



AI in IoT and Edge Computing – Intelligent Automation and Real-Time Processing

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DOI - 10.5281/zenodo.17312953

Abstract:

The landscape of distributed computing is undergoing a profound transformation, driven by the convergence of Artificial intelligence (AI), the Internet of Things (IoT), and edge computing. combined together, these technologies are developing into intelligent systems that are capable of perceiving their environment, making autonomous decisions and act with precision. Although they provide scalability, traditional cloud-based IoT architectures struggle with high latency, network congestion, and concerns about privacy [1][2]. By performing data processing and intelligence closer to the source, edge computing aims to address these inherent problems, facilitating real-time analysis and prompt decision-making [3]. These edge-enabled IoT systems show promising possibilities in contextual awareness, adaptive optimization, predictive maintenance, and intelligent automation across highly diverse networks when augmented with Artificial Intelligence [4][5].

To quantitatively evaluate the performance of edge-enabled Intelligent systems, we conducted a simulated ECG monitoring experiment comparing cloud-only and edge-hybrid deployments. We extend beyond a review by introducing a heuristic Efficiency–Effectiveness Score (EES), as a consolidated metric for assessing system performance under multiple operational constraints to quantify trade-offs between latency, energy, and accuracy. Results indicate that edge-hybrid deployment significantly reduces latency and energy usage while maintaining high accuracy. Practical applications in healthcare, industrial automation, and autonomous mobility are discussed through case studies, while future research directions highlight promising opportunities for energy-efficient, secure, and semantically aware edge intelligence ecosystems.

Keywords: Artificial Intelligence, Internet of Things, Edge Computing, Intelligent Automation, Real-Time Processing, TinyML, Federated Learning, Latency Minimization, Edge Intelligence.

Introduction:

The Internet of Things (IoT) devices are expanding at an astonishing pace, growing into the tens of billions globally, within just a few years—has created remarkable opportunities for automation, seamless connectivity, and the extraction of data-driven insights [2]. However, this explosive growth also introduces a set of complex challenges, particularly in terms of computational requirements, latency-sensitive operations, and persistent concerns about data privacy [1].

While traditional, cloud-centric IoT frameworks are adept at handling large-scale data aggregation and analytics, often fail to meet the real-time processing demanded by critical applications, such as autonomous vehicles, industrial automation, or continuous health monitoring [3]. Communication delays caused by the need to transfer data to distant servers, along with bandwidth limitations and security concerns, highlight the necessity of transitioning toward edge-focused computing architectures [3][4]. Edge computing directly

addresses these issues by relocating computation closer to where the data is generated [3]. This approach enables immediate data processing, minimizes latency in decision-making, and offers stronger privacy protections [3]. When artificial intelligence is integrated into these edge systems, they gain the capability to interpret complex data, anticipate future events, and autonomously make decisions without relying solely on cloud infrastructure [4][5]. As a result, AI-powered edge IoT platforms can serve as the foundation for intelligent automation, adapting rapidly to changing environments [5].

To quantify these benefits, we conducted a simulated ECG monitoring experiment comparing cloud-only and edge-hybrid deployments, evaluating latency, accuracy, bandwidth, and energy consumption. We also introduced the Edge Effectiveness Score (EES) as a unified metric for assessing system performance under multiple operational constraints. Results show that edge-hybrid systems achieve substantial improvements in responsiveness and efficiency, demonstrating the practical value of AI-enabled edge architectures. This paper provides a comprehensive analysis of integrating AI within IoT and edge computing contexts. It focuses on architectural models, deployment techniques, real-time data processing, intelligent automation, and the emerging challenges faced in these systems. Further, it explores real-world applications and future research directions aimed at building more efficient, secure, and scalable edge-enabled intelligent systems [1][4].

Background and Literature Review:

1. IoT and Cloud-Centric Architectures:

The earliest IoT systems relied heavily on centralized cloud infrastructures for data

aggregation, analysis, and storage [2]. While this approach proved effective for large-scale insights and batch processing, these architectures introduced notable limitations. Specifically, latency introduced by the physical distance between devices and remote cloud servers can be

a significant obstacle for time-sensitive applications [1]. Bandwidth limitations also emerge, particularly while transmitting high-volume data streams, such as video feeds or telemetry from autonomous vehicles, medical devices and advanced sensor networks [2][7].

