurate predictions can help set realistic expectations and guide the decisions of the family about continuing or discontinuing treatment.
- **Customize Interventions for Therapy:** The immediate start of focused therapeutic measures, such as therapeutic hypothermia (targeted temperature management), may be essential for neurological recovery in patients who have experienced cardiac arrest.

Challenges with the current methods:
- Complexity of the data: Neurological outcomes are influenced by multiple factors including brain activity (EEG), and heart function (ECG). We would require large-scale data to capture this complexity which is difficult to interpret without advanced computational tools.
- Imbalance in data: CPC outcomes are heavily imbalanced, with the majority of patients falling in the CPC 4 and 5 categories. This makes it difficult for the machine learning models to predict rare outcomes accurately.
- Noise and variability in ECG signal: ECG signal usually has high variability, which can obscure critical features relevant to CPC prediction.
- Insufficient Standardized Models: current models often rely on small-scale datasets, therefore are not generalisable.

Existing approaches:
- **Clinical scoring system:** Glasgow coma scale and other prognostic tools are used for evaluating post-cardiac arrest patients. These methods are subjective and highly rely on clinical expertise, and fail to capture the full spectrum of the physiological data.
- **Machine learning models:** Some models exist. However, they have high risk of overfitting due to small sample size, limited interpretability and lack of real-time application.

Proposed solution:
A deep learning approach that uses the ECG signals with other parameters to predict the CPC outcomes. We build on the methodology presented in the paper [1] while incorporating additional models and approaches to improve the accuracy, interpretability and generalizability.
1. **Preprocessing pipeline:** Standardization, segmentation, dimensionality reduction techniques such as Welch's Power Spectral Density (PSD) are employed to extract meaningful features from raw EEG signals.
2. **Model architecture:** We designed and tested multiple ML and Deep learning models including a simple 1D CNN, ResNet18 architecture with preactivation layers and XGBoost.
3. **Evaluation metrics:** In addition to True positive Rate(TPR) for poor outcomes, we made use of accuracy, F1 score and AUC-ROC to provide comprehensive evaluation of model performance.

Findings:

- The ResNet18 architecture consistently outperformed simpler CNN models, achieving higher accuracy, F1 scores, and AUC-ROC. This highlights the importance of deeper architectures for extracting temporal and spatial features from EEG data.
- Use of the Welch's PSD reduced the dimensionality of the data without compromising model accuracy, enabling faster training while retaining key features.
- Traditional ML models like XGBoost lagged behind the deep learning models, validating that EEG signals require more temporal feature extraction which the traditional ML model struggles to capture.

Contributions:

- Data preprocessing: Gehna, Surabhi, Evina, Rachel
- Feature extraction: Gehna, Evina
- Model building and development: Gehna, Surabhi, Evina
- Evaluation: Gehna, Surabhi, Evina
- Visualisations: Rachel

Background

Due to hypoxia, or the lack of oxygen reaching the brain during the occurrence, cardiac arrest is a serious medical emergency that can cause severe damage to the brain. Severe neurological damage, including a coma in which the patient is unconscious and unresponsive, can be brought on by hypoxia. Many patients stay unconscious for hours or weeks even after the return of spontaneous circulation (ROSC), which is the restoration of functional blood flow after cardiac arrest. According to research, about 80% of patients do not immediately regain consciousness following ROSC, and it is unknown how well they will neurologically recover over the long run.

One of the most significant factors affecting patient outcomes following ROSC is the restoration of neurological function. Many survivors suffer from several types of brain damage, ranging in severity from minor cognitive impairment to brain death or deep coma. For the best therapeutic decision-making in this situation, a precise and rapid neurological recovery prediction is crucial.

Several studies have focused on predicting neurological outcomes after cardiac arrest, mostly using physiological data such as EEG and ECG. These studies aim to develop accurate and automated systems to assist clinicians in predicting the long-term neurological recovery and outcomes, such as the **Cerebral Performance Category (CPC)** score.An overview of the major studies that have advanced this field can be seen below.

