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# IoT-Based Rule Control for Environmental Stability in Vanilla Post-Harvest Processing Facilities

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**Abstract:** Environmental control is a crucial factor in maintaining the stability of the vanilla post-harvest processing process, particularly because temperature and relative humidity influence the drying process, aroma, and product quality. This study aims to characterize the environmental conditions of a vanilla processing facility and evaluate the implementation of a rule-based Internet of Things (IoT) system for automatic ventilation control. The system uses temperature and humidity sensors connected to an ESP32 via MQTT communication and implements control rules on edge devices. Monitoring was conducted over 14 days in three zones of the facility, resulting in 336 hourly observations divided between baseline and rule-based control conditions. The results show that rule-based control has a greater impact on humidity than temperature. The average relative humidity decreased from 82.63% to 80.30% ($p < 0.001$), accompanied by a decrease in the standard deviation from 6.90 to 4.79%. The proportion of observations meeting the target range of 22–28 °C and 70–85% RH increased from 57.7% to 76.2%. The greatest impact on humidity was found in the ventilation outlet zone. These findings demonstrate that IoT-based rule-based control is a lightweight, transparent, and practical approach to improving environmental stability in vanilla post-harvest processing facilities.

**Keywords:** Internet of Things; Vanilla Post-Harvest; Environmental Monitoring; Rule-Based Control; Relative Humidity

## 1. Introduction

Vanilla (Vanilla planifolia) is an economically valuable plantation commodity requiring careful post-harvest handling to obtain stable quality and market value. Unlike conventional agricultural products that may be sold shortly after harvest, vanilla undergoes a sequence of post-harvest processes involving conditioning, drying, sweating, stabilization, and storage. Vanilla quality is heavily influenced by post-harvest stages—specifically scalding, fermentation, and drying—which aim to generate the primary aroma compound, vanillin. Environmental conditions during these processes, particularly temperature and humidity, play a crucial role in determining the successful development of the flavor, aroma, microbial stability, and final quality of the vanilla product (Kurniasari et al., 2025).

Digital frameworks for smart post-harvest management have been recognized to reduce food loss and waste and to improve product quality (Adediran et al., 2025). Automated platforms for monitoring food drying and preservation are used to prevent spoiling and keep freshness for some agricultural commodities (Divya & Prasad, 2025; K.S et al., 2024; Rani, 2024; Tailor et al., 2025). Excessively high relative humidity reduces the rate of moisture removal and increases the risk of unwanted microbial growth, while high temperature can accelerate moisture loss and compromise product quality. Hence, environmental management demands continuous characterization and rapid responses in addition to assessment (Lamberty & Kreyenschmidt, 2022).

This problem can be investigated in an appropriate agricultural environment such as Rembangan, Jember, East Java. The Rembangan area is in the Jember highlands and is dominated by plantation and horticultural land use. According to the local spatial study, the Rembangan area has an elevation of about 536 m above sea level and a temperature range of about 20–30 °C. Jember, more generally, has a great deal of humidity throughout the year. The monthly average RH values in Jember in 2024 based on BPS data ranged from approximately 83% to 95%, and the maximum monthly humidity was often 97–100%. These characteristics make Rembangan a good environment to study the dynamics of temperature and RH related to agricultural processing.

Recently, researches have shown the feasibility of IoT technology for V. planifolia. Galushasti et al. (2025) designed an IoT-based microclimate control system for the generative stage of vanilla. They stressed the importance of automatically monitoring temperature, humidity, and light during vanilla production. Subono et al. (2022) examined the feasibility of IoT-based vanilla drying with fuzzy logic control for organic farming groups in East Java. Instead, the microclimate management in the cultivation phase and generic drying arrangements differ from dedicated post-harvest processing plants, which require a continuous characterization of the indoor environmental dynamics, spatial placement of sensors and automated ventilation control related to drying and conditioning (Frayssignes, 2023; Shirshetti, 2025; Spagnuolo et al., 2023).

This challenge presents an opportunity for Internet of Things (IoT) technology to be applied across various agricultural and storage domains, such as mushroom cultivation (Hendinata & Fikri, 2023; Mahmud et al., 2024; Yuliza & Antonisfia, 2025), traditional fermentation (Sari et al., n.d.; Valentino et al., 2025), storage of grain and crop (Smart Monitoring Framework, 2024; Zuhri et al., n.d.), cold chain logistics (Garrido-López et al., 2024; Islam et al., 2024; Lingeswari et al., 2025; Siddiqua et al., 2022). The temperature and RH readings can be gathered constantly by a distributed sensor network (Rahman et al., 2020; Vijayalakshmi et al., 2022) and interpreted by an embedded controller or node platform based on predetermined rules (Hailan et al., 2023; Haka et al., 2023; Kaliappan et al., 2023). If the environmental conditions are outside the predefined limitations, the system can automatically operate the ventilation or environmental control equipment (Yuliza & Antonisfia, 2025; Zhou, 2025).

Compared to complex artificial-intelligence-based systems, rule-based control has several advantages for small-to-medium agricultural facilities. The algorithm is transparent, requires low computational costs, is easy to verify, and can run on low-cost embedded hardware (Visconti et al., 2020). These features are pertinent in rural agricultural environments where Internet connectivity, technