

IoT Based HealthCare Monitoring & Alert System

Prof. Dr. M. Sakhivel 

Head, Department of Computer Science and Engineering,
Sengunthar Engineering College (Autonomous), Tiruchengode, India

csehod@scteng.co.in

<https://orcid.org/0000-0003-4163-6630>

Ajay jeyakaran .M, Devakumaraesh. K, Jhayaadharsh. A. B,

UG Students, Department of Computer Science and Engineering,
Sengunthar Engineering College (Autonomous), Tiruchengode, India

ajayjeyakaran3@gmail.com, kumareshdeva0@gmail.com, jhayaadharshab@gmail.com



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BibTeX Key Prof. Dr. Sakhivel@2026IoT

Orcid: <https://orcid.org/0009-0004-9398-7488>

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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. Relative to this context, we proposed the remote patient health monitoring in smart homes by using the concept of fog computing at the smart gate way. 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.

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

INTRODUCTION

CISCO coined the term fog computing which allows software applications to run on the edge of the network devices rather than on cloud computing data centers. 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. Currently, the number of IoT based applications is more than the number of Fog-based applications. However, the number Prabal Verma and Sandeep K. Soodare with Guru Nanak Dev University Regional Campus Gurdaspur, Punjab, India. (e-mail: pra-balverma357@gmail.com, san1198@gmail.com)

In addition, at fog layer, each fog node communicate 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 requires 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. iv) Real-time alert based decision making with information deliverance in various circumstances to the doctor and care givers. This paper is framed in different sections. Section II provides an overview of some of the important literature in the field of Fog and IoT based monitoring system. The proposed layered frame work for Fog assisted smart home patient monitoring system is presented in Section III with complete explanation. Section IV discusses the experiments and performance analysis of the proposed real-time classification algorithms with relevant results. Finally, Section V concludes the paper with some appropriate remarks.

RELATED WORK

The fog computing based patient health monitoring system is a new concept in this era. Deploying fog server reduces the bandwidth requirement and increases the efficiency of the network by providing real-time information to the mobile users nearer to the edge of the network. Concentrating on these concepts, we divided the related work into two subsections

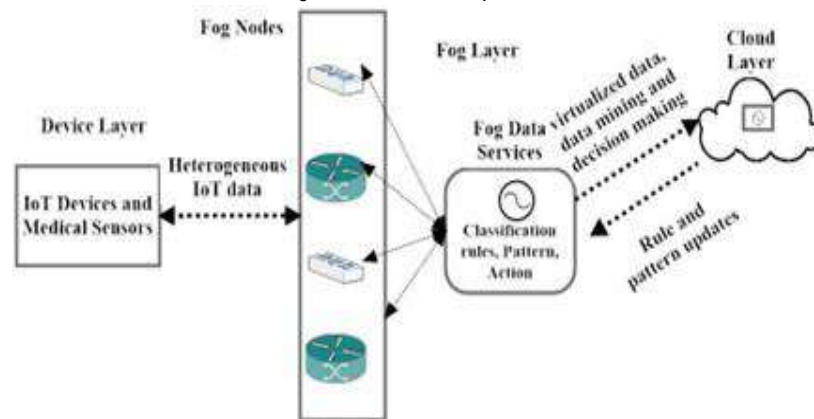


Fig.1.Fog computing basic model

- i) Fog computing in Health Care System
- ii) IoT based Remote Health Monitoring.

