

Sugeno Fuzzy Model Free Reinforced Transformation Based Data Processing for Healthcare Sources in IoT Environment

Sellam Veerappan

SRM Institute of Science and Technology

Kannan Natarajan

SRM Institute of Science and Technology

Arunkumar Gopu

Velagapudi Ramakrishna Siddhartha Engineering College

Ramesh Sekaran

Velagapudi Ramakrishna Siddhartha Engineering College

Manikandan Ramachandran

Sastra University

Vidhyacharan Bhaskar (✉ meetvidhyacharan@yahoo.com)

San Francisco State University <https://orcid.org/0000-0003-3820-2081>

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SUGENO FUZZY MODEL FREE REINFORCED TRANSFORMATION BASED DATA PROCESSING FOR HEALTHCARE SOURCES IN IOT ENVIRONMENT

Sellam Veerappan

Department of Computer Science and Engineering,
SRM Institute of Science and Technology Ramapuram Campus,
Chennai, India.

Email: sellamv@srmist.edu.in

Kannan Natarajan

Department of Computer Science and Engineering,
SRM Institute of Science and Technology Ramapuram Campus,
Chennai, India.

Email: n.kannan.k@gmail.com

Arunkumar Gopu,

Department of Computer Science and Engineering,
Velagapudi Ramakrishna Siddhartha Engineering College,
Vijayawada, Andhra Pradesh, INDIA.

E-mail: arunkumar.goge@gmail.com

Ramesh Sekaran

Department of Information Technology,
Velagapudi Ramakrishna Siddhartha Engineering College,
Vijayawada, Andhra Pradesh, India -520007

Email:sransaran1989@gmail.com

Manikandan Ramachandran

School of Computing,
SASTRA Deemed University,
TamilNadu, India.

Email:srmanimt75@gmail.com

Vidhyacharan Bhaskar

Dept. of Electrical and Computer Engineering,
San Francisco State University,
San Francisco, CA 94132, USA.

Email: vcharan@gmail.com

Abstract

Modern computer sciences and information technologies are anticipated to bring transformative influence in part that mobile communication technologies play in society. To completely take advantage of the services bestowed by modern computer sciences and information technologies, the evidence of the economic and business case is an essential prerequisite. Existing research engulfs several transformative computing methods based on sensors area obtainable as service contain optimize resource management, data processing/storage and security provisioning. With transformative computing being on edge, real-time data must be necessitated for healthcare data analytics. The conventional cloud server cannot address the latency requirements of healthcare IoT sensors. To survive with how to handle these services, we introduce a hybrid method integrating Sugeno Fuzzy Inference (SFI) and Model-free Reinforcement Learning to enhance healthcare IoT and cloud latency. The objective is to lessen high latency between healthcare IoT devices. The proposed Sugeno Fuzzy Model-free Reinforcement Learning Data Computing (SF-MRLDC) method uses a Sugeno Fuzzy Inference model integrated with a Model-free Reinforcement Learning model data computing in a healthcare IoT data analytics environment. The simulation results of the SF-MRLDC method show that it is computationally efficient in terms of latency by ensuring better response time.

Keywords: Transformative Computing, Sugeno Fuzzy Inference, Model-free, Reinforcement Learning, Data Computing

1. Introduction

In recent years, the Transformative Computing prototype is progressed and elucidates novel bifurcation of contemporary computer sciences and information mechanics. This new mechanism permits integrating sensor signals and wireless communication mechanization with data analysis and Artificial Intelligence (AI) techniques. This transpiring technology's primary objective is an association of low-level data extraction obtained from IoT sensors communicating in a global manner that permit transmission and collection of necessitated data securely for analytical evaluation. This association results in enhancing computational probability, data extraction efficiency, acquiring of data, initiating from sensor networks till augmented cognition.

Web services are considered to be the middleware designed in such a manner to assist the interaction between several software entities and devices over the Web, therefore applied in multimedia, transacting E-commerce, and information processing. However, managing these services is a sought-after subject in IoT research. Transformation-based processing was proposed in [1] to optimize the effectiveness of resources in IoT data, information and knowledge via Data Graph, Information Graph and Knowledge Graph. With these, both the conversion cost and storage cost involved during transformation-based processing was said to be reduced in a significant manner.

Conventional predictions for self-reported personalities have numerous disadvantages and depend heavily on the users' responses, making the overall process time-consuming and laborious. Pearson Correlation Personality Prediction was proposed in [2] by integrating physical activity intensity data with existing phone activity data to estimate the personality trait score. Followed by which interesting correlations between human activity patterns and personality traits were analyzed. Finally, support vector regression was utilized for predicting the personality scores. With these models, mean absolute error and mean squared error was found to be minimized for each personality trait.

Transforming influences of the emerging prototype on cloud computing systems were proposed in [3]. Another novel computing methodology was designed based on cognitive application in transformative computing tasks [4], with data collected from numerous sources and extracted via sensors, ensuring adequate data processing. A novel optimization algorithm was designed using quasi affine transformation to obtain local optimization I [5] via the evolutionary algorithm, therefore enhancing accuracy.

In recent few years, there has been an evolution of a new computational paradigm called transformative computing. It integrates Artificial Intelligence (AI) with wireless data from numerous sensors—followed by a deep analysis of data for several purposes done by employing AI techniques. A cognitive security protocol was designed in [6] for securing wireless systems. A review of complicated network operators and their transformative impacts were analyzed in [7].

Numerous use cases around IoT devices employ either smartphones or wearable sensors to capture the users' data. Moreover, the cloud also applies decision making via machine learning and AI. Therefore, both the IoT environment and the cloud infrastructure for healthcare data analytics are critical due to the high response time involved in the data processing. The requirement of transformative computing supporting robust data processing for IoT environment is a mandatory requirement for service providers. This current research concentrates on the cloud architecture for healthcare data analytics. We classify it into three layers, via IoT layer, Fog layer and Cloud layer, and the method called SF-MRLDC.

The paper is ordered as: In Section 2, the relation of previous work in healthcare data analytics, cloud computing, fog computing, transformative computing is reviewed. In Section 3, the proposed method is analyzed with the aid of a block diagram and algorithm. In section 4, the simulation settings are presented along with the dataset description and the parametric definitions. Section 5 includes the discussion analysis of SF-MRLDC. Section 6 concludes the paper.

2. Related Works

Extraordinary advancement in wireless networking, AI, and sensors are bringing about a vibration shift. With this, a new paradigm has said to be emerged called transformative computing. The paradigm can be, in other words, defined as the integration of computing and communication technologies to reconsider our day-to-day computational experiences. Discussion regarding the management of resources, complex processing and analyzing signal inference for building analytics was proposed [9]. A comprehensive view of learning mechanisms to design body-induced artefacts and related challenges was presented in [10]. Another building block necessitated edge-native application, promoting blueprint of transformative technology with the influence of wearables and edge AI was proposed in [11].

In [12], a MAC protocol was proposed to resolve data delivery issues due to the body and postural mobility with the Centroid K-means clustering method. Another optimized hybrid technique using the genetic algorithm to attain maximum fitness in minimum iterations was proposed [13]. However, with vast data being gathered from numerous sensors, fog computing was applied in [14] to help patients suffering from chronic diseases.

Several research works have been performed to obtain new, effective and significant healthcare industry mechanisms with which healthcare monitoring can be performed promptly to reinforce the healthcare industry. A review of conventional methods in IoT-DHSSs, considering several aspects like monitoring mechanisms, communication and computing strategies, was presented in [15]. Yet another analysis factor affecting IoT-based smart hospital was proposed in [16]. A comprehensive survey of artificial intelligence-based classification for edge intelligence was presented in [17]. A review of privacy preservation mechanisms for resource-oriented sensors in IoT was investigated in [18]. The influence of IoT in healthcare globally was proposed in [19] with the new transformative computing in progress, different types of signals acquired for IoT seconds, data processing between sensors and users poses a significant threat in healthcare data analytics concerning response time. Due to low-level signal acquisition, global communication between sensors results in a higher latency rate and increases response time. Existing Transformation-based data processing method utilized information and knowledge via Data Graph, Information Graph and Knowledge Graph to deal with latencies. The proposed SF-MRLDC method concentrates on efficient data delivery by minimizing the latency involved.

3. Methodology

Internet-of-Things (IoT) produce a massive volume of data that are found to be initially processed, analyzed and filtered utilizing cloud data centers. With the enormous acceptance availed globally, IoT devices are made accessible in Healthcare. As a result of enormous data analytics, the response time in the cloud environment is said to get increased. The escalation or surges in response time results in outcome in latency to end-users or patients in Healthcare.

The main objective here remains in minimizing the latency of IoT so that the data transfer time is also satisfactory. Moreover, both the data volume and connectivity involved in the internet may cause high network latency. Fog nodes acting as gateway node between IoT sensors ' $S = S_1, S_2, \dots, S_n$ ' and fog server ' F ' to resolve latency issues. In our work, the total latency is the fusion of communications and network latency.

The research work proposes a hybrid method that integrates Sugeno Fuzzy Inference (SFI) and Model-free Reinforcement Learning to enhance healthcare IoT and cloud latency. This method combines healthcare IoT sensors with the cloud and employs fog services with the SF-

MRLDC algorithm. SF-MRLDC algorithm carries out aggregate workloads on IoT data to minimize latency and response time in health data analytics.

3.1 Transformative Computing System model

System model for transformative computation for healthcare IoT seconds with the cloud is presented. Figure 1, given below, shows the block diagram of the Transformative Computing System model.

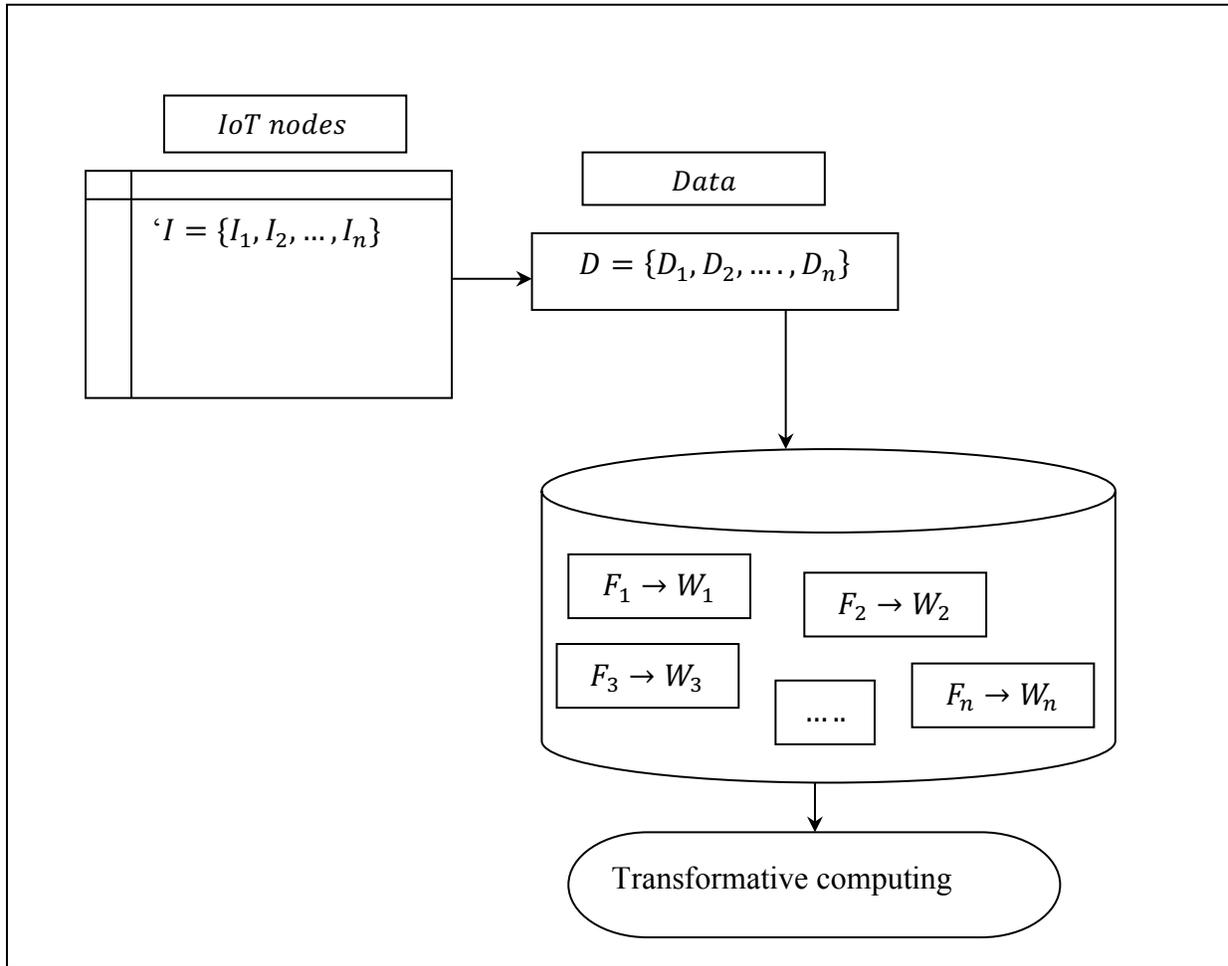


Fig. 1 Transformative Computing System model

As shown in the above figure, let us consider a set of IoT nodes ' $I = \{I_1, I_2, \dots, I_n\}$ ' (i.e., users) which are processing a set of data ' $D = \{D_1, D_2, \dots, D_n\}$ ' that produce workload on the server ' $W = \{W_1, W_2, \dots, W_n\}$ ', with fog server represented as ' $F = \{F_1, F_2, \dots, F_n\}$ '. With the

above system model, the objective of the proposed method remains in data processing between the IoT nodes or sensors and the fog server in a computationally efficient manner (i.e., minimize latency, response time and maximize profitability)

3.2 System overview

Transformative Computing technologies have got hold of an immense leap forward in the services being provided that is instituted via the emergence of numerous novel, innovative mechanisms ensuing low latency, massive communications via higher throughput. The main objective of rising technology is to connect low-level signal acquisition, initiate from smart or IoT sensors, with global communication that permits transmitting and collecting required data for semantic analysis or analytical evaluation. This work is computationally efficient towards minimizing latency and maximization of profitability using the Sugeno Fuzzy Model-free Reinforcement Learning Data Computing (SF-MRLDC) method. Figure 2 shows the block diagram of the SF-MRLDC method.

The below figure shows that the Sugeno Fuzzy Model-free Reinforcement Learning Data Computing block diagram comprises three unique layers: healthcare IoT layer, fog layer, and cloud layer. The first layer, also referred to as the healthcare IoT layer, comprises behavioral context recognition sensor IoT devices. These devices contain measurement from sensors comprising main activity and secondary activity acquired from either iPhones or Android. The user's behavioral context recognition data is then classified accordingly to the interfaces for data analytics. Next, the classified data for analytics is sent to the fog layer. Finally, time-sensitive data are selected utilizing machine learning. Finally, the patient historical data is transmitted to the cloud layer for efficient data storage/processing.

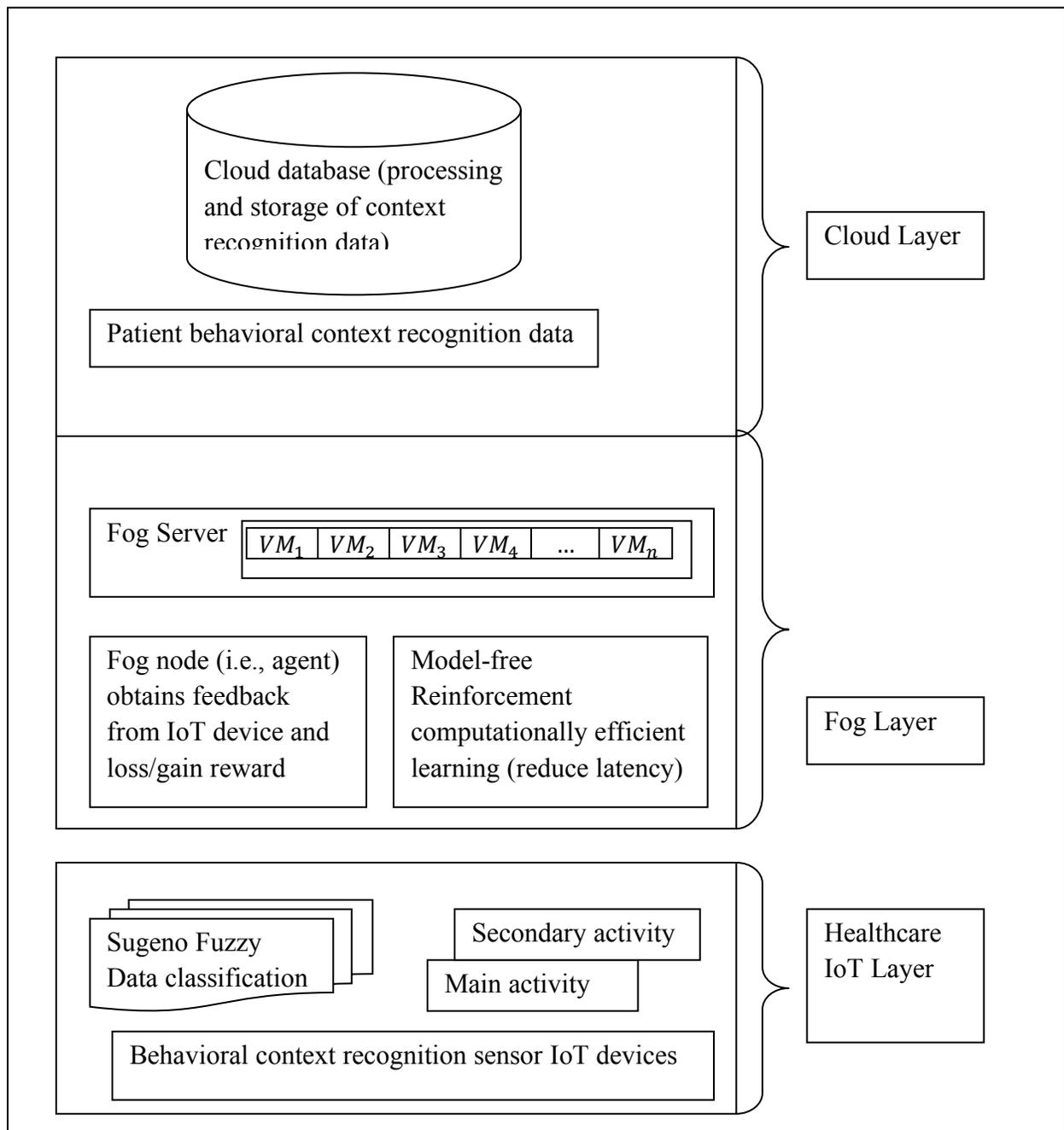


Fig. 2 Block diagram of Sugeno Fuzzy Model-free Reinforcement Learning Data Computing method

3.3 Sugeno Fuzzy Model-free Reinforcement Learning Data Computing

In Reinforcement Learning (RL), a learner and an agent exist, followed by the surrounding called the environment. On the other hand, the environment issues rewards and the updated state based on the agent's actions. Therefore, as far as reinforcement learning is concerned, the agent is not learnt, whereas only given positive or negative rewards based on its actions. The Markov Reward Process (MRP) comes in here.

The MRP involved in our work comprises of four tuples ' $\langle SS_i, AS_i, TPD_i, R_i \rangle$ ', where, ' $SS_i = \{ss = (SS_{alloc}, D_{alloc}, Q)\}$ ' represents the state space, ' $SS_{alloc} \in N(1 \leq SS_{alloc} \leq N)$ ' represents sensors which include data for assignment as requested by users, ' $D_{alloc} \in N(1 \leq D_{alloc} \leq D_{max})$ ' refers to the number of data to be assigned in timestamp and ' $Q = \{D_1, D_2, \dots, D_n \in Q\} | \{Rem(D_1, D_2, \dots, D_n \in Q)\}$ ' refers to several data and presently prevailing in fog node queue.

Moreover, ' $AS_i = \{as = (a_{FOG}, D_{S \rightarrow F})\}$ ' refers to the action space where, ' a_{FOG} ' is described as the adjacent node to fog node and, ' $D_{S \rightarrow F}$ ' is described as the number of data sent to the fog node. Next ' $TPD_i: SS_i * AS_i * SS_i \rightarrow [0,1]$ ' refers to the transition probability distribution corresponding to a new state, ' s' ' from an old state ' s ' for a given action ' A '. Finally, the reward, ' R_i ' for a given action, ' A ' at state ' s ' is mathematically expressed as given below.

$$R_i(A) = IU_i(s, A) - [IL(s, A) + D_{alloc}(s, A)] \quad (1)$$

From the above equation (1), the reward function is estimated based on the instantaneous utility function, ' IU_i ', instantaneous latency ' IL ' and data allocation, ' D_{alloc} ' for given action ' A ' at state ' s ' respectively. The instantaneous utility function, ' $IU_i(s, A)$ ' is then estimated as given below.

$$IU_i(s, A) = r_i \log(D_i^{loc} + D_i^{FOG}) \quad (2)$$

From the above equation (2), the instantaneous utility function is arrived at based on the reward, ' r_i ' concerning the data processed locally, ' D_i^{loc} ' and data to be in a queue in the fog node, ' D_i^{FOG} '. The instantaneous latency ' IL ' is then mathematically formulated as given below.

$$IL(s, A) = \frac{COMM_L^{FOG} + Net_L^{FOG}}{D_i^{loc} + D_i^{FOG}} \quad (3)$$

From the above equation (3), the instantaneous latency is estimated based on the communication latency, ' $COMM_L^{FOG}$ ' and the network latency, ' Net_L^{FOG} .' Then, then full circle timestamp necessitated by data from an IoT sensor to fog node and from fog to IoT sensor via Sugeno Fuzzy Inference model. The block diagram of the Sugeno Fuzzy Inference model for estimating the latency for two types of users (i.e., iPhone and Android) is shown in figure 3.

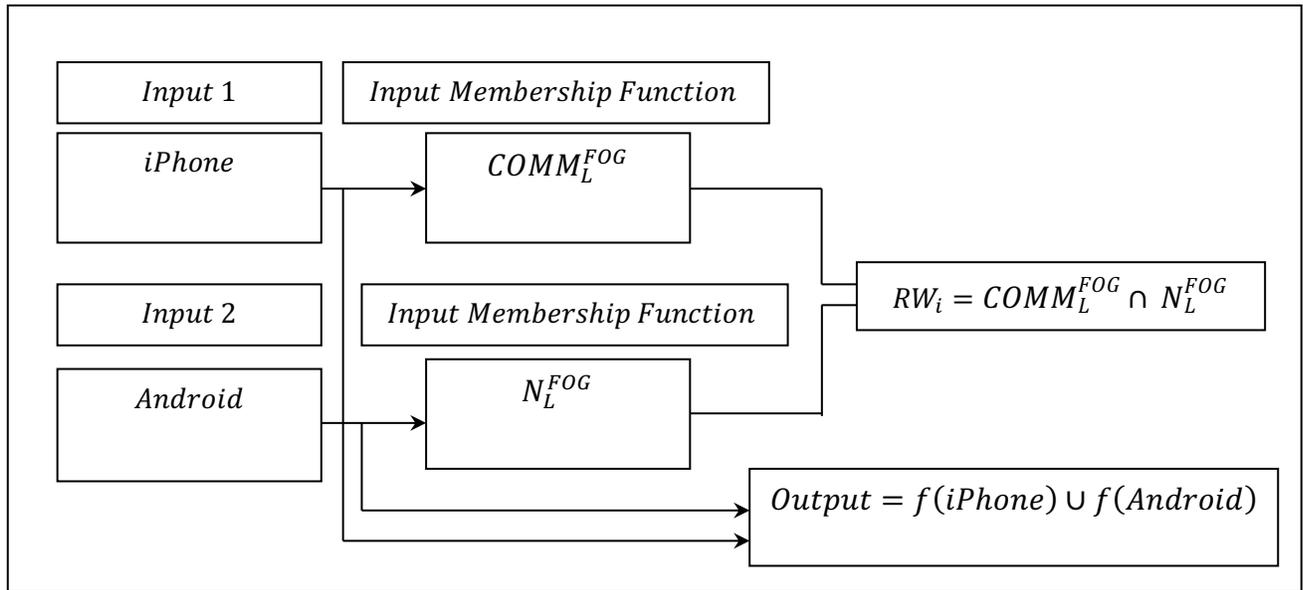


Fig. 3 Block diagram of Sugeno Fuzzy Inference Model

As shown in figure 3, the Sugeno Fuzzy Inference model utilizes a single output membership function obtained from either '*iPhone*' or '*Android*' of input values. The de-fuzzification process for the Sugeno system as efficient as it utilizes the weighted sum of fewer data points than calculating the centroid of the two-dimensional area. It is mathematically represented as given below.

