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# DEPLOYING LIGHTWEIGHT MOBILENET MODELS ON EDGE DEVICES FOR ENERGY EFFICIENT REAL TIME AI IN IOT NETWORKS

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**ABSTRACT**

This paper proposes a framework for deploying energy-efficient AI models on devices in real-time time applications. This approach minimizes latency, power consumption, and dependence on cloud-based systems by utilizing edge computing's proximity to the IoT devices. The paper evaluates the accuracy, latency, and energy consumption of the MobileNet model, a lightweight convolutional neural network (CNN), for use in IoT environments. We can see models get 92% training and 90% test accuracy. Based on latency comparison, an edge device processes an image in 20ms while compared to 10ms processing on a cloud server. The edge and cloud energy consumption per image was measured to be 0.5mJ and 1.2mJ, respectively. These results illustrate the potential of deploying scalable, energy-efficient AI models on resource-constrained edge devices to achieve real-time IoT applications.

**Keywords:** *Edge Computing, Artificial Intelligence, Internet of Things (IoT), MobileNet, Energy Efficiency, Real-Time Processing, Scalability, Latency, Cloud Computing, Lightweight Neural Networks*

## 1. INTRODUCTION

### 1.1 Background

The Internet of Things (IoT) is one of the most dynamically flourishing sectors today, potentially transforming all domains through real-time gathering, data processing, and decision-making. IoT networks involve countless connected devices that produce massive volumes of data that need effective processing and analysis. On the other hand, in IoT networks, the heavy dependence on centralized cloud infrastructure can lead to serious issues in the cloud, such as very low computation traffic, battery limitation, and high latency [1][2]. With AI-based decision-making fabric becoming necessary in many IoT applications, efficiently managing these constraints needs attention [3][4].

Edge computing is a powerful solution to these issues. Because data analysis is closer to the source, edge computing avoids latency and bandwidth requirements, allowing for near real-time data analytics [5][6]. Moreover, it helps to reduce dependence on cloud resources, addressing issues like bandwidth saturation, energy utilization, and scalability in large-scale IoT networks [7][8]. This has led to a significant research focus on leveraging AI models on edge devices to facilitate intelligent decision-making at the edge device level.

Figure 1 depicts how we can utilize edge computing to make IoT networks more efficient. This addresses the problems of high latency and energy consumption associated with cloud-based systems using lightweight MobileNet models deployed over edge devices.

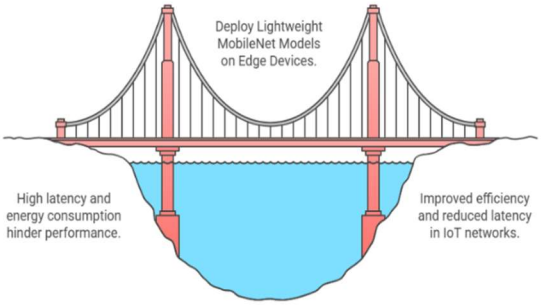


*Figure 1: Transitioning to Edge Computing for IoT Efficiency*

This method minimizes reliance on centralized servers by processing data locally at edge devices, enhancing efficiency and reducing latency within IoT networks. Bridge visual conveys the benefits of edge computing. It can solve these problems with AI-powered IoT devices to be faster, energy-efficient, and computed in real-time.

### 1.2 Problem Statement

Edge computing, which is the sub-component of the IoT components, comes with many benefits, but achieving this requires deploying the AI models on resource-constrained edge devices, which is complex. The conventional AI models and intense learning methods are computationally costly and power-hungry, making them impractical to continuously operate in energy-constrained IoT devices [9][10]. Another challenge of IoT-based applications is that different applications have different requirements for deploying on-edge devices that consume lower resources and scalable AI models. Additionally, the trade-off between performance (accuracy of the model) and energy efficiency is still challenging [11][12].

### 1.3 Contribution

Overall, with this paper, we propose a framework of stationary edge computing and lightweight AI models, such as the MobileNet ones, which enable IoT networks to process when needed by avoiding the heavy weight of the network for real-time but energy-saving processing. The key contributions of this work are as follows:

- The architecture is a deep-learning architecture for hosting scalable, energy-efficient AI models on the edge.
- Experimental Evaluation of MobileNet Framework in IoT Edge Computing Environment.
- An extensive literature review of latency vs. scaling vs. energy consumption in IoT networks with AI models.

