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# Cloud-centric IoT based disease diagnosis healthcare framework

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## HIGHLIGHTS

- Proposing fog assisted IoT enabled disease diagnosis framework for the m-health perspective.
- Forming a health diagnosis system at server side for computing User Diagnosis Results (UDR).
- Handling the disease severity by adopting alert generation mechanism.
- Developing a smart student interactive diagnosing system for disease prediction.
- Comparing various state-of-the-art classifiers in the current domain for determining the best classifier for particular disease.

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## ABSTRACT

In the last few years, the m-healthcare applications based on Internet of Things (IoT) have provided multi-dimensional features and real-time services. These applications provide a platform to millions of people to get health updates regularly for a healthier lifestyle. Induction of IoT devices in the healthcare environment have revitalized multiple features of these applications. The big data generated by IoT devices in healthcare domain is analyzed on the cloud instead of solely relying on limited storage and computation resources of handheld devices. Relative to this context, a cloud-centric IoT based m-healthcare monitoring disease diagnosing framework is proposed which predicts the potential disease with its level of severity. Key terminologies are defined to generate user-oriented health measurements by exploring the concept of computational sciences. The architectural prototype for smart student healthcare is designed for application scenario. The results are computed after processing the health measurements in a specific context. In our case study, systematic student perspective health data is generated using UCI dataset and medical sensors to predict the student with different disease severity. Diagnosis schemes are applied using various state-of-the-art classification algorithms and the results are computed based on accuracy, sensitivity, specificity, and F-measure. Experimental results show that the proposed methodology outperforms the baseline methods for disease prediction.



## 1. Introduction

The recent proliferation of information and communication technology and embedded systems has evolved a new technology: Internet of Things (IoT). IoT enables people and objects in the physical world as well as data and virtual environments to interact with each other [4,18]. Many applications using IoT as the main data acquisition component form smart environments such as smart transportation, smart homes, smart healthcare, and smart cities as part of a prosperous digital society. Due to the advancement in IoT based medical devices and sensors, medical care and healthcare are two of the most potential research areas [5]. The rising cost of healthcare and occurrence of many diseases around the world urgently required the transformation of healthcare from a hospital-centric system to a person-centric environment. Focusing on disease management and personal well-being issue, we proposed a system which utilizes ubiquitous sensing capabilities of IoT devices to predict the possibilities of a potential disease in a patient.

IoT and cloud computing are mutually dependent on each other. In combination they both become a powerful platform for monitoring patients at the remote site providing continuous health information to doctors and caretakers. IoT is supported by virtual unlimited capabilities and resources of the cloud to compensate its technological constraints (e.g. storage, processing, and energy). On the other hand, the cloud can get benefits from IoT by extending its scope to deal with real things in the real world and for delivering a large number of new services in a distributed and dynamic manner. However, IoT centric-cloud architecture can be extended for the development of new applications and services in the smart environment [28,37].

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In our approach, Cloud-centric IoT based health diagnosis system is proposed using computational science methodology. In experiment section, smart student interactive health system is defined for IoT environment. Using IoT medical system, a series of measurements are used to collect information like frequent changes in health parameters over time and occurrence of abnormal conditions numerously during a definite time interval. Moreover, IoT devices and medical sensor readings can be utilized effectively in diagnosing a disease with its severity during a specific time interval. The syntax is defined for carrying out the diagnosis process in the cloud-centric environment. Three subsystems are designed to carry out disease diagnosing process. Firstly, IoT devices and medical sensor based readings are acquired using user subsystem. Then for data analysis, component-based cloud subsystem is defined to carry out disease diagnosing process. Lastly, different alert based signals are sent to responder and caregiver for future necessary action based on the results computed at the cloud subsystem.

In health domain, IoT context uses an extensive historical dataset of continuous measurements over a period of time to diagnose a disease. The diagnosis in a healthcare environment requires an accumulative set of measurements for effective results which cannot be possible by having a single clinic visit. In this regard, the paper contributes by (i) Proposing fog assisted IoT enabled disease diagnosis framework for the m-health perspective. (ii) Forming a health diagnosis system at server side for computing User Diagnosis Results (UDR). (iii) Handling the disease severity by adopting alert generation mechanism. (iv) Developing a smart student interactive diagnosing system for disease prediction. (v) Comparing various state-of-the-art classifiers in the current domain for determining the best classifier for different diseases.

Personal healthcare using IoT devices will provide a way to healthy life with low cost. Hence, effective healthcare system emphasizing on patient-centric practice is designed using medical IoT devices.

In the proposed system, the general framework of IoT based m-health disease diagnosis system is described. In Section 2, a survey on various IoT based health monitoring systems with different data mining methodologies have been discussed. In Section 3, we define key terms related to our proposed model and computing system for potential disease diagnosis with alert generation mechanism. In Section 4, a complete assessment of the smart student interactive system is conducted. Moreover, the prototype for Smart Student Interactive System (SSIS) has been defined in the form of template pattern. Furthermore, statistical results related to applicability of classification algorithm for different diseases have been discussed. Section 5 concludes the paper with some important discussion about future work and limitations.

## 2. Related research

This section analyze and realize various health monitoring systems and data mining methods used in IoT based healthcare environment. Firstly, different frameworks are discussed related to health monitoring system followed by data mining methods used in retrieving real-time health information.

### 2.1. IoT based health monitoring system

In 2016, Hossain and Muhammad [19] presented a real-time health monitoring system, named as Healthcare Industrial IoT (HealthIoT). This system has significant potential for analyzing patients' healthcare data to negate death circumstances. This healthcare IoT framework collects the patient data using medical devices and sensors. Moreover, to avoid identity theft or clinical errors by health professionals, the security procedures like watermarking and signal enhancement have been incorporated into this framework. In 2016, Gope and Hwang [17] defined a new technology based on IoT medical devices' advancements termed as body sensor network (BSN). In this framework, the patient can be monitored using different tiny-powdered and light-weight sensor networks. Moreover, the security requirements in developing BSN-healthcare system was also considered in this framework. In 2015, Gelogo et al. [16] discussed the background of IoT along with its application in u-healthcare perspective. An ideological framework of IoT for u-healthcare was presented by the authors. In 2014, Xu et al. [36] solved the heterogeneity problem of the data format in IoT platform by using semantic data model. Further, resource-based data accessing method (UDA-IoT) is designed to process IoT data ubiquitously. Moreover, an IoT-based system for handling medical emergencies was presented to demonstrate the collection, integration, and interoperation of IoT data. In 2013, Banee et al. [6] explained the latest methods and algorithms to analyze data collected from wearable sensors in health monitoring environment. The data mining tasks such as anomaly detection, prediction, and decision making have been applied on continuous time series measurements collected from wearable sensors. In 2014, Zhang et al. [40] discussed the methodologies for developing m-health based apps: namely website builder and applications builder to monitor patients remotely using IoT based healthcare medical system. They developed web-based applications for providing health information of patients to responders (doctors) outside a medical setting. Moreover, these authors also used IoT based health monitoring to measure adverse health outcomes including alcohol intake and therapeutic effects of medical interventions [41,39]. In 2015, Hussain et al. [20] proposed a people-centric sensing framework for elderly and disabled people. The aim of the methodology is to provide a service-oriented emergency response in case of the abnormal condition of the patient. In 2015, Islam et al. [21] proposed an intelligent collaborative security model to minimize risks in an IoT-based healthcare environment. In addition, they surveyed advances in IoT healthcare technologies. Moreover, particular emphasis is given to review the state-of-art network architecture/platform, applications and industrial developments in IoT-based healthcare solutions. In 2015, Catrinucci et al. [10] proposed a Smart Hospital System (SHS) using technological advancements, mainly RFID, WSN and smart mobiles. These technologies interoperate with each other through an IPv6 over low-power wireless personal area network infrastructure. In 2015, Kakria et al. [24] defined a framework for the vital sign monitoring system in human. The system measures the pulse rate and body temperature from a remote location. Moreover, an IoT enabled network infrastructure and the computational processor is used to generate emergency signals in case of abnormalities in health measurements. In 2014, Maia et al. [27] proposed a Web middleware platform for connecting patients with a doctor using wearable body sensors, known as EcoHealth. Moreover, the aim of the proposed methodology is to improve remote health monitoring infrastructure and diagnosis for patients. In 2013, Jara et al. [23] defined an interconnection framework for mobile health (m-health) based on IoT. They introduced technical innovations for empowering health monitors and patient devices with Internet capabilities. In 2015, Kim et al. [25] developed an emergency situation monitoring system using context motion tracking for chronic disease patient. The system diagnose the current status of the patient based on contextual information and provides necessary information by analyzing life habits of the patient. In 2012, Istepanaian et al. [22] introduced a new and novel concept of 4G health. They illustrated the multidisciplinary nature of the importance of this healthcare delivery concept. In 2014, Box et al. [9] proposed and implemented an intelligent home based platform, termed as iHome Health-IoT. This platform includes

