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An intelligent framework for workouts in gymnasium: M-Health perspective☆

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ABSTRACT

The Internet of Things (IoT) Technology has the potential to capture real-time health related parameters everywhere. Henceforth, in this paper, the Cloud Centric IoT (CCIoT) Technology is utilized to assess the health related attributes of a trainee during exercise sessions in a gymnasium. The proposed system have the capabilities to predict the probabilistic vulnerability to health parameters of a trainee during workouts. For this purpose, back-propagation based Artificial Neural Network (ANN) technique is used as a prediction model, layered into three stages, i.e. Monitoring, Learning, and Prediction. Also, the probabilistic vulnerability is represented in real-time using color-coded technique, depicting the health state of the trainee. The proposed system has been validated using an experiment in which five people were monitored for six days at different gymnasiums. Results are compared with different state-of-the-art techniques for determining the overall effectiveness of the proposed system.

1. Introduction

Innovative developments in the Information and Communication Technology (ICT) is delivering efficient services in various sectors such as healthcare, transportation, logistics, and agriculture [1]. The automation of remote data sensing, and its real time analyzation for decision making depict its revolutionary impact [2]. In the healthcare domain, this emerging technology has paved way for the future of medical industry leading to wireless health data acquisition and assessment, mobile healthcare, and remote doctor interventions for provisioning medical care in emergencies [3]. More importantly, it has raised the level of healthcare to form a sustainable balance between optimal healthcare resource utilization and patient-oriented healthcare servicing. Moreover, real-time health data acquisition, its analyzation and sharing are some of the vital applications in mobile healthcare. In general, the concept of healthcare servicing in real-time incorporates seamless healthcare delivery anywhere.

Research Field: With the growing awareness of regular exercise, people around the globe are spending considerable time and wealth for this vital health activity. Infact, the doctors and healthcare professionals have been continuously emphasizing on the various benefits of exercises for both healthy and unhealthy people. Furthermore, the World Health Organization (WHO) has recommended two-hour daily exercise session for healthy and disease-free life [4]. Due to these reasons, people have shifted to healthcare gymnasiums and other body fitness centers for their routine workout exercises to keep them

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physically and mentally fit. These places have been considered as appropriate places for maintaining personal fitness. However, during long and forceful exercise sessions, there can be severe health conditioning, especially in these places where surrounding environment changes regularly. Moreover, an instantaneous health adversity can become a causing factor for serious health effect, and permanent health loss. Infact, Kemmler and von Stengel [5] has provided several evidences that forceful exercises can result in serious health risks including heart attacks, shocks, lung diseases, and high blood pressure, especially among people with low body immunity. Moreover, the changes in environmental in form of humidity, and temperature during exercise sessions at the gymnasium and other workout centers have a direct effect on the health of a trainee. Henceforth, wireless health monitoring and its simultaneous analyzation in real-time are necessary for providing an optimal healthcare environment during exercise sessions.

Motivation: With the increase use of Mobile Internet and the Cloud Centric Internet of Things (CCIoT) Technology, the way in which data is perceived, transmitted, and analyzed has transformed significantly. This has been made possible by various IoT sensors, actuators, and other Internet-enabled devices that can be easily placed in any environment. These smart devices can be easily installed at different places in gymnasium centers and gymnasium's equipments so that during the exercise sessions, real-time health attributes of the trainee can be effectively captured and transmitted to the connected database. Moreover, with the automated compilation of health related data and statistics, it is possible to develop a proactive health assessment model that is capable of predicting, and quantifying health conditions like health vulnerability, and health adversity in real-time.

Contribution: With the above mentioned aspects, the work presented in this paper is focused on monitoring the real-time health attributes of a trainee during exercise sessions using the CCIoT Technology, and analyzing them for predicting the real-time health vulnerability. Studies have shown that an individual's health is mostly influenced by the surrounding environment, especially where the multiple health affecting factors like humidity, temperature, and noise changes seamlessly. As a result, with the frequent changing of the gymnasium's environment, these places are vulnerable to health adversity of a trainee. Acquisition of these health affecting factors using IoT Technology formulates the monitoring core of the proposed framework. In addition to this, a novel prediction model based on Artificial Neural Network (ANN) technique is proposed to predict the probabilistic vulnerability on the trainee health during exercise sessions. This impact can be visualized using the color coded technique, where the vulnerability probabilities of trainee's health are mapped onto grayscale imagery regions. Moreover, this vulnerabilistic prediction model of healthcare can effectively used to provide healthcare services in different places like hospitals, and homes. Based on the proposed model, an application scenario of the intelligent treadmill is presented with the functionality of displaying color mapped health vulnerability, automatic speed adjustment, and alert generation in emergency medical cases.

Organization: The remainder of the paper is organized as follows. Section 2 overviews some of the important contributions in the field of CCIoT Technology and ANN technique for healthcare servicing. The proposed architecture is detailed in Section 3. Performance evaluation of the proposed model is performed in Section 4. Finally, Section 5 concludes the paper with some important discussions.

2. Literature review

The CCIoT Technology has been successfully utilized in various healthcare applications. This section reviews some of the important literatures in the field of CCIoT based Healthcare Monitoring Systems. In addition to this, a sub-section is made to discuss some of the important usages of ANN technique in the healthcare industry.

2.1. CCIoT based health monitoring

Researchers have put forth several CCIoT based healthcare monitoring scenarios to depict the effectiveness of utilizing CCIoT Technology for healthcare services.

Yang et al. [6] have proposed a home based Health-IoT platform for analyzing the health conditions including heart rate, and blood pressure of a person. Specifically, the presented platform comprises of three major components, (i) an intelligent medicine box with enhanced connectivity and interchangeability (ii) a smart pharmaceutical packaging with communication and actuation capability (iii) an intelligent wearable biomedical sensor with state-of-the-art printing technology. The major objective of the presented platform is to use IoT devices for home-based healthcare servicing to achieve high efficiency and accuracy in medical decision making.

Work presented by Fanucci et al. [7] is aimed at developing an integrated ICT system for acquiring daily vital signs of chronic heart failure patients from home. The collected health data is automatically transmitted to the connected hospital database for access by the healthcare professionals. The presented system was comprised of bio-medical sensors, and actuators to acquire data about Electrocardiogram (ECG), oxygen level, and blood pressure. Appropriate thresholds were determined to generate alert signals to doctors during the medical emergency case. Implementation of the presented model showed high efficiency for determining vital signs of patients, thereby aiding doctors with early interventions and effective decision making.

Kim and Lee [8] presented an energy efficient technique for monitoring hospital-based patients using IoT Technology. The technique utilizes different clustering algorithms and minimum spanning tree technique for minimizing the energy consumption within the IoT sensor network. Simulation results showed that the presented technique is effective for the deployment in the hospital environment.

Hossain and Muhammad [9] provided a CCIoT infrastructure for analyzing the real-time health data. Various IoT devices were utilized for wireless monitoring of different vital signs, health analyzation and remote doctor intervention in medical emergency cases. As an experimental implementation, the platform was used to monitor ECG and other health-oriented data by mobile devices, which were securely connected to the cloud storage for remote access by doctors. Results showed that the presented infrastructure persist high degree of efficiency and accuracy.

Salem et al. [10] presented a fault detection approach in wireless sensing of health attributes. The presented approach was a collaborative methodology of Haar wavelet decomposition, Holt-winters forecasting method, and Hampel filters. A smartphone was used to analyze the acquired health data in real-time. Moreover, alarm signals were generated after detecting a medical emergency situation of the patients. Authors were able to register efficient results during the implementation of the presented system.

Brugarolas et al. [11] extended the concept of human health monitoring using IoT Technology to include acquisition of vital signs among animals. Authors presented a non-invasive IoT sensor system comprising of ECG, Photoplethysmogram, and Inertial measurement units for capturing health signs among animals. Specifically, authors used IoT devices with electrodes with polymer coating to acquire accurate health data values. In the experimental trial, the presented system registered high rate of accuracy in acquiring health vital signs among dogs and thereby, presents various benefits for dog handlers.

2.2. Modeling Artificial Neural Network (ANN) in healthcare

ANN is the expert system model for analyzing and predicting data values proactively by using certain predefined mathematical functions. In the healthcare sector, this predictive technique has been effectively utilized by various researchers for providing pro-active healthcare services.

Chen et al. [12] presented an approach to predict smog-related health hazard. Health-related data are acquired in real-time by IoT sensors and social media portals. Authors have used microblogging text and weather information for modeling smog-related health hazard and smog severity. In the experimental trial, the ANN-based predictive technique was used to forecast health hazard by acquiring IoT based observations. Moreover, a comparative analysis was performed with other state-of-the-art prediction models to determine the overall accuracy of the presented system. Results depicted that the approach was capable of predicting accurate health severity level and therefore, can be used as an early warning and prevention systems.

