Prediction of Cardiac Patients Readmissions to the ER by Wearable-Based Time Series and Machine Learning

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Abstract

The large number of hospitalizations and surgeries caused by the high incidence of cardiac disease makes patient monitoring essential to ensure a safe recovery and reduce the risk of readmission. Smartwatches can be powerful, non-invasive allies in monitoring cardiac patients due to their potential for early intervention, thereby reducing the need for emergency hospitalizations. Using physiological signals including blood pressure (SBP and DBP), heart rate (HR), and oxygen saturation (SpO2), collected by the smartwatch, along with each patient's medical history, a machine learning model was built for the binary classification of patients based on Emergency Room (ER) readmission. We used the Uniform Manifold Approximation and Projection (UMAP) algorithm for feature extraction and a Random Forest (RF) classifier for this task. The model combining SBP, DBP, and SpO2 signals yielded the best performance, achieving a mean balanced accuracy of 76.89 ± 7.77% and a mean AUC of 77 ± 7.77%. Despite this, the model struggled to correctly identify the positive class and showed significant performance variance between cross-validation folds, with F1-scores ranging from 40 to 80%. While the findings demonstrate the potential of this approach, the significant performance variability among folds shows the need for larger datasets to improve model robustness for clinical application.

1. Introduction

The rising incidence of cardiac disease worldwide over the past decade has led to an increase in hospitalizations and cardiovascular surgeries [1], which underscores the need for strategies that not only prevent these conditions but also enhance postoperative recovery. In this context, remote patient monitoring has emerged as a promising strategy to improve postoperative care by enabling personalized health management outside the hospital setting [2]. Wearable devices, such as smartwatches, are promising technologies in this approach, providing continuous, near real-time data capture in addition to their portability and non-invasive nature [3]. This allows for the early identification of subtle physiological changes before they turn into serious complications, thereby facilitating timely interventions and reducing the need for emergency hospitalizations [4].

In the context of postoperative recovery from cardiac surgery, data from photoplethysmography (PPG) and electrocardiogram (ECG) sensors integrated into smartwatches have been investigated for building predictive models. Heart rate data from PPG sensors, combined with the medical history of post-cardiac surgery patients has previously been used to develop Machine Learning models for the immediate detection of Paroxysmal Atrial Fibrillation, yielding promising results [5, 6]. Despite the significant potential of artificial intelligence, the high false-negative rate in existing models indicates that substantial challenges must be overcome to achieve optimal performance in clinical settings [7].

This study extracts features from signals captured by the smartwatch using Uniform Manifold Approximation and Projection (UMAP), a technique commonly used for dimensionality reduction and data visualization. We then evaluate the performance of the baseline Random Forest (RF) model in classifying patient readmission to the Emergency Room (ER) by combining these features with the patients' medical histories. This work contributes to the development of more effective telemonitoring systems.

2. Material and Methods

2.1. Dataset

The dataset used in this work was collected from 49 patients at the Heart Institute of the Hospital of USP, covering

individuals with mitral or aortic valve disease, coronary artery disease, or aortic disease. The data is composed of two parts: a tabular set of patient information and signals collected during a 30-day telemonitoring period from patients in post-surgical recovery. The tabular data consists of 14 features from each patient's medical history, including age, weight, sex, presented symptoms, and pre-existing conditions. Some features in the medical history are related to cardiological diseases, consisting of binary indicators for conditions such as arrhythmia, chest pain, prior myocardial infarction, or signs of heart failure.

Furthermore, physiological signals from the Samsung Galaxy Watch5 smartwatch were collected during the telemonitoring period using FAPO SI[3] platform [8], which is an internal tool created for this purpose. Among the signals are systolic (SBP) and diastolic (DBP) blood pressure, heart rate captured with photoplethysmogram (HR_PPG), mean heart rate from the electrocardiogram (HR_ECG), and oxygen saturation (SpO2). The captured data were transmitted in near real-time to the FAPO-SI telemonitoring platform [8, 9], with two daily extractions of the watch's data.

Only 9 of the 49 patients were readmitted to the Emergency Room (ER) during the telemonitoring period. These individuals constitute the positive class, resulting in a highly imbalanced dataset. For each readmission event, the classification on the Manchester scale and the number of days in the interval between the start of telemonitoring and the readmission were recorded. Even with an imbalanced dataset, the problem was modeled as a binary classification of readmissions to the ER.

2.2. Pre-Processing

Except for the PPG-derived heart rate, all signals were captured asynchronously, as each measurement was individually initiated by the patient. This resulted in unsynchronized data, since signal acquisitions often had different durations. Accordingly, the data required preprocessing before the model could be constructed.

