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Research Article

Q-BodyFogNets: A Novel Energy-Aware Deep Learning Framework for Predicting Heart Diseases in Fog-BAN Environments

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Abstract:

The Internet of Things (IoT), Fog, and Edge Computing are key innovations that have transformed body area networks (BAN) and their communication techniques. This combination of IoT with wireless networks has led to significant advancements, enabling energy and latency-aware BANs, which play a crucial role in smart healthcare applications. Recently, machine learning and deep learning algorithms have been applied to IoT-enabled BANs to address these limitations. However, the complexity of these learning algorithms can impact the overall network performance, and achieving both low power consumption and high diagnosis accuracy remains underdeveloped. This paper presents a novel, intelligent, and adaptive Q-learning framework for Fog-based body area networks (QAL-Fog-BAN) that handles incoming data from various dynamic BAN nodes. It deploys less complex recurrent neural networks (LCRNN) to achieve solutions such as energy-efficient and QoS-aware paths for medical data transmission. The paper also introduces a novel dataset, built using the ifOGSIM API and Python libraries. This approach collects network-centric parameters across seven attributes and 15,687 data points, which are used for evaluation and analysis of the proposed method's effectiveness in Fog-BAN networks. Comprehensive testing is performed with the collected data samples, and several metrics—such as accuracy, precision, recall, specificity, and F1-score—are assessed and compared with other intelligent Fog-BAN networks, including LEAF-NETS, FUELNETS, and WORN-DEAR. Simulation results demonstrate that the proposed design performs better than existing architectures and plays a major role in achieving lower energy consumption in Fog-BAN networks.

1. Introduction

1.1 Body Area Networks

Body Area Networks (BAN) are a recent development that enable the continuous transmission of a patient's well-being, as well as the detection and transmission of related health information to a server. In the current evaluation, BAN is integrated with AI and IoT to enhance its performance in assessing illnesses and monitoring patient health data, while optimizing the energy consumption of BAN nodes within the network.

1.2 Internet of Things Enabled Body Area Networks

Body Area Networks (BAN) and IoT working together have greatly advanced task planning, implementation, and execution. IoT-enabled BAN devices, powered by batteries, connect with sensors, microcontrollers, and smartphones to gather patient health data and send it to the cloud via gateways. However, the limited battery life of these hubs makes continuous health monitoring challenging [1-3]. Fog and edge computing now serve as essential links between cloud systems and BAN-IoT devices, enhancing quality of service (QoS) [4-6]. Fog nodes are integrated into BAN-IoT devices to collect and process data locally, reducing the need for a centralized network [7-9]. Over the last decade, artificial intelligence (AI) has seen remarkable development, along with the introduction of several machine learning (ML) and deep learning (DL) algorithms in Fog-BAN environments. This integration has had a positive impact on improving QoS in these networks. For instance, recent algorithms such as No-LEAF-Nets [10], FUEL-Nets [11], and WORN-DEAR [12] have shown promise by deploying ML and DL techniques like Long Short-Term Memory (LSTM) and Optimized Long Short-Term Memory (O-LSTM) in Fog-based BAN networks for smart healthcare applications. However, the non-adaptive nature and high complexity of these existing algorithms still need to be addressed to achieve higher performance and more efficient data transmission.

1.3 Motivation

To address the challenges outlined above, this paper introduces an Energy-Aware and QoS-Aware Adaptive Learning framework for Fog-BAN networks. The framework utilizes adaptive Q-learning and Modified Gated Recurrent Units (GRU) to achieve high performance and efficient disease diagnosis based on the data collected from biosensors deployed on an individual's body.

1.4 Contribution

This paper proposes QBODYNETS, a novel hybridization of Adaptive Q-learning and Modified Gated Recurrent Networks for the accurate prediction of heart diseases. Additionally, it introduces a FogSIM-based Data Creation and Gathering Unit (DCGU) for evaluating the proposed method. Also, a novel dataset was created using iFogSim, containing 15,687 data points covering seven essential network-centric parameters. This dataset enhances the framework's evaluation in Fog-BAN systems, ensuring a detailed analysis of both QoS and healthcare metrics, improving overall performance and prediction accuracy. To our knowledge, this is the first approach of its kind that achieves high Quality of Service (QoS) alongside a high prediction ratio. The primary contributions of this work are summarized below:

1. The paper introduces a novel simulation testbed running on the iFogSim simulator, which emulates a real-time Fog-BAN-IoT framework for efficient data transmission.
2. It presents a hybrid combination of Q-learning and Modified GRU to achieve high accuracy in heart disease prediction.
3. Finally, the paper adopts various evaluation metrics to analyze the superiority of the proposed approach.

1.5 Organization

The rest of the article is organized as follows: Section 2 provides an overview of related works proposed by different authors. Section 3 discusses the system and energy model, dataset collection, pre-processing, and proposed architecture. Section 4 explores the experimental setup, outcomes, and performance evaluations, while Section 5 summarizes the paper with directions for future enhancement.

2. Related Works

A unique calculation proposed by Perumal and Prabukumar (2018) introduces the WORN-DEAR framework for BAN-IoT networks, focusing on energy-efficient scheduling and routing through DL-based adaptive distance-energy features. This approach is implemented using an ESP8266 WiFi SoC interface and the Cooja-Contiki network testing environment across multiple test scenarios. When compared to other AI-based models such as logistic regression, naive Bayes, SVM, and KNN, the system demonstrated a remarkable accuracy of 98% when utilizing LSTM. However, a notable limitation of this method is its high computational complexity [13].

A clever and energy-efficient WBAN model developed by N. Bilandi et al. is introduced for evaluating and validating COVID-19 patients. This model classifies patients based on whether they have COVID-19 or the seasonal flu. An irregular forest model describes the symptoms and determines whether the user is experiencing COVID-19 or the seasonal flu after the user presents their symptoms to the cloud. The proposed model effectively enhances the power efficiency and organizational life of the WBAN by using a LoRa module as a relay hub. The LoRa technology serves as a potent means of transmitting information packets, yielding a more reliable framework. This model reduces power consumption by utilizing LoRa technology for accurate transmission of biosensor readings and achieves a classification precision of 88.6%. However, there is still room for improvement in the transmission delay associated with WBAN [14].