Li et al. [13] provided an intelligent predicting model based on ANN technique for determining the severity of menopausal symptoms. Various data samples were acquired from several hospitals for system modeling. Authors have analyzed nine important risk factors for the presented system. Some of them included age, educational background, and employment status. The collected data was used to train the presented system for achieving high accuracy during prediction stage of the ANN technique. Implementational assessment of the model showed that the system persists high accuracy and efficiency for the prediction of health-related severity.

Gjoreski et al. [14] presented a context-aware reasoning system for predicting energy expenditure among people during health and sports activities. The presented approach included extraction of multiple health features from the accumulated data values and use it as training context for the ANN technique. The statistical analysis of the presented system showed that the approach is more accurate in providing pro-active energy expenditure values and is highly effective in health monitoring.

Another context-aware system is presented by Garcia et al. [15] for analyzing the daily activities of a person. Various data values like biometric data, fitness data, and medical information were acquired in real-time from different embedded IoT sensors. Authors used these data values to generate set of expert rules to infer different levels of medical alerts for the users during routine activities. Moreover, in the experimental implementation, authors used a smartwatch and smartphone to determine the overall system efficiency. Results showed that the presented approach is highly effective and accurate in determining acquisition errors during various user activities.

Kupusinac et al. [16] presented an intelligent system for early prevention of atherosclerosis and cardiovascular diseases. The Matlab-based solution comprised of ANN technique and evolutionary algorithm for predicting the cardio-metabolic risk in the patients. The overall procedure of determining the risk was divided into two phases. The initial phase included diagnostic methods for preliminary estimation of cardio-metabolic risk. In the second phase, this information was used to identify the people with high-risk rate for early care. More than 90% accuracy was registered by authors during the deployment of the system.

3. Proposed model

The layered architecture of the proposed IoT based healthcare monitoring system inside a smart gymnasium is shown in Fig. 1. The proposed model comprises of four phases, namely Data Sensing Phase, Classification Phase, Mining Phase and finally Prediction and Visualization Phase. Every phase performs certain predefined tasks, thereby providing necessary services to the adjacent phases. Initially, data regarding various attributes of physical health, environment, dietary, and behavior are captured by different IoT devices embedded inside a gymnasium, depending upon their respective sensation range. Some of the commercial IoT devices for data capturing are shown in Table 1. This captured data is then transmitted to the connected

Table 1
Commercial wearable IoT sensors. Abbreviations: RD Raw Data; EE Energy Expenditure; HR Heart Rate; Temp. Temperature; DT Distance Traveled; BP Blood Pressure; PR Pulse Rate; Y Available; X Not Available; O Optional.

Device Name	Manufactured By	Accelerometer	Gyroscope	Magnetometer	Pressure	Temperature	Light	Microphone	Event Button	Other	ECG/HR	Respiratory Rate	Oximeter	Blood Pressure	Galvanic Skin Response	Heat Flux	Perspiration	Hydration Level	Wireless	Discrete Output
ActivePal	Pal Tech	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Steps, Activity, Duration, Time
MoveMonitor	McRoberts	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Activity,EE
AX3 Watch	Axivity	✓	X	X	X	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X	RD
Motion Watch 8	CamNtech	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Sleep, Activity
Actiheart 8	CamNtech	✓	X	X	X	X	X	X	X	X	✓	X	X	X	X	X	X	X	X	RD, Activity, HR
RT6 Research Tracker	Stayhealthy	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	RD, Kcal
EXL-S3	Exel	✓	✓	✓	✓	✓	✓	X	X	X	X	X	X	X	X	X	X	X	✓	RD, Orientation
Basis	Basis	✓	X	X	X	✓	X	X	X	X	✓	X	X	X	X	X	X	X	X	Sleep, HR, Temp, Calorie
x-BIMU	x-io	✓	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	RD
One	Fitbit	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	EE, Steps, DT, Sleep Time
Shine	Misfit	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	Steps, Calories, EE, RD, MET
wGT3X-BT Monitor	ActiGraph	✓	X	X	X	X	X	X	X	X	X	O	X	X	X	X	X	X	✓	Sleep, time, Efficiency, Light
Up/Up24	Jawbone	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Sleep, Activity Intensity, EE
Physilog 4	Gait Up	✓	✓	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Temporal/Spatial gait analysis
Wireless Activity	iHealth	✓	X	X	X	X	X	X	X	X	X	X	X	X	O	O	X	X	X	Sleep, EE, DT, Steps
Checklight	MC10	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	Head Impacts, Count, Intensity
FitCore	BodyMedia	✓	X	X	✓	X	X	X	X	X	X	X	X	X	✓	✓	X	X	✓	RD, EE, Activity, Sleep
Wellograph	Wellograph	✓	X	X	X	X	X	X	X	X	✓	X	X	X	X	X	X	X	✓	HR, Steps,Active time, Calories
Pulse	Withings	✓	X	X	X	X	X	X	X	X	✓	X	X	X	X	X	X	X	X	HR,BP, SpO2, ECG, HRV
Scout	Scanadu	X	X	X	X	X	X	X	X	X	X	X	✓	✓	X	X	X	X	X	HRV, Stress, BP
Hydrate	MC10	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	X	Hydration Level
Mio Fuse	Mio	✓	X	X	X	X	X	X	X	X	✓	X	X	X	X	X	X	✓	✓	HR, Stress, Calorie, Sleep
Rhythm +	Scosche	X	X	X	X	X	X	X	X	X	✓	X	X	X	X	X	X	✓	✓	PR, Calorie, Pace, Distance
Wireless BP	iHealth	✓	X	X	X	X	X	X	X	X	✓	X	X	X	✓	X	X	X	✓	Systolic/Diastolic BP, HR
Shimmer 3	Shimmer	✓	✓	✓	✓	✓	X	X	X	X	✓	✓	X	X	X	X	X	X	✓	RD

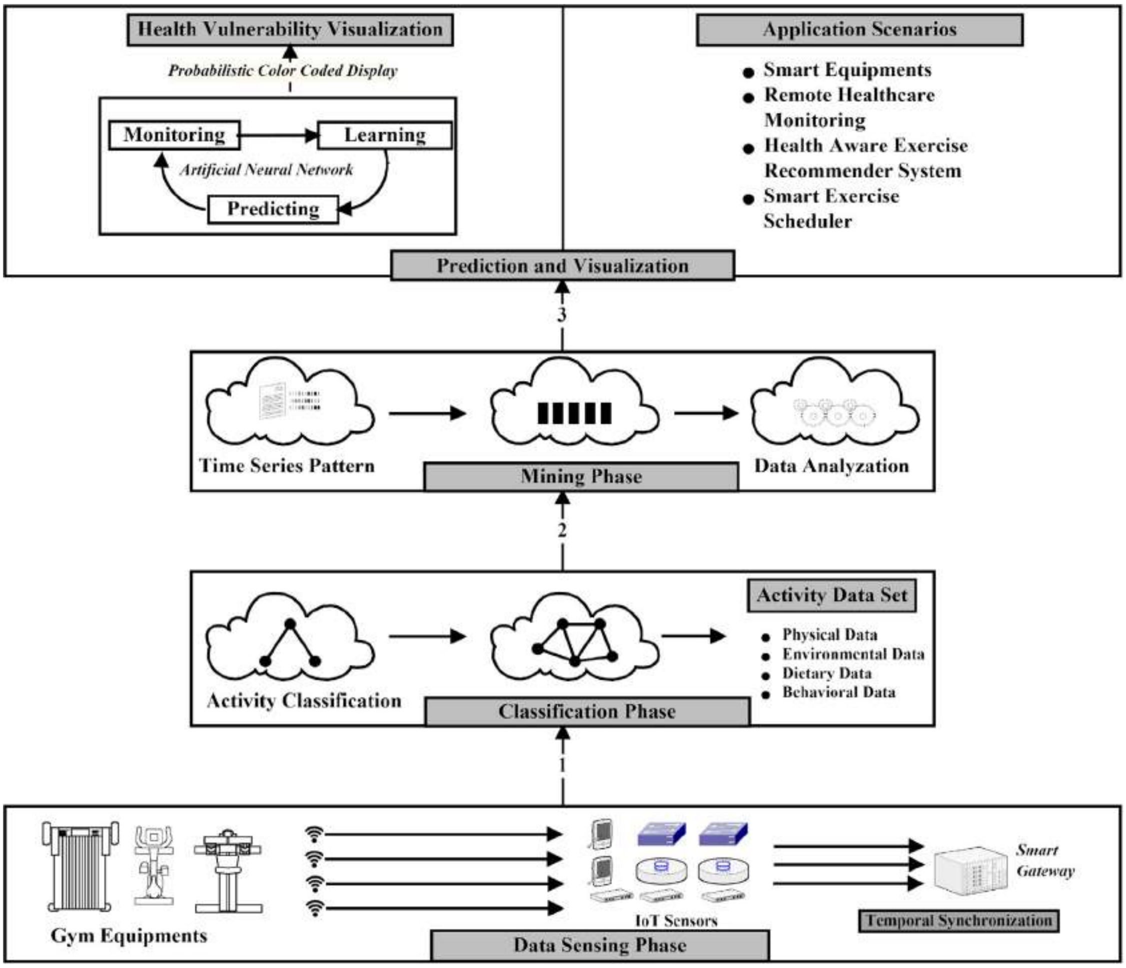

Fig. 1. Proposed architecture of smart workouts.

cloud storage for performing activity classification. The mining phase extracts real-time data values for these activities using Temporal Mining technique. These activities perform an important role in the overall assessment of a trainee's health state during exercises. Prediction and Visualization perform an efficient analysis of the data values during the workout sessions and formulates a probabilistic prediction model to quantify the health vulnerability of a trainee during exercises. This quantification is then mapped using a color coded technique to present the information of health vulnerability to the trainee in real-time. The detailed procedure of every phase is explained ahead.

