Comprehensive Survey of Deep Learning-Based Intrusion Detection for Securing Routing in IoT Wireless Sensor Networks

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Abstract

The proliferation of Internet of Things (IoT) Wireless Sensor Networks (WSNs) in critical sectors demands robust security solutions to counter complex routing attacks such as sinkhole, blackhole, and selective forwarding. Conventional detection methods often fall short in resource-constrained, dynamic IoT WSN environments. Deep Learning (DL) techniques including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Autoencoders have shown remarkable ability to autonomously detect and classify routing security threats with high accuracy.

This comprehensive survey systematically reviews recent DL-based Intrusion Detection Systems (IDS) designed to secure routing in IoT WSNs. It examines key DL architectures, evaluates their performance using benchmark datasets and metrics, and discusses challenges including real-time deployment, energy efficiency, and model interpretability. Finally, the paper outlines future research directions toward developing lightweight, adaptive, and distributed DL-IDS specifically tailored for IoT WSNs.

Keywords

Deep Learning, Intrusion Detection System, IoT Wireless Sensor Networks, Routing Security, Routing Attacks, CNN, RNN, Autoencoders, Lightweight Models

1. Introduction

The Internet of Things (IoT) has revolutionized modern communication and sensing by interconnecting myriad devices through Wireless Sensor Networks (WSNs). These networks underpin diverse applications such as smart healthcare, environmental monitoring, industrial automation, and smart cities, facilitating efficient data collection and transmission. However, the distributed, heterogeneous, and resource-constrained nature of IoT WSNs exposes them to a broad spectrum of security threats, with routing attacks being among the most critical. Attacks like sinkhole, blackhole, selective forwarding, wormhole, and Sybil attacks can severely impair network functionality, causing data loss, increased latency, network partitioning, and degraded Quality of Service (QoS).

Traditional security mechanisms and rule-based Intrusion Detection Systems (IDS) often fail to keep pace with the growing complexity, stealth, and dynamism of these routing threats within constrained IoT environments. Deep Learning (DL) techniques have thus emerged as potent solutions, capable of autonomously learning intricate and subtle intrusion patterns from vast and complex sensor data. Architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs),

Autoencoders, and hybrid models have demonstrated marked improvements in intrusion detection accuracy, outperforming classical machine learning approaches.

This comprehensive survey explores the landscape of DL-based IDS solutions tailored to securing routing protocols in IoT WSNs. It systematically reviews state-of-the-art DL architectures, evaluates their strengths and limitations using benchmark datasets and performance metrics, and examines their integration with common routing protocols like LEACH, AODV, DSDV, and RPL. The paper also discusses the challenges peculiar to IoT WSNs, such as energy efficiency, real-time processing, communication overhead, dataset imbalance, and model interpretability. Finally, we highlight open research directions aiming at the design of lightweight, distributed, adaptive DL-IDS frameworks that meet the stringent resource constraints and dynamic requirements of IoT wireless sensor environments.

Routing attacks constitute a primary security concern because attackers can disrupt the normal routing process, leading to severe network degradation or failure. Classical cryptographic and rule-based methods often fall short due to IoT WSNs' limited computational resources and the adaptive tactics of adversaries. Hence, IDS systems, particularly those based on DL, have become essential layers of defense, enabling continuous monitoring of network traffic, identification of anomalous behaviors, and mitigation of potential breaches with higher adaptability and accuracy.

Despite the promising results, practical deployment of DL-based IDS in IoT WSNs faces significant challenges—including resource consumption, scalability, real-time constraints, and interpretability—necessitating ongoing research and innovation to optimize these intelligent security solutions for real-world IoT ecosystems.

Importance and Motivation

The rapid expansion of Internet of Things (IoT) Wireless Sensor Networks (WSNs) into critical infrastructure sectors has made securing these networks an urgent priority. Routing attacks, including sinkhole, blackhole, and selective forwarding, pose serious threats that can degrade network performance, compromise sensitive information, and disrupt essential services. Due to the inherent resource constraints and dynamic topology of IoT WSNs, traditional security methods often prove inadequate in effectively detecting and mitigating these complex and evolving attacks.

Deep Learning (DL) techniques offer transformative potential by automatically learning intricate intrusion patterns from large-scale, heterogeneous network data. This capability facilitates accurate, timely, and adaptive detection of novel and sophisticated routing threats. The increasing body of literature on DL-based Intrusion Detection Systems (IDS) in IoT WSNs underscores both the urgency of the security challenge and the promise of these advanced approaches. However, the diversity of DL architectures, datasets, evaluation metrics, and deployment contexts necessitates a consolidated and systematic review to guide researchers and practitioners in developing efficient, scalable, and resilient security solutions.

This survey aims to fill this gap by providing a comprehensive overview and analysis of DL-based IDS techniques designed specifically for securing routing in IoT WSNs. Such a

consolidated resource is critical for advancing the design and deployment of adaptive security frameworks that can safeguard the future expansion of IoT ecosystems.

