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Research Article

Developing IoT Performance in Healthcare Through the Integration of Machine Learning and Software-Defined Networking (SDN)

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ABSTRACT

In this era of rapid growth of the Internet of Things (IoT) in healthcare, the networking solution must be robust and efficient for smooth data transfer and the network. It is very well established that Deep Learning (DL) is a subset of Machine Learning (ML) and has shown great promise in enhancing network performance through intelligent data analysis and making smart decisions. The wide deployment of Wireless sensor networks and Mobile ad hoc networks (MANET) is why they are used in healthcare applications, as they offer low-cost deployment and real-time data exchange. Nevertheless, WSNs suffer limitations in energy availability due to their inherent constraints. However, the energy consumption in a WSN routing is a significant problem because of resource limitations. Integrating ML in a Software Defined Networking (SDN) framework shows the possibility of network resource optimization and a sustainable network architecture. Typically, conventional routing annoys most about shortest path algorithms, where nodes are used unevenly, and critical nodes die early from battery depletion. This work proposes a new DRL-based algorithm for maximizing traffic distribution and maintaining energy consumption equilibrium across the nodes in WSNs to improve their lifetime. The model proposes dynamically changing routing paths to preserve the nodes' loading with a limited power supply system to persist the network lifespan and thus improve efficiency. However, the approach adds some hops to the average packet transmissions per hop. Still, it delays the first node's energy depletion long enough to provide sustained network operability in IoT-driven healthcare environments. The experimental results validate the effectiveness of the proposed method in furthering the network functionality and reliability for data transmission, thereby making it a viable solution for the next generation of IoT healthcare networks.

1. INTRODUCTION

The rapid growth of the IoT in healthcare has resulted in the need for adaptive and intelligent networking solutions. Currently, the new networking architectures like the MANETs use static routing protocols, which are not very flexible enough to cope with the dynamic network topologies. This is due to the constantly increasing need for real-time continuity in data transmission in healthcare applications. The constraints associated with these constraints are addressed by SDN, which separates the control and data planes, thereby enabling centralized control over the network resources. Unlike traditional networks, SDN uses a centralized controller, which dynamically routes packets to their destination following real-time network conditions and packet characteristics [1]. Network energy constraints lead to the problem of optimizing routing in WSNs. Recently, ML techniques have become incorporated into SDN controllers to increase the optimization of mechanisms, especially in complex WSN environments, including efficient routing. Although the majority of previous work on routing has predominantly relied on shortest-path algorithms that can cause congestion of the network and unbalanced energy consumption among nodes [2], new types of routing strategies, including adaptive bandwidth allocation and asymmetric throughput, have been developed recently to address shortcomings like congestion, bottleneck and unbalanced energy consumption. As healthcare IoT networks are dynamic, intelligent routing mechanisms that consider energy efficiency, network load, and real-time traffic conditions are needed. Thanks to ML assistive routing optimization, SDN can always tune routing strategies for best resource utilization, minimize latency, and extend network life [3].

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This study presents a novel solution to WSN resource optimization within an SDN by leveraging DRL to assist a C-R for intelligent routing. RL is a good fit in dynamic environments because the strategies are learned from network interactions during each period in a way that adapts to observed conditions [4]. RL techniques train a neural network (NN) to predict the optimal routing paths, considering the node energy level, to avoid early malfunctions of the specific nodes. With this approach, SDN controllers can make energy-aware routing decisions to improve the network's energy efficiency and sustainability. This research aims to increase the life of WSNs in IoT-driven healthcare applications by using an RL-based routing strategy. A method is proposed in which data traffic load is balanced dynamically among the sensor nodes to reduce the energy consumption discrepancy and the premature failure of nodes. The proposed RL can learn with a reward-based mechanism that prioritizes energy-intensive routes, thus minimizing energy-intensive transmissions and ensuring optimal data flow across the network [5]. Conventional ML models require offline training, and so are static. At the same time, the RL-based approaches are adaptive to learning in real time and continue optimizing as they see the network conditions changing. Section II reviews the related work in SDN, ML-based routing, and energy-efficient WSN. The proposed DRL-based networking methodology is detailed in Section III, including the model architecture and the training. The performance of the proposed approach is demonstrated with experimental results and performance evaluations in Section IV. Finally, Section V concludes with core findings and research options for future work.

2. RELATED WORKS

In recent years, SDN, ML, and WSN integration has received considerable attention because it allows an adaptive and energy-efficient communication framework for IoT-driven applications such as healthcare. This is followed by a review of the existing works for SDN-enabled WSN architectures, ML-based routing schemes, and energy-optimized topology design to increase the longevity of the networks.

Unlike traditional WSNs, most dynamic and decentralized routing protocols in static WSNs tend to suffer from less efficient resource utilization with high latency and scalability problems. SDN has been recognized as a promising paradigm for addressing these challenges by introducing a logically centralized control plane that provides the network with global state awareness [6]. While traditional WSNs allow for static best-effort packet forwarding, SDNs address this problem via policy enforcement flexibility and real-time network optimization reconfiguration. The application of SDN in WSNs has been explored in several studies to improve network control and adaptability. In [7], an SDN-based WSN framework is proposed that dynamically changes the routing paths according to the network conditions to address the network congestion and improve transmission efficiency. Likewise, [8] presented an energy-aware routing protocol controlled by SDN to increase network lifespan by prioritizing nodes with more incredible residual energy. However, these methods are primarily based on pre-defined routing heuristics and may not be sensitive enough to the characteristics of dynamic healthcare applications.

