

IoT-Based Anomaly Detection for Long-Term Care Using Principal Component Analysis and Isolation Forest [†]

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Abstract

Taiwan's rapid demographic shift toward a super-aged society has heightened demand for long-term care, yet limited staffing creates safety risks from fires; heating, ventilation, and air conditioning failures; and health incidents. To address this, we propose an IoT-based intelligent environmental monitoring and early-warning system designed for care facilities. The three-layer architecture integrates sensors for temperature, humidity, light, air quality, and noise; employs ESP-NOW and wireless fidelity mesh for reliable networking; and supports user interfaces with real-time anomaly alerts. Using PCA and Isolation Forest for efficient anomaly detection, the modular, node-based design enhances safety, reduces manpower burden, and enables scalable smart services.

Keywords: isolation forest; principal component analysis; anomaly detection; IoT; long-term care

1. Introduction

Taiwan's population is aging rapidly, having entered an aged society in 2018 and projected to become a super-aged society within eight years, faster than many other countries [1]. This is driven by declining birth and death rates, reducing the number of adult children available to support elderly family members and decreasing co-residence with children [1,2]. Consequently, elderly individuals in poor health increasingly rely on long-term care facilities, while these institutions face severe manpower shortages—by the end of 2023, 29,205 staff were responsible for 50,446 residents. To address rising care demand and limited staffing, this study proposes an intelligent environmental monitoring and early-warning system integrating IoT and AI. The system collects data via multiple sensors and uses low-power ESP-NOW communication and scalable wireless fidelity (Wi-Fi) Mesh networks for real-time data transmission and control. Principal component analysis (PCA) reduces data dimensionality while preserving major variance, enhancing computational efficiency. Upon detecting anomalies, the system automatically alerts caregivers, improving monitoring accuracy, response timeliness, and the safety and quality of life of elderly residents.



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2. Environmental Factors in Long-Term Care Facilities

Older adults in long-term care facilities often exhibit reduced adaptability to environmental conditions, making them particularly vulnerable to risks associated with temperature, humidity, air quality, lighting, and noise. Extreme temperatures can increase the likelihood of cardiovascular events and frostbite, and pose heightened risks for individuals with dementia [3–5]. Inappropriate humidity levels may contribute to respiratory and dermatological problems [6]. Poor air quality, characterized by elevated levels of CO₂, CO, formaldehyde, total volatile organic compounds (TVOCs), particulate matter (PM₁₀, PM_{2.5}), and ozone, exacerbates respiratory and cardiovascular diseases [7]. Insufficient lighting negatively affects mobility, mood, and fall risk [8], while excessive noise may lead to hearing loss, cardiovascular complications, and nervous system disorders [9].

Traditional manual inspections of environmental conditions are labor-intensive, slow to address individual needs, and prone to monitoring gaps, thereby compromising resident safety. To overcome these limitations, IoT and AI technologies are integrated. Such systems enable real-time monitoring, automated adjustments, and abnormal event detection, creating an intelligent, resident-centered environmental management framework that enhances both safety and quality of care.

3. Methodology

We adopted IoT to improve operational efficiency in long-term care facilities by combining low-power wireless communication (ESP-NOW, Wi-Fi Mesh) with anomaly detection using PCA and Isolation Forest. IoT consists of perception, network, and application layers, enabling real-time sensing, transmission, and intelligent applications [10]. Wired networks offer high stability but are costly and inflexible, while wireless networks are more flexible but face interference and security issues [11]. ESP-NOW enables secure, low-power, connectionless communication between devices [12], while Wi-Fi Mesh with edge computing enhances coverage, stability, and low-latency data processing [13,14]. PCA reduces dimensionality and handles multicollinearity by transforming correlated variables into principal components [15], and Isolation Forest detects anomalies by isolating sparse data points through random partitioning [16]. To strengthen information security, the system adopts a closed network with ESP-NOW and Wi-Fi Mesh, authorizing only trusted devices and verifying data integrity to reduce attack risks and ensure secure, efficient operation.

4. System Structure

We designed an environmental parameters management system for long-term care facilities, covering network connectivity as well as data analysis and anomaly detection applications, to achieve automatic monitoring and intelligent control of environmental parameters, as presented in Figure 1.

