Hash Polynomial Two Factor Decision Tree using IoT for Smart HealthCare Scheduling

Author Details:
Dr. Manikandan Ramachandran
Assistant Professor,
School of Computing,
SASTRA Deemed University,
Thanjavur, India.
Mobile: +91-9944998490
Email: srmanimt75@gmail.com

Dr. Rizwan Patan
Assistant Professor
School of Computing Science and Engineering,
Galgotias University,
NCR Delhi
India-201307
Mobile: +91-9700266476
Email: prizwan5@gmail.com

Dr. Amir H. Gandomi
Professor of Data Science
1- Faculty of Engineering & Information Technology, University of Technology Sydney, Ultimo, NSW 2007, USA
2- School of Business, Stevens Institute of Technology, Hoboken, NJ 07030, USA
Email: gandomi@uts.edu.au (Corresponding Author)

Dr. Perumal Sivanesan, Ph.D.,
Assistant Professor,
School of Computing,
SASTRA Deemed University,
Thanjavur, India.
Mobile: +91-4362-264105
Email: ps.nesan@gmail.com

Dr. Hariharan Kalyanaraman, Ph.D.,
Assistant Professor,
School of Computing,
SASTRA Deemed University,
Thanjavur, India.
Mobile: +91-4362-264105
Email: harikalyan87@gmail.com

Hash Polynomial Two Factor Decision Tree using IoT for Smart HealthCare Scheduling

Ramachandran Manikandan[1], Rizwan Patan[2], Amir H. Gandomi[3*], Perumal Sivanesan[4], Hariharan Kalyanaraman[5]

[1,4,5]School of computing, SASTRA Deemed University, India

[2]School of computer science and engineering, Galgotias University, India

[3]School of Business, Stevens Institute of Technology, Hoboken, NJ 07030, USA

Email: srmanimt75@gmail.com, prizwan5@gmail.com, a.h.gandomi@gmail.com, ps.nesan@gmail.com, harikalyan87@gmail.com

Abstract

The steady growth of an aging population and increased frequency of chronic disease led to the development of Smart Health Care (SHC) systems. While patient prioritization is the core of any SHC system, handling the response time by medical practitioners is a prevailing challenge. With advancements in information technology, the concept of the Internet of Things (IoT) has made it possible to integrate SHC systems with the Cloud environment to not only ensure patient prioritization according to disease prevalence, but also to minimize response time. In this work, an IoT-based scheduling method, called the Hash Polynomial Two-factor Decision Tree (HP-TDT) is proposed to increase scheduling efficiency and reduce response time by classifying patients as being normal or in a critical state in minimal time. The HP-TDT scheduling method involves three stages including the registration stage, the data collection stage, and the scheduling stage. The registration phase is carried out through Open Address Hashing (OAH) model for reducing the key generation response time. Next, the data collection stage is performed using the Polynomial Data Collection (PDC) algorithm. By incorporating PDC, computation overhead is reduced because a number of operations are considered during data collection. Finally, scheduling is performed by applying two-factor, entropy and information gain according to a decision tree. With this, scheduling efficiency is improved due to the

classification of patients as being normal or in a critical state. The proposed method minimizes response time, computational overhead, and improves essential scheduling efficiency.

Keywords: Smart Health Care, Internet of Things, Cloud environment, Hash Polynomial, Two-factor, Decision Tree

1. Introduction

In today's world of highly challenging and swiftly progressing conditions, senior citizens are experiencing several challenges predominantly associated with health. Recently, the world's population has reached greater influence on global and regional public health action. The evolution of the Internet of Things (IoT) makes it feasible for medical institutes to ensure quality, convenient, and pervasive healthcare services.

Privacy-preserving smart IoT-based healthcare was previously investigated to design a novel two-fold access control mechanism for supporting both normal and emergency situations (Yang et al., 2019). This healthcare system was found to be not only self-adaptive in normal situations, but also in emergency situations. In the case of normal applications, healthcare staff with proper attribute secret keys has the privilege of data access. In emergency applications, patient's medical data was recovered using a password-based break-glass access mechanism. To minimize the space complexity in the big data storage system, a secure deduplication technique was intended to take away the redundant medical files with the same data. The main advantage of privacy-preserving smart IoT-based healthcare was that the remaining medical file after deduplication was accessed by all data users authorized by different original access policies. The two-fold access control mechanism provided higher security in smart healthcare big data storage system. Due to the duplication, the time taken to accessing the secure medical data was improved.

Based on the human nervous system and cognitive abilities, a set of autonomic cognitive design patterns were previously investigated to provide a mechanism to mitigate the problems in design complexity of smart IoT-based systems (Mezghani *et al.*,2017). This method also considered both big data and scalability management. The primary objective of these autonomic cognitive design patterns was to provide both generic and reusable solutions for providing a flexible and smart IoT-based system to collect data and make decisions accordingly. Besides, these autonomic cognitive design patterns were articulated within a model-driven mechanism with the objective of incrementally refining both the functional and nonfunctional system requirements.

Instantiated pattern sets were integrated for developing a flexible cognitive monitoring system to manage patient health, which addresses response time and scalability management. Despite addressing response time and scalability management, the computational overhead incurred in identifying the cognitive design patterns than the IoT-based scheduling method.

With the help of the above discussion, an SHC system is an essential and important application for providing immediate health services to the patient. An SHC system generally monitors patient health to offer recovery services for critical conditions. Though, the scheduling performance of conventional work was not enough. In addition to that, privacy-preserving IoT-based healthcare was designed to identify unauthorized users while transmitting medical data. However, the response time was not reduced. Therefore, this research work aims to improve scheduling efficiency and reduce response time in SHC systems. The HP-TDT method was designed to enhance scheduling efficiency and reduce response time.

The rest of the paper is formulated as follows. In Section 2, a review of related SHC systems for IoT based on a cloud environment is presented. Section 3 describes the proposed HP-TDT method with the help of a block diagram and algorithms. Section 4 describes the experimental design. Section 5 analyzes and discusses the results. Section 6 contains conclusion of the paper.

2. Related works

In recent years, harmony between smart health care and technology has extensively increased across the world. For example, IoT and Cloud environment are progressively achieving popularity for next generation SHC systems. Advantages of the healthcare IoT technologies that related to smart sensors for health care applications were previously analyzed (Firouzi, et al., 2018). A survey of Structural Health Monitoring (SHM) was previously investigated (Tokognonet al., 2017). The framework handled complex and large amounts of data collected from sensors installed on structures. However, computational overhead was not minimized while handling large data collections.

Another SHM IoT-based platform was previously designed (Abdelgawad and Yelamarthi 2017). In this work, the size and location of damage in structures were found, and steps were taken to handle the issues via a mathematical model. Security analysis was not performed in SHM IoT-based platform.

The state-of-the-art research work related to a wearable IoT healthcare system was presented in (Baker et al., 2017) where the sensors are placed in the patient's body with the objective of monitoring several health indices, communication standards required for the corresponding indices, and the design of the cloud environment. Also, the design of the paper differentiated itself from the previous survey by taking into account every crucial component of an IoT-based healthcare system. The survey did not attain significant improvements in the field of IoT-based healthcare.

The increased number of people suffering from chronic diseases necessitates the use of long-term remedies, which requires the identification of probable solutions for ensuring cost-effective and high-quality services. An Ambient Intelligent (AI) system was designed with the objective of assisting every task for monitoring and enhancing the quality of life (Triberti and Barello 2016). Although AI system ensures the quality of life but, the level of patient's adaptation to the disease condition was not identified. To address this issue, a descriptive study (Colicchio et al., 2016) was conducted using classification methods, which ensured security and including validity. However, this study failed to reduce misclassification.

In recent years, sensors have become an unavoidable part of our everyday lives. This is because sensors are ambient and embedded in smartphones. A Physical Activity Change Detection (PACD) approach was designed (Sprint, G.*et al.*, 2016) to measure the significance of detected changes and analyze the nature of the changes to track physical activity and respond accordingly. Although tracking was claimed to have been made more efficiently, the classification of tracking was not done. To address this issue, a vision-based proposal was made using the classification system that classified normal and abnormal gait (Hidalgo et al., 2016). Although the approach minimized computation time, accurate classification was not attained.