Furthermore, transmitting sensitive information to remote servers raises significant privacy and regulatory concerns that are particularly pronounced in sectors like healthcare, finance, and industrial automation [4][9].

2. Edge Computing Paradigm:

Edge computing essentially relocates computational processes closer to the point where data is generated [3]. Edge nodes, whether as localized micro-data centres, embedded accelerators, or intelligent gateways, are designed to support prompt data analysis and decision-making right at the source [3][5]. Processing data locally, edge computing offers notable reductions in latency and bandwidth usage, while also enhancing the overall resilience of the system [3][5]. This paradigm is particularly advantageous for applications requiring rapid response times, including autonomous vehicles, smart manufacturing, or telemedicine, where even milliseconds can affect safety, efficiency, or patient outcomes [7][10].

3. AI Integration with IoT and Edge:

Integrating artificial intelligence with edge computing significantly enhances IoT systems by introducing predictive, adaptive, and autonomous features [4][5]. AI models

operating at the edge can detect anomalies, anticipate failures, improve operational efficiency, and support intelligent automation without the need for continuous reliance on cloud connectivity [4][5]. Innovations such as TinyML, federated learning, and model compression now enable advanced AI models to run on devices with limited resources, supporting scalability, safeguarding privacy, and promoting energy efficiency [8][6]. Localizing AI processing empowers edge-enabled systems that respond intelligently to variable environments, resulting in robust and autonomous networks capable of ongoing learning and adaptability [6][4].

Architectural Models for AI-Enabled IoT Edge Systems:

A comprehensive AI-enabled IoT edge system generally follows a three-tier architecture consisting of three layers [3][4]:

Perception Layer: This layer consists of sensors, actuators, and low-power microcontrollers that collect raw

environmental data. Initial preprocessing, such as noise filtering, feature extraction, and basic analytics, occurs here. devices in this layer operate with significant resource constraints. Efficient, lightweight computation is critical at this stage [1][8].

Edge Layer: This Layer consists of nodes equipped with GPUs, TPUs, or FPGAs, enabling local inference, federated learning, and latency-sensitive control tasks. This layer is responsible for filtering and preprocessing data, transmitting only essential information to the cloud. The primary goal here is to ensure rapid response times and optimize bandwidth usage [3][4].

Cloud Layer: The cloud serves as a supervisory layer, supporting centralized analytics, long-term data storage, global model training, and system orchestration. While the edge layer manages immediate responses, the cloud facilitates long-term intelligence, model refinement, and coordination across devices [1][2].

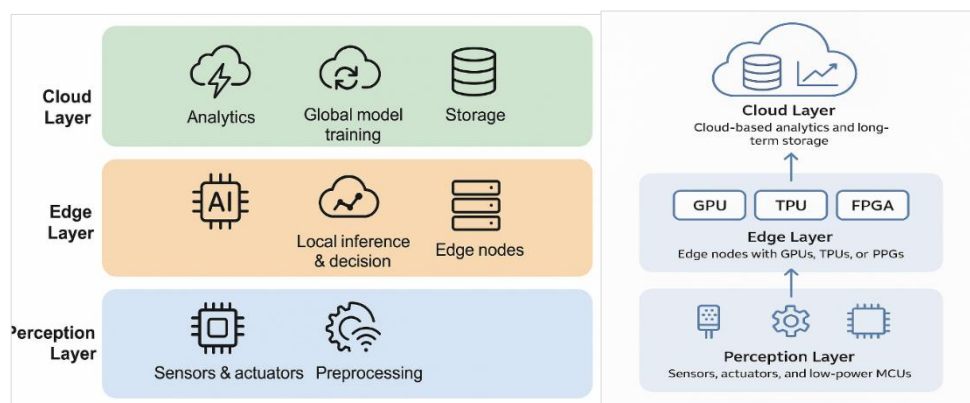


Figure 1: Layered architecture of AI-enabled IoT with edge intelligence.

