Implementation of Event Triggering Algorithm for Remote Patient Monitoring using Fog Computing

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***Abstract*:- Internet of Things (IoT) technology provides a competent and structured approach to handle service deliverance aspects of healthcare in terms of mobile health and remote patient monitoring. IoT generates an unprecedented amount of data that can be processed using cloud computing. But for real- time remote health monitoring applications, the delay caused by transferring data to the cloud and back to the application is unacceptable. R elative to this context, we proposed the remote patient health monitoring in smart homes by using the concept of fog computing at the smart gateway. The proposed model uses advanced techniques and services such as embedded data mining, distributed storage, and notification services at the edge of the network. Event triggering based data transmission methodology is adopted to process the patient's real-time data at Fog Layer. Temporal mining concept is used to analyze the events adversity by calculating the temporal health index (THI) of the patient. In order to determine the validity of the system, health data of 67 patients in IoT based smart home environment was systematically generated for 30 days. Results depict that the proposed BBN classifier based model has high accuracy and response time in determining the state of an event when compared with other classification algorithms. Moreover, decision making based on real-time healthcare data further enhances the utility of the proposed system.**

Keywords: Internet of things (IoT), Fog Computing, Temporal Mining, Temporal Health Index (THI), Bayesian Belief Network (BBN).

1. I NTRODUCTI ON

CI SCO coined the term fog computing which allows software applications to run on the edge of the network devices rather than on cloud computing datacenters. Fog computing not only brings the cloud computing paradigm to the edge of the network but also addresses unsupported or unfit fundamentals of cloud paradigm. The problems like edge location, high latency, location awareness, reliability, and moving data to the best location for processing are resolved by fog computing [1] [2]. Fog can be described as placing light- weight cloud like facility at the proximity of the mobile users. Indispensably, Fog is deployed at location sites, by providing engaged localization services desirable to mobile users. Fog based IOT system consists of three layers namely device layer, fog layer, and cloud layer, as shown in Fig.1. The fog layer first analyses the health data collected from various IoT and medical sensors only notifies the cloud layer in case of an adverse event happening situation. However, the number of Fog-based applications is increasing. As expected, in 3-5years, the number of Fog-based applications might become more than the IoT itself. Fog layer analyses the real time- sensitive data at the network edge instead of sending a vast amount of data to the cloud.
In addition, at fog layer, each fog node communicates with other nodes in its computing environment to initiate an action. Because of the proximity to the end-users compared to the cloud data-centers, fog layer has the potential to offer services like latency reduction for Quality of Service (QOS) and stream mining resulting in superior-user experience. Furthermore, many applications are recently developed using IOT technology which requires real-time data analysis and decision making. Cloud computing setup cannot fulfill real-time requirements in many applications. In addition, IoT applications such as Smart Grid, Smart Homes, and ICU are latency sensitive and therefore require immediate analysis of data and decision making as a conduction of action [3]. So, an intermediate layer has been proposed by Cisco termed as fog layer which can perform real-time analysis of data generated by IoT device with minimum-latency. Fog computing can increase the effectiveness of most of the IOT applications which in turn can increase the number of smart environments. In our approach, Fog assisted-IOT enabled smart home patient monitoring system is developed by considering various event instances. Fog layer calculates the event severity in real-time and then sends selected data to the cloud for further analysis. The objectives of our paper are i) Monitoring patient in the smart home environment using IOT devices. ii) Fog computing based event classification for real-time response. iii) Event triggering mechanism based temporal mining of patient health data at Cloud layer. Real-time alert based decision making with information deliverance in various circumstances to the doctor and care givers.

2. RELATED WORK

The fog computing based patient health monitoring system is a new concept in this era. Deploying fog server reduces the bandwidth Concentrating on these concepts, we divided the related work into two subsections i) Fog computing in Health Care System ii) IoT based Remote Health Monitoring.

➢ Fog Computing in Health Care System

In 2016, Ahmad et al. [4] proposed a framework for health-care known as Health Fog in which fog layer is used as an intermediary layer between cloud and the end users.

2017, Negash et al. [7] focused on a smart e-health gateway implementation for use in the fog computing layer. They emphasized mainly on connecting a network to such gateways, both in home and hospital us.