A SHC system for efficient patient monitoring and diagnosis for prevention and early-stage disease detection was presented in (Jeong, et al.,2016). Security of patient health information was not addressed.

Although an IoT-based smart health care system provides an enhanced and better solution for smart healthcare management, its adoption by end users was infrequent. A partial least square structural equation modeling was designed (Pal et al., 2018) to explore smart home services of health care. Although actual adoption of smart home services in healthcare was achieved, security and privacy aspects were not addressed. To address this issue, Integrated Circuit Metric (ICM) technology was designed (Tahir *et al.*, 2018) with the objective of achieving security, authentication, and confidentiality without compromising the resource demand. Key generation time was not minimized.

With no definite cure for dementia and costs increasing exponentially, a Technology Integrated Health Management (TIHM) was designed via machine learning algorithms to improve the accuracy of detection (Enshaeifar et al. 2018). The TIHM used the IoT to enable solutions for monitoring dementia, but, time span (the period of time. i.e. daily or weekly scale) taken for identifies unusual patterns was longer. A review of methods based on IoT for healthcare along with ambient-assisted living, also referred to as the Internet of Health Things (IoHT) was presented in (Rodrigues *et al.*, 2018). This review discussed the most recent journal articles and specifications available in the market. Although the methods increased the IoHT, a deeper understanding of IoHT and security requirements was not considered.

Another smart care beds for elderly patients were previously designed (Hong2018). with the objective of minimizing mortality rate. However, this study failed to measure the weight of elderly patients with impaired mobility.

A design for intelligent healthcare systems and mobile computing was previously presented (Ma*et al.*, 2108). Although the system increased performance of the system; the quality of services was not improved.

Two innovative algorithms were investigated with the objective of improving the reliability and lifetime of the operable device working condition during a working day by applying low-frequency movement characterization and adaptive heart rate (Roda-Sanchez, *et al.*, 2018). The algorithms increase the efficiency of the services, but the safety requirements were not ensured.

A privacy protection user authentication and key agreement scheme was designed (Chen, Y *et al.*, 2017) by applying the elliptic curve Diffie-Hellman algorithm to attain higher security. Privacy problems were not considered during the authentication and key establishment processes.

A supportive framework called decision-making based IOT process was designed (Abdel-Basset, M *et al.*, 2018) for gathering and processing required information in smart education environments. The framework increased the security of data gathering but it could not be applied to healthcare fields.

Smart Service Systems were developed (Lim &Maglio 2018) by integrating machine learning algorithms and metrics for the analysis of text data. The system did not consider time metrics.

A neural network model was introduced (Lacher *et al.*, 1995) for effectively categorizing the financial health of a firm. The model did not effectively predict when the data exhibited significant nonlinearities.

In (Ramaswamy, V *et al.*, 2005), the high levels of call completion rates were maintained through preserving the quality of services in American Telephone & Telegraph (AT&T) network. However, scheduling was not performed while handling a large number of customers.

A discrete-time model was developed (Liu &Xie 2018). to considerably decrease the total waiting time of patients without increasing staff capacity. The model did not maintain stability.

An integrated model was designed (Martinez-Caro *et al.*, 2018) to explore the relationship between the capabilities of patients to effectively use information and communication technologies and the success of IoT-based healthcare services. However, predictive capabilities were not at required level.

An IoT-based health prescription assistant model was introduced to obtain proper suggestions from physicians (Hossain, M *et al.*, 2018). However, the response time was unable to be minimized. A novel integer linear programming (ILP) model for assignment and scheduling efficient home care services was previously introduced (Cappanera&Scutellà2014). However, this model failed to solve the larger home care instances.

A Markov decision process and approximate dynamic programming approach (Diamant, *et. al.,*2018). was employed for solving dynamic patient scheduling. While handling a larger number of patients, overhead was not minimized. A workforce management and scheduling under flexible demand (Villarreal, *et. al.,*2015) was designed to resolving a staff planning and scheduling problem. Although the method increased scheduling efficiency, the privacy-preservation of patient data was not solved.

Patient classification was performed using individual patient characteristics through the scheduling process (Salzarulo *et al.*, 2016). Although patient scheduling efficiency was improved with less cost function, security remained unsolved.

Big data enabled smart healthcare system (Md Ileas Pramanik et al. 2017) for offering intra and inter organizational business operation. However, the security of medical information is crucial and generally low. The heartbeat period for transmission suppression algorithms was described in (Kojo Sarfo Gyamfi et al. 2019) depends on the Bayes risk minimization for reducing the cost of the heartbeat transmission. However, time consumption was not effectively reduced.

In the analyzed papers, the authors employ different healthcare systems using IoT for scheduling patients for timely rescue operations, but there are no changes on the fly in the balancing of computational overhead and response time. A lower response time affects early diagnosis and patient treatment. In this way, computational overhead and response time be explored. In addition, the security of patient health information remains an unsolved issue in IoT.

The work proposed in this paper reduces the response time by applying the Open Addressing Hash model in which the key generation center specifically generates the key for the registered user through mapping. Next, the computational overhead is minimized by applying the Two-factor Decision Tree scheduling algorithm, which is discussed in the next sections.

3. Hash Polynomial Two-factor Decision Tree Scheduling

Internet of Things (IoT) is a type of network comprised of several physical objects. With IoT, not only information but also communication technology is connected to the Internet via multiple embedded devices, with the objective of performing data accumulation and transmission between two parties. One of the key advances is that such devices can be linked to massive resource pools such as the cloud. The unification of embedded devices and cloud servers suggests that IoT is comprehensively relevant to several aspects of our lives in clouding security, privacy, scheduling, and many other concerns. Based on the above information, an IoT for Smart Health Care (SHC) towards scheduling method, called the Hash Polynomial Two-factor Decision Tree (HP-TDT) is introduced.

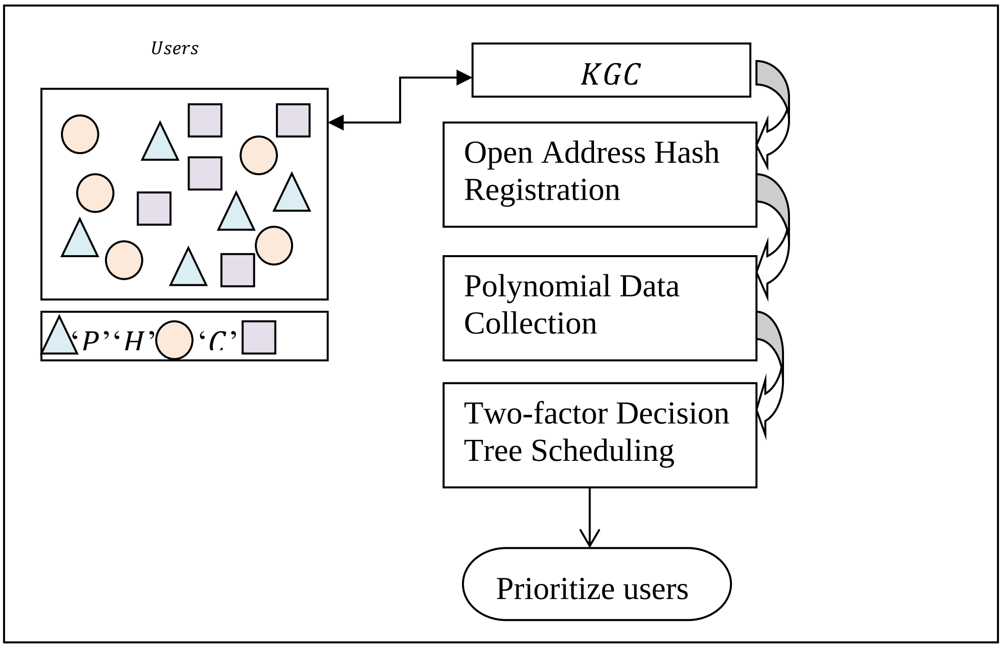

Figure 1. Block diagram of IoT using HP-TDT

In the proposed HP-TDT method, each user (i.e., patient 'PP', hospital 'HH', and cloud ('CC') registers at the key generation center ('KGC'). The 'KGC' in turn issues a pair of public keys ('BK') and private keys ('RK') that allow users to communicate. The user is also issued the pivotal key ('PK') for encrypting private health information. Consider an IoT for SHC systems that includes four entities: user 'U_p, U_H, U_C'cloud data storage 'CDS', 'KGC', and IoT medical Sensor 'MS'. Figure 1 shows the block diagram of the proposed HP-TDT method.