Intelligent Automation in Edge IoT Systems:

1. Closed-Loop Control and Decision Making:

Edge-AI systems enable closed-loop automation, allowing sensing, reasoning, and actuation occur in near real-time [5][10]. In

industrial environments, embedded AI models can regulate motor speeds autonomously, adjust process parameters, control robotic arms, and manage energy consumption based on real-time sensor inputs. This enhances operational efficiency and also limits the need for human intervention [5][10].

2. Predictive and Self-Healing Systems:

Edge-based AI supports predictive maintenance by analyzing anomalies in equipment vibrations, temperature changes, or energy consumption patterns [5][10]. Self-healing mechanisms allow nodes to independently reroute tasks, recalibrate sensors, or isolate malfunctioning components, resulting in system resilience, uptime, and reliability [5][6].

3. Distributed Intelligence and Federated Learning:

Federated learning allows collaborative training of AI models across multiple devices without centralizing sensitive data [6][4]. This decentralized approach maintains privacy while enabling edge nodes to learn collectively from diverse environments.

Such approaches are especially beneficial in healthcare, finance, and other privacy-sensitive domains, producing high-quality models while preserving data sovereignty [4][9].

Real-Time Processing Techniques:

1. Latency Optimization:

Achieving genuine real-time performance requires meticulous latency management - across sensing, preprocessing, inference, and actuation [3][7]. For instance, autonomous vehicles need to maintain end-to-end inference times below 50 milliseconds to ensure safe perception, decision-making, and actuation [7]. Strategies such as data prioritization, streamlined communication protocols, and on-device filtering contribute significantly to latency reduction and boosting the reliability of system [3][7].

Experimental Validation: To evaluate latency performance, we simulated ECG monitoring using cloud-only and edge-hybrid deployments. The results, summarized in Figure 2, indicate that the edge-hybrid approach significantly reduces both median (P50) and 90th percentile (P90) latency.

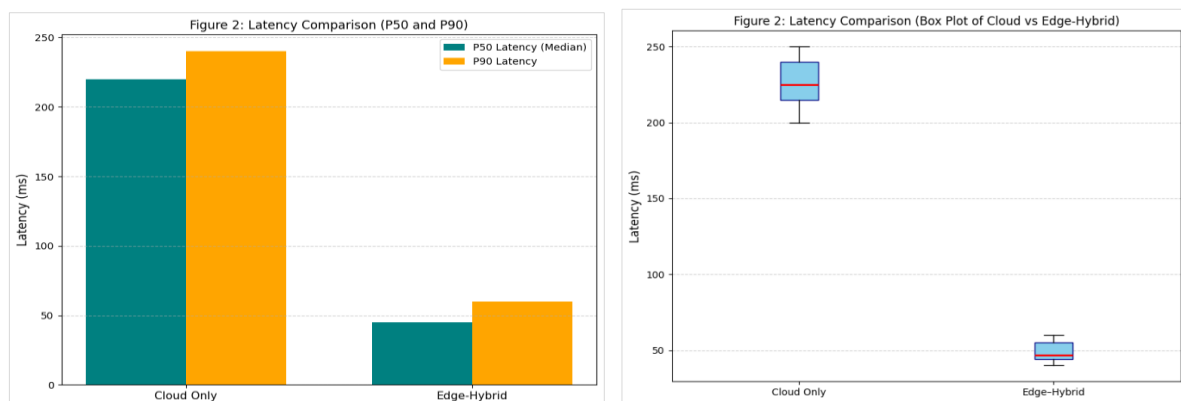


Figure 2: Comparison of P50 and P90 latency for cloud-only and edge-hybrid ECG monitoring. edge-hybrid deployment reduces median latency by approximately 81% compared to cloud-only deployment

2. TinyML and Model Compression:

TinyML enables the deployment of machine learning models to operate efficiently

on microcontrollers and other devices with limited resources [8]. TinyML offers devices with limited computing resources (also low-

powered or battery powered devices) the ability to deploy cost effective machine learning models for more efficient and robust applications that require predictive modelling, intelligent & real time decision making. [8]

Techniques such as pruning, quantization, and knowledge distillation help reduce model size and computational demands, while still preserving accuracy [8]. By adapting these approaches, the AI models can be deployed directly on edge devices with memory and energy constraints, facilitating

local inference and rapid response without relying on cloud dependency [8][3].