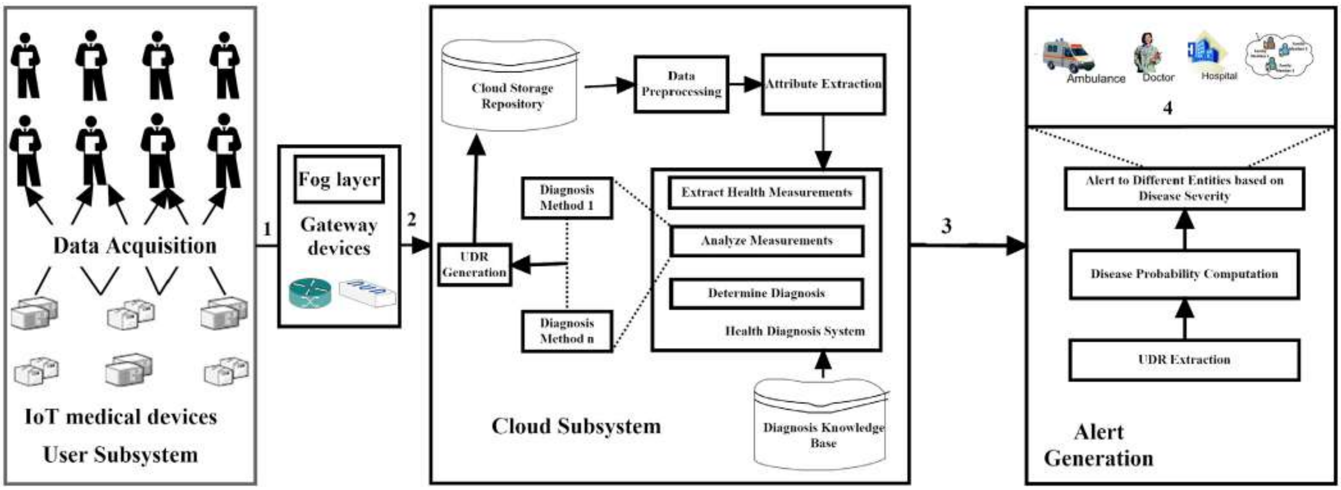


**Fig. 1.** A conceptual framework for IoT based m-health disease diagnosing system.

an open-platform based intelligent medical box (iMedBox) with enhanced connectivity for the combination of devices and services. Moreover, intelligent pharmaceutical package (iMedPack) and bio-medical sensor devices are incorporated in the proposed methodology. In 2017, Sood and Mahajan [32] designed a fog assisted cloud-based healthcare system to diagnose and prevent the outbreak of chikungunya virus. The state of chikungunya virus outbreak is determined by temporal network analysis at cloud layer using proximity data.

### *2.2. Data mining methodologies in IoT health environment*

In 2012, Patil and Wadhai [29] proposed different real-time data stream mining algorithms with a methodology to detect concept drift problem in real-time streaming data. In 2013, Lai et al. [26] studied the concept and architecture of BSN along with signal acquisition and context-aware sensing. However, the focus was mainly on sensors, data fusion, and network communication. In 2015, Dhobley et al. [14] used mobile application based SMS alert for medical emergency handling based on the sensory data provided to the central server. In 2010, Dass and Kumar [12] proposed a real-time data streaming algorithm known as Kaal which is significantly better than other algorithms. In 2015, Bhandari et al. [7] proposed an improved version of Apriori algorithm for real-time applications which reduces the time and space for scanning the whole database searching on the frequent itemsets. In 2008, Yin et al. [38] proposed a novel two-phase approach for detecting abnormal activities based on wireless sensors attached to the body. State Vector Machine (SVM) and Kernel Non-Linear Regression (KNLR) methods are used to detect abnormal activities in a body. In 2015, Assuno et al. [3] discussed approaches and environments for carrying out analytics on clouds for big data applications. They emphasize on four important areas of big data analytics namely, data management, model development, visualization and business models. Through a detailed survey, they provided future directions on cloud-supported big data computing and analytics solution. In 2015, Andreolini et al. [2] presented an adaptive algorithm for scalable and reliable cloud monitoring. This algorithm dynamically balances the amount and quality of time-series data. In 2017, Bhatia and Sood [8] presented an intelligent healthcare framework based on IoT technology to provide ubiquitous healthcare to a person during his/her workout sessions. The authors utilized the artificial neural network model to predict the persons health-related vulnerability using Bayesian belief network classifier.

## 3. Proposed work

The proposed methodology is described in Fig. 1. The conceptual framework of IoT based m-Health Monitoring system consists of three phases. In phase1, users' health data is acquired from medical devices and sensors. The acquired data is relayed to cloud subsystem using a gateway or local processing unit (LPU). In phase 2, the medical measurements are utilized by medical diagnosis system to make a cognitive decision related to personal health. In phase 3, an alert is generated to the parents or caretakers in context of person's health. Moreover, if emergency situation prevails then alert is also generated to the nearby hospital to handle the medical emergency. The details regarding each phase is described ahead:

### *3.1. User subsystem*

Users' health data is acquired by data acquisition system, which allows seamless integration of intelligent, miniature low-power sensors and other medical devices. These sensors are planted in, on or around the human body to monitor body function. In our methodology, the person's body sensor network is composed of both wearable and implanted sensor devices. Each sensor node is integrated with bio-sensors such as ECG/EEG and Blood pressure etc. These sensors collect student physiological parameters in structured and unstructured form, forward them to a coordinator known as a local processing unit (LPU) or Gateway forming fog layer, this can be a portable device or smart-phone. Since heterogeneous IoT devices have different internal clock structure, therefore they need to be synchronized for timely processing at cloud layer [11]. Moreover, in the current perspective where time is an important attribute, the gateways must be programmed to provide temporal synchronization for various datasets before transmission. Acquired data are transmitted to the connected cloud storage repository, using wireless communication media such as mobile networks 3G /CDMA /GPRS as shown in Fig. 1. For the purpose of data security during transmission, the channel is secured with Secure Socket Layer (SSL) for providing security and protection. The time stamp synchronization of various category of sensors is shown in Table 1. Fog layer composed of gateways, act as synchronization devices for the timely relay of data to the cloud layer for further processing [13].

