Random Forest and Attention-Based Networks in Quantifying Neurological Recovery

Mostafa Moussa[1], Hessa Alfalahi[1], Mohanad Alkhodari[1,2], Leontios Hadjileontiadis[1,3], Ahsan Khandoker[1]

[1] Department of Biomedical Engineering, Khalifa University of Science and Technology, Abu Dhabi, UAE
[2] Cardiovascular Clinical Research Facility, Radcliffe Department of Medicine, University of Oxford, Oxford, UK
[3] Department of Electrical and Computer Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece

Abstract

Introduction: *Cardiovascular disease is generally considered the most prevalent cause of morbidity in the modern world, and cardiac arrest, in particular, causes nearly 50 % of deaths linked with heart attack and stroke in the US. Surviving cardiac arrest could still lead to brain injury and, consequently, death. Our main aim is to mitigate incorrect prognoses in measuring patients' recovery by exploiting the power of machine learning.* ***Methods:*** *We use the training set from the unofficial phase comprising 607 comatose adults following recovery from cardiac arrest to develop two attention-based networks using various features. 486 subjects are used for training and 10-fold cross-validation; the remainder is used for testing and evaluation.* ***Results:*** *Despite an official challenge score of 0.00,* ***Team_KU****'s best attention-based models yielded a testing accuracy of 62.00 %, an F-measure of 61.20 %; beating our random forest used in the unofficial phase at 55.58 %, and an area under the receiver operating characteristics (AUC) of 0.63 for outcome classification and a mean absolute error of 2.49 for CPC prediction with 607 subjects; nearly half of the provided data in the official phase.* ***Conclusion:*** *This study paves the way toward implementing efficient machine learning to assess brain injury in comatose patients, even in resource-restricted settings. Thus allowing early, automated prediction of recovery.*

1. Introduction

Cardiovascular diseases, more specifically cardiac arrests, are a common cause of morbidity in the modern world with low rates of survival, and even in that scenario, survivors can become comatose, following which could be severe brain injury, which is the most common cause of death [1–3]. During care, physicians make their prognoses based on experience and knowledge, which results in hospitalization and care for good ones and possible withdrawal of life support for poor ones. This makes an incorrect, poor prognosis dangerous and should not be left up to the subjective interpretation of the patient's condition. Therefore, continuous monitoring of patient brain activity via electroencephalography (EEG) [4] and other vitals, such as electrocardiography (ECG), is necessary to provide proper prognosis and care. Using EEG and ECG signals eliminates subjectivity in predicting neurological outcome and certain patterns in brain activity, for example, enable and encourage the development of automated methods of prognosis [5–9].

Automating prognosis mitigates subjectivity and eliminates the need for specialists to inspect the EEGs and ECGs and draw conclusions, making the prognostic methodology applicable in environments where neurologists are not readily available. Consequently, this reduces the cost of prognosis and makes it less time-consuming. To this end, the International Cardiac Arrest Research Consortium (I-CARE) developed a dataset gathered from seven hospitals in the United States, and we, ***Team_KU*** use that dataset to develop our models for the 2023 George B. Moody Physionet Challenge [10–12]. The official dataset comprises patient information, EEG data, ECG data, and neurological outcomes from a large number of subjects at 1,020, with the EEG and ECG recordings being up to 72 hours. The patients were comatose following cardiac arrest and had their brain activity monitored via a 19-channel EEG and their heart rhythm recorded via ECG. Their recovery is recorded as part of patient information, which includes their ages, sexes, the hospital they were in, the time of return to spontaneous circulation following cardiac

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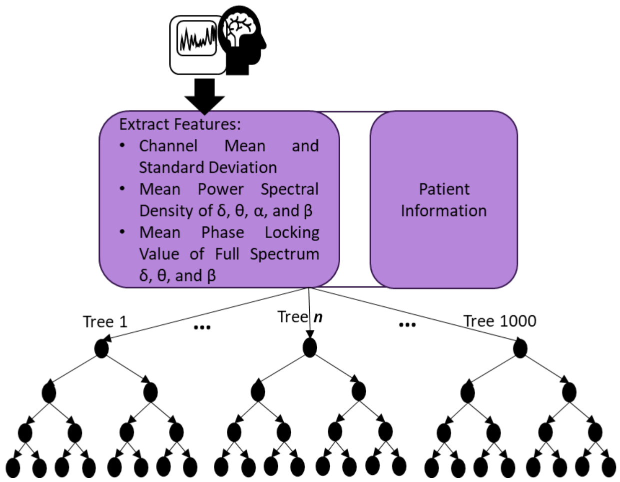

