Journal of Ambient Intelligence and Humanized Computing
https://doi.org/10.1007/s12652-020-02421-0

ORIGINAL RESEARCH

Deep learning based energy efficient novel scheduling algorithms for body-fog-cloud in smart hospital

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Received: 12 April 2020 / Accepted: 23 July 2020

Abstract
Recent innovative development in Internet of Things, usage of wearable devices in body area networks has become smarter and has reached new perception, in terms of connectivity and diagnosis. Energy consumption, latency and network coverage are some of the research issues occurred in IoT based body area network. To address latency issue, in this work, networks could adopt to the Fog architectures to perform computation, data analysis and storage near to the users. To improve battery life period of sensor nodes an intelligent proactive routing algorithms for body-fog-cloud area networks are needed. In this research a novel algorithm called as modified WORN-DEAR algorithms for BAN-IoT networks is proposed to achieve energy efficient routing and scheduling using the principle of deep learning based adaptive distance-energy features. This work is simulated on Cooja-Contiki network simulator and implemented on different test beds with ESP8266 WIFI SoC interface. Final results were compared with existing WORN-DEAR algorithm and achieved higher accuracy of 98% in LSTM compare to other machine learning algorithms such as logistic regression, naïve bias, SVM and KNN.

Keywords Internet of Things (IoT) · BAN (body area networks) · Fog architecture · WORN-DEAR · L-NO-DEAF

1 Introduction

With an advent of Internet of Things (IoT), body area networks (BAN) has now moved to brighter side of technology in terms of computation, implementation and diagnosis (La et al. 2019). Internet of things based wearable devices consists of battery powered nodes interfaced with sensors, microcontrollers and transceivers. These battery powered nodes are energy-starving which makes them the unsuitable for the pervasive diagnosis of health parameters (Wu et al. 2017; Qi and Xin 2016). Meanwhile, IoT-BAN networks also suffers from the other traditional cloud computing parameters such as data computation, data security and traffic mechanism. To decrease the problems of WAN-IoT, a new layer in local area network called as edge or FoG computing was introduced (Shahid et al. 2020). In this FoG computing environment all regular network processing starting from data collection to storage are performed nearer to the end users (EUs).

In paper (Bonomi et al. 2012) the Cisco proposed fog computing with localized philosophy of big data. This paper proposed distributed and localized processing which can be done in FoG layer. These fogs are reaching its next level in order to ensure optimization in their services, a proper deep learning (DL) and machine learning (ML) algorithms can be applied on the millions of terabytes of data. In the body area Network scenario hence Fog computing can be treated as "the next big thing" (Janakiram 2018). This work integrates IoT, big data and cloud computing with intelligent into them.

Fog computing is new advanced architecture between cloud server and IoT devices but it is not a replacement for IoT cloud networks. The main motivation of introducing the FoG is to enhance the quality of service (QoS) and quality of experience (QoE) of the end users (Shahid et al. 2020). This layer acts like a middleware between user and cloud services which is more flexible. Within the user vicinity the user can process their request using Fog nodes or cloud. Hence FoG nodes are important entity in this architecture that consists of three general processing capabilities required for networking operations. Fog nodes can dissipate several function in different forms in variety of places (Amira et al. 2019).

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As a increasing popularity of FoG enabled IoT, a new paradigm needed to incorporate into that such as applying some intelligent in their regular processing so as to enable the task more efficient. Data analytics, prediction for future, decision support systems are some of the techniques required in an intelligent manner. This type of optimized networks is more contexts aware and dynamic in nature. Using these parameters, system will optimize performance metrics that is energy consumption, latency and bandwidth of end users. In whole IoT time sensitive application a smart powerful computation is brought into the closure part of the end user. This is one of the benefits of FoG architecture that is intelligence can be incorporated into FoG layers near to end user. Hence they significantly reduce the problems in general architecture and increases network scalability for IoT applications. Concurrently, IoT applications such as smart hospital (Iqrar et al. 2019) aim to be human-driven in nature, due to technological development this is very important tin integrate human tasks into machine oriented intelligent by considering the system performance in terms of energy and latency.

The implementation of fog architecture on BAN-IoT devices is new paradigm for an effective collection of medical data with an efficient diagnosis. Although it is considered to be more efficient, several challenges such as energy consumption, low latency and high data throughput using intelligent scheduling needs to be addressed for better implementation. The paper proposes the new protocol called modified WORN-DEAR (Kumaresan and Prabukumar 2018) algorithms which integrates the fog architecture for BAN devices.

1.1 Contribution of the work

The contribution of the research work is tri-folded.

1. First the implementation reconfigurable software for fog gateways for the BAN devices and to establish an effective communications with the fog gateways with short distance.
2. Secondly, implementation of deep learning algorithms in fog gateways for an intelligent data scheduling principles without sacrificing the energy consumption, low latency and high data throughput.
3. Thirdly, development of test beds based on the WIFI transceivers for an effective implementation of the proposed protocol for training, testing and analyzing the health condition of patients.

Remaining paper is organized like this, In Sect. 2 narrates the back ground work needed for the research, Sect. 3 is explaining about related works similar to this problems statement. Section 4 discusses the proposed architecture, working principles. Experimental setup, results, performance evaluations were explained in Sects. 5 and 6 gives the conclusion and future enhancement of the work for further improvisation.

2 Background work

2.1 Recurrent neural networks overview

As mentioned in Hochreiter and Schmidhuber (1997) and Sutskever et al. (2014), RNN one hidden layer of each neural network are connected with another neural network hidden layers. But according to RNN, the same hidden layers nodes are connected. One of the important characteristics of RNN is that, it can efficiently learn the time series data because it has the ability to encode the prior data into the process of learning in the existing hidden layer (Sutskever et al. 2014). In RNN methodology, the direct form of graphs can be formed by nodes along with its sequences. Hence dynamic behavior can be exhibited for time of sequences. This uses internal memory (state) for the process of sequences of input. So RNN network utilizes the past data for the prediction of future values. If the Interval time between the past data and current data for prediction is large in practical applications, then this methodology not able to memorize the past data significantly, so still there is a vanishing gradient problem (Eck and Schmidhuber 2002), hence the predicted outcomes are not satisfactory in some real time scenario. In order to overcome this issue, RNN performance has been enhanced, LSTM network has introduced.

2.2 LSTM—an overview

A long short-term memory network is combination of RNN with LSTM units (Vinyals et al. 2015). The LSTM network consists of 3 cells namely input gate, output gate, forget gate. Cell is known to be LSTM memories to remember the values over the time intervals and used to control information flow. Let xt be input at time t, the hidden layer output is ht and its former output is ht − 1, the cell input state is Ct, the cell output state is Gt and its former state are Ct-1 and Gt-1, the three gates' states are j_t T_f and T0. The structure of the LSTM cell indicates that both Gt and ht are transmitted to the next neural network in RNN. To calculate Gt and ht, the following equations are used (Sutskever et al. 2014) (Fig. 1).

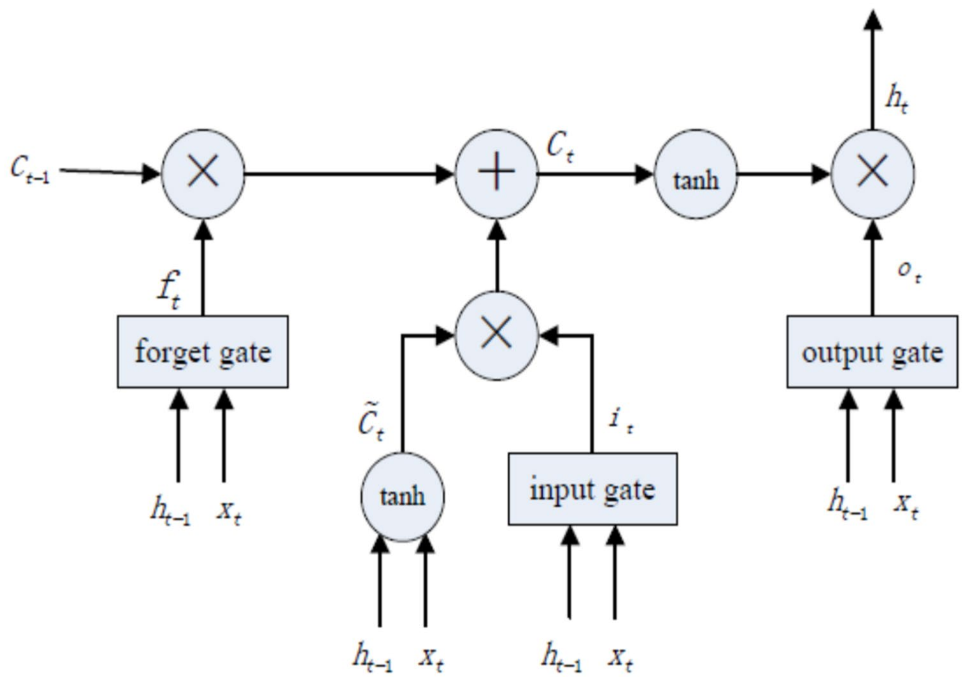
The input gate is given as

$$j_t = \theta\left(G_l^i \cdot O_t + G_h^i \cdot e_{t-1} + s_i\right). \tag{1}$$

The forget gate is given as

$$T_f = \theta\left(G_l^f \cdot O_t + G_h^f \cdot e_{t-1} + s_f\right). \tag{2}$$

Fig. 1 Structure of LSTM



Output gate is calculated as

$$T_o = \theta\left(G_l^0 \cdot O_t + G_h^o \cdot e_{t-1} + s_o\right). \tag{3}$$

Cell input is given as

$$\tilde{T}_C = \tanh\left(G_l^C \cdot O_t + G_h^C \cdot e_{t-1} + s_C\right), \tag{4}$$

where $G_l^0, G_l^f, G_l^i, G_l^C$ are the weights matrices connecting the input gates to the output layers whereas $G_h^i, G_h^f, G_h^o, G_h^C$ are the weight matrices connecting the gate inputs to the hidden layers. Also s_i, s_f, s_o, s_C are the bias vectors and tanh is considered to be hyperbolic function. Secondly cell output state is calculated and it is given as follows as

$$T_C = k_t \times \tilde{T}_C + T_f \times T_{t-1}. \tag{5}$$

Also hidden layer output is calculated which is then given as

$$e_t = T_o \times \tanh\left(T_C\right). \tag{6}$$

3 Related works

Kumaresan et al. in paper (Kumaresan and Prabukumar 2018), proposed a new hybrid model for enhancing the energy-efficiency in low-power healthcare applications. Smart devices are the examples of low-power healthcare devices. The proposed model hybrids the recent trending network such as wireless body area network with IoT as BIOT and also configured the wake-on reconfigurable networks (WORN). The WORN algorithm optimizes performance based on the distance energy adaptive rule sets (DEAR). This concept is working based on threshold frequency there is no intelligent in this.

Base station energy requirement is very important; in paper (Agrawal et al. 2020) this concept is explained. This sink or base station need to be maintained properly since its doing several processing. Various types of sensors such as soil, moisture, temperature, wind direction, wind speed, camera, drone etc. are used to continuously monitor the field in precision agriculture, and connect to the base station. At random point if time, based on multiple wireless communications medium, this sink has different modes of power requirements such as low power, medium power, and high power modes. This work proposed a novel product density model with the improved duty cycling algorithms using only one metrics that is residual energy. Other metrics such as RSSI (received signal strength indicator) and distance are not included in this paper.

Result accuracy and response time these two performance metrics considerations are missing in current fog models. Paper (Tuli et al. 2020) the author proposed a novel framework called HealthFog which is combining ensemble deep learning in edge computing devices. This framework is deployed in real time for automatic heart disease analysis and predictions. Currently this novel framework was worked with file based concepts where all the collected input datas are converted seamlessly taking decision directly. This is more user friendly than the existing systems. In this an intelligent technique by considering RSSI, high energy and lower distance with future prediction is missing.

In IoT network the connectivity issues with quality of services (QoS) parameter is considered in paper (Samanta and Misra 2018). In order to maximize throughput and reduces packet delivery delay the authors Amit Samanta and Sudip Misra proposed a dynamic connectivity establishment and cooperative scheduling scheme. First, to secure the reliable connectivity among WBANs and APs dynamically, he formulated a selection parameter using a price-based approach. And also formulated utility function for the WBANs to offer QoS using a coalition game-theoretic approach. It's a prototype model real time implementation with mobility is missing in this without intelligent algorithms.

In paper (Vivekanandan and Praveena 2020) the author Vivekanandan proposed a hybrid model using convolution neural network (CNN) and long-short term memory (LSTM)-based deep learning model (CNN–LSTM) for detecting shilling attack in energy efficient recommender systems. From the user profile deep-level attributes are derived to train deep learning model using the transformed network architecture. To enhance the efficiency and robustness of network model existing shilling attack detection methods uses features selection artificially.

The author in paper (Selem et al. 2019) proposed temperature heterogeneity energy (THE) aware routing protocol for WBAN. The performance metrics considered here is sensor node lifetime and packet throughput. To fulfill these desired tradeoffs, the sensed data is classified into three data levels with variable transmission priority to each level. The classifications are emergency (abnormal) data priority 7 (highest priority), critical data priority 6 and normal data assigned priority 5. "THE" protocol is based on a utility function that chooses the WBAN's parent node (PN) that has the largest amount of remaining energy, the highest data rate, the minimum distance to the coordinator and the minimum sensor's temperature. Hopping the data through the parent node (two-hops) is applicable for the data with normal priority while high priority data (critical and emergency) is transmitted to the coordinator in one-hop only. The proposed "THE" protocol's performance validation performed via Monte Carlo simulation analysis which proves that "THE" protocol achieved better performance against conventional protocols (SIMPLE and iM-SIMPLE) in terms of network lifetime, number of dead nodes, total remaining energy, and throughput. In this intelligent techniques in missing with good accuracy.

Zia in paper (Uddin et al. 2020) proposed a sequential information based deep learning algorithm called as recurrent neural network (RNN) for behavior recognition in body sensor-based system. They performed data collection and fusion from multiple body sensors such as electrocardiography (ECG), accelerometer, magnetometer, etc. Using the concept Kernel Principle Component Analysis (KPCA) all the extracted features are further enhanced. These robust features are used to train an activity RNN and later used for behavior recognition. The system has been compared against the conventional approaches on three publicly available standard datasets and finally achieves good performance.

In paper (Ahmed et al. 2015) the author presented a novel routing techniques such as Link-Aware and Energy Efficient protocol (LAEEBA) and Cooperative Link-Aware and Energy Efficient protocol for wireless body area networks (Co-LAEEBA). The proposed work considered two important factors that is collaborative learning and path loss. By considering remaining energy and distance the cost functions are introduced to learn and select the most feasible route. This simulated model is compared with other protocols by considering various performance metrics.

Xigang et al. in paper (Huang et al. 2011) proposed an energy-efficient cooperative communication mechanism for WBANs. They had done the performance analyzation in various modes such as direct transmission, single-relay cooperation, and multi-relay cooperation etc. Even though lots of analyzation happened there is lacking in intelligent part in this.

To achieve energy efficient WBAN the author Tauqir et al. in paper (Tauqir et al. 2013) proposed the new distance aware protocol called DARE. This new protocol has experimented in indoor hospital for patient health monitoring by placing ECG, pulse rate, heart rate, and temperature sensor in their body. They used different topology by placing the sink at the different occasions. This work also proposed on relay placement on the body for the effective communication from the sink to nodes. The DARE can be compared with M-ATTEMPT and achieve 15% reduction in energy consumption and 25% increase in network lifetime.

In paper (Giles et al. 1994; Schuster and Paliwal 1997; Duan et al. 2016; Eck and Schmidhuber 2002; Graves et al. 2013) all the authors were explained about the involvement of artificial neural network in real time application. One of the application such as travel time prediction to inform real time traffic condition can be explain briefly in paper (Duan et al. 2016). Since travel time is irregular in nature in this paper, they used LSTM neural network model, for travel time prediction. Highway roads are providing travel time data based on that prediction happened well in advance and disaster events are stopped earlier using LSTM. Here LSTM model is used in travel time prediction system there is no energy constraint metrics here and used application also differed.

4 General work flow mechanism of proposed architecture

The architecture of the proposed system is shown in Fig. 2a, b. This three tier architecture consists of reconfigurable sensor nodes (RSN) based BAN mounted on the monitored patients which starts sending the data to the intelligent fogs

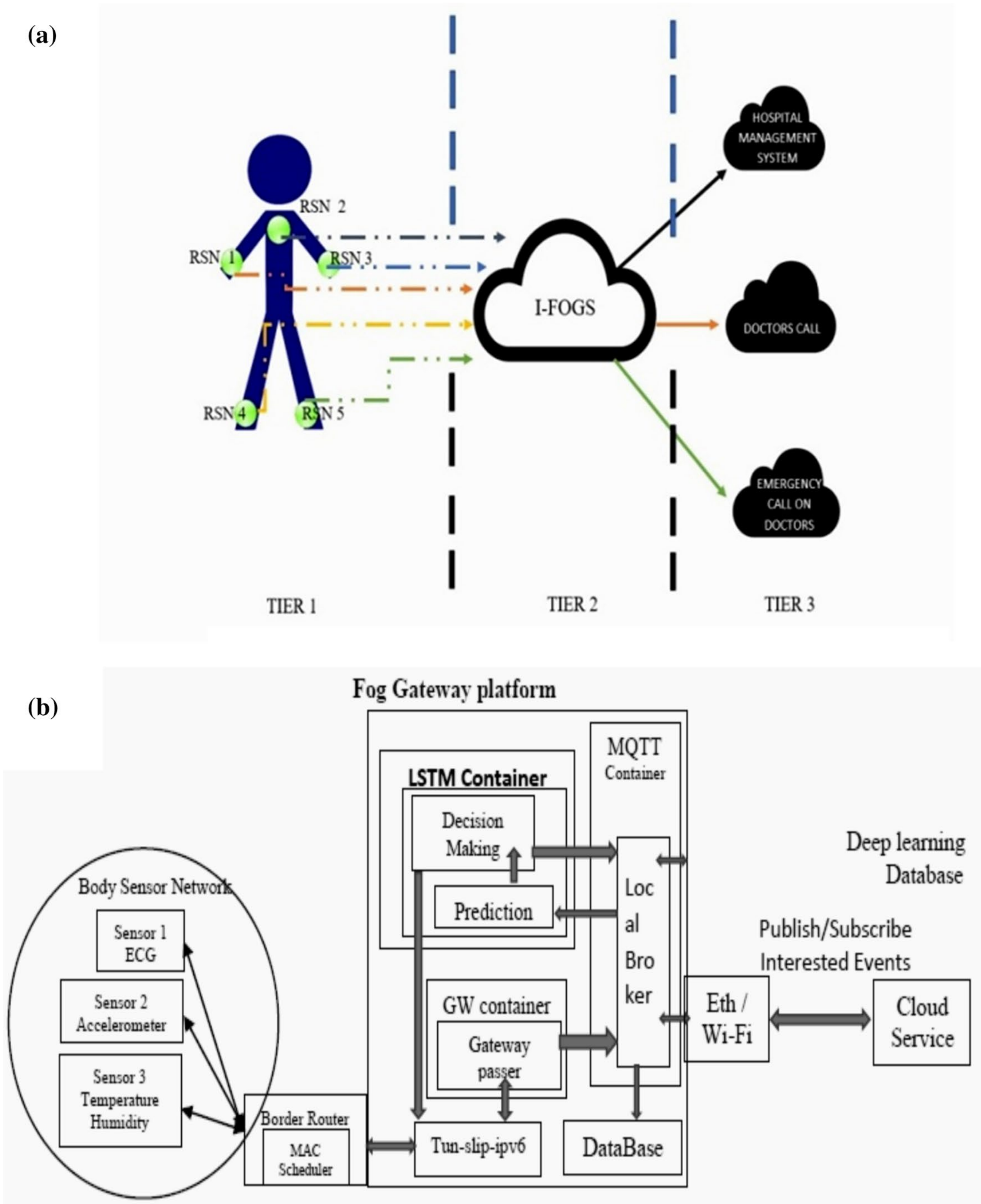


Fig. 2 **a** Working mechanism of proposed architecture. **b** Proposed network architecture

in star topology. In the second tier, fog gateway receives the data from the RSN and runs specialized, intelligent services on it from which it sends the data for further processing.

The divide and conquer methodology has been adopted in fog nodes' gateway software architecture, which makes the software easily updated and deployed without affecting the services. The third tier consists of cloud architectures which connects the hospital management systems, doctor's call and emergency call (La et al. 2019).

4.1 Proposed network architecture

The proposed system architecture is depicted in Fig. 2b. A BAN, attached on human body for monitoring health condition continuously. Multiple sensors such as accelerometer, heartbeat, respiration, temperature and humidity are placed on human body. The entire sensors, sending the sensed information to the nearest gateway, all the sensor nodes are connected with its sink in star topology structure. This gateway acts like middleware and forward the collected data to the cloud server for further processing parallel and the fog node will do some internal services locally. Based on the result of health conditions of the patient, an automatic adaptation happened in these FoG nodes. Several modules are packaged into different containers with their dependencies. This will help to make it easier for the software using newly trained classifier model to deploy and update the process without disturbing the running service. Deep learning is one container with ML classifier algorithms to detect human health conditions. Also, a MAC scheduler is deployed directly at the border-router to run the adaptive MAC scheduling rule based on the decision of the deep learning module.

As Fig. 3 shows, the workflow of the proposed system model which includes*Data collection*—Gathering of sensor data.*Data cleaning*—Removing unwanted and noisy data.*Model training*—Create neural network model using machine learning algorithms.*Testing*—test the model using real time data set.*Deployment stage*—Deploy the network in real time to monitor elder patient in home or hospital environment. In this paper the data sets are collected in real time manner by placing several sensors in their body and its subject to pre-processing and feature extraction which are depicted in Fig. 2.

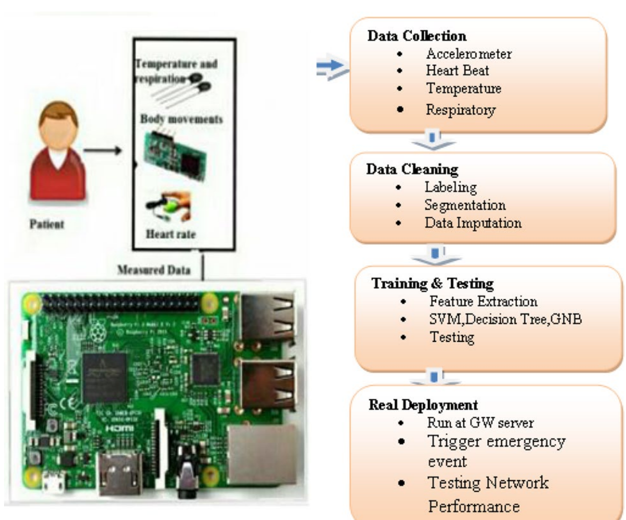


Fig. 3 Deep learning phases of work flow model

4.2 Reconfigurable sensor node BAN

The reconfigurable sensor nodes are mounted on patient's body which is then consist of biological heterogeneous sensors interfaced with the microcontroller and IoT transceivers. The firmware can be updated and depends on the command signals from the fog nodes. These proposed reconfigurable sensor nodes works in the three different phases such as initialization phase, energy-reconfiguration phase (ERP) and transmission phases.

4.2.1 Initialization phase

All the RSN remains to be in-active mode (sleep mode) and initial level of energy in all RSN are given in equation

$$\text{Einitial} = \text{Emax\_enrgy\_transceiver} + \text{Emax\_energy\_microcontroller} + \text{Esensing} \quad (7)$$

where Einitial – Initial EnergyEmax_enrgy_transceiver = initial energy of the microcontroller (SoC) usedEsensing = sensing energy for the sensors.

The initial energy of all nodes are considered to have maximum residual energy of the nodes. Figure 4 shows the working mechanism of initialization phase. The nodes gets control signal (CS) from the fog nodes (FN) which makes the sensing units to awaken state (AS). This initialization is used for the making the nodes to start sensing the body parameters (Kumaresan and Prabukumar 2018).

4.2.2 Measurement phase

After initialization, fog nodes send the control signals in which the reconfiguration nodes evokes from the sleep mode and starts measuring the body parameters. The measured

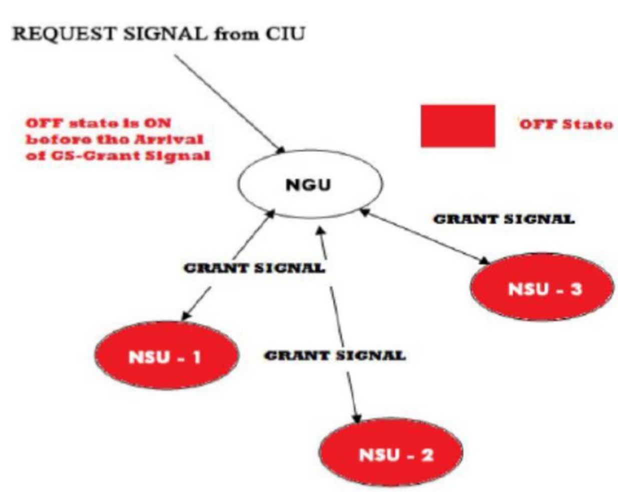


Fig. 4 Working mechanism of initialization phase

Start bit	Source address	RSSI	Residual Energy	Sensing Data	Priority Bit	Fog Destination Address	Stop Bit

Fig. 5 Data frame format from the reconfiguration sensor networks

body parameters are transmitted to the fog for further processing. The measured body parameters are transmitted in the frame format which is shown in Fig. 5.

The format starts from one bit of start bit (1-bit), 1 bytes of start address, RSSI of signal, residual energy, sensing data of transmitting nodes, priority bit followed by 1 byte of destination address and 1 bit of stop bit. Totally 8 bytes of data are transmitted to the fog nodes which uses for the decision phase.

This measurement phase works on the two different stages which are given as normal mode and emergency mode. In normal mode, signals are normally acquired from the nodes and transmit to the fog nodes whereas mode of transmitting the emergency data to fog nodes is categorized as emergency mode.

4.2.3 Transmission phase

The energy consumed by the reconfigurable nodes are given by the equation

$$\mathrm{EN,F} = \{\mathrm{ESensing} + \mathrm{ET}\}, \tag{8}$$

where EN, F = energy consumed by the transmission nodes to fog gateways N = 1,2,3…..N − 1

$$\mathrm{ET} = \mathrm{Emicrocontroller} + \mathrm{Etransmission}, \tag{9}$$

Emicrocontroller = energy consumed by the microcontroller/SoC interfaced with the sensorsESensing = energy consumed by the sensors which senses from the body parameters.

All the BAN sensor nodes start sensing the body parameters and transmit to the fog gateways in TDMA fashion. Once the fogs decide the predicted energy paths, energy-reconfiguration phase will be evoked.

4.3 Intelligent and learned fogs

To convert human domain parameters into network centric mechanism, this work employed the light-weight machine learning/deep learning modules on fog gateways. It aims for the accurate prediction of energy-efficient paths and an accurate detection of emergency data from the various patients. This leads to adaptive allocation of energy to the nodes and intelligent MAC scheduling based on the data categorization.

As shown in Fig. 2b, the intelligent fogs designed in the proposed networks consist of three wafers such as data collector and feature extractor, energy-efficient predicted paths (EEPS) and emergency scheduler (ES). The following phases of the fog gateways are discussed as follows.