### *3.2. Cloud layer*

The health-based sensory IoT data of each user is stored at Cloud-based platform. Since the data is ubiquitously sensed and

**Table 1**
Timestamp Synchronization.

| S.NO | Category | Description |
|---|---|---|
| 1 | No clock | Sensors do not have internal clock |
| 2 | Absolute | Sensors sense data depending upon internal clock |
| 3 | Relative | Sensors sense data depending upon other devices |
| 4 | Non Synch | Sensors internal clock is not synchronized |

required for different time units, so it is stored at cloud side server called as cloud storage repository. The health-related measurements are transferred to medical diagnosis system, where the analysis and diagnosis mechanism is followed to determine the person's health condition. The diagnosis method is based on predefined terms collected from medical books, medical practical experience, and advisors. Moreover, tenant database is maintained to provide users' personal information only to authorized doctors and caretakers. The information is derived in the form of record known as user diagnosis result (UDR) and consists of the relation {potential disease, severity, probability}. The following section emphasis on how users health diagnosis process is carried out, followed by cognitive decisions in the form of alert generation mechanism. The key terms used for diagnosis purpose is explained ahead with the help of corollary.

*3.2.1. Key terminology used for diagnosis user disease*

This proposed methodology defines some terms and concept for diagnosis of disease with IoT context related to the user. The system defines some rules and procedure adopted for diagnosis of user disease using IoT sensors.

**Corollary 1** (*User*)**.** *A user is a person whose health status is determined by using IoT based health application. Let $USER_i$ be a specific person with some Identification ID provided to the server. This ID is used for personal information gathering and medical measurements. Furthermore, identification number uniquely define a person from other persons in terms of record values. Lastly, the user profile can be interpreted as confidential information of user maintained in user profile database. Let User_Profile be a record of ($USER_i$, PERSONAL $DATA_u$, $PROFILE\_TYPE_v$). This means specific profile type of $USER_i$ with PERSONAL $DATA_u$. The user profile gives detail knowledge to the authorities related to person's previous health information. For example, user profile type "age" with personal information "23" and another record like "heredity disease" may be taken into consideration as a user profile. The details regarding personal profile generation is described in Table 2.*

**Corollary 2** (*Sensors Related Terms*)**.** *In IoT based healthcare system, medical-sensors are used to diagnose the person's health condition. A medical sensor represented as $SEN_i$ is used for measuring the health conditions such as blood pressure, ECG, temperature and other health-related parameters. Moreover, sensors can be medical or other implanted monitoring devices in the user IoT system.*

**Corollary 3** (*Context-specific information*)**.** *Context in our domain is defined as a circumstance that forms the setting for an event or information generated from one or more sensor values. In our health domain, contexts are confined to heterogeneous medical data retrieved from various IoT medical sensors. Let $COT_y$ is a context form acquired from sensor $SEN_{i.........}SEN_j$. These sensors give specific information about user health measurements and situated environment. Examples of context in medical domain can be temperature and blood pressure. Moreover, measurements are the health values computed related to a context at a particular time. In medical diagnosis system, the records of measurements are defined for a definite time. Let MESR be a record of ($USER_i$, $COT_y$, $TIME_x$, $VAL_n$), which states that measurement of $CONTEXT_y$ for a $USER_i$ during $TIME_x$ of $VAL_n$.*

**Corollary 4** (*Disease and Diagnosis*)**.** *Medical doctor examines the person's medical data and determines the probability of the potential disease. Moreover, the person's medical data is collected during definite time intervals so that results drawn from medical data is effective and correct. The result of medical diagnosis is the probability of the potential diseases with its severity. The disease type in user domain is specified as $DESS_p$, means the diagnosis disease is of type p defined in DESS set. Lastly, Diagnosis methods must be incorporated into our system to generate health results. Moreover, potential disease related to the user is derived from diagnosis rules.*

*3.2.2. Syntax generation mechanism*

The syntax required for diagnosis health-related diseases can be explained with the help of different definitions in the following section:

**Definition 1** (*Syntax Generation*)**.** Let the user diagnosis system instance (UDIGS) consists of relation ($DIGM_i$, $DESS_p$, *Level*, *Probability*) where $DIGM_i$ is the measurement derived from diagnosis method and $DESS_p$ is the disease name, *Level* defines the degree of significance, *Probability* defines the reliability of UDIGS current instance. Therefore, UDIGS is defined in the form of tuple relation as <UDIGS> := '('<DIGM> ',' <DESS> ',' <Level> ','<Probability> ')'.

**Corollary 5.** *Disease name set consists of various diseases taken into consideration. The syntax is described as <DESS> := $DESS_1$/$DESS_2$/$DESS_{3..........}$/$DESS_n$, where each $DESS_j$ is disease type. Similarly, we can define level set as <Level> := $Level_1$/$Level_2$/$Level_3$/ ............./$Level_n$/null, where $Level_j$ predict the different level of a given disease. In most of the cases, <Level> = null implies that the disease*

**Table 2**
Health attributes collected by m-health monitoring system.

| S.NO | Users attributes | Explanation |
|---|---|---|
| 1 | Age | Age of user in years. |
| 2 | Gender | Whether the user is male or female. (0/1) |
| 3 | Weight | Weight of user in kg |
| 4 | BMI | Body mass index of user (kg/$m^2$) |
| 5 | BP systolic | Systolic blood pressure (mmHg) |
| 6 | BP diastolic | Diastolic blood pressure (mmHg) |
| 7 | Haemoglobin A1c | Glycated haemoglobin A1c of user (%) |
| 8 | Gastro intestinal tract | Gastro intestinal index (1–5) |
| 9 | Body temperature | User current body temperature. |
| 10 | Stress index | User stress calculation based on ECG/EEG pattern. |
| 11 | Respiration index | Respiration index calculation. |
| 12 | Family history | User family history related to diseases. |
| 13 | History of disease | Users' previous health history. |
| 14 | Belongs to high-risk area. | Location of theuser home. (0/1) |