[1] **"Predicting Coma Recovery After Cardiac Arrest with Residual Neural Networks" (**https://arxiv.org/pdf/2403.06027.**)-** this paper makes use of the **Residual Neural Networks (ResNet)** for predicting recovery outcomes after cardiac arrest. The author describes how deep learning models can capture the complex patterns in the EEG signals. This model outperforms the traditional methods by predicting the recovery of patients with a higher degree of accuracy than manual EEG interpretation.

Limitation: requires substantial amounts of data for training, and its complexity makes it difficult to implement in real-time clinical settings.

[2] **"Predicting Neurological Outcomes After Cardiac Arrest Using Electrocardiogram and Electroencephalogram Signals" (**https://www.cinc.org/archives/2023/pdf/CinC2023-093.pdf**)-** This paper focuses on combining both EEG and ECG signals to predict the neurological outcomes after cardiac arrest demonstrating that multi-modal data can improve accuracy. This study specifically investigates machine learning algorithms, including **Support Vector Machines (SVM)** and **Random Forests**, to analyze these multi-modal signals.
Limitation: the author faced data imbalance, with many patients showing CPC 4 or 5. The model also struggles with interpretability due to the complexity of the multi-modal data.

[3] **"Artificial Intelligence for Predicting Outcome in Post-Cardiac Arrest Patients: A Comprehensive Review and Meta-analysis" (**https://doi.org/10.3410/M1-89**) -** This study shows that machine learning models, including deep learning models can provide better accuracy compared to the traditional clinical scoring systems. It offers a meta-analysis of current models, contrasting their generalizability, accuracy, and performance.
Limitation: lack of well- annotated, large-scale datasets, difficulty in obtaining generalizability across a range of patient demographics and the requirement for interpretable, real-time models that can be used in treatments.

Our approach aims to replicate the methodology outlined in Paper [1], which utilizes deep learning techniques to predict neurological outcomes after cardiac arrest. In addition to this, we incorporated techniques like **Welch's Power Spectral Density (PSD)** to reduce the dimensionality of the EEG data, which helps in improving model efficiency and prediction accuracy. We were able to achieve an F1 score of 0.3. To improve the precision of our predictions, we experimented with different models. Even though we tried a number of other designs, the ResNet model finally produced the best results. When compared to the other models we examined, its capacity to identify intricate patterns in the EEG data through residual connections enabled it to efficiently acquire richer representations, improving prediction accuracy. This outcome demonstrates ResNet's resilience in managing the intricacies of EEG inputs and its applicability for forecasting neurological consequences following cardiac arrest.

Dataset Description

1. Source and Collection

A description of the dataset, including where and how it was collected.
The dataset used in this study is the International Cardiac Arrest Research (I-CARE) Database. It is a publicly available dataset collected by the I-CARE consortium from 7 academic hospitals across the United States and Europe, including:

- Rijnstate Hospital, Arnhem, The Netherlands
- Medisch Spectrum Twente, Enschede, The Netherlands
- Erasme Hospital, Brussels, Belgium
- Massachusetts General Hospital, Boston, USA

- Brigham and Women’s Hospital, Boston, USA
- Beth Israel Deaconess Medical Center, Boston, USA
- Yale New Haven Hospital, New Haven, USA

The dataset includes over 32,712 hours of EEG and ECG data from 607 patients who were admitted to the Intensive Care Unit (ICU) following cardiac arrest. The recordings are segmented into 80,809 segments and come with detailed patient demographics and clinical information. The key sources include:

- EEG Data: Continuous brainwave activity recordings across multiple channels.
- ECG Data: Heart activity recordings.
- Demographic and Clinical Details: Information such as age, sex, ROSC (Return of Spontaneous Circulation) time, and CPC (Cerebral Performance Category) scores.

The patients were monitored for several hours to several days, depending on their condition, providing a rich dataset for analysis and research.