$$COMM_L^{FOG} = COMM_L^{FOG}(Req) + COMM_L^{FOG}(Res) \quad (4)$$

$$COMM_L^{FOG}(Req) = \frac{Size(D)}{S(SR)+F(SR)} * D_{S \rightarrow F} \quad (5)$$

From the above equation (4), the communication latency request, ' $COMM_L^{FOG}(Req)$ ' is estimated based on the size of data ' $Size(D)$ ', IoT sensor service rate ' $S(SR)$ ', Fog node service rate ' $F(SR)$ ' and number of data sent by the sensor to the fog node, ' $D_{S \rightarrow F}$ ' respectively. Then, the communication latency response, ' $COMM_L^{FOG}(Res)$ ' is estimated as given below.

$$COMM_L^{FOG}(Res) = \frac{Size(D)}{F(SR)+S(SR)} * D_{S \rightarrow F} \quad (6)$$

From equation (6), the communication latency response is estimated based on data size ' $Size(D)$ ' and the respective number of data transmitted by sensor to fog node, ' $D_{S \rightarrow F}$ '. Finally, network latency, ' N_L^{FOG} ' is formulated as below.

$$N_L^{FOG} = \frac{DF*HC*[TD_s+TD_{loc}+TD_{FOG}]}{TD} \quad (7)$$

From the above equation (7), the network latency is arrived at based on the delay factor ' DF ', hop count ' HC ', total data sent from the sensor, ' TD_s ' total data sent locally, ' TD_{loc} ' and total data sent from fog node, ' TD_{FOG} ' to the overall data ' TD '. With the transformative computing paradigm approaching a new branch of state-of-the-art computer sciences and information technology, initiating from sensors to augmented cognition, our work minimizes the latency involved. A hybrid approach called associative reinforcer Learning is utilized.

In our proposed method, the learning fog node works as a controller whose prime task is detecting the current state ' s ' with action ' A ' followed by a transition probability matrix. To minimize the latency and maximize profitability, Model-free Reinforcement Learning is applied that estimates different state, ' s ' and respective reward ' r '. With numerous identifications, the learning fog node acting as controller updates function so that the following function is obtained as given below.

$$Q(s, A) \rightarrow (1 - \alpha_i)Q(+s, A) + \alpha_i[R_i(A) + \gamma, MAXQ(s', A)] \quad (8)$$

From equation (8), ' α_i , where α_i lies between 0 and 1' represents the learning rate, where, ' α_i ' a tradeoff balance among old weight and new weight is ensured, with ' Q ' indicates

the quality of action ‘ A ’ on state ‘ s ’ and ‘ $Q(s',A')$ ’ indicates a quality function for transition state, ‘ s' ’ and action, ‘ A' ’.

With the above equation, the problems concerning the transition states and rewards for transformative computing related to the healthcare domain are addressed. The fog node in the fog log works as a controller that keeps an eye on the present state and action. Moreover, the fog node obtained information about the new state, ‘ s' ’ and reward ‘ r ’. Upon completion of the transition, the ‘ $Q - function$ ’ is updated. With the aid of this equation, the issue related to updating in the transition probability function reward is addressed based on Model-free Reinforcement Learning. The pseudo-code representation of the Sugeno Fuzzy Model-free Reinforcement Learning Data Computing (SF-MRLDC) algorithm is given below.

<p>Input: IoT nodes ‘$I = \{I_1, I_2, \dots, I_n\}$’, data ‘$D = \{D_1, D_2, \dots, D_n\}$’, workload ‘$W = \{W_1, W_2, \dots, W_n\}$’, fog server ‘$F = \{F_1, F_2, \dots, F_n\}$’, state ‘$s$’, action ‘$A$’</p>
<p>Output: Computationally efficient (minimum latency, response time) transformative data processing</p>
<p>1: Initialize reward, ‘r_i’, data locally processed, ‘D_i^{loc}’, data to be in a queue in the fog node, ‘D_i^{FOG}’, size of data ‘$Size(D)$’, IoT sensor service rate ‘$S(SR)$’, Fog node service rate ‘$F(SR)$’, data sent by the sensor to the fog node, ‘$D_{S \rightarrow F}$’</p> <p>2: Initialize total data sent from the sensor, ‘TD_s’, total data sent locally, ‘TD_{loc}’, total data sent from fog node, ‘TD_{FOG}’, overall data ‘TD’, learning rate, ‘α_i’</p> <p>3: Initialize Sugeno Fuzzy Inference System membership function, ‘$\mu_1(iPhone)$’, ‘$\mu_1(Android)$’ get the transformative function as ‘$\mu_1(COMM_L^{FOG})$’, ‘$\mu_1(N_L^{FOG})$’</p> <p>4: Begin</p> <p>5: For each IoT nodes ‘I’ with data ‘D’</p> <p>6: For each workload ‘W’ to be assigned with the fog server ‘F’</p> <p>7: Estimate reward function using equation (1)</p> <p>8: Estimate instantaneous utility function using equation (2)</p> <p>9: Estimate instantaneous latency ‘IL’ using equation (3)</p> <p>10: If transformative function = ‘$\mu_1(COMM_L^{FOG})$’</p> <p>11: Evaluate overall communication latency using equation (4)</p> <p>12: Evaluate communication latency request using equation (5)</p>

13: Evaluate communication latency response using equation (6)
14: **End if**
15: **If** transformative function = ' $\mu_1(N_L^{FOG})$ '
16: Measure network latency using equation (7)
17: **End if**
18: Estimate quality function using equation (8)
19: **End for**
20: **End for**
21: **End**

Algorithm 1 Sugeno Fuzzy Model-free Reinforcement Learning Data Computing (SF-MRLDC)

The above Sugeno Fuzzy Model-free Reinforcement Learning Data Computing (SF-MRLDC) algorithm, each IoT nodes ' I ' (consisting of Universally Unique Identifier) with data ' D ' (behavioral context recognition data) to be transferred to the respective fog node originating from IoT sensors, the objective remains in minimizing the latency along with the response time involved in information processing. This objective is achieved in our work by integrating Sugeno Fuzzy Inference (SFI) and Model-free Reinforcement Learning.

The Sugeno Fuzzy Inference (SFI) model is computationally efficient processing between IoT sensors or IoT sensors and fog nodes. It is said to be ensured as it utilizes a weighted average of a few data points (i.e., IoT sensors) rather than estimating the centroid of the two-dimensional area, reducing response time in information processing.

Next, with the aid of Model-free Reinforcement Learning, both computation and network latency are reduced by introducing a quality function for the transition state. With these two models, the transformative computing involving healthcare data analytics processing is ensured with minimum latency and response time.

4. Simulation and evaluation parameters

The system model is simulated in CloudSim. Table 1 illustrates the simulation parameters that shows the dataset description obtained from [20]. The Extra Sensory dataset comprises data collected from 60 users, with each user identified using a universally unique identifier (UUID). From each user, thousands of instances are obtained in intervals of 1 minute. Moreover, every example consists of the measurements obtained from the user's smartphone and a smartwatch. The users were students, both undergraduate and graduate, from the UCSD campus. Here, a total of 34 iPhone users and 26 Android users, including 34 females and 26 males with 56 right-handed and 2 left hands, 2 defined themselves as using both left hand and right hand were utilized for simulation.