➢ I OT based remote health monitoring

IoT based remote monitoring systems have been suggested by various researchers due to their high efficiency in delivering intensive time-sensitive information to the clients. In 2011, Suh, et al. [9] proposed a wireless sensor based system for chronic heart failure patients. The system comprised of three-tier architecture consists of sensors, web servers, and databases. The system, upon implementation, registered a high rate of acceptability and feasibility in detecting different heart-related symptoms. In 2013, Jara et al. [10] proposed an interconnection framework for mobile health by utilizing the ubiquitous sensing capability of IoT devices. They introduced technical innovations for empowering health monitors and medical devices with internet capabilities.

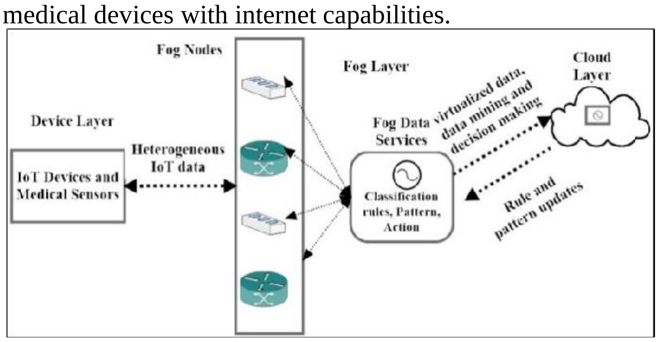

Fig.1. Fog computing basic model

3. PROPOSED SYSTEM

The main objective of this model is to monitor patients requiring intensive care at remote using Fog centric IoT technology. Fog layer consists of fog nodes, located at the network edge as shown in Fig.1. Moreover, Fog features like real-time interactive services, mobility support, and scalability can serve as an optimal choice in IoT based health monitoring environment. The proposed layered approach for Fog based smart remote patient monitoring is composed of five layers, namely: i) Data Acquisition Layer (DAL) ii) Event Classification Layer (ECL) iii) Information Mining Layer (I ML) iv) Decision Making Layer (DML) v) Cloud Storage Layer (CSL). Each layer performs its requisite function, thereby providing efficient services for adjacent layers.

❖ ***Data Acquisition Layer***

Data Acquisition Layer performs the task of data retrieval from IoT devices about various events inside home environment related to the patient directly or indirectly. Data is retrieved ubiquitously from various wireless hardware devices embedded at different locations at home and from body sensing network of the patient. These hardware devices work on wireless sensing phenomenon and have the capability of sensing and transmitting data in real-time. Each sensor node is integrated with bio-sensors and other medical sensors. Person's physiological and environmental parameters are collected in textual, graphical and numeric form by coordinator known as Fog.

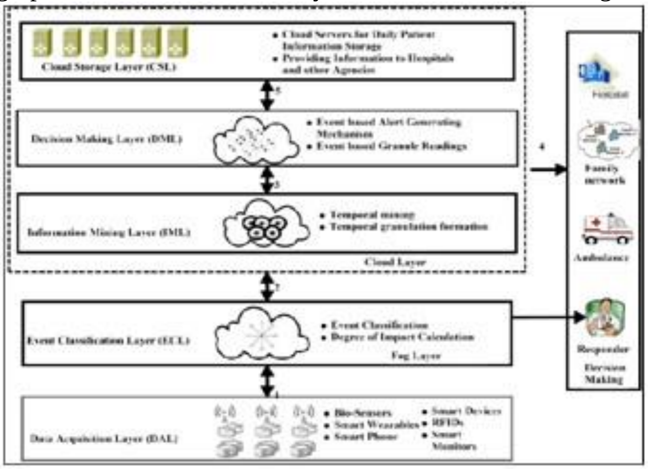

Fig.3 Layered architecture of the proposed system

❖ ***Fog Layer***

Event Classification: The patient communicates with this system by firstly registering his/her information at first Instance by answering questions related to health history and personal details. After registration, a unique identification number is provided to the patient by the cloud server. To perform the classification, cloud layer provides the patient identification (PID) and attribute sets related to health history of the patients to the appropriate fog node. The transmission channel is secured with Secure Socket Layer (SSL) for providing security and protection among different entities in the system. The current application scenario works in event triggered mode.

A sensitive or abnormal event indicates that the sampled data of a parameter is beyond its normal range. High temp, glucose level, bp are some of the instance of the sensitive event.

❖ ***Cloud Layer***

Analyzable format since patient health is a Sensitive parameter; data mining is purely based on temporal. Mining technique temporal mining is data mining technique for extracting data sets in time series pattern (tsp).

➢ Algorithm1Patient State Determination at Fog Layer

Input: N number of health attribute values, prefixed the threshold value for each attribute.