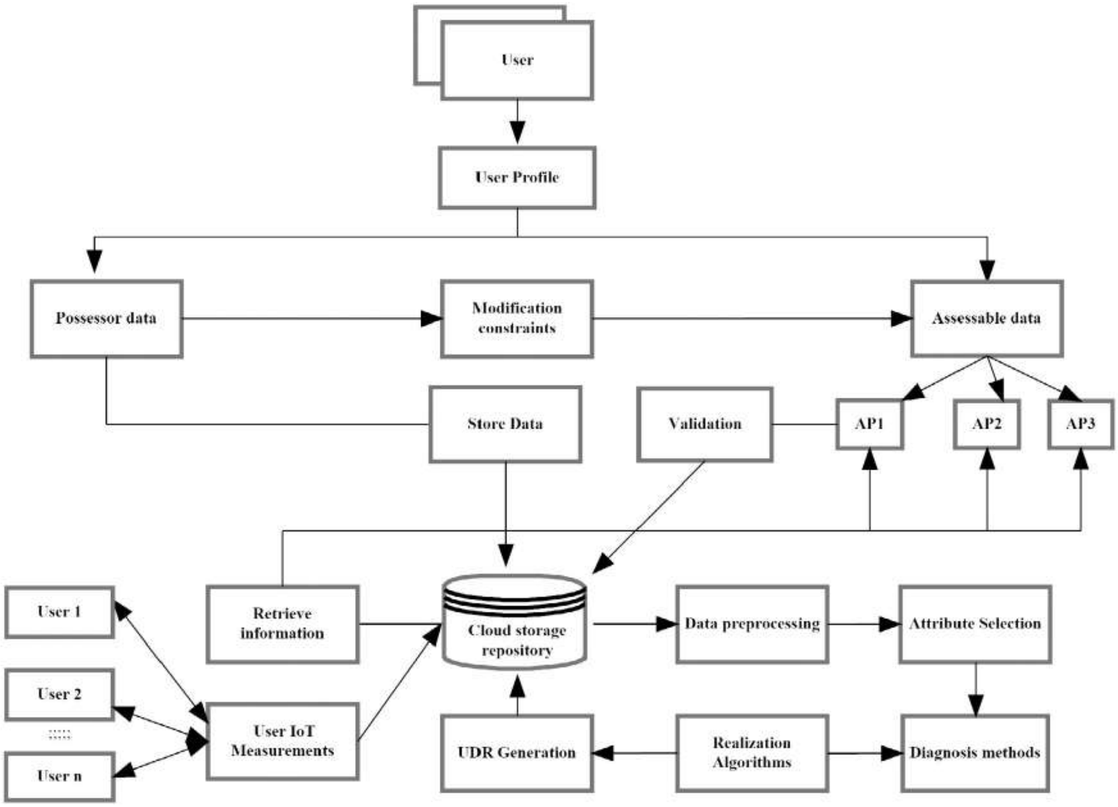


**Fig. 2.** Flow diagram of our Cloud-Centric IoT (CCIoT) diagnosis security system.

*severity does not exist. Moreover, <Probability> computes the reliability of the UDIGS instance.*

**Corollary 6.** *The most important field to focus on in UDIGS is the <DIGM>. In a medical environment, users health-related diseases can be predicted based on diagnosis schemes. Therefore, <DIGM> is described as single diagnosis scheme or logical combination of two diagnosis schemes. Hence, its syntax can be defined as <DIGM> := <Single-COND>/<Single-COND> <Logical Operator> <Single-Condition>. Single-COND is a single unit comprises a set of three different methods to diagnose a disease like symptoms in users. Therefore, <Single-COND> := <Scale-COND>/<Pattern-COND>/<Frequency-COND>.*

**Definition 2** (*Diagnosis Knowledge System (DKS)*)**.** To draw better diagnosis results, renowned doctors use several sources of data which are acquired from medical books, previous medical investigated articles and other information agents. We define the source of data as Diagnosis Knowledge System, which consists of different diagnosis rules adopted by the proposed methodology as shown in Fig. 1. In the proposed healthcare system, DKS is described in machine-oriented format since this play significant role in user disease diagnosis. The syntax of DKS is defined as <DKS> := <UDIGS>/<UDIGS> <DKS>.

**Definition 3** (*User Diagnosis Result*)**.** After collecting user health information from IoT devices and analyzing them by looking up for applicable Diagnosis Knowledge System, the doctor makes a diagnosis, considered as decision-making or cognitive decision process. UDR is generated by measuring the context values measurements and describing the user health status as $UDR{:}(USER_i, T_{start}, T_{end}) \rightarrow (DESS_p, Level, Probability)$.

*3.2.3. Security aspect in the proposed methodology*

The information flow at different levels is based on security mechanism is shown in Fig. 2. The system provides *role based access control* mechanism so that user critical health information remain protective. Two types of user roles are described in our Cloud-centric IoT (CCIoT) system (1) Possessor data and (2) Accessible data. Since user medical data resides in our cloud-centric IoT, therefore the user himself is designated as a possessor of data. Additionally, at times, user personal data must be provided to doctors or parents/caretakers. To distinguish, persons from each other we use the terminology Assessed Partner (AP). We impose constraints on AP for providing only the requisite information as necessary.

Three types of AP are defined in our CCIoT system: (1) Doctors (AP1) (2) Parents/caretakers (AP2) (3) Anonymous (AP3). Doctors are continuously provided with user SDR record information. Moreover, doctors can prescribe new medicines to the user based on his SDR record by following proper validation system. The validation mechanism works on the methodology of granting access to a doctor who can access the CCIoT application. After the completion of validation, the recommended medicines are saved on the cloud which can be accessed by AP2. An assessable partner designated as AP2 only read the SDR record of the user during different time intervals. Lastly, AP3 mainly composed of government agencies or a research firm that may require user health information for developing new drugs or medicine.

The CCIoT security mechanism is based on the symmetric key cryptography and role-based access mechanism (RBAM). In our proposed system, the security mechanism is based on encrypting the user password with “private key” allotted by trusted third party (TTP). Moreover, TTP is an entity that implements the security process in our proposed system. Moreover, it provides

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access only to the appropriate users who are registered with CCIoT.

After the authentication phase, the authorization is based on the role of different users. Since possessor data owner has the power to impose constraints on a number of accessible partners and providing different authorization to them (AP's). Moreover, before storing the user UDR record onto the cloud storage repository a solitary key *Zz* is issued by TTP for sharing between possessor data and rest of AP's under consideration. This key is utilized by the system as encryption mechanism before storing UDR record onto the cloud. Therefore, any AP's having access to the "*Zz*" can decrypt the user health data and access it based on the authorization provided to him by the possessor data. Hence, security concept in our proposed methodology is validated using symmetric key cryptography.

#### 3.2.4. User diagnosis result generation

The Algorithm 1 demonstrates the basic way to diagnose disease in user's health domain. The proposed methodology computes results of diagnosis using three different conditions (i) Scale_ Condition (ii) Pattern_ Condition and (iii) Frequency _Condition. These three conditions execute their analytics-based algorithm by generating the result from the health measurements taken by IoT health devices. The Result. Size ( ) function generates the result of a person suffering with a particular disease using above mentioned diagnosing conditions. If result of any of these three condition falls under the range of irregularity scale, then add the result to potential diseases UDR ( ) function. Lastly, return the UDR( ) tuples with information. The UDR() tuple consists of results computed from relative probability generated from probabilistic score of a person related to a particular disease using different conditions. For example, considering hypertension disease, the UDR results from diagnosis methods: scale, pattern and frequency is as {"hypertension", "Stage 1", 67}, {"hypertension", "Stage 1", 73} and {"hypertension", "Stage 1", 70}. The resultant UDR considered will be mean of these three probabilistic values i.e. UDR = {"hypertension", "Stage1", 70}. Similarly for other diseases like infectious or respiratory the stage field is set to null but probabilistic value is calculated for each disease. The generated UDR probability decides the next action to follow after results are generated. The alert generation system is totally based on the UDR probabilistic value explained in Algorithm 2.

### 3.3. Alert generation in proposed methodology

In our health domain, user diagnosis result based information is utilized to generate alert to doctors and caregivers. The user $UDR{:}(USER_i, T_{start}, T_{end}) \rightarrow (DESS_p, Level, Probability)$ is considered as the input record to generate warning or emergency alerts. In our methodology, alert generation is based on user-health state and probabilistic value generated for disease $DESS_p$ *noted as* $P(DESS_p)$. The $T_{start}$ gives the information related to starting time of the diagnosis procedure and continued up to $T_{end}$ time. The disease type is determined using $DESS_p$ attribute, disease stage is optional and determined by *Level* attribute, and probability defines the reliability of the disease. Firstly, the user's UDR is retrieved from the diagnosis module. If the UDR instance probabilistic value is less than the prefixed threshold value then register the person health state as *Safe*. On the other hand, if the probabilistic value is greater than the prefixed threshold value then put person health to *Unsafe*. Moreover, an alert based threshold ($\alpha$) has been considered to implement alert generation mechanism as follows:

