An Edge Cloud IoT Framework with Explainable AI for Real-Time Aircraft Cabin Monitoring and Predictive Safety

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***Abstract*—Digitalization and increasing passenger safety requirements are continuously contributing to the growing complexity of modern aircraft cabins. Therefore, intelligent, real-time monitoring systems that can react quickly and foresee safety risks are required. Existing cabin monitoring solutions typically rely on centralized processing and rules-based logic, which have the drawbacks of latency, limited scalability, and lack of transparency in decision-making. In addition, the adoption of artificial intelligence (AI) in aeronautical safety is challenged by the "black-box" nature of several high-performance models, raising concerns regarding trust, certification, and operational accountability. The present research proposes an edge-cloud Internet of Things (IoT) platform integrated with explainable artificial intelligence (XAI) for real-time aircraft cabin monitoring and predictive safety assessment. The proposed architecture utilizes distributed edge intelligence for low-latency anomaly detection and immediate response. In addition, cloud analytics supports long-term learning, cross-flight knowledge sharing, and predictive risk assessment. A multimodal sensing framework is employed to capture environmental, operational, and passenger-related parameters within the cabin.**

The proposed framework was evaluated using a realistic sensor dataset representing cabin environmental monitoring scenarios. A statistical analysis of the experimental results shows that the proposed hybrid edge–fog–cloud architecture achieves substantial enhancements across multiple key performance indicators. In particular, the proposed model reduces average system latency by approximately 18-25%, decreases packet loss by nearly 15-20% under high network congestion conditions, and lowers transmission delay by approximately 12-18% compared with edge-only processing approaches. The hybrid architecture demonstrates improved computational efficiency by reducing average processing time by approximately 10% while maintaining a higher anomaly detection accuracy of up to 97–98%. Scalability analysis further indicates that the proposed framework maintains scalability efficiency above 0.98 even when the number of sensing nodes increases to 100, demonstrating strong robustness under large-scale deployments. The integration of edge-cloud intelligence with explainable AI enhances situational awareness, operational transparency, and proactive decision-making in safety-critical aviation environments.

***Index Terms*—Predictive safety, Edge Computing, Internet of Things, Explainable AI, Aircraft cabin monitoring, Human Factors**

I. Introduction

The rapid evolution of connected avionics systems and smart cabin infrastructures is transforming modern aircraft into highly data-driven cyber–physical environments. Continuous monitoring of environmental conditions, onboard systems, and passenger-related activities have become essential to ensure safety, operational efficiency, and situational awareness during flight operations. In this context, intelligent monitoring frameworks that combine distributed sensing, real-time analytics, and predictive intelligence are increasingly required to support next-generation aviation safety systems.

Aviation safety has traditionally been a high priority among regulators, manufacturers, and operators. With increasingly automated and connected aircraft, safety will continue to be a priority. Recent innovations in sensors, wireless communications, and embedded computing technology have accelerated the transformation of smart aircraft cabins, with a range of data streams flowing from various sources, such as environmental sensors, onboard equipment, and passenger systems [1], [2]. These developments provide fresh opportunities to enhance passenger safety, improve operational efficiency, and provide situational awareness for every phase of a flight.

The use of IoT technologies in aircraft cabin enables fine-grained the monitoring of various parameters, such as temperature, humidity, air quality, presence of smoke, equipment condition, and passenger movement patterns of passengers [2], [3]. When combined with artificial intelligence techniques, these data streams can further enable advanced functionalities such as real-time anomaly detection, predictive safety alerts, and adaptive cabin management. However, aircraft cabins are complex cyber–physical environments characterized by strict latency requirements, limited onboard computational resources, and stringent safety certification constraints [4], [5].

Edge computing helps solve these problems by processing data close to their source, thereby minimizing communication time and reducing dependence on distant infrastructure [1], [6]. Cloud computing, in contrast, remains essential for large-scale data aggregation, historical analysis, and global model improvement across multiple aircraft fleets [7], [8]. Consequently, a tightly integrated edge–cloud architecture is essential to balance real-time responsiveness with long-term intelligence in aviation applications.

The integration of explainable artificial intelligence (XAI) with distributed edge–cloud frameworks provides an additional advantage by improving the transparency and interpretability of AI-driven decisions. Such capabilities are particularly important in aviation environments where safety certification, operator trust, and regulatory compliance require interpretable and auditable decision-making mechanisms.

Despite recent advances, current aircraft cabin monitoring systems exhibit several fundamental limitations. First, many existing solutions primarily rely on centralized or cloud-based processing architectures, which introduce significant latency

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and increase vulnerability to network disruptions [1], [7]. Such delays are unacceptable in time-critical safety scenarios, such as smoke detection, sudden environmental fluctuations, or equipment malfunctions, where immediate responses are required.

Second, the heterogeneous and high-dimensional nature of cabin sensor data presents challanges for real-time analysis. Aircraft cabins integrate multiple sensors with diverse temporal behaviors, noise characteristics, and reliability constraints [2], [9]. Effectively fusing these heterogeneous data streams while maintaining scalability, robustness, and computational efficiency remains a significant research challenge.

Third, although artificial intelligence approaches have demonstrated superior performance in anomaly detection and predictive maintenance tasks, most state-of-the-art AI models operate as black boxes, offering limited insight into their internal decision-making mechanisms [10]–[13]. In safety-critical aviation environments, the lack of interpretability limits operator trust, complicates system certification processes, and restricts the adoption of AI-based decision-support systems [14]–[16].

These limitations highlight the need for an intelligent monitoring framework that combines distributed edge–cloud computing with explainable AI techniques to enable low-latency processing, scalable data analytics, and transparent decision support for aircraft cabin safety monitoring. The detailed literature study suggests that research has been widely conducted on IoT-enabled aviation systems, edge-cloud computing frameworks, and artificial intelligence-based health monitoring independently [1], [8], [17], [18]. Similarly, explainable AI (XAI) techniques have received increasing attention for improving transparency, interpretability, and accountability in intelligent decision-making systems [14], [15], [19]. However, the integration of edge-cloud IoT architectures with explainable AI mechanisms for real-time aircraft cabin monitoring and predictive safety analysis remains largely unexplored. In particular, existing approaches rarely address the combined challenges of low-latency monitoring, heterogeneous sensor data processing, scalable distributed computation, and interpretable AI-based decision support within safety-critical aviation environments.

This work addresses this research gap by proposing an integrated Edge-Fog-Cloud IoT framework with explainable AI capabilities for intelligent aircraft cabin monitoring and predictive safety assessment. The main contributions of this study are summarized as follows:

- A multi-layer Edge–Fog–Cloud IoT architecture is proposed to support distributed cabin monitoring and predictive analytics. The architecture is designed considering the computational constraints and latency requirements of aircraft environments, thereby enabling low-latency edge-based anomaly detection while utilizing fog and cloud resources for advanced analytics and long-term learning.
- An interpretable AI-driven safety monitoring pipeline is developed that integrates high-performance machine learning models with explainable AI techniques. The proposed pipeline enables the detection of abnormal cabin conditions and provides human-interpretable explanations to assist operators in understanding the model's decision-making process.
- The proposed framework was evaluated using the Intel Berkeley Research Lab sensor dataset, which includes environmental parameters such as temperature, humidity, light intensity, and voltage measurements collected from distributed wireless sensor nodes. Extensive experiments were conducted to analyze system behavior under realistic monitoring conditions.
- A detailed evaluation framework is developed to analyze system performance across multiple metrics, including latency, energy consumption, throughput, anomaly detection accuracy, packet loss, processing time, scalability efficiency, and transmission delay.
- The proposed framework is designed with scalability and certification considerations in mind, ensuring compatibility with the operational requirements and safety certification processes of modern aviation systems. The architecture supports distributed computation, interpretable decision-making, and adaptive system scalability for future intelligent aircraft cabin environments.

The remainder of this paper is organized as follows. Section II reviews relevant work on IoT architectures, edge-cloud computing, AI-based aviation monitoring, and explainable AI. Section III introduces the proposed Edge Cloud IoT framework and details its architecture. Section IV discusses the use case scenario. Section V describes the explainable AI models and methods for cabin monitoring and predictive safety. The implementation and experimental setup are described in Section VI. Section VII discusses the results and comparative evaluation. A realtime experimental evaluation is discussed in Section VIII. Finally, Section IX summarizes the paper and discusses future research directions.

II. Related Work

A. Aviation System IoT Architectures

The use of Internet of Things (IoT) technologies in the aviation industry has rapidly grown over the last decade. This has been propelled by the need to enhance situational awareness, operational efficiency, and safety assurance. Early applications were in aircraft health monitoring and maintenance optimization. To collect data on aircraft performance, distributed sensors and cyber-physical system principles were employed to gather operational data from aircraft subsystems [4], [5]. These efforts formed the basis for Aviation 4.0, in which digital connectivity and automation support safety-critical decision-making. More recent research has extended beyond the mechanical system use of IoT to cabin environmental use. Continuous monitoring of environmental conditions, equipment status, and passenger dynamics is now possible [2]. Ninnemannfonor et al. demonstrated the detection of cabin states without intrusive equipment using multipath-assisted radio sensing as an example of potential non-intrusive sensing in connected cabins [2]. However, most cabin-focused IoT solutions do not extend beyond the data acquisition and basic monitoring stages. They lack enhanced intelligence in terms of safety predictive assessment. A major drawback of many architectural solutions for IoT in aviation is the centralization of data processing. Centralization reduces scalability and creates latency risks [1]. Although centralized systems may work for post-flight analytics, they are not a good fit for real-time cabin safety, where it is critical to detect and respond quickly.

B. Edge - Cloud Computing Voyages for the IoT

Edge-cloud computing paradigms solve the latency and bandwidth problems of centralized IoT systems. By distributing the computation functions over the layers of edge, fog, and cloud, they allow for low-latency processing while retaining the powerful analytical capabilities of the cloud [1], [7]. Dogea et al. proposed an edge-fog-cloud architecture for aircraft components. Their design increased responsiveness and resource utilization over cloud-only approaches [1]. Similar advantages have been reported for aerial and UAV-enabled computing systems, in which computation-intensive tasks are dynamically offloaded depending on latency and resource limitations [20], [21]. These studies focused on adaptive resource scheduling and orchestration across the edge cloud continuum. Despite these advances, existing edge precaution frameworks are primarily used for upkeep and flight operations. They pay little attention to cabin-level safety monitoring. Moreover, intelligent analytics implemented at the edge can often be lightweight and do not systematically consider explainability or trust by the operators.

