

Develop A Novel Deep Learning Routing with IoT for Improving the Performance of Efficient Data Transmission and Attack Detection in 5G WSN

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DOI: [https://doi.org/10.63001/tbs.2026.v21.i04.S.I\(4\).pp493-514](https://doi.org/10.63001/tbs.2026.v21.i04.S.I(4).pp493-514)

KEYWORDS

*5G; Internet of Things;
 Routing Protocols;
 Data Transmission;
 Deep Learning;
 Attack Detection;
 Wireless Sensor Networks*

Received: 20/09 /2026

Accepted :07/10/2026

Published: 17/10/2026

Abstract

Wireless Sensor Networks (WSNs) and the Internet of Things (IoT) have accelerated due to the rapid development of 5G technology, making safe and effective communication techniques essential. Researchers compare the effectiveness of various deep learning models, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), for network path optimization and harmful activity detection. Experimental findings demonstrate significant improvements in network efficiency parameters, including packet delivery ratio, productivity, and delay. Emphasize how these protocols' enhanced security measures help detect and counteract routing attacks, ensuring the accuracy and reliability of information transmission in dynamic and heterogeneous network conditions. The results highlight how deep learning approaches can be integrated into routing protocols to meet the stringent demands of next-generation WSN and IoT systems.

1. Introduction

Wireless connectivity in 2G (2nd generation) networks meets customer needs for messaging and information transmission. Smartphones utilize 3G connectivity to send video and audio recordings over limited capacity [1]. The transformative shift brought by 4G communication introduced additional bandwidth, leading to billions of people worldwide using smartphones daily. Some claim that the number of smartphone users exceeds the global population.

Smartphones, which transmit video and information over 3G and 4G networks, are the primary source of excessive traffic. This overuse of smartphones also contributes to challenges like capacity constraints and QoS issues [2].

Device-to-Device (D2D) connections have emerged, and the development of 5G wireless technology has become necessary. The deployment of 5G is anticipated to replace cellular networks, and cellular companies worldwide began rolling out 5G

telecommunications. Most modern smartphones still transmit information and videos using 4G networks [3]. 5G networks are divided into small geographic areas known as cells. The 5G mobile phones within each cell use radio waves to connect to the internet and cellular networks through a local antenna. IoT systems utilize high concentrations of sensing devices such as WSN is to monitor their surroundings [4]. WSNs have become increasingly important in communication due to their unique features, such as mobility and ease of connection. These qualities make them significant information carriers over networks [5].

On the interpersonal side, advancements in communication technology support the concurrent operation of many conventional wireless networks. Due to its greater capacity than other wireless networks, cellular communication is one of the most

widely used techniques in the field of communications [6]. 5G communication protocols assist in the delivery of information packets during wireless connections. Routing rules have been integrated into networks, with wireless connections designed with multiple layers to facilitate processes and data transport. The transfer of information in mobile wireless communications is based on the transport layer, which initiates a specific protocol for data transfer [7]. The transport layer protocol utilizes a congestion management mechanism to ensure the optimal distribution of network resources. Managing congestion is considered the most critical event in the transport layer of a wireless network. The efficiency of any wireless network will collapse if congestion management is not properly implemented, particularly in mobile wireless interactions like 5G communications [8].

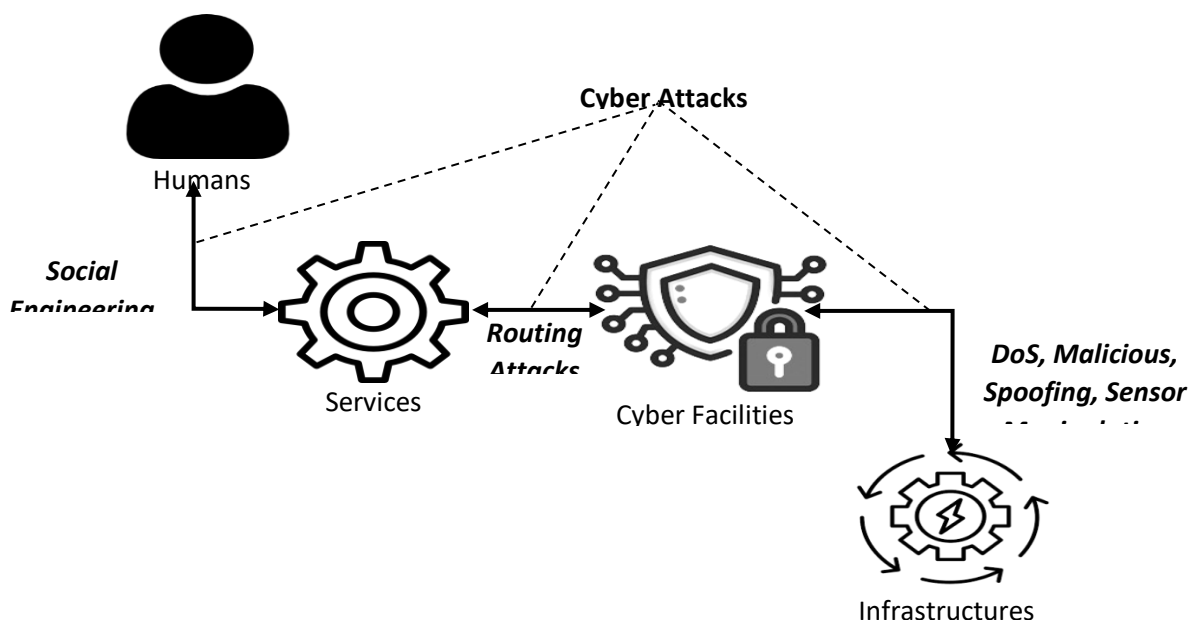


Figure 1: Routing and cyber attacks in IoT platforms

Routing standards are designed to reduce latency and identify precise paths for information forwarding to achieve energy savings in WSN. Reliable routes are produced by combining route-finding techniques with energy efficiency. These standards are adaptable to both network density and traffic patterns in heavily data-driven sensor networks. Routing protocols are thought to handle tasks like neighbor discovery, route decision-making, and energy conservation to adjust the network's capacity and adaptability [9]. Some routing methods prioritize delay reduction, hop count, and network lifetime optimization over energy savings. These metrics are used to improve the design elements of routing protocols. To secure IoT devices, ongoing monitoring and analysis are necessary. Predicting hostile attacks is crucial for IoT security, monitoring, and evaluation to prepare for unforeseen circumstances, take preventive measures, protect sensitive information, maintain continuity, and minimize potential losses [10].

