A Scalable Cloud-Based Medical Adherence System with Data Analytic for Enabling Home Hospitalization

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Abstract Medication non-adherence is one of the most significant concerns in managing chronic diseases which has inevitable consequences. While various technologies and research have been developed and carried out to monitor medical adherence for patients, their approaches lack in terms of the assurance of medicine consumption and the cost effectiveness of their solutions. This paper provides a cloud-based medical adherence system that can track patients’ medicine intake based on the physical effects of the medicine on their bodies by tracking their vital signs. A machine learning model is trained to classify the patient health status and this data is used to determine whether their bodies are responding to the medicine, which is used to alert doctors to enable home hospitalization. The use of this system is proposed to serve as a secondary decision support provider to compliment and ease the decision-making process done by doctors.

Keywords Medical adherence · Home hospitalization · Machine learning

1 Introduction

1.1 Background

Medicine adherence is defined as the extent to which a patient follows the treatment plan by consuming the medicines prescribed by their doctor [1]. Not-adhering to a treatment plan can result in undesirable clinical consequences and substantial increase in hospitalization costs [2]. Recent research highlighted that most patients
do not follow the instructions provided by their doctors which results in significant increase in hospitalizations and doctor visits [3].

In recent years, home hospitalization technologies have been the focus of many researchers and healthcare companies [4]. The two main aspects of home hospitalization are medicine adherence and health status monitoring for patients. Different approaches to detect medical adherence are used in this field, some use blood test evaluation, some rely on patient’s self-assessment feedback while others use pill dispensers to detect whether the medicine was taken. These solutions can provide useful information on the behavior of the patient, but they lack in terms of cost efficiency, illness type and how practical they can be achieved.

This paper aims to provide a solution that can assist doctors to monitor the health status and medicine intake by analyzing the patient’s vital signs throughout the day. We leverage machine learning to identify the health condition of the patient and match that to the timeline set by doctors for medicine intake. The trained model takes major vital signs as input which are measured by off-the-shelf medical proven instruments. The data taken is logged and processed on cloud and provides the output in terms of recommendation to doctors who can then decide to adjust medicine dosage or frequency or schedule an appointment with the patient.

1.2 Literature Review

Many efforts were made in the field of medical adherence and home hospitalization. Providing a home hospitalization solution to patients proved to reduce in-hospital days of patients [5]. One key feature that is necessary for enabling home hospitalization is the ability to monitor the patient’s health status remotely and track their adherence to medications. Tripathi et al. [6] proposed the usage of tracking sensors and wearable devices to collect information about the patient, then the data is pushed to an online server where the decision is made to contact family members, ambulance or clinical support. Other researchers such as Zulkifli et al. [7] developed a health monitoring and information system to enable smart health environment. Their solution links patients, health service staff and doctors. Patients can provide feedback to doctors using their smartphones and doctors will respond to their reports to check if they need to schedule an appointment for the patient or continue treatment from home. Home hospitalization is receiving huge attention for what it can provide in terms of reduction of hospitalization time, reduction of treatment cost and freeing up doctors’ time. Hernández et al. [8] conducted a study on early discharge care service by enabling patients to stay at home for some time of their hospitalization treatment. They requested nurses to visit these patients frequently and measure their vital signs and enter them to an online system for doctors to access. The study was conducted for ten years and provided promising results as the service reduced the hospitalization time by six days [8]. Lobato et al. [9] conducted a study on forty patients divided into two groups, the first group received their care at the hospital while the other group was sent back home and had their health status monitored regularly and received
the same treatment as the first group. After the patients fully recovered and were discharged from the hospital, it was noticed that there is no significant difference between patients who were staying at home and those who stayed at the hospital. Federman et al. [10] conducted a study on patients who require inpatient-care and sent a group of them to receive care at home. Patients had their vital signs monitored by nurses and health professionals, then all patients were asked to review their treatment process and the results showed better rating for those who received treatment at home. Sherif et al. [11] proposed a method to enable home hospitalization by tracking medicine intake for patients using embedded hardware. Their approach relied on patients reporting their medicine adherence using an alarm button which connects to a monitoring dashboard. This approach provides a good method for patients monitoring but it does not guarantee that the patient has taken the medicine when they send the acknowledgment. This can only be verified by tracking patient physical condition and monitoring their vital signs. Daramola et al. [12] followed a similar method by reporting medicine intake using smartphone application and rely on patient self-reporting which does not guarantee medicine intake. Kumar et al. [13] proposed a similar approach for medicine adherence tracking using medicine dispenser. This method assumes that the medicine was taken whenever the patient opens the dispenser to take medicine. However, this also does not guarantee the medicine intake. Hence, this paper aims to verify the consumption of medicine by tracking vital signs of patients and reporting irregular readings regularly.