A. 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. Authors mainly concentrated on enhancing and flexibly controlling the data privacy issues in healthcare systems. To enhance the system security, cloud access security broker (CSAB) is integrated with Health Fog. Moreover, cryptographic primitives were also defined to increase the utility of the Health Fog. In 2016, Nandyala and Kim [5] presented an architectural view of IoT based u-healthcare monitoring system. This architecture mainly emphasized on advantages of Fog computing which interacts more by serving closer to the edge at Smart Homes and Smart Hospitals. In 2015, Gia et al. [6] proposed an enhanced cloud-based Fog computing system in which bio-signals are analyzed at the fog server side for real time applications. In 2017, Negashetal.[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 use. Moreover, features of the gateway in fog implementation are discussed and evaluated. In 2017, Rahmani et. al [8] used the concept of Fog computing in Healthcare IoT systems. An intermediary layer of intelligence is defined between sensor nodes and cloud. A prototype of a smart e-health Gateway is presented for implementation. They also implemented an IoT-based Early warning score (EWS) health monitoring to practically show the efficiency of the system by addressing a medical case study.

B. IoT 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. In 2013, Bane et al. [11] reviewed the current methods and algorithms used to analyze data from wearable sensors in healthcare services. They emphasized on anomaly detection, prediction and decision making when considering a particular time series measurements. Moreover, details regarding the suitability of particular data mining and machine learning methods were discussed using properties of datasets in experimental validation section. In 2013, Tomar and Agrawal [12] also explored the utility of various data mining techniques such as classification, clustering, association, regression in the health domain. Recommendation related to the suitability of available data mining techniques is suggested.

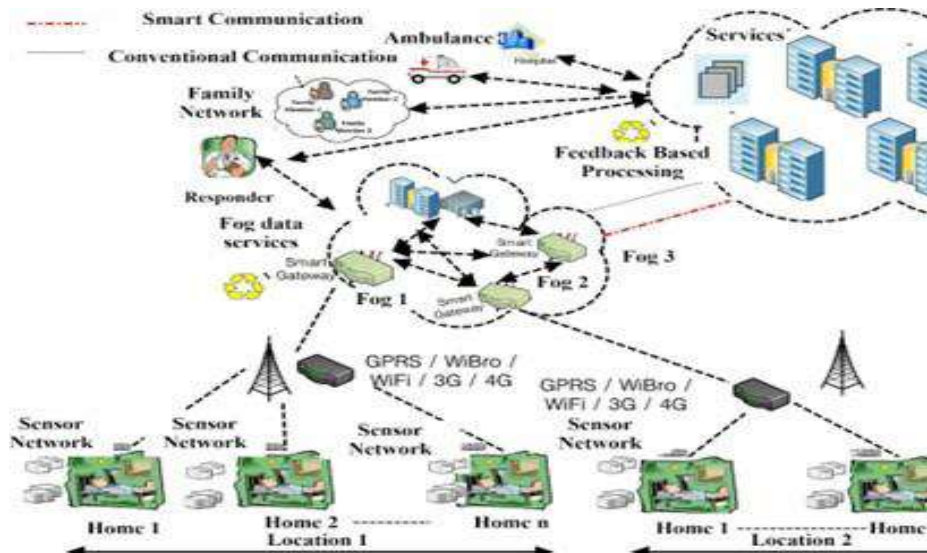


Fig.2. Fog computing based patient monitoring in smart home

In 2014, Xu et al. [13] provided a framework for medical services during an emergency by using IoT technology. A semantic model is designed to store and manage data generated by various IoT devices in real-time. Moreover, authors proposed a resource based data acquisition and processing methodology for IoT data during emergency medical services. In recent years, many researchers have proposed cloud assisted intelligent home based real-time monitoring systems [14][15] but have not laid emphasis on emergency and delay related parameters. Therefore, to handle health emergencies in real-time, fog computing based smart home environment is explained ahead.

III. PROPOSED SYSTEM

Fig. 2 demonstrates the basic work flow of various entities in the fog-assisted smart home environment. In smart communication mechanism, fog layer can retrieve the requisite information related to patient health history from cloud layer. On the other hand, in conventional communication, the updates related to fog node actions are transferred to the cloud with patient details for future necessary actions, further explained in Section III.B. To increase the novelty aspect of our proposed model, a layered architecture of Fog based Smart Home remote patient monitoring system is shown in Fig.3. By incorporating various IoT devices, sensors, and other internet assisted hardware devices, the system forms a sensor network capable of capturing different patient-oriented events in an efficient manner. 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 (IML) iv) Decision Making Layer (DML) v) Cloud Storage Layer (CSL). Each layer performs its requisite function, thereby providing efficient services for adjacent layers.

