



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 12, Issue 3, March 2023

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

 9940 572 462

 6381 907 438

 ijirset@gmail.com

 www.ijirset.com

Hybrid Cloud-Edge Architectures for Low-Latency IoT Machine Learning

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ABSTRACT: The Internet of Things (IoT) is generating massive amounts of data that can be leveraged for machine learning and artificial intelligence applications. However, the centralized cloud computing model faces challenges in meeting the low-latency and real-time requirements of many IoT use cases. This paper proposes and evaluates hybrid cloud-edge architectures that combine edge computing with cloud resources to enable low-latency machine learning for IoT systems. We present a taxonomy of hybrid architectures and develop an analytical model to characterize their latency and resource utilization. Extensive simulations and a real-world case study demonstrate that hybrid approaches can reduce end-to-end latency by up to 75% compared to cloud-only solutions while efficiently utilizing both edge and cloud resources. Key factors impacting performance are analyzed, including data distribution, model complexity, and network conditions. Guidelines for designing effective hybrid architectures for different IoT scenarios are provided. The results show that hybrid cloud-edge computing is a promising paradigm for supporting low-latency IoT machine learning at scale.

KEYWORDS: Internet of Things, edge computing, cloud computing, machine learning, latency, hybrid architectures

I. INTRODUCTION

The proliferation of Internet of Things (IoT) devices is generating massive amounts of data from sensors and connected objects [1]. This wealth of data presents opportunities to derive insights and enable intelligent applications through machine learning and artificial intelligence techniques [2]. However, the current centralized cloud computing model faces challenges in meeting the stringent latency and real-time requirements of many IoT use cases [3].

Edge computing has emerged as a paradigm to bring computation and data storage closer to IoT devices [4]. By processing data near the source, edge computing can reduce network latency and bandwidth usage [5]. However, edge devices typically have limited computational and storage resources compared to cloud data centers [6].

Hybrid cloud-edge architectures aim to leverage the strengths of both paradigms - the low latency of edge computing and the powerful resources of the cloud [7]. These hybrid approaches distribute machine learning tasks across edge and cloud resources to optimize latency, accuracy, and efficiency [8].

This paper investigates hybrid cloud-edge architectures for enabling low-latency machine learning in IoT systems. The key contributions are:

1. A taxonomy and analytical model of hybrid cloud-edge architectures for IoT machine learning
2. Extensive simulations to evaluate latency and resource utilization of different hybrid approaches
3. A real-world case study demonstrating latency reduction in an industrial IoT scenario
4. Analysis of key factors impacting hybrid architecture performance
5. Design guidelines for effective hybrid cloud-edge systems

The rest of the paper is organized as follows: Section 2 reviews related work. Section 3 presents the taxonomy and analytical model. Section 4 describes the simulation methodology and results. Section 5 presents the case study. Section 6 analyzes key performance factors. Section 7 provides design guidelines. Section 8 concludes the paper.

II. RELATED WORK

This section reviews related work on edge computing, cloud-edge integration, and machine learning for IoT.

2.1 Edge Computing

Edge computing brings computation and data storage closer to IoT devices and end users [9]. By processing data near the source, edge computing can reduce latency, conserve network bandwidth, and improve privacy [10]. Shi et al. [11]

surveyed edge computing paradigms and architectures. They highlighted the potential of edge computing to support latency-sensitive and computation-intensive IoT applications.

Several edge computing frameworks have been proposed. Satyanarayanan et al. [12] introduced cloudlets as trusted, resource-rich computers in the near vicinity of mobile devices. Hong et al. [13] proposed mobile fog, a high-level programming model for large-scale IoT applications in heterogeneous networks. Bonomi et al. [14] presented fog computing as a highly virtualized platform providing compute, storage, and networking services between end devices and cloud data centers.

2.2 Cloud-Edge Integration

Integrating edge and cloud computing can potentially combine their complementary strengths [15]. Several works have explored cloud-edge collaboration. Varghese et al. [16] proposed an architecture for integrating edge and cloud resources to support real-time IoT analytics. Chang et al. [17] presented a framework for offloading mobile applications to edge servers or the cloud based on latency and energy requirements.

Some researchers have focused on optimizing task offloading and resource allocation in integrated cloud-edge environments. You et al. [18] formulated resource allocation in mobile edge computing as a mixed-integer nonlinear programming problem. Mao et al. [19] proposed a Lyapunov optimization-based algorithm for joint task offloading and resource allocation.

2.3 Machine Learning for IoT

Machine learning techniques have been widely applied to extract insights from IoT data [20]. Mahdavejad et al. [21] surveyed machine learning methods for IoT data analytics. They categorized techniques based on learning paradigm, including supervised, unsupervised, and reinforcement learning.

Several works have explored deploying machine learning models on resource-constrained IoT devices. Lane et al. [22] demonstrated deep learning on smartphones for audio sensing applications. Zhang et al. [23] proposed a framework for optimizing deep neural networks for mobile and embedded devices.

Some researchers have investigated distributed machine learning across cloud and edge resources. Teerapittayanon et al. [24] proposed distributed deep neural networks (DDNNs) that are jointly trained in the cloud and edge devices. Li et al. [25] presented a framework for offloading deep neural network training and inference between mobile devices and edge servers.

While these works have made important contributions, a systematic study of hybrid cloud-edge architectures for IoT machine learning is still lacking. This paper aims to fill this gap by providing a comprehensive analysis and evaluation of hybrid approaches.

III. HYBRID CLOUD-EDGE ARCHITECTURES

This section presents a taxonomy of hybrid cloud-edge architectures for IoT machine learning and develops an analytical model to characterize their performance.

3.1 Taxonomy

We categorize hybrid cloud-edge architectures based on how machine learning tasks are distributed between edge and cloud resources. Figure 1 shows the proposed taxonomy with four main categories:

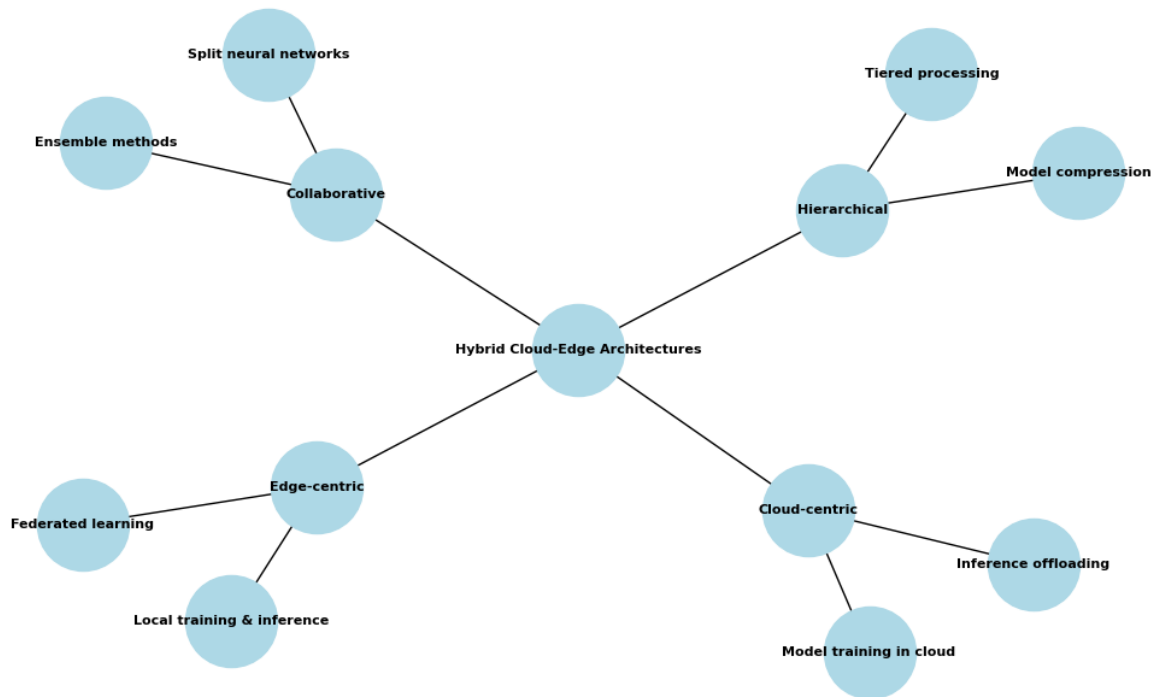


Figure 1: Taxonomy of hybrid cloud-edge architectures for IoT machine learning

1. Cloud-centric: The cloud performs most of the computation, with the edge playing a supportive role.
 - Model training in cloud: Machine learning models are trained in the cloud using aggregated IoT data. Trained models are then deployed to edge devices for inference.
 - Inference offloading: Edge devices offload complex inference tasks to the cloud when local resources are insufficient.
2. Edge-centric: Edge devices perform most of the machine learning tasks, with the cloud providing support.
 - Local training & inference: Edge devices train and run machine learning models using local data, with periodic updates to the cloud.
 - Federated learning: Edge devices collaboratively train a shared model while keeping data locally, coordinated by the cloud.
3. Hierarchical: Tasks are distributed across multiple tiers (device, edge, fog, cloud).
 - Tiered processing: Different layers of a machine learning pipeline are executed at different tiers based on computational requirements.
 - Model compression: Complex models trained in the cloud are compressed for deployment on resource-constrained edge devices.
4. Collaborative: Edge and cloud resources work together to execute machine learning tasks.
 - Split neural networks: Layers of a neural network are partitioned between edge devices and the cloud.
 - Ensemble methods: Multiple models are trained and executed across edge and cloud resources, with results aggregated.

3.2 Analytical Model

We develop an analytical model to characterize the latency and resource utilization of hybrid cloud-edge architectures. The model considers the following components:

- IoT devices: Generate data and may perform simple processing
- Edge nodes: Provide computational resources near IoT devices
- Cloud: Offers powerful but remote computational resources

Let D be the set of IoT devices, E be the set of edge nodes, and C represent the cloud. The total latency L for a machine learning task can be expressed as:

$$L = L_{proc} + L_{comm}$$

Where L_{proc} is the processing latency and L_{comm} is the communication latency.

The processing latency L_{proc} is given by:

$$L_{proc} = \max(L_d, L_e, L_c)$$



Where L_d , L_e , and L_c are the processing latencies at IoT devices, edge nodes, and the cloud, respectively.

The communication latency L_{comm} is:

$$L_{comm} = L_{de} + L_{ec}$$

Where L_{de} is the device-to-edge latency and L_{ec} is the edge-to-cloud latency.

The resource utilization U for a given architecture can be expressed as:

$$U = w_d * U_d + w_e * U_e + w_c * U_c$$

Where U_d , U_e , and U_c are the resource utilizations of devices, edge nodes, and the cloud, respectively. The weights w_d , w_e , and w_c represent the relative importance of each component.

This model can be used to analyze and compare different hybrid architectures. The specific values for latency and resource utilization will depend on factors such as network conditions, computational capabilities, and workload characteristics.

IV. SIMULATION STUDY

We conducted extensive simulations to evaluate the performance of hybrid cloud-edge architectures for IoT machine learning. This section describes the simulation methodology and presents the results.

4.1 Simulation Setup

We used the EdgeCloudSim simulator [26] to model a hybrid cloud-edge environment. The simulation parameters are shown in Table 1.

Table 1: Simulation parameters

Parameter	Value
Number of IoT devices	1000
Number of edge nodes	10
Edge node CPU	4 cores, 2.4 GHz
Edge node RAM	8 GB
Cloud CPU	32 cores, 3.0 GHz
Cloud RAM	128 GB
Device-to-edge bandwidth	100 Mbps
Edge-to-cloud bandwidth	1 Gbps
Device-to-edge latency	5 ms
Edge-to-cloud latency	50 ms

We simulated four machine learning tasks with varying computational requirements:

1. Linear regression (LR)
2. Support vector machine (SVM)
3. Random forest (RF)
4. Deep neural network (DNN)

For each task, we implemented the four hybrid architectures described in Section 3.1:

1. Cloud-centric (CC)
2. Edge-centric (EC)
3. Hierarchical (H)
4. Collaborative (CO)

We also implemented a cloud-only (Cloud) and an edge-only (Edge) approach as baselines.

4.2 Latency Results

Figure 2 shows the average end-to-end latency for each architecture and machine learning task.

