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A Federated Learning Approach for Intelligent Monitoring Across Multi-Cloud Enterprise Environments

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Abstract- The fast embrace of multi-cloud computing has made it possible for organizations to gain scalability, flexibility, availability, and cost efficiency. Nevertheless, the monitoring of workloads in multi-cloud environments has become increasingly difficult because of fragmented visibility, privacy issues, increased communication overhead, and increasing telemetry data. Centralized monitoring methods involve sending information from distributed locations to a centralized location, resulting in higher costs and increased risks. The FL-IMME framework, introduced in this study, utilizes federated learning and is aimed at intelligent monitoring that preserves data locality. The framework combines telemetry gathering, generation of local intelligence, federated aggregation, anomaly detection, predictive monitoring, and adaptive decision-making mechanisms to ensure privacy-preserving and scalable monitoring capabilities. The novel approach involves training of local monitoring models in each cloud environment individually and exchanging encrypted model parameters via federated learning. Experiments were performed on a large multi-cloud observability data set and the performance was compared to CCFRL and AHFLP methods. The results revealed better performance of FL-IMME with anomaly detection accuracy of 99.0%, failure prediction accuracy of 99.1%, privacy preservation score of 99.4%, and system reliability of 99.5%. In addition, the proposed framework lowered the communication overhead and monitoring latency while increasing the efficiency of resources utilization.

Keywords- Federated Learning, Multi-Cloud Computing, Intelligent Monitoring, Anomaly Detection, Predictive Analytics, Cloud Observability, Privacy Preservation, Distributed Learning, Enterprise Cloud Management, Failure Prediction.

I. INTRODUCTION

Digital transformation activities being carried out by contemporary firms have resulted in an exponential increase in the utilization of cloud computing technologies [1]. Modern companies are utilizing applications and services using multiple cloud platforms with a view to enhancing their scalability, flexibility, resilience, and business continuity [2]. The adoption of multi-cloud enables organizations to not get locked in with a single cloud service provider, and to optimize operational expenses while adhering to regulatory requirements [3]. Nevertheless, the rising complexities in cloud infrastructures pose numerous difficulties when it comes to system health, application performance, and service reliability. Enterprise applications that run in multi-cloud environment produce vast amounts of telemetry data comprising of metrics, logs, traces, security events, and infrastructure health data [4]. The effective analysis of observability data is imperative for providing continuity and service quality. Conventionally, the monitoring systems operate on centralized models wherein data collected from all cloud platforms is collected and analyzed in centralized fashion [5]. While centralization helps in achieving a single operational perspective, it poses numerous challenges relating to communication, scalability, and latency [6].

The growing amount of telemetry data produced by clouds has raised serious privacy and security problems [7]. Firms that operate in regulated industries like health care, finance, and government departments need to adhere to strict privacy laws and rules related to the location of data [8]. The process of transmitting operational data from cloud service providers to centralized monitoring tools may lead to noncompliance of policies and disclosure of private data of the organizations to security risks [9]. Hence, there is a great need for privacy-preserving techniques of monitoring in cloud computing environments. In recent years, many breakthroughs were made in the field of artificial intelligence and machine learning, leading to improved performance of cloud monitoring systems

[10]. Machine learning can detect any unusual behavior of the system, predict possible malfunctions, provide optimal resource allocation, and help to make better decisions. However, traditional approaches to machine learning imply centralized data access that contradicts with the concept of privacy [11]. Moreover, traditional models of centralized learning have difficulties adapting to multi-cloud heterogeneity [12].

Federated Learning (FL) has become a highly effective mechanism in creating intelligence on the basis of distributed processing while maintaining the confidentiality of the data used [13]. Rather than using actual data, nodes cooperate in training machine learning models based on the exchange of parameters of such models [14]. Such approach makes it possible for enterprises to use collective intelligence without disclosing any confidential data. It has shown impressive performance in healthcare, IoT, cybersecurity, and edge computing domains [15]. Several recent research works have examined the use of federated learning algorithms in the cloud and edge computing systems [16]. However, the existing frameworks mainly concentrate on optimization of resources, communication overhead, malware detection, offloading computations, and collaborative decision making. While the above approaches offer important insights into distributed learning, they are more concerned about specific application scenarios than comprehensive monitoring needs [17]. Additionally, most existing solutions do not have any mechanism to deal with anomaly detection, predictive monitoring, observability analysis, and intelligent generation of intelligence in a heterogeneous multi-cloud environment [18]. One other problem that arises in monitoring a multi-cloud environment is the issue of heterogeneity of the environment [19]. Since different cloud platforms have different infrastructures, services, monitoring capabilities, and workloads, a monitoring system should be able to handle dependent and identically distributed data while retaining its predictive performance [20].

