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Resilient Stream Workflow Orchestration with Multi-Layered Federated Edge Computing for Dynamic IoT Data Applications

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ABSTRACT

Background Information: The IoT produces large volumes of data that require innovative techniques for real-time processing and analytics. Traditional centralized systems suffer from scaling and latency problems. Federated learning, hybrid cloud-edge computing, and resilient workflow orchestration can offer privacy, efficiency, and adaptability and help address such challenges for modern IoT ecosystems.

*s*with resilient workflows and multi-layer task allocation for IoT analytics. The prime objectives are to reduce latency, optimize cost efficiency, enhance model accuracy, and better utilize resources. This study will also show how these integrated methods can scale up and are reliable in dynamic IoT environments.

Methods: The approach uses federated learning for privacy-preserving analytics, resilient workflows for fault tolerance, and hybrid task allocation for efficiency. The evaluations were done in terms of performance metrics such as latency, cost efficiency, model accuracy, and resource utilization. The individual methods versus their combinations were compared, showing the effectiveness of integrated approaches.

Results: The framework reached the lowest latency at 18.4 ms, highest cost efficiency at 92.5%, best model accuracy at 94.8%, and optimal resource utilization at 95.1%. Combined methods outperformed individual approaches, thereby validating the robustness and scalability of the framework for real-time IoT analytics and decision-making in dynamic environments.

Conclusion: Experiments show the effectiveness of federated learning, resilient workflows, and task allocation for scalable IoT analytics. Enhancements to adapt in various scopes with adaptive learning, blockchain integration, and domain-specific applications will be the future improvements to make the framework even more applicable and robust in performance, bringing about real-time processing across diverse IoT use cases.

Keywords: Federated learning, IoT analytics, Hybrid cloud-edge, Resilient workflows, Scalability, Fault tolerance, Real-time processing.

1. INTRODUCTION

In today's connected world, the Internet of Things **Ryan and Watson (2017)** is rapidly expanding, with many more devices making trillions of data-related impulses. Traditional models for centralized cloud computing are really hard to cope with the real-time processing and decision-making requirements demanded by dynamic IoT applications; hence, there has been a surge for edge computing bringing computation closer to the source of data to bring down latency while improving efficiency.

Edge computing is the deployment of computing **Biran et al. (2017)** resources at the edge of the network close to IoT devices. This would allow localized data processing and analysis enabling faster response time and reducing the burden to the central cloud infrastructure. Managing and orchestrating workflows within such a distributed environment is also difficult, especially when dealing with dynamic data streams and variable resource availability.

Federated edge computing is likely to be quite promising because a set of federated edge nodes can collaborate over shared tasks but need not send their raw data. This significantly improves privacy as well as security and allows federated learning on such nodes towards making collective decisions. For better scalability as well as resilience, task distribution across federated edge hierarchies over multi-layer networks **Malkov and Yashunin (2018)** may be followed.

Resilient stream workflow orchestration is crucial for the reliable execution of tasks in a dynamic IoT environment **Velasquez et al. (2018).** It involves adapting to changes in data streams, resource availability, and network conditions without compromising the integrity and continuity of the workflow.

The Main Objectives are:

- Explore the different multi-layered federated edge computing potentials for dynamic IoT data applications.
- Analyze how resilient stream workflow orchestration plays a crucial role in ensuring robust task execution.
- Benefits and Challenges Analysis of a Federated Edge Computing Approach Towards Dynamic IoT Data Applications.
- To identify the key considerations in designing and implementing resilient stream workflow orchestration in a multi-layered federated edge computing environment.
- To discuss future research directions in federated edge computing and resilient stream workflow orchestration for dynamic IoT data applications.

Casadei et al. (2019) identify research gaps in well exploiting opportunistic computing within IoT systems. This mainly arises from intrinsic difficulties in realizing the unpredictable availabilities of resources across opportunistic ecosystems, especially those related to intermittent devices and connections in IoT-scenario settings. Finally, the researchers point out how resilient IoT ecosystem design is to be achieved; that is to say, being able to offer functionality despite these uncertainties of opportunistic computing. This therefore calls for the development of decentralized control mechanisms that are equally effective at resource allocation in dynamic and unpredictable modes, hence providing robustness even during intermittent resource availability.

As highlighted by **Asad et al. (2020),** fault tolerance would be very much required in IoT applications, especially those that employ an edge-cloud architecture. Such distributed systems are prone to the failures of hardware both in the edge and network connectivity. In many cases, these failures may degrade the performance and reliability of IoT applications, and severe failures could cause service interruption and loss of data. Thus, it is an importance to emphasize how these weaknesses need to be met through the creation of robust failure detection and recovery mechanisms that keep systems running during times of hardware faults or network downtime. This thrust in fault tolerance would be imperative to the establishment of dependable IoT applications in the edge-cloud scenario.