3. Split and Cascaded Inference:

Edge AI systems frequently employ split inference architectures, where lightweight models perform on-device preliminary analysis, while more complex models handle further processing at edge nodes [3][4]. Additionally, cascaded or early-exit models can offer rapid, approximate predictions, deferring intensive computations until truly necessary. This strategy helps with balancing computational efficiency, latency, and prediction accuracy [4][8].

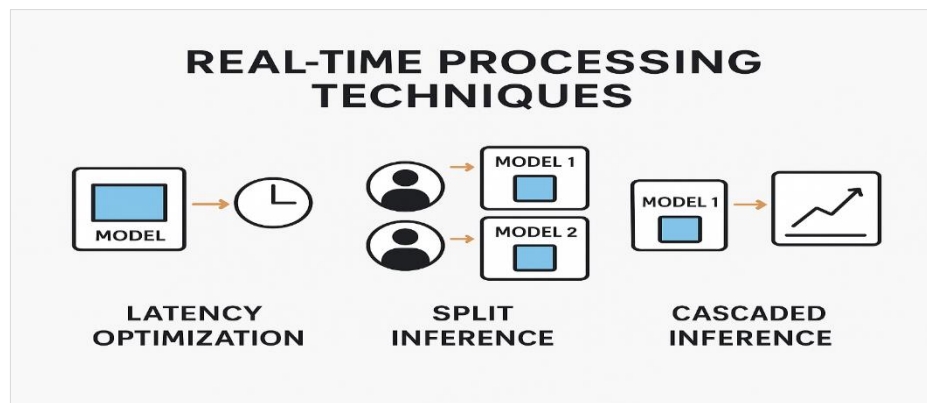


Figure 3: Real-Time Processing Techniques (Latency Optimization & Split/Cascaded Inference).

Case Studies:

1. Healthcare Monitoring:

Wearable and implantable devices integrated with edge AI are capable of detecting anomalies, such as arrhythmias, in real-time [9][4]. This enables immediate alerts and significantly reduces response times compared to traditional cloud-based approaches. Additionally, federated learning enables population-level insights while preserving privacy, as sensitive health data remains stored locally [6][9].

2. Methodology:

To empirically demonstrate the advantages of AI-enabled edge computing over traditional cloud-based IoT architectures, we conducted a simulation-based case study for ECG arrhythmia detection comparing a cloud-only pipeline against an edge-hybrid deployment.

Parameter values (latency, bandwidth, accuracy, energy per inference) were selected from published device measurements and empirical studies [Refs].

To aggregate performance into a single interpretable metric, we propose the Evaluation metric

Edge Effectiveness Score (EES):

$$EES = \frac{Accuracy}{Latency \times Energy}$$

- **Latency (ms)** – end-to-end response time from signal acquisition to alert generation.
- **Bandwidth Usage (MB/hr)** – average data transmitted per device.
- **Accuracy (%)** – anomaly detection precision/recall as reported in similar studies [9][10]
- **Energy (mJ)** – consumed per inference.

⇒ A higher EES indicates a more efficient trade-off between accuracy, speed, and energy

It is worth noting that EES is not intended as a universal standard, but as an exploratory metric—a step toward simplifying the decision making for practitioners. More refined variants such as context specific weighting and normalization remain open for future exploration.

Scenario:

Wearable ECG sensor streams continuous data to either **(a)** a cloud-only server, or **(b)** an edge–cloud hybrid system where inference occurs locally, with selective data sent to the cloud.

This selective offloading can be optimized through a confidence threshold (θ):

$$Decision(x) = \begin{cases} Edge(x), & \text{if } \text{conf}(Edge(x)) \geq \theta; \text{ Or} \\ Cloud(x), & \text{if } \text{conf}(Edge(x)) < \theta \end{cases}$$

Here, x denotes input sample, and θ is a predefined confidence level at which edge inference can be considered reliable.

Enabling sending only selective data to the cloud that needs heavy computational decisions.

