

A Multimodal Monitoring Approach to Predicting the Onset of Physiological Incidents Using Machine Learning

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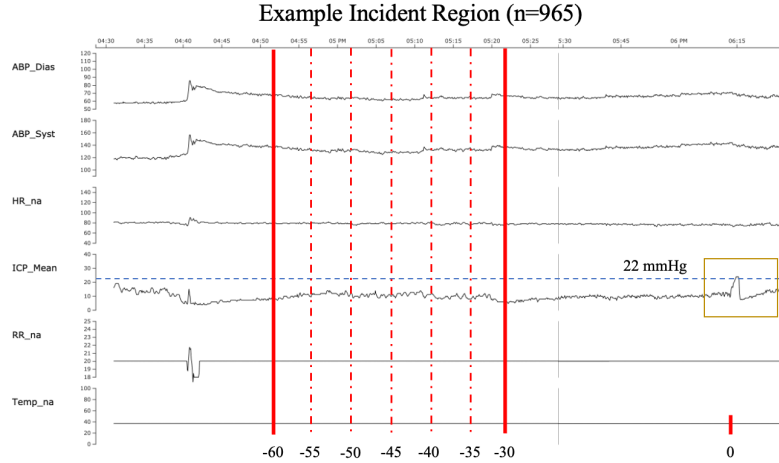
INTRODUCTION

Traumatic Brain Injury (TBI) is a complex, heterogeneous disease affecting millions of people in the U.S. each year [1]. Multimodal monitoring (MMM) is a relatively new attempt to access and monitor the brain post injury by incorporating multiple sources of information recorded in the intensive care unit (ICU) [2]. As a result, MMM has led to the creation of exhaustive datasets, allowing for the integration of many different signals and modalities pertaining to the management of severe TBI [2-4]. One of the most pressing questions about a TBI patient is whether an incident, or an event, will occur in the near future [5]. Additionally, clinicians require sufficient time before the onset of an event to administer a drug to the patient to avoid the oncoming event. Therefore, the aim of this work is to detect whether physiological events will occur in the future using the multimodal physiological data as features. In this study, we leverage both the breath and resolution of physiological data to predict the onset of physiological incidents 30 minutes before their onset. Specifically, we focus on three physiological events, namely high intracranial pressure (ICP), out of range diastolic arterial blood pressure (ABP), and out of range systolic ABP, using seven relevant modalities.

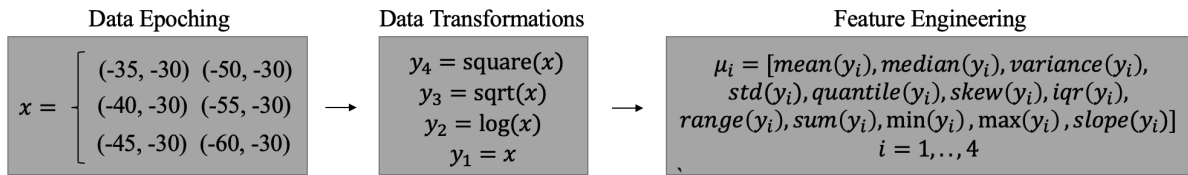
Previous explorations of machine learning applied to the neurocritical care data focus on incorporating low-frequency physiological measurements with other temporally low-resolution features such as laboratory test results and images [6]. On the other hand, our study focuses on analyzing the high-resolution physiological data.

