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Next Generation Risk Stratification of ICU Patients using Machine Learning

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ABSTRACT

Personalized Remote patient monitoring in the intensive care unit (ICU) is a critical observation and assessment duty required for precision medicine. We recently developed a cloud-based intelligent. We use a remote patient monitoring (IRPM) architecture that is state-of-the-art in risk classification. The most accurate prediction is made using machine learning, but with few characteristics that rely on vital indicators. Physiological characteristics gathered within and outside of hospitals are widely employed. We made a big contribution in this effort. enhance the basic IRPM framework's capability by developing three machine learning models for Measurements of readmission, abnormalities, and next-day vital signs We give a formally represented version of a feature engineering algorithm, as well as the construction and validation of three replicable machine learning algorithms ICU patient readmission, anomaly, and next-day vitals prediction models.

Keywords: *Decision Tree, Random forest Classifier, SVM, Logistic Regression*

1. INTRODUCTION

Precision health and medicine is a relatively new initiative that aims to improve equitable care and overall individual and population health through targeted observation and assessment, early detection, prevention, and treatment, as well as precision health promotion and engagement. Intensive care units (ICUs) often collect and use a high volume of patients' data to enable physicians and ICU nurses to make timely decisions in delivering high-quality critical care. The use of artificial intelligence (AI) and machine learning (ML) methods to improve the care and treatment of critically ill patients has grown substantially in recent years. ML approaches for analysis of clinical datasets offer great promise for the delivery of personalized medicine and targeted treatment, but these approaches must be customized and optimized, for each specific application. We have recently

developed a cloud-based intelligent remote patient monitoring (IRPM) framework In this work, we significantly improve the functionality of the initial IRPM system by building three machine learning models for three clinical outcomes: readmission, abnormality, and next-day vital sign measurements. Our motivation for building those three machine learning models is two-fold:
1) To achieve the goal of studying the three clinical outcomes (readmission, abnormality, and next-day vital sign);
2) To test if more powerful machine learning models can be deployed in the IRPM framework.

A. Framework for Intelligent Remote Patient Monitoring (IRPM)

The following modules make up our IRPM framework (Figure 1):
1) Intelligent ICU patient monitoring (IICUPM) module: The hospital system may load clinical and demographic data for either a single patient or a patient population through the IICUPM module's interface. In order to evaluate the data and produce risk rating results, the module offers five predictive ML models.
2) The out-of-hospital module, which addresses specific patients as opposed to the IICUPM module. The module's interface allows for the uploading of a patient's wearable device measurements (such as heart rate and SPO2) into an anomaly ML prediction model, which produces a final evaluation or risk score.

3) IRPM core system and database: The data is sent to the ML model development modules via the IRPM core system, which is accessed by the IICUPM and out-of-hospital interfaces. The ML models return the outcomes of data processing back to the IRPM framework so that they may be stored in the database.

B. Clinical Considerations

Precision clinical medicine frequently use prognostic models to explicitly integrate indicators from which risks of a certain endpoint may be computed for individual patients. The clinical objective is to make sure that patients are put on the right treatment route, which includes the right kind and amount of ICU care. Through the out-of-hospital module, the proposed framework offers digital health services geared at patients as well as healthcare providers. Part of the IRPM framework's continuous development is discussed in this article. We created a dashboard prototype that may be utilised for patient triage and care navigation.

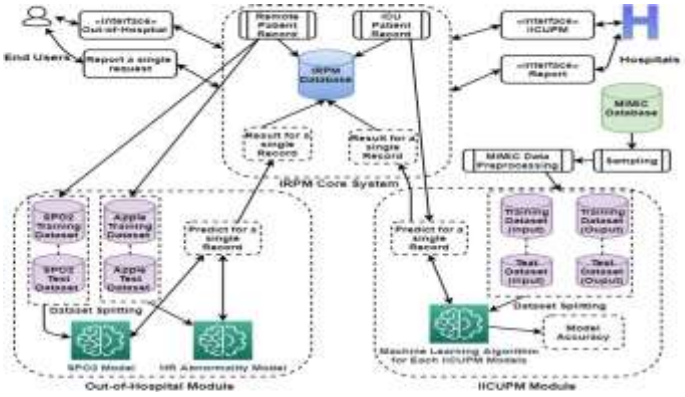


FIGURE 1. The intelligent remote patient monitoring (IRPM) framework is comprised of intelligent ICU patient monitoring (IICUPM) and out-of-hospital modules. MIMIC stands for the medical information mart for intensive care.