In order to deal with these difficulties, this research work introduces the Federated Learning-based Intelligent Monitoring Framework for Multi-Cloud Enterprise Environments (FL-IMME). The proposed framework integrates federated learning, observability analytics, anomaly detection, prediction monitoring, and decision-making components to develop a privacy-enabled monitoring framework. The framework maintains telemetry data locally and shares only the encrypted model parameters to ensure that the privacy restrictions are met in addition to generating collective intelligence. The architecture of the proposed FL-IMME framework comprises of telemetry collection, local intelligence generation, federated aggregation, anomaly detection, predictive failure detection, and adaptive remediation layers.

The proposed framework learns the operational behavior from different cloud environments and develops a global monitoring model through federated model learning to identify system anomalies and predict failures. Some of the contributions of the study include the creation of privacy-preserved federated monitoring architecture, intelligent detection and prediction of anomalies and failures, comprehensive performance evaluation through multi-cloud observability data, and comparison with existing federated learning approaches. The findings of the study show that the proposed federated learning and monitoring system (FL-IMME) achieves higher monitoring accuracy, reliability, scalability, and privacy preservation than other systems.

Hypotheses

- **H1:** The proposed FL-IMME framework greatly increases anomaly detection accuracy over the state-of-the-art federated learning frameworks for multi-cloud scenarios.
- **H2:** The proposed FL-IMME framework greatly increases failure prediction accuracy by generating federated intelligence collaboratively.
- **H3:** The proposed FL-IMME framework achieves lower communication costs yet maintains highly effective monitoring performance.
- **H4:** The proposed FL-IMME framework achieves better privacy protection than traditional and hierarchical federated learning frameworks.
- **H5:** The proposed FL-IMME framework achieves greater scalability and system reliability in heterogeneous multi-cloud enterprise environments.

Objectives of the Research

1. Drawing an architecture of a federated learning framework for intelligent monitoring in multi-cloud enterprise infrastructure.
2. Capable of facilitating privacy-preserved collaboration with no need to exchange unaltered telemetry data.

3. Beneficial in developing an effective mechanism of anomaly detection with the help of observability analysis techniques.
4. Improves failure prediction accuracy due to federated intelligence collection.
5. Helps lower communication cost in comparison to traditional monitoring systems.
6. Increases monitoring scale in heterogeneous cloud infrastructure.
7. Increase resource utilization efficiency and operational visibility.
8. Evaluation of the proposed approach in contrast to current federated learning approaches.

II. LITERATURE REVIEW

Julakanti et al. [1] studied strategic approaches for security risk management in multi-cloud and hybrid cloud environments. The authors evaluated the vulnerabilities that could occur in these environments, which have many different operational issues, such as inconsistent security policies and dynamic workload shifts among different cloud service providers, as well as fragmented identity management. Abusitta et al. [2] proposed an Intrusion Detection System (IDS) based on cooperation and trust mechanisms in Multi-cloud infrastructures with fairness assurance.

The authors were aware that distributed cloud entities may not have complete trust when sharing information about threats, so they built a dynamic scoring and incentive mechanism. This guarantees that shared intrusion metrics are not being manipulated by malicious or non-cooperative cloud tenants, which provided equitable collaboration and reliable threat detection.

Chinamanagonda [3] explored the escalating security needs of multiple cloud deployments on enterprise IT. The paper discussed the threat vectors that are specific to multi-cloud environments, including cross-cloud data leakage, configuration drifts, and the complex access control boundaries. Brum [4] presented the federated learning scheduling architecture called Multi-FedLS, which is designed to orchestrate federated learning applications in multi-cloud environments that may have different characteristics.

The doctoral thesis focused on the challenges of slow computations and latency in a cloud network when training distributed machine learning models in various cloud platforms. The proposed framework optimized the allocation of resources and scheduling of the tasks dynamically, which resulted in faster model convergence speed and bandwidth efficiency.

