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Fog-based Edge AI for Robotics: Cutting-edge Research and Future Directions

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Abstract

The fusion of Fog-based Edge Artificial Intelligence (AI) is an emerging and transformative research area within robotics. This research examines the significant potential of augmenting robotic systems by integrating Edge AI and Fog Computing, aiming to enhance their cognitive abilities, independence, and operational effectiveness. The feasibility of real-time data analysis and decision-making is enhanced by deploying AI algorithms at the network edge, near the robots, and by leveraging fog computing capabilities. This study investigates the diverse implementations of Fog-based artificial intelligence (AI) in robotics. These applications encompass autonomous navigation, object detection, and human-robot interaction. By showcasing these examples, the research demonstrates the potential for a transformative impact on the capabilities of robotic systems through the integration of Fog-based AI.

Additionally, this study explores the obstacles and potential advantages within this interdisciplinary field, providing valuable perspectives on the promising avenues that can facilitate advancements in robotics by leveraging the combined power of Fog-based Edge Artificial Intelligence. This study elucidates how the amalgamation of Fog Computing and Edge AI confers enhanced capabilities upon intelligent robotic systems, enabling them to operate autonomously in real time. This integration effectively addresses the obstacles commonly encountered in conventional cloud-based AI systems, such as latency, internet connectivity, and data security concerns. The study highlights the importance of architecture, security, and ethical factors in utilizing robotic intelligence. It emphasizes the need for data protection standards and transparency to ensure responsible and reliable utilization of this technology in a rapidly changing environment.

Keywords: Fog Computing, Cloud Computing, Artificial Intelligence, Robotics, Internet of Things

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1. Introduction

The convergence of AI and robotics has made possible autonomous and intelligent machines that can perform complex tasks with precision and adaptability [1]. Robots are increasingly used in manufacturing, logistics, healthcare, and domestic assistance as they become part of our daily lives [2],[3]. Real-time data processing and decision-making are crucial to robotics adoption. Powerful cloud-based AI systems have latency issues and require stable internet connectivity [4],[5]. Fog computing and Edge AI can solve these problems and unleash robotics' full potential [6]. Fog computing addresses cloud computing's latency, bandwidth, and privacy issues. Fog computing brings cloud computing to the network edge, where sensors and robots collect data, enabling data processing and decision-making [7]. Robots can use fog nodes or edge devices to access AI capabilities in real-time without sending massive amounts of data to cloud servers [8],[9].

This research paper explores the fascinating intersection of fog-based Edge AI and robotics, a cutting-edge domain that could revolutionize robotics and enable new applications and capabilities. Fog computing and Edge AI can improve robotic system efficiency, autonomy, and responsiveness, opening up exciting possibilities in various industries and daily life [10].

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As with any new technology, fog-based Edge AI for robotics must be overcome to reach its full potential. We will identify these challenges to advance the field and propose future research.

The research background is expected to encompass the understanding that the Internet of Things (IoT) presents significant opportunities for transformation in diverse fields such as smart cities, healthcare, agriculture, and manufacturing. However, it is also acknowledged that the IoT can worsen ecological issues. Hence, there is a growing recognition of the necessity for GIoT solutions as scholars and professionals endeavor to leverage the potential of IoT to tackle objectives related to environmental sustainability. The research background establishes the foundation for examining the various applications, practices, levels of awareness, and challenges related to the Green Internet of Things (GIoT). The overarching objective is to harmonize the advancements in IoT technology with environmentally sustainable practices, thereby mitigating the negative ecological consequences associated with its implementation.
The primary research contributions of this study involve an extensive examination of applications of the Global Internet of Things (GIoT) in various sectors, with a specific focus on demonstrating how the Internet of Things (IoT) can be effectively utilized to promote and enhance environmental sustainability objectives. Moreover, this paper illuminates the increasing recognition of Green Internet of Things (GIoT) practices among businesses and policymakers, highlighting the growing awareness of IoT's role in addressing ecological issues.