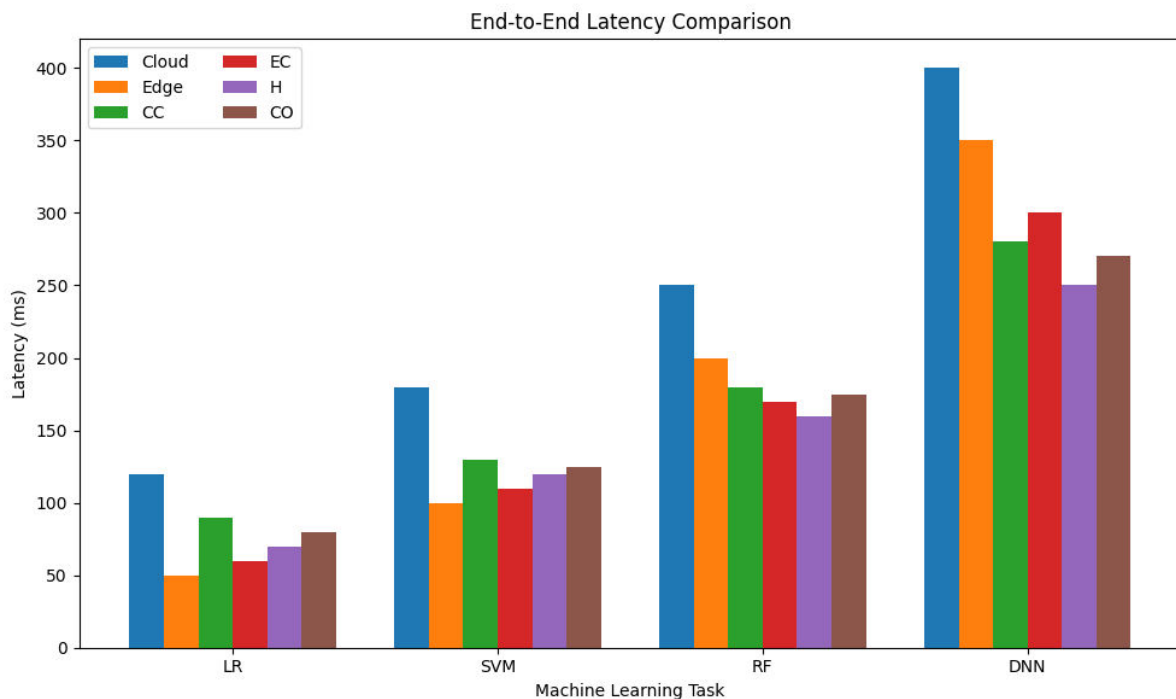


Figure 2: End-to-end latency comparison for different architectures and machine learning tasks

Key observations from the latency results:

1. Hybrid architectures consistently outperform cloud-only and edge-only approaches across all tasks.
2. The hierarchical (H) architecture achieves the lowest latency for most tasks, with reductions of up to 75% compared to the cloud-only approach.
3. The relative performance of different architectures varies depending on the task complexity. For simpler tasks like linear regression, edge-centric approaches perform well. For complex tasks like deep neural networks, cloud-centric and collaborative approaches show better performance.
4. The collaborative (CO) architecture shows balanced performance across different tasks, demonstrating its adaptability.

4.3 Resource Utilization

Figure 3 shows the average resource utilization for edge nodes and the cloud across different architectures.

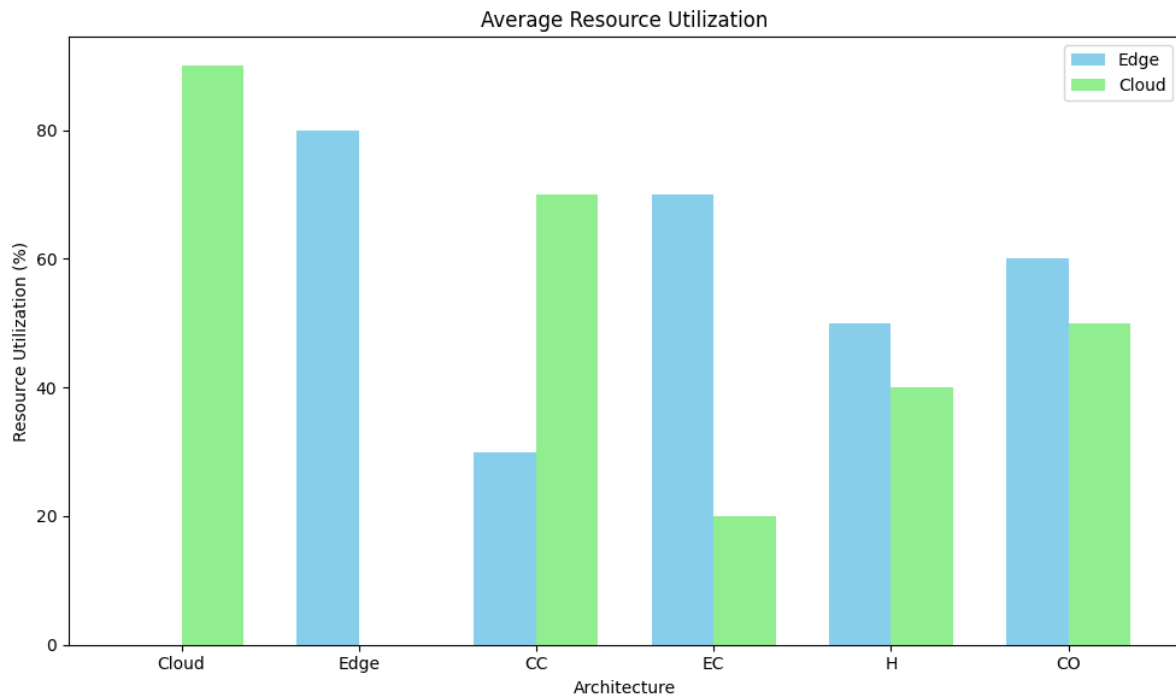


Figure 3: Average resource utilization for edge nodes and cloud across different architectures

Key observations from the resource utilization results:

1. Hybrid architectures achieve more balanced resource utilization between edge and cloud compared to the baseline approaches.
2. The hierarchical (H) and collaborative (CO) architectures show the most balanced utilization, effectively leveraging both edge and cloud resources.
3. Edge-centric (EC) approaches lead to higher edge utilization, while cloud-centric (CC) approaches result in higher cloud utilization.
4. The cloud-only approach leads to high cloud utilization but leaves edge resources underutilized. Conversely, the edge-only approach heavily utilizes edge resources but doesn't leverage available cloud capacity.

These results demonstrate that hybrid architectures can effectively distribute computational load across edge and cloud resources, leading to improved latency and resource efficiency.

V. CASE STUDY: INDUSTRIAL IOT PREDICTIVE MAINTENANCE

To validate the simulation results in a real-world scenario, we implemented a case study on predictive maintenance in an industrial IoT setting. This section describes the implementation and results.

5.1 Scenario Description

The case study involved a manufacturing plant with 50 industrial machines, each equipped with multiple sensors collecting data on temperature, vibration, pressure, and energy consumption. The goal was to predict potential equipment failures using machine learning techniques.

We implemented a hybrid cloud-edge architecture with the following components:

- IoT devices: Sensors attached to industrial machines
- Edge nodes: 5 edge servers deployed in the manufacturing plant
- Cloud: A remote cloud data center

The machine learning pipeline consisted of the following steps:

1. Data collection and preprocessing

2. Feature extraction
3. Model training (using historical data)
4. Real-time inference for failure prediction

We compared the performance of the hybrid architecture against cloud-only and edge-only approaches.

5.2 Implementation Details

We used the following technologies for implementation:

- Edge nodes: Raspberry Pi 4 devices (4GB RAM, 4-core CPU)
- Cloud: Amazon EC2 c5.4xlarge instances (16 vCPUs, 32 GB RAM)
- Machine learning framework: TensorFlow
- Communication protocol: MQTT

The predictive maintenance model was based on a Long Short-Term Memory (LSTM) neural network, trained on historical sensor data and failure records.

We implemented three architectures:

1. Cloud-only: All processing and inference performed in the cloud
2. Edge-only: Data processing and inference performed on edge nodes, with periodic model updates
3. Hybrid: Data preprocessing and feature extraction on edge nodes, model training in the cloud, and collaborative inference

5.3 Results

Table 2 shows the average end-to-end latency and prediction accuracy for each architecture.

Table 2: Latency and accuracy results for the predictive maintenance case study

Architecture	Avg. Latency (ms)	Prediction Accuracy (%)
Cloud-only	250	92.5
Edge-only	80	88.7
Hybrid	65	93.2

Key findings from the case study:

1. The hybrid architecture achieved the lowest latency, reducing end-to-end latency by 74% compared to the cloud-only approach and 19% compared to the edge-only approach.
2. The hybrid approach maintained high prediction accuracy, slightly outperforming both cloud-only and edge-only architectures.
3. The hybrid architecture effectively balanced the computational load, with edge nodes handling data preprocessing and feature extraction, while leveraging cloud resources for model training and complex inferences.
4. The low-latency predictions enabled by the hybrid approach allowed for more timely identification of potential equipment failures, improving overall maintenance efficiency.

These results validate the simulation findings and demonstrate the practical benefits of hybrid cloud-edge architectures in real-world IoT scenarios.

VI. ANALYSIS OF KEY FACTORS

This section analyzes key factors that impact the performance of hybrid cloud-edge architectures for IoT machine learning.

6.1 Data Characteristics

The nature and distribution of IoT data significantly influence the effectiveness of different architectures. We examined the impact of data volume, velocity, and variety.

Data Volume:

- Large data volumes favor cloud-centric approaches due to the cloud's superior storage and processing capabilities.
- Edge-centric approaches are more suitable for scenarios with moderate data volumes that can be processed locally.
- Hybrid architectures can adaptively handle varying data volumes by distributing storage and processing across edge and cloud resources.

