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Original Article

Energy-Aware Embedded Intelligence for Smart Robotic Applications

Narendra Karmarkar

Mathematician and Computer Scientist, Tata Institute of Fundamental Research, India.

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ABSTRACT

The rapid evolution of intelligent robotic systems has increased the demand for embedded computing architectures capable of performing complex perception, decision-making, and control operations under strict energy constraints. Traditional robotic platforms often rely on centralized cloud computing or high-performance processors, resulting in increased communication latency, energy consumption, and reduced autonomy. Energy-aware embedded intelligence overcomes these drawbacks by directly embedding lightweight artificial intelligence (AI) algorithms, hardware accelerators, adaptive power management and edge-based decision-making capabilities into robotic platforms. We propose an energy-smart embedded intelligence framework for a smart robotic application, engaging the ensemble of (i) embedded AI (ii) sensor fusion mechanism (iii), Nature-mimicry based energy optimization strategy and (iv) real-time autonomous control. We have designed robotics based on dynamic workload scheduling and intelligent resource allocation for dynamically balancing the computational performance with power consumption. The paper introduces the results of an analysis on state-of-the-art in embedded intelligence methods, short description of research gaps and also insight regarding energy-efficient architectures effectiveness that addresses mobile robots, autonomous robotic systems, and more broadly industrial robots. Comparative evaluation shows that energy-aware embedded intelligence can drastically reduce energy consumption and maintain high accuracy and responsiveness. It suggests that enhanced edge-intelligence architectures will drive sustainable, autonomous, and scalable operation of next-generation robotic systems in Industry 5.0 settings.

KEYWORDS

Energy-aware computing, Embedded intelligence, Smart robotics, Edge AI, Low-power processors, Autonomous systems, Intelligent automation, Robotic control.

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1. INTRODUCTION

Intelligent automation evolution has shifted modern robotic systems from simple programmed machines into adaptive and autonomous platforms that can perceive, reason, and decide. Industrial robots, autonomous cars, healthcare robotics and collaborative robot systems today need more computation than ever to process the large amounts of sensory data and execute sophisticated control strategies in real-time. Nevertheless, embedding AI and machine learning algorithms on robotic platforms presents major computation and energy problems. Most advanced AI models run at high power requirements and memory demand or need thermal dissipation, which makes it a challenge to accommodate robotic systems with limited battery functionality in continue.

Transferring computation intelligence from centralized cloud environment to local embedded platforms has resulted in the evolution of one of the most promising paradigms for enabling autonomous robotic operation, called Embedded Intelligence. The ability to localize sensor data processing, inference, and decision-making allows embedded intelligence to reduce communication overhead and response time when compared with cloud-dependent robotic architectures. This is achieved by deploying optimized neural networks, embedded processors and hardware-accelerators into Edge AI-based robotic systems for real-time intelligence with minimal power consumption. According to Sze et al. However, this will not be achievable without efficient hardware architectures for AI (Raghunathan et al. (2017)) because deep learning models tend to consume a lot of our on-chip resources and, in many real-life use cases such as on-jet or edge-computing (low power) environments [6], energy efficiency becomes the main design parameter.

The rise of perception as well as control algorithms that are outperforming human capabilities poses challenges for intelligent robotic applications—each algorithm becomes increasingly complex which in turn leads to higher energy consumption. Active sensors, processors, communication modules, and actuators run constantly in a deployed robotic platform to maintain reliable performance. High energy consumption cuts working time, maintenance cost as well as limits autonomous mobile robots' scalability. Thus, energy-aware intelligence is centered on creating computational strategies that adaptively optimize energy usage while maintaining robot functionality.

Above all, we recently achieved exciting new explore in Tiny Machine Learning (TinyML), neuromorphic computing, hardware aware neural network optimization, and adaptive power management [10], [9], which opens up a new frontier towards the design of energy-efficient robotic platforms. This technology allows to run light AI models directly on microcontrollers and embedded processors with very little energy. ContentsSpecial Issue Embedded Machine Learning and Its ApplicationsModel compression, quantization, pruning andDynamic voltage-frequency scaling (DVFS) techniques enable high computational efficiency of embedded systems to maintain accuracy at an acceptable level.