S. Amudha Mary et al. utilized fog networks for medical service applications, employing three AI models for the predictive analysis of hospital admissions based on patients' medical conditions. Individual models are trained appropriately based on the health status of patient data, and the emergency admission predictions are based on three different AI algorithms: logistic regression, decision trees, and gradient-boosted algorithms. Overall, the Random Forest algorithm outperformed logistic regression, decision trees, and other algorithms. Additionally, the AI algorithms align with preplanned span scheduling for the overview of patients' status with precision. However, a fundamental limitation of this system is that it leads to time complexity when processing large datasets [15].

Y. Chang et al. propose an efficient distributed deep learning (EDDL) system to address the challenges mentioned above. Specifically, they adopt an adjusted incomplete block design (BIBD) strategy to reduce computational loads on Fog nodes by systematically eliminating some data streams in DNNs. By employing aggregated convolution techniques, they propose a practical approach to jointly guide both horizontal and vertical model partitioning. Furthermore, they integrate multitasking learning and ensemble learning methods to further enhance inference accuracy. Simulation results confirm the effectiveness of the EDDL structure in achieving a significant reduction in computational burden and memory footprint, with only a slight loss of inference accuracy. However, this structure struggles to handle large data in real-time environments [16].

Mabrook S. Al-Rakhami et al. investigated the implementation of a deep neural network (DNN) model in a Cloud-Fog edge processing system to detect and monitor aggressive driver behavior. Their approach utilizes robust models and datasets based on sensor measurements, cost-effective wireless networks, cloud and Fog edge computing systems, and the Internet. Test results demonstrated that the DNN model improved detection accuracy by 1.84% compared to existing methods without pre-processing data from bio-signal sensors. Furthermore, the network performance results highlight the performance and impact of the proposed algorithm. However, a significant limitation of this system is its increased time complexity when processing large datasets [17].

The multi-class attack detection is conducted by K. Kalaivani et al. using the proposed integrated CNN with an LSTM-based Fog Computing Intrusion Detection ICNN-FCID model. The accuracy of attack identification provided by this model is approximately 96.5% when tested using the benchmark dataset NSL-KDD. The execution of our model is unmatched, as evidenced by comparisons between its precision and that of conventional and other recent deep learning approaches. The ICNN-FCID model is utilized in fog layer devices for monitoring business traffic and identifying attacks. Consequently, the cloud server and fog layer devices can protect IoT devices from malicious clients and are generally available to provide various forms of assistance [18].

For IoT sensor applications employing integrated deep learning, Anand Singh Rajawat et al. presented a Fog big data analysis model and BPNN analysis model, which establish new benchmarks for anticipated machine-to-machine communication practices. They propose FBDAM to enhance key Fog applications built on smart city datasets (parking, transportation, security, and sensor IoT datasets). In various smart city dataset IoT application scenarios, they considered several deep and machine learning models. However, the only drawback of this structure is that it requires extensive computation time and handles a large amount of data [19].

To manage such vast amounts of data gradually, Lei Zhang et al. proposed the concept of transmitted fog computing. The design of current distributed systems can benefit significantly from the use of LT codes (LTC), which minimize the delay in processes such as lattice augmentation in deep learning techniques. This study hypothesizes that fog nodes could prove inadequate. To reduce latency, we apply improved LT codes to the grid duplication of the distributed fog computing process. According to mathematical findings, the enhanced LTC-based plan can reduce overhead and latency while decreasing the computational complexity of distributed fog computing. However, this structure still leads to time complexity [20].

Liang, Y. et al. present an innovative Fog-enabled prediction system for machining process optimization. The framework incorporates dynamic prediction, with a CNN-based model executed to identify potential flaws in customized machining processes. Intensive computational tasks such as CNN training and system re-optimization in response to identified flaws are carried out progressively in the cloud layer to leverage its computational capabilities. With the implementation of the system, energy efficiency and productivity improved by 29.25% and 16.50%, respectively. Compared to a cloud-based system, this Fog framework achieved a 70.26% reduction in bandwidth requirements between shop floors and the cloud, along with a 47.02% decrease in data transfer time. However, the system does not meet real-time requirements [21].

In their study on integrating cloud and edge computing for IoT data analysis, Grolinger et al. propose a deep learning-based methodology for data reduction concerning edge and cloud AI. The encoder component of the auto encoder is positioned at the edge to minimize data characteristics. The reduced data is then transmitted to the cloud, where it can be used directly for AI purposes or further expanded with the auto encoder's decoder component. The proposed method has been evaluated based on its effectiveness in recognizing human actions. Results reveal that a 77% data reduction resulted in only a 1% change, while a 50% data reduction had no significant impact on classification accuracy. However, the primary drawback is its computational complexity [22].

3. Proposed Methodology

The framework of the proposed algorithm is delineated in Figure 1 and consists of three important sections:

First Part: QoS and Patient Data Collection Module in the Fog-BAN Module

Second Part: Converting the non-QoS environment into a QoS-aware environment using the Proposed Learning Algorithm for the Fog-BAN Module

Third Part: Prediction of heart-related diseases, particularly heart attacks, using patient data.

As illustrated in Figure 1, the first part comprises a data collection component that gathers various data from the Fog-BAN nodes created in the IFogSim simulators. The collected data are stored in the Fog as separate databases (DB), with RAM provided in each Fog device.

In the second part, the data stored in the Fog as separate DBs are used to train the proposed model, which selects energy-efficient paths to achieve lower energy consumption, higher throughput, and reduced latency. Finally, the nodes send patient data using the QoS-selected path, where the Fog analyzes and predicts heart attacks using the proposed learning model and transmits the results to a nearby hospital cloud.