4.3.1 Data collector and feature extractor

The data from the sensor nodes are collected and used for training fog gateways which can take the necessary and mandatory decisions. Table 1 shows the list of sensor data collected from different patients in various time intervals. Totally five different sensors such as temperature, heart beat, reseparation, MEMS1 and MEMS2 (in different positions left leg and right arms) are fixed in patient body for monitoring their health status. From this emergency data are used for the prediction of energy-efficient paths and allocation of time slots for an emergency data. Table 2 shows the list of features used for the classification which are taken from Table 1 emergency patient data.

Table 2 shows the list of features used for the prediction of energy-efficient paths and allocation of time slots for an emergency data. These features are node, analog to digital values, priority bit.

Latitude value, longitude value, received signal strength indicator (RSSI) etc. used for the classification which are taken from Table 1 emergency patient data. These features which are sent from sensor nodes, were used for the prediction of the energy efficient paths and scheduler for the emergency data.

4.3.2 Energy-distance LSTM based fogs

After collecting the data features from the different sensor nodes, the proposed network uses the LSTM for the energy efficient prediction paths and cognitive rule sets for scheduling of the different tasks. Out of the data features, energy w.r.t. to the various distance are taken as the input features for proposed LSTM methods. In this section, the usage of LSTM has been explored for the prediction of energy efficient paths. LSTM is closely related with recurrent neural networks (RNN).

From the above table it is clear that the fog allocates the time slots based on the level of energies in the BAN-IoT networks and priority of the bit. The LSTM based Fog gateways act in such a way that the there is no loss of data and it take cares about the energy levels of the BAN-IoT network also.

Table 1 Real time patient health monitoring data set

Patient ID	Temperature sensor	Respiration sensor	Heart beat sensor	MEMS1 sensor	MEMS2 sensor
P1	23	72	119	151	152
P2	24	83	116	140	161
P3	22	79	131	150	136
P4	43	85	121	150	138
P5	16	57	92	140	151
P6	34	82	103	162	140
P7	22	81	102	176	150
P8	32	65	119	146	150
P9	31	79	118	144	140
P10	34	48	91	142	162
P11	16	65	118	152	176
P12	43	72	112	161	144
P13	40	70	129	136	142
P14	32	58	133	138	152
P15	34	52	132	173	161

Table 2 Features extracted for the prediction of energy efficient path and scheduling of data

Node	Adc_value	Priority bit	Lat1	Lon1	RSSI1	Lat2	Lon2	RSSI2
1	328	1	64	58	15	32	43	25
2	154	0	45	87	70	50	80	35
3	256	1	23	35	64	43	56	74
4	354	1	88	15	85	78	34	83
5	232	0	58	54	8	68	24	12
6	154	0	23	81	62	33	71	72
7	128	0	10	64	52	20	64	42
8	154	0	23	81	62	33	71	72
9	128	0	10	64	52	20	64	42

4.4 Efficient energy path prediction LSTM

For the prediction of the energy efficient paths in BAN-IoT networks, we construct the LSTM and RNN network in fog gateways as shown in figure. At the distance or location d, input network is designed based on the energy data collected from the nodes, output layer is the predicted energy. The output vectors are calculated by the equation

$$\mathrm{Epn} = \mathrm{G2} \times \mathrm{h(t)} + \mathrm{a}, \tag{10}$$

where Epn is the predicted energy of the nodes, h (t) is the hidden layer and a is bias weights. The optimization of the other hyper parameters were used as discussed by Vivekanandan and Praveena (2020). Below figure shows the implementation of the proposed LSTM and energy values of nodes with the respective distances are predicted using the LSTM mechanism. The individual node‘s energy is predicted for each and every distance and compared with different energy thresholds which decides the energy efficient paths. Figure shows the decision of the energy efficient paths. The cognitive rule sets for energy efficient data transmission path are given

$$E(F,N) \;= E_{n\_1} \quad \text{if } E_{p1} <= E_{n\_1}$$
$$E_{p1} \text{ if } E_{p1} > E_{n\_1}$$
$$\ldots\ldots\ldots\ldots$$
$$E_{n\_n} \text{ if } E_{pn} <= E_{n\_n}$$
$$E_{pn} \text{ if } E_{pn} > E_{n\_n}$$

Where E(F,N) is the Energy paths from the Fog nodes to BAN-IoT networks . E_{n_n} is the energy threshold for BAN-IoT nodes and E_{pn} is the predicted energy

After selecting the energy of the nodes based on the priority of the bit, time slots are allocated for further processing. Table 3 illustrates the intelligent phase of the proposed network for cognitive scheduling the data based on energy-distance and priority bits. The pseudo code for the complete mechanism of working is given as follows as (Wu et al. 2017).

4.5 Pseudo-code for the proposed cognitive LSTM for no deaf networks

Requirement:

Input Energy E={ E_{n_1} ,E_{n_2}, E_{n_3}, E_{n_4}......................E_{n_n}},
Predicted Energy E_p ={E_{p1}, E_{p2}, E_{p3}, E_{p4},.......................................E_{pn}}
N_{th} =6 Max-Epoch =4000 Min-Epochs=500
for N= 1 to 6**do**
Initialization: initialize Θ randomly

$L^{n}_{\text{best-val}} = +\infty$

Adjusting theta Θ:

for epoch = 1 to Max − Epoch

do

Do forward propagation recurrently using equation (1)-(7) to compute

$\tilde{E}_{t+1}$, t = 1, 2, · · · ,

Compute output error:E, $Et + 1$,t= 1, 2, · · ·

Perform backward propagation through to compute the deviations ΔΘ

Update Θ: Θ = Θ + ΔΘ

Perform forward propagation recurrently to update the network states using equation (1)-(6)

Perform forward propagation recurrently to compute $Ep = \{E\tilde{x}_{t+1}$, t = T1 + 1, T1 + 2, · · · , T2}

Calculate the cost function on validation set $L_{\text{this-val}}$

if$L_{\text{this-val}} < L^{n}_{\text{best-val}}$ **then**

if$L_{\text{this-val}} < L_{\text{best-val}} \times 0.99$

then

Min−Epoch = Max(Epoch×2, Min−Epoch)

End

End

End

End process:

5 Experimental setup

The proposed algorithm called as modified WORN-DEAR (L-No-Deaf) is implemented in Contiki OS and the experiments are carried in the test beds where NodeMCU

Table 3 Illustration of the cognitive rule sets implemented in L-No-deaf networks for data scheduling and processing

Node ID	Energy factors from nodes	Energy predicted for the nodes	Priority bits	Decision phase	Rank priority scheduling for processing
01	En_1	Ep1	0	Ep1 ≤ En_1	2
02	En_2	Ep2	1	Ep1 ≤ En_2	1
03	En_3	Ep3	1	Ep1 > En_3	3
04	En_4	Ep4	0	Ep1 > En_4	4
05	En_5	Ep5	0	Ep1 > En_5	5

ESP8266 boards with the in built operating system XTOS and interfaced with the different biological sensors with its fog gateway are tabulated in Table 3. Figure 6 illustrates the placement of the nodes to form the BAN-IoT networks. Several evaluation parameters were calculated such as accuracy, selectivity and sensitivity and compared with the other exiting machine learning algorithms. Furthermore, network centric parameters such as the energy consumption, latency and throughput were calculated and compared with exiting BAN networks such as WORN-DEAR in which the proposed algorithms outperforms the other algorithms (Fig. 7, Table 4).

6 Results and discussions

The parameters such as accuracy, precision rate and F1 rates were calculated for the different iterations and these parameters were compared with the exiting machine learning algorithms. The test beds mentioned in the section are used for collecting the data and implementing the proposed L-No-DeaF networks which is modified version of WORN-DEAR. The mathematical expressions for calculating the above parameters are given as follows

$$\text{Accuracy} = \frac{\text{TR}}{\text{TNI}} \times 100 \tag{11}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{TN}} \times 100 \tag{12}$$

$$\text{F1} - \text{calls} = \frac{\text{TN}}{\text{TP} + \text{TN}} \times 100, \tag{13}$$