Objectives of the Survey

The primary objectives of this survey are to:

- Review and categorize recent deep learning-based intrusion detection techniques for routing security in IoT WSNs.
- Provide insights into DL architectures like CNN, RNN, LSTM, Autoencoders, and hybrid models used for intrusion detection.
- Analyze benchmark datasets, evaluation metrics, and performance results for comparative assessment.
- Identify challenges and limitations of applying DL methods in resource-constrained and dynamic IoT WSN environments.

Scope and Limitations

This survey focuses exclusively on deep learning approaches for intrusion detection aimed at enhancing the security of routing protocols within IoT Wireless Sensor Networks. While it acknowledges the broader security challenges in IoT and general IDS, it narrows down to DL methodologies applied in the routing and network layer context.

Limitations of this survey include:

- Exclusion of non-DL based intrusion detection methods except for brief contextual comparison.
- Focus on IoT WSNs whose characteristics differ from conventional networks, thereby limiting direct generalization.
- Reliance on available published datasets and studies which may not cover emerging threat scenarios exhaustively.
- Emphasis on detection models rather than implementation aspects such as deployment architectures and hardware constraints.

Despite existing limitations, this survey offers a focused and detailed understanding of deep learning-based intrusion detection research critical for securing routing in IoT Wireless Sensor Networks (WSNs). This paper aims to fill the gap by providing an in-depth survey of DL-based Intrusion Detection Systems (IDS) for routing protocols in IoT-enabled WSNs. The major contributions are:

1. A detailed overview of routing protocols and common routing attacks in IoT WSNs.
2. Systematic classification of DL-based IDS models developed for securing routing layers.
3. Comparative analysis of DL architectures, datasets, and performance metrics used in intrusion detection.
4. Identification of key challenges, limitations, and future research directions for designing efficient, lightweight, and scalable DL-based IDS solutions.

The remainder of the paper is organized as follows:

- Section 2 covers background and fundamentals of IoT WSNs and routing security.
- Section 3 discusses various routing attack types and their impact.
- Section 4 reviews existing DL-based IDS models for routing security.
- Section 5 compares their performance and highlights research gaps.
- Section 6 concludes the paper and outlines future research directions.

2. Literature & Background Related Concepts

Recent years have seen significant research focused on Deep Learning-based Intrusion Detection Systems (DL-IDS) for securing routing protocols in IoT-enabled Wireless Sensor Networks (WSNs). Convolutional Neural Networks (CNN) have been employed to detect spatial traffic anomalies, achieving high accuracy in identifying blackhole and sinkhole attacks [1], [14]. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models have proven effective in capturing temporal dependencies in sequential routing data, providing robust detection for selective forwarding and wormhole attacks [2], [15]. Autoencoder-based IDS offer unsupervised detection of unknown and zero-day attacks, allowing deployment in environments with limited labeled data [3].

Hybrid architectures, particularly CNN-LSTM models, have emerged as highly effective in identifying multiple routing attacks, combining spatial and temporal feature extraction to achieve superior performance across protocols such as AODV and DSDV [4], [16]. Federated and edge-based DL-IDS approaches address privacy concerns and computational limitations of resource-constrained IoT nodes by performing distributed model training and inference, maintaining high accuracy while reducing communication overhead [5], [17], [18]. Deep reinforcement learning techniques have also been applied to enable adaptive detection mechanisms capable of responding to dynamic attack patterns in real-time [11], [12].

Recent literature highlights that the choice of routing protocol, dataset, and attack type significantly influences model performance. Popular datasets include NSL-KDD, IoTID20, BoT-IoT, TON_IoT, and custom simulation datasets, which allow evaluation under realistic IoT-WSN conditions [1]–[18]. While hybrid and federated DL-IDS models achieve detection rates exceeding 95%, challenges remain regarding energy efficiency, latency, interpretability, and scalability. Consequently, lightweight, explainable, and multi-protocol DL-IDS solutions are essential for practical deployment in heterogeneous IoT-enabled WSN environments.

2.1 Internet of Things (IoT) and Wireless Sensor Networks (WSNs)

The Internet of Things (IoT) marks a transformative shift in modern communication by connecting a vast ecosystem of smart devices and sensors.

