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ORIGINAL RESEARCH

Internet of Health Things (IoHT) for personalized health care using integrated edge-fog-cloud network

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Abstract

This paper proposes a mobile healthcare framework based on edge-fog-cloud collaborative network. It uses edge and fog devices for parameterized health monitoring, and cloud for further health data analysis in case of abnormal health status. The continuous location change of users is a critical issue, and the connection interruption and delay in delivering health related data may be fatal in case of emergency. In this direction, in the proposed framework, mobility information of the users is considered and the users' mobility pattern detection is performed inside the cloud for advising the user regarding nearby health centre. From the theoretical analysis, it is observed that the proposed framework reduces the delay and energy consumption of user device by $\sim 28\%$ and $\sim 27\%$ respectively than the cloud only health care model. The proposed healthcare framework has been implemented in the laboratory and health data of few student volunteers are analyzed to predict their health status. The experimental analysis also shows that the proposed mobility prediction model has better precision, recall value and time-efficiency than the existing models.

Keywords Health monitoring · Edge-fog-cloud network · Mobility prediction · Internet of Health Things (IoHT)

1 Introduction

The rapid advances in sensor-based systems and Internet technologies have enabled a new dimension of health care technology namely Internet of Health Things (IoHT). IoHT is the exchange and processing of the data for health status monitoring of individuals by integrating sensor or IoT devices with advanced mobile technologies (da Costa et al. 2018). IoHT can become a demanding application for personalized health care leveraging on fog, edge and cloud computing. In a cloud based health care system, the health data are collected using body area network (BAN) or body sensor network (BSN) and then stored and processed inside the cloud servers. In BAN, there are several sensors attached with human body and varied health data e.g. body temperature, blood pressure etc are collected by these sensors.

With availability of several body sensors, it is possible to design and develop a low-cost wearable system to capture values of various health parameters of human body (e.g. blood pressure, heart/pulse rate, oxygen level, body temperature etc.) and to predict the health status of individuals based on the collected data and contextual information (e.g. atmospheric condition, user's location, activity etc.). These sensor nodes collect health parameter values and transmit to the connected smart phone. Next, the data is processed and health status is predited by the smartphones. But smart phones are resource hungry. Therefore, the computationally complex applications are difficult to execute in the resource-limited smart phones.

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Therefore, in the existing mobile health (m-health) applications the data are stored and analysed at the server side (Solanas et al. 2014; Hassanalieragh et al. 2015; Doukas and Maglogiannis 2012; Kaur and Chana 2014; De et al. 2017). Nevertheless, to minimize the energy and power consumption, the data can be processed at various levels and can be harvested in cloud through edge-fog-cloud infrastructure. The users can access the health data as well as get alerts through mobile apps (applications) if abnormal health status is detected. In this work, we propose a hierarchical structure of IoHT framework, which facilitates efficient personalized health care.

While cloud servers provide large storage and computing capability, access to long distant cloud servers may enhance the delay. Moreover, if the user is in mobility, connection interruption may frequently occur. As a result health data transmission to the cloud and receiving the result after analysis also gets affected. Hence, along with health status prediction, user's mobility data analysis is also very important to predict the current location and deliver the result accordingly. For predicting location sequences appropriate movement pattern modelling (Ghosh and Ghosh 2018b) is required. The mobility data of the users is analysed inside the cloud servers, and based on the analysis the current location of the user is found. The preliminary health data analysis takes place inside the edge/fog devices, and the health status is detected. If the detected health status denotes abnormality, then the data is sent to the cloud for further analysis. The cloud suggests the nearby health centre based on the detected health problem and the current location of the user. In the current work, we have integrated spatial data with health data for not only advising regarding the health status but also providing information regarding nearby health centre after predicting patient's mobility pattern.

1.1 Motivations and contributions

For real time health monitoring system, delay is a crucial parameter with respect to Quality of Service (QoS). The objective is to propose a health monitoring system which will improve the QoS in terms of delay and energy consumption. Usually for indoor region, IoHT framework has been applied. However, the user while present outside the home, then also can suffer from health problem such as certain increase in blood pressure. In such circumstances to provide prompt healthcare, the mobility data has to be integrated and analysed along with the health data. Our objective is to integrate the geolocation data of the user along with health data, so that the user's mobility pattern, present traffic states can be analysed and nearby health centre can be suggested based on the current health condition.

The key contributions of this work are:

1. An IoHT framework has been proposed based on edge-fog-cloud collaborative network for personalized health care and providing assistance in case of emergency. The mobility or continuous location change of users are taken into consideration in the proposed framework.
2. The patient's mobility prediction model is proposed to advice the user regarding nearby health centre while abnormal health condition is detected. The mobility prediction model shows better precision than the existing models.
3. The proposed framework has been implemented and tested with health data of 40 student volunteers. Their individual health status is predicted based on the health data and contextual information.
4. The delay and energy consumption while using the proposed framework are determined and theoretical analysis presents that the proposed framework is delay-aware and energy-efficient than the cloud only health care framework.

The rest of the paper is organized as follows. Section 2 presents the related works. The proposed IoHT framework is described in Sect. 3. Section 4 analyses the performance of the proposed framework. Finally, the conclusion is drawn in Sect. 5.

2 Related work

Electronic health (e-health) care is a demanding research area with a focus on smart health monitoring (Solanas et al. 2014). Mobile health (m-health) care system has become very popular nowadays. Most of the smart phones contain various applications through which user activity can be predicted based on BMI (Body Mass Index), pulse rate etc. Apple Healthkit, Samsung S Health, Microsoft Health and Google Fit are well-known applications. To detect blood pressure level, blood sugar level, ECG etc. health sensor devices also exist.

In case of m-health care, for health data processing cloud servers are used (Solanas et al. 2014; Hassanalieragh et al. 2015; Doukas and Maglogiannis 2012; Kaur and Chana 2014; De et al. 2017). The IoT and cloud has been integrated to provide pervasive health care in Doukas and Maglogiannis (2012). To monitor the health status of the newborns in the neonatal health care unit of a hospital and for taking initiative if health condition becomes abnormal, a cloud based health care system along with a mobile app has been discussed in De et al. (2017). However, health data transmission to the cloud and receiving result after data analysis becomes a challenge due to communication and propagation delays as well as mobility of the user. The use of small cell base station in indoor health monitoring has reduced the power consumption (Mukherjee and De 2014). These small cells perform preliminary health status prediction by comparing the collected health data with their respective normal range (De and Mukherjee 2014; Mukherjee and De 2014; De and Mukherjee 2015). Nevertheless, the contextual information is also very important while detecting the health status, for example, if a user has done swimming for half an hour and then his/her health status is checked, then the result will differ if the health status checking is performed when the same user is in relax mode. The user's location and the corresponding atmospheric condition is also important in predicting health status. For the people living in smart cities, context-aware health care system has been proposed in Solanas et al. (2014).

For delay and energy optimization fog computing has emerged (Ahmad et al. 2016; Verma and Sood 2018; Ghosh et al. 2019b; Tuli et al. 2019; Mukherjee et al. 2020). In a fog computing framework, the intermediate devices between the end nodes and cloud servers, such as switch, router etc., participate in data processing. These intermediate devices are called fog devices. To provide the IoT applications a platform independent interface for execution and interaction of computing instances, FogBus has been proposed in Tuli et al. (2019). Integration of health care with fog computing has introduced Health Fog (Ahmad et al. 2016). In health fog the health data are processed inside the fog devices. Another fog-cloud based IoHT framework has been proposed in Mukherjee et al. (2020), where game theory has been used for selecting fog device. But existing mobile health care systems have not highlighted the mobility aware health monitoring. The motivation of this work is to introduce a mobility aware IoHT which will deal with the challenges of delay, energy consumption etc.

