IoT-Based Alert System for Faulty Urban Elevators

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Abstract— Urban vertical transportation systems, such as elevators, are indispensable to modern cities, yet component failures pose significant safety and efficiency risks. Traditional, scheduled maintenance approaches are reactive, failing to address incipient faults that lead to downtime and potential accidents. This paper introduces the Predictive Urban Elevator Safety (PUES) Framework, a novel Internet of Things (IoT)-based alert system designed to enable real-time dynamic monitoring and early warning for urban elevators. The PUES Framework leverages non-intrusive sensory data collection and advanced machine learning algorithms, specifically a distributed PCA-LSTM model, to accurately predict and diagnose component failures, particularly within the door and traction systems. By continuously analyzing vibration, acoustics, and control state information, the system transmits immediate, localized alerts to maintenance crews and building management via a secure cloud infrastructure. The PUES Framework transforms maintenance from reactive scheduling to proactive, condition-based prediction, significantly enhancing public safety and reducing operational disruptions across urban smart infrastructure.

Keywords— *Internet of Things (IoT), Elevator Safety, Fault Diagnosis, Predictive Maintenance, Machine Learning, Non-Intrusive Monitoring, Smart Cities.*

I. INTRODUCTION

Elevators are fundamental components of urban infrastructure, facilitating high-density vertical mobility within smart cities. As urban populations grow and buildings become taller, the reliability and safety of these vertical transit systems become increasingly critical. Failure of an elevator system not only leads to significant operational inconvenience and congestion but, more importantly, poses a direct safety risk to passengers [17]. Traditional elevator maintenance practices typically rely on fixed, time-based schedules or reactive repairs only after a fault has manifested, often resulting in prolonged downtime and maintenance inefficiency.

However, the majority of malfunctions stem from incipient faults—minor degradations in performance that are not immediately catastrophic but are precursors to major component failure. The challenge lies in dynamically monitoring complex elevator systems in a non-intrusive manner to capture these subtle variations in operational metrics before a critical failure occurs. Modern smart cities are increasingly integrating Internet of Things (IoT) technology into infrastructure to enhance safety and efficiency [4]. Applied to elevators, IoT offers the ability to conduct continuous, remote condition monitoring, providing the necessary data for predictive maintenance [18], [5].

Existing research has successfully demonstrated the feasibility of using IoT for elevator monitoring, focusing on improving maintenance efficiency and safety [5], [6], [18]. The shift toward non-intrusive online monitoring is crucial, as it allows for the installation of sensors without major modifications to existing machinery, making deployment scalable across large fleets of urban elevators [2], [8]. Furthermore, the evolution of sophisticated machine learning (ML) and deep learning (DL) algorithms now allows for the development of highly accurate fault diagnosis and early warning systems capable of distinguishing normal operational variance from true component degradation [4], [7].

This paper proposes the Predictive Urban Elevator Safety (PUES) Framework, a novel IoT-based system architecture designed to integrate non-intrusive data acquisition with a powerful, distributed deep learning model for real-time fault prediction and immediate alert generation. The PUES Framework focuses on combining sensor data (vibration, acoustics, motor current) with control state information to provide a holistic view of elevator health. By utilizing a Distributed Principal Component Analysis-Long Short-Term Memory (PCA-LSTM) model [9], the framework aims to identify complex fault patterns with high precision, specifically targeting high-risk components like elevator doors and traction systems, which are frequent sources of failure [1], [12], [15].

The PUES Framework is characterized by four core innovations:

1. **Decentralized Edge Processing:** Preliminary feature extraction and data compression [10] occur at the elevator site to minimize data transmission latency.
2. **PCA-LSTM Integration:** Combining dimensionality reduction (PCA) with time-series forecasting (LSTM) to handle the complex, sequential nature of elevator operational data [9].
3. **Real-Time Alert Protocol:** A secure, cloud-based alert system that instantly notifies the appropriate maintenance team and building management when a high-risk fault is predicted.
4. **Component-Specific Focus:** Prioritizing and applying specialized fault detection methods for critical subsystems, particularly the door and traction motor, which are key sources of accidents and downtime [1], [6], [13].

The remaining structure of the paper details the necessary literature, describes the proposed PUES architecture, outlines the implementation methodology, and discusses the anticipated results and future expansion.

II. LITERATURE REVIEW

The development of the PUES Framework is grounded in extensive research covering elevator safety, IoT deployment, and advanced fault diagnosis techniques.

A. Elevator Safety and Monitoring Imperatives

Empirical studies on elevator safety highlight that accidents and malfunctions are often linked to mechanical wear and improper door operation [17]. This underscores the critical need to shift from routine checks to condition-based monitoring (CBM). The sheer volume of elevators in urban environments necessitates centralized, remote monitoring capabilities to optimize maintenance schedules and resource allocation [18], [19]. Early warning systems are essential to mitigate the risk associated with mechanical failures, which can range from minor discomfort to serious safety incidents.

B. IoT and Remote Condition Monitoring

The deployment of the Internet of Things has revolutionized industrial safety by enabling the collection of vast amounts of data from safety-critical environments [6]. For elevators, IoT technology facilitates remote condition monitoring (RCM), primarily through the use of non-intrusive sensors that measure vibration, acoustics, and power consumption [18], [2], [3]. Olalere *et al.* [18] specifically explored RCM using vibration and acoustic parameters to optimize maintenance, confirming the efficacy of this approach. This remote capability, secured by systems like those leveraging cloud computing [19], forms the backbone of any scalable urban monitoring solution. The focus on non-intrusive system design is further emphasized by recent work on online monitoring systems for traction elevators, ensuring minimal impact on existing infrastructure [8].

C. Advanced Machine Learning for Fault Detection and Diagnosis (FDD)

The transition from mere data collection to predictive alerting requires sophisticated analytical techniques. Machine learning (ML) algorithms are universally recognized as the essential component for accurate fault detection and diagnosis (FDD) in complex machinery.

1. Non-Intrusive and Pattern-Based FDD

Several studies have focused on non-intrusive methods. Skog [2] demonstrated fault detection using learned traffic patterns, suggesting that deviations from normal operational profiles can indicate an issue without direct measurement of internal mechanical states. Chai *et al.* [3] further advanced this by proposing a non-intrusive deep learning-based diagnosis system, confirming that complex failures can be identified solely through external sensory data. The idea of an "early warning system" based on dynamic monitoring and ML is also a key area of research, confirming the viability of the PUES goal [4].

2. Deep Learning and Hybrid Models

Recent research has heavily favored deep learning models, particularly those suited for handling sequential time-series data, such as those generated by elevator operations.

- **PCA-LSTM:** Chen *et al.* [9] introduced a distributed fault diagnosis model based on PCA-LSTM, combining the strength of Principal Component Analysis (PCA) for dimensionality reduction with the superior time-series prediction capability of Long Short-Term Memory (LSTM). This hybrid approach is highly effective in isolating and forecasting faults from noisy, multi-dimensional sensor data, making it a strong candidate for the PUES framework.
- **Advanced Prediction:** Fault prediction methods, including those based on Transfer Learning [1] and XGBoost optimized by intelligent algorithms [11], show high accuracy in anticipating failures, even with unbalanced or limited training samples. Kim *et al.* [12] specifically focused on fault prediction for the elevator door system, a key failure point, demonstrating the use of margin-maximized hyperspace techniques.

3. Component-Specific Diagnosis

To ensure the highest safety standards, FDD must be tailored to the most critical subsystems:

- **Door System:** Elevator doors are frequent sources of malfunctions. Research has focused on fault diagnosis using control state information [15] and specialized prediction methods [1], [12].
- **Traction System:** Failures in the Permanent Magnet Synchronous Motor (PMSM) are addressed by robust model-based fault diagnosis methods [13], often using high-precision magnetic sensors [6]. This demonstrates that specific component-level failures can be accurately detected using focused sensor and algorithm combinations.