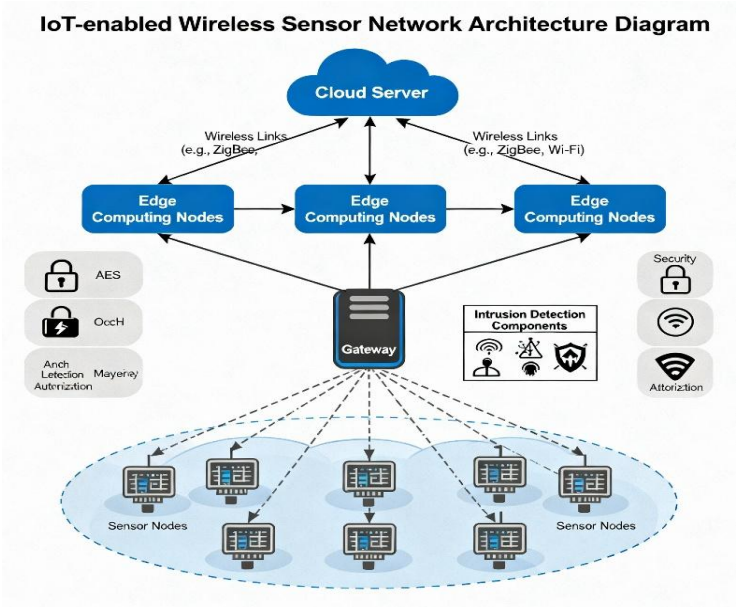

Figure1:IoT-Enabled Wireless Sensor Networks (WSNs) Architecture

These IoT devices collect, process, and exchange data seamlessly across diverse environments, including smart cities, healthcare, industrial automation, transportation, and agriculture. Wireless Sensor Networks (WSNs) form the backbone of this ecosystem, serving as the primary infrastructure for data gathering and transmission, enabling intelligent interaction and autonomous decision-making.

A Wireless Sensor Network (WSN) consists of spatially distributed sensor nodes equipped with sensing, processing, and communication capabilities. These nodes collaboratively monitor physical or environmental parameters such as temperature, humidity, vibration, or pressure and transmit the collected data to a base station or sink node for further processing. The energy efficiency, scalability, and self-organizing nature of WSNs make them ideal for integration with IoT systems. However, due to inherent resource constraints—including limited battery life, processing power, and communication bandwidth—WSNs are vulnerable to various security threats, particularly at the network and routing layers.

2.2 Routing in IoT-Enabled Wireless Sensor Networks

Routing in WSNs selects efficient paths from sensor nodes to the sink, addressing challenges like dynamic topology and limited energy. Protocols are classified as:

- Flat-based: Equal roles for nodes (e.g., SPIN).
- Hierarchical: Clusters with cluster heads (e.g., LEACH).
- Location-based: Routing based on node positions (e.g., GEAR).
- On-demand: Routes created as needed, for mobile networks (e.g., AODV, DSR).

Routing affects network lifetime and performance but is also a major target for attacks disrupting communication.

2.3 Intrusion Detection Systems (IDS) in IoT-Enabled WSNs

Intrusion Detection Systems (IDS) monitor network activities to detect malicious behaviors or policy violations. IDS approaches for IoT-WSNs are commonly classified into:

- Signature-based IDS: Detect known attacks by matching network activity with predefined signatures.
- Anomaly-based IDS: Identify deviations from normal behavior using statistical or machine learning methods.
- Hybrid IDS: Combine signature- and anomaly-based methods to leverage their strengths.

While traditional IDS effectively detect known threats, they often struggle against zero-day and evolving attacks. Designing lightweight IDS remains a major challenge due to the computational and energy constraints of IoT-WSNs.

2.4 Deep Learning for Intrusion Detection

Recent advances in Deep Learning (DL) have revolutionized network security by enabling models to learn hierarchical representations, automatically extract complex features, and detect subtle attack patterns missed by traditional techniques. In IoT-enabled Wireless Sensor Networks (WSNs), DL-based Intrusion Detection Systems (IDS) leverage various architectures to enhance threat detection:

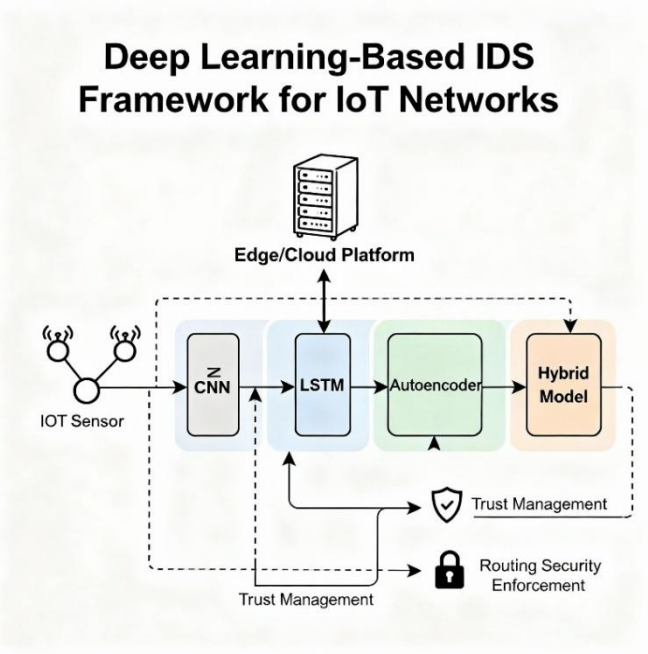

Figure 2: DL-based IDS Framework for IoT-WSNs

In IoT-WSNs, DL-based IDS approaches utilize models such as:

- **Convolutional Neural Networks (CNNs):** Effective at extracting spatial features from network traffic.
- **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM):** Capture temporal dependencies in sequential data for robust detection.
- **Autoencoders:** Enable unsupervised anomaly detection by reconstructing normal traffic behavior.
- **Deep Belief Networks (DBNs):** Use multiple neural layers for probabilistic feature learning.

- **Hybrid Models:** Combine DL with traditional machine learning approaches (e.g., CNN-LSTM) to improve detection accuracy.