The raw signals underwent a multi-step preprocessing procedure. Initially, zero and NaN entries were imputed by sampling random values from the existing data within the same signal. Following this, the signals for each patient were temporally aligned by selecting only the overlapping time interval where all signals were present. For the tabular historical data, NaN values were replaced with zeros. One-Hot Encoding was applied to categorical features, and numerical features were normalized.

Due to varying sampling rates, this alignment resulted in signal vectors of different lengths across patients. To create uniform input vectors for the model, we standardized the length of each signal type to the median length observed for that signal across all patients. All signals were normalized. Figure 1 shows the signals from a single patient after preprocessing.

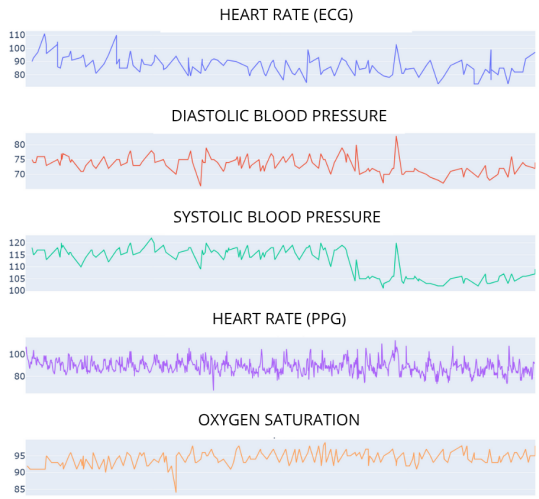


Figure 1. Example of a patient's signals after preprocessing.

2.3. Feature Extraction and Model Architecture

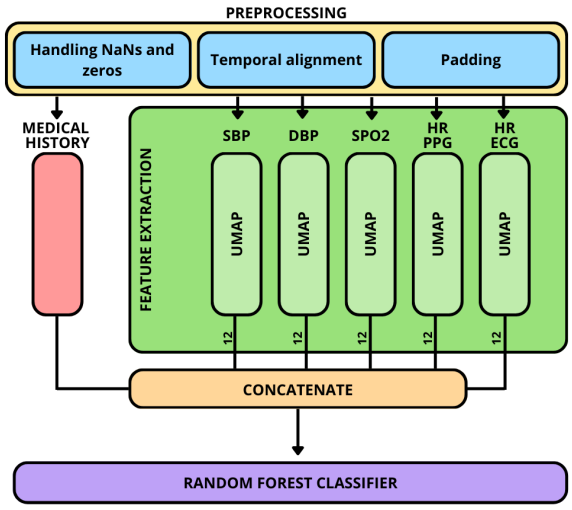


Figure 2. Flowchart of the proposed method for building the model to classify patient readmissions to the ER.

Feature extraction was performed using the Uniform Manifold Approximation and Projection (UMAP) algorithm, chosen for its ability to preserve significant topological structures of the data. Each non-tabular signal was individually projected onto a 12-dimensional embedding space. This dimensionality was chosen to be compatible with the number of available samples, as UMAP requires

the output dimension to be smaller than the sample count to ensure a robust projection.

The model's architecture was subsequently designed to assess the predictive power of different data combinations. To this end, various configurations were tested, either including or omitting the historical tabular data. In each configuration, the UMAP embeddings from the chosen signals were concatenated. The resulting feature vector was then used as input for a Random Forest classifier for the binary classification of patients based on their visit to the emergency room. Figure 2 shows the flowchart of the method adopted in this study.

3. Experimental Results and Discussion

The RF classifier was trained and evaluated on the previously described dataset of 49 patients using 3-fold cross-validation for the task of ER visit classification. Binary and macro F1-scores, balanced accuracy, and the area under the ROC curve (AUC) were the metrics used to evaluate performance.

For the presented model, the combination that excludes the tabular medical history data and concatenates the SBP and DBP signals with SpO2 demonstrated the highest capability to differentiate between positive and negative classes, achieving a mean balanced accuracy of 76.89 $\pm$ 7.77 %. Although the folds were separated in a stratified manner, as shown in Table 1, the difference in the metrics for each fold is due to patient-specific characteristics, since an ER visit is not necessarily caused by an alteration in the monitored vital signs. The significant performance gap between folds 1 and 2, with respective binary F1-scores of 40 and 80 %, indicates that further improvements to the model's robustness are needed. Future work should focus on enlarging the dataset to address this limitation.

Figure 3 displays the Receiver Operating Characteristic (ROC) curves for each of the 3 folds for the classification model using the DBP, SBP, and SpO2 combination. The mean area under the curve (AUC) obtained was 77 ± 7.77 %.