It has been widely explored how to integrate ML techniques in SDN-based WSNs to improve decision-making and enhance routing efficiency. The shortest path routing and heuristic-based approaches do not change dynamically due to network variations. Adaptive routing decisions have been improved to some extent by ML models - specifically, supervised and reinforcement learning approaches have been proven beneficial. In the study [10], a Q-leaning-based routing mechanism is proposed to enhance the SDN controllers to apply learned optimal paths according to the historical performance of the network. They achieved successful packet loss rate reduction and overall throughput improvement. This Q learning is based on discrete state action mapping, which may not help much in a complex IoT environment. Since routing is often formulated as an optimal control problem, [11] proposed a DRL-based routing model based on deep neural networks to approximate optimal routing policies to overcome this limitation. Improving both energy efficiency and end-to-end delays was their result. However, deploying DRL models in resource-constrained WSNs is difficult due to the extensive training data requirements and computational resources required in DRL models.

Using sensor nodes with a limited battery capacity still makes energy consumption crucial in WSNs. Previous studies have proposed energy-aware routing protocols to minimize network lifetime. As part of the clustering-based approaches, the Low Energy Adaptive Clustering Hierarchy (LEACH) is widely used to lower energy dissipation by forming the sensor nodes into clusters [12]. Nevertheless, the LEACH-based approach suffers from scalability issues and irregular energy consumption. However, the results of recent ML-based energy-efficient routing have been promising. In [14, 13], they introduced an energy-aware RL-based routing protocol that dynamically chooses the next node for forwarding from the set based on energy levels and traffic conditions. As a result, their method significantly increased the lifespan of the network in comparison to the traditional routing schemes. In addition, hybrid approaches integrate SDN, ML, and energy-efficient techniques to locate optimal resource allocation in the network. The result of [15] is a DRL model of SDN integration for energy balancing between sensor nodes, having better longevity and reliability of the network.

Though SDN-enabled WSNs and ML-based routing mechanisms are progressing more, the research gaps are left unaddressed. Most existing studies optimize routing without the dynamics of energy constraints of WSN nodes. In addition, DRL-based models enable adaptive learning at the expense of the computational cost, leading to challenges in the real-time deployment of the models in the IoT healthcare environment. Furthermore, no complete solutions can enable SDN, use ML, and integrate energy-aware routing in a single framework. A concise comparison of different methodologies is given in Table 1, alongside contributions and limitations. It is found that while SDN improves the network management task and ML improves routing efficiency, a DRL-based unified SDN framework is required to provide energy-aware, adaptive, and scalable routing solutions for WSN-based IoT applications.

TABLE I. COMPARATIVE ANALYSIS OF RELATED WORKS

Ref.	Approach	Key Contributions	Limitations
[7]	SDN-Based WSN	Dynamic routing adjustment to improve packet delivery	Lacks energy-aware optimization
[8]	Energy-Aware SDN	Prioritizes nodes with higher residual energy	Does not integrate ML for adaptive learning
[10]	Q-Learning-Based Routing	Optimizes path selection based on historical data	Limited scalability in complex IoT environments
[11]	Deep Reinforcement Learning (DRL)	Uses deep learning to improve adaptive routing	High computational requirements
[13]	Hybrid SDN-ML Approach	Integrates ML for real-time decision-making in IoT networks	Requires large-scale datasets for effective learning

This study proposes a novel DRL-based SDN framework for resource consumption optimization in WSNs used in IoT-driven healthcare applications to fulfill these limitations. As shown in Figure 1, it contains an adaptive architecture, a reinforcement learning-based energy-aware routing strategy, and comprehensive evaluations of existing techniques to improve the reliability and sustainability of the WSN.

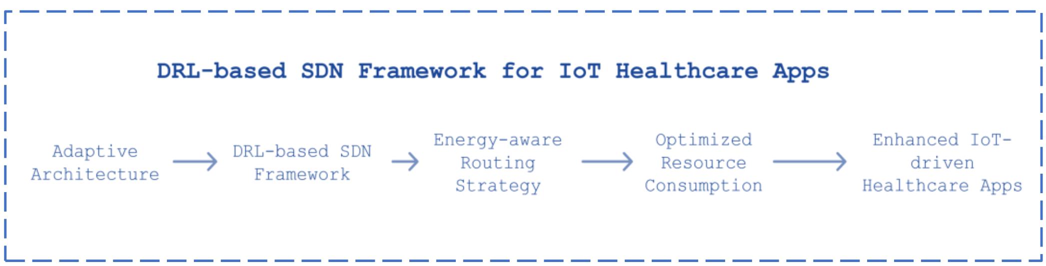

Fig. 1. Overview of the DRL-based SDN framework for optimizing resource consumption in WSNs within IoT-driven healthcare applications.

3. PROPOSED DRL-BASED ROUTING METHODOLOGY

With that, IoT-driven healthcare applications have been developing rapidly and are significantly demanding WSNs for real-time data collection, transmission, and processing. WSNs are an essential tool in the healthcare environment; they have been used as an integral aspect of applications such as patient monitoring, emergency response, and remote diagnostics. However, the limited battery life of the sensor nodes keeps energy efficiency and network longevity as the major obstacles. In this work, we argue for an SDN-based routing approach that enables DRL to optimize the energy consumption and reliability of a network used in healthcare IoT systems. The proposed method in the Health Monitoring network scheme makes achieving dynamic packet forwarding possible without excessive energy depletion in sensor nodes, guaranteeing sustained operation. A typical IoT Healthcare WSN topology is illustrated in Figure 2, which presents how medical sensors work with relay nodes and a central gateway to disseminate data.