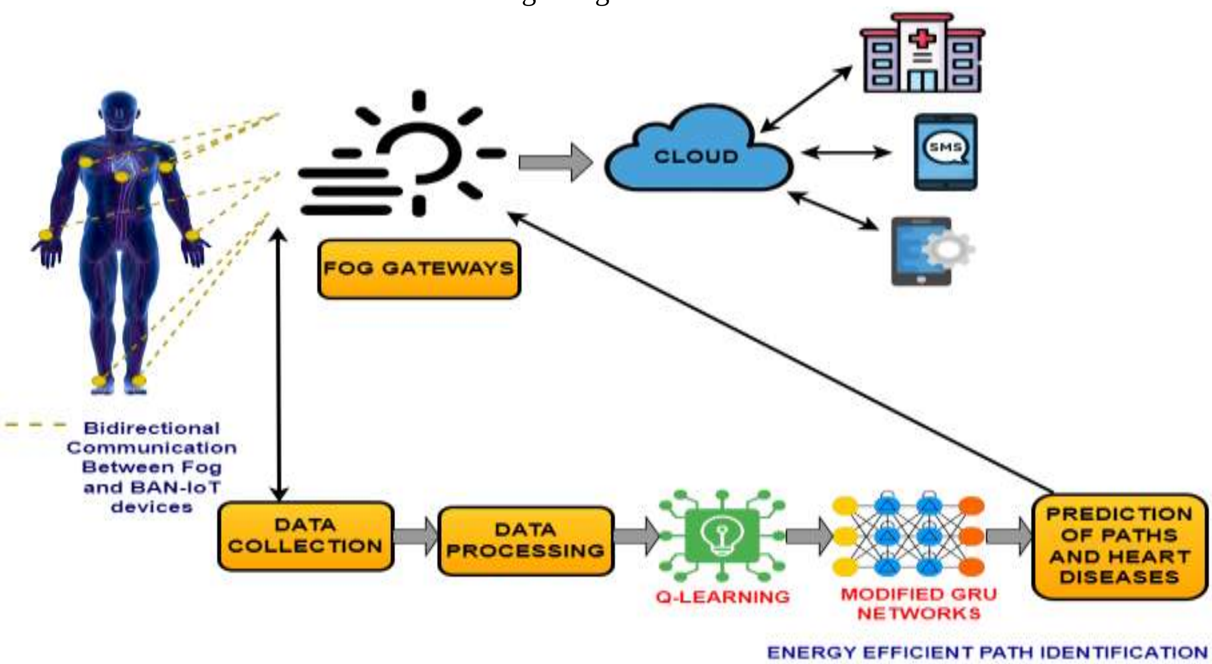

***Figure 1.** Proposed Architecture for Fog -Based BAN-IoT Devices*

3.1 System Model

In general, the idea of implementing Fog/Edge Computing paradigms in the BAN-IoT network is to facilitate QoS-aware data transmission in order to minimize latency and energy consumption. This study presents a system model designed around parameters such as placement, location, sensor data, and initial energy levels. The BAN-IoT nodes are deployed so that medical sensors interface with IoT transceivers. Similarly, Fog gateways are established for every 10 nodes to collect and analyze data. The research primarily focuses on heart-related diseases, specifically heart attacks.

3.2 Energy Models

The patient's body is covered with IoT-based sensor nodes, which consist of biologically heterogeneous sensors connected to a microcontroller and IoT transceivers. Command signals from the Fog nodes are used to update the firmware, which is an upgradable component. Equation (1) is utilized to determine the initial energy level [23]

$$E_{Initial} = E_{max\_enrgy\_transceiver} + E_{max\_energy\_microcontroller} + E_{sensing} \quad (1)$$

Where $E_{initial}$ →Initial Energy of the nodes, $E_{max\_enrgy\_transceiver}$ →Maximum Energy of the Microcontroller utilized. $E_{sensing}$ → Sensing Energy for the sensors. The energy usage of the BAN-IoT nodes is described by the following equation,

$$E_{N,F} = \{E_{Sensing} + E_T\} \quad (2)$$

Where E_T= Energy consumed by the BAN-IoT nodes to the Fog gateways with N=1,2,3, ….. N-1

$$E_T = E_{microcontroller} + E_{transmission} \quad (3)$$

$E_{microcontroller}$ → Energy used by the sensors' interfaced microcontrollers. $E_{Sensing}$ → energy used by the sensors that gather data from body parameters [24]. All BAN-IoT sensor nodes begin by measuring body characteristics and then transmit data in TDMA mode to the Fog gateways. These energy models deployed in Fog nodes determine various energy levels based on location and distance.

3.3 Data Collection Component

IFogSim component is used to collect important heart disease data and QoS-related metrics, such as pulse rate, temperature, ECG data, and motion detection [25,26]. The iFogSim Simulator is utilized to generate raw data, which consists of both QoS-related and body-related sensor data. Figure 2 illustrates the creation of nodes in the iFogSim Simulator and the recording of the data. Algorithm-1 presents the generation of synthetic datasets from the recorded raw datasets.