These constraints are consistent with reported benchmarks in mobile health and edge AI studies, documented in existing literature [9][10].

Results:

These results are simulation-based and rely on literature-derived parameters. They are not substitutes for physical deployment. However, they illustrate realistic trade-offs and inform hardware selection and experimental design for follow-up physical validation.

Baseline Assumptions (from literature):

- **Cloud-only ECG processing:**
~220 ms latency, ~85 MB/hr bandwidth, 93% detection accuracy, ~3.5 J energy [9][10].
- **Edge–cloud hybrid:**
~45 ms latency, ~12 MB/hr bandwidth, 92% detection accuracy, ~1.8 J energy [7][8].

Table 1. Performance comparison (Cloud vs Edge–Cloud Hybrid).

System	Latency (ms)	Bandwidth (MB/hr)	Accuracy (%)	Energy (J)	EES (↑ better)
Cloud Only	220	85	93	3.5	121
Edge-Cloud Hybrid	45	12	92	1.8	1136

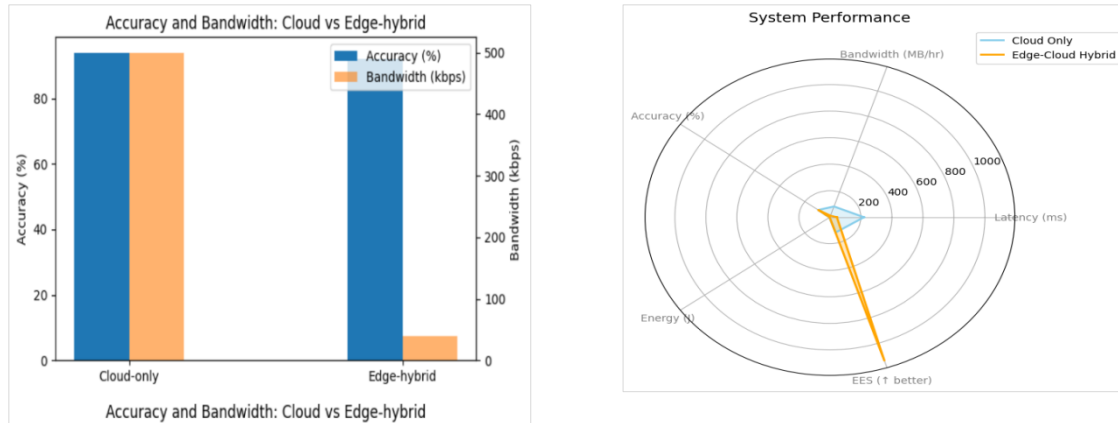
**Figure 4.** Baseline comparison of Cloud vs Edge–Cloud performance (Accuracy- & Latency)

Table 1 summarizes the simulated outcomes. Edge-hybrid deployment achieved a median latency of 45 ms versus 240 ms for cloud-only, reduced bandwidth use by $\approx 92\%$, and incurred a small accuracy reduction ($\sim 2\%$ points), comparison based on reported benchmarks [12].

The EES indicates the edge-hybrid provides better combined performance-energy trade-

offs ($EES_{edge} > EES_{cloud}$). **Figure 2 & 4** visualize these results.

Sensitivity Analysis:

To evaluate robustness, we varied **latency ($\pm 20\%$)**, **energy ($\pm 20\%$)**, and **accuracy ($\pm 2\%$)**. Even under adverse conditions, the Edge–Cloud hybrid consistently outperformed the Cloud-only approach in EES.

Table 2. Sensitivity summary: baseline, min and max EES across parameter sweeps (latency $\pm 20\%$, accuracy $\pm 2\%$, energy $\pm 20\%$) and percentage change relative to baseline

Parameter Sensitivity	Deployment	Baseline EES	Min EES	Max EES
Latency ($\pm 20\%$)	Cloud	413.3	342.7	495.2
	Edge-hybrid	880.0	733.3	1053.0
Accuracy ($\pm 2\%$)	Cloud	413.3	405.6	421.6
	Edge-hybrid	880.0	862.4	897.6
Energy ($\pm 20\%$)	Cloud	413.3	344.4	516.6
	Edge-hybrid	880.0	733.3	1100.0