**Algorithm 1**: Disease diagnosis in proposed methodology

**Input:** A set of values (i.e. series of measurement for a context type )
**Output**: Set of records ( Disease, Level, Expression for Value, probability)
**Begin** {
// For a given measurement value, perform scale _ based analysis.
Scale _Result = execute Scale Analytics (measurements);
Irregular Scale_Result = Scale_Result. Size( );
// For a given measurement value, perform pattern_ based analysis.
Pattern_Result = execute Pattern Analytics (measurements);
Irregular Pattern_Result = Pattern_ Result. Size ( );
// For a given measurement value, perform frequency_ based analysis.
Frequency_Result = execute Frequency Analytics (measurements );
Irregular Frequency_Result = Frequency_Result. Size ( );
If ( Irregular Scale_Result = Irregular Scale_Result Range or Irregular Pattern_Result = Irregular Pattern_
Result Range or Irregular Frequency_Result = Irregular Frequency_Result Range)
UDR. add (Disease, Level, Probability);
Return UDR ;}
**End**

1. If ($USER_i$*_HEALTH* $=$ *Unsafe*) *AND* ($P(DESS_p) < \alpha$) then system generates warning alert signal to doctor and caretakers. This signal helps the doctor or caregiver to get timely information about the person health to avoid future causalities.
2. If ($USER_i$*_HEALTH* $=$ *Unsafe*) *AND* ($P(DESS_p) > \alpha$) then generate emergency signal to the nearby hospital so that emergency situation can be handled on the spot. The alert messages are also delivered to doctors and caretakers on their respective devices.

The Algorithm 2 precisely describes the alert generation mechanism. The alert generation completely depends upon the diagnosis instance matrix UDR as described above. The disease name with its probability gives certain knowledge to the doctor and caretaker about person current health status. In addition, if emergency situation prevails then alert will be send to emergency medical provider so that nearby hospitals and doctor can be intimated to handle medical emergency effectively. Moreover, this diagnosis method in IoT environment is less intrusive to the users and helps the caretaker as well as doctor with comfort in taking care of patient. Lastly, this proposed methodology helps the doctor to diagnose the disease at the initial stage so that early precautions can be taken for better healthcare.

**Algorithm 2:** Alert Generation in Proposed Methodology.

**Input**: $UDR{:}(USER_i, T_{start}, T_{end}) \rightarrow (DESS_p, Level, Probability)$
**Step 1**: Retrieve user probabilistic value related to $DESS_p$ during starting time $T_{start}$, and ending time $T_{end}$.
**Step2**: If (probabilistic value > threshold value), then goto Step 4 else goto Step 3.
**Step 3**: $USER_i$*_HEALTH* $=$ *Safe* ;
Calculate New SDR after N time unit; Go to Step 1;
**Step 4**: $USER_i$*_HEALTH* $=$ *Unsafe*;
If ($USER_i$*_HEALTH* $=$ *Unsafe*) *AND* ($P(DESS_p) < \alpha$)
Generate Warning alert to family members , goto Step 1;
Else if ($USER_i$*_HEALTH* $=$ *Unsafe*) *AND* ($P(DESS_p) > \alpha$)
Generate emergency alert signal to responder with users temporal health information.
**Step 5**: Transfer current *UDR ( )* to the concerned Doctor and Care-Takers.
**Step 6**: Exit.

## 4. Smart student diagnosis system with experiments

### 4.1. Smart student diagnosis system

The main motive of proposed health diagnosis system is to generate student diagnosis result (SDR) based on the health measurements collected by medical IoT devices as shown in Fig. 3. The diagnosis methods for the proposed system is based on DKS, which prevents health-related causalities related to students. To verify

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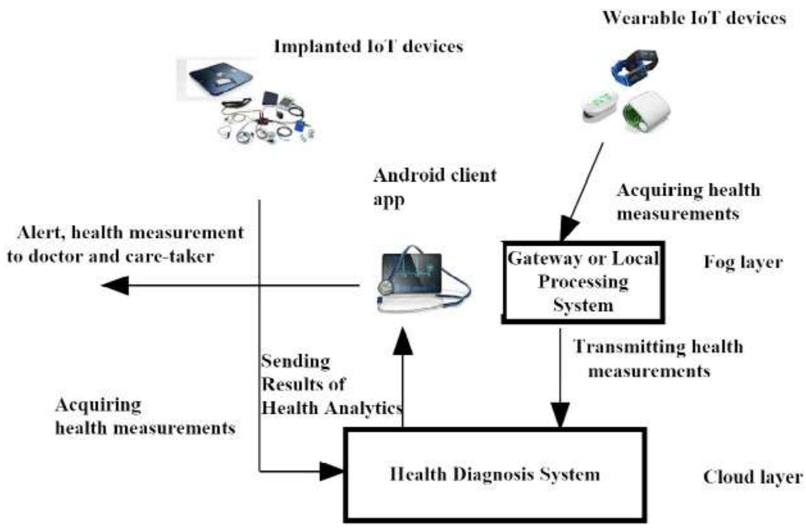


**Fig. 3.** Interactive student healthcare system.

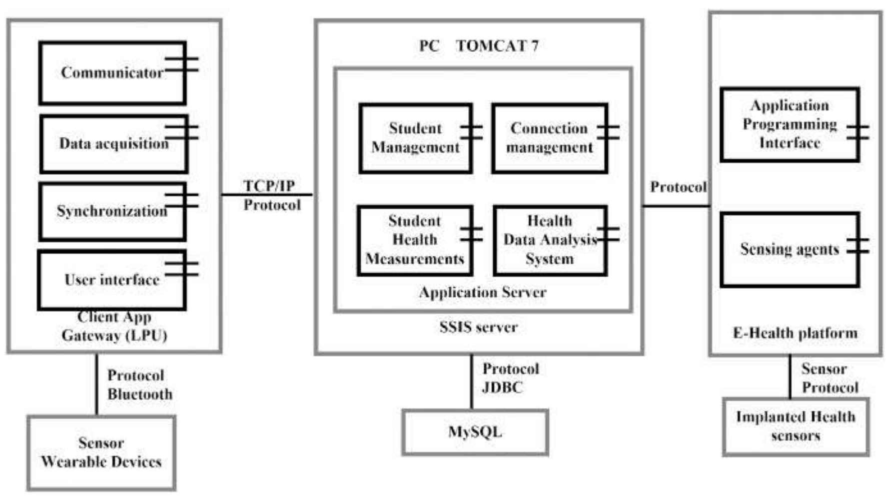


**Fig. 4.** Architecture of the smart student interaction system for disease diagnosis.

the stability and practicability of the proposed scheme, smart student interactive system prototype is described with experimental results.

The architecture of smart student health care system is described using Fig. 4. Firstly, the student health condition is determined based on the health data collected by various medical IoT devices in SSIS system. The medical data related to weight, gastrointestinal tract, body temperature, blood oxygen, blood pulse, ECG, and EEG is measured using medical sensors. Moreover, the Gateway or local processing unit (LPU) is used to synchronize the health data on temporal bases from various medical IoT devices. Then, these health measurements are utilized by SSIS server to generate student diagnosis result (SDR) record. Further, with various medical IoT sensors, the SSIS provides functionality like. (i) Obtaining student's health measurements from IoT devices. (ii) Recording student health data. (iii) Computing disease severity. (iv) Establishing SDR ( ) record for each student. Among these activities, the detection of potential disease and calculating the SDR ( ) record is according to the Algorithm 1.

### 4.2. Diagnosis steps in the smart student interactive system

The health measurements are collected by medical and other sensors at the client side, while diagnosis process and SDR index calculation must be done at cloud server side. The cloud storage repository helps in retrieving SDR for each student by computing the complexity of each diagnosis scheme. Therefore, the architecture is defined according to the necessity in Fig. 4.

