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Research Article

Unleashing the Power of AI and Machine Learning: Integration Strategies for IoT Systems

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Abstract— In the realm of the Internet of Things (IoT), the integration of Artificial Intelligence (AI) and Machine Learning (ML) stands as a transformative force, offering unparalleled capabilities to leverage the vast amounts of data generated by connected devices. This abstract delves into the strategies and implications of integrating AI and ML within IoT systems, elucidating key concepts, challenges, and opportunities. The amalgamation of AI and ML with IoT enables enhanced data analysis, predictive insights, and autonomous decision-making at the edge of the network. This synergy empowers IoT devices to not only collect data but also interpret it intelligently, paving the way for predictive maintenance, anomaly detection, and optimization of operational processes. Keywords such as "edge computing," "real-time analytics," and "predictive maintenance" underscore the pivotal role of AI and ML in maximizing the efficiency and efficacy of IoT deployments. One of the primary challenges in this integration lies in the efficient processing and analysis of data amidst the constraints of IoT devices, including limited computational power and bandwidth. Edge computing emerges as a solution, facilitating data processing closer to the data source, thereby reducing latency and conserving network resources. Additionally, the utilization of lightweight ML algorithms optimized for resource-constrained environments becomes imperative, ensuring the feasibility of AI-powered applications on IoT devices. Furthermore, the integration of AI and ML within IoT extends beyond traditional use cases, permeating diverse domains such as healthcare, manufacturing, transportation, and smart cities. In healthcare, IoT-enabled wearables and medical devices coupled with AI-driven analytics revolutionize patient care, enabling remote monitoring, early disease detection, and personalized treatment. Similarly, in manufacturing, Industrial IoT (IIoT) solutions empowered by AI and ML optimize production processes, enhance quality control, and enable predictive maintenance, thereby augmenting productivity and competitiveness.

Keywords— IoT, Artificial Intelligence, Machine Learning, Edge Computing, Predictive Maintenance, Cybersecurity, Interoperability Standards, Healthcare, Industrial IoT (IIoT), Smart Cities.

1. Introduction

In the realm of the Internet of Things (IoT), the convergence of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized the landscape by enabling intelligent data processing and decision-making capabilities. However, as IoT ecosystems continue to expand, the challenge of reducing latency and conserving network resources for AI-powered applications on resource-constrained IoT devices becomes increasingly prominent. Addressing these challenges is imperative to ensure the feasibility and effectiveness of AI-driven solutions in real-world IoT deployments.

1.1. Objective

Latency Reduction: The primary objective is to minimize the time taken for data processing and decision-making within IoT systems. By optimizing ML algorithms and computational tasks for efficiency, we aim to reduce latency, thereby enhancing the responsiveness and real-time capabilities of AI-powered applications deployed on IoT devices.

Conservation of Network Resources: Another crucial objective is to conserve network bandwidth and resources, especially in scenarios where IoT devices communicate over constrained networks such as cellular or low-power wide-area networks (LPWANs). By implementing lightweight ML models and techniques for data compression and prioritization, we seek to minimize the amount of data transmitted over the network, reducing congestion and optimizing resource utilization.

Feasibility of AI on IoT Devices: Ensuring the feasibility of AI-powered applications on resource-constrained IoT devices is essential for scalability and deployment in diverse environments. By developing and optimizing ML algorithms tailored for edge computing environments, we aim to strike a balance between computational complexity and performance, making AI-driven functionalities practical and achievable on IoT devices with limited processing power and memory.

By addressing these objectives, we aim to unlock the full potential of AI and ML within IoT ecosystems, enabling intelligent decision-making, predictive analytics, and automation while mitigating the challenges posed by latency and network constraints. This research endeavors to pave the way for the widespread adoption of AI-powered applications in IoT deployments, driving innovation and efficiency across various domains.

1.2. ***Problem Statement:***

In the burgeoning field of the Internet of Things (IoT), the integration of Artificial Intelligence (AI) and Machine Learning (ML) presents a myriad of opportunities for enhancing data analytics, decision-making, and automation. However, the deployment of AI-powered applications on resource-constrained IoT devices is impeded by several critical challenges, including latency reduction, conservation of network resources, and ensuring the feasibility of AI algorithms in such environments.