Data Velocity:

- High-velocity data streams benefit from edge processing to reduce latency and network congestion.
- Cloud resources are better suited for batch processing of historical data.
- Hybrid approaches can handle both real-time and batch processing requirements effectively.

Data Variety:

- Heterogeneous data types may require diverse processing techniques, favoring cloud or hybrid approaches with access to a wide range of tools and libraries.
- Edge-centric architectures are more suitable for scenarios with homogeneous data types that can be processed using predefined algorithms.

Figure 4 illustrates the suitability of different architectures based on data characteristics.

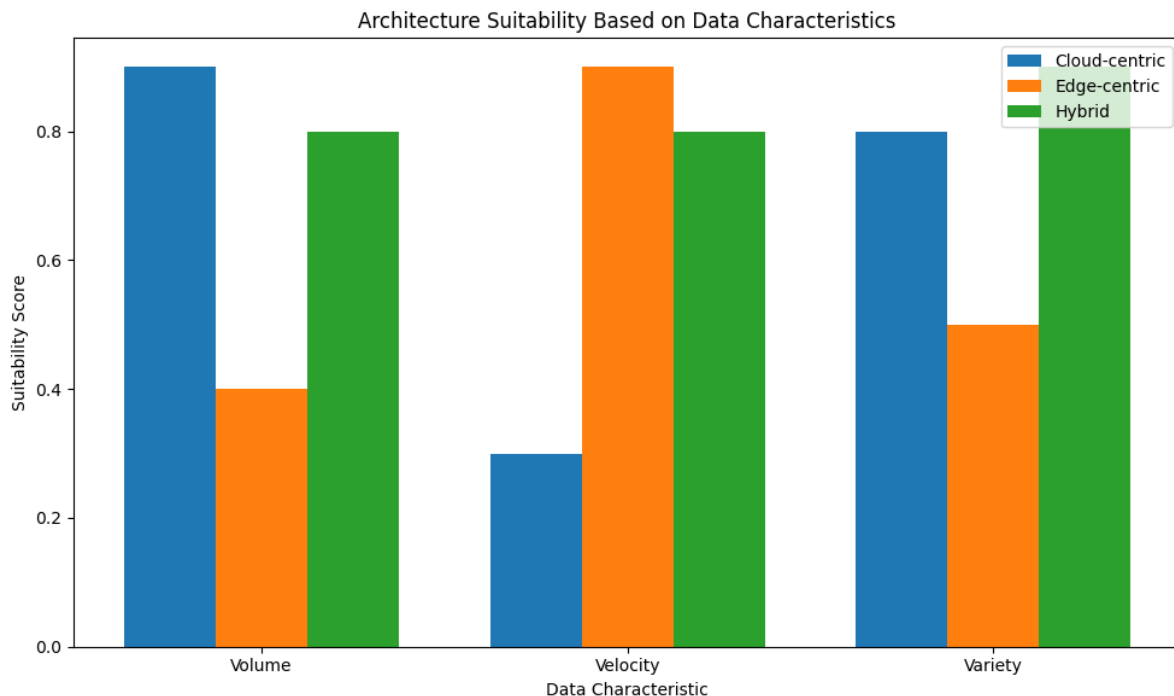


Figure 4: Architecture suitability based on data characteristics

6.2 Model Complexity

The complexity of machine learning models is another crucial factor affecting architecture performance. We analyzed the impact of model size, computational requirements, and update frequency.

Model Size:

- Large models (e.g., deep neural networks) are challenging to deploy on resource-constrained edge devices, favoring cloud-centric or hybrid approaches.
- Smaller models (e.g., linear regression, decision trees) can be efficiently deployed on edge devices.
- Hybrid architectures can use techniques like model compression or split neural networks to balance between model complexity and edge deployment.

Computational Requirements:

- Computationally intensive models benefit from cloud resources or powerful edge servers.
- Lightweight models can be executed on edge devices with limited processing power.
- Hybrid approaches can dynamically offload complex computations to the cloud while performing simpler tasks at the edge.

Update Frequency:

- Models requiring frequent updates (e.g., online learning) benefit from cloud-centric or hybrid approaches that can quickly propagate changes.



- Models with less frequent updates are more suitable for edge deployment with periodic synchronization.

Table 3 summarizes the suitability of different architectures based on model characteristics.