3.1. Data sensing phase

Initial phase of the proposed model is dedicated to acquire health data values. The main objective of this phase is to capture data about various attributes inside the gymnasium in real-time during the workout sessions of a trainee. For this purpose, various heterogeneous IoT devices are infixed in different places of the gymnasium, gymnasium's equipment, and body wearable. The data about health attributes like heart rate, sweat, respiration rate, and blood pressure are captured by various biosensors placed on smart wearable and smart watches. Data regarding gymnasium's environment like room temperature, humidity level, and oxygen level are captured by environmental sensors. In addition to this, data involving nutritional intake during exercise sessions are captured by Radio Frequency Identification (RFID) tags, and smart mouth sensors. The data regarding the trainee's behavior like anxiety, and stress level are acquired by smart sensors attached on body wearable. However, due to the heterogeneity of the internal clock infrastructure for various IoT devices, these data values are not synchronized for appropriate data acquisition. Therefore, data sensed by IoT devices are synchronized on the basis of a universal time stamp. For this purpose, a smart gateway is programmed to perform the task of data synchronization on the basis of time. The synchronized data values are transmitted to the connected cloud storage over a wireless network channel. This network channel is secured with the Secure Socket Layer (SSL) to provide network security

Table 2
Summarization of data fusion algorithms.

Level of extraction	Fusion methods	Type of feature extracted	references
Signal Level	Weighted Average	Static Signal	[17]
Signal Level	Kalman Filters	Dynamic Signal	[18]
Signal Level	Particle Filtering	Stochastic Signal	[19]
Non-Parametric Feature Level	K-Nearest Neighbor	Statistical values	[20]
Non-Parametric Feature Level	Decision Trees	Statistical values	[20]
Non-Parametric Feature Level	Support Vector Machine	Statistical values	[21]
Non-Parametric Feature Level	Artificial Neural Network	Statistical values	[22]
Parametric Feature Level	Gaussian Mixture Model	Statistical values	[23]
Parametric Feature Level	K-Means	Statistical values	[20]

Table 3
Classification of datasets.

Data Set	IoT technology used	Parameters	Instances of sensitive events
Physical Dataset	Bio-Sensors, and Smart Wearables	Heart rate, Blood pressure, Respiration rate, and Sweat loss	High heart rate, High blood pressure, and High sweat loss
Environmental Dataset	Room Sensors, Noise Sensors, Pressure and Temperature Sensors	Oxygen level, Noise level, and Humidity level	Low oxygen level, and High humidity
Dietary Dataset	Swallow Sensors, and RFID Tags	Nutritional value, Form, and Quantity	Overdose, and Wrong form
Behavioral Dataset	Smart Wearables, and Bio-Sensors	Stress level, and Anxiety level	High anxiety level, and High stress level

during the data transmission. Also, to enable data security at the cloud storage, multiple security procedures are indulged. These include Data Encryption, User Authentication, and Credential Mapping.

3.2. Classification phase

Data acquired in the cloud comprises of several heterogeneous attributes. Moreover, each of them is related to health directly and indirectly. Therefore, it is necessary to classify them into appropriate datasets. However, due to the heterogeneity of data values, different feature extraction and fusion mechanisms must be utilized for the effective classification. Table 2 summarizes some of the important feature abstraction techniques that are developed by researchers. Based on the effective classification, datasets are compiled into four types of categories as shown in Table 3. Each of the dataset has been detailed ahead.

(a) Physical Dataset
The physical dataset includes data about physiological attributes of a trainee. In other words, data about heart rate, blood pressure, respiration rate, and sweat comprises this dataset. These are vital in assessing the overall health of a trainee during workout sessions. In addition to these, this dataset can be extended to include other attributes like force, and pressure exerted during exercising. Such kind of data can be easily acquired by smart gloves, and smart wearables.

(b) Environmental Dataset
Gymnasium's environment is important in analyzing the effect on the health of a trainee during the exercise. The presence of a large number of people leading to suffocation, inappropriate oxygen supply, and high room temperature are some of the common factors for health adversity among trainees. Therefore, the data about oxygen supply, room temperature, and humidity level are compiled together to formulate the environmental dataset.

(c) Dietary Dataset
This type of dataset includes the nutritional intake of a trainee during workout sessions. The level of steroids, protein, carbohydrates, and fats are some of the attributes of the nutrition intake. This mainly varies from one trainee to another, depending upon the exercise schedule.

(d) Behavioral Dataset
A trainee exercising in the gymnasium is often faced with the scenario of high anxiety and stress level. Sometimes this can result in adverse health condition leading to medical emergencies. Therefore, it is important to consider these data values for overall health assessment. Based on this, the behavioral dataset is comprised of data values regarding the anxiety level, stress level and, restlessness.

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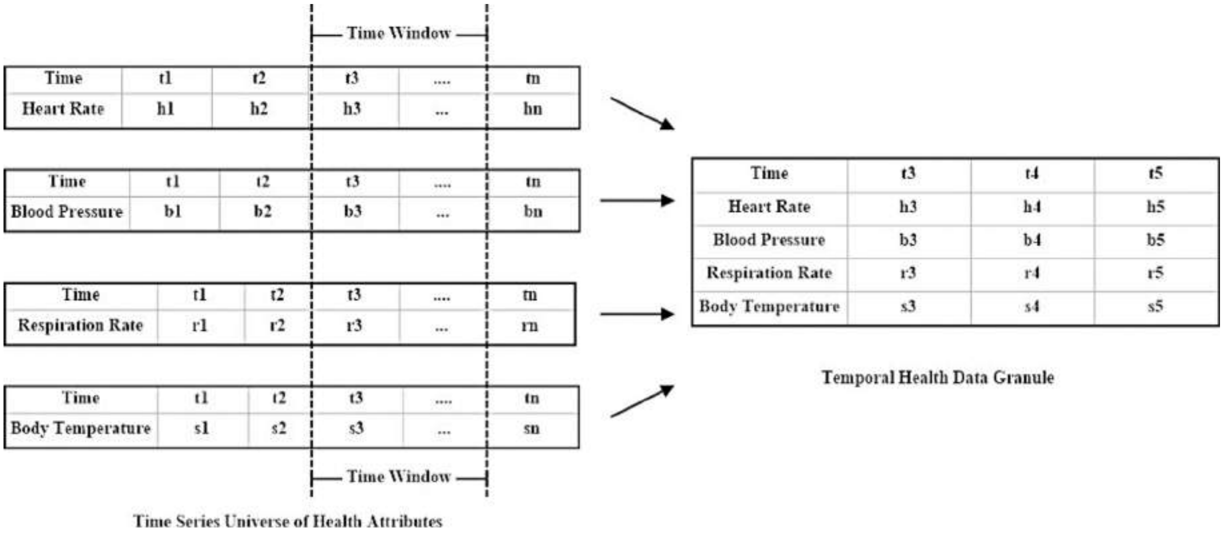

Fig. 2. Formulation health data granule.

3.3. *Mining phase*

Data stored in the cloud database is comprised of temporally diverse data values. In other words, there are some data values that change instantly within seconds, while some data values change over a period of a few minutes. Since time is an important attribute for these health-oriented data values, therefore the extraction of data from cloud storage is performed by using Temporal Data Mining technique. This will result in effective analyzation of a trainee's health in real time. Temporal Mining is a data mining technique that extracts data values for various attributes from cloud storage in the form of time series pattern. These time series patterns are comprised of values in association with the time at which respective data values are sensed.