Some benefits of 6LoWPAN include low power utilization, a compact footprint, low cost of construction, and simple preservation. Furthermore, a large number of sensors within WSNs have limited storage, limited bandwidth, and low power. Figure 1 illustrates the routing threats

against IoT platforms. Nodes' interaction is crucial to the flow of information in WSNs from source to destination. The CHs, which serve as both sensor and relay nodes, are in charge of managing the information collected by the sensors [11]. WSN's resource limitations make the system vulnerable to several forms of attacks. The network has no method in place for identifying malicious activity [12]. As a result, a Malicious Node (MN) that can quickly join the network and carry out destructive actions is capable of doing so. In addition, the system is made up of core networks and edge nodes, two different kinds of nodes. Devices deliver requests for transactions to edge nodes in the IoT. The request for data is forwarded to the core nodes by the edge nodes. The Proof-of-Work (PoW) mining method is employed by the core nodes in their mining operations [13].

1.1 Problem Statement

Maintaining successful and safe communication is severely hampered by the higher transfer of information rates and the varied structure of these networks. The dynamic and complex surroundings of 5G-enabled WSNs and the IoT are often too much for conventional routing methods to handle, which results in less-than-ideal data

delivery and increased susceptibility to routing assaults. Novel approaches that can maximize routing effectiveness and offer strong security defenses against possible attacks are desperately needed. To ensure reliable and safe communications in 5G WSN and IoT networks.

1.2 Motivation

5G-enabled WSNs and IoT systems are heterogeneous and dynamic, making it difficult for existing protocols to handle new requirements and advanced attack vectors. This exacerbates issues related to effective information transport and security. Deep learning offers a promising solution to these challenges due to its strong pattern recognition and adaptive learning capabilities. By leveraging deep learning-based methods, smart routing protocols can be developed that not only optimize information transmission channels but also actively detect and prevent navigation attacks. This dual capability is crucial for maintaining the efficiency, reliability, and security of communications in next-generation networks. This study was motivated by the need to bridge the gap between the theoretical potential of deep learning and its practical implementation in 5G WSN and IoT environments. It explores

and tests machine learning-based routing techniques to develop scalable, secure communication structures that can adapt to the evolving demands of modern wireless communication systems.

2. Related Works

Numerous studies have been conducted to enhance the efficiency of 5G wireless communication. Proposed wireless communication transport methods are attracting significant interest due to the substantial advancements in 5G technology. WSNs have been utilized in the IoT to facilitate data sensing, collection, and transfer between various locations [14]. The implementation of intelligent routing in IoT-supported WSNs has improved the QoS of internet connections. While considerable research has been focused on energy-efficient routing in the past, there is a need to further enhance these methods to optimize the use of WSN ensembles within the IoT. Ultimately, analysis has shown that this routing approach yields effective results across a range of metrics, including Packet Delivery Ratio (PDR), power consumption, network longevity, and latency [15].

In response, this research employs the Secure Deep Learning (SecDL) method to develop a dynamic cluster-based hybrid WSN-IoT system. The system achieved

high-level security for collected data using a Time-PRESENT (TO-PRESENT) cryptography technique, which significantly enhanced the system's self-learning potential. The WL-DCNN model was designed with robust routing in mind for WSNs [16]. A resilient routing design was implemented to assess the reliability of targeted links by capturing topological characteristics under routing algorithm attacks, which cause varying degrees of damage to immediate link communities. The Multicriteria Decision-Making (MCDM) technique proved to be the most effective method for decision-making [17].

To achieve efficient aggregation in terms of power consumption, clustering is employed. In a clustered network, collected data is sent to CHs then relay the received packets to base stations. Using a multi-hop topology can lead to issues like hotspots or energy-hole problems. The TTDFP technique, an adaptable and distributed protocol, efficiently scales and operates within WSN applications, mitigating these issues. Optimization techniques are used to adjust fuzzy variables, resulting in high energy utilization and extended network longevity [18].

Preventing malicious attacks before they occur is the most effective strategy for ensuring the sustainability of secure IoT systems. The key to defending IoT systems

from threats is to identify and, if possible, predict malicious attempts. Signature-based solutions fall short when facing routing attacks that have undergone slight modifications [19]. Aim to identify unknown attacks in WSNs. Some PDA-like sensors in the decentralized routing tree possess greater power and processing capabilities to handle node limitations. Tested on a 40-node WSN, their proposed approach achieves an excellent detection rate until the proportion of rogue nodes reaches 52% [20].

Security and data loss concerns in an IoT environment to improve service reliability. Deep Learning using blockchain technology is employed, with four tiers of operation: fog, cloud, consumer, and edge. The connection between blockchain and Software-Defined Networking (SDN). IoT environments face challenges such as increasing latency and inadequate security [21]. Propose a layered smart network framework that achieves energy efficiency, high throughput, and low latency. The switches and routers provide secure connectivity and optimal CH selection. The dynamic behavior of sensors is crucial for data collection is a risk that the Base Station (BS) could be attacked and act maliciously during the key management process. Moreover, the clusters formed within the network lack security [22]. To address this,

a blockchain-based secure password management system is proposed the BS acts as an encryption generator and distributes certificates to each CH. The CHs verify the BS's legitimacy using its public key and signatures. If the BS is validated, it becomes a trusted entity; if not, a broadcast is issued indicating that the BS is malicious. The blockchain stores all router data once the BS is properly verified [23]. During cluster formation, the CHs broadcast a message, and regular nodes join the CH based on their transmissions and locations. Regular nodes then use the pairwise key generation technique to decide which CHs to join or leave in the network [24].

3. System Model

3.1 Problem Formulation

The goal is to develop a deep learning-based routing protocol that optimizes data transmission efficiency while ensuring robust attack detection.