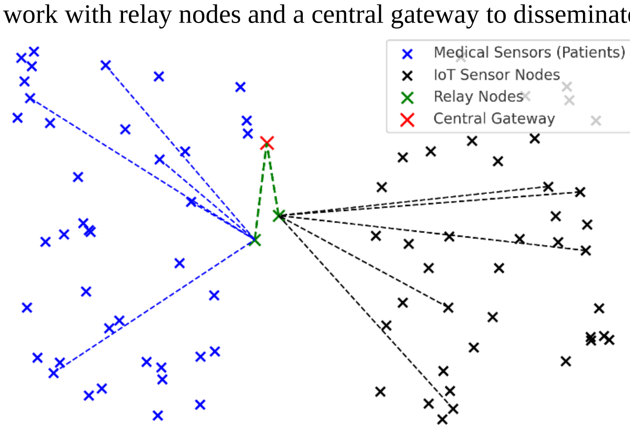

Fig. 2. IoT Healthcare WSN topology, showcasing medical sensor connectivity.

3.1. Model Architecture and Feature Representation

In this approach, SDN-enabled WSN is coupled with ML steps to increase the efficiency of packet routing and thus prolong the network's lifespan. The model utilizes a Feedforward Neural Network (FFNN) to predict forwarding rewards according to real-time network conditions and node energy levels. Even more critical in IoT-based healthcare networks is that medical sensors must communicate with healthcare providers 24/7. Input to the FFNN is a one-dimensional vector that summarizes the current state of the network with the following key attributes:

a) **Remaining energy of each node**: IoT healthcare applications need the remaining energy to prevent the nodes from early failure in medical monitoring networks.
b) **Distance from each node to the source:** This guarantees efficient data gathering from IoT-based medical sensors in real-time from nodes at a given distance from each node to the source.
c) **Distance from each node to the destination**: Supports uninterrupted communication between wearable sensors and healthcare servers.
d) **Packet transmission time**: Ensures low latency for time-sensitive healthcare applications, such as ICU monitoring.
e) **Nodes traversed by the packet**: Prevents routing loops which maintain the data integrity in electronic health record (EHR) systems – Nodes traversed by the packet

For the input, we have 5N attributes, where N is the number of sensor nodes of the network, capped at 100 for standardization. The output layer in the FFNN comprises 100 neurons; each neuron denotes a possible forwarding node. Based on this, the next hop is selected as a node with the highest output value for efficient and energy-aware packet delivery in healthcare IoT systems.

Hence, for energy-efficient and adaptive routing to work ideally in IoT-based healthcare networks, FFNN is used within the SDN framework. An FFNN was designed to process real-time network parameters and predict optimal routing decisions regarding energy consumption, network topology, and packet transmission cost. Thus, the proposed model dictates intelligent packet forwarding in WSNs to prevent low energy depletion and low latency data transmission of medical data. A total of dense layers stacked sequentially together are used to construct the FFNN model, in which each layer extracts spatial and temporal features from the input data for optimally predicting the next-hop nodes. The first layer passes the network status and node-specific attributes, and the subsequent ones perform nonlinear transformations and weight adjustments to refine the decision. The last layer has 100 output nodes, each representing a forwarding node, and the node with the maximum value would be selected as the optimal next hop. The adaptability and scalability of the model are guaranteed due to its structure. They can be used for several IoT healthcare scenarios, such as patient monitoring, emergency response systems, and wearable medical sensor networks. The detailed FFNN configuration for the framework of IoT healthcare-based SDN is outlined in Table 2.

TABLE II. FFNN IMPLEMENTATION DETAILS

Layer	Output Shape	Parameters
Dense-1 (512)	(None, 512)	256,512
Dense-2 (256)	(None, 256)	131,328
Dense-3 (128)	(None, 128)	32,896
Dense-4 (100)	(None, 100)	12,900
Total Parameters	**433,636**	**Trainable: 433,636**

Figure 3 illustrates the FFNN architecture, highlighting the interaction between input features, hidden layers, and the output layer, which collectively optimize data transmission in IoT healthcare networks.

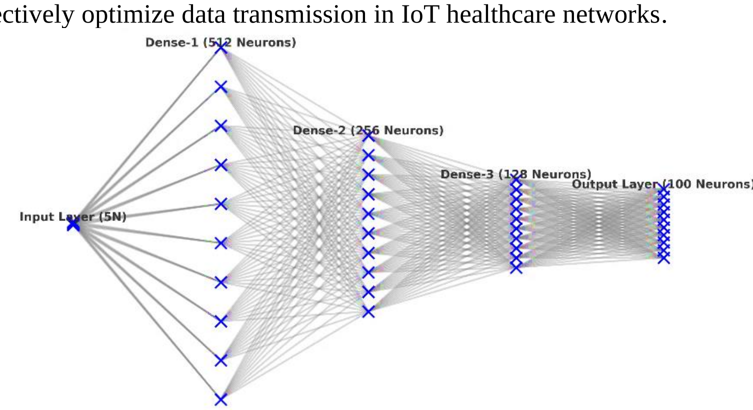

Fig. 3. FFNN Architecture for IoT-Driven Healthcare Data Transmission.

3.2. IoT-Based Packet Forwarding Algorithm for Healthcare Networks

To efficiently transmit data for IoT in healthcare systems, a 2D representation of node connectivity and packet traversal history is created so that the neural network can learn routing decisions effectively.