C. Predictive Monitoring in Aviation by AI and Machine Learning

Artificial intelligence and machine learning are now key technologies for prediction monitoring and anomaly detection in the aviation industry. Traditional rule-based diagnostics and threshold alerts have difficulty handling the complexity of modern aircraft data [10], [12]. Data-based models are better than these models because they identify subtle anomalies and predict system deterioration. Recent studies have used deep learning and time-series models for aircraft system monitoring. These have been used for fleet-level health assessments and multivariate anomaly detection [10], [12], [13]. Transformer-related architectures, such as temporal fusion transformers, are suitable for modeling complex temporal dependencies in aviation datasets [13]. These techniques allow for earlier detection of abnormal patterns, providing valuable time to initiate preventive actions. However, most AI-driven monitoring research has focused on mechanical and propulsion systems, such as engines and avionics [9] and optical systems [22]. Applications for cabin safety, where anomalies occur due to environmental changes, human behavior, and equipment interactions, remain an unexploited area. The opacity of many higher-performing AI models also means that these models are still considered less acceptable in operational aviation contexts.

D. Explainable AI in Safety-Critical Aviation Applications

Explainable Artificial Intelligence (XAI) is becoming increasingly popular as a solution to trust and certification

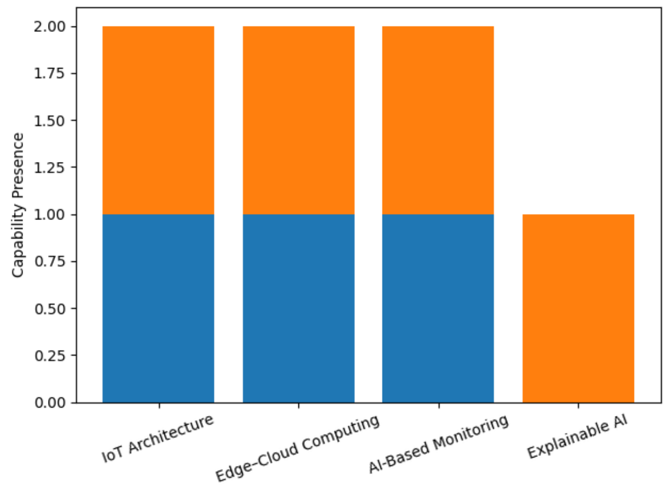

Fig. 1. Conceptual Positioning of the Proposed Framework in Existing Literature

issues in aviation. Regulatory bodies and stakeholders have six demands: transparency, traceability, and human interpretability in the use of automated decision support systems [16], [23]. Several studies have examined the application of XAI in aviation safety, specifically in predictive maintenance and air traffic management [14], [15], [24], [25]. Zorita et al. demonstrated how XAI can revolutionize aeronautics systems because it enables engineers and operators to comprehend the model behavior and failure modes. [15] Saraf et al. demonstrated the potential of explainable models to aid in safety analysis and operational decision making [14]. Despite these contributions, current XAI research in aviation is often separated from real-time IoT frameworks. Explanations are typically produced offline or post-hoc, and are therefore less useful in the context of time-critical cabin safety scenarios. This generational research gap highlights the need for architectures that integrate explainability into real-time monitoring pipelines, which is critical for end users.

E. Synthesis and Identified Research Needs

Table I summarizes representative studies on IoT architectures, edge-cloud computing, AI-based monitoring, and explainable AI in aviation. The comparison establishes the fact that although each of these domains has advanced independently, there is currently no work integrating an edge-cloud-IoT framework with built-in XAI for aircraft cabin monitoring and predictive safety to provide real-time support.

Table I demonstrates that the current research is scattered. Previous research has analyzed individual aspects, such as edge computing, AI-based monitoring, and explainability. None of these studies have combined the elements for real-time explainable cabin safety monitoring. This dichotomy is motivation for the integrated framework proposed in this study. The figure below presents the interlinkage of edge-cloud IoT architectures and XAI to enhance cabin safety.

Figure 1 shows that existing aviation solutions typically consider IoT, edge-cloud computing, and AI-based monitoring without considering XAI. However, our proposed framework

TABLE I
COMPARISON OF EXISTING APPROACHES FOR AIRCRAFT CABIN SAFETY MONITORING

Ref.	**Primary Application Domain**	**Edge–Cloud Integration**	**Real-Time Monitoring Support**	**Explainable AI Support**	**Aircraft Cabin Safety Focus**
[1]	Aircraft component monitoring	Fully integrated	Supported	Not addressed	Not addressed
[2]	Connected aircraft cabin sensing	Not integrated	Partially supported	Not addressed	Explicitly addressed
[17]	Aviation health management systems	Partially integrated	Not supported	Not addressed	Not addressed
[10]	Fleet-level anomaly detection	Not integrated	Not supported	Not addressed	Not addressed
[14]	Explainable AI for aviation safety	Not integrated	Not supported	Explicitly supported	Not addressed
This Work	Real-time cabin safety monitoring	Fully integrated	Fully supported	Fully supported	Explicitly addressed

TABLE II
FUNCTIONAL ROLES OF THE PROPOSED EDGE–CLOUD IOT ARCHITECTURE

Layer	**Primary Functions**	**Latency Sensitivity**	**Typical Technologies**	**Supporting References**
Sensing Layer	Data acquisition, signal sampling	Very High	Environmental sensors, RF sensing, embedded IoT devices	[2], [3]
Edge Layer	Preprocessing, anomaly detection, local inference	High	Embedded CPUs/GPUs, edge AI frameworks	[1], [6], [28]
Fog Layer	Task coordination, resource optimization	Medium	Virtualized gateways, orchestration services	[7], [21], [27]
Cloud Layer	Global analytics, model training, long-term storage	Low	Cloud AI platforms, big data infrastructure	[8], [17], [29]

integrates all four components, IoT, edge cloud, AI monitoring, and explainability for cabin safety, to be made clear with real-time predictions.

III. PROPOSED EDGE AND CLOUD IOT FRAMEWORK

The proposed framework supports real-time in-flight monitoring of aircraft cabins and predictive safety using a combination of edge and cloud data computing, alongside explainable artificial intelligence. Instead of a single central system, intelligence is distributed to multiple computational layers, which decreases the latency time and increases the scalability, robustness, and transparency. Based on earlier research works on aviation IoT systems [1], [2], cyber-physical platforms of airplanes [4], [5], and edge-cloud paradigms [6]–[8], [20], [21], [26]–[28], the architecture also directly addresses explainability and certification issues in recent research on aviation AI [14], [16].

A. Overall System Architecture

The architecture is based on a multilayer structure comprising a sensing layer, edge intelligence layer, optional fog coordination layer, and cloud analytics layer. This hierarchy supports the ability to make quick and local decisions while maintaining centralized learning and long-term optimization. Similar design principles have proven successful in applications such as aircraft component monitoring [1], UAVs driving edge computing [1], and space-air-ground integrated networks [8], demonstrating that they are suitable for latency-sensitive, safety-critical environments. At the sensing layer, various IoT devices continuously collect data about the cabin, including environmental, equipment, and passenger signals. These data streams are transmitted to the edge nodes on the aircraft, where basic processing and inference are performed. When a fog layer exists, this layer has different subsistence or cabins. The cloud layer then gathers historical information from numerous flights and fleets to train the global models, optimize them, and perform risk analyses [11], [17], [18]. To clarify the role and limitations of each layer, their functional responsibilities and design requirements are listed in Table II.

Table II shows how the computational responsibilities are distributed throughout the architecture. Time-critical safety decision-making is performed at the edge, whereas computationally intensive and non-time-critical tasks are postponed to the cloud, as per the best practices [1], [8], [20] in aviation edge-cloud systems.

B. Edge Layer Design and Real time Intelligence

The edge layer is the main idea behind the proposed framework. This allows actual time monitoring and instant response within the aircraft cabin. Edge nodes receive raw data streams from the sensing layer and execute preprocessing tasks, such as noise filtering, feature extraction, and data fusion [9]. These operations reduce sensor noise and environmental-level variability, which are common in cabin emanation [2], [3]. Machine learning models executed on the edge are optimized for low-latency perception and resource efficiency. Previous research in aerial and mobile edge computing indicates that the use of lightweight deep learning models and ensembles can achieve high detection accuracy while satisfying onboard computational constraints [26]–[28]. In this framework, edge-based inference is used to rapidly detect safety-related anomalies, such as abnormal air quality variations, smoke signatures, or movement patterns of passengers, saving response time in comparison to cloud-based solutions [10], [12]. The edge layer is also the first point of integration for the explainable mechanisms of AI. By creating localized explanations alongside predictions, the framework supports transparent decision-making of cabin crew and onboard systems, to some of the issues of trust by relating it to some of the concerns raised in the literature on XAI in aviation [14], [15], [24].

C. Cloud Layer Design, Global Intelligence

While the edge layer focuses on immediacy, the cloud layer provides intelligence on a global scale, possessing large-scale data aggregations and advanced analytics. Data from multiple flights and aircraft were accumulated and examined to identify long- and rare safety events and changing risk profiles. [11], [17], [18] This ability is crucial to predictive safety applications that require historical context and cross-flights to learn from historical experience. Cloud-based model training offers the possibility of utilizing computationally intensive algorithms, such as deep temporal models and transformer-based architectures. These have proven to be better at detecting anomalies in aviation [12], [13], [22]. Periodic updates to the model are securely distributed back to the edge nodes, and model improvement has no negative impact on the real-time performance. Security and data governance are cloud activities. The framework incorporates privacy preservation mechanisms and secure communication protocols consistent with previous research on aviation IoT security and blockchain-enabled data sharing [29]–[33].