C. Contributions Summary

This article offers three contributions:

• Building on our most recent work on the IRPM framework, we provide three more machine learning (ML) models in the IICUPM module for risk stratification of ICU patients, including readmission, abnormality, and next-day vital sign measurements.

• In addition to providing three transparent and reproducible ML models, we also present details of a feature engineering algorithm that can be used in various critical care settings.

• To demonstrate that our solutions can predict health outcomes with respectable performance, we offer two distinct solutions for data with unbalanced classes and three different variations for forecasting next day vital sign measurements. In order to establish the optimum usage for our IICUPM module, we analysed all suggested solutions and tested them using ICU patient data from a publically accessible database.

2. RELATED WORK

We talk about the development of ML models for ICU-related outcome prediction. As a result, patient readmission to the ICU has been researched by certain researchers. As an illustration, Rajkomar et al. [7] created a deep learning (DL) model to forecast an unscheduled 30-day hospital readmission. In contrast to readmission after release from the hospital, we predict readmission to the ICU within the same stay in our study. The Medical Information Mart for Intensive Care (MIMIC) database has been used in certain research to design and use ML models to predict health status [8]–[10]. To increase the accuracy of their models, the majority of these researchers employed a long set of characteristics. Below, we touch on a few of them.

Only a few research, according to the MIMIC website, explain the creation and use of prediction models for ICU readmission using the MIMIC database. To the best of our knowledge, there has never been a study done on the prediction of ICU patient readmission and abnormality based on balanced categorization utilising just vital signs and demographic variables from MIMIC. Additionally, we are not aware of any studies that attempted to predict the vital sign measures of ICU patients the following day. Recurrent neural networks (RNNs) with long short-term memory were used by Lin et al. [11] to create models to predict ICU patient readmission within 30 days after release (LSTM). They made use of 17 chart events, 4 demographic characteristics, and the International Classification of Diseases, Ninth Revision (ICD-9) code among other features from the MIMIC III database. In this work, we make readmission predictions for patients without first knowing their illnesses or diagnoses.

With the use of patient data collected prior to ICU discharge, Fialho et al. [12] created a model for predicting ICU readmission. Data from 893 non-readmitted patients and 135 readmitted patients were included in their dataset. They made advantage of a number of MIMIC-II characteristics, including the flow of urine, the results of 15 laboratory tests, and 6 monitoring signals. Only 11 input variables and data from the first day of each patient's ICU stay were included in our study. In order to create a balanced classification with the same overall number of samples in both the readmitted patient class and the non-readmitted patient class, we incorporate unbalanced approaches. In order to predict hospital readmission in juvenile asthma patients from a community hospital in Memphis, Tennessee, Shin et al. [13] developed three prediction models utilising two ML algorithms. They also employed 12 features, which included socioeconomic and biomarker variables as well as demographic characteristics. Predicting readmission within a year of the original hospitalisation was the objective. They contrasted a model that is based primarily on clinical variables taken from the patient record with a model that is based solely on socioeconomic features collected from the patients' home area. They discovered that the socioeconomic factor-based model had accuracy comparable to that of the biomarker-based model.

3. THE QUANTILES APPROACH

In this part, we introduce the quantiles technique, which not only concentrates on baseline patient characteristics but also adds deeper features to the data through feature engineering stages.

A. Personal baseline important sign features

A patient will typically have a baseline set of vital sign measurements that are frequently regularly distributed [18]. A person's vital signs include their body temperature, heart rate, breathing rate, arterial systolic and diastolic blood pressure, peripheral oxygen saturation, and blood sugar level (GL). Because they are measured often, these vital signs are easily accessible through the electronic health record (EHR).