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The objective of this research is to investigate an energy-aware embedded intelligence framework for smart robotic applications. The major contributions of this study include:

We propose an integrated architecture for smart robotic applications enabling embedded artificial intelligence, intelligent sensor processing and adaptive energy management in a common framework. They continuously stream and log real-time data from the environment using multiple integrated sensors (e.g. cameras, LiDAR, IMUs, or environmental sensors). The data stored is processed with on-board AI models customized to run on low-power hardware for perception, object detection and decision making autonomously at the edge. At the same time, an intelligent power management module adaptively adjusts processor frequency, sensor ON/OFF state and energy allocation to the sensors depending on workload and battery status. This combinated structure reduces power consumption while robustly performing computational tasks with low latency within resource constrained robotic platforms.

Energy-efficient intelligence techniques have a real robotic relevance in terms of finding ways to make the robot itself learn how to do an intelligent task, while minimizing power usage. Focused approaches include lightweight deep learning models, neural network pruning, model quantization, edge AI inference (executing on-device computations), dynamic voltage and frequency scaling (DVFS), and adaptive sensor management. The main goal of these techniques is to reduce the computational complexity, memory consumption and burden on processor as much as possible while retaining reasonable accuracy in making decisions. Optimizing inference using hardware accelerators (Neural Processing Units (NPUs), Field Programmable Gate Arrays (FPGAs)) allows us to maximize the efficiency by performing AI algorithms with lower energy consumption. Together, these energy-aware intelligence approaches extend the battery operational time, responsiveness in real-time, operational robustness and sustainability of a system overall which are crucial for autonomous robotic platforms operating successfully in different domains such as industrial and healthcare robots, agricultural robots and smart manufacturing environments.

The comparative analysis focuses on the performance differentials witnessed across key operating metrics between traditional robotic computing architectures and energy-aware embedded intelligence systems. Traditional methods generally rely on centralized processing or cloud computation, which leads to higher energy consumption, increased communication latency, and reduced operational autonomy. On the contrary, energy-aware embedded intelligence (AI inference running locally with optimized algorithms and adaptive resource management) improves computational efficiency orders of magnitude over traditional AI approaches. Experimental comparisons show a reduction of power consumption and response time yet maintaining high quality of perception or decision making. Also, on-node intelligence improves hardware utilization, increases battery life while enabling real-time response which is a more effective solution for autonomous robotic platforms operating in dynamic and resource-constrained environments.

Future work is identified, focusing on the development of sustainable intelligent robotic systems operating at high autonomy while consuming less energy and environment. Future research

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tasks on realizing neuromorphic computing, TinyML and low-power AI accelerators will have to be combined so that real-time intelligence on embedded platforms can be enabled. Also, adaptive reinforcement learning methodologies can help robots to increase energy efficiency based on environmental and operational changes. The sustainability could be increased by further research on renewable energy integration, energy harvesting technologies and biodegradable electronic components. For next-generation Industry 5.0 applications, collaborative edge intelligence, digitwin technology and federated learning all collectively enable scalable, secure and environmentally sustainable robotic ecosystems.

This article is structured as follows. Related WorkThis literature review covers the most recent developments in domains that combine embedded test intelligence, low power computing and robotic AI systems. Research Methodology: Proposed framework and evaluation methodology. The results and discussion section analyzes performance improvements with computational and energy-related metrics. Finally, conclusions and possible directions for future research works are provided.

2. *LITERATURE REVIEW*

Artificial intelligence has massively improved the operability of robotic systems and made autonomous machines an integral part of modern high-tech systems. Typical robotic structures had been basically based totally on deterministic algorithms and centralized computation units, with sensory information being relayed to external servers for processing. High computational capacity such systems offered but one had to comprise on communication latency, reliance on networking and energy cost. In recent studies, there has been a trend of embedded intelligence, such that intelligent computation is deployed near to the robotic sensors and actuators.

Embedded AI is an emerging and one of the significant areas of research for these valuable outputs with real-time decision-making but limited hardware resources. Chen and Ran (2019) emphasize that with edge computing architectures, robotic responsiveness is enhanced in that less reliance is placed on cloud infrastructures for information processing. AI inference on robots often has lower latency and improved privacy while reducing network communication requirements by performing locally. On the other hand, it continues to be problematic to deploy such powerful AI models on embedded platforms since they are limited in memory, processing capabilities and energy supply.