3.3.1. *Formalizing time series data abstraction*

As discussed before, abstracting the useful information from the cloud database is an important task in the current perspective. Therefore, the temporal mining is formally used in the form of time series pattern as described ahead.

Definition 1 (Time Series Pattern (TSP))**.** Given a data attribute d and time window Δt of size n time units, then Time Series Pattern (TSP) is defined as a ordered finite set ([(d_i, t_i)], >), where the couple (d_i, t_i) comprises of a value d_i belonging to the domain of some numerical or ordinal values, and a timestamp t_i belonging to the time domain Δ t. In general, TSP can be represented by: $[< d_1, t_1 >, < d_2, t_2 >,,, < d_n, t_n >]$.

Definition 2 (Temporal Data Abstraction (TDA_{abs}))**.** Given a universe Time Series (TS) for various attributes such that TS $\equiv$ [TSP] 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 an abstraction specification and b_{abs} is the application of abstraction to a specific dataset.

Definition 3 (Temporal Data Granule (TDG))**.** Given TSP and corresponding TDA_{abs} function, then Temporal Data Granule(TDG) is the associated data values of various attributes abstracted in a given time window Δt. TDG is represented in the form of a tuple $[< Start, End > < TDA_{abs} > < d_1, t_1 >, < d_2, t_2 >, < d_3, t_3 >]$

where Start and End are the functions denoting the beginning and termination of the time window. An instance of formulation of TDG for health data granule is shown in Fig. 2. In addition to this, size of the time window can be altered depending upon the application scenario.

3.3.2. *Data analyzation*

Real-time analyzation of the data values for various attributes is important for assessing a trainee's health state during workout sessions. For this purpose, a probabilistic health state indicator is defined. It provides an analytical measure for the health state of a trainee in real-time during workout sessions. Determination of the health vulnerability indulges an analysis of the data values that are abstracted using TDA_{abs}. For the purpose of determining the initial health state, an algorithm based on the probabilistic association method is proposed. The algorithm compares real-time data attributes with threshold values and assigns predefined probabilities based on this comparison. The total probability is evaluated using influencing factor and is compared with the prefixed threshold for vulnerability determination. It is important to notify that these threshold values are generic and non-personalized. Pseudo code of the proposed algorithm is mentioned in the form of Algorithm 1.

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Algorithm 1 Probabilistic health vulnerability determination procedure.

procedure INPUT DATA VALUES FOR VARIOUS ATTRIBUTES IN THE FORM OF TEMPORAL DATA ABSTRACTION. ASSOCIATED PROBABILITIES FOR EVERY DATASET, PROBABILISTIC HEALTH STATE VULNERABILITY, PREFIXED THRESHOLD VALUES FOR VARIOUS ATTRIBUTES, CONSTANTS α, β, γ ARE THE ASSOCIATED INFLUENCING FACTORS PREFIXED FOR PERSONAL HEALTHCARE, STATE INDICATOR VARIABLE = [SAFE, RISKY, VULNERABLE, UNSAFE, HIGHLY VULNERABLE, NORMAL]
Acquire real time values for attributes
Compare physical attributes with the prefixed threshold values
If sensed values $_{\text{physical}}>$ Thresholds, Determine associated probability (P_p)
Compare environmental attributes with the prefixed threshold values
If sensed values $_{\text{environmental}}>$ Thresholds, Determine associated probability(P_e)
Compare behavioral attributes with the prefixed threshold values
If sensed values $_{\text{behavioral}}>$ Thresholds, Determine associated probability (P_b)
Compare dietary attributes with the prefixed threshold values
If sensed values $_{\text{dietary}}>$ Thresholds, Determine associated probability (P_d)
Probabilistic Health State Vulnerability (PHSV) = $(P_p) + \alpha(P_e) + \beta(P_b) + \gamma(P_d)$
Value (PHSV) $\rightarrow$ State Indicator Variable

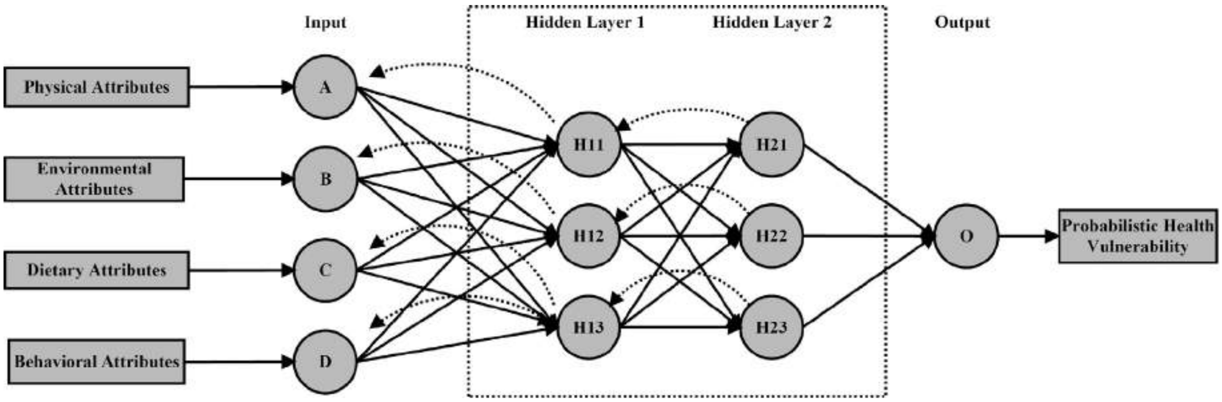

Fig. 3. Artificial Neural Network.

3.4. Prediction and Visualization Phase

This phase is further composed of two sub-phases, namely Prediction Phase and Visualization Phase. Each phase has important decision-making perspectives and is discussed ahead.

3.4.1. Prediction phase

The health state of a trainee is dynamic throughout the workout sessions as it depends upon a multiple number of health-oriented parameters. So, initial evaluation of health state prior to the sessions is not the effective estimation measure for providing continuous healthcare, especially for a trainee with long and vigorous exercise sessions. Moreover, it will not prevent the health state vulnerability of the trainee. Henceforth, a prediction system is required that can proactively predict the vulnerability to the trainee's health for effective and efficient deployment of the smart healthcare environment. In the proposed model, this phase uses a back-propagation based ANN technique. It proactively predicts the probabilistic health state vulnerability of a trainee on the basis of his exercising sessions. By using the back-propagation based ANN technique, the proposed system is able to learn the personalized health sensitive attributes for dynamic threshold estimation. This leads to the efficient prediction of probabilistic health state vulnerability in real-time on the basis of these sensitive parameters. The back propagation is a systematic methodology for training multi-layer ANN based models. Based on a complex mathematical foundation, it has a large domain of applicability for computing efficient results. The main objective of ANN technique is to form a balance between the capability to respond to the input parameters and generate effective response in the form of outputs. The proposed model incorporates the back propagation ANN technique because of the complex assessment of health attributes with each passing unit of time during the exercise sessions. It will help the proposed model in efficient training and hence will result in better probabilistic predictions. Fig. 3 shows an overview of the back-propagation based ANN technique for the proposed model. It has four input neurons for attributes, two hidden layers with three neurons for the deep learning and one output neuron for predicting probabilistic health state vulnerability. The overall procedure of prediction by the back-propagation based ANN technique is composed of three iterative stages, namely monitoring, learning and predicting. The task in every stage has been detailed ahead.

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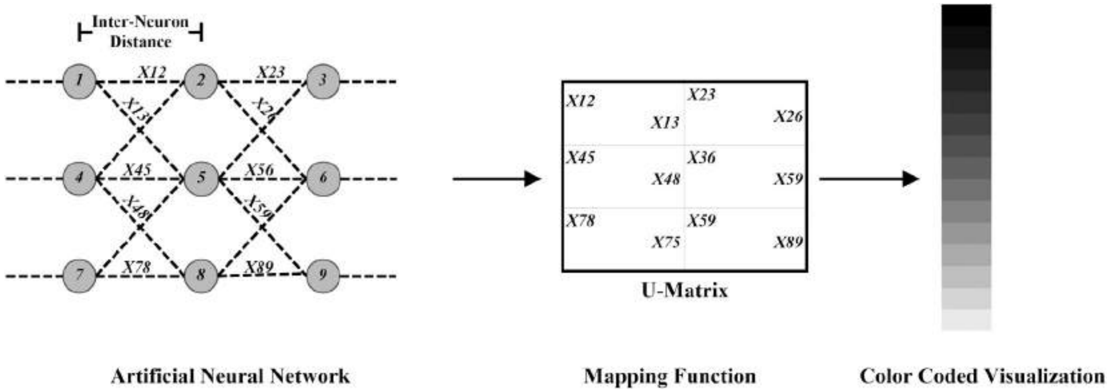

Fig. 4. U-Matrix based color coded mapping of ANN.