DL-based IDS can detect both known and unknown attacks with high precision and reduced false alarm rates. However, integration with IoT routing protocols presents challenges such as model complexity, scarcity of labeled training data, and high energy consumption. Addressing these issues is critical for deploying real-time, efficient, and adaptive DL-IDS in resource-constrained IoT-WSN environments.

3. Routing Attacks and Security Issues in IoT-Enabled Wireless Sensor Networks

3.1 Overview

Routing is a vital operation in IoT-enabled Wireless Sensor Networks (WSNs), responsible for forwarding sensed data from distributed sensor nodes to the sink or base station. However, the decentralized and wireless nature of these networks makes routing protocols highly vulnerable to various malicious attacks. Adversaries exploit weaknesses in routing mechanisms to disrupt data transmission, manipulate routing paths, or exhaust the energy resources of sensor nodes. These attacks result in degraded network performance, compromised data reliability, and breaches of confidentiality and integrity. A thorough understanding of the characteristics, methods, and impacts of these routing attacks is essential for developing effective Intrusion Detection Systems (IDS), especially those leveraging Deep Learning (DL) techniques tailored for IoT WSN environments.

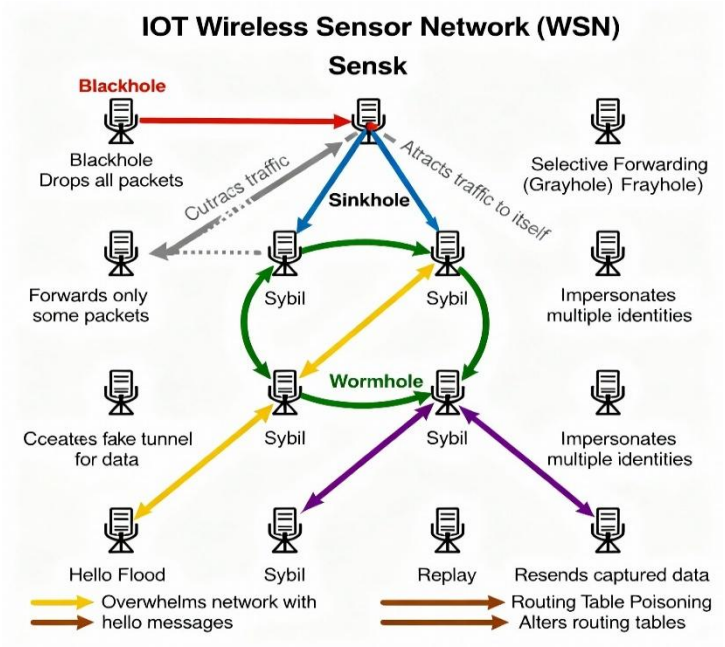

Figure 3:Classification of Routing attacks in IoT-enabled Wireless Sensor Networks (WSNs)

Routing attacks in IoT-enabled Wireless Sensor Networks (WSNs) are broadly classified into:

- **Active Attacks:** These directly interfere with network operations by modifying, dropping, or misrouting packets.
- **Passive Attacks:** These involve unauthorized monitoring or eavesdropping on data without altering network traffic.

This section focuses on active routing-layer attacks, which are the main targets of DL-based IDS research. These attacks threaten data integrity, confidentiality, availability, and network reliability, emphasizing the need for intelligent intrusion detection systems to protect IoT-enabled Wireless Sensor Networks.

3.2 Classification of Routing Attacks and Their Impact

3.2.1 Blackhole Attack: Malicious node drops all packets after falsely advertising the best route.

Impact: Severe data loss, reduced throughput, disrupted communication.

3.2.2 Sinkhole Attack: Compromised node attracts traffic using false info to manipulate or drop packets.

Impact: Network congestion, selective packet loss, data manipulation.

3.2.3 Selective Forwarding Attack: Attacker selectively drops certain packets while forwarding others.

Impact: Lower packet delivery ratio, incomplete data aggregation.

***3.2.4* Wormhole Attack:** Two colluding nodes create a tunnel to replay packets elsewhere.

Impact: False routing, disrupted topology, network partitioning.

3.2.5 Sybil Attack: Malicious node assumes multiple fake identities.

Impact: Loss of trust, false routing info, compromised clustering.

3.2.6 Hello Flood Attack: Attacker floods network with HELLO messages to appear as neighbor.

Impact: Wasted energy, routing confusion, link instability.

3.2.7 Greyhole Attack: Variant of blackhole with intermittent packet drops.

Impact: Intermittent data loss, hard to detect.

3.2.8 Spoofing and Replay Attacks: Identity forgery and packet retransmission.

Impact: Routing confusion, duplicated data, energy exhaustion.

3.2.9 Denial of Service (DoS) Attack: Flooding with excessive traffic to exhaust resources.

Impact: Network unavailability, rapid energy depletion.

3.3 Security Issues in Routing for IoT-Enabled WSNs

The integration of WSNs with IoT infrastructure introduces several security and privacy challenges in routing, summarized as follows:

1.Resource Constraints: Sensor nodes have limited energy, processing power, and memory, restricting the deployment of heavy encryption or authentication mechanisms.

