IoT Based Classification of Vital Signs Data for Chronic Disease Monitoring

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***Abstract*— Nowadays chronic diseases are the leading cause of deaths in India. These diseases which include various ailments in the form of diabetes, stroke, cardiovascular diseases, mental health illness, cancers, and chronic lung diseases. Chronic diseases are the biggest challenge for India and these diseases are the main cause of hospitalization for elder people. People who have suffered from chronic diseases are needed to repeatedly monitor the vital signs periodically. The number of nurses in hospital is relative low compared to the number of patients in hospital, there may be a chance to miss to monitor any patient vital signs which may affect patient health. In this paper, real time monitoring vital signs of a patient is developed using wearable sensors. Without nurse help, patient know the vital signs from the sensors and the system stored the sensor value in the form of text document. By using data mining approaches, the system is trained for vital sign data. Patients give their text document to the system which in turn they know their health status without any nurse help. This system enables high risk patients to be timely checked and enhance the quality of a life of patients.**

Keywords—chronic diseases; cardiovascular disease; vital signs; wearable sensors; data mining.

I. Introduction

According to a latest report by the Delhi based Public Health Foundation of India (PHFI), chronic diseases are the leading cause of deaths in India. Every year more than five million people are suffered from this disease. These diseases which include various ailments in the form of diabetes, stroke, cardiovascular diseases, mental health illness, cancers, and chronic lung diseases will cost India around Rs 280 trillion between 2012 and 2030 in terms of economic output. For preventive health management, urged for the need of a cost effective health system.

People who have suffered from chronic diseases are monitored their vital signs continuously. Vital signs include the measurement of temperature, respiratory rate, pulse, blood pressure and blood oxygen saturation. It provides information about a patient's state of health. They can identify the existence of any medical problem, illness and person’s body physiological stress In hospitals both in ICU ward and general ward nurses take care of chronic disease patients. In home also, we can monitor vital signs of a patients with the help of nurses. These are the normal way of monitoring vital signs.

Normally elder people are suffered a lot from chronic disease. They cannot go to hospital regularly and also hospitalization cost also increases. In hospital, the nurses ratio is low compared to patients. Sometimes nurses have missed to take vital signs data of patients. With the lack of vital sign monitoring, patient undergoes many problems. For checking the vital signs data to be healthy or unhealthy, we need nurse or doctor advice and again cost is increased. To make an elder citizen happier, we have to develop a telemedicine system.

Telemedicine is the combination of telecommunication and Information technologies in order to provide a clinical health care at a distance. Advances in sensor and interconnect technologies, healthcare can include collecting patient data dynamically to prevent care, diagnostics, and even measure treatment results. Today, wireless sensor-based systems gather medical data and deliver care directly to patients. IoT related healthcare is based on IoT as a network of devices that connect directly with each other to capture and share vital data. It combines sensors, microcontrollers and gateways where sensor data is further analyzed. Data mining techniques are used to find the healthy and unhealthy vital signs data using classification model without nurse help.

Chronic Disease monitoring system captured vital signs data via medical sensors, data mining algorithms to analyze the data and medical professionals can wirelessly access the information and make diagnoses and treatment recommendations based on the data. These applications generate huge amount of data. This vital data from the sensor is mined through data mining techniques and from this model patient automatically know the vital signs data be healthy or unhealthy.

II. RELATED WORK

A detailed survey is carried out on data mining applications in the healthcare sector to extract useful information from large databases. Data mining algorithms plays a significant role in prediction and diagnosis of the diseases. Normally they prepared databases or used already available dataset for finding information. Data mining tasks are Association Rule, Patterns, Classification and Prediction, Clustering. Most common modeling objectives are classification and prediction. Healthcare industry generates large amounts of data about patients, hospital resources, disease diagnosis, electronic patient records, medical devices etc. These large data are analyzed because data is rich and information is poor. There may be different type of data mining algorithms used for different diseases. Data mining techniques are applied on different diseases such as Heart Disease, Cancer, HIV/AIDS, Brain Cancer, Tuberculosis, Diabetes, Mellitus, Kidney dialysis, Dengue IVF, Hepatitis C.

Kidney disease is predicted by using classification algorithms such as Naïve Bayes and Support Vector Machine. And focused on finding the best classification algorithm based on accuracy and execution time. Researchers used synthetic kidney function test dataset for analyzing kidney diseases and found svm classification algorithm is best.