Table 1 Dataset description

S. No	Features	Range	Average
1	Age	18 – 42	24.7
2	Height	145 – 188	171
3	Weight	50 – 93	66
4	Body Mass Index	18 – 32	23
5	Labelled examples	685 – 9706	5139
6	Additional unlabeled examples	2 – 6	1150
7	Average applied labels per example	1.1 – 9.7	3.8
8	Days of participation	2.9 – 28.1	7.6

As far as devices were concerned, users in Extra Sensory has various phone devices, with iPhone generations, 4, 4S, 5, 5S, 5C, 6 and 6S with operating system versions from iOS-7 to iOS-9. Moreover, Android devices, such as Samsung, Nexus, HTC, Moto G, LG, Motorola, One Plus One, Sony, were utilized. Sensors utilized were numerous in range and included high-frequency motion-reactive sensors (accelerometer, gyroscope, magnetometer, watch accelerometer), location services, audio, watch compass, phone state indicators and additional sensors. Also, not all the sensors were available all the time. Performance evaluation is performed by measuring the response time, latency, and communication cost.

4.1 Latency

Latency is an assessment of delay. In wireless communication technology like IoT, latency assesses the time consumed for specific data (i.e., healthcare data in our scenario) to reach its destination (i.e., time is taken for some data to reach the destination in the network. It is either between IoT sensors or between IoT and fog node). Latency is calculated in milliseconds (ms).

$$L = \sum_{i=1}^n A_i * [COMM_L^{FOG} + N_L^{FOG}] \quad (9)$$

From the above equation (9), the latency ' L ' is measured based on the communication latency, ' $COMM_L^{FOG}$ ' and the network latency, ' N_L^{FOG} ' concerning the actions involved in the simulation.

4.2 Response time

Response time refers to the total amount of time it consumes to respond to a request (i.e. data processing) for service (i.e., healthcare service). In other words, response time is the sum of service time and wait time.

$$Res_t = \sum_{i=1}^n A_i * [Ser_t + P_t] \quad (10)$$

From the above equation (10), the response time, ' Res_t ' is measured based on the service time, ' Ser_t ', pause time or wait time, ' P_t ' concerning the number of actions ' A_i ' considered for simulation. It is measured in terms of milliseconds (ms).

4.3 Communication cost

Finally, the communication cost refers to the number of bits' communication between IoT sensors or IoT sensors and fog nodes. It is measured in terms of bits per second.

$$CC = \sum_{i=1}^n A_i * [TD_s + TD_{loc} + TD_{FOG}] \quad (11)$$

From the above equation (11), the communication cost ‘ CC ’ is measured based on the total data sent from the sensor, ‘ TD_s ’ total data sent locally, ‘ TD_{loc} ’ and total data sent from fog node, ‘ TD_{FOG} ’ concerning the corresponding numbers of actions ‘ A_i ’.

5. Discussion

Raw measurements were recorded from various sensors for each behavioral context recognition data processing for 30 different users involving 500 unique actions. A fair comparison was made with state-of-the-art methods, Transformation-based processing [1], Pearson Correlation personality prediction [2], concerning the proposed SF-MRLDC method conduct the performance evaluation. An average of 10 simulation runs was conducted. The data processing learning obtained from the SF-MRLDC method is compared with the Transformation-based processing [1], Pearson Correlation personality prediction [2] to verify the proposed measurement latency Table 2.

Table 2 The experimental results of latency using SF-MRLDC, Transformation-based processing [1], Pearson Correlation personality prediction [2]

Actions	Latency (ms)		
	SF-MRLDC	Transformation-based processing	Pearson Correlation personality prediction
50	11.75	13.25	14.75
100	12.15	15.15	17.25
150	14.35	18.25	21.25
200	15.95	21.45	23.55
250	21.25	25.85	28.15
300	28.45	31.35	35.13
350	32.55	35.95	38.25
400	35.15	41.25	45.55
450	38.35	45.55	50.25
500	40.55	50.35	58.15

Similarly, data processing learning obtained from the SF-MRLDC method is compared with the Transformation-based processing [1], Pearson Correlation personality prediction [2] to verify the proposed measurement response time as shown in Table 3.

Table 3 The experimental results of response time using SF-MRLDC, Transformation-based processing [1], Pearson Correlation personality prediction [2]

Actions	Response time (ms)		
	SF-MRLDC	Transformation-based processing	Pearson Correlation personality prediction
50	7	8.5	9.75
100	8.15	9.55	10.25
150	9.55	11.35	12
200	11.35	14	15.55
250	13.45	15.15	16
300	15	17	18.15
350	16.25	18.15	20.25
400	18.35	21.55	23.15
450	20	24	25
500	21.25	25.35	27.15

Finally, transformative computing efficiency concerning data processing learning using the SF-MRLDC method are compared with the Transformation-based processing [1], Pearson Correlation personality prediction [2] for verifying the proposed measurement communication cost as illustrated in Table 4.

Table 4 The experimental results of communication cost using SF-MRLDC, Transformation-based processing [1], Pearson Correlation personality prediction [2]

Actions	Communication cost (bits/second)		
	SF-MRLDC	Transformation-based processing	Pearson Correlation personality prediction
50	3000	2550	2220
100	3250	3000	2285
150	3700	3250	2415
200	3850	3350	2535
250	3900	3500	2815
300	4050	3815	3000
350	4120	4000	3015
400	4150	4050	3050
450	4200	4100	3025
500	4250	4125	3155

6. Performance analysis

In this section, the performance analysis of three different parameters, latency, response time and communication cost using three different methods, SF-MRLDC, Transformation-based processing [1], Pearson Correlation personality prediction [2], are presented. Simulations are conducted using Cloud Sim simulation for an average of 30 users, both male and female, with an average action being recorded as 500. Figure 4 shows the average actions against the latency of the first 30 users.

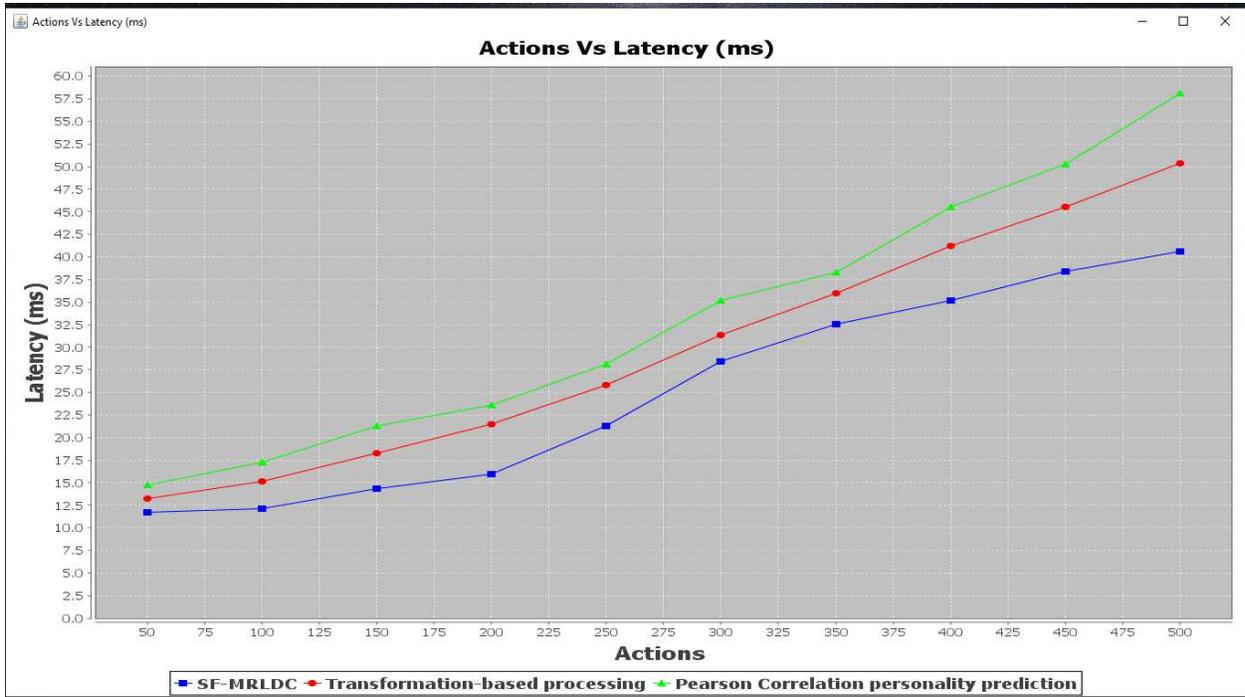


Fig. 4 Graphical representation of latency

From Figure 4, the latency of the SF-MRLDC method is better than [1] and [2]. The average latency is improved by 63% and 25% compared to [1] and [2] for simulation of 10 runs. From the figure latency being directly proportional to actions, increasing the number of actions by participants based on a universally unique identifier ultimately causes an increase in the number of sensors being sensed and resulting in higher latency. However, improvement is found to be observed in the SF-MRLDC method. This improvement is because the data processing of healthcare data analytics by input membership function by Sugeno Fuzzy Inference model is done based on the weighted sum of fewer data points rather than calculating the centroid of the two-dimensional area.

