Real-time Patient Monitoring

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Abstract
In the era of fast paced lifestyle more and more people are being diagnosed with chronic diseases which in turn demands immense medical resources. With the kind of volume hospitals and healthcare centers are dealing with, the importance of the remote monitoring is being recognized.

Healthcare's relies largely on technology and over the past few years this has only increased. Data acquisition

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Healthcare;Patient;MAchine Learning;Artificial Inteligence;Remote Monitoring;Blood Pressure;Health Check

ACM Classification Keywords
Computing methodologies;Computing methodologies:Machine learning;Computing methodologies:Machine learning:Machine learning approaches

Introduction

The suggested system is expected to work towards health parameter analysis like body temperature, blood pressure, heart rate, sleep analysis etc to predict the lifestyle and chronic illness lead by imbalance of these parameters.

False Negatives and False Positives

The single-day prediction and time-windowed prediction compute false/true positive alerts and false negative read- missions, which may incur unnecessary nursing costs and readmission costs, respectively. This mechanism helps convert the prediction accuracy performance of RMS into the associated medical costs. Since the nurses respond only to the measurements predicted as ‘positive’, the false positive and true positive rates must be computed. Thus, single-day predictions are used to calculate false positive and true positive rates.

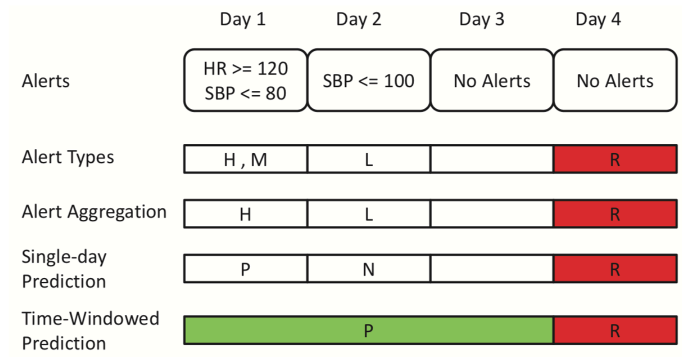

Figure 1 : Adverse event prediction

The readmission cost is computed based on the number of readmission events that were not predicted by the RMS in a w-day window. Unlike general classification problems, readmission prediction in remote monitoring environments involves prediction in a time window. For example, when a nurse receives a positive alert, she/he provides intervention to further investigate the physical status of the associated patient. Under an assumption that each intervention successfully prevents any possible readmission within w days, positive or negative alerts that follow an intervention do not further effect the results of predicting the readmission. This implies that having at least one positively classified alert within w days prior to the actual readmission must be considered as a successful prediction. Thus, we further process single-day predictions and combine them to generate time- windowed predictions. The time-windowed prediction labels a window as ‘positive’ if there exists at least one positive single-day prediction within the window, and ‘negative’ otherwise. According to this rule, the three-day time-windowed prediction in the example in Figure 2 is labeled as ‘P’.

In summary, the system platform produces (i) false positive and true positive alert rates based on single-day prediction (denoted as fp and tp, respectively) and (ii) false negative readmission

Prediction using Analysis

The proposed analytics-based prediction model begins with feature extraction which extracts statistical features and alert-related features from the data. The proposed analytics-based model includes a number of statistical and physiological features in addition to those binary features associated with the alerts. For example, in order to consider the recent physiological status of the patient, the alert information of the patient in the past 5 days from the date of the issued alert is aggregated. To do so, high,medium, and low-priority alerts are assigned weights of 2, 1, and 0, respectively, and the sum of the alert weights of the past 5 days (including the weight of the issued alert) is considered as a feature. For another example, normalized maximum in the last 7 days, which is the percentage of the maximum weight gain in last 7 days compared to the the patient's weight on the date of the issued alert, is considered is calculated as a feature.

In order to provide a configurable analytics performance, the system employs a penalty-sensitive classifier based on a support vector machine (SVM) classifier. A penalty-sensitive classifier is a meta classifier that makes the standard classifier (e.g., SVM) penalty-sensitive by assigning misclassification penalties to the desired classes. As a result, the classifier selects a class that minimizes the expected penalty rather than the most likely class . This work employs the MetaCost algorithm, which creates an additional layer of learning on top of the SVM to effectively minimize the desired penalty.

No.	Description
1	Weight of the issued alert
2	Sum of the alert weights within the past 5 days
3	Absolute weight gain in last seven days
4	Normalized weight gain in last seven days
5	Raw Heart Rate Value

Table 1 : Features used by analytics engine

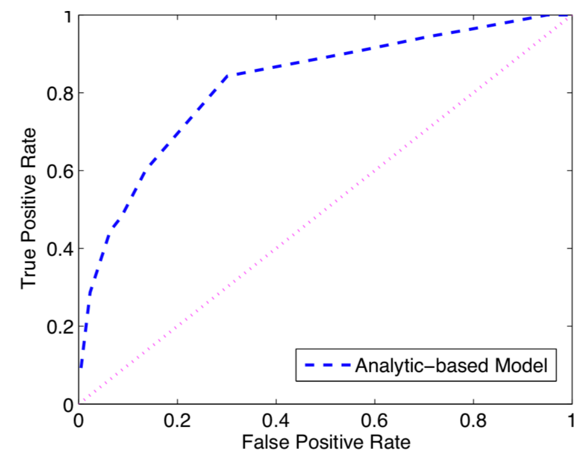

Figure 2 : Readmission prediction performance of the proposed analytic model

Experimental results

The remote monitoring system is currently in the midst of a two year on-going clinical study. A total of 486 patients enrolled between October 2019 and April 2020 were included. in this experiment. A total of 12, 680 alerts were generated as a results of monitoring these patients. This resulted in 6, 435 aggregated alerts after applying the 'Alert Aggregation' process in Figure 1. This section reports the read- mission prediction accuracy, the associated medical costs of the conventional RMS model, and those of the proposed analytics-based model.

Conclusion

As the real-time Patent Monitoring continues to collect health parameter of client. System will continue evaluating data pattern for accuracy.

We are expecting significant increase in user base with compatibility with more devices which will enable the system to include more attributes to provide early alerts for maximum possible illness.

System will also make available sample data for research purposes.

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