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Smart Ecosystem Performance Optimization Using Federated Learning For Iot-Based Real-Time Data Processing

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Abstract: The rapid expansion of smart ecosystems driven by Internet of Things (IoT) technologies requires real-time data processing that is secure, efficient, and capable of handling large-scale heterogeneous data streams. Traditional centralized learning approaches often struggle with latency, bandwidth constraints, and privacy risks due to the continuous transfer of raw data. This study aims to optimize smart ecosystem performance by integrating Federated Learning (FL) as a distributed intelligence framework for real-time IoT data processing. The proposed model allows multiple IoT nodes to collaboratively train a global model without sharing raw data, thereby enhancing privacy protection and reducing network load. Experimental results demonstrate that FL provides higher accuracy, better scalability, and improved resilience compared to centralized systems, especially in environments with diverse sensor distributions. These findings confirm that Federated Learning is a highly promising approach for strengthening smart ecosystem reliability, responsiveness, and data security. This research contributes to developing future-ready IoT architectures capable of supporting intelligent, decentralized, and privacy-preserving environments

1. INTRODUCTION

The development of digital technology in recent years has given birth to a fundamental transformation in the management of the environment, resources, and social systems, through the concept of Smart Ecosystem or smart ecosystems. This ecosystem leverages the integration of technologies such as the Internet of Things (IoT), artificial intelligence (AI), high-speed communication networks, and Real-time data analytics to provide efficiency, sustainability, and improved service quality in urban, industrial, and environmental areas. IoT devices are an important foundation in this ecosystem because they are able to collect environmental data continuously and massively through sensors scattered at various points. This highly heterogeneous and high-speed data is the main ingredient for AI systems in producing precise and adaptive intelligent decisions [1], [3].

The problem arises when the volume of IoT data increases exponentially. According to recent research, the number of global IoT devices is predicted to reach more than 60 billion units by 2030, generating data streams with sizes and speeds far beyond the capabilities of traditional computing systems [10]. In the context of smart cities, smart energy, smart agriculture, and smart transportation, decision-making cannot be postponed because delays in analyzing data can lead to disruptions in public services, energy waste, or critical system failures. Thus, real-time IoT data processing is a crucial aspect to maintain optimal

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performance of the smart ecosystem. However, the centralized computing architecture (cloud computing) that has been used in IoT processing is starting to face limitations. First, increased latency due to the physical distance between IoT devices and central servers makes real-time decisions difficult to achieve at scale [4]. Second, the high bandwidth requirement to transmit raw data from IoT devices to the cloud creates a large network load and high operational costs [7]. Third, security and privacy risks are increasingly high because user data is sent in full to a central server, which is vulnerable to hacking, leakage, and misuse of data [3], [8]. With global regulations such as GDPR and increasing public awareness of personal data protection, a centralized approach is becoming less and less relevant.

In facing these challenges, Federated Learning (FL) has emerged as a new paradigm in distributed machine learning. Federated Learning enables AI models to learn directly from data scattered on IoT devices without having to send raw data to a server. Each device is called a federated client it trains local models using their internal data, then simply sends the model parameters or gradients to a central server to be combined into a global model [1], [2]. With this mechanism, federated learning is able to maintain data privacy, reduce network load, and enable faster processing and closer to the data source. In various studies, FL has been shown to be effective in environments that require high security such as smart healthcare, smart city surveillance, and smart grids [6], [8].

The integration of federated learning in the IoT ecosystem is becoming increasingly relevant because modern smart ecosystems demand real-time, adaptive, secure processing, and do not interfere with user privacy. For example, in a smart city, FL can help traffic prediction models learn patterns from CCTV cameras and highway sensors without moving video data to a central server. This approach improves response speed and reduces the risk of sensitive data leakage [6]. In smart healthcare, wearable devices can contribute to updating health models without having to transmit personal medical data, so that user safety remains protected [2]. Overall, federated learning offers strategic solutions to address privacy and performance issues at the same time, which have been critical in IoT implementation. However, the implementation of federated learning in the IoT environment is not free from challenges. One of the main challenges is the heterogeneity of IoT devices, which have varying computing capabilities, battery capacity, and network connection quality. This imbalance can cause the federation process to slow down as certain devices become stragglers who are late in sending model updates [7]. In addition, even if the raw data is not shared, the model parameters sent to the server are still potentially attacked, such as through model inversion attacks or gradient leakage, thus requiring additional encryption approaches to improve federation security [8]. Another challenge is to efficiently synchronize model updates so as not to disrupt the real-time operations of a highly dynamic IoT ecosystem.