4.1. Network and Connectivity

The system was designed based on a three-layer IoT architecture consisting of sensing nodes, security nodes, and control nodes. The sensing nodes collect environmental parameters in real time and transmit them to the security nodes. The security nodes handle data relaying, transmission verification, and pairing authentication to ensure data security. The control nodes manage controllable devices and automatically adjust the indoor environment.

4.2. Workflow of Nodes

The intelligent long-term care environment management system integrates sensing, security, and control nodes within a Wi-Fi mesh network to ensure reliable multi-node co-operation. Sensing nodes collect environmental data and employ multi-level self-checks, including hardware diagnostics, data validity verification, and transmission connectivity confirmation, to maintain stability and respond to anomalies in real time (Figure 2). Security nodes parse and validate incoming JavaScript Object Notation data, reset anomaly counters for valid data, log and count errors, and issue alerts if thresholds are exceeded, distinguishing temporary errors from systemic faults (Figure 3). Control commands are transmitted through Hypertext Transfer Protocol Secure with hierarchical anomaly handling, including limited retries and administrator notifications to enhance stability and reduce manual monitoring (Figure 4). Fault-tolerant mechanisms at control nodes combine hardware and transmission anomaly counters to identify temporary interference versus permanent failures, ensuring timely fault handling and system safety (Figure 5). Additionally, a data processing mechanism within the Mesh network checks for duplicates, verifies data integrity, processes actionable information, and forwards it efficiently, supporting stable and secure network operation (Figure 6).

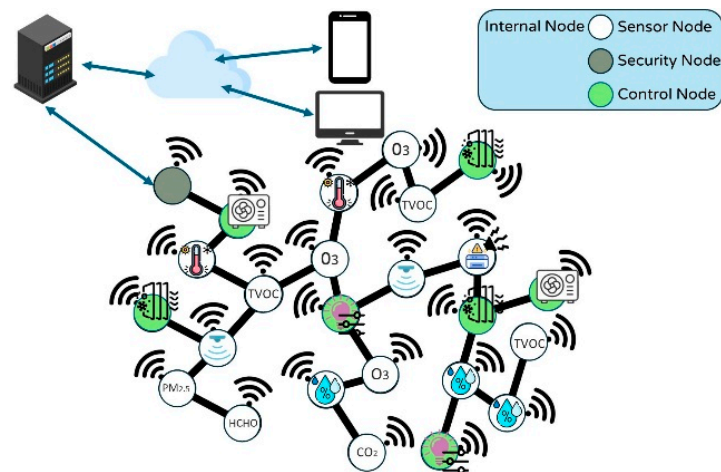


Figure 1. Network and connectivity architecture.

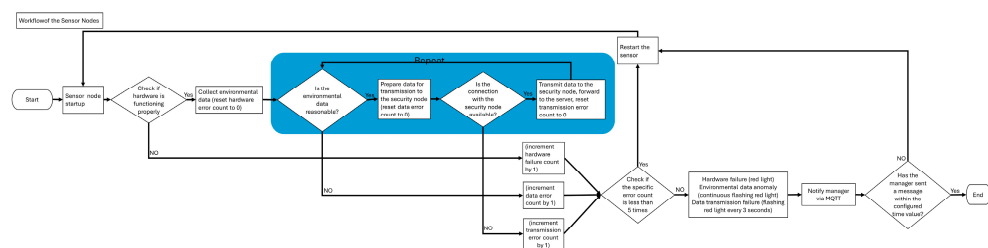


Figure 2. Workflow of the sensor node.

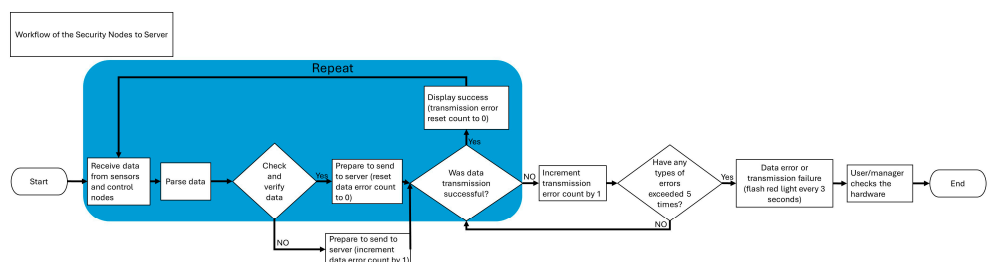


Figure 3. Workflow of the security node to server.