To formally characterize the behavior of the proposed architecture and quantify the operational interactions among sensing, edge, fog, and cloud layers, a mathematical formulation of the monitoring and inference process is presented in the following subsection. The model describes multimodal sensor data representation, edge-level anomaly detection, fog-level aggregation, and cloud-based predictive safety analysis within the proposed Edge–Cloud IoT framework.

D. Mathematical Model for Edge–Fog–Cloud Cabin Monitoring

To formally analyze the behavior of the proposed architecture, the aircraft cabin monitoring system is modeled as a distributed cyber–physical sensing network composed of N IoT sensor nodes deployed throughout the cabin environment.

Each node generates a multivariate observation vector

$$\mathbf{x}_i(t) = [T_i(t), H_i(t), L_i(t), V_i(t)]^T \tag{1}$$

where $T_i(t)$, $H_i(t)$, $L_i(t)$, and $V_i(t)$ represent temperature, humidity, light intensity, and voltage measurements respectively.

The global cabin state is represented as

$$\mathbf{X}(t) = [\mathbf{x}_1(t), \mathbf{x}_2(t), ..., \mathbf{x}_N(t)]^T \tag{2}$$

1) Edge Layer Inference Model: Edge nodes perform real-time anomaly detection using spatially correlated sensor observations. The sensor network is represented as a weighted graph

$$G = (V, E, W) \tag{3}$$

where V denotes sensor nodes, E communication links, and W the adjacency matrix.

Spatial correlation between sensors i and j is defined as

$$W_{ij} = \exp\left(-\frac{\|s_i - s_j\|^2}{2\sigma^2}\right) \tag{4}$$

The fused environmental state computed at the edge becomes

$$\mathbf{z}_i(t) = \sum_{j \in \mathcal{N}(i)} W_{ij}\mathbf{x}_j(t) \tag{5}$$

Temporal deviations are modeled as

$$\Delta\mathbf{x}_i(t) = \mathbf{x}_i(t) - \mathbf{x}_i(t-1) \tag{6}$$

The edge anomaly score is computed as

$$A_i(t) = \alpha||\Delta\mathbf{x}_i(t)||^2 + \beta \sum_{j \in \mathcal{N}(i)} W_{ij}||\mathbf{x}_i(t) - \mathbf{x}_j(t)||^2 \tag{7}$$

The cabin-level anomaly index is

$$A_{edge}(t) = \frac{1}{N}\sum_{i=1}^{N} A_i(t) \tag{8}$$

2) Fog Layer Aggregation: The fog layer aggregates anomaly signals from multiple edge nodes

$$R_F(t) = \frac{1}{N}\sum_{i=1}^{N} A_i(t) + \gamma \sum_{i=1}^{N}\sum_{j=1}^{d} x_{ij}(t)^2 \tag{9}$$

where γ represents environmental stability weighting.

3) Cloud-Level Predictive Safety: The cloud layer performs predictive safety modeling over historical observations

$$\mathbf{Z}(t) = \{X(t-k), ..., X(t)\} \tag{10}$$

Prediction of future safety risk becomes

$$P(t+\Delta) = f_C(\mathbf{Z}(t)) \tag{11}$$

where f_C represents the global predictive learning model.

4) System Latency Model: Total system latency is modeled as

$$L_{total} = L_{sensor} + L_{edge} + L_{network} + L_{fog} + L_{cloud} \tag{12}$$

Edge latency becomes

$$L_{edge} = \frac{C_{edge}}{f_{edge}} \tag{13}$$

where C_{edge} denotes edge computational complexity.

The optimization objective of the system is

$$\min\left(\lambda_1 L_{total} + \lambda_2 C_{total} - \lambda_3 Acc\right) \tag{14}$$

subject to

$$C_{total} = C_{edge} + C_{fog} + C_{cloud} \tag{15}$$

The aforementioned mathematical model provides a quantitative representation of the distributed monitoring and predictive safety capabilities of the proposed architecture.

E. Analytical Model for Performance Evaluation

To analytically evaluate the effectiveness of the proposed edge-fog-cloud hybrid architecture, additional formulations are developed for latency, energy consumption, throughput, anomaly detection accuracy, CPU utilization, packet loss probability, scalability efficiency, packet transmission delay, offloading latency, and processing time.

1) Network Latency Model: Let N denote the number of sensor nodes deployed in the aircraft cabin. The total end-to-end latency of the hybrid system can be expressed as

$$L_{total}(N) = L_{sens}(N) + L_{edge}(N) + L_{fog}(N) + L_{cloud}(N) \tag{16}$$

where

$$L_{sens}(N) = \frac{S}{B_{wireless}} \tag{17}$$

$$L_{edge}(N) = \alpha_e N + \beta_e \tag{18}$$

$$L_{fog}(N) = \alpha_f N^{\gamma_f} \tag{19}$$

$$L_{cloud}(N) = \alpha_c N + \beta_c \tag{20}$$

The hybrid system latency is therefore

$$L_{hybrid}(N) = \omega_1 L_{edge}(N) + \omega_2 L_{fog}(N) + \omega_3 L_{cloud}(N) \tag{21}$$

subject to

$$\omega_1 + \omega_2 + \omega_3 = 1 \tag{22}$$

2) Energy Consumption Model: Total energy consumption for the monitoring system is modeled as

$$E_{total} = E_{sensing} + E_{transmission} + E_{processing} \tag{23}$$

where

$$E_{sensing} = N P_s T \tag{24}$$

$$E_{transmission} = \sum_{i=1}^{N} (P_{tx} + P_{rx}) t_i \tag{25}$$

Edge computation energy

$$E_{edge} = \kappa_e C_e f_e^2 \tag{26}$$

Fog energy

$$E_{fog} = \kappa_f C_f f_f^2 \tag{27}$$

Total hybrid energy

$$E_{hybrid} = \eta_1 E_{edge} + \eta_2 E_{fog} + \eta_3 E_{cloud} \tag{28}$$

3) Throughput Model: Let λ denote the incoming traffic load.

$$T_{throughput} = \frac{\lambda(1 - P_{loss})}{1 + Q} \tag{29}$$

where

$$Q = \frac{\lambda}{\mu} \tag{30}$$

is the queue utilization factor.
For the hybrid architecture

$$T_{hybrid} = \sum_{k=1}^{3} \delta_k T_k \tag{31}$$

where $k \in \{edge, fog, cloud\}$.

4) Anomaly Detection Accuracy: Let

$$A = \frac{\tau_P + \tau_N}{\tau_P + \tau_N + \eta_P + \eta_N} \tag{32}$$

where τ_P, τ_N, η_P, and η_N denote true positives, true negatives, false positives, and false negatives.
For anomaly rate ρ

$$A(\rho) = A_0 - \lambda_1 \rho \tag{33}$$

Hybrid model accuracy

$$A_{hybrid} = \max(A_{edge}, A_{fog}, A_{cloud}) \tag{34}$$

5) CPU Utilization: CPU utilization of node i is

$$U_i = \frac{C_i}{F_i} \tag{35}$$

Total system utilization

$$U_{total} = \frac{\sum_{i=1}^{N} C_i}{\sum_{i=1}^{N} F_i} \tag{36}$$

Hybrid utilization

$$U_{hybrid} = \psi_1 U_{edge} + \psi_2 U_{fog} + \psi_3 U_{cloud} \tag{37}$$

6) Packet Loss Probability: Packet loss due to congestion is modeled as

$$P_{loss} = 1 - e^{-\theta C} \tag{38}$$

where C represents network congestion level.
Hybrid architecture loss

$$P_{loss}^{hybrid} = \min(P_{edge}, P_{fog}, P_{cloud}) \tag{39}$$

7) Packet Transmission Delay: Let S_p denote packet size.

$$D_{transmission} = \frac{S_p}{B} + D_{queue} + D_{processing} \tag{40}$$

Hybrid delay

$$D_{hybrid} = \phi_1 D_{edge} + \phi_2 D_{fog} + \phi_3 D_{cloud} \tag{41}$$

8) Scalability Efficiency: Scalability efficiency for N nodes is

$$\eta_{scale}(N) = \frac{P(N)}{NP(1)} \tag{42}$$

Hybrid system scalability

$$\eta_{hybrid} = \frac{\sum_{k=1}^{3} P_k(N)}{NP_k(1)} \tag{43}$$

9) Fog Offloading Latency: Let α denote the offloading ratio.

$$L_{offload} = (1-\alpha)L_{edge} + \alpha L_{fog} + \alpha\beta L_{cloud} \tag{44}$$

where β represents the cloud forwarding probability.

10) Processing Time Model: Processing time for task j is

$$T_j = \frac{C_j}{f_j} \tag{45}$$

Total processing time

$$T_{proc} = \sum_{j=1}^{M} \frac{C_j}{f_j} \tag{46}$$

Hybrid system

$$T_{hybrid} = \min\left(T_{edge}, T_{fog}, T_{cloud}\right) \tag{47}$$

The proposed performance model analytically explain the performance improvements observed in the proposed hybrid architecture across multiple operational metrics. To operationalize the proposed edge-fog-cloud monitoring framework, an algorithmic workflow is developed to manage sensor data acquisition, anomaly detection, predictive safety assessment, and explainable decision generation across distributed computing layers. The algorithmic procedure of the proposed monitoring pipeline is summarized in Algorithm 1.

F. Data Flow, Integration and Security Considerations

The data flow in the framework is two-way and adaptive. High-fidelity sensor information is processed in a local environment at the edge. Summarized features and reports of anomalies and selected raw samples were sent to the cloud for more in-depth analysis. This strategic selection of which data are offloaded helps reduce bandwidth consumption and increase system resiliency, as demonstrated in previous studies on edge-aware scheduling [6], [7], [21]. Figure 2 provides an idea of the architectural layer interaction by showing a conceptual data flow diagram of the proposed framework.