A. Data Acquisition Layer (DAL)

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. Therefore, these parameters results are converted into an adequate format by fog nodes before sending for further analysis at cloud layer. Fig. 1 shows the basic functioning of fog sub-system in our proposed methodology. Moreover, Fog nodes are programmed to synchronize the whole data collected from heterogeneous devices over a universal time stamp. Comprises of those events that can lead to patient health in the severe state. A sensitive or abnormal event indicates that the sampled data of a parameter is beyond its normal range. High temperature, glucose level, blood pressure are some of the instances of the sensitive event. Normal events are those events whose occurrence does not affect the patient health state. To classify the patient event data as abnormal or normal, Bayesian Belief Network (BBN) classifier is used [16]. It works on the principle of conditional probability and Naive Bayes classification procedure.

Any event I will be classified into normal class (N) and abnormal class (A) based on the readings (R) only if $P(N/R) > P(A/R)$, where $P(A/R)$ defines the probability of event I having class A for health data reading R. Similarly, $P(N/R)$ is defined as the probability of an event I have a class (N) if he/she has health data readings (R) which can be easily derived using Bayes Theorem as follows: 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 as shown in Table I. The transmission channel is secured with Secure Socket Layer (SSL) for providing security and protection among different entities in the system.

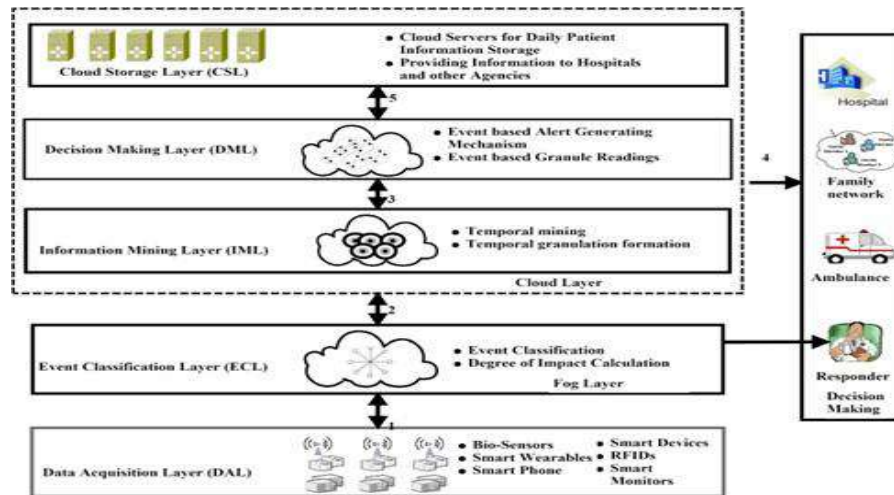


Fig.3. Layered architecture of the proposed system

The current application scenario works in event triggered mode. In this mode, the requisite real-time sampled data is stored at the fog nodes. The fog layer will conduct a data handling process by interacting with other fog nodes and fog data services for analysis. The data handling process compares the sampled data of each parameter with the corresponding range of normal values which is predetermined by practitioners. Heterogeneous data from various medical devices is converted into a requisite format before classification. Different datasets are formed to classify an event into two classes, namely normal event class, and abnormal event class. Abnormal event class comprises of those events that can lead to patient health in the severe state. A sensitive or abnormal event indicates that the sampled data of a parameter is beyond its normal range. High temperature, glucose level, blood pressure are some of the instances of the sensitive event. Normal events are those events whose occurrence does not affect the patient health state. To classify the patient event data as abnormal or normal, Bayesian Belief Network (BBN) classifier is used [16]. It works on the principle of conditional probability and Naive Bayes classification procedure. Any event I will be classified into normal class (N) and abnormal class (A) based on the readings(R) only if $P(N/R) > P(A/R)$, where $P(A/R)$ defines the probability