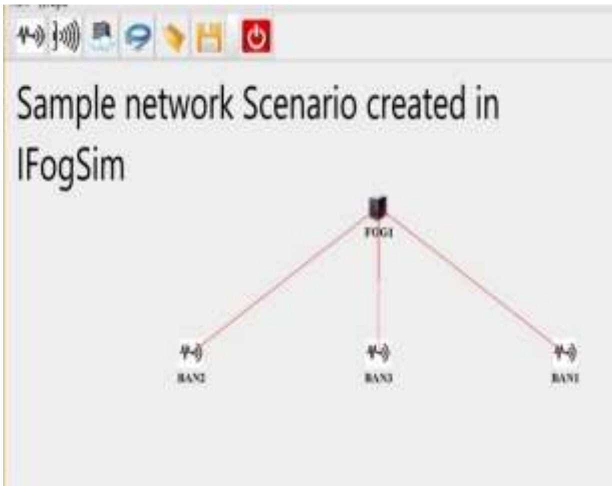

Figure 2. *Sample Network Scenario Created for the Experimentation*

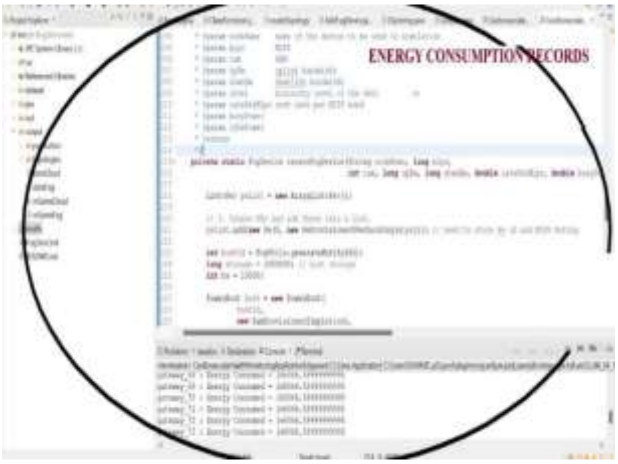

Figure 3. *QoS related Data Records Obtained from the IFogSim Simulator used for the Data collection report*

ALGORITHM-1: Synthetic Data Generation from Recorded Raw Data

Step 1: Fetching the Data from the User Nodes

Step2: Filtering the QoS related data such as Energy, Location, Delay and Drop ratio

Step 3: Categorizing the Data in accordance with High Energy and Less Location (Distance)

Step 4: Broadcast the Nodes with the Highest Energy

Step 5: Gathering the Health-Related Data and Pre-processed for the Prediction

Based on the High Energy and Low Distance model, the nodes are classified into very high energy nodes, high energy nodes, and low energy nodes. A total of 15,473 data points were recorded, covering both QoS metrics and healthcare-related data. These data points were collected across various timestamps and distances, making the dataset unique in its integration of QoS-related data with critical health information which ensures both patient data privacy and security. This combination enables a comprehensive evaluation of the proposed Q-learning and GRU-based prediction framework. Unlike traditional datasets that often focus solely on medical data, this dataset facilitates a dual analysis of energy consumption patterns and transmission efficiency in Fog-BAN networks, providing a broader and more detailed performance assessment.

3.4 Data Pre-Processing Techniques

The data gathered from BAN-IoT devices are pre-processed to filter for QoS-related data. Approximately 15,473 datasets were collected from the IFogSim simulator [27] and pre-processed for further analysis. In the first step, QoS data and heart-related data are filtered using a collaborative filtering technique. The data is then classified as high energy nodes based on the energy levels and locations of the BAN-IoT nodes. The filtered QoS data are presented in Table 1. Figure 3 is QoS related Data Records Obtained from the IFogSim Simulator used for the Data collection report. From the Table 1, high energy nodes are designated as 1, while low energy nodes are marked as 0. Specifically, energy levels greater than or equal to 15,679 microjoules and distances greater than 3 are considered high energy nodes. Additionally, the recorded ECG data, distance, and pulse rate of patients are also used to classify the data into critical and non-critical categories. Table 2 displays this categorization of data. After classification, the data are split into three categories: training data, testing data, and validation data.

The testing data helps refine the model's effectiveness, as it can be rebuilt using training samples based on the testing performance. In contrast, the validation data, which does not influence the final model's development, is used to measure the model's effectiveness against unobserved data. Table 3 illustrates the partitioning of the data structure.

Table 1. *Representation of QoS Related Data Samples Recorded from IFoGSIM Simulator*

Node ID	Energy Consumed(uJ)	Location (metres)	RAM Usage	Uplink Bandwidth	Downlink Bandwidth	Idle Power(W)	Label
1	158932.9022	4m	20%	5	3	3.3	1
2	169933.933	6m	20%	4	3	3.3	1
3	169965.90	4	20%	5	3	3.3	1
4	168929.90	4	20%	5	3	3.3	1
5	167654.903	4	20%	5	3	3.3	1
6	156759.89	3	20%	5	3	3.3	1
7	154389.90	3	20%	5	3	3.3	1
8	168962.90	5	20%	5	3	3.3	1
9	167902.90	5	20%	5	3	3.3	1
10	156789.13333	3	20%	5	3	3.3	1
11	178902.675	6	20%	5	3	3.3	1
12	167433.90	5	20%	5	3	3.3	1
13	**145678.452**	**2**	**20%**	**5**	**3**	**3.3**	**0**
14	167893.90	4	20%	5	3	3.3	1
15	156783.90	3	20%	5	3	3.3	1

Table 2. *Classification of Data based on Patient's records*

Node ID	ECG Sensor	Pulse Sensor	Distance	Position	Label
1	150	100	4 meters	345	1
2	142	120	5 meters	342	1
3	100	88	4 meters	245	1
4	89	78	4 meters	234	1
5	120	115	4 meters	289	1
6	66	65	6 meters	303	0
7	89	84	4 meters	332	1
8	130	120	4 meters	338	1
9	167	150	5 meters	43	1
10	100	99	4 meters	100	1

Table 3. *Splitting of Data Used for the Training, Testing and Validation*

Sl.no	Total Raw Data	Training (70%)	Testing (20%)	Validation (10%)
1	15473	10,832	3095	1548

3.5 Proposed Learning Model

The suggested learning approach ensembles for the combination of Q-Learning and Modified GRU networks for the prediction of the energy saving nodes and prediction of heart attacks. The detailed description of Q-learning and gated recurrent units is detailed first in preceding section.