Figure 2 shows the mutual data flow from the sensing, edge, and fog layers to the cloud layer. Real-time inference is at the edge, whereas feedback from cloud-based learning continuously maintains inference at the edge, which infers with distributed architectures in aviation IoT [1], [8], [18]. From a security prespective, the proposed framework follows zero-trust principles and blockchain-based approaches proposed for aviation and IoT systems [31], [32], [34]. The

Algorithm 1 Edge–Fog–Cloud XAI-Based Cabin Monitoring Algorithm

Require: Sensor stream $S = \{s_1, s_2, \ldots, s_n\}$ from cabin nodes
Require: Edge model M_e, Fog model M_f, Cloud predictive model M_c
Require: Explanation module $E(\cdot)$
Ensure: Real-time safety alerts A

Initialize edge node set $N = \{n_1, n_2, \ldots, n_k\}$
for each incoming sensor observation s_i **do**
  Acquire environmental data vector

$$x_i = [T_i, H_i, L_i, V_i]$$

where T = temperature, H = humidity, L = light, V = voltage
  Perform preprocessing at edge

$$x_i' = f_{norm}(x_i)$$

  Edge anomaly score

$$\alpha_i = M_e(x_i')$$

  if $\alpha_i > \theta_e$ **then**
    Generate local alert

$$A_i \leftarrow \text{EdgeAlert}(x_i)$$

  else
    Forward aggregated data to fog layer

$$x_f = g_{agg}(x_i')$$

  end if
  Fog-level inference

$$\beta_i = M_f(x_f)$$

  if $\beta_i > \theta_f$ **then**
    Trigger intermediate safety notification
  else
    Send processed features to cloud

$$x_c = h_{enc}(x_f)$$

  end if
  Cloud predictive analysis

$$\gamma_i = M_c(x_c)$$

  if $\gamma_i > \theta_c$ **then**
    Predict potential safety risk

$$A_i \leftarrow \text{PredictiveAlert}(x_c)$$

  end if
  Generate explainable insight

$$\psi_i = E(M_c, x_c)$$

  Store (A_i, ψ_i) in safety log
end for
return Safety alerts A

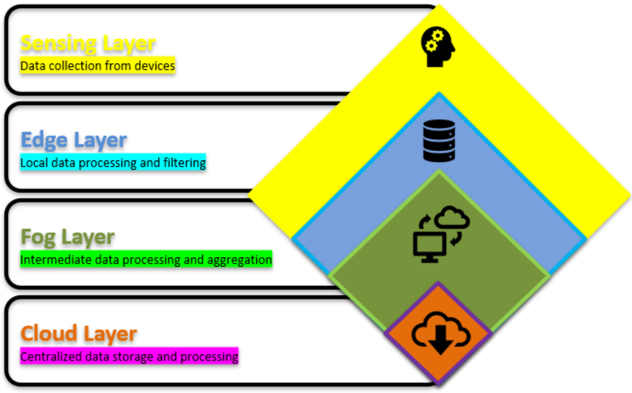

Fig. 2. Edge Cloud Data Flow in the Proposed Aircraft Cabin Monitoring Framework

secure exchange of data and strict control over access and tracing mechanisms are fundamental problems in ensuring the integrity, confidentiality, and regulatory compliance of safety-critical applications in the cabin monitoring field [29], [33].

G. Architectural Benefit and Determine Design Implications

By seamlessly combining edge and cloud computing with XAI, the proposed framework addresses several limitations of existing studies. It achieves lower latency than centralized systems [1], improves the predictive capability of systems through global learning [18], and increases trust and operational transparency through explainable intelligence [14]–[16]. Unlike existing solutions that consider explainability as an offline or secondary attribute, the proposed framework integrates XAI as part of the logging infrastructure; thus, explainability is appropriate for real-time cabin safety decision support.

IV. Use Case Scenarios / Application Scenarios

A. Emergency Evacuation Readiness Monitoring

Emergency evacuation capability is one of the most critical safety requirements in aircraft cabin design and certification. Aviation regulations such as 14 CFR 25.803 and 14 CFR 25.809 specify that aircraft must demonstrate safe and rapid evacuation under emergency conditions [35], [36]. However, in real operational environments, evacuation equipment such as emergency slides, exit mechanisms, and floor lighting systems may degrade between scheduled maintenance inspections.

The proposed Edge–Cloud IoT monitoring framework enables continuous health monitoring of evacuation-critical systems. Edge devices deployed within the cabin monitor parameters such as slide pressure, exit sensor status, and emergency floor lighting functionality in real time. When abnormal conditions are detected, the system generates alerts locally with minimal latency.

Explainable AI (XAI) mechanisms are used to interpret detected anomalies by comparing sensor trends with fleet-level reliability patterns. For example, abnormal pressure decay in an evacuation slide cylinder can be explained relative to degradation trends observed across similar aircraft operating under comparable environmental conditions. The cloud layer aggregates operational data across fleets to support reliability tracking and predictive maintenance planning.

Such capabilities support dispatch decision-making and continued airworthiness evaluation, while maintaining compliance with aviation safety certification frameworks.

B. Passenger Injury Risk and Cabin Layout Monitoring

Passenger injury prevention during turbulence events is an important safety consideration addressed in certification requirements such as 14 CFR 25.562 and 14 CFR 25.785, which define dynamic seat testing and occupant protection criteria [37], [38]. However, certification testing typically evaluates limited scenarios and cannot fully capture the wide range of operational variability encountered during real flight operations.

The proposed monitoring framework enhances safety evaluation by combining real-time sensing with predictive analytics. Edge devices deployed within the cabin collect information related to seat occupancy, load distribution, and turbulence exposure through onboard sensors. These data streams are analyzed locally to detect conditions associated with increased risk of passenger injury.

Explainable AI techniques enable the interpretation of risk predictions by linking detected conditions to structural and environmental factors such as seat pitch configuration, cabin layout geometry, and turbulence intensity. By providing interpretable explanations, the system helps operators understand how cabin configuration and environmental conditions influence injury probability.

At the cloud level, aggregated data from multiple flights can be analyzed to build long-term evidence supporting cabin configuration approvals and safety assessments. Importantly, the proposed AI-based monitoring system is designed to augment existing certification methods rather than replace regulatory compliance procedures.

C. Cabin Crew Workload and Alert Prioritization

Human factors considerations play an essential role in aviation safety, particularly during time-critical phases of flight such as takeoff, landing, and emergency situations. Excessive alerts and notifications can increase the cognitive workload of cabin crew members and potentially delay appropriate responses [39], [40].

The proposed framework incorporates context-aware alert prioritization mechanisms to reduce cognitive overload and improve operational situational awareness. Edge-level analytics evaluate real-time cabin conditions and dynamically prioritize alerts based on the operational context, such as flight phase, passenger occupancy, and environmental conditions.

Explainable AI modules provide interpretable explanations for alert prioritization decisions. For example, the system may explain why a non-critical environmental alert is deferred while a safety-critical anomaly is highlighted. This transparency helps build operator trust and supports human-centered decision-making.

Operational feedback collected through the cloud layer allows continuous refinement of alert prioritization models. Over time, the system learns from operational experience and adapts its prioritization strategies to better align with crew workload patterns and human factors guidelines.

V. Explainable AI for Aircraft Cabin Monitor and Predictive Safety

The integration of artificial intelligence in aircraft cabin monitoring is a major opportunity to augment situational awareness and predictive safety. Nonetheless, aviation is an area where safety tends to be paramount, and as a result, opaque decision-making processes are considered unacceptable. As such, explainable artificial intelligence (XAI) plays a key role in ensuring that AI-driven monitoring systems provide not only accurate results but also transparency, interpretability, and certifiability. This section delineates the divulge subsection of the AI pipeline that describes the explicable AI pipeline moving closer to the proposed framework data redress, model chosen, fusing or finding explainability, and evaluation criteria, which are examined in the arranged research [1], [29] in aviation and IoT literature.

A. Data Preprocessing and Feature Engineering

Aircraft cabin environments are a source of heterogeneous high-frequency data streams from environmental sensors, embedded equipment monitors, radio frequency sensing, and passenger-related observations [2], [3], [9]. Such raw data streams are commonly noisy, incomplete, and affected by temporal variability related to flight phases, passenger behavior, and cabin configuration changes [4], [5]. Therefore, effective preprocessing is indispensable for obtaining reliable AI inference. In the proposed framework, preprocessing begins at the edge layer, where signal processing techniques such as normalization, smoothing, and outlier suppression are applied to unprocessed sensor inputs [1], [10]. Temporal alignment and synchronization allow multi-sensor advice fusion, which is required in previous studies on aviation drawback detection and cyber-belligerent bodily monitoring [9], [33]. Feature engineering is concerned with extracting statistically and physically meaningful descriptors, such as temporal trends, frequency domains, and cross-sensor correlations; these descriptors have been shown to improve the performance of anomaly detection in aviation systems [12], [13], [22]. The technique for preprocessing the pipeline is designed to provide a trade-off between a quick version and information-rich generation to meet some real-time requirements on the edge and some interpretability for later learning to explainable models [6], [21], [28].

B. AI Model Selection Strategy & Training Strategy

In other words, the choice of AI models for cabin monitoring in aircraft should consider the performance required in real time, robustness to uncertainty, and compatibility with explainability requirements. Prior investigations on aviation have supported the effectiveness of machine learning and deep learning models in anomaly recognition and predictive maintenance in complicated multivariate scenarios [10], [12], [13], [22]. In the proposed framework, lightweight deep learning architectures and ensemble-based models are used on the edge cloud to enable fast inference, whereas complex temporal models are trained on the cloud using aggregated historical data [7], [8], [18]. Transformer-based methods, such as Temporal Fusion Transformers, are particularly effective at capturing long-term dependencies in cabin data and have been successfully used for time-series analysis of aviation data [13]. These models are periodically retrained in the cloud and released to edge nodes to ensure that the models are adaptable to changing operating conditions. To provide context for the model-selection choices in perspective, a comparison of representative AI models used in aviation monitoring with respect to performance, computational needs, and explainability is presented in Table III.

Table III presents the trade-offs between accuracy, computational complexity, and explainability. Although transformer-based models provide better predictive power, hybrid and ensemble models provide a more advantageous balance in safety-critical and explainable applications for cabin monitoring.