METHODS

A subset of the data collected from the multi-site Transforming Research and Clinical Knowledge in TBI (TRACK-TBI) data consortia was harmonized and uploaded to a remote cloud repository. Using 36 patients from two sites, we built a raw data set containing ICP, peripheral capillary oxygen saturation (SpO₂), heart rate (HR), respiratory rate (RR), temperature, diastolic ABP, and systolic ABP [7]. In order to have a patient's data included in the study, there had to be regions of temporally matched physiological data over these seven modalities for at least 30 minutes. As the goal of our study was to observe the modality incidents in pathophysiology, data from healthy controls was not collected. Further, healthy patients are not typically available for this analysis. Most of the time, multimodal data is particularly invasive, such as measuring ICP using an external ventricular drain. Instead, within range regions are used as controls. Features from these seven modalities were extracted through windows of varying lengths 30 minutes to 60 minutes before the onset of a defined event. These events include ICP greater than 22 mmHg, diastolic ABP above 89 mmHg or below 60 mmHg, and systolic ABP above 139 mmHg or below 90 mmHg for at least a minute. We consider 6 different windows of varying sizes spanning from 30 minutes to x minutes before the onset of an event, where $x = 35, 40, 45, 50, 55,$ and 60 minutes. Each window had 84 features, composed of various statistics (mean, median, variance, quantile ($n=10$), standard deviation, skew, interquartile range, range, sum, minimum, maximum, and slope) for the time series and the logarithm, square, and square root transformations of the time series.



(a) An example incident ($n=965$) for ICP over the threshold of 22 mmHg for approximately one minute is shown in the gold rectangle on the right. The regions used in feature engineering are labeled with solid red lines and dashed red lines.



(b) The preprocessing steps used to encode the data represented in (a) into relevant features for machine learning. First, data epoching broke the 30-minute region into regions with variable lengths. Next, four transformations were applied on each of these regions. Finally, 12 functions resulted in 21 features for each transformed input.

Figure 1. Illustration of the feature extraction methodology

This feature engineering technique to discover relevant features has been proven effective in other applications [5] (Figure 1). From the raw data, 504 features per modality (3,528 in total) were calculated for our classification problem. Over 5,000 sample regions from each of these three modalities were collected from across all 34 patients.

RESULTS

In our study, we exploit classical logistic regression, support vector machine (SVM), random forest, k-nearest neighbor, one-class SVM, extreme gradient boosting, and deep neural networks (DNN). Several metrics such as accuracy, precision, recall, and F1-score were extracted for each method. Due to an observed unbalanced class distribution, four different scenarios were analyzed based on this distribution (balanced or unbalanced) in the data set: training balanced and testing balanced, training balanced and testing unbalanced, training unbalanced and testing balanced, and training unbalanced and testing unbalanced. Although the best model to use for this problem would be a state-of-the-art model, we explore a bottom-up approach to this problem for two reasons: 1) state-of-the-art models have not been extensively studied for high-resolution physiological multimodal data in neurocritical care, and 2) clinicians often want explainable models to enhance judgement contrary to replacing it [8]. Therefore, simpler algorithms may provide a better intuition to why the events of interest might occur in the future.

ICP was best predicted by random forest ($n=100$) in a balanced-balanced distribution ($n=382$) with an accuracy of 94%, a precision of 94%, a recall of 93%, and an F1-score of 94%. For diastolic ABP, it was best predicted with a balanced-unbalanced distribution using random forest ($n=100$) with an accuracy of 75%, a precision of 76%, a recall of 77%, and an F1-score of 75%. Systolic ABP was best predicted in a balanced-unbalanced distribution using random forest with a reported accuracy of 80%, a precision of 81%,

a recall of 81%, and a F1-score of 80%. According to our study, random forest was the best model and outperformed complex machine learning models, such as DNN.

FUTURE WORK

The largest limitation of this study is that we did not collect enough patient event data. Despite this shortcoming, the accuracy metrics illustrate good overall performance for the available data. The proposed model was able to predict the ICP incidents from different patients across two sites accurately which illustrates the sufficient robustness against overfitting. Further external validation is necessary to determine whether that is in fact the case. It might be worthwhile to include more sites, metrics, and modalities in the future to learn relationships amongst different physiological phenomena. Parameter selection was limited.