Geographic information system (GIS) is used to collect, store, process and analyse geospatial data. A geospatial object refers to single geographical property which is characterized by a geospatial concept. The IoT-edge-fog-cloud network has been integrated with geospatial services for enhancing the service quality for time critical applications in Ghosh et al. (2019b). Owing to the pervasiveness of sensor technologies and advancements in location acquisition methods, a vast amount of GPS traces are accumulated in our daily lives. It provides huge opportunity to the research community to leverage the movement pattern information and facilitating varied location aware services (Krakiwsky et al. 1988; Gong et al. 2017; Ghosh and Ghosh 2019; Ghosh et al. 2019a; Zheng 2015). There are several existing works to model and store human movement patterns based on trajectory analysis (Lv et al. 2012; Vlachos et al. 2002; Cheng et al. 2013; Karatzoglou et al. 2018; Liu et al. 2016; Zhang et al. 2017). Liu et al. has presented deep learning architecture named ST-RNN to model frequent movement patterns considering spatial and temporal contexts and predicting next location sequences effectively (Liu et al. 2016). The spatio-temporal information analysis for traffic forecasting has been discussed in Zhang et al. (2017, 2019). Geolocation information analysis and movement prediction has been illustrated in Zhang et al. (2015); Ye et al. (2009); Ghosh and Ghosh (2017a, 2018a, 2016). A context-aware trajectory graph has been proposed to model the changes of movement patterns in different contexts of an academic premises in Ghosh and Ghosh (2016). Similarly, researchers are also devoted to extract association rules from frequent movement paths of users to summarize their mobility traces and predict travel demand efficiently. Yang et al. have presented a framework to extract patterns (rules) from individual mobility traces (Yang et al. 2019). For instance, they extract rules like "In 70% of the days, person X visits POI Y; or visits shopping mall once in a week". Others works also have aimed to extract such frequent patterns deploying several novel rule mining techniques (Ye et al. 2009; Ghosh and Ghosh 2017a). The authors in Amirat et al. (2019) have proposed a mobility prediction framework named NextRoute by providing efficient noise tolerance strategy. The authors have claimed that probabilistic or data mining models are noisy and large amount of information are lost in the training process. To detect and forecast abnormal events from traffic data, the authors have presented a framework using Discrete Fourier Transform to detect unforeseen events apriori in Gao et al. (2019).

There are several works on effective forecasting of traffic flows (Zhang et al. 2017, 2019). The authors have proposed a deep learning approach to forecast crowd flows in different regions of a city using several factors such as weather and intra-region traffic in Zhang et al. (2017). A multi-task deep learning framework has been proposed in Zhang et al. (2019), where both the node flow and edge flow are predicted. The authors (Zhang et al. 2015) explore different sensor-records such as air-quality, bike/vehicle data, and finds out co-evolving patterns by assembling the individual sensors' patterns into a single pattern. Another interesting study (Kim et al. 2018) has revealed that human personality and their visited locations are somewhat related. In this regards, another study (Ghosh and Ghosh 2017b) has categorized users (student/ faculty/ staff) based on their movement patterns. The academic performances of students are predicted from their daily mobility patterns as well (Ghosh and Ghosh 2018a). On the other side, an enhanced localization solution has been proposed in (Papandrea and Giordano (2014)). The authors have deployed advanced machine learning techniques to model human mobility for reducing mobile device resources when continuous localization information is required. A classification model for mobility pattern has been discussed in Yang et al. (2019), where a correlation model between mobility pattern and regional function characteristics has been developed. A delay and mobility aware cloud-fog-edge-IoT framework, named, Mobi-IoST has been proposed to provide efficient assistance in the time of emergency in Ghosh et al. (2019b). The authors have also proposed novel and generic mobility modelling and location prediction techniques for reducing delay and power consumption in time-critical application. The most relevant places visited by the individuals have been discovered using probabilistic finite automaton in Salomón et al. (2018).

All of these are a broad range of applications of trajectory data to find out interesting and meaningful patterns to provide several location-aware services. However, the analysis of trajectory data in case of health monitoring is an emerging area which has been focused in the present work by integrating trajectory analysis with health monitoring. In our present work, a novel edge-fog-cloud framework is proposed for assisting users in the time of medical-emergency considering the mobility of the user. In the framework, a multi-layer trajectory graph is deployed to model the mobility patterns. The generative adversarial network is used to predict the location sequences, where the framework is capable to assist users in time of emergency. To the best of our knowledge, although there are several works on IoHT, this work is the first attempt to utilize the mobility knowledge along with the parameterized health monitoring in edge-fog-cloud collaborative network to facilitate delay and energy efficient health monitoring and assisting users regarding their health status.

Table 1 List of acronyms with full forms used

Acronym	Full form
API	Application Program Interface
AWS	Amazon Web Services
BAN	Body Area Network
BMI	Body Mass Index
BP	Blood Pressure
BSN	Body Sensor Network
CNN	Convolutional Neural Network
EC2	Elastic Compute Cloud
ECG	Electro Cardio Gram
GAN	Generative Adversarial Networks
GPS	Global Positioning System
IoHT	Internet of Health Things
IoST	Internet of Spatial Things
IoT	Internet of Things
LAN	Local Area Network
LCSS	Longest Common Subsequence
LSTM	Long Short-term Memory
MLMPG	Multi-Layer Mobility Pattern Graph
MQTT	Message Queuing Telemetry Transport
OSM	OpenStreetMap
POI	Point Of Interest
QoS	Quality of Service
SFTP	Secure File Transfer Protocol
SPO2	Saturation of Peripheral Oxygen

3 IoHT driven personalized healthcare framework

In this section we have proposed an edge-fog-cloud framework for health monitoring. A mobility pattern detection model is also proposed for predicting user mobility to advice the user regarding nearby health centres in case of emergency. Before going to the discussion on the proposed framework, the acronyms used in this paper along with their full forms are provided in Table 1.

3.1 Edge-fog-cloud based IoHT

The proposed IoHT framework is designed based on edge-fog-cloud based collaborative network. The sensors of BAN are attached with human body and health data e.g. pulse rate, blood pressure, body temperature etc. are collected. The contextual information such as ambience information e.g. room temperature, humidity, pressure, user's current and previous activities e.g. walking, sleeping etc., user's profession, age, health profile etc. are also sent to the fog device. In the proposed system, the location information of the user is also sent to the fog device along with health data and contextual information. In the proposed health care system, edge/fog devices process the collected health data. The fog device is connected with the cloud servers. The user's mobility information is stored and processed inside the cloud servers.

Working model Fig.1 shows that the IoHT framework based on edge-fog-cloud based network. As observed from the figure the IoHT framework has the following major components:

- BAN (or BSN) composed of sensor nodes for collecting health parameter data,
- User's mobile device as edge device, that collects the contextual information and user's location,
- Fog devices,
- Cloud servers.

The working flow diagram of the proposed system is pictorially depicted in Fig.2. The working model of the proposed system consists of the following steps:

1. Sensor nodes collect health data categorically:

    - If there are h health parameters, e.g. blood pressure, heart rate, body temperature etc., there will be h sensor nodes.