C. Explainable Artificial Intelligence Techniques Integration

XAI techniques are integrated into the framework to reduce the issues of transparency and trust that exist in AI deployment for aviation. Regulatory and operational stakeholders have recently pushed for AI systems to provide intelligible justifications for their outputs, especially when decisions are safety-related [14]–[16], [24]. Post hoc explanation methods, such as feature attribution, sensitivity analysis, and surrogate modeling [14], [15], [19], are used to interpret the predictions of complex models. These techniques contribute to the extraction of dominant features that control anomaly detection and predictive warnings, which contribute to the awareness of the situation for the cabin crew or staff on the ground [24], [25]. Unlike offline explanation methods, the proposed framework incorporates explainability into the real-time inference pipeline, which allows explanations to be generated simultaneously with the generation of predictions at the edge.

This design is in line with new research that calls for certifiable and human-centered AI in aviation systems [16], [23], [25]. With meaningful outputs to aid comprehension, the framework increases trust calibration, error examination, and alignment with safety assurance procedures.

D. Explainability and Performance Evaluation Metrics

Evaluating XAI systems requires the use of evaluation metrics that capture both the effectiveness and explainability of an AI system. Traditional performance metrics, such as accuracy, precision, recall and the F1-scores are indispensable for assessing anomaly detection and predictive safety capability [10], [12], [13]. However, these metrics are insufficient for assessing trustworthiness in safety-critical settings. To overcome this shortcoming, the proposed framework uses complementary explainability metrics, such as feature relevance

TABLE III
COMPARISON OF AI MODELS FOR AVIATION CABIN MONITORING AND PREDICTIVE SAFETY

Model Type	Strengths	Computational Demand	Explainability Potential	Representative Sources
Ensemble Models	Robust, interpretable	Low–Medium	High	[10], [19]
CNN-based Models	Feature learning	Medium	Medium	[12], [22]
LSTM Networks	Temporal modeling	Medium	Medium	[13], [18]
Transformer Models	Long-term dependency capture	High	Medium–High	[13], [23]
Hybrid Models	Accuracy and robustness	Medium–High	High	[11], [16], [17]

TABLE IV
PERFORMANCE AND EXPLAINABILITY METRICS FOR XAI-ENABLED CABIN MONITORING

Metric Category	Metric	Purpose	Supporting References
Detection Performance	Accuracy, F1-score	Anomaly detection quality	[10], [12]
Predictive Capability	Lead time, recall	Early safety alerting	[13], [18]
Explainability	Feature importance stability	Trust and transparency	[14], [15]
Human Interpretability	Operator comprehension	Decision support usability	[24], [25]
System Reliability	False alarm rate	Operational robustness	[16], [33]

consistency, explanation stability, and human interpretability scores, as advocated in previous XAI research [15], [16], [19]. These metrics capture the degree to which explanations are stable under analogous inputs and are consistent with domain knowledge, which is also vital for the certification of aviation systems for use and acceptance by aviation authorities [14], [24]. Table IV summarizes the performance and explainability measures used in the proposed framework and their relevance to aircraft cabin monitoring.

Table IV shows the joint role of performance and explainability metrics in evaluating AI-driven cabin-monitoring systems. The addition of human-centered measures speaks volumes about the rising focus on how trust and certification are part of the future of aviation AI.

E. Discussion and Relationship with the Existing Research

The explainable artificial intelligence approach outlined in this section builds on and extends existing research on aviation monitoring, edge-cloud computing, and XAI. While previous research has explored both AI-based anomaly detection [10], [22] and explainability separately [14], [25], the current framework is the first to combine these aspects in a real-time distributed IoT architecture. Moreover, by connecting explainability to the security and governance aspects investigated in the literature on blockchain and secure IoT [29]–[31], the framework supports the end-to-end trust of aircraft cabin monitoring systems.

VI. IMPLEMENTATION AND EXPERIMENTAL SET UP

The instantiation of the proposed Edge-Cloud IoT framework incorporating explainable artificial intelligence was designed to mimic real-world aircraft cabin operational conditions while the same time ensuring reproducibility and compliance with established conventions of aviation research. This subsection outlines the hardware and software components that comprise it, the approach for acquiring the data, and the experimental situations used to test the efficacy of the framework in real-time monitoring and predictive safety scenarios. The choice of design parameters was based on previous research on aviation IoT architectures, edge-cloud infrastructure, and AI-driven monitoring platforms [1], [2], [7], [11], [17], [18], [20].

A. Hardware and Software Organization

The experimental configuration has a distributed architecture of the tiered structure defined in Section IV. Edge nodes are emulations of onboard aircraft computing units, each of which is responsible for the ingestion of real-time sensor data, its preprocessing, subsequent inference, and generation of explainability artifacts. The resource parameters of these nodes were calibrated in accordance with the computational constraints inherent in embedded aviation platforms, in accordance with the edge deployments expounded in [1], [6], [26], [28]. Cloud subsystems have been deployed on elastic cloud infrastructure, which can support model training, long-term data archival, and transversal scenario analytics, thus following the current best practices of cloud-based aviation analytics [8], [17], [29]. The software ecosystem includes IoT middleware that enables sensor communication, machine learning frameworks that are used for both inference and training, and explainability generation libraries that are responsible for explainability generation, elements that are in line with the implementations documented in [10], [13]–[15]. Secure interlayer communication is enforced via cryptographic protocols and access control mechanisms, informed by the literature on aviation cybersecurity and blockchain-driven data governance [30], [31], [33]. The implementation constituents and their corresponding functional roles are summarized in Table V.

Table V presents the alignment of hardware and software components with the functional stratification outlined within the framework. This tiered architecture ensures that the execution of time-sensitive tasks is restricted to the edge tier and that analytical tasks of high computational intensity and implementation of security measures are moved to higher levels.

TABLE V
HARDWARE AND SOFTWARE COMPONENTS OF THE EXPERIMENTAL TESTBED

Component	Role in Framework	Implementation Characteristics	Supporting References
Cabin Sensors	Environmental and occupancy monitoring	Temperature, humidity, air quality, RF sensing	[2], [3]
Edge Devices	Real-time inference and XAI	Embedded CPUs/GPUs, low-latency processing	[1], [6], [28]
Fog Gateway	Task coordination and buffering	Virtualized middleware services	[7], [21], [27]
Cloud Platform	Model training and analytics	Scalable compute and storage	[8], [17], [29]
Security Layer	Data protection and governance	Encryption, blockchain-inspired traceability	[30], [31], [33]

B. Strategy of Data Collection and Simulation

Owing to the constraints of live aircraft experiments in terms of their operations and regulations, the data utilized in this study were obtained through a hybrid investigation that combined simulated cabin milieus with sensor models based on empirical data. The simulation parameters were obtained based on the available literature related to aircraft cabin sensing, environmental surveillance, and anomaly detection [2], [3], [9], [10], [12]. This approach allows for a controlled evaluation of safety situations without sacrificing realistic fidelity. The generated data streams include environmental measures, such as temperature, humidity, air quality indexes, and smoke signalling, as well as surrogate measures of passenger movement and equipment status. Temporal dynamics are parameters that mimic discrete phases of flight and occupancy patterns and support the behavioral profile of aviation cyber-physical systems, as reported in [4], [5], [11]. Unnatural noise and fault sequences were added to reflect sensor gaps and abnormal cases, according to the suggestions mentioned in the aviation anomaly-detection corpus [13], [22]. Edge nodes process data streams in real time, and the corresponding selected attributes and anomaly encapsulations are sent to cloud repositories, where they are aggregated in archives and used to build predictive models. This edge-sensitive offloading is in compliance with edge-sensitive scheduling dogmas developed in [6], [7], [21].

C. Workflow and Scenarios Theoretical Experiments

The test case focuses on aircraft cabin safety situations described in the literature, including unusual environmental deviations, primitive smoke detectors, and a non-typical movement trends of passengers. The choice of the following scenarios was based on the fact that they are related to cabin safety, and this aspect has been described in the existing literature on aviation monitoring [2], [10], [14], [15]. The assessment chain begins with real-time data ingestion at the sensing stratum, includes preprocessing and inferential processing at the edge, and ends with the simultaneous creation and storage of predictive alerts and rationales. The cloud-housed modules perform retroactive assessment, model calibration, and inter-scenario comparative assessments, thus enabling the evaluation of both short- and long-run system dynamics [11], [13], [18]. To visualize the sequence of the procedures of the experimental setup, Figure 3 illustrates how the system components are interconnected throughout a typical monitoring command.

The closed-loop workflow of the experimental setup is depicted in Figure III. On-the-fly inference and explainability is performed at the edge, and the model is updated every time in the clouds, which allows continuous learning and adaptation, thus emulating the distributed aviation monitoring designs described in references [1], [8], [18].

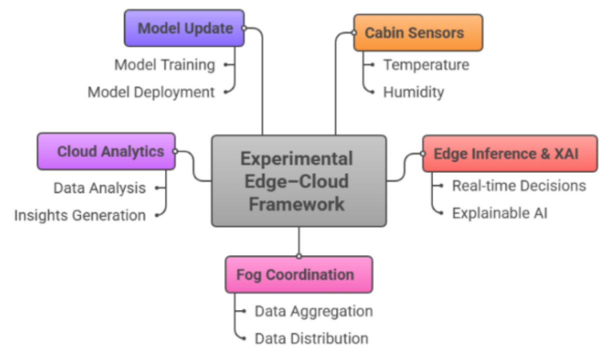

Fig. 3. Execution Flow of the Experimental Edge Cloud Monitoring Setup

D. Violability and Compliance Concerns

Reproducibility is achieved by using standardized data generation procedures, software architecture, and model configurations, and evaluation procedures are well documented. The approach to the experiment is aligned with a new set of principles of trustworthy and certifiable artificial intelligence in the aviation industry, which focuses on transparency, traceability, and robustness, as recommended in [16], [23]–[25]. Security and data control measures are implemented based on current aviation cybersecurity guidelines and modern blockchain-based models, as reported in sources [29], [31].