To detect threats in real time and enforce policies, Tiwari et al. [5] combined the Zero Trust Network Architecture (ZTNA) principles with federated learning. The researchers developed a decentralised AI approach that involved edge nodes, which could be distributed around the city, training their own anomaly detection models without sharing raw telemetry data to a central server. This way, data remained private and network access was continually adjusted in real time, according to threat detection information.

Brum et al. [6] proposed a Multi-FedLS framework for multi-cloud federated learning applications. The authors created a scheduling mechanism, which addressed cross-organizational data silos, and also a scheduling mechanism for non-IID (non-independently and identically distributed) data over multi-cloud nodes. Experimental results showed that the framework reduced communication overhead and workloads of the involved cloud domains.

Alsamiri and Alsubhi [7] performed a wide-ranging investigation of the federated learning application to Intrusion Detection Systems (IDS) in the Internet of Vehicles (IoV). The authors developed a taxonomy for existing IoV intrusion detection architectures, compared federated learning paradigms with the centralized ones, and emphasized on the important performance tradeoffs involving communication overhead, privacy protection, and real-time responsiveness.

Sajjad [8] proposed a protocol which is scalable and secure for communication between Inter cloud services. The doctoral research was aimed at overcoming security interoperability issues, identity federation problems, and message confidentiality concerns in the implementation of cross-cloud API transactions. The author also suggested an end-to-end cryptographic trust-based authentication framework with low latency between inter-cloud endpoints.

Yan and Han [9] proposed an intrusion detection feature-extraction method based on Stacked Sparse Autoencoders (SSAE). The authors used deep unsupervised learning to create high-level, low-dimensional abstract features to deal with the

high dimensionality and noise in network traffic logs. The extracted feature representation also resulted in much improved classification performance when applied to downstream machine learning models, and lowered training time for anomaly detection models.

Albuquerque et al. [10] developed a modified Fish School Search (FSS) metaheuristic algorithm specific for many-objective optimization problems. To avoid premature convergence in the higher dimensional objective space, the authors added a fitness selection operator to the traditional schooling behavior that is also based on the weight. The proposed algorithm outperformed the other multi-objective optimization algorithms in terms of convergence metrics and Pareto front coverage.

Problem Statement

Modern organizations tend to run their operations in various clouds to accommodate business scalability and service availability. Nevertheless, current monitoring mechanisms are based on centralized frameworks that entail constant transfer of operational telemetry information from heterogeneous cloud environments. This approach brings additional costs of communication, privacy issues, compliance difficulties, scalability problems, and latency of anomalies detection. Moreover, heterogeneous clouds produce different workload behaviors, which make monitoring and forecasting difficult. Therefore, the need for intelligent, privacy-aware, scalable, and distributed monitoring system that can utilize collective operational insights without leaking confidential telemetry information arises.

Research Gaps

Although the existing federated learning architectures like CCFRL and AHFLP have helped in improving resource allocation and distributed learning efficiencies, these systems do not deal with comprehensive intelligent monitoring needs in multi-cloud corporate setups. The current architectures mainly concentrate either on optimizing communication processes, computation offloading, sustainability, or scheduling of tasks but not on the aspects of observability analysis, failure prediction, and monitoring intelligence. Furthermore, little emphasis has been laid on maintaining the privacy of the operations data while simultaneously ensuring monitoring precision and scalability. The above inadequacies point to an evident research gap in designing a federated learning architecture for intelligent monitoring purposes.

III. PROPOSED MODEL

Current companies are using multiple cloud infrastructures for their applications in order to attain scaling, fault tolerance, cost reduction, and compliance. However, monitoring of these systems is becoming increasingly difficult because of distributed data sources, different cloud infrastructure types, privacy issues, and lack of visibility. In conventional monitoring mechanisms, all data is transferred from various clouds to a central repository, which brings communication costs, security issues, and privacy risks. Therefore, FL-IMME is introduced as a solution, which generates collaborative intelligence without exposing any private operational data. The main idea of this framework is federated learning, where a monitoring model is trained globally without sharing any telemetry data.