3.5.1 Q-Learning Concepts

One crucial component of machine learning in artificial intelligence systems is reinforcement learning (RL) [28-30]. In BAN-IoT networks, Q-learning, a subfield of reinforcement learning, is extensively utilized [31-33]. The foundation of RL is a sequential decision problem, where the agent interacts with the environment, chooses an action, and, in response to the action's performance, receives reinforcement from the environment in the form of a reward before moving on to the next stage. Figure 4 illustrates the reinforcement learning framework. Here, the agent's objective is to perform the best possible action and achieve optimal decisions to maximize the global discounted reward over the long term. A policy is a plan or manner of conduct for the learning agent; it describes the action to be executed

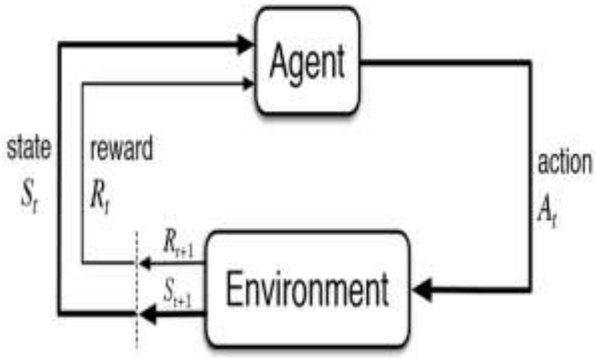

Figure 4. *Reinforcement learning framework*

at each state represented by t while mapping from state to action. The objective of RL, in feedback to the learning algorithm, is to maximize the reward. The success of reinforcement learning is largely attributed to Q-learning, a procedural version of the off-policy model-free method frequently referred to as the Q-learning algorithm. Q-learning is a leading algorithm for solving related problems and approximates the value of state-action pairs by using samples collected during interactions with the environment. The discrete-time Q-function is represented by Equation (4).

Thus, Q-learning, as a reinforcement learning method, is formulated using the Markov Decision Process (MDP). This MDP specifies parameters including states, actions, rewards, and their associated probabilities as (S, A, P, R) and $P_{zz'}^{a}$. Let z be the current state and z' be the next state with action value a.

$$P_{zz'}^{a} = Prob\{z_{i+1} = z' | z_t = z, a_t = a\} \quad (4)$$

The reward function for states z and z' is given as $R_{z_t z_{t+1}}^{a}.t$.The overall reward function of the current state is:

$$R_t = \sum_{z_{t+1} \in Z} P_{s_t s_{t+1}}^{a_t} R_{z_t z_{t+1}}^{a_t} |_{z_t = z, a_t = a} \quad (5)$$

3.5.2 Gated Recurrent Units (Gru)

GRU is regarded a highly appealing variant of Long Short-Term Memory (LSTM) networks. The concept, introduced in aims to merge the forget gate and input vector into a single vector. This network supports long-term sequences and memories while significantly reducing complexity compared to LSTM networks. Figure 5 is GRU -network Architecture.

The following equations, proposed by Chung, illustrate the characteristics of GRU.

$$h_t = (1 - x_t) \odot h_{t-1} + x_t \odot h_t \tag{6}$$

$$\widetilde{h_t} = g(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h \tag{7}$$

$$z_t = \sigma(W_h x_t + U_z h_{t-1} + b_z) \tag{8}$$

$$r_t = \sigma(W_h x_t + U_r h_{t-1} + b_r) \tag{9}$$

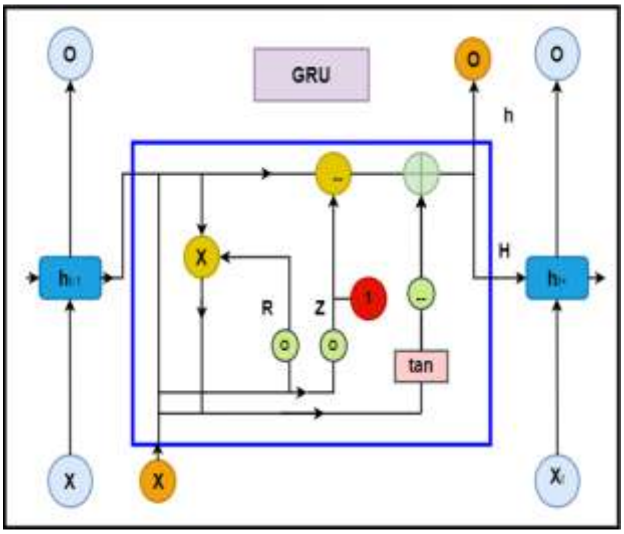

Figure 5. *GRU -network Architecture*

The overall GRU characteristic equation is represented by

$$P = GRU\left(\sum_{t=1}^{n}[x_{t,} h_{t,} z_{t,} r_t\big(W(t), B(t), \eta(tannh)\big)\right] \tag{10}$$

where W(t) represents the weights, and B(t) denotes the bias weights at the current instant, Zt and rt are the update and reset gates, xt is the input feature at the current state, yt is the output state, and ht is the module's output at the current instant. The pre-processed energy data is utilized to extract temporal features using these GRU networks. The GRU model adapts to various scenarios with significant changes and employs a modified GRU for training. The key equations defining the GRU behavior include the update equation for the hidden state, reset gate, and the characteristic equation involving weights, biases, and gates. In the modified GRU, unlike the standard GRU, the gates (update and reset) are computed using only bias weights, leading to a reduction in the total number of parameters. This makes the model more lightweight and efficient, improving its adaptability to various scenarios without compromising performance.

3.6 Adaptive Learning and Prediction

The proposed learning algorithm combines both Q-Learning and a modified Gated Recurrent Unit (GRU) to predict heart disease. The Markov Decision Process (MDP) is employed to manage data reception at fog nodes by selecting BAN nodes based on high-priority data. To minimize random exploration, pre-computed policies with varying values are used during the initial stages, as outlined in equations (4) and (5). Fog nodes collect input from individual BAN nodes, compute the data for each node, and compare it against pre-defined rules that involve various data priority functions. Q-learning ranks the BAN-IoT nodes according to the adaptive environment and shares the ranking information with other BAN nodes. The reward policy RRR specifies the rewards for actions that select BAN-IoT nodes with high-priority data. The primary goal of the MDP is to identify BAN-IoT nodes with high priority based on the measured patient data. Actions are performed immediately after receiving data frames from the other BAN-IoT nodes. For modelling rewards, a straightforward yet effective strategy is adopted by assigning a value of 1 to those nodes that have achieved the desired energy thresholds.