Algorithm 1: Packet Forwarding in IoT-Enabled Healthcare Networks

Input: List of hops, node locations
Output: 2D representation of hops
1. Initialize a 100×100 matrix with a default value of -1.
2. For each hop in the packet's route:
   - Identify the current node's location in the healthcare WSN.
   - Assign a normalized value (between 0 and 1) based on the packet's journey.
3. Return the updated matrix, ensuring optimal routing in real-time patient monitoring applications.

This technique also prevents the wastage of energy incurred by continuously transmitting the IV and vital signs through wearable IoT sensors to medical servers without further causing a delay in transmitting the information.

3.3. Training Process of DRL Model in IoT Healthcare Networks

The proposed DRL model is designed to train the model to fine-tune the routing decisions and deal with energy restrictions in WSNs employed in IoT Healthcare systems. The proposed method goes beyond traditional routing forests to minimize hop count. Still, it incorporates energy-aware decision-making so the network utilization is more balanced and nodes have a longer lifetime. In the healthcare context, this is particularly important as the processing of continuous sensor data is needed for different patient monitoring, ICU surveillance, and emergency alerts in real-time. Learning is reinforcement learning, and the model learns optimal routing strategies through interacting with the environment.

1) Exploration and Exploitation in Routing for the Internet of Things

However, neither the DRL model based on FFNN nor the initial training process possess prior knowledge of optimal routing paths during the early stages of training. Incorporated in the planning model is a random exploration that ensures that the model does not become biased towards a set of paths to follow. With this choice of packet forwarding, packet forwarding decisions are made randomly in the early training iterations so that the network can explore different routing possibilities. The exploration phase is crucial for finding alternate paths to better energy efficiency and load distribution in a healthcare sensor network.
During training, the model learns to start from random exploration to exploitation; with increasing training, it slowly relies on FFNN predictions for deciding. Through this transition, routing paths are chosen according to what has been learned, sending packets in a way that conserves energy while delivering packets. The system continually adjusts the tradeoff between exploration and exploitation by gradually decreasing the probability of making random decisions so its learning ability gets refined without becoming stuck to suboptimal solutions too early. This achieves optimal energy-aware routing for mission-critical healthcare applications like wearable IoT sensors, patient monitoring in real-time in a remote location, and real-time care alert systems in ICU.

2) IoT packet routing in healthcare requires a reward function.

A reward function is designed to score the quality of routing decisions on which to train. Specifically, the reward function is designed such that packets are forwarded through nodes that have the best efficiency and sustainability of the network. It has to take into consideration the following key factors as a reward function:

a) Sensor node failures are prevented in patient monitoring systems by prioritizing nodes with higher energy reserves.
b) Prevent redundant packet forwarding and provide low latency for real-time ICU monitoring.
c) Critical for emergency healthcare alerts in IoT medical networks, packet delivery should be ensured reliable.

The reinforcement learning model learns to prioritize communication paths that maximize network longevity and reliability by including these criteria. As such, it is well suited for mission-critical healthcare IoT uses.

3) Q-Learning Update for Healthcare IoT Networks

An FFNN model is continuously updated with routing decisions using the Q-learning algorithm so that the system can adapt to real-time changes in the network. Specifically, the expected reward (Q value) to take action for each training step is updated based on the current routing decision and resulting network state. The standard Q learning formula is followed for an update of the Q value:

$$\text{Original } Q(s,a)=Q(s,a)+\propto(R(s,a))+\gamma \max Q^{\wedge\prime}(s^{\wedge\prime},a^{\wedge\prime}) \quad (1)$$

Where:

- $Q(s, a)$= Expected reward for action aa in state ss.
- $\mathrm{R}(s, \mathrm{a})$ = Immediate reward for forwarding the packet.
- γ= 0.9 (discount factor), prioritizing long-term network stability **in** IoT healthcare applications**.**
- α= Learning rate, ensuring adaptive routing in medical sensor networks**.**

The training process of the Q learning algorithm allows the FFNN model to adapt dynamically to the change in IoT-driven healthcare networks. Over successive iterations of training, the Q values of the model are updated and refined to help the model make better decisions about packet routing. In addition to using this iterative learning procedure to stabilize the network and optimize the transmission efficiency of data under circumstances where lifelike data have to be monitored in a critical healthcare setting, such as ICU monitoring, remote patient monitoring, and emergency medical alert systems, there is also the necessity for these devices to run on batteries as a consequence of their intervention. Overtraining, the model shifts away from randomly exploring and prefers policies that lead to long-term energy efficiency and PDR. The Q value update equation enables the model to learn to give higher rewards to optimal routing paths faster and make a better decision. The training convergence graph, the progression of the expected reward (Q value) over several iterations, is shown in Figure 4. The graph results show the model convergence point; that is, the model can stabilize routing decisions at the expense of low latency and low energy-efficient packet forwarding in IoT healthcare networks.

