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MOBILE SYSTEMS

Temporal Informative Analysis in Smart-ICU Monitoring: M-HealthCare Perspective

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Abstract The rapid introduction of Internet of Things (IoT) Technology has boosted the service deliverance aspects of health sector in terms of m-health, and remote patient monitoring. IoT Technology is not only capable of sensing the acute details of sensitive events from wider perspectives, but it also provides a means to deliver services in time sensitive and efficient manner. Henceforth, IoT Technology has been efficiently adopted in different fields of the healthcare domain. In this paper, a framework for IoT based patient monitoring in Intensive Care Unit (ICU) is presented to enhance the deliverance of curative services. Though ICUs remained a center of attraction for high quality care among researchers, still number of studies have depicted the vulnerability to a patient's life during ICU stay. The work presented in this study addresses such concerns in terms of efficient monitoring of various events (and anomalies) with temporal associations, followed by time sensitive alert generation procedure. In order to validate the system, it was deployed in 3 ICU room facilities for 30 days in which nearly 81 patients were monitored during their ICU stay. The results obtained after implementation depicts that IoT equipped ICUs are more efficient in monitoring sensitive events as compared to manual monitoring and traditional Tele-ICU monitoring. Moreover, the adopted methodology for alert generation with information presentation further enhances the utility of the system.

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Keywords Remote patient monitoring · M-Health · ICU · Temporal associative granulation (TAG) · Internet of things (IoT)

Introduction

Innovative growth in Information and Communication Technology (ICT) has brought significant revolution in everyday lives [1, 2]. Development of numerous applications in different areas of healthcare, agriculture, transportation, logistics and other industrial sectors depicts its amazing impact [3, 4]. In the field of healthcare such technologies have raised the level of service design, implementation and deliverance, thereby giving rise to mobile health (m-health) systems and telemedicine [1, 5]. More importantly, this vision extends its realm to form a balance between remote patient-oriented care and optimal healthcare resource utilization [6]. Remote health monitoring for adult and critical patients, and health data sharing during medical emergency are important applications of m-health and telemedicine, which were difficult earlier due to under developed technology [7, 8]. One of such application is Tele-ICU that has been considered as an important area of research for monitoring critical patients under intensive observation from remote sites. ICU brings together patients with high death risk who require immediate, multiple health care intervention in a complicated environment [9]. On a contrary, studies have shown that ICUs are notable for high morbidity and mortality rates [10, 11]. Moreover, ICUs are vulnerable to adverse events than that of other healthcare facilities [12, 13]. According to a survey in [14], 87 % patients in ICU were registered with medical errors out of which 15.3 % resulted in adverse health conditions. ICU environment including noise, and room temperature also have an important role in delivering effective curative services [15, 16]. Patient with critical health conditions require time sensitive, intense surveillance by concerned doctors, and caregivers. This demand to more hospital staff availability and continuous monitoring, which even in the case of big hospitals, is a daunting task. However, in such a scenario, monitoring efficiently from a distant has added a new dimension to maintain patient wellness [17]. Increase in the usage of Mobile Internet, Internet of Things, and Cloud Computing have altered the course of information acquisition, storage, and analyzation [1, 18, 19]. IoT clubbed with cloud computing is a powerful platform for monitoring patients requiring continuous surveillance in ICUs by doctors, healthcare professionals, and caregivers from a remote site. This has been possible due to fairly inexpensive, secure, and reliable sensors. By embedding these wireless sensors inside ICU room, along the bedside, and on wearables, it has become possible to monitor both microscopic as well as macroscopic patient conditions. Moreover, early compilation of health statistics, identification of harmful healthcare anomalies, and remote doctor interventions have raised the level of diagnostic monitoring. Acquiring data about the minute level of activity inside the ICU and its influence on patient health has become a strategic tool to implement intensive care to patients. Analysis of such patient-oriented activities over temporal basis is vital for both doctors as well as to the patient in providing curative and diagnostic services. The traditional monitoring system only focuses on medication data and its temporal health effect. Moreover, other data like physical environment and dietary data are often ignored. This results in ineffective healthcare service provisioning. This paper provides a framework for monitoring critically ill patients in ICU from mobile site based on cloud centric IoT. The framework is designed to monitor various events or activities in an ICU room environment that are relevant to patient health directly and indirectly. Many studies have depicted that patient in ICU is more vulnerable to death or health severity from the ambient physical environment. Moreover, research also shows that most of the time patient in ICU is diagnosed with a new symptom due to medication error. Surveillance over such events comprises the monitoring core of the proposed system. These events are monitored by various sensors embedded inside the ICU room based on sensation area. Moreover, temporal analysis is performed by formation of temporal granules of different levels, resulting in Temporal Associative Granulation (TAG). Furthermore, an alert system with event presentation is proposed which helps doctors in early detection of patient severity, along with presenting important activity information. Thereby, timely actions can be taken in the direction of patient care.

This paper is divided into various Sections. Literature review is given in Section 2 having the details about various ongoing researches in remote patient monitoring, Tele-ICU, and mobile healthcare. Section 3 gives the detailed model architecture and related issues of IoT equipped monitoring in ICU. An experimental study is performed and various results are depicted in Section 4. Finally, the paper is concluded in Section 5.

Literature review

This section reviews some of the important works in the current perspective.

Remote patient monitoring

Ever since the advancement of mobile technology and telemedicine, numerous developments have been taking place in the healthcare sector [20]. Remote patient monitoring is well served with these wireless and ubiquitous sensing technology [21]. Giger et al. [22] have presented an analytical approach to monitor patient from a remote site. The proposed methodology was implemented in adult patients, and higher acceptance rate was registered. Variables like subjective norm, perceived usefulness, and feasibility were considered for acceptance. Moreover, results were drawn depicting linear trends among these different variables. Varshney [21] has proposed a conceptual model for ubiquitous patient monitoring to explore various complexities associated with it. The model captures process complexity, parameters and decision making criterion in different stages during remote monitoring. Moreover, various decision protocols and technologies have been depicted for supporting different processes. A study performed by Clarke et al. [23] have analyzed various operational scenarios and related requirements for monitoring patients remotely. For this, a framework is defined to indicate observational conditions of the sensing devices and transmitting gateway. Moreover, an extension to timestamp format of HL7 has been defined for distinguishing between local and universal time. Reliability is considered in the case of devices with simple or no clocks for timestamp provisioning. Hande et al. [24] have addressed the usage of wireless sensor network for monitoring vital sign in patients. Robust mesh networks have been designed using crossbow mechanical devices for routing data to base station within the hospital. Nodes used in network infrastructure were self-powered and retrieve energy via solar panels. Suh et al. [25] have described a three-tier remote system (named WANDA) for monitoring health related measurements for patients with Congestive Heart Failure (CHF). It comprises sensors, web servers, and database. In addition to this, a feedback system has been provided for regulating readings of CHF patients. The system is designed to detect key clinical symptoms indicating heart failure at early stages. Another kind of heart failure (chronic) is monitored in the work presented by Fanucci et al. [26]. An integrated ICT system is described for the purpose of acquiring vital signs of a patient and transmitting it to the Healthcare Information

System for remote patient monitoring. Moreover, the authors have developed a multi-channel Integrated Circuit for efficient cardiac data acquisition. Various medical experiments were performed for the proposed system and results showed that the system is capable of early detection of adversity in vital signs. Authors concluded that the proposed system allows early home intervention, and hospitalization reduction. A feasibility study has been presented by Sund et al. in [27]. Two objectives are considered by the authors for the study. One is to verify if electronic diary can be used with a portable spirometer by the patients suffering from Chronic Obstructive Pulmonary Disease (COPD) and another is to determine the values of symptom detection of acute exacerbations COPD. Real time data is sent during monitoring and corresponding score is evaluated from the initial phase to the final phase. During experimentation, results depicted early detections of symptoms among various patients. Moreover, with early doctor intervention, hospitalization of patients was considerably reduced.

Tele-ICU

Tele-ICU means using the off-site command center for monitoring patient in distant ICU by means of information exchange and communication technology. Many articles have been published regarding the importance and usefulness of indulging the concept of Tele-ICU in hospitals. Kumar et al. [28] have discussed the efficiency and cost-effectiveness of different applications in Tele-ICU. In addition, various barriers have been discussed that hinders its adoption in a broader way. The work presented by Hoonakker et al. [29] discusses various future opportunities for nurses while working at Tele-ICU. Khunlertkit and Carayon [30] presented a qualitative study analysis of Tele-ICU. Results depict that availability of extra resources and information reduces the mortality rate and period of ICU stay. Moreover, Tele-ICU improved compliance in evidence based medicine, medication management, and early detection of critical signs. A review article is published by Ramnath and Khazeni [31] depicting various advantages of centralized monitoring for ICUs. The authors have drawn conclusions that Tele-ICU has reduced mortality rate and enhanced staff acceptance, especially in rural areas.

