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Integrated Edge Intelligence Systems for Real-Time Decision Making in Autonomous Engineering Applications †

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Abstract

Autonomous engineering systems such as self-driving vehicles, industrial robots, and smart infrastructure require real-time decision-making capabilities to operate safely and efficiently. Traditional cloud-centric computing architectures often suffer from latency, bandwidth limitations, and reliability challenges when processing large volumes of sensor data. Integrated edge intelligence systems address these limitations by enabling data processing, machine learning inference, and control decisions directly at the network edge. This paper proposes an integrated edge intelligence framework designed for real-time decision-making in autonomous engineering applications. The framework combines edge computing nodes, artificial intelligence models, and distributed sensor networks to support low-latency analytics and autonomous control. Experimental results demonstrate that edge-based decision-making significantly reduces response time while improving system reliability and scalability. The proposed system is evaluated through simulations involving autonomous robotics and smart infrastructure monitoring. The results indicate that integrated edge intelligence architectures can significantly enhance system performance and operational efficiency in complex autonomous engineering environments.

Keywords: autonomous engineering; industrial robots; artificial intelligence; process innovation

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1. Introduction

Autonomous engineering systems are increasingly used in applications such as smart manufacturing, autonomous vehicles, intelligent transportation systems, and industrial robotics. These systems rely heavily on large volumes of sensor data to perceive their environment and make operational decisions. Traditional cloud-based computing architectures often struggle to process such data in real time due to network latency, bandwidth constraints, and reliability issues.

Edge computing has emerged as a promising solution for addressing these challenges. Edge computing enables data processing closer to the data source by deploying computing resources at the network edge. This architecture reduces communication delays and improves real-time decision-making capabilities [1].

Integrated edge intelligence systems extend this concept by embedding artificial intelligence (AI) models within edge devices (Figure 1). These systems allow autonomous engineering applications to perform local data processing, machine learning inference, and

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control operations without relying solely on centralized cloud platforms. Edge intelligence is particularly beneficial in time-critical environments where immediate decisions are required.