As shown in Figure1, the block diagram of the IoT using the HP-TDT method includes three stages. The first stage includes registration between users with the 'KGC'. The second stage includes data collection at the 'CDS'. Finally, notification for efficient scheduling is performed. Registration between users is carried out using Open Address Hash Registration to minimize key generation response time. Next, data collection is performed at the CDS using the Polynomial Data Collection algorithm. By applying a polynomial factor, the computational overhead is reduced. Finally, based on the priority of the state, the patient's data are scheduled by a two-factor decision tree via IoT medical sensor. IoT using HP-TDT is explained below.

3.1 Network model

The proposed work models network topology as an undirected graph 'G(V, E)' with vertices (patient, hospital, and cloud) 'V(G)' connected by links 'E(G)'. In this scenario, the publishers are the patient and the cloud, whereas the subscriber that is interested in receiving the notifications is the hospital. The set of sensor-publishers (for Patient, Hospital) are denoted as 'SP_P, SP_H'. the subscribers interested in receiving alerts are denoted as 'SP_c'and the cloud service as 'C∈V'.

3.2 Open Address Hash registration

The registration phase is the first step toward the design of IoT for SHC systems. The registration phase is performed via the Open Address Hashing (OAH) model. The reason for using the OAH model is that the availability of a random set of sizeable and possible public and private keys at the KGC increases the possibility of collision occurrence. This is due to the probability of at least two of the keys in the KGC being hashed to the same slot in which the wrong keys may be generated for each user, which would increase the key generation response time. In this work, to reduce key generation response time, the Open Address Hash registration phase is presented.

By applying the OAH model in the registration phase, the patient 'U_p' and the hospital 'U_H' perform initial registration at the 'KGC'. The 'KGC' evaluates a pair of BK' and 'RK' for each user. The user acquires the cloud's 'BK' 'a' and 'PK' to either performs encryption or decryption to obtain medical information, along with the BK and RK generation time 'TT'. The block diagram of the Open Address Hash registration phase is shown in Figure 2.

As shown in Figure 2, the block diagram of OAH includes three parts: the user, cloud, 'BK' and 'KGC'. For each user, along with the public key provided by the cloud, the 'KGC' generates a public key and a private key using the OAH model. By using the OAH model for user registration, different hash functions in the sequence perform mapping with different locations in the hash table.

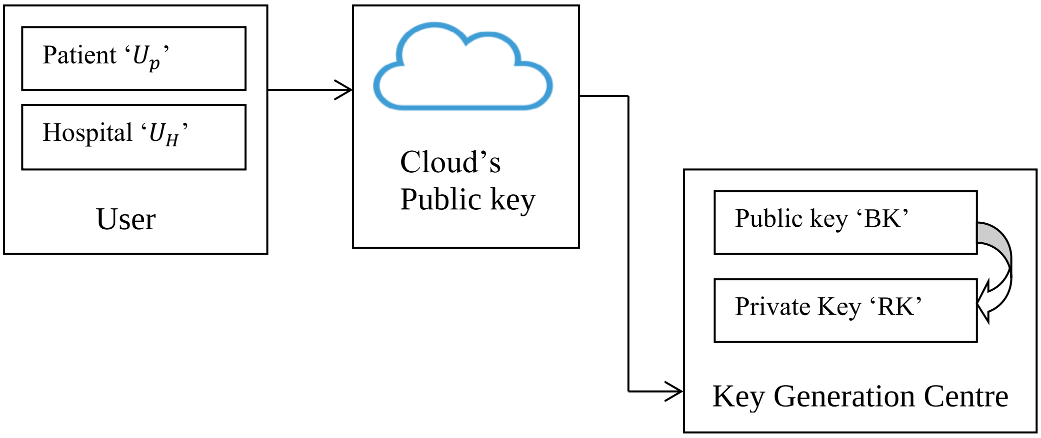

Figure 2. Block diagram of Open Address Hash Registration

In this work, two different hash functions, 'h_0' and 'h_1', are used to generate a 'BK' and a 'RK', respectively, for each user 'U_P, U_H, U_C'. This is mathematically formulated as shown below.

$$BK_p = h_0(ID_p, a, T) \tag{1}$$

$$BK_H = h_0(ID_H, a, T) \tag{2}$$

$$BK_C = h_0(ID_C, a, T) \tag{3}$$

From equations (1), (2), and (3), for each user 'U' with identification 'ID' and the cloud's public key 'a' for different time intervals 'T', a corresponding private key is generated.

$$RK_p = h_1(BK_p, a, T) \tag{4}$$

$$RK_H = h_1(BK_H, a, T) \tag{5}$$

$$RK_C = h_1(BK_C, a, T) \tag{6}$$

Similarly, from equations (4), (5),and (6), for each user 'U' with identification 'ID' and cloud's public key 'a' for different time intervals 'T', a corresponding private key is generated. The pseudo-code representation of OAH is shown below.

Algorithm 1 OAH algorithm

Input: User 'U_P, U_H, U_C', cloud's public key 'a', users public key 'K_P, K_H, K_C', time 'T'

Output: Key generation (public key 'BK', private key 'RK', pivotal key 'PK')

Begin

For each user 'U_P, U_H, U_C' with the cloud's public key 'a'

For 'i=0 to n-1'

If [$h_i(x)$ =x]', **then**

Return '$h_i(x)$'

Obtain a public key for the patient, hospital, and cloud using equations (1), (2) and (3)

Obtain a private key for the patient, hospital, and cloud using equations (4), (5) and (6)

End if

If [$h_i(x) = \emptyset$], **then**

Return 'absent'

End if

End for

End for

End

As shown in the above OAH algorithm, the 'KGC' obtains '(K_P, BK_P, RK_P)', '(K_H, BK_H, RK_H)', and '(K_C, BK_C, RK_C)' for each user and sends them to the corresponding end users for further communication. By applying OAH during registration, the collision between key selections is reduced. Because of this, key generation response time is further reduced. At first, the patient and the hospital perform initial registration through the key generation center using OAH model. For each user, 'KGC 'generates the pair of a public key and a private key. With this public and private key, the user performs encryption or decryption for accessing the medical records. By using the OAH registration process, the collision between key selections is minimized and also key generation response time is further reduced.

3.3 Polynomial Data Collection

Upon successful registration between the patient, hospital, and cloud via 'KGC', the next part in the design of the proposed method is data collection between the patient, hospital, and cloud. During an emergency, multiple co-located sensors in IoT SHC systems may initiate and forward similar sensed data/events to the cloud server. Therefore, in this work, a data collection mechanism is designed to use at least some of these publications for the detection of emergencies rather than the collection of all data.

This is performed using the Polynomial Data Collection (PDC) algorithm. By using the PDC algorithm, complexity (i.e., the computational complexity) is taken into account in order to classify the algorithm based on the behavior of the number of operations it needs to perform, not on the constant time regardless of the input size. As a result, computation complexity is reduced.

Using the PDC algorithm, two schedules are constructed from each registered publisher '$SP\epsilon SP_P, SP_H$' to the assigned gateway router 'C'. These two schedules are the shortest path that identifies the perfect shortest path 'PSP' (in terms of the weight factor of sensor 'i') between 'SP' and 'C', in case of the critical state. This is mathematically formulated as shown below.

$$\text{PSP (f) =MIN C (V, E, G)} \tag{7}$$

From equation (7), the 'PSP' is obtained according to the minimum cost involved in mapping vertex 'V' and its corresponding entropy and the information gained of sensor 'i' (obtained in the next section). Other than the shortest path, the maximal disjoint paths (i.e., minimum number of common nodes/links) from each ' $SP\epsilon SP_P, SP_H$' to 'C'.

$$\text{MDP(f)=Overall Space PSP(f)} \tag{8}$$

From equation (8), the maximal disjoint paths 'MDP' is the path other than the perfect shortest path obtained, in case of the normal state. The pseudo-code representation of 'PDC' is shown below.