Figure 5, given below, shows the response time against 500 different actions obtained from different sensors. The figure denotes that response time is less in SF-MRLDC than [1] and [2].

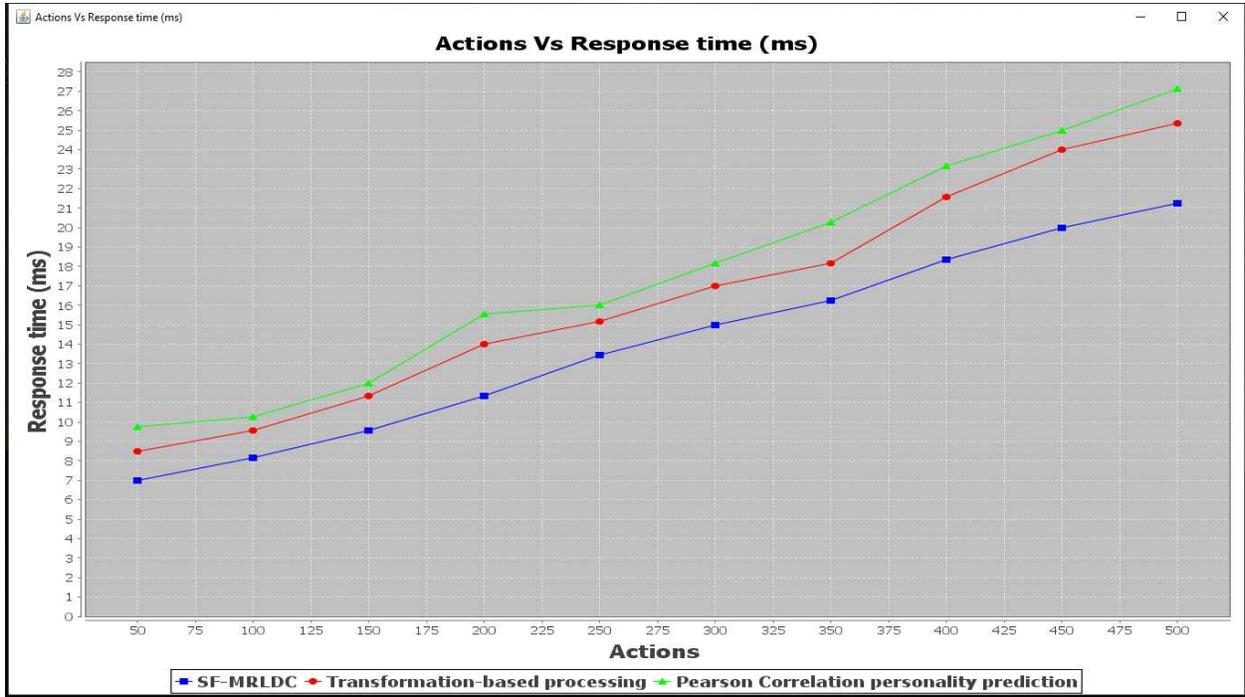


Fig. 5 Graphical representation of response time

From the above figure, it is also inferred that increasing the numbers of actions or sensory data collected from different numbers of participants also increases the response time. With ‘50’ numbers of different unique actions involved in transformative computing for healthcare data processing, the service time is ‘0.015ms’, and the pause time is ‘0.125ms’. Using SF-MRLDC, the service time is ‘0.030ms’ and the pause time is ‘0.140ms’ using [1] and the service time being ‘0.040ms’ and the pause time being ‘0.155ms’, the overall response time was observed to be ‘7ms’, ‘8.5ms’, ‘9.75ms’ respectively. With this in the SF-MRLDC method, response time is minimized by a factor of 15% compared to [1] and 21% compared to [2]. This improvement is because the instantaneous utility function in the SF-MRLDC method is arrived at based on the reward concerning the data locally processed and data to be in a queue in the fog node.

Figure 6 illustrates the communication cost per participant for the first 500 actions in the SF-MRLDC method and other state-of-the-art methods. Communication cost for each participant is minimal in the SF-MRLDC method. The average communication cost is reduced by 53% and 40% in the SF-MRLDC method compared to [1] and [2].

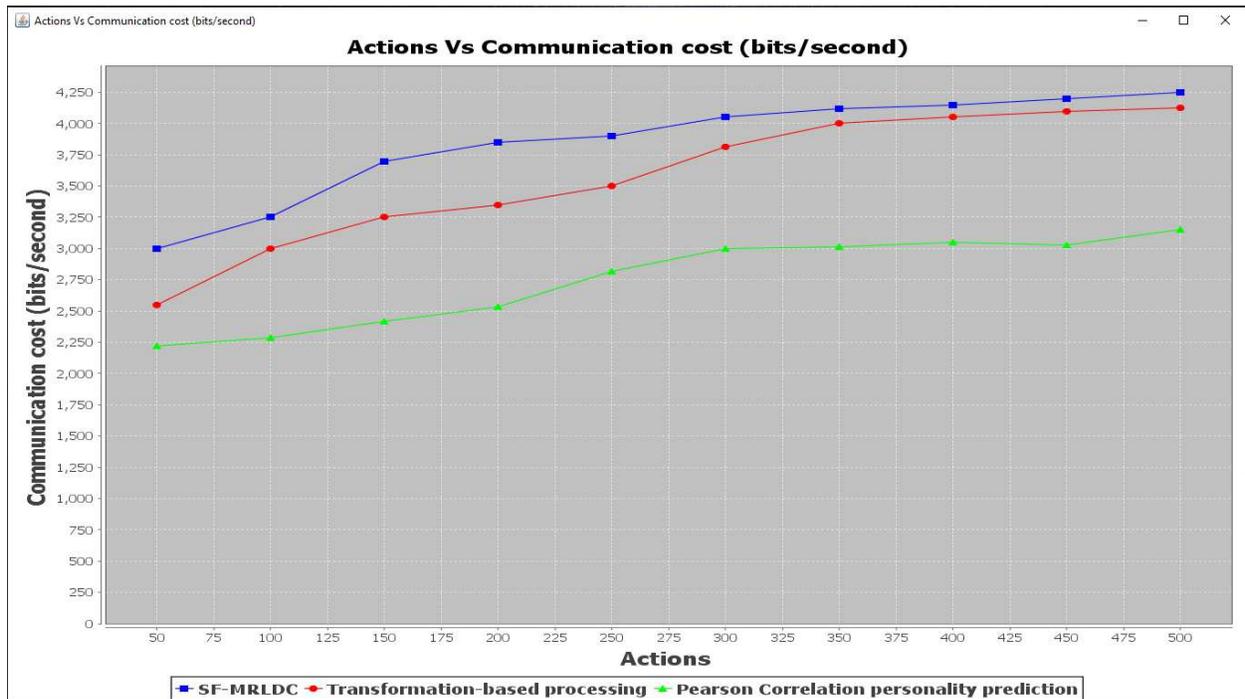


Figure 6 Graphical representation of communication cost

The above figure shows ‘50’ numbers of different unique actions in transformative computing for healthcare data processing. The total data sent from a sensor is ‘20bps’, and those sent locally being ‘15bps’. The fog node sends total data of ‘25bps’ was found to be using the SF-MRLDC method. The total data sent from a sensor is ‘18bps’, and those sent locally is ‘12bps’, and from the fog node is ‘21bps’, [1]. Total data sent from sensor being ‘16bps’, total data sent locally being ‘10bps’ and total data sent from fog node being ‘18bps’ using [2], the overall communication cost using the three methods were found to be ‘3000 bits/second’, ‘2550 bits/second’ and ‘2220 bits/second’ respectively. The improvement was due to applying the Sugeno Fuzzy Model-free Reinforcement Learning Data Computing (SF-MRLDC) algorithm. Using this algorithm, first using the Sugeno Fuzzy Inference (SFI) model, computationally efficient processing between IoT sensors is based on the weighted average of IoT sensors rather than evaluating a centroid. Next, using Model-free Reinforcement Learning, computation and network latency are minimized via a transition state's quality function.