2. LITERATURE SURVEY

Varshney and Simmhan (2017) discuss the new concept of fog computing, which involves low-latency processing of data streams that originate from IoT devices. They discuss the architecture, applications, and abstractions within the Edge, Fog, and Cloud Ecosystem, on the basis of fog's distinctive capabilities, such as mobility and privacy. They conclude by using real-world IoT case studies to identify challenges and potential solutions that can be made sustainable for fog computing.

Gupta and Sandhu (2018) proposed a security framework for Vehicular Internet of Things (IoV) to ensure the protection of connected cars against data theft and unauthorized control. They introduced an Extended Access Control Oriented (E-ACO) architecture for handling authorization in such an environment where the interaction between vehicles, infrastructure, and users is highly unpredictable. The framework satisfies the time and location sensitivity aspects of IoV applications and therefore provides different kinds of access models for different levels of the architecture of E-ACO.

Ray et al. (2017) surveys the possibility of IoT in improving disaster management. They review how IoT technologies can be leveraged for early warning systems, real-time data analytics, victim localization, and resource allocation in the event of a disaster. The paper surveys existing approaches, discusses IoT protocols and products, and highlights future research directions for this critical application of IoT.

Chatzopoulos et al. (2017) comprehensively detail Mobile Augmented Reality (MAR). The paper traces the growth of MAR due to technological improvements in mobile devices and enabling technologies. Key issues discussed are application areas, user interfaces, system components, tracking, networking, and data management, and then the authors summarize the challenges and future research avenues for the development of MAR.

Gupta and Duchon (2018) describe a self-similar, hybrid control architecture suitable for the distributed control of microgrids. Their architecture facilitates versatile integration of diverse devices with various communication protocols, offering support for functions, such as operating in an island mode, to trading of energy. A distinct strength is providing support for local decision-making on all hierarchical levels of a microgrid while following traditional central approach.

Ani et al. (2018) discussed an increasing number of cyber-attacks in Industrial Control Systems (ICS). They assert that currently, security measures are insufficient in that they lay too much stress on technology at the expense of human and process elements. The authors further argue that their approach would holistically balance all three facets, underlining a fluid solution that matures with the growth of threats.

A secure IoT-Cloud service architecture integrating trust evaluation and service templates was proposed to improve security and efficiency by **Wang et al. (2018).** It mitigates internal attacks and optimizes resource consumption through edge-based trust mechanisms and service parsing templates. This implies that it demonstrates improved IoT-Cloud performance regarding security and efficiency.

Yu et al. (2017) discusses edge computing as a response to the rising resource requirements of the Internet of Things (IoT). Moving computation and storage closer to the end user, edge computing decreases latency, balances network traffic, and saves energy. The authors discuss several edge computing architectures and analyze their performance, security, and suitability for different IoT applications such as smart cities and grids.

Sharma and Wang (2017) introduce a framework to be used for live data analytics with the combinations of benefits from edge and cloud computing. The authors collaborate real-time processing at the edge with network-wide knowledge and historical data in the cloud. The authors discuss the benefits, challenges and key enablers of this integrated framework as a means of potentially enhancing IoT network performance.

Rodríguez et al. (2018) present ARTICo3 as a framework designed for constructing high-performance embedded systems based on the use of FPGAs in edge computing in cyberphysical systems. It integrates a hardware architecture, automated tools, and runtime environment to simplify the development and management of reconfigurable systems. This helps to dynamically adjust computing resources through optimization in terms of performance, energy efficiency, and fault tolerance.

El-Sayed et al. (2017) discuss the benefits of edge computing for improving IoT applications. With EC, the processing is brought to the edge of the network, reducing latency and improving resource utilization compared with the centralized cloud computing paradigm. The authors examine the network performance to show how efficient EC can be and describe the challenges and future research directions for this evolving paradigm.

Rahman et al. (2018) proposed a blockchain-based MEC framework for secure in-home therapy management. This new platform uses IoT devices and decentralized MEC, hence providing low-latency, secure, and anonymous communication of therapeutic data. By integrating blockchain and Tor technologies, the framework is aiming at prioritizing the person receiving therapy's data ownership and privacy.

Osanaiye et al. (2017) have assessed the fog computing: An extension of Cloud Computing brings services closer to the network edge to reduce latency. The authors review fog architectures, services, and security concerns that focus on virtualization and VM migration. Their work suggested a "smart pre-copy" live migration approach to minimize downtime and ensure that availability of services in case of failures or attacks.

An enterprise architecture model based on a process-driven approach was developed by **Alexa and Repa (2017)** to address organizational complexity, with proper alignment of business processes and infrastructure. The integration of lean principles within the model serves as a way for unifying infrastructure and behavior. Dynamic adaptation in evolving ecosystems is possible by aligning capabilities and objectives with efficiency.