of event I having class A for health data reading. Similarly, $P(N/R)$ is defined as the probability of an event I have a class (N) if he/she has health data readings (R) which can be easily derived using Bayes Theorem as follows: 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 as shown in Table I. The transmission channel is secured with Secure Socket Layer (SSL) for providing security and protection among different entities in the system. Here, $P(R/N)$ is the probability of having reading (R) when any event happening is calculated with N class. $P(N)$ is the probability of an event having normal class based on vital health parameters and $P(R)$ is the probability of having health readings (R). Naive Bayes classifier assumes conditional independence of all attributes, which is not possible while dealing with health attributes in patient healthcare domain. To overcome this issue, a two-stage BBN classifier is considered which consists of an important set of attributes described in Table I for correct prediction of the event. Fig. 4 shows a two-stage BBN for the proposed system. Environmental factors and patient's medical history plays a vital role in predicting the occurrence of an event in smart home patient monitoring environment. Moreover, patient's medical history consists of complex compound attributes (cardiac problem, diabetes, and other factors) so its results are computed in the first stage of BBN classification. The second stage of BBN classifier uses the output of the first stage BBN as well as some important distinct attributes to classify event based on Degree of Impact (DOI) score.

Definition #1: Degree of Impact(DOI): Given an event j in the time-interval $[t_i, t_{i+k-1}]$ where k is the number of time instances, the degree of impact is defined as the probabilistic value which can classify an event as in normal range or in an abnormal range. When an abnormal event happens, the transmission of current time-stamped data from the fog data services to cloud will be activated. A sequence of monitored vital signals (the pre and post five minute's signals of the event) will be sent to cloud layer for further analysis. Event Dataset: Studies have shown that people having regular health problems have reduced level of body immunity [9]. Therefore, such patients are more vulnerable to health problems as compared to other persons. Smart home patient health ambient environment is a heterogeneous environment which consists of different types of datasets defined ahead.

1. Health Related Dataset (HRD) : Health dataset includes data values that are directly concerned with patient health. These values are collected from the patient body sensor network. External monitors are used for calculating heart rate, nasal sensors for respiratory rate, arterial catheter sensors for blood pressure, pulse oximeter sensor for blood oxygen saturation, a temperature sensor for fever, glucometer adaptor for glucose level and pen handled Electrocardiograph (ECG) devices for heart-related issues. Moreover, patient health history is provided to each fog node by fog data services, which is nearer to the cloud server.

