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Heart Failure Prediction Technique using Complex Event Processing

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Abstract:*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 in world. Here, we propose new health monitoring techniques to the prediction of heart failures. In this, we propose 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 it is combined with the statistical approach. For the extraction heart defects of patients C4.5 algorithm and, to the prediction of heart failure multilayer perceptron (MLP) model will be consider. First phase is to collects health parameters. Second phase is to process the collected data using an analysis rule. This proposed system continuously monitors heart patient and it predicts heart failures strokes based on the related symptoms. When a critical condition occurs then it alters patients and cardiologist.*

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

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 pre-processing 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]. However, the use of health is very limited, due to the processing of the network requirements of the infrastructure. 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 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 practical.

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.

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 two goals for this work. Firstly, propose a monitoring approach to remotely extract health parameters from patients suffering from heart failure. It will then define an analytical approach to automatically calculate and update the health threshold at the run time.

A smart home monitoring system for tracks vital signs in patients with CHF. The system collects vital signs (SpO2, Electro Cardio Graph (ECG), Blood Pressure (BP), and Body Weight) and sends them to a hospital information system that is evaluated by a physician. The aim of this system is to reduce the number of face-to-face visits of each patient with help of CHF.

In this paper study about the Literature Review done, in section II, the Proposed Approach Modules Description, Mathematical Modeling, Algorithm and Experimental setup in section IIIand at final we provide a Conclusion in section IV.

II. LITERATURE REVIEW

Here we present the literature review of existing techniques:

Here, they present a review on thePreferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) and guidelines of database search was 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 they 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 are 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 [2].

Storing information is also a problem due to a large amount of sensor data generated by each sensor. In this [3], they 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.

In this paper, they propose 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 (Fig. smartphone under the supervision of experts). Performance analysis shows that the proposed system is reliable and useful due to high speed [4].

In this, they presented PhysioDroid this technique provides personalized tools for remote monitoring and evaluation of user conditions [5]. 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 are 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, they 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].

This article describes Wanda (Weight and Activity with Blood Pressure Monitoring System); a study that uses sensor technology and wireless communication to monitor health-related measurements of patients with CHF. The WANDA system is a three-tier architecture that consists of sensors, web servers, and server databases. The system was developed in conjunction with the UCLA School of nursing and the California wireless Institute of health for early detection of major clinical symptoms indicative of CHF-related decomposition [9]. This 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 architecture, the identification of 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 to health on a remote server of the hospital where the detected complex event.

III. PROPOSED APPROACH

A. Problem Statement

Develop a health monitoring application that remotely extracts health parameters from patients which are suffering from heart failure disease. Second, we define an analysis approach that automatically computes and updates health thresholds values at runtime.

B. Proposed System Overview

The block diagram of the proposed architecture is shown in Figure 1 below. Detail 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 is Linear Regression, Missing Enrollment Data, Search Signal, Clinical Data Security Projects, and Early Adaptive Alarm.

The proposed system including models such as server and data warehouse processing, pre-processing, characterization of extraction, classification of heart defects using C 4.5, prediction of heart failure using multi-perceptron model (MLP), the recommendation of treatment of patients as a gym, stress management level.

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:

- **Processing Servers and Storage:**
  Here firstly stored data in a database such as Mysql, No-SQL. So, the history of patients is created.
- **Data Preprocessing:**
  In data pre-processing stage, data is pre-processed and missing values of replace with threshold values or zero.
- **Feature Extraction:**
  After data pre-processing, feature values of data are calculated using the principal component analysis techniques. The goal of PCA is to data reduction and ranking of high impact columns.