Algorithm 2 PDC algorithm

Input: Registered publisher 'SP_P, SP_H', gateway router 'C', time 'T'

Output: Data collection

1: **Begin**

2: **For** each registered publisher ' $SP\epsilon\ SP_P, SP_H$' to the assigned gateway router 'C' at Time 'T'

3: Identify the perfect shortest path 'PSP' using equation (7)

4: Send corresponding data between 'SP_H and C'

5: Identify maximal disjoint paths using equation (8)

6: Send corresponding data between 'SP_H and C'

7: **End for**

8: **End**

As shown in the above PDC algorithm, for each registered publisher, the algorithm initially identifies the shortest path or the critical state based on the minimum cost involved in mapping vertex 'V' and its corresponding entropy and the information gained of the sensor by using polynomial distribution. Next, the algorithm identifies the maximal probable disjoint paths or the normal state via polynomial distribution based on the Overall space of Perfect shortest path by using PDC algorithm. Only one exponential calculation is performed to identify the critical state using polynomial distribution. The normal state is measured using this identified value. Therefore, the computational overhead incurred in identifying the normal or critical state is minimized.

3.4 Two-factor Decision Tree Scheduling

Decision Tree Scheduling represents a tree-formed structure that denotes classification knowledge. For performing the classification, the number of attributes is taken from the healthcare dataset.

$$a_1, a_2, a_3, \dots a_n \in D_h \tag{9}$$

In equation (9),$a_1, a_2, a_3, \dots a_n$ denotes an attribute andD_h denotes a healthcare dataset. Consider the attributes blood pressure 'BP', 'ECG' and glucose level 'GL' of the data set. A decision tree is a top-down approach from a root node and involves partitioning the data into different subsets containing instances with similar values. A two-factor decision tree is used to classify patient data through the set of rules. The tree consists of a root node, branches, and leaf nodes. The top node indicates a root node in the tree that contains the attribute. The branch node processes the attributes based on the set of rules. Finally, the leaf node in the tree contains a class label. Generally, developing a decision tree model involves two steps, tree construction and tree pruning. In tree construction, recursively split the tree according to selected attributes with the information gain. In tree pruning process, it tries to identify and remove the irrelevance branches (that might lead to outliers). In this way, the pruning method is a search algorithm that reduces the size of decision trees by removing sections of the tree that provide little power to classify instances. Pruning reduces the complexity of the final classifier, and hence it improves predictive accuracy by the reduction of overfitting potential. For example, in decision tree model, consider two branch nodes for predicting the state using 'BP', one branch node predict the critical state of the patient and the other is predicting the normal state of the patient. If 'BP' of the patient is higher than the threshold value, patient in critical state and disease predicted by using tree construction method. In this case, an attribution for the normal state is irrelevant. Therefore, it is reduced by using pruning method.

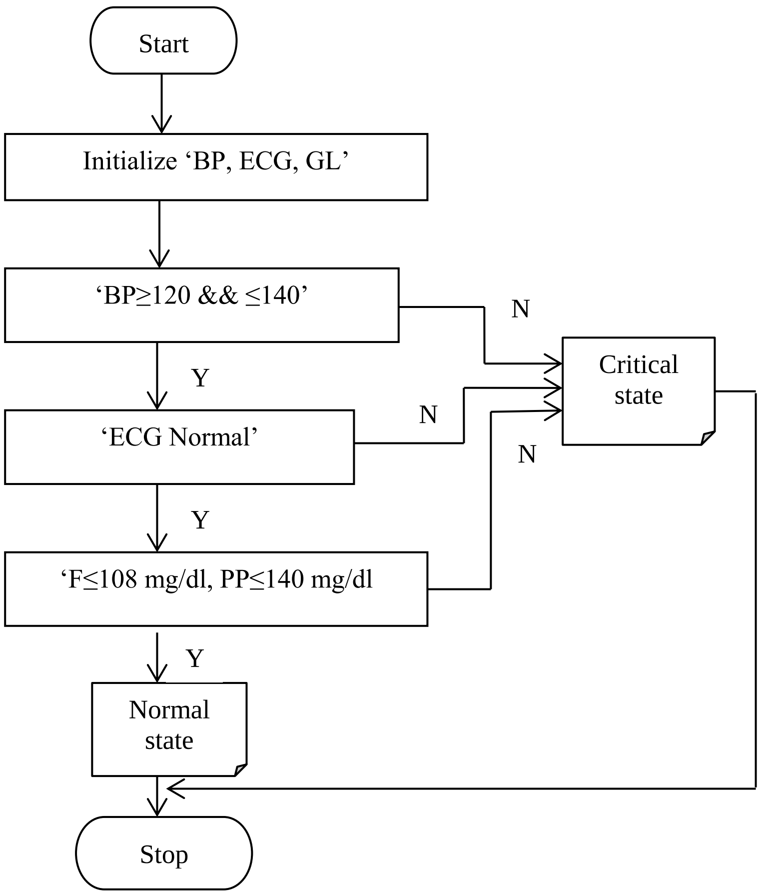

Figure 3. Flow diagram of Two-factor Decision Tree Scheduling

This process continues until all the attributes have been tested. In this work, a Two-Factor Decision Tree Scheduling was performed. Figure 3 shows the flow diagram of Two-factor Decision

Tree Scheduling. As shown in the flow diagram in Figure 3, initialization of the values of the attributes '$Attr = BP, ECG, GL$'is the first step. Following initialization, threshold values of 'BP_t, ECG_t, GL_t' are compared with the actual values to determine whether compared values are either critical state 'CS' or normal state 'NS'. The decision tree uses the concept of information gain and entropy as two factors for the classification of normal state or critical state. The first factor (i.e., entropy) is the measurement of information entropy associated with each possible attribute value, which is the negative logarithm of the probability mass function for the value. Entropy is mathematically formulated as shown below

$$Entropy(P) = -\sum_{C \in c_1, c_2} Prop(C) \log_2 Prop(C) \tag{10}$$

In equation (10), 'C' represents the set of class labels (i.e., normal state (C_1)or critical state (C_2) that categorizes the rules and 'Prop (c)' represents the proportion of patients 'P' belonging to class 'C'. The second factor (i.e., information gain) refers to the anticipated minimization of entropy due to splitting the training samples according to their attributes. The decision tree selects the best attributes for splitting the patient into different subsets at each step. For each iteration, the best attributes are selected based on information gain, which is measured as follows:

$$Gain(P, Attr) = Entropy(P) - Prob_p(V) - Entropy(P_V) \tag{11}$$

In equation (11), 'Attr' represents the attribute relative to the collection of samples 'P' and 'V' denotes the set of values 'V'. The attribute with maximum information gain is selected to make a decision to split all possible values for attributes 'P_V' is the subset of attribute in which the samples 'P' has the set of values 'V'. Finally, '$Prob_p(V)$' represents the probability that sample 'P' belongs to the patient condition attributes normal or critical state based on the threshold valueBP_t, ECG_t, GL_t. After classifying patient condition, priority-based scheduling is performed. A critical patient condition state is given higher priority than the normal state. Higher priority is scheduled first to the physicians than lower priority. This process increases scheduling efficiency. The pseudo-code representation of Two-factor Decision Tree Scheduling is shown below.

Algorithm 3. Two-factor Decision Tree Scheduling

Input: Registered publisher ‘SP_P, SP_H’, attributes‘$Attr = BP_t, ECG_t, GL_t$’, threshold‘BP_t, ECG_t, GL_t’

Output: Prioritize registered publisher based on two-factors

1: **Begin**

2: **For** each registered publisher ‘SP_P, SP_H’

3: **For** each Attribute ‘$Attr$’

4: Measure entropy value using equation (10)

5: Measure information gain using equation (11)

6: **If** ‘$BP \leq BP_t$’ && ‘$ECG == ECG_t$’ && ‘$GL \leq GL_t$’ then

7: normal state

8: **Else**

9: Critical state

10: **End if**

11: **End for**

// Decision Tree pruning process//

12: Constructing tree for each attribute

13: if BP, ECG, GL > threshold value then

14: Critical state

15: else

16: normal state

17: Normal state attributions are removed by using pruning method

18: Assign high priority p_h to critical state

19: Assign Low priority P_l to normal state

20: Schedule high priority to the physician

21: **End for**

22: **End**

As shown in the Two-factor Decision Tree Scheduling algorithm above, the algorithm starts with obtaining attribute values for each registered publisher. The attributes refer to the values of 'BP', 'ECG' and 'GL'. Two factors, entropy and information gain, are measured with these three attributes. The threshold values are compared with these two resulting n values to schedule the process, depending on the sensitivity of the condition of the patient. The sensor with higher values has higher priority because of the critical state. In contrast, the sensor with lower values has a lower priority because of the normal state. The two factor decision tree algorithms is impelmented to efficiently schedule the normal state or critical state of the patient. In this method, irrelevant attributions are removed by using pruning method.