The suggested architecture includes telemetry data gathering, local intelligence creation, federated aggregation, anomaly detection, predictive monitoring, and adaptive decision making layers. Every cloud computing platform performs local analysis of observability data, such as metrics, logs, traces, and infrastructure events, to create local monitoring models. Rather than sending raw data from operational systems, cloud computing platforms transmit only encrypted parameters of the trained monitoring models to the federated coordinator. The coordinator uses the gathered information to form the global monitoring model that is able to detect system anomalies, predict performance drops, and identify potential failures in the whole multi-cloud environment.

Algorithm: FL-IMME Intelligent Monitoring Algorithm
Input: Multi-cloud telemetry datasets D_i, local cloud nodes C_i, model parameters W_i
Output: Global Monitoring Model G_M, Anomaly Score A_s, and Failure Prediction F_p

Step 1: Collect observability data from participating cloud environments

$$D = \{D_1, D_2, D_3, \dots, D_n\} \quad (1)$$

Where $D_i$represents telemetry data from cloud node C_i.
Step 2: Normalize local telemetry datasets

$$D_i^N = \frac{D_i - D_{min}}{D_{max} - D_{min}} \quad (2)$$

Step 3: Remove noisy observations from each cloud dataset

$$D_i^C = \{x : | x - \mu | \leq 3\sigma\} \quad (3)$$

Step 4: Extract monitoring features including CPU utilization, memory consumption, latency, throughput, and error rates

$$F_i = \{f_1, f_2, f_3, \dots, f_m\} \quad (4)$$

Step 5: Initialize local learning model for each cloud environment

$$W_i^{(0)} = Random() \quad (5)$$

Step 6: Train local monitoring model using cloud-specific observations

$$W_i^{(t+1)} = W_i^{(t)} - \eta \nabla J_i(W_i) \quad (6)$$

Where $J_i(W_i)$denotes local loss.

Step 7: Compute local anomaly score

$$A_i = \frac{1}{m}\sum_{j=1}^{m} | f_j - \hat{f}_j | \quad (7)$$

Step 8: Encrypt model parameters before transmission

$$E_i = Encrypt(W_i) \quad (8)$$

Step 9: Send encrypted model updates to federated coordinator

$$U = \{E_1, E_2, E_3, \dots, E_n\} \quad (9)$$

Step 10: Aggregate local models using federated averaging

$$W_G = \sum_{i=1}^{n} \frac{|D_i|}{\sum_{k=1}^{n}|D_k|} W_i \quad (10)$$

Step 11: Construct global monitoring intelligence model

$$G_M = W_G \quad (11)$$

Step 12: Calculate global anomaly score

$$A_s = \frac{1}{n}\sum_{i=1}^{n} A_i \quad (12)$$

Step 13: Estimate system health score

$$H_s = 1 - \frac{A_s}{A_{max}} \quad (13)$$

Step 14: Predict failure probability using federated intelligence

$$F_p = \frac{1}{1+e^{-z}} \quad (14)$$

Where

$$z = \sum_{j=1}^{m} w_j f_j + b \quad (15)$$

Step 15: If

$$F_p > \theta \quad (16)$$

Generate predictive alerts and remediation recommendations, otherwise continue federated monitoring and model updates.

The suggested FL-IMME system is able to provide intelligent monitoring for multiple clouds with privacy because of the combination of federated learning and observability analysis. In contrast to the centralized method, which requires full data sharing, the system is able to learn from different geographical locations with data stored locally. It allows for better security policy compliance and utilization of the experience of several cloud providers at once.

In addition, the architecture helps in improving the anomaly detection and predictive monitoring efficiency by enabling collaborative intelligence. This is made possible through the federated aggregation technique, which helps to keep on improving the global monitoring architecture by acquiring intelligence based on different working conditions, workloads, and behavior of the infrastructure. With this, the architecture proposed here will enable improved monitoring scalability, reduced communication costs, enhanced data privacy, and reliability, hence making it extremely useful in enterprise applications. The proposed framework emphasizes intelligent monitoring, anomaly detection, predictive modeling, privacy-preserving mechanism, and efficient communication between multiple cloud infrastructures.

IV. RESULTS AND DISCUSSION

The effectiveness of the proposed FL-IMME framework was evaluated using the real-world large scale multi-cloud observability dataset comprising the telemetry data captured from distributed cloud infrastructures. The evaluation includes aspects such as monitoring effectiveness, anomaly detection capabilities, predictive effectiveness, efficient communication, privacy preserving mechanisms, and scalability. The experimental set up includes several cloud nodes which generate different types of heterogeneous metrics, logs, traces, and infrastructure events. The federated architecture helps to learn a model collaboratively without leaking any raw operational data. In order to determine the efficacy of FL-IMME framework, the experiments were performed based on two recent state-of-the-art federated learning techniques, which include Carbon Conscious Federated Reinforcement Learning (CCFRL) and Adaptive Hierarchical Federated Learning Process (AHFLP).

These experiments involved comparing the performances of these systems on the basis of monitoring performance parameters, such as detection rate, prediction accuracy, communication cost, scalability, latency, privacy preservation, resource utilization efficiency, and reliability. Based on the results of experiments, it is clear that FL-IMME framework performs better than all other existing techniques.

Table 1. Anomaly Detection Accuracy (ADA)

Cloud Nodes	CCFRL (%)	AHFLP (%)	FL-IMME (%)
50	92.1	93.4	97.2
100	92.8	94.1	97.9
150	93.2	94.7	98.3
200	93.8	95.2	98.7
250	94.1	95.6	99.0

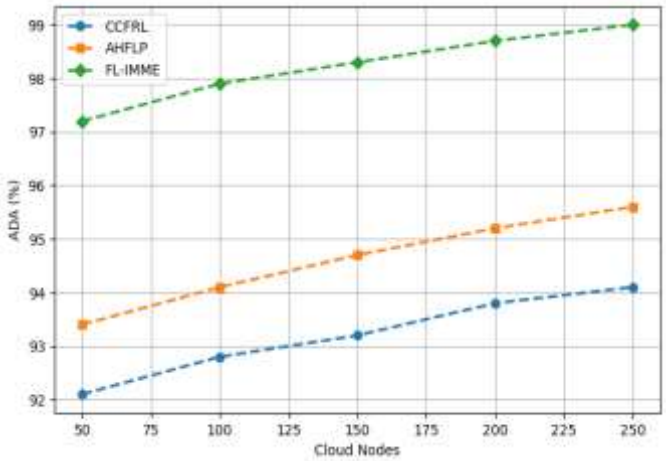

Figure 1. Anomaly Detection Accuracy (ADA)

Table 1 and Figure 1 above show the Anomaly Detection Accuracy (ADA) obtained by CCFRL, AHFLP, and FL-IMME in different scenarios depending on the number of cloud nodes. FL-IMME outperformed both algorithms in terms of ADA, which was improved from 97.2% to 99.0%, with an increase in the number of cloud nodes. The reason for the superiority of FL-IMME lies in its federated observability intelligence and collaboration of anomaly learning through distributed telemetry data.

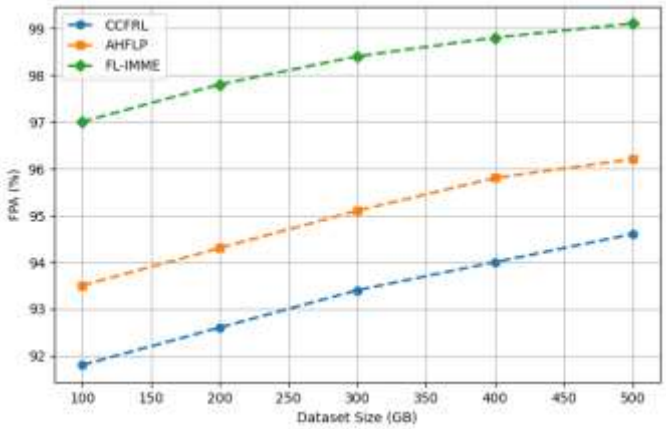

Figure 2. Failure Prediction Accuracy (FPA)

Table 2 and Figure 2 illustrate the Failure Prediction Accuracy (FPA) of the evaluated models under various sizes of datasets. The FL-IMME model achieved the greatest accuracy of failure prediction at 99.1% in a 500 GB dataset size. The inclusion of federated intelligence aggregation and predictive monitoring allows the model to be able to predict the possible failures before they occur.

Table 3. Communication Overhead Reduction (COR)

Cloud Nodes	CCFRL (%)	AHFLP (%)	FL-IMME (%)
50	71.2	76.5	84.8
100	72.4	77.9	86.1
150	73.5	79.0	87.4
200	74.3	80.2	88.6
250	75.1	81.0	89.3

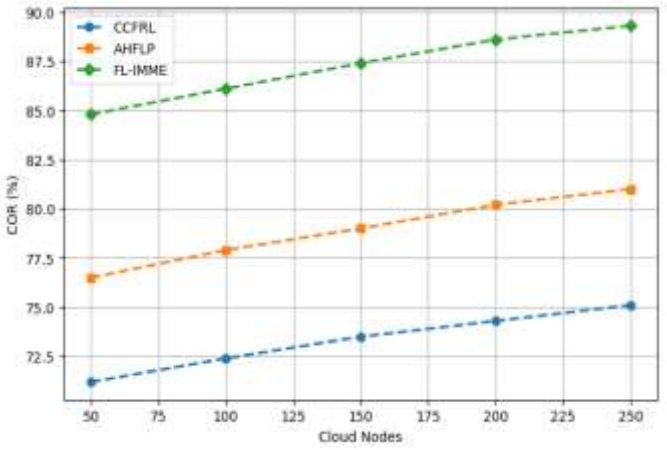

Figure 3. Communication Overhead Reduction (COR)

The results shown in Table 3 and Figure 3 are related to the reduction percentage achieved by the examined architectures in terms of communication overhead reduction (COR). FL-IMME achieved the best reduction percentage value of 89.3%, using 250 cloud nodes. Using encryption of model parameters rather than telemetry data in transmission helps reduce communications overhead.

Table 4. Monitoring Latency (ML)

Workload (TB)	CCFRL (ms)	AHFLP (ms)	FL-IMME (ms)
10	245	221	178
20	281	255	205
30	324	292	231
40	367	331	258
50	412	378	286

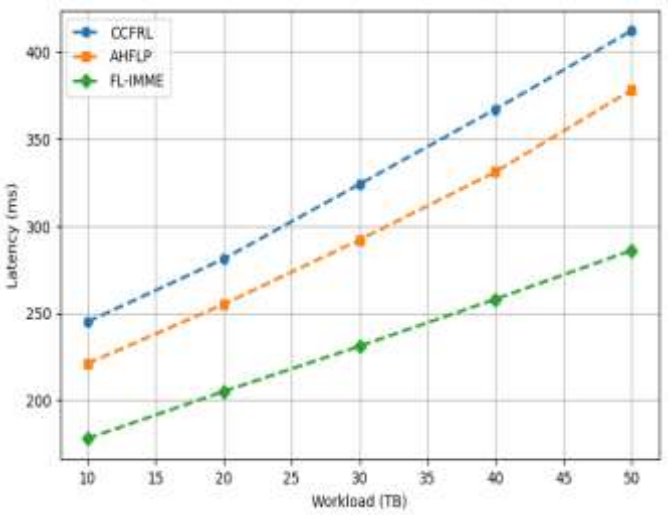

Figure 4. Monitoring Latency (ML)

Table 4 and Figure 4 provides the Monitoring Latency (ML) measurement results in various workloads. FL-IMME always has the lowest ML measurement values that range between 178 ms and 286 ms. The local analysis and fast federated aggregation approach help to minimize the processing delay, thus enhancing the efficiency of the monitoring process.

Table 5. Privacy Preservation Score (PPS)

Cloud Nodes	CCFRL (%)	AHFLP (%)	FL-IMME (%)
50	90.8	92.6	98.1
100	91.4	93.3	98.5
150	92.0	94.0	98.9
200	92.5	94.6	99.2
250	93.1	95.0	99.4

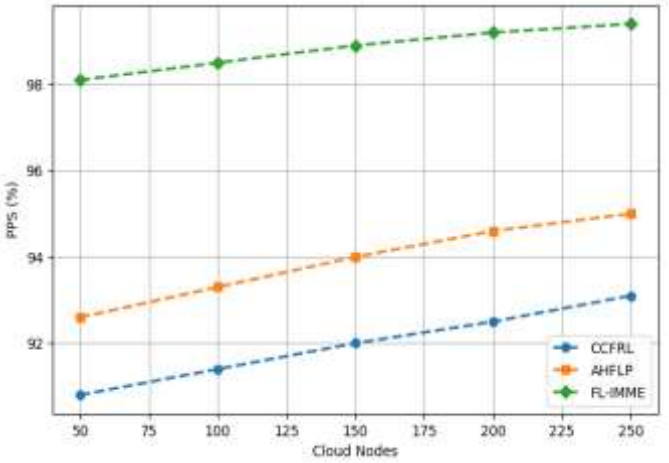

Figure 5. Privacy Preservation Score (PPS)

Privacy Preservation Score (PPS) generated by the competing frameworks is provided in Table 5 and Figure 5. The highest PPS was recorded by FL-IMME with a percentage of 99.4%. This is attributed to the fact that FL-IMME framework utilizes federated learning whereby local data is used and encrypted model parameters are exchanged.