Figure 1. The baseline approach followed to predict recovery using random forest for the unofficial phase. Patient Information is described in the final paragraph of Section 1.

arrest (ROSC), the location of the event- or whether the cardiac arrest occurred out of the hospital (OHCA), the cardiac rhythm at the time of resuscitation, targeted temperature management (TTM)- or the desired control temperature, and neurological outcome. The cardiac rhythm field describes whether the abnormality of cardiac rhythm could be treated via shock (defibrillation), like ventricular fibrillation or tachycardia, or not like asystole or flat-lining, and neurological outcome is measured using the Cerebral Performance Category (CPC) scale of 1-5, where 1 represents the best outcome of neurological function where the patient can return to independent living, 2 represents moderate neurological disability but maintains independent living, 3 represents severe disability, 4 represents unresponsive wakefulness syndrome (UWS), where the patient displays reflexive behavior but without signs of consciousness [13], and 5 is dead. The neurological outcome is further simplified or binarized, where CPCs 1 and 2 constitute a good outcome, and 3, 4, and 5 constitute a poor one.

2. Methodology

The challenge aims to develop an objective method to predict neurological recovery without requiring specialized individuals to make prognosis simpler for environments lacking that resource. We originally thought of going along these lines when developing our algorithm as well; we aimed to develop a methodology that is not resource-intensive to make the objective automated prediction even less demanding and expensive.

Using the EEG and ECG signals as inputs directly into any of our models would greatly increase computational cost. Instead, we opt to pre-process the signals and extract features, even reducing the number of channels in some experiments. The EEG and ECG signals were bandpass filtered using the frequency range $[0.1Hz - 30Hz]$ and resampled at 100 Hz.

Our first experiment in the unofficial phase involved developing a random forest algorithm using various features extracted from the EEG and ECG data, as shown in Figure 1. Moving onto the official phase, however, we sought to take advantage of the large amount of available data, so we used deep learning techniques. We also sought to take advantage of the attention mechanism, which essentially uses weighted multiplication to focus on parts of the input that correlate most with the model output [14].

However, since the score obtained in the unofficial phase showed promise, albeit not optimal, we wanted to use the random forest architecture. Hence, our first algorithm involved designing an artificial neural network in a structure similar to a random forest using the principles of decision trees and attention [15–17]. The first algorithm, dubbed RF-N1, consists of a fully connected layer with rectified linear units (ReLU) activation and batch normalization followed by an output fully connected layer with Softmax activation and an additional twist: that output layer is, in turn, followed by a local self-attention layer with ten heads and ten keys and queries. The aforementioned make up a "tree," and we include 1,000 "trees" in parallel for each configuration. The outputs from the "trees" are connected to a weighted addition layer, which is in turn connected to a global attention layer that then feeds into the final classification (outcome) or regression (CPC) layer. The second configuration is dubbed RF-N2 and is similar in structure. Still, instead of inputting the whole input, we input only half of it, like "bagging" into the first fully connected layer in each "tree," and the second half is fed into the second fully connected layer in the "tree." Figure 2 describes both random forest-based neural networks.

The second algorithm involves inputting the extracted features into a self-attention layer with four heads and four keys, followed by a feed-forward block comprising two fully connected layers with as many units as the square of the number of features in each. One fully connected layer with 10,000 units and the SoftMax and classification/regression layer are added afterward. This transformer network, as shown in Figure 3, is adapted from Baevski *et al.*'s work, but feature and positional encoding are omitted [18].

We use the data of 486 subjects for training and 10-fold cross-validation and 121 subjects for testing and gauge performance based on classification accuracy, F-measure, and area under the receiver operating characteristics curve (AUROC), and regression mean absolute error (MAE).