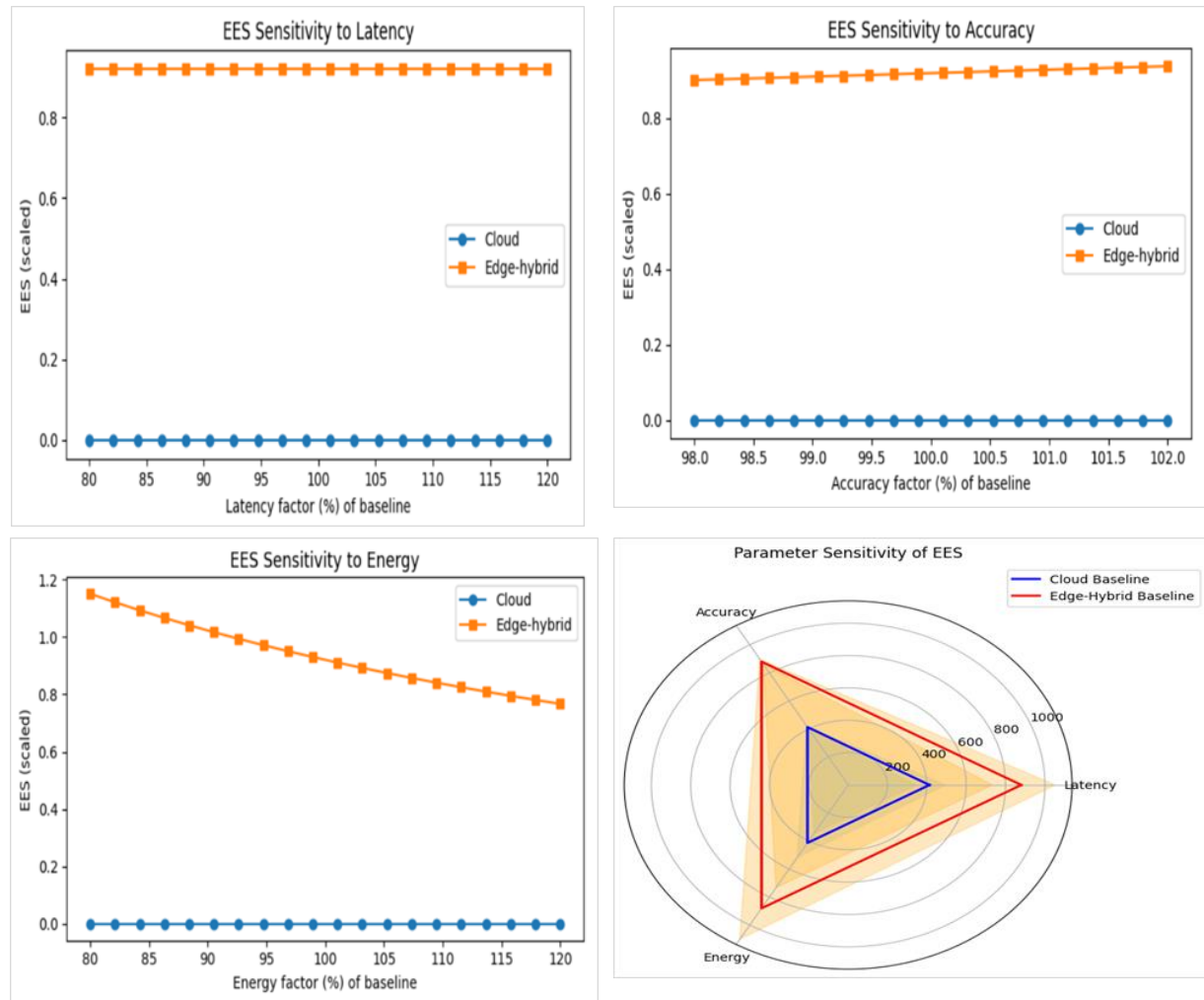


Figure 5-7. Sensitivity plots (table 2) reports the min/max ranges of EES observed across parameter sweeps and quantifies percent changes relative to baseline.