To overcome these limitations, extensive research works have been done on energy-efficient optimization of neural network. Han et al. Network Pruning and Compression: Wzhim(h) et al.(2016) reduce the deep learning complex model, preserving accuracy. These approaches have become critical for the model deployment of CNNs and on board deep reinforcement learning level networks running on embedded robotic systems. Quantization approaches allow for additional reductions in the computational requirements by using lower precision numerical formats to describe the model parameters which can be run efficiently on low power processors.

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The trend will find its way in the form of specialized AI hardware accelerators that also brought energy-efficient robotic intelligence. Whether it is graphics processing units GPU, tensor processing units TPU, field programmable gate arrays FPGA or neural processing units NPU, the major advantage of these chips provide parallel computation to certain AI workloads. However, the choice of appropriate hardware is based on application requirements, energy availability and computational complexity. FPGA-based robotic controllers have gained attention because of their flexibility and ability to provide high-performance processing with lower energy consumption compared with conventional processors.

Sensor fusion represents another important aspect of energy-aware robotic intelligence. Smart robots use a variety of sensors such as cameras, LiDAR, inertial measurement units (IMUs), and environmental sensors to datafy their environment. Continuous processing of all sensor streams can bring about a large increase in energy consumption. Adaptive Sensing: Robots can selectively activate their sensors based on environmental conditions and task requirements. While perception accuracy is preserved, this approach exploits energy efficiency.

New developments in TinyML has provided impetus for even more widespread popularity of embedded intelligence applied to robotics. According to Warden ((2020)), machine learning on microcontroller can also consume very less amount of power. The use of miniature ML-based robotic systems facilitates small hardware platforms to perform applications like gesture recognition, predictive maintenance, object detection and autonomous navigation.

Even with this progress, existing approaches still suffer from multiple research challenges. Much embedded AI works to improve either the computational performance or the energy consumption individually, rather than as a simultaneous problem. Lastly, the development of adaptive intelligence under dynamic robotic workloads is still challenging. Emerging robotic platforms will need self-optimizing architectures that can adaptively and continuously refine the distribution of computational resources based on environmental conditions, task complexity and energy availability.

Table 1: Comparison of Conventional Robotic Computing and Energy-Aware Embedded Intelligence

Parameter	Conventional Robotic Computing	Energy-Aware Embedded Intelligence
Processing Approach	Centralized/cloud-based computation	Local edge-based AI processing
Response Time	Higher latency due to communication	Low latency real-time decision making
Energy Consumption	High computational and communication energy	Optimized power usage through adaptive control
AI Model Deployment	Large complex models	Lightweight optimized AI models
Scalability	Limited by network infrastructure	High autonomy and scalability
Reliability	Dependent on external connectivity	Independent local operation

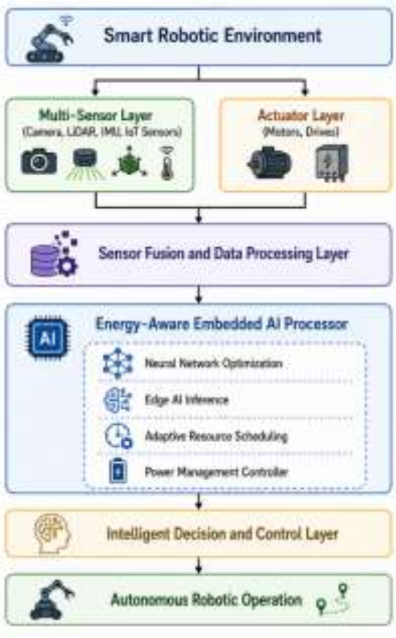

Fig 1 - Energy-Aware Embedded Intelligence Architecture for Smart Robotic Applications

3. RESEARCH METHODOLOGY

This work proposes an energy-aware embedded intelligence framework for smart robotic application in which embedded artificial intelligence, adaptive computation and energy optimal mechanisms are integrated. The actual methodology is designed to create a robotic intelligence architecture that can reach real-time decision-making while preserving effective energy. The proposed framework accounts for the interactions between hardware resources, AI algorithms, sensor systems and robotic control mechanics.