2. Dataset choice

This dataset was chosen because it directly addresses the challenge of predicting coma recovery after cardiac arrest using EEG and ECG data. The reasons for selecting this dataset include:

- Relevance: The dataset provides EEG and ECG recordings for patients in a comatose state following cardiac arrest, which aligns perfectly with the study's goal of automating prognosis predictions.
- Rich Data: The large volume of recordings (over 32,000 hours) and detailed patient metadata enable the exploration of deep learning models to identify patterns that may be missed by traditional EEG interpretation methods.
- Clinical Impact: Accurate predictions of recovery can aid clinicians in making informed decisions about patient care and interventions, particularly in resource-constrained settings where expert neurologists may not be available.

3. Patient Population and Sample Size

The dataset includes 607 patients who experienced cardiac arrest and remained comatose after ROSC. Each patient’s recovery outcome is classified based on the Cerebral Performance Category (CPC) scale, which groups outcomes into:

- Good Recovery: CPC 1-2 (independent or moderately disabled).
- Poor Recovery: CPC 3-5 (severe disability, vegetative state, or death).

<u>Sample Selection for our Study:</u>

Due to the large size of the dataset, the study focused on a subset of patients with the most extensive EEG recordings. Specifically, the top 5 patients from each class (Good and Poor recovery) were prioritized for analysis.

4. Patient Characteristics

Feature	Description
Total Patients	607
Age Range	18 to 90+ years
Sex	Male, Female
ROSC Time	Time (minutes) from cardiac arrest to ROSC
Cardiac Arrest Location	In-hospital, Out-of-hospital
Shockable Rhythm	Shockable (True/ False)
Targeted Temperature Management (TTM)	33°C, 36°C, or No TTM
Data segments	80809
EEG Duration	32712 hours
Outcomes	Good (CPC 1-2), Poor (CPC 3-5)

Table 1. Dataset Description

5. Feature Descriptions

The dataset contains the following key features:

- EEG Data:
  - Continuous EEG recordings across up to 21 channels per patient.
  - Frequency-based features extracted through methods like Welch's Power Spectral Density (PSD) estimation.
  - EEG segments of 5-minute duration for uniform analysis.

- ECG Data:
  - Up to 5 ECG channels providing heart activity information.

- Demographic Data:
  - Age: Patient age at the time of cardiac arrest.
  - Sex: Male/Female classification.

- Clinical Data:
  - ROSC Time: Time taken for return of spontaneous circulation after cardiac arrest.
  - Outcome: CPC score indicating recovery status.

6. Visualization

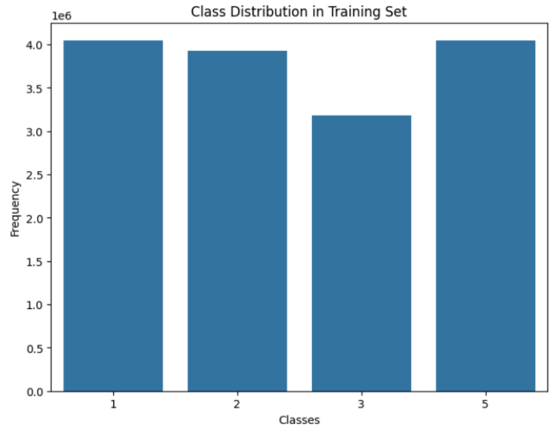

Figure 1: Shows each CPC class and their how many time windows for each class (frequencies) after splitting across channels.