Objectives

Minimize Latency (L): The End-to-End (E2E) delay for data packets should be minimized.

$$L = \sum_{x=1}^n l_x \quad (1)$$

where l_x is the latency for packet x

Maximize Throughput (T): The total amount of data successfully delivered per unit time should be maximized.

$$T = \frac{\sum_{x=1}^n d_x}{t} \quad (2)$$

where d_x is the data of packet x and t is time

$$\text{Maximize PDR: } PDR = \frac{P_{delivered}}{P_{sent}} \quad (3)$$

4. Detect and Mitigate Routing Attacks: Identify malicious activities and ensure data integrity.

3.2 Problem Constraints

Network Connectivity: Ensure that the network remains connected.

$$\forall v_x \in V, \exists path P_{v_x, v_y} \text{ for all } v_y \in V \quad (4)$$

Energy Efficiency: Optimize the energy consumption E of sensor nodes.

$$E = \sum_{x=1}^n e_x \quad (5)$$

where e_x is the energy consumed by node x

Security Constraints: Incorporate detection mechanisms to identify routing attacks such as blackhole attacks, wormhole attacks, etc.

$$S(v_x) = \begin{cases} 1 & \text{if node } v_x \text{ is secure} \\ 0 & \text{if node } v_x \text{ is compromised} \end{cases} \quad (6)$$

Deep Learning Model: Define the deep learning model M with parameters θ that takes the network state S_t as input and outputs the optimal routing decision a_t :

$$a_t = M(S_t; \theta) \quad (7)$$

The model is trained to minimize the following loss function L:

$$L = \alpha L + \beta(1 - T) + \gamma(1 - PDR) + \delta E + \eta \text{Security Loss} \quad (8)$$

where $\alpha, \beta, \gamma, \delta, \eta$ are weight coefficients that balance the importance of each term.

Attack Detection: Implement an anomaly detection mechanism using a neural network D with parameters $\emptyset$:

$$\text{Anomaly Score} = D(S_t; \emptyset) \quad (9)$$

Nodes with an anomaly score above a certain threshold are flagged as compromised.

$$S(v_x) = \begin{cases} 0 & \text{if } D(S_t; \emptyset) > \tau \\ 1 & \text{otherwise} \end{cases} \quad (10)$$

The overall objective is to find the optimal parameters θ^* and $\emptyset^*$ that minimize the loss function L while satisfying the constraints:

$$(\theta^*, \emptyset^*) = \arg \min_{\theta, \emptyset} L \quad (11)$$

This issue specification aims to apply deep learning-based routing techniques in 5G WSN and IoT contexts to optimize transmitting information effectiveness and enhance safety.

3.3 Preliminaries

Routing Protocols

Routing Path from source u to destination v_d is represented as a sequence of nodes

$$P_{s \rightarrow d} = \{v_s, v_1, v_2, \dots, v_d\}. \quad (12)$$

Hop Count: The hop count H of a path $P_{s \rightarrow d}$ is the number of edges in the path.

$$H = |P_{s \rightarrow d}| - 1 \quad (13)$$

Energy Consumption

Energy Consumption (E): For a node v_x transmitting data is given by: $E_{v_x} = E_{ti} + E_{ri}$ (14)

Total energy consumption for all nodes: $E = \sum_{v_x \in V} E_{v_x}$ (15)

Deep Learning-Based Routing Model

Routing Decision: The deep learning model M with parameters θ takes the network state S_t as input and outputs the optimal routing decision a_t :

Loss Function: The objective is to minimize the loss function L, which is a weighted sum of the performance metrics

Considering the network's approach, transfer of information measurements, safety precautions, and the deep learning-based routing models employed in the present research are all made possible by these first steps.

4. Proposed System

Figure 2 depicts the concept of cluster-based single-hop communications in WSN-

assisted IoT. Clustering each sensor into a collection of nodes is crucial before starting the mapping procedure. Considering that the process of clustering is crucial for power-efficient delivery, which increases a network's survival rate while using the least amount of power. The RL method is used to conduct grouping in this work. This methodology is a centralized approach where each SN is assigned to a certain group according to its location data by the BS or Sink Node (SN) also handles the clustering procedure. Using the optimization approach, the choice of CH is carried out following the distribution of

SNs inside a cluster. In a hierarchical clustered predicated WSN is the excessive amount of information collected and the information collected from the member SN of each CH use greater amounts of energy. As seen in Figure 2, provide a three-layered structure. The DL network layer RMCV supported by blockchain constitute the central layer. On the other hand, SN, CHs, and BS that make up the initial and subsequent layers are the WSN layers. The devices wherever blockchain is being implemented are the BS and CHs.