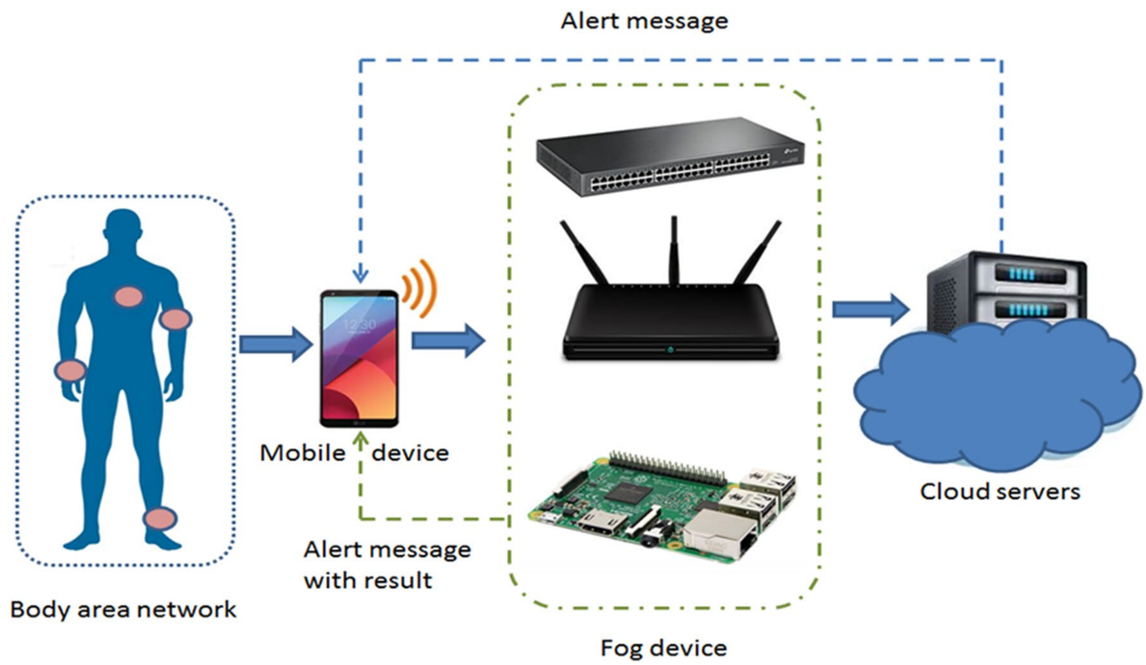


Fig. 1 Edge-fog-cloud based IoHT framework

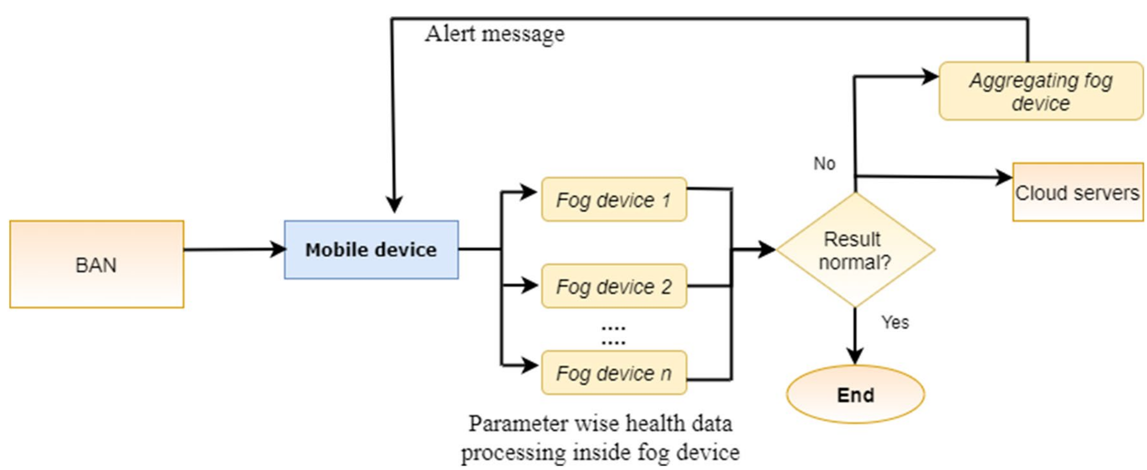


Fig. 2 Data flow diagram of the proposed IoHT framework

- Sensor nodes send their respective data to the user's mobile device that works as edge device.

2. Mobile device sends the data to the fog devices along with the contextual information (ambience information such as pressure, temperature, humidity, health profile of individuals, previous set of activities) and geolocation information of the user:

   - As a fog device may not be capable of performing exhaustive computation, multiple fog devices are considered for multiple health data processing in the proposed framework. Each fog device processes respective health parameter data. If there are h health parameters, there will be e fog nodes to process the data, where $e \leq h$. An aggregating fog device is used to aggregate the result received from the fog devices. Few health parameters are closely interrelated, for example, blood pressure and heart rate. The processing of closely interrelated health parameters will be performed inside a single fog device.

- If the collected health parameter data seems to be abnormal (i.e. does not fall in the normal range) with respect to the contextual information and user's location, the corresponding fog device sends the result along with contextual information and user's location to the aggregating fog device and to the cloud servers.
- The aggregating fog device aggregates the result and predicts the health condition.
- If the predicted health status is abnormal, an alert message with the predicted health status is sent to the user's mobile device. Based on the geolocation information and mobility information of the user, the mobility pattern of the user is found and next location to be visited is predicted. The mobility pattern detection is discussed in Sect. 3.3. The cloud generates information regarding nearby health centre to advice the user in case of emergency.

3. Cloud servers store the health data for further analysis. The health care centres can access the data from the cloud servers for treatment of the patient.

3.2 Health status detection

The collected data of different health parameter are analyzed to detect the health status of a person. If the collected value falls within the normal range with respect to the user's current location and contextual information, the health status of the person with respect to the respective health parameter seems normal. Hence, the data is discarded. Otherwise, the health status of the person seems abnormal, and the processing fog device sends the result to the aggregating fog device and to the cloud for further analysis. The aggregating fog node sends alert message to the user. Let there are h health parameters and e fog devices for processing health data, where $e \leq h$. Let with respect to the contextual information and location of the user, the normal upper and lower limit of a health parameter q are q_{ul} and q_{ll} respectively, and the collected value is q_c, where $q \in h$. If $q_{ll} \leq q_c \leq q_{ul}$, the data is discarded. Otherwise, the data is abnormal. Hence, the corresponding fog device (let y) sends the result to the aggregating fog device (let x) and to the cloud. The collected result from one or more fog devices for a particular user u, is aggregated inside the aggregating fog device x. Let the result from the fog devices for a user u are $r_1, r_2, ..., r_k$ where $k \leq e$, then the final health condition is predicted based on the data aggregation. The detected health condition is denoted as a function of the results, given by,

$$H_u = f(r_1, r_2, ..., r_k) \tag{1}$$

The detected health status is sent to the user's mobile device to alert him/her, and the result is sent to the cloud for further analysis.

3.3 Mobility pattern prediction

Latency is a crucial factor in real-time health monitoring. If a patient needs immediate medical assistance such as admitting to the hospital, then the information regarding the nearest health care centre needs to be extracted from the Google Map, and the route with minimum congestion has to be recommended. In this direction, this work aims to model the traffic information as well as the POI such as health care center, medicine shop and the individuals' frequently visited path. We will start with discussing few preliminary terms and subsequently describing the proposed method to model and store such movement information, which will be beneficial in predicting efficient route in case of medical emergency.

1. *GPS trajectory* (G) The time-stamped sequences of location traces (latitude, longitude) is represented by GPS trajectory or log or trace. $G : (lat_1, lon_1, t_1) \rightarrow (lat_2, lon_2, t_2) \rightarrow (lat_n, lon_n, t_n)$, where n location traces in increasing timestamps are represented. The GPS log is accumulated in a *.json* file in our use-case.
2. *Road network* (R) The underlying road structure of the study region is represented by R, which is a directed graph. The number of road-segments are the edge set (E) and their intersections are represented by the vertex set (V) of the graph. The directions of the roads are not static and they change based on the time of the day or in weekends. An array list is maintained to consider such changes of road directions throughout the week. POIs are the landmarks of the area, such as, residential buildings, commercial area etc. Each of the raw GPS trajectory is converted to semantic trajectory when we append such POIs along with the underlying road segments.
3. *Stay-point and trajectory-segment* Trajectory-segment is defined as sequences of stop and move. The stop-points depict that the user has spent some time-duration (d) at a particular location. The time-duration is greater than some threshold value i.e. $d > T_{thresh}$. The distance (dis) between the GPS points logged in this time-interval is less than some threshold value D_{thresh} i.e. $dis < D_{thresh}$. The stay-points of a trajectory represent that the user has performed some activities. The trajectory-segment is constructed by two stay-points and the intermediate points within these two stay-points.

$$Traj\_Seg := (S_1, POI_1, t_1^s, t_1^f), g_a, g_{a+1}, g_{a+2}, \dots, g_b, (S_2, POI_2, t_2^s, t_2^f) \quad (2)$$

where S_1 and S_2 are two stay-points, and $g_a, \dots g_b$ are the intermediate GPS points from stay-point S_1 to S_2. The timestamps t_i^s and t_i^f represent the start and finish time of time-duration spent in the stay-point i respectively. To remove the GPS error induced due to sensor errors, we have utilized filtering technique. The GPS log is smoothened using Kalman filtering technique (Krakiwsky et al. 1988) and formalized as:

$$p_t = A' p_{(t-1)} + w_{(t-1)} \quad (3)$$

where location at time t is p_t and the process noise is w_{t-1}. The present state to next state is associated in matrix A' in the log.

$$z_t = Hp_t + v_t \quad (4)$$

This is the measurement equation. The relation between measured point (z) and logged location (p) is represented as H, and the measurement noise is v. The measurement noise is calculated from the sensor accuracy value, which is logged in the mobility data file extracted from Google Map Timeline[1]. The detailed process is described in Ghosh et al. 2020. Next, the road network structure is appended with the raw GPS log, which is defined as Map-matching. In the present work, the map-matching process of Gong et al. 2017 has been followed, where both local topological information and global similarity measure are considered. The OSM road network features (highway, one/two way etc.), width, length of roads are extracted and augmented in this process. Finally, the geotagged information (POI information) of each location trace (raw GPS log) are augmented using an iterative reverse geocoding (Ghosh and Ghosh 2019) and Google Place API. Since the data-volume of the trajectory traces are huge, we have deployed a grid-based approach and a variant of quadtree (Zheng 2015) to store the movement information of each grid in different time-scales.