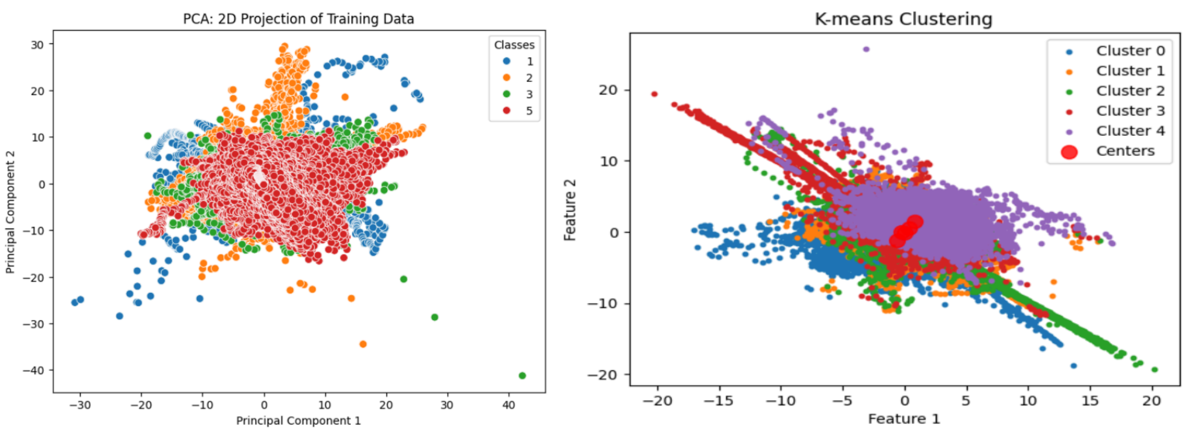

Figure 2. PCA Visualization illustrates the overlap of EEG data from different classes (left); Visualization of the K-means separation and overlap of EEG data from different classes (right)

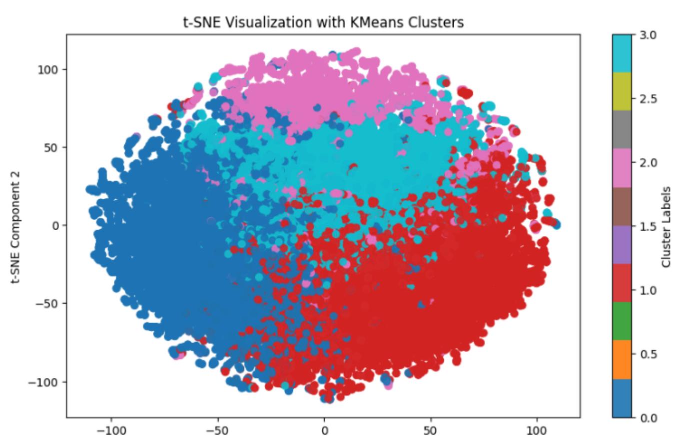

Figure 3. t-SNE which means clusters Visualization to show a more non linear way of clustering with the EEG data and classes.

7. **Data Preprocessing and Dimensionality Reduction**
   To prepare the EEG data for model training, the following preprocessing steps were applied:

   - Cropping EEG Windows:
     - Randomly extracted 5-minute segments from the continuous EEG recordings to standardize input size.

   - Handling Missing Values:
     - Used linear interpolation to estimate and fill missing (NaN) values within the EEG data.

   - Channel Normalization:
     - Normalized each EEG channel by subtracting the mean and dividing by the standard deviation to ensure uniform data distribution.

   - Resampling:
     - Downsampled all EEG recordings to a consistent sampling rate of 100 Hz for uniformity across patients.

   Standardizing the EEG segment length and sampling rate ensures the model processes inputs of uniform size. Handling NaN values and normalizing channels reduces the impact of artifacts and noise on model performance. And segmenting the data into 5-minute windows helps manage the large volume of EEG recordings and allows for efficient training.

Methodology

Our approach follows the standard pipeline commonly adopted in machine learning research. First, we preprocess the raw dataset to ensure compatibility with the model's requirements. Once transformed into the desired format, the data is used to develop and train various model architectures. Our experiments included exploring multiple configurations and parameters to identify the most effective approach. Additionally, we aimed to replicate the methodology presented in the paper "Predicting Coma Recovery After Cardiac Arrest With Residual Neural Networks" to better understand its findings and implications.

Following model construction, we trained and evaluated the models. The evaluation metric used in the paper, tailored for this specific domain, focused on the True Positive Rate (TPR) for predicting poor outcomes while maintaining a False Positive Rate (FPR) below 0.05 at 72 hours post-recovery of spontaneous circulation. While this metric is domain-specific, we extended the evaluation to include commonly understood metrics such as testing accuracy, F1 score, and AUROC, to make the results more interpretable for a broader audience.