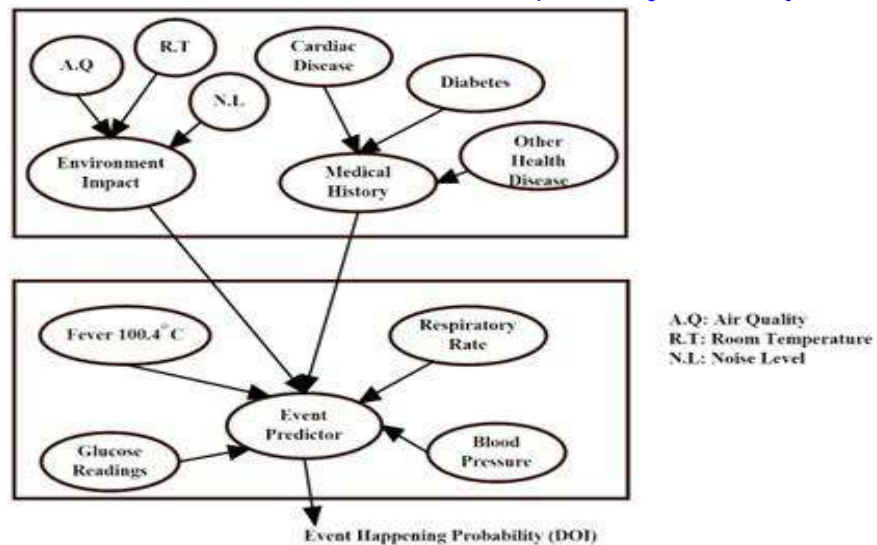


Fig.4. Two-stage Bayesian belief network for event detection

2. Environment Related Dataset (ERD): Method of conditional probability. Mathematically, THI ($TGS(P_i), \Delta t$) is represented. Many health researches have shown the importance of the environment for patient health. Therefore, in this study patient's environment related values are captured and stored in Environmental Dataset. It includes room temperature, room noise, air quality etc. Such kind of data is acquired by various sensors placed at different locations in the room.

3. Behavioral Related Dataset (BRD): In most of the cases, patients having regular health problems are bound to bed rest. Prolonged bed rest can lead to stress, anxiety, and restlessness among patients. Sensors are embedded along bedside or smart-wearable are used to capture such values for unstable patients. Mobile EMOTIV Electroencephalography (EEG) sensors are used as an electrophysiological monitoring method to record the electrical signals of the brain to handle behavioral related issues. Moreover, ECG and EEG signals consist of trillions of data points which cannot be analyzed at fog layer [17]. Therefore, whenever the patient DOI exceeds a certain level, fog layer immediately sends ECG and EEG signals to cloud layer for further analysis.

B. Cloud Layer: Information Mining Layer (IML): Information mining layer aims at extracting useful data from fog data services in real-time. In other words, it focuses on analyzing temporal diverse data retrieved from fog layer into a common analyzable format. Since patient health is a time-sensitive parameter, data mining is purely based on temporal mining technique [18]. Temporal mining is data mining technique for extracting datasets in time-series pattern (TSP).

Definition #2: (Time-series pattern) Given an attribute K and time window (Δt), a Field Time Series (FTS) can be defined as a set of m values over a certain time period: $\{ \langle t(s), v(s) \rangle, \langle t(s+1), v(s+1) \rangle, \dots, \langle t(s+m-1), v(s+m-1) \rangle \}$. Often the values are identified for a specific well-defined points in time, in which case the value may be viewed as a vector $\langle v(s), v(s+1), \dots, v(s+m-1) \rangle$. Here $\Delta t = |t(s+m-1) - t(s)|$ temporal granule for the time-series, formed using sliding window (SW) concept.

Corollary 1: Temporal Granule Series (TGS) at an instance t_a is defined as attributes selected from various datasets to form a relation set A_i , where i is an event type.

Corollary 2: Given a Temporal Granule Series (TGS) for a certain time interval Δt , a Temporal Health Index (THI) ($TGS(P_i), \Delta t$) is defined as a probabilistic value calculated from attributes values selected in TGS. Often multiple TGS's are parallelly analyzed to generate patient temporal health index.

In other words, THI determines the patients' health sensitivity index whenever an adverse event is detected. Higher THI value indicates that the health events are in adverse direction of patient's health and vice-versa. Moreover, the importance of THI lies in the fact that any abnormality in patient health can be conveyed to the responder (doctor) so that appropriate actions can be taken by the concerned emergency medical provider. To evaluate the THI value, one can adopt the averagely weighted or unsafe) and E_i denotes the severity of occurrence of event by computing results from temporal granule formation as shown in Fig. 5. Moreover, the parallelism concept with data abstraction at cloud layer can be achieved using Map and Reduce functions [19]. Map Reduce is parallel programming paradigm for distributed cloud databases and are commercially available. They provide a convenient way for programmers to process large data sets. Moreover, final monitored data in a fog-assisted smart home healthcare environment is stored at the private cloud for future references.

Algorithm 1 Patient 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 = Unsafe. Goto Step 4

Step2.2: Else Patient State = Safe

Step 3: Return Patient State.

Step3: Trigger the Event Occurrence=True

Step 3.1: Generate early warning signal to responder.