The next step is to model the movement patterns such that the correlations can be extracted and utilized to predict the optimal path in an efficient way. Here, we propose MLMPG for each individual moving agent. In a typical multi-layer graph, the vertices of one graph are correlated with the vertices of other graph by node-mapping function. MLMPG is defined by three layers of inter-dependent graph. In the first level, the road network layer is present, where the nodes are road intersection points, and the edges are road segments. In the next layer, the POI information and grids are present. Here, the POI-specific data are stored in different grids. Finally, the top-most layer is constructed by the real-time GPS points of the moving agents. Formally, MLMPG is defined as follows. $MLMPG := (l_1, l_2, l_3, M)$, where $l_a = (N_a, L_a)$, $a \in 1, 2$ *and* 3, and M denotes the node mapping function having 3×3 dimension, and $M_{i,j} : N_i \times N_j \rightarrow [0, 1]$.

Each layer (l_1, l_2 *and* l_3) has set of nodes and links among the nodes. To form the top-most layer (l_3), clustering is performed to group the movement patterns over different time-scales. Here, the similarity-matrix is first computed, where the matrix has c connected components, and T_t is the input mobility traces at time t. The similarity function (*SimCS*) is based on the variant of LCSS distance measure among different trajectory traces:

$$SimCS(Tra_i, Tra_j) = \begin{cases} 0 & if(i == 0) or (j == 0) \\ SimCS(Tra_{i-1}, Tra_{j-1}) & if((Tra_i == Tra_j) \\ +C \times Min(Tra_{i-1}, Tra_j) & and(Tra_{i+1} \neq Tra_{j+1}) \\ MAX(SimCS(Tra_{i-1}), Tra_j), SimCS(Tra_i, Tra_{j-1}) & if(Tra_i \neq Tra_j) \end{cases} \quad (5)$$

where *Tra* is the set of mobility traces, TScore represents the time-stamp value. Here, we have used the stay-point duration, velocity, timestamp and sequences of visits of places as mobility features in the similarity function. Algorithm 1 presents the steps of MLMPG construction.

[1] https://www.google.com/maps/timeline?pb

Algorithm 1 Construction of Multi-layer Mobility Pattern Graph (MLMPG)

```
Input: GPS traces (G)
Output: MLMPG with nodes and links of 3 layers
1: for all g ∈ G do                                   ▷ pre-processing step
2:     g' ← Error-filtering (g)                       ▷ Kalman Filtering
3:     G'.insert(g')
4: end for
5: i=0
6: for all g_i ∈ G' do                                ▷ Trajectory segmentation step
7:     S'=NULL
8:     j:= i+1
9:     t : checkTemp(g_i, g_j)                        ▷ Check the temporal threshold
10:    if t == 0 then
11:        break
12:    end if
13:    if (dist(g_i, g_j) <= D_thresh) then           ▷ Check the distance threshold
14:        S'.insert(g_i, g_j)
15:        go to line 8
16:    end if
17:    S.insert(S')                                   ▷ Stay-point detection
18: end for
19: MLMPG(l_1, l_2, l_3) ← NULL                      ▷ Initialize MLMPG
20: for all s_i ∈ S do                                ▷ Construct layer 2 with POI
21:    P ← geoTagg(s_i)
22:    createNode(n[P])
23:    insert(l_2.n)
24: end for
25: for all ∈ e_a ∈ E do                              ▷ Construct layer 1 with Road network
26:    for all e_b ∈ E and e_a! = e_b do
27:        flag ← intersect(e_a, e_b)
28:        if flag==1 then
29:            createNode(n[e_a, e_b])
30:            insert(N_1.n)
31:            insert(L_1.e_a)
32:            insert(L_1.e_b)
33:        end if
34:    end for
35: end for
36: for all t_i ∈ T do
37:     j:= i+1
38:    dist : computeLCSS(t_i, t_j)                   ▷ Based on equation 5
39: end for
40: A: compute the similarity matrix (dist)
41: clust ← Cluster(T, A)
42: for all c ∈ clust do
43:    createNode(n[P])                               ▷ Construct layer 3 from mobility traces
44:    insert(l_3.n)
45:    insert(l_3.l)
46: end for
47: Output: MLMPG(l_1, l_2, l_3)
```

In the next step, the optimal path is predicted based on the present traffic state and the present location of the moving agent. Here, we have used a variant of GAN in this paper. The major reason for using GAN is the low availability of real-time data. It is observed that conventional neural networks are not effective when noise is present in the data. Here, the mobility traces and health information are quite sparse in nature, and the model needs to learn from a limited amount of training data. Further, the overfitting issue needs to be eliminated for better accuracy.

Generative Adversarial Network (GAN) is used to predict the optimal path considering all the mobility states at the time of visit. The mobility states represent the traffic density at different road-segments of the city. Typically, the model aims to predict the traffic density and suggests optimal path with reduced travel-time. Initially, this mobility sequences (*Tra*) are fed into the generator block having encoder, pooling and decoder unit. It converts the inputs into fixed-length representations. It may be noted that in the proposed approach, deep LSTM architecture is used, which allows the network to learn at different time scales over the input. Furthermore, they can make better use of parameters by distributing them over the space through multiple layers. The output of this step is passed through the discriminator layer, where the target is to reconstruct the input sequence and minimize the adversarial loss ($Loss_{adv}$). First, the iterations are carried out with the training instances. The discriminator is updated by descending the stochastic gradient:

$$P_D = P_D - \alpha_D \sum_{i=1}^{m} \frac{\delta Loss_{adv}(tra^i, path^i)}{\delta P_D} \tag{6}$$

$$P_G = P_G - \alpha_G \sum_{i=1}^{m} \frac{\delta Loss_{gen}(tra^i, path^i)}{\delta P_G} \tag{7}$$

where the discriminator parameter and generator parameter are defined by P_D and P_G. The model is trained for m input instances. The learning rates for discriminator (α_D) and generator (α_G) are set to 0.02 and 0.04 respectively. The model predicts the optimal path (*path*) based on the traffic states and the movement pattern of the individual. By predicting the movement pattern of individuals, the location to be visited after a particular point of time can be determined. If a moving user's health status is predicted as *abnormal* based on the collected health data and contextual information, then the nearby health centre as well as the corresponding route can be provided to the user. One of the objectives of this work is to present an end-to-end system to improve the clinical/ personalized health care infrastructure for the citizen of the developing countries, such as India. The public health care system in the remote villages is in poor condition. There is no multi-specialty hospitals/ health facilities and the local health care centers may not be able to provide required treatment to the patients. In such alarming scenario, it is necessary to deploy an automated system, which will be capable to preliminary analyze the health status of the citizen and assist in the time of emergency. In case, the emergency occurs when the user is driving the car (sudden rise of blood pressure or any other critical parameter), the system triggers an alert notification to the nearby health care center and other members (such as on-site caregivers or relative/ friends of the user). The health status of the user along with the present location are sent to the nearest health care center so that immediate actions are taken.

3.4 Location based health status determination and notification

In Sect. 3.3, the mobility pattern of a user has been predicted. If the user is residing at the indoor region, then the mobility pattern prediction model finds out the nearby health centre based on the current location. While the aggregating fog device is sending the health status to the user based on the user's health parameter values and contextual information, then the route to the nearby health centre is also notified to the user.

If the patient is at outdoor region, then the mobility pattern prediction model finds out the current location of the user. Now, in this case, two situations are possible. As the user is at outdoor region, it may not be possible that multiple fog devices will be present nearby the user. If multiple fog devices are not present, then the health data is sent to the cloud along with contextual information to predict the health status of the user. If abnormal health status is predicted, the cloud sends the result to the user based on the predicted current location of the user.

If the user is a patient residing in an ambulance, then multiple fog devices will be located inside it. Then using multiple fog devices the health status of the user is predicted and continuous health monitoring is performed. However, the location information is sent to the cloud periodically. Hence, based on the health condition the optimum route to nearby health centre will be provided.

3.5 Delay and energy consumption of user device in proposed framework

The delay between the sending and receiving nodes is determined as the summation of the communication, propagation, data processing and queuing delays. The uplink communication delay is given as $(1 + u_f)(D_u/R_u)$, where u_f, D_u and R_u are the uplink failure rate, amount of data transmission in uplink, and uplink data transmission rate respectively, between the sending and receiving nodes. The downlink communication delay is given as $(1 + d_f)(D_d/R_d)$, where d_f, D_d and R_d are the downlink failure rate, amount of data transmission in downlink, and downlink data transmission rate respectively, between the sending and receiving nodes. Hence, the total communication delay between the sending and receiving nodes is given as,

$$T_c = ((1 + u_f)(D_u/R_u)) + ((1 + d_f)(D_d/R_d)) \tag{8}$$

The propagation delay is given as,

$$T_p = d_{sr}/S_p \tag{9}$$

where d_{sr} is the distance between the sending and receiving nodes, and S_p is the propagation speed. The processing delay of a node is given as,

$$T_p = D_p/S_{pr} \tag{10}$$

where D_p is the amount of data processed and S_{pr} is the processing speed.