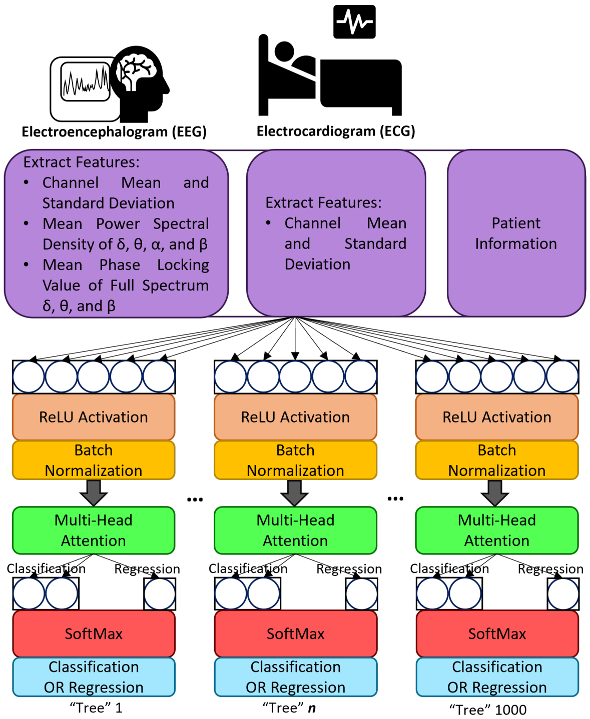

Figure 2. The novel approach utilized in the official phase of the challenge. Patient Information is described in the final paragraph of Section 1.

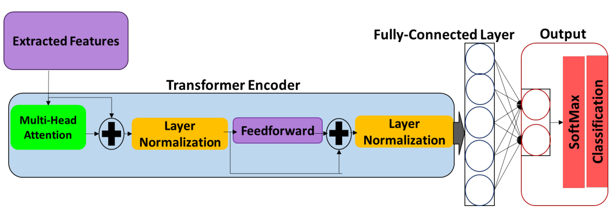

Figure 3. The second algorithm. Extracted features are described in Figure 2.

3. Results

During experimentation, we would gauge the performance of our outcome classification models based on accuracy and our CPC regression models based on the mean square error. Still, in the end, the best model is selected based on the Challenge Score metric. The challenge score is defined as the true positive rate (TPR) at a false positive rate (FPR) of 0.05 after 72 hours post-ROSC at each hospital for outcome classification as shown in Equations 1 and 2. θ_h is the largest decision threshold for hospital $\boldsymbol{h}$, and the true positive, false positive, and false negative in Equation 2 represent the sum of true positive, false positive, and false negative, respectively, over all hospitals at their respective largest decision threshold θ_h.

$$FPR_{\theta_h} = \frac{FP_{\theta_h}}{FP_{\theta_h} + TN_{\theta_h}} < 0.05 \quad (1)$$

$$ChallengeScore(TPR) = \frac{TP}{FP + FN} \quad (2)$$

Our successful submissions yielded a Challenge Score of 0.00 for all recording times (12-72 hours), likely due to the small number of features as present in the provided feature extraction function, so instead, we show the aforementioned metrics in Table 1 for our baseline model (random forest with surrogate decision split and using features such as power spectral densities and phase locking values), the better-performing random forest-based network, and the transformer network.

Table 1. Testing results with the 121 subjects from the unofficial phase set, Challenge scores obtained in the unofficial phase (RF) and official phase (RF-N1 and Transformer), and cross-validation challenge scores with the 486 subjects.

Algorithm	Random Forest (RF)	RF-N1	Transformer
Accuracy (%)	71.83	45.50	62.00
F-Measure (%)	55.58	42.60	61.20
AUROC	1.00	0.638	0.658
CPC - MAE	1.66	3.98	2.49
Challenge Score	0.29	0.00	0.00
Cross-Validation Score	0.30	0.18	0.20

4. Discussion

We mainly use the metrics stated earlier like accuracy and F-measure due to their ubiquity in literature and due to unsatisfactory official Challenge scores. Furthermore, we developed our models using the unofficial phase dataset because it is smaller than the official dataset. However, a few subjects from the official dataset were used to ensure our models more or less worked on that set.

Despite the subpar official 72-hour Challenge Score achieved by our models, they performed moderately in terms of classification accuracy at around 62 %, so we believe remedying the errors in the unsuccessful submissions, as well as optimization of the extracted features, feature selection, pre-processing, and network structure would yield promising results in terms of both accuracy and challenge score. However, if we look past training time and computational cost, we could train our models directly with the available EEG and ECG signals, enhancing performance even more. Further future work could involve using different models for regression and classification since the regression models' training performance was sub-optimal when utilizing the same network as the classification ones. In this vein, we foresee that employing data augmentation methods could boost the models' outcomes.

5. Conclusion

Brain injury is a common complication following cardiac arrest, and an accurate and rapid prognosis of neurological recovery can be unfeasible in many settings, not to mention subjective, possibly causing preventable death. Therefore, an automated prognosis means could save time, money, and, more importantly, lives. To that end, we use the I-CARE dataset provided for the George B. Moody Physionet Challenge 2023 to develop models that would classify neurological outcomes and CPC from patients with known neurological outcomes and CPC, among other information, as well as their EEG and ECG signals. We use the patient information and features extracted from both signals to develop our classification and regression models to keep the computational cost down and temporal resolution up. Our main model was a neural network that utilized the attention mechanism in a random forest-like structure and yielded an accuracy, F-measure, and a CPC mean absolute error and we believe that, without time constraints, we can develop more robust models.