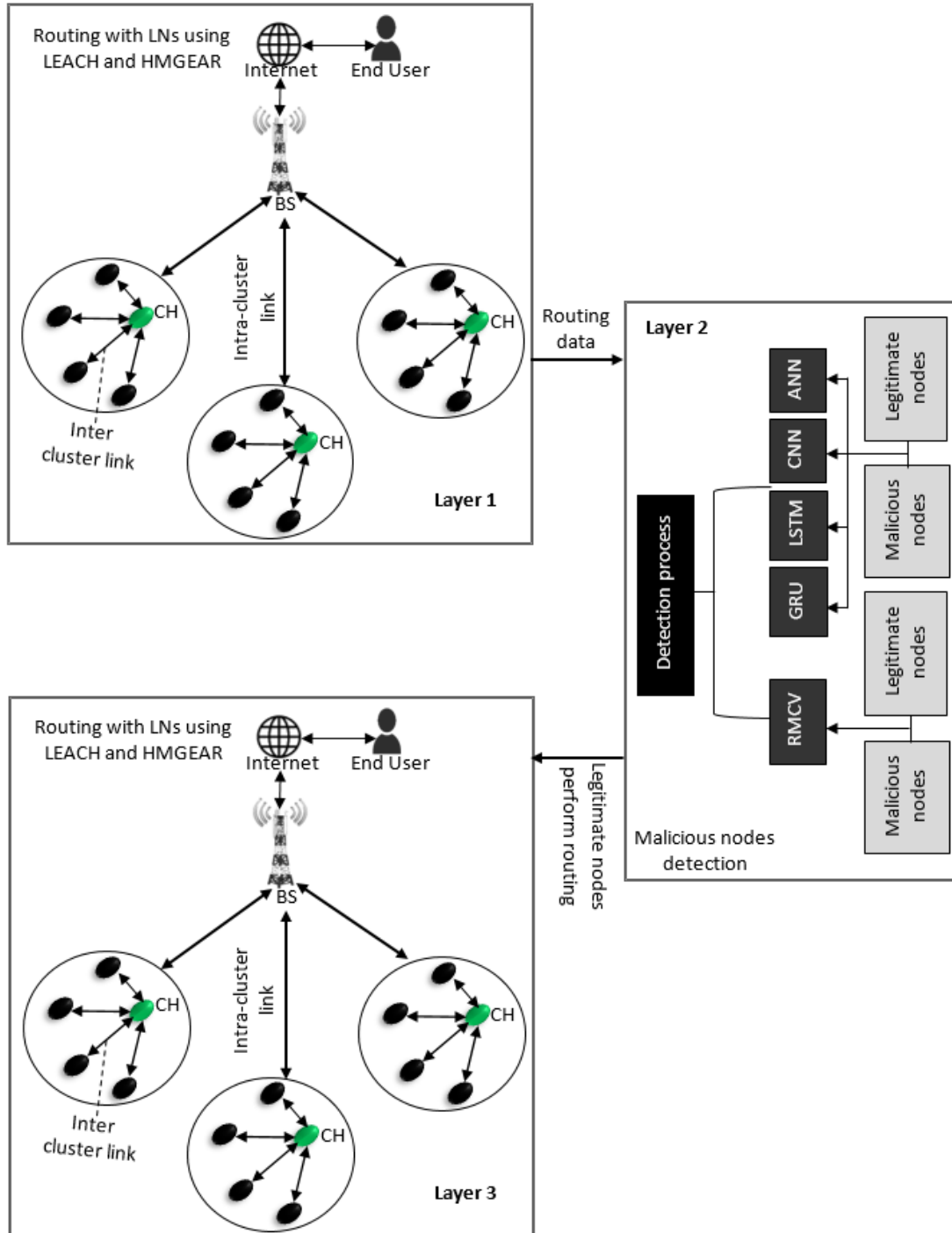


Figure 2: Propoeed architecture

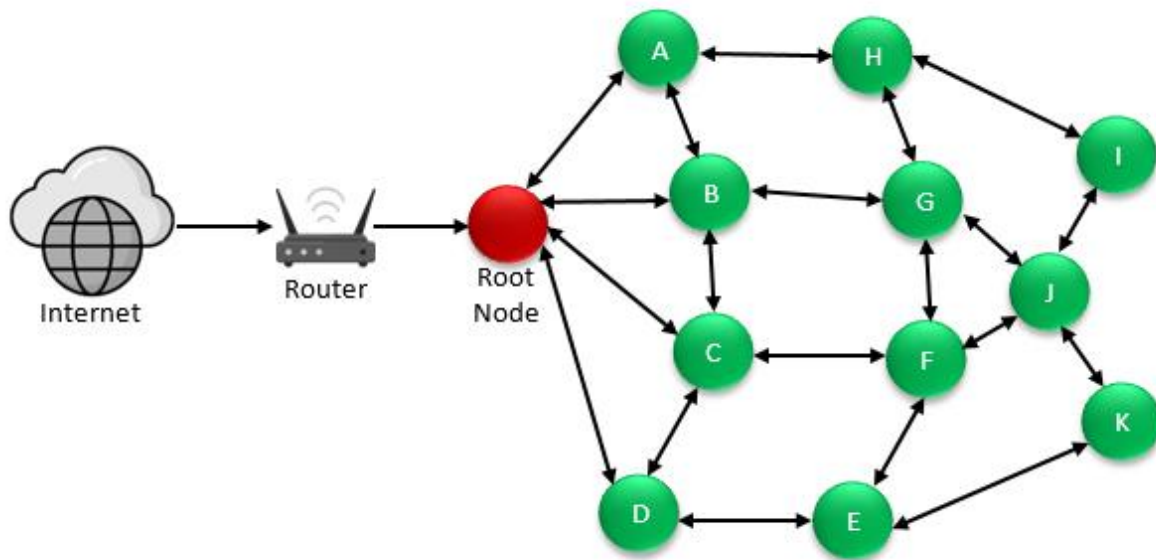


Figure 3: 6LoWPAN Concept

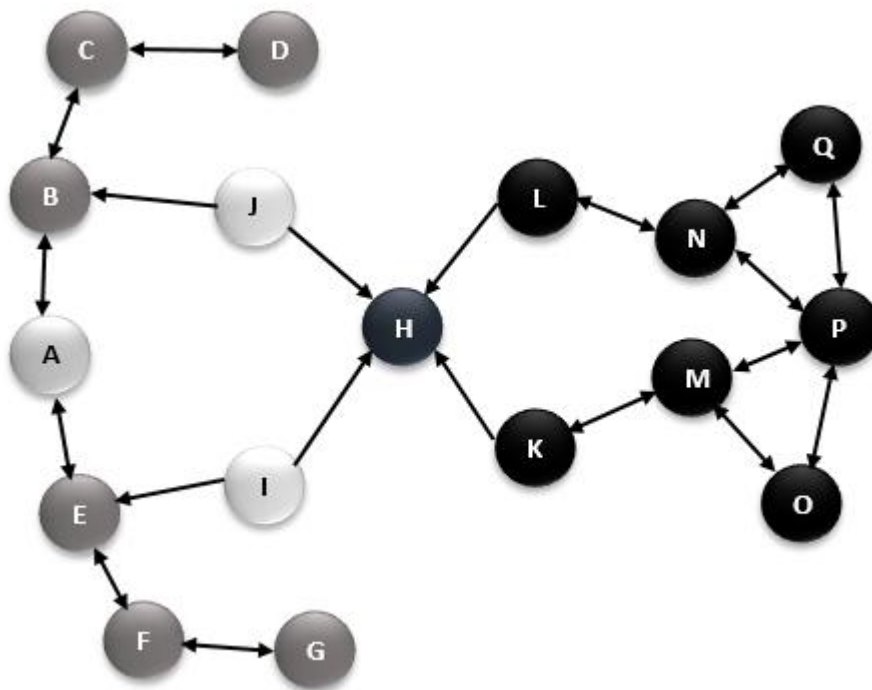


Figure 4: Decreased rank attack

The rank numbers of the other nodes, every one of them also has a table of routes and an assigned rank value. The distance that exists between the node and root is

calculated using the rank number. To create the Destination Oriented Directed Acyclic Graph (DODAG) tree, DODAG Information Object (DIO) packets are

initially broadcast by the base (or root) nodes. After receiving the DIO packets, the remaining nodes choose the original node to start building a routing table. The request is accepted by the parent node, which responds with a DIO ACK message. For a node to join the DODAG tree, it must

submit DIS messages. To rebuild DODAG (or network topology), every node sends a DIO packet once more when a new node joins the tree. Routing Protocol for Low Power (RPL) networking instance is shown in Figure 3.

