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Machine Learning Techniques for Energy-Efficient Routing in IoT Communication Networks

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Abstract
The rapid proliferation of the Internet of Things (IoT) has transformed modern communication infrastructures by enabling seamless connectivity among heterogeneous smart devices, sensors, and autonomous systems. However, the limited energy resources of IoT devices and the increasing demand for scalable, reliable, and low-latency communication have created significant challenges for routing and network sustainability. Traditional routing protocols often struggle to optimize energy consumption while maintaining network performance in dynamic and resource-constrained IoT environments. Machine Learning (ML) techniques have emerged as promising solutions for enabling intelligent, adaptive, and energy-efficient routing in IoT communication networks through predictive analysis, autonomous decision-making, and real-time optimization. This study investigates the role of machine learning techniques, including supervised learning, unsupervised learning, reinforcement learning, deep learning, and hybrid optimization models, in enhancing routing efficiency and minimizing energy consumption in IoT communication networks. The research examines how ML-based routing frameworks improve packet delivery ratio, reduce communication overhead, optimize path selection, prolong network lifetime, and enhance Quality of Service (QoS) in heterogeneous IoT ecosystems. Furthermore, the study explores major challenges affecting ML-enabled energy-efficient routing, including resource limitations, computational complexity, security vulnerabilities, scalability issues, data heterogeneity, and model adaptability in dynamic networking environments. By analyzing recent advancements and intelligent routing mechanisms, the paper highlights the transformative potential of machine learning in developing sustainable, autonomous, and energy-aware IoT communication infrastructures. The findings indicate that ML-driven routing techniques significantly improve energy efficiency, network reliability, and communication performance, thereby supporting the development of scalable smart city applications, industrial automation, healthcare systems, and intelligent environmental monitoring networks.

Keywords
Machine Learning (ML), Energy-Efficient Routing, Internet of Things (IoT), IoT Communication Networks, Reinforcement Learning, Deep Learning, Wireless Sensor Networks (WSN), Energy Optimization, Smart Networks, Routing Protocols, Quality of Service (QoS), Intelligent Systems, Network Lifetime, Edge Computing, Sustainable Communication.

1.Introduction

The rapid growth of the Internet of Things (IoT) has significantly transformed modern communication systems by enabling seamless interconnectivity among billions of smart devices, sensors, embedded systems, and intelligent applications. IoT communication networks facilitate real-time information exchange across diverse domains, including smart cities, healthcare systems, industrial automation, environmental monitoring, transportation, agriculture, and intelligent homes. The increasing deployment of heterogeneous IoT devices has enhanced operational efficiency, automation, and intelligent decision-making capabilities in various sectors. However, the large-scale expansion of IoT ecosystems has also introduced substantial challenges related to communication reliability, scalability, energy efficiency, and sustainable network management [1].

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IoT communication devices are generally constrained by limited battery capacity, processing capability, memory resources, and communication bandwidth. Since many IoT devices operate in remote, inaccessible, or harsh environments, frequent battery replacement or manual maintenance becomes difficult and economically inefficient. Consequently, energy consumption has emerged as one of the most critical challenges affecting the performance, sustainability, and operational lifetime of IoT communication networks. Efficient routing mechanisms are essential for minimizing unnecessary energy utilization while ensuring reliable packet transmission and maintaining communication quality [2].

Traditional routing protocols in IoT communication networks often rely on predefined path selection methods and static optimization strategies that are unable to efficiently adapt to dynamic networking environments. Conventional routing approaches such as flooding, shortest path routing, and clustering-based communication mechanisms frequently experience performance degradation due to changing network topologies, device mobility, traffic congestion, and energy imbalance among communication nodes. These limitations may result in increased packet loss, communication delays, reduced network lifetime, and inefficient utilization of limited energy resources [6].

Wireless Sensor Networks (WSNs), which serve as the foundational communication infrastructure for many IoT systems, particularly

2. Literature Review

Akyildiz et al. (2002) provided one of the earliest comprehensive studies on Wireless Sensor Networks (WSNs), emphasizing their communication architecture, sensor deployment mechanisms, routing challenges, and energy limitations. The authors highlighted that energy consumption remains one of the most critical concerns in sensor-based communication systems because sensor nodes typically rely on battery-powered operations. Their study established the importance of designing energy-aware routing protocols to improve communication sustainability and network lifetime in IoT communication environments [1].

Heinzelman et al. (2000) introduced the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol as an energy-efficient communication mechanism for wireless microsensor networks. The proposed clustering-based routing approach minimized energy dissipation by dynamically selecting cluster heads and reducing communication overhead. The study demonstrated that adaptive clustering mechanisms significantly improve network lifetime and reduce energy consumption, thereby laying the foundation for future intelligent routing strategies in IoT communication systems [6].

Lindsey and Raghavendra (2002) proposed the Power-Efficient Gathering in Sensor Information Systems (PEGASIS) protocol to improve communication efficiency in sensor-based networks. Their chain-based communication strategy minimized energy expenditure by reducing direct communication between nodes and base stations. The research indicated that optimized communication paths could substantially improve routing efficiency and prolong the operational lifespan of communication networks [7].

Yick et al. (2008) conducted a comprehensive survey of Wireless Sensor Networks and discussed critical issues related to communication protocols, energy optimization, scalability, and system reliability. The authors emphasized that energy-aware communication mechanisms are necessary to address challenges associated with limited battery resources and dynamic communication environments in IoT ecosystems [8].

Al-Fuqaha et al. (2015) explored enabling technologies, communication protocols, and application domains associated with the Internet of Things. Their study identified energy management, communication scalability, routing optimization, and Quality of Service (QoS) as major research challenges affecting IoT communication systems. The authors emphasized the importance of intelligent communication frameworks capable of dynamically adapting to changing network conditions [2].

Perera et al. (2014) investigated context-aware computing within IoT systems and highlighted the importance of intelligent decision-making for communication optimization. The authors suggested that adaptive systems capable of analyzing environmental context and communication patterns could significantly improve routing performance and resource utilization across heterogeneous IoT environments [9].

Goodfellow, Bengio, and Courville (2016) discussed the role of Deep Learning in intelligent data analysis and autonomous decision-making systems. Their work demonstrated how deep neural networks process complex communication datasets to identify hidden patterns and optimize system behavior. The study laid the theoretical foundation for applying Deep Learning techniques to intelligent routing and energy optimization in communication networks [3].

Haykin (2009) extensively discussed Artificial Neural Networks and learning mechanisms capable of solving complex optimization problems. The study emphasized the effectiveness of neural learning approaches in prediction, classification, and adaptive communication management, which are highly relevant to intelligent IoT routing frameworks [5].

Sutton and Barto (2018) introduced Reinforcement Learning as an adaptive learning framework where intelligent agents optimize decisions through continuous interaction with dynamic environments. Their study highlighted the applicability of Reinforcement Learning in communication systems requiring autonomous routing decisions, energy optimization, and adaptive resource allocation under uncertain network conditions [4].

Buczak and Guven (2016) reviewed data mining and Machine Learning techniques applied to cybersecurity and intelligent communication systems. The authors emphasized that predictive learning approaches improve system intelligence by enabling anomaly detection, adaptive learning, and intelligent communication management, which are increasingly important in energy-aware IoT routing systems [11].

Chen et al. (2017) examined Machine Learning applications in wireless communication networks and highlighted the role of Artificial Intelligence in intelligent communication optimization. Their study demonstrated how neural networks and predictive models enhance communication reliability, optimize routing efficiency, and reduce energy consumption in wireless networking environments [12].

Liu et al. (2020) explored Artificial Intelligence techniques for next-generation wireless communication systems and emphasized the role of Machine Learning in intelligent routing optimization, communication reliability, and adaptive networking mechanisms. The authors concluded that AI-enabled communication frameworks significantly improve system performance in dynamic networking environments [13].

Khan et al. (2020) specifically investigated Machine Learning approaches for energy-efficient wireless communication in IoT environments. Their findings indicated that ML-driven routing mechanisms substantially reduce communication overhead, improve packet delivery performance, and enhance energy optimization across heterogeneous IoT ecosystems [14].