Electrocardiogram (ECG), oxygen saturation (SpO2), heart rate (HR), Photoplethysmography (PPG), blood glucose (BG), respiratory rate (RR), and blood pressure (BP and specific disease or problems related to the mentioned health parameters are concentrated. Wearable medical sensor is used to collect raw data and these data is used for training data to learn the model. For testing purpose they used any instance of raw data from any patient. For data processing, they used data mining approach.

A survey on architecture for IoT and big data mining system. A lot of IoT devices are there sensors, actuators, cameras, RFID etc. These raw data may be structured, semi structured and unstructured data. Data processing is based on big data techniques such as Hadoop, HDFS, Storm, and Oozie and the data analysis is done by data mining techniques.

Another approach considered 9 clinical conditions such as angina, sepsis, and respiratory failure, along three physiological measurements (i.e. heart rate, blood pressure, and respiration rate). Normally these physiological parameters in clinical center are time series data and these data is mined based on some rule. These rules are in the form of textual representation which is easily readable by human.

III. PROPOSED SYSTEM

We propose a chronic disease monitoring system for elderly patients. Here we gather a raw data from medical sensor and using these sensors we build a model. Any real time data may given to the model and the model returns these real time data may healthy or unhealthy which is very useful

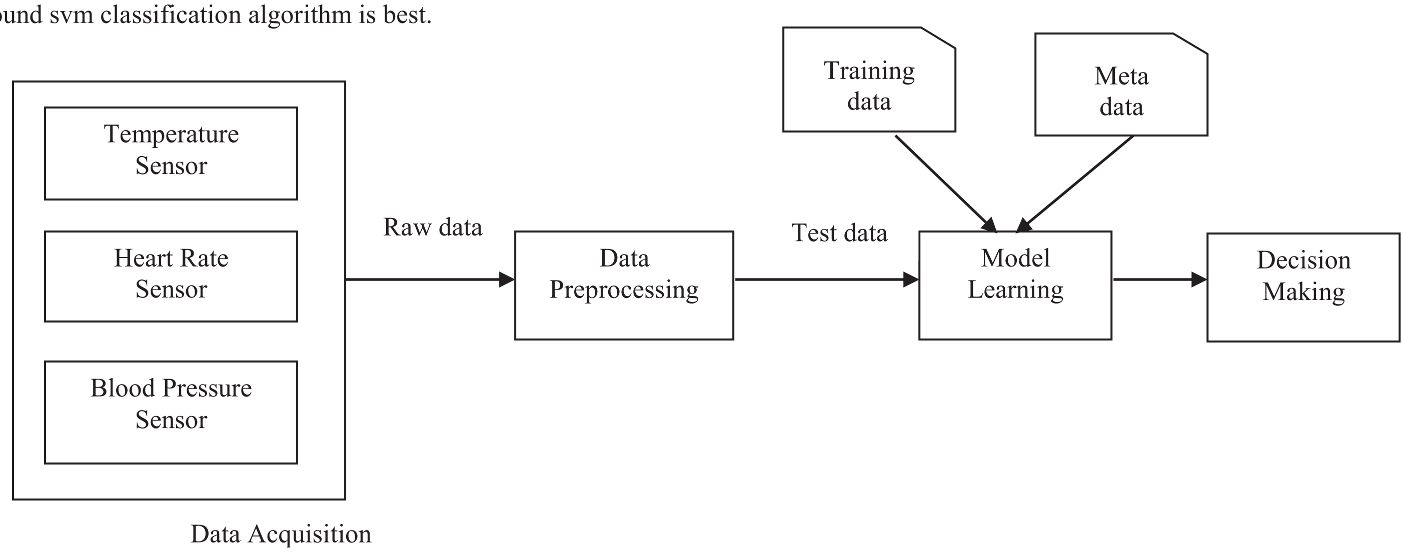

Fig 1. Chronic Disease Classification Model

chronic diseases are needed to monitor their vital signs periodically. For every periodic instance, with the help of nurses in hospital, patient knows their status. This is time consuming process. So, we have build a model and the sensor value will be given to the model and the model gives the health condition of a patient. By using this model, cost is reduced and without nurse help patient know their condition. Fig 1. represents the block diagram of the system.

A. Data Acquisition

The medical sensor is used to capture a vital signs data from a patient. Here temperature, heart rate and blood pressure sensor is used to acquire a physiological data from a patient. The arduino microcontroller is able to read the raw data from the medical sensor. There are many versions of arduino. In this project, we use Arduino ATMEGA 2560. The 10 bit analog to digital converter (ADC) is internally built in Arduino microcontroller. With the help of arduino IDE software, we can turn the sensor value in to physiological output.