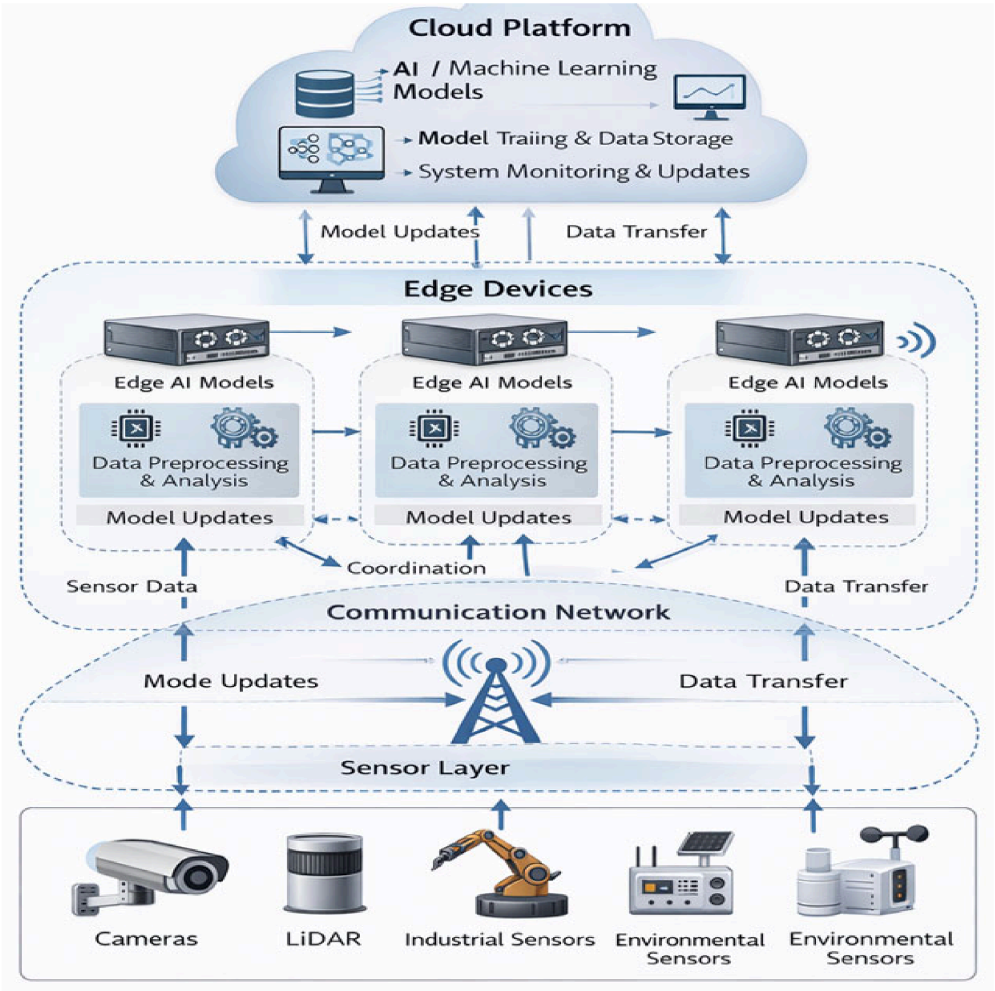


Figure 1. Integrated Edge Intelligence System Architecture.

Recent advancements in deep learning, edge processors, and distributed computing architectures have accelerated the development of edge intelligence systems. These technologies enable autonomous systems to process complex sensor data streams such as video, LiDAR, and environmental measurements in real time [2].

This research proposes an integrated edge intelligence framework designed to support real-time decision-making in autonomous engineering systems. The proposed architecture combines edge computing nodes, distributed sensor networks, and AI-driven analytics to enhance system performance and reliability.

2. Literature Review

Edge computing has gained significant attention as a solution for processing large-scale data generated by Internet of Things (IoT) devices and autonomous systems. Unlike traditional cloud computing architectures, edge computing enables data processing near the data source, reducing latency and network congestion [3].

Several studies have demonstrated the advantages of edge intelligence for autonomous engineering applications (Table 1). For example, edge-based machine learning systems have been successfully used in autonomous vehicles to process camera and LiDAR data for

object detection and navigation tasks [4]. By performing inference locally, these systems significantly reduce decision latency.

Another important research area is distributed edge intelligence, where multiple edge nodes collaborate to process data and share computational resources. This approach improves scalability and enables efficient handling of large-scale sensor networks [5].

Edge intelligence has also been applied in industrial automation. Smart factories increasingly deploy edge computing platforms to perform predictive maintenance, anomaly detection, and process optimization. These systems analyze machine sensor data in real time to detect potential equipment failures before they occur [6].

Despite these advancements, several challenges remain in deploying edge intelligence systems. These include limited computational resources at edge nodes, energy constraints, and security concerns associated with distributed data processing. Addressing these challenges is essential for enabling reliable and scalable edge intelligence architectures.

Table 1. Summary of Edge Intelligence Research in Autonomous Systems.

Study	Technology/Method	Application Area	Key Contribution
Shi et al. (2016) [1]	Edge computing architecture	Internet of Things (IoT) systems	Proposed the foundational architecture and challenges of edge computing for real-time data processing.
Satyanarayanan (2017) [2]	Edge computing platforms	Mobile and distributed systems	Introduced the concept of cloudlets and emphasized low-latency computing at the network edge.
Zhou et al. (2019) [3]	Edge intelligence framework combining AI and edge computing	Autonomous systems and IoT	Demonstrated how integrating AI with edge computing enables real-time decision-making in intelligent systems.
Mao et al. (2016) [4]	Mobile edge computing with dynamic computation offloading	Autonomous vehicles and mobile systems	Proposed algorithms for optimizing computation offloading between edge devices and cloud servers.
Zhang et al. (2019) [5]	Deep learning for mobile and wireless networks	Intelligent transportation and networking systems	Investigated how deep learning models can be deployed at the edge for efficient data processing.
Deng et al. (2020) [6]	Edge intelligence architectures	Industrial IoT and smart manufacturing	Presented frameworks for integrating AI capabilities into distributed edge computing infrastructures.

3. Methodology

This research proposes an Integrated Edge Intelligence Architecture (IEIA) designed for real-time decision-making in autonomous engineering systems (Figure 2).