Abdel-Basset et al. (2020) proposed energy-aware IoT routing frameworks using Machine Learning algorithms to optimize communication efficiency and prolong network lifetime. Their study demonstrated that intelligent routing mechanisms outperform conventional routing protocols by reducing unnecessary energy consumption and enhancing routing adaptability [15].

Otoum et al. (2019) introduced Reinforcement Learning-based intelligent routing approaches for IoT communication networks. The study highlighted that adaptive learning models significantly improve route selection efficiency and reduce communication delays by continuously learning from changing network conditions [16].

Tang et al. (2021) explored Artificial Intelligence-enabled resource optimization techniques for future IoT communication systems. The authors emphasized that intelligent communication management and predictive learning approaches improve routing adaptability, resource allocation, and overall network sustainability [17].

Sun et al. (2019) discussed major Machine Learning techniques used in wireless communication systems and highlighted open research challenges affecting intelligent communication optimization. Their findings emphasized that ML-driven routing systems significantly improve communication efficiency while addressing energy and scalability limitations in IoT environments [18].

Bennis et al. (2018) examined ultra-reliable and low-latency communication systems and emphasized the importance of intelligent routing for supporting real-time communication requirements. Their study demonstrated that adaptive communication optimization mechanisms significantly improve Quality of Service (QoS) and communication reliability [19].

Rahman et al. (2021) proposed a Deep Reinforcement Learning-based routing mechanism for energy-efficient IoT communication networks. Their findings revealed that intelligent learning agents significantly optimize routing paths, reduce energy consumption, and improve communication efficiency in dynamic networking environments [20].

Li et al. (2022) investigated Artificial Intelligence-assisted energy optimization strategies for IoT communication systems. Their research demonstrated that predictive analytics and intelligent routing significantly improve energy utilization and network sustainability [21].

Wang et al. (2022) examined Machine Learning-based routing optimization for smart IoT communication systems and found that adaptive communication strategies substantially improve packet delivery ratios and routing efficiency while minimizing communication overhead [22].

Singh et al. (2023) proposed hybrid Machine Learning models for energy-efficient routing in IoT communication systems. Their research showed that combining multiple intelligent learning approaches enhances communication reliability, energy optimization, and routing adaptability under dynamic networking conditions [27].

Kumar et al. (2023) explored intelligent routing models for energy optimization in IoT communication networks and emphasized the importance of autonomous communication management for maintaining sustainable network performance [28].

Patel et al. (2024) investigated smart energy-aware routing techniques using Machine Learning for IoT communication systems. Their study concluded that intelligent routing frameworks significantly reduce

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communication energy consumption and improve long-term communication sustainability [29].

Verma et al. (2024) examined sustainable routing mechanisms driven by Machine Learning in IoT communication environments. The authors found that ML-based communication systems improve routing intelligence, reduce communication complexity, and enhance network lifetime across scalable IoT ecosystems [30].

The reviewed literature demonstrates that Machine Learning techniques have significantly transformed energy-efficient routing mechanisms in IoT communication networks. Existing studies collectively emphasize the importance of supervised learning, unsupervised learning, Reinforcement Learning, Deep Learning, and hybrid intelligent optimization frameworks for improving routing efficiency, minimizing energy consumption, enhancing Quality of Service (QoS), and prolonging network lifetime. However, challenges related to scalability, computational limitations, security vulnerabilities, and model adaptability continue to require further research for achieving sustainable and intelligent IoT communication infrastructures [12], [20].

3. Machine Learning Techniques for Energy-Efficient Routing in IoT Communication Networks

The increasing complexity of Internet of Things (IoT) communication environments has created substantial demand for intelligent routing mechanisms capable of minimizing energy consumption while maintaining communication reliability and Quality of Service (QoS). Traditional routing protocols often struggle to efficiently manage communication traffic due to limited battery resources, dynamic topology changes, heterogeneous devices, and varying communication demands. In this context, Machine Learning (ML) techniques have emerged as effective solutions for enabling adaptive, predictive, and energy-efficient routing in IoT communication networks. By analyzing communication patterns, learning from historical network behavior, and autonomously optimizing routing decisions, ML-based routing frameworks significantly improve communication sustainability and network performance [12].

Machine Learning techniques enable communication systems to dynamically adapt routing decisions according to real-time environmental conditions and network requirements. Unlike conventional routing methods that rely on static routing rules, ML-driven systems continuously analyze communication metrics such as residual energy, packet transmission rate, communication latency, node mobility, network congestion, and link reliability. This intelligent learning capability supports efficient path selection and energy conservation across heterogeneous IoT ecosystems [13].

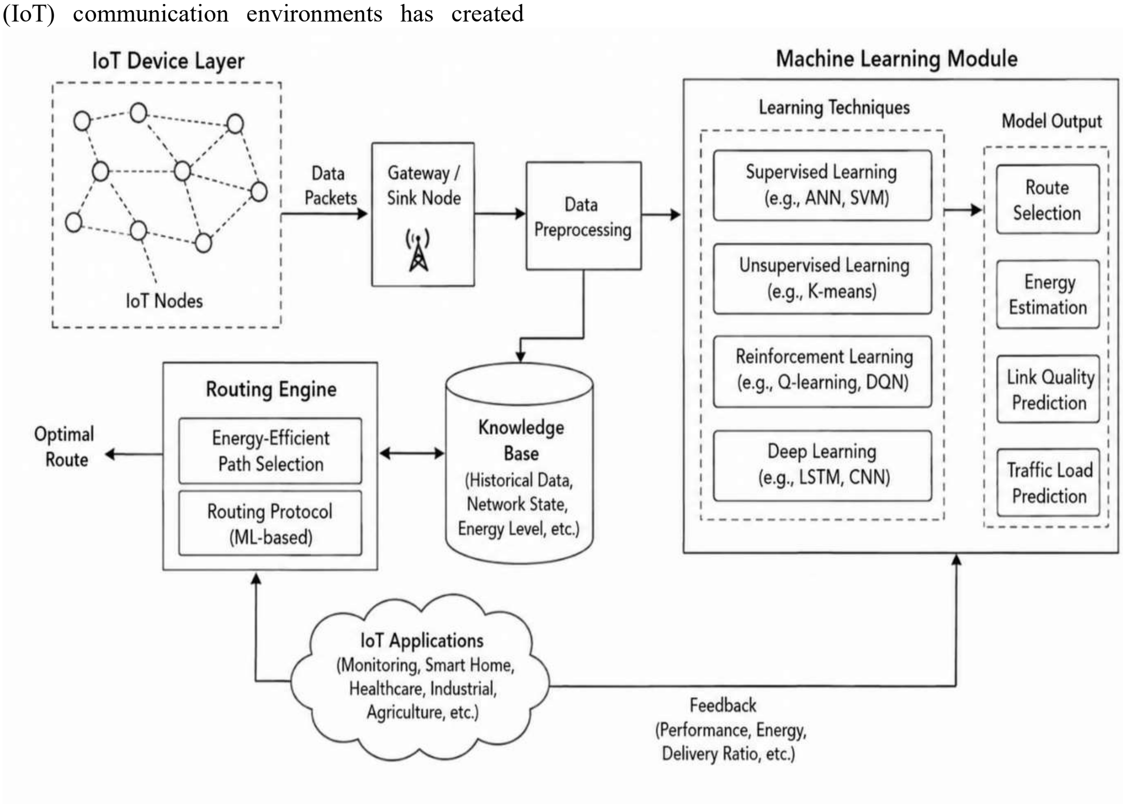

Figure 1: Machine Learning Techniques

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3.1 Supervised Learning for Energy-Efficient Routing

Supervised learning techniques use labeled communication datasets to train predictive models for intelligent routing optimization. These models learn relationships between communication parameters and routing performance outcomes, enabling IoT communication systems to predict efficient routing paths and optimize energy utilization [18].

