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HEART FAILURE PREDICTION TECHNIQUES BASED ON COMPLEX EVENT PROCESSING

Manaswini Sudhal[1],Prof. Shubhangi Vairagar[2]

Department of Computer Engineering Siddhant College of Engineering Sadumbre, Savitribai Phule, Pune University, Pune[1]

Abstract: **Computer plays an important role in every aspect of life. Computers allows huge amount of storage, does processing of information at very high speed. Many computer software are used to diagnose diseases. Networking makes faster communication between doctor and patient. Digital storage of data result in massive amount of data of Patient. It is impossible for human to analyze the huge amount of data. Machine learning provides a way to find out various patterns and reason about the data. Machine learning has three models classification, clustering and regression. Various classification algorithms are available to classify the data and predict result like Decision tress C4.5, Neural Network MLP, KNN etc. According to the WHO (World Health Organization), chronic diseases such as cancer, coronary heart disease, diabetes mellitus type 2, and chronic obstructive pulmonary diseases are among the world's most common diseases constitute. Because of this, about 60% of all deaths occur worldwide. Here, present new health monitoring techniques to the prediction of heart failures. In this system, develop edge-computing based Complex Event Processing (CEP) techniques with the Remote Patient Monitoring (RPM) for the remote healthcare applications. This approach is based on the CEP, combined with the statistical approach. For the prediction of heart failure multilayer perceptron (MLP) model is used. The system firstly, collects health parameters after that process data using analysis rules. This proposed system continuously monitors heart failures patients and after that, it predicts heart failures strokes based on the related symptoms. When a critical condition occurs then it alerts patients. An experimental result shows that the MLP is more accurate than C4.5.**

Keywords:-Heart Failures Prediction, C4.5, WHO, Remote Patient Monitoring, and Multilayer Perceptron.

I INTRODUCTION

Real-time health data collection is very common nowadays. This data is processed by various signal processing and machine learning algorithms. The procedure of mining and reasoning are similar in different applications. Researchers and engineers working with real-time signals perform similar preprocessing and processing steps prior to derivation. The collected data can be used to get real-time offline multiple results of the condition of the patient [2]. The real health app requires real-time analysis of high-resolution sensor data as well as data from other sources. At the same time for collection of data from many users and local processing of all the data on a single computer can be achieved by calculation constraints, reliability, recovery scalability, fault/power supply problems, etc. It is not possible practically.

Recently, there has been a great interest in optimizing algorithms and increasing the efficiency of the system through system implementation [3]. But these methods only suggest a solution to a particular problem. They include design decisions that are difficult to generalize due to certain assumptions in the problem. The application of these challenges requires the implementation of a dependent machining platform efficient enough to work under real-world hardware and software constraints. It also applies to commonly enough support problems at the same time. This work and the construction of this problem will solve the intelligent distribution of the computational load published contract scheme.

The analysis of health data generally represents the diameter of a pre-defined basis of the extracted health measure compared. Symptoms can be detected when the readings are higher or lower than the threshold. Early detection of symptoms of heart failure can support the prediction of heart failure stroke and so they can be avoided. Therefore, the most important task is to define the “Accurate” threshold. The accuracy of the analysis depends strongly on the accuracy of the threshold used.

The cardiologist defines and updates the thresholds based on the measurements of the patient and the conducted interview with the patient [4]. In fact, cardiologists confirm that the values of the thresholds are not the same for all patients and can vary even for the same patients. As a result, there are 2 goals for this work. Firstly, propose a monitoring approach to remotely extract health parameters from patients suffering from heart failure will then define an analytical approach to automatically calculate and update the health threshold at the run time.

II REVIEW OF LITERATURE

Mdhaffar Afef, Charfi Khalil, Freisleben Bernd, and Abid Leila [1], presented the health analysis technique for the prediction of heart failure stroke and for this they used a combination of CEP (complex event processing) technology with statistical approaches. Advantage of this approach is that the, it automatically calculated thresholds and it can be updated at the runtime. For this experiment, they used MIMIC II Waveform Database Matched Subset from the Physionet benchmark.