Mathematically, reward function for this deciding the Emergency BAN-IoT is modified based on Equation (5)

$$\boldsymbol{R(E,d)} = \sum\nolimits_{z_{t+1}\in Z} P^{A_t}_{s_t s_{t+1}} R^{A_t}_{z_t z_{t+1}} |_{z_t=z, A_t=A} \tag{11}$$

$$\textbf{Where } \boldsymbol{s_t = N(s) = \{Max(Sensor\ Values)\}} \tag{12}$$

$$\boldsymbol{s_{t+1} = s_t = N(s) = \{Max(Sensor\ Values)\}} \tag{13}$$

The equation (12) and (13) are mathematical representation of each state of nodes to reach the best rewards.

Steps	Algorithm-2 // Pseudo_Code Proposed Q-Learning
1	Input data = Nodes' Energy, Distance, Data,
2	Output: Energy aware paths, reward function
3	Initialize the Node's Position
4	Initialize the Node's Energy
5	For j=1 to Max_episodes
6	Formulate the s_t using Eqn (12)
7	Initialize the R =0
8	For t=1 to N then
9	If D(i)>D(t) where i=Number of Nodes D(i)-Data From the nodes,D(t)-thershold
10	Select the action A= N(i)
11	Else
12	Select the normal action

```
13    Take action A and generate the next state s_{t+1}
14    Calculate s_{t+1} using equation (13) and reward
      function using equation (11)
15    If s_{t+1} != s_t
16            Set s_t = s_{t+1}
17            Update reward function
18    Else
19    Go to step 9
20    End
21    End
22    End
23    End
```

Once the Fog decides the emergency BAN-IoT nodes based on the rewards, the corresponding nodes communicate with cloud using Fog gateways for the better treatment and recovery process. Table 4 details the hyper parameters used to train the suggested network.

Table 4. *Hyperparameters Used for the Training the Modified GRU Cells*

Sl.No	Hyperparameters	Description
1	Learning rate	0.001
2	No of Epochs	200
3	Batch Size	30
4	No of Hidden layers	200

The hyperparameters, including a learning rate of 0.001 and a batch size of 30, were chosen based on empirical results from several trials. This selection aimed to balance convergence speed and model accuracy for better generalization to unseen data.

4. Results and Discussions

4.1 Experimental Setup

The proposed framework is implemented on an Intel i7 CPU with a 256 GB SSD, an 8 GB NVIDIA GPU, and 8 GB of RAM, operating at a frequency of 3.25 GHz. IFogSim is utilized to record datasets from the IoT-BAN-Fog environments. IFogSim is a Java-based API that runs on the Eclipse IDE. Approximately 100 nodes were deployed, interfacing with three medical sensors: ECG, pulse, and motion sensors. Table 5 presents the simulation parameters used for the experimentation. A total of 15,479 raw data points were recorded, encompassing seven attributes, and were used for training the network. The proposed training network was developed using TensorFlow libraries with the Keras API and trained on Google Colab. The selected hardware, including high-performance GPUs and ample memory, efficiently handles large datasets and complex computations, accelerating model training. The configuration is compatible with deep learning libraries like TensorFlow, optimizing performance while also considering energy efficiency to reduce costs.

Table 5. *Parameters of Simulation Used in the Experiment*

S.No	Simulation Parameters	Specifications
1	No of Nodes deployed	100
2	No of Fog gateways	05
3	Initial Energy in each BAN Nodes	0.0016 Joules
4	Distance variation from each BAN nodes	5-10metres
5	Transceivers Equipped	WIFI
6	Uplink Bandwidth	200 Mbps
7	Downlink Bandwidth	100 Mbps
8	RAM in Fog gateways	2GB
9	No of Attributes recorded	07

4.2 Evaluation

The proposed algorithm was evaluated in two parts: prediction performance and QoS performance. Metrics such as accuracy, precision, recall, specificity, and F1-score were assessed during the predictive accuracy analysis and compared with other current deep learning-based Fog-BAN systems. The mathematical formulas used to evaluate the improved GRU's prediction performance in identifying heart attacks are shown in Table 6. Additionally, network-centric metrics such as energy usage, latency, and throughput are calculated and compared against other existing methods.

Table 6. *Mathematical Expression used for Calculating the Performance Metrics*

SL.NO	Performance Metrics	Mathematical Expression
01	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Sensitivity or recall	$\frac{TP}{TP+FN}$ x100
03	Specificity	$\frac{TN}{TN+FP}$
04	Precision	$\frac{TN}{TP+FP}$
05	F1-Score	$2.\frac{Precison * Recall}{Precision + Recall}$

TP is True Positive Values, TN is True Negative Values, FP is False Positive and FN is False negative values

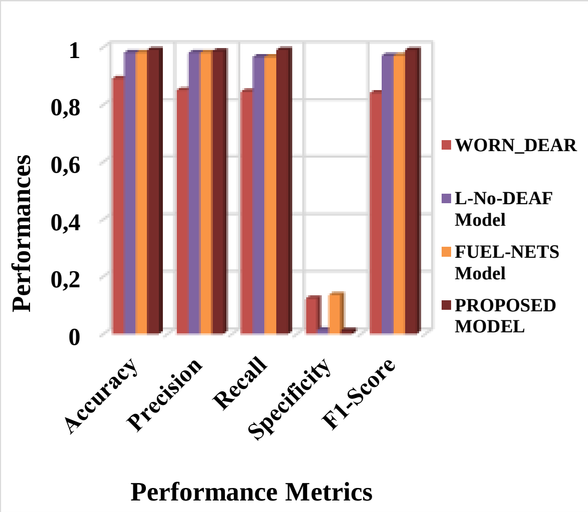

Figure 6. *Comparison of the Proposed DL method's Performance with 20% Test Datasets*

