Quantifying Neurological Recovery in Resource-Restricted Environments with Random Forest

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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 coma and subsequently, brain injury that could nevertheless result in death. Our main aim is to mitigate the existing issue of incorrect prognosis in measuring patients' recovery, by exploiting the power of machine learning.* ***Methods:*** *To this end, we use the dataset comprising 1,020 comatose adults following recovery from cardiac arrest to develop a rapid and resource-efficient machine-learning model. We train a random forest with 1000 trees and surrogate decision split on average power spectral density of beta, theta, delta, and alpha waves, average phase-locking values of the full spectrum, beta, theta, and delta waves, as well as the signal mean, standard deviation, and quality index. Other features such as Pearson's correlation coefficients, Lyapunov exponents, average skewness, and average kurtosis were considered, but the aforementioned features were selected due to minimal redundancy and best training performance.* ***Results: Team_KU****'s baseline model-the random forest- yielded a 10-fold cross-validation accuracy of 71.83 %, an F1-score of 55.58 %, and an area under the receiver operating characteristics (AUC) of 1.00 for outcome classification and a mean square error of 2.74 for CPC prediction with the supplied training set of 607 patients and yielded an unofficial challenge score of 0.09, 0.21, 0.18, and 0.24 with 12-hour, 24-hour, 48-hour, and 72-hour data, respectively.* ***Conclusion:*** *This study paves the way toward implementing efficient machine learning for the assessment of brain injury in comatose patients, even in resource-restricted settings. Thus allowing early prediction of neurological recovery with less high-cost machinery and dependency on medical experts.*

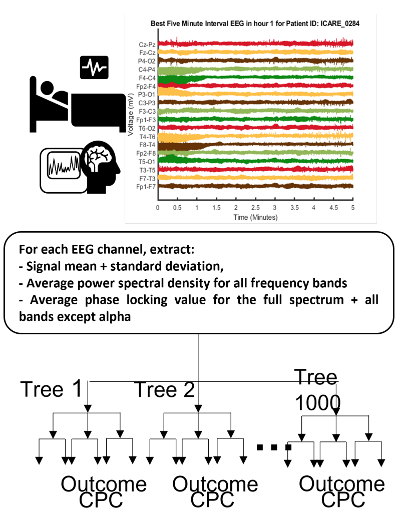

Figure 1. The complete approach followed to predict recovery using random forest and VGG-16. The best five-minute intervals from each of the 72 hours were recorded and then features are extracted to train the model.

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