Md Islam, Wang Xiaoyi, and Hayley Germack [2], they present a review on the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) and guidelines of database search were conducted between 2005 and 2016. Key elements of the selected research-health care sub-areas, data mining techniques, types of data analysis, and data sources-provide a systematic view of development in this area know that the existing literature is mainly examining the analysis in clinical and administrative decision making. The popularization of the electron Karte in the clinical care is considered, the utilization of the data which the human produces is the mainstream. However, analysis-based websites and social media data have been on the rise in recent years.

The use of automatic devices for monitoring biological parameters in real time is an effective tool for improving the quality of life of patients. The integration of mobile communication with wearable devices has facilitated the transition from clinical-oriented monitoring to patient-oriented monitoring. This paper proposes a real-time monitoring system; this system is conceptualized for the providing an instrument for patients, with the help of which they can easily monitor, analyze and save their own vital signs using wearable sensors and Android devices such as smartphone or tablet, offering an effective solution in terms of decrease in time, human error and cost [3].

Storing information is also a problem due to a large amount of sensor data generated by each sensor. Manashty Alireza, Light Janet and Yadav Umang [4], proposed the HEAL (Health Event Aggregation Lab) model that provides developers with services to use previously processed similar data and relevant identified symptoms. The proposed Architecture is cloud-based and provides services for input sensors, IOT devices, and content providers. The ultimate goal of the system is to fill the gap between symptoms and diagnostic trend data to accurately and quickly predict health anomalies.

Kakria Priyanka and Kitipawang Peerapong [5] proposes real-time heart monitoring techniques, taking into account the cost, ease of use, accuracy, and security of data. The system is conceived to provide an interface between doctor and patients for two-way communication. The aim of this work is to assist remote cardiac patients in obtaining the latest medical services, which otherwise could not be possible due to the low doctor-patient ratio. The developed monitoring system is then estimated for 40 people (ages 18 to 66 years) using wearable sensors, the holding device. Performance analysis shows that the proposed system is reliable and useful due to the high speed.

Banos Oresti, Damas Miguel, Villalonga Claudia, and Pomares Hector, presented PhysioDroid this technique provides personalized tools for remote monitoring and evaluation of user conditions [6]. The PhysioDroid system provides a comprehensive and continuous analysis of vital functions such as Heart Rate, Electrocardiogram, Skin Temperature Respiration Rate, and Body Movement, it also helps to empower patients and improve clinical understanding. PhysioDroid consists of a wearable monitoring device and an Android application that provides the storage, collection, and processing of physiological sensor data. The versatility of the developed application allows you to use it for both ordinary users and professionals, and the reduced cost of PhysioDroid makes it available to most people. To illustrate the capabilities of PhysioDroid, two examples of use for health assessment and sports training were presented.

The Complex Event Processing (CEP) uses an event-driven approach and correlates various sensor flows with spatiotemporal constraints to detect anomalies. This article presents CEP techniques which are CEP based Remote Health Monitoring System (CRHMS). The proposed CRHMS uses biosensors (Respiration Rate, Heart Rate, Blood Pressure, and ECG) to collect vital parameters and environmental sensors (Global Positioning System (GPS), Accelerometer) to identify the context of an elderly patient who is home alone. These sensor parameters are collected on the android phone and sent as a stream to this system to detect anomalies in vital signs and generate alerts [6].

Timeliness and flow processing are critical to justify the need to develop a new class of systems capable of processing not only general data but also event notifications from various sources to identify interesting situations with respect to the traditional Database Management System (DBMS). Accordingly various systems namely Information Flow Processing systems (IFP), have emerged and are competing in recent years. In this paper, autho propose how semantic technologies can contribute to the field of complex events and explore their support in health monitoring. This approach combines the semantic web methodology and the CEP model in the health monitoring platform [7].

Advances in the development of medical devices and in widespread use the existence of networks of data transmission allow you to equip more patients' devices telemetering. As a result, the interpretation of the data collected is becoming increasingly complex. Medical observations are traditionally interpreted in two competing ways: using established rule-based theories and statistically (possibly leading to new theories). In this article, they learn a hybrid approach that allows both evaluating a fixed set of rules and coexisting with machine learning [8].

