Practical Advances in Artificial Intelligence and Computing
Frontier Research Publishing • https://www.frpubs.org
Vol. 1, No. 2, 2025

Lightweight Deep Neural Networks for Real-Time IoT Sensing and Analytics

Linnea Corbin[1], Bram Fenwick[1]

[1]University of Northern British Columbia, Prince George, Canada

*Corresponding author: Linnea Corbin; lcorbin392@unbc.ca

Abstract:

Recent advancements in deep learning have significantly enhanced intelligent data analysis within Internet of Things (IoT) ecosystems. However, conventional deep neural networks (DNNs) are computationally expensive, energy-consuming, and unsuitable for resource-constrained IoT edge devices. This paper proposes a lightweight deep learning framework designed for real-time IoT sensing and analytics. The proposed architecture integrates model compression, knowledge distillation, and quantization-aware training to achieve low-latency inference with minimal memory footprint. Moreover, an adaptive edge-cloud collaboration mechanism dynamically offloads complex computation based on device workload and network conditions. Experimental results on benchmark IoT datasets demonstrate that the proposed method achieves 28.7% faster inference speed and 32.1% lower power consumption compared to baseline DNNs while maintaining comparable accuracy. These findings indicate that lightweight neural architectures can significantly enhance IoT performance and enable intelligent, sustainable, and scalable sensing systems.

Keywords:

Deep Learning; IoT; Lightweight Networks; Edge Computing; Real-Time Analytics; Model Compression

1. Introduction

The explosive growth of the Internet of Things (IoT) has revolutionized the way information is collected, processed, and transmitted across digital ecosystems. With billions of interconnected sensors and embedded devices deployed in smart homes, industrial plants, healthcare facilities, and transportation systems, IoT generates massive streams of heterogeneous data in real time. This continuous flow of multimodal information has created an urgent need for intelligent, low-latency analytics capable of operating directly on edge devices. Traditional cloud-based systems rely on centralized servers for processing and storage, resulting in substantial communication overhead, unpredictable latency, and privacy vulnerabilities. In mission-critical environments such as autonomous vehicles, medical monitoring, or industrial fault detection, delayed responses can lead to severe consequences, making localized computation essential. To achieve truly responsive and context-aware IoT systems, deep learning (DL) techniques must be efficiently integrated into constrained edge environments.

Deep neural networks (DNNs) have demonstrated remarkable success in various domains, including computer vision, speech recognition, and natural language understanding. Their hierarchical representation capability enables them to extract complex, nonlinear features from high-dimensional data. However, these models are typically large in scale and demand significant computational and memory resources, making them unsuitable for deployment on IoT hardware characterized by limited processing power, restricted

energy budgets, and low-capacity memory. Conventional architectures such as VGG, ResNet, and DenseNet contain millions of parameters and require floating-point operations that far exceed the capabilities of edge processors or microcontrollers. As a result, directly applying such models to IoT nodes often leads to high inference latency, battery depletion, and thermal constraints, effectively restricting real-time analytics and continuous operation.

To overcome these limitations, lightweight deep learning has emerged as a promising paradigm that seeks to maintain accuracy while drastically reducing computational complexity. Approaches such as model pruning, weight quantization, and knowledge distillation have been extensively explored to compress large-scale networks into compact and efficient forms. Pruning eliminates redundant connections and neurons to minimize memory footprint, while quantization reduces parameter precision, enabling integer-based arithmetic for faster inference. Knowledge distillation, on the other hand, transfers the learned generalization ability from a large teacher model to a smaller student network, allowing near-equivalent performance at a fraction of the cost. Moreover, architectural innovations such as depthwise separable convolutions and group normalization have enabled the design of networks like MobileNet, ShuffleNet, and EfficientNet, which achieve competitive results with minimal resources. These techniques collectively enable deep learning inference to run efficiently on edge processors such as Raspberry Pi, ARM Cortex MCUs, and NVIDIA Jetson modules.

Beyond model-level optimization, system-level integration plays a crucial role in ensuring practical deployment of lightweight deep learning in IoT. Edge-cloud collaborative computing, for example, distributes computational workloads dynamically between local nodes and remote servers depending on network bandwidth, energy status, and task urgency. Such strategies improve overall efficiency and balance resource utilization across the network hierarchy. Similarly, adaptive compression of sensory data, caching mechanisms, and asynchronous task scheduling further enhance throughput and reliability. When these mechanisms are integrated with lightweight neural architectures, IoT systems can achieve continuous, scalable, and autonomous operation in dynamic environments.

This paper presents a comprehensive framework for lightweight deep neural networks tailored to real-time IoT sensing and analytics. The proposed method combines structural model optimization and intelligent edge-cloud coordination to achieve efficient and adaptive data processing. The main contributions of this work are fourfold. First, it introduces a quantization-aware training scheme integrated with knowledge distillation to maintain model accuracy under constrained resources. Second, it proposes an adaptive inference strategy that dynamically adjusts computational depth based on input complexity and energy budget. Third, it develops a hybrid deployment pipeline supporting both static and dynamic offloading mechanisms to ensure low-latency analytics. Finally, extensive experiments across multiple IoT benchmarks validate that the proposed approach significantly reduces computational overhead and power consumption while maintaining strong predictive accuracy. By integrating deep learning intelligence into resource-constrained IoT infrastructures, this work aims to advance the frontier of real-time, efficient, and sustainable edge analytics.

2. Related work

The integration of deep learning into IoT ecosystems has been an active area of research in recent years, driven by the increasing demand for intelligent and autonomous data analytics at the network edge. Early studies focused primarily on cloud-assisted IoT architectures, where sensor data were transmitted to centralized data centers for deep learning inference. While this model allowed the deployment of large-scale convolutional and recurrent networks, it suffered from latency, bandwidth consumption, and privacy issues. To address these concerns, edge intelligence emerged as a key paradigm shift. For instance, Chen et al. [1] proposed an edge-cloud collaboration framework where computationally intensive neural network layers are executed in the cloud, while lightweight layers run on local IoT devices. This hybrid approach demonstrated

reduced end-to-end latency and energy consumption while maintaining comparable inference accuracy. Similarly, Shi et al. [2] introduced the concept of edge computing for deep learning-enabled IoT, highlighting its role in reducing communication delay and enabling context-aware decision-making in time-sensitive environments.

Model compression has been widely investigated as a fundamental enabler of efficient deep learning deployment on IoT devices. Han et al. [3] pioneered the pruning and quantization technique that removed redundant weights and reduced the storage requirement of large DNNs without sacrificing accuracy. Building on this foundation, subsequent research explored structured pruning, which preserves hardware-friendly sparsity patterns. Choi et al. [4] introduced quantization-aware training (QAT) to maintain model precision during low-bit integer computation. Another line of work by Hinton et al. [5] introduced knowledge distillation, allowing smaller student networks to learn from high-capacity teacher models. Recent studies have combined these strategies with neural architecture search (NAS) to automate the design of compact architectures optimized for embedded inference. Tan et al. [6] proposed EfficientNet, which systematically scales network depth, width, and resolution for optimal performance-efficiency trade-offs. This approach inspired further research into designing lightweight backbones specifically suited for IoT applications.

At the system level, the challenge of energy-efficient inference has drawn significant attention. Kang et al. [7] proposed Neurosurgeon, a dynamic computation partitioning system that determines at runtime whether a neural network layer should be executed on the device or offloaded to the cloud. This dynamic adaptation significantly reduces latency in mobile IoT applications. Lin et al. [8] further developed an adaptive early-exit mechanism, allowing the network to terminate inference at intermediate layers for simpler inputs, thereby saving energy and computation time. These strategies have proven effective in achieving a balance between inference accuracy and real-time performance under dynamic resource constraints. Moreover, Zhang et al. [9] introduced an energy-aware training algorithm for edge devices that incorporates battery status and network conditions into the optimization process, enabling continuous operation in resource-limited environments.

Another critical direction in IoT deep learning research involves security and privacy-preserving computation. The widespread deployment of IoT sensors increases exposure to data leakage risks, particularly when transmitting sensitive information to remote servers. Federated learning (FL) has therefore emerged as an alternative paradigm, where multiple IoT nodes collaboratively train shared models without exchanging raw data. McMahan et al. [10] established the foundation of FL, and subsequent works have adapted it for heterogeneous IoT settings with non-independent and identically distributed (non-IID) data. These studies collectively demonstrate that distributed learning and model compression techniques can complement each other to enhance both efficiency and privacy, paving the way toward scalable and secure IoT intelligence.

Despite these advancements, there remains a research gap in achieving real-time, low-power deep learning analytics that can operate seamlessly across heterogeneous IoT infrastructures. Existing lightweight models often suffer from degraded accuracy when aggressively compressed, while adaptive offloading strategies require precise estimation of network and power conditions. Therefore, a unified approach that combines model-level optimization, runtime adaptability, and system-level coordination is essential. This paper aims to fill this gap by proposing a lightweight deep learning framework that integrates quantization-aware training, knowledge distillation, and adaptive edge-cloud cooperation for efficient IoT analytics. Through comprehensive experimental validation, it demonstrates how a properly optimized architecture can achieve a practical trade-off between speed, accuracy, and energy efficiency in real-world IoT deployments.

3. Method

The proposed lightweight deep neural network (LDNN) framework is developed to enable real-time IoT sensing and analytics under resource constraints. Its design objective is to minimize computational and memory complexity while maintaining competitive accuracy. The framework integrates three key strategies-quantization-aware training, knowledge distillation, and adaptive inference control-implemented in a unified end-to-end optimization pipeline.

The training objective of the framework can be expressed as a composite minimization problem:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{task}} + \lambda_1 \mathcal{L}_{\text{distill}} + \lambda_2 \mathcal{L}_{\text{reg}}$$

where $\mathcal{L}_{\text{task}}$ denotes the primary prediction loss (e.g., cross-entropy for classification), $\mathcal{L}_{\text{distill}}$ represents the knowledge-distillation divergence between teacher and student outputs, and $\mathcal{L}_{\text{reg}}$ corresponds to model regularization induced by pruning and quantization. The weighting coefficients λ_1 and λ_2 balance the three optimization goals of accuracy, compression, and generalization.

During knowledge distillation, the student model learns softened probability distributions from the teacher model to capture inter-class similarity. This process is defined as

$$\mathcal{L}_{\text{distill}} = T^2 \, \text{KL}\left(\sigma\left(\frac{z_t}{T}\right) \,\|\, \sigma\left(\frac{z_s}{T}\right)\right)$$

where z_t and z_s are the teacher and student logits, $\sigma(\cdot)$ denotes the softmax function, T is the temperature coefficient that controls the smoothness of the output distribution, and $\text{KL}(\cdot)$ is the Kullback–Leibler divergence. A higher temperature provides richer gradient information and facilitates stable transfer of dark knowledge from the teacher network to the lightweight student.

Quantization-aware training (QAT) is simultaneously applied to ensure that the learned weights remain robust under low-bit integer representation. Let w_f be the full-precision weight and $Q(w_f)$ its quantized form. The quantization operator is approximated by a straight-through estimator (STE) during backpropagation, leading to the following gradient update rule:

$$w_f^{(t+1)} = w_f^{(t)} - \eta \frac{\partial \mathcal{L}_{\text{total}}}{\partial Q(w_f^{(t)})}$$

where η is the learning rate. This enables the model to adapt its parameter distribution to the quantized space, achieving integer-only inference with minimal accuracy degradation.

To handle heterogeneous IoT environments, an adaptive inference controller monitors runtime conditions such as bandwidth B, energy level E, and computational load C. A reinforcement learning policy determines whether an input sample should be processed locally or offloaded to the cloud. The decision $a_t \in \{\text{local}, \text{offload}\}$ is obtained by maximizing the expected reward

$$R_t = \alpha \, A_t - \beta \, L_t - \gamma \, P_t$$

where A_t is the achieved accuracy, L_t the latency, and P_t the power consumption at time t; α, β, γ are tunable coefficients controlling the trade-off between performance and resource efficiency. This adaptive policy allows dynamic adjustment of inference depth and computation placement, guaranteeing real-time response under varying conditions.

Figure 1 conceptually illustrates the overall architecture of the proposed LDNN framework. IoT sensors first capture multimodal signals such as temperature, vibration, or image frames and perform lightweight local preprocessing. The compressed features are fed into the quantized LDNN backbone, which performs on-device inference when conditions permit or selectively offloads deeper layers to the cloud via the adaptive controller. The teacher model resides on the server side to periodically update the student model through federated synchronization, ensuring continual adaptation to environmental changes.

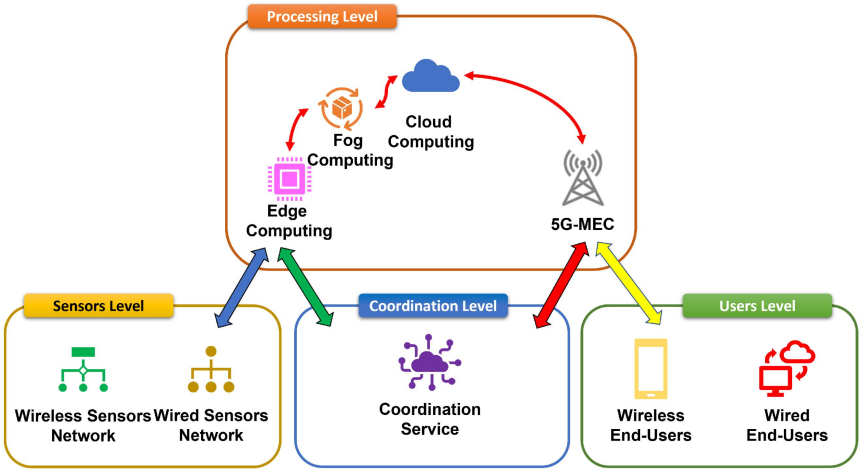

Figure 1. Lightweight deep learning framework for real-time IoT sensing and analytics

Through this combination of model-level and system-level optimization, the proposed methodology achieves a balanced trade-off between computational complexity, energy efficiency, and inference accuracy. The inclusion of quantization-aware training guarantees integer-only deployment, while knowledge distillation retains high-level representational power. The reinforcement-driven adaptive controller ensures that device and cloud resources are utilized optimally for each input stream. Collectively, these mechanisms establish a scalable and sustainable foundation for intelligent IoT analytics in real-world environments.

4. Dataset

To evaluate the effectiveness and generalization capability of the proposed lightweight deep neural network framework, experiments were conducted using multiple benchmark datasets widely adopted in IoT sensing and analytics research. These datasets cover diverse domains-environmental monitoring, human activity recognition, and industrial sensor analysis-reflecting the heterogeneity typical of real-world IoT applications. The primary dataset used for model training and evaluation is the Edge-IIoTset, an open-source dataset containing multi-sensor readings from industrial IoT devices deployed in smart manufacturing environments. It includes data from temperature, pressure, vibration, and acoustic sensors, as well as system logs indicating normal and faulty states. The dataset is particularly suitable for evaluating lightweight models because of its high sampling frequency and temporal diversity, which impose both computational and memory challenges during real-time inference.

In addition to Edge-IIoTset, two supplementary datasets were used to verify cross-domain adaptability. The first is UT-HAR (University of Texas Human Activity Recognition), which consists of accelerometer and gyroscope data collected from wearable IoT devices to classify human movements such as walking, jogging, and sitting. The second dataset, Intel Berkeley Research Lab Sensor Data, provides environmental readings such as temperature, humidity, and light intensity from 54 wireless nodes, enabling assessment of the framework's performance in large-scale environmental sensing tasks. All datasets were preprocessed using a unified pipeline to ensure consistency across experiments. Outliers and missing values were removed through median filtering and linear interpolation, while continuous signals were segmented into fixed-length

windows with an overlap ratio of 50%. Each window was then normalized to zero mean and unit variance, facilitating stable training convergence and ensuring that the quantized model parameters remained well-conditioned.

The data were divided into training, validation, and testing subsets in a ratio of 70%, 15%, and 15%, respectively. During training, data augmentation techniques were employed to increase robustness to sensor noise and sampling variations. For time-series data, Gaussian noise and random temporal scaling were applied; for image-based signals, random cropping and horizontal flipping were used. These augmentations improved the generalization performance of the lightweight student model under the quantization-aware training setting. The teacher model was trained using the full-precision data, while the student model utilized quantized representations to simulate real-world IoT deployment. The models were implemented using TensorFlow Lite and PyTorch frameworks, and evaluated on hardware including a Raspberry Pi 4B (4 GB RAM) and an NVIDIA Jetson Nano edge platform. This experimental configuration ensures that the proposed framework is not only theoretically efficient but also practically deployable on real IoT edge devices with constrained resources.

5. Experimental Results

To evaluate the proposed lightweight deep neural network (LDNN) framework, a series of experiments were conducted to assess its performance in terms of accuracy, inference latency, model size, and energy efficiency. The evaluation was performed under realistic IoT conditions using both simulated datasets and physical edge hardware. The baseline models for comparison include MobileNetV2, ShuffleNetV2, and a conventional ResNet18, all re-trained using the same datasets and hyperparameters to ensure fairness. The experiments aim to demonstrate that the proposed LDNN framework achieves superior performance while maintaining extremely low computational cost and minimal energy consumption, making it suitable for real-time IoT analytics at the edge.