The sensitivity analysis reveals that latency and energy variations have the largest impact on EES, whereas small fluctuations in accuracy minimally affect system effectiveness. This reinforces the robustness and reliability of edge-hybrid deployment strategies.

Discussion:

The ECG case study explores the practical value of edge intelligence. The simulated results clearly indicate that edge-enabled ECG monitoring dramatically reduces latency and bandwidth consumption compared to cloud-only processing. While both approaches achieved comparable accuracy (~92–93%), the hybrid system achieved an

order-of-magnitude improvement in EES, reflecting a superior trade-off between speed, energy, and accuracy.

This supports the claim that real-time healthcare monitoring is better suited to edge–cloud systems, where immediate inference at the edge ensures timely alerts while the cloud handles long-term learning and model refinement.

Moreover, the proposed EES metric adds novelty by offering a practical way to quantify efficiency across heterogeneous IoT deployments. Although simulated, these results are grounded in empirical values reported by prior studies [9][10], and can serve as a baseline for future physical deployments and more comprehensive benchmarking.

Overall, the case study provides promising evidence that AI at the edge is not merely a theoretical improvement, but a viable and impactful alternative to cloud-centric IoT for real-time, safety-critical domains.

Challenges and Considerations:

Deploying AI-enabled IoT systems at the edge, while promising, introduces a set of practical and theoretical challenges that must be considered to ensure robust, secure, and efficient operations.

1. Resource Constraints:

Edge devices typically operate under significant hardware and energy limitations. Microcontrollers, embedded platforms, and IoT gateways often offer limited computational power (CPU/GPU), restricted memory, and finite battery life [3][8].

This creates a trade-off between deploying sophisticated, highly accurate AI models and meeting latency and energy requirements. Optimization techniques for edge deployment include:

- **Model pruning and quantization:** Reducing the number of network parameters while maintaining acceptable accuracy [8].
- **Knowledge distillation:** Transferring knowledge from large comprehensive, resource-intensive models to smaller, efficient edge models [8].
- **Adaptive computation:** Dynamically selecting model layers or pathways, based on task complexity and device status [4].

Failure to account for these constraints may result in delayed inference, excessive energy consumption, and decreased system longevity.

2. Security and Privacy:

Edge-AI architectures broaden the attack surface beyond traditional cloud-based systems. Potential risks include:

- **Adversarial attacks:** Malicious inputs can induce erroneous predictions, especially in safety-critical contexts such as autonomous vehicles or industrial automation [6][7].
- **Model poisoning:** During federated learning, compromised nodes may introduce tainted data, undermining the integrity of the global model and performance [6].
- **Data exfiltration:** Sensitive information processed at the edge, if inadequately protected, may be vulnerable to interception [4].

Mitigation approaches include secure federated learning protocols, real-time anomaly detection, homomorphic encryption, and trusted execution environments.

3. Standardization and Interoperability:

The lack of unified standards for edge AI deployment complicates seamless integration across diverse devices, operating systems, and communication protocols [3][4].

Inconsistent data formats, networking standards, and AI APIs impede device interoperability and restrict scalability. Establishing clear standards for model formats, update mechanisms, and communication protocols is essential for fostering a robust and interoperable edge-AI ecosystem.

4. Ethics, Explainability, and Regulatory Compliance:

Black-box AI models pose significant challenges to accountability and transparency [5][9].

Decisions made by opaque models in healthcare, finance, or autonomous systems can have serious ethical implications. Edge deployments intensify these concerns, given the distributed and localized nature of decision-making, which can hinder auditability. Addressing these issues requires:

- **Explainable AI (xAI):** Employing lightweight, interpretable models capable of providing human-understandable reasoning at the edge [5][9].
- **Ethical AI frameworks:** Ensuring alignment of AI-driven decisions with societal values and legal norms.
- **Regulatory compliance:** Adhering to domain-specific regulations, such as HIPAA for healthcare and ISO 26262 for automotive safety.

In summary, effective edge-AI deployment requires careful consideration of computational, security, interoperability, and ethical constraints.