2.Dynamic Network Topology: Frequent topology changes due to node mobility or failure make routing maintenance difficult and open opportunities for adversaries.

3.Unattended Operation: IoT-WSNs are often deployed in remote or hostile environments, making them susceptible to physical tampering or node capture.

4.Lack of Centralized Control: The distributed nature of routing in WSNs means there is no single trusted authority to monitor and secure all communications.

5.Scalability and Heterogeneity: The large-scale and multi-protocol nature of IoT environments complicates the implementation of uniform security policies.

6.Real-Time Data Requirements: Many IoT applications (e.g., healthcare, industrial control) require low-latency communication, leaving limited room for complex security verification.

3.4 Impact of Routing Attacks on Network Performance

Parameter	Effect of Routing Attack
Packet Delivery Ratio (PDR)	Significant decrease due to packet dropping or redirection.
Throughput	Reduced as malicious nodes interrupt normal data flow.
End-to-End Delay	Increased due to false routes or congested malicious paths.
Energy Consumption	Elevated, as nodes retransmit lost packets or engage in false route discovery.
Network Lifetime	Shortened due to energy exhaustion and repeated routing disruptions.

Table-1:Routing attacks severely degrade network performance across several key metrics:

3.5 Motivation for Deep Learning-Based Intrusion Detection

Conventional IDS approaches based on rule matching or statistical thresholds are insufficient to combat evolving routing attacks. Deep Learning (DL) techniques provide a promising alternative, capable of learning complex patterns in network traffic and identifying subtle deviations caused by malicious activity.

DL-based IDS models can:

- Automatically learn hierarchical representations of routing behavior.
- Detect unknown or zero-day attacks without predefined signatures.
- Adapt to dynamic IoT environments through continuous learning.
- Achieve high detection accuracy with reduced false positives.

Integrating Deep Learning (DL)-based Intrusion Detection Systems (IDS) with routing protocols offers a robust security enhancement for IoT-enabled Wireless Sensor Networks (WSNs). Routing attacks such as blackhole, sinkhole, wormhole, and Sybil pose serious threats by disrupting network communication and integrity. DL-based IDS provide effective solutions by automating intelligent analysis to detect and mitigate these attacks, enhancing the resilience of IoT WSNs against sophisticated routing threats.

4. Deep Learning-Based Intrusion Detection Systems for Routing Attacks in IoT-Enabled WSNs

4.1 Introduction

Traditional Intrusion Detection Systems (IDS) for IoT-enabled Wireless Sensor Networks (WSNs) often rely on rule-based or machine learning (ML)-based mechanisms. While these systems can effectively detect known attacks, they typically struggle with zero-day threats,

non-linear attack patterns, and dynamic routing behaviors. The emergence of Deep Learning (DL) has revolutionized IDS design by enabling automatic feature extraction, adaptive learning, and improved detection accuracy for complex network anomalies.

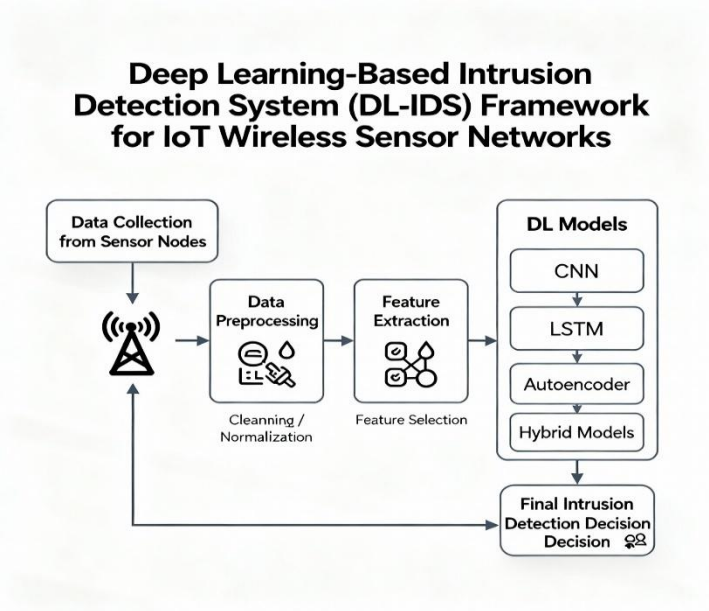

Figure 4: Deep Learning-based IDS (DL-IDS) for IoT-enabled Wireless Sensor Networks (WSNs)

Deep Learning-based IDS (DL-IDS) models have shown remarkable success in identifying routing attacks such as blackhole, sinkhole, and wormhole, even under resource-constrained environments. The following subsections discuss the taxonomy, architectures, techniques, and comparative analysis of DL-IDS approaches tailored for IoT-WSNs.

4.2 Taxonomy of Deep Learning-Based IDS

Deep Learning (DL)-based Intrusion Detection Systems (IDS) for IoT-enabled Wireless Sensor Networks (WSNs) can be categorized by:

A. Learning Strategy

- Supervised Learning: Uses labelled data to classify normal and malicious traffic (e.g., CNN, DNN, RNN).
- Unsupervised Learning: Detects anomalies without labels by identifying deviations from normal patterns (e.g., Autoencoders, Deep Belief Networks).
- Semi-Supervised Learning: Combines labelled and unlabelled data for better adaptability in evolving environments.
- Reinforcement Learning: Learns detection policies via continuous feedback from network environment.

