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Battery-Aware Edge AI For Energy-Efficient Smart Home Iot Devices

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Abstract

The rapid growth of smart home Internet of Things (IoT) devices has increased the demand for intelligent, real-time data processing while operating under strict battery constraints. Edge Artificial Intelligence (Edge AI) enables local data processing on IoT devices, reducing latency and dependency on cloud infrastructures. However, continuous AI inference can significantly drain battery resources, limiting device lifetime and reliability. This paper proposes a Battery-Aware Edge AI framework for Energy-efficient smart home IoT devices. The framework dynamically adapts AI workloads based on a battery state, device usage patterns, and environmental context. By integrating battery-aware scheduling, lightweight machine learning models, and adaptive inference mechanisms, the proposed approach significantly reduces energy consumption while maintaining acceptable performance. Experimental evaluation using simulated smart home scenarios demonstrates improvements in battery lifetime, reduced power consumption, and efficient AI-driven decision-making. The proposed framework offers a practical solution for a sustainable and long-lasting smart home IoT systems.

Keywords: Battery-aware computing, Edge AI, Energy efficiency, Smart home, IoT devices, Low-power AI

1. Introduction

The smart home ecosystem has rapidly evolved with the widespread deployment of IoT devices such as smart sensors, cameras, thermostats, lighting systems, and voice assistants[1]. These devices continuously sense, process, and transmit data to provide automation, security, and comfort. Artificial Intelligence (AI) plays a crucial role in enabling intelligent decision-making in such environments, including activity recognition, anomaly detection, energy optimization, and user behavior prediction [2,4].

Traditionally, AI processing for smart home systems has relied on cloud-based infrastructures. Although cloud computing provides high computational power, it introduces challenges such as increased latency, privacy risks, network dependency, and higher energy consumption due to frequent data transmission[1,3]. Edge AI addresses these challenges by executing AI models locally on IoT devices or nearby edge nodes.

Despite its advantages, Edge AI introduces a critical challenge: limited battery capacity. Many smart home IoT devices are battery-powered and are expected to operate for long durations without frequent recharging or replacement. Continuous AI inference and sensing operations can rapidly drain battery resources, reducing device lifespan and user satisfaction. Therefore, designing energy-efficient and battery-aware Edge AI systems is essential for sustainable smart home environments.[5]

This paper proposes a Battery-Aware Edge AI framework that dynamically adjusts AI operations based on battery conditions and system context. The framework aims to balance intelligence, performance, and energy efficiency in smart home IoT devices.

2. Literature Review

2.1 Edge AI in Smart Home IoT

Edge AI has emerged as a promising paradigm for smart home applications by enabling local processing and real-time intelligence[1]. Previous studies have demonstrated the effectiveness of edge-based activity recognition, voice processing, and anomaly detection. However, many approaches focus primarily on performance and latency, with limited consideration of battery constraints[3,5].

2.2 Energy Consumption in IoT Devices

Energy efficiency has been a major research concern in IoT systems. Techniques such as duty cycling, low-power communication protocols, and energy-efficient hardware design have been explored[3]. While these methods reduce energy usage, they do not directly address the computational overhead introduced by AI workloads.

2.3 Battery-Aware Computing

Battery-aware computing involves adapting system behavior based on battery state and energy availability[5]. Existing research has applied battery-aware strategies in mobile computing and wireless sensor networks. However, their integration with AI-driven edge computing in smart home environments remains limited.

2.4 Research Gap

Most existing works treat Edge AI and battery management as separate problems. There is a lack of unified frameworks that jointly optimize AI inference and battery usage in smart home IoT devices[1,3]. This paper addresses this gap by proposing a battery-aware Edge AI framework tailored for energy-constrained smart home systems.