Step 3.2: Send vital data to the Cloud storage repository for analysis

Step4: Exit

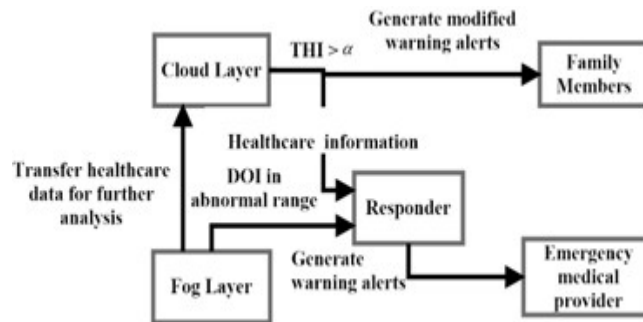


Fig.5. Temporal abstraction based granulation

Algorithm 2 Alert Generation with Temporal Health Index Calculation at Cloud Layer

Input: Event set = Health \cup Behavioural \cup Environmental

Step 1: Using Algorithm 1, Determine the State of the Patient.

Step2: Determine current time stamp.

Step3: If (Patient State= Unsafe and Any Event Occurrence =True), goto

Step 4 else gotoStep8//Any Event Occurrence is a variable used for managing an event. //

Step4: Do

Step4.1: Create a check point.//Check-point is a save point in time space. //

Step4.2: Empty Log//Record of events//

Step4.3: Start new session.//Granule formation for events.//

Step5: Add Event attributes to the Log for granulation based temporal information generation.

Step6: After Δt time, Determine Temporal Health Index (THI) of the patient.

Step7: If $(THI(TGS(I), \Delta t) > \alpha)$

Step7.1: Transfer log and health attribute information to the responder for emergency handling as shown in Fig. 5.

Step7.2: Generate modified early warning signal to family members.

Step 8: Repeat Step 1 after a definite time interval.

Step9: Exit

Decision Making Layer (DML): In other words, Fog layer determines the patient health state as a safe state (SS) or unsafe state (US). SS denotes that there is no need to calculate the $THI(TGS(I), \Delta t)$ value of the patient. On the other hand, US denotes 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 of 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 determining the DOI and is already explained in Section III.B. Algorithm2demonstrates that *AnyEventOccurrence* is an important parameter in fog-cloud based decision making procedure. Since, fog layer deals with events which are relatively simple. Therefore, for effective decision-making, event-based vital signals must be transferred to the cloud layer for computing patient's THI value. Log (record of events) can be used as a temporary buffer to store and analyze different event information over a sensitivity scale to generate THI value. The threshold value (α) is compared with $THI(TGS(P), \Delta t)$ value which is prefixed by the practitioner authorities. Threshold level (α) is different for each patient and is set based on patients' previous health history. Moreover, THI value is generated by computing mean result of each temporal granule instance taken into consideration as shown in Fig.5. If THI value surpasses threshold level then the patient must be shifted to hospital for emergency medical service. Fig. 6 demonstrates the real-time decision making in IoT based fog assisted smart home environment. The responder is intimated about patient health state via alert warning signal system from the statistics computed using DOI at fog layer. Moreover, the responder is also provided with patient's time-sensitive health information after computing the THI value at cloud layer. Based on this information, responder makes a decision on assigning the degree of urgency to the emergency medical provider. In addition, if the value of THI is above the threshold level, patients' family members are informed by generating modified warning alerts.

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 developing new vaccine or medicine for particular disease and survey respectively. Lastly, this layer also sends application rules and pattern updates to fog data services as shown in Fig. 1 for handling different applications.

EXPERIMENTAL SETUP AND ANALYSIS

This section evaluates the performance of the proposed framework and analyzes the results for efficiency purposes. Experimental setup of the proposed system is divided into four parts for proper understanding.

- i) Creation of smart home-based patient-oriented data.
- ii) Training and testing of BBN classifier.
- iii) Performance analysis of the proposed system on Amazon EC2.
- iv) Fog assisted IoT technology readiness level in smart homes.