Heinze Theodor, Wierschke Robert, Lowis Martin, and Schacht Alexander [9], discuss WANDA (an activity with weight and blood pressure monitoring system); using sensor technology and wireless communication, where they oversee the measurement of CHF patient’s health-related sensors, consisting of three-layer architecture in the WANDA system, web-server-based. This study, paired with the UCLA nursing school and the UCLA Wireless Health Institute, shows that CHF patients whose readings are monitored by WANDA are less likely to fall out of the healthy range in order to allow early detection of critical clinical symptoms that indicate decomposition associated with CHF. In addition, WANDA provides a useful feedback system for regulating the reading of CHF patients.

The article presents an Edge-Computing-Based complex event processing (CEP) Architecture for remote patient monitoring (RPM), which is an important issue in the context of remote health [10]. In this, they identify complex events that may indicate impending health problems is performed on a mobile device that receives data from sensors attached to the patient's body. Identified a set of activities are sent to the hospital server in the cloud for further processing. Modern technology used RPM for the mobile device as an agent of the gateway of the internet of things to forward streams of sensor data of health on a remote server of the hospital where the detected complex event.

Sensor data web enablement is an important mission in providing access anytime, anywhere. In particular, it is indispensable in telemedicine monitoring of elderly patients who are alone at home. Continuous monitoring is necessary for the patient to wear body wireless sensor information for the parameters. Sensor Web Enablement (SWE) is a platform to make the raw sensor data available on the web to become accessible to physicians for making a clinical diagnosis, collecting sensor data effectively and implementing Service Oriented Architecture (SOA). Using the web to capture the raw relationships between events, to find out the complexity of the threat, it is possible to overcome these challenges [11].

The system is designed to be independent of and adaptable to therapy and decease. To achieve this goal, there must be a classification machine for both data models. The realization of the approach to this flexibility will help open data models, computer simulations of updated “Static” rules, machine learning. At present, the integration of case-based inference components as described in the paper is considered [12].

System applications are provided for recording activities, events, and potentially important medical symptoms. The activity such as walking and traveling is detected from the motion of the body recorded by the P-wave of the ECG signal, the complex of QRS, and the accelerometer sensor analyzing the T-wave on the server to which the features of the ECG are connected to the base station receiving data from the wireless sensor of the patient body. IEEE802. 154 are used for wireless communication between sensors and base stations. If any abnormality occurs on the server the alarm status will send to the doctor's personal digital assistant (PDA) [13].

Anliker U., Lukowicz P., and Schmid R. [14], Alert Portable Telemedical Monitoring (AMON) techniques proposed which were wearable medical monitoring and warning system for the high-risk heart/respiration patient was described. The system includes a continuous collection and evaluation of multiple indications, an intelligent multi-parameter medical emergency detection and a cell connection to a medical center. By integrating the entire system into a discreet wrist-mounted enclosure and applying aggressive low-power design techniques, it interferes with patient's daily activities in the first two and a half years of this EU IST-sponsored project, the AMON consortium has developed a wrist-mounted device, a communication link, and a comprehensive medical center software package.

III PROPOSED APPROACH

Proposed System Overview

The block diagram of the proposed architecture is shown in figure 1 below. A detailed description of this architecture: Congestive Heart Failure (CHF) occurs when the heart is unable to provide enough blood for a healthy physiological condition. CHF usually occurs when the heart tissue becomes ischemic due to blockage of the coronary vessels. The data used for data analysis such as Linear Regression, Missing Enrollment Data, Search Signal, Clinical Data Security Projects, and Early Adaptive Alarm. In this architecture, the threshold values are automatically computed by using statistical approaches. The generated thresholds depend on the patient state and his/her historical measurements. The idea consists of detecting heart failure symptoms and consequently predicting critical situations (i.e., strokes). Modules of this system architecture are given below:

The proposed system consists of different modules listed below:

Module Description:

- **Module 1: Processing Servers and Storage**

In this module find out the health indicator such as heart rate, blood pressure. These data are collected from three sensor BP sensor, temperature sensor, and Heart rate.