B. Deteriorating Patient Conditions

Sequentially recorded vital signs are frequently processed in research studies using time series analyses or by aggregating them for each patient using some metric (e.g., mean or median). Therefore, rather than utilising data that may range much from the median when dealing with successive vital sign measurements, some researchers [12] utilise the mean value of the vital sign observations. In our method, we contend that a patient's health frequently deteriorates at either a high or low level of measurement. Due to the fact that they document significant changes in a patient's health condition, we think that these observations are crucial.

C. The Quantiles Approach Feature Engineering

ALGORITHM

With the quantiles strategy, which we first presented [6], we undertake feature engineering by focusing on the high and low quantiles of observations of a patient's vital signs. Our earlier research shown that the quantiles technique offers a larger data set for the creation of new characteristics. The stages taken by the feature engineering technique are given in Algorithm 1. A list of patient samples P and two desired probabilities are the algorithm's three inputs. Feature Engineering Algorithm, Algorithm 1

```
INPUT: P, PPF_H, PPF_L
OUTPUT: V_Quantiles
for p_i ∈ P do
    S ← ICUStays(p_i)
    for s_j ∈ S do
        Vbaseline ← Vitals(sj,day1)
        for vk ∈ Vbaseline do
            v_k ← Normalize(v_k)
            v_k ← SortAscending(v_k)
            Mean_k ← mean(v_k)
            Means ← Means + Mean_k
            ObsinQ_1toQ4 ← count(v_k)
            DiscreteValue_L ← PPF(v_k,PPF_L)
            DiscreteValue_H ← PPF(v_k,PPF_H)
            for obs_i ∈ v_k do
                if obs_i ≤ DiscreteValue_L then
                    QObs_k ← QObs_k + obs_i
                    ObsinQ_1 ← ObsinQ_1 + 1
                end if
                if obs_i ≥ DiscreteValue_H then
                    QObs_k ← QObs_k + obs_i
                    ObsinQ_4 ← ObsinQ_4 + 1
                end if
            end for
            ModMean_k ← mean(QObs_k)
            ModMeans ← ModMeans + ModMean_k
            ModSD_k ← standardDev(QObs_k)
            ModSDs ← ModSDs + ModSD_k
            QPercent_k←QuantilePercentage(ObsinQ_1toQ4,ObsinQ_1,ObsinQ_4)
            QPercents ← QPercents + QPercent_k
        end for
    end for
end for
V_Quantiles ← Means+ModMeans+ModSDs+QPercents
return VQuantiles
```

for PPFH, PPFL, and the percent point function (PPF). The method repeatedly goes over each patient in P and each ICU stay in S. It extracts the baseline vital sign features Vbaseline from just the first day, normalises the observations in those features using the probability density function (PDF), and then ranks them in ascending order. Following this, the method extracts two discrete values, DiscreteValueL and DiscreteValueH, using the PPF function. It then utilises these values as thresholds to extract observations that fall in the low and high quantile ranges. The list of modified means ModMeans, the list of modified standard deviations ModSDs, and the list of quantile percentages QPercents of each baseline vital sign characteristic are all calculated for each vital sign in Vbaseline.

Including the updated features alongside the existing ones A new list of VQuantiles is generated by VBaseline that has a higher prediction potential than would be possible with just baseline vital sign characteristics alone. Equation is used to determine how to calculate the quantiles percentage, Qpercent (1). The vital sign observations that occur in the first and fourth quantiles, respectively, are represented by the abbreviations ObsinQ1 and ObsinQ4.

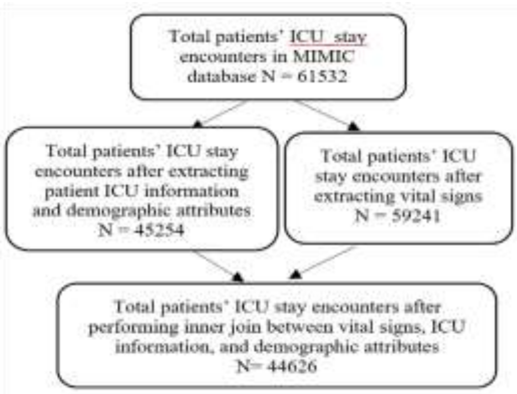
$$Q_{Percent} = \frac{\#ObsinQ_1 + \#Obs.in\ Q_4}{\#ObsinQ_1 toQ_4} \quad (1)$$