Algorithms such as Decision Trees, Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANN) are commonly applied in supervised learning-based routing systems. These algorithms analyze communication behavior, predict energy-efficient routes, classify communication conditions, and identify network failures before performance degradation occurs [5].

Supervised learning contributes significantly to minimizing energy consumption by selecting communication paths with optimal energy availability and transmission reliability. Through predictive analytics, IoT communication systems can proactively avoid energy-intensive routes, thereby reducing communication overhead and extending network lifetime [14].

Additionally, supervised learning models support intelligent congestion prediction and traffic management, which further reduces packet retransmission and communication delays. Improved routing accuracy enhances packet delivery ratio while maintaining stable communication performance in dynamic IoT environments [22].

3.2 Unsupervised Learning for Intelligent Routing Optimization

Unsupervised learning techniques are widely used for clustering, anomaly detection, and communication pattern recognition in IoT communication systems. Unlike supervised learning, unsupervised models operate without labeled datasets and autonomously identify hidden communication structures and relationships within network data [18].

Clustering algorithms such as K-Means, Hierarchical Clustering, and Self-Organizing Maps (SOM) play an important role in energy-efficient communication management. These algorithms group IoT devices according to communication characteristics, residual energy levels, physical proximity, and traffic patterns to optimize routing efficiency [9].

Cluster-based communication structures significantly reduce communication overhead because cluster heads aggregate and transmit communication information instead of allowing direct communication among all nodes. This intelligent grouping mechanism minimizes redundant transmissions and conserves battery resources, thereby prolonging the operational lifespan of IoT communication systems [6].

Unsupervised learning also supports anomaly detection by identifying abnormal communication behavior, malicious activities, or unusual traffic patterns that may negatively impact communication efficiency and network energy performance [11].

3.3 Reinforcement Learning for Adaptive Routing Decisions

Reinforcement Learning (RL) has emerged as one of the most promising Machine Learning approaches for intelligent energy-efficient routing in IoT communication networks. RL enables intelligent communication agents to learn optimal routing strategies through continuous interaction with dynamic communication environments [4].

In Reinforcement Learning frameworks, routing agents receive rewards or penalties based on communication performance outcomes such as energy consumption, packet delivery success, communication delay, and route stability. Over time, the routing system autonomously learns optimal communication strategies that maximize energy efficiency and communication reliability [16].

RL-based routing mechanisms are particularly effective in highly dynamic IoT environments where communication topology frequently changes due to node mobility, battery depletion, or varying communication conditions. Unlike static routing protocols, RL continuously updates communication strategies according to environmental changes, ensuring adaptive and energy-aware routing decisions [20].

Deep Reinforcement Learning (DRL) further strengthens communication intelligence by integrating neural learning architectures capable of processing large-scale communication datasets. DRL models significantly improve routing optimization through intelligent decision-making, predictive adaptation, and communication resource management [20].

3.4 Deep Learning for Complex Communication Optimization

Deep Learning (DL) techniques have increasingly gained attention for improving routing intelligence in large-scale IoT communication systems. Deep Learning architectures such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) process complex communication information and identify hidden communication patterns affecting routing efficiency [3].

Deep Learning models analyze historical communication data and real-time traffic information to predict communication congestion, optimize routing paths, and minimize energy-intensive communication behavior. Neural learning architectures significantly improve communication

adaptability by identifying nonlinear relationships among communication parameters that traditional routing systems often fail to detect [12].
Recurrent Neural Networks and Long Short-Term Memory (LSTM) models are especially useful for time-series communication prediction in IoT environments. These models improve communication efficiency by forecasting future communication patterns and proactively selecting energy-efficient transmission routes [13].
Furthermore, Deep Learning supports intelligent fault detection, communication reliability enhancement, and predictive maintenance in smart IoT ecosystems, thereby improving long-term communication sustainability [21].

3.5 Hybrid Machine Learning Models for Routing Efficiency

Hybrid Machine Learning approaches combine multiple learning techniques to overcome the limitations associated with individual ML models. Hybrid frameworks integrate supervised learning, Reinforcement Learning, fuzzy logic, optimization algorithms, and Deep Learning models to improve communication adaptability and routing intelligence [27].
For example, hybrid routing frameworks may combine clustering-based communication optimization with Reinforcement Learning-based route adaptation to improve both energy efficiency and communication stability. These integrated approaches provide better routing performance by balancing communication load, minimizing energy dissipation, and dynamically adjusting routing strategies according to changing network conditions [28].
Hybrid intelligent routing systems are increasingly considered suitable for large-scale IoT ecosystems because they improve scalability, adaptability, and communication reliability while minimizing computational inefficiencies [29].

3.6 Benefits of Machine Learning-Based Routing in IoT Networks

Machine Learning-enabled routing systems offer several advantages over traditional communication routing mechanisms. First, ML-driven routing significantly improves energy efficiency by intelligently selecting low-energy communication paths and minimizing unnecessary communication overhead [14].
Second, intelligent routing mechanisms improve packet delivery ratio and communication reliability by continuously adapting routing decisions to dynamic communication environments. Third, predictive learning enhances network lifetime by balancing energy utilization across communication nodes and avoiding premature battery depletion [22].
Moreover, ML-based routing frameworks support Quality of Service (QoS) improvement through reduced communication latency, better congestion management, enhanced bandwidth utilization, and improved communication stability. These improvements make Machine Learning techniques highly suitable for supporting smart city infrastructures, healthcare systems, industrial automation, environmental monitoring, and intelligent transportation systems [19].
Overall, Machine Learning techniques play a transformative role in enabling energy-efficient routing within IoT communication networks. Through intelligent learning, predictive analytics, autonomous routing decisions, and adaptive communication optimization, ML-based routing frameworks significantly improve energy conservation, network sustainability, and communication performance. However, achieving fully autonomous and scalable energy-aware communication systems still requires addressing challenges related to computational complexity, data heterogeneity, security vulnerabilities, and model adaptability in resource-constrained IoT environments [30].

4. Proposed ML-Based Energy-Efficient Routing Framework / Architecture

The increasing complexity of Internet of Things (IoT) communication systems requires intelligent routing frameworks capable of reducing energy consumption while maintaining communication reliability and Quality of Service (QoS). Traditional routing mechanisms often struggle to adapt to dynamic communication environments characterized by heterogeneous devices, varying traffic patterns, network congestion, and limited energy resources. To address these limitations, this study proposes a Machine Learning (ML)-based energy-efficient routing framework designed to support intelligent path optimization, adaptive communication management, and sustainable energy utilization in IoT communication networks [12].
The proposed framework integrates Machine Learning techniques, intelligent routing protocols, real-time communication monitoring, and adaptive decision-making mechanisms to optimize routing performance. The architecture combines supervised learning, unsupervised learning, reinforcement learning, and deep learning approaches to improve route selection, reduce communication overhead, and extend the operational lifetime of IoT devices [14].