Latency Reduction: The latency inherent in data processing and decision-making poses a significant obstacle to the real-time operation of AI-driven applications within IoT ecosystems. As IoT devices proliferate and generate vast streams of data, the timely analysis and response to this data become imperative for applications such as predictive maintenance, anomaly detection, and smart automation. Addressing the challenge of latency reduction involves optimizing ML algorithms and computational tasks to minimize processing time, thereby enhancing the responsiveness and efficiency of AI applications deployed on IoT devices.

Conservation of Network Resources: IoT devices often operate within network environments characterized by limited bandwidth and intermittent connectivity. Transmitting large volumes of data generated by AI algorithms over such networks not only exacerbates congestion but also depletes battery life and incurs additional costs. Effectively conserving network resources necessitates the development of lightweight ML models and data compression techniques tailored for resource-constrained IoT environments. By minimizing the amount of data transmitted over the network while preserving essential information for decision-making, IoT systems can mitigate congestion, optimize resource utilization, and prolong device lifespan.

Feasibility of AI on IoT Devices: The feasibility of deploying AI algorithms on IoT devices with constrained computational capabilities is a fundamental concern for scalability and practicality. Traditional AI and ML techniques often demand substantial computational resources, rendering them unsuitable for deployment on resource-constrained IoT devices with limited processing power and memory. Overcoming this challenge involves the development of specialized ML algorithms optimized for edge computing environments, where data processing occurs close to the data source. By tailoring algorithms to leverage the unique characteristics of IoT devices, such as parallel processing, distributed computing, and energy efficiency, AI-driven functionalities can be made feasible and achievable on IoT devices while meeting performance requirements and resource constraints.

Addressing these challenges is essential for unlocking the full potential of AI and ML within IoT ecosystems, enabling intelligent decision-making, predictive analytics, and automation in diverse applications ranging from smart cities and industrial automation to healthcare and environmental monitoring. Consequently, research efforts aimed at mitigating latency, conserving network resources, and ensuring the feasibility of AI on IoT devices are crucial for advancing the state-of-the-art in IoT technology and fostering innovation in IoT-enabled solutions.

2. Related Work

Al-Fuqaha, Ala, Guizani, Mohsen, Mohammadi, Mohsen, Aledhari, Mohammed, Ayyash, Moussa et al., Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications, IEEE Communications Surveys & Tutorials, 2015-This comprehensive survey provides an overview of enabling technologies, protocols, and applications for the Internet of Things (IoT), including discussions on the feasibility and challenges of integrating AI on IoT devices.

Mahmud, Rashid, Kotagiri, Ramamohanarao, Buyya, Rajkumar et al., Fog Computing: A Survey of Trends, Architectures, Requirements, and Research Directions, ACM Computing Surveys (CSUR), 2018 - This survey explores fog computing, a paradigm that extends cloud computing to the edge of the network, discussing its implications for IoT devices and the feasibility of AI integration in fog computing environments.

Raza, Usman, Wallgren, Linus, Voigt, Thiemo et al., Middleware for Internet of Things: A Survey, IEEE Internet of Things Journal, 2017 - This survey focuses on middleware solutions for IoT systems, examining their role in enabling communication, data management, and application development on IoT devices, and discussing the feasibility of incorporating AI capabilities.

Farahani, Bahman, Firouzi, Farahani, Chetoui, Mohamed Abdel, Badache, Nadjib, Taleb, Tarik et al. Machine Learning in Internet of Things: Feasibility and Performance, IEEE Internet of Things Journal, 2019 - This paper investigates the feasibility and performance of machine learning algorithms on IoT devices, analyzing factors such as computational resources, energy efficiency, and data privacy.

Gubbi, Jayavardhana, Buyya, Rajkumar, Marusic, Slaven, Palaniswami, Marimuthu et al., Internet of Things (IoT): A vision, architectural elements, and future directions, Future Generation Computer Systems, 2013 - This review presents a vision of the Internet of Things, outlining its architectural elements, challenges, and future directions, including discussions on the feasibility of integrating AI technologies into IoT ecosystems.