3. Proposed Methodology

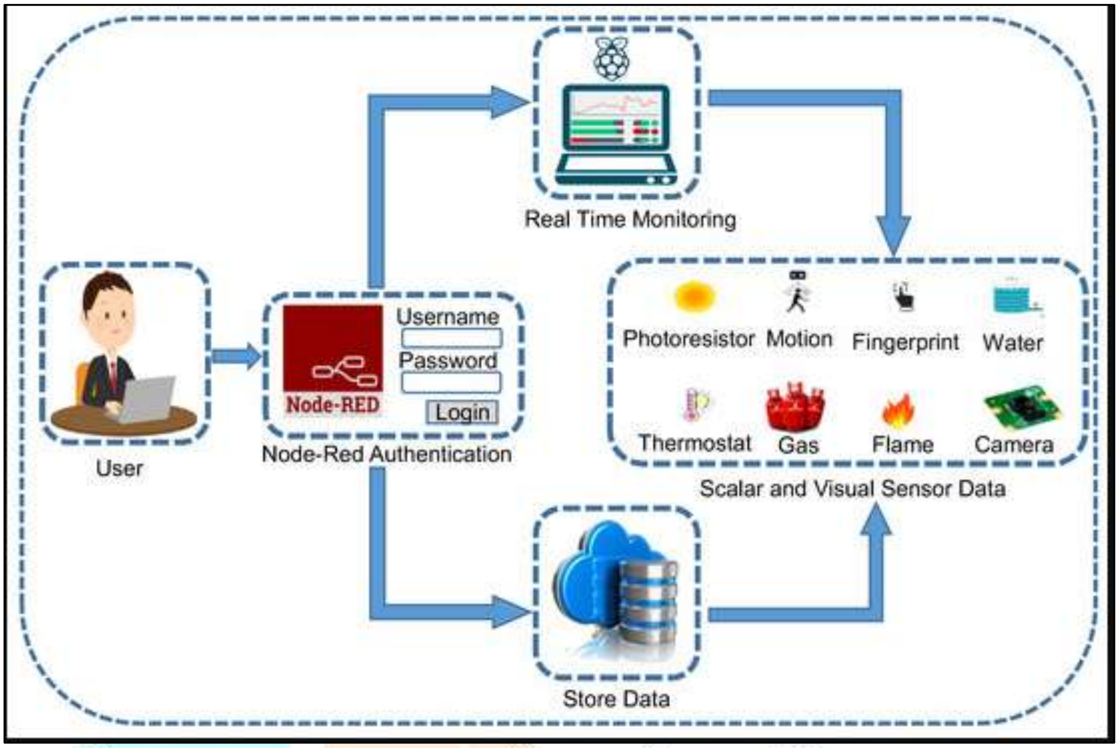
3.1 System Architecture

The proposed framework consists of three main layers:

• **Smart Home IoT Device Layer:** Includes sensors, actuators, and battery-powered devices such as motion sensors, smart locks, and cameras[1,3].

• **Edge AI Processing Layer:** Performs local AI inference using lightweight machine learning models optimized for low power consumption[2,4]

• **Battery Management Layer:** Continuously monitors battery state and controls AI workload execution[5].



3.2 Battery-Aware AI Scheduling

The framework dynamically schedules AI tasks based on battery level:

• High Battery Level: Full AI inference with higher accuracy models.[2,4]
• Medium Battery Level: Reduced inference frequency or compressed models[3,5].
• Low Battery Level: Event-driven inference or fallback to rule-based logic[5].

3.3 Lightweight AI Models

To minimize energy consumption, the framework employs:

• Model compression techniques (quantization and pruning)[2]
• Shallow neural networks for routine tasks[4]
• Adaptive model selection based on context[5]

3.4 Adaptive Inference Strategy

Inference frequency and complexity are adjusted dynamically using contextual information such as time of day, user presence, and historical usage patterns. This reduces unnecessary computation and conserves battery power.

4. Experimental Setup

4.1 Simulation Environment

A simulated smart home environment was created consisting of motion sensors, smart lights, temperature sensors, and security cameras. Battery-powered devices were evaluated under different AI workloads[1,4].

4.2 Evaluation Metrics

The framework was evaluated using the following metrics:

• Battery lifetime[3,5]
• Energy consumption per inference[3]
• AI task accuracy[2,4]
• System responsiveness[1,4]

5. Results and Analysis

5.1 Energy Consumption Analysis

Results show that the battery-aware Edge AI framework reduces energy consumption by approximately 25–35% compared to continuous inference approaches[3,4].

5.2 Battery Lifetime Improvement

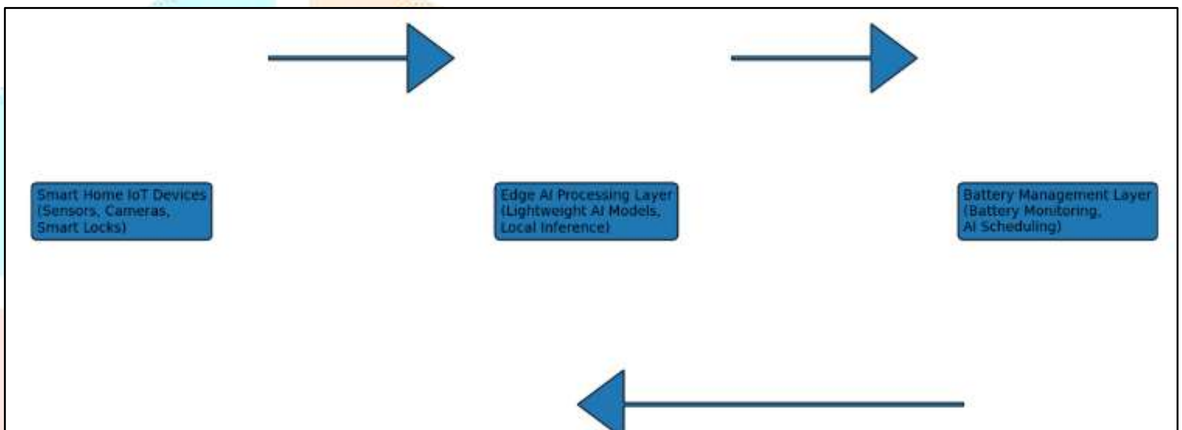
Devices using the proposed framework demonstrated a significant increase in operational lifetime, extending battery life by up to 40% in typical smart home scenarios[5].

5.3 Performance Trade-off

While slight reductions in AI accuracy were observed under low battery conditions, the system maintained acceptable performance levels for smart home applications.