Stage 1: Monitoring

In the monitoring stage, the system monitors various health attributes during the exercise sessions of a trainee. These data attributes are acquired continuously using the IoT Technology as discussed before. Initially, the system determines the static health state vulnerability of the trainee using Algorithm 1. It is composed of the pre-determined non-personalized thresholds for estimating a trainee's health state vulnerability. Based on this, the system stores these data attributes after every workout session. These stored attributes are further used for training the model.

Stage 2: Learning

In the Learning stage, the model uses various stored data attributes of health states for training back-propagation based ANN model for predicting the future health state vulnerability. The predicted health state (on the basis of data attributes) are compared with the current health attributes for determining the errors in the prediction phase. These error values are used by the ANN technique to increase the precision level of the prediction process.

Stage 3: Predicting

This is the final stage of the overall learning process in back-propagation based ANN model. The system will automatically predict the health state of a trainee during exercise sessions using the trained ANN technique and helps in proactively intimating the trainee about the health adversity. After certain iterations, the precision of the system increases, thereby leading to accurate health assessment for predicting the adversarial effect on trainee's health.

3.4.2. Visualization phase

The level of exercise intensity depends upon several important factors. First, the length of exercise (time duration) and secondly, the force, and pressure that a trainee is putting during the exercise sessions. In addition to these, the surrounding environment has a vital role on the health of a trainee during exercises. In all cases, there is a direct impact on a trainee's health state considering heart rate, blood pressure, and other vital signs. Henceforth, it is necessary to indicate real-time health vulnerability due to an exercise session before the occurrence of serious health loss. In this research, we adopt the color coded visualization technique for indicating vulnerability level during an exercise session with consideration to the health state. Self-Organized Unified Distance matrix (U-Matrix) is used to map interneuron distance of ANN model onto colors. The detailed explanation of color-coded mapping can be found in [24]. Specifically, the distance between neighboring neuron is evaluated and visualized with different gray-scale colorings. A dark coloring between the neurons corresponds to large distance indicating a large inter-neuron gap, and therefore high health vulnerability. Similarly, light color indicates minimal inter-neuron distance and therefore implies the low health state vulnerability. Fig. 4 depicts the overview of color-coded mapping using the U-Matrix method. Formally, it is represented as

Maximal Inter-Neuron Gap → Dark Color → High Probabilistic Health State Vulnerability
Minimal Inter-Neuron Gap → Light Color → Low Probabilistic Health State Vulnerability

3.5. Application scenario: intelligent treadmill

This section provides an application scenario of Intelligent Treadmill equipment based on the proposed methodology. The treadmill is a common mechanical equipment that is available in almost all gymnasiums and workout centers. Because of its multipurpose utility in walking, jogging, and running, this equipment has also been utilized at home for exercise. The proposed intelligent treadmill (Fig. 5) is aimed at monitoring the health attributes of a trainee during exercise and prevents him from over exertion and other health problems. This is possible by a display unit which is used for visualizing health vulnerability, and an automatic self-adjusting panel that can alter the speed of the treadmill by detecting the health severity of the trainee. In addition to this, it has the capability to generate medical alerts during emergency cases. The detailed composition of an intelligent treadmill is explained ahead.

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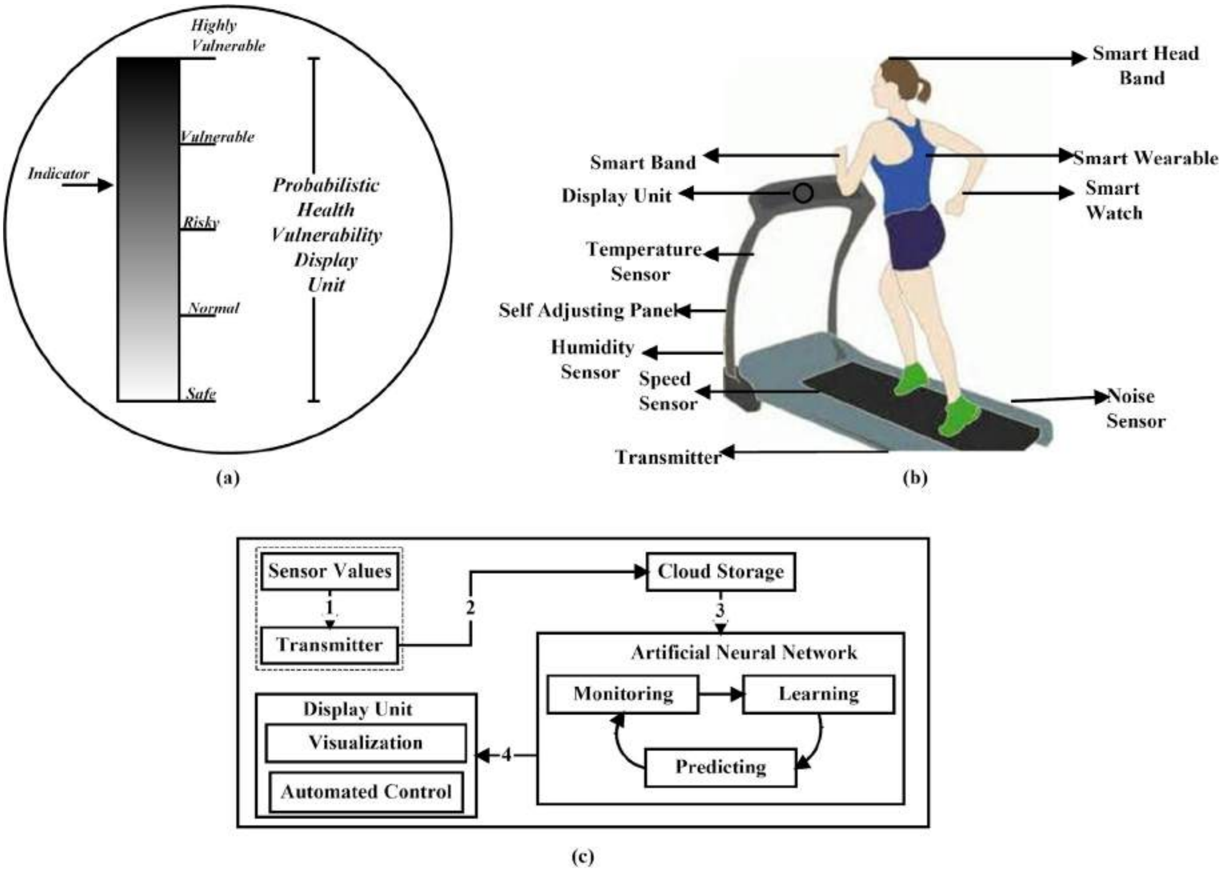

Fig. 5. Application scenario: intelligent trademill; (a) Display unit;(b) IoT sensor; (c) Working environment.

3.5.1. Composition

Various IoT devices and wireless sensors are embedded in the operation panel of the treadmill. Fig. 5(b) shows an overview of different components of the intelligent treadmill that are used for providing predictive healthcare services. Display Unit is used to indicate the heath state vulnerability with appropriate color mapped scale indicator as shown in Fig. 5(a). RFID tags are used for identification purpose of a trainee. A temperature sensor is used to monitor the room temperature during the exercise session. In order to determine the humidity level of the environment, the humidity sensor is embedded. Other important sensor includes noise sensor and speed sensor for noise monitoring and speed control respectively. Apart from using IoT sensors on the treadmill itself, there are other devices like bio-sensors, and smart wristbands, which are used for acquiring data about health. All these devices are connected to the smart gateway sensor of the treadmill that transmits the synchronized data values to the cloud database for in-depth analyzation.

3.5.2. Working scenario

Fig. 5(c) shows an overall information flow in the deployment of the intelligent treadmill. In the working environment, RFID tag identifies an individual during the beginning of every exercise session. This identification is vital in providing a personalized healthcare environment for every individual. Health-oriented attributes are acquired in real-time from various sensors attached on the treadmill, which is then transmitted to the connected cloud storage through the smart transmitter. Smart transmitter tags a universal timestamp with every data attribute to enable temporal synchronization. These data values are analyzed by the proposed system for formulating a health prediction model using back-propagation based ANN technique. ANN assesses these health attributes and automatically sets up dynamic threshold values for health state vulnerability. These threshold values will be personalized for an individual depending upon the physical and environmental attributes. During the workout sessions, various sensors of smart treadmill continuously monitor these attributes for health state vulnerability assessment. Based on the probabilistic distribution of health state vulnerability, a mapping function determines the appropriate color code for predicted vulnerability, which is displayed to the user in real time. Moreover, this can be extended to include other healthcare services like automatic speed alteration, and medical alert generation as discussed before. For instance, as soon as the health state of a trainee is predicted to be vulnerable by the proposed model, a signal is transmitted to the self-adjusting panel of the treadmill. The self-adjusting panel is an automatic control panel that regulates

Table 4
Demographic information.