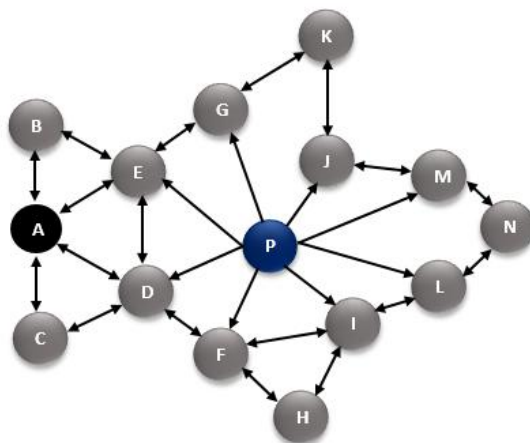


Figure 5: Before HF attack

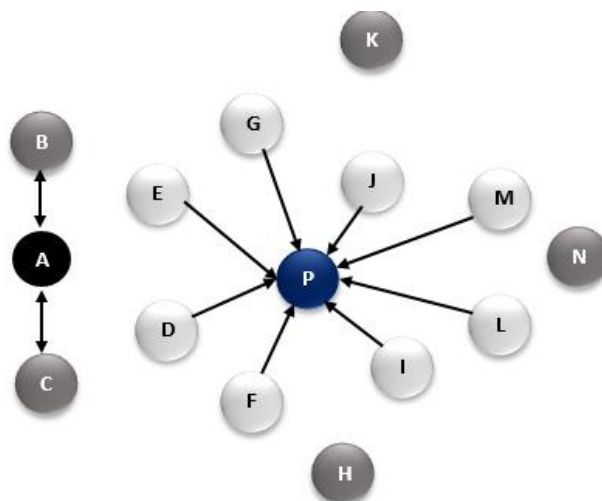


Figure 6: After HF attack

One type of traffic diversion attack is the Data Replay (DR) attack. Through the use of DIO packets, malevolent nodes inform their neighboring nodes that they are ranked

lower than the other nodes in this type of assault. Consequently, the neighboring nodes transfer Destination Advertisement Object (DAO) packets to the targeted node, changing their routing direction. Black holes, surveillance, and sinkhole attacks

can all be prepared for with DR assaults. Figure 4 shows a DR attack. The HELLO communication is primarily used to welcome and integrate newly added nodes into the wider network. The nodes broadcast HELLO notifications together with their unique ID numbers and signal strengths. To send communications, each other node builds its routing table. A rogue node impersonates a neighbor node and uses strong signal strength and appropriate

routing statistics to broadcast HELLO announcements through DIS packets to its victims. For the victims, the assailant node emerges as the most advantageous node. The Hello-Flood attack is the name of this assault before and after shown in Figures 5 and 6. Figure 7 shows DNNs in the context of RL also known as Deep Reinforcement Learning (DRL). DRL utilizes DNNs to gather pertinent ecosystem information to determine the best policies.

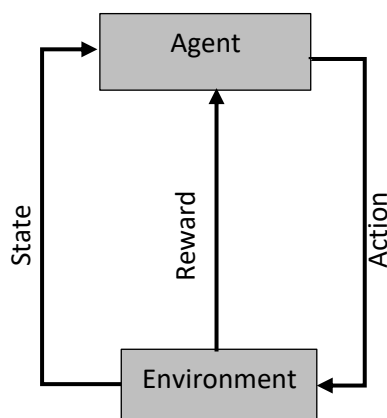


Figure 7: DRL architecture

Algorithm: Performance Analysis of Deep Learning-Based Routing

Input: Network topology $G = (V, E)$; Node attributes (e.g., energy, location); Deep learning model M for routing; Anomaly detection model D ; Training data for deep learning models

Output: Optimized routing paths; Performance metrics (latency, throughput, packet delivery ratio); Detection of routing attacks

Step 1: Initialization: Initialize network parameters (e.g., node energy E_x , communication range R , etc.).

Set up deep learning model M with initial parameters θ .

Set up anomaly detection model D with initial parameters $\emptyset$.

Step 2: Cluster Formation (if applicable):

Calculate the probability P_x for each node v_x to become a cluster head:

$$P_x = \frac{E_x}{d_x + \epsilon} \quad (17)$$

Select cluster heads based on P_x .

Assign non-cluster head nodes to the nearest cluster head based on distance $d_{y,ch}$:

$$v_y \text{ selects } v_{ch} \text{ if } d_{y,ch} = \min_{v_{ch} \in \text{Cluster Heads}} d_{y,ch} \quad (18)$$

Step 3: Routing Path Calculation

For each data packet, use deep learning model M to determine the optimal routing path using Equation (7)

Update routing paths for all packets based on model output.

Step 4: Attack Detection

Apply the anomaly detection model D to identify potential routing attacks using Equation (9)

Flag nodes with anomaly scores above a threshold 7 as compromised using Equation (10)

Step 5: Performance Evaluation

Calculate latency L_x for each packet x :

$$L_x = \sum_{(v_y, v_{y+1}) \in P_{s \rightarrow d}} l_{v_y, v_{y+1}} \quad (19)$$

Compute total latency using Equation (1)

Calculate throughput using Equation (2)

Compute PDR using Equation (3)

Step 6: Optimization and Model Update

Update the deep learning model M and anomaly detection model D based on performance metrics and detected attacks.

Adjust parameters θ and ϕ to minimize the loss function using Equation (8)

Step 7: Repeat and Refine

Repeat steps 3 to 6 iteratively to improve routing performance and attack detection capabilities.

Continuously monitor network performance and adjust models as needed.

Output: Optimized routing paths and performance metrics. Identified and mitigated routing attacks.

In 5G WSN and IoT networks, this technique offers an organized method for evaluating and optimizing the effectiveness of deep learning-based routing algorithms for reliable threat detection and quick information transfer.