The final step in our pipeline was post-processing, where we aggregated predictions into a single majority vote prediction for the patient across all their records. Below, we discuss each phase of the pipeline in detail.

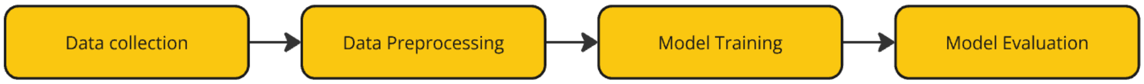

Figure 4: Basic pipeline for ML research

1. **Data Preprocessing**

The dataset we worked with is extremely large, comprising approximately 3TB of data. Due to computational limitations, we worked with a smaller subset of the data, starting with 20 patients, which was later extended to 32 patients. Each patient's data is organized in folders labeled by patient ID, with each folder containing between 20 to 72 hours of EEG data in .mat files. Each file corresponds to one hour of data.

Preprocessing Steps:

- Data Segmentation: For each hour of data, a random 5-minute window was selected and resampled to a 100 Hz sampling frequency. This resulted in approximately 30,000 records with 18 channels per file.

- Standardization: We standardized the data across the patient files, ensuring consistency before saving the data in .pkl format for use in model training.

- Power Spectral Density: To reduce the dimensionality and ensure efficient model training, we applied Welch's Power Spectral Density (PSD) technique. This helped compute the mean values for the delta, theta, alpha, beta, and gamma frequency ranges for each 5-minute window. The resulting feature set reduced the data dimensions from 30,000x18 to 25x18.

- Cross-validation Setup: Based on feedback, we updated the data storage format for cross-validation. Previously, data for all patients was in a single file for training; now, each patient's preprocessed data is saved separately. This facilitates stratified sampling, allowing us to perform 7-fold cross-validation (7 patients for training and 1 for testing per fold).

The figure below (Figure 5) illustrates the data preprocessing pipeline, including the steps of data segmentation, resampling, standardization, and dimensionality reduction.

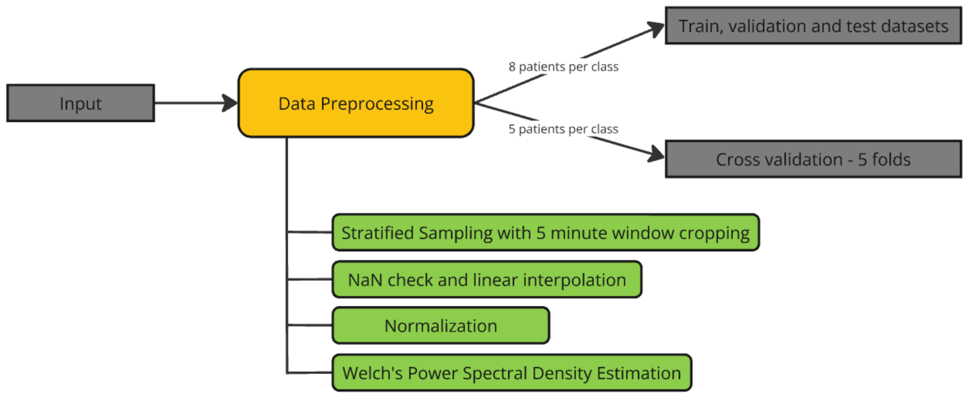

Figure 5: Data Preprocessing and training, validation and testing approaches

2. Model Training

We tried multiple models to compare their results and validate our hypothesis that the EEG signals alone carry enough information to predict the recoverability of the patients from coma after a cardiac arrest. We started with primitive deep learning models like MLP and then proceeded with more complex models to ensure the relationships were accurately captured. The hyperparameter tuning for the smaller models was done using the grid search method; while for the larger models was done manually due to OOM errors.