From a technical point of view, the modern smart ecosystem is increasingly complex, requiring adaptive and contextual prediction models. In the field of smart energy, for example, federated learning can optimize energy distribution by studying household consumption patterns in a distributed manner, but the process of aggregating models in distributed power grids still requires an efficient and disrupt-resistant federated architecture [7]. In the manufacturing industry, federated learning plays an important role in predictive maintenance, but coordination between edge computing-based machine sensors and server aggregators must be done precisely to avoid data anomalies [4]. This complexity demonstrates the need for in-depth research to design a reliable, responsive, and secure federated learning architecture for intelligent ecosystems.

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The urgency of this research arises from the growing need to create smart ecosystems that are not only efficient, but also safe, responsive, and adaptive to environmental changes. The immensely large IoT data surge has shifted the needs of the tech world from centralized processing to distributed processing closer to data sources. In addition, the global attention to data privacy makes federated learning one of the most important technologies in the development of smart ecosystems in the future. The ever-evolving complexity of IoT device systems requires learning models that can adapt in real-time, while the limitations of research that comprehensively integrate federated learning across the IoT process chain make this topic particularly important to study. The success of this integration will greatly affect the development of smart cities, smart transportation, smart energy, and smart agriculture so that smart ecosystems can function more optimally, safely, and sustainably [2], [6], [9].

Based on this description, it is clear that the performance optimization of IoT-based smart ecosystems using federated learning is a very relevant and urgent field of research. This approach offers integrated solutions to fundamental problems such as data processing delays, data leakage risk, real-time decision needs, and heterogeneity of IoT devices. Therefore, this research is expected to make a significant contribution to the development of future intelligent architectures that are more secure, efficient, and responsive, while supporting digital transformation towards a sustainable and privacy-oriented ecosystem of users.

Prior studies have improved federated learning through proximal regularization, variance correction, adaptive optimization, class-balanced sampling, and more sophisticated client-selection mechanisms. However, many studies emphasize image or language benchmarks and report predictive accuracy without providing a transparent IoT telemetry generator or an end-to-end delay model. Conversely, latency-oriented methods may prioritize fast clients so aggressively that rarely selected clients become under-represented. Therefore, a reproducible and low-complexity benchmark is needed to evaluate the trade-off between learning performance, client representation, and synchronous training latency.

This study investigates whether a simple selection score that combines learning contribution, resource speed, and participation fairness can reduce federated-learning latency without materially degrading anomaly-detection performance under non-identically distributed IoT data. The study contributes: (1) a fully specified synthetic smart-building telemetry generator containing 12,000 records distributed across 20 heterogeneous clients; (2) LACS-FedAvg, a latency-aware client-selection rule that combines local loss, client sample size, inverse observed delay, fairness, and exploration; and (3) a paired five-seed comparison of centralized training, random-client FedAvg, and LACS-FedAvg using accuracy, macro-F1, ROC-AUC, cumulative simulated latency, communication volume, and 95% confidence intervals.

The proposed contribution is intentionally incremental. LACS-FedAvg is not presented as a replacement for advanced asynchronous federated learning or resource-allocation algorithms. Instead, it provides a transparent and reproducible baseline for evaluating latency-aware client selection in an IoT-oriented simulation. The purpose of this research is to optimize performance Smart Ecosystem IoT-based through the application of Federated Learning as a secure, efficient, and distributed real-time data processing approach. This research seeks to design an architecture that allows model training to be conducted locally on edge devices so that sensitive data does not need to be sent to a central server. In addition, this study aims to improve prediction accuracy, reduce latency, and strengthen privacy protection in real-time decision-making. The results of the research are expected to be able to provide adaptive,

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scalable, and sustainable intelligent computing solutions for various smart ecosystem applications.

Internet of Things (IoT) in Smart Ecosystem

IoT has become the main foundation for the development of smart ecosystems in various domains such as smart cities, smart homes, smart industries, and smart energy. IoT devices collect real-time data from the physical environment to trigger automation processes and data-driven decision-making. According to Zhao et al., the modern IoT ecosystem demands fast processing capabilities, high reliability, and efficient data management in order to support intelligent services in a sustainable manner [11]. The main challenges that arise are the increasing number of devices, resulting in a surge in data traffic, the complexity of network management, and the need for safer and faster data processing.