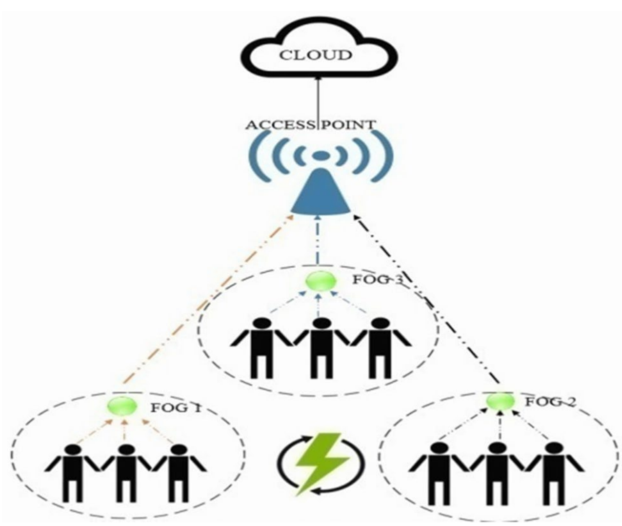


Fig. 6 Experimental setup for the testing the proposed network architecture

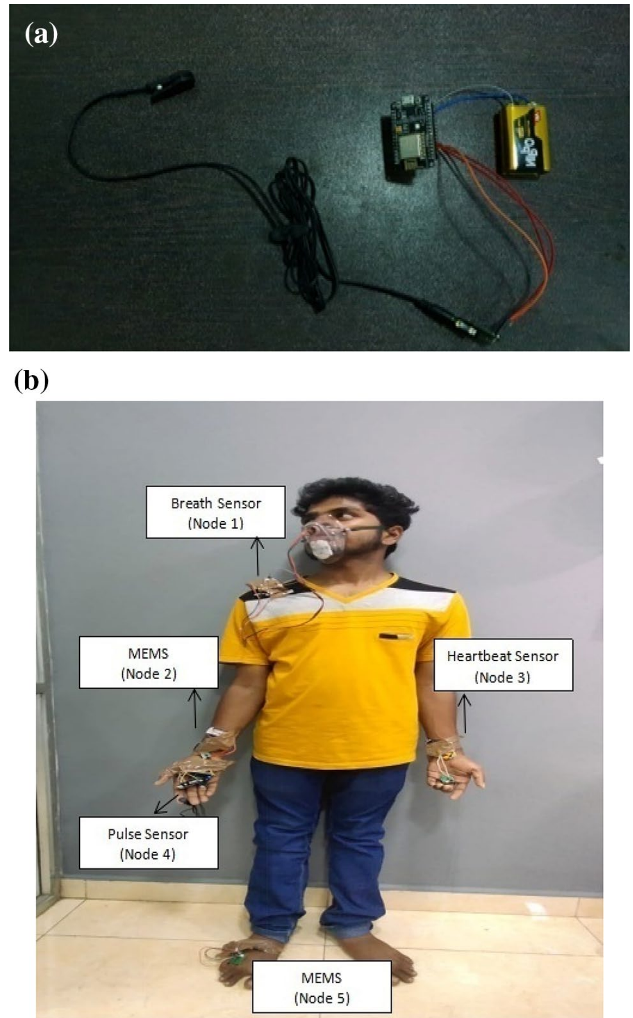


Fig. 7 **a** Nodes with microcontroller integrated with the sensors and transceivers. **b** Experimental setup for the placement of nodes to form fog-BAN-IoT networks

Table 4 Illustration of test beds used in the experimentation

Sl. no	Parameters used	Specifications
01	Main CPU	Cortexm3
02	Transceivers used	WIFI/ESP8266 test beds
03	No of sensors used (n)	09
04	ADC interfacing	MCp3008
05	Supply voltage	3.3 V
06	Gateway-fog	NodeMCU interfaced with the Python IDE for data analytics
07	Cloud	IBM Watson/ThingSpeak
08	Simulator	Contiki-OS-Cooja Simulator
09	No of users/nodes	05

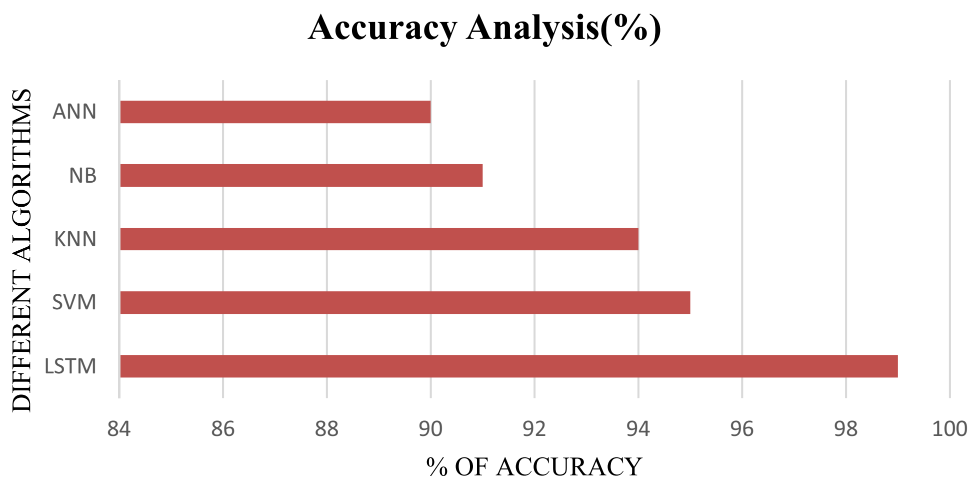


Fig. 8 Comparative analysis between the different machine learning algorithms with proposed LSTM deep learning algorithms

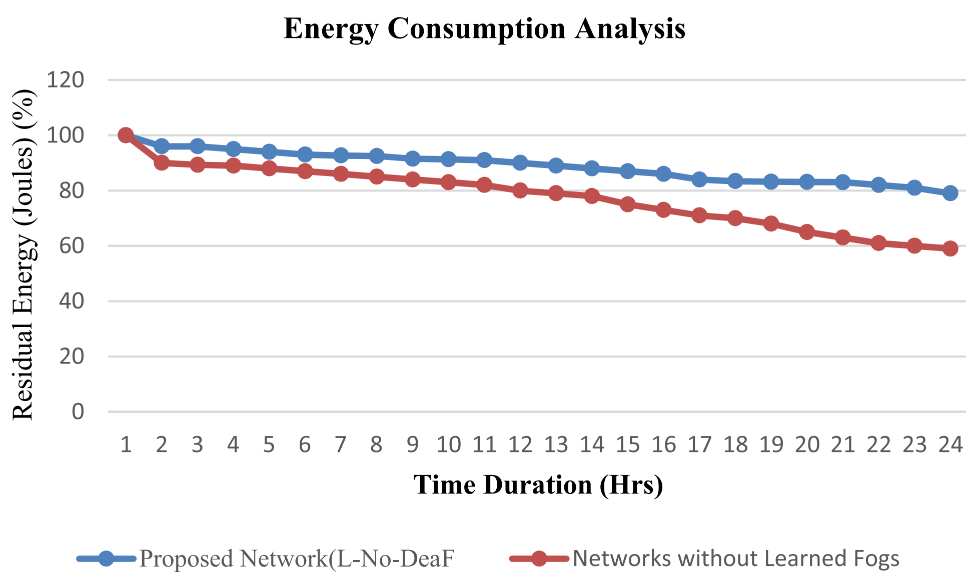


Fig. 9 Comparative analysis of proposed networks with the other fogless non intelligent IoT network when d = 5 m

where TP and TN represents true positive and true negative values and TR and TNI represents number of detected results and total number of iterations.

6.1 Accuracy calculation

The accuracy has been calculated for different machine learning algorithms (Table 5) on the developed test beds as shown in Figs. 8, 9.

Table 5 Accuracy calculation

S. no	Algorithm name	Accuracy (%)
1	Artificial neural networks	90
2	Naïve bayes	92
3	KNN machines algorithm	94
4	Support vector machines	95
5	Proposed LSTM	98

Table 6 Performance evaluation for the LSTM in the proposed networks

Output_values	Precision	Recall	F1-score
0	0.98	0.98	0.92
1	0.97	0.96	0.91
2	0.96	0.94	0.91

Table 7 Performance evaluation for different machine learning algorithms with the proposed LSTM

Sl. no	Algorithms	Output_values	Precision	Recall	F1-score
01	Proposed LSTM	0	0.98	0.98	0.92
		1	0.97	0.96	0.91
		2	0.96	0.94	0.91
02	Support vector machines	0	0.94	0.92	0.90
		1	0.93	0.92	0.90
		2	0.92	0.91	0.90
03	KNN machines	0	0.94	0.92	0.91
		1	0.89	0.90	0.92
		2	0.90	0.91	0.86
04	Naïve bayes	0	0.84	0.82	0.81
		1	0.76	0.75	0.73
		2	0.72	0.73	0.75
05	Artificial neural networks	0	0.68	0.72	0.71
		1	0.65	0.67	0.62
		2	0.62	0.59	0.61

The receiver operating characteristics (RoC) is another metrics for evaluating the performance of the proposed LSTM with adaptive energy and distance features, with the RoC characteristics, we have generated precision, recall and f1-score.

Table 6 represents the precision,f1-score and recall for the proposed algorithms and comparison between the proposed and other machine learning algorithms are depicted in Table 7.

In the evaluation parameters, we have analyzed the network centric parameters such as energy consumption, packet delivery ratio latency and throughput and compared with the other existing algorithms which are discussed in the preceding section.