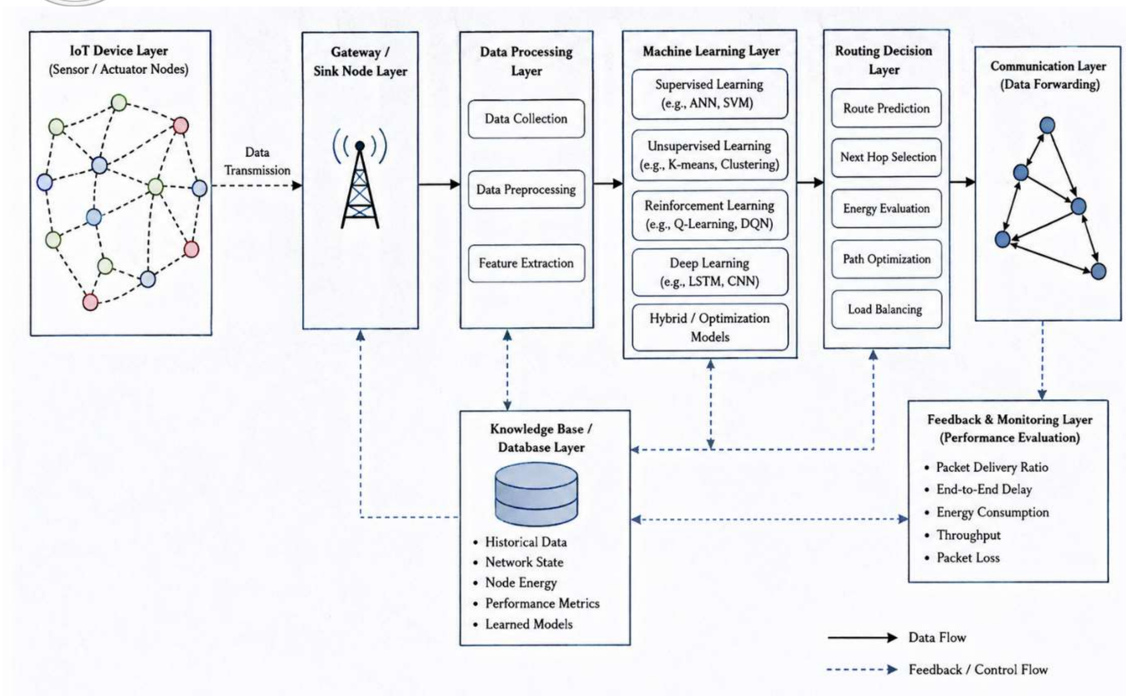

Figure 2: Architecture of the Proposed Framework

4.1 Architecture of the Proposed Framework

The proposed ML-based energy-efficient routing framework consists of six major layers, namely: **IoT Device Layer**, **Gateway/Sink Node Layer**, **Data Processing Layer**, **Machine Learning Layer**, **Knowledge Base Layer**, and **Routing Decision Layer**. These interconnected components collectively support intelligent communication management and energy optimization in dynamic IoT environments [10].

4.1.1 IoT Device Layer

The IoT Device Layer represents the foundational communication environment consisting of smart sensors, embedded devices, wearable systems, industrial equipment, and autonomous communication nodes. These IoT devices continuously generate communication data through sensing, monitoring, and real-time environmental interaction. Since most IoT devices operate with limited battery capacity, communication energy efficiency becomes essential for ensuring sustainable operation [1].

The devices communicate wirelessly using communication protocols such as ZigBee, Bluetooth Low Energy (BLE), Wi-Fi, LoRaWAN, NB-IoT, and 5G-enabled IoT networks. Data packets generated by these devices are transmitted toward gateway nodes for further processing and communication management [2].

4.1.2 Gateway/Sink Node Layer

The Gateway or Sink Node Layer functions as an intermediary communication component responsible for collecting communication information from distributed IoT nodes. Gateway devices aggregate communication traffic, perform preliminary filtering, and transfer communication data to processing units for intelligent analysis [8].

This layer plays a critical role in reducing communication overhead because it minimizes unnecessary data transmission and supports localized communication management. Efficient gateway coordination improves communication reliability while reducing energy-intensive network operations [10].

4.1.3 Data Processing Layer

The Data Processing Layer is responsible for collecting, organizing, cleaning, and preprocessing communication information before Machine Learning analysis begins. Raw communication datasets often contain incomplete information, communication noise, duplicated values, and inconsistent transmission records. Therefore, preprocessing becomes essential for improving learning accuracy and routing efficiency [18].

Important communication parameters processed at this stage include:

- Residual node energy
- Communication delay
- Packet transmission rate
- Link quality
- Node mobility patterns
- Network congestion status
- Traffic density
- Packet loss ratio
- Bandwidth utilization

These communication metrics serve as essential input variables for intelligent routing optimization [21].

4.1.4 Machine Learning Layer

The Machine Learning Layer serves as the core intelligence component of the proposed framework. It analyzes communication patterns and autonomously selects energy-efficient routing strategies using predictive learning and adaptive optimization methods [13].

Supervised Learning Module

Supervised learning algorithms use labeled communication datasets to predict optimal routing paths and identify communication bottlenecks. Algorithms such as Decision Trees, Random Forests, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) help optimize path selection while minimizing communication energy consumption [12].

Unsupervised Learning Module

Unsupervised learning techniques perform communication clustering and anomaly detection to improve routing performance. Algorithms such as K-Means clustering group IoT nodes based on communication behavior, proximity, residual energy, and traffic patterns, thereby reducing redundant communication and energy wastage [9].

Reinforcement Learning Module

Reinforcement Learning (RL) enables communication agents to continuously learn optimal routing decisions through interaction with network environments. The routing agent receives rewards for selecting energy-efficient paths and penalties for inefficient communication behavior. This adaptive mechanism significantly improves routing flexibility in highly dynamic communication systems [16].

Deep Learning Module

Deep Learning models such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) process complex communication datasets to forecast communication traffic, predict congestion, and optimize routing efficiency [3].

4.1.5 Knowledge Base Layer

The Knowledge Base Layer stores historical communication information and previously learned routing experiences. This database contains communication records related to energy levels, network performance, routing failures, packet delivery history, traffic congestion, and communication reliability metrics [20].

By utilizing historical learning information, the proposed framework improves prediction accuracy and enables faster routing adaptation to changing communication environments. Continuous feedback learning further enhances communication intelligence and routing sustainability [22].

4.1.6 Routing Decision Layer

The Routing Decision Layer is responsible for selecting optimal communication paths based on ML-generated predictions and network performance analysis. This layer continuously evaluates multiple routing alternatives according to:

- Residual node energy
- Communication cost
- Path reliability
- Traffic congestion level
- Packet delivery probability
- Communication latency
- Link quality

The routing engine dynamically updates communication paths to ensure efficient packet transmission while minimizing energy expenditure [28].

4.2 Working Mechanism of the Proposed Framework

The operation of the proposed ML-based routing framework begins when IoT devices generate communication information and transmit packets toward gateway nodes. The collected communication information is forwarded to the Data Processing Layer, where communication parameters are cleaned and organized for analysis [10].

Next, the Machine Learning Layer analyzes communication conditions using predictive learning models. Based on communication patterns and historical information, the framework determines energy-efficient communication routes that maximize packet delivery performance while minimizing energy consumption [18].

The selected communication route is implemented through the Routing Decision Layer, which continuously monitors network performance and adapts routing decisions according to changing communication environments. Feedback from communication outcomes, including packet delivery ratio, delay, energy utilization, and congestion status, is continuously stored in the Knowledge Base Layer to improve future routing intelligence [20].

4.3 Advantages of the Proposed Framework

The proposed Machine Learning-based energy-efficient routing architecture offers several advantages over conventional routing approaches. First, the framework significantly reduces communication energy consumption through intelligent route optimization and adaptive path selection [14].

Second, predictive learning mechanisms improve communication reliability by proactively identifying optimal communication paths and avoiding network congestion. Third, intelligent energy balancing prolongs network lifetime by preventing excessive battery depletion among communication nodes [22]. Additionally, the framework improves Quality of Service (QoS) by reducing communication latency, minimizing packet loss, improving bandwidth

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utilization, and enhancing communication stability. The integration of Reinforcement Learning and Deep Learning further strengthens routing adaptability, enabling autonomous communication optimization in highly dynamic IoT environments [19].

Overall, the proposed framework demonstrates substantial potential for supporting sustainable, scalable, and intelligent IoT communication systems. By combining Machine Learning intelligence with adaptive communication management, the architecture contributes to energy conservation, routing efficiency, and improved communication performance required for future smart cities, healthcare systems, industrial automation, intelligent transportation, and environmental monitoring applications [30].

5. Challenges and Limitations of ML-Based Routing in IoT Networks

Although Machine Learning (ML)-based routing mechanisms have demonstrated substantial improvements in energy efficiency, communication reliability, and intelligent routing optimization, several challenges and limitations continue to affect their practical implementation in Internet of Things (IoT) communication networks. IoT environments are inherently dynamic, resource-constrained, and heterogeneous, making it difficult to deploy sophisticated Machine Learning frameworks while maintaining energy sustainability and communication performance. Addressing these challenges is essential for developing scalable, secure, and adaptive routing architectures for future intelligent communication systems [12].