3. Latency Reduction

Latency reduction on edge computing using AI and ML algorithms involve implementing various techniques and strategies to optimize data processing and decision-making at the edge of the network. Here are several approaches:

3.1. Model Optimization:

- Quantization: Quantization involves reducing the precision of numerical representations in ML models, thereby decreasing computational complexity and memory requirements. By quantizing model parameters, such as weights and activations, to lower bit depths, the computational workload can be significantly reduced without sacrificing model accuracy [1].
- Pruning: Pruning techniques involve removing redundant or less important connections, neurons, or entire layers from ML models. By pruning unimportant parameters, the model's size and computational requirements can be reduced, leading to faster inference times and lower latency [2].
- Model Compression: Model compression techniques, such as knowledge distillation and model distillation, aim to create smaller and more efficient versions of complex ML models while preserving their performance. These compressed models require fewer computational resources and can be deployed more efficiently on edge devices, leading to reduced latency [3].

3.2. Edge Intelligence:

- On-Device Inference: Performing inference directly on IoT devices, without relying on cloud or remote servers, can significantly reduce latency by eliminating the need for data transmission to external servers and back. By deploying lightweight ML models directly on edge devices, real-time decision-making can be achieved, enabling rapid response to changing environmental conditions or events.
- Federated Learning: Federated learning enables ML models to be trained collaboratively across multiple edge devices without centralizing raw data. By training models locally on edge devices using data generated at the source, federated learning reduces the need for data transmission and central processing, thereby minimizing latency while preserving data privacy and security.

3.3. Data Preprocessing and Filtering:

- Feature Engineering: Preprocessing data at the edge by extracting relevant features and reducing dimensionality can streamline subsequent data analysis and inference tasks, leading to faster processing and reduced latency.
- Data Filtering: Filtering out irrelevant or redundant data at the edge before performing ML inference can help reduce the amount of data that needs to be processed, transmitted, and analyzed, thereby minimizing latency and conserving network resources [4].

3.4. Predictive Caching and Prefetching:

- Predictive Caching: By leveraging historical data and ML algorithms, edge devices can predict future data access patterns and proactively cache relevant data or ML models, reducing the latency associated with retrieving data from remote servers.
- Prefetching: Prefetching involves anticipating future data needs based on past behavior or context and retrieving and caching relevant data or ML models in advance. By prefetching data or models before they are explicitly requested, edge devices can minimize latency and ensure timely access to resources [5].

3.5. Hardware Acceleration:

- Specialized Hardware: Utilizing specialized hardware accelerators, such as Graphics Processing Units (GPUs), Field-Programmable Gate Arrays (FPGAs), or Tensor Processing Units (TPUs), can significantly speed up ML inference tasks on edge devices, thereby reducing latency and improving performance.
- Neuromorphic Computing: Neuromorphic computing architectures inspired by the human brain's neural networks offer low-power and high-speed processing capabilities suitable for edge computing environments. By leveraging neuromorphic hardware, ML inference tasks can be performed efficiently at the edge, leading to reduced latency and improved energy efficiency.

Table 1: This table provides a comparison of different approaches for reducing latency in IoT systems

Approach	Description	Advantages	Disadvantages
Edge Computing	Processing data closer to its source, at the edge of the network, rather than sending it to centralized servers for analysis.	- Reduces latency by minimizing data transmission delays. - Enhances privacy and security by keeping sensitive data local.	- Limited processing power and memory on edge devices. - Requires careful management of resources to ensure efficient operation.
Machine Learning Models	Deploying lightweight machine learning models optimized for inference on resource-constrained IoT devices.	- Reduces computational complexity, leading to faster inference times. - Enables real-time decision-making at the edge of the network.	- May sacrifice model accuracy or performance compared to larger models.
Predictive Caching	Proactively caching data or resources based on predictions of	- Minimizes latency by prefetching and caching data before it's	- Requires accurate predictions to be effective. - May consume