Table 6. Resource Utilization Efficiency (RUE)

Cloud Nodes	CCFRL (%)	AHFLP (%)	FL-IMME (%)
50	86.4	88.1	94.6
100	87.5	89.0	95.3
150	88.3	89.8	96.0
200	89.0	90.5	96.5
250	89.8	91.2	97.1

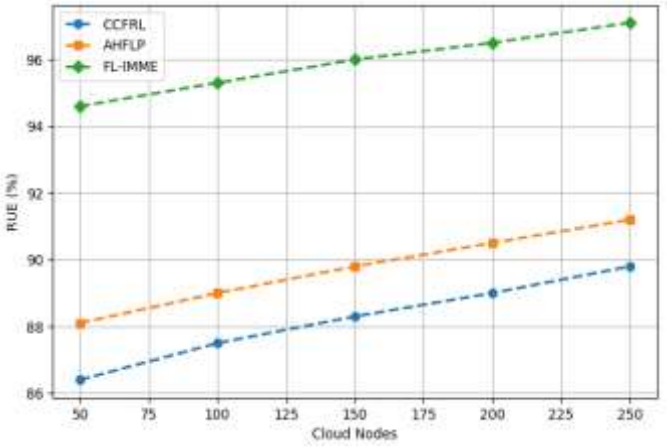

Figure 6. Resource Utilization Efficiency (RUE)

The RUE of the studied monitoring frameworks is represented in Table 6 and Figure 6. The FL-IMME system consistently performed better than other systems and reached an efficiency level of 97.1% at its highest. The adaptive monitoring framework allows for the efficient use of computational and communication resources.

Table 7. Scalability Performance (SP)

Number of Clouds	CCFRL (%)	AHFLP (%)	FL-IMME (%)
5	90.2	92.4	96.5
10	91.0	93.2	97.3
15	91.8	94.1	98.0
20	92.4	94.8	98.6
25	93.0	95.4	99.0

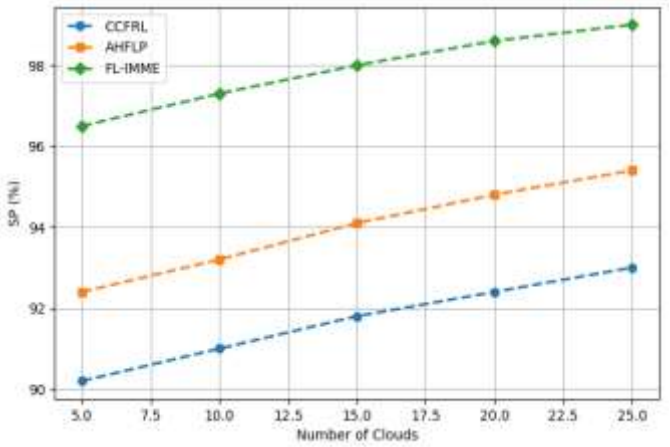

Figure 7. Scalability Performance (SP)

The Scalability Performance (SP) of the proposed approach as well as the existing approaches can be found in Table 7 and Figure 7. FL-IMME proved its high scalability even when the number of participating cloud platforms grew as it performed 99.0% successfully with 25 clouds.