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References

[1] Graham R, McCoy MA, Schultz AM. Strategies to improve cardiac arrest survival: a time to act 2015;.

[2] Mehra R. Global public health problem of sudden cardiac death. Journal of Electrocardiology 2007;40(6):S118–S122.

[3] Rundgren M, Westhall E, Cronberg T, Rosen I, Friberg H. Continuous amplitude-integrated electroencephalogram predicts outcome in hypothermia-treated cardiac arrest patients. Critical Care Medicine 2010;38(9):1838–1844.

[4] Hoedemaekers C, Hofmeijer J, Horn J. Value of EEG in outcome prediction of hypoxic-ischemic brain injury in the ICU: A narrative review. Resuscitation 2023;109900.

[5] Chen B, Song FQ, Sun LL, Lei LY, Gan WN, Chen MH, Li Y, et al. Improved early postresuscitation EEG activity for animals treated with hypothermia predicted 96 hr neurological outcome and survival in a rat model of cardiac arrest. BioMed Research International 2013;2013.

[6] Zheng WL, Amorim E, Jing J, Wu O, Ghassemi M, Lee JW, Sivaraju A, Pang T, Herman ST, Gaspard N, et al. Predicting neurological outcome from electroencephalogram dynamics in comatose patients after cardiac arrest with deep learning. IEEE Transactions on Biomedical Engineering 2021;69(5):1813–1825.

[7] Hirsch LJ, Fong MW, Leitinger M, LaRoche SM, Beniczky S, Abend NS, Lee JW, Wusthoff CJ, Hahn CD, Westover MB, et al. American clinical neurophysiology society's standardized critical care EEG terminology: 2021 version. Journal of Clinical Neurophysiology Official Publication of the American Electroencephalographic Society 2021; 38(1):1.

[8] Hofmeijer J, Beernink TM, Bosch FH, Beishuizen A, Tjepkema-Cloostermans MC, van Putten MJ. Early EEG contributes to multimodal outcome prediction of postanoxic coma. Neurology 2015;85(2):137–143.

[9] Khazanova D, Douglas VC, Amorim E. A matter of timing: EEG monitoring for neurological prognostication after cardiac arrest in the era of targeted temperature management. Minerva Anestesiologica 2021;87(6):704–713.

[10] Reyna MA, Amorim E, Sameni R, Weigle J, Elola A, Bahrami Rad A, Seyedi S, Kwon H, Zheng WL, Ghassemi M, et al. Predicting neurological recovery from coma after cardiac arrest: The george b. moody physionet challenge 2023. Computing in Cardiology 2023;50:1–4.

[11] Amorim E, Zheng WL, Ghassemi MM, Aghaeeaval M, Kandhare P, Karukonda V, Lee JW, Herman ST, Sivaraju A, Gaspard N, et al. The international cardiac arrest research (i-care) consortium electroencephalography database. Critical Care Medicine 2023;.

[12] Goldberger AL, Amaral LA, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE. Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. Circulation 2000;101(23):e215–e220.

[13] van Erp W, Lavrijsen JCM, Koopmans RTCM. [the unresponsive wakefulness syndrome: Dutch perspectives]. Nederlands Tijdschrift Voor Geneeskunde 2016;160:D108.

[14] Luong MT, Pham H, Manning CD. Effective approaches to attention-based neural machine translation. arXiv Preprint arXiv150804025 2015;.

[15] Aytekin C. Neural networks are decision trees. arXiv Preprint arXiv221005189 2022;.

[16] Li J, Shi J, Chen J, Du Z, Huang L. Self-attention random forest for breast cancer image classification. Frontiers in Oncology 2023;13:1043463.

[17] Konstantinov AV, Utkin LV, Lukashin AA, Muliukha VA. Neural attention forests: Transformer-based forest improvement. arXiv Preprint arXiv230405980 2023;.

[18] Baevski A, Zhou Y, Mohamed A, Auli M. wav2vec 2.0: A framework for self-supervised learning of speech representations. Advances in Neural Information Processing Systems 2020;33:12449–12460.

Address for correspondence:

Mostafa Moussa
Department of Biomedical Engineering, Khalifa University of Science and Technology, Abu Dhabi, UAE, 127788
mostafa.moussa@ku.ac.ae