The research paper is organized systematically, consisting of seven distinct sections. The discussion begins by establishing a fundamental comprehension in Section 2, wherein the basic principles of Fog Computing and Edge AI are explicated. Section 3 of the paper examines Fog-based Edge AI Architectures specifically designed for robotics, investigating the underlying design principles and practical implementations. In the subsequent section, Section 4, the examination of Fog-based Data Processing and Communication in Robotics is undertaken, focusing on enhancing data flow optimization and reducing latency. Section 5 explores the strategies employed in fog-based Edge AI systems to achieve efficient data processing and communication. This section provides valuable insights into the management of resources in such scenarios. Section 6 of this study evaluates various machine learning algorithms deemed appropriate for Edge AI implementation in robotic applications. The evaluation focuses on assessing the suitability and performance of these algorithms. Section 7 of the paper delves into the critical elements of Security and Privacy in the Fog-based Edge AI Robotics domain, specifically emphasizing data protection within this interdisciplinary framework. The systematic arrangement of this organization guarantees a thorough examination of the convergence of Fog Computing, Edge AI, and robotics, offering readers a coherent sequence of concepts and discoveries.

The paper "Blockchain-Based Physically Secure and Privacy-Aware Anonymous Authentication Scheme for Fog-Based VANETs" This paper introduces a pioneering authentication framework for Fog-based VANETs, featuring blockchain for decentralized security, physically secure access, and robust privacy measures like zero-knowledge proofs. It addresses Sybil attacks and eavesdropping, promising improved network integrity. Practical validation is essential to affirm its multifaceted approach to VANET security and privacy enhancement.

Fog computing for the internet of things: Security and privacy issues
This innovative system combines IoT and fog computing to enhance security. Its key feature is event-driven surveillance, reducing latency by processing video data at the fog layer. IoT devices improve security event detection and real-time decision-making while optimizing power usage. Scalability and practical use cases demonstrate its effectiveness in diverse settings. Encryption and access controls for data protection should be further addressed. The "IoT-Guard" system represents cutting-edge security management technology.

The paper "A Resource Recommendation Model for Heterogeneous Workloads in Fog-Based Smart Factory Environment" advances smart manufacturing and fog computing. It uses an innovative resource recommendation model to solve complex workload issues in smart factories. This model intelligently allocates fog layer computing and networking resources and prioritizes and categorizes heterogeneous workloads to maximize resource use. Smart factories can optimize operational efficiency and reduce costs by adapting dynamically to changing workload demands thanks to their real-time decision-making capability. Scalability ensures the model can grow with the factory's needs. Experimental validation could strengthen the paper's practicality by showing how the model can improve smart factory performance and competitiveness. This paper provides a novel approach to workload management in smart factories that could enhance the quality of production and efficiency.

The paper "Multi-Fogs-Based Traceable Privacy-Preserving Scheme for Vehicular Identity in Internet of Vehicles" advances IoV by addressing privacy and security. The paper's main contribution is a privacy-preserving scheme for vehicular identity protection in the IoV landscape. The multi-fog architecture of this innovative scheme protects vehicle identities and ensures traceability when needed. By hiding real vehicle identities, unauthorized tracking is prevented, improving privacy. The scheme's traceability allows authorized entities to identify vehicles under certain conditions, improving IoV ecosystem accountability and security. The multi-fog architecture's efficiency and low latency make IoV's real-time communication needs practical. Security mechanisms like encryption and authentication are likely integrated to prevent threats. The paper's practical applications and use cases demonstrate the scheme's realworld relevance in improving IoV vehicular privacy, security, and accountability. This paper presents a cutting-edge solution to improve IoV privacy preservation, making connected vehicular environments safer and more secure.

This paper, titled "Green Internet of Things (GIoT): Applications, Practices, Awareness, and Challenges," explores GIoT's many aspects. It shows how GIoT can reduce environmental impact, optimize resource utilization, and improve energy efficiency across industries. The paper also discusses the growing awareness and adoption of GIoT practices and IoT's role in sustainability. It also acknowledges GIoT implementation challenges like power consumption, data privacy, and scalability. This paper covers the GIoT landscape, including its applications, emerging practices, raising awareness of its benefits, and complex challenges as it combines IoT technology with green and sustainable principles.

2. Fog Computing and Edge AI

Fog Computing and Edge AI, two interconnected and powerful technologies, are changing data processing, analytics, and decision-making in the IoT and AI era [11]. These two paradigms solve the problems of traditional cloud computing models by providing real-time solutions for data-intensive tasks in resource-constrained and latency-sensitive environments [12][13].