ACKNOWLEDGEMENTS

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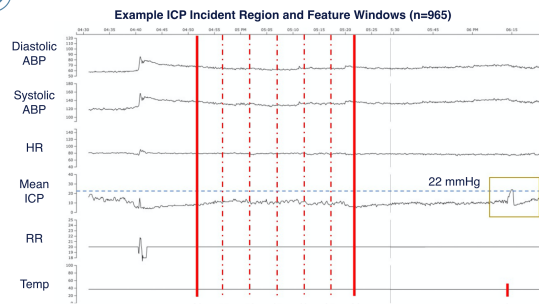
INTRODUCTION

- TBI is a complex, heterogeneous disease affecting millions of people in the U.S. each year
- MMM is a new attempt to monitor the brain post injury by incorporating multiple sources of information recorded in the ICU
- One of the most pressing questions about a TBI patient is whether an incident will occur within an hour so they can administer a drug to the patient to avoid the oncoming event
- Therefore, the aim of this work is to detect whether high ICP, out-of-range systolic ABP, or out-of-range diastolic ABP will occur in the near future using seven modalities as features

METHODS

- Thirty-six patients from the TRACK-TBI data consortia containing regions of time synchronized ICP, SpO2, HR, RR, temperature, diastolic ABP, and systolic ABP are aggregated
- Regions with ICP greater than 22 mmHg, diastolic ABP above 89 mmHg or below 60 mmHg, and systolic ABP above 139 mmHg or below 90 mmHg for at least a minute are tagged as incidents
- The regions 60 minutes to 30 minutes before their onset are targeted for feature engineering
- We consider 6 different windows of varying sizes spanning from 30 minutes to x minutes before the onset of an event, where x = 35, 40, 45, 50, 55, and 60 minutes
- Each window has 84 features, composed of various statistics for the time series and the logarithm, square, and square root transformations of the time series
- From the raw data, 504 features per modality (3,528 in total) are calculated for our classification problem. Over 5,000 sample regions from each of these three modalities are collected from across all 34 patients
- We evaluate logistic regression, SVM, random forest, KNN, one-class SVM, XGBoost, and DNN on four variations of this data set based on the class distribution

RESULTS



ICP Incident Classification Results

Train-Test Class Distribution	Metrics	Logistic Regression	Support Vector Machine	Random Forest	K-Nearest Neighbor	Extreme Gradient Boost
Balanced-balanced	Precision (%)	87.5	90.0	94.0	90.0	92.5
	Recall (%)	88.0	89.5	93.0	89.5	92.5
	F1 (%)	87.5	89.5	94.0	89.5	92.5
	Accuracy (%)	88.0	90.0	94.0	90.0	92.0

Systolic ABP Incident Classification Results

Train-Test Class Distribution	Metrics	Logistic Regression	Machine Forest	Random Forest	K-Nearest Neighbor	Extreme Gradient Boost
Balanced-balanced	Precision (%)	59.5	64.0	67.0	64.0	63.5
	Recall (%)	60.0	64.5	67.0	63.5	63.5
	F1 (%)	59.5	64.5	67.0	64.5	63.5
	Accuracy (%)	60	64.0	67.0	64.0	64.0

Diastolic ABP Incident Classification Results

Train-Test Class Distribution	Metrics	Logistic Regression	Support Vector Machine	Random Forest	K-Nearest Neighbor	Extreme Gradient Boost
Balanced-balanced	Precision (%)	66.0	68.5	73.0	71.5	77.5
	Recall (%)	66.0	68.5	73.0	71.5	77.5
	F1 (%)	66.0	68.5	73.0	71.5	77.5
	Accuracy (%)	66.0	69.0	73.0	71.0	76.0

- One-class SVM and DNN are omitted from these results because of poor results (< 70% accuracy)
- The three other train-test class distribution sets are also omitted because of their poor test results due to biases in the class distribution

CONCLUSION

- Overall, high ICP was the best predicted incident compared to out-of-range diastolic ABP and out-of-range systolic ABP
- Across all predicted incidents, random forest was the best performing classifier

FUTURE WORK

- Apply methodology on a larger cohort of neurocritical care patients
- Evaluate methodology on patients from single-site and multi-site studies to observe site-specific bias
- Separate out-of-range ABP into above-threshold and below-threshold classes
- Include more modalities for incident prediction and as features in the model

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