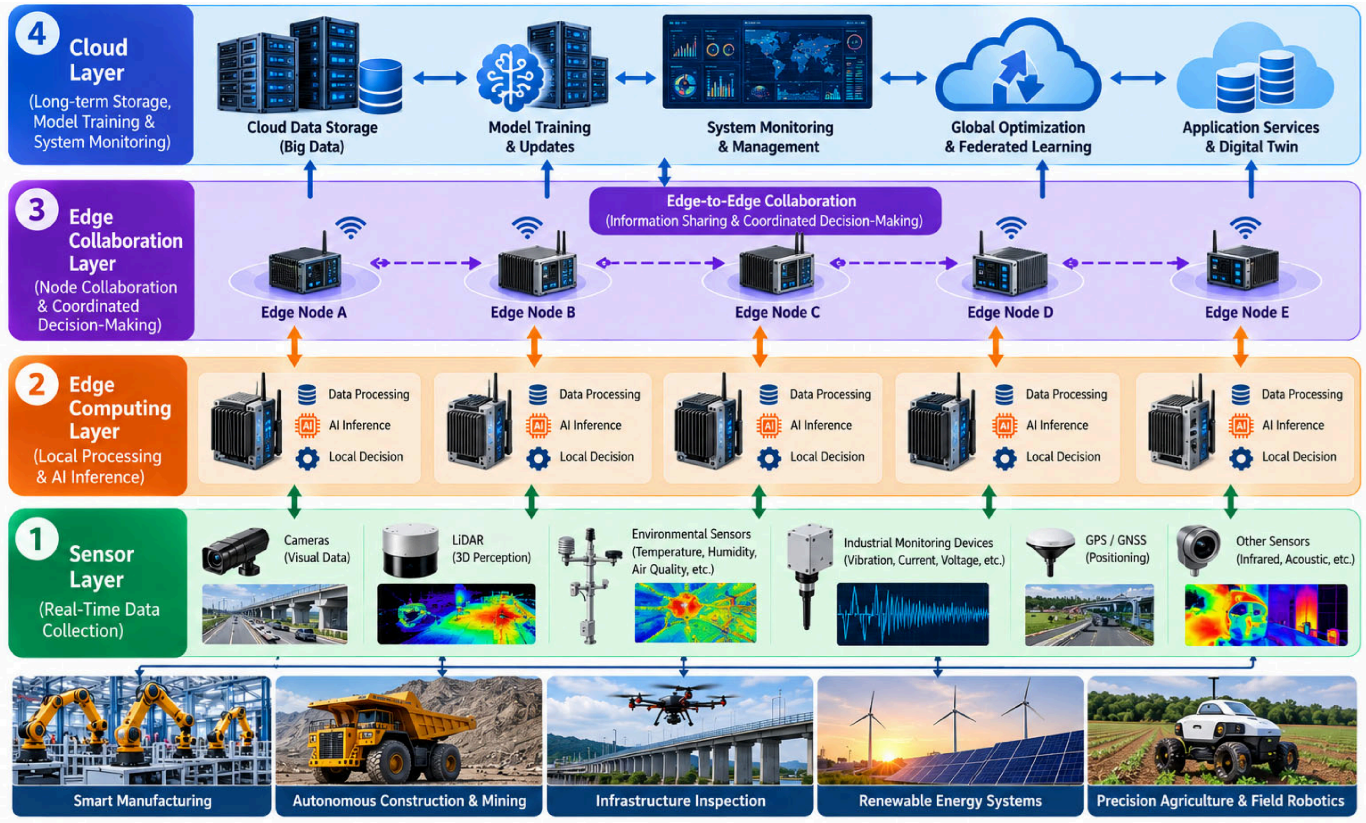


Figure 2. The proposed four main layers system architecture.

3.1. System Architecture

The proposed system consists of four main layers:

- Sensor Layer—Distributed sensors collect real-time data from the environment. These sensors may include cameras, LiDAR, environmental sensors, and industrial monitoring devices.
- Edge Computing Layer—Edge nodes located near the sensors perform local data processing and machine learning inference. These nodes are equipped with embedded AI accelerators capable of executing deep learning models.
- Edge Collaboration Layer—Multiple edge nodes communicate with each other to share information and coordinate decision-making.
- Cloud Layer—The cloud platform performs long-term data storage, model training, and system monitoring.

3.2. Data Processing Workflow

Sensor data are first processed at the edge node using lightweight AI models. Critical decisions are made locally when latency-sensitive events occur. For non-critical tasks, data are transmitted to the cloud for further analysis and model optimization.

3.3. Decision-Making Model

The decision-making system employs deep neural networks trained using historical sensor data. These models perform tasks such as object detection, anomaly detection, and predictive maintenance. The trained models are deployed on edge devices to enable real-time inference. Table 2 summarizes the major components of the edge intelligence architecture and their roles in enabling real-time decision-making in autonomous engineering systems.