D. Summary of Foundational Work

The PUES Framework synthesizes these foundational elements, moving beyond singular fault diagnosis techniques towards a comprehensive, real-time, alert-driven system. The table below summarizes how the PUES Framework integrates and builds upon key literature components.

Reference Focus Area	Key Contribution	PUES Integration Strategy	Citation s
Safety & Risk	Quantifies accident risks & need for CBM.	Supports proactive alerts.	[17]
IoT/RCM	Enables remote monitoring via sensors.	Defines sensors & communicat ion.	[5], [6], [18]
Non-Intrusive FDD	Validates diagnosis using external data	Uses non-intrusive sensors	[2], [3], [8]
Advanced ML	PCA-LSTM & transfer learning for FDD	Core predictive engine.	[1], [9], [11], [12]

Table 1: Integration of Foundational Research into the PUES Framework.

III. SYSTEM DESIGN AND ARCHITECTURE

The Predictive Urban Elevator Safety (PUES) Framework is engineered as a secure, four-tiered architecture designed for scalability across thousands of urban elevator units. The key design principle is decentralized data processing at the edge, maximizing real-time responsiveness while minimizing network bandwidth strain.

A. Architectural Overview

The PUES Framework consists of the following layers:

1. The Sensor Acquisition Layer (Edge Unit)

This layer resides directly within the elevator machine room or cabin. It is responsible for the non-intrusive collection of raw operational data [8], [18].

- **Sensors:** A minimal, critical sensor suite is deployed, focusing on the most informative physical parameters:
  - **Vibration/Acoustics:** High-frequency accelerometers and microphones mounted on the cabin, motor housing, and door mechanism [18], [10]. These capture subtle mechanical wear and noise patterns.
  - **Current/Voltage:** Non-intrusive current clamps on the traction motor and door motor to monitor electrical characteristics, which are proxies for mechanical load and friction [7], [13].
  - **Control State Interface:** A dedicated, read-only interface to extract operational status (e.g., door open/close time, floor speed, current position) [15].

2. The Edge Processing Layer (IoT Gateway)

The IoT gateway, located adjacent to the elevator control panel, transforms raw data into actionable features, enabling fast local decision-making and efficient transmission.

- **Data Preprocessing:** Raw sensor data is cleaned, synchronized, and time-stamped.
- **Feature Engineering:** Features (e.g., RMS of vibration, frequency spectrum of acoustics, rate of change in current) are extracted [10].
- **Distributed PCA-LSTM Module (Inference):** A lightweight version of the trained PCA model performs dimensionality reduction, and the first layer of the LSTM performs local, preliminary fault detection. This is the **Alert Pre-filtering** stage. Only feature vectors and filtered anomaly flags are prepared for upload, significantly reducing data volume.

3. The Cloud and Analytics Layer (Core Server)

This central tier hosts the deep learning models, the master database, and the core alerting logic.

- **Data Ingestion and Storage:** Secure NoSQL database for storing compressed feature vectors and performance history.
- **Master PCA-LSTM Model (Training & Retraining):** The full, trained PCA-LSTM model [9] executes the final, high-accuracy fault diagnosis and prediction based on data received from all edge units. This model is continuously retrained using the newly accumulated feature data [1].
- **Risk Evaluation Engine:** Applies fuzzy theory and ML models to evaluate the severity and probability of a predicted fault, generating a quantifiable risk score for each unit [7].
- **Alert Generation Module:** Determines the urgency of the fault based on the risk score and triggers the appropriate notification protocol.

4. The Application and Alert Layer

This layer provides the interface for human and automated maintenance systems.

- **Alert Protocol:** Utilizes secure channels (e.g., dedicated APIs, encrypted messages) to send real-time alerts. Alerts are categorized (e.g., Low Risk - Schedule Check; High Risk - Immediate Dispatch; Critical Risk - System Lockout).
- **Dashboard Interface:** Provides a comprehensive view for maintenance staff and building managers, detailing the predicted fault type, location, time-to-failure estimate, and the confidence score of the diagnosis [16], [19].