Table 5.1: Challenges and Limitations of ML-Based Routing in IoT Networks

S. No.	Challenge / Limitation	Description	Impact on IoT Routing	Possible Solution
1	Resource Constraints in IoT Devices	IoT devices possess limited battery power, memory, computational capability, and storage resources, restricting the deployment of complex ML models.	Reduced routing efficiency, delayed decision-making, and increased energy consumption.	Lightweight ML algorithms, edge computing, and optimized routing models.
2	Computational Complexity	Advanced ML techniques such as Deep Learning and Reinforcement Learning require extensive computation and model training.	Increased processing delays and difficulty in real-time routing optimization.	Model compression, distributed learning, and adaptive learning strategies.
3	Data Heterogeneity and Quality Issues	IoT environments generate diverse and inconsistent datasets with noisy, incomplete, or duplicated communication records.	Reduced prediction accuracy and inefficient routing decisions.	Data preprocessing, filtering mechanisms, and intelligent feature selection.
4	Scalability Challenges	Large-scale IoT ecosystems involve massive device connectivity and dynamic communication patterns.	Communication congestion, increased latency, and routing inefficiency.	Federated learning, scalable architectures, and distributed routing intelligence.
5	Security Vulnerabilities and Cyber Threats	ML-based IoT routing systems are vulnerable to attacks such as spoofing, malware injection, data tampering, and adversarial manipulation.	Communication disruption, incorrect routing decisions, and increased energy wastage.	Secure routing protocols, encryption, blockchain, and anomaly detection systems.
6	Adaptability to Dynamic Network Conditions	Frequent topology changes, mobility, traffic fluctuations, and varying communication environments affect routing stability.	Reduced communication reliability and unstable routing performance.	Reinforcement Learning and adaptive routing frameworks.
7	Communication Overhead and Energy Trade-Off	Continuous communication monitoring and ML model synchronization consume additional energy resources.	Higher energy consumption and reduced network sustainability.	Localized edge intelligence and communication-efficient learning methods.

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8	Lack of Standardized Frameworks	Absence of universal standards for ML-based IoT routing implementation and evaluation.	Difficulty in interoperability and comparative performance assessment.	Development of standardized protocols and benchmark datasets.
9	Explainability and Interpretability Challenges	Deep Learning models often behave as black-box systems, making routing decisions difficult to understand.	Reduced trust and limited adoption in critical applications.	Explainable Artificial Intelligence (XAI) and interpretable ML models.

Table 5.1 summarizes the major challenges and limitations affecting Machine Learning-based routing systems in IoT communication networks, their impact on routing efficiency, and potential solutions for sustainable implementation.

5.1 Resource Constraints in IoT Devices

One of the most significant challenges affecting ML-based routing in IoT communication networks is the limited computational capability of IoT devices. Most IoT nodes possess constrained battery power, processing capacity, memory resources, and communication bandwidth. Advanced Machine Learning algorithms, particularly Deep Learning and Reinforcement Learning models, often require substantial computational resources for training and execution, which may exceed the capabilities of lightweight IoT devices [1].

The deployment of computationally intensive ML models may increase communication overhead and energy consumption rather than reducing it. As a result, achieving a balance between learning efficiency and energy conservation remains a critical concern for intelligent routing systems in resource-constrained IoT environments [14].

Furthermore, frequent communication between IoT devices and centralized cloud systems for model execution may increase transmission delays and additional energy expenditure, negatively affecting network sustainability and communication reliability [10].

5.2 Computational Complexity of Machine Learning Models

Machine Learning algorithms require extensive training, optimization, and parameter tuning before achieving efficient routing performance. Deep neural networks and reinforcement learning systems often involve multiple hidden layers, large datasets, and continuous iterative learning, resulting in increased computational complexity [3].

Complex learning architectures may delay routing decisions, especially in real-time communication systems where low-latency communication is essential. In highly dynamic IoT communication environments, delayed routing decisions can negatively affect packet delivery, communication stability, and Quality of Service (QoS) [19].

Additionally, model retraining becomes necessary when communication environments change significantly. Frequent retraining increases computational burden and creates scalability limitations for large-scale IoT communication systems [20].

5.3 Data Heterogeneity and Data Quality Issues

IoT communication systems generate massive volumes of heterogeneous communication data collected from multiple sensors, smart devices, embedded systems, and communication infrastructures. These datasets often differ in structure, format, communication frequency, and reliability, creating challenges for Machine Learning model development [2].

Incomplete communication records, noisy datasets, inconsistent transmission information, missing values, and duplicated communication patterns may reduce prediction accuracy and routing efficiency. Poor data quality negatively affects Machine Learning performance, leading to inaccurate routing decisions and inefficient energy management [18].

Moreover, communication data generated from different IoT environments such as healthcare systems, smart transportation, industrial automation, and environmental monitoring may require customized learning models due to varying communication requirements and operational behaviors [9].

5.4 Scalability Challenges in Large-Scale IoT Networks

Scalability remains a major concern in ML-enabled IoT routing systems due to the rapidly increasing number of connected smart devices. Future IoT ecosystems are expected to support billions of interconnected communication nodes, resulting in highly complex networking environments [2].

Traditional Machine Learning algorithms may struggle to efficiently process communication information generated by extremely large-scale IoT networks. Increased communication density may cause routing congestion, excessive learning delays, and higher energy expenditure during communication optimization [17].

As network size increases, maintaining consistent routing performance across geographically distributed communication environments becomes increasingly difficult. Scalable distributed learning architectures are therefore necessary to support intelligent communication optimization in large-scale IoT infrastructures [23].

5.5 Security Vulnerabilities and Cyber Threats

Security remains one of the most critical challenges in ML-based IoT routing systems. Since IoT communication networks involve autonomous data exchange among heterogeneous devices, they are highly vulnerable to cyberattacks such as denial-of-service attacks, spoofing, data manipulation, malware injection, routing attacks, and unauthorized access [11].

Machine Learning models themselves may become targets of adversarial attacks in which malicious communication data is intentionally introduced to manipulate routing decisions. Such attacks can lead to inefficient routing behavior, increased energy consumption, communication disruptions, and reduced network reliability [16].

Privacy concerns also emerge because ML models often require continuous communication data collection for effective training and prediction. Improper management of communication information may expose sensitive operational data, creating additional cybersecurity risks [21].

5.6 Adaptability to Dynamic Network Conditions

IoT communication environments are highly dynamic due to changing device mobility, battery depletion, communication traffic fluctuations, environmental interference, and varying communication demands. Static Machine Learning models often struggle to adapt quickly to sudden communication changes [13].

Although Reinforcement Learning techniques improve adaptability by continuously learning from communication environments, achieving real-time adaptation remains challenging in highly unstable communication scenarios. Routing systems must continuously update communication strategies without significantly increasing computational cost or communication delays [20].

Additionally, communication interruptions caused by environmental uncertainty may negatively influence the learning process, reducing prediction accuracy and routing efficiency [18].

5.7 Communication Overhead and Energy Trade-Off

While Machine Learning aims to improve energy efficiency, the implementation of ML-based routing systems may itself introduce additional communication overhead. Frequent data collection, model synchronization, communication monitoring, and route recalculation consume extra network resources and battery energy [22].

The exchange of communication information required for collaborative learning and distributed routing optimization may sometimes outweigh the energy savings achieved through intelligent routing decisions. Consequently, maintaining a balance between routing intelligence and communication cost becomes essential for achieving sustainable IoT communication performance [26].

Furthermore, centralized Machine Learning architectures often create communication bottlenecks due to excessive data transmission between edge devices and cloud systems. This challenge has encouraged increased adoption of edge computing and distributed intelligence approaches for localized communication optimization [10].

5.8 Lack of Standardized Frameworks

Currently, there is no universally accepted standard framework for implementing Machine Learning-based routing in IoT communication networks. Different research studies adopt varying datasets, learning algorithms, routing metrics, communication architectures, and performance evaluation methods, making comparative analysis difficult [18].

