Why Do We Need a Remote Health Monitoring System? A Study on Predictive Analytics for Heart Failure Patients

Mohammad Pourhomayoun
California State University, Los Angeles
CA, 90032
mpourho@calstatela.edu

Nabil Alshurafa
Northwestern University
Northwestern Univ., Chicago
IL, 60611
nabil@northwestern.edu

Foad Dabiri
WANDA Inc.
WANDA Inc., San Francisco
CA, 94104
foad@yourwanda.com

Ehsan Ardestani
WANDA Inc.
WANDA Inc., San Francisco
CA, 94104
ehsan@yourwanda.com

Ahsan Samiee
WANDA Inc.
WANDA Inc., San Francisco
CA, 94104
ahsan@yourwanda.com

Hassan Ghasemzadeh
School of EECS
Washington State University
Pullman, WA, 99164-2752
hassan@eecs.wsu.edu

Majid Sarrafzadeh
UCLA, Computer Science Dept.
UCLA, Los Angeles
CA, 90095
majid@cs.ucla.edu

ABSTRACT

Body area networks and remote health monitoring systems allow for collecting physiological data from patients, and provide a platform to utilize analytics algorithms to predict medical conditions. This paper presents an effective predictive analytic approach for hospital readmission prediction for patients with Congestive Heart Failure (CHF) and based on the physiological data collected in last days of hospital stay. We examine the proposed algorithm on the Electronic Health Records (EHR) of UCLA Hospital containing over 10 million clinical measurements collected from approximately 10,000 patients hospitalized at the UCLA Medical Center. The results show that it is possible to predict medically adverse events (e.g. hospital readmissions) for CHF patients if we have access to recent physiological measurements. This study suggests that a remote health monitoring system can provide an effective platform to reduce readmission rates by early prediction of readmissions based on freshly collected data, and then applying appropriate early clinical interventions to prevent the readmission.

Keywords

mHealth, Remote Health Monitoring Systems (RHMS), Predictive Analytics, Cognitive Heart Failure (CHF).

1. INTRODUCTION and MOTIVATION

As the number of elderly people has grown rather quickly over the past few decades, it is essential to seek alternative and innovative ways to provide affordable healthcare to the aging population [1]. A compelling solution is to enable pervasive healthcare for the elderly or patients with chronic disease in order to shift healthcare services from hospital settings to a remote and home-based scenarios [1]-[8]. Furthermore, the increasing cost of chronic disease management necessitates to utilize effective data analytics techniques, which can help early diagnosis, health condition prediction, and medically adverse event prevention (e.g., hospital readmissions, emergency visits, heart attack, and death) [3][5][6]. As of October 2012, the US government stared the Hospital Readmission Reduction Program, which levies punishment on hospitals with high readmission rates [5]. Congestive Heart Failure (CHF) is one of the leading causes of hospitalizations in the US. Statistics show that 20% to 30% of CHF patients are readmitted to hospitals within 30 days after discharge [5][9][10]. The increasing cost of re-hospitalization demonstrates the necessity of developing effective predictive techniques, which can forecast readmission in advance, and allow for appropriate intervention at early stage to prevent re-hospitalization.

In this paper, we investigate the possibility of predicting hospital readmission based on the physiological measurements collected in the last couple of days of stay in the hospital before discharge. In particular, we focus on CHF patients admitted to the UCLA Medical Center.

2. METHODS

2.1 Data

In this paper, we use the Electronic Health Records (EHR) of UCLA Hospital containing over 10 million clinical measurements collected from about 10,000 patients hospitalized at the UCLA Ronald Reagan Medical Center. The data contains of various contextual and physiological parameters such as vital sign information, demographics, laboratory results, and other physiological measurements.

In this study, we focus on CHF patients admitted to the hospital. We use the physiological measurements collected in the hospital in the last three days before discharge. In particular, we use systolic and diastolic blood pressure, heart rate, oxygen saturation SO2, respiration rate, body temperature, and weight, along with age, gender, and race as the main parameters to predict hospital readmission. Some of this measurements have been collected on daily basis (such as weight). However, some of these metrics have been collected multiple times a day. For example, blood pressure and heart rate have been measured every 15 minutes. In case multiple measurements, we calculate and use mean value as the daily average of each metric.

2.2 Predictive Analytics Algorithm

The first step in predictive analytics is to preprocess the data and extract the most informative features. Statistical and morphological parameters are the most common features used for data analytics. In this study, we derived total 90 features for each data sample (in this context, a data sample refers to a patient admission). The statistical features include mean, median, rms, minimum, maximum, variance, first/last sample, maximum fluctuation, standard deviation, and skewness of the set of measurements collected in the last 3 days of hospital stay.

We have to note that only a small portion of these 90 extracted features will be eventually used in the classification stage. In this study, after applying supervised feature selection, only the best 15 features are selected. Then, for the sake of reducing the redundancy and avoiding overfitting, we applied another layer of unsupervised dimensionality reduction, and selected only 8 features for the classification stage.