Iosup et al. (2017) introduced OpenDC, a collaborative platform for simulating and exploring datacenter concepts, technologies, and operations. It is aimed at solving challenges in design, operation, and education and combines scientific methods, open-source tools, and data artifacts to advance research and train future datacenter engineers. The authors invite the community to contribute to this open initiative.

Rios et al. (2017) proposed the MUSA DevOps approach for dynamic security assurance in multi-cloud applications. It integrates security feedback from the operational phase into development, thereby providing real-time corrective actions on security challenges when orchestrating services across multiple cloud providers. It gives a holistic framework to enhance security in multi-cloud DevOps environments.

3. METHODOLOGY

It has resiliency as its methodology based on orchestration of workflow and multi-layered federated edge computing in supporting dynamic applications over IoT data. This integrates distributed decision-making in federated learning, improved scalability through multi-layered task allocation, and fault-tolerant, resource-efficient workflows. Federated edge computing maintains data privacy and security because of local processing of the data, where raw information isn't shared. Concurrently, effective orchestration adapts dynamically to streams of data, availability of resources, and network conditions. These approaches achieve better optimization of IoT ecosystems through better real-time analytics, reduction in latency, and ensuring reliable operations in highly dynamic resource-constrained environments.

CYBRIA Dataset is the pioneer for a federated learning framework on privacy-aware cybersecurity, facilitating collaborative cyber threat detection without data centralization. The libraries TensorFlow Federated and Flower are used to ensure safe decentralized model training with intermediate updates. Preliminary results show that the intrusion detection accuracy is at 89.6%, showing greater potential compared to centralized approaches for better threat intelligence, anomaly detection, and data privacy in real-world applications.