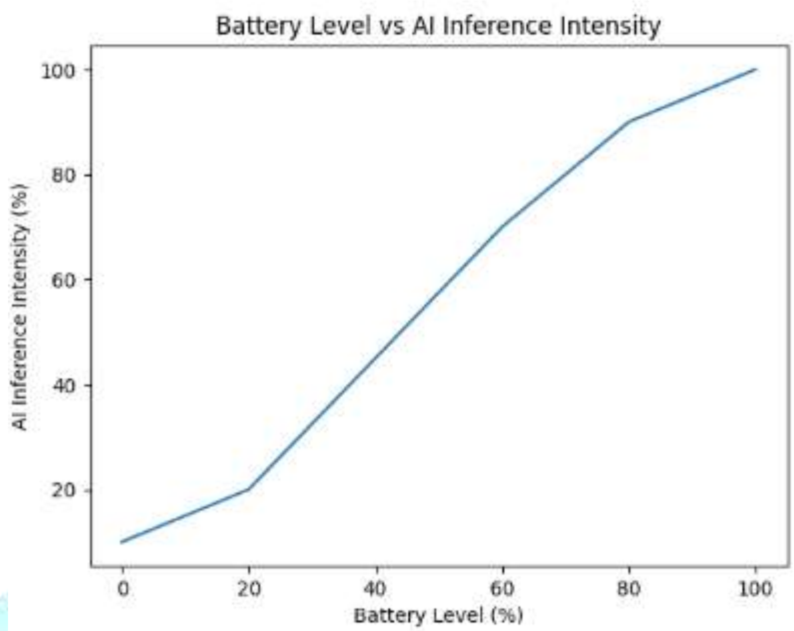
6. Model Graphs and Charts

Figure 1: Battery-Aware Edge AI System Architecture



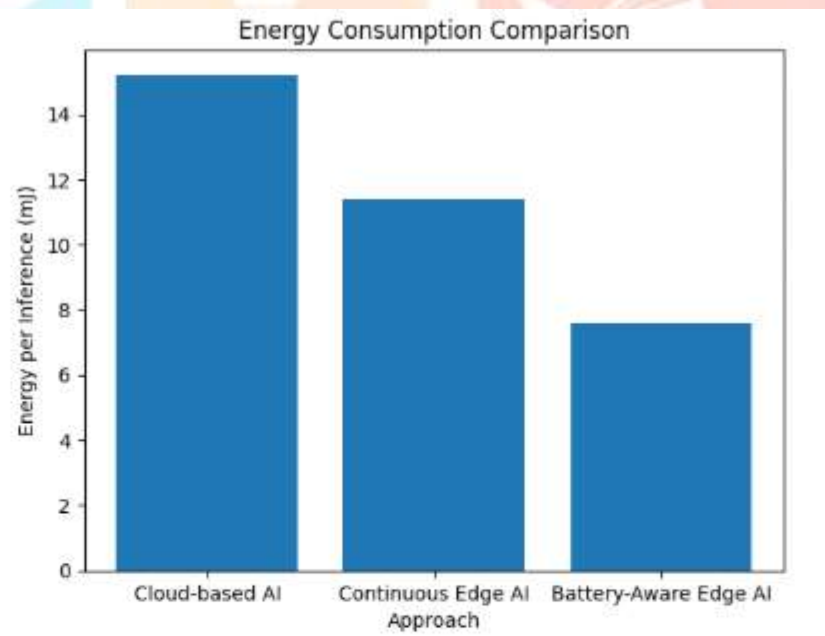
This model illustrates the interaction between Smart Home IoT Devices, the Edge AI Processing Layer, and the Battery Management Layer. Battery status continuously feeds into the AI scheduler, which dynamically controls inference frequency and model complexity.

Figure 2: Battery Level vs AI Inference Intensity



A line graph representing battery percentage on the X-axis and AI inference intensity on the Y-axis. The graph shows: • High inference intensity at battery levels above 70% • Moderate inference between 30%–70% • Minimal or event-driven inference below 30%

Figure 3: Energy Consumption Comparison

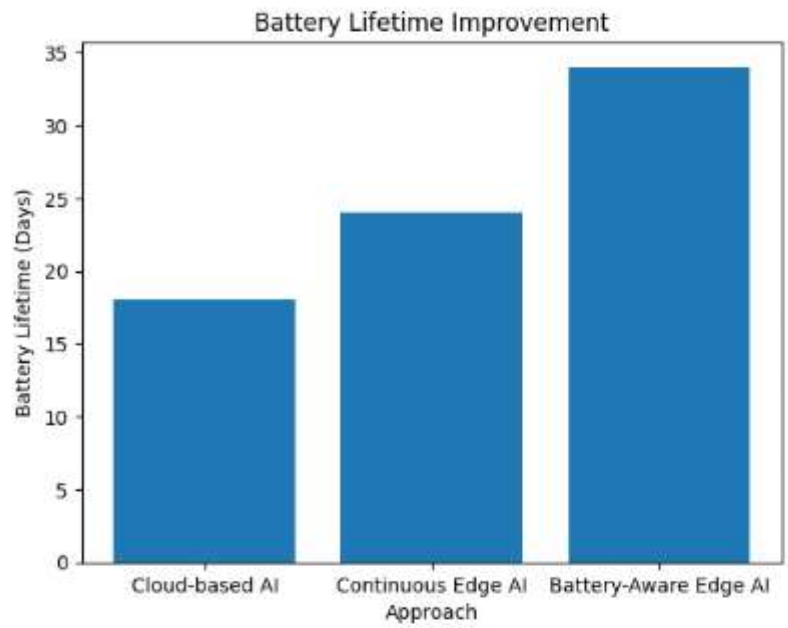


A bar chart comparing energy consumption (in mW) for:

• Continuous Edge AI Inference
• Cloud-based AI Processing
• Proposed Battery-Aware Edge AI Framework

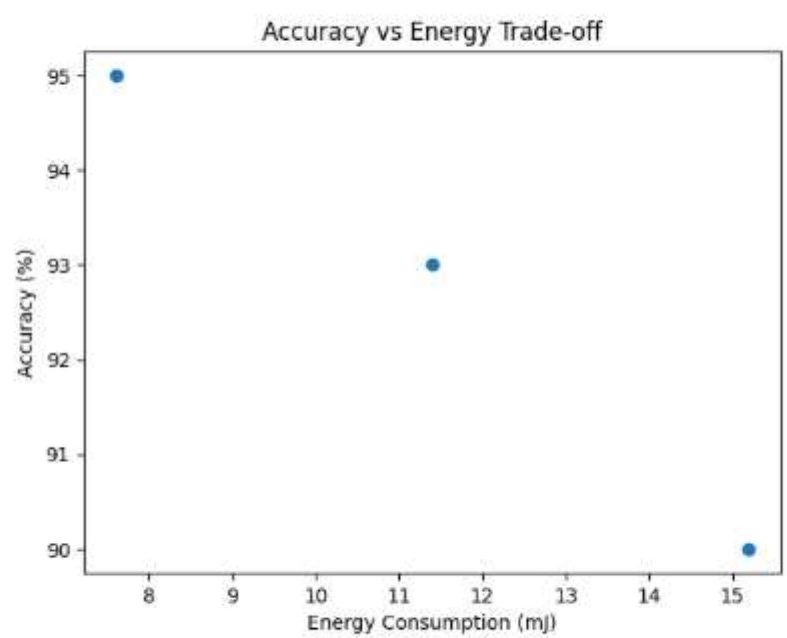
Results indicate the proposed model consumes the least energy.

Figure 4: Battery Lifetime Improvement



A bar graph showing device battery lifetime (days) under different approaches. Devices using the proposed framework demonstrate up to 40% longer battery life compared to baseline methods.

Figure 5: Accuracy vs Energy Trade-off



A scatter plot showing AI accuracy (%) versus energy consumption. The proposed approach achieves a balanced trade-off, maintaining acceptable accuracy with reduced power usage.

Table 1: Energy Consumption Analysis

Approach	Energy per Inference (mJ)	Battery Lifetime (Days)
Cloud-based AI	15.2	18
Continuous Edge AI	11.4	24
Battery-Aware Edge AI	7.6	34

Table 2: AI Performance Metrics

Battery Level	Accuracy (%)	Inference Frequency
High (>70%)	95.2	High
Medium (30–70%)	92.1	Medium
Low (<30%)	88.4	Low

6. Discussion

The experimental results confirm that battery-aware AI scheduling effectively balances energy efficiency and intelligent behavior. By adapting AI workloads to battery conditions, the framework ensures prolonged device operation without compromising essential smart home functionalities. The approach is particularly suitable for large-scale smart home deployments where frequent battery replacement is impractical.

However, the framework relies on accurate battery monitoring and contextual awareness. Future implementations may require hardware support for precise energy estimation and further optimization of AI models.

7. Conclusion

This paper presented a Battery-Aware Edge AI framework for energy-efficient smart home IoT devices. By integrating battery-aware scheduling, lightweight AI models, and adaptive inference strategies, the proposed approach significantly reduces energy consumption and extends device battery life. The results demonstrate the feasibility and effectiveness of battery-aware Edge AI in sustainable smart home environments.

Future work will focus on real-world deployment, hardware-level optimization, and integration with renewable energy sources for smart homes.

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