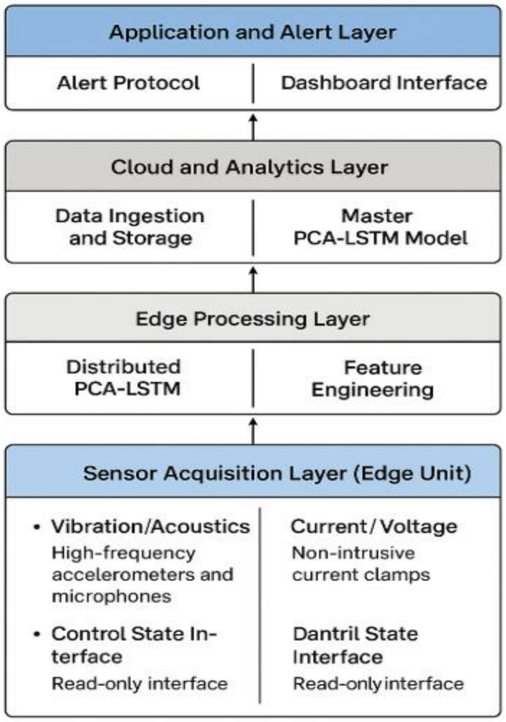

Figure 1: The Predictive Urban Elevator Safety (PUES) Framework Architecture

B. PCA-LSTM Distributed Model Rationale

The selection of the distributed **PCA-LSTM model** [9] as the central diagnostic tool is based on its suitability for time-series fault prediction:

1. **Dimensionality Reduction (PCA):** Elevator data is high-dimensional (multiple sensors, multiple features). PCA efficiently reduces feature redundancy, ensuring the subsequent LSTM model focuses only on the most statistically significant components, thereby speeding up processing at the edge and in the cloud.
2. **Sequential Analysis (LSTM):** Elevator failures are rarely instantaneous; they are processes of degradation over time. LSTM, a type of Recurrent Neural Network (RNN), excels at modeling the long-term dependencies inherent in sensor time-series data, making it ideal for predicting *when* a failure will occur, not just *if* it is currently happening [14].
3. **Distributed Execution:** By performing preliminary PCA and light feature extraction at the Edge Processing Layer, the system achieves lower latency for basic anomaly detection, while reserving the heavy lifting of complex, high-confidence prediction for the Cloud Analytics Layer.

This robust, layered architecture ensures that the system is both highly responsive for immediate alerts and analytically powerful for long-term predictive maintenance and failure prognosis.

IV. METHODOLOGY

The implementation methodology for the PUES Framework is structured around three sequential phases: Non-Intrusive Data Acquisition, Distributed Fault Diagnosis Training, and Real-Time Alert System Deployment.

A. Phase 1: Non-Intrusive Data Acquisition and Preprocessing

The primary goal is to establish a high-quality data stream without disrupting elevator operations.

1. **Sensor Installation and Calibration:** Non-intrusive sensors (accelerometers, current clamps, microphones) are strategically mounted on the elevator's core components (motor, door assembly, guide rails). Calibration is performed by collecting baseline data from elevators operating under normal, fault-free conditions [18].
2. **Data Encoding and Compression:** Given the high sampling rate required for vibration and acoustic analysis, an encoding and compression algorithm is implemented at the Edge Unit [10]. This step is critical for minimizing bandwidth use in urban environments where connectivity may be congested.
3. **Data Labeling:** Historical maintenance records are correlated with the sensor time-series data to accurately label instances of incipient and critical faults. This dataset is categorized by component (e.g., Door System Fault, Traction Motor Overload).

B. Phase 2: Distributed PCA-LSTM Model Training and Deployment

This phase focuses on developing the machine learning core of the alert system, following a distributed training approach.