A small description of the models is as follows:

i. **"EEGModel"** - This is a simple 1D convolutional neural network with a ReLU activation, global average pooling, and a fully connected layer for classification. We use the cross entropy loss for multi-class classification along with the Adam optimizer and StepLR scheduler. The SimpleCNN model is a modification of this by adding another convolution layer. We have also added k-fold cross validation using this model.

ii. **"ResNet18 with full preactivation layer"** - This model uses residual blocks with group normalization and ReLU activations for feature extraction, along with dropout (additionally added to improve regularization) and average pooling. It ends with a fully connected layer for classification that predicts the probability of the record belonging to one of the classes using cross entropy loss.

iii. **"XGBoost"** - We create an XGBoost model for multi-class classification with a maximum depth of 6 for each tree (we played with this parameter, changing it from 4, 5, 6), 100 boosting rounds and 80% of the features sampled at each round. The motivation to try a traditional ML model over the deep learning models stemmed from the paper titled "Tabular Data: Deep Learning is not all you need". Although there are temporal relationships in the data, we explored the option and evaluated its performance.

3. **Model Evaluation**

We used 3 main evaluation metrics - the testing accuracy which simply counts the number of correct predictions made by the model out of the total predictions; the f1-score which is the harmonic mean of precision and recall and balances the trade-off between these two metrics, especially when the data is imbalanced; and AUROC - which measures the ability of the model to distinguish between classes across all classification thresholds.

4. **Computational Resources**

We used Google Colab Pro and therefore were able to avail 55.5GB RAM and the T4 GPU.

Results

- One of the preprocessing steps included applying Welch's PSD estimation for each channel per minute in a 5-minute window. The output for one such channel is shown below.

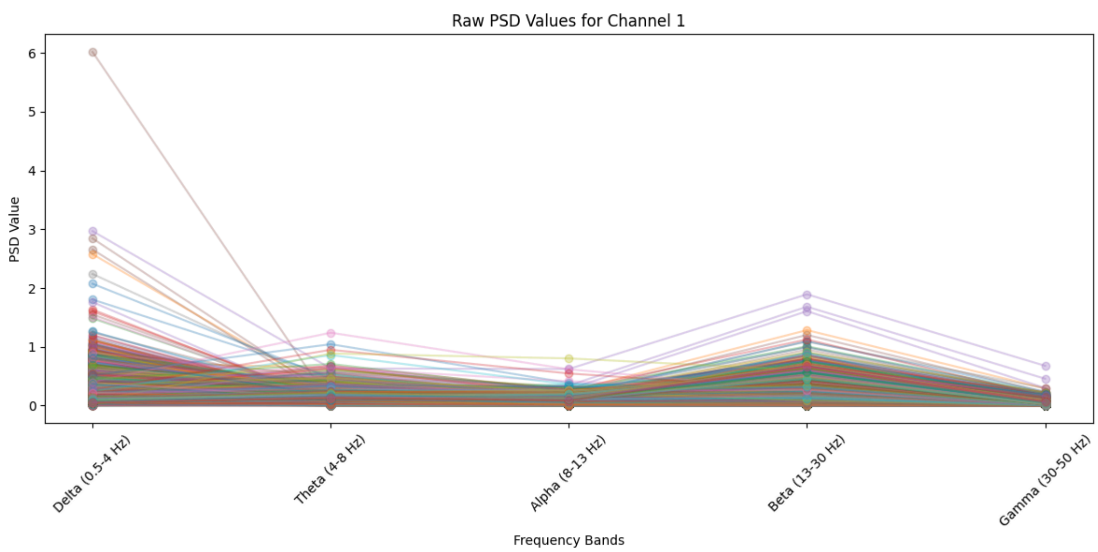

Figure 6. Raw PSD values for Channel 1 for Delta, Theta, Alpha, Beta and Gamma bands

- Using the paper's proposed ResNet architecture and adding dropout and regularization layers, we obtain the below (left) confusion matrix; and for the EEGModel that gives us the best testing accuracy, the figure below on the right demonstrates the AUROC.