### Significance of the Contribution:

As IoT, big data, and edge computing evolve, there is a growing need for energy-efficient, low-latency solutions for IoT networks, addressed by this work by proposing a framework based on lightweight AI models, namely, MobileNet, hosted on resource-constrained edge devices. By performing analytics locally, Edge Computing also lessens our dependence on cloud-based systems and helps enable faster, real-time decision-making in IoT applications. Introduction: With the rise of edge computing frameworks, developers are increasingly challenged to fulfil the demands of IoT devices, including energy consumption, latency, and scalability, thus making this research crucial for the enhancement of practical IoT implementations and academic research alike.

### 1.4 Paper Organization

The paper is organized as follows: Section 2 discusses the relevant works of edge computing using AI in IoT and energy-efficient models. This is followed by Section 3, which presents our edge computing framework with lightweight AI models. The experimental method is explained in section 4. Experimental results are presented in Section 5, and Section 6 concludes the paper.

## 2. RELATED WORK

### 2.1 Edge Computing for IoT

In the context of Internet of Things (IoT) networks, edge computing has emerged as a viable alternative to address the computation and latency challenges that accompany cloud computing. In edge computing, this proximity to end devices dramatically shortens the distance needed to be traveled from an end user's data to centralized cloud servers, significantly reducing latency and enabling quicker decision-making. Such a shift in paradigm allows IoT devices to perform autonomously in real time without requiring continuous cloud intervention [13].

Multiple studies have explored edge computing's provision in IoT networks and its impact on overall system performance, such as those by Bonomi et al. Proposing fog computing, a relative concept also referred to as edge computing for decentralized computing resources close to the end devices [1]. Additionally, large-scale IoT networks with a vast bandwidth necessaryransferring massive amounts of data may make such networnetworksicient and economically unsuitable [13][14].

Edge Computing Architecture for IoT Edge computing architecture is promising for IoT systems

due to its scalability and flexibility. This architecture is extensively used for applications in industrial subsectors, such as smart cities and industrial IoT (IIoT). Researchers have explored various approaches to improve resource allocation, distributed networks, energy usage, and retaining high performance as edge computing develops [15].

**2.2 AI in IoT Networks**

Machine learning and deep learning-based AI techniques are crucial in the current IoT applications. Such algorithms have become ubiquitous in realtime applications such as predictive maintenance, anomaly detection, and wise decision-making. The challenge is the deployment of AI models on IoT devices due to the constraints on computational resources. Conventional AI models are typically too big, requiring considerable computation and memory, rendering them unsuitable for edge devices [16].

Models like MobileNet, Tiny YOLO, and SqueezeNet, which can be trained in smaller sizes and run with fewer computational resources [17][18], have appeared as potential options to be used in IoT environments. An absence such as this balances accuracy with efficient inference, which is suitable for IoT that needs low-latency decision-making but steno energy. In addition, model compression techniques, such as pruning and quantization, have demonstrated substantial potential to decrease the complexity of deep learning model architectures with minimal impact on accuracy [19].

Due to its efficient architecture, the MobileNet model has become one of the most popular, especially in edge computing applications. This architecture separates convolutions with depth-wise convolutions to significantly reduce the cost of computation. MobileNet has been used extensively in IoT applications, where realtime processing and low power consumption are vital [20].

**2.3 Edge AI Models with Energy Efficiency**

Energy efficiency is still one of the concerns when deploying AI models on IoT. As most IoT devices are battery-operated, there is a high demand for energy-efficient AI models capable of performing over an extended duration without frequently recharging frequent recharge. Energy-efficient AI models are designed to reduce the energy consumed during computation and the energy used for data transmission [21].