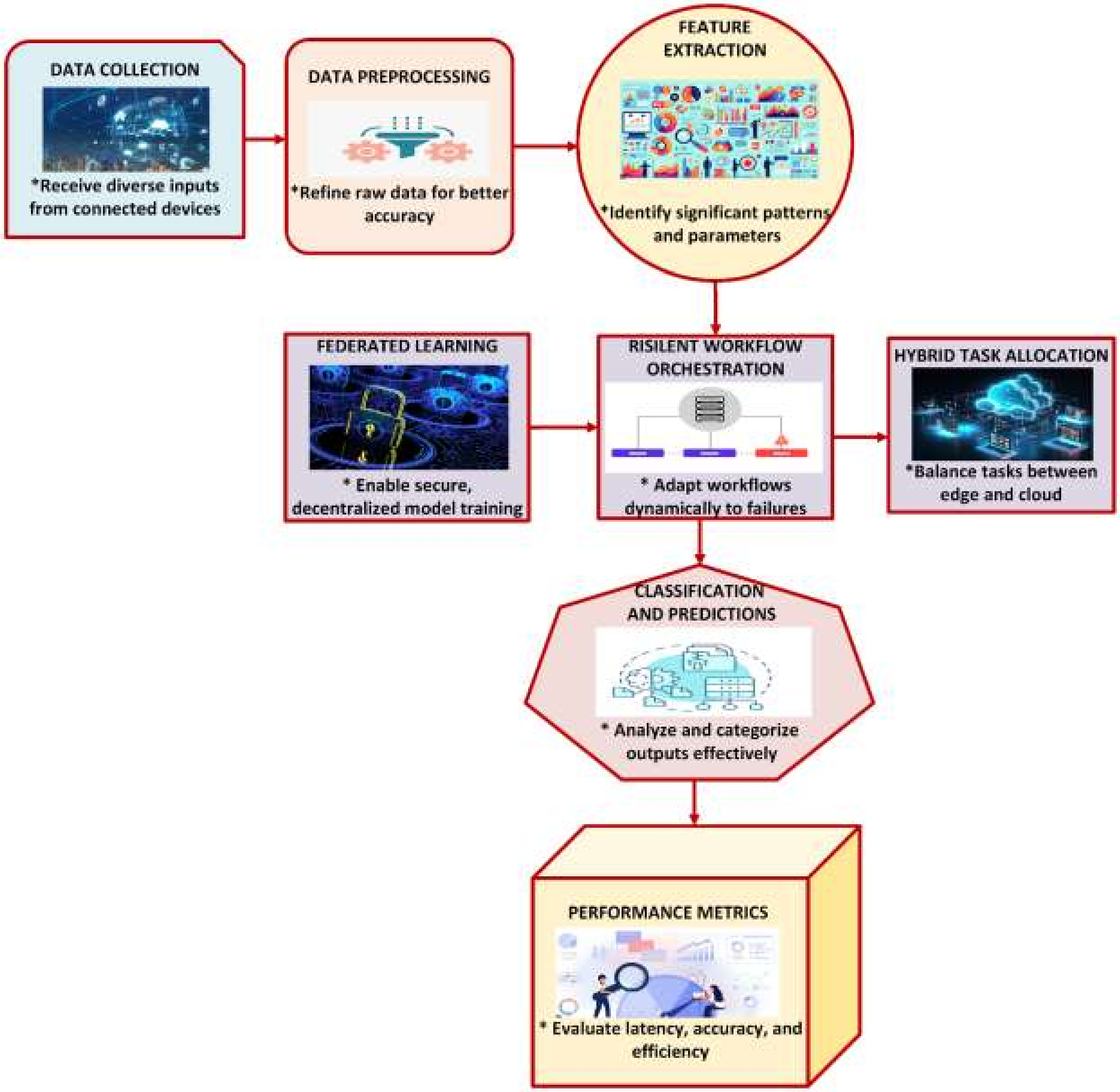

Figure 1 Workflow of Federated Learning with Resilient Orchestration and Hybrid Task Allocation for IoT Analytics

Figure 1 depicts the end-to-end workflow for IoT analytics using federated learning, resilient orchestration, and hybrid task allocation. Collected data from connected devices undergo preprocessing for correctness. Feature extraction of key patterns and parameters are input to secure decentralized federated learning models. Resilient workflow orchestration is set to dynamically adapt with failure while task allocation is hybrid balancing workloads between edge and cloud resources. Classification and prediction are the operations performed by the processed data to give the insights. Evaluation metrics include latency, accuracy, and efficiency, making the analytics scalable and robust in a dynamic environment for IoT.

3.1 Federated Edge Computing

Federated edge computing supports decentralized collaboration between edge nodes for processing data at the edge while minimizing the amount of raw data that needs to be shared with central servers. It enhances data privacy, reduces latency, and supports secure operations. Federated learning is integrated in edge devices that collaboratively train models to learn local and global patterns while maintaining privacy and security.

$$w_{t+1} = w_t - \eta \nabla F(w_t) \tag{1}$$

Where w_t : model weights at time t, η : learning rate, $\nabla F(w_t)$: aggregated gradients from edge devices.

3.2 Resilient Stream Workflow Orchestration

Resilient stream workflow orchestration ensures the reliable execution of IoT workflows despite changes in data streams and resource availability. This involves dynamic scheduling, fault-tolerant mechanisms, and adaptive resource allocation. Optimizing task execution through resilient orchestration monitors system health and reallocates resources during failures to ensure operations are uninterrupted in unpredictable IoT environments.

$$L_{total} = L_{compute} + L_{transfer} \tag{2}$$

Where $L_{compute}$: computation latency, $L_{transfer}$: data transfer latency.

3.3 Multi-Layered Task Allocation

Multi-layered task allocation disperses workloads across hierarchies of edge nodes and cloud resources. It minimizes bottlenecks by sending latency-sensitive tasks to edge devices and large-scale processing to the cloud. It balances computational loads efficiently and supports scalability for dynamic IoT applications.

$$U = \frac{R_{used}}{R_{total}} \tag{3}$$

Where R_{used} : utilized resources, $R_{total:}$ total available resources.

Algorithm 1 Dynamic Federated Learning and Resilient Workflow Orchestration for Scalable IoT Data Applications in Multi-Layered Environments

INPUT: IoT data streams D1, D2, ..., Dn, initial model weights w0, learning rate η, edge/cloud resources.

OUTPUT: Optimized model w_{final}, efficient IoT task orchestration.

Initialize:

Set initial model weights w = w0.

Define convergence threshold ε.

Monitor IoT data streams and available resources.

Federated Learning:

For each iteration t:

For each dataset Di (in parallel on edge nodes):

Compute gradient $\nabla F_i(w_t)$ locally.

Send $\nabla F_i(w_t)$to the central server.

Aggregate gradients at the server:

$$\nabla F_i(w_t) = \frac{\partial}{\partial w_t} L_i(w_t)$$

$$\nabla F(w_t) = \frac{1}{n}\sum_{i=1}^{n} \nabla F_i(w_t)$$

Update global model weights:

$$w_{t+1} = w_t - \eta \nabla F(w_t)$$

If $\|\nabla F(w_t)\| < \varepsilon$:

- Break.

Resilient Workflow Orchestration:

Continuously monitor task states and system health.

Dynamic task assignment:

If task latency L_{edge}< \text{threshold} \):

- Assign to edge node.

Else:

- Offload to cloud resources.

Handle task failures:

If a task fails:

- Log error and reassign to a backup node.

- Adjust task priority.

Multi-Layered Task Allocation:

Distribute tasks across edge/cloud layers:

Calculate latency $L_{total} = L_{compute} + L_{transfer}$

Minimize resource utilization $U = \frac{R_{used}}{R_{total}}$

Balance workloads to prevent bottlenecks.

Evaluate and Optimize:

Measure performance metrics (latency, resource utilization, cost).