3.5 Contributions

Based on the described strategy, the main contributions of the HP-TDT method are described below.

- **The HP-TDT was designed to improve the performance of response time via collision reduction in an SHC system as compared to conventional methods:** Due to collision occurrence in KGC, the probability of at least two of the keys in the KGC being hashed to the same slot in which the wrong keys may be generated for each user, which would increase the key generation response time. In order to overcome these issues, Open Addressing Hash model is used to addressing the response time issue through collision detection for enhancing performance.
- **The computational overhead is reduced during data collection by using Polynomial Data Collection (PDC) algorithm:** Data collection is performed at the CDS using the PDC algorithm. By applying a polynomial factor, the computational overhead is reduced. PDC algorithm identifies the differentiation between the normal and critical states efficiently. Only one exponential calculation is performed to identify the critical state using polynomial distribution. Here, the normal state is measured using this identified value. As a result, the computational overhead incurred in identifying the normal and critical states are minimized.

- **The Two-factor Decision Tree algorithm is implemented to increase the scheduling efficiency by efficient classification of patient data according to normal and critical states**: The decision tree uses the concept of information gain and entropy as two factors for the classification to the normal state or critical state. The number of critical patients is high and, therefore, the scheduling process takes too much time in order to schedule the patient. By coupling the decision tree algorithm to our system, it takes less time to schedule the patient and scheduling efficiency is increased.

4. Experimental setup

Based on the design described above, IoT-based cloud computing was implemented in JAVA platform using Cloud Sim simulator. Several experiments were conducted to evaluate the performance of our proposed SHC system. A healthcare dataset (Healthcare dataset) was used in the experiments. The reason for using Kaggle is that it supports a variety of dataset publication formats. Kaggle datasets are not open, accessible data formats better supported on the platform, but possess the advantage of working with more users regardless of the tools being used.

Columns included in the dataset are patient ID, gender, age, hypertension, heart disease, marital status, work type, residence type, average glucose level, BMI, and smoking status. One hundred fifty different users (i.e., patient) ranging between15 to 70 years of age were considered for the experiments. The experiments were repeated ten times. The performance of the proposed method (an IoT using Hash Polynomial Two-factor Decision Tree (HP-TDT) Scheduling method for SHC systems) was compared with two existing methods: privacy-preserving smart IoT-based healthcare (Yang *et al.*, 2019)and autonomic cognitive design patterns (Mezghani *et al.*, 2017). In order to evaluate the performance of IoT based on SHC systems, three different parameters such as key generation time, computational overhead and scheduling efficiency were tested in the JAVA platform.

5. Results &Discussions

In this section, the performance of the HP-TDT method is evaluated and compared with state-of-the-art methods.

5.1 Key generation time

In this section, the response time of the HP-TDT method is evaluated and compared with privacy-preserving smart IoT-based healthcare (PPS-IoT) proposed by Yang *et al.*,(2019)and autonomic cognitive design patterns (ACDP) proposed by Mezghani *et al.*, (2017), based on the number of patients involved as input in a Cloud environment in the comparison experiments. Key generation time depends on the number of cloud user placed in the cloud environment where the request is processed. The key generation time is shown below.

$$KGT = \sum_{i=1}^{n} P_i * time\ (Public\ Key) + time\ (Private\ Key) \quad (12)$$

From equation (12), the key generation time is obtained according to the time required to obtain the public key '$time\ (Private\ Key)$' and private key '$time\ (Private\ Key)$' with respect to the patients 'P_i'.

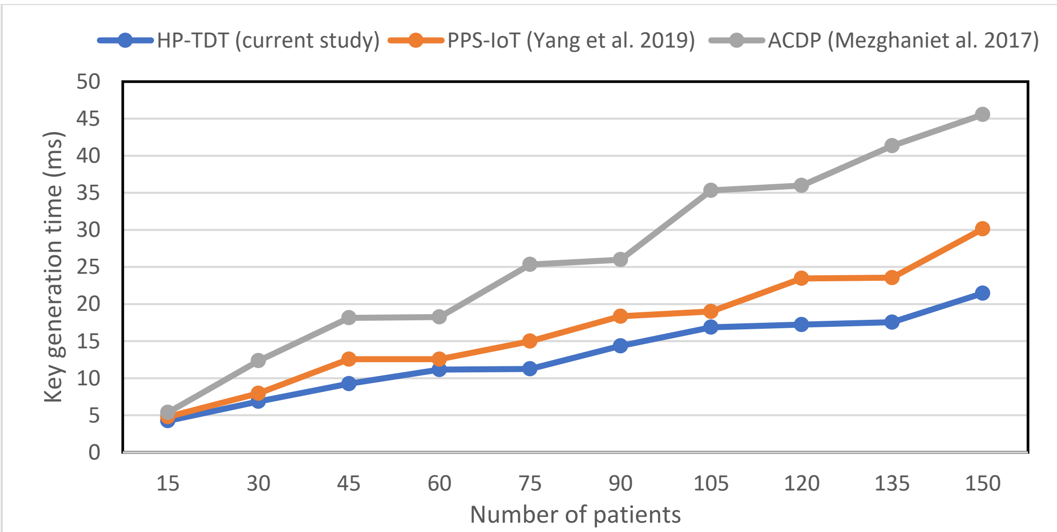

Figure 4 Comparison of different methods in terms of key generation time.

Figure 4 shows the key generation time of all three methods. This experiment was performed to verify the high efficiency of the key generation time with respect to the number of patients in IoT for SHC systems. In this experimental environment, two different hash functions were combined to achieve the high-efficiency key generation time. The key generation time was compared with PPS-IoT and ACDP by capturing the same number of patients. As illustrated Figure4, the experimental result of key generation time for a different number of patients with the same size (e.g., 15, 30, 45…,150) in the key generation phase was considered. Based on this experiment, we learned that: 1) the key generation time is proportional to the number of patients and 2) to handle the same number of patients for key generation, HP-TDT method requires less time than PPS-IoT and ACDP methods. Hence, as shown in Figure 4, the key generation time increases with an increase in the number of patients and has insignificant gaps when the number of patients is greater than 60; i.e., the key generation time for SHC systems in the HP-TDT method is lower than PPS-IoT and ACDP which is because of the application of OAH in the HP-TDT method. The reasons for this are twofold. First, existing PPS-IoT and ACD P methods perform key generation over IoT in a cloud server using model-driven methods with the aid of a cognitive monitoring system password-based mechanism, whereas in the HP-TDT method, two different hash functions were applied, which minimized the collision between key selections. Second, for performing key generation, the existing PPS-IoT and ACDP methods applied a single edge to avoid service failures for optimization, which is compromised in case of a large file or large number of patients, whereas in the HP-TDT method, key generation is performed for different time intervals and then key generation was performed with the optimal number of keys. This, in turn, reduced the key generation time and therefore the response time between the patients and the cloud in IoT system using HP-TDT method by 20% as compared to PPS-IoT and 47% as compared to ACDP. Hence, with the quick response time, physicians or medical practitioners can swiftly attend to the patients.

5.2 Computational overhead

In the HP-TDT method, computational overhead measures the storage that is consumed to carry out the SHC system. Computational overhead is evaluated in terms of kilobytes (KB) and is mathematically formulated as shown below.

$$CO = P_i * Storage(MDP(f)) \tag{13}$$

Using equation (13), the overhead incurred for SHC systems is estimated with respect to a different number of patients (P) (i.e., samples). The lower the communication overhead, the more efficient the method is said to be. The computational overhead incurred for IoT based on cloud environment is one of the challenges to be addressed for S9HC systems. With an increase in the number of patients, minimization of computational overhead cannot be attained; however, optimization can be achieved. The comparison of computational overhead for HP-TDT method was measured and compared with PPS-IoT (Yang *et al.*, 2019) and ACDP (Mezghani *et al.*, 2017) methods and the results are plotted in Figure 5. The results reported in Figure 5confirm that with an increased number of patients, the computational overhead is also increased.