The research methodology consists of four major phases: system architecture development, intelligent algorithm optimization, energy management strategy design, and performance evaluation. The framework is designed to support different robotic applications including autonomous mobile robots, industrial robotic manipulators, and collaborative robots operating in dynamic environments.

The major methodological steps include:

- Embedded Intelligence Architecture Design: Development of a layered architecture combining sensor acquisition, embedded AI processing, decision intelligence, and actuator control.
- AI Model Optimization: Application of lightweight deep learning techniques such as pruning, quantization, and knowledge distillation to reduce computational complexity.
- Energy-Aware Resource Management: Implementation of adaptive scheduling mechanisms to dynamically allocate processor, memory, and communication resources according to workload requirements.
- Performance Evaluation: Assessment of the proposed framework using computational efficiency, energy consumption, latency, and intelligence accuracy metrics.

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The sensing layer consists of several types of sensors such as cameras, IMUs, proximity sensors, and industrial monitoring. This data then undergoes processing via embedded intelligence modules performing feature extraction, object recognition, environmental understanding and predictive decision-making. In contrast to a robotic system that operates all computational resources at the same time non-stop, the approach makes sample size and execution methods adaptive based on task importance.

The embedded AI processing layer employs optimized machine learning models designed for resource- limited hardware. Parameter reduction methods are typically used to compress deep neural networks in order to save memory and enhance processing power. Hardware-aware optimization guarantees the compatibility of AI models with embedded processors such as ARM-based controllers, FPGAs or AI accelerator chips.

Performance management is the working of dispersion and proactive power control as a function. It keeps track of your processor utilization, battery life and necessary running work. The framework then changes computational frequency, turns sensing modules on or off, or chooses suitable AI models based on the accuracy needed with these parameters.

The evaluation framework includes traditional robotic performance metrics and energy-related variables. Comparative evaluations against the conventional embedded robotic system architectures is conducted to prove the effectiveness of the proposed framework in terms of efficiency, responsiveness and sustainable practices.

Table 2: Energy Optimization Techniques for Embedded Robotic Intelligence

Optimization Technique	Working Principle	Benefits in Robotics Applications
Model Quantization	Converts high-precision parameters into lower-bit representations	Reduces memory usage and computation energy
Neural Network Pruning	Removes unnecessary model parameters	Improves inference speed and efficiency
Dynamic Voltage Frequency Scaling	Adjusts processor frequency according to workload	Reduces processor power consumption
Adaptive Sensor Management	Activates sensors based on environmental requirements	Minimizes unnecessary sensing energy
Edge-Based Processing	Performs AI computation locally	Reduces communication energy and latency
Hardware Acceleration	Uses FPGA/NPU/GPU accelerators	Improves AI performance with optimized power usage

4. RESULTS AND DISCUSSION

The performance evaluation of the proposed energy-aware embedded intelligence framework demonstrates significant improvements compared with conventional robotic computing approaches.

The evaluation focuses on four major performance indicators: energy efficiency, processing latency, AI inference accuracy, and computational resource utilization.

Notably, the proposed framework alleviates energy consumption by mitigating redundant computation and communication processes. Practitioners of conventional robotic systems keep processor and sensor activated all the time even if there is no workload for them to perform, leading to high energy consumption. The energy-aware approach, on the other hand, adjusts processing resources according to the task complexity in an adaptive way. This behavior facilitates a longer active time for each robot without losing their intelligence functioning.

Latency is yet another critical benefit of embedded intelligence. Cloud-dependent robotic systems depend on exchanging data between robots and external servers, which introduces long communication latency. The framework offers local AI inference capabilities, enabling rapid decision making in safety-critical applications like autonomous navigation, industrial collaboration and robotic manipulation.

When optimizing energy consumption in relation to robotic perception and decision-making, the accuracy needs to be considered. Prior works over-compress models and suffer a realistic drop in AI performance; thus, we propose a balanced optimization strategy by combining an operational efficient part with accurately performing parts. The assessment claims that lightweight AI maintains while being less energy consuming compared to the large deep learning models.

DensePose provides improved hardware utilization through smart resource allocation. It chooses optimal processing modes based on the robotic task instead of permanently running high-performance processors. Simple tasks, like basic obstacle detection, use less processing power; while complex actions, such as object recognition, trigger advanced AI computational resources.