Algorithm3

To create datasets for smart home patient monitoring

Input: Patient oriented data {Patient category \cup health data \cup environmental data \cup number of datasets required}

Output: Health record datasets for each category.

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

Step2: For $n \leq$ required number of records do

Step2.1: Assign value to health attributes as shown in Table1 using probability set defined for each category.

Step2.2: Assign value to environmental attributes as shown in Table1 using probability set defined for each patient category.

Step2.3: Generate a new record by joining values of all attributes.

Step2.4: 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. Endif End.

1. Creation of smart home based patient oriented data: Due to the high criticality of the application domain, smart home monitoring based patient datasets are systematically generated so that most of the cases can be covered in our experimental section. Initially, based on patient's health history attributes as shown in Table 1, 67 patients are classified into three categories i) healthy patient ii) patient exposed to diseases iii) patient with serious diseases. To effectively generate health record (HR) datasets for each category above, we utilize the static datasets, namely health data and environmental data. Health dataset was retrieved from UCI data repository comprising of 17,806 data instances of multiple time frames. It includes body temperature, blood pressure, heart rate and glucose level. Moreover, environmental data were obtained from US EPA data repository comprising of more than 18,000 data instances about environment attributes. Data acquired from these various datasets is stored at Amazon EC2 cloud. Using these datasets, we generated health record datasets by setting probabilities for health attributes and environmental attributes related to each category mentioned above. The criteria used to generate HR datasets for each category is shown in Algorithm 3.
2. Training and testing of BBN classifier: Systematic datasets generated using Algorithm 3 are utilized to test and train BBN-classifier. This classifier is used in our proposed methodology to categorize an event occurrence into normal and abnormal range. IoT healthcare dataset of 67 patients is utilized to develop a Bayesian network using R Studio based "bn learn" package. This package runs on Amazon EC2 virtual machine with four virtual CPUs and 2GB of RAM. This Table shows that, "gs" and "fast.iamb" can be selected for the proposed system due to less response time and more learned arcs. However, for further experiments, "fast.iamb" has been used in this section. Trained BBN classifier is tested in Weka3.7 [20] to compute various statistical parameters. BBN classification is divided into two separate BBN components called as first and second stage, as explained in Section III. Experimental evaluation in three stages, explained as follows:

1. The first stage calculates the probability of environmental exposure and patient medical history.
2. The second stage calculates event happening probability when the first stage probabilities are statistically retrieved.
3. Complete BBN calculates event happening probability when both BBN stages work collaboratively.

Summary of these three BBN models tested under Weka 3.7 is shown in TableIV and TableV. 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 listed in Table IV. Moreover, with the level of results conceived from the statistical parameter in Table V, we justify the applicability of the two-stage BBN classifier in our proposed system.

1) Performance analysis of the proposed system: Patient sampled event instance data are stored in fog node provided by Amazon. In our proposed system, different Amazon Machine Image (AMI) with default instance "m4.2xlarge" [21] is chosen to run on CentOS 7 with a Linux 2.6.32 Xen Kernel. Different classification algorithms such as neural network, k-nearest neighbour, and linear regression are also implemented to compare with our proposed BBN based method as shown in Fig.7, 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 [22] we find a statistically positive correlation between Fog assisted IoT technology readiness (scale from 1 to 10) and the number of participants in the experiments conducted (Spearman's rho coefficient $r_{xy} = +0.439$, $p < 0.002$).

2) In addition, we find randomized controlled trials between Fog assisted IoT technology 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 $\chi^2 = 11.464$, $p < 0.001$, $df = 1$ and Phi association coefficient = +0.451). Fig. 8 shows the fog assisted IoT technology readiness level versus a number of participants per condition or behavior addressed in the area of smart homes and health monitoring technologies.

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 IoT 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.