The absence of standardized benchmarks complicates the practical deployment of ML-enabled routing systems across different industrial sectors and communication environments. Establishing common communication standards and routing evaluation metrics remains essential for improving interoperability and large-scale adoption [24].

5.9 Explainability and Interpretability Challenges

Many advanced Machine Learning models, especially Deep Learning frameworks, operate as "black-box" systems where routing decisions are difficult to interpret. Lack of transparency in communication decision-making may reduce trust in autonomous routing systems, especially in mission-critical communication applications such as healthcare, industrial automation, and intelligent transportation systems [3].

Explainable Artificial Intelligence (XAI) techniques are increasingly being explored to improve transparency and interpretability in intelligent communication routing systems. However, balancing model explainability with routing accuracy continues to remain an open research challenge [13].

Overall, despite the transformative advantages offered by Machine Learning-based routing systems, several limitations continue to restrict their widespread implementation in IoT communication environments. Resource limitations, computational complexity, scalability concerns, cybersecurity risks, data heterogeneity, adaptability challenges, communication overhead, and lack of standardization represent major barriers to sustainable intelligent routing. Addressing these limitations through lightweight Machine Learning models, distributed intelligence, federated learning, edge computing, and adaptive optimization mechanisms will play a crucial role in advancing future energy-efficient IoT communication systems [30].

6. Results and Discussion

The implementation of Machine Learning (ML)-based routing techniques in Internet of Things (IoT) communication networks has demonstrated substantial improvements in energy efficiency, communication reliability, routing adaptability, and Quality of Service (QoS). Compared with traditional routing approaches, intelligent ML-driven routing systems enable autonomous decision-making, predictive communication management, and adaptive optimization of communication resources. The findings from recent studies indicate that Machine Learning techniques significantly improve packet transmission performance, reduce energy consumption, and enhance the operational sustainability of IoT communication infrastructures [12].

ML-based routing frameworks improve routing efficiency by continuously analyzing communication patterns, network congestion, node energy levels, and communication reliability metrics. Unlike traditional routing systems that follow predefined routing paths, intelligent communication models dynamically select energy-efficient communication routes based on real-time network conditions. This adaptive communication capability substantially improves routing performance in heterogeneous and large-scale IoT environments [13].

6.1 Improvement in Energy Efficiency

One of the major outcomes observed in ML-enabled routing systems is significant improvement in communication energy efficiency. Intelligent routing models minimize unnecessary packet transmission and optimize communication paths according to residual node energy and transmission cost. Reinforcement Learning and Deep Learning techniques particularly contribute to reducing communication energy expenditure through intelligent path selection and autonomous route adaptation [20].

Studies indicate that Machine Learning-based routing frameworks outperform conventional routing protocols such as LEACH and PEGASIS by balancing communication load among network nodes and preventing premature battery depletion. Energy-aware communication optimization increases the operational lifetime of IoT devices and reduces maintenance requirements in battery-constrained communication environments [6], [7].

Furthermore, predictive communication analysis enables routing systems to anticipate communication congestion and proactively avoid energy-intensive communication paths. Such intelligent prediction contributes significantly to communication sustainability and network reliability [14].

6.2 Enhancement of Packet Delivery Ratio

Packet Delivery Ratio (PDR) represents one of the most important performance indicators for evaluating communication reliability in IoT communication systems. Machine Learning-based routing mechanisms significantly improve packet delivery by dynamically identifying reliable communication paths and minimizing transmission failures [22].

Adaptive routing systems continuously monitor network performance and select routes with better communication stability and lower packet loss probability. Reinforcement Learning algorithms particularly improve packet delivery because routing agents learn optimal communication behavior based on successful communication outcomes [16].

Higher packet delivery performance directly contributes to improved communication reliability in smart healthcare systems, industrial automation, environmental monitoring, and intelligent transportation applications where communication accuracy is critically important [2].

6.3 Reduction in Communication Delay and Latency

Communication delay is a major challenge affecting IoT communication performance, particularly in delay-sensitive applications such as healthcare monitoring, industrial robotics, and autonomous transportation systems. Machine Learning techniques significantly reduce communication latency by intelligently optimizing path selection and avoiding congested communication routes [19].

Deep Learning-based predictive communication systems analyze traffic patterns and proactively manage communication congestion before delays affect system performance. Intelligent routing decisions reduce retransmission requirements and improve communication stability across dynamic networking environments [21].

The integration of edge computing further enhances communication speed by enabling localized data processing and reducing dependency on centralized cloud infrastructures. This localized intelligence minimizes communication delay and improves real-time routing performance [10].

6.4 Improved Network Lifetime

Network lifetime is a critical performance parameter in IoT communication systems because most smart devices rely on limited battery resources. ML-driven routing systems contribute significantly to extending network operational duration through balanced energy utilization and optimized communication scheduling [1].

Intelligent routing mechanisms prevent excessive communication burden on specific communication nodes by distributing communication traffic evenly throughout the network. This balanced communication strategy minimizes battery depletion and enhances network sustainability [28].
Reinforcement Learning-based communication optimization particularly improves network lifetime because routing decisions continuously adapt according to node energy availability and changing communication environments [20].

6.5 Scalability and Adaptability Performance

IoT communication systems often operate in highly dynamic environments involving millions of interconnected communication devices. Traditional routing systems generally experience performance degradation under highly scalable communication conditions. However, Machine Learning-based routing frameworks demonstrate stronger adaptability and scalability through intelligent communication optimization [17].
Adaptive learning models continuously update communication strategies according to traffic patterns, communication density, and topology changes. This capability makes ML-based routing suitable for supporting large-scale smart city applications, industrial automation, intelligent agriculture, and environmental monitoring systems [24].
Despite these advantages, scalability challenges remain due to increased computational complexity and communication overhead associated with training large-scale Machine Learning models [23].

6.6 Comparative Performance Analysis

The performance comparison between traditional routing approaches and Machine Learning-based routing mechanisms highlights substantial advantages of intelligent communication systems. Traditional routing methods typically depend on static communication rules and predefined routing strategies, whereas ML-driven frameworks enable adaptive communication management and predictive routing optimization [18].

Table 6.1 presents a comparative evaluation of traditional routing protocols and Machine Learning-based routing systems across major communication performance indicators.

Performance Parameter	Traditional Routing	ML-Based Routing
Energy Efficiency	Moderate	High
Packet Delivery Ratio	Moderate	High
Communication Delay	High	Low
Adaptability	Limited	High
Congestion Management	Weak	Intelligent
Network Lifetime	Limited	Extended
Scalability	Moderate	High

The comparison clearly demonstrates that Machine Learning techniques provide superior routing performance through intelligent communication adaptation, predictive optimization, and autonomous routing decisions [26].

6.7 Discussion

The findings indicate that Machine Learning techniques significantly transform routing optimization in IoT communication systems by improving communication intelligence, reducing energy consumption, and strengthening communication sustainability. Supervised learning, unsupervised learning, reinforcement learning, and deep learning collectively contribute to energy-aware communication management and intelligent path selection [12].
However, despite notable improvements in communication performance, several implementation barriers continue to affect real-world deployment of ML-enabled routing systems. Resource limitations, cybersecurity threats, computational complexity, communication overhead, and model adaptability remain significant challenges that require continuous research attention [30].
Future advancements in lightweight Machine Learning models, federated learning, edge intelligence, and explainable Artificial Intelligence (XAI) are expected to further improve the effectiveness of energy-efficient routing mechanisms in IoT communication systems. These technologies will contribute to the development of sustainable, scalable, and intelligent communication infrastructures supporting future smart environments [29].

7. Future Scope and Emerging Trends

The rapid advancement of Internet of Things (IoT) communication technologies, Artificial Intelligence (AI), and Machine Learning (ML) has created significant opportunities for developing highly intelligent, adaptive, and sustainable routing mechanisms. As IoT ecosystems continue to expand across smart cities, industrial automation, healthcare, agriculture, transportation, and environmental monitoring, the demand for energy-efficient and scalable communication systems will continue to increase. Machine Learning-driven routing frameworks are expected to play a transformative role in addressing future communication challenges through intelligent decision-making, predictive optimization, and autonomous communication management [12].