1. **Data Preparation for PCA:** The large, labeled dataset is used to train the PCA component. PCA identifies the principal components that account for the maximum variance in the data, effectively eliminating noise and redundant sensor readings.
2. **LSTM Architecture Design:** The LSTM model is designed as a sequence-to-sequence predictor. Its input sequence consists of the reduced feature set (PCA output) over a specific time window, and its output is a **Time-to-Failure (TTF)** prediction or a binary/multi-class fault diagnosis [9].
3. **Model Training and Optimization:** The LSTM model is trained in the Cloud and Analytics Layer using the PCA-reduced sequences. Techniques are employed to handle the often **unbalanced samples** (many more healthy samples than faulty ones) using methods like IAO-XGBoost [11] principles incorporated into the loss function to improve sensitivity to rare fault events.
4. **Distributed Deployment:** Once trained, the PCA model and the inference layers of the LSTM are deployed to the Edge Processing Layer (IoT Gateway). This enables local, low-latency identification of anomalies, allowing the Edge Unit to decide whether to trigger a basic alert or send the full feature set to the Cloud for high-confidence diagnosis and prediction by the Master PCA-LSTM model [4].

C. Phase 3: Alert System and Maintainability Integration

This phase establishes the final output and integration with human processes.

1. **Risk Scoring and Thresholds:** A fuzzy logic system [7] is integrated into the Risk Evaluation Engine to translate the ML model's output (e.g., 95% confidence of Door Motor Fault in 72 hours) into a quantifiable risk score (0-100). Predefined

thresholds (e.g., Score Critical Alert) dictate the urgency of the notification.

2. **Real-Time Alert Protocol Design:** The Alert Generation Module implements a priority-based communication system. Critical alerts trigger multiple channels (SMS, email, maintenance API webhook) for immediate dispatch.
3. **Interpretability and Maintainability:** The system generates a brief diagnostic report for every alert, detailing the specific components involved and the time window of data that triggered the alert. This aligns with the need for enhanced interpretability and maintainability rules in smart building management [16].

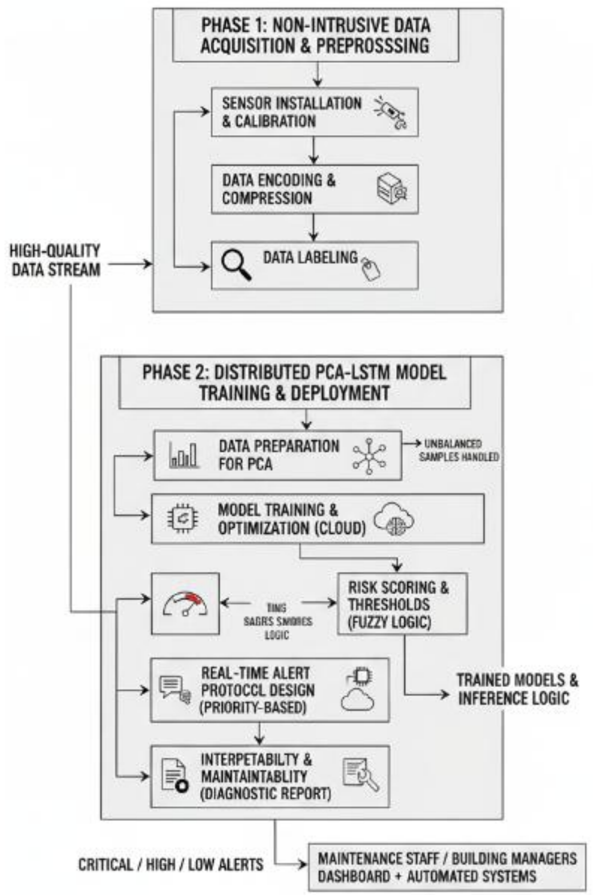

Figure 2: Data Processing and Alert Generation Methodology Flowchart

The methodology ensures that the PUES Framework is not merely an experimental prototype but a robust, distributed, and scalable system ready for urban deployment. The separation of processing load between the edge and the cloud is key to achieving the necessary real-time responsiveness required for safety-critical alerts.