M- health based on cloud computing platform

Cloud computing is considered as an effective platform in a wide variety of applications in different industrial fields in order to achieve ubiquitous data access [1]. In the healthcare sector, services based on cloud computing have the potential to reduce the costs encountered by patients [32]. He et al. [33] have proposed a layered architecture based on private cloud for healthcare service provisioning. The message queue is considered as a cloud engine, resulting in relative independence of various layers of the proposed model. Massive semi-structured and unstructured data are accessed by the private cloud. Results drawn upon testing depict that cloud platform is sufficient in handling requests from ubiquitous healthcare environment. Bahga and Madisetti [34] have discussed about new flexibility in the development of advance level healthcare application based on cloud computing. A framework for integrating heterogeneous health data is designed. Results showed that the system is easily accessible, and efficient in analyzation of dispersed healthcare data. In applications involving patient record maintenance, security is one of the prime requirements when considered on IoT backed up cloud computing platform, especially when remote monitoring is to be performed. Poon et al. [35] have proposed a biometric method by indulging intrinsic human body features as an authentication identity key for performing inter-sensor communication. Architecture based on the body area sensor network has been designed to optimize resource utilization and to establish an enhancement in controlling, scheduling and programming of the entire system. Sahoo [36] has studied various challenges such as privacy and security issues concerning m-health deployment in practical applications. A secure engineering process is proposed to provide architecture level protection with security and privacy legislation. Moreover, different use cases are defined, illustrating various security concerns among these contexts.

All the above mentioned work shows different aspects of Remote patient monitoring, Tele-ICU and Cloud based M-Health provisioning.

Proposed strategy

The proposed strategy for remote monitoring ICU patient is comprised of four layers, namely data acquisition and synchronization, event classification and cloud storage, information mining and analyzation and finally information presentation. All layers perform independently, thereby providing an efficient service environment for the adjacent layers. Initially, data is captured in real-time from various heterogeneous sensors in the data acquisition layer. These hardware devices are embedded in different places in ICU ensuring accurate data sensation. The data is sensed with respect to local or global clock. Therefore, synchronization layer is added to ensure universal synchronization among sensed data which is vital during data correlation. The collected data is transmitted to the cloud over a secure channel through centralized gateway. Cloud layer provides storage for the data received from various ICU sensors. Since heterogeneous data are sensed by different sensors depending upon various events, these are classified into different categories. Information mining and analyzation layer performs the task of extraction of information based on temporal analysis and formulation of data granules at different levels. An alert based system is proposed to generate alerts to doctors along with a presentation of different events. The entire system model is depicted in the Figs. 1 and 2.

Data acquisition and synchronization layer

Data acquisition

Data is acquired ubiquitously from different sensors embedded in ICU. The collected data comprises of textual data (medication data, dietetic data), graphical data (electrocardiographs, and electroencephalograph), and numeric data (blood pressure reading, and body temperature reading). Therefore, it is converted to a common format before transmission. Data about vital signs of patient health like body temperature, heart rate, and respiration rate are sensed by bio-sensors, and other smart sensors. Data about medication is either sensed by RFID-Tag recognition mechanism or are manually entered into the system by administering personnel. Critical patients are sensitive to room environment conditions. Therefore, the room environment is monitored by sensors for air quality, noise, cleanliness, room temperature, and other toxic substance availability that can infect a patient directly or indirectly. Several studies depict that long stay in ICU leads to behavioral discomfort among patients. Moreover, high anxiety levels, and stress level, sometimes become a cause of severity of patient health. Such behavioral data are collected by biosensors attached to the patient's body and along the bedside. Data about meal consumption is automatically sensed by bedside sensors and other smart sensors. Table 1 depicts a brief classification of IoT sensors utilized for monitoring and collecting data. Since data is acquired by heterogeneous sensors with different internal clock structure, they require universal time synchronization for efficient data abstraction and correlation.

Data synchronization

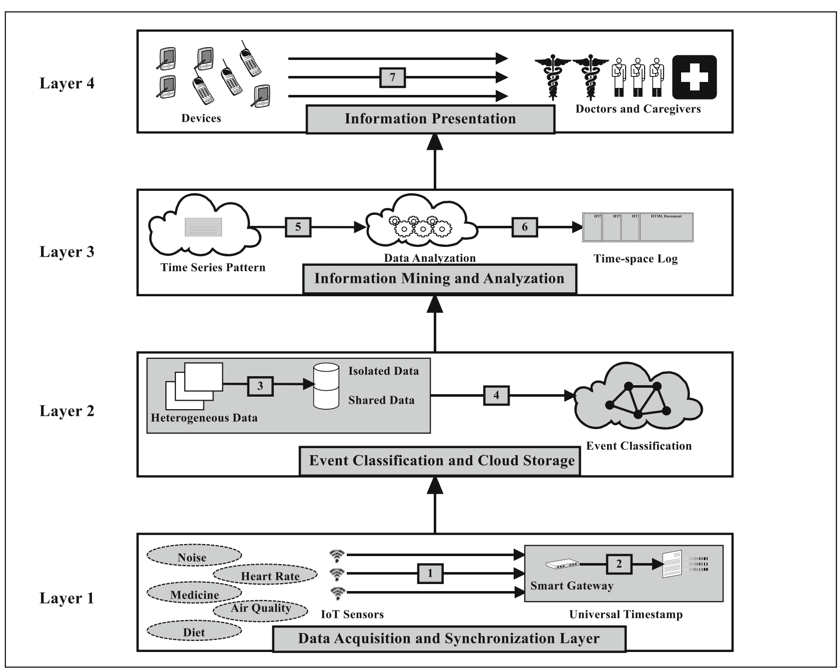
Data synchronization layer is appended with the data acquisition layer for performing the task of global time synchronization for collected data. Centralized gateway is programmed for synchronizing different activities on a universal timestamp. Sensors and other devices used in remote monitoring have heterogeneous capabilities of internal clock, namely synchronized, non-synchronized, and no clock. Gateway maintains a universal timeline, thereby providing a global time instance for every sensed data, irrespective of their internal clock. This time unit is tagged with the sensed data before transmitting. Clarke et al. [23] have classified IoT sensors into four categories for synchronization as shown in Table 2. The synchronized data from gateway is transmitted over a connected network channel. This channel is secured with Secure Socket Layer (SSL) for providing security and protection during data transmission. Data received at the cloud is stored at a server where it is processed for further analysis.

Event classification and cloud storage

Event classification

It provides categorization to various events occurring in ICU room into different datasets. These events include both vital events and non-vital events. Vital events are the patient-

Fig. 1 Architecture of IoT based Remote Monitoring



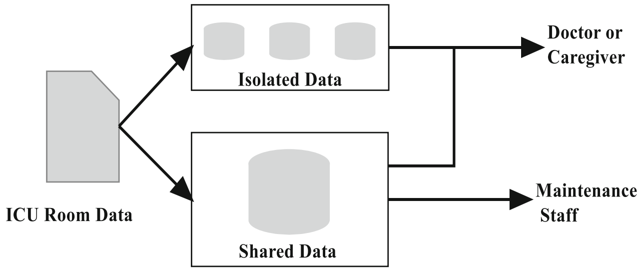


Fig. 2 Isolated Data Storage and Shared Data Storage

oriented data that include health condition (heart rate, blood pressure, ECG, and respiratory rate). However, non-vital events include medicinal information (medicine type, form, and quantity), environmental data (room temperature, air quality, and noise level), behavioral data (anxiety level, and stress discomfort) and dietary information (food type, and form).

Health data Health dataset includes data values that are oriented around patient health. Data values like heart rate (from external monitor), respiratory rate (from nasal sensor), blood pressure (from arterial catheter sensor), blood oxygen saturation (from pulse oximeter sensor), and ECG waveform, fever are some of the examples that comprise health data. In case where a patient is critically ill, health data can also include central venous pressure, cardiac output, pulmonary artery pressure (from catheter sensor) and other data for detailed monitoring.