After feature selection stage, the best set of features will be used in classification stage to build a prediction model. In this research, we tried various classification algorithms such as SVM, Random Forest, BayesNet, and Logistic Regression. According to our results, SVM classifier provided fast and the most accurate prediction results for our dataset. We use Monte-Carlo algorithm with 500 runs to make sure that the results are not random or biased. In each round, we randomly split the dataset into training and testing sets (with no overlap), the training set is used to train a new classifier model, and the testing set is used to examine the classifier. In each round, we calculate the Area Under Curve (AUC) of Receiver Operating Characteristic (ROC) to evaluate the accuracy of the classifier. The average of all 500 AUCs (derived from 500 runs) will be used to represent overall accuracy and the ability of the system to correctly classify the outcomes and predict hospital readmissions.

3. RESULTS

Figure1 shows the results of readmission prediction for CHF patients based on the physiological measurements collected in the last three days of stay in the hospital (last three days before discharge). We examined the results for prediction within various time windows (e.g. prediction within 7 days after discharge, within 8 days, …). For each time window, we ran a Monte-Carlo algorithm with 500 runs.

The results show that the prediction accuracy degrades severely by extending the prediction time window from one-week to one-month. Predictions beyond one month are only a little better than random guess.

4. CONCLUSION

This paper presented an end-to-end predictive analytic algorithm to predict hospital readmission based on the physiological measurements collected in the last three days of stay in hospital. The results show that it is possible to predict the readmissions happening after discharge based on the physiological data collected before discharge. However, the prediction accuracy degrades rapidly when prediction window extends from one week to one month. For example, the AUC is about 0.63 for CHF readmission prediction within the first week. However, the AUC degrades to 0.57 for prediction within the first two weeks, and 0.55 for prediction within the first month (which is only slightly better than random guess). This results suggest that it is possible to accurately predict the hospital readmissions for CHF patients if we have access to recent physiological measurements. One effective approach to this end is to employ Remote Health Monitoring Systems (RHMS), which allow for collecting continuous data from patients, providing a platform to utilize analytics algorithms to predict medical conditions, and applying clinical interventions to prevent medically adverse events such as hospital readmissions, emergency visits, heart attack, or death. Remote health monitoring can revolutionize the healthcare system by increasing the efficiency of medical services, expanding the reach of healthcare services to every part of the population, and reducing the costs of chronic disease managements.

In summary, this study suggests that RHMS can provide an effective platform to reduce readmission rates by early prediction of readmission based on freshly collected data, and then applying effective early intervention to prevent the readmission.

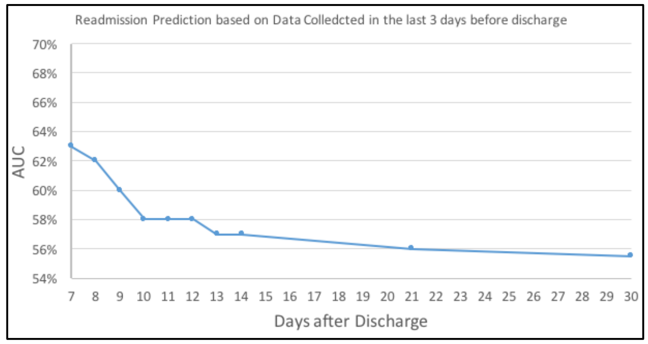

Figure 1. Readmission prediction based on the data collected in the last three days of stay at hospital.

5. ACKNOWLEDGMENTS

The authors would like to appreciate WANDA Inc. (www.yourwanda.com) for valuable help and support. The authors would like to thank the Ronald Reagan UCLA Medical Center, and David Geffen School of Medicine at UCLA.

6. REFERENCES

[1] M. Pourhomayoun, et al. "Context-Aware Data Analytics for Activity Recognition," International Conf. on Data Analytics, DATA ANALYTICS 2015, July 19 - 24, 2015, France.

[2] M. Lan, et. al., "WANDA: An End-to-End Remote Health Monitoring and Analytics System for Heart Failure Patients," Wireless Health Conf., 2012b.

[3] M. K. Suh, et al., "A Remote Patient Monitoring System for Congestive Heart Failure," JOMS, June 2011a.

[4] N. Alshurafa, et al. "Improving Compliance in a Remote Health Monitoring System through Smartphone Battery Optimization". IEEE J Biomed Health Inform, 2014.

[5] S. I. Lee, et. al., Remote Health Monitoring Systems: What Impact Can Data Analytics Have on Cost? in Wireless Health, 2013.

[6] M. Pourhomayoun, et. al., "Multiple Model Analytics for Adverse Event Prediction in Remote Health Monitoring Systems," IEEE EMBS Conference on Healthcare Innovation & Point-of-Care Technologies, 2014, pp. 106-110.

[7] K. Hung and Z. Yuan-Ting, Implementation of a WAP-based telemedicine system for patient monitoring, Information Technology in Biomedicine, IEEE Trans. on, 2003.

[8] A. G. Logan, et al., "Mobile Phone–Based Remote Patient Monitoring System for Management of Hypertension in Diabetic Patients," American Journa of Hypertention, 2007.

[9] J. S. Ross, et. al., "Recent national trends in readmission rates after heart failure hospitalization," Circulation: Heart Failure, vol. 3, pp. 97-103, 2010.

[10] S. F. Jencks, M. V. Williams, and E. A. Coleman, "Rehospitalizations among patients in the Medicare fee-for-service program," New England Journal of Medicine, 2009.