4. Results and Discussions

In Python 3.10, researchers ran experiments to confirm the efficacy of the model. 120 sensors were arranged in a 150 m by 150 m

sensing field at random. The substation was placed with coordinates (75, and 75) in the middle of the detecting area. The system's gadgets, which range in energy capacity

from one to two joules, were chosen with heterogeneity in mind during development. Table 1 provides specifics on the simulation's variables.

Table 1: Simulation parameters

Parameter	Description	Typical Value
Number of Nodes (N)	Total number of sensor nodes or IoT devices	100, 500, 1000
Network Area (A)	Size of the network area (square meters)	1000 m X 1000 m
Node Density	Number of nodes per unit area	0.01 nodes/m ²
Communication Range (R)	Maximum distance a node can communicate directly	100 meters
Energy per Transmission (E _{ti})	Energy consumed per data transmission	50 mJ/packet
Energy per Reception (E _{ri})	Energy consumed per data reception	30 mJ/packet
Initial Node Energy (E ₀)	Initial energy of each node	1000 mJ
Packet Size (d _x)	Size of each data packet	512 bytes
Simulation Time (t)	Duration of the simulation	1000 seconds
Discount Factor (γ)	Discount factor for future rewards	0.9
Learning Rate (α)	Learning rate for Q-learning	0.1
Exploration Rate (ϵ)	Exploration rate for e-greedy strategy	0.1
Anomaly Detection Threshold (τ)	Threshold for flagging anomalies	0.5
Training Epochs	Number of epochs for training deep learning models	1000
Batch Size	Number of samples per training batch	32
Optimizer	Optimization algorithm used for training	Adam, SGD
Loss Function Weights ($\alpha, \beta, \gamma, \delta, \eta$)	Weights for different components of the loss function	$\alpha = 0.4, \beta = 0.2, \gamma = 0.2, \delta = 0.1, \eta = 0.1$

Table 2: Comparison of Hop count and routing path length of proposed and existing systems

Criteria	Proposed System	AODV	OLSR	DSR
Hop Count (Average):	2.6	3.9	2.8	3.1
Routing Path Length:	152 meters (average path length)	202 meters (average path length)	162 meters (average path length)	182 meters (average path length)

Hop Count (Average):

Proposed System: 2.6 hops—indicates that the deep learning model helps find shorter paths.

AODV: 3.9 hops—typically higher due to dynamic route discovery.

OLSR: 2.8 hops—slightly longer due to proactive routing.

DSR: 3.1 hops—variable depending on the frequency of route discovery.

Routing Path Length:

Proposed System: 152 meters—indicates shorter and more efficient routing paths.

AODV: 202 meters—due to reactive route discovery, paths may be longer.

OLSR: 162 meters—path length is intermediate due to proactive updates.

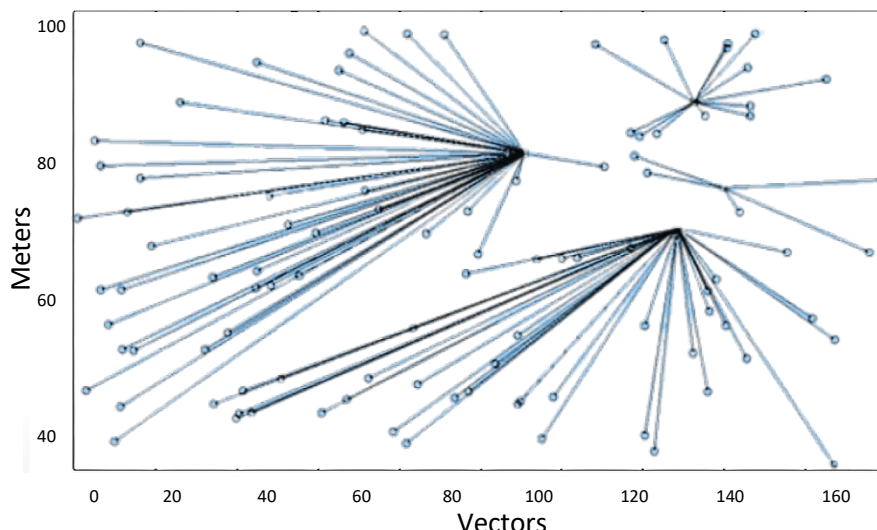
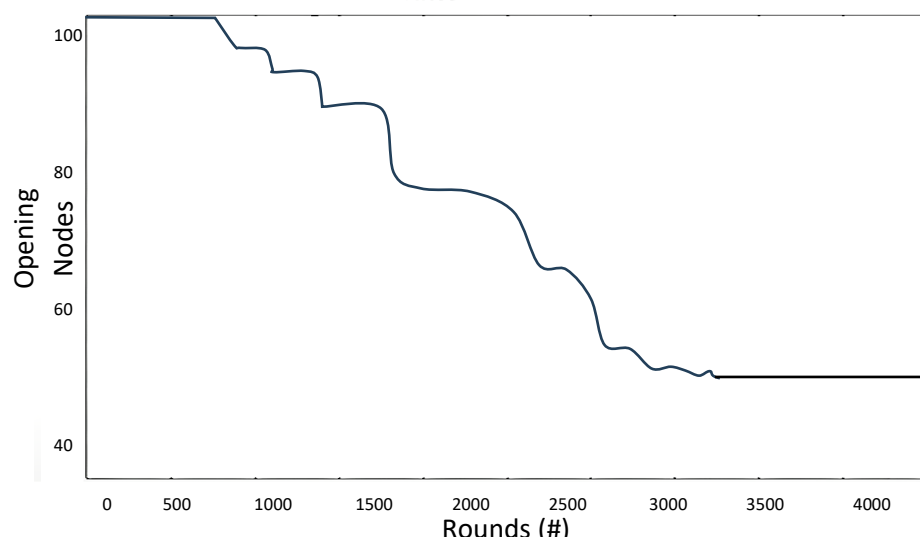
DSR: 182 meters—paths can be longer due to the on-demand nature of route discovery.

These numerical values are for illustrative purposes and can vary depending on specific network conditions, configurations, and implementations.