- **Module 2: Data Preprocessing**

In data preprocessing stage, input data which collected from sensor i.e. raw data are transformed into the understandable format and data is preprocessed, smoothing noisy data and missing values are replaced with threshold values or Zero.

- **Module 3: Feature Extraction**

After the data preprocessing feature values of data are calculated using principal component analysis techniques. The goal of PCA is to data reduction and ranking of high impact columns. After selecting high impacted columns it extracted features from this column like weight, blood presser, and body temperature.

- **Module 4: Classification and Prediction using C4.5**

The C4.5 algorithm builds the decision trees from a set of training data. Such as the training dataset S = $\{S_1, S_2 \ldots S_n\}$ already classified samples data and each sample S_i consists of the P-dimensional vector such as $(X_{1,i}, X_{2,i} \ldots X_{p,i})$ where, X_i is represent attribute values or features of sample as well as class in which S_i. At each node of the tree, C4.5 chooses the attribute of the data that most effectively splits its set of samples into subsets enriched in one class or the other. It creates training, testing files using extracted features and performs classification.

- **Module 5: Classification and Prediction using MLP**

It creates training, testing files using extracted features and performs classification using MLP. The MLP classifier trains the data using back propagation algorithm. It passed the input attributes to the input layer of MLP model. The activation function used to train the data was sigmoid activation functions. With multiple hidden layers, it could reduce errors while training the data.

- **Module 6: Recommendation of Treatment to Patients :**

Finally, this system recommends treatment to patients.

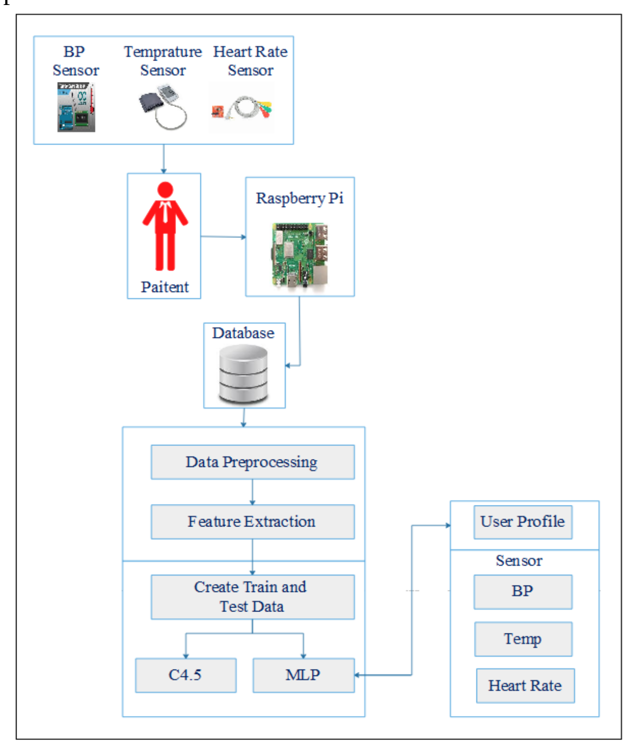

Figure 1:Proposed System Architecture

Algorithm

- **Algorithm 1: C4.5 Algorithm**

Process:

1. Check for the below base cases:
   i. All the samples in the list belong to the same class. When this happens, it simply creates a leaf node for the decision tree saying to choose that class.
   ii. None of the features provide any information gain. In this case, C4.5 creates a decision node higher up the tree using the expected value of the class.
   iii. An instance of previously-unseen class encountered. Again, C4.5 creates a decision node higher up the tree using the expected value.
2. For each attribute a, find the normalized information gain ratio from splitting on a.
3. Let a_best be the attribute with the highest normalized information gain.
4. Create a decision node that splits on a_best.
5. Recur on the sublists obtained by splitting on a_best, and add those nodes as children of the node.