In the proposed framework, the sensor nodes collect health data and send to the mobile device. The mobile device sends the health data along with contextual information to the fog devices, which then sends data to the cloud according to necessity. Here, uplink communication takes place from sensor nodes to the mobile device, mobile device to fog devices and fog devices to the cloud, and downlink communication takes place from cloud/fog device to the mobile device if health status seems abnormal. Let the uplink communication delay from sensor nodes to the mobile device is T_{smc}, from mobile device to processing fog devices is T_{mfc}, and from processing fog devices to aggregating fog device is T_{fac}, and from aggregating fog device to cloud is T_{acc}. Let the downlink communication delay from cloud to mobile device is T_{cmc}, and from fog device to mobile device is T_{fmc}. Then the communication delay is given as,

$$T_{cprop} = f(T_{smc}, T_{mfc}, T_{fac}, T_{acc}) + f(T_{cmc}, T_{fmc}) \tag{11}$$

The propagation delay is given as,

$$T_{pprop} = f(T_{smp}, T_{mfp}, T_{fap}, T_{acp}) \tag{12}$$

where the propagation delay between sensor nodes and the mobile device is T_{smp}, between mobile device and processing fog devices is T_{mfp}, and between processing fog devices and aggregating fog device is T_{fap}, and between aggregating fog device and cloud is T_{acp}. Let the processing delay of a fog device y is T_{pry}, and to determine the health status k processing fog nodes and one aggregating fog node (x) are used. Let the processing delay of cloud to determine the current location of the user along with route to nearby health centre is T_{prcl}. Then the processing delay is given as,

$$T_{prprop} = f(T_{prm}, T_{prcl}) \tag{13}$$

where $T_{prm} = f(max(T_{pr1}, T_{pr2}, .., T_{prk}), T_{prx})$ and T_{prx} is the processing delay of the aggregating fog node x. Let the queuing delay is T_{qprop}. Then the total delay of the proposed framework is given as,

$$T_{prop} = T_{cprop} + T_{pprop} + T_{prprop} + T_{qprop} \tag{14}$$

During communication the user device's (mobile device) energy consumption is given as,

$$E_{cprop} = e_m.T_{cprop} \tag{15}$$

where e_m is the energy consumption of a mobile device in active mode. During propagation the user device's energy consumption is given as,

$$E_{pprop} = e_i.T_{pprop} \tag{16}$$

where e_i is the energy consumption of a mobile device in idle mode. During processing of health and mobility data inside the fog devices and cloud, the user device's energy consumption is given as,

$$E_{prprop} = e_i.T_{prprop} \tag{17}$$

where e_i is the energy consumption of a mobile device in idle mode. During queuing period, the user device's energy consumption is given as,

$$E_{qprop} = e_i.T_{qprop} \tag{18}$$

where e_i is the energy consumption of a mobile device in idle mode. The total energy consumption of the user device is given as,

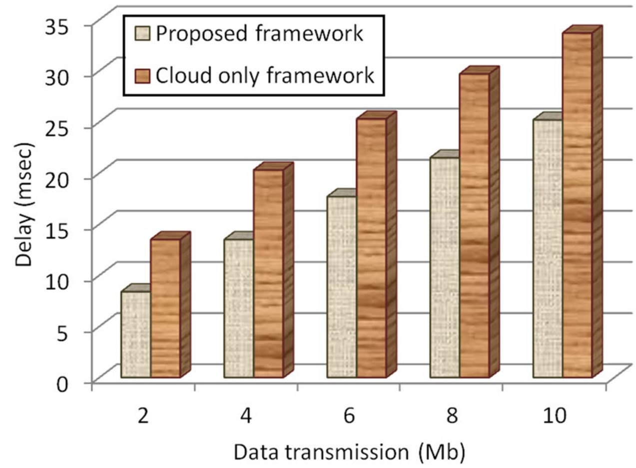


Fig. 3 Total Delay: Proposed IoHT framework and Cloud only health care framework

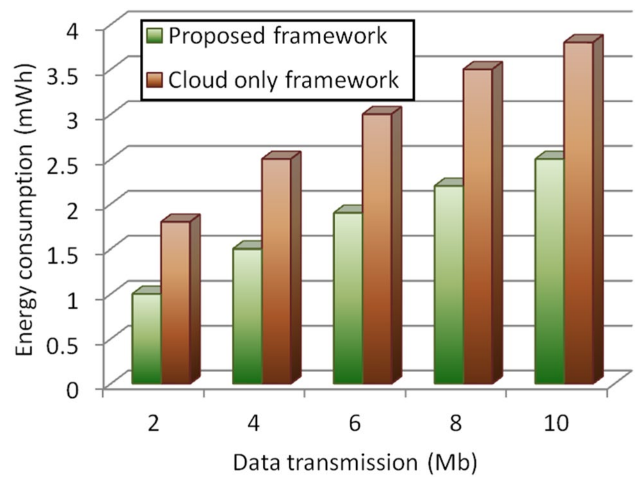


Fig. 4 Energy consumption of user device: Proposed IoHT framework and Cloud only health care framework

$$E_{prop} = E_{cprop} + E_{pprop} + E_{prprop} + E_{qprop} \tag{19}$$

The delay and energy consumption of user device in proposed IoHT framework and existing cloud only health care framework are compared in Sect. 4.

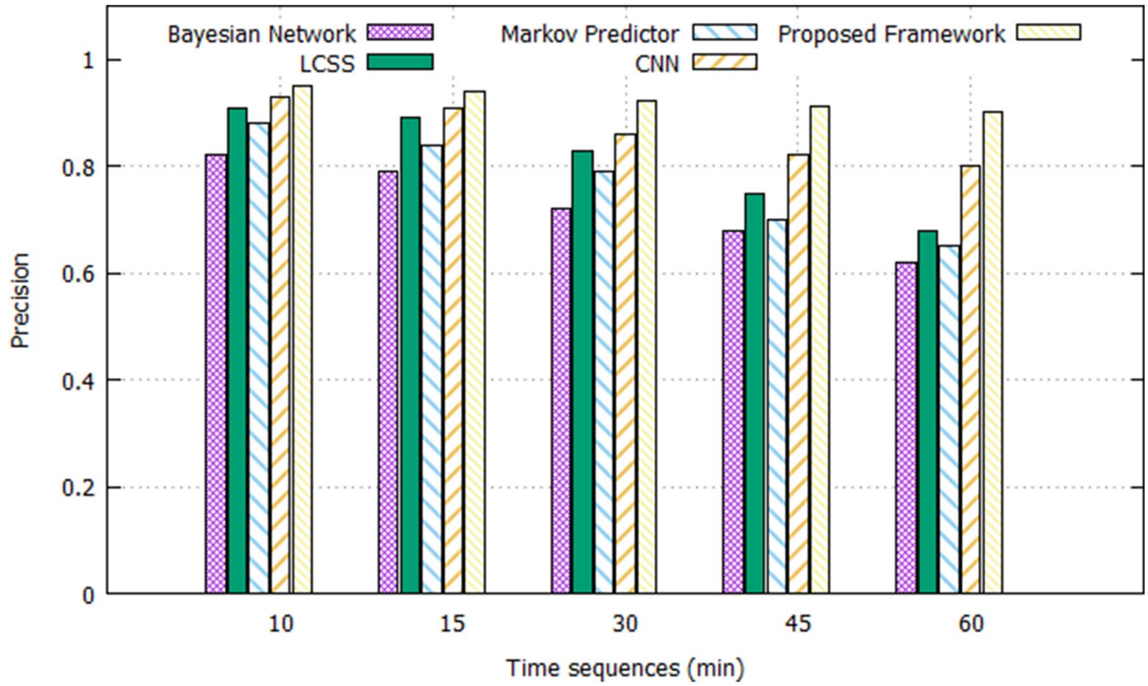


Fig. 5 Precision value of path prediction based on different time-length of the trajectories

4 Performance evaluation

This section presents theoretical and experimental analysis. The theoretical analysis has been performed using MATLAB R2015a. The proposed framework has been implemented in the IIT Kharagpur laboratory, where different student volunteers' health data along with contextual information are collected and processed to predict their health status.