Medicinal data This type of data includes medicinal data concerning the treatment procedure of the patient. Specifically, it includes name, type, form and quantity of medicine included in the treatment procedure. Such kind of data is either manually registered or is sensed by RFID-Tag mechanism and other sensors attached to the patient bedside. Time is appended trivially by gateway to this dataset hence medicinal delay is detected automatically.

Environmental data Monitoring ICU room environment, considering cleanliness, maintenance, and other general-purpose services that affect patient health indirectly is vital for critical patients that are vulnerable to allergies. The presence of toxic waste in a room, improper disposal of waste materials is sensed by chemical sensors embedded in ICU room. Other environmental data, like room temperature, and oxygen level are important attributes that are sensed continuously by respective sensors.

Behavioral data Behavioral data comprise of statistics regarding the behavioral aspects of patient during ICU stay. Anxiety level, stress level, and restlessness are important attributes detected by various bio-sensors and monitors in the room.

Dietary data Dietary data include data about food or supplement consumed by the patient during ICU stay. Such data is acquired by monitors or sensors embedded along the bedside. Time is trivially recorded during consumption.

Cloud storage

Cloud storage provides a global platform for storing ubiquitous sensed data anytime and anywhere. After gateway transmits the acquired data for each time instance, it is stored in cloudside database for remote access. An isolated temporal database is maintained for providing privacy and security to the patient's health data. The database is partitioned into two sections for storing shareable and non-sharable data. Shareable data is stored for provisioning of shared access for room maintenance, and cleaning purposes while non-shareable include patient-oriented data like demographic data, health data, and medicinal data. In the current perspective, there are two categories of users that can access the cloud database. First category includes authorized caregivers, and doctors of the concerned patient and have access to both isolated data and shared data, while the second category belongs

Table 1 Classification of Events

S.No.	Dataset	Attributes	Description	IoT Technology Used
(1)	Health Data	Heart rate, Blood pressure, Respiration rate, ECG	Data about health condition about patient under consideration	Smart wearable, Body sensors, Heart sensor, and ECG monitor
(2)	Medicinal Data	Strength, Type, Form, Proportion	Data about medication given to patient	RFID tag, Bedside sensor, and Camcorder
(3)	Environmental Data	Noise level, Light, Room temperature, Air-quality, Toxic waste	Data about ICU room environmental conditions	Room sensor, Chemical detector, Noise sensor, and Light sensor
(4)	Behavioural Data	Stress, Anxiety, Restlessness	Data regarding behavioural aspects of patient during ICU stay	Bio-Sensors, Smart wearable, and Monitor
(5)	Dietary Data	Nutritional value, Quantity, Nature	Data about eatables consumed by the patient	RFIDs, and Swallow sensor

Table 2 Timestamp Synchronization for Sensors

S.No.	Category	Description
(1)	No Clock	Sensors does not have internal clock
(2)	Non-Synch	Sensors does have internal clock but is not synchronized
(3)	Absolute Time	Sensors sense data depending upon absolute time.
(4)	Relative Time	Sensors sense data relative to other device.

to the hospital staff which retrieves data from shared data storage only for general medical purposes.

Information mining and analyzation

Information mining

Data stored in the cloud includes time inconsistent data as there are some data values that do not vary (or occur) with time while other change in every instance of time. For example heart rate, in case of a person suffering from heart failure condition, is inconsistent while medicinal event occurs only at prescribed times. Data having temporal diversity is often non-predictable. Therefore, information is mined over temporal basis for further analysis. Moreover, associations (or aggregations) are made with respect to health data in terms of Attribute Time Series (ATS) and Data Time Series (DTS).

Definition 1: − *Given an attribute, h, an Attribute Time Series (ATS) is defined as a set of n values over a window of a certain time period: {<t(1), h(1)>,<t(2), h'(1)>,<t(3), h"(1) > .... < t (n), h'"(1)>}*

- In definition 1, n denotes the number of time instances for retrieving the values of a specific attribute.
- For each time unit, each data value corresponds to attribute value at that time unit. For instance, <t (1), h (1) > means a value of an attribute is h (1) at t (1) time unit.
- Attribute vector (for instance) of t (1) time unit is represented as: <h (1), h' (1), h" (2) ....>

Definition 2: − *Given a time unit t (1) of a specific instance, a Data Time Series (DTS) is defined as set of m attribute values for a given dataset at that instance: {<t(1), h(1)>,<t(1), h(2)>, <t(1), h(3) > .... < t(1), h(m)>}*

- In definition 2, m belongs to different attributes of the dataset considered for monitoring purpose.
- Each attribute is monitored at specific time t (i), resulting in m data values for m different attributes. Hence at any instance, data vector can be represented as < h (1), h (2), h (3) ......h (n) > .

Every value corresponding to specific attributes and datasets can be retrieved in the form of ATS and DTS respectively, thereby formulating Medicinal Data Time Series (MDTS), Health Data Time Series (HDTS), and so on. In general, these time series can be represented as XDTS and XATS where X can be varied according to specific attribute or dataset to be retrieved.

Definition 3: − *Given Time Series (TS) for different instances such that TS ≡ {XATS|XDTS} and domain Δt of time window, then TDA_{abs} is an abstraction function represented by a tuple < a_{abs}, b_{abs}>, where a_{abs} is a data abstraction specification and b_{abs} is the application of abstraction to that data.*

- In definition 3, TDA_{abs} is the Temporal Data Abstraction function, depicting extraction of time based data values from the cloud.
- Based on this abstraction, the specific values of various datasets can be analyzed efficiently.

Information analyzation

This layer analyzes the information desired to doctors or caregivers about patient context. Patient under critical circumstances are monitored for providing continuous information. Information analyzation using time series will i) provide continuous information about patient health context ii) aid in efficient decision making by doctors iii) improve alert generation process for emergency situations iv) aid in extracting desired attributes in given time window. This requires integration of different datasets over temporal basis. The technique adopted for integration is termed as Temporal Associative Granulation (TAG). Associative granulation provides integration of different datasets and concerned attributes in a given time window forming a temporal granule. Specifically, three kinds of abstractions can be drawn using TAG analysis, providing different layers of information to doctors or caregivers efficiently.

Abstraction level 1: Intra-attributal TAG (attribute level) *Given ATS for specific attribute, A, Intra-Attributal TAG is a granule for multiple time units and is represented < AID, [<A (1), A(2), A(3).......A (n)>, T(s), T(e)]>*

- In abstraction 1, AID represents attribute identifier which is unique for every attribute.

- Sub-part < A(1), A(2), A(3)......A(n) > represents the ATS granule for attribute from starting time T(s) till end time T(e).
- The time interval between a start time and end time is depicted as Sliding Window (SW). Therefore, SW = |T(s)-T (e)|. T(s) = T (e) for instant monitoring.
- In Fig. 3, for instance, a temporal granule is formed for heart rate measured for n + 1 time units. This data granule comprises of values for time window (t (3) to t (6)).

Abstraction level 2: Inter-attributal TAG (tuple level) *Given ATS for two or more attributes of a specific dataset, then Inter-Attributal TAG is a data granule comprising of values for the associated attributes in a specific time window and is represented as* < [*AID*(*1*), *AID*(*2*), *AID*(*3*).... *AID*(*m*)], [<*A1*(*1*), *A1*(*2*), *A1*(*3*)……*A1*(*n*)>,<*A2*(*1*), *A2*(*2*), *A2*(*3*).....*A2*(*n*) > ...... <*Am*(*1*), *Am*(*2*), *Am*(*3*)........*Am*(*n*)], *T*(*s*), *T*(*e*) > .

- In abstraction 2, AID (m) represents attribute identifier for mth attribute.
- T(s) and T (e) depicts the start and end time unit respectively for data values observation.
- Am (n) gives the mth attribute value for nth time unit.
- Figure 4 depicts a snapshot of health dataset with different attribute values measured over time. The granule formed over a time window (t (3) to t (6)) gives temporal values for associated attributes, namely heart rate, blood pressure, and ECG waveform.

Abstraction level 3: Inter-data TAG (relational level) *Given DTS of attribute values for different datasets, Inter-Data TAG can be viewed as a granule for two or more different attribute values for associated datasets in a specific time window. It can be represented as* < [{*DID*, *AID*}(*1*,*1*), {*DID*, *AID*}(*2*,*2*),{*DID*, *AID*}(*3*, *3*).....{*DID*, *AID*}(*p*,*m*)],[<*A1*(*1*), *A1*(*2*), *A1*(*3*).....*A1*(*n*) > <*A2*(*1*), *A2*(*2*), *A2*(*3*).....*A2*(*n*) > ...... < *A m*(*1*), *Am*(*2*), *Am*(*3*).....*Am*(*n*)], *T*(*s*),*T*(*e*) > .