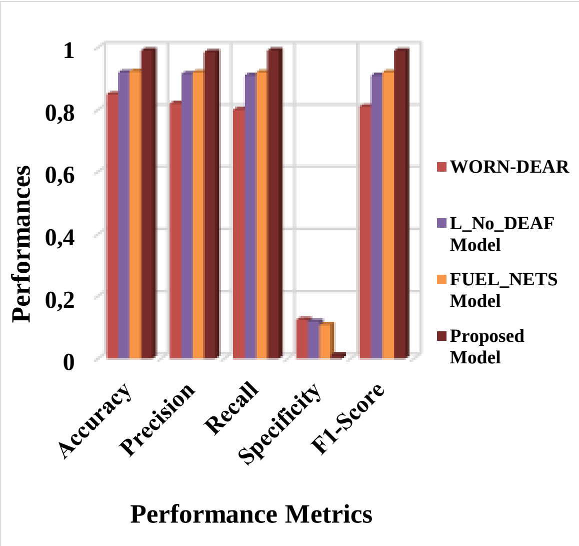

Figure 7. *Comparative Performance of the Proposed Deep Learning Algorithm with 30% Test Dataset*

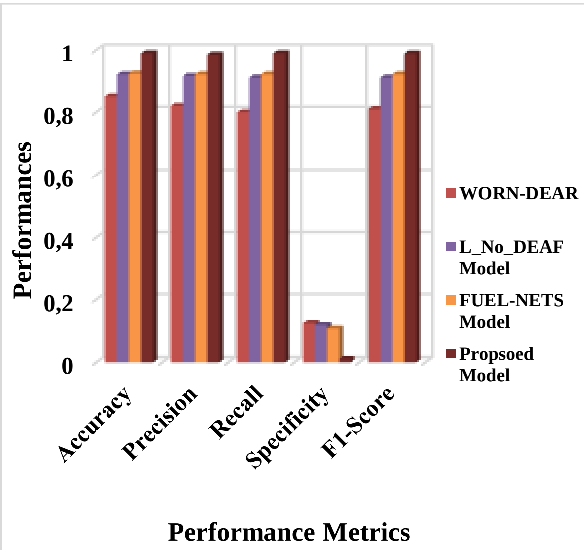

Figure 8. *Evaluation of the Proposed DL method's Performance with 40% Test Datasets*

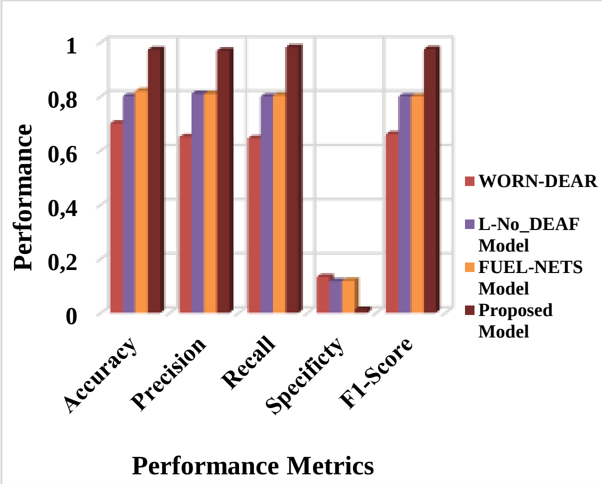

Figure 9. *Comparative Performance Analysis of the Proposed DL method with 40% Testing Data*

Figures 6-9 illustrate the performance of various deep learning architectures used in Fog-BAN networks. Figure 6 demonstrates that the proposed Q-BODYNETS and FUEL-NETS, along with L-No-DEAFNETS, show promising performance in predicting heart attacks. In contrast, the WORN-DEAR algorithm produced the least effective predictions. Figures 7-9 reveal that the performance of other existing algorithms declines gradually as the number of testing datasets increases, whereas the proposed Q-BODYNETS maintains stable performance despite the growing dataset size. Notably, Q-BODYNETS and FUELNETS exhibit similar performance as the dataset size increases from 10% to 30%. However, Q-BODYNETS outperforms FUELNETS when the dataset size reaches 40%, as shown in Figure 9. Overall, these results indicate that the proposed method, integrating Q-learning with a modified GRU, demonstrates superior performance in predicting heart diseases. The accuracy of these predictions directly impacts patient outcomes by ensuring timely and precise diagnoses, leading to quicker interventions and improved treatment plans. This minimizes potential errors, reduces complications, and enhances overall patient care. The second phase of the evaluation involves calculating and comparing QoS characteristics with other existing techniques, focusing on metrics such as energy usage, latency, and packet delivery ratio (PDR). Figure 10 shows the energy consumption of various existing algorithms compared to the proposed algorithm. In this evaluation, residual energy is calculated over three minutes as the number of nodes increases. Figure 10 clearly illustrates that the proposed Q-BODYNETS uses only 32% of energy, even as the node count increases from 20 to 100. In comparison, FUELNETS consumes 56% of energy, L-No-DEAF consumes 65%, while WORN-DEAR and DARE utilize 68% and 75% of energy, respectively. This indicates that the inclusion of adaptive Q-learning produces the most promising results compared to non-adaptive deep learning algorithms.

Figure 11 presents the packet delivery ratio (PDR) of the different algorithms, calculated by comparing input data bytes transmitted to data received. From Figure 11, it is evident that Q-BODYNETS achieves the highest PDR of 99%, while FUEL-NETS and L-No-DEAF NETS achieve good PDRs of 92% and 90%, respectively. WORN-DEAR and DARE algorithms perform the least, attaining PDRs of 72% and 70%. This trend shows that the absence of intelligent methods in the WORN-DEAR and DARE algorithms leads to lower PDRs as node counts increase. Furthermore, the lack of adaptive characteristics in FUEL-NETS and L-No-DEAF NETS results in degraded performance (from 100% to 92%) as the number of datasets increases. Overall, Figure 11 illustrates that the integration of adaptive learning yields better PDR than existing algorithms. Figure 12 illustrates the delay analysis for various algorithms in transmitting medical data to fog gateways. Latency is calculated based on the time taken for data to arrive from reconfigured nodes to the fog gateways, as recorded in iFogSIM. The performance trends observed in Figures 10 and 11 are similarly reflected in Figure 12, where the proposed Q-BODYNETS achieves lower latency even as the number of nodes increases. The proposed model demonstrates scalability with larger datasets and diverse medical conditions. However, as the dataset size grows, adjustments to the model architecture (e.g., increasing the number of hidden layers or units) and optimizations in training time will be required.