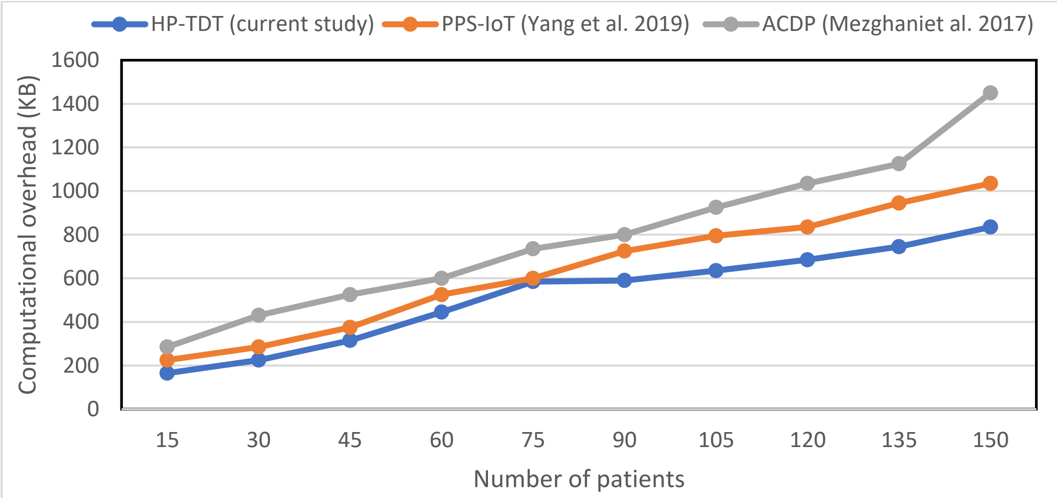

Figure 5 Comparison of different methods in terms of computational overhead.

Figure 5 shows the comparative performance of computational overhead for 15 different patients collected at ten different time intervals involving various activities (i.e., measuring BMI or glucose levels). As a result, 150 different patients are shown on the x-axis and computational overhead is shown on the y-axis. With the increase in the number of patients using KAGGLE datasets with different age groups of 25 and 40 collected from both genders, the computational overhead of SHC also increases. As a result, computational overhead increases with an increase in the number of patients. As a simulation in which‘15’ patients were considered for experimentation, the required to rage was found to be ‘11’ using HP-TDT method, ‘15’ using PPS-IoT and ‘19’ when applied with ACDP However, performance analysis of computational overhead using HP-TDT method is comparatively better than PPS-IoT and ACDP methods. This is because of the shortest paths using the Polynomial Data Collection (PDC) algorithm. By applying the PDC algorithm, differentiation between the normal and critical state are made efficiently as the classification is made according to the behavior of how many operations to be performed and not on the constant time consumed irrespective of the input size as done in (Yang *et al.*, 2019) and (Mezghani *et al.*, 2017) using PPS-IoT and ACDP methods, respectively. As a result, computation complexity is reduced by applying the HP-TDT method. The results also show that the computational overhead for data collection is found to be comparatively smaller using HP-TDT method by 18% as compared to PPS-IoT and 34% as compared to the ACDP method.

5.3 Scheduling efficiency

Finally, the scheduling efficiency, i.e., successful patients assigned with the physicians, is measured. In the HP-TDT method, scheduling efficiency refers to the number of successful patients assigned with the physicians performed in a Cloud environment based on the number of patients. The scheduling efficiency is measured as shown below.

$$SE = \sum_{i=1}^{n} [PBS/P_i] * 100 \tag{14}$$

In equation (14), the scheduling efficiency 'SE' is the ratio of the patients being scheduled 'PBS' to the number of patients 'P_i' waiting to be scheduled. The scheduling efficiency is measured in terms of percentage (%).

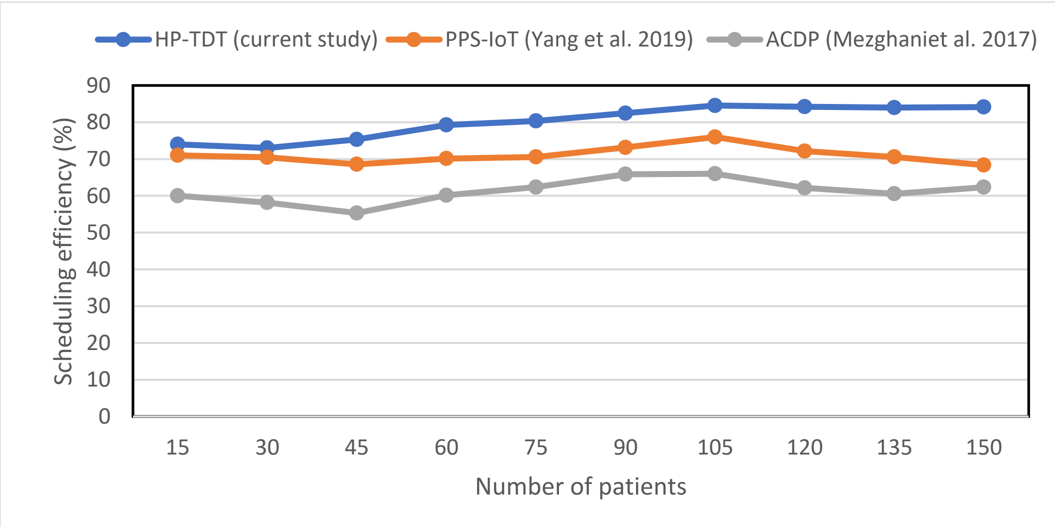

Figure 6 Comparison of different methods in terms of scheduling efficiency.

The targeting result of scheduling efficiency using the HP-TDT method is compared with two state-of-the-art methods: PPS-IoT and '19' when applied with ACDP in Figure 6 for visual comparison based on a varied number of patients. The HP-TDT method differs from PPS-IoT (Yang *et al.*, 2019) and ACDP (Mezghani *et al.*, 2017) methods in that the Two-factor Decision Tree Scheduling algorithm was applied for scheduling of patients in the cloud environment for IoT-based SHC systems. With simulation being conducted for 15 patients, the values of the attributes 'BP, ECG, GL' were initially initialized. Next, assigned values were compared to threshold values. The application of this algorithm optimizes scheduling by applying entropy. With optimized scheduling, the normal and critical state of the patient is differentiated by applying the information gain with respect to the threshold factors (separately for BP, ECG, and glucose level). By two-factor decision tree scheduling algorithm, the high priority is scheduled to the physician first followed by low priority. In the proposed system HP-TDT Therefore, the scheduling efficiency using HP-TDT method is found to be improved by 14% as compared to PPS-IoT and 33% as compared to ACDP.

5.4 AUC (Area Under a Curve)

AUC curve is plotted with two performance metrics, scheduling accuracy and false-positive rate. Scheduling accuracy is defined as the number of patients correctly identified from the decision tree. The false-positive rate is defined as a number of patients incorrectly identified. Figure 7 shows the Area under a Curve for measuring the accuracy of the proposed technique. For finding the area under the curve integrate of y = f(x) between x = a (false-positive rate=2) and x = b (false-positive rate=8) are calculated. Where y is the scheduling accuracy. Areas under the x-axis will come out negative rate and areas above the x-axis will be positive rate in between the 2-8 interval.