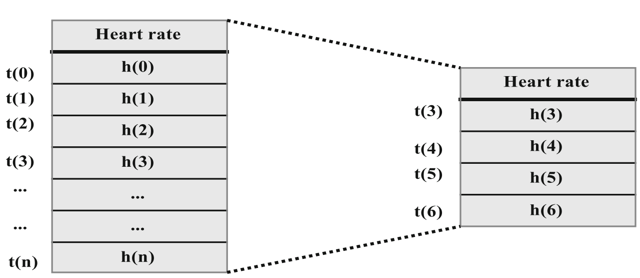


Fig. 3 Abstraction Level 1

- The sliding window is represented using start time T(s) and end time T (e).
- {DID, AID} (p,m), in abstraction 3, depicts data identifier and attribute identifier for pth dataset and mth attribute value respectively.
- In Fig. 5, Inter Data TAG is formed depicting different datasets and corresponding attributes. Initially granule is formed for specific attributes of various datasets in a time window, which are associated for the formulation of a final granule, consisting of these associated attribute values.

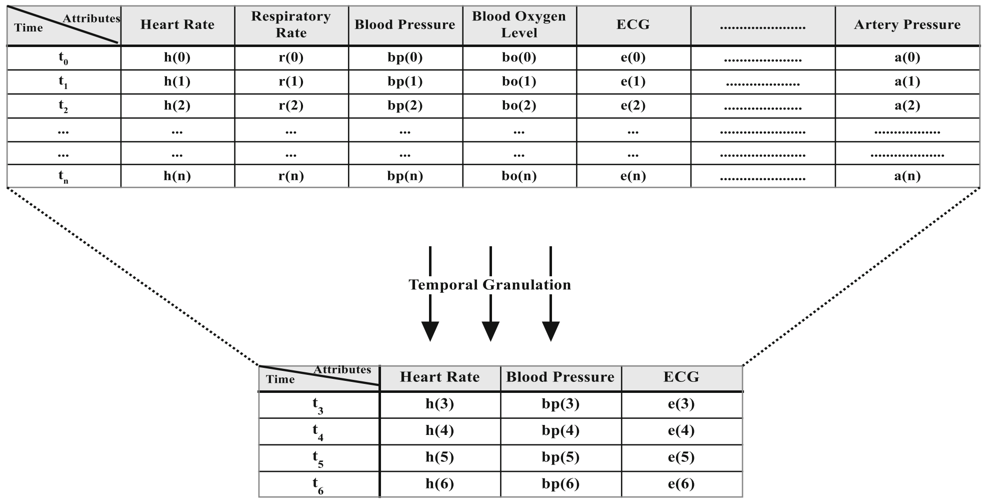
Information presentation

Granule formation will allow doctors or caregivers to acquire information about patient condition from wider perspectives. However, a large number of parameters, variables and outcome possibilities increase the traffic load and complexity of making decisions in healthcare environment [37]. The cognitive efforts have been considered for presentation of information in diagnosing patient's health condition [38]. Improvement in the information presentation like focusing on important information first, and color coding are ways to enhance the decision making by healthcare professionals [5]. There are three types of remote monitoring processes, namely: Continuous, Regular and Alert-based. Continuous monitoring requires large resource utilization in transmitting information for each instance to the doctor. Moreover, traffic generated at each instance is very large. Regular monitoring allows transmission of data after fixed time instances irrespective of the patient's health condition. This type of monitoring is useful, but it also requires large resource utilization. Finally, the third type of monitoring is alert based, where an alert is generated when patient's health condition reaches life threatening state. This study is confined to alert based monitoring system. Conventional alert systems are focused on patient's health severity only and are insufficient in providing intensive medical information. Therefore, a modified approach is adopted by incorporating presentation of events during alert generation.

Time-based event presentation during alert generation

An integrated temporal based event presentation method is proposed for the generation of alert to doctors or caregivers. Time is considered as an independent

Fig. 4 Abstraction Level 2



attribute and therefore becomes an organizational basis for event occurrence and alert generation. A state of the system is defined on the basis of patient's health attributes, events affecting the health, and timestamp for the occurrence of those events. Mathematically, state of the system is denoted by S = (P, E, ΔT) where P is a set denoting patient's health condition, ie P = {Safe (S), Unsafe (U)}. E denotes the events occurring in the time space of ΔT. In other words, E is a dataset represented as E = {Medicinal, Environmental, Behavioral, Dietary}. ΔT is the time difference between two timestamps, which is considered as a temporal space or sliding window. The patient's health state is classified as safe or unsafe depending upon on the health attributes according to Algorithm 1. Patient personalized thresholds for

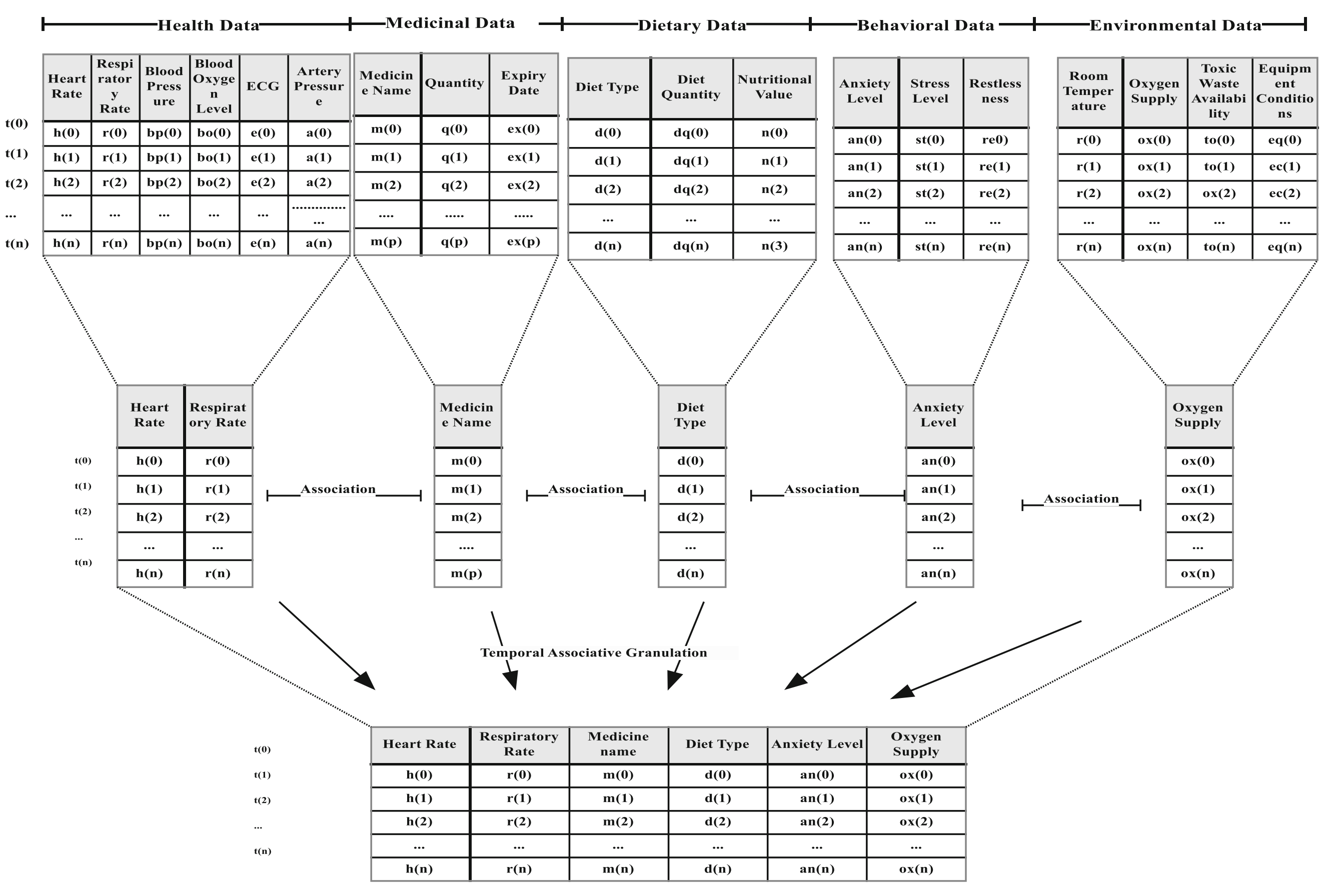


Fig. 5 Abstraction Level 3

various health attributes are prefixed by a doctor, which are

Algorithm 1: Patient State Determination

Input: N number of health attributes values, Prefixed threshold values the attributes.
Step 1: Determine attributes for the current timestamp
Step 2: For i = 1 to N
  Step 2.1: If (Attribute_Value(i)>Threshold Value(i)) Then Patient_State = Unsafe
  Step 2.2: Else Patient_State = Safe
Step 3: Return Patient_State and Exit
Output: Current State of the patient