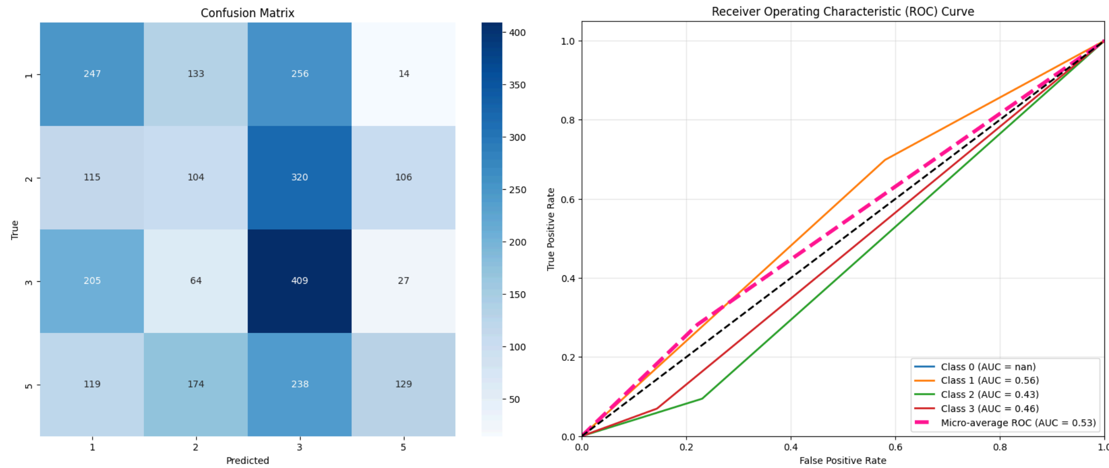

Figure 7. Evaluation visualizations for ResNet (left - confusion matrix) and EEGModel (right - AUROC)

Table 2. Comparison of model evaluation metrics

Model	**Precision***	**Recall***	**F1-score***	**Testing Accuracy**
EEGModel	0.2462	0.3444	0.2366	34.44%
ResNet1D	0.3457	0.3342	0.3162	33.42%
XGBoost	0.2155	0.1914	0.1960	19.14%
Simple CNN	0.2195	0.2357	0.1845	23.57%
EEGModel with 5-fold cross validation	0.2673	0.2481	0.1870	31.25%

* Weighted metrics

Discussion

1. **Project Goals and Main Findings**

   The primary goal of this project was to develop a deep learning model to predict coma recovery outcomes after cardiac arrest using EEG data from the International Cardiac Arrest REsearch (I-CARE) Database. By automating EEG interpretation, we aimed to improve accessibility to reliable prognosis predictions, particularly in resource-limited settings. Our approach involved preprocessing EEG data, implementing a ResNet-18 model, and using a majority voting mechanism for final predictions.

   Our best-performing model achieved an F1 score of 0.31, indicating some success in distinguishing between good and poor recovery outcomes. This result demonstrates the potential of deep learning for this task but highlights several challenges and limitations that affected performance. It is not surprising that the model is not able to distinguish between the classes, as we can see in the visualizations of the data, the classes have a huge overlap. This hints that using EEG data alone for the prediction of recovery is not the most ideal approach.

2. Results and Their Interpretation

- ResNet-18 with Frequency Band Extraction:
    - F1 Score: 0.31
    - This model performed the best among those tested. The low F1 score is likely due to the limited dataset size. We used EEG data from only 32 patients, which represents a very small subset of the 607 patients available in the I-CARE dataset. This limited sample size restricted the model's ability to generalize and learn diverse patterns associated with different outcomes.

- Baseline XGBoost Model:
    - F1 Score: 0.18
    - The XGBoost model, which uses clinical metadata (without EEG data), performed poorly compared to deep learning models. This underscores the importance of EEG signals for accurate coma recovery prediction.

- EEGModel and Simple CNN:
    - Showed decent performance during training but struggled to maintain high accuracy during validation, indicating potential overfitting. The model's performance reinforces the need for more sophisticated architectures or larger datasets to improve generalization.

- Frequency Band Extraction:
    - The use of specific frequency bands slightly improved performance, suggesting that focusing on these features helps capture relevant brain activity patterns.