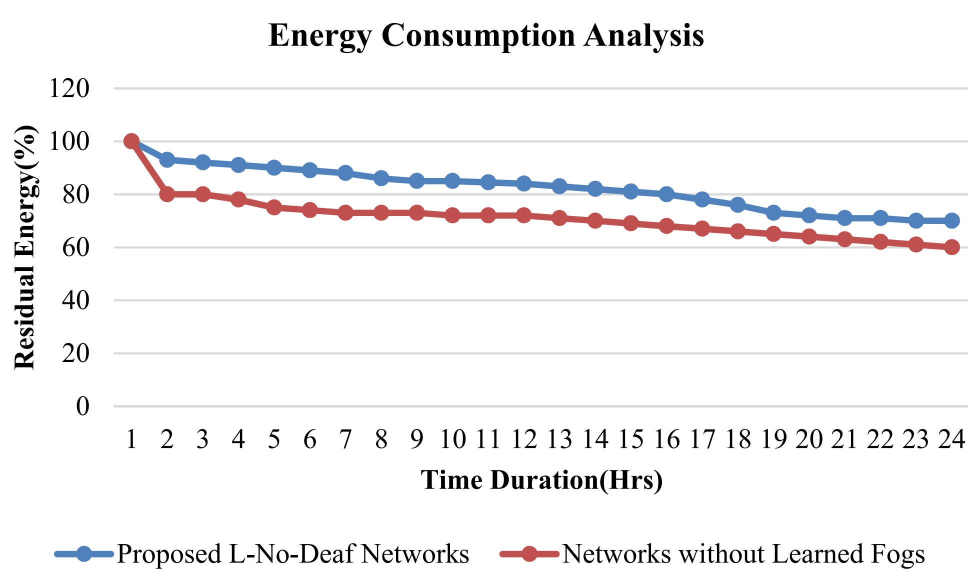
6.2 Energy metric evolution

Scenario-I: In this scenario, proposed network has been implemented in the test beds, which are allowed to run for 24 h continuously and energy-time consumption curve for different cases of distances were calculated. In this evaluation, proposed network is compared with the fogless cloud driven networks at the various distance were analyzed. The energy consumption of the networks are calculated by the following mathematical expression (Samanta and Misra 2018)

$$Ec = Er\_1 + Er\_2 + Er\_3 + Er\_4 + Er\_5 + \cdots \cdots Er\_n$$

where Ec = total average energy consumption of proposed network architectureEr_1—Residual Energy after

Fig. 10 Comparative analysis of proposed networks with the other fogless non intelligent IoT network when d = 8 m



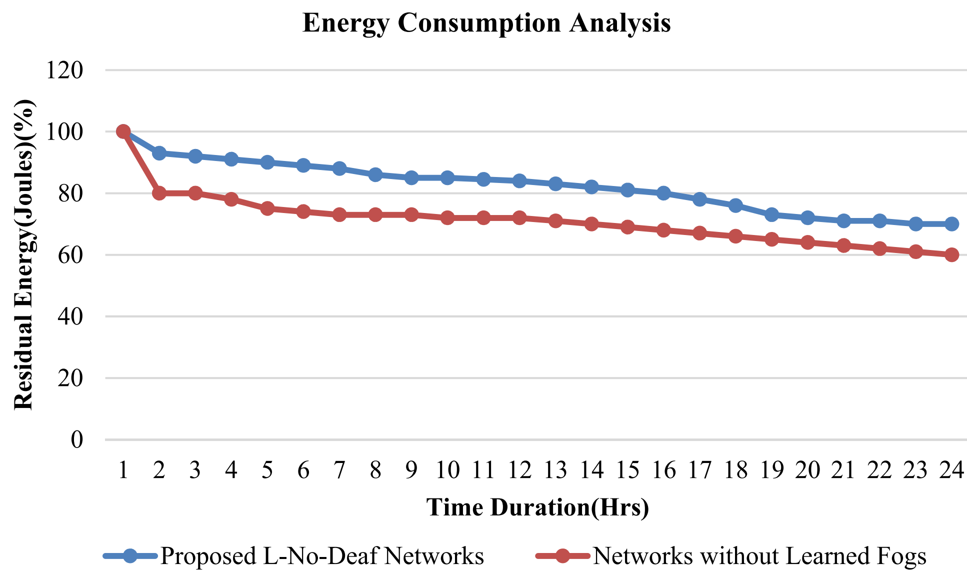


Fig. 11 Comparative analysis of proposed networks with the other fogless non intelligent IoT network when d = 12 m

Transmission of the Sensor Data from the Node_1Er_2—Residual Energy after Transmission of the Sensor Data from the Node_2 (Kumaresan and Prabukumar 2018)Er_3—Residual Energy after Transmission of the Sensor Data from the Node_3Er_4—Residual Energy after Transmission of the Sensor Data from the Node_4Er_5—Residual Energy after Transmission of theSensor data from the Node_5.

Figures 9, 10 and 11 shows the comparative analysis between the proposed network and cloud driven networks for the different distance. In this scenario, distance between nodes and gateways is considered. In all figures, average energy consumption of the proposed network in all distance is about 20–25% is low when compared with the existing cloud driven network which consumes nearly 40% of energy for 24 h duration at different distances. Furthermore, to validate the proposed network, we have compared with the existing algorithm WORN-DEAR (Agrawal et al. 2020) and analyzed the energy consumption curves.

From the above Figs. 12, 13 and 14, it is clear that the energy consumption of the proposed network is 20% whereas the existing algorithm consumes nearly 30–40%. It is also clear that the energy consumed by proposed network remains to be 20% even at the various distances.

6.3 Packet delivery ratio (PDR)

The packet delivery ratio of the proposed network architecture has been calculated by the mathematical expression-PDR = No of Data Bytes Received at Fog Nodes/No of Data Bytes Sent from the Source Nodes (Fig. 15).

From the above Fig. 16, packet delivery ratio is maintained at 90–95% at the different distance where as the

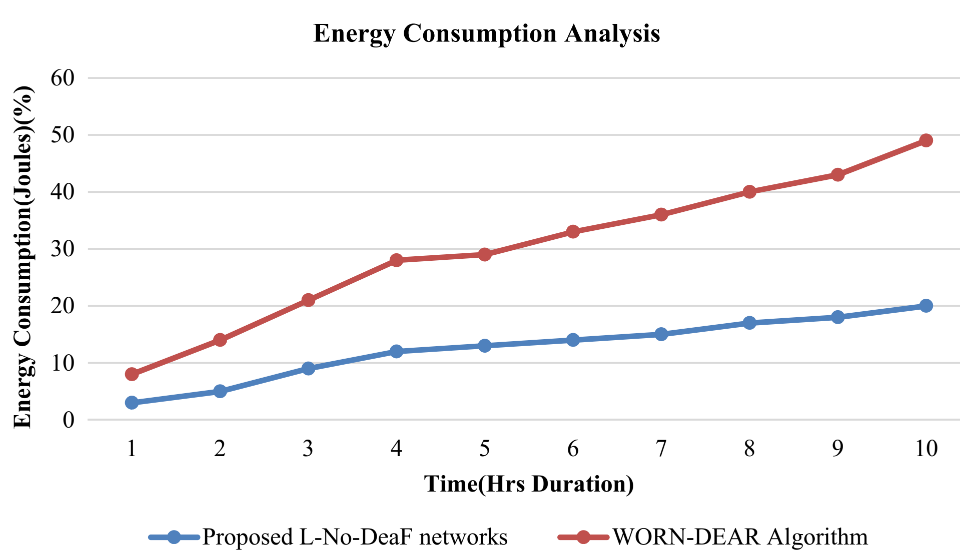


Fig. 12 Energy consumption analysis between the proposed network and existing WORN-DEAR network when d = 5 m

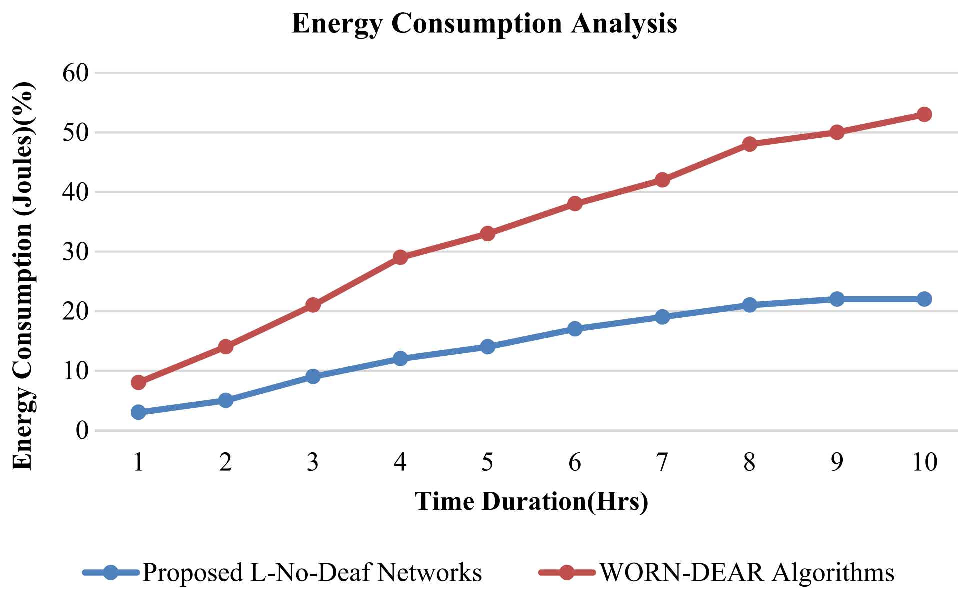


Fig. 13 Energy consumption curves between the proposed network and existing WORN-DEAR network when d = 8 m