Table 2. Edge Intelligence Components and Functions.

Component	Description	Function in Edge Intelligence System
Sensor Nodes	Distributed sensors such as cameras, LiDAR, industrial sensors, and environmental sensors	Collect real-time data from the physical environment and transmit it to nearby edge devices
Edge Computing Devices	Embedded computing platforms equipped with AI accelerators and processors	Perform local data processing, machine learning inference, and real-time decision-making
Edge Collaboration Layer	Communication and coordination mechanisms among multiple edge nodes	Enable data sharing, distributed analytics, and coordinated decision-making across edge devices
Communication Network	Wireless or wired communication technologies such as 5G, Wi-Fi, or IoT protocols	Facilitate data transmission between sensors, edge devices, and cloud platforms
Cloud Platform	Centralized computing infrastructure for large-scale analytics and model training	Perform AI model training, long-term data storage, and system monitoring
AI Models	Deep learning and machine learning algorithms deployed on edge nodes	Analyze sensor data, detect patterns, and generate real-time operational decisions
Data Management Module	Data filtering, preprocessing, and aggregation mechanisms	Reduce data transmission loads and ensure efficient processing at edge devices
Control and Decision Module	Autonomous control algorithms integrated into edge devices	Execute automated decisions and control actions in autonomous engineering applications

4. Results

The proposed integrated edge intelligence system was evaluated through simulation experiments involving autonomous robotic systems and industrial monitoring scenarios. The experimental environment consisted of multiple sensor nodes generating continuous data streams, which were processed by distributed edge computing devices.

The results demonstrate significant improvements in system response time compared with cloud-based architectures. In the cloud-only configuration, decision latency averaged approximately 250 ms due to network transmission delays (Figure 3). In contrast, the proposed edge intelligence architecture reduced latency to approximately 45 ms, enabling real-time decision-making.

Another important performance metric is system reliability (Table 3). Edge intelligence systems maintain operational functionality even when cloud connectivity is temporarily unavailable. During simulated network disruptions, edge nodes continued processing sensor data and performing local decision-making tasks.

The proposed architecture also demonstrated improved scalability (Figure 4). As the number of sensors increased, the distributed edge processing approach prevented network congestion and reduced data transmission loads. Edge nodes filtered and processed raw sensor data locally before transmitting only relevant information to the cloud.

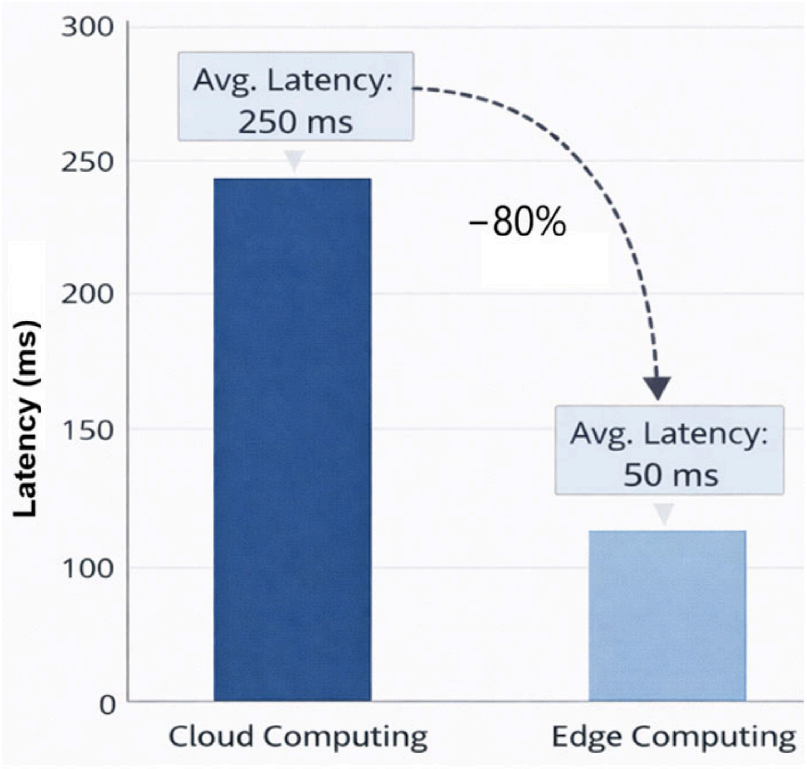


Figure 3. Latency Comparison Between Cloud and Edge Computing Systems.