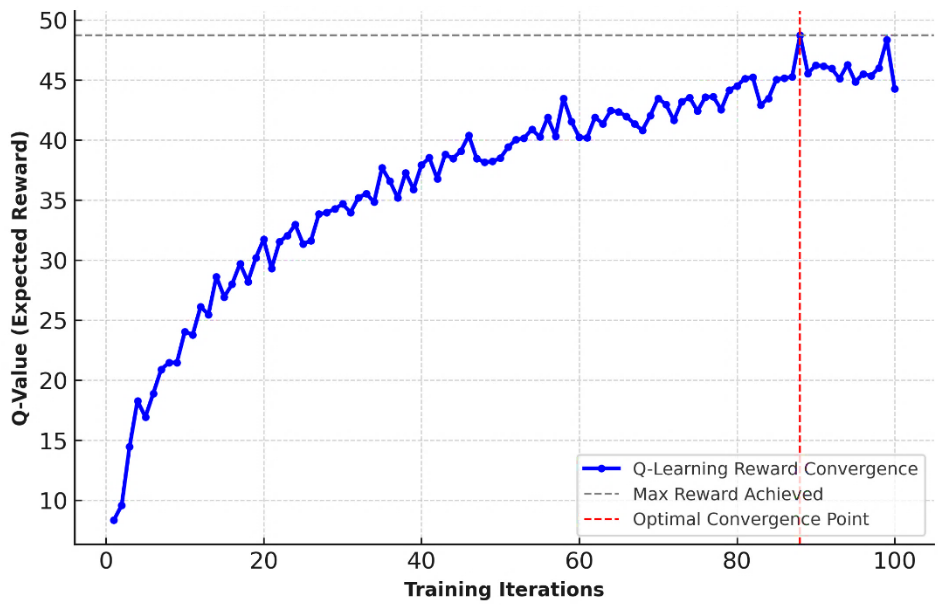

Fig. 4. Training Convergence Graph.

3.4. Training Termination Conditions in IoT Healthcare Environments

The DRL model is trained until all nodes run out of their energies or a critical failure occurs during the immediate re-training process. In IoT healthcare applications, where there must be uninterrupted data transmission from medical sensors to healthcare providers, it is necessary to ensure that an application is robust and adaptive in the learning mechanism [16]. Unlike static routing protocols that may fail in a dynamic environment, the proposed DRL-based routing model keeps checking the network condition and changes the routing strategy to obtain the highest network longevity [17].

Certain situations may trigger immediate re-training to avoid healthcare data transmission problems. If the first node becomes unreachable, we must find an alternative routing path to prevent any disruption within the patient monitoring system [18]. In real-time healthcare applications, if we talk about ICU monitoring or wearable IoT medical devices, it is essential to have continuous data transmission to provide accurate diagnostics and timely medical interventions. Second, forwarding a packet to an energy-depleted node may cause network partitioning, leading to delay or failure in systems such as emergency alerts or vital sign tracking systems [19]. It proactively routes around low-energy nodes to increase network resilience in the healthcare environment [20].

The DRL model also integrates a loop detection function to avoid redundant transmissions of packets, which may happen when suboptimal routing decisions are made. The routing loops excessively increase energy consumption and network congestion, which adversely affect the healthcare IoT system, where low latency data transmission is required [21]. The

model achieves efficient resource utilization, resulting in a stable, resourceful, and responsive network by introducing loop prevention strategies. In addition, excessive hop counts (i.e., more than 100 hops) immediately re-train the data delivery to ensure that medical data is delivered promptly. Reducing this delay is a prerequisite for healthcare applications where small transmission delays can translate into severe health conditions [22].
This method's adaptive learning process strengthens the network resilience, allowing for intelligent packet forwarding and energy-efficient and unbroken healthcare IoT communication. The proposed DRL-based routing methodology uses ML-driven decision-making to optimize SDN-based WSN architecture by integrating ML-driven decision-making within SDN-based WSN architecture for IoT healthcare applications [23]. The main contributions of the proposed approach are:

a) Energy-aware routing optimizes power across network nodes to prevent sensor depletion in continuous patient monitoring systems.
b) Based on real-time adaptive packet forwarding by dynamically changed network condition characteristics in healthcare IoT environment, reinforcement learning-based optimization.
c) Low latency, minimizing the delay in transmitting medical data—significant for emergency medical data alerts and monitoring systems in the ICU.
d) By uniting the Scalable SDN framework with ubiquitous medical data exchange among distributed IoT healthcare networks, interoperability and reliability in data exchange are enforced.

In the next section, we demonstrate the results from our experimental framework, using the proposed DRL-based routing model in real-world healthcare scenarios. The model's performance is validated based on network lifetime, energy consumption, packet delivery ratio, and transmission delays [23-30].

4. EXPERMENTAL RESULTS AND PERFORMANCE EVALUATIONS

This section presents the experimental results and performance evaluation of the proposed DRL-based SDN routing model for IoT healthcare networks. A performance illustration compares the proposed model with existing state-of-the-art techniques using key performance metrics such as network lifespan, PDR, and average hops per packet transmission. Below, we detail the experimental setup, performance analysis, and results.

4.1. Experimental Setup for IoT-Driven Healthcare Networks

A Python-based WSN simulation on a Windows system (Intel® Core™ i7-7700, 2.8GHz, 16GB RAM) was used to evaluate the proposed FFNN-based routing model using Keras as the model training framework. Healthcare environments were represented as WSNs with randomly generated IoT-enabled WSNs, with each sensor lying in a 1000 × 1000 m² area. To generate WSNs for network configuration, sensor nodes equal to 8, 16, and 32 were randomly distributed over a 1000 × 1000 m² area. At 2 Mbps network speed and 1024bytes packet size, data was simulated and sent in the network. The model of energy consumption was defined as follows:

- Nodes: 8–32 IoT medical sensors (e.g., wearable health monitors, ICU telemetry devices).
- Data Rate: 2 Mbps, Packet Size: 1024 bytes.
- Energy Model: 5×10^ −9 J per transmission, Initial Energy: 1 J per node.
- Idle Energy Consumption: 10^ −10 J/s, Transmission Range: 300 m.

For fairness, the FFNN was trained with 100 IoT WSN scenarios at random, and evaluation was made using a test set. The model's performance regarding routing efficiency, network life span, and Packet Delivery Rate (PDR) in IoT healthcare applications is assessed.