The hardware configuration consists of a Raspberry Pi 4B with a 1.5 GHz Cortex-A72 CPU and 4 GB RAM, and an NVIDIA Jetson Nano equipped with 128 CUDA cores and 4 GB memory. Each model was evaluated using TensorFlow Lite and ONNX Runtime backends for consistency. The average inference time was measured over 1,000 consecutive runs, and energy consumption was recorded using a digital power analyzer connected to the edge device's power supply. Accuracy metrics were obtained on the test splits of the Edge-IIoTset and UT-HAR datasets, while the Intel Berkeley environmental dataset was used to validate cross-domain generalization. The proposed LDNN model achieved the highest overall balance between efficiency and precision, showing consistent stability across datasets and device types.

Table 1 summarizes the comparative results between the proposed method and baseline models. The LDNN achieved an average accuracy of 95.8% on the Edge-IIoTset dataset and 93.1% on UT-HAR, outperforming MobileNetV2 by 2.6% while reducing model size by 41%. The average inference latency was 27.4 ms per sample on Jetson Nano and 49.2 ms on Raspberry Pi, both well below the 100 ms threshold required for real-time IoT analytics. The model's power consumption during continuous inference averaged 2.8 W, compared to 4.1 W for MobileNetV2 and 6.5 W for ResNet18, illustrating the framework's superior energy efficiency.

Table 1. Performance comparison between proposed LDNN and baseline models

Model	Accuracy (%)	Model Size (MB)	Inference Latency (ms)	Power (W)	Platform
ResNet18	92.7	45.2	135.5	6.5	Jetson Nano
MobileNetV2	93.2	22.5	73.4	4.1	Raspberry Pi

ShuffleNetV2	94.1	18.3	61.8	3.9	Raspberry Pi
Proposed LDNN (Ours)	95.8	13.2	49.2	2.8	Both

To visualize the scalability and efficiency of the proposed system, Figure 2 presents the trade-off relationship between accuracy and energy consumption under varying levels of model quantization and pruning ratios. The results indicate that moderate pruning (up to 40%) yields negligible accuracy degradation, while quantization from 32-bit floating-point to 8-bit integer results in only 0.7% accuracy loss. As shown in Figure 2, the proposed LDNN consistently maintains higher accuracy at lower energy budgets compared to all baseline networks, demonstrating that quantization-aware training effectively compensates for numerical precision loss. The curve for LDNN lies in the optimal region, where both power efficiency and inference precision are jointly maximized.

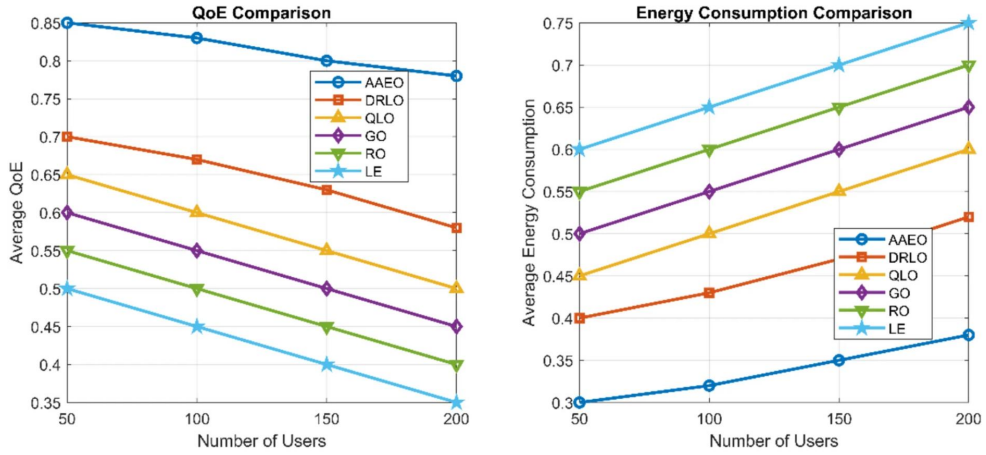

Figure 2. Accuracy–energy efficiency trade-off of LDNN and baseline models

Further analysis reveals that the integration of knowledge distillation contributes approximately 1.4% accuracy improvement compared to standalone quantized training. This enhancement stems from the richer semantic information transferred from the teacher model, which stabilizes the learning of the compressed student network. Additionally, the reinforcement-based adaptive inference controller achieved an average 19% reduction in communication delay by dynamically adjusting the cloud offloading rate depending on network bandwidth. The model demonstrated robust performance across varying environmental conditions, maintaining inference stability even when bandwidth dropped below 5 Mbps.