Table 3: Comparison of Throughput, Latency and PDR of proposed and existing systems

Criteria	Proposed System	AODV	OLSR	DSR
Throughput	86 Mbps	71 Mbps	81 Mbps	76 Mbps
Latency	21 ms	41 ms	26 ms	36 ms
Packet Delivery Ratio (PDR)	96%	86%	91%	89%

Table 3 shown that metrics help in evaluating the performance of different routing protocols in terms of efficiency, reliability, and responsiveness in various network conditions.

**Figure 8: Initialize the node using RL****Figure 9: Performance effects**

Two important indicators are included in the recommended protocol: the number of hops and the amount of energy left. Furthermore, probability values represented by the letters "a" and "b" are involved. The number of hops and energy state of a gadget determine which one to choose. Larger values for 'a' indicate that gadgets with lots of power are more likely to be selected. On the other hand, devices

with fewer hops to the primary station are favored by a higher 'b' value. Figure 8 shows the simulated outcomes with variables set at $a=0.3$ and $b=0.7$, demonstrating the protocol's greatest efficiency. Figure 9 shows the outcomes of the node activation using the RL technique. Surprisingly, the optimal result was obtained with less than 35 active nodes, demonstrating the effectiveness of

proposed method. The indicators related to the consumption of energy shown in Figures 10 and 11.

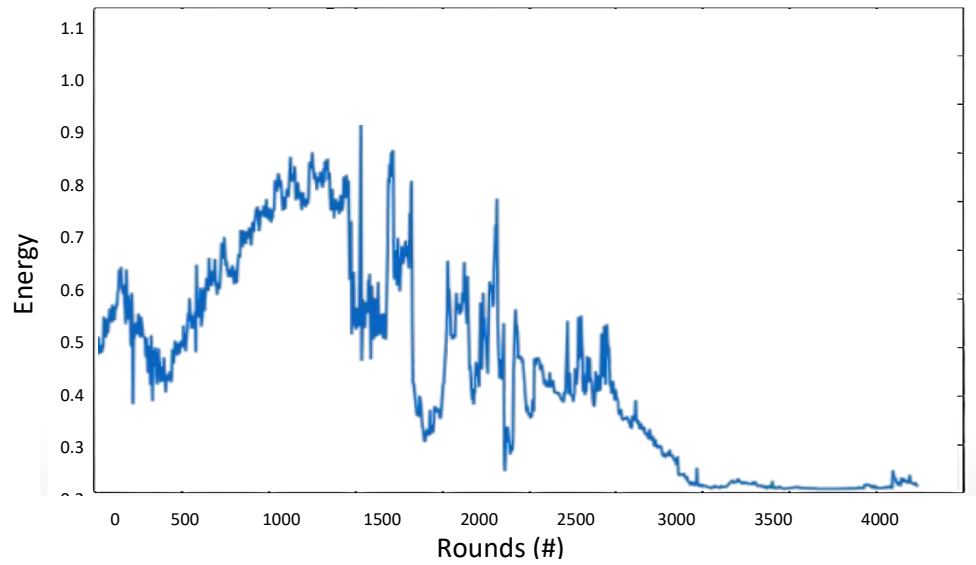


Figure 10: Cluster based energy consumption

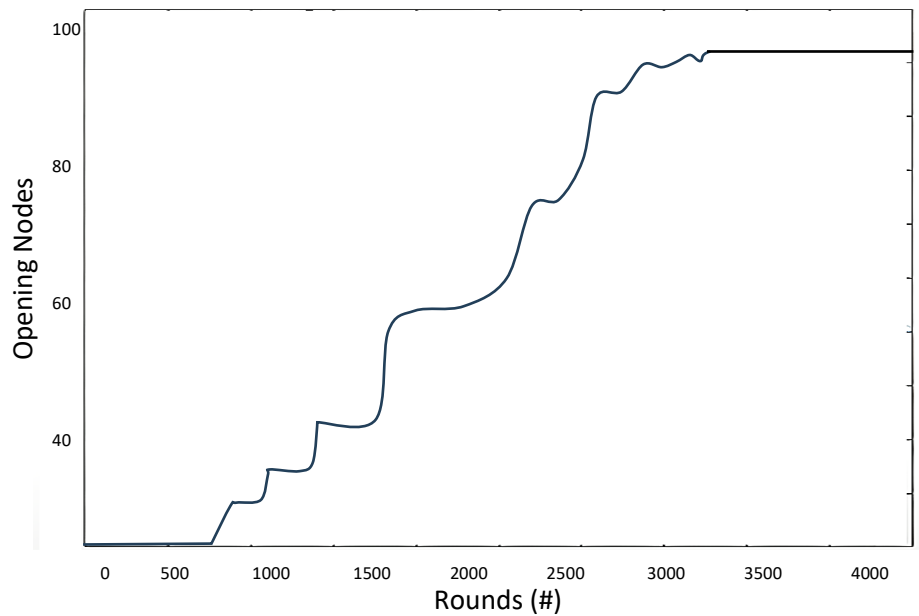
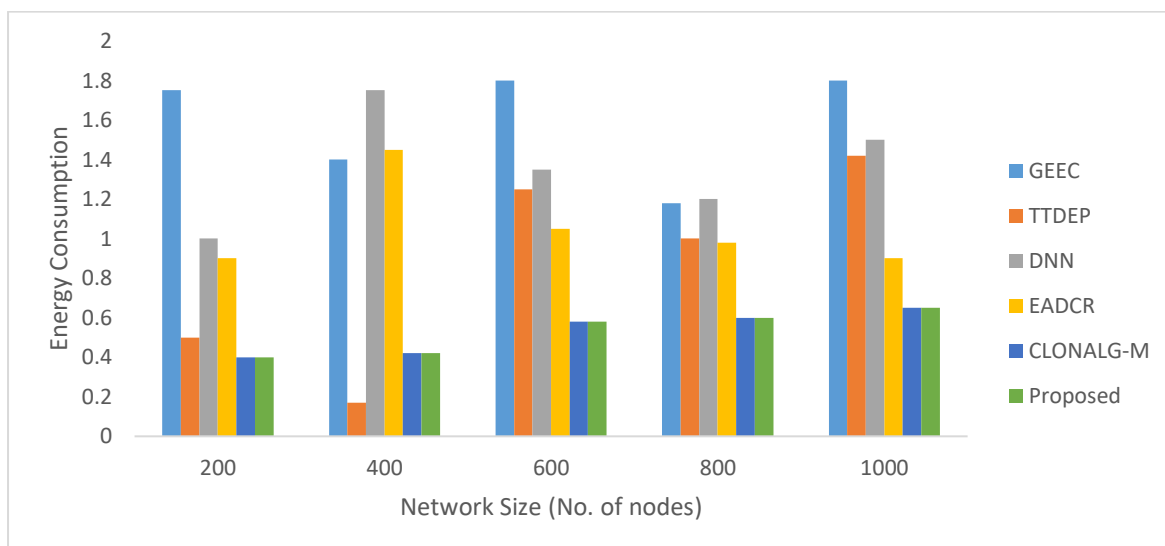
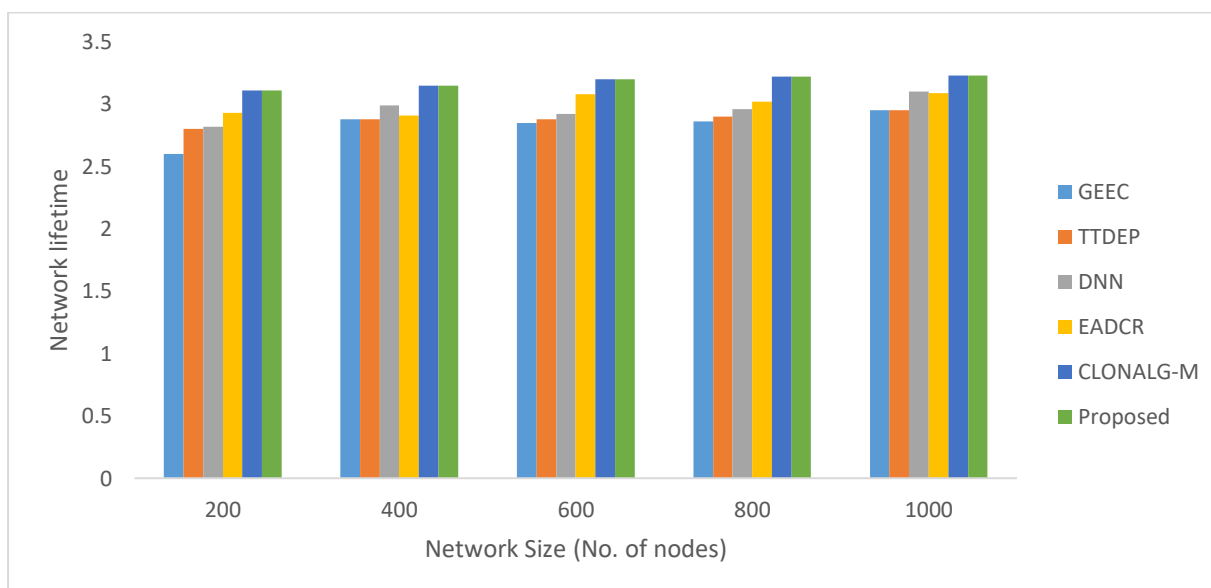