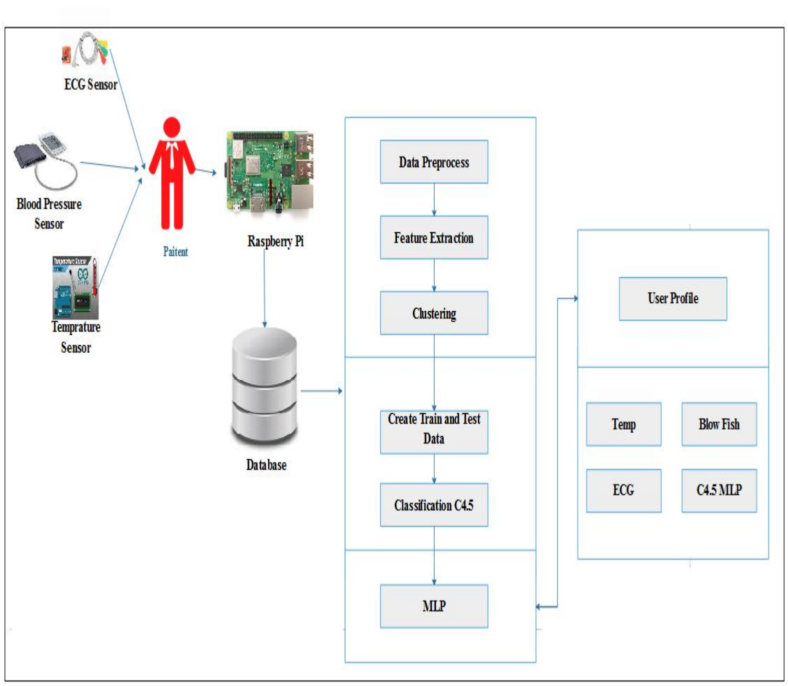

Figure 1: Proposed System Architecture

- **Classification of heart failures classes are detected using C4.5:**
  After selecting highly impacted columns we extract features like weight, blood presser, body temperature and ECG. Then we are creating training, testing files using extracted features and perform classification using C4.5
- **Prediction of Heart failures by MLP:**
  Here, the classified data is provided as input MLP algorithm and prediction of heart failures is calculated using multi-perceptrons model (MLP).
- **Recommendation of treatment to patients:**
  Finally, this system recommends treatment to patients like Gym, stress level management.

C. Algorithm

Algorithm 1: K-Means Clustering Algorithm

Let, X = {x_1, x_2,x_3,……..,x_n} be the set of data points and V = {v_1,v_2,…….,v_c} be the set of centers.

1. Randomly select 'c' cluster centers.
2. Calculate the distance between each data point and cluster centers.
3. Assign the data point to the cluster center whose distance from the cluster center I is minimum of all the cluster centers.
4. Recalculate the new cluster center using 'c_i' where 'c_i' represents the number of data points in the i^{th} cluster.
5. Recalculate the distance between each data point and new obtained cluster centers.
6. If no data point was reassigned then stop, otherwise repeat from step 3.

Algorithm 2: 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 3: Multi-Level Perceptron Model (MLP) Algorithm:

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

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

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D. 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 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 features and P_{21}, P_{22}...P_{2n} are number of features.
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):**

$$Simple\ MA\ (t) = \frac{\sum_{l}^{P} Values_i}{P}$$

   The Weighted Moving Average (WMA):

$$Weighted\ MA(t) = \frac{\sum_{l}^{P}(p-l)Values_i}{\sum_{l}^{P}(p-l)}$$

6. **Clustering:**

$$M_i^{t+1} = \frac{1}{|S_i^t|}\sum_{x_i \in S_i^t} X_j$$

   Where each x_i is assigned to exactly one S^t.
7. **Classification:**

$$S\ = -\sum_{i=1}^{k}\{[frq(c_i,S)/|S|]log_2[freq(c_i,s)|S|]\}$$

   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.
8. **MLP:**
   The two common activation functions are both sigmoids, and are described by

$$y(v_i) = \tan h\ (v_i)$$

   and

$$Y(v_i) = \ (1 + \ e^{-v_i})^{-1}$$

   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, $y_i$is the output of the i^{th} node (neuron). V_i is the weighted sum of the input connections.

IV. RESULT AND DISCUSSION

Expected Result: Table 1 shows that comparison between existing system C4.5 algorithm and proposed systemMLP algorithm. A proposed technique is more accurate than the existing techniques.

Table 1: Comparison of C4.5 and MLP Algorithm

Algorithm	Accuracy in %
C4.5	90
MLP	93

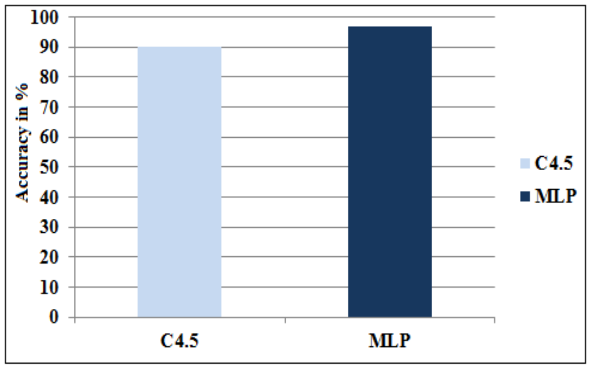

Figure 2: Comparison Graph of C4.5 and MLP Algorithm

V. CONCLUSION AND FUTURE SCOPE

In this, we present a new health monitoring techniques to the prediction of heart failures. In this, we develop edge-computing based Complex Event Processing (CEP) techniques with the Remote Patient Monitoring (RPM) for the remote healthcare applications. We firstly stored data in a database such as Mysql, No-SQL and history of patients is created. After that data is pre-processed and missing values of are replaced with threshold values or zero. Feature values of data are calculated using the principal component analysis (PCA) techniques. Here, extracted features are given to the classification using C4.5 algorithm and prediction of heart failures is calculated using multi-perceptron's model (MLP).This technique can be used to the prediction of heart failures of patients.Form score of the result it is recommended of treatment to patients like Gym, stress level management etc.

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