4.2. Performance Analysis

The proposed FFNN-based SDN routing model runs 578,382 seconds, significantly longer than Zhing et al. [24] and Stampa et al. [26]. Unlike the above approach by Z. Abbood et al. [31], which had the highest network lifespan (638,169 seconds), they also suffered a larger average hop count (12.37), implying a higher routing complexity. To overperform Rohan Zhing et al. [24] (72.55%), Stampa et al. [26] (64.71%), the PDR of the proposed approach was 83.37%. Nevertheless, Lin [27] obtained a slightly lower PDR (81.68%), and Z. Abbood et al. [31] the same (82.47%). The results of these experiments suggest that the introduced approach can provide a good balance between network longevity and packet delivery success. The results from other approaches are compared with the performance of the proposed method in Table 3.

TABLE III. PERFORMANCE COMPARISON OF ROUTING TECHNIQUES

Technique	Avg hops	Avg lifespan (s)	PDR
FFNN*	8.31	578382	83.37
Lin et al. [27]	9.32	578122	81.68
Zhing et al. [24]	10.53	541840	72.55
Stampa et al. [26]	8.76	520364	64.71
Z.abbood et al. [31]	12.37	638169	82.47

4.3. Network Lifetime and Energy Efficiency

The FFNN-based routing model prolongs network life by limiting energy consumption more equitably to sensor nodes than shortest path routing. Using this strategy results in a slight increase in the hop count. However, it significantly benefits network sustainability, crucial in IoT-based healthcare applications requiring long-term sensor function. The proposed method prevents premature node depletion and maintains continuous data collection and transmission, essential for remote patient monitoring, ICU alert systems, and portable medical devices.

Figure 5 illustrates the Training Loss Convergence Curve of the FFNN Model in IoT Healthcare Networks, where the FFNN-based approach keeps the low-energy node from being overloaded, increasing the network lifetime. Moreover, Figure 6 shows the average number of hops over time, which reveals that though the routing path is generally longer using the proposed method, it secures better load balancing on the link level and network stability on the node level. It is also shown in Figure 7 that the proposed model has high PDR for longer routes, meaning that longer routes do not affect PDR, which is an indication of efficient and reliable data transmission in the healthcare WSNs.

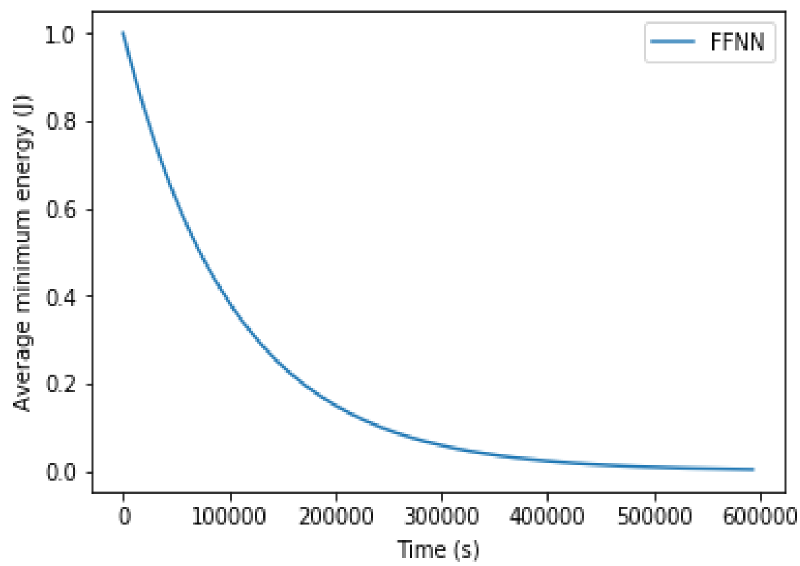

Fig. 5. Training Loss Convergence Curve for FFNN Model in IoT Healthcare Networks.

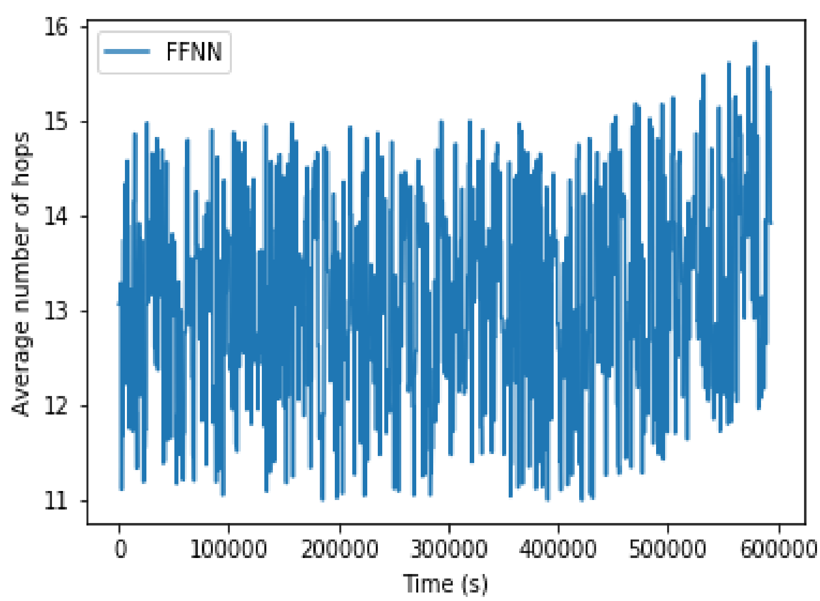

Fig. 6. Average number of hops versus time for routing techniques.