Output: Current state of the patient.

Step1: Determine attributes for the current context.

Step2: Calculate Degree of Impact (DOI).

Step2.1: If (DOI value in Abnormal Range) Then Patient State= U n safe. Go to Step 4

Step2.2: Else Patient State= Safe

Step3: Return Patient State.

Step4: Trigger the Event Occurrence= True

Step4.1: Generate early warning signal to responder.

Step4.2: Send vital data to the Cloud storage Repository for analysis.

Step5: Exit

❖ ***Decision Making Layer (DML)***

In other words, Fog layer determines the patient health state as a safe state (SS) or unsafe state (U S). SS denotes that there is no need to calculate the THI (TGS (I), Δt) value of the patient. On the other hand, US denote that the patient health is unstable and an immediate course of action is required by the responder. Moreover, if the patient health state is unsafe, then Any Event Occurrence = True will be triggered for two necessary actions. Firstly, the responder is intimated with early warning signals. Secondly, real-time health data

❖ ***Cloud Storage Layer (CSL)***

This layer plays a vital role in receiving and aggregating health data summaries of patients from various fog nodes as shown in Fig. 3. Moreover, this layer also provides information to decision making layer related to hospital location and other services for handling an emergency situation. Summarized data can be used by many hospitals and government agencies for of different machine learning algorithms are depicted. However, for further experiments, "fast.iamb" has been used in this section. Trained BBN classifier is tested in Weka 3.7 [20] to compute various statistical parameters. BBN classification is divided into two separate BBN components called as first and second stage, and experimental evaluation in three stages, explained as follows:

The first stage calculates the probability of environmental Exposure and patient medical history. Sampled event instanced at a are stored in fog node provided by Amazon. In our proposed system, different Amazon Machine Image (AMI) withed fault instance"m4. 2xlarge" is chosen to run on Cent OS 7 with a Linux 2.6.32Xen Kernel. Different classification algorithms such as neural network, k- nearest neighbor, and linear regression are also implemented to compare with our proposed BBN based method as shown in Fig.4, so that the utility of BBN in real-time monitoring environment can be experimentally justified.

➢ Fog assisted IOT technology readiness level in smart-homes:

Furthermore, from the smart home literature survey [19] we find a statistically positive correlation between Fog assisted IoT technology readiness (scale from 1to10) and the number of participants in the experiments conducted (Spear-The second stage calculates event happening probability when the first stage probabilities are statistically retrieved.

Complete BBN calculates event happening probability when Both BBN stages work collaboratively.

At different stages, BBN's classify event happening sensitivity with an accuracy of more than 85%. The detailed accuracy of each class parameter using BBN classifier is observed. Moreover, with the level of results conceived from the statistical parameter, we justify the applicability of the two-stage BBN classifier in our proposed system.

➢ Performance analysis of the proposed system:

Developing a new vaccine or medicine, for particular disease or survey oriented respectively. Lastly, this layer also sends application rules and pattern updates to fog data services as shown in Fig.1 for handling different applications. The patient is transferred to cloud layer for further analysis.

Algorithm 1: shows the procedure for determining the state of the patient based on sampled health and environmental attributes reading at Fog node. However, the parameters which are of direct interest are used to calculate the patient health state. In addition, the threshold value of concerned health and environmental attributes are fixed for determination.