Figure 4 shows the confusion matrix for the same model. It demonstrates the model's high capability in correctly identifying and classifying the negative class, but its difficulty in classifying the positive class. This is also reflected in the difference between the obtained binary and macro F1-scores, where the macro score is notably higher.

While the top-performing combinations in Table 2 always include SBP and SpO2, some results remain weak. For instance, the third-highest mean F1-score (from the SBP, HR_PPG, SPO2, and history combination) is merely 55.95 $\pm$ 13.78 %. In a binary classification context, this performance level is barely distinguishable from random guessing, highlighting the model's unreliability with these inputs.

Table 1. Performance metrics in % from 3-fold cross-validation using the DBP, SBP, and SpO2 combination.

Fold	F1-binary	F1-macro	Balanced Accuracy
1	40.00	46.32	67.86
2	80.00	88.15	83.33
3	66.67	79.49	79.49
mean	62.22 ± 16.63	71.32 ± 18.03	76.89 ± 7.77

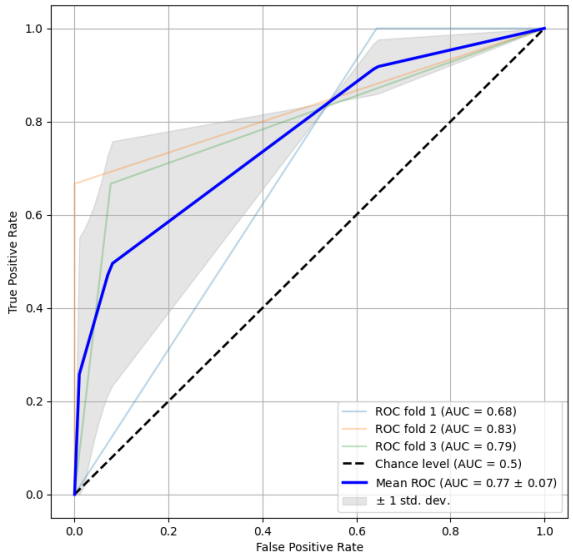


Figure 3. Receiver operating characteristic (ROC) of the Random Forest algorithm with three-fold cross validation.

Table 2. Comparison of F1-binary, F1-macro, and Balanced Accuracy metrics in % for the three best-performing signal combinations in the classification model.

Signal combination	F1-binary	F1-macro	Balanced Accuracy
DBP, SBP, SPO2	62.22 ± 16.63	71.32 ± 18.03	76.89 ± 7.77
DBP, SBP, SPO2, history	61.01 ± 18.26	73.53 ± 14.96	74.91 ± 9.32
SBP, HR_PPG, SPO2, history	55.95 ± 13.78	68.07 ± 14.16	76.06 ± 11.53

4. Conclusions

This study demonstrated the potential of using data from wearable devices to support patient telemonitoring, specifically by utilizing UMAP for feature extraction from time-series signals and a classic Random Forest model for ER readmission classification. The combination of systolic blood pressure (SBP), diastolic blood pressure (DBP), and oxygen saturation (SpO2) to predict cardiac patient readmission to the ER proved to be the most promising under the conditions in which this experiment was conducted. The model achieved an acceptable overall performance,

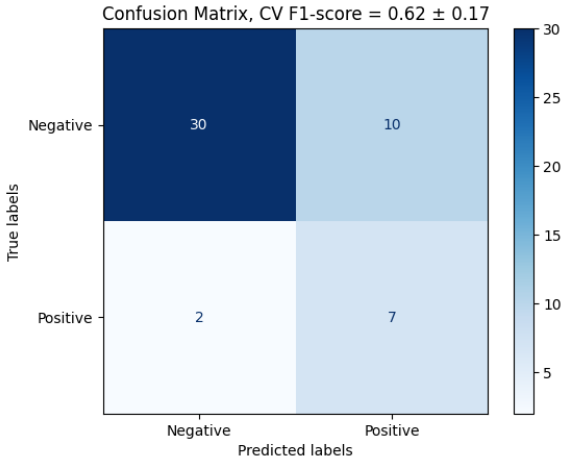


Figure 4. Confusion matrix of Random Forest Classifier using the DBP, SBP, and SpO2 combination.

with a mean balanced accuracy of 76.89 $\pm$ 7.77% and a binary F1-score of 62.22 $\pm$ 16.63 %.

One of the main identified limitations concerns the model's difficulty in correctly classifying the positive class, even though it is effective in identifying the negative class. Furthermore, there is a large variation in performance among the cross-validation folds, with F1-scores ranging from 40 to 80 %, which may be related to the limited variability within the dataset. Future prospects include the addition of new data to the dataset.

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