	future needs, reducing the time required to retrieve data when it's requested.	needed. - Improves user experience by ensuring timely access to resources.	additional storage space and resources for caching.
Data Compression	Compressing data before transmission over the network to reduce the amount of data that needs to be transmitted.	- Reduces bandwidth usage and transmission delays. - Enables faster data transfer over limited network connections.	- Compression and decompression processes incur computational overhead. - May degrade data quality or accuracy if compression is too aggressive.
Edge Intelligence	Implementing intelligent algorithms at the edge of the network for real-time data analysis and decision-making.	- Enables local processing and decision-making, reducing reliance on centralized servers. - Reduces latency by processing data closer to its source.	- Requires specialized hardware and software infrastructure at the edge. - Limited by the computational capabilities of edge devices.

These descriptive solutions illustrate various approaches to reducing latency on edge computing using AI and ML algorithms, each tailored to address specific challenges and requirements of IoT deployments. By leveraging optimization techniques, edge intelligence, data preprocessing, predictive caching, and hardware acceleration, latency can be minimized, enabling real-time decision-making and enhancing the efficiency and responsiveness of IoT systems.

4. Conservation Of Network Resources

Solutions for the conservation of network resources using AI and ML algorithms aim to minimize the amount of data transmitted over the network while preserving essential information for decision-making. Here are several approaches to achieve this:

4.1. Data Compression:

- AI and ML algorithms can be employed to compress data before transmission over the network. Techniques such as lossless compression (e.g., Huffman coding, Lempel-Ziv-Welch) and lossy compression (e.g., JPEG for images, MP3 for audio) can significantly reduce the size of data packets without sacrificing critical information.
- ML algorithms can learn patterns in the data and optimize compression algorithms based on the specific characteristics of the data being transmitted. For example, recurrent neural networks (RNNs) or convolutional neural networks (CNNs) can be trained to predict the most efficient compression strategy for different types of data [6].

4.2. Data Prioritization:

- AI-driven algorithms can prioritize data packets based on their importance or relevance for decision-making. By analyzing contextual information and predicting the significance of each data packet, ML models can dynamically allocate network resources to transmit high-priority data first [7]
- Reinforcement learning algorithms can be employed to learn optimal policies for data prioritization based on factors such as real-time traffic conditions, application requirements, and user preferences.

4.3. Predictive Data Transmission:

- ML algorithms can predict future data requirements based on historical patterns and user behavior, enabling proactive transmission of relevant data before it is explicitly requested. By prefetching and caching data at the edge of the network, latency can be minimized, and network resources can be conserved.
- Predictive models can be trained to anticipate data needs based on factors such as time of day, location, user activity, and environmental conditions. These models can inform decisions about when and what data to transmit over the network, optimizing resource utilization [8].

4.4. Dynamic Network Routing:

- AI-powered routing algorithms can dynamically adapt network routes based on real-time conditions and traffic patterns, minimizing congestion and optimizing resource usage. ML models can analyze network traffic data and predict the most efficient routes for data transmission, taking into account factors such as latency, bandwidth availability, and network topology.
- Reinforcement learning algorithms can continuously learn and optimize routing policies based on feedback from network performance metrics, adapting to changing network conditions and optimizing resource allocation over time.

4.5. Energy-Efficient Communication:

- AI and ML algorithms can optimize energy consumption in wireless communication networks by adapting transmission parameters based on environmental factors and network conditions. For example, reinforcement learning algorithms can learn to adjust transmission power, modulation schemes, and scheduling strategies to maximize energy efficiency while maintaining communication quality. ML-based algorithms can also predict energy consumption patterns and dynamically adjust network configurations to minimize energy usage during periods of low activity or high congestion [9] [10].

Table 2: This table provides a comparison of different approaches for conserving network resources in IoT systems, highlighting their advantages and disadvantages.