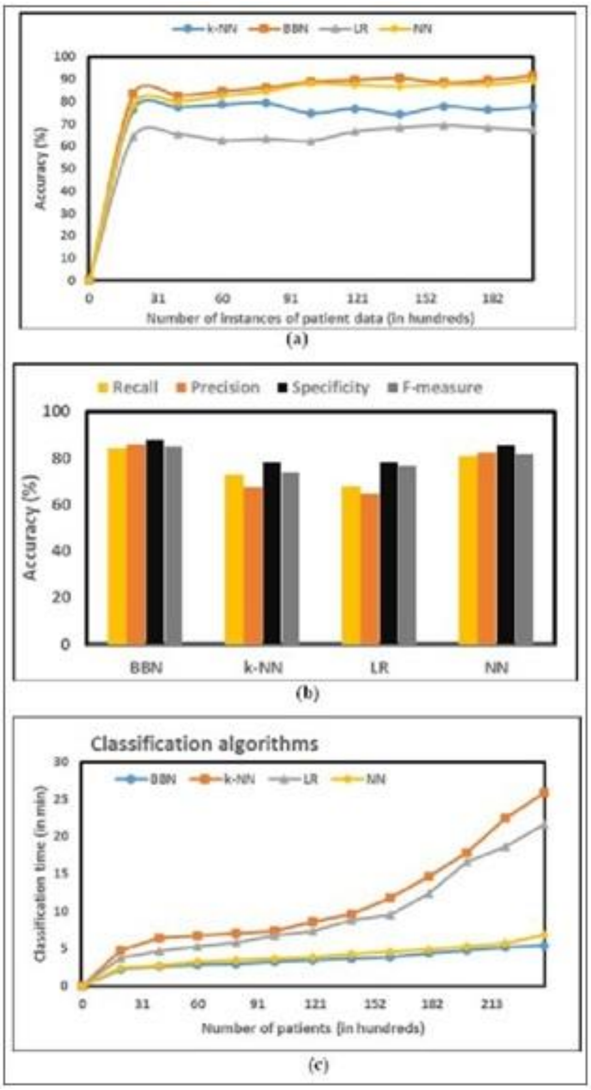

Fig.7 (a) Performance analysis of various classification tools over the Amazon Fog. (b) Accuracy of classification algorithms. (c) Classification time of each algorithm

Algorithm 2: To create data sets for smart home patient monitoring Input: Patient oriented data {Patient category ∪ health data ∪ Environmental data∪ number of data sets required}

Output: Health record data sets for each category.

Step 1: Let "n" be the number of records required at different time instancesinitializedwith1.

Step2.1: Assign value to health attributes as shown using probability set defined for each category.

Step2.2: Assign value to environmental attributes using probability set defined for each patient category.

Step2.3: Generate a new record by joining values of all attributes.
Step 2.4: If a new record with same values of patient readings is already present in data base then discard the new record Else Add the new record.
Step2.5: Increment "n" by one. End if End for readiness (8 and 9) and the study type (Pearson $\chi 2$ =5.673, p<0.014, df =1 and Phi association coefficient= +0.451). Also to find a positive association between Fog assisted IoT technology level (6) and study type we computed technical feasibility (Pearson $\chi 2$ =11.464, p<0.001, df =1andPhi association coefficient = +0.451).
From the Fig. 8, one can reach the conclusion that the types of conditions or behavior addressed by smart homes that are best handled in fog assisted I oT based smart home monitoring system are monitoring chronic pulmonary disease, health-related quality life and heart conditions of patients' with less focus on fall detection and monitoring daily activities in smart homes. Man's rho coefficient rxy= +0.439, p<0.002). In addition, we find randomized controlled trails between Fogs assisted IoT technology

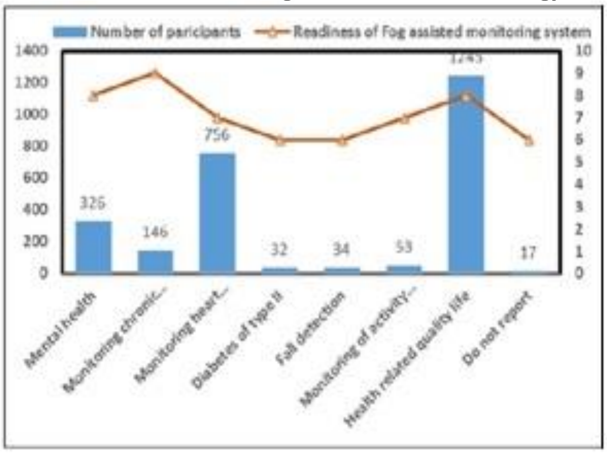

Fig.8 Smart home monitoring conditions vs fog assisted IoT technology readiness

4. CONCLUSION

It is quite apparent from the proposed framework that IoT based fog computing is delivering more effective patient sensitive information to the end users. I n this paper, we introduced fog layer at a gateway for augmenting health monitoring system that requires quick processing with minimal delay. We have classified patient health state as safe or unsafe using fog computing services by reducing the amount of data that is transferred to the cloud for processing and analysis. Real- time event instances are monitored at fog layer for computing event adversity. In addition, event triggering mechanism is adopted to transfer patients' health-related vital signal to cloud layer whenever patient state transitions to an unsafe state. Temporal health index (THI) of the patient is computed at cloud layer to determine the urgency of the situation. Different events are correlated in the form of temporal data granule for effective decision making. Information deliverance to the responder from cloud layer plays a pivotal role in handling medical emergencies. Lastly, a real-time alert generation with event severity computation further enhances the utility of the proposed system.

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