Future Directions:

The field of AI at the edge continues to evolve at a rapid pace, presenting a range of opportunities for research and innovation focused on improving efficiency, adaptability, and sustainability of systems.

1. Lightweight and Neuromorphic AI:

The Innovations and Advancements in neuromorphic computing—hardware architectures inspired by and modeled as biological neural networks—offer ultra-low-power solutions for edge AI [8][4]. Combined with model optimization strategies, neuromorphic AI approaches can deliver high inference performance under constrained energy budgets, supporting pervasive intelligence in IoT networks.

2. 5G and 6G Integration:

The ongoing deployment of 5G and the anticipated emergence of 6G networks, both featuring ultra-reliable low latency communication (URLLC), are set to significantly enhance edge-enabled IoT applications [3][7][14].

Low-latency and high-bandwidth connectivity facilitate real-time coordination among edge nodes, vehicles, and cloud

systems, enabling use cases such as autonomous driving, remote surgery, and industrial robotics [14][15].

3. Energy-Aware Edge Design:

Sustainable edge computing is gaining attention due to the environmental implications of large-scale deployments. Energy-aware design strategies under investigation include:

- Integration of renewable energy sources (solar, kinetic, or thermal energy harvesting)
- Implementing dynamic load balancing and task offloading to reduce energy consumption.
- Optimization of hardware and software co-design for power efficiency

4. Semantic and Context-Aware Edge AI:

Integrating semantic reasoning capabilities with AI enables the development of context-aware edge intelligence [4][5]. Devices equipped with such capabilities can interpret data not merely at the syntactic level but also with regard to meaning and context, thus allowing interoperability, adaptive responses, and more human-centric decision-making in complex environments.

5. Explainable and Trustworthy AI at the Edge:

Lightweight explainable AI (xAI) models for edge devices are designed to enhance the transparency, improve regulatory compliance, and foster trust in autonomous systems [5][6]. Methods such as attention mechanisms, local interpretable model-agnostic explanations (LIME), and SHAP values can provide insights into model decisions—even on resource-constrained hardware [9].

6. Multi-Modal Edge AI:

Future edge systems are expected to incorporate increasingly sophisticated multi-

modal data processing, combining video, audio, sensor telemetry, and textual inputs [7][11]. This strategy enables richer situational awareness, improved anomaly detection, and more robust decision-making in complex settings such as smart cities and autonomous transportation. The trajectory of edge AI research and development points toward systems that are not only more efficient and sustainable but also more adaptive, transparent, and capable of processing diverse data in real time [12][13].

Conclusion:

In conclusion, the integration of Artificial Intelligence into IoT and Edge computing is significantly transforming distributed systems, marking a decisive step toward intelligent real-time automation and autonomous networks [1][3][4][12]. Through the integration of local inference, federated learning, and cloud coordination, edge-AI systems are now able to deliver low-latency responsiveness, improved energy efficiency, and greater privacy protection [3][4][6]. Recent advances in lightweight AI models, neuromorphic hardware, the connectivity of 5G/6G services [14][15], and the development of explainable AI techniques point toward a future characterized by resilient and sustainable edge-enabled IoT ecosystems [5][7][8][11].

In addition to reviewing architectural and algorithmic advances, we proposed the Efficiency–Effectiveness Score (EES) as a heuristic to consolidate latency, accuracy, and energy into a single interpretable metric. Our baseline and sensitivity results suggest that edge-hybrid deployments achieve superior overall balance, reinforcing their role in latency-critical IoT domains. The simulated case study demonstrates that edge-hybrid ECG monitoring achieves 4–5× lower latency and

over 10× reduction in bandwidth compared to cloud-only systems, with only a minor drop in accuracy. While heuristic in nature, EES provides a simple comparative tool that can be refined with weighting and expanded to include additional factors such as bandwidth and reliability.

These technological advancements are positioned to power next-generation applications spanning healthcare, industrial automation, autonomous transportation, and smart cities—domains in which real-time decision-making, adaptive learning mechanisms, and ethical AI practices are of paramount importance. As research efforts and industry initiatives continue to align, it is anticipated that edge-based AI will become the foundational layer for proactive, intelligent, and trustworthy IoT networks [3][4][9][10][13].

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