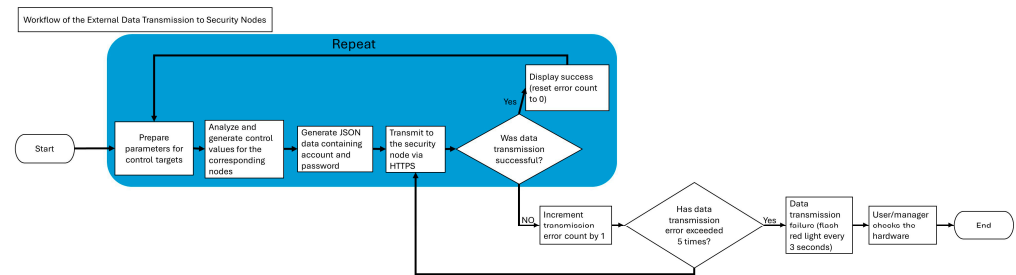


Figure 4. Workflow of the external data transmission to the security node.

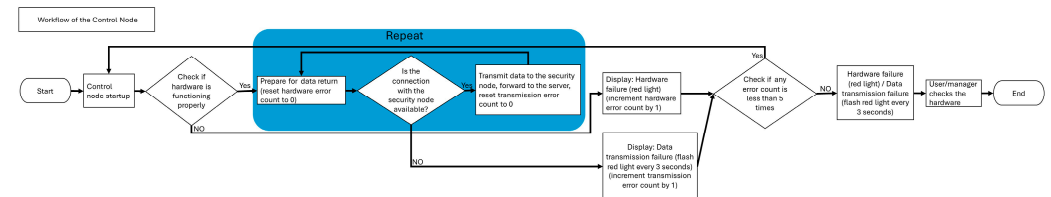


Figure 5. Workflow of the control node.

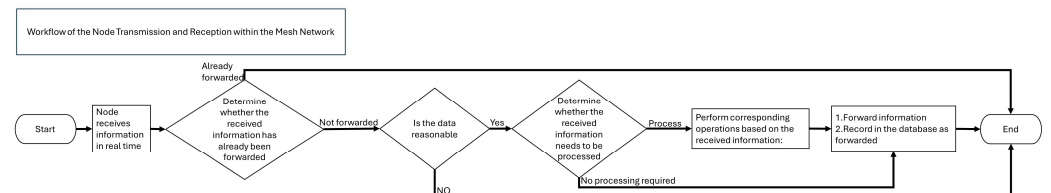


Figure 6. Workflow of the node transmission and reception within the mesh network.

4.3. Workflow of Machine Learning

The system's machine learning workflow consists of model training and anomaly detection. During training, labeled normal sensor data are integrated, preprocessed, and standardized to normalize feature scales, then subjected to PCA for dimensionality reduction. If the retained variance meets a threshold, the reduced data train the Isolation Forest model; otherwise, the original standardized data are used. The trained model and parameters are stored for deployment and management (Figure 7). For anomaly detection, incoming data are preprocessed and standardized before being evaluated by the stored model. Normal data are labeled and stored, while anomalies trigger administrator verification. False positives are relabeled as normal, confirmed anomalies are stored, and subsequent mechanisms are activated. If cumulative false positives exceed a threshold, the system recommends model retraining and data cleaning to prevent bias-related misjudgments [17] (Figure 8).

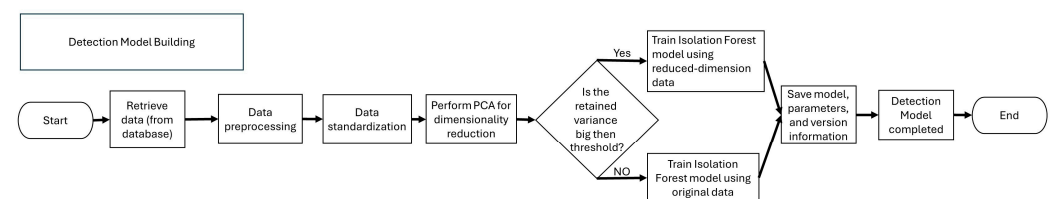


Figure 7. Model building.