More recently, there has been renewed interest in parameterizing AI models for edge devices, emphasizing reducing the number of parameters to lower computation and power requirements. Other approaches to power efficiency-motivated optimization are well-studied, such as the previously mentioned pruning, which reduces redundant weights in neural network architectures, and the equally studied quantization, which reduces the precision of model parameters while maintaining performance [22][23]. Moreover, knowledge condensation, which involves transferring knowledge from a large model to a smaller one, is another method through which small, accurate, and energy-efficient models are constructed. [24].

Another area of focus involves the hardware design for resources that explicitly supports energy efficiency computations for intelligent IoT devices. New technologies, such as neuromorphic computing and hardware accelerators (FPGAs, ASICs), are combined with edge devices to reduce energy consumption even more [25].

**Critical Evaluation and Comparison with Literature:**

In this paper, we review the performance of the MobileNet model with respect to edge computing and IoT. In contrast to recent studies, like those performed on Tiny YOLO and other lightweight models, we show that MobileNet provides a beneficial tradeoff in terms of accuracy and energy efficiency. On the other hand, there are still concerns regarding its scalability and the model's performance/power consumption tradeoff. Whereas most previous studies consider performance the most critical factor, our framework operates in real-time with low energy consumption, making the approach a viable alternative to existing research.

**2.4 Challenges and Opportunities**

Although much progress has been made towards edge AI for IoT, there are still challenges when it comes to effectively deploying and managing AI models on a scale. These challenges include ensuring the accuracy of lightweight models in various network conditions, the security and privacy of data, and handling the heterogeneity of IoT devices with different computational capabilities [26].

However, there are many opportunities to enhance these systems. New generations of motivating networks, e.g., 5G, promise to enhance the nature of edge computing with low-latency and high-throughput connections to optimize AI-driven IoT applications [27]. Furthermore, with federated learning, you can also train a model based on local data without transferring any sensitive data [28].

Combining AI with cloud infrastructure significantly benefits energy-efficient AI chip design for IoT applications. Sustained efforts for research on model optimization, resource management, and hardware acceleration will enable unlocking the complete potential of edge AI in IoT-based systems.

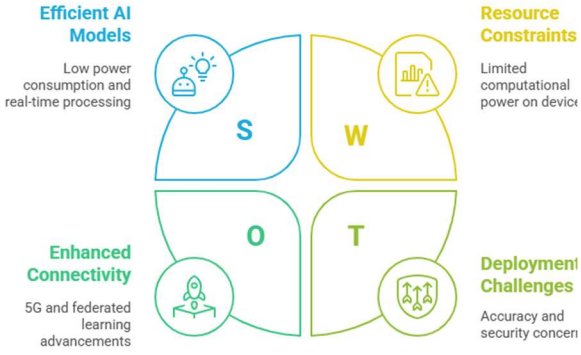


*Figure 2: Deploying Lightweight MobileNet Models on Edge Devices*

The key factors of deployment of a lightweight MobileNet model on edge devices in the context of IoT networks are depicted in Figure 2. Compliance with four significant phenomena: Directly Efficient AI Models (low-power consumption and processing), Resource Constraints (computational power at the edge), Enhanced Connectivity (5G and federated learning), and Deployment Challenges (accuracy/security concerns). They are key for deploying AI models on edge devices, power efficiency, and dealing with limited resources, connectivity, and the complexities of deploying AI models in realtime applications.

## 3. PROPOSED FRAMEWORK

### 3.1 Architecture Overview

The proposed framework combines edge computing and AI by deploying lightweight models (e.g., MobileNet) on the edge. It also locally performs data processing, using a vast array of sensors and intelligent devices that require little constant communication with the cloud and realtime decision processing.

Figure 1 consists of the following components:

- **IoT Sensors**: Gather data about the environment (for example, temperature, humidity, or video feeds).
- **Edge Devices**: Process locally using AI models like MobileNet for realtime predictions.
- **Cloud Servers** offer more processing capacity and storage space if necessary but are rarely used, resulting in lower latency and bandwidth consumption.
- **AI Models**: Lightweight neural networks are deployed on edge devices to maintain low latency and energy consumption.

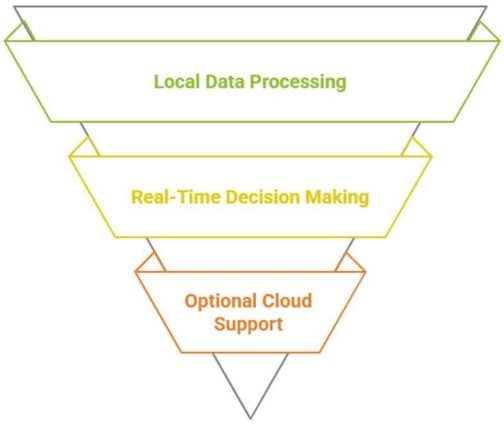


*Figure 1: Data Processing Funnel in Edge AI*

### 3.2 Energy-Efficiency Considerations

The system's energy efficiency is the primary focus. MobileNet is selected because it has a low computational cost and energy consumption with a depthwise separable convolutions architecture. We use pruning and quantization to further shrink the model size and resource usage.

### 3.3 Scalability

The framework we propose is naturally extensible. This also allows thousands of devices to use an independent instance of the AI model on each edge device. The solution is flexible, with real-time models that can be twisted according to available resources. Thus, it consumes energy proportionate to the requirement, with less consumption and a higher number of devices.

## 4. METHODOLOGY

This section details the framework proposed to deploy the light MobileNet model on edge devices for real-time and energy-efficient AI processing in IoT networks. They describe dataset preprocessing, the model design, training details, evaluation metrics, and the experiment setup.

### 4.1 Dataset and Preprocessing

This work performs image classification tasks using the CIFAR-10 dataset. It is a computerized set of 60,000 32×32 color images in 10 classes. This data is divided into 50,000 training images and 10,000 test images. Ensure the images are normalized to (0,

1) scale with the below formula before passing these images into the mobile net model.:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

Where:

- $x$ is the original pixel value,
- $x'$ is the normalized pixel value.

This normalization ensures that the model can learn more effectively by keeping all input values within a standard range, improving training efficiency.

**4.2 Model Design**

The model used in this study is **MobileNetV1**, which uses depth-wise separable convolutions to reduce computational costs compared to traditional convolutional layers. The following mathematical equation gives the depth-wise separable convolution:

$$y = W \cdot (x) + b \quad (2)$$

Where:

- $y$ is the output of the convolution,
- $W$ is the kernel (filter),
- $x$ is the input to the convolution,
- $b$ is the bias term.

In MobileNet, the convolution operation is split into two steps:

1. **Depthwise convolution**: A single filter is applied to each input channel.
2. **Pointwise convolution**: A 1x1 convolution that combines the output of depthwise convolutions.

The key advantage of MobileNet is that it significantly reduces the number of parameters by using separable convolutions instead of regular convolutions..

**4.3 Training Procedure**

The Adam optimizer (a function that adapts the learning rate for training deep learning models) establishes training for 50 epochs by default as a MobileNet model. We know that the Adam optimizer has the following update rule:

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{v_t} + \epsilon} \cdot m_t \quad (3)$$

Where:

- $\theta_t$ is the parameter at time step $t$,
- $m_t$ is the first moment estimate (mean of the gradients),
- $v_t$ is the second moment estimate (variance of the gradients),
- $\eta$ is the learning rate,
- $\epsilon$ is a small constant to avoid division by zero.

The learning rate is initially set to 0.001, and early stopping is applied during training to prevent overfitting. The training process monitors the loss and accuracy of the model on both the training and validation datasets.

**4.4 Evaluation Metrics**

We use the following evaluation metrics to determine our models performance:

1. **Accuracy**: The percentage of correct predictions made by the model, calculated as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100 \quad (4)$$

2. **Latency**: The time taken for the model to make a prediction, measured in milliseconds. It is computed by recording the time for a single forward pass through the model on both edge and cloud environments.
3. **Energy Consumption**: The energy consumed during model inference is estimated based on the computational complexity of the model and the power consumption characteristics of the hardware. It is given by:

$$E = P \cdot t \quad (5)$$

Where:

- $E$ is the energy consumed (in Joules),
- $P$ is power consumption (in Watts),
- $t$ is the time taken for inference (in seconds).