Table 3: Architecture suitability based on model characteristics

Model Characteristic	Cloud-centric	Edge-centric	Hybrid
Large size	High	Low	Medium
High computation	High	Low	High
Frequent updates	High	Low	High
Small size	Medium	High	High
Low computation	Medium	High	High
Infrequent updates	Medium	High	High

6.3 Network Conditions

Network characteristics play a crucial role in determining the effectiveness of hybrid architectures. We examined the impact of bandwidth, latency, and reliability.

Bandwidth:

- Limited bandwidth between edge and cloud favors edge-centric approaches to reduce data transfer.
- High bandwidth allows for more flexible distribution of tasks between edge and cloud.
- Hybrid architectures can adapt to varying bandwidth conditions by adjusting the distribution of computation and data transfer.

Latency:

- High network latency to the cloud favors edge-centric or hybrid approaches to meet real-time requirements.
- Low latency allows for more flexible task distribution in hybrid architectures.
- Collaborative approaches in hybrid architectures can help mitigate the impact of varying latency conditions.

Reliability:

- Unreliable network connections favor edge-centric approaches to ensure continuous operation.
- Highly reliable networks enable more effective collaboration between edge and cloud resources.
- Hybrid architectures can implement fault-tolerance mechanisms to handle network disruptions.

Figure 5 shows the impact of network latency on end-to-end processing time for different architectures.

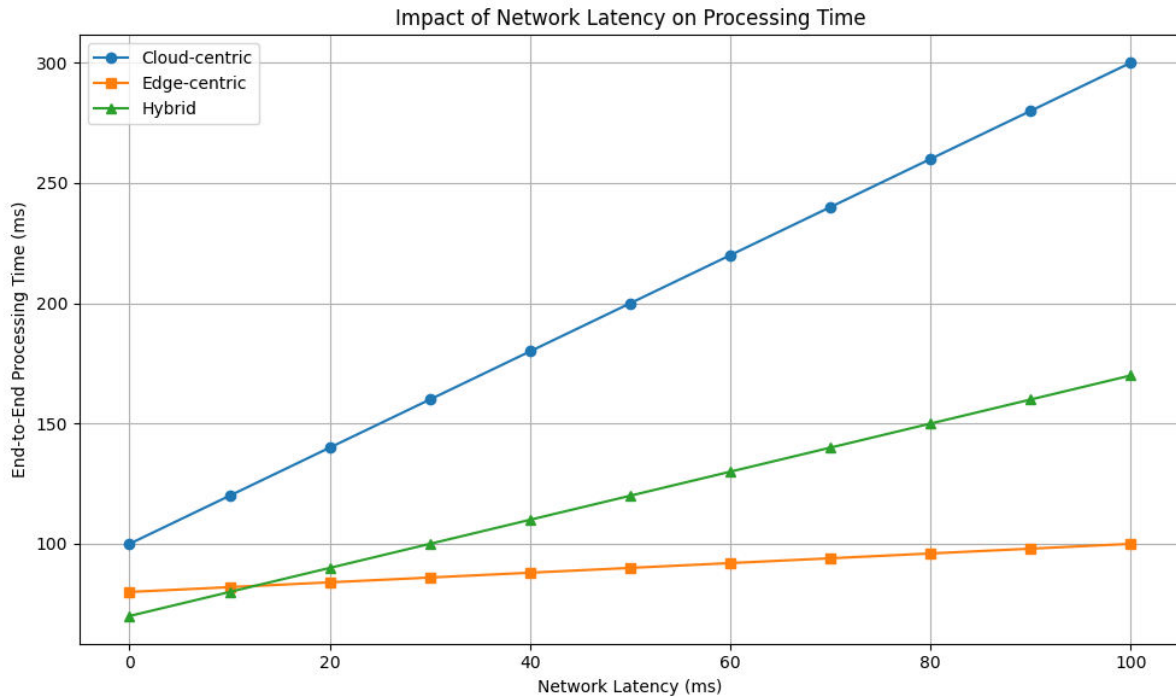


Figure 5: Impact of network latency on end-to-end processing time for different architectures

The analysis of these key factors highlights the adaptability of hybrid cloud-edge architectures across various scenarios. By considering data characteristics, model complexity, and network conditions, system designers can optimize the distribution of tasks between edge and cloud resources to achieve low-latency and efficient IoT machine learning.