S.No.	Person ID	Age	Gender	Height	Weight
1)	P1	25 years	Female	151 cm	160 lbs
2)	P2	35 years	Male	181 cm	220 lbs
3)	P3	27 years	Male	153 cm	170 lbs
4)	P4	20 years	Female	162 cm	155 lbs
5)	P5	32 years	Male	175 cm	179 lbs

Table 5
Details of exercise sessions and monitoring environment.

Major type of exercise	Monitoring parameters	Sensors used	Output generated
Chest and Intensity Set	Heart Rate, Breathing Rate, and Sweat Loss	Chest Straps and HRM	Statistical and Signal
Back and Abs	Abdomen Sweat Loss, and Muscular Pressure	Stomach Straps, and Pressure Sensor	Statistical
Shoulder, and Forearm	Breathing Rate, Arm Pressure, Shoulder Pressure	Body Wearable, Smart Arm Bands	Statistical
Biceps, Triceps and Abs	Arm Pressure, Heart Rate, Breathing Rate	Smart Arm Band, and Stomach Belts	Statistical and Signal
Leg Press	Knee Pressure, Breathing Rate, and Heart Rate	Smart Knee Band, and Smart Wearables	Statistical and Signal

the speed of the treadmill when a vulnerable state is predicted. In the situation of medical emergency, an alert signal is sent to the remote doctor. Generation of medical alert signals to the doctor can be manually adjusted during actual deployment of the treadmill.

4. Experimental evaluation

This section performs statistical analysis of the proposed system for determining the performance aspects in real-world scenarios. The presented model is comprised of three major steps. In the first step, IoT devices are used to acquire various data values in the ambient workout environment. In the second step, these data values are extracted using a temporal mining technique from the cloud database. Finally, a back-propagation based ANN technique is designed to analyze a trainee's health during exercising and proactively predict the vulnerability for adversity. Based on these three steps, experimental evaluation of the proposed system is performed to realize following three objectives.

(i) Analyze the information acquisition efficiency of IoT devices with respect to surrounding environment during exercise sessions.
(ii) Statistically determine the temporal mining efficiency of the proposed system for real-time healthcare deliverance.
(iii) Determine the prediction efficiency of the ANN technique for the current application scenario.

For an overall assessment of the proposed healthcare prediction system, results are compared with various state-of-the-art techniques.

4.1. Experimental environment

The environment opted for system deployment is inspired from real world scenarios. With voluntary consent, five people were monitored using IoT devices for one week during their thirty minutes exercise sessions at different gymnasiums. Table 4 gives an overview of their demographic information. As it can be seen from the system implementation that the environment selected for monitoring includes multiple factors for influencing a trainee's health. For the purpose of indulging various health attributes, different exercise sessions are considered for the week. As far as nearly 26,503 datasets were obtained during system implementation. These included 12,509 instances of health datasets, 6313 instances of environmental datasets, 5490 instances of behavioral datasets and 2191 instances of dietary datasets. Health data sets were acquired after every five seconds of the interval, while environmental data sets were captured after every 10 s of interval. The behavioral and Dietary dataset was captured statistically after fixed intervals. Table 5 provides an insight of various exercising sessions performed for 1 week. Moreover, by including most of the exercising sessions, system accuracy can be obtained during prediction process. IoT devices are placed at various places of the gymnasium, gymnasium's equipment, and body wearables. However, placement of these devices was regularly monitored for correct data acquisition. Data collected from these devices are transmitted to Amazon EC2 cloud storage, which is further analyzed in real time using STATA tool. However, due to heterogeneous ambient environments, only cumulative results are discussed for the proposed system.

4.2. Acquisition efficiency of IoT devices

IoT devices are used for capturing data about different health-oriented parameters. As previously mentioned, these are small, battery powered hardware devices capable of transmitting information in real-time. In the current scenario where

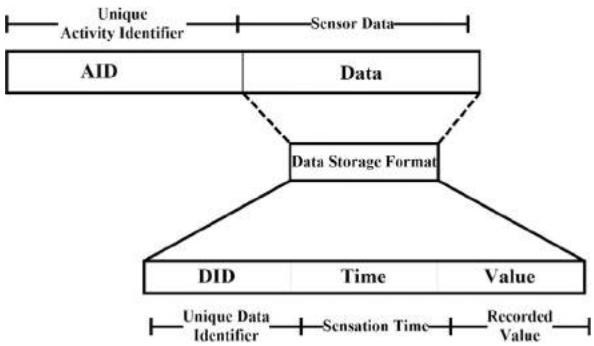

Fig. 6. Cloud based data storage format.

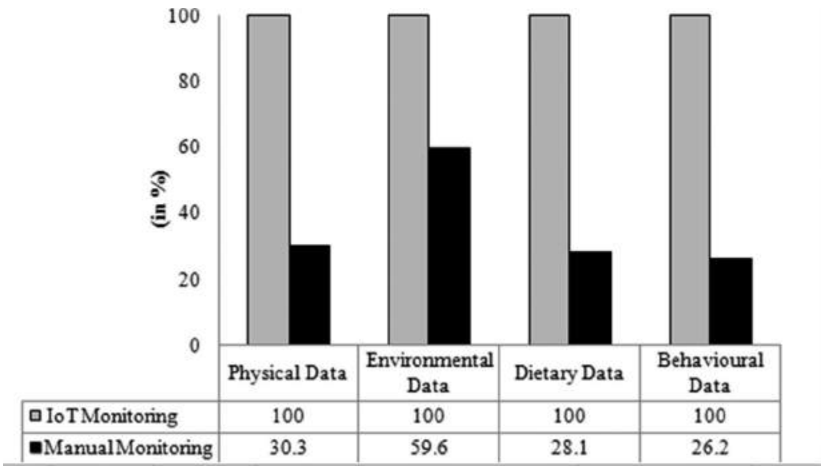

Fig. 7. Acquisition efficiency.

multiple factors are acquired in a synchronized manner, datasets are stored in a common storage format for effective analyzation. Fig. 6 shows the common storage format of various data values. “DID” depict the unique data identifier for the attribute data. “Time” indicates the time at which data is sensed. “Value” registers the data value sensed by the respective sensor. Data acquisition efficiency is defined as the ability to acquire event information in the surrounding environment of the gymnasium during workout sessions. For the purpose of determining this type of efficiency, a comparison is performed with the manual monitoring procedure. In manual procedures, data is captured by a physical person present in the gymnasium. Based on these values, comparative results are obtained as shown in Fig. 7. Results show that the data acquired by various IoT devices are higher than those acquired by manual monitoring procedure. Specifically, IoT devices are able to acquire more than 69.7% of physical data values as compared to manual monitoring. As far as environmental data is concerned, more than 40.4% of the values are registered by IoT devices in comparison to the manual acquisition. Similarly, in the case of dietary and behavioral information, IoT devices registered more than 71.9% and 73.8% values with respect to the manual monitoring procedure. Therefore, it can be concluded that IoT devices are highly capable of sensing data about different events in an efficient manner. In other words, data acquisition efficiency of the proposed system is very high.

4.3. Temporal mining efficiency

Data abstraction efficiency concerns with the back-end processing of the proposed system. In other words, it depicts the efficiency of the proposed system in terms of data accumulation, storage, extraction and finally analyzation from the cloud database. This type of efficiency is evaluated in terms of total time taken by the system for the capturing of data values and decision making. Detailed Results are shown in Fig. 8. In order to determine the temporal efficiency of the proposed model, results are compared with state-of-the-art mining techniques namely, co-location mining and rule mining. However, it is important to note that for effective assessment only the mining technique is changed while rest of the architecture is unaltered during implementation. As it can be seen from Fig. 8(a), in the current scenario, the proposed temporal mining technique is able to abstract physical data values in average time of 12.32 s for large number of datasets as compared to other mining techniques, with an average time of 15.23 s for co-location mining, and 17.23 s for rule mining. In addition to this, results for environmental datasets are depicted in Fig. 8(b), which shows the superiority in data abstraction with