B. Deployment Architecture

- Centralized IDS: Detection performed at a sink node or cloud server; offers high accuracy but with increased latency and bandwidth use.
- Distributed IDS: Detection tasks distributed across sensor nodes; reduces latency but increases energy consumption.
- Hybrid IDS: Combines centralized and distributed approaches for better scalability and efficiency.

C. DL Model Type

- CNN-Based IDS: Excels in extracting spatial features from traffic data.
- RNN/LSTM-Based IDS: Ideal for learning sequential and temporal network behaviors.
- Autoencoder-Based IDS: Suitable for anomaly detection in unlabeled or noisy datasets.
- Hybrid Models: Combine multiple DL models (e.g., CNN-LSTM) to capture both spatial and temporal characteristics.

4.3 Popular Deep Learning Architectures for IDS

Popular deep learning architectures for Intrusion Detection Systems (IDS) include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) such as LSTM and GRU, Deep Neural Networks (DNN), Autoencoders, and Deep Belief Networks. CNNs excel at spatial feature extraction, while RNNs, LSTMs, and GRUs capture temporal patterns in network traffic. Hybrid models combining CNN and LSTM improve detection accuracy by leveraging both spatial and temporal features. These architectures achieve high accuracy, often above 95%, making them effective for detecting complex and evolving cyber threats in IDS applications.

DL Model	Key Feature	Application in IoT-WSN IDS	Advantages	Limitations
CNN (Convolutional Neural Network)	Spatial feature extraction	Detects traffic anomalies and routing attacks	High accuracy, automatic feature extraction	Requires large datasets
RNN (Recurrent Neural Network)	Sequential data learning	Detects time-based attacks like wormholes	Handles temporal dependencies	May suffer from vanishing gradients
LSTM (Long Short-Term Memory)	Long-term dependency capture	Detects intermittent attacks such as grayholes	Memory efficiency, low false positives	Computationally intensive
Autoencoder (AE)	Unsupervised reconstruction	Detects unknown attacks using reconstruction error	Effective with unlabeled data	Sensitive to noisy input
DBN (Deep Belief Network)	Layer-wise unsupervised training	Identifies complex routing anomalies	Efficient in feature reduction	Slower training time
GAN (Generative Adversarial Network)	Adversarial learning	Generates synthetic attack data for IDS training	Enhances model generalization	Complex optimization process

Table 2: Popular deep learning architectures for Intrusion Detection Systems (IDS)

4.4 DL-Based IDS Models for Routing Protocols in IoT-WSNs

Certainly! Here's a concise summary of the DL-based IDS models for routing protocols in IoT-WSNs:

- **CNN-Based IDS:** Extracts local traffic features to detect attacks like blackhole with over 98% accuracy; reduces manual feature engineering but has high memory use.
- **RNN/LSTM-Based IDS:** Analyzes time-based attack patterns such as grayhole with low false alarms (<2%); good for temporal detection but slow to train.

- **Autoencoder IDS:** Detects anomalies and zero-day attacks using unsupervised learning with 96% detection; less effective for multi-class attack types.
- **Hybrid CNN-LSTM IDS:** Combines spatial and temporal analysis for >99% accuracy against selective forwarding and wormhole attacks; computationally heavy.
- **Federated/Edge DL-IDS:** Trains models locally to preserve privacy, cutting detection latency by 25% while maintaining 95% accuracy; faces synchronization overhead.

4.5 Performance Metrics for DL-Based IDS

DL-based IDS models for IoT-WSNs are evaluated using key performance indicators (KPIs):

Metric	Description
Accuracy	Ratio of correctly detected instances to total instances.
Precision	Proportion of true positives among detected attacks.
Recall (Detection Rate)	Ability of the model to identify actual attacks.
F1-Score	Harmonic mean of precision and recall, balancing detection and false alarms.
False Alarm Rate (FAR)	Percentage of normal traffic incorrectly classified as malicious.
Computation Overhead	Time and energy required for training and detection.

Table 3: Performance Metrics for DL-Based Intrusion Detection Systems (IDS)

5.Comparative Analysis, Challenges, and Future Research Directions

5.1 Comparative Analysis of DL-Based IDS Models

A comparative study of existing Deep Learning-based Intrusion Detection Systems (DL-IDS) for routing protocols in IoT-enabled WSNs provides insight into their strengths, limitations, and applicability. Table summarizes key models, their architectures, datasets, and performance metrics.