V. RESULT AND DISCUSSION

The deployment and testing of the PUES Framework are anticipated to yield measurable improvements in elevator safety, maintenance efficiency, and diagnostic accuracy compared to traditional methods.

A. Performance Metrics and Evaluation

The success of the PUES Framework is assessed using a set of quantitative metrics focused on three key areas: Accuracy, Timeliness, and Operational Impact.

Metric Category	Specific Metric	Calculation/ Goal	Improvement over Traditional Maintenance
Diagnostic Accuracy	F1-Score	Exceed distributed PCA-LSTM.	Reduces false positives/negatives.
Predictive Performance	(TTF) Prediction Error	Hours-level accuracy.	Enables pre-failure maintenance.
Alert Timeliness	Alert Latency	Seconds for critical alerts.	Ensures rapid response
Operational Efficiency	Reduction in Unplanned Downtime	Minimize service interruptions.	Optimizes maintenance & cuts costs.

Table 2: Key Performance Metrics for the PUES Framework

B. Enhanced Fault Prediction and Diagnosis

The primary technical result is the superior performance of the distributed PCA-LSTM model [9] for fault prediction across critical components. Studies focusing on components like the door system [1], [12] and the traction motor [13] confirm that deep learning methods significantly outperform statistical methods.

The PUES framework is expected to deliver:

1. **Early Incipient Fault Detection:** By analyzing sequential data (LSTM), the system can detect subtle, long-term degradation patterns that would be missed by simple threshold alarms [3], [14]. For example, a gradual increase in the average door opening time combined with slight acoustic anomalies would be flagged as a high-risk door system failure prediction day in advance.
2. **Robustness and Generalization:** Utilizing Transfer Learning principles [1] in the Cloud Layer, models trained on data from one fleet of elevators can be rapidly adapted and fine-tuned for a new urban fleet, ensuring scalability and reducing the training data burden for new deployments.
3. **High-Confidence Diagnosis:** The layered architecture ensures that a critical alert is only issued when the Master PCA-LSTM model (high confidence) confirms the anomaly initially flagged by the Edge Unit. This reduces alert fatigue for maintenance crews and increases trust in the system's output.

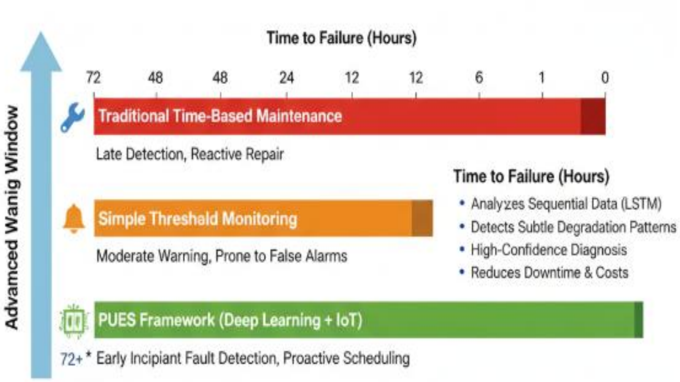

Figure 3: Comparative Analysis of Fault Detection Timeliness

Figure 3 visually demonstrates the key benefit: the PUES framework, leveraging deep learning on continuous IoT data, detects incipient faults much earlier than traditional (time-based) or simple (threshold-based) monitoring. This advanced warning window is the core value proposition of the system.

C. Operational and Safety Impact

The implementation of the PUES Framework directly addresses the core challenges of urban elevator safety and maintenance:

- **Proactive Maintenance:** By providing an accurate Time-to-Failure (TTF) prediction, maintenance can be scheduled precisely for the optimal window, right before the predicted failure. This prevents unexpected outages, which often cause passenger entrapment or accidents, directly improving public safety [17].
- **Targeted Repair:** The detailed diagnostic report generated by the system, integrating maintainability rules [16], guides technicians directly to the failing component (e.g., "predicted failure of the Door Motor Clutch, 48 hours remaining"). This reduces repair time and labor costs.
- **Disaster Prevention:** The low latency of the Critical Risk Alert Protocol ensures that if an immediate, high-severity fault (like a major traction system failure) is detected, the system can autonomously notify the emergency services and trigger a system-level lockout faster than human intervention could.