1.3 Motivation

The primary objective of this study is to enhance patients’ adherence to medication without the need of special equipment or the supervision of nurses and caregivers. With the recent spread of COVID-19 pandemic, where thousands of people have been hospitalized and many healthcare facilities ran out of resources to accommodate the increasing numbers of patients, many patients with minor symptoms were asked to stay at home and monitor their health status [14]. This pandemic raised the significant need to enable home hospitalization. Thus, we propose a complimentary tool that helps to predict the behavior of the patients and highlight their behavior to their doctors so they can make better decisions while patients rest at home.

2 System Architecture and Data Analysis

The proposed method composes of three main sections: data preparation and data preprocessing, training and validating a machine learning model to classify medication adherence behavior and a method for doctors to validate the result and advise on the patient condition based on the given prediction as well as data collected from patients.
2.1 Data Pre-processing and Data Collection

The four main indicators of health status for patients are heart rate, blood pressure, temperature and blood oxygen saturation. Thus, these parameters are taken into consideration in our design where the focus was to prepare a labeled dataset that is collected by medical professionals for patients diagnosed with medical conditions. We leveraged on a renown public health dataset known as Medical Information Mart for Intensive Care III—MIMIC-III which includes health-related data of more than 40,000 patients who were admitted to intensive care units—ICU. The dataset contains abundant information about patients including readings of vital signs as well as doctors diagnosis. Data were taken at 1-h frequency and keyed into the system by caregivers. However, the data is not consistent in terms of what data is available for each patient. In order to train an accurate machine learning model, the data must be properly formatted. We filtered out the patients who had more than four readings taken per day including heart rate, blood pressure, temperature and oxygen saturation along with doctor diagnosis.

Machine learning models for classification need data for normal people, not diagnosed with any medical condition as well as the prepared data for patients diagnosed with diseases. However, there is no publicly available dataset with the criteria that we have, so we collected data for healthy people to be used for the model training.

2.2 Training Recurrent Neural Network Model

Two models are proposed to provide useful information as a second opinion for doctors. The first model is a binary classifier to identify patient health status as normal or abnormal depending on the vital signs measured. The prediction will be based on the labeled dataset provided with normal and abnormal flags.

The binary classifier aims to provide a prediction based on the vital signs labeled data by grouping all diagnoses under one single category labeled as abnormal readings while normal readings are labeled as normal.

Three types of classifiers are selected to be tested and validated with the prepared dataset. These classifiers are K-NN, linear Support Vector Machine (SVM) and kernelized SVM with radial basis function (RBF). The models are selected according to the size of the dataset that we prepared and the type of classification that is needed. Model training will be using Scikit-learn which is well known for classification algorithms [15].

The multiclass classifier aims to provide a predictive suggestion on the diagnostic category of the patient based on the vital signs. Diagnoses are categorized into different groups such as heart issues, respiratory illness, blood pressure etc., which the doctor will later confirm or deny to provide a feedback data that can be used later for training a more accurate model.
2.3 Application Layer

In order to achieve the objectives of improving medical adherence and enabling reliable home hospitalization solutions, an application layer is built on top of the developed machine learning models. The application will enable doctors to set up a time schedule to measure the vital signs of the patient depending on the medication schedule. The patient, at home, with the assistance of caregivers if necessary, will key in the vital signs readings to the system at the given time.