Algorithm 2: Alert Generation with Event Information

Input: Event Set = {Health∪ Medication ∪ Dietery ∪ Behavioural ∪ Environmental}
Step 1: Using Algorithm 1, Determine health state of the patient
Step 2: Determine current timestamp
Step 3: If patient State = Safe, then goto Step 4 Else goto Step 7
Step 4: Do
  Step4.1: Create a checkpoint
  \\ *Checkpoint is a save point in time space*
  Step4.2: Empty Log
  Step 4.2: Start the sliding window
  \\ Granule *formation for Events*
Step 5: If Any_Event_Occurance = True
  If P (WA) > $\boldsymbol{\beta}$, Generate Warning Alert
  Else, Add Event to Log
  \\ *Any_Event_Occurance is a variable for managing event*
  \\ $\boldsymbol{\beta}$ *is per-patient personalized threshold*
Step 6: After ΔT time space, Goto Step 1
Step 7: Do
  Step 7.1: Generate Emergency Alert Signal
  Step 7.2: Transfer {Log Information ∪ Health Attributes} to Doctor or Caregiver
Step 8: Exit

used in forming rules to determine patient's health state. Moreover, the determination of patient's health state is important for generating medical alerts to doctors and caregivers. Two types of alerts are generated by the system, namely: Emergency Alert (EA) and Warning Alert (WA). EA signal is generated when the patient's health state is unsafe. On the other hand, WA depicts that an undesired event/s has occurred, that can lead patient health to an unsafe state. WA is dependent on prefixed patient sensitivity factor (α) for that event (Table 3). Generation of WA in ΔT time space can be determined as $P\,(WA) = \alpha^* \,[(P(E))/(P(U))]_{\Delta T}$ where P (E) and P (U) are probability for occurring of sensitive event and patient's health in an unsafe state respectively. Overall procedure for the proposed alert generation is depicted in Algorithm 2. Initially, various health attributes are analyzed by using Algorithm 1 for determining patient's health state. If the patient's health is found to be in a safe state, a checkpoint is saved in the cloud database. Embedded IoT devices continuously transmit data about various events in the ambient environment of the ICU to a temporary log storage in the cloud. These data values are analyzed for patient's health sensitiveness based on prefixed thresholds. If sensitive events are registered, WA is generated to the concerned doctors. After prefixed ΔT time unit, the system reevaluates the patient's health state. If at any instance, the patient's health is analyzed to be in unsafe safe, EA is generated to the concerned doctors, along with the delivery of log information. Moreover, the checkpoint is terminated at this stage and the monitoring process is repeated. The alert messages are delivered to healthcare professionals on their respective devices. Such devices are designed and equipped with several features such as color coded display, self-customized way of alert message generation and interface personalization tool. The system is medically effective as it is designed to generate medical alert signals along with the transmission of event information. Moreover, other customized levels of data abstractions can also be obtained, depending upon the patient's health. Furthermore, by the proposed methodology, the system is capable of enhancing the medical decision-making of concerned doctors for efficient diagnostic services.

Performance evaluation

In this section, the proposed framework is evaluated experimentally. The system is deployed in three major steps. In the first step, data is sensed by various embedded IoT devices in the ICU room environment. In the second step, temporal mining performs data abstraction for various datasets from the cloud storage. Finally, alert based information is presented to the concerned doctors and caregivers. Based on these three steps, an experimental implementation is performed to analyze the system performance from three important aspects.

(i) Assessing the data acquisition efficiency for IoT equipped ICU healthcare environment.
(ii) Determining the temporal efficiency of the proposed framework during emergency states.
(iii) Statistically evaluate the alert generation procedure by the proposed system.

Experimental environment

Due to the sensitiveness of the application domain, the experiment was carefully performed in 3 ICUs for 1 month after the permission of the Mareez Sehat Aayog (Ethics Committee), concerned doctors, patients, and family members. In the entire procedure, 81 patients (who were atleast 18 years older) with accidental, cardiac and neurological cases were cautiously monitored. Moreover, certain measures were simultaneously taken during the deployment stage to avoid any kind of inconvenience to the patients under study. However, it was ensured that the objective of the implementation was not compromised due to these measures and results were obtained with a high

Table 3 Anomalies

Medicinal	Environmental	Behavioral	Dietary
-Wrong medicine	-High noise	-High anxiety level	-Wrong meal
-Wrong form	-Poor air quality	-High-stress level	-Wrong form
-Wrong type	-Presence of toxic waste	-Restlessness	-Wrong type
-Wrong strength	-Equipment failure		

degree of accuracy. In order to evaluate the dynamics of the objectives, the system was compared with the manual patient monitoring system and traditional Tele-ICU system simultaneously. In manual patient monitoring system, medical staff continuously intervened at the patient site for obtaining health values. Tele-ICU systems monitored patients at a distant via installation of conventional cameras in ICUs. Various ICU specialist pharmacists were indulged as independent observers for monitoring ICU patients. On the other hand, various biosensors and room sensors were embedded in the ICUs for the proposed system, depending upon the sensation capability. Table 1 provides a list of various sensors indulged for the purpose of data acquisition. Data collected from these IoT devices was stored in Amazon EC2 cloud storage [39] for computations. The acquired data values were analyzed by using IBM SPSS statistics [40], and various conclusions were drawn regarding the proposed system. Moreover, by comparing the proposed system with other monitoring techniques, various benefits of the IoT equipped ICU facility can be determined.

Data acquisition efficiency

Various IoT devices were embedded appropriately in all ICU rooms for sensing different categories of datasets. Due to temporal diversity of these events, these were categorized as continuous events and occasional events. Continuous events included those data values that require continuous surveillance like heart rate, blood pressure, room temperature, and noise. On the other hand, events that were discontinuous comprises occasional datasets. Medication ingestion, urination, stool and meal ingestion are some of the examples of occasional events. The complete list of these events, thus formed comprised of 53 different events. The analysis of this resulted in 28 continuous events while 25 occasional events. During the monitoring process, a single day data acquisition resulted in both kinds of events. Therefore, event set for 1 day comprises of all such events and corresponding values. The formulation of event set for a single day monitoring was stored in a common format as depicted in Fig. 6. In the format, presented fields "Dataid" and "Aid" include the unique identifier for the dataset and attribute set respectively. "Sensor value" contains the various data measurements acquired by the ICU sensors. A boolean field "Type" was included in the format for classification of events on the basis of threshold values. A boolean value 0 indicated that an event was below threshold while a boolean value 1 depicted an event with a value higher than the threshold. Finally, the field "Time" registered the time at which data was sensed. The process, as mentioned earlier, was repeated for 30 days and nearly 990 events were registered including continuous and occasional events. Data acquisition efficiency concerns with the data sensing capability of the proposed framework as compared to the manual monitoring procedure and conventional Tele-ICU system. The implementation of the proposed framework resulted in microscopic and macroscopic data acquisition as compared to other procedures. As clearly seen from the Figs. 7, 8, 9, and 10, IoT devices registered high anomalies occurring in the 30-day monitoring process where as other procedures did not capture such events effectively. Specifically, more than 19.6 and 44.2 % anomalies regarding health were captured by IoT-ICUs in comparison to Tele-ICUs and manual monitoring ICUs respectively. Similarly, in the case of medicinal data acquisition, more than 44 % anomalies with respect to Tele-ICU and 60.1 % anomalies with respect to manual monitoring were registered by proposed IoT equipped ICU. Moreover, anomalies regarding stress level, and anxiety level that affects patient indirectly are easily incorporated into the system by the proposed framework. This numerates to more than 62.3 % as compared to Tele-ICU and 75.3 % as compared to manual monitoring procedures. Furthermore, high rates of environmental anomalies (more than 33.2 and 52.1 % with respect to Tele-ICUs and Manual Monitoring respectively) were registered by the IoT devices that impacted patient's health in ICUs. Therefore, based on the above results, it is concluded that the proposed system persist high degree of data acquisition accuracy as