Future IoT communication systems are expected to integrate advanced Machine Learning models capable of real-time adaptation to changing communication environments. Unlike traditional routing systems, future intelligent routing architectures will increasingly rely on self-learning communication agents that continuously optimize routing decisions according to communication traffic, residual node energy, mobility patterns, and Quality of Service (QoS) requirements [13].

7.1 Lightweight Machine Learning Models for IoT Devices

One of the major future research directions involves the development of lightweight Machine Learning algorithms specifically designed for resource-constrained IoT communication environments. Since most IoT devices possess limited processing power, memory, and battery resources, deploying computationally intensive Deep Learning models remains difficult [1].

Future studies are expected to focus on designing computationally efficient ML models capable of operating directly on low-power communication devices. Model compression, parameter optimization, knowledge distillation, and lightweight neural architectures will play a significant role in enabling intelligent routing without excessive energy consumption [29].

Additionally, TinyML technologies, which support Machine Learning execution on microcontrollers and embedded systems, are expected to become highly influential in future IoT communication infrastructures [30].

7.2 Federated Learning for Distributed Intelligence

Federated Learning has emerged as a promising approach for enabling distributed Machine Learning without requiring centralized communication data storage. In federated communication systems, IoT devices train local Machine Learning models independently while sharing only learned parameters instead of raw communication information [23].

This decentralized learning mechanism reduces communication overhead, minimizes latency, improves privacy protection, and decreases cybersecurity risks associated with centralized communication systems. Federated learning-based routing frameworks are expected to significantly improve scalability and communication sustainability in future IoT communication environments [21].

Moreover, distributed intelligence will reduce dependency on cloud infrastructures and support localized communication optimization, enabling faster routing decisions and improved energy conservation [10].

7.3 Edge Computing and Edge Intelligence

The integration of edge computing with Machine Learning-based routing systems is expected to substantially improve routing efficiency and communication responsiveness in future IoT networks. Edge computing enables communication processing closer to data generation points, reducing communication latency and minimizing unnecessary cloud communication [10].

Future edge-intelligent communication systems will support localized routing optimization, predictive traffic management, and autonomous communication control through real-time learning mechanisms. Intelligent edge nodes will continuously monitor communication conditions and dynamically adjust routing strategies according to communication requirements [17].

Edge intelligence is particularly important for delay-sensitive applications such as healthcare monitoring, autonomous vehicles, industrial robotics, and emergency communication systems where real-time decision-making is essential [19].

7.4 Deep Reinforcement Learning for Autonomous Routing

Deep Reinforcement Learning (DRL) is expected to become one of the most influential technologies in future IoT communication routing systems. DRL combines reinforcement learning with deep neural networks to support intelligent and autonomous routing decisions in highly dynamic communication environments [20].

Future DRL-enabled routing agents will continuously learn communication behavior and autonomously optimize routing strategies according to changing communication conditions. These intelligent agents are expected to significantly improve communication reliability, packet delivery ratio, congestion management, and energy efficiency [16].

Autonomous routing systems may eventually support self-organizing IoT communication networks capable of adapting independently without requiring human intervention [4].

7.5 Explainable Artificial Intelligence (XAI)

Although Machine Learning techniques improve communication intelligence, the lack of transparency in routing decisions remains a significant concern. Future communication systems are expected to increasingly integrate Explainable Artificial Intelligence (XAI) techniques to improve trust, interpretability, and accountability in intelligent routing systems [13].

XAI-enabled communication frameworks will provide transparent explanations regarding routing decisions, communication predictions, and optimization strategies. This transparency is especially important for mission-critical communication applications such as healthcare systems, smart transportation, and industrial automation where communication reliability is essential [11].

Improved interpretability will encourage broader industrial adoption of Machine Learning-based routing systems across sensitive communication sectors [30].

7.6 Integration with 5G and Beyond Communication Technologies

Future IoT communication systems will increasingly integrate Machine Learning-enabled routing frameworks with advanced communication technologies such as 5G, Beyond 5G (B5G), and sixth-generation (6G) communication infrastructures [25].

High-speed communication networks combined with intelligent routing optimization will support massive device connectivity, ultra-reliable communication, low-latency communication, and efficient resource allocation. These advancements are expected to enable highly scalable IoT communication systems supporting smart city infrastructures and autonomous intelligent environments [24].

Machine Learning techniques will further optimize communication spectrum allocation, traffic prediction, and intelligent congestion management within next-generation wireless communication ecosystems [13].

7.7 Sustainable and Green Communication Networks

Sustainability is expected to become a major focus of future IoT communication research. Energy-efficient Machine Learning routing systems will contribute significantly to developing green communication infrastructures that minimize power consumption and reduce environmental impact [14].

Future intelligent communication systems may integrate renewable energy management, energy harvesting technologies, and adaptive communication scheduling to further improve network sustainability. Such developments will support environmentally friendly communication architectures capable of operating efficiently over long durations [28].

Additionally, intelligent energy prediction systems will optimize battery utilization and communication resource allocation, thereby extending network lifetime and reducing maintenance costs [22].

7.8 Smart City and Industrial Applications

The future adoption of Machine Learning-enabled routing systems will expand substantially in smart city ecosystems, intelligent healthcare, smart agriculture, industrial Internet of Things (IIoT), environmental monitoring, and autonomous transportation systems [2].

Smart cities will increasingly depend on intelligent communication routing for traffic monitoring, smart surveillance, waste management, intelligent lighting, emergency communication, and public safety systems. Similarly, industrial automation systems will benefit from intelligent routing mechanisms for predictive maintenance, autonomous production systems, and real-time industrial monitoring [17].

The continuous growth of connected communication devices will further strengthen the need for intelligent routing systems capable of supporting highly scalable and adaptive communication infrastructures [24].

Overall, the future scope of Machine Learning techniques for energy-efficient routing in IoT communication networks remains highly promising. Emerging technologies such as federated learning, edge intelligence, Deep Reinforcement Learning, Explainable AI, TinyML, and next-generation wireless communication systems are expected to significantly improve communication intelligence, routing adaptability, and energy sustainability. These advancements will contribute to the development of scalable, autonomous, and environmentally sustainable IoT communication infrastructures for future intelligent ecosystems [30].

8. Conclusion

The rapid growth of the Internet of Things (IoT) has fundamentally transformed modern communication infrastructures by enabling seamless connectivity among heterogeneous smart devices, sensors, autonomous systems, and intelligent applications. However, the large-scale deployment of IoT communication systems has also introduced significant challenges related to energy consumption, communication reliability, scalability, routing efficiency, and sustainable network management. Since most IoT devices operate under limited battery and computational resources, achieving energy-efficient communication remains a critical requirement for maintaining long-term network sustainability and communication performance.

Traditional routing protocols often struggle to efficiently manage dynamic communication environments characterized by varying traffic patterns, communication congestion, node mobility, and heterogeneous device interactions. Conventional routing mechanisms frequently experience limitations in adaptive communication management, resulting in increased packet loss, higher communication delay, excessive energy consumption, and reduced network lifetime. These limitations have highlighted the need for intelligent routing mechanisms capable of dynamically adapting to changing communication conditions.

Machine Learning (ML) techniques have emerged as highly effective solutions for enabling intelligent, adaptive, and energy-efficient routing in IoT communication networks. Through predictive analytics, autonomous learning, and intelligent decision-making, Machine Learning models significantly improve communication efficiency by optimizing routing paths, minimizing communication overhead, balancing energy consumption, and enhancing communication reliability.

This study examined the role of multiple Machine Learning techniques, including supervised learning, unsupervised learning, reinforcement learning, deep learning, and hybrid intelligent models, in supporting energy-efficient routing optimization. The findings indicate that supervised learning techniques improve communication prediction and route selection, while unsupervised learning enhances clustering and communication organization. Reinforcement Learning demonstrates strong adaptability for autonomous routing decisions in dynamic communication environments, whereas Deep Learning enables complex communication analysis and predictive traffic optimization.