The SSIS client i.e. Gateway collects the health data from wearable sensor devices and send that to the SSIS after temporal synchronization. Moreover, the SSIS server also collect the health data from implanted health sensors using e-health platform and then apply diagnosis method to generate the health index of the student.

To realize and analyze diagnosis method, the following steps are taken into consideration. (1) Selecting appropriate diagnosis method for health measurement analysis. (2) Way to conduct diagnosis process. (3) Executing different method.

**Step 1**: The proposed diagnosis process is implemented in SSIS server so that analysis results can be generated and transferred to care-takers or doctors. For this study, the SSIS server analyses the possibility of a student-related disease like obesity, waterborne disease or infectious diseases, autism etc. The parameters like stress index, blood glucose level, gastrointestinal index are used to compute the severity of the disease. Table 3 shows diagnosis scheme used for diagnosis the diseases related to the student in various context. To correctly analyze the severity of the disease correct diagnosis method must be applied. For example, to diagnose the waterborne or infectious disease, frequency and scale

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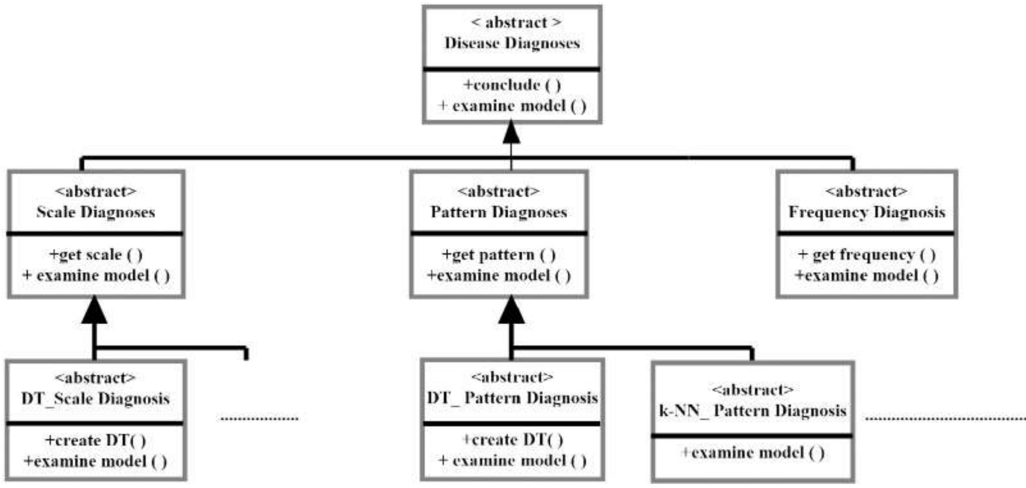


**Fig. 5.** Design of student diseases diagnosis using object oriented template pattern.

**Table 3**
Diagnosis scheme in proposed system.

| Disease | Diagnosis method | IoT health measurements |
|---|---|---|
| 1. Obesity | Scale based | Blood pressure, Body weight |
| 2. Water borne or infectious disease | Scale based<br>Frequency based | Camera pill (gastro intestinal tract), ECG, Temperature sensor |
| 3. Heart-related diseases | Pattern-matching<br>Frequency matching | ECG pattern |
| 4. Hypertension | Scale based<br>Frequency based | Blood pressure |
| 5. Respiration index | Pattern-matching<br>Frequency matching | Respiration sensor |
| 6. Stress index | Pattern-matching based<br>Frequency-based | Emotiv EPOC sensor and other stress measuring sensors |

based matching can be used. The parameters like body weight, gastrointestinal tract and stress frequency during a time-interval [t-$\Delta$t, t] yields better results when realized using k-NN classification algorithm. Similarly, to diagnose hypertension or hypotension, scale based diagnosis scheme is realized using decision tree classifier algorithm to generate accurate results. To diagnose student stress level, a wireless EEG device Emotiv EPOC is used to record EEG signals from different channels [15]. The baseline filter is used to obtain baseline corrected recording by subtracting the average of the signals from all electrodes from the original signal. The signal power is computed by converting the discrete time signal to frequency domain using Discrete Fourier transform. Fast Fourier transform (FFT) is used with hamming window to convert and process the time domain EEG signal. The power spectral density (PSD) is calculated for theta (4–8 Hz), alpha (8–12 Hz) and beta (12–30 Hz) band to determine the average power in the specified frequency range. Further, the EEG power spectrum features are correlated with stress levels. The data files containing extracted features from the training stage are fed into SVM classifier to determine the induced level of stress.

**Step 2**: In our SSIS system, three diagnosis conditions are measured based on diverse algorithms. In this study, the different diseases are analyzed using diagnosis schemes. Furthermore, machine learning algorithms are applied for each disease and the one with high accuracy is chosen to produce SDR ( ) record. For example, to diagnose infectious disease, simple if-else statements are not effective to draw accurate results. In Fig. 6, decision tree based scale oriented diagnosis scheme is described to generate accurate results.

**Step 3**: Student health data measurement system is designed to incorporate diverse diagnosis scheme with different classification algorithms. *Disease Diagnosis is* an important class in analyzing health data. The *Disease Diagnosis* is designed in such a way that it is applicable to three diagnosis schemes i.e., *Scale Diagnosis, Pattern Diagnosis*, and *Frequency Diagnosis*. The applicability is defined using object-oriented template pattern. Using this pattern, each component can be redefined without changing its overall structure as shown in Fig. 5. The *conclude* ( ) class defines the over-all physical structure of the diagnosis algorithm, whereas *examine model* ( ) analyze the data for a particular diagnosis scheme.

Fig. 5 shows that *Disease Diagnosis* class having three subclass: *Scale Diagnosis, Pattern Diagnosis*, and *Frequency Diagnosis.* Moreover, each of this subclass is further apprehended with different classification algorithms such as Decision Tree, Support Vector Machine (SVM), and k- Nearest Neighbor (k-NN). The *DT_ Scale Diagnosis, DT_ Pattern Diagnosis* , *DT_ Frequency Diagnosis* are the subclasses of decision tree algorithm in different diagnosis schemes. Furthermore, decision tree algorithm for identifying infectious and hypertension disease in student domain is defined in Fig. 6. The three conditions are measured in this decision tree algorithm to generate a disease of infectious class. Four parameters patterns are analyzed in this decision strategy. The parameters like Body temperature pattern, Body weight pattern, Gastrointestinal pattern and Stress pattern is computed for a particular time-interval ($\Delta$t). If a student comes under this parameter range then he is having a high probability of diagnosis with infectious disease as shown in Fig. 6. This machine learning algorithm is easily incorporated in <COND> field described in Section 3. In addition to that, a decision tree for diagnosing hypertension is also shown in Fig. 6 (b). Moreover, using *scikit-learn* library these features are converted