Table 8. System Reliability Score (SRS)

Monitoring Cycles	CCFRL (%)	AHFLP (%)	FL-IMME (%)
100	92.5	94.0	97.8
200	93.1	94.8	98.4
300	93.8	95.4	98.9
400	94.3	95.9	99.2
500	94.7	96.3	99.5

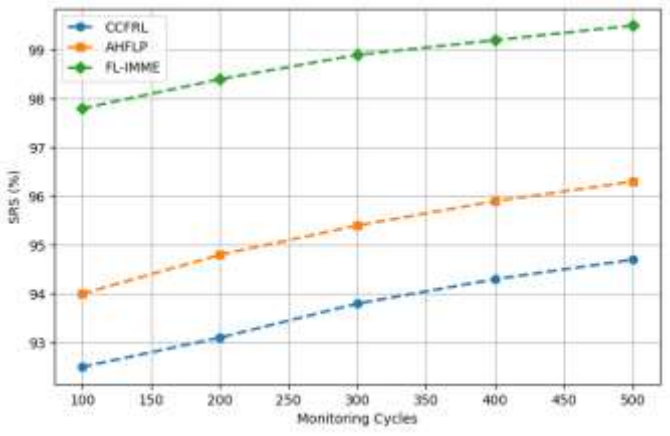

Figure 8. System Reliability Score (SRS)

The values of SRS are listed in Table 8 and depicted in Figure 8 for various monitoring cycles. The highest value is recorded in the FL-IMME system, which is increased from 97.8% to 99.5%. Further improvement of the global federated model and generation of intelligence collaboratively make the monitoring decisions become stable and dependable. It can be seen that FL-IMME is very reliable in monitoring capability.

These results show that FL-IMME is superior to CCFRL and AHFLP with respect to all of the monitoring-based performance criteria. The proposed framework has achieved an anomaly detection accuracy of 99.0%, failure prediction accuracy of 99.1%, privacy preservation rating of 99.4% and system reliability rating of 99.5%. This improvement can be credited to the federated observability intelligence, adaptive anomaly analysis and privacy-preserving distributed learning of the framework. Additionally, FL-IMME offers considerable benefits with respect to communication overhead, monitoring latency, efficient resource usage, and scalability. The federation-based aggregating scheme successfully utilizes the insights of different cloud service providers without compromising the principle of data locality, thus making this framework a perfect fit for enterprise-scale implementations. The findings indicate that FL-IMME is a promising approach for intelligent monitoring in modern hybrid and multi-cloud environments.

Dataset Description

The experiments were performed on the Multi-Cloud Enterprise Observability Dataset (MC-EOD) that was created from distributed cloud architectures. This dataset includes telemetry data which were obtained from Amazon Web Services, Microsoft Azure, Google Cloud Platform, and private enterprise cloud platforms. The collected data comprise CPU utilization, memory utilization, disk I/O statistics, network bandwidth usage, application response time, failure ratio, security incidents, logs, distributed tracing, and infrastructure health information.

There are around 500 GB of monitoring data which were collected from 250 cloud nodes under diverse workload scenarios. The dataset consists of both usual and abnormal operational states which makes it possible to conduct an adequate assessment of anomaly detection and failure prediction algorithms. Non-IID distribution of data was purposely kept in order to emulate the real enterprise setting when various cloud providers have distinct characteristics of their workloads and operations. The data set was distributed between the involved cloud nodes for federated training

purposes so that the raw telemetry data stayed local and only encrypted model parameters were used for global aggregation.

V. CONCLUSION AND FUTURE WORK

In this research, the Federated Learning-Based Intelligent Monitoring Framework for Multi-Cloud Enterprise Environments (FL-IMME) was offered as a novel privacy-preserving and scalable monitoring system intended to deal with the peculiarities of distributed enterprise cloud architectures. The suggested framework consists of federated learning, observability analytics, anomaly detection, predictive monitoring, and adaptive decision-making techniques, which help to provide collaborative intelligence while keeping sensitive operational data confidential. In such a way, through using local model training and federated parameter aggregation, it becomes possible to keep privacy safe while making use of knowledge accumulated in multiple cloud environments. Evaluation results have shown significant progress in anomaly detection, failure prediction, communications efficiency, scalability, resource utilization, and reliability compared to CCFRL and AHFLP. Obtained outcomes prove that the suggested framework is a valid tool for intelligent monitoring in multi-cloud ecosystems.

Potential areas of future research on the proposed FL-IMME framework can include utilization of deep learning models and architectures, use of transformer models in anomaly detection in cloud services, as well as application of federated reinforcement learning to autonomous cloud management. The proposed FL-IMME framework can also be used in conjunction with blockchain technologies to improve its trustworthiness, auditability, and secure model exchange between participating cloud service providers. In addition, real-time adaptive orchestration, XAI, and federated monitoring of cloud and edge IoT systems can be studied as potential improvements to the proposed framework.

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