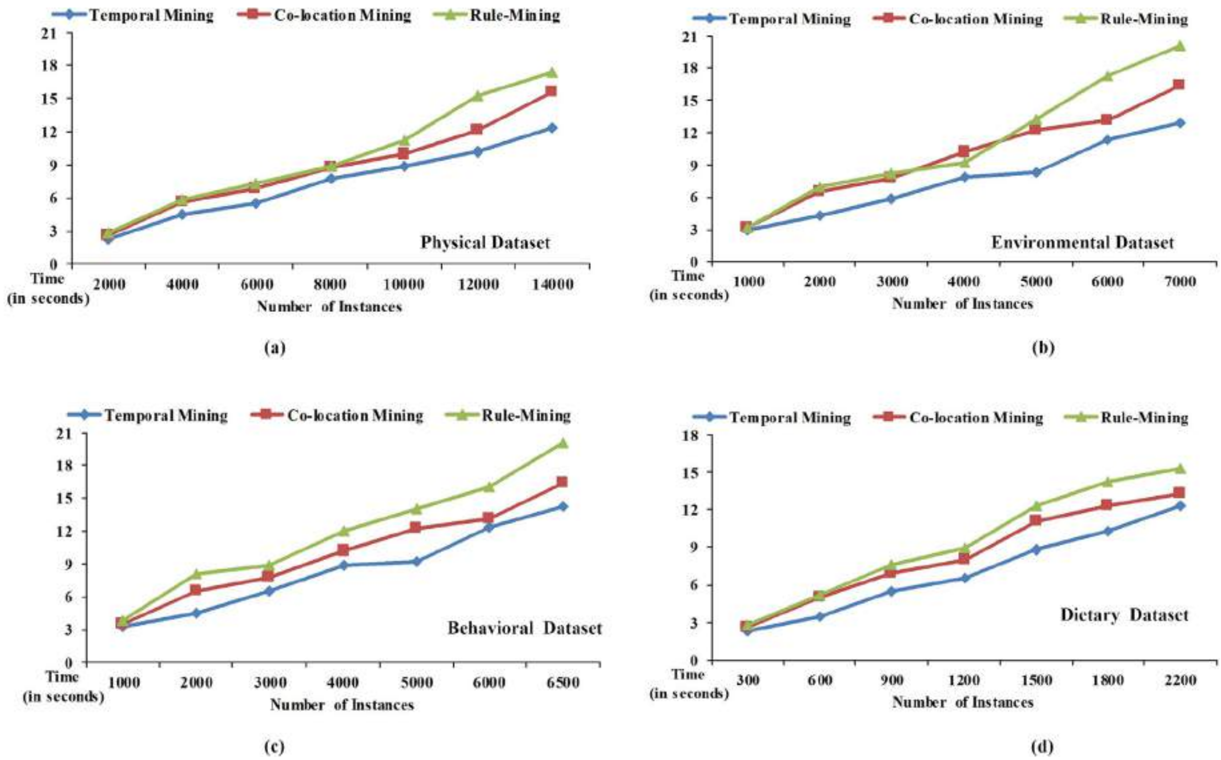

Fig. 8. Temporal efficiency assessment [(a) Physical Dataset, (b) Environmental Dataset, (c) Behavioral Dataset, (d) Dietary Dataset].

an average time of 9.23 s in comparison to 11.23 s for co-location mining and 12.30 s for rule mining. Moreover, for dietary datasets Fig. 8(c)) and behavioral datasets (Fig. 8(d)), temporal mining is able to acquire better performance (average running time 7.23 s for dietary and 9.23 s for behavioral data) as compared to other techniques. Therefore, it is clearly inferred from these statistics that temporal mining persists high temporal efficiency.

4.4. Prediction efficiency

The incorporation of back-propagation based ANN technique for predicting the health severity condition is an important feature of the proposed system. Prediction efficiency concerns with analyzation of health state vulnerability of a trainee during intensive workouts. During the entire six day monitoring procedure, there were several cases where health condition was detected to be severe for various people. Based on the prediction results, various statistical parameters like accuracy, sensitivity, specificity, and f-measure are evaluated for the proposed system as shown in Fig. 9. These statistical values are compared with state-of-the-art prediction models, namely Support Vector Machine (SVM) and Bayesian Prediction technique for better evaluation. Due to statistical output generation, results were computed for physical, environmental and behavioral datasets.

(a) From Fig. 9(a) and (b), it can be seen that high sensitivity value (averaging to 92.5%) and accuracy value (averaging to 91.2%) was registered for the environmental dataset. It indicates that the usage of ANN technique for prediction purpose is highly efficient in healthcare scenario as compared to SVM prediction technique with sensitivity and accuracy values averaging to 91.4% and 90.1% respectively, and to Bayesian prediction technique with 90.1% sensitivity and 88.2% accuracy. In addition to this, the specificity rates in Fig. 9(c) for ANN prediction technique is high for various physical datasets averaging to 88.2% in comparison to 87.7% and 82.6% for SVM and Bayesian prediction technique respectively. Moreover, ANN model was able to acquire higher f-measure averaging to 89.9% as compared to other techniques depicting higher performance of ANN technique for environmental datasets.

(b) Fig. 9(e) shows the results for behavioral datasets for sensitivity evaluation. As it can be seen that high values (averaging to 91.9%) were acquired for ANN prediction models as compared to SVM (averaging to 90.2%) and Bayesian model (averaging to 89.2%). Accuracy results, shown in Fig. 9(f) depicts that ANN model is more accurate with an average value of 88.3% as compared to SVM with an average value of 87.2% and Bayesian model with an average value of 85.3%. From specificity and f-measure results shown in Fig. 9(g) and (h) with average values of 83.9% and 84.2%, respectively, it is clearly concluded that the proposed system is able to acquire better performance for behavioral datasets as compared to other data abstraction techniques.

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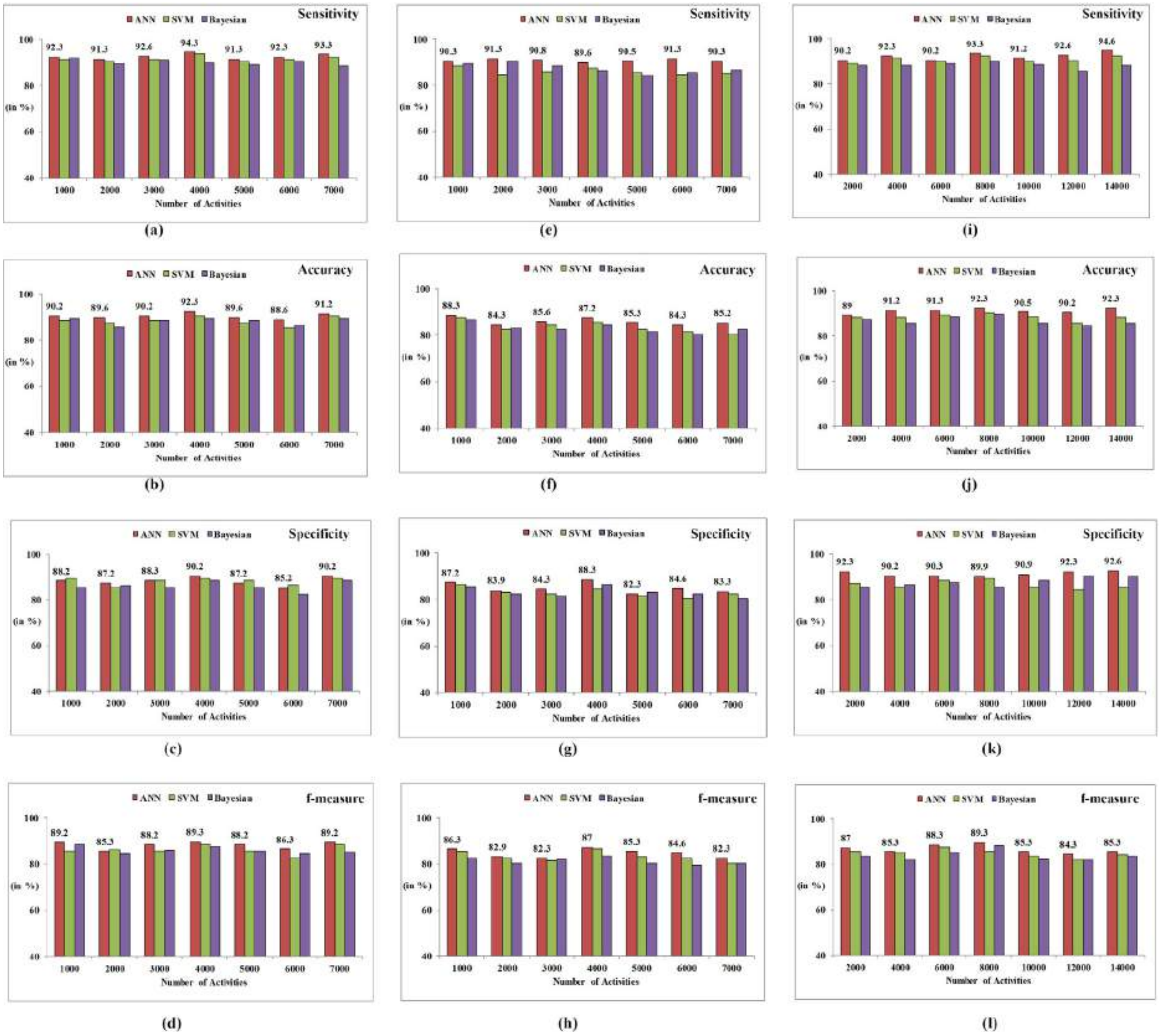

Fig. 9. Statistical analyzation for state-of-the-art comparisons. (a,b,c,d) Environmental Dataset; (e,f,g,h) Behavioral Dataset; (i,j,k,l) Physical Dataset. [Use color monitor for better visualization].