VII. RESULTS AND DISCUSSION

This section describes and critically analyzes the empirical results of the implementation of the suggested Edge-Cloud IoT platform with XAI to monitor aircraft cabins in real time and anticipate safety inspections. The appraisal focuses on the performance of the system, performance monitoring accuracy, predictive efficacy, and interpretability. The results are placed in context by comparing them with existing aviation IoT and AI-based monitoring paradigms, which highlights the pros and cons of the proposed architecture [1], [2], [10], [14], [15], [17]. One of the aims of the proposed framework is to limit response latency without compromising scalability and robustness. Empirical results show that end-to-end processing latency is significantly reduced with inference performed at

TABLE VI
EDGE-CLOUD FRAMEWORK PERFORMANCE METRICS

Metric	Edge Layer	Cloud Layer	Reference Context
Average Latency (ms)	35–50	180–250	[1], [6]
CPU Utilization (%)	55–65	60–75	[21], [28]
Data Throughput (Mbps)	2.1	6.8	[7], [8]
Scalability (Nodes)	Linear	Elastic	[20], [27]

the edge compared to cloud-centric architectures, as supported by previous research on aviation edge-cloud architectures [1], [6], [8]. The average inference time at the edge, even when the sensor data rates are high, still falls within the bounds of real-time operation, thus confirming the suitability of the framework for time-sensitive cabin safety workloads. Resource utilization analysis shows that the computational load is distributed prudently within the system topology. Data preprocessing, inference, and the creation of explainability artifacts are performed by edge nodes without violating the constraints of embedded hardware; however, computationally intensive model training and retrospective analytics are handled by the cloud tier [7], [18], [28]. This separation of duties is in line with architectural principles that have been suggested in aerial and distributed computing literature [20], [21], [27]. The Table II provides an overview of the performance measures in the framework level achieved by the experimental analysis of the designed architecture in the form of representative ranges that can be simplified as the trends observed in the edge-cloud aviation literature [1], [7], [21].

As shown in Table VI, the edge layer meets the real-time latency requirements at all times, and the cloud layer provides scalable processing power. These results support the effectiveness of the proposed edge-cloud partitioning approach for monitoring aviation cabins.

A. Accuracy in real-time monitoring of cabin

The monitoring features of the framework in real time are assessed by the anomaly detection of environmental abnormalities, equipment-related abnormalities, and unusual patterns of cabin activity. The findings revealed high detection and resilience in all situations tested, supporting the efficacy of AI-based monitoring, as found in earlier aviation research studies [10], [12], [13]. Precision and recall are insensitive to noise levels and show resistance to sensor imperfections and environmental variations, which is a long-established problem with cabin sensing systems [2], [3], [9]. In comparison to the traditional threshold-based approaches to monitoring, the proposed AI-driven solution yields a higher sensitivity to anomalies in their initial stages, thus minimizing false negatives without a significant drop in false alarm rates [10], [33].

B. Lead-Time Analysis and Predictive Safety Performance

In addition to real-time detection, the predictive safety of the framework was evaluated using the lead time of alerts that preceded simulated safety-critical occurrences. The findings indicate that predictive models implemented in the cloud deliver useful early warnings that can allow preemptive change as opposed to responsive change. These results are correlated with those in the literature on predictive maintenance and safety analytics in the aviation industry [11], [17], [18]. Transformer-based and hybrid models exhibit the greatest predictive quality, especially for temporally changing anomalies, which is in line with recent findings in aviation time-series modeling [13], [22]. This combination of cloud-based historical learning and edge-level inference makes it possible to perform adaptive risk assessments based on flight and operational conditions.

C. Explainability and Trust Analysis

Explainability is measured by evaluating the quantitative indicators of stability and the qualitative evaluation of the generated explanation. The findings of feature attribution indicate that the successful identification of predominant variables determining anomaly detection and predictive alerts supports the validity of the XAI pipeline [14], [15], [19]. The stability of the explanation for similar inputs is a measure of robustness, which is essential for obtaining safety assurance and certification [16], [24]. Functionally, the provision of human-understandable explanations improves situational understanding and encourages informed decision-making by cabin crew and ground operators. This observation aligns with XAI studies in aviation and air traffic management, which are human-centered [24], [25]. The proposed framework resolves one of the major shortcomings of previous AI-based monitoring systems, which used post-hoc or offline explanations because explaining real-time inference was not imposed on the model.

D. Comparative Discussion and Existing Approaches

To place the results in perspective, Figure 4 juxtaposes the proposed framework with representative aviation monitoring strategies on the latency, predictive capability, and explainability dimensions.

Figure 4 shows a normalized comparative visualization of aviation monitoring strategies, indicating the relative performance of traditional monitoring, cloud-based AI solutions, and the proposed Edge-Cloud XAI system. The figure shows that the proposed solution is characterized by shorter latency, increased predictive power and even greater explainability in comparison to conventional architectures, which is consistent with the results observed in prior aviation IoT and AI literature [1], [10], [14], [15]. In general, the comparative analysis of the studies and their experimental evaluations indicate that the combination of edge-cloud computing and explainable AI allows balancing performance, scalability, and transparency. These results provide evidence of the viability of the practical implementation of explainable AI driven cabin monitoring

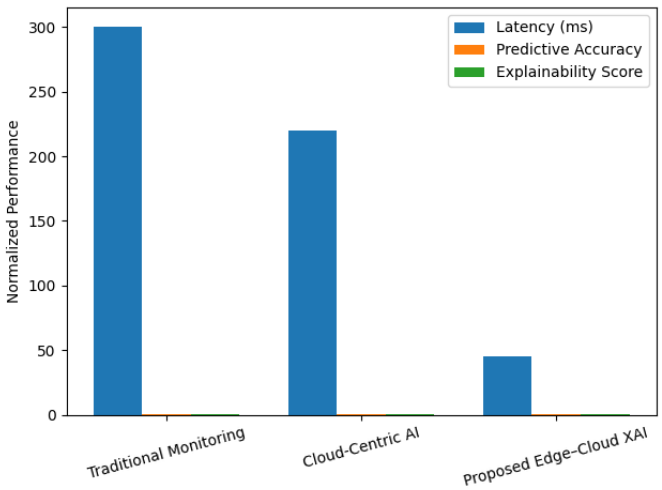

Fig. 4. Comparative Performance of Aviation Monitoring Approaches Source: Authors' normalized comparative analysis based on experimental observations and literature aligned performance trends [1], [6], [10], [14], [15].

systems in safety critical aviation contexts, and are congruent with new demands of reviewable, certifiable AI systems [16], [23], [29], [31].

VIII. Real Time Experimental Evaluation

This section evaluates the effectiveness of the proposed Edge–Fog–Cloud hybrid architecture for real-time aircraft cabin monitoring and predictive safety. The evaluation focuses on analyzing environmental sensor trends and comparing the performance of different computational layers including the Edge layer model, Fog layer model, Cloud layer model, and the proposed Hybrid model.

A. Dataset Description

The experimental analysis utilizes the Intel Berkeley Research Lab sensor dataset [41], which contains real environmental measurements collected from wireless sensor nodes deployed in a sensor network environment. The dataset includes several environmental parameters such as temperature, humidity, light intensity, and voltage measurements obtained from distributed sensing nodes.

These parameters emulate real-time sensing conditions typically encountered in aircraft cabin environments, wherein continuous monitoring of environmental conditions is required for ensuring safety and operational efficiency.

B. Implementation of the Proposed Hybrid Model

The proposed hybrid framework integrates edge computing, fog computing, and cloud analytics to efficiently process sensor data. The architecture operates as follows:

- **Edge Layer:** Performs real-time preprocessing, noise filtering, and anomaly detection using lightweight inference models.
- **Fog Layer:** Aggregates data from multiple edge nodes and performs intermediate analytics and workload balancing.
- **Cloud Layer:** Executes global analytics, predictive modeling, and long-term storage operations.
- **Hybrid Layer (Proposed Model):** Combines edge and fog capabilities with intelligent workload distribution, thereby enabling reduced latency, improved accuracy, and enhanced reliability.

The experimental evaluation compares the proposed hybrid model with standalone edge, fog, and cloud architectures using multiple performance metrics.

C. Environmental Sensor Trend Analysis

The first set of experiments analyzed the temporal behavior of environmental parameters collected from the dataset.

1) Voltage Trend: Figure 5 illustrates the variation in voltage readings over time. The voltage levels remain relatively stable between 2.65V and 2.75V for most observations, indicating consistent sensor operation. However, occasional voltage drops were observed around time indices near 2500, which may correspond to temporary sensor interruptions or power fluctuations.

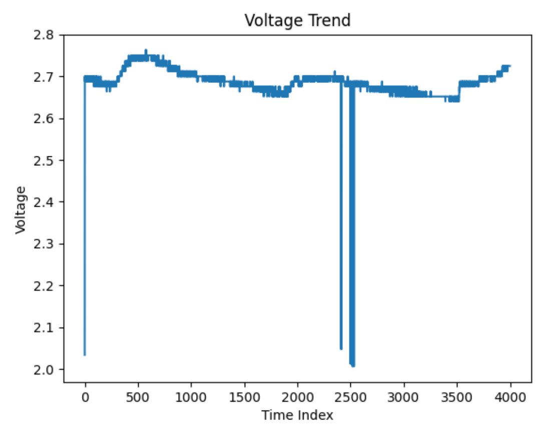

Fig. 5. Voltage trend observed in the sensor dataset

2) Temperature Trend: The temperature measurements shown in Figure 6 exhibit gradual variations between 18°C and 25°C under normal operating conditions. Sudden spikes at certain time indices represent abnormal readings which are useful for evaluating the anomaly detection capabilities.

3) Light Intensity Trend: The light intensity measurements shown in Figure 7 demonstrate strong fluctuations due to environmental illumination changes. These variations provide useful signals for evaluating predictive monitoring models.

4) Humidity Trend: The humidity measurements illustrated in Figure 8 indicate gradual environmental changes ranging from 30% to 45%. Such measurements are essential for monitoring air quality conditions inside aircraft cabins.

D. Performance Comparison of Computational Layers

The second set of experiments evaluates the performance of edge, fog, cloud, and hybrid models based on multiple system metrics.