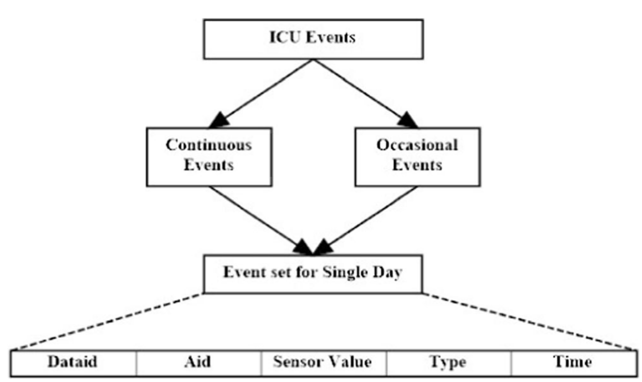


Fig. 6 Data Storage Format

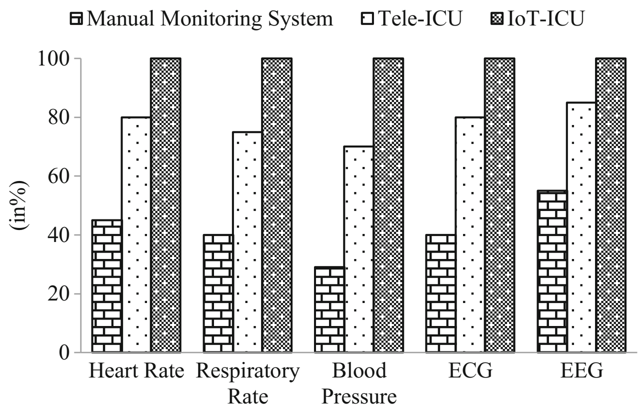


Fig. 7 Health related Anomaly Detection

compared to manual monitoring system and tradition Tele-ICU monitoring.

Temporal efficiency

Patients administered to ICUs are vulnerable to considerable health related risks. These include both life threatening risks that were health sensitive (emergency) and non-life threatening risks that were non-sensitive to patient health (warning). In either situation, immediate doctor intervention is required. During the 30-day monitoring procedure, nearly 146 times life threatening conditions had occurred. These included increased heart rate, high blood pressure, mental shocks, and heart attacks. On the other hand, non-life threatening events included increased room temperature, high noise, and other anomalous events. These counted to nearly 182 times during the entire monitoring procedure. Figure 11 depicts the weekly occurrences of both kinds of situations in all ICUs under study.

Temporal efficiency is concerned with the effectiveness of the system to generate alerts to concerned doctors based on these situations. The appropriate methodology is adopted to determine such kind of efficiency. Delay in informational deliverance to the concerned doctor is considered as an important parameter in the overall system.

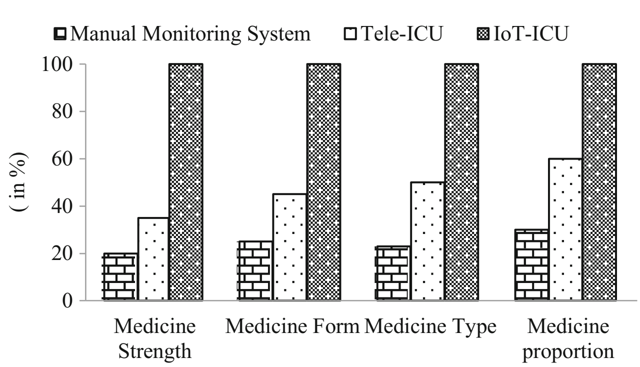


Fig. 8 Medicinal related Anomaly Detection

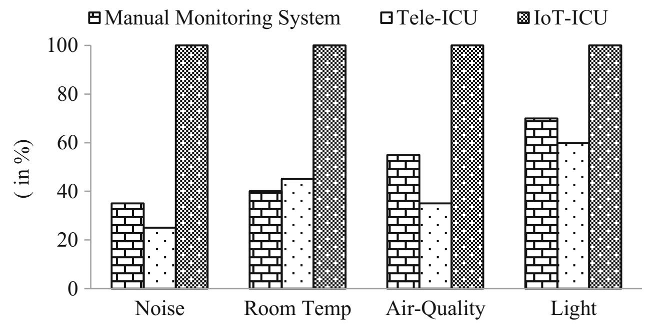


Fig. 9 Environment related Anomaly Detection

Mathematically delay can be evaluated as

$$\text{Delay} = T_{Deliverance} - T_{Occurance}$$

$T_{Deliverance}$ is the time at which doctor received the information about the occurrence of the event in ICU whereas $T_{Occurance}$ is the time at which the event occurred. The comparison is performed with respect to other procedures in order to evaluate the temporal efficiency of the system. Figure 12 summarizes the results depicting the evaluated delay in terms of time units for various monitoring procedures. The results show that the proposed system is more efficient as compared to the other monitoring. Moreover, low values of time delay were registered during the occurrence of medical emergency situations. This resulted in immediate intervention of the concerned doctors or caregivers for providing necessary healthcare services.

Statistical analysis for alert generation

In this section, the system is evaluated analytically in determining the efficiency of alert generations. In other words, different statistical parameters are evaluated for various alerts given to the concerned doctors. As mentioned in the previous section, two types of alerts are generated by the proposed system, namely warning alerts and emergency alerts. The main objective of statistically analyzing the alert generation process is to determine the "false positive" alerts based on total number of generated alerts. Moreover, other parameters like precision, sensitivity, and mean absolute error are also

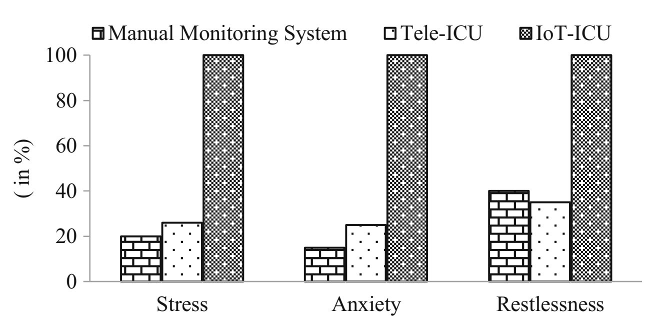


Fig. 10 Behavior related Anomaly Detection

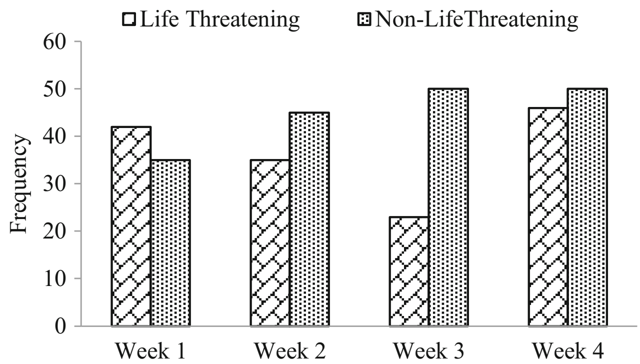


Fig. 11 Occurrences of Alerts

Table 4 Statistical Results

S. No.	Parameter	Value (in %)
1	False Positive alert	3.15
2	Sensitivity	87.41
3	Specificity	94.33
4	Precision	91.20
5	Coverage	97.56
6	Mean Absolute Error	3.11
7	Root Mean Square Error	2.56
8	Relative Absolute Error	7.87
9	Root Relative Squared Error	3.43

evaluated for the proposed system. Table 4 depicts the summarization of statistical results obtained for the proposed model over the entire monitoring procedure. Proposed system registered low rate of False Positive Alert, numerating to 3.15 % indicating high accuracy in alert generation. Moreover, high value of Precision (91.20 %), Sensitivity (87.41 %), Coverage (97.56 %) and Specificity (94.33 %) show high performance of the proposed system. Furthermore, low error rates in the form of Mean Absolute Error (3.11 %), Root Mean Square Error (2.56 %), Relative Absolute Error (7.87 %) and Root Relative Squared Error (3.43 %) were obtained for the alert generation process.