(c) Fig. 9(i) shows the results about physical datasets for sensitivity evaluation. High value averaging to 91.6% was registered for ANN model in comparison to SVM model (average value 90.2%) and Bayesian model (average value 90.2%). Moreover, from Fig. 9(j) it can be seen that accuracy results are better for ANN model with an average value of 91.2% in comparison to SVM (90.2%) and Bayesian (91.2%). In addition to this, better performance was achieved for specificity and f-measure in the case of ANN model as depicted in Fig. 9(k) and (l), thereby indicating the superiority of the proposed model in the current scenario.

Henceforth, it is clearly concluded that the proposed system persists statistical results in comparison to other state-of-the-art decision making models. Therefore, it can be inferred that back propagation based ANN model is highly efficient in providing effective healthcare environment during workouts.

4.5. Overall system stability

In addition to the results obtained in the previous sections, the proposed system is also analyzed for stability measurement. Stability measure determines the overall system stability over the passage of time for achieving certain accuracy level. It is measured in terms of Average Absolute Shift (AAS). Higher value of AAS indicates unstable behavior of the system while lower values indicate high system stability. Fig. 10 shows an overall result of AAS for the 6-day monitoring procedure. Re-

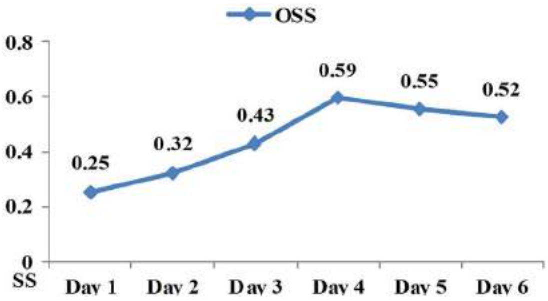

Fig. 10. Overall system stability[SS:system stability].

sults shows that the AAS value lies in the range of 0.25–0.59 with averaging to 0.32 for the proposed system. Low value of AAS indicates that the proposed system persists high level of system stability for time.

4.6. Comparative analysis

In this section, a comparative analyzation is performed with various state-of-the-art related studies to provide the in-depth assessment of the proposed healthcare model. Specifically, seven challenging studies have been considered namely, Yang et al. [6], Fanucci et al. [7], Kim and Lee [8], Hossain and Muhammad [9], Salem et al. [10], and Brugarolas et al. [11]. Each of these studies has been compared on the basis of ten important specifications. These include Application Domain, Major Contribution, Sensation Technology Used, Activity Set, Mining Technique Used, Real Time Perspective, Predictive Model, Output Display, Cloud Storage, Data Security Mechanism. Each of these parameters presents important system assessment specifications for different healthcare frameworks. The summarization of the comparisons is shown in Table 6.

1) **Application Domain**
Application Domain provides information about the specific domain of application for which a study has been performed. In other words, it indicates the service domain of the presented research for effective implementation.
2) **Major Contribution**
This parameter provides important information about the contributions performed in the respective research. It overviews various brief aspects of the research that determines overall utility of the presented framework.
3) **Sensation Technology Used**
Since the premier aim of the presented application domain is to monitor and analyze health oriented parameters in real time, it becomes indispensable to determine the underneath technology utilized for performing this task. Henceforth, this parameter is used to analyze a system based on the type of sensing technology used for acquiring health and other related data.
4) **Activity Set**
Activity Set indicate different types of categorical data that have been acquired by the system. It varies from one architecture to another depending upon the objective and framework design of the proposed model.
5) **Data Mining Technique Used**
Health Data is stored in the database for in-depth analyzation. However, abstracting important information from the database is an important parameter that must be taken into consideration for efficient results. Therefore, data mining technique provides information about various techniques/mechanisms that are used by different researchers to abstract information from the database.
6) **Real Time Perspective**
Real-time perspective indicates the time sensitiveness of a presented architecture. In other words, it provides information regarding time consideration for output generation in order to depict the utility of healthcare system.
7) **Predictive Model**
The predictive model aims at depicting the proactive behavior of an architecture. Since health is a dynamic variable therefore, it becomes important to perform effective prediction to provide enhanced utility to this vital domain of application.
8) **Output Display**
Output Display provides information about the way in which output is generated by a system. In other words, the way in which results are perceived by the targeted user represents this parameter. There are various ways for generating outputs, namely statistical quantification, color coded visualization, and alert generation. Henceforth, it is necessary to determine the output generation mechanism of a system for overall utilization.
9) **Cloud Storage**
Cloud-based data storage is a recent data storage mechanism for ubiquitous access. Apart from storing a large amount of data at cloud database, it is feasible to assess data anywhere and anytime. Therefore, this parameter provides information about data storage mechanism that has been utilized by various researchers for storing health data.

Table 6
Comparative analysis.

Parameters	Yang et al. (2014)	Fanucci et al. (2013)	Kim and Lee (2014)	Hossain and Muhammad (2016)	Salem et al. (2014)	Brugarolas et al. (2016)	Proposed Model
References	[6]	[7]	[8]	[9]	[10]	[11]	–
Application Domain	Home-based Healthcare	Heart Failure Monitoring	Hospital based Healthcare	Emergency Healthcare	Smartphone based Healthcare assessment	Dog Healthcare	Gym Workout-based Healthcare
Major Contribution	Intelligent Medicine box for home based healthcare services	Chronic Heart Failure detection from home using integrated ICT Technology	Remote Patient Monitoring inside Hospital using clustering technology	CCIoT Healthcare architecture for medical emergency cases	Smartphone based Healthcare assessment for minimizing false emergency alarms	Health attributes monitoring in dogs using ICT Technology	Workout based CCIoT Framework for predictive monitoring and visualization of probabilistic health state vulnerability
Sensation Technology Used	IoT	Bio-Sensors and Actuators	Body Sensor Network	CCIoT	Body Sensor Network	Electrodes with Polymer Coating	CCIoT
Activity Set	Vital Sign (Heart Rate, Blood Pressure, and Temperature)	ECG, SpO2, and Blood Pressure	Vital Sign (Heart Rate, Blood Pressure, and Temperature)	Vital Sign (Heart Rate, Blood Pressure, and Temperature)	Vital Sign (Heart Rate, Blood Pressure, and Temperature), and Physical Posture	Vital Sign (Heart Rate, and Temperature)	Vital Sign (Heart Rate, Blood Pressure, and Temperature), Physical, Behavioral, and Dietary
Mining Technique Used	Not Applicable	Software Defined Networks	Heterogenous Clustering techniques	Temporal and Spectral Mining	Co-relation Mining	Not Applicable	Temporal Mining
Real Time Perspective?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Predictive Model	No	No	No	No	No	No	Yes (ANN)
Output Display	Statistic	Statistic	Statistic	Alert Generation	Statistic	Alert Generation	Color coded Display
Cloud Storage?	No	No	No	Yes	No	No	Yes
Data Security Mechanism	No	No	Yes	No	No	No	SSL, and Credential Mapping

10) Data Security Mechanism

Health data is confidential data and is, therefore, vulnerable to several security attacks. Hence, it becomes essential to provide certain data security mechanism at the network level and database level for effective data storage. This parameter provides information regarding various security techniques that are adopted by different researchers for securing health data.

5. Conclusion

In this paper, we have proposed a healthcare prediction model using CCIoT Technology. The model is based on data classification and analyzation techniques to attain the overall objectives of effective healthcare. In addition to this, the prediction model uses a back-propagation based ANN technique for determining health state vulnerability in a novel quantifiable form. For validating the proposed model and determining its overall effectiveness, an experimental implementation has been performed where five voluntary participants were selected and monitored for six days during their respective workout sessions. Results were analyzed in the form of data acquisition efficiency, data classification efficiency, temporal efficiency and prediction efficiency. In all the cases, the proposed model was able to register superior performance in comparison to other state-of-the-art techniques. Therefore, it is concluded that the presented system is highly efficient in providing healthcare services to a trainee during workouts in a gymnasium.

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