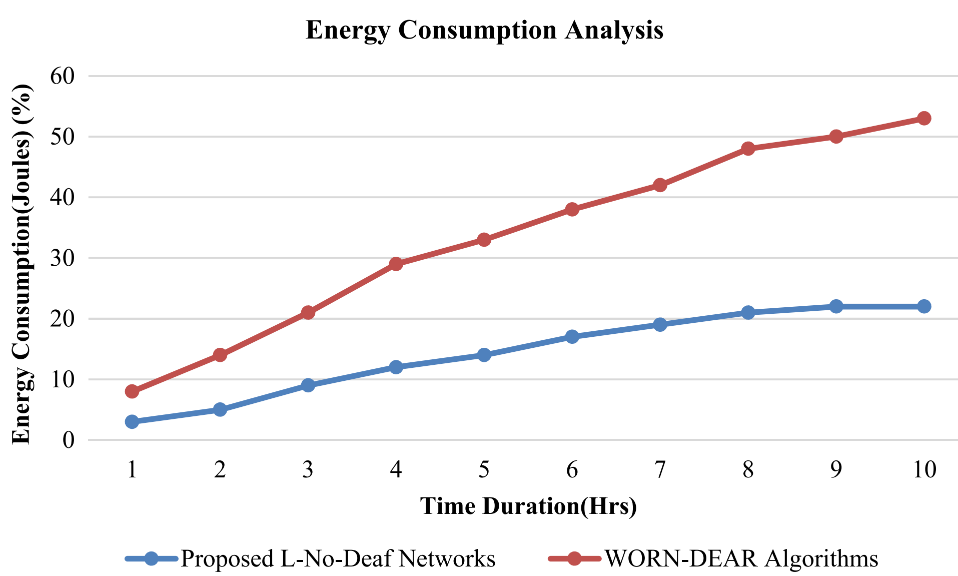
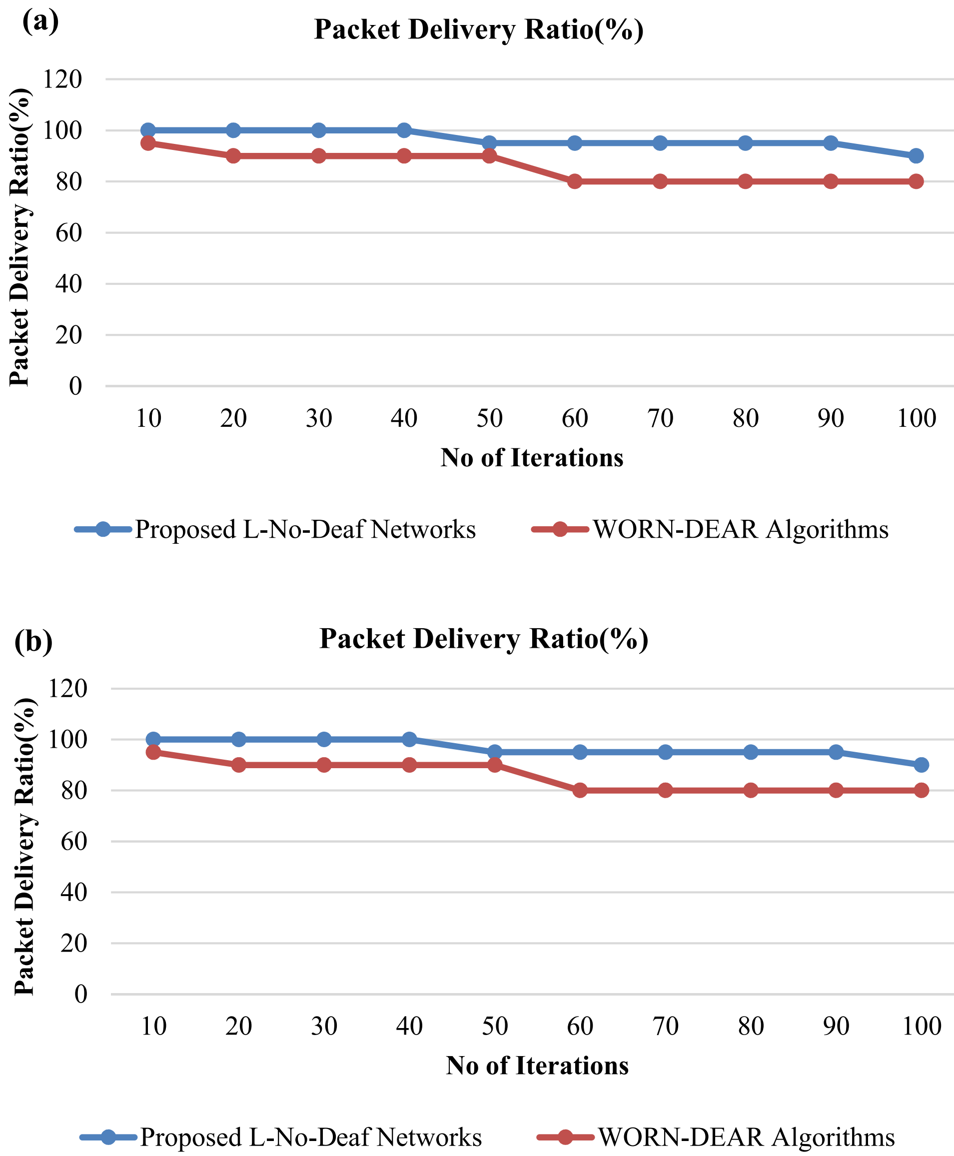


Fig. 14 Energy consumption curves between the proposed network and existing WORN-DEAR network when d = 12 m

Fig. 15 Reform LSTM structure



existing algorithms varies from 90-80% which we can conclude the proposed architecture outperforms the existing algorithms at various distance (Iqrar et al. 2019).

6.4 Latency analysis

The time delay or latency has been calculated based on the response time from the fog gateways to the different nodes which carries ‘n’ bytes of sensor data.

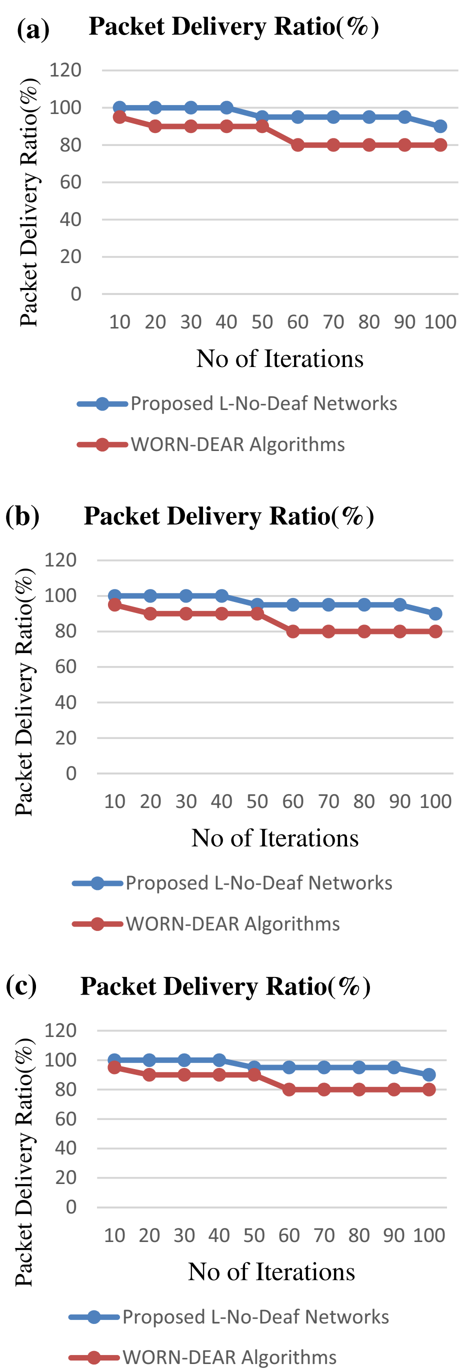


Fig. 16 **a** Packet delivery ratio for the proposed network and existing network when d = 2 m. **b** Packet delivery ratio for the proposed network and existing network when d = 8 m. **c** Packet delivery ratio for the proposed network and existing network when d = 12 m

From the Figs. 17 and 18, latency is measured in terms of response time of the fog networks in reply to the emergency data from the different nodes. The response time is nearly reduced to 50% when compared to the already existing traditional cloud networks and WORN-DEAR algorithms.

6.5 Throughput analysis

Throughput has been analyzed for the proposed network by using the mathematical expressions which is given asThroughput Analysis: N × Twhere N number of data, T time per s.

From the above Figs. 19, 20 and 21 throughput of the proposed network architecture is maintained at constant rate even the distance varies from 5 to 12 m whereas the throughput of the existing cloud driven Worn-Dear algorithms decreases as the distance increases.

7 Conclusion

This paper proposes a new intelligent fog driven BAN networks for monitoring the patients' health conditions by analyzing different characteristics such as energy consumption, network coverage and throughput latency. The deep learning algorithms have been integrated in fog gateways to achieve an energy efficient network with high performance. The experimental setup with the Node MCU with XTOS operating systems were built for testing and validating the proposed algorithms along with the existing algorithm such as cloud driven BAN based WORN-DEAR networks. Meanwhile, the paper also discusses about the validation of the deep learning algorithms along with the other machine learning algorithms in terms of accuracy of prediction, precision and f1-score. The proposed network integrates learning techniques in fog gateways using modified WORN-DEAR algorithm and outperformed the existing algorithm which finds its suitability for smart health care applications in emergency cases. This work is applicable for indoor environment only. In future we can try the same setup for outdoor environment by considering mobility also. We can apply the same concept in real time scenario for further analysis to get more accurate result about these algorithms. Some trusted security algorithms can be introduced in FoG gateway to prevent any attacks in WBAN in future.