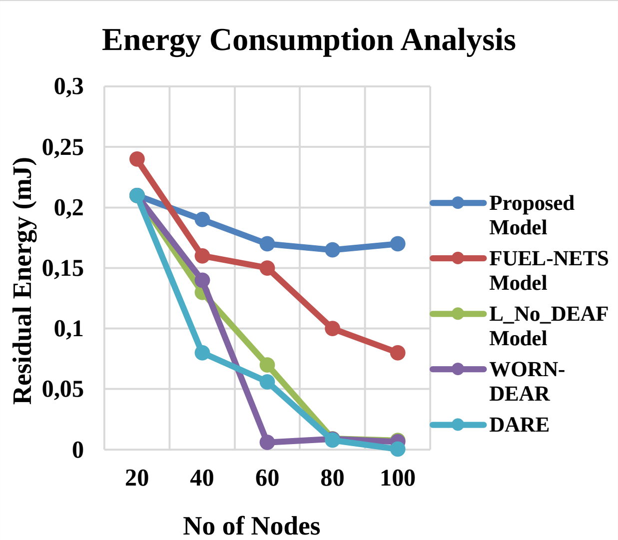

Figure 10. *Energy Usage of Different learning-based Fog-BAN networks for the increased number of Nodes.*

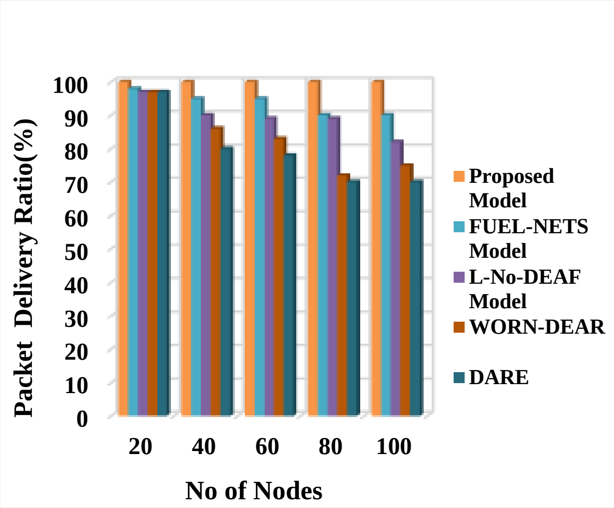

Figure 11. *Packet Delivery Ratio (PDR) of the Different learning-based Fog-BAN networks for the increased number of Nodes.*

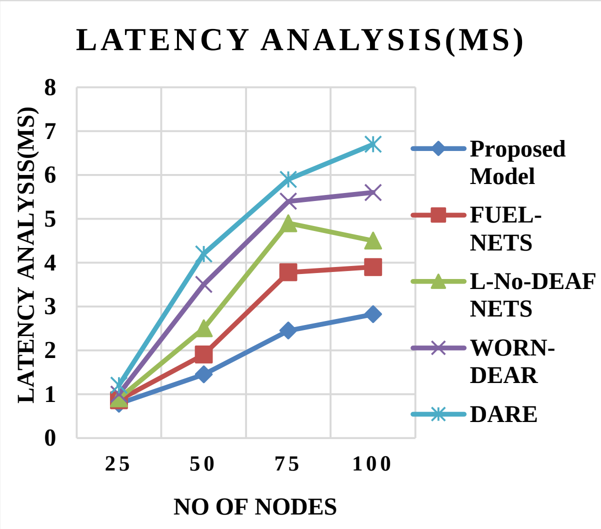

Figure 12. *Latency Analysis of the Different learning-based Fog-BAN networks for the increased number of Nodes.*

5. Conclusion And Future Enhancement

This work demonstrates our efforts to deploy a novel strategy for intelligent fog gateways in BAN-IoT networks, aiming to achieve optimal QoS performance and high prediction accuracy. The paper introduces a unique dataset collection method using iFogSim and the Eclipse IDE. Furthermore, we present Q-BODYNETS, a novel approach that integrates Q-Learning and modified GRU networks to facilitate QoS-enriched transmission and enhanced prediction accuracy. Specifically, the proposed algorithm effectively adapts to dynamic changes within the BAN environment, leading to improved performance. Extensive experimentation was conducted, during which 15,473 datasets were collected and utilized for training the network. To validate the effectiveness of Q-BODYNETS, its performance was compared with other intelligent Fog-BAN networks, such as FUEL-NETS and L-No-DEAFNETS, as well as non-intelligent methods like DARE and WORN-DEAR. The experimental results indicate that Q-BODYNETS outperforms existing algorithms in terms of energy efficiency, latency, packet delivery ratio (PDR), and prediction accuracy.While the proposed Q-BODYNETS has demonstrated promising performance in BAN networks, its training time is slightly higher compared to other deep learning algorithms. Therefore, there is a need for robust optimization techniques to further enhance the proposed algorithm's energy efficiency and reduce delay. Additionally, testing the proposed network in real-time environments is essential for the effective implementation of smart healthcare applications. Deploying a Fog-BAN network for healthcare requires initial hardware investments in Fog nodes and sensors, along with ongoing costs for energy and software updates. Seamless integration with hospital management and cloud platforms is essential, and future research should enhance compatibility with electronic health records, which can be adapted to monitor other chronic conditions such as diabetes and hypertension, as well as improve data security.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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