4.1 Theoretical analysis

The delay and energy consumption of the user device while using the proposed IoHT framework has been determined and compared with only cloud based health care framework. The delay in case of using the proposed framework and mobile device's energy consumption during that period are determined using Eqs. (14) and (19) respectively, and presented in Fig. 3 and Fig. 4 with respect to the amount of data transmission (in Megabits (Mb)). From these figures, it is observed that the proposed IoHT framework reduces the delay and energy consumption by $\sim 28\%$ and $\sim 27\%$ respectively than the cloud only health care framework (De and Mukherjee 2015; Kaur and Chana 2014). The delay is measured in millisecond (msec) and the energy consumption is measured in milliWatt-hour (mWh). In the proposed framework the fog device participates in data processing, which lowers the delay and energy consumption than the health care system where long distant cloud is used for storage and analysis of health data. It is observed from the theoretical analysis that the proposed framework reduces the energy consumption and delay with respect to the cloud only health care system.

4.2 Experimental analysis of the proposed mobility prediction model

The performance of the proposed mobility prediction model discussed in Sect. 3.3 is evaluated by comparing with other baseline methods (Lv et al. 2012; Vlachos et al. 2002; Cheng et al. 2013; Karatzoglou et al. 2018). The mobility datasets are collected from 145 volunteers [(students, staffs and faculty members of Indian Institute of Technology Kharagpur (IIT KGP)] for 28 months time-span. The mobility data is logged using the GPS-enabled smart-phone devices of the volunteers. The performance evaluation of the proposed method is carried out in two major aspects. Firstly, we measure the precision and recall of the prediction of the path of different length. We compare our method with four well-known predictive approaches, namely Bayesian network (Lv et al. 2012), LCSS (Vlachos et al. 2002), Markov-predictor (Cheng et al. 2013), CNN (Karatzoglou et al. 2018).

It is observed from the Figs. 5 and Fig. 6 that for different time-length of trajectories the performance of our method (Proposed Framework) is significantly better than the baseline methods. Our method has achieved 0.871 and 0.931 recall values for 60 min and 10 min time length of trajectory respectively. The precision value is 0.901 and 0.95 for 60

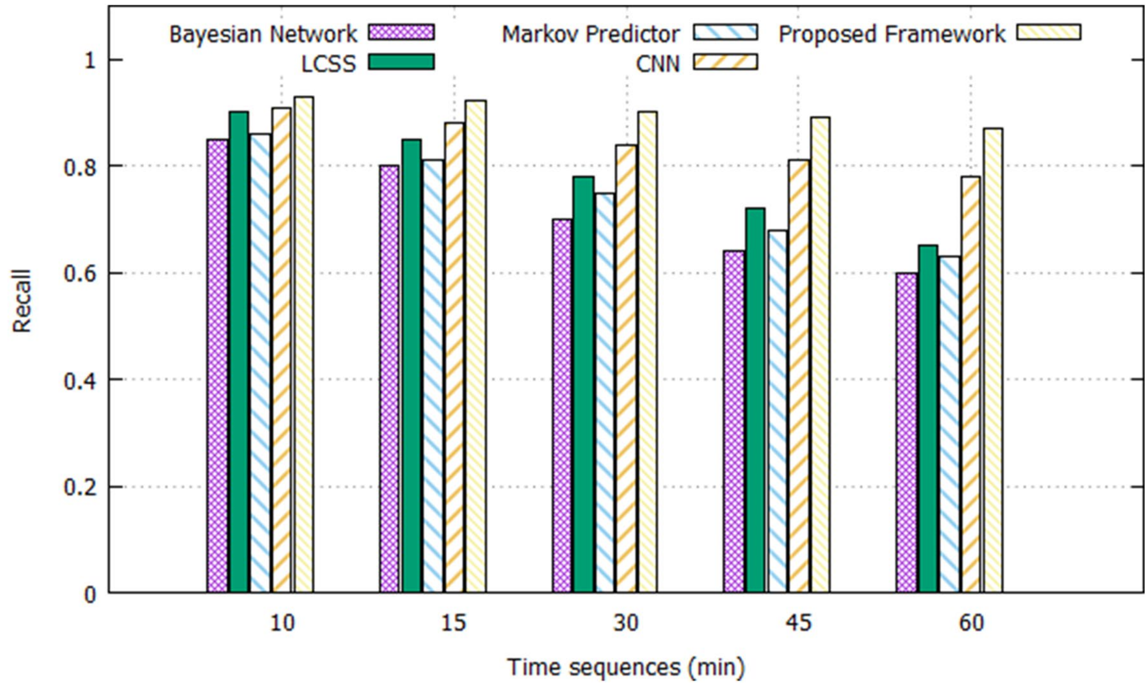


Fig. 6 Recall value of path prediction based on different time-length of the trajectories

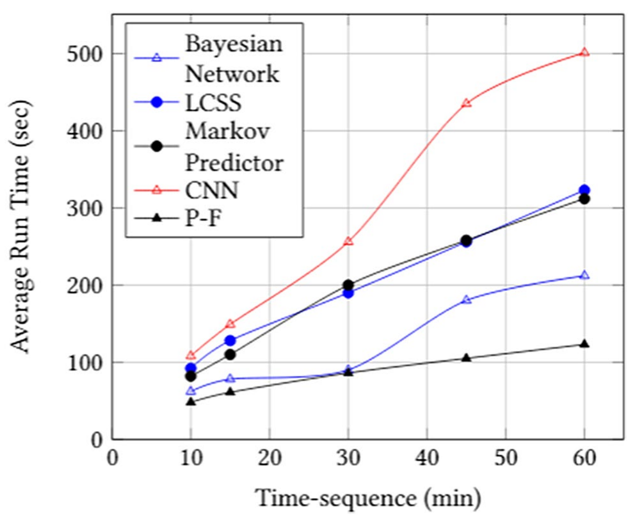


Fig. 7 Average run-time for path prediction over different time-length of the trajectories

min and 10 min time length of trajectory respectively. On the other side, it is observed that the precision and recall values drop with the increase of time-length in the experiment. When the precision and recall values of path prediction are quite higher in our method, it is also capable to predict path more efficiently for longer sequences of trajectories. Fig. 7 reports the execution time of baseline methods and our proposed method. The execution time is measured in second (sec). The performance of our method is notified by P–F (Proposed Framework). It is observed that our method is capable to predict path in less execution time compared to other methods. Hence, it may be observed that the proposed model can predict individuals' mobility patterns at less time but with higher precision, which is vital for mobility based real time health monitoring. Also, the proposed framework is capable to predict the optimal path of long time-sequence efficiently. As reported in the Figs. 5 and 6, the precision and recall of the path prediction for time-sequences 10–60 are quite high. This demonstrates that the system can predict the optimal path of next 10mins to 60mins/ an hour to reach the destination effectively. Therefore, in case, the communication is lost for a specific time-window, the mobile device of the user can store the path for next one hour, and assists even if there is no access to fog/ cloud data. Once the communication is set, the cloud server will send the updated path accordingly. Regarding the processing of health data in the fog-devices, if the communication is lost, the mobile devices will store the data for some time. When the connectivity is resumed, it will forward the data to the fog-device for further processing.

4.3 Implementation of proposed framework in a testbed

We have implemented the edge-fog-cloud based IoHT framework in IIT Kharagpur. A BAN is formed to collect the data with respect to the health parameters: blood pressure, body temperature, pulse rate and SPO2. The collected