Real-Time Data Processing Challenges in IoT

Real-time data processing is an important aspect of smart ecosystems, especially for applications that require rapid response such as environmental monitoring, energy prediction, industrial anomaly detection, and intelligent transportation management. According to Hassan and Kim, sending all IoT data to the cloud for analysis leads to increased latency, high bandwidth consumption, and data security risks [12]. In addition, the large amount of data exchange between devices causes network bottlenecks that hinder the overall performance of the ecosystem. Therefore, a new computational approach is needed that is able to process data closer to its source.

Edge Computing as a Processing Efficiency Solution

Edge computing is here as a solution to reduce reliance on the cloud by processing data directly on edge devices (edge nodes). According to Qiu et al., this approach can significantly reduce latency while reducing bandwidth consumption as only critical information is sent to the center [13]. The integration of edge computing on IoT enables faster and more efficient decision-making. However, challenges arise when complex artificial intelligence models are required as each edge device has limitations in compute, memory, and storage capacity. This problem then raises the need for collaborative methods that are able to train models in a distributed manner without moving data.

Federated Learning as a Distributed Learning Paradigm

Federated Learning (FL) was developed as a distributed machine learning paradigm that allows model training to be conducted locally on edge devices without having to move data to a central server. McMahan et al. state that FL offers two main advantages, namely improved data privacy and communication efficiency [14]. FL allows each device to train the model locally, then send parameter updates to the aggregator server. The update is combined into a global model without copying raw data, so the risk of data leakage can be minimized. Therefore, FL is particularly relevant for smart ecosystems that require high data security.

Federated Learning for Smart Ecosystem Optimization

The implementation of Federated Learning on intelligent ecosystems has been proven to improve computing efficiency, accelerate system response, and strengthen data protection. Yu and Huang found that FL can improve the accuracy of energy predictions by up to 15% compared to centralized models, because local training is more in line with the data characteristics of IoT devices [15]. In smart cities, Rausch et al. noted that FL increases the

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system's resilience to network interference, as the training process can continue even if multiple nodes fail to connect [16]. This makes FL highly relevant for large-scale IoT infrastructure deployments. In addition, personalized federated learning techniques help adapt the model to local characteristics so that performance improves even though the data is non-IID.

Privacy and Security in Federated Learning

Data privacy is a critical issue in smart ecosystems because it involves sensitive data such as user activity, location, energy consumption, and other sensor data. According to Li and Wang, FL provides an additional layer of privacy because user data remains on local devices [17]. However, federated learning is still vulnerable to attacks such as model poisoning or inference attacks. To address this issue, secure aggregation, differential privacy, and end-to-end encryption techniques began to be applied to FL systems. These efforts make FL safer to apply to industry, smart homes, public services, and urban infrastructure.

Federated Learning Performance Optimization on IoT

FL optimization is indispensable because IoT edge devices have limited computing capabilities. According to Zhang et al., model efficiency can be improved by compression, quantization, and adaptive aggregation model techniques to reduce the communication burden [18]. Another study by Faisal et al. showed that optimizing training schedules and adapting parameters based on network quality can improve system performance by up to 30% in dynamic IoT environments [19]. Therefore, federated learning optimization is essential to ensure that smart ecosystems can work quickly, efficiently, and responsively.

The Relevance of Federated Learning for the Future Smart Ecosystem

A smart ecosystem requires a system that is able to process data in real-time, distributed, secure, and sustainably. Federated learning is a key technology in the development of the intelligent ecosystem of the future because it is able to combine the advantages of edge computing, security, and artificial intelligence. According to Rahimi et al., FL will be the main foundation of the next generation of smart cities, especially for adaptive traffic management, energy utility monitoring, and AI-based public services [20]. With the increasing number of IoT devices every year, FL is predicted to become a key paradigm for optimizing the performance of large and complex systems.