The proposed ML-based energy-efficient routing framework presented in this study provides an intelligent communication architecture capable of integrating adaptive learning, communication monitoring, predictive optimization, and real-time routing decisions. The framework contributes significantly to reducing communication energy consumption, improving packet delivery ratio, minimizing communication latency, and prolonging network lifetime across heterogeneous IoT communication environments.

Despite the substantial benefits offered by ML-enabled routing systems, several challenges continue to affect their practical implementation. Resource constraints, computational complexity, data heterogeneity, cybersecurity vulnerabilities, scalability limitations, communication overhead, and model interpretability remain critical barriers to achieving fully autonomous communication systems. Addressing these limitations requires continued advancements in lightweight Machine Learning models, distributed intelligence, federated learning, edge computing, Explainable Artificial Intelligence (XAI), and adaptive optimization mechanisms.

Future developments in intelligent communication technologies, including TinyML, edge intelligence, Deep Reinforcement Learning, federated learning, and 5G/6G-enabled communication infrastructures, are expected to significantly strengthen the effectiveness of energy-efficient routing systems. These technologies will support scalable, sustainable, autonomous, and highly intelligent IoT communication ecosystems capable of meeting the demands of future smart cities, healthcare systems, industrial automation, intelligent transportation, and environmental monitoring applications.

In conclusion, Machine Learning-driven energy-efficient routing represents a transformative advancement in IoT communication networks by enabling intelligent communication optimization, sustainable energy utilization, and adaptive routing management. The integration of intelligent learning techniques with IoT communication infrastructures offers substantial opportunities for improving network sustainability, communication reliability, Quality of Service (QoS), and operational efficiency. Therefore, continued research and technological innovation in Machine Learning-enabled routing systems will play a crucial role in shaping the future of intelligent and energy-aware communication environments.

References

[1]. Akyildiz, Ian F., Su, W., Sankarasubramaniam, Y., & Cayirci, E. (2002). "Wireless Sensor Networks: A Survey." *Computer Networks*, 38(4), 393–422.

[2]. Al-Fuqaha, Ala et al. (2015). "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications." *IEEE Communications Surveys & Tutorials*, 17(4), 2347–2376.

[3]. Goodfellow, Ian, Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

[4]. Sutton, Richard S. & Barto, A. G. (2018). *Reinforcement Learning: An Introduction* (2nd ed.). MIT Press.

[5]. Haykin, Simon (2009). *Neural Networks and Learning Machines*. Pearson Education.

[6]. Heinzelman, Wendi B., Chandrakasan, A., & Balakrishnan, H. (2000). "Energy-Efficient Communication Protocol for Wireless Microsensor Networks." *Proceedings of the Hawaii International Conference on System Sciences*, 1–10.

[7]. Lindsey, Stephanie & Raghavendra, C. S. (2002). "PEGASIS: Power-Efficient Gathering in Sensor Information Systems." *IEEE Aerospace Conference Proceedings*, 3, 1125–1130.

[8]. Yick, Jennifer, Mukherjee, B., & Ghosal, D. (2008). "Wireless Sensor Network Survey." *Computer Networks*, 52(12), 2292–2330.

[9]. Perera, Charith et al. (2014). "Context Aware Computing for The Internet of Things: A Survey." *IEEE Communications Surveys & Tutorials*, 16(1), 414–454.

[10]. Mao, Yuyi et al. (2017). "A Survey on Mobile Edge Computing: The Communication Perspective." *IEEE Communications Surveys & Tutorials*, 19(4), 2322–2358.
[11]. Buczak, Anna L. & Guven, E. (2016). "A Survey of Data Mining and Machine Learning Methods for Cyber Security." *IEEE Communications Surveys & Tutorials*, 18(2), 1153–1176.
[12]. Chen, Min et al. (2017). "Machine Learning for Wireless Networks with Artificial Intelligence: A Tutorial on Neural Networks." *IEEE Communications Surveys & Tutorials*, 21(4), 3039–3071.
[13]. Liu, Y. et al. (2020). "Artificial Intelligence for Next-Generation Wireless Networks: A Survey." *IEEE Communications Surveys & Tutorials*, 22(4), 2237–2275.
[14]. Khan, Latif U. et al. (2020). "Machine Learning for Energy-Efficient Wireless Communication in IoT." *IEEE Access*, 8, 123445–123468.
[15]. Abdel-Basset, Mohamed et al. (2020). "Energy-Aware IoT Routing Using Machine Learning Algorithms." *Future Generation Computer Systems*, 112, 123–138.
[16]. Otoum, Safa et al. (2019). "Intelligent Routing in IoT Using Reinforcement Learning Techniques." *IEEE Access*, 7, 120125–120138.
[17]. Tang, Fei et al. (2021). "Artificial Intelligence Empowered Resource Optimization for Future IoT Networks." *IEEE Wireless Communications*, 28(6), 48–55.
[18]. Sun, Y. et al. (2019). "Application of Machine Learning in Wireless Networks: Key Techniques and Open Issues." *IEEE Communications Surveys & Tutorials*, 21(4), 3072–3108.
[19]. Bennis, Mehdi et al. (2018). "Ultra-Reliable and Low-Latency Wireless Communication." *Proceedings of the IEEE*, 106(10), 1834–1853.
[20]. Rahman, M. A. et al. (2021). "Deep Reinforcement Learning-Based Energy-Efficient Routing for IoT Communication Networks." *Wireless Personal Communications*, 118(4), 2957–2975.
[21]. Li, X. et al. (2022). "AI-Assisted Energy Optimization in IoT Communication Systems." *Journal of Network and Computer Applications*, 198, 103297.
[22]. Wang, T. et al. (2022). "Machine Learning-Based Routing Optimization for Smart IoT Networks." *Computer Communications*, 188, 50–63.
[23]. Park, J. et al. (2021). "Communication-Efficient Distributed Learning over Wireless Networks." *IEEE Communications Magazine*, 59(4), 16–22.
[24]. You, Xiaohu et al. (2021). "Future Intelligent Wireless Networks for IoT and Beyond." *Science China Information Sciences*, 64(1), 1–74.
[25]. Shafi, Mansoor et al. (2017). "5G: A Tutorial Overview of Standards, Trials, Challenges, Deployment, and Practice." *IEEE Journal on Selected Areas in Communications*, 35(6), 1201–1221.
[26]. Zhou, X. et al. (2022). "Adaptive Machine Learning-Based Routing for Energy Conservation in IoT Networks." *IEEE Access*, 10, 78910–78925.
[27]. Singh, A. et al. (2023). "Hybrid Machine Learning Models for Energy-Efficient IoT Routing." *Wireless Networks*, 29(5), 1821–1838.
[28]. Kumar, R. et al. (2023). "Energy Optimization in IoT Communication Networks Using Intelligent Routing Models." *Journal of King Saud University – Computer and Information Sciences*, 35(7), 101682.
[29]. Patel, S. et al. (2024). "Smart Energy-Aware Routing Techniques Using Machine Learning for IoT Networks." *Future Internet*, 16(2), 54.
[30]. Verma, P. et al. (2024). "Machine Learning-Driven Sustainable Routing in IoT Communication Systems." *Sensors*, 24(3), 1125.
[31]. L.K.Suresh Kumar , Mohammed Abdul Bari , "Zero-Day Attack Detection In Multi-Tenant Cloud Environments Using Variational Autoencoders ," International Journal of Applied Mathematics, ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)Volume 38 No. 3s, 2025.
[32]. Dr.Abdul Bari ,Dr. Imtiyaz khan , Dr. Rafath Samrin , Dr. Akhil Khare , " VPC & Public Cloud Optimal Perfomance in Cloud Environment ",Educational Administration: Theory and Practic,ISSN No : 2148-2403 Vol 30- Issue -6 June 2024