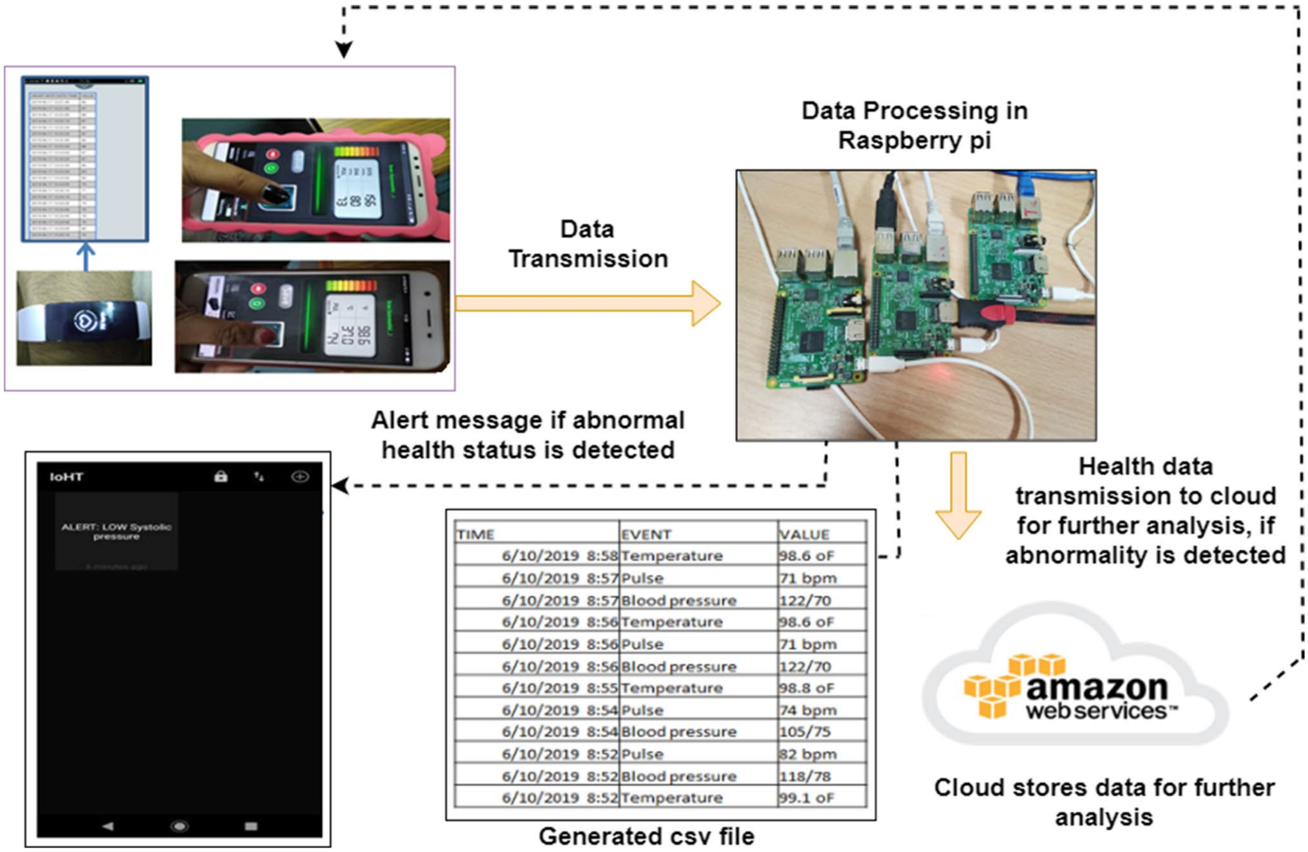


Fig. 8 Experimental Setup in the Spatial Data Science laboratory of IIT Kharagpur

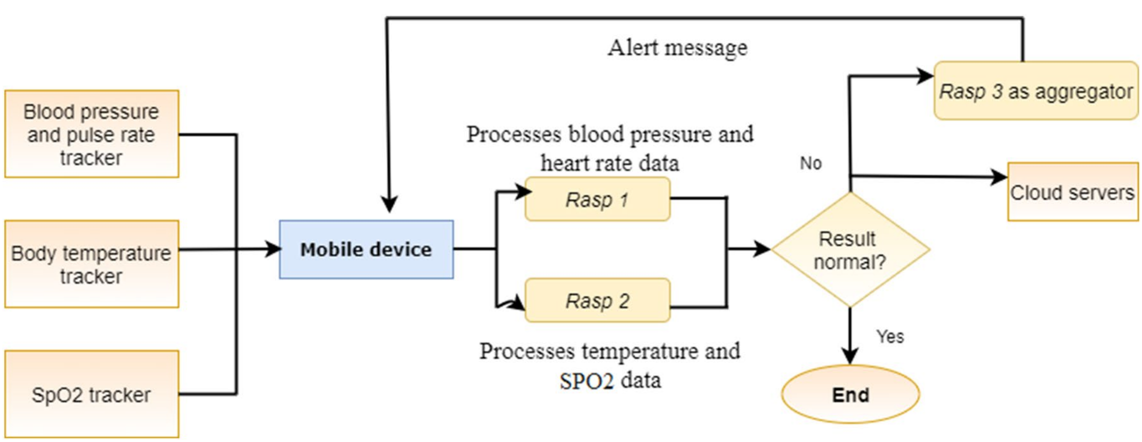


Fig. 9 Data flow diagram of the implemented IoHT framework

health data is transmitted to the fog devices, which process the data. In case of abnormal health condition, the result is sent to the cloud and an alert message is sent to the user. To implement the proposed framework, we have used the following components:

1. BAN composed :
   (a) Blood pressure with pulse rate (heart rate) tracking module
   (b) Body temperature tracker
   (c) SPO2 tracker.
2. Smart phone as edge device.
3. Three Raspberry Pi as fog devices:

(a) One is used to process blood pressure data (systolic and diastolic) and pulse rate data
(b) One is used to process temperature data and SPO2 data
(c) One is used to aggregate the result.

4. Amazon EC2 server as cloud

The smart phone and three Raspberry Pi are under the same LAN. The health data are exported in .csv files inside the smart phone. The .csv files containing the health data are transferred to the Raspberry Pi working as fog devices. Raspberry Pi 1 (Rasp 1) processes blood pressure data (systolic and diastolic) and pulse rate data. Raspberry Pi 2 (Rasp 2) processes the temperature and SPO2 data. Raspberry Pi 3 (Rasp 3) is used as the aggregating device. The implemented IoHT framework is presented in Fig. 8 and the corresponding flow diagram is shown in Fig. 9.

The prototype uses BAN, three Raspberry Pi (Raspberry Pi 3 Model B), an EC2 instance in AWS cloud (AWS EC2 instance t2.micro), and android smartphone (Android 9 with QPython application (app) for python support). The program running on a Raspberry Pi fetches the health parameter data recorded by the corresponding health monitoring device using the related API, for example, Rasp 1 fetches the pulse rate data recorded by the health monitoring device using the Intraday Heart Rate API for python provided by Fitbit. The data comes in the form of a .csv file. As soon as the file is downloaded in the system, an event is triggered by the watcher.py file running as a background process. The file is then read line by line and when any value crosses a predefined threshold (for example, pulse rate goes above 90 bpm) an alert notification is pushed to the android device using the MQTT protocol. On Raspberry Pi this is handled by mosquitto package for linux and on the Android device this is done by a Python code leveraging QPython's compiler. On the completion of processing, the program generates two files, one containing the log messages and the other containing data for future analysis. The second file is pushed to an EC2 instance using the SFTP. For this work, the Raspberry Pi and Android smart phone do not need to be in the same network as long as they are connected via some MQTT broker.

The range of the systolic blood pressure data is considered:

– Low blood pressure (Hypotension): < 120 mmHg,
– Normal blood pressure: 120–140 mmHg,
– Pre-hypertension: 141–160 mmHg,
– High blood pressure (Hypertension stage): 161–180 mmHg,
– High blood pressure crisis (emergency): > 180 mmHg.

Table 2 Collected temperature, pulse rate and blood pressure values of a volunteer

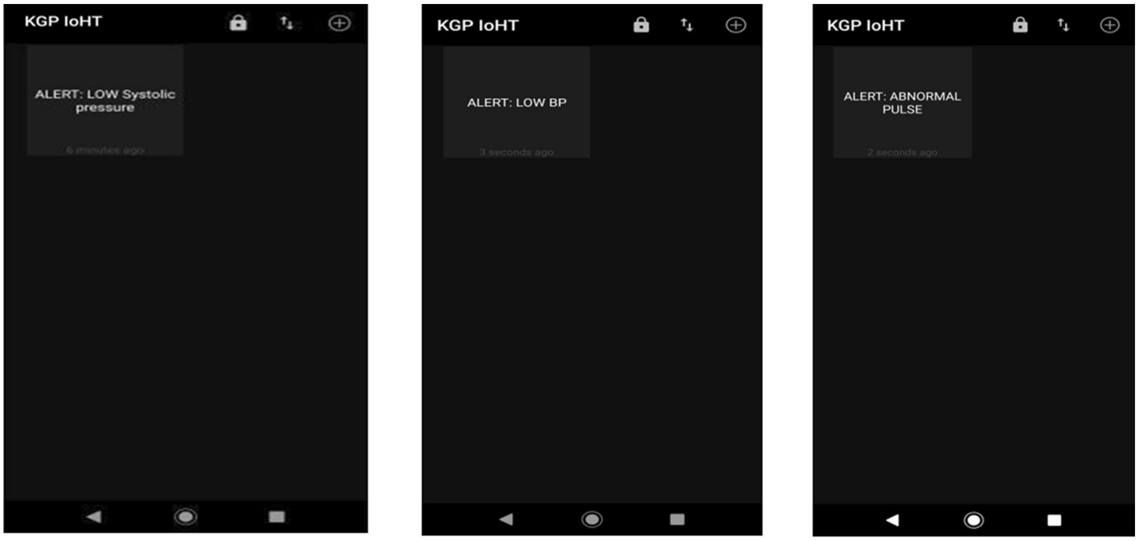
Date	Time	Temperature (^0F)	Pulse rate (bpm)	Blood Pressure (mmHg)
06/10/2019	08:56	97	71	122/70
06/10/2019	08:58	97	71	122/70
06/10/2019	12:42	98	54	105/55
06/10/2019	15:34	98	68	118/68
06/10/2019	15:43	98	65	115/72
06/10/2019	16:03	97	60	105/75
06/10/2019	16:48	97	64	115/72
06/10/2019	18:14	97	61	105/75
06/10/2019	21:15	97	65	118/70