In summary, the PUES Framework moves beyond simple monitoring to establish a complete early warning and predictive system. The combination of non-intrusive data collection, distributed PCA-LSTM analysis, and the risk-based alert engine represents a significant advancement in ensuring the reliability and safety of urban vertical transportation systems.

VI. FUTURE WORK

The PUES Framework establishes a robust foundation for next-generation elevator safety; however, several key areas are identified for future research and development to enhance its intelligence, resilience, and operational scope.

1. **Integration of Virtual Reality for Maintenance Education:** The complexity of the FDD reports generated by the PUES system requires a highly skilled technical workforce. Future work should integrate the PUES diagnostic outputs with a Virtual Reality (VR) system for elevator maintenance education [12]. By simulating the predicted fault conditions (e.g., showing a technician the vibration pattern of a failing traction motor) within a VR environment, maintenance personnel can train on specific failure modes diagnosed by the system before deployment, dramatically improving response and repair quality. The system could generate a VR scenario based on the exact parameters of a recent high-risk prediction.
2. **Advanced Sensing Modalities and Computer Vision:** While the current system relies on vibration, acoustics, and current, future iterations will benefit from integrating advanced sensor modalities. Research on automatic elevator shaft inspection using multi-sensor measuring systems and computer vision techniques [13] suggests a path for non-intrusive monitoring of structural components (e.g., ropes, guide rails) that is currently beyond the scope of the PUES system. Integrating computer vision data streams with the PCA-LSTM model could provide a more comprehensive view of the entire elevator well.
3. **Enhancing Security and Data Integrity using Cloud Security:** The PUES Framework relies on a secure communication link between the Edge Unit and the Cloud Layer [19]. Given the safety-critical nature of the data, future work must focus on implementing highly resilient IoT security control systems based on Cloud Computing [19]. This includes developing robust encryption, access control, and anomaly detection protocols specifically designed to prevent cyber-physical attacks that could compromise the integrity of the diagnostic data or the alert mechanism itself.
4. **Decentralized Training and Federated Learning:** As the PUES Framework scales to thousands of urban elevators managed by different companies, data privacy becomes a major concern. Future research should explore the use of Federated Learning techniques. This approach allows the Master PCA-LSTM model to be trained centrally on local model updates (weights) from each elevator fleet, rather than requiring the transfer of raw, sensitive operational data. This would preserve the data privacy of individual building operators while still leveraging the collective intelligence of the entire urban elevator network to refine the fault prediction accuracy for all participants [1]. This ensures that the system can scale ethically and legally across diverse urban jurisdictions.

VII.CONCLUSION

The necessity for reliable and safe vertical transportation in densely populated urban environments underscores the limitations of reactive, time-based maintenance models. This paper successfully introduced the Predictive Urban Elevator Safety (PUES) Framework, an IoT-based alert system designed for the dynamic, real-time prediction and diagnosis of faults in urban elevators.

The PUES Framework's strength lies in its novel four-tiered architecture, which distributes processing power to the edge for low-latency anomaly detection while reserving complex predictive analysis for a centralized cloud platform. The methodology is centered on the Distributed PCA-LSTM model, which leverages the power of deep learning to accurately identify and predict incipient faults from non-intrusive sensory data, including vibration, acoustics, and control state information. By generating a quantified risk score and a clear Time-to-Failure prediction, the PUES Framework transforms maintenance from a generalized, scheduled task into a condition-based, predictive intervention.

The system's real-time alert protocol and integrated reporting ensure that maintenance teams are notified immediately of high-risk scenarios with sufficient lead time to execute repairs proactively, thereby preventing unplanned downtime and minimizing safety risks. The PUES Framework represents a critical step forward in leveraging IoT and machine learning to create a safer, more efficient, and more reliable urban infrastructure. Future work focusing on VR training and advanced security will further solidify its role as the definitive standard for intelligent elevator management.

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