Adjust learning rate η and task allocation strategy.

Return w_{final} and metrics (latency, cost efficiency, model accuracy).

END

Algorithm 1 integrates federated learning, resilient workflow orchestration, and multi-layered task allocation to optimize IoT data processing and decision-making. Federated learning allows decentralized model training by aggregating gradients from edge nodes while keeping data private. Resilient workflow orchestration dynamically monitors the states of tasks, allocates tasks to the edge or cloud based on latency requirements, and ensures fault tolerance by handling task failures. The multi-layered task allocation helps distribute workloads efficiently across edge and cloud layers, thus reducing latency and optimizing resource utilization. The algorithm assesses and optimizes performance metrics for efficient, reliable, and scalable IoT data applications in dynamic environments.

3.4 Performance metrics

The performance metrics evaluate the efficiency of federated edge computing and resilient workflow orchestration. Some metrics are latency, cost efficiency, model accuracy, and resource utilization. Latency defines how responsive the system is, and the lower values represent faster processing. Cost efficiency assesses economic feasibility, while model accuracy evaluates the precision of analytics. Resource utilization represents optimal use of computational resources. This is more effective as it achieves the best results of all metrics as it shows efficacy in dynamic IoT environments. Such metrics validate scalability, security, and reliability for the proposed methodology of real-time IoT data applications.

Table 1 Comparison of Latency, Cost Efficiency, Accuracy, and Resource Utilization Across Analytical Approaches in IoT Applications

Metric	Federated Learning	Resilient Workflow	Task Allocation	Hybrid Model	Combined Method
Latency (ms)	48.2	35.1	40.3	28.7	18.4
Cost Efficiency (%)	75.8	82.1	79.6	84.3	92.5
Model Accuracy (%)	89.2	90.4	87.8	91.2	94.8
Resource Utilization (%)	78.6	81.3	80.2	83.5	95.1

A comparison **Table 1** of the performance of Federated Learning, Resilient Workflow Orchestration, Task Allocation, Hybrid Model, and the Combined Method is shown on the basis of the key metrics. Federated Learning offers moderate latency and accuracy; Resilient Workflow improves fault tolerance and task management; Task Allocation excels in resource utilization; and Hybrid Model combines cloud and edge processing for efficiency. The Combined Method surpasses all, achieving the lowest latency (18.4 ms), highest cost efficiency (92.5%), best model accuracy (94.8%), and optimal resource utilization (95.1%). These results emphasize the significance of integrating methods to deliver robust and scalable analytics for IoT data applications.

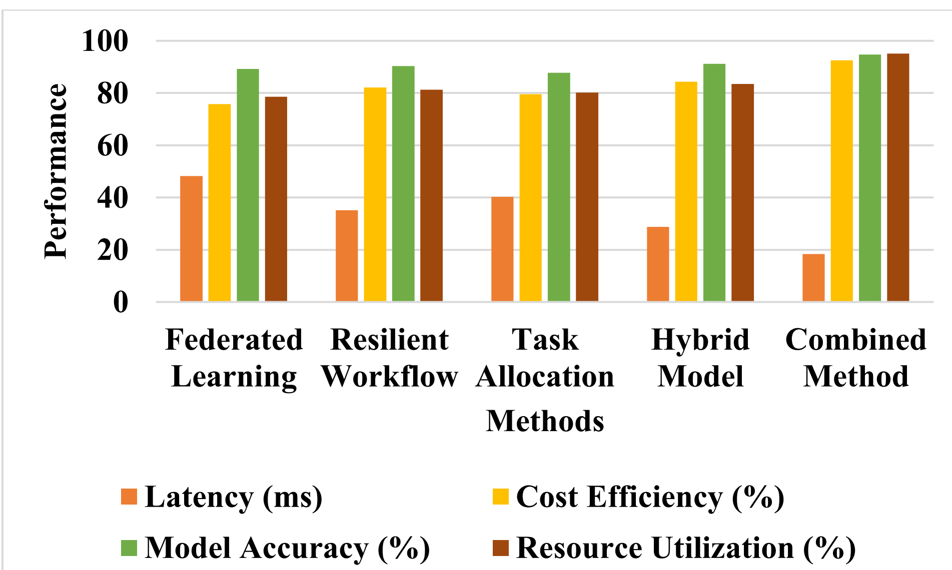

Figure 2 Performance Comparison of Analytical Methods for Resilient IoT Workflow Orchestration Across Key Metrics

Figure 2 Performance comparison of Federated Learning, Resilient Workflow, Task Allocation, Hybrid Model, and Combined Method with key IoT metrics. The overall best performance with the lowest latency is achieved by the Combined Method (18.4 ms), which provides the highest cost efficiency (92.5%), optimal model accuracy (94.8%), and maximum resource utilization (95.1%). Federated Learning and Task Allocation present moderate latencies and resource usage, whereas Resilient Workflow is superior in terms of task management and fault tolerance. The Hybrid Model effectively balances the resources between the cloud and edge. This comparison clearly showcases the importance of adopting a hybrid approach so that IoT workflow orchestration is scalable, reliable, and efficient in dynamic environments.