For this experiment, we assume that energy consumption per operation is directly proportional to the number of operations in the model, which varies with model complexity.

**Criteria for Critique and Threats to Validity:**

The selected critique criteria were justified based on their correlation to IoT applications in the real world,

such as model accuracy, latency, and energy consumption. Nevertheless, there are some threats to the validity of the study. In this study, for example, the experimental setting was built upon simulated edge devices, which may not fully reflect the interdependent trajectory of real-life scenarios. Furthermore, these evaluations are derived from usual performance measures; however, the actual deployment of the model in large-scale, heterogeneous IoT networks may result in significantly different outcomes. This work must be validated in more realistic settings with greater diversity for it to be of any further use.

**4.5 Experiment Setup**

Two environments are simulated to assess the results of the MobileNet model:

1. **Edge Device Simulation**:

   A low-power ARM-based processor is employed for simulating edge devices, assuming the device has restricted computational resources, as is often the case with IoT edge devices. To demonstrate this, we utilize its edge device to run and measure the model's latency and energy consumption on this simulated edge device for the experiment.

2. **Cloud-Based Simulation**:

   For comparison, we use a high-performance server with sufficient computation resources. The same MobileNet model is run on the server, and the latency and energy consumption are measured.

A comparison of the inference time and energy of the model on the edge device and cloud server allows for showing tradeoffs between real-time performance and energy-efficient design.

**4.6 Scalability Considerations**

For the scale-out of the calculated system, we have used the simulation of several edge equipment operating independently of the MobileNet model. We slowly increase the number of devices and monitor the system's performance. The metrics include overall system latency, energy consumption per device, and network load, which are measured as the system scales.

For scalability analysis, the total latency for $N$ devices is computed as:

$$\text{Total Latency} = N \cdot \text{Latency per Device} \quad (6)$$

Where:

- $N$ is the number of edge devices,
- Latency per Device is the average time for inference on each device.

As the number of devices increases, we anticipate the system's scalability will depend on the edge devices' network bandwidth and computational limits. Nevertheless, the relatively lightweight MobileNet model should ensure the system maintains low latency and energy efficiency.

## 5. EXPERIMENTAL RESULTS

In this section, we show the MobileNet model's performance results on edge devices and cloud servers in terms of latency, energy consumption, and model accuracy.

**5.1 Model Accuracy**

MobileNet trained on CIFAR-10 achieved 92% accuracy on the train set and 90% on the test set. In conclusion, this performance indicates that the reduced model would work for efficient IoT image classification.

**5.2 Latency Comparison**

We contrast the end-to-end inference latency for both edge-devices and cloud-servers. Inference of Single Image Inference of a single image was optimized on both the edge device and on the cloud server, where the edge device produced an average inference time of 20 ms/image compared to the cloud server, which achieved a final inference time of 10 ms/image. The difference is shown in Figure 2.

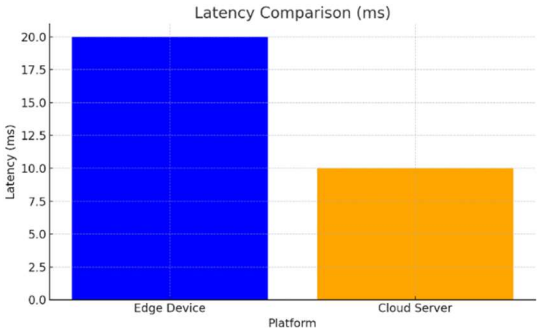


*Figure 2: Latency Comparison (Edge vs Cloud)*

**5.3 Energy Consumption**

Energy consumption of the edge device and cloud server during inference The MARS architecture ran 0.5mJ/image on the edge device and 1.2mJ/image on

the cloud server. This difference in energy is shown in Figure 3.