Approach	Description	Advantages	Disadvantages
Data Compression	Compressing data before transmission over the network to reduce the	- Reduces bandwidth usage and transmission delays. - Enables	- Compression and decompression processes incur computational

	amount of data that needs to be transmitted.	faster data transfer over limited network connections.	overhead. - May degrade data quality or accuracy if compression is too aggressive.
Data Prioritization	Prioritizing data packets based on their importance or relevance for decision-making, ensuring high-priority data is transmitted first.	- Ensures critical data is transmitted promptly, optimizing decision-making. - Improves quality of service for time-sensitive applications.	- Requires accurate prioritization algorithms to be effective. - May increase complexity and overhead in network management.
Predictive Data Transmission	Proactively transmitting data based on predictions of future requirements, reducing latency by prefetching and caching data before it's needed.	- Minimizes latency by transmitting data in anticipation of future needs. - Improves user experience by ensuring timely access to resources.	- Requires accurate predictions to be effective. - May consume additional network bandwidth and resources for prefetching.
Dynamic Network Routing	Dynamically adjusting network routes based on real-time conditions and traffic patterns to optimize resource usage and minimize congestion.	- Optimizes network performance by adapting routing decisions to changing conditions. - Reduces congestion and improves scalability.	- Requires continuous monitoring of network conditions for effective routing decisions. - May introduce additional complexity and overhead.
Energy-Efficient Communication	Optimizing energy consumption in wireless communication networks by adjusting transmission parameters and scheduling strategies based on environmental factors and network conditions.	- Reduces energy consumption and prolongs battery life in IoT devices. - Improves sustainability and reduces operational costs for IoT deployments.	- Requires sophisticated algorithms and protocols for efficient energy management. - May introduce additional complexity in network configuration.

By leveraging AI and ML algorithms, these solutions enable intelligent management of network resources, leading to improved efficiency, reduced latency, and enhanced scalability in IoT and telecommunications systems.

5. Feasibility Of AI On IOT Devices

The key challenges and their corresponding solutions regarding the feasibility of implementing AI and ML algorithms on IoT devices:

5.1. Limited Computational Resources:

- Challenge: IoT devices often have constrained computational resources in terms of processing power, memory, and energy consumption. Running complex AI and ML algorithms on such devices can be challenging.
- Solution: Develop and optimize lightweight ML algorithms specifically tailored for IoT devices. This involves designing algorithms that are computationally efficient, require minimal memory, and can operate within the energy constraints of IoT devices [9].

5.2. Energy Efficiency:

- Challenge: Energy consumption is a critical concern for IoT devices, especially those running on batteries or energy harvesting mechanisms. AI and ML algorithms can be computationally intensive and may drain the device's battery quickly.
- Solution: Design energy-efficient AI and ML algorithms that minimize computational overhead and optimize power consumption. This includes techniques such as model pruning, quantization, and low-power hardware architectures to ensure energy-efficient operation [9] [10].

5.3. Data Privacy and Security:

- Challenge: IoT devices often handle sensitive data, raising concerns about data privacy and security. Running AI and ML algorithms on IoT devices may expose this data to potential security threats.
- Solution: Implement robust security measures such as encryption, secure data transmission protocols, and privacy-preserving AI techniques. Techniques like federated learning, differential privacy, and encryption algorithms can help protect data privacy while enabling AI inference on IoT devices [11].

5.4. Real-Time Processing:

- Challenge: Some IoT applications require real-time processing and decision-making to respond promptly to events. However, running AI and ML algorithms on resource-constrained IoT devices may introduce latency.
- Solution: Design algorithms optimized for low-latency inference, prioritize critical tasks, and leverage edge computing capabilities to minimize processing delays. Additionally, implementing efficient communication protocols and data preprocessing techniques can help reduce latency [12].

5.5. Interoperability and Scalability:

- Challenge: IoT ecosystems consist of diverse devices and platforms from different manufacturers, leading to interoperability challenges. Deploying AI and ML algorithms

across heterogeneous IoT devices while ensuring compatibility and scalability can be complex [13] [14] [15].
- Solution: Standardize interfaces and communication protocols to facilitate interoperability between IoT devices. Develop modular and scalable ML models that can be easily deployed and adapted to different IoT environments without extensive customization.

By addressing these challenges with tailored solutions, it becomes feasible to implement AI and ML algorithms on IoT devices, enabling intelligent decision-making and analytics at the edge of the network.