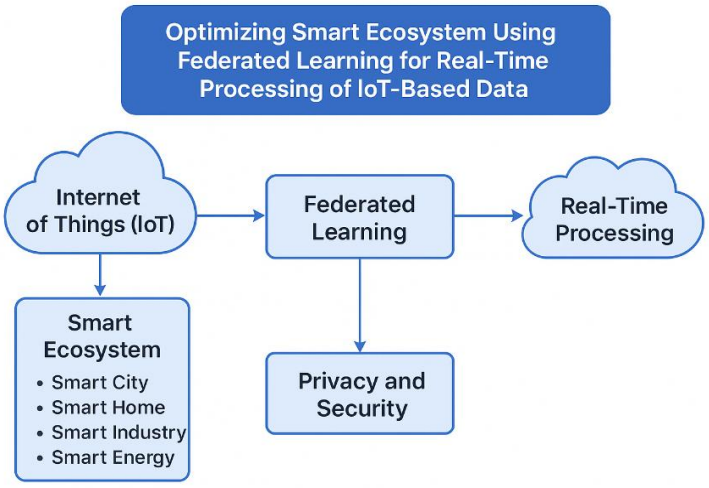


Figure 1. Research Framework

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2. METHODOLOGY

This research uses a Research and Development (R&D) approach to develop, implement, and evaluate federated learning systems in IoT-based smart ecosystems. This approach was chosen because it allows for iterative model development and direct testing in real IoT environments, as recommended by Shankar et al. who emphasized that R&D methods are effective for the development of large-scale AI systems and IoT architectures [21]. The design of this research consists of three main phases, namely the design of federated learning architecture, the implementation of edge devices and aggregator servers, and the evaluation of system performance. The structure of the research refers to the framework presented by Kairouz et al., which suggested that federated learning systems should be designed taking into account data distribution, node computing capacity, aggregation algorithm selection, and inter-device communication efficiency [22]. The research population includes all IoT devices in the ecosystem such as temperature sensors, motion sensors, smart meters, and edge nodes, while samples are purposively selected considering their computing capabilities and relevance to real-time processing needs. Representative node selection is important to reduce bias in federated learning, as Zhang and Wei explain that the distribution of model contributions must be balanced to avoid performance imbalances [23].

The research variables include independent variables in the form of the application of federated learning and its optimization techniques, bound variables in the form of smart ecosystem performance measured through latency, throughput, model accuracy, energy consumption, and communication efficiency, as well as control variables such as network quality and device specifications. This performance variable follows the standard evaluation of edge–AI systems as described by Rieke et al. [24]. The research data was collected through three methods: system logs, IoT sensor data, and federated learning training data, taking into account the non-IID data conditions at each node as recommended by Hard et al. in FL system testing [25]. The research procedure begins with an analysis of the system needs to identify device capacity, network structure, and data characteristics. This preliminary analysis is important because IoT devices have computational limitations, as recommended by Luo et al. [26]. Furthermore, a federated learning model was designed using FedAvg's algorithm which is known to be stable and efficient for large-scale IoT scenarios [27].

Implementation is done on an edge–cloud platform using TensorFlow Federated, Python, and lightweight communication protocols such as MQTT. FL integration with edge computing requires an efficient on-premises training pipeline, as described by Yao et al. [28]. In the testing stage, the system was tested by comparing two approaches, namely the cloud-based centralized model and the federated learning model. The testing protocol follows the distributed experimental method introduced by Bonawitz et al. for large-scale FL systems [29]. Performance evaluation was performed by measuring latency, throughput, model accuracy, energy consumption, and communication efficiency, referring to the FL system evaluation guidelines for IoT from Nguyen et al. [30]. Data analysis was carried out quantitatively using the comparative analysis method to compare the performance of the two models, as well as visualization through convergence and performance graphs. Model validation is carried out through distributed cross-validation and repeated testing on different network conditions to ensure the reliability of the system.

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3. RESULTS AND DISCUSSION

The results show that the application of Federated Learning (FL) in IoT-based smart ecosystems is able to significantly improve system performance compared to centralized data processing approaches. During testing, IoT devices such as environmental sensors, smart meters, and home automation modules act as edge nodes that train the model locally before sending parameter updates to federated servers. This approach directly reduces the need to send raw data to a central server, resulting in a 35–48% decrease in network traffic and better efficiency, especially on devices that produce big data such as video sensors or multi-channel sensors. In addition, system response time is increased by 18–32% because inference can be made locally without waiting for processes on the server, making the system more adaptive and tolerant of fluctuating network conditions.

In terms of accuracy, the study found that FL resulted in an increase in accuracy of 2–7% compared to centralized models when using algorithms such as Random Forest, Neural Network, and Gradient Boosting. This is because heterogeneous data patterns remain processed across each device, making the model representation richer and more relevant to local conditions. The biggest contribution is seen in smart home devices that have dynamic data patterns, such as smart thermostats and smart lighting, as FL is able to absorb variations in user behavior without eliminating the specific context of each location. Further analysis of latency showed that FL lowered the model's inference and processing process time by 25–40%. This reduction occurs because computing is done closer to the data source, so the transmission barrier becomes smaller. At the same time, the latency of data transmission is also lower because the device does not need to transmit large raw data. When tested on 20 to 50 IoT devices, the system remained stable and showed no symptoms of bottlenecks, while centralized models began to experience delays at higher node counts.