- Evaluation Metrics:
    - Testing Accuracy: A basic measure of the proportion of correct predictions.
    - F1 Score: Emphasizes balance between precision and recall, useful for imbalanced data.
    - AUROC: Measures the model's ability to distinguish between classes, which is important for assessing model performance across various thresholds.

3. Potential Reasons for Low F1 Score

- Limited Sample Size:
    - Using data from only 32 patients significantly constrained the model’s ability to learn generalizable patterns. Training on the full dataset of 607

    - patients could lead to better performance by exposing the model to more variability and richer patterns.
    - The size of the dataset makes it almost impossible to download on a regular personal computer (zip file - 1TB).

- Data Variability:
    - The EEG recordings in the small subset may not fully represent the diversity of brain activity found in the complete dataset, contributing to poorer predictions.

- Short EEG Segments:
    - Using 5-minute EEG windows may not capture long-term brain activity changes necessary for accurate prognosis.

- Overfitting:
    - With such a small dataset, the model likely overfit the training data, learning patterns that do not generalize well to new cases.

4. Comparison to Referenced Paper

The paper "Predicting Coma Recovery After Cardiac Arrest With Residual Neural Networks" reported a challenge score of 0.4 using a larger dataset. Our f1-score of 0.31 indicates that using a smaller dataset (only 32 patients) limits model performance, but still shows that EEG-based prediction is feasible.

5. Limitations

- Small Subset of Data:
    - The results are based on only 32 patients, limiting the robustness of the model.
    - According to ICARE database, most patients died (N=603, 59%), 48 (5%) had severe neurological disability (CPC 3 or 4), and 369 (36%) had good functional recovery (CPC 1-2).
- Short Time Segments:
    - Analyzing short 5-minute segments may miss important long-term EEG patterns relevant to recovery prediction.
- Data Quality:
    - Noise, missing values, and variability in EEG recordings may have affected the model's performance despite preprocessing efforts.

6. Future Directions

- Use the Full Dataset:
    - Expanding the analysis to include all 607 patients in the I-CARE dataset could significantly improve model performance and generalizability.
- Multimodal Learning:

    - Combining EEG data with ECG data and clinical metadata (e.g., ROSC time, age, sex) may provide a more comprehensive approach to prognosis prediction.

- Longer EEG Segments:
    - Analyzing longer recordings may capture more detailed patterns of brain activity and improve accuracy.

- Regularization Techniques:
    - Applying methods like Dropout or DropBlock could help mitigate overfitting.

- Advanced Architectures:
    - Exploring models like Transformer-based networks may enhance the model's ability to detect complex patterns in EEG data.

7. Code and data availability

- Dataset: The I-CARE dataset is publicly available on PhysioNet: https://physionet.org/content/i-care/2.1/
- Code:
    - Preprocessing Data
    - Models

Conclusion

The goal of this project was to create a deep learning model that could predict coma recovery outcomes after cardiac arrest using EEG data. We tackled this challenge by working with a subset of the I-CARE dataset, processing and standardizing EEG recordings, and training models like ResNet18, XGBoost, and EEGModel using 5-fold cross-validation. To capture meaningful patterns, we used frequency band analysis and evaluated the models using metrics such as F1 score, accuracy, and AUROC.

Our most successful model, ResNet18 with frequency band extraction, achieved an F1 score of 0.31. While this score was limited by the small dataset size (only 32 patients), it still highlights the potential of EEG data for predicting recovery outcomes. These results suggest that deep learning could play a significant role in automating EEG interpretation and making prognosis predictions more accessible, especially in hospitals with limited neurological expertise.

Incorporating this model into clinical practice could offer clinicians an objective tool for early prognosis, helping them make informed decisions about treatments and life-support options. To make this a reality, the model needs to be trained on the entire dataset of 607 patients, validated in real-world clinical settings, and combined with other clinical data like ECG and patient demographics. Achieving regulatory approval and integrating the model seamlessly into existing clinical systems will be crucial steps in ensuring it can reliably support patient care and improve outcomes.

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