Binary predictions will be made based on these inputs, then they will be matched to the schedule of medicine intake. In case the readings showed normal result of the patient vital signs, we will assume that medicine is taken at the right dosage at the right time. Conversely, if the readings are classified as abnormal, they will be presented at the doctor dashboard along with the measured values and the doctor can confirm or deny the prediction. The doctor feedback is then logged and stored in a database for future use as a closed loop system that takes doctors recommendations as input. In case at the next measuring time the results showed abnormal readings again, a red flag will be raised for the doctor to take action to change the dosage of the treatment or the frequency of taking the medicine or they can arrange for appointment with the patient in critical cases.

Multiclass predictions provide an estimate diagnosis of the patient in case the vital signs are not normal. These predictions are then sent to the doctor dashboard when they respond to the patient alert. We do not provide a medical advice based on this; we just provide a predictive information for doctors who can select which prediction is accurate that will be logged into a database and be used again to train the model to provide an improved results in terms of accuracy as more predictions are verified by doctors.
The application of this monitoring process will eventually enable doctors to monitor patients’ behavior to treatment while they stay at home. By following their medicine schedule and reporting their vital signs regularly as requested by their doctors, our method can fill in the gap of identifying normal body conditions and reporting any irregular readings of the vital signs where doctors can verify the predictions and request for appointments or change treatment dosage.

3 Results and Discussion

3.1 Data Preparation

A well labeled and filtered dataset is prepared which consists of five features and one label. The features included in the dataset are Oxygen Saturation, Blood Pressure (diastolic), Blood pressure (systolic), Heart Rate and Temperature along with a label named condition which identifies whether the readings are considered normal or abnormal.

The prepared dataset consists of the following parameters:

- Blood pressure (diastolic)
- Blood pressure (systolic)
- Heart rate
- Blood oxygen level
- Temperature
- Label.

After filtering patients’ readings for abnormal readings to contain only those who have more than 3 readings per day, a total of 1384 rows were extracted. Feature extraction was then performed to obtain the mean, median, min, max and standard deviation. A similar process was done on 102 normal readings that we collected manually with the help of a general physician. Both tables were then combined with the patient ID removed and assigned a label of ‘0’ for normal reading and ‘1’ for abnormal reading.

We are in the process of gathering more data for normal people which will improve system accuracy as the data that we have now is asymmetrical with the larger proportion being the abnormal readings taken from the MIMIC-III dataset and consequently produces less accurate results due to bias caused by the imbalanced data.

3.2 Model Training

Since the prepared dataset consists of 102 rows of normal readings and 1384 rows of abnormal readings, we catered for imbalanced data training. This dataset was
split with the ratio of 50% to 50% for training and testing, respectively. Repeated Stratified K-Fold cross validation was used to split the data with random state set to 1, n_splits set to 4 and n_repeats set to 10 times. One key feature of Repeated Stratified K-Fold cross validation is that it provides balanced weights of training and testing dataset when dealing with imbalanced data as it provides the same proportion of observations with a given categorical value [15]. Another key feature is setting the random state to a specific number which guarantees the same generation of the training and testing sets when adjusting other parameters of the classifiers, so we have a consistent training and testing samples. Splits and repeats setting allows us to train different variations of the same model and recording their accuracy and performance as the training and testing results for large datasets vary according to the sampled data. After splitting the data into training and testing sets, we trained three different models to evaluate their performance.

The first model is k-NN Classifier, which was trained with ‘n_neighbors’ set to five, ‘weights’ set to ‘uniform’, ‘algorithm’ set to ‘auto’ and ‘metric’ set to ‘minkowski’. The training produced the following results (Table 1).