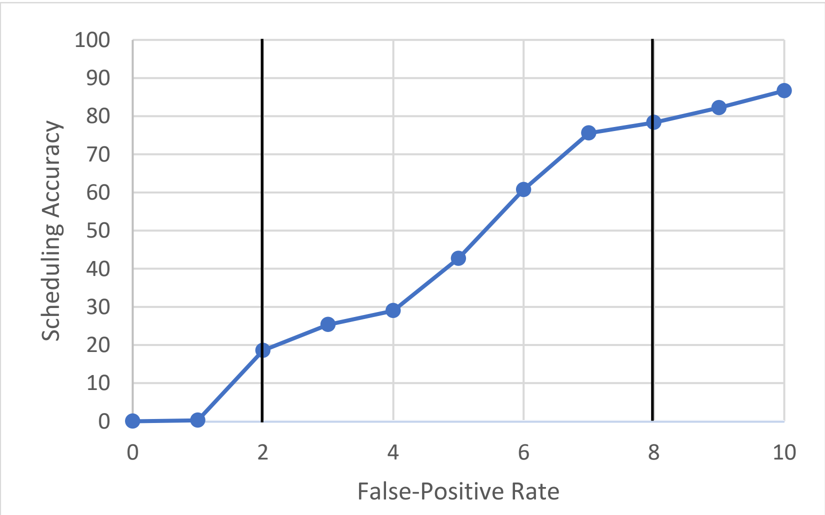

Figure 7. Represents the diagram of area under the curve

5.5 Scheduling Time

Scheduling time is defined as the time taken to schedule the number of patients.

$$scheduling\ time$$
$$= Number\ of\ Patients$$
$$\times time(to\ classifying\ one\ patient\ as\ normal\ or\ abnormal)\ (ms)$$

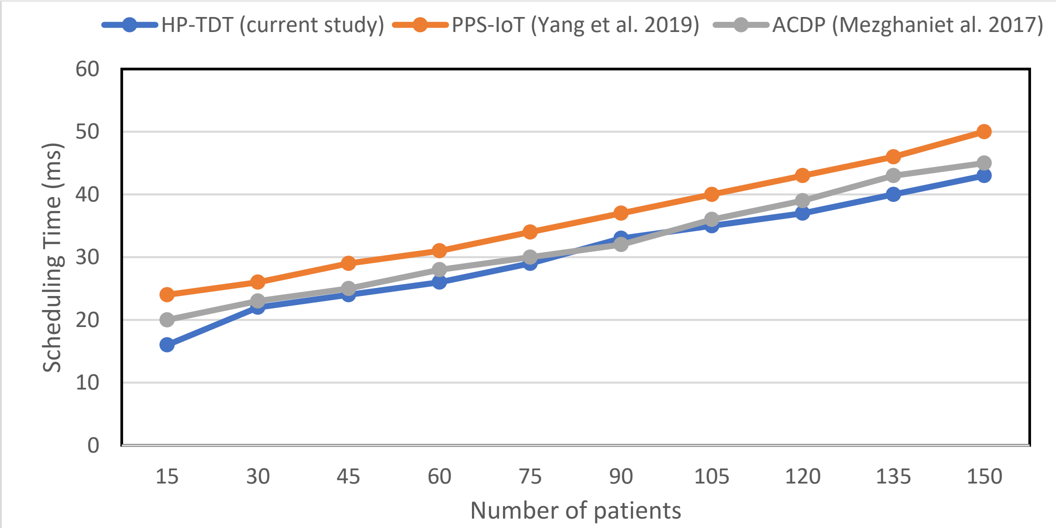

Figure 8 Comparison of different methods in terms of scheduling Time

Figure 8 shows a comparison of the scheduling time of the proposed method and two state-of-the-art methods published recently. The targeting results of scheduling time using these methods are visualized for a varied number of patients. From this figure, on average, there are about 20% and 7% of scheduling time reduction by the proposed HP-TDT technique in comparison with two existing methods, PS-IoT and ACDP, respectively.

6. Conclusions

The proposed method consists of three parts: key generation, data collection, and notification. The method starts with initial registration or key generation performed by the ‘KGC’ by applying the OAH model. Next, for registered users, data collection at the cloud data storage is performed by applying a Polynomial Data Collection algorithm. The PDC algorithm is applied to the registered users and was designed in such a manner that the normal and critical state of patients can be differentiated via the shortest path and maximal disjoint paths. Finally, Two-factor Decision Tree Scheduling algorithm was applied at the cloud for swift detection of critical stage patient send toper form Two-factor Decision Tree Scheduling algorithm scheduling accordingly. The HP-TDT was implemented to validate the proposed method. Extensive experiments were conducted to demonstrate the effectiveness and robustness of the proposed method in terms of key generation time, computational overhead, and scheduling efficiency. Future work will focus on designing low cost and low power consumption for the SHC system to perform efficient patient analyses. In the future, the scalability of the method will be verified by evaluating the proposed method using different kinds of datasets. In addition, advanced classification techniques may be developed in the future to further increase the classification and scheduling process.

References

Abdel-Basset, M., Manogaran, G., Mohamed, M., & Rushdy, E. (2018). Internet of things in smart education environment: Supportive framework in the decision-making process. *Concurrency and Computation: Practice and Experience*, e4515.

Abdelgawad, A., &Yelamarthi, K. (2017). Internet of things (IoT) platform for structure health monitoring. *Wireless Communications and Mobile Computing, 2017*.

Baker, S. B., Xiang, W., & Atkinson, I. (2017). Internet of things for smart healthcare: Technologies, challenges, and opportunities. *IEEE Access*, *5*, 26521-26544.

Cappanera, P., &Scutellà, M. G. (2014). Joint assignment, scheduling, and routing models to home care optimization: a pattern-based approach. *Transportation Science*, *49*(4), 830-852.

Chen, Y., Martínez, J. F., Castillejo, P., &López, L. (2017). A privacy protection user authentication and key agreement scheme tailored for the Internet of Things environment: PriAuth. *Wireless Communications and Mobile Computing, 2017*.

Colicchio, T. K., Facelli, J. C., Del Fiol, G., Scammon, D. L., Bowes III, W. A., &Narus, S. P. (2016). Health information technology adoption: Understanding research protocols and outcome measurements for IT interventions in health care. *Journal of biomedical informatics*, *63*, 33-44.

Diamant, A., Milner, J., &Quereshy, F. (2018). Dynamic Patient Scheduling for Multi-Appointment Health Care Programs. *Production and Operations Management*, *27*(1), 58-79.

Enshaeifar, S., Zoha, A., Markides, A., Skillman, S., Acton, S. T., Elsaleh, T., ...&Rostill, H. (2018). Health management and pattern analysis of daily living activities of people with dementia using in-home sensors and machine learning techniques. *PloS one*, *13*(5), e0195605.

Firouzi, F., Rahmani, A. M., Mankodiya, K., Badaroglu, M., Merrett, G. V., Wong, P., &Farahani, B. (2018). Internet-of-Things and big data for smarter healthcare: from device to architecture, applications and analytics.

Healthcare dataset: https://www.kaggle.com/asaumya/healthcare-data. [Last Accessed on 20 March 2019]

Hong, Y. S. (2018). Smart Care Beds for Elderly Patients with Impaired Mobility. *Wireless Communications and Mobile Computing*, *2018*.

Hossain, M., Islam, S. R., Ali, F., Kwak, K. S., & Hasan, R. (2018). An Internet of Things-based health prescription assistant and its security system design. *Future Generation Computer Systems*, *82*, 422-439.

Jeong, J. S., Han, O., & You, Y. Y. (2016). A design characteristics of smart healthcare system as the IoT application. *Indian Journal of Science and Technology*, *9*(37).

Kojo Sarfo Gyamfi, James Brusey, Elena Gaura, Ross Wilkins, "Heartbeat design for energy-aware IoT: Are your sensors alive?", Expert Systems with Applications Volume 128, 15 August 2019, Pages 124-139

Lacher, R. C., Coats, P. K., Sharma, S. C., &Fant, L. F. (1995). A neural network for classifying the financial health of a firm. *European Journal of Operational Research*, *85*(1), 53-65.

Lim, C., &Maglio, P. P. (2018). Data-driven understanding of smart service systems through text mining. *Service Science*, *10*(2), 154-180.

Liu, R., &Xie, X. (2018). Physician Staffing for Emergency Departments with Time-Varying Demand. *INFORMS Journal on Computing*, *30*(3), 588-607.

Ma, X., Wang, Z., Zhou, S., Wen, H., & Zhang, Y. (2018). Intelligent healthcare systems assisted by data analytics and mobile computing. *Wireless Communications and Mobile Computing*, *2018*.

Martínez-Caro, E., Cegarra-Navarro, J. G., García-Pérez, A., & Fait, M. (2018). Healthcare service evolution towards the Internet of Things: An end-user perspective. *Technological Forecasting and Social Change*, *136*, 268-276.

Mezghani.,Exposito, E., &Drira, K. (2017). A model-driven methodology for the design of autonomic and cognitive IoT-based systems: Application to healthcare. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *1*(3), 224-234.