Overall system stability

Moreover, in addition to the results derived in the previous sections, the proposed system is evaluated for stability measurement. Since the system is influenced by the timely instances of various events, it is vital to determine the temporal stability performance. Generally, this kind of measurement is defined in terms of Mean Absolute Shift (MAS). Lower value of shift indicates higher stability of the system over time while the higher value of shift implies lower system stability. The results obtained over 30-day monitoring procedure are shown in Fig. 13. MAS for the proposed system was registered in range of (0.12–0.55), indicating that the system is highly stable.

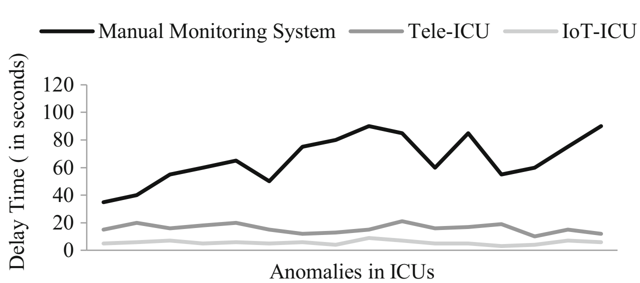


Fig. 12 Delay in Information Deliverance

IoT-ICU vs tele-ICU vs manual monitoring: Feature analysis

During the 30-day monitoring procedure in the IoT equipped ICUs, several important features were determined such that it can become an important paradigm for providing effective healthcare services in future. Moreover, with the incorporation of ICT in intensive healthcare domains like ICUs, several medical benefits can be obtained [41, 42]. A comparative analysis mentioned ahead, depicts some of the important advantages of the proposed model with respect to conventional monitoring procedures (Table 5).

(i) Medical decision making plays an important role in analyzing a patient's health condition. Conventional monitoring procedures requires regular human intervention for determination of patient's health severity. However, error in medical judgement can result in adverse effects on a patient's health. On the other hand, since the proposed IoT equipped ICU is based on per-patient personalized threshold values, patient's health state can be efficiently analyzed for severity and sensitivity.
(ii) One of the limitation of conventional monitoring procedures is the inability to detect health related anomalies like wrong medication, and wrong room temperature. Such anomalies can lead to life threatening conditions,

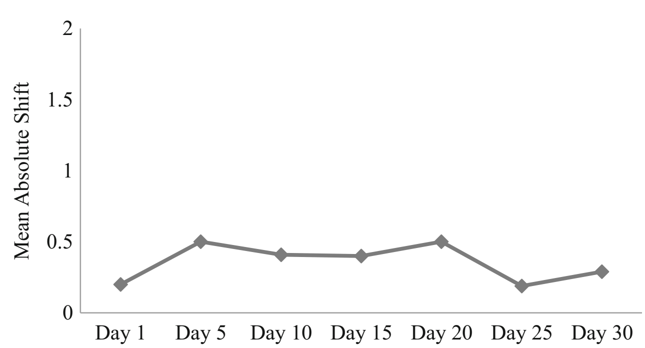


Fig. 13 System Stability

Table 5 Feature Analysis

Features	Manual Health Monitoring Procedure	Tele-ICU Monitoring Procedure	Proposed IoT-ICU Monitoring Procedure
Human Biasness	Yes	Yes	No
Human Error	Yes	Yes	No
Real-time Information Deliverance	No	Limited	Yes
Patient-centric Approach	No	Limited	Yes
Remote Access	No	Limited	Yes
Healthcare Resource Utilization	Maximum	Intermediate	Minimum
Time Delay	Maximum	Intermediate	Minimum

especially for the patients with high death risks. Inability to detect these errors inside ICUs at early stages make the conventional monitoring procedures highly ineffective. In the proposed methodology, since IoT sensors are used to monitor every health-oriented event inside the ICU, these anomalies can be efficiently detected with generation of medical alerts.

(iii) An important advantage of the proposed IoT equipped ICUs is the ability to deliver intensive information about various events to concerned doctors in real time. This information is very important in analyzing a patient's health condition, especially in medical emergency cases. Limited information deliverance in emergency makes the conventional monitoring procedures medically ineffective.

(iv) Various IoT devices are used for collecting data about different events. These devices not only acquire health oriented data, but captures data about every event in the ambient physical environment of the patient. Moreover, analyzation of patient's health condition is performed on the basis of personalized threshold values. This conceptualizes to a patient-centric approach for providing healthcare services in ICUs.

(v) Since computations are performed over globally accessible cloud computing environment, doctors are able to assess patient's health condition anytime and anywhere. In other words, the proposed system persists high degree of remote accessibility for patient's health conditions in comparison to other monitoring systems.

(vi) Automated health monitoring, health state analyzation, and alert generation results in reduction of healthcare resource utilization. Moreover, in hospitals with limited healthcare resource availability, doctors will be able to provide effective medical services to the patients with the proposed methodology.

(vii) IoT devices are capable of transmitting data with minimum delay. Moreover, with cloud computing technology, real time analyzation of patient's health can be performed. Furthermore, in medical emergency cases, alerts can be efficiently generated in real time. This makes the proposed system highly preferable for providing efficient healthcare services in ICUs.

Based on these features, it can be concluded that the proposed framework is more effective in monitoring ICU patients in comparison to traditional ICU monitoring procedures.

Conclusion and future challenges

In this paper, a framework of IoT based remote monitoring in ICU is presented. The proposed model addresses various issues concerning patient health and surrounding environment. Specifically, two important aspects have been considered, namely (i) temporal mining for various health related issues and (ii) alert generation procedure with information deliverance for various critical circumstances. Both these aspects are incorporated in the model for enhancing the overall effectiveness and utility. Temporal mining abstracts the common synchronized data about various ICU activities from the cloud storage which is then processed for alert generation. Moreover, temporal granulation allows the delivery of information in specific time to the concerned doctors. This leads to time sensitive, efficient decision making in the direction of patient care. The performance of the model is determined by implementing it in 3 ICUs and monitoring various administered patients for 30 days in succession. In order to justify the utilization of the system, the model is compared with the manual monitoring procedure and traditional Tele-ICU system. Results show that proposed methodology registered a high degree of performance as compared to other monitoring procedures.

There are many important challenges that must be addressed in the research to be carried out in future. One of the significant challenges include network availability for continuous data transmission. Moreover, network load efficiency is another issue that must be addressed for efficient utilization of network resources.