1. Body Temperature

Temperature is a measure of the degree of heat intensity. The human body's core temperature varies from day to day and from time to time. These fluctuations are not more than ±1ºC. The normal human body temperature is 37 ºC External and internal heat sources influence body temperature.

A thermistor indicates temperature by a change in electrical resistance. The analog input pins of the Arduino can only measure voltage, so the electrical resistance of a thermistor cannot be measured directly. Thermistor temperature sensor is shown in Fig 2.

Fig 2. Thermistor Temperature Sensor

A simple technique for converting the (variable) resistance of the thermistor to a voltage is to use the thermistor in a voltage divider. The voltage divider circuit is shown in Fig 3.

The voltage divider has two resistors in series. The upper resistor is the thermistor, with variable resistance Rt. The lower resistor has a fixed resistance R. A voltage Vs is applied to the top of the circuit. The output voltage of the voltage divider is Vo, and it depends on Vs and R, which are known, and Rt, which is variable and unknown. Vo is measured by one of the analog input pins on the Arduino.

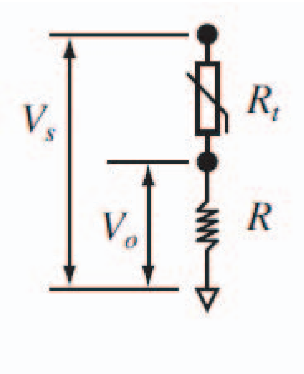

Fig 3. Voltage Divider Circuit

$$R_t = R(\frac{v_s}{v_o} - 1) \qquad (1)$$

Equation (1) is used to compute the thermistor resistance from the measurement of Vo.Use Steinhart-Hart equation to translate resistance value to temperature value.

$$1/T = A + B\ln(R) + C(\ln(R))^3 \qquad (2)$$

A, B & C are Steinhart-Hart parameters, R is resistance in ohms & T is temperature in kelvin. Temperature value is calculated from equation (2). Then convert kelvin to celsius & celsius to farenheit.

2. Heart Rate

Finger measuring hear beat sensor is used to measure heart rate. It uses bright infrared (IR) LED and a phototransistor to detect the pulse of the finger, a red LED flashes with each pulse. The infrared LED is the one side of the finger, and phototransistor on the other side of the finger. IR LED emits the rays into finger and the photo transistor captures the reflected rays. This reflected ray gives the number of pulses detected by the sesnsor. Heart rate sensor is represented in Fig 4.

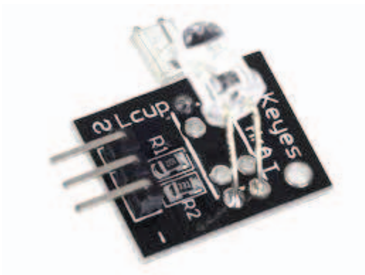

Fig 4. Fingertip Measuring Heart rate sensor

3. Blood Pressure

It measures the force of blood inside the blood vessel. Measurement shows how well the heart is working. SPD (Smart Pressure Device) is a series of silicon based pressure sensors is used to measure blood pressure. These sensors are generally available in plastic inline or dual inline packaging. SPD sensors are generally available in two operation modes namely gauge type and absolute type. In gauge type the pressure is measured with respect to the atmospheric pressure. There is a small vent on the package for getting contact with the atmosphere.SPD015G pressure sensor is represented in Fig 5.

An instrumentation amplifier based on quad opamp LM324 is used for conditioning the output voltage from the pressure sensor. The cuff is placed in the left arm and then connected to pressure sensor vent which converted from mechanical energy into electrical energy. The output voltage is directly proportional to mmHg pressure value.

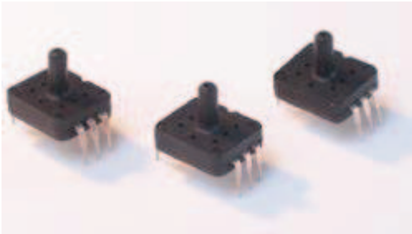

Fig 5. SPD015G Blood Pressure sensor

B. Data Preprocessing

The vital signs vary different for day to day and time to time for an individual patient. So for a particular patient we have captured different instances of value and check the value is somewhat same for all the samples. And there may noisy data also captured by sensor. Sometimes the medical sensor may affected by any environmental factors also. We have eliminated the noisy data from the raw data and the test data is prepared.