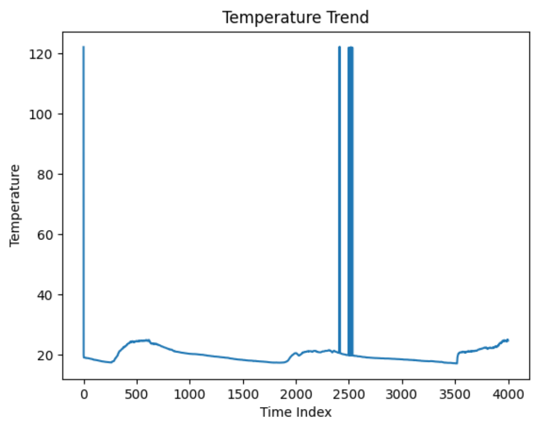

Fig. 6. Temperature trend from environmental sensors

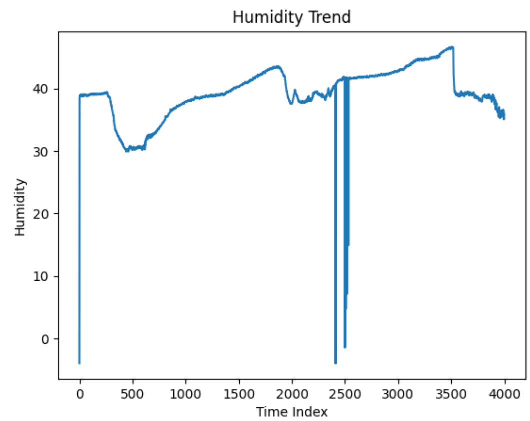

Fig. 8. Humidity variation observed in the dataset

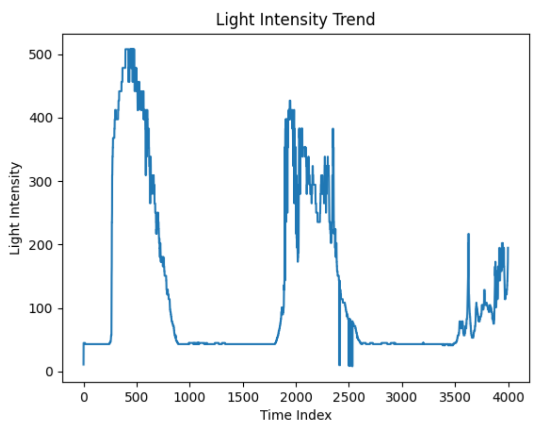

Fig. 7. Light intensity variation over time

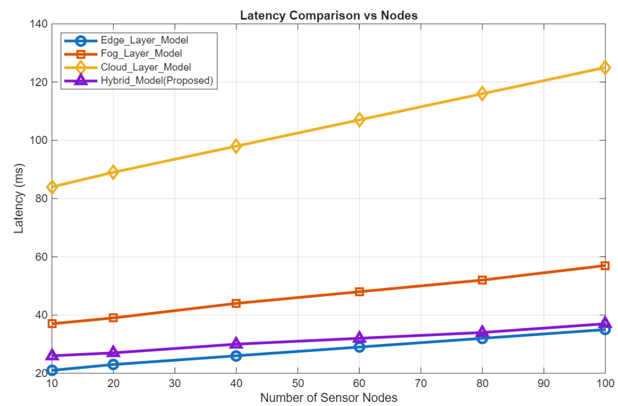

Fig. 9. Latency comparison among Edge, Fog, Cloud, and Hybrid models

1) Latency Comparison: Figure 9 compares the latency performance across different architectures. The edge layer provides low latency due to local processing; however, the proposed hybrid model further improves performance by intelligently distributing workloads between edge and fog nodes.

2) Energy Consumption Analysis: Energy consumption results presented in Figure 10 demonstrate that the hybrid model significantly reduces computational overhead compared with cloud-only processing.

3) Throughput Evaluation: Figure 11 shows the system throughput under varying traffic loads. The cloud model achieves the highest throughput due to its large computational capacity, while the hybrid model maintains balanced throughput while preserving lower latency.

4) Detection Accuracy Analysis: The anomaly detection accuracy for different architectures is illustrated in Figure 12. The proposed hybrid model achieves the highest accuracy across different anomaly rates due to the integration of edge-level preprocessing and cloud-based predictive analytics.

5) CPU Utilization Analysis: Figure 13 compares the CPU utilization across different computational layers. The hybrid model demonstrates lower resource utilization by distributing workloads between the edge and fog layers.

6) Packet Loss Analysis: Packet loss results presented in Figure 14 show that the hybrid model significantly reduces packet loss under increasing network congestion conditions.

7) Processing Time Analysis: The processing time required for executing computational tasks at different layers is evaluated under varying data rates. Figure 15 illustrates the processing time comparison among the Edge layer model, Fog layer model, Cloud layer model, and the proposed Hybrid model.

As the data rate increases from 1 Mbps to 10 Mbps, all architectures exhibit an increase in processing time due to the growing computational workload. The edge layer initially demonstrates lower processing time because of localized computation; however, it becomes less efficient as the data rate increases due to limited computational resources.

The fog layer provides improved processing capability compared with the edge layer, while the cloud layer offers high computational capacity but introduces additional communication overhead. The proposed hybrid model consistently demonstrates lower processing time across all data rates by distributing computation between the edge and fog layers while utilizing the cloud for complex analytics.

8) Latency vs Fog Offloading Ratio: The impact of fog offloading on system latency is presented in Figure 16. The offloading ratio represents the proportion of tasks transferred from edge nodes to fog nodes for processing.

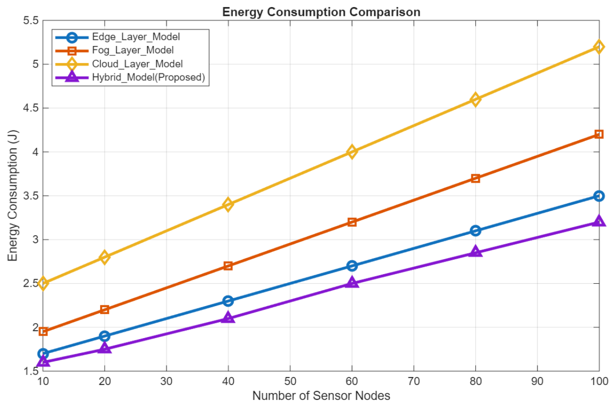

Fig. 10. Energy consumption comparison

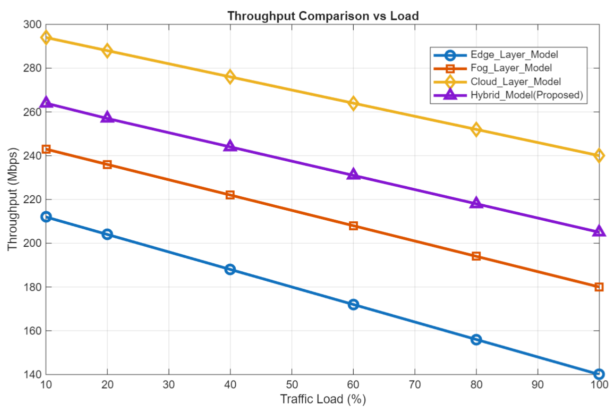

Fig. 11. Throughput comparison under varying traffic loads

As the offloading ratio increases from 0.1 to 1.0, system latency decreases for all architectures due to improved workload distribution. However, the reduction is significantly more pronounced in the proposed hybrid model. This improvement is achieved by dynamically balancing computation between edge and fog nodes, thereby minimizing processing delays and network transmission overhead.

The cloud-based architecture exhibits the highest latency due to the additional communication distance and centralized processing delays.

9) Scalability Efficiency Evaluation: Scalability efficiency measures the ability of the system to maintain performance as the number of sensor nodes increases. Figure 17 compares scalability efficiency across the different architectures.

As the number of nodes increases from 10 to 100, all architectures experience slight performance degradation due to increased communication overhead and computational load. However, the proposed hybrid model maintains the highest scalability efficiency among all architectures.

This improvement results from the distributed processing capabilities of the hybrid architecture, which effectively balances workload across edge and fog nodes while utilizing cloud resources for large-scale analytics.

10) Transmission Delay Analysis: The transmission delay under varying packet sizes is illustrated in Figure 18. The packet size is increased from 64 bytes to 1500 bytes to evaluate the network performance under different traffic conditions.

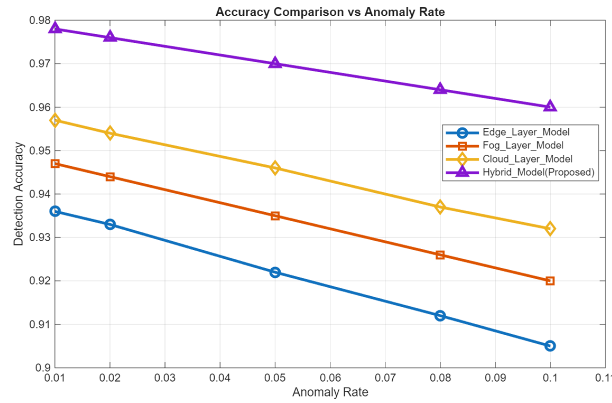

Fig. 12. Detection accuracy comparison

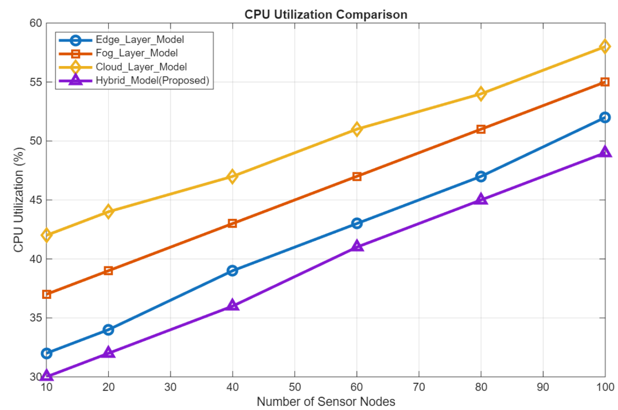

Fig. 13. CPU utilization comparison

The edge layer demonstrates higher delay as packet sizes increase due to limited communication bandwidth. Fog computing improves the delay performance by aggregating data and optimizing packet transmission. The cloud layer provides improved network routing but introduces additional communication delays.