The range of the diastolic blood pressure data is considered:

– Low blood pressure (Hypotension): < 60 mmHg,
– Normal blood pressure: 60–80 mmHg,
– Pre-hypertension: 81–89 mmHg,
– High blood pressure (Hypertension stage): 90–99 mmHg,
– High blood pressure crisis (emergency): > 100 mmHg.

If the collected systolic or diastolic value or both indicates hypotension, pre-hypertension, hypertension, or high blood pressure crisis, the result is sent to the aggregating node i.e. Rasp 3. Rasp 3 sends an alert to the user's smart phone. The normal pulse rate is considered 55–80 per minute. If the collected pulse rate is below 55 or above 80, the result is sent to Rasp 3. Rasp 3 sends an alert to the user's smart phone. For temperature the normal range is considered $96 - -98.6^0F$. The normal SPO2 level is considered ≥ 95%. If the collected temperature is below 96^0F or above 98.6^0F, the result is sent to Rasp 3. Rasp 3 sends an alert to the user's smart phone. If the collected SPO2 is < 95%, the result is sent to Rasp 3. Rasp 3 sends an alert to the user's smart phone. The collected pressure data, pulse rate (wrist measured heart rate) and temperature data of a student volunteer is presented in Table 2. The temperature is measured in degree Fahrenheit (^0F), pulse rate is measured in beats per minute (bpm), and blood pressure is measured in millimeters of mercury (mmHg where Hg stands for the mercury symbol). An alert message is sent to the smart phone of the student volunteer in case of abnormal health status, as shown in Fig. 10.

We would like to mention that the health data is collected voluntarily from a small set (40) of students. Here the students are both under graduate and graduate students (including Ph.D. students and research staffs of the laboratory). Amongst them, it is observed that 32 users are suffering from pre-hypertension. These 32 people are categorized based on age group and



(a) Alert message displayed in the user's smart phone (systolic pressure low)

(b) Alert message displayed in the user's smart phone (systolic and diastolic pressure low)

(c) Alert message displayed in the user's smart phone (abnormal pulse rate)

Fig. 10 Alert message displayed in user's smart phone in case of abnormal health status

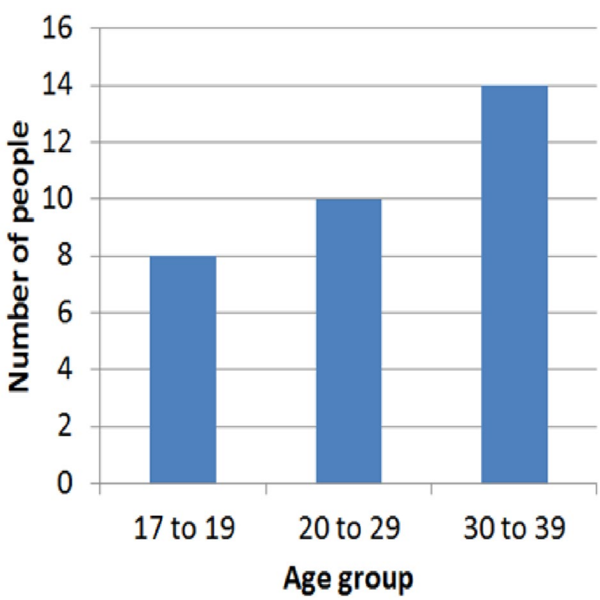


Fig. 11 Number of people suffering from pre-hypertension (category: age group)

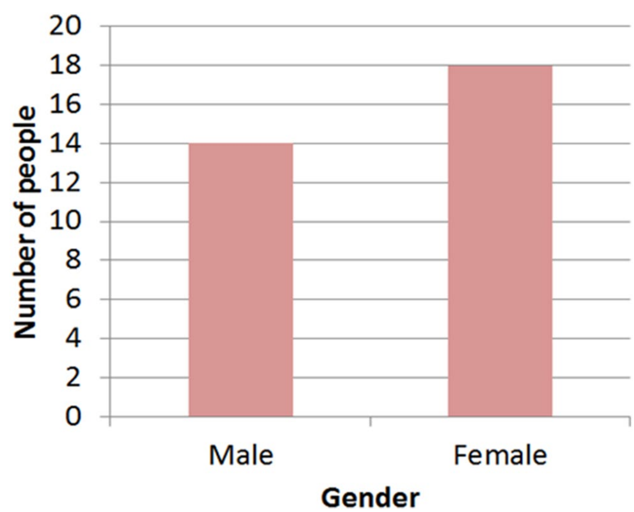


Fig. 12 Number of people suffering from pre-hypertension (category: gender)

gender, as observed from Figs. 11 and 12. Here it has to be noted that in the age group 17–19 we have under graduate students. In the age span 20–29 we have under graduate, post graduate as well as Ph.D. students including research staffs. In the age span 30–39 we have the Ph.D. students including research staffs. From Fig. 11 we observe that the number of patients suffering from pre-hypertension increases with the age. From Fig. 12 we observe that the number of male and female suffering from pre-hypertension are 14 and 18 respectively. For verification the medical history of these volunteers have been checked and the precision has been calculated as $\frac{tp}{tp+fp}$, where *tp* stands for true positive, *fp* stands for false positive. It is observed that the results obtained from our experimental analysis provides 96% precision with respect to the medical history of the volunteers.

The main objective of the experiment is to analyse the feasibility of the proposed framework. For instance, we demonstrate that the framework is capable of collecting health, movement data, storing/ analysing these information and recommending any medical advise based on the analysis. We do not aim to provide any clinical observations/ statistics based on this collected data. Since, this data is not the complete data-set of the students (IIT Kharagpur campus has more than 8000 students), the count of the students having hyper-tension is not the statistical representation of the health of the student community. However, from the theoretical and experimental analysis we can conclude that the proposed framework has lower delay and lower energy consumption of the user device than the cloud only framework, and the mobility pattern prediction model has better precision than the existing models.

5 Conclusions and future work

Smart health care is an emerging area nowadays. In this work we have proposed a mobility-aware IoHT framework based on edge-fog-cloud based collaborative network. Fog devices process the health data to reduce energy consumption and delay than the cloud only system. It is also demonstrated thorough simulation study that our framework has outperformed the existing cloud only health care solution by $\sim$ 28% less delay and $\sim$ 27% less energy consumption of the device. The mobility or continuous location change of users is an critical issue in case of real time health monitoring, and the mobility of users have been considered in the proposed framework. The mobility pattern modelling and prediction model have been presented in the paper, and the mobility model outperforms the existing models with respect to precision, recall value and execution time. In the institute laboratory, we have implemented the proposed IoHT framework and analyzed the health status of few student volunteers. The blood pressure, body temperature, pulse rate and SPO2 are collected, and analyzed inside the Raspberry Pi used as fog device. Different categories of data are processed inside different fog devices to distribute the load. The Raspberry Pi in case of abnormal health status send the result to another Raspberry Pi used as aggregating fog device and to the cloud for further analysis. The aggregating node after receiving result from different Raspberry Pi aggregate the result and predict the health status and sends an alert message to the user's smart phone if the predicted health status is abnormal. In future we will explore optimum resource allocation algorithms for edge-fog-cloud based collaborative network. Further, we will try to integrate with health centre so that we can have access to the health data collected by medical practitioners as well as incorporate their knowledge and expertise for making the system more viable. We strongly believe that the proposed mobility-aware IoHT framework will also act as the foundation of health monitoring of elderly people and assisting them in medical emergency.

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