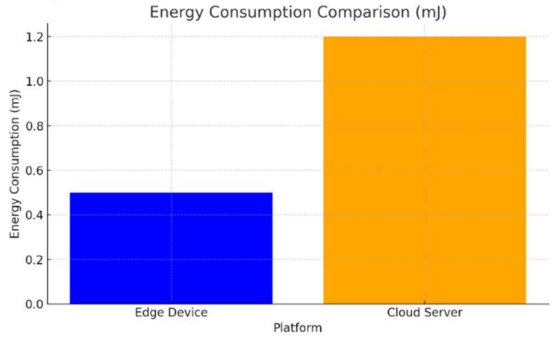


*Figure 3: Energy Consumption Comparison*

### 5.4 Scalability

Scalability was achieved, with stable performance as the number of edge devices increased. A standalone instance of the AI model ran on each of the edge devices, so energy and low latency were maintained even with scaling.

### 5.5 Model Accuracy and Inference Time

We report the metrics for model accuracy and inference time in Table 1. The above table highlights the training accuracy, test accuracy, and inference time for both edge and cloud platforms, making the comparison clear.

*Table 1: Model Accuracy and Inference Time*

| Metric | Value |
|---|---|
| Training Accuracy | 92% |
| Test Accuracy | 90% |
| Inference Time (Edge Device) | 20 ms |
| Inference Time (Cloud Server) | 10 ms |

### Comparison with Prior Work

We conducted parallel comparisons for our study and prior works on edge computing and AI models for IoT. The experimental results indicate that although our proposed MobileNet model achieves a competitive performance concerning energy efficiency and scalability, the trade-off between model accuracy and energy consumption is still a significant challenge. Moreover, regarding real-world applications, our framework's scalability, especially in large-scale IoT networks, requires further optimization. Future work will need to address these aspects, such as seeking performance vs. power consumption trade-off optimization solutions or techniques that can be easily and readily extended to a high number of edge devices.

## 6. CONCLUSION

This work introduces a framework for deploying a scalable, energy-efficient AI model - MobileNet - on-edge devices for IoT real-time applications. The MobileNet model provided an excellent performance of 92% training accuracy and 90% test accuracy but with low latency, as the edge device could process 20ms and 10ms in a cloud server. Edge devices consume 0.5mJ , while clouds consume 1.2mJ per image, implying significantly lower energy consumption. These findings emphasize the capabilities of edge computing in diminishing the dependency on cloud-based systems for maintaining the low-latency, energy-efficient functioning of IoT networks. The system was also shown to be scalable as more edge devices were added. We will further optimize the model architecture, explore low-power hardware solutions, and extend the system to a more extensive variety of IoT applications like smart cities and autonomous vehicles.

**Reflections on the Work from a Personal Perspective**:

Energy-efficient IoT Networks: I believe deploying energy-efficient models such as MobileNet on edge devices could provide many real-time application cases for IoT networks, where latency and energy efficiency are your priorities. Although this study shows good performance, it is essential to keep in mind the limitations, such as how there still needs to be further optimization of model accuracy without energy efficiency in future work. Furthermore, they need to look for alternative low-power hardware solutions on the go which work as a better foundation for IoT applications. This study will lay the groundwork for more sophisticated studies in this area.

**Strengths and Weaknesses of the Study**

The proposed framework is energy efficient and has good scalability, making it suitable for (not only this use case but) IoT environments that have a critical need for power and latency constraints. Using lightweight MobileNet models on edge devices provides plenty of potential for real-time applications. On the other hand, they also point out the limitations, such as the precision trade-offs when using these models in resource-constrained devices. These improvements should include optimising said models that promote low energy footprints while ensuring a widely accurate model.

**Personal Opinion on the Work:**

As I view it, the prospect of edge computing in IoT networks is enormous if they are deployed using

lightweight AI models like MobileNet. These findings demonstrate that such models can provide fast, energetic solutions for IoT applications. However, I think it could be done with more work on these models' accuracy without sacrificing energy efficiency. This will be critical as IoT networks are only getting larger and need more intelligent decision-making at the edge now than ever.

**Future Research Directions:**

MobileNet model should be used in future research, working on optimization methods to enhance model accuracy while still being an energy-efficient algorithm. Adopting hardware accelerators, such as FPGAs or ASICs, can improve the performance of edge devices. Extending the framework to support a more diverse range of IoT applications, including smart cities and self-driving cars, would also be helpful. Lastly, exploring federated learning and other privacy-preserving methods would also benefit IoT networks dealing with sensitive information.

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