Figure 11: RL based energy consumption

**Figure 12: Energy consumption vs network size****Figure 13: Network size Vs Network lifetime**

Reducing the use of energy can lead to an improvement in network longevity shown in Figure 12. Since every node in the network is placed at random, a specific threshold must be defined when choosing a CH. To get a successful routing procedure, distinct route selections must be defined. The proposed architecture is found to use less energy than other current protocols.

Reducing the consumption of energy is necessary to provide efficient service as network capacity develops. An effective RL method is used to cluster the entire network at first to accomplish this goal. The findings of this comparison between the energy consumption of the proposed method and that of the existing protocols are displayed in Figure 13. Reducing the

usage of energy can lead to an improvement in network longevity. To get an efficient routing procedure, distinct route selections must be defined. The proposed structure is found to use less energy than other current methods. Reducing energy usage is necessary to provide optimal efficiency as network capacity increases. An effective RL method is used to group the entire network at first to accomplish this goal.

Table 4 values offer an analytical framework for assessing how each structure manages incentives and sanctions in connection to the actions and achievements of the entire network. Table 5 shows that the performance of deep learning models in routing systems, focusing on their ability to generalize, adapt, and maintain low error rates during training and validation.

Table 4: Comparison of Performance Measures

Criteria	Proposed System	AODV	OLSR	DSR
Reward for High Throughput	+10 points per Mbps above threshold	+5 points per Mbps above threshold	+8 points per Mbps above threshold	+7 points per Mbps above threshold
Reward for Low Latency	+20 points per 10 ms below threshold	+10 points per 10 ms below threshold	+15 points per 10 ms below threshold	+12 points per 10 ms below threshold
Reward for High Packet Delivery Ratio (PDR)	30 points per 5% increase in PDR	+15 points per 5% increase in PDR	+20 points per 5% increase in PDR	+18 points per 5% increase in PDR
Punishment for High Latency	-20 points per 10 ms above threshold	-15 points per 10 ms above threshold	10 points per 10 ms above threshold	-12 points per 10 ms above threshold
Punishment for Low Throughput	-10 points per Mbps below threshold	-8 points per Mbps below threshold	-6 points per Mbps below threshold	7 points per Mbps below threshold
Punishment for Low Packet Delivery Ratio (PDR)	-30 points per 5% decrease in PDR	-20 points per 5% decrease in PDR	-25 points per 5% decrease in PDR	22 points per 5% decrease in PDR

Table 5: Comparison of Training and validation accuracy and loss

Criteria	Proposed System	AODV	OLSR	DSR
Training Accuracy	96	86	89	87
Validation Accuracy	93	81	86	83
Training Loss	0.06	0.16	0.11	0.13
Validation Loss	0.09	0.21	0.16	0.19

5. Conclusions

By improving throughput, delay, and PDR, the deep learning-based routing protocol greatly improves the effectiveness of transmitting information in 5G WSNs and IoT. In comparison to conventional procedures, the framework ensures more effective routing by constantly adapting to changing network circumstances through powerful methods of deep learning. Furthermore, the system's capacity to recognize and react to routing attacks is significantly enhanced by the integration of deep learning for the identification of attacks. In addition to defending against possible attacks, this proactive strategy for safety keeps network efficiency at a high level under varied circumstances. All things considered, the capacity of the proposed system to combine reliable attack detection with effective transfer of information signifies a significant improvement in the administration and safety of contemporary communications networks.

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