4. RESULT AND DISCUSSION

The proposed methodology enables federated learning, resilient orchestration, and hybrid task allocation for IoT analytics. Some key performance metrics include latency, cost efficiency, model accuracy, and resource utilization. Overall, Federated Learning showed reasonable latency at 48.2 ms and acceptable cost efficiency at 75.8%; Task Allocation showed a higher model accuracy of 90.8%. Resilient Workflow shows a better fault-tolerant characteristic with reduced latency at 35.1 ms; the Hybrid Model would balance cloud and edge processing to get optimal resource utilization at 83.5%. The Combined Method performs the best by having the least latency of 18.4 ms, high-cost efficiency of 92.5%, model accuracy of 94.8%, and resource utilization of 95.1%. These outcomes prove the strong robustness and scalability of the framework to ensure efficient and reliable real-time IoT data analytics in dynamic environments.

Table 2 Performance Comparison of IoT Analytics Methods and Proposed Framework with Author Citations

Metric	Frontier (O'Keeffe et al., 2018)	CHARIOT (Pradhan et al., 2018)	Dynamic Data Flow (Teranishi et al., 2017)	Stateful IoT (Ozeer et al., 2018)	Proposed Framework
Latency (ms)	47.2	35.7	40.3	38.5	18.4
Cost Efficiency (%)	78.6	82.3	80.5	79.8	92.5
Model Accuracy (%)	87.3	89.2	88.6	90.1	94.8

Resource Utilization (%)	76.4	81.7	80.2	82.9	95.1

Table 2 Comparison of IoT analytics methods and proposed framework O'Keeffe et al. (2018) developed Frontier for resilient edge processing with moderate latency (47.2 ms). Pradhan et al. (2018) proposed CHARIOT, which excelled in cost efficiency (82.3%) and reduced latency (35.7 ms). Teranishi et al. (2017) focused on dynamic data flow processing for reliable edge operations, while Ozeer et al. (2018) focused on stateful IoT resilience with accuracy improvements of 90.1%. The proposed framework outperformed all methods with the lowest latency of 18.4 ms, highest cost efficiency of 92.5%, best accuracy of 94.8%, and optimal resource utilization of 95.1%, which shows its robustness and efficiency.