C. Model Learning

We have built a model with the help of training data and Meta data. The training data consists of 500 patient health records which contains three different vital signs and their health conditions. These test data is a supervised learning method and the model is built using classification methods. The healthy condition of a patient varies different for different people and this information is stored in meta data. The meta data consists of healthy conditions of babies, toddlers, pre schoolers, teenagers, adults and old people.

1. Naïve Baeysian Classification

The Prior knowledge and observed data is combined to build a naive Bayesian model. The objects are classified based on probabilistic model specification. It uses Bayes theorem to classify data objects and the attributes that describe data instances are class conditional independence. Naive Baeysian classifier takes the highest hypothesis value to classify the objects.

2. J48 Classification

J48 classification method generates a decision tree for a given dataset. The dataset is split recursively and apply the j48 classification algorithm for each partition of a dataset. The partition that has highest information gain is selected as best attribute and based on the attribute classify the data objects.

3. SVM Classification

SVM is used for both linear and non linear data. The training time is increased in svm but it gives high accuracy. There is a hyperplane be formed based on the training data and for a test data the model searches in a hyperplane. SVM is based on binary classification and the data objects may fall on any category.

D. Decision Making

Once the test data is given to model and the model gives healthy or unhealthy data. From the health data status, patient knows our condition. If it is unhealthy means, patient take medicine to avoid the disease in earlier stage.

IV. RESULTS AND DISCUSSION

Table 1 shows the correctly classified and incorrectly classified instance of healthy fields of vital signs by applying different classification algorithms. Naive Bayes, J48 and SVM algoritms are used for classification.

Table I
Classification of vital signs

Vital signs	**Classification Algorithms**	**Correctly Classified Instances (%)**	**Incorrectly Classified Instances (%)**
Temperature	Naïve Bayesian	75	25
	J48	95.83	4.17
	SVM	95.83	4.17
Heart Rate	Naïve Bayesian	66.67	33.33
	J48	95.83	4.17
	SVM	95.83	4.17
Systolic Blood Pressure	Naïve Bayesian	85.71	14.29
	J48	95.24	4.76
	SVM	95.24	4.76
Diastolic Blood Pressure	Naïve Baeysian	95.84	4.16
	J48	100	0
	SVM	100	0

Among 3 different classification algorithms, J48 and SVM gave better results.

To measure the performance of the system, we used precision, Recall and F-Measure.

Precision is used to check the selected objects are correct among entire objects. The formula for precision is represented in equation(3).

$$precision = \frac{TP}{TP + FP} \tag{3}$$

Recall is used to check the correct objects are selected among the entire objects. The formula for recall is represented in equation(4).

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \tag{4}$$

F-Measure is used to combine both precision and recall. The formula for F-Measure is represented in equation(5).

$$F - Measure = \frac{2 * precision * recall}{precision + recall} \tag{5}$$

Table 11 shows the accuracy measure of different classification algorithms for vital signs.

Table II
Accuracy Measure of Classification Algorithm

Vital signs	Classification Algorithms	Precision	Recall	F-Measure
Temperature	Naïve Bayesian	0.824	0.750	0.747
	J48	0.922	0.958	0.939
	SVM	0.922	0.958	0.939
Heart Rate	Naïve Bayesian	0.807	0.667	0.628
	J48	0.962	0.958	0.958
	SVM	0.962	0.958	0.958
Systolic Blood Pressure	Naïve Bayesian	1.000	0.857	0.921
	J48	1.000	0.952	0.975
	SVM	1.000	0.952	0.975
Diastolic Blood Pressure	Naïve Bayesian	0.964	0.958	0.958
	J48	1.000	1.000	1.000
	SVM	1.000	1.000	1.000

V. CONCLUSION AND FUTURE WORK

In this paper, we have captured the vital sign data for patients using medical sensor. Then we removed the noise from the raw data and convert the raw data into test data in preprocessed step. We have trained a model and the model is learned by supervised method. And also meta data is also maintained for finding the health condition of patients. The model returned the vital sign data be healthy or not. From this status, patient takes medicine to detect early disease.

The medical sensors will produce enormous amount of data. Some classification algorithms cannot classify large amount of data. So we move onto Big data techniques. Map reduce algorithm can be used to find the health status. And dependency of a disease can also be found for further analysis.

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