Algorithm 2: Multi-Level Perceptron Model (MLP)

Algorithm:

1. Step 1: Initialize weights at random, choose a learning rate η
2. Until the network is trained:
3. For each training example i.e. input pattern and target output(s):
4. Step 2: Do forward pass through the net (with fixed weights) to produce output(s)
   a. i.e., in forwarding Direction, layer by layer:
      i. Inputs applied
      ii. Multiplied by weights
      iii. Summed
      iv. 'Squashed' by the sigmoid activation function
      v. Output passed to each neuron in the next layer
   b. Repeat above until network output(s) produced
5. Step 3: Back-propagation of error
   i. Compute error (delta or local gradient) for each output unit δ_k
   ii. Layer-by-layer, compute error (delta or local gradient) for each hidden unit δ_j by back-propagating errors (as shown previously)
6. Step 4: Next, update all the weights Δwij By gradient descent, and go back to Step 2

The overall MLP learning algorithm, involving forward pass and backpropagation of error (until the network training completion), is known as the Generalised Delta Rule (GDR), or more commonly, the Back Propagation (BP) algorithm.

Mathematical Model

Let S be system such that

S = Let S be the system such that

S = {I, P, O, Sc, Fc}

Where;

I = Input of system

P = Process in system

O = Output of System

Sc = Success case of output of system

Fc = Failure case of output of system

I = {I1, I2… In};

Where;

I = Input dataset

Process: Collection of data from the different sensor of patients' body part.

1. P1 = {I1} *// Read dataset*
2. P2 = {P1};
   P2 = {P_{21}, P_{22}… P_{2n}}
   Where, P2 represent the set of feature and P_{21}, P_{22}...P_{2n} are number of feature.
3. **Pre-processing of data:**
   In this section, data is converted into the CSV files.
4. **Feature Extraction:**
   Here features are extracted.
5. **Moving Average (MA):**
   $$Simple\ MA\ (t) = \frac{\sum_i^p Values_i}{p} \quad (1)$$
   The Weighted Moving Average (WMA):
   $$Weighted\ MA(t) = \frac{\sum_i^p (p-i) Values_i}{\sum_i^p (p-i)} \quad (2)$$
6. **Classification:**
   $$S = -\sum_{i=1}^{k} \{[frq(c_i, S)/|S|] log_2 [freq(c_i, s)|S|]\} \quad (3)$$

   Where, |S| is the number of cases in the training set, C_i is a class, i = 1, 2… k, k is the number of classes, freq(C_i, S) and is the number of cases in $C_{i...}$

7. **MLP:**
   The two common activation functions are both sigmoids and are described by
   $$y(v_i) = \tan h\ (v_i) \quad (4)$$
   and
   $$Y(v_i) = (1 + e^{-v_i})^{-1} \quad (5)$$

`

The first is a hyperbolic tangent that ranges from -1 to 1, while the other is the logistic function, which is similar in shape but ranges from 0 to 1. Here, $_{Yi}$ is the output of the ith node (neuron). $V_{i\ s}$ the weighted sum of the input connections.

IV RESULT ANALYSIS

A. *Experimental Setup*

For this work, the required technologies:

- **Software Technology:**
  6. Technology: Core Java
  7. Tools: JDK 1.8, Netbeans 8.0.2
  8. Operating System: Windows 7
- **Hardware Technology:**
  1. System: Pentium IV 2.4 GHz.
  2. Hard Disc: 40 GB.
  3. RAM: 512 MB.
  4. Sensor 1: BP (Blood Presser Sensor)
  5. Sensor 2: Body Temperature Sensor
  6. Sensor 3: Heart Rate Sensor

B. *Dataset*

In this project MIMIC II waveform database used it matched subset from the Physionet benchmark this database is available on online and it is collected from bedside patient monitors in adult and neonatal ICU (Intensive Care Units). Waveforms include one or more ECG signals, and it also includes continuous ABP (Arterial Blood Pressure) waveforms.