4. METHOD

A. Selection of Populations And Data Extraction:

From the MIMIC-III (v1.4) adult patient ICU database, which is accessible to the general public, we retrieved hospital admission data [9]. The database is set up so that each hospital admission may include one or more stays in the intensive care unit, and each ICU stay may last for a number of days. A patient can have multiple notes on observations on any one day. We began with a total of 61,532 ICU stays (Figure 2) and only used data from the first day of a patient's stay to extract information. This yielded a total of 45,254 distinct ICU stays containing demographic information (age, sex, height, and weight). 59,241 ICU stay encounters with information on seven vital sign characteristics were integrated with that (BT, HR, RR, SBP, DBP, SpO2, and GL).

The total after merging was 44,626.



B. Variable Selection And Model Conceptualization

Each model's justification is outlined in Table 1. The readmission model's objective is to forecast readmission risk, which may be a sign that the patient might benefit from being in a different type of ICU than the one they are currently in. The hospital system may opt to change the type of ICU a patient is in or delay their discharge while providing them with higher levels of care. The readmission model's outcome variable is a binary feature.Stating if a patient has had a single hospital admission and been readmitted to the ICU (readmission = 1) or not (readmission = 0). We define a readmission episode as one in which a patient was hospitalised to the intensive care unit (ICU), released to the proper hospital population, and then readmitted to the ICU once again during a single hospital stay. A patient is not regarded as having been readmitted if they had already been admitted to the ICU and released from the hospital once.Model conceptualization and variable selection are shown in TABLE 1.

Model	Rationale	Predictors (Operationalization)	Clinical Outcome
Readmission risk	Predicting Readmission Risk Call to action: 1. Delay discharge 2. Increase care level 3. ICU transfers	Demographics and vital signs from first day of ICU admission	A binary feature indicating whether a patient had been admitted to the ICU, or discharged, then readmitted to the ICU during a single hospital admission.
Abnormality risk	Predicting patients at risk of showing undesired health conditions	Demographics and vital signs from first day of ICU admission	A binary feature indicating whether a patient is normal (normality=0) or abnormal (normality=1). Abnormality in our case is defined as the presence of one or more of the following undesired health conditions in a patient record: a. Mortality b. Readmission to the ICU within a single hospital admission or c. Prolonged ICU length-of- stay.
Next day vital sign reading	Predicting daily vital signs, thus providing early warnings about potential deterioration in a patient's condition based on prior physiological measurements in the baseline	Demographics and vital signs in reference to a time point in the baseline, where the baseline values could be measured on: a. Day_{i-1} b. Day_{i-1} to Day_k c. $Day_{i-1} + dev.errors$	A numeric feature that indicates the mean of each vital sign reading on the next day of a patient's ICU stay in reference to a baseline.

The abnormality model seeks to identify the patient population at risk of manifesting undesirable medical problems. A patient's abnormality, which is a binary characteristic that indicates whether a patient is normal (normality = 0) or abnormal (normality = 1), is the outcome for the abnormality model. A patient's medical record including one or more of the following undesirable health conditions is considered abnormal: death, readmission to the intensive care unit, or an extended stay in the unit.

Clinical objectives for readmission and abnormality are distinct. We employ three criteria, one of which is the readmission flag, to gauge irregularity. We solely utilise the readmission flag as a statistic for measuring readmission. The readmission flag in both models must meet the "during a single hospital admission" condition.

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C. Readmission Model

A binary classification issue with two classes—non-readmitted (N = 41,597 stays) and readmitted (N = 3,029 stays)—is what the readmission prediction reduces to. Due to this, data show classifications that are lopsided, with 93.21% of patients in the non-readmitted class and just 6.79% in the readmitted class [19].

TABLE 2. Patient baseline characteristics.