2.1 Fog Computing:

Fog Computing extends cloud computing to the network's edge. Fog computing uses computing resources at the network edge, usually in the local area network or near data sources, instead of sending data to centralized data centers for processing. This reduces data transmission to remote cloud servers by allowing data processing, storage, and analysis closer to data generators. Fog computing reduces latency, conserves network bandwidth, protects data, and ensures real-time responsiveness [14]. Fog computing distributes computational tasks to edge devices to speed up data transfer between endpoints, improving decision-making and user experience. In data privacy and security situations, fog computing allows localized data processing [15].

2.2 Edge AI:

Instead of using cloud-based AI platforms, edge AI deploys AI algorithms and models directly on edge devices or in the local network. Edge devices like smartphones, IoT sensors, and robotics can perform intelligent tasks without internet connectivity or remote servers thanks to edge AI [16]. Edge devices can run AI algorithms locally and make instantaneous decisions, reducing latency and improving system performance. Edge AI also allows offline operations, ensuring functionality even without the internet. Remote areas benefit from this.

2.3 Combining Fog Computing and Edge AI:

Both technologies improve data-intensive application efficiency and responsiveness, so their convergence is natural [17]. Fog computing infrastructure can process and analyze data locally at the network's edge, bringing AI capabilities closer to data sources and end-users. Figure 1 presents the benefits of integrating different technologies.

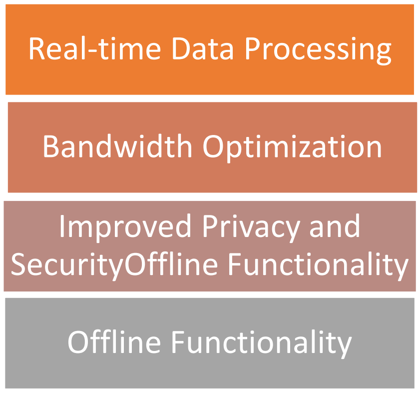

Figure 1: Integration benefits

This integration benefits many areas, including:
Real-time Data Processing: Autonomous vehicles, industrial automation, and healthcare monitoring require real-time data processing and AI-based decision-making [18].
Fog computing with Edge AI reduces latency by minimizing data travel between edge devices and cloud servers, resulting in faster responses and better user experiences.

3. Fog-based Edge AI Architectures for Robotics

Researchers and developers are exploring new architectures that utilize fog computing, edge AI, and robotics. Fog-based Edge AI architectures for robotics aim to give robots real-time intelligence, efficient data processing, and increased autonomy for various applications [19]. This section discusses fog-based Edge AI architectures for robotics.

3.1 Fog Node-Embedded Edge AI:

The robot's environment is strategically placed in fog nodes. These fog nodes run AI models and algorithms to analyze sensor data and provide immediate insights. The fog nodes help the robot's onboard processing unit offload computation-intensive tasks and make real-time decisions based on local information. Swarm robotics and collaborative robot environments require low-latency responses and distributed intelligence [20]. Mobile fog robotics integrates fog computing infrastructure into the robotic platform. The robot processes data and runs AI algorithms locally as a fog node. This architecture benefits robots in remote or dynamic environments with intermittent network connectivity. These fog-computing robots can operate autonomously and adapt to changing conditions without cloud resources.

3.2 Hierarchical Fog-based Edge AI:

The robotic system deploys multiple fog nodes at different hierarchical levels. A multi-tiered fog computing architecture uses these nodes for edge AI. Lower-tier fog nodes near robots process real-time sensor data and make essential decisions. Higher-tier fog nodes at the network edge or in centralized computing units can perform more complex computations and long-term planning. Hierarchical structures optimize resource utilization, responsiveness, and scalability [21].

3.3 Fog-to-Cloud Robotics:

Fog computing connects robots to the cloud in this architecture. The cloud provides large-scale data analysis, long-term learning, and robot knowledge sharing, while the fog nodes handle most AI processing tasks [22]. This architecture balances edge-based real-time decision-making and cloud-based AI model computational power, making it suitable for robots that need local intelligence and extensive cloud resources.

3.4 Federated Edge AI for Robotics:

Federated Edge AI trains AI models across fog nodes without sharing raw data. Federated edge AI lets robots collaborate and update their AI models while protecting data. This architecture enables robots to learn from each other in diverse environments without compromising sensitive data [23].

4. Fog-based Data Processing and Communication in Robotics

4.1 Robotics Fog Data Processing and Communication:

Robotic fog computing requires fog-based data processing and communication. Fog computing decentralizes computing and storage around robotic systems, enabling efficient data handling, analysis, and communication. This method improves latency, data privacy, bandwidth optimization, and real-time responsiveness over cloud-based data processing. Fog-based data processing and transmission are changing robotics [24].

4.2 Local Data Processing:

Fog computing lets robots process data near the source. Localized data processing reduces latency and helps robots make context-aware judgments by avoiding sending vast amounts of raw sensor data to faraway cloud servers. Fog-based data processing lets autonomous vehicles assess sensor data like LIDAR and video feeds onboard to react to changing road conditions and potential threats.

4.3 Real-time decisions:

Fog computing helps robotic systems make real-time decisions. Robots can react quickly to changing situations using edge-deployed AI algorithms to process data streams [25]. Time-sensitive applications like collaborative robotics and industrial automation require fast reactions for task completion and safety.

4.4 Edge AI Data Filtering and Compression:

Fog computing lets robots filter and compress data using edge AI. Edge AI algorithms can evaluate data locally and relay only essential insights to the cloud or other fog nodes. This reduces bandwidth utilization, network load, and data transmission costs [26].

4.5 Cloud offloading:

Fog-based data processing lets robots intelligently shift computation-intensive activities to the cloud or higher-tier fog nodes. This allows robots to handle the most immediate processing needs at the edge while using cloud resources for more complicated and resource-intensive activities. Robots can optimize system performance by balancing local autonomy and cloud-based computational power [27].

4.6 Network connectivity:

Mobility or environmental constraints make network connectivity difficult in many robotics applications. Localized data processing in fog computing allows offline capabilities. In challenging circumstances, fog computing-equipped robots can operate and make choices even when disconnected from the cloud.

4.7 Data Privacy:

Fog-based data processing improves robotics data privacy and security. Since most data processing happens at the edge, sensitive data can be processed locally in the robotic environment. This protects sensitive data during transmission [28]. Edge AI can anonymize or aggregate data before transmission, safeguarding user privacy.

5. Strategies for efficient data processing and communication in fog-based Edge AI systems

Fog-based Edge AI systems need efficient data processing and transmission to maximize resource utilization, minimize latency, and improve performance. These solutions optimize data processing and fog node-edge device connection. Fog-based Edge AI systems can analyze and communicate data efficiently using these methods:

Data Filtering and Aggregation: Edge data filtering and aggregation reduces data sent to fog nodes or the cloud. Edge devices can preprocess data locally and provide only pertinent information or aggregated summaries. This conserves bandwidth and computational resources, improving data processing and communication [29].

5.1 Local Decision-Making AI:

Lightweight AI models on edge devices enable real-time decision-making in data generation. Edge AI lets edge devices process data locally, decreasing the cloud's need for decisions. This strategy improves reaction times, reduces network congestion, and increases system autonomy, making it more resilient to intermittent network access. Edge caching and data replication improve data processing efficiency. Caching edge data or AI models reduces cloud data retrieval. Data replication across edge nodes ensures data availability and redundancy, boosting data processing operations.

5.2 Dynamic Resource Allocation:

Dynamic resource allocation in fog-based Edge AI systems optimizes computing resources. Edge devices adapt processing power and memory to workload and application needs. This dynamic resource allocation prioritizes key jobs while allocating enough resources to non-essential ones. Load balancing: Distributing data processing duties over different fog nodes prevents resource constraints and optimizes workload distribution. Load balancing efficiently distributes jobs to fog nodes, preventing performance degradation from overburdened nodes [30]. Direct edge-to-edge communication reduces data transfer to fog nodes or the cloud, improving efficiency. Edge-to-edge communication can reduce latency and enhance coordination in collaborative robotics.

5.3 Hybrid Edge-Cloud Processing:

This architecture lets edge devices and cloud servers share data processing activities. The cloud can handle less urgent jobs while the edge handles urgent ones. This method optimizes local autonomy and cloud computing power.

5.4 Context-Aware Data Processing:

Application context and needs to determine data processing strategies in context-aware data processing. Edge devices can modify their data processing and communication mechanisms to meet system needs by considering environmental circumstances, task complexity, and available resources.

6. Evaluation of different machine learning algorithms suitable for Edge AI in robotic applications

When considering machine learning algorithms for robotic applications, it is essential to consider factors like computing efficiency, memory demands, accuracy, and adaptation to resource-constrained edge devices [31]. The following are some of the machine learning approaches and evaluation criteria that Edge AI uses for robotics:
Because SVMs are so effective at classification and regression work, they are frequently used in Edge AI for robotics applications. The training phase of an SVM is computationally inexpensive, but the inference phase may require more resources. This could be a problem for edge devices that have limited resources. A large number of edge devices are capable of meeting the modest memory needs of SVM. When properly calibrated, SVMs are capable of accurately classifying structured data. There is a possibility that support vector machines (SVMs) are not as adaptable to dynamic robotic situations as online learning or incremental updates. Due to their high processing efficiency and low memory requirements, decision trees are another common alternative used in Edge AI in robotics. Because of how quickly they learn and conclude, decision trees are an excellent choice for real-time processing on edge devices. Because they are reliable for classification and regression, decision trees can be used in various robotic applications. Because decision trees are more interpretable and can support incremental learning, they are suited for use in multiple contexts.

Random Forests are frequently utilized as part of fog-based Edge AI systems for robotics. During the training phase, they require more computational resources than individual decision trees, but their parallelization allows them to use edge device cores. Random Forests require more memory because of the ensemble nature of the model they produce. Nevertheless, some edge devices can make use of them. Their accuracy is high across a variety of datasets and activities. Because of their design's ensemble nature, they can also tolerate concept drift and incremental updates, making them adaptable in dynamic robotic environments. DNNs are particularly effective in AI applications such as robotics. Large DNNs are challenging to install on resource-constrained edge devices because of the enormous computing and memory space required. Although DNNs can learn complex patterns from raw data, it is possible that they will not function properly in all edge-based contexts.

On the other hand, more compact and effective DNN architectures such as MobileNets are now being developed to strike a compromise between accuracy and resource efficiency. Because of their capacity for online learning and incremental updates, they are well-suited for various robotic applications; nevertheless, updating large DNN models on edge devices may be challenging. K-Nearest Neighbors, also known as KNN, is utilized by edge AI robotics. KNN is an efficient enough algorithm for real-time processing on edge devices. KNN has modest requirements for memory, making it suitable for edge devices with limited resources. Its accuracy is comparable to that of other methods in data distributions that are clearly described. The fact that KNN uses fixed training data and is sensitive to irrelevant or noisy properties are two factors that restrict the flexibility of KNN in dynamic environments. KNN is helpful for robotic applications when the data distribution is consistent and can be easily understood by the algorithm.

7. Security and Privacy in Fog-based Edge AI Robotics

Because of its distributed and linked nature, fog-based Edge AI robots prioritize data security and privacy. Data is encrypted and authenticated during transmission and storage to overcome these issues to ensure privacy even if intercepted. TLS and SSH prevent eavesdropping and illegal access. Role-based access and multi-factor authentication limit data and resource access, reducing security concerns [32]. Real-time anomaly detection and intrusion prevention systems detect and stop attacks. Federated learning and differential privacy enable privacy-preserving collaboration. Encrypted and signed firmware and software upgrades prevent tampering and apply the latest security patches. Tamper-resistant hardware and secure boot methods safeguard edge and fog nodes from physical threats. In many applications, GDPR and HIPAA compliance is essential. Transparency promotes data responsibility and stakeholder trust. Finally, explicit data retention and deletion regulations prevent data exposure and misuse by removing unnecessary data. These extensive security and privacy protections address the particular issues of fog-based Edge AI robotics in a networked and distributed environment.

8. Conclusion

Robotics research is advancing with fog-based Edge AI. Fog Computing allows robotic systems to use AI algorithms at the network edge for real-time data processing, reduced latency, and better decision-making. This integration enables autonomous robots to navigate complex surroundings more precisely and facilitates seamless human-robot interaction.

For widespread use and success, emerging technologies must overcome difficulties. These problems include optimizing edge device resource management, data security and privacy, and interoperability and standardization. The future of Fog-based Edge AI in robots is bright and full of research and development potential. This field will advance because to AI algorithms, edge computing, and robotics hardware. AI, edge computing, and robotics researchers must collaborate to maximize this integration's potential. This connection enhances robot intelligence and efficiency through real-time data processing, better decision-making, and lower latency. Fog-based Edge AI in robotics will usher in a new era of intelligent and adaptive robotic systems with many applications in numerous industries and daily life as academics and practitioners continue to explore and improve.

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