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# HeartCast: Predicting acute hypotensive episodes in intensive care units

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ABSTRACT

Acute hypotensive episodes (AHEs) are serious clinical events in intensive care units (ICUs), and require immediate treatment to prevent patient injury. Reducing the risks associated with an AHE requires effective and efficient mining of data generated from multiple physiological time series. We propose HeartCast, a model that extracts essential features from such data to effectively predict AHE. HeartCast combines a non-linear support vector machine with best-feature extraction via analysis of the baseline threshold, quartile parameters, and window size of the physiological signals. Our approach has the following benefits: (a) it extracts the most relevant features; (b) it provides the best results for identification of an AHE event; (c) it is fast and scales with linear complexity over the length of the window; and (d) it can manage missing values and noise/outliers by using a best-feature extraction method. We performed experiments on data continuously captured from physiological time series of ICU patients (roughly 3 GB of processed data). HeartCast was found to outperform other state-of-the-art methods found in the literature with a 13.7% improvement in classification accuracy.



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## 1. Introduction

Patients in intensive care units (ICUs) often have to be continuously monitored using a spectrum of medical sensors. The data streams from the ICU equipment often arrive at high transmission rates (e.g., 125 samples per second), and traditional methods for managing such data consist of automatic alarms that, for example, use rule-based detection to identify urgent events and then require follow-up through manual intervention [28,21,17,5]. However, those systems often produce a large number of false alarms, and the alarms are therefore often ignored by medical experts. It is challenging for medical professionals to effectively identify various critical events that can occur in an ICU, and this paper explores a systematic solution to utilize the high-volume data streams in such settings. In particular, our focus is on detection of acute hypotensive episodes (AHE).

Hypotension refers to an abnormally low blood pressure. Generally, blood pressure is measured in the ICU using a manometer, and the patient is diagnosed with hypotension when the systolic and diastolic pressures are less than 90 mmHg and 60 mmHg, respectively [1]. If the blood flow is too low to effectively deliver enough oxygen and nutrients to vital organs, a dangerous situation could arise where the patient faints, becomes visually impaired, or sustains multiple organ damage. An AHE is defined to be any period of 30 min or more during which, a minimum of 90% of the mean arterial blood pressure (ABP) measurements is less than or equal to 60 mmHg [23]. The risks associated with an AHE can be reduced through timely and appropriate intervention, but if not promptly treated, an AHE may result in irreversible damage to vital organs and even death. Previous clinical interventions have attempted predicting occurrence of AHE and have also proposed solutions [25,20,2,12,14,15]. Accurate prediction would enable physicians to respond to the onset of AHE in a timely manner and would also offer clear benefits to patients by improving the quality of care and increasing the possibility of survival.

When data from physiological signals, including ABP, are available, we are able to predict AHE more quickly and accurately. In this paper, we present a method that improves the accuracy of AHE prediction by analyzing such physiological signals and essential features extracted from such signals, and are best classified by its non-linear support vector machine (NL_SVM). To extract the most relevant features from the data, we use three elements: a baseline threshold based on the normal blood pressure range, a quartile parameter that is one of the three points that divide a range of data into four equal parts, and a window size to select a very small part of the entire data. Thus, our method, HeartCast, is capable of improving the accuracy of AHE detection.

The main idea is to simultaneously provide the most relevant features of the signals and apply the best learning model possible to improve AHE prediction. The most relevant features can be extracted using a few methods that decrease the size of the data necessary for training, which is especially important for quick processing and improves accuracy by eliminating noise. The best learning model must have both a fast execution time and improved performance. We expect HeartCast to provide a fast runtime with high performance.

Our contributions are the following:

– ***Careful feature selection***: Our method provides good "over-unity" that can make the better results with little effort with respect to detection and prediction of AHE.
– ***Effectiveness***: HeartCast provides a high performance by combining selected features and by using a NL_SVM classifier.
– ***Robustness against missing values and noise/outliers***: Missing values, noise, or outliers can be treated using the quartile parameter.
– ***Observation***: Most patients have "white noise," but a few patients have "pink noise" in their signals.

The remainder of this paper is organized as follows: Section 2 presents the proposed method for improved AHE prediction; Section 3 describes the results of experiments of the proposed method; Section 4 discusses the advantages of using our method and the significance of correct data analysis; and finally, conclusions are drawn in Section 5.