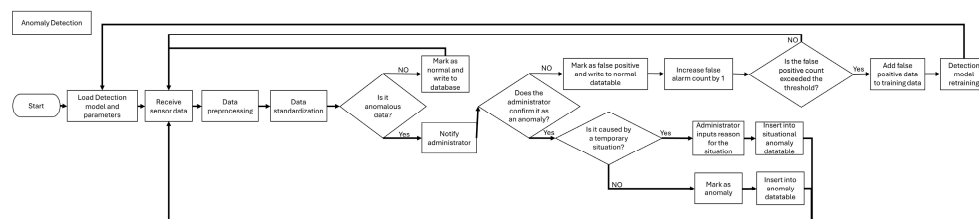
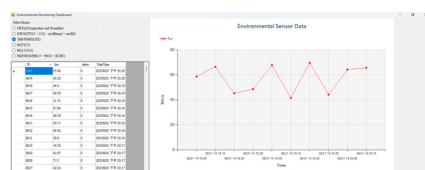


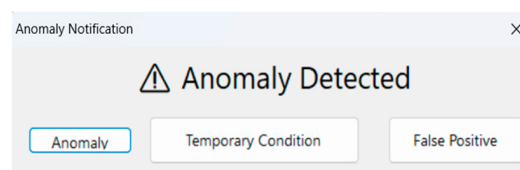
Figure 8. Anomaly detection.

5. Interface Design

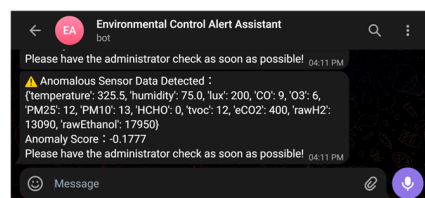
The system uses Microsoft Windows Forms (C# .NET Framework) to provide a graphical user interface with two main pages: the environmental monitoring dashboard, as shown in Figure 9a and the administrator notification/anomaly confirmation page, as shown in Figure 9b. As shown in the Figure 9a, the timestamps are displayed in a 12-h format, where the term “下午” represents p.m. The dashboard integrates a fault-tolerant architecture with hardware and transmission anomaly counters, checking hardware status and connectivity with security nodes, performing limited retries for anomalies, and triggering visual alerts and administrator notifications when thresholds are exceeded to ensure stability and timely fault handling. As shown in Figure 9c, the anomaly notification page alerts the administrator via communication software (e.g., Telegram) when anomalies are detected, allowing them to confirm the anomaly, mark it as caused by a temporary condition as shown in Figure 9d, or relabel it as a false positive, with data stored appropriately for subsequent processing or model optimization.



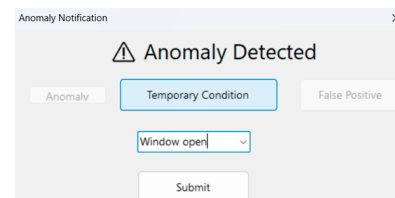
(a)



(b)



(c)



(d)

Figure 9. (a) Environmental monitoring dashboard; (b) anomaly alert system; (c) instant messaging (Telegram); (d) input the reason for the temporary condition.

6. Conclusions

To address the challenges of caregiver shortages and environmental safety risks faced by long-term care institutions in Taiwan’s aging society, we designed an IoT-based intelligent environmental monitoring and early warning system. The system adopts a three-layer IoT architecture that integrates multiple environmental sensors and incorporates ESP-NOW and Wi-Fi Mesh technologies to achieve low-power, highly stable data transmission, while also providing self-healing capabilities to ensure reliable network operation. In data processing, the system applies PCA to the high-dimensional, multivariate data generated by multiple sensors, performing feature extraction and dimensionality reduction to reduce computational load while preserving the main variance structure. Then, the unrelated principal components are input into the Isolation Forest algorithm to identify environmental anomalies in real time without the need for labeled data. Since anomalous data are sparse

and easily separable in the feature space, the system enhances the accuracy of anomaly detection. In addition, the system integrates edge computing and modular design, enabling real-time alerts and continuous optimization of the detection model. The system reduces the workload of caregivers and proactively safeguards resident safety and demonstrates strong scalability, with the potential to be applied to other intelligent indoor environments.

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