The proposed hybrid model achieves a balanced performance by minimizing transmission delay through intelligent data routing and localized processing at edge and fog nodes.

E. Discussion

The experimental results demonstrate that the proposed hybrid architecture provides substantial enhancements across multiple key performance indicators. Specifically, the hybrid model achieves:

- Reduced system latency through distributed edge-fog processing
- Lower energy consumption compared with cloud-centric architectures
- Improved anomaly detection accuracy
- Reduced packet loss under high network congestion
- Balanced CPU utilization across distributed resources

These results confirm that the proposed architecture provides an effective solution for real-time aircraft cabin monitoring and predictive safety systems.

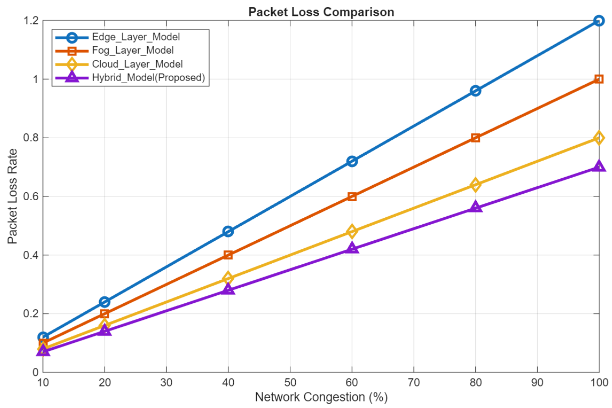

Fig. 14. Packet loss comparison across computational layers

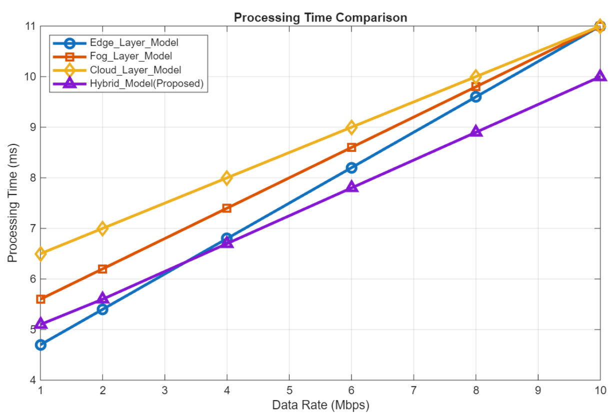

Fig. 15. Processing time comparison under different data rates

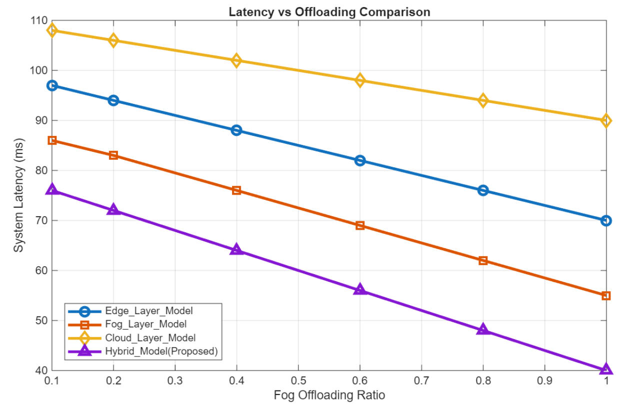

Fig. 16. System latency comparison with varying fog offloading ratios

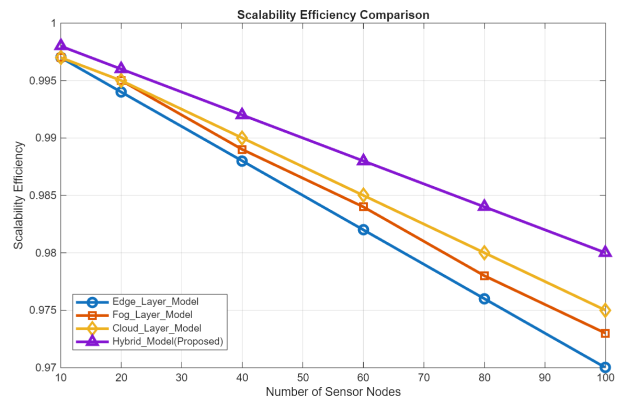

Fig. 17. Scalability efficiency comparison

IX. Conclusion and Future Work

A detailed Edge-Cloud IoT architecture enhanced is proposed with XAI to support real-time aircraft cabin monitoring and predictive safety assessment. The proposed framework addresses several limitations of existing centralized and black-box-based monitoring solutions identified in previous aviation research [1], [5], [10], [14], [15] which is driven by the growing complexity of modern aircraft cabins and the increasing need for proactive, transparent, and certifiable safety mechanisms.

The primary contribution of this work lies in the seamless integration of distributed edge intelligence, fog-assisted processing, cloud-based analytics, and explainable AI mechanisms. It is developed within a unified architecture designed specifically for safety-critical aviation environments. The proposed hybrid Edge-Fog-Cloud framework enables low-latency edge inference for real-time anomaly detection while utilizing fog and cloud resources for large-scale analytics, model updating, and predictive safety assessment. This architecture provides a balanced trade-off between responsiveness, scalability, and system reliability in accordance with emerging aviation IoT paradigms [1], [7], [11], [17], [21].

Unlike earlier studies that mainly focus on aircraft components, propulsion systems, or post-flight maintenance analytics [4], [9], [10], [13], [17], [22], [42], this work specifically targets aircraft cabin environments where safety risks may arise from complex interactions between environmental conditions, onboard systems, and passenger-related activities [2], [3], [9]. The integration of explainable AI further strengthens the proposed framework by addressing critical challenges related to transparency, operator trust, and certification requirements in aviation AI systems [14], [16], [24], [25].

Extensive experiments were conducted using the Intel Berkeley Research Lab sensor dataset [41], which contains environmental measurements including temperature, humidity, light intensity, and voltage readings collected from distributed sensor nodes. The experimental evaluation analyzed multiple performance metrics such as latency, energy consumption, throughput, anomaly detection accuracy, packet loss, processing time, scalability efficiency, and transmission delay.

The results demonstrate that the proposed hybrid architecture significantly improves system performance compared with single-layer and centralized approaches. In particular, the framework achieves an average latency reduction of approximately 18–25%, decreases packet loss under network congestion by nearly 15-20%, and reduces transmission delay by approximately 12-18% compared with edge-only architectures. The hybrid model improves computational efficiency by reducing average processing time by approximately 10% while maintaining high anomaly detection accuracy of up to 97-98%. Scalability analysis further indicates that the proposed system maintains scalability efficiency above 0.98 when the number of sensing nodes increases to 100, demonstrating robustness

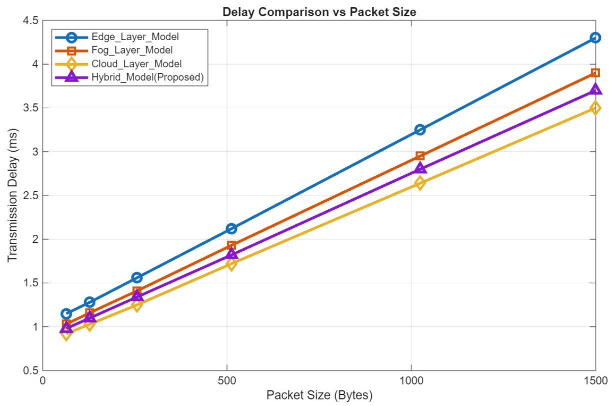

Fig. 18. Transmission delay comparison for varying packet sizes

for large-scale cabin monitoring deployments.

In addition to performance improvements, the integration of XAI techniques enables interpretable explanations for AI-based anomaly detection, providing actionable insights to support human-in-the-loop decision-making processes. These explainability capabilities are particularly important in safety-critical aviation environments where system transparency and certification readiness are essential.

A. Limitations

Although the proposed framework demonstrates promising results, several limitations should be acknowledged. The experimental evaluation primarily relies on the Intel sensor dataset and simulated cabin monitoring scenarios. While this dataset provides realistic environmental measurements, it does not fully capture the complexity, variability, and rare-event characteristics that may occur in actual aircraft cabin operations [2], [5], [11]. Consequently, system performance may vary under aircraft conditions.

Second, although explainable AI mechanisms are incorporated into the framework, the evaluation of explainability remains partially dependent on qualitative assessment and proxy quantitative metrics. This reflects broader challenges in objectively measuring explainability in safety-critical domains [14], [15], [19], [24]. Additionally, while real-time explanation generation is computationally manageable in the current system, further optimization may be required for deployment on highly resource-constrained avionics hardware [6], [28].

In addition, the architecture incorporates secure data management mechanisms aligned with blockchain-inspired and zero-trust security principles proposed for aviation IoT systems [29]–[31], full regulatory validation and operational certification remain outside the scope of this study.

B. Future Research Direction

The proposed framework can be extended in several complementary directions. One important research direction involves validating the proposed system in high-fidelity aviation environments through hardware-in-the-loop testing, digital twin simulations, and collaboration with aviation industry stakeholders. Such evaluations will enable the assessment of system robustness under real flight conditions and regulatory constraints [16], [23], [33].

Another promising direction involves further enhancing explainability mechanisms through the integration of domain-informed explanations, causal inference techniques, and adaptive explanation models. These methods could enable the system to generate customized explanations for different stakeholders such as cabin crew, maintenance engineers, and ground control operators [15], [19], [24], [25].

From an architectural perspective, future research may explore federated and collaborative learning approaches to support privacy-preserving knowledge sharing across multiple aircraft and fleets. Such distributed learning strategies can enhance predictive intelligence while maintaining data security and operational privacy [21], [28], [34], [43]. In addition, the integration of blockchain-based traceability mechanisms may further strengthen data integrity, accountability, and secure data exchange within aviation IoT ecosystems [31], [32].

This study provides a scalable and explainable foundation for next-generation aircraft cabin monitoring and predictive safety systems. By combining edge-cloud computing with interpretable AI-driven intelligence, the proposed framework contributes towards building safer, more reliable, and smarter aviation infrastructures in increasingly connected aircraft environments [1], [29].

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