A. *Expected Result*

Table III shows that comparison between existing system C4.5 algorithm and proposed system MLP algorithm. A proposed technique is more accurate than the existing techniques. Here, True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN). If a heart disease is proven present in a patient, the given diagnostic test also indicates the presence of heart disease, the result of the diagnostic test is considered true positive. Similarly, if a disease absent in a patient, the diagnostic test suggests the heart absent as well, the result is True Negative (TN). Both true positive and true negative proven condition (also called the standard of truth). However, no medical test is perfect. If the diagnostic test indicates the presence of disease in a patient who actually has no such disease, the test result is False Positive (FP). Similarly, if the result of the diagnosis test suggests that the disease is absent for a patient with a disease for sure, the test result is False Negative (FN). Both false positive and false negative indicate that the test results are opposite to the actual condition. Here, accuracy is calculated using this formula:

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

TABLE I. A CONFUSION MATRIX

	Patient with Heart Disease	**Patient without Heart Disease**
Patient with Heart Disease	TP	FN
Patient without Heart Disease	FP	TN

The data are collected from a standard dataset that contains 282 records. Table II shows that the accuracy of the proposed system, here TP rate is 258 is accurately classified. 14 records are wrongly classified, FP rate is also 14 and FN rate is 14.

TABLE II. RESULT FOR ACCURACY OF MLP SHOWING 98.99%

	Patient with Heart Disease	**Patient without Heart Disease**
Patient with Heart Disease	285	14
Patient without Heart Disease	14	10

TABLE III. COMPARISON OF C4.5 AND MLP ALGORITHM

Algorithm					
C4.5			MLP		
Precision	Recall	F1	Precision	Recall	F1
84.75%	100%	91.74%	87.18%	98.99%	95.00%

Figure 2 shows that the graph of accuracy comparison between existing system C4.5 algorithm and proposed system MLP algorithm. Result graph shows that the proposed system is more accurate than the existing system.

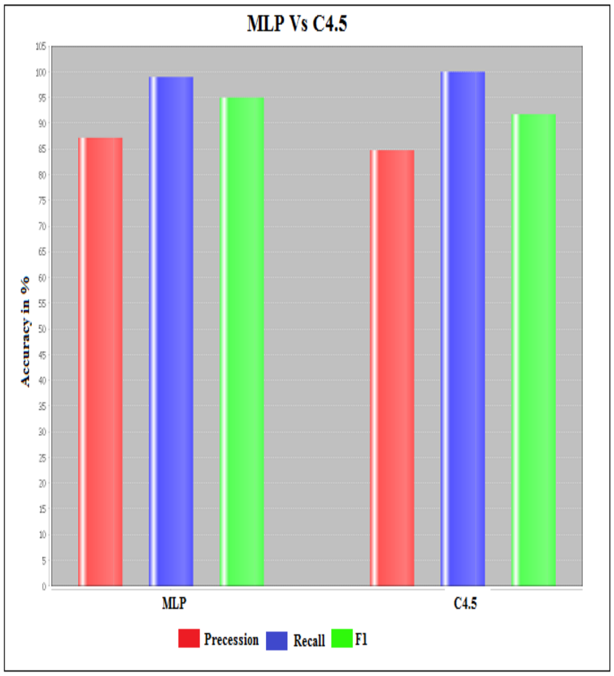

Fig. 1. Accuracy Comparision Graph of MLP and C4.5 Algorithm in Precision, Recall and F1

V CONCLUSION AND FUTURE WORK

In this, present new health monitoring techniques to the prediction of heart failures. In this, develop edge-computing based Complex Event Processing (CEP) techniques with the Remote Patient Monitoring (RPM) for the remote healthcare applications. It firstly, stored data in a database such as CSV file, and history of patients is created. After that data is preprocessed and missing values are replaced with threshold values or Zero. Feature values of data are calculated using the principal component analysis (PCA) techniques. Here, prediction of heart failures is calculated using multi perceptrons model (MLP). This technique can be used to the prediction of heart failures of patients. From a score of the result, it is recommended of treatment to patients like Gym, stress level management, etc. As a part of future work, this technique is applicable to other cardiovascular diseases.

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