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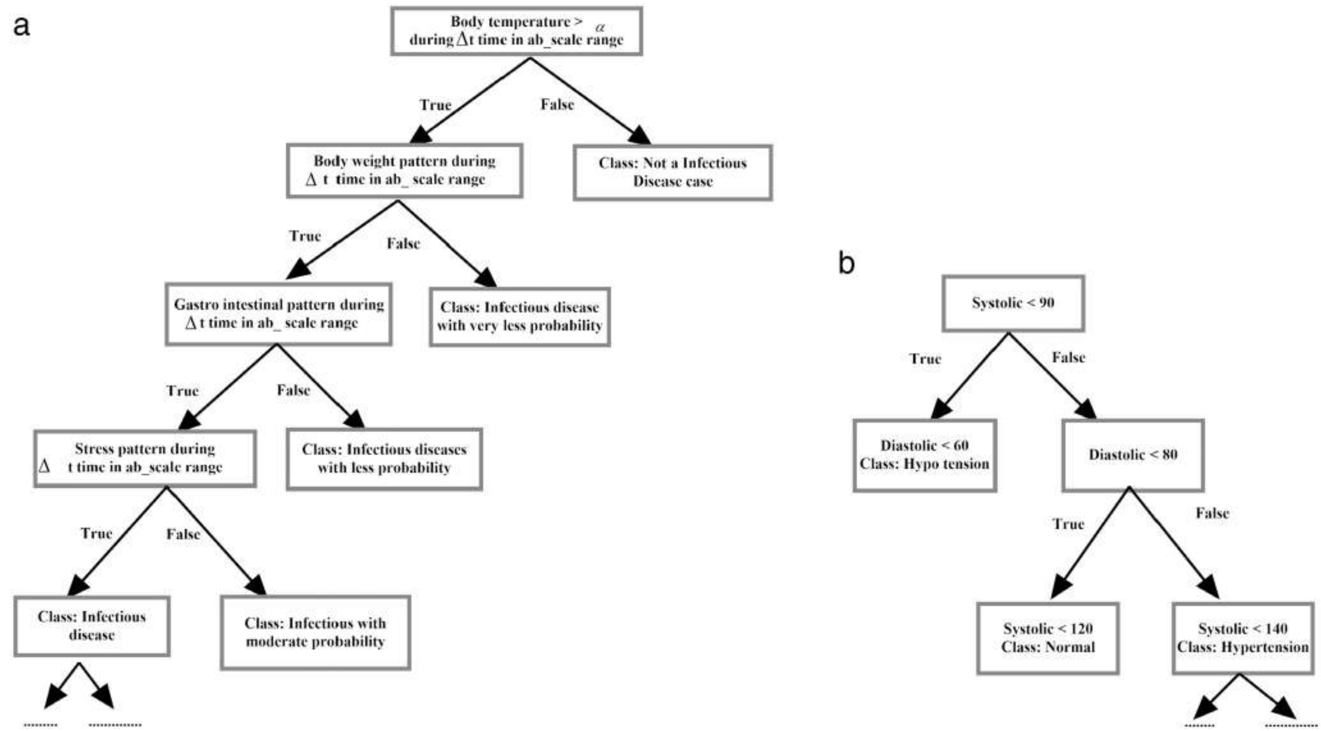


**Fig. 6.** Decision tree for diagnosis (a) infectious (b) hypertension disease.

to software implementation [31]. The classes in our prototype are implemented with python by using the *scikit*-learn library. It is an open source machine learning library which incorporates various classification, regression and clustering algorithms.

### 4.3. Experiment evaluation

To validate our proposed system, the results are computed from following datasets:
(i) UCI data repository comprising thousands of data instances for multiple time frames to diagnose a student with obesity, infectious, respiratory and heart-related diseases [33].
(ii) Random generation of EEG signal using Emotiv EPOC sensor data for stress level identification in 25 students.

The test cases to diagnose the potential disease are developed using existing knowledge of medical professionals. The test cases are checked physically by comparing student health symptoms acquired from UCI data repository and sensor measurement data with appropriate diagnosis rule. Moreover, the data mining operations in our experiment section are performed by WEKA [35] Toolkit. In our implementation, we manage our application by changing it into service components sets defined by Web Service Resource Framework (WSRF) standards. Moreover, we established a third party cloud namely Amazon EC2 [1] for data analysis. It is an Infrastructure as a service (IaaS) provider that helps in generating various types of machine instances. In our system, different Amazon Machine Image (AMI) with default instance "m1.small" is chosen to run on CentOS 6.7 with a Linux 2.6.32Xen Kernel. Results are obtained from various datasets and are compared with various state-of-the-art baseline techniques for different diseases.

#### 4.3.1. Data segmentation

Data segmentation is used to analyze datasets obtained from online data repositories for a given time window $\Delta t$. For student health-related disease, we used cross-modality search via regression method to identify various severity attributes for different diseases in a given time window. Appropriate parameters as specified by [30] were adjusted to obtain efficient results for the datasets. Moreover, for stress level computation, 25 students EEG data is obtained from Emotiv EPOC device. The stress computation in student domain is effectively discussed in Section 4.2. The results based on segmentation of datasets are discussed ahead.

#### 4.3.2. Data classification efficiency

Data classification efficiency determines the categorization of data values into severity and non-severity class. For different diseases, various statistical measures are included to evaluate classification efficiency for the proposed model. These include accuracy, specificity, sensitivity, and F-measure. In order to determine the best classifier for different diseases, state-of-the-art baseline classifiers are incorporated. Results are obtained by comparing different type of datasets for a particular disease. The diseases like obesity and respiration index are easy to calculate from the direct readings of one or two attributes. On the other hand, complex diseases like infectious, heart-related and stress index required proper classification methods.

For optimized results, rigorous validation approach namely 4-fold cross-validation is used to calculate the statistical results for different diseases. Firstly, the data are partitioned into 4 folds, three folds are used as training data and one fold is used as the testing data [34]. Each fold of the data has a chance to be testing data, the entire process is run for 4 times and average statistical results are obtained for the different classifier. The resulting analysis for three diseases is explained ahead.

#### 4.3.3. Result analysis

For infectious and heart-related disease, four different classifiers were indulged, namely Decision Tree (DT), k-Nearest Neighbor (k-NN), Naïve Bayes (NB) and Support Vector Machine (SVM). However, the test cases are same for the proposed system and only classifiers are changed for experiment purposes. Results obtained for different classifiers are shown in Fig. 7.
(i) Plots in Fig. 7(a–d) illustrate the comparison results of Accuracy, Specificity, Sensitivity and F-measure for infection oriented