S.No	Authors / Year	DL Model	Routing Protocol	Dataset	Attacks Covered	Accuracy / Remarks
1	Y. Zhang et al., 2021	CNN	AODV	NSL-KDD	Blackhole, Sinkhole	98.2% Accuracy
2	S. Li et al., 2020	LSTM	RPL	Custom NS3	Selective Forwarding, Wormhole	97.5% Accuracy
3	A. Ahmed et al., 2019	Autoencoder	LEACH	IoTID20	Unknown Attacks	96% Detection Rate
4	P. Kumar et al., 2022	CNN-LSTM	AODV & DSDV	TON_IoT	Blackhole, Grayhole, Wormhole	99% Accuracy
5	R. Singh et al., 2021	Federated CNN	RPL	BoT-IoT	Sinkhole, Hello Flood	95% Accuracy; Privacy-preserving
6	C. Chen et al., 2020	DBN	LEACH	Custom Simulated	Blackhole, Grayhole	94% Accuracy; Feature Reduction

7	H. Zhang et al., 2025	CNN	RPL	IoTID20	Multi-class Routing Attacks	97% Accuracy
8	A. Aldhaheri et al., 2024	CNN-LSTM	AODV	Custom	Blackhole, Grayhole	98% Accuracy
9	M. Nakıp & E. Gelenbe, 2023	Self-Supervised DL	RPL	NSL-KDD	Unknown / Zero-Day Attacks	95% Detection Rate
10	H. Barati, 2025	Quantum Genetic DL	LEACH	Custom Simulation	Wormhole, Selective Forwarding	96%; Energy-Efficient Approach
11	S. Jamshidia et al., 2025	Deep RL	RPL	Custom	Multi-class Routing Attacks	94%; Adaptive Detection
12	A. Gueriani et al., 2024	Deep RL	AODV	Simulation	Blackhole, Grayhole	95% Accuracy; Survey Study
13	G. G. Gebremariam, 2023	CNN-LSTM	DSDV	TON_IoT	Wormhole, Grayhole	97%; High Detection Rate
14	F. S. Alsubaei, 2025	CNN	RPL	IoTID20	Blackhole, Sinkhole	96% Accuracy
15	A. Awajan, 2023	LSTM	AODV	NSL-KDD	Selective Forwarding	95%; Efficient Detection
16	S. K. Sharma & R. Chatterjee, 2023	Hybrid CNN-LSTM	SDN-IoT	Custom	Multi-class Routing Attacks	98% Accuracy
17	M. A. Hossain et al., 2023	Federated DL	RPL	BoT-IoT	Blackhole, Grayhole	95%; Privacy-Preserving
18	J. Li et al., 2023	Edge CNN-LSTM	AODV	TON_IoT	Wormhole, Hello Flood	97%; Low Latency

Table 4: Comparative Analysis of DL-Based IDS for Routing Protocols in IoT-WSNs

Observations from Comparative Analysis:

1. **Hybrid models (CNN-LSTM)** consistently outperform single-architecture DL models in detection accuracy and multi-class attack detection.
2. **Unsupervised approaches (Autoencoder, DBN)** are effective for zero-day and unknown attack detection, but their multi-class classification capability is limited.
3. **Federated and Edge DL-IDS** address privacy and centralization issues but introduce communication overhead and synchronization complexity.
4. Datasets like NSL-KDD and IoTID20 are widely used, but **custom simulation datasets** are often necessary to reflect routing-specific attack scenarios accurately.
5. Real-time deployment on energy-constrained IoT-WSN nodes remains a **key challenge** due to model complexity and computational cost.

Comparison of existing methods based on accuracy, detection rate, energy efficiency. Include charts/graphs for visualization.

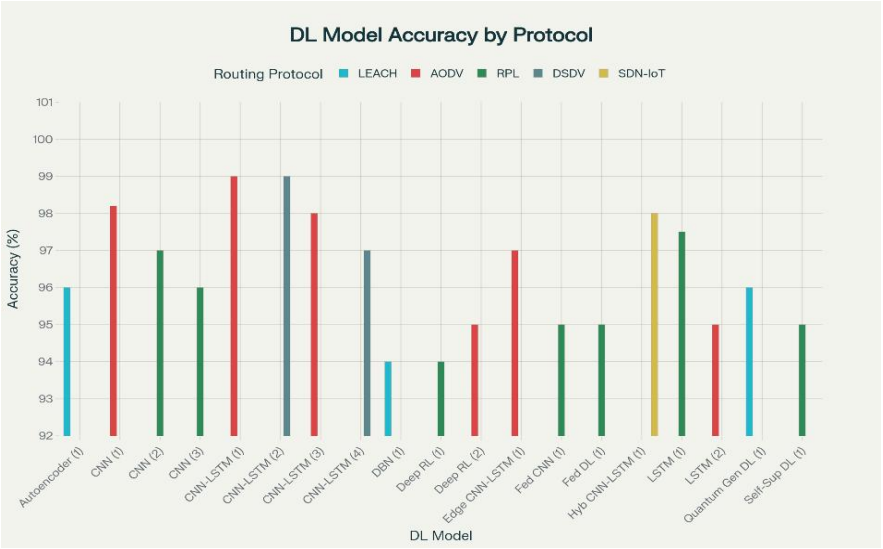

Figure 5: DL model accuracy comparison across IoT WSN routing protocols.