Md Ileas Pramanik, Raymond Y.K.Lau, HalukDemirkan, Md. Abul KalamAzad, "Smart health:Big data enabled health paradigm within smart cities", Expert Systems with Applications Volume 87, 30 November 2017, Pages 370-383

Nieto-Hidalgo, M., Ferrández-Pastor, F. J., Valdivieso-Sarabia, R. J., Mora-Pascual, J., &García-Chamizo, J. M. (2016). A vision-based proposal for classification of normal and abnormal gait using RGB camera. *Journal of biomedical informatics*, *63*, 82-89.

Pal, D., Funilkul, S., Charoenkitkarn, N., &Kanthamanon, P. (2018). Internet-of-things and smart homes for elderly healthcare: An end user perspective. *IEEE Access*, *6*, 10483-10496.

Ramaswami, V., Poole, D., Ahn, S., Byers, S., & Kaplan, A. (2005). Ensuring access to emergency services in the presence of long Internet dial-up calls. *Interfaces*, *35*(5), 411-422.

Roda-Sanchez, L., Garrido-Hidalgo, C., Hortelano, D., Olivares, T., & Ruiz, M. C. (2018). OperaBLE: An IoT-Based Wearable to Improve Efficiency and Smart Worker Care Services in Industry 4.0. *Journal of Sensors*, *2018*.

Rodrigues, J. J., Segundo, D. B. D. R., Junqueira, H. A., Sabino, M. H., Prince, R. M., Al-Muhtadi, J., & De Albuquerque, V. H. C. (2018). Enabling technologies for the internet of health things. *IEEE Access*, *6*, 13129-13141.

Salzarulo, P. A., Mahar, S., & Modi, S. (2016). Beyond patient classification: using individual patient characteristics in appointment scheduling. *Production and Operations Management*, *25*(6), 1056-1072.

Sprint, G., Cook, D. J., &Schmitter-Edgecombe, M. (2016). Unsupervised detection and analysis of changes in everyday physical activity data. *Journal of biomedical informatics*, *63*, 54-65.

Tahir, H., Tahir, R., & McDonald-Maier, K. (2018). On the security of consumer wearable devices in the Internet of Things. *PloS one*, *13*(4), e0195487.

Terr, D. (2010). Polynomial Time. *From MathWorld--A Wolfram Web Resource, created by Eric W. Weisstein*. http://mathworld.wolfram.com/PolynomialTime.html.

Tokognon, C. A., Gao, B., Tian, G. Y., & Yan, Y. (2017). Structural health monitoring framework based on Internet of Things: A survey. *IEEE Internet of Things Journal*, *4*(3), 619-635.

Triberti, S., &Barello, S. (2016). The quest for engaging AmI: Patient engagement and experience design tools to promote effective assisted living. *Journal of biomedical informatics*, *63*, 150-156.

Villarreal, M. C., Goldsman, D., &Keskinocak, P. (2015). Workforce Management and Scheduling Under Flexible Demand. *Service Science*, *7*(4), 331-351.

Yang, Y., Zheng, X., Guo, W., Liu, X., & Chang, V. (2019). Privacy-preserving smart IoT-based healthcare big data storage and self-adaptive access control system. *Information Sciences*, *479*, 567-592

Appendix:

TABLE A1: COMPARISON STUDY

Reference	**Approach**	**Objective**	**Pros**	**Cons**
C. Jr. Arcadius *et al. (2017)*	Survey of Structural health monitoring framework	Handled complex and large amount of collected data from sensors	Sense and collected useful information	Computational overhead was not minimized
Ahmed Abdel Gawad and Kumar Yelamarthi *(2017)*	SHM platform embedded with IoT	Detected the size and location of damage in structures	Correctly checked whether the sheet was healthy or not	Security analysis was not performed

Stephanie Baker *et al. (2017)*	Standard model for application in future IoT healthcare systems	Monitored several health indices and communication standards	Improved security in the cloud	Attained significant improvements in the field of IoT-based healthcare
Stefano Triberti and Serena Barello *(2016)*	Ambient Intelligent (AI) system	Task monitoring	Improved the quality of life	Validity was not ensured
Tiago K. Colicchio *et al. (2016)*	Survey of classification methods	Classified and characterized variables to measure the impact of information technology on healthcare	Ensured security and validity	Data misclassification was not minimized
Gina Sprint *et al. (2016)*	Physical Activity Change Detection (PACD) approach	Physical activity change detection	Tracked physical activity of users	Did not find the ability to perform accurate tracking
Mario Nieto-Hidalgo *et al. (2016)*	vision-based approach	Classified normal or abnormal gait	Minimized computation time	Classification performance was not efficient.
Joon-Soo Jeong *et al. (2016)*	Smart Healthcare System	Disease diagnosis and treatment of patients in the healthcare industry	Monitored and diagnosed disease at an early stage	Security of patient health information was not addressed
Deba jyoti Pal *et al. (2018)*	Partial least square structural equation modeling	Explored smart home services of health care	Explored the process of adopting smart home services in healthcare	Security and privacy aspects were not addressed
Hasan Tahir *et al. (2018)*	Integrated Circuit Metric (ICMetric) technology	Achieved security	Scheme provided High levels of security and authentication	Key generation time was not minimized.
Shirin Enshaeifar *et al. (2018)*	Technology Integrated Health Management (TIHM)	Discovered changes in the health of participants'	Increased the accuracy of detecting abnormalities	Increased the timespan for detecting abnormalities

Joel J. P. C. Rodrigues *et al. (2018)*	Reviewed methods based on IoT	Analysed remote healthcare monitoring	Improved the Internet of Health Things (IoHT)	Security was low.
Youn-Sik Hong *(2018)*	Smart care bed prototype system	Sensed pressure on the body of a patient to minimize the mortality rate	Found various postures of patients to be more effective	Higher mobility
Xiao Ma *et al. (2018)*	Intelligent healthcare systems	Provided more intelligent, professional, and personalized healthcare services	Enhanced performance of healthcare services	Quality of service was not improved
Luis Roda-Sanchez *et al.(2018)*	Two innovative algorithms	Improved reliability and lifespan of the Opera BLE device	Improved efficiency	Did not ensure safety at work
Yuwen Chen *et al.(2017)*	Privacy protection user authentication and key agreement scheme	Ensured secrecy of the key and avoided gateway access	Increased security	Privacy problems were not considered
Mohamed Abdel-Basset *et al. (2018)*	Decision-making model based on IoT	Gathered and processed required information	Increased security and minimized cost	Did not apply healthcare fields
Chiehyeon Lim, Paul P. Magliob *(2018)*	Smart Service Systems	Analyzed text data	Developed a unified conceptualization of smart service systems	Time analysis was not performed
R.C. Lacher *et al.(1995)*	Neural network model	Classified the financial health of a firm	Minimizes the error	Did not effectively predict the data
Ramaswamy V.*et al. (2005)*	Queuing models	Increased access to emergency services	Ensured the safety of the customers	Scheduling was not performed

Ran Liu and Xiaolan Xie *(2018)*	Simple discrete-time analytical model	Estimated patient waiting time	Significantly reduced the total waiting time of patients	System stability was not improved
Eva Martínez-Caro *et al.* *(2018)*	Integrated model	Provided IoT-based healthcare services	Offered better quality of healthcare services	Predictive capabilities were not improved
Mahmud Hossain *et al.* *(2018)*	IoT-based health prescription assistant model	Provided quality healthcare services to remote locations	Minimized communication and computation latency	Response time was not minimized
Paola Cappanera and Maria Grazia Scutellà *(2018)*	Integer linear programming (ILP) model	Assigning and scheduling the pattern of efficient home care services	Minimized operating costs	The larger home care instances were not solved
Adam Diamant *et al. (2018)*	Markov decision process using approximate dynamic programming approach	Scheduled several and serial appointments for patients	Increased scheduling practices	Overhead was not minimized
Monica C. Villarreal *et al.* *(2015)*	Workforce and demand scheduling model (WDSM)	Planned and scheduled the staff and demand	Increased scheduling efficiency	Privacy-preservation was not performed
Peter A. Salzarulo *et al.* *(2016)*	Appointment scheduling system	Classified patients using individual patient characteristics	Improved efficiency of patient scheduling and minimized the cost function	Security remained unsolved.
Proposed Model	Hash Polynomial Two-factor Decision Tree (HP-TDT) model	Smart health care scheduling	Increased scheduling efficiency	