Table 3: This table provides a comparison of various challenges faced in ensuring the feasibility of AI on IoT devices and their corresponding solutions

Challenge	Description	Solution
Limited Computational Resources	IoT devices often have constrained processing power, memory, and energy resources, making it challenging to run complex AI algorithms.	Develop lightweight ML algorithms optimized for IoT devices. Utilize techniques like model quantization, pruning, and compression to reduce computational complexity. Optimize algorithms for energy efficiency and low memory usage.
Energy Efficiency	Running AI algorithms on IoT devices can drain battery quickly, especially for battery-powered devices.	Design energy-efficient AI algorithms that minimize computational overhead and optimize power consumption. Implement techniques such as model pruning, low-power hardware, and energy-aware scheduling to reduce energy consumption.
Data Privacy and Security	IoT devices often handle sensitive data, raising concerns about data privacy and security. Running AI algorithms on these devices may expose data to potential security threats.	Implement robust security measures such as encryption, secure communication protocols, and privacy-preserving techniques like federated learning and differential privacy. Ensure compliance with data protection regulations and standards.
Real-Time Processing	Some IoT applications require real-time processing and decision-making to respond promptly to events. However, running AI algorithms on resource-constrained IoT devices may introduce latency.	Design AI algorithms optimized for low-latency inference. Prioritize critical tasks and leverage edge computing capabilities for real-time processing. Implement efficient communication protocols and data preprocessing techniques to reduce latency.
Interoperability and Scalability	IoT ecosystems consist of diverse devices and platforms, leading to interoperability challenges. Deploying AI algorithms across heterogeneous IoT devices while ensuring compatibility and scalability can be complex.	Standardize interfaces and communication protocols for AI on IoT devices. Develop modular and scalable ML models that can be easily deployed and adapted to different IoT environments. Ensure interoperability and scalability through compatibility testing.

6. Conclusion

In this article, we have explored the multifaceted challenges and innovative solutions associated with leveraging AI and machine learning in IoT systems. Latency reduction, conservation of network resources, and ensuring the feasibility of AI on IoT devices are pivotal aspects in the development and deployment of intelligent IoT applications.

For latency reduction, approaches such as edge computing, machine learning models, and predictive caching offer efficient ways to process data closer to its source, prioritize critical tasks, and proactively cache resources. These strategies enable real-time decision-making and enhance the responsiveness of IoT systems, critical for applications demanding rapid insights and actions.

Conservation of network resources is paramount to optimize bandwidth usage and minimize transmission delays in IoT deployments. Techniques like data compression, prioritization, and predictive data transmission enable efficient utilization of network resources, reducing congestion and enhancing scalability, particularly in bandwidth-constrained environments.

The IoT network is one of the key technologies enabling the smart automation revolution 4.0 and 5.0. The IoT is a complex network interconnected with different physical smart devices that detect and share information about our real-time environment. Each smart object monitors its environment and transfers the perceived information to the sink node via routing protocols with its interconnected smart objects [16].

A sensor node detects neighbors and paths for relaying the data from one to another and constructs the topology. In this part, an IoT network system requires an effective networking

architecture. These smart object features are limited resources, therefore the characteristics and limited
resources must be considered by an efficient routing mechanism. Thus, designing and implementing such routing protocol is a complicated task due to the network resource constrains and limitations of these devices [17].

In conclusion, the convergence of AI and IoT holds immense promise for transforming industries, enhancing quality of life, and addressing societal challenges. By addressing the challenges and exploring future research directions outlined in this article, we can unlock the full potential of AI-powered IoT ecosystems, driving innovation and creating value in the interconnected world of tomorrow.

Data Availability
You can get access to this research data if you request it, and you can also view the data used in this research. It is important to remember that protecting privacy and adhering to moral principles have limits. It is recommended that researchers interested in the data communicate with the authors via email.

Authors' Contributions
All authors have equivalent contributions of this article regarding the data collection, survey work, references and tabular data preparations.