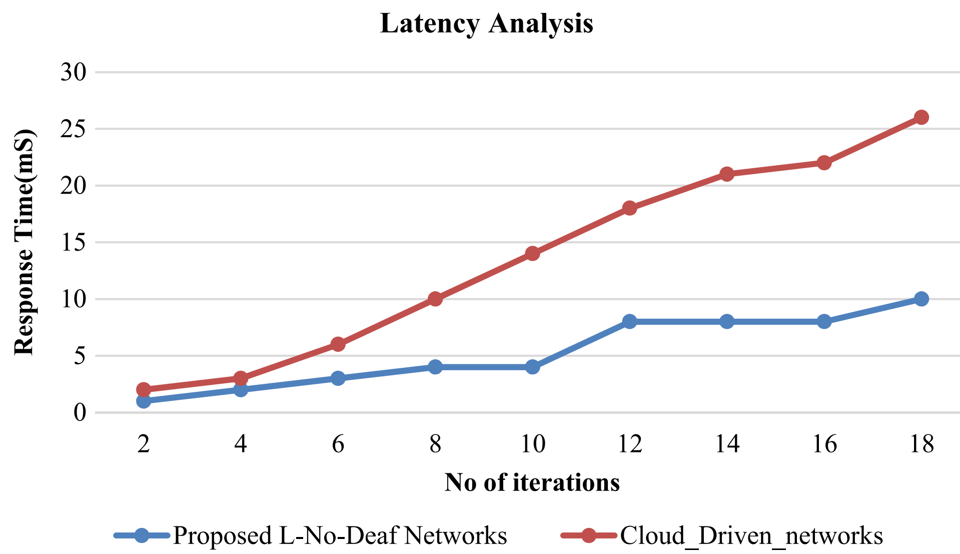


Fig. 17 Latency analyses for the proposed L-No-Deaf networks and cloud driven BAN networks

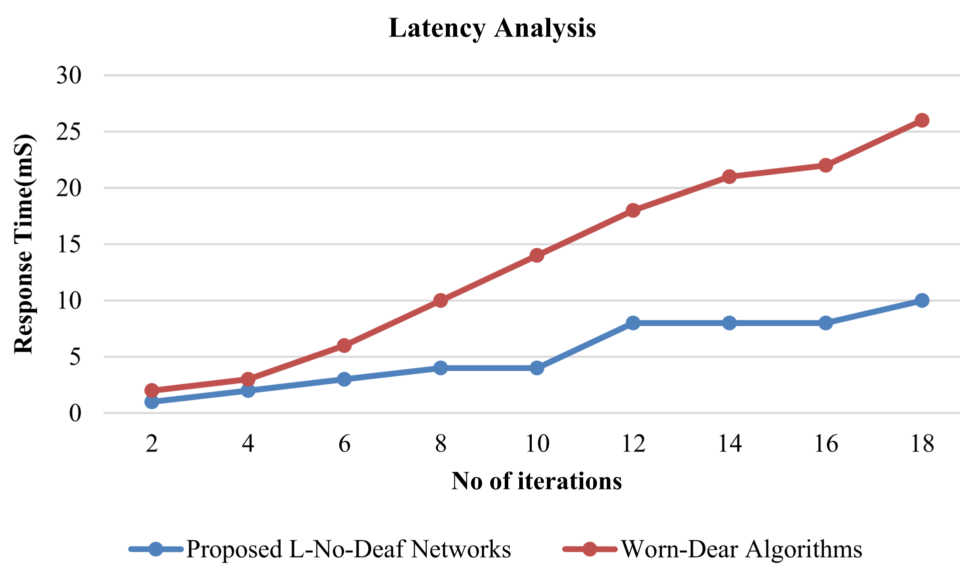


Fig. 18 Latency analysis for the proposed L-No-Deaf networks and the Worn-Dear algorithms

Fig. 19 Comparative analysis for the proposed network architecture with the existing cloud driven WORN-Dear algorithms at d = 5 m

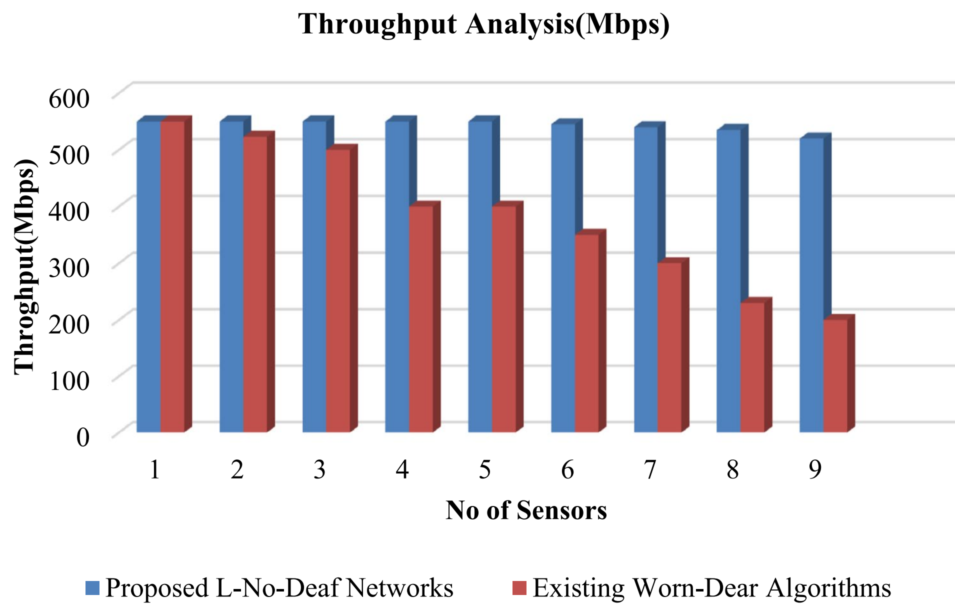
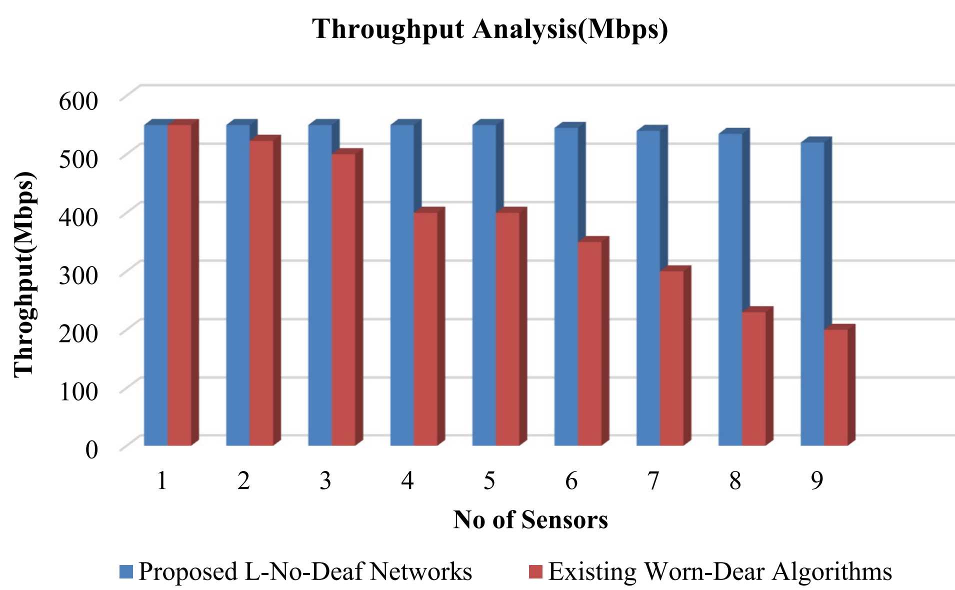


Fig. 20 Comparative analysis for the proposed network architecture with the existing cloud driven WORN-Dear algorithms at d = 8 m



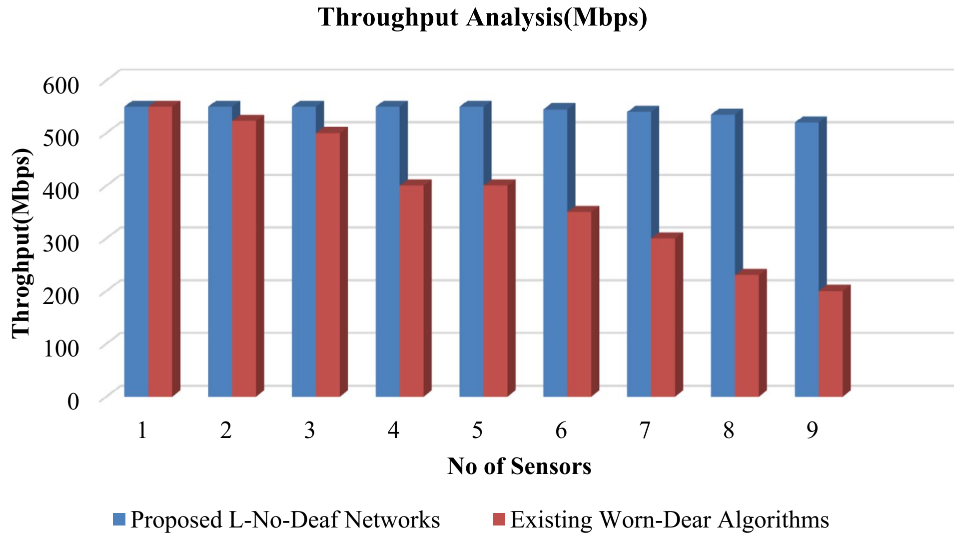


Fig. 21 Comparative analysis for the proposed network architecture with the existing cloud driven WORN-Dear algorithms at d = 10 m

Funding We haven't received any funding from any sources.

Compliance with ethical standards

Conflict of interest Amudha S. declares that he has no conflict of interest. Murali M. declares that he has no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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