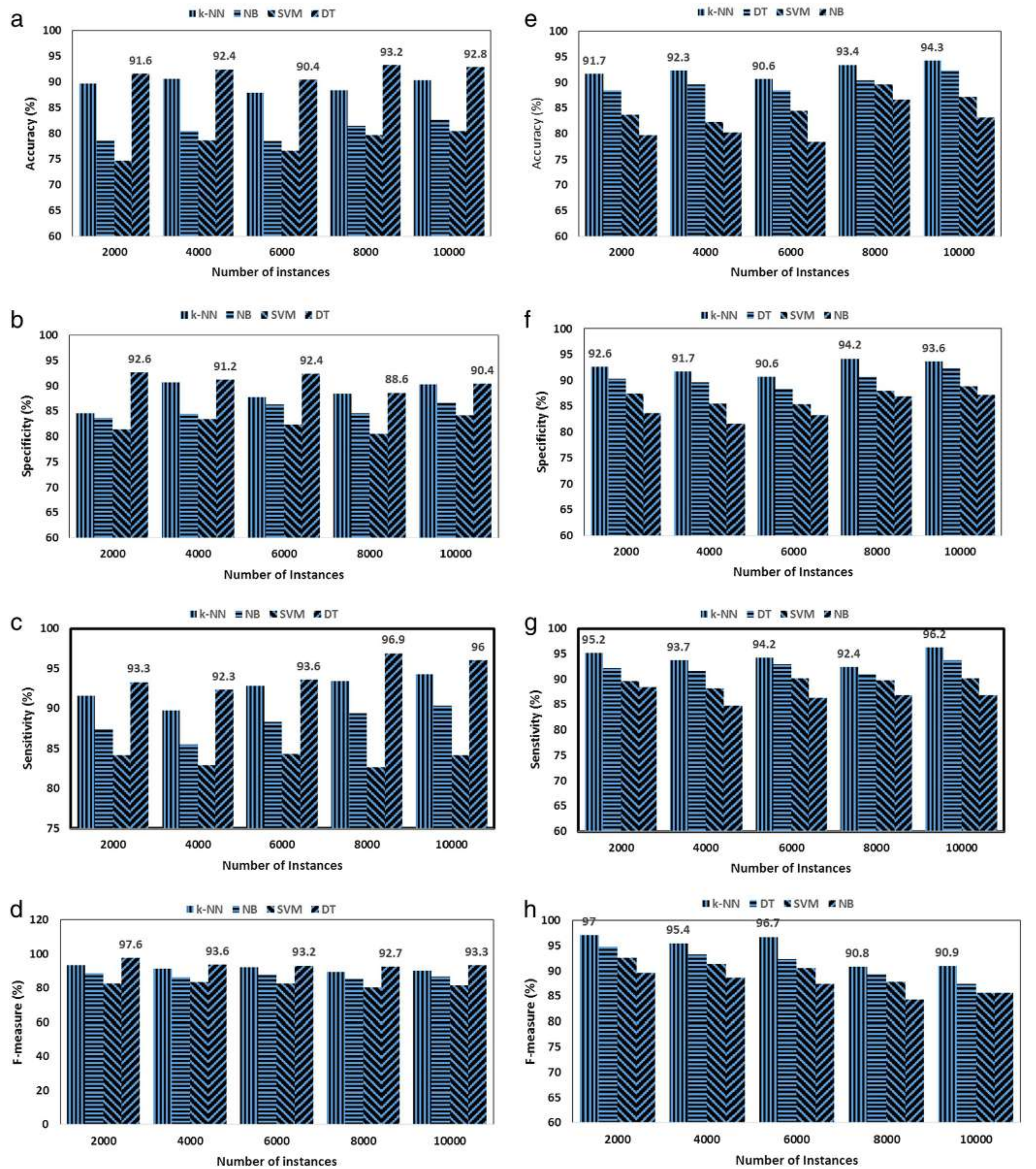


**Fig. 7.** Comparison results for classification efficiency; Infectious dataset (a) accuracy, (b) specificity, (c) sensitivity, (d) F-measure; heart-disease related dataset (e) accuracy, (f) specificity (g) sensitivity (h) F-measure.

data instances. The comparison results are provided for above mentioned state-of-the-art classifier models. From the results, it can be seen that in the current scenario, Decision tree (C 4.5) model has superior performance over other classification techniques. Specifically, DT was able to achieve better accuracy in diagnosing a student with infectious diseases, numerating to 92.8% compared to other techniques of k-NN (90.3%), SVM (80.4%) and NB (82.6%) respectively. In case of specificity, DT was able to acquire the higher value of 93.3% as compared to k-NN (90.2%), SVM (81.5%) and NB (86.7%). Similarly, DT yields 90.4% and 96% value respectively for sensitivity and F-measure, which is comparatively higher than other classifiers. Therefore, it can be concluded that in diagnosing a person with infectious diseases, DT classifier is highly efficient.

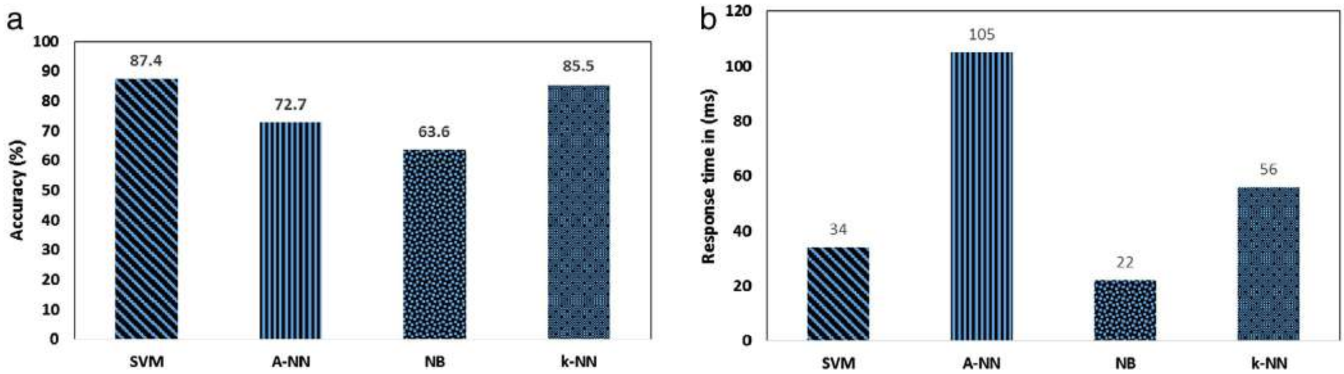


**Fig. 8.** Classifiers accuracy and response time in stress level identification.

(ii) Plots in Fig. 7(e–f) demonstrate various comparison results of classifiers in diagnosing a person with heart-related diseases. Based on the results from heart-related dataset instances, the k-NN classifier is highly efficient as far as statistical evaluation is concerned.
(iii) Plots in Fig. 8(a–b) shows the accuracy of classifiers namely; SVM, Artificial Neural Network (ANN), NB and k-NN with response time in determining the stress level of the student. From the results, we conclude that SVM has the highest accuracy of 87.4% in determining the stress level of the student with a response time of 34 ms respectively. Moreover, choosing right classifier improves the overall quality of SSIS system. Lastly, the following conclusion can be drawn from the proposed diagnosis system:
(a) *Practicality of the proposed diagnosis scheme*: This case study verifies the practicality of the diagnosis schema by using software technology like a scikit-learn library.
(b) *Extendibility of the diagnosis scheme*: The proposed diagnosis method is implemented using the various machine learning algorithm. Further, new classifier can be easily accommodated in the proposed methodology for different diagnosis schemes.

## 5. Conclusion

With the indulgence of medical devices in IoT environment, the diagnosis process can be made more effective and reliable. The key-points of the paper is to describe conceptual framework of the m-healthcare system generating user diagnosis result (UDR) based on health measurements provided by medical and other sensors. Moreover, this formal model consists of key terms, concepts, disease diagnosis methodology and alert generation mechanism. The main motive behind generating results from different diagnosis schemes is to utilize different sets of IoT measurements over a stipulated time for better health analysis. Furthermore, the proposed SSIS is a patient-centric approach to draw results from data collected by medical sensors for continuous well-being, monitoring and maintenance. Using this proposed methodology we can conclude that patterns, scale, and frequencies based diagnosis results play a significant role in identifying a person with potential disease type. Moreover, statistical results are quite helpful in choosing best classifier for a particular disease taken into consideration.

### *5.1. Limitation and future work*

To provide more versatility to the proposed system in terms of diagnosis methods, new <COND> can be incorporated as a future prospect. Scale-COND, Pattern-COND, and Frequency-COND can be refined in future for effective evaluation. The statistical measurements can be developed from the proposed platform when deployed in the physical world. Moreover, the accuracy of the proposed system can be compared with gold-standard investigation methods used by medical professionals. Lastly, this methodology can serve in future as the theoretical foundation for providing better healthcare services in the digital world.

## Conflict of interest statement

The authors have NO affiliations with or involvement in any organization or entity regarding any financial interest (such as honoraria; educational grants; participation in speaker's bureaus; membership, employment, consultancies, stock ownership, or expert testimony or patent-licensing arrangements), or non-financial interests (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or material discussed in this manuscript.

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