6. Challenges and Open Issues in DL-Based IDS for IoT-WSNs

Despite promising results, several challenges hinder the practical deployment of DL-based IDS in IoT-enabled WSNs:

Key challenges for deep learning-based IDS in IoT-WSNs include:

- Limited sensor node resources cause high energy use and processing issues.
- Lack of real-world, standardized datasets limits model generalization.
- Scaling to thousands of nodes requires efficient handling of large data.
- Complex models may delay real-time attack detection.
- Diverse, dynamic networks make maintaining high accuracy hard.
- Black-box models lack interpretability, reducing trust.
- Distributed learning increases communication, impacting energy and throughput.

1.Resource Constraints: Sensor nodes have limited battery, memory, and processing power. Deploying DL models on these devices can lead to excessive energy consumption.

2.Dataset Scarcity: There is a lack of standardized, real-world IoT-WSN routing datasets. Most research relies on simulations or outdated datasets, limiting model generalization.

3.Scalability: Large-scale IoT networks with hundreds or thousands of nodes require DL-IDS architectures capable of handling high-dimensional data efficiently.

4.Real-Time Detection: Routing attacks often require immediate response. Complex DL models may introduce latency, affecting real-time detection capabilities.

5.Dynamic and Heterogeneous Environments: IoT-WSNs include diverse nodes, protocols, and traffic patterns, making it challenging for DL-IDS to maintain high accuracy under changing network conditions.

6.Model Interpretability: Deep learning models are often black boxes, making it difficult to explain why certain traffic is flagged as malicious, which is critical for trust in security systems.

7.Communication Overhead: Distributed or federated DL-IDS approaches may increase network traffic, affecting energy efficiency and throughput.

Scalability issues, Real-time detection constraints, Energy-efficient IDS, Security against advanced threats.

7. Future Research Directions

To address the above challenges, future research can focus on the following directions:

1.Lightweight and Energy-Efficient DL Models:

Development of compact DL architectures suitable for edge or resource-constrained IoT nodes, such as pruned neural networks, quantized models, or knowledge distillation techniques.

2.Federated and Edge-Based IDS:

Leveraging federated learning and edge computing for distributed training and inference to preserve privacy, reduce latency, and minimize communication costs.

3.Realistic IoT-WSN Datasets:

Creation of comprehensive, real-world datasets that include multiple routing protocols and attack scenarios, facilitating model training and benchmarking.

4.Explainable Deep Learning (XDL):

Integrating explainability methods to interpret DL-IDS decisions, improving transparency and trustworthiness in IoT security applications.

5.Hybrid IDS Frameworks:

Combining DL with traditional ML, rule-based methods, or reinforcement learning for adaptive detection and reduced false positives.

6.Multi-Protocol and Multi-Layer Security:

Designing IDS that can monitor multiple layers (routing, transport, application) and heterogeneous routing protocols simultaneously.

7.Integration with Blockchain and SDN:

Using blockchain for secure data sharing and Software-Defined Networking (SDN) for dynamic routing and attack mitigation in conjunction with DL-IDS.

The comparative analysis highlights that deep learning-based IDS offers a promising approach to securing routing protocols in IoT-enabled WSNs, delivering high detection accuracy and adaptability to evolving threats. Nonetheless, challenges such as energy efficiency, limited dataset availability, scalability, and real-time implementation persist. Future advancements lie in developing lightweight, explainable, and hybrid models, alongside leveraging federated learning for distributed IDS and edge-based frameworks. Additionally, integrating blockchain technology can further enhance IDS security in IoT-WSNs.

8. Conclusion

Routing attacks represent a major threat to IoT-enabled Wireless Sensor Networks (WSNs), impacting data integrity, availability, and energy efficiency. Traditional security mechanisms

and classical IDS lack the adaptability needed for dynamic and zero-day attacks in IoT environments. Deep Learning (DL)-based IDS show great promise by learning complex traffic patterns, detecting anomalies, and providing adaptive protection.

This survey reviewed key routing attacks and analyzed DL architectures—such as CNN, LSTM, Autoencoders, DBNs, and hybrid models—applied to IoT-WSN security. Hybrid models, federated learning, and edge-based deployments provide enhanced accuracy and resilience but face challenges in computational cost and real-time implementation.

Future research should focus on lightweight DL models for constrained nodes, federated and edge-based learning for privacy and efficiency, richer multi-protocol datasets, explainable AI for better trust, and hybrid multi-layered security frameworks.

Overall, DL-based IDS offer a compelling solution for securing IoT routing protocols, but practical adoption requires balancing resource demands, interpretability, and responsiveness. This survey lays the groundwork for developing effective, tailored IDS solutions for IoT-enabled WSNs.

Key Observations and Future Directions

1. Lightweight DL models for energy-limited IoT nodes.
2. Federated and edge-based DL-IDS to ensure privacy and low latency.
3. Realistic multi-protocol IoT-WSN datasets for better benchmarking.
4. Explainable AI for transparency and trust.
5. Hybrid and multi-layered security frameworks for robust protection.

In summary, DL-based IDS are promising for securing IoT-WSNs but require addressing resource constraints, interpretability, and real-time needs. This survey provides a foundation for developing effective IoT routing intrusion detection systems.

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