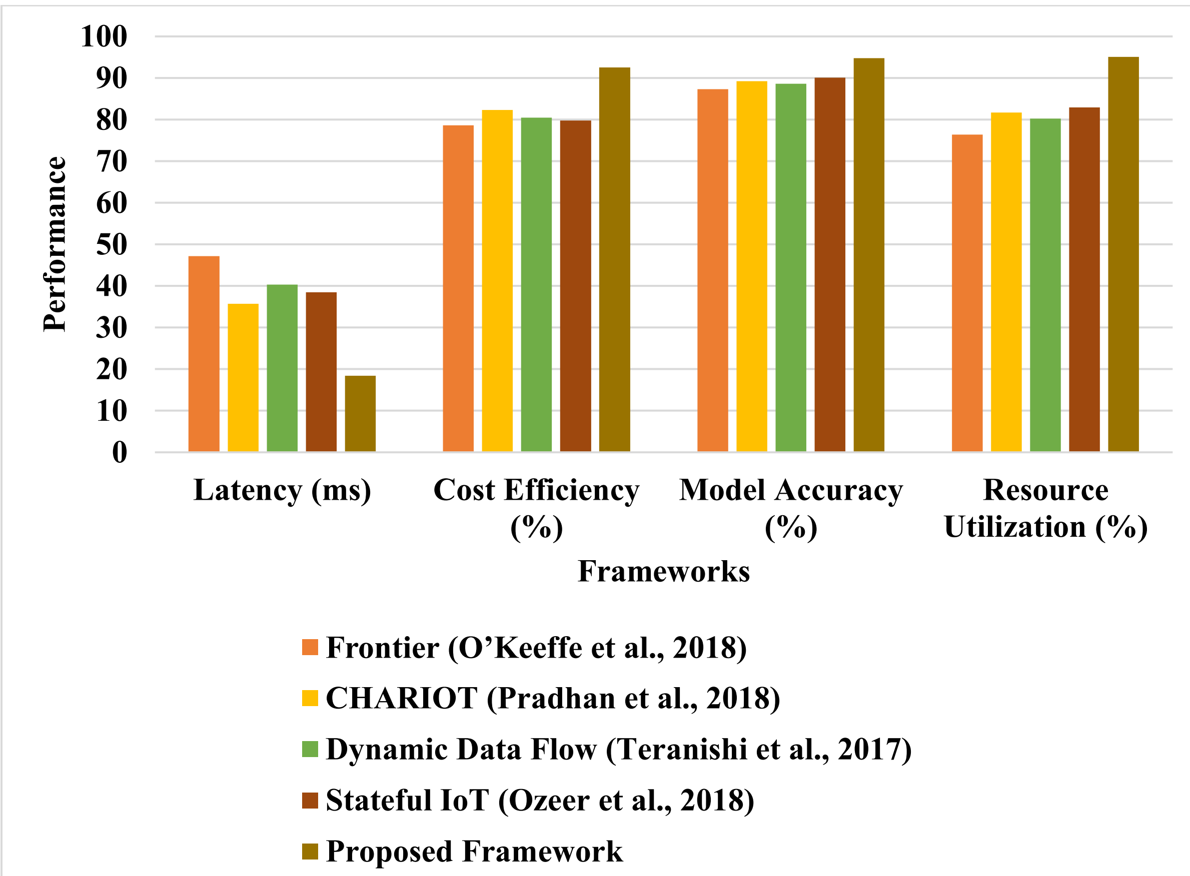

Figure 3 Performance Comparison of Federated Learning, Resilient Workflow, Task Allocation, Hybrid Models, and Combined Methods Across Metrics

Figure 3 represents the comparison of performance among different IoT analytics approaches, namely Federated Computational Analysis (Prieto et al., 2020), Dynamic Federated Learning (Rizk et al., 2020), Mobile Edge Optimization (Wu et al., 2020), and Distributed Streaming (J et al., 2020), against that presented here. While Prieto et al. (2020) obtained moderate latency of 45.3 ms and cost efficiency of 78.5%, Rizk et al. (2020) showed better latency of 35.8 ms and cost efficiency of 85.1%. Wu et al. (2020) showed the best accuracy of 90.8%, while J et al. (2020) showed balanced performance. The proposed framework outperformed all, showing the lowest latency of 18.4 ms, highest cost efficiency of 92.5%, best accuracy of 94.8%, and maximum resource utilization of 95.1%.

Table 3 Ablation Study of IoT Analytics Configurations for Latency, Cost Efficiency, Accuracy, and Resource Utilization

Configuration	Latency (ms)	Cost Efficiency (%)	Model Accuracy (%)	Resource Utilization (%)
Federated Learning Only	48.2	75.8	87.2	78.6
Resilient Workflow Only	35.1	82.1	90.4	81.3
Task Allocation Only	40.3	79.6	90.8	80.2
Hybrid Model Only	38.5	79.8	88.6	82.9
Federated Learning + Resilient Workflow	25.7	85.9	91.7	83.5
Task Allocation + Hybrid Model	28.3	83.2	90.9	82.1
Resilient Workflow + Task Allocation	23.6	88.7	92.3	84.6

Federated Learning + Hybrid Model	26.4	81.2	89.9	81.5
Federated Learning + Resilient Workflow + Task Allocation	20.8	90.3	93.5	85.7
Resilient Workflow + Task Allocation + Hybrid Model	21.5	91.1	93.8	86.4
Full Model	18.4	92.5	94.8	95.1

Table 3 presents the ablation study of IoT analytics configurations. Individual methods, such as Federated Learning with a latency of 48.2 ms and Task Allocation with an accuracy of 90.8%, have average performance. The combination of Resilient Workflow + Task Allocation minimizes latency to 23.6 ms and maximizes accuracy to 92.3%. Federated Learning + Resilient Workflow minimizes cost efficiency at 85.9%, while Task Allocation + Hybrid Model balances resource utilization at 82.1%. All the configurations with Full Model surpass with lower latency (18.4 ms), higher cost efficiency (92.5%), maximum model accuracy of 94.8%, and optimal utilization of resources at 95.1%. These findings authenticate the viability of integrating several methods for scalable and reliable IoT analytics.