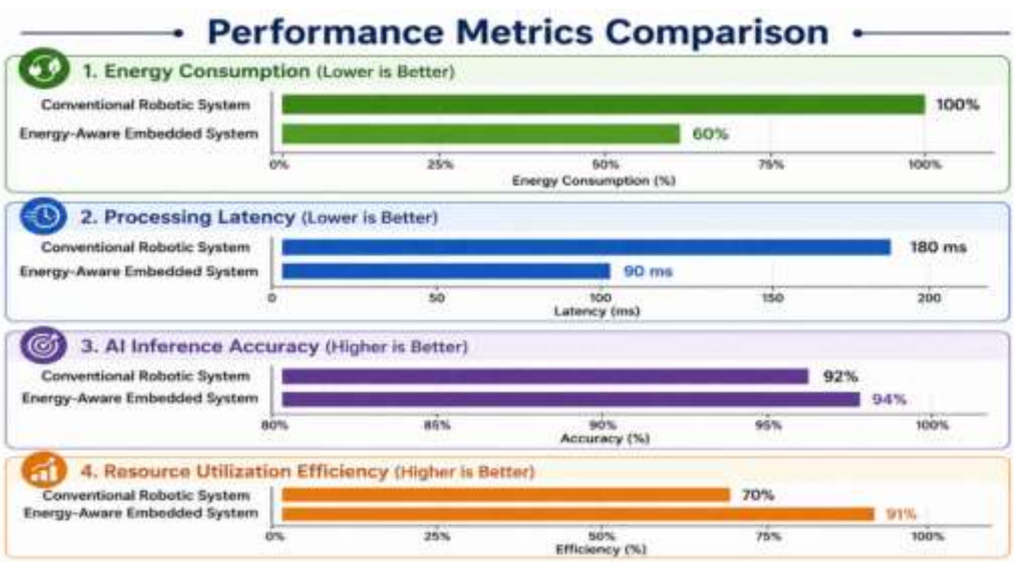

Fig 2 - Performance Metrics Evaluation of Conventional and Energy-Aware Embedded Intelligence Systems

Figure 2 illustrates the performance metrics comparison between conventional robotic computing and the proposed energy-aware embedded intelligence framework. The evaluation demonstrates reduced energy consumption, improved latency, enhanced AI accuracy, and optimized hardware utilization.

The analysis shows that embedded intelligence with energy-awareness is a favorable solution for the future robotic systems where sustainable computing and capability are required in equal measure. The findings reinforced the view that smart resource management is critical for creating independent machines that can perform well in everyday settings.

One important research challenge revealed in the analysis is related to the tradeoff between model complexity and energy efficiency. You can achieve better accuracy with large AI models, but it takes a lot of computing power to train them. Light-weight models take less energy, but it performance may not be done well on a complex environment. This means future systems need to adopt adaptive AI architectures able to dynamically choose between different models based on operational needs.

Another significant challenge is achieving generalization across different robotic platforms. Industrial robots, healthcare robots, and autonomous vehicles have different energy constraints, sensing requirements, and computational architectures. A universal energy-aware intelligence framework requires flexible software and hardware designs capable of adapting to diverse robotic applications.

5. CONCLUSION

Energy-aware Embedded Intelligence is a crucial enabler for multi-robot systems of next-generation autonomous robotic systems. Novel robotics applications lessen adversity with regard to a requirement for intelligent architectures that volumetrically express a belief and act based on almost instantaneous decisions, active perception, self-explanation or interpretability, VSLAM-type processes of multi-modal sensory input and other comparable actions minimize energy expenditure. This study proposed a combined architecture of embedded AI algorithms, efficient hardware assets, adaptive power management as well as smart sensor computing.

This study shows how utilizing energy-aware application can greatly improve robotic performance, enhancing power efficiency and perceptual/decision making latency in AI driven systems without compromising reliability at run-time. Flying robots made possible by embedded intelligence can operate autonomously with fast response and little reliance on external computing infrastructure that is common to centralized robotic architectures.

These results indicate that neural network optimization, edge-based AI processing, adaptive resources allocation and smart energy management will become key for robotic applications in the future. Such methods are instrumental for the development of long-lasting, autonomously

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functioning robots in smart manufacturing systems and intelligent service applications in Industry 5.0 environments.