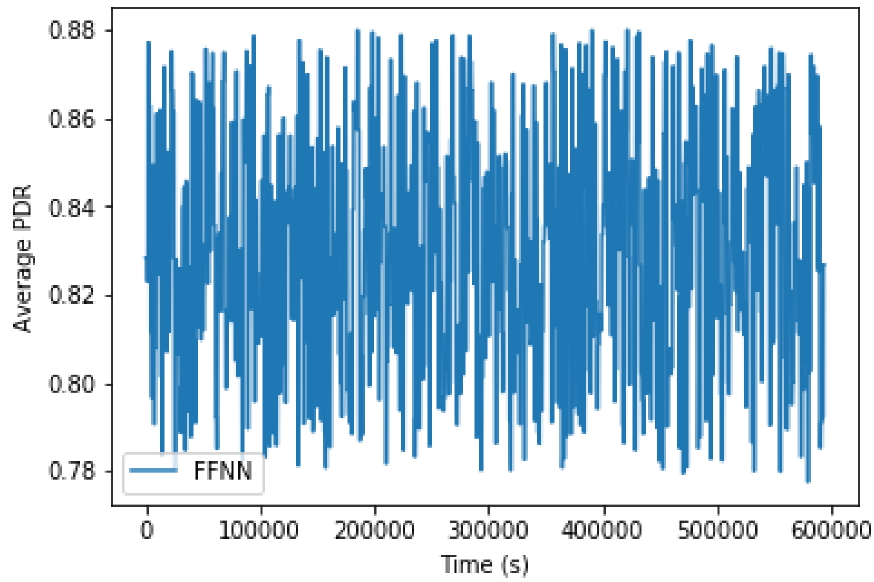

Fig. 7. PDR performance over time.

4.4. Impact on IoT Healthcare Networks

The proposed FFNN-based routing model greatly enhances network longevity and packet delivery reliability and is suitable for real-time IoT healthcare applications. Continuous data collection and transmission are essential in critical scenarios like remote patient monitoring to make an accurate diagnosis and intervene in time. Emergency alert networks also require high PDR to ensure critical urgent medical alerts arrive promptly at healthcare providers. Energy–efficient routing mechanisms for wearable IoT medical devices (e.g., heart rate monitor, glucose sensor) facilitate energy-efficient operations that enable long–term patient monitoring.

The previous figure (Figure 8) is used to illustrate further the effectiveness of the proposed model, where an average number of hops to the base station over different routing techniques shows that the FFNN-based method balances network load while keeping an efficient routing path. The performance of the network lifespan is presented in Figure 9, which shows that the proposed approach extends WSN operational time to a more significant extent than other existing methods. Lastly, Figure 10 presents the PDR and illustrates that the proposed FFNN-based routing model is highly reliable for packet delivery, which is highly important in healthcare IoT networks.

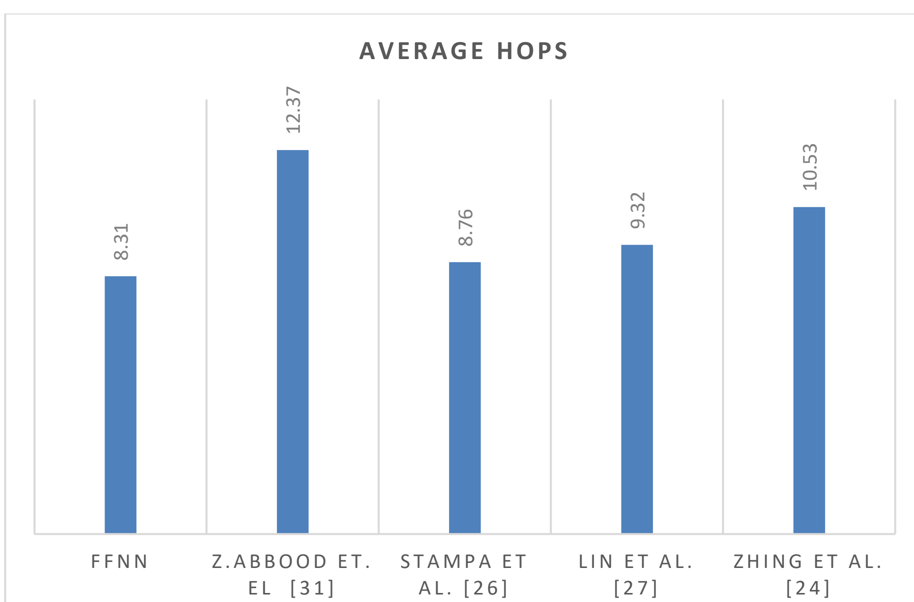

Fig. 8. Comparison of average hops across methods.