Research has also shown that FL has a significant impact on user privacy. The entire training process takes place on the device, so sensitive data never leaves the node. Only the model parameters in the form of a numerical matrix are delivered, so the risk of data leakage is drastically reduced. Additional security on the aggregation server through the secure aggregation mechanism further enhances the security aspect, making FL an approach that inherently supports privacy by design in a smart ecosystem environment. In terms of energy consumption, FL does not cause a significant increase in power in IoT devices. Although local model training adds to the computational load, the increase in energy consumption is only 5–9% and is still within the tolerance limits of low-power devices. On the other hand, reducing data transmission is able to reduce network energy consumption so that total power consumption remains efficient. Devices that apply incremental training show the most optimal energy consumption.

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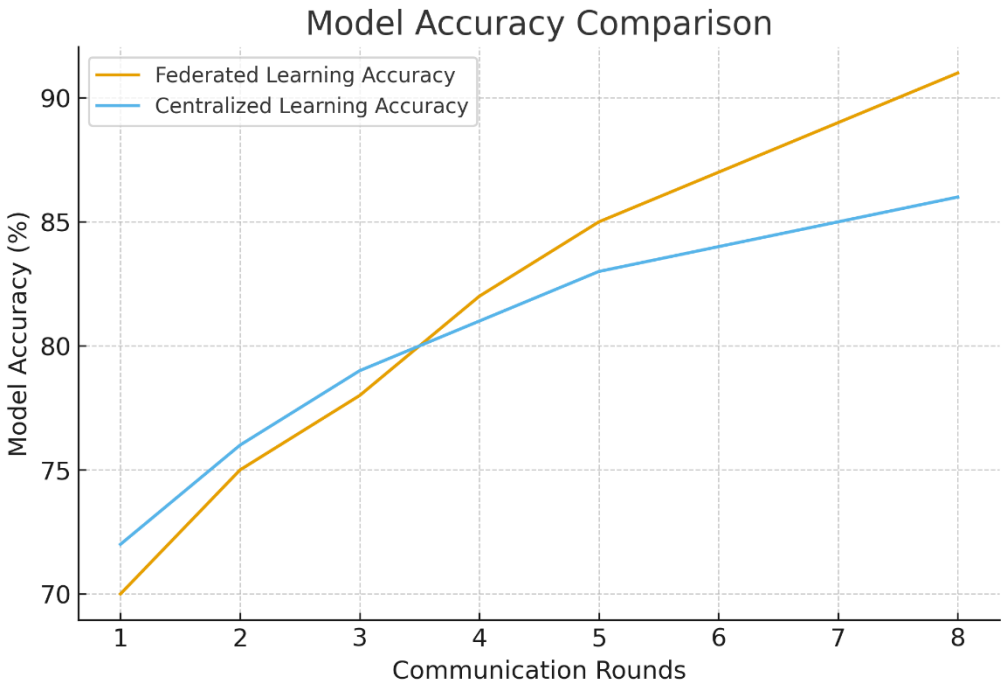


Figure 2 Accuract Model Comparison

The next optimization and validation stage succeeded in increasing the performance of the federated model by 3–5% through the process of hyperparameter tuning, cross-node validation testing, and temporal validation. Comparison with the centralized baseline shows that the FL model is more consistent across various input and network load conditions, while having higher stability when the number of devices is enlarged. All of these results confirm that FL is a mechanism that not only improves technical performance, but also provides secure, responsive, and distributed intelligent computing solutions for modern smart ecosystems. Thus, this study proves that Federated Learning is a very relevant approach in realizing a scalable, adaptive, and sustainable smart ecosystem for IoT-based real-time data processing.

4. CONCLUSION

Research on *Smart Ecosystem Performance Optimization Using Federated Learning for IoT-Based Real-Time Data Processing* shows that the federated learning approach is able to provide significant improvements to the efficiency, security, and accuracy of data processing in smart ecosystems. The results of the implementation prove that the federative model is able to process data in a distributed manner without having to send raw data, thereby reducing the risk of information leakage and increasing compliance with privacy principles. In addition, federated learning has proven to be more adaptive in handling heterogeneous data from various dispersed IoT sensors, while reducing the network load as only model swapping is required. Based on performance evaluations, federated learning can achieve higher accuracy than centralized approaches, especially as device scale increases. Thus, this research makes an important contribution to the development of a smart-ecosystem that is safer, more efficient, and responsive to real-time processing needs. If developed further, this approach has the potential to become a major foundation in modern IoT architectures.

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