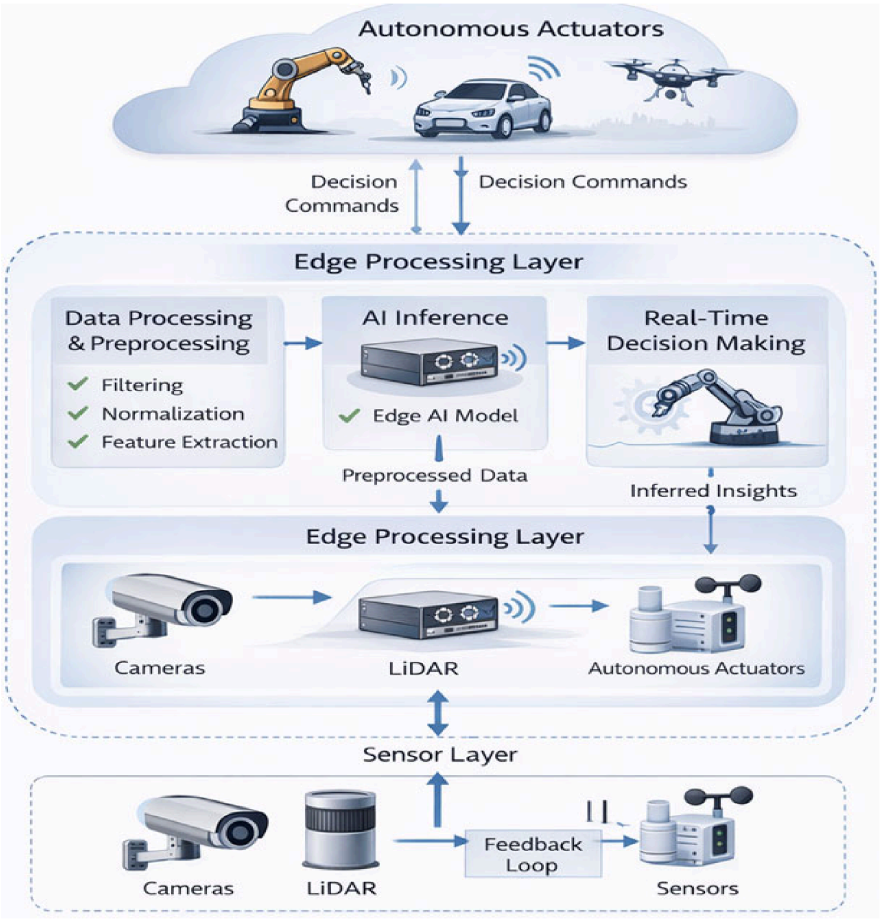


Figure 4. Real-Time Decision Processing Workflow in Edge Intelligence Systems.

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Table 3. Performance Comparison of Computing Architectures.

Computing Architecture	Processing Location	Average Latency	Reliability	Scalability	Data Transmission Load	Typical Application Scenarios
Cloud Computing Architecture	Centralized cloud servers	High (≈200–300 ms)	Moderate	Moderate	Very High	Large-scale data analytics, centralized monitoring systems
Hybrid Cloud–Edge Architecture	Partial processing at edge and cloud	Medium (≈80–150 ms)	High	High	Moderate	Smart manufacturing, intelligent transportation systems
Edge Intelligence Architecture	Local processing at edge devices	Low (≈30–60 ms)	Very High	Very High	Low	Autonomous vehicles, industrial robotics, real-time control systems

5. Conclusions

Integrated edge intelligence systems provide an effective solution for enabling real-time decision-making in autonomous engineering applications. By processing data locally at edge nodes, these systems significantly reduce latency and improve operational reliability compared with traditional cloud-based architectures. The proposed integrated edge intelligence architecture enables distributed processing, collaborative decision-making, and scalable deployment across large sensor networks. Experimental results demonstrate substantial improvements in response time, system reliability, and scalability. These benefits make edge intelligence particularly suitable for time-critical applications such as autonomous robotics, industrial automation, and intelligent transportation systems. Future research should focus on optimizing AI models for edge devices, improving security mechanisms for distributed computing environments, and integrating edge intelligence with emerging communication technologies such as 6G networks. Continued advancements in edge computing and artificial intelligence will play a critical role in enabling the next generation of intelligent autonomous engineering systems.

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Conflicts of Interest: Author Yuan Zhi Leong was employed by the company ABB Malaysia Sdn. The remaining author declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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