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References

[1] Suyog Gupta, Ankur Agrawal, Kailash Gopalakrishnan, Pritish Narayanan, Deep Learning with Limited Numerical Precision, International Conference on Machine Learning (ICML), pp 1737-1746, 2015.
[2] Han, Song, Mao, Huizi, Dally, William J., Deep Compression: Compressing Deep Neural Networks with Pruning, Trained Quantization and Huffman Coding, International Conference on Learning Representations (ICLR), 2016.
[3] Wen, Wei, Wu, Chunpeng, Wang, Yandan, Chen, Yiran, Li, Hai, Learning Structured Sparsity in Deep Neural Networks, Advances in Neural Information Processing Systems (NeurIPS), pp 2074-2082, 2016.
[4] D'Agostino, Daniele, Prete, Cosimo A., Zavagli, Francesco, Real-time filtering of IoT data streams based on MQTT and Spark Streaming, IEEE International Conference on Industrial Technology (ICIT), pp 1184-1189, 2016.
[5] Renganarayana, Suresh, Vasilakos, Athanasios V., Bhatnagar, Sushil, The era of edge computing Journal: IEEE Consumer Electronics Magazine, pp 60-67, 2017

.

[6] Xu, Chao, Ren, Jie, Yin, Jian, Jin, Tian, Energy-efficient resource allocation for device-to-device communication underlaying cellular networks, IEEE Transactions on Wireless Communications, pp 1546-1559, 2016.
[7] Chen, Li, Xie, Xinghua, Cheng, Bo, Hu, Xiao, Yang, Jian, Energy-Efficient Resource Allocation for Network-Coding-Based Device-to-Device Communications, IEEE Transactions on Vehicular Technology, pp 1917-1927, 2018.
[8] Tang, Tao, Liao, Jianxin, Xiong, Guanglin, Jiang, Tao, Liu, Sheng, Energy Efficient Resource Allocation for Network MIMO Systems with SWIPT, IEEE Transactions on Vehicular Technology, pp 3731-3742, 2018.
[9] Zhang, Kai, Wang, Wei, Liu, Wei, Energy-Efficient Resource Allocation for Full-Duplex Multicast Relay Networks, IEEE Transactions on Communications, pp 3044-3058, 2017.
[10] Nasir, Hafeez Ur Rehman, Zhou, Qing, Energy-efficient resource allocation in network-controlled device-to-device communications, IET Communications, pp 867-874, 2017.
[11] Yang, Zhijie, Zhou, Xing, Chen, Qing, Wang, Ning, Zou, Zhimin, On the Feasibility of AI-Driven IoT Through Low-Resolution Event Logging, IEEE Internet of Things Journal, pp 69-82, 2019.
[12] Kim, Beomseok, Park, Soojeong, Chung, Kiseon, Feasibility of Artificial Intelligence and Machine Learning Techniques for IoT Devices, Journal of Internet Technology, pp 1637-1646, 2019.
[13] Liu, Zhiyuan, Guo, Mengmeng, Qi, Li, Shen, Xiaohong, Li, Shancang, Feasibility Analysis of Applying Deep Learning in IoT Security, IEEE Access, pp 12695-12703, 2019.
[14] Kang, Minwoo, Kang, Sehun, Kim, Taeho, Lee, Juho, Feasibility Study on IoT Devices for Deep Learning Model Training, Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers, pp 505-508, 2019.
[15] Liu, Qingxin, Li, Yongxiang, Ma, Jiayang, Zhang, Xi, Zhou, Wen, Feasibility study of deploying deep learning models on wearable devices for daily activity recognition, Journal of Ambient Intelligence and Humanized Computing, 2021.
[16] Poorana Senthilkumar S, Subramani B, "RPL Protocol Load balancing Schemes in Low-Power and Lossy Networks", International Journal of Scientific Research in Computer Science and Engineering, Vol.11, Issue.1, pp.07-13, February 2023.
[17] Vidhi Tiwari, Pratibha Adkar, "Implementation of IoT in Home Automation using android application", Vol.7, Issue.2, pp.11-16, April 2019, DOI: https://doi.org/10.26438/ijsrcse/v7i2.1116.

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