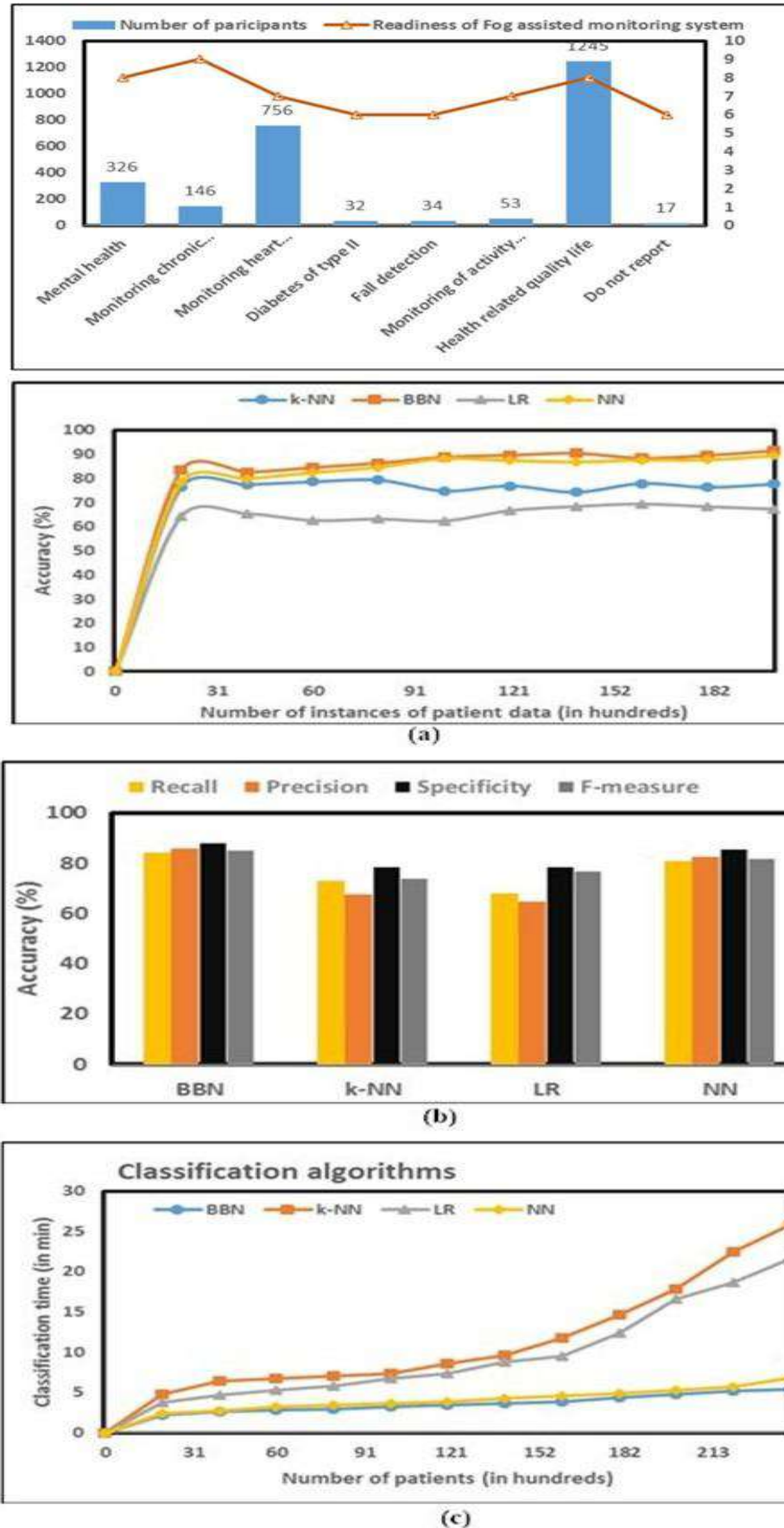


Fig.8. Smart home monitoring conditions vs fog assisted IoT technology readiness

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. In 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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