7. Conclusion

We presented the hybrid method of Sugeno Fuzzy Model-free Reinforcement Learning Data Computing (SF-MRLDC) to reduce the latency and response time with maximum communication cost. It is achieved by utilizing two different models. With the Sugeno Fuzzy Inference model, latency and response time were reduced due to the estimation of weighted sum instead of measuring a centroid. Moreover, using Model-free Reinforcement Learning, the communication cost or the bits per second transmitted between sensors or sensor and fog node is improved due to the associative factor. The proposed method consumes significantly less latency and response time than other translation-based processing methods [1], Pearson Correlation personality prediction [2]. Further, the communication cost is also improved, making the system more efficient for data processing involving transformative computing.

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Conflict of Interests

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Data Availability statement:

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Code Availability

Not Applicable.

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Figures

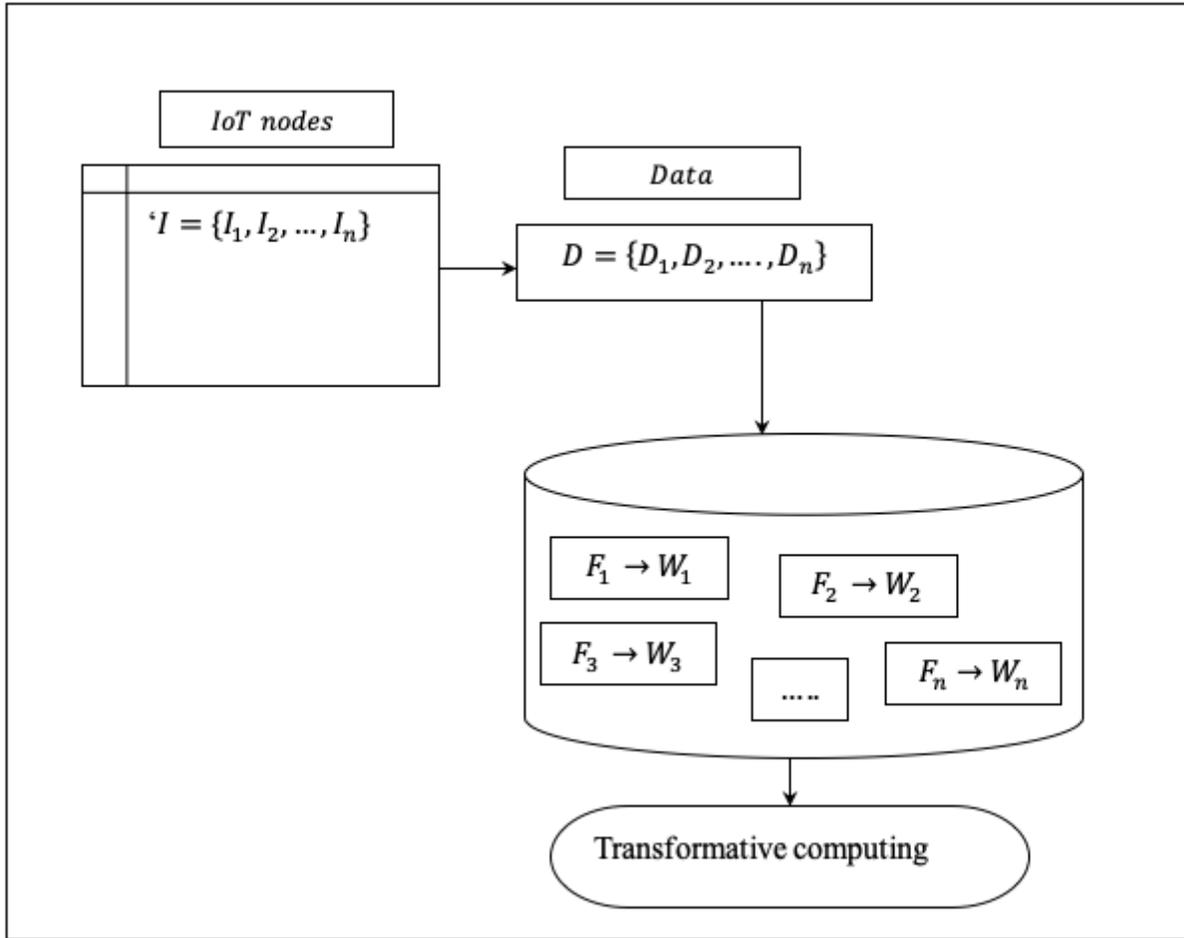


Figure 1

Transformative Computing System model

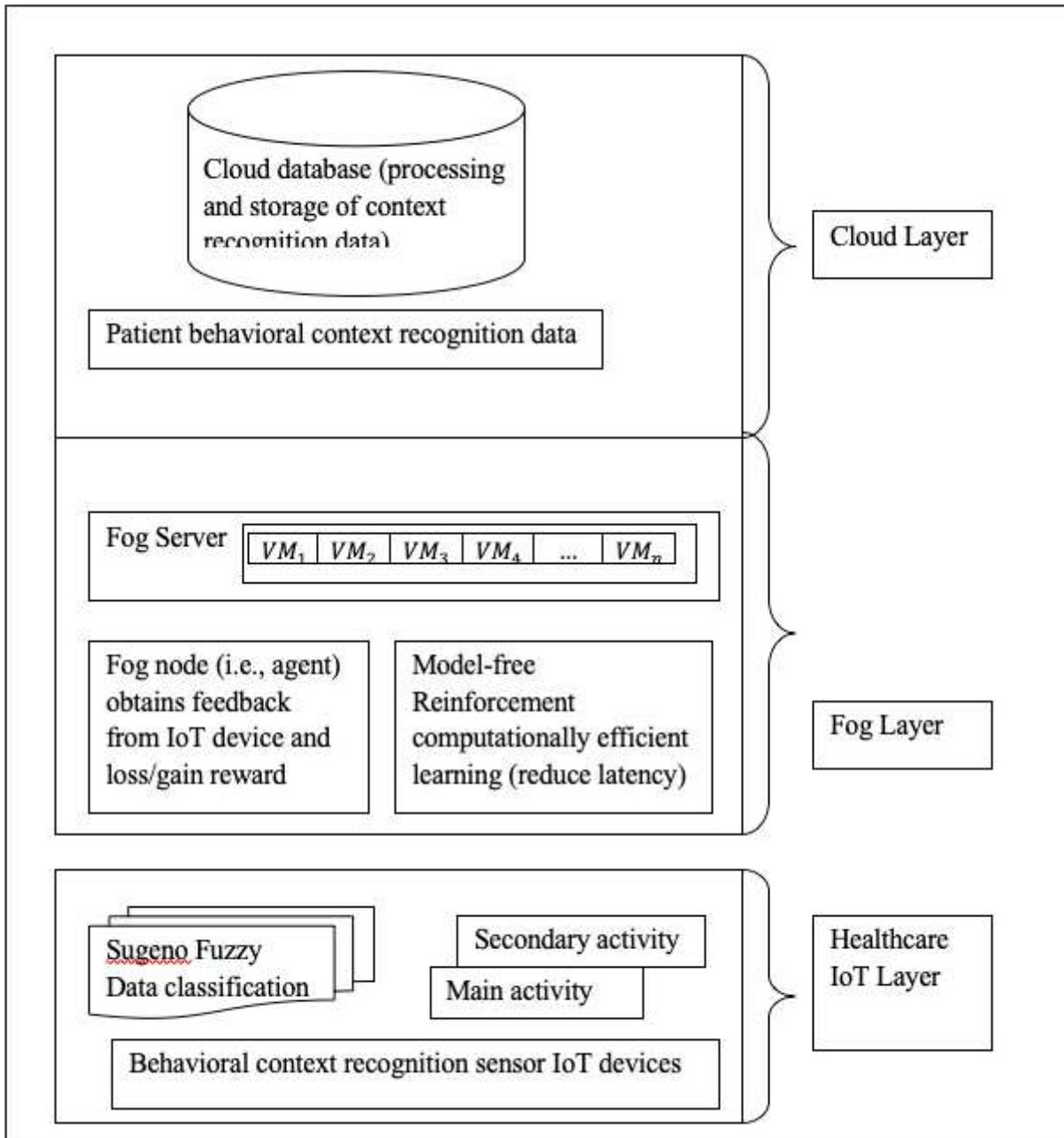


Figure 2

Block diagram of Sugeno Fuzzy Model-free Reinforcement Learning Data Computing method