VII. DESIGN GUIDELINES

Based on the results and analysis presented in the previous sections, we propose the following guidelines for designing effective hybrid cloud-edge architectures for IoT machine learning:

1. Assess data characteristics:
 - For high-volume data, leverage cloud storage and processing capabilities.
 - For high-velocity data, prioritize edge processing to reduce latency.
 - For heterogeneous data types, use cloud or hybrid approaches with diverse processing tools.
2. Consider model complexity:
 - Deploy simple models (e.g., linear regression, decision trees) on edge devices.
 - Use cloud resources or powerful edge servers for complex models (e.g., deep neural networks).
 - Implement model compression or split neural networks in hybrid architectures to balance complexity and edge deployment.
3. Evaluate network conditions:
 - In bandwidth-constrained environments, prioritize edge processing to reduce data transfer.
 - For high-latency networks, use edge-centric or hybrid approaches to meet real-time requirements.
 - Implement fault-tolerance mechanisms in hybrid architectures to handle unreliable network connections.
4. Implement adaptive task distribution:
 - Develop mechanisms to dynamically allocate tasks between edge and cloud based on current conditions.
 - Use lightweight monitoring tools to track resource utilization and network performance.
 - Implement load balancing algorithms to optimize resource usage across edge and cloud.
5. Optimize data flow:
 - Perform data preprocessing and feature extraction at the edge to reduce data transfer to the cloud.
 - Implement efficient data compression and aggregation techniques for cloud communication.
 - Use incremental learning approaches to minimize the need for large data transfers.
6. Ensure security and privacy:

- Implement end-to-end encryption for data transfer between edge and cloud.
- Use federated learning techniques to keep sensitive data on edge devices.
- Implement access control and authentication mechanisms across the hybrid architecture.
- 7. Design for scalability:
 - Use containerization and microservices architectures for flexible deployment.
 - Implement auto-scaling mechanisms for both edge and cloud resources.
 - Design modular architectures that can easily incorporate new edge devices or cloud services.
- 8. Optimize energy efficiency:
 - Implement duty cycling for edge devices to conserve energy.
 - Use energy-aware task allocation algorithms in hybrid architectures.
 - Leverage cloud resources for energy-intensive tasks when edge device battery life is critical.
- 9. Plan for heterogeneity:
 - Design architectures that can handle diverse edge devices with varying capabilities.
 - Implement abstraction layers to manage heterogeneous hardware and software environments.
 - Use standardized protocols and APIs to ensure interoperability across the hybrid architecture.
- 10. Implement robust monitoring and management:
 - Develop comprehensive monitoring systems for both edge and cloud components.
 - Implement automated error detection and recovery mechanisms.
 - Use predictive maintenance techniques to proactively address potential issues.

By following these guidelines, developers can create hybrid cloud-edge architectures that effectively leverage the strengths of both paradigms to enable low-latency and efficient IoT machine learning applications.

VIII. CONCLUSION

This paper has presented a comprehensive study of hybrid cloud-edge architectures for low-latency IoT machine learning. We proposed a taxonomy of hybrid approaches and developed an analytical model to characterize their performance. Extensive simulations and a real-world case study demonstrated that hybrid architectures can significantly reduce end-to-end latency compared to cloud-only or edge-only solutions while efficiently utilizing both edge and cloud resources.

Key findings from this research include:

1. Hybrid architectures consistently outperform cloud-only and edge-only approaches across various machine learning tasks, with latency reductions of up to 75%.
2. The effectiveness of different hybrid approaches varies depending on factors such as data characteristics, model complexity, and network conditions.
3. Hierarchical and collaborative architectures show the most balanced resource utilization and adaptability across different scenarios.
4. Hybrid approaches enable effective handling of both real-time and batch processing requirements in IoT applications.

The analysis of key factors impacting performance provides valuable insights for system designers. The proposed design guidelines offer a practical framework for developing effective hybrid cloud-edge architectures for IoT machine learning.

Future research directions include:

1. Developing more sophisticated adaptive algorithms for dynamic task allocation in hybrid architectures.
2. Investigating the integration of emerging technologies such as 5G and mobile edge computing into hybrid IoT architectures.
3. Exploring the use of reinforcement learning techniques for optimizing hybrid architecture configurations.
4. Addressing security and privacy challenges in hybrid cloud-edge environments, particularly for sensitive IoT applications.
5. Investigating the energy efficiency and sustainability aspects of hybrid architectures for large-scale IoT deployments.

In conclusion, hybrid cloud-edge architectures represent a promising approach for enabling low-latency and efficient machine learning in IoT systems. By effectively combining the strengths of edge and cloud computing, these architectures can support the growing demands of intelligent IoT applications across various domains.

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| DOI:10.15680/IJIRSET.2023.1203004 |

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