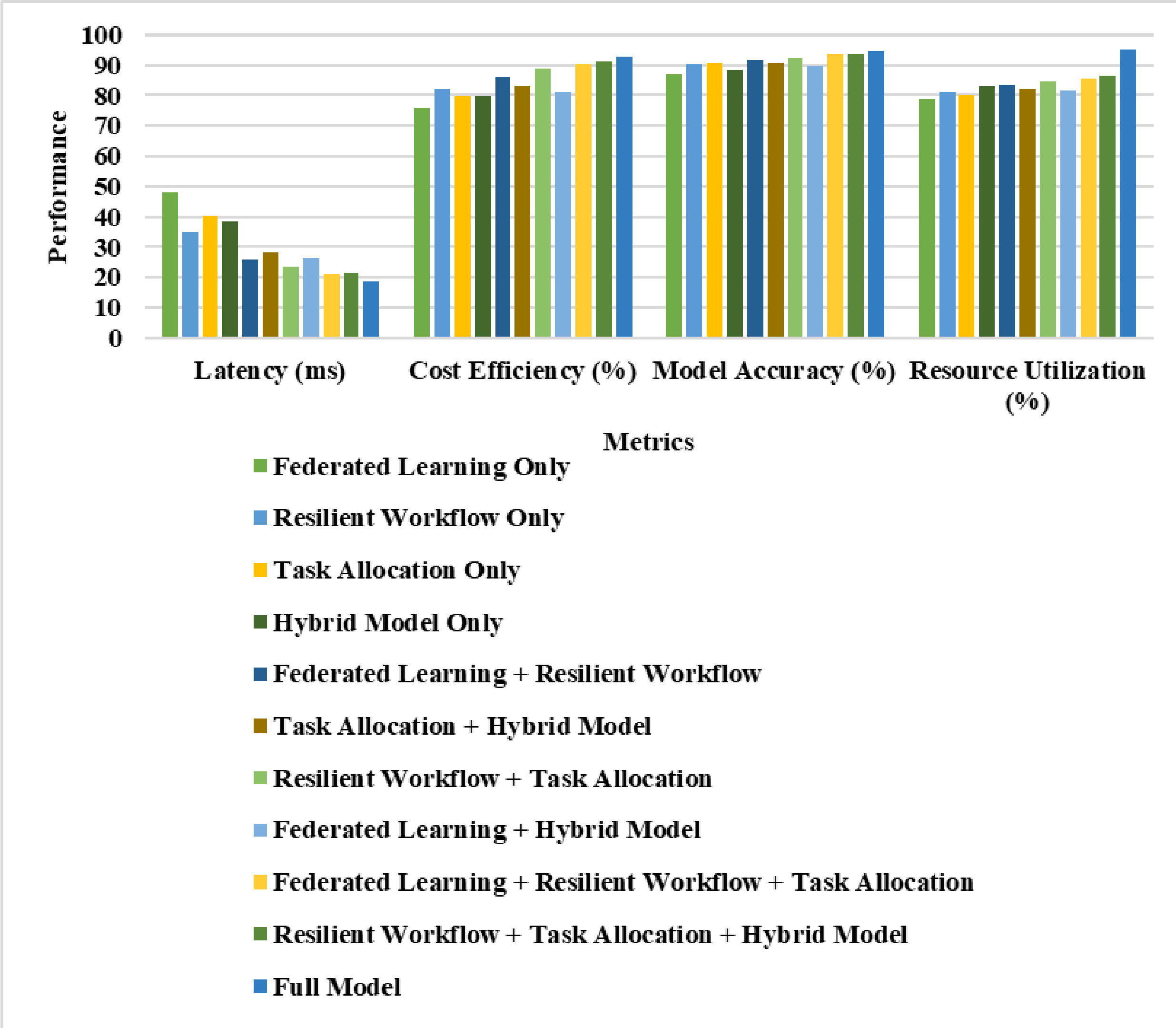

Figure 4 Ablation Study of IoT Analytics Configurations for Latency, Cost Efficiency, and Resource Utilization

Figure 4 shows an ablation study about comparing the individual and combined configurations of IoT analytics methods. Individual methods include Federated Learning (48.2 ms latency, 75.8% cost efficiency), Task Allocation with 90.8% accuracy. Their combined configuration improved the performance further in Resilient Workflow + Task Allocation for 23.6 ms latency and 92.3% accuracy. The Full Model, which involves the integration of all methods, outperformed others with lower latency at 18.4 ms, greater cost efficiency at 92.5%, maximum model accuracy at 94.8%, and efficient resource utilization at 95.1%. All these results reveal the importance of the integration of methods toward scalable and reliable IoT analytics in dynamic environments.

5. CONCLUSION AND FUTURE ENHANCEMENT

This paper illustrates the effectiveness of federated learning with resilient workflow orchestration and multi-layered task allocation for IoT analytics. In the proposed framework, the latency was the lowest at 18.4 ms, cost efficiency at 92.5%, the best model accuracy at 94.8%, and optimal resource utilization at 95.1%. Federated learning offers data privacy, resilient orchestration provides fault tolerance, and multi-layered task allocation balances the computational loads. Future versions of the mechanism may involve adaptive federated learning techniques for efficient convergence with dynamic learning rates. Further, the integration of blockchain ensures enhanced security over data, and AI-driven optimization may further help in increasing efficiency. Extending the framework to other domains such as healthcare and autonomous systems may validate its robustness. Advanced failure recovery mechanisms and predictive analytics may prevent failure and ensure the operation continues uninterruptedly even in highly dynamic environments. These improvements will ensure that the framework is much stronger, scalable, and suited to a variety of IoT applications within dynamic environments.

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