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References

1. Da Xu, L., He, W., and Li, S., Internet of Things in Industries: A Survey. *IEEE Transactions on Industrial Informatics* 10:2233–2243, 2014. doi:10.1109/TII.2014.2300753.
2. Zhang, P., Kogure, Y., Matsuoka, H., Akutagawa, M., Kinouchi, Y., and Zhang, Q., A Remote Patient Monitoring System using a Java-enabled 3G Mobile phone. *Conference Proceedings of IEEE Engineering in Medicine and Biology Society*, 2007. doi:10.1109/IEMBS.2007.4353138.
3. Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., and Ayyash, M., Internet of Things: A Survey on Enabling Technologies, Protocols and Applications. *IEEE Communications Surveys and Tutorials* 17:2347–2376, 2015. doi:10.1109/COMST.2015.2444095.
4. Gubbi, J., Buyya, R., Marusic, S., and Palaniswami, M., Internet of Things (IoT): A Vision, Architectural elements, and Future directions. *Future Generation Computer Systems* 29:1645–1660, 2013. doi:10.1016/j.future.2013.01.010.
5. Varshney, U., A Model for Improving Quality of Decisions in Mobile Health. *Decision Support Systems* 62:66–77, 2014. doi:10.1016/j.dss.2014.03.005.
6. Xu, B., Xu, L., Cai, H., Jiang, L., Luo, Y., and Gu, Y., The Design of a M-Health Monitoring System based on a Cloud Computing Platform. *Enterprise Information Systems*, 2015. doi:10.1080/17517575.2015.1053416.
7. Fang, S., Da Xu, L., Member, S., Zhu, Y., Ahati, J., Pei, H., Yan, J., and Liu, Z., An Integrated System for Regional Environmental Monitoring and Management Based on Internet of Things. *IEEE Transactions on Industrial Informatics* 10:1596–1605, 2014. doi:10.1109/TII.2014.2302638.
8. Agoulmine, N., Ray, P., and Wu, T. H., Efficient and Cost-effective Communications in Ubiquitous Healthcare: Wireless sensors, Devices and Solutions. *IEEE Communications Magazine* 50:90–91, 2012. doi:10.1109/MCOM.2012.6194387.
9. Camiré, E., Moyen, E., and Stelfox, H. T., Medication Errors in Critical Care: Risk factors, prevention and disclosure. *CMAJ* 180:936–943, 2009. doi:10.1503/cmaj.080869.
10. Chalfin, D. B., Cohen, I. L., and Lambrinos, J., The Economics and Cost-effectiveness of Critical Care Medicine. *Intensive Care Medicine* 21:952–961, 1995. doi:10.1007/2FBF01712339.
11. Thomas, E. J., Lucke, J. F., Wueste, L., and Weavind, L., Association of Telemedicine for Remote Monitoring of Intensive Care Patients with Mortality, Complications, and Length of Stay. *Journal of American Medical Association* 302:2671–2678, 2013. doi:10.1001/jama.2009.1902.
12. Kyriacou, E., Pattichis, M. S., Pattichis, C. S., Panayides, A., and Pitsillides, A., M-Health E-Emergency Systems: Current Status and Future Directions. *IEEE Antennas and Propagation Magazine* 49:216–231, 2007. doi:10.1109/MAP.2007.371030.
13. Welters, I. D., Gibson, J., Mogk, M., and Wenstone, R., Major sources of Critical Incidents in Intensive Care. *Critical Care*, 2011. doi:10.1186/cc10474.
14. Vesin, A., Schwebel, C., Arnodo, P., et al., Selected Medical Errors in the Intensive Care Unit Results of the IATROREF Study: Parts I and II. *American Journal of Respiratory and Critical Care Medicine* 181:134–142, 2010. doi:10.1164/rccm.200812-1820OC.
15. Johansson, L., Bergbom, I., Waye, K. P., Ryherd, E., and Lindahl, B., The Sound Environment in an ICU Patient Room- A Content Analysis of Sound Levels and Patient Experiences. *Intensive and Critical Care Nursing* 28:269–279, 2012. doi:10.1016/j.iccn.2012.03.004.
16. Thompson, D. R., Hamilton, D. K., Cadenhead, C. D., Swoboda, S. M., Schwindel, S. M., Anderson, D. C., et al., Guidelines for Intensive Care Unit Design. *Critical Care Medicine* 40:1586–1600, 2012. doi:10.1097/CCM.0b013e3182413bb2.
17. Ball, M. J., and Lillis, J., E-health: Transforming the Physician / Patient Relationship. *International Journal of Medical Informatics* 61:1–10, 2001. doi:10.1016/S1386-5056(00)00130-1.
18. Perera, C., Zaslavsky, A., Christen, P., and Georgakopoulos, D., Context Aware Computing for The Internet of Things: A Survey. *IEEE Communications Surveys and Tutorials* 16:414–454, 2014. doi:10.1109/SURV.2013.042313.00197.
19. Guo, B., Zhang, D., Wang, Z., Yu, Z., and Zhou, X., Opportunistic IoT: Exploring the Harmonious Interaction between Human and the Internet of Things. *Journal of Network and Computer Applications* 36:1531–1539, 2013. doi:10.1016/j.jnca.2012.12.028.
20. Sneha, S., and Varshney, U., Enabling ubiquitous patient monitoring: Model, Decision Protocols, Opportunities and Challenges. *Decision Support Systems* 46:606–619, 2009. doi:10.1016/j.dss.2008.11.014.
21. Varshney, U., A Framework for Supporting Emergency Messages in Wireless Patient Monitoring. *Decision Support Systems* 45:981–996, 2008. doi:10.1016/j.dss.2008.03.006.
22. Giger, J. T., Pope, N. D., Vogt, H. B., Gutierrez, C., Newland, L., Lemke, J., et al., Remote patient monitoring acceptance trends among older adults residing in a frontier state. *Computers in Human Behavior* 44:174–182, 2015. doi:10.1016/j.chb.2014.11.044.
23. Clarke, M., Schluter, P., Reinhold, B., and Reinhold, B., Designing Robust and Reliable Timestamps for Remote Patient Monitoring. *IEEE Journal of Biomedical and Health Informatics* 19:1718–1723, 2014. doi:10.1109/JBHI.2014.2343632.
24. Hande, A., Polk, T., Walker, W., and Bhatia, D., Self-powered Wireless Sensor Networks for Remote Patient Monitoring in Hospitals. *Sensors* 6:1102–1117, 2006. doi:10.3390/s6091102.
25. Suh, M., Chen, A., Woodbridge, J., Tu, M. K., Kim, J. I., Nahapetian, A., Evangelista, L. S., and Sarrafzadeh, M., A Remote Patient Monitoring System for Congestive Heart Failure. *Journal of Medical Systems* 35:1165–1179, 2011. doi:10.1007/s10916-011-9733-y.
26. Fanucci, L., Saponara, S., Bacchillone, T., Donati, M., Barba, P., Sanchez-Tato, I., and Carmona, C., Sensing Devices and Sensor Signal Processing for Remote Monitoring of Vital Signs in CHF Patients. *IEEE Transactions on Instrumentation and Measurement* 62:553–569, 2013. doi:10.1109/TIM.2012.2218681.
27. Sund, Z. M., Powell, T., Greenwood, R., and Jarad, N. A., Remote Daily Real-time Monitoring in Patients with COPD-A Feasibility Study using a Novel Device. *Respiratory Medicine* 103:1320–1328, 2009. doi:10.1016/j.rmed.2009.03.017.
28. Kumar, S., Merchant, S., and Reynolds, R., Tele-ICU: Efficacy and Cost-effectiveness of Remotely Managing Critical Care. *Perspectives in Health Information Management* 10:24–29, 2013. doi:10.2174/1874431101307010024.
29. Hoonakker, P. L. T., Carayon, P., McGuire, K., Khunlertkit, A., Wiegmann, D. A., Alyousef, B., Xie, A., and Wood, K. E., Motivation and Job Satisfaction of Tele-ICU Nurses. *Journal of Critical Care* 28:315. e13–315.e21, 2013. doi:10.1016/j.jcrc.2012.10.001.
30. Khunlertkit, A., and Carayon, P., Contributions of Tele-Intensive Care Unit (Tele-ICU) Technology to Quality of Care and Patient Safety. *Journal of Critical Care* 28:315.e1–315.e12, 2013. doi:10.1016/j.jcrc.2012.10.005.

31. Ramnath, V. R., and Khazeni, N., Centralized monitoring and virtual consultant models of tele-ICU care: a side-by-side review. *Telemedicine and E-Health* 20:962–971, 2014. doi:10.1089/tmj.2014.0024.
32. Sultan, N., Making use of Cloud Computing for healthcare provision: Opportunities and Challenges. *International Journal of Information Management* 34:177–184, 2014. doi:10.1016/j.ijinfomgt.2013.12.011.
33. He, C., Fan, X., and Li, Y., Toward Ubiquitous Healthcare Services with a Novel Efficient Cloud platform. *IEEE Transactions on Biomedical Engineering* 60:230–234, 2013. doi:10.1109/TBME.2012.2222404.
34. Bahga, A., and Madisetti, V. K., Healthcare Data Integration and Informatics in the Cloud. *Computer* 48:50–57, 2015. doi:10.1109/MC.2015.46.
35. Poon, C. C. Y., Zhang, Y. T., and Di Bao, S., A Novel Biometrics Method to Secure Wireless Body Area Sensor Networks for Telemedicine and M-health. *IEEE Communications Magazine* 44:73–81, 2006. doi:10.1109/MCOM.2006.1632652.
36. Sahoo, P., Efficient Security Mechanisms for mHealth Applications using Wireless Body Sensor Networks. *Sensors* 12:12606–12633, 2012. doi:10.3390/s120912606.
37. Jerome, G., *How Doctors Think*. Houghton Mifflin, Boston, 2007.
38. Kushniruk, A. W., and Patel, V. L., Cognitive Evaluation of Decision Making Processes and Assessment of Information Technology in Medicine. *International Journal of Medical Informatics* 51:83–90, 1998. doi:10.1016/S1386-5056(98)00106-3.
39. Amazon Cloud Services. https://aws.amazon.com/ec2/. Accessed 14 January 2016.
40. IBM SPSS Statistics Software. http://www01.ibm.com/software/analytics/spss/. Accessed 30 January 2016
41. Mari, D., An Overview of the Internet of Things for People with Disabilities. *Journal of Network and Computer Applications* 35:584–596, 2012. doi:10.1016/j.jnca.2011.10.015.
42. Atzori, L., Lera, A., and Morabito, G., The Internet of Things: A Survey. *Computer Networks* 54:2787–2805, 2010. doi:10.1016/j.comnet.2010.05.010.