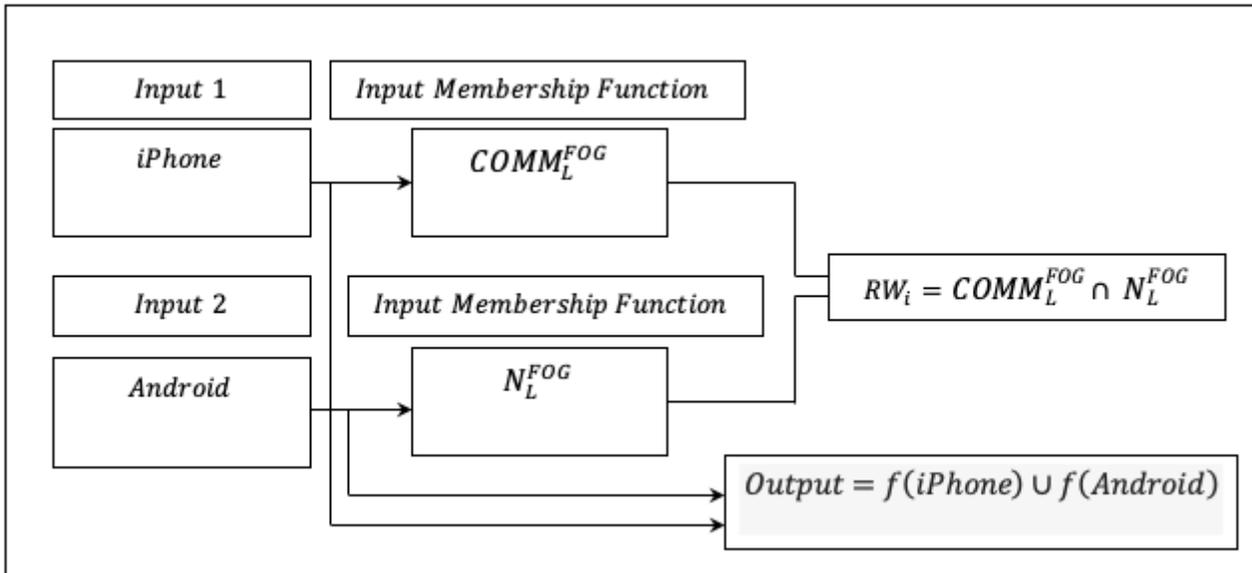


Figure 3

Block diagram of Sugeno Fuzzy Inference Model

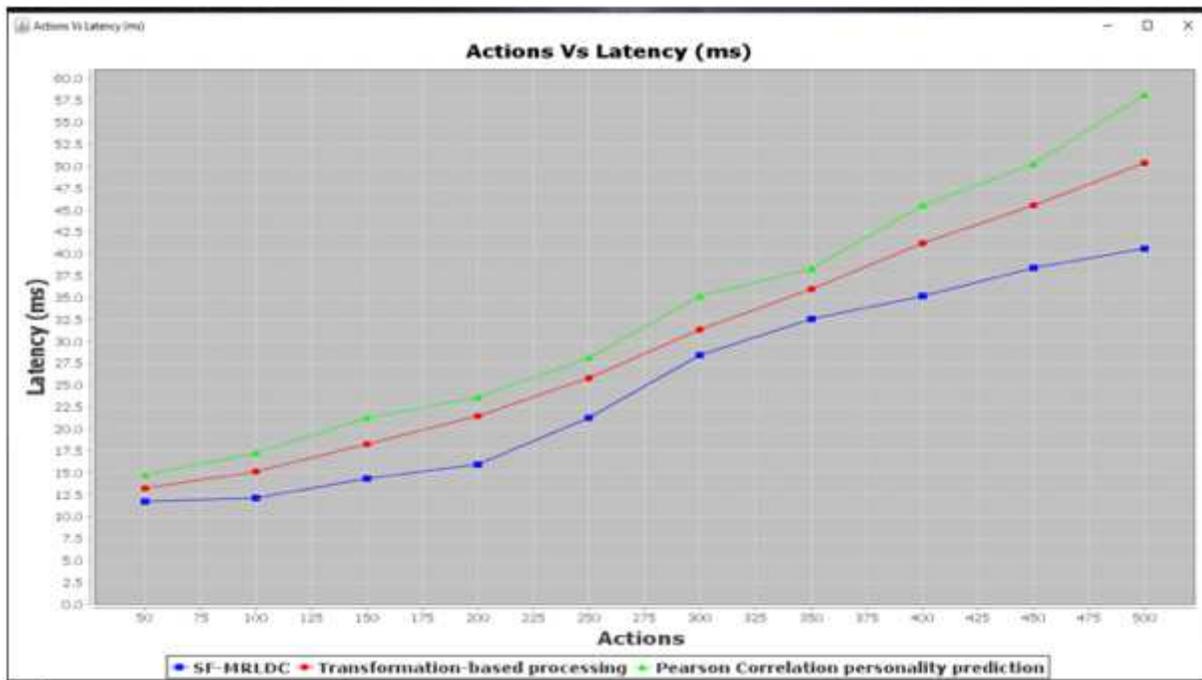


Figure 4

Graphical representation of latency



Figure 5

Graphical representation of response time

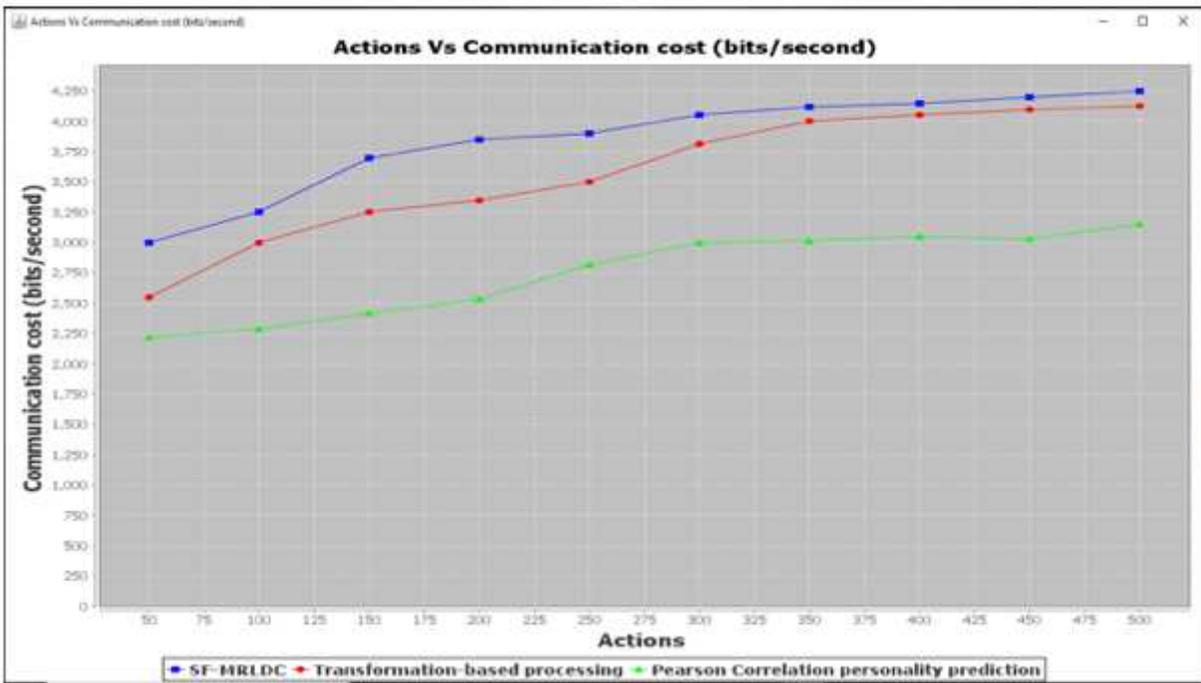


Figure 6

Graphical representation of communication cost