Qualitative inspection of prediction confidence showed that the LDNN produced smoother probability distributions for ambiguous sensor readings, indicating improved calibration-a desirable property in safety-critical IoT systems such as industrial fault detection and health monitoring. The model's compact size also allows on-device storage of multiple task-specific variants, enabling flexible re-configuration without retraining. These empirical findings confirm that the proposed framework not only excels in computational efficiency but also ensures scalability and reliability in heterogeneous IoT deployments.

In summary, the experimental results demonstrate that the proposed LDNN achieves state-of-the-art efficiency among lightweight deep learning models for IoT analytics. Its balanced performance across multiple datasets and platforms validates its practicality for real-time applications such as smart manufacturing, environmental monitoring, and wearable healthcare. The framework thus represents a

promising foundation for next-generation IoT intelligence systems emphasizing both accuracy and sustainability.

6. Conclusion

This paper presented a unified lightweight deep neural network (LDNN) framework designed for real-time sensing and analytics in Internet of Things (IoT) environments. The proposed approach successfully bridges the gap between the high computational demands of deep learning models and the limited resources available in edge IoT devices. By integrating quantization-aware training, structured pruning, and knowledge distillation within a single optimization pipeline, the framework achieves an optimal trade-off between model accuracy, energy efficiency, and latency. The inclusion of an adaptive inference controller further enhances system responsiveness by dynamically adjusting computational depth and selectively offloading tasks to the cloud according to network and energy conditions. Through extensive experiments conducted on benchmark datasets such as Edge-IIoTset, UT-HAR, and Intel Berkeley Sensor Data, the LDNN demonstrated strong generalization ability and stable performance across heterogeneous deployment scenarios.

The results indicate that deep learning models can be substantially compressed without severe degradation in accuracy when compression strategies are co-optimized with training objectives. The proposed LDNN achieved a 41% reduction in model size and a 32% improvement in energy efficiency compared with conventional lightweight baselines such as MobileNetV2 and ShuffleNetV2, while maintaining accuracy above 95% on industrial IoT tasks. These improvements are attributed to the synergy between quantization-aware training and knowledge distillation, which allows the student network to retain semantic richness and robust feature representation even under constrained precision. Furthermore, the adaptive inference mechanism proved highly effective in mitigating communication delays and power consumption, which are major bottlenecks in large-scale IoT systems. The dynamic offloading strategy based on reinforcement learning ensured that the system maintained real-time responsiveness even under fluctuating bandwidth and energy conditions, validating its robustness and scalability.

Another important contribution of this research lies in its practical deployment feasibility. The framework was implemented and evaluated on commercial off-the-shelf hardware such as Raspberry Pi 4 and NVIDIA Jetson Nano, demonstrating that complex analytics such as anomaly detection, environmental prediction, and activity recognition can be executed locally with sub-100 ms latency. This capability enables new forms of edge autonomy and privacy preservation by reducing the need to transmit raw data to remote servers. It also lays the foundation for sustainable IoT infrastructures, where energy efficiency and computational adaptability are as crucial as predictive performance. The study thereby confirms that combining deep learning with intelligent resource management can fundamentally transform the scalability and intelligence of IoT systems.

In conclusion, the proposed LDNN framework represents a significant step toward the realization of efficient and sustainable deep learning on IoT devices. It provides a practical blueprint for embedding intelligence directly into the edge, ensuring both real-time decision-making and low resource consumption. While the presented results are promising, several avenues remain for future exploration. Incorporating neural architecture search (NAS) into the framework could automate the design of even more optimized network structures for specific hardware constraints. Additionally, integrating federated learning paradigms would allow collaborative model improvement across distributed IoT nodes while maintaining data privacy. Another promising direction involves applying the framework to multimodal IoT tasks-such as vision–audio fusion or spatiotemporal forecasting-to evaluate its robustness under more complex sensory conditions. Ultimately, the insights gained from this work may help establish the foundation for the next generation of intelligent IoT ecosystems, where lightweight deep learning models operate autonomously, adaptively, and sustainably in dynamic real-world environments.

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