The confusion matrix of the obtained results from the k-NN classifier shows good result of predicting abnormal readings but the accuracy of classifying normal readings is low, thus this model is not fit for our goal.

The second model is kernelized SVM. The hyperparameters used were as follows: C set to 1, ‘kernel’ set to ‘rbf, and ‘class_weight’ set to ‘{0:0.93, 1:.07}’ for imbalanced data. The training produced the following results.

Compared to the previously trained model, kernelized SVM shows a better performance as shown in Table 2. The confusion matrix shows great performance on normal

| Normal (actual) | Abnormal (predicted) | Accuracy (%) |
|----------------|----------------------|--------------|
| Normal (predicted) | 30 | 21 | 58.8 |
| Abnormal (actual) | 13 | 679 | 98.1 |
| Precision | 0.792 |
| Recall | 0.748 |
| F1 score | 0.975574 |

| Normal (actual) | Abnormal (predicted) | Accuracy (%) |
|----------------|----------------------|--------------|
| Normal (predicted) | 47 | 4 | 92.1 |
| Abnormal (actual) | 89 | 603 | 87.1 |
| Precision | 0.652 |
| Recall | 0.870 |
| F1 score | 0.8748317 |
Table 3  Linear support vector classifier test results

|                     | Normal (predicted) | Abnormal (predicted) | Accuracy (%) |
|---------------------|--------------------|----------------------|--------------|
| Normal (actual)     | 44                 | 7                    | 86.3         |
| Abnormal (actual)   | 114                | 578                  | 83.5         |
| Precision           | 0.540              |                      |              |
| Recall              | 0.629              |                      |              |
| F1 score            | 0.8371467          |                      |              |

Table 4  Linear support vector classifier test results

| Model name       | Precision | Recall | F1 score          |
|------------------|-----------|--------|------------------|
| K-NN             | 0.792     | 0.748  | 0.975574         |
| SVM SVC          | 0.652     | 0.870  | 0.8748317        |
| SVM Linear SVC   | 0.540     | 0.629  | 0.8371467        |

and abnormal class in terms of predictions and these result in a better F1 score and recall.

The third model trained is linear SVM configured with ‘penalty’ set to 12, ‘loss’ set to ‘squared_hinge’, ‘class_weight’ set to ‘balanced’ and ‘intercept_scaling’ set to 1. The training process produced the following results.

As showed in Table 3, the linear SVM model showed a moderate performance with slightly decreased accuracy for abnormal class compared to the previous classifier. This was reflected on the F1 score, recall and precision.

Table 4 summarizes the results of these three trained models using two evaluation metrics, Accuracy and F1 score.

By comparing the metrics of the three trained models, as shown in Table 4, SVM SVC is selected based on its accuracy. Further improvements in terms of asymmetrical data training techniques or by adding more data to the collected dataset will be done in the future. The promising results shows the ability to fully integrate the system components and obtain positive results eventually.

4 Conclusion and Future Direction

This paper aims to improve medical adherence for patients taking their treatment at home and provides a solution for doctors to keep track of patients’ behavior and provide feedback on their condition. We leveraged on supervised learning to train machine learning models with the prepared dataset. The prepared dataset consists of data of vital signs labeled with their medical condition if they are diagnosed with some illness or labeled as normal otherwise. The proposed application that is built on top of these models will provide doctors with a dashboard to monitor patients
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medication adherence and provide feedback on the output of the prediction models which can be fed back again to the system input for improved results. We strongly believe that this system will improve medication adherence and provide a method to enable home hospitalization which is on high demand nowadays. The trained model only provide prediction of whether the vital signs are normal or abnormal, however, in order to provide a more helpful estimation, we need to give a score for the degree of which the readings are abnormal. For example, the output could be low, medium, high or normal. In order to further improve the model accuracy, there should be a feedback path for doctors to approve or reject the predictions made by the model which will be used to train and improve another version of the model. We are still collecting data to improve our results and carry out further tests to verify the methodology.

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