Variable	Operationalization	Value
Sex	N (%)	
	Male	25,241 (56.56)
	Female	19,385 (43.44)
Age	Mean (SD), years	64.35 (16.87)
Height	Mean (SD), cm	160.66 (11.76)
Weight	Mean (SD), kg	80.45 (23.47)
HeartRate_mean	Mean (SD), beats/min	85.99 (15.59)
sysbp_mean	Mean (SD), mmHg	118.75 (16.90)
diasbp_mean	Mean (SD), mmHg	60.47 (10.89)
RespRate_mean	Mean (SD), breaths/min	18.93 (4.05)
Tempc_mean	Mean (SD), °C	36.84 (0.62)
SpO2_mean	Mean, %	(97.27%)
Glucose_mean	Mean (SD), mg/dL	138.74 (41.86)

The data with unbalanced classes is supported by a number of resampling methods. The under-sampling of the majority class and the over-sampling of the minority class are two of the most common ones. In our scenario, the non-readmitted patients (3,029 samples) represent the majority class whereas the readmitted patients (3,029 samples) represent the minority class (41,597 samples). While oversampling creates additional samples by duplicating samples in the minority class, undersampling might lead to the discarding of patient data that could lead to model under-fitting. The latter may need more processing capacity to process the additional samples (83,194 samples compared to only 6,058). Therefore, we decided to employ the under-sampling strategy. We use a different strategy to get over this approach's drawback.

• Under-sampling of majority class re-sampling: using this technique, we maintained the 3,029 patients in the minority class and randomly deleted patients from the majority class, keeping just 3,029 of the class's overall 41,597 patients.

• Clustering of majority class re-sampling: In this method, the 41,597 patients in the majority class were grouped together using the k-means clustering algorithm.

before recombining them to get 3,029 patients, similarly sized groups (in this example, 5 clusters of 606 samples each) were created (Figure3). The reason for choosing 5 clusters is because we saw a considerable decrease in the WCSS value at 5 clusters after using the elbow approach.

5. RESULTS

A. Readmission Model

We present the results of the two patient population selection approaches in the readmission model.

1) UNDER-SAMPLING OF MAJORITY CLASS

Using RF and the quantiles technique, the accuracy of readmission prediction on the test set was 55.45%, and using SVM and the quantiles approach, it was 55.25%. The readmission model's accuracy increased by a maximum of 2.57% on the test set when it used RF and the quantiles technique. Additionally, RF had the best specificity (0.59), proving that it is more accurate than the other algorithms in predicting which patients won't require a readmission to the intensive care unit. The model employing the SVM algorithm with the quantiles technique may predict patients at risk of ICU readmission better than the other algorithms, as evidenced by the SVM's maximum sensitivity (0.56). The highest AUROC (0.59) was achieved by the SVM algorithm utilising the quantiles technique in predicting the test set's ICU patients' likelihood of readmission.

2) CLUSTERING RE-SAMPLING APPROACH

The RF algorithm with the quantiles technique yielded the greatest readmission model accuracy using the clustering resampling strategy on the test set, 67.53%, while SVM and the quantiles approach reached 64.10% accuracy (Table 3). The accuracy improvement on the test set when comparing the baseline and quantiles techniques was 2.00% for SVM and 6.03% for RF. This implies that the clustering resampling strategy improved the model accuracy more than the undersampling approach did.

SVM has the highest sensitivity (0.758), indicating that it is more sensitive than the other algorithms in identifying patients who are at risk of readmission. Contrarily, RF achieved the best specificity (0.606), suggesting that the model including RF and the quantiles

6. DISCUSSION

Machine learning methods applied to clinical datasets provide huge promise for tailored drug deliveryHuman illness therapy that is aimed Adding to our foundationWe propose three replicable risk indicators as part of our recent creation of an intelligent ICU patient monitoring (IICUPM) platform.ML models for stratification Our findings suggest that we can construct balanced predictive models for ICU patient readmission and anomaly with more precision by combining Combining ML and a quantiles technique that focused solely on important variables signs. To prevent incorrect findings and low precision in the presented two data options for the readmission model. Having unequal classes: one that employs under-sampling approach, as well as one that use the clustering re-sampling method. We also provide three methods for identifying predictors of Vital sign measures taken the next day in relation to a baseline. We created regression models utilizing two distinct classifications. algorithms to each method In general, we discovered that the error compensation strategy outperformed the average . The measured method fared the poorest. The outcome suggests that employing the most current vital sign measures achieves the least error, especially when accounting for prior blunders In addition to offering three clear this work adds a functionality to replicable ML models. Developing an algorithm that may be used in a variety of critical care contexts.

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