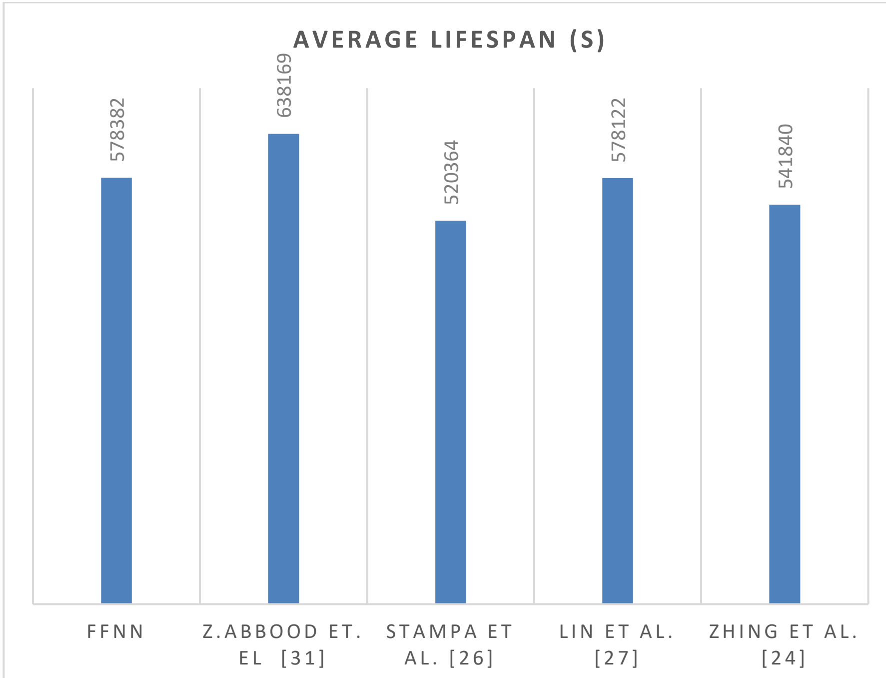

Fig. 9. Comparison of network lifespan across methods.

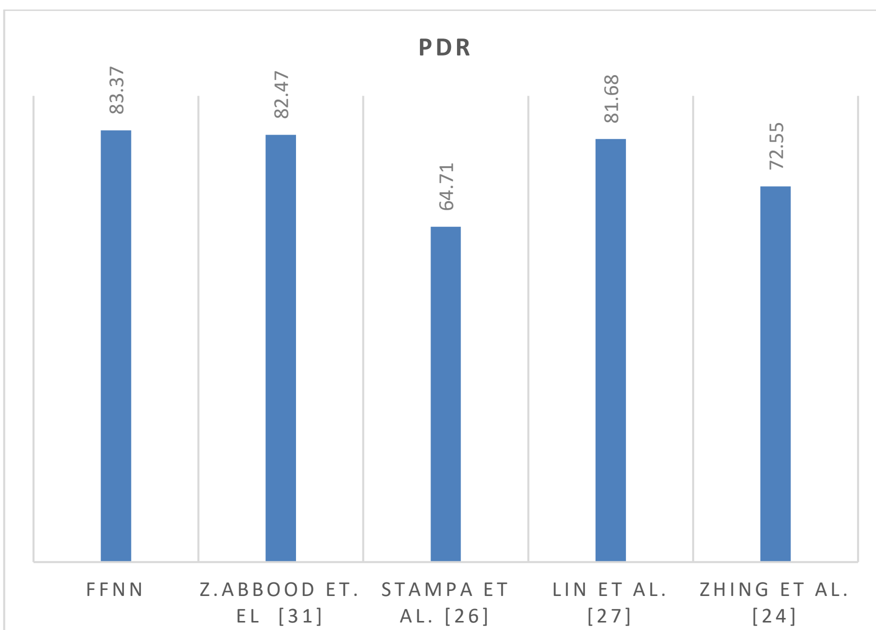

Fig. 10. PDR performance across routing techniques

The proposed FFNN based on routing is present in some cases to extend the routing path but maintains a balance of network energy consumption and network lifespan. However, for IoT healthcare applications, including sustainability of the network over ultra-low latency is not an issue anymore. The above SDN-FFNN framework achieves a more energy-efficient routing mechanism, higher PDR, and operationally more sustainable network, which is appropriate for critical healthcare applications depending on the continuous flow of information. Using the DRL model based on FFNN, no individual node is prematurely exhausted, providing more stable and reliable WSN performance. It was found experimentally that the proposed FFNN-based SDN routing model improves network performance in IoT healthcare environments by extending network lifetime and achieving a high PDR (83.37 %). Energy-aware routing prevents early node failures, resulting in an extended operating network. With slightly longer routing paths, the model delivers most packets with significantly better rates than several existing methods.

4. CONCLUSION

This research presented an FFNN-based routing model as an SDN-enabled WSN architecture to improve packet flow control and network efficiency in IoT-based healthcare applications. The proposed method dynamically balances the network load among the sensor nodes to significantly enhance the network longevity while maintaining a high PDR. Deep learning techniques and the SDN framework can make intelligent routing decisions that save energy consumption and prevent premature early node depletion for real-time patient monitoring, emergency healthcare networks, and wearable medical devices. As stated, the results of the experiments demonstrate that the FFNN-based approach achieves higher performance than traditional routing techniques as it utilizes the concept of network sustainability instead of shortest-path routing. Despite a higher number of hops, this trade offers even energy distribution through all nodes of WSN, increasing its lifespan. The proposed model was shown to have a high PDR and maintain data transmission efficiently and reliably, a key requirement in healthcare IoT networks. Among this study's key findings is that intelligent forwarding of packets via reinforcement learning can balance and avoid overloading specific nodes at the perfect time to prolong network life. WSNs deployed in critical healthcare environments can have higher resilience and extraordinary adaptability to route packets through alternative paths instead of following only the shortest path algorithm. Next, future research will enhance the SDN framework by embedding decentralized decision-making mechanisms wherein each node selects the next hop independently without the constant need for the SDN controller. This approach could be used with optimal routing efficiency yet reduced communication overhead. Also, the computational complexity of neural network models will be optimized to run in real-time in resource-constrained IoT healthcare devices. Furthermore, the proposed model can be further enhanced to address the changing needs of intelligent healthcare IoT systems by refining adaptive learning techniques and reducing dependency on control in centralized.

Conflicts of Interest

The paper states that there are no personal, financial, or professional conflicts of interest.

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