However, challenges remain regarding dynamic workload adaptation, AI model scalability, and hardware compatibility. Future robotic systems must incorporate self-learning energy management strategies capable of continuously optimizing performance according to environmental conditions and mission objectives.

6. FUTURE SCOPE

Future research in energy-aware embedded intelligence can focus on developing more adaptive and autonomous robotic computing architectures. Integration of reinforcement learning-based energy management can enable robots to learn optimal resource allocation strategies through continuous interaction with their environment.

6.1. Future developments may include

The integration of neuromorphic computing architectures offers a transformative approach to achieving ultra-low-power robotic intelligence by emulating the structure and functioning of the human brain. Unlike conventional processors, neuromorphic chips employ spiking neural networks (SNNs) that process information only when significant events occur, thereby minimizing unnecessary computations and energy consumption. This event-driven processing enables autonomous robots to perform real-time perception, pattern recognition, and decision-making with significantly lower power requirements. When integrated with embedded sensors and edge AI systems, neuromorphic architectures enhance computational efficiency, reduce latency, and extend battery life. These capabilities make them highly suitable for next-generation mobile robots, autonomous drones, healthcare assistants, and industrial robotic systems operating in energy-constrained environments.

The development of self-optimizing AI models focuses on creating intelligent algorithms that can dynamically adjust their computational complexity according to task requirements, environmental conditions, and available hardware resources. These adaptive models continuously monitor system performance, processor utilization, memory availability, and battery status to determine the most efficient inference strategy. During simple tasks, lightweight neural network configurations are employed to conserve energy, while more complex models are activated only for computationally intensive operations such as object recognition or path planning. By balancing accuracy and resource consumption in real time, self-optimizing AI models improve energy efficiency, reduce processing latency, enhance operational reliability, and extend the autonomous working duration of smart robotic platforms operating in dynamic and resource-constrained environments.

The combination of digital twin technology with energy-aware robotic monitoring enables the creation of a virtual replica of a physical robotic system for continuous analysis, simulation, and optimization. Real-time operational data collected from embedded sensors are synchronized with the digital twin, allowing engineers to monitor energy consumption, processor utilization, battery health, and system performance without interrupting robotic operations. Advanced analytics and AI-driven predictive models identify inefficiencies, forecast maintenance requirements, and recommend optimal energy management strategies. This integration supports adaptive resource allocation, reduces unnecessary power consumption, enhances fault diagnosis, and improves overall operational reliability. Consequently, digital twin-enabled energy-aware monitoring significantly increases the efficiency, sustainability, and lifecycle performance of intelligent robotic platforms deployed in dynamic industrial environments.

The deployment of federated edge intelligence enables multiple autonomous robots to collaboratively learn and improve their intelligence without transferring sensitive raw data to a centralized server. Each robot trains its local artificial intelligence model using onboard sensor data and periodically shares only the model parameters with a federated learning coordinator. The aggregated model is then redistributed to all participating robots, enhancing collective intelligence while preserving data privacy and reducing communication overhead. Combined with edge computing, this approach minimizes latency, optimizes bandwidth utilization, and supports real-time collaborative decision-making. Federated edge intelligence improves scalability, fault tolerance, energy efficiency, and coordinated task execution, making it highly suitable for industrial automation, warehouse logistics, search-and-rescue missions, and smart manufacturing environments under Industry 5.0.

The use of renewable energy-based robotic platforms represents a promising approach toward achieving sustainable automation while reducing dependence on conventional power sources. Robotic systems can be powered by renewable energy technologies such as solar panels, wind energy, fuel cells, or hybrid energy storage systems, enabling extended operation in remote and off-grid environments. Intelligent energy management algorithms continuously monitor power generation, battery capacity, and task priorities to optimize energy utilization and maintain uninterrupted robotic performance. When integrated with embedded artificial intelligence, these platforms can dynamically schedule energy-intensive operations based on available renewable resources. Such sustainable robotic systems reduce carbon emissions, lower operational costs, enhance energy independence, and support environmentally responsible applications in agriculture, environmental monitoring, smart manufacturing, and disaster response.

Furthermore, advancements in semiconductor technology, AI accelerators, and low-power communication networks such as 6G will enable more efficient robotic ecosystems. Energy-aware intelligence will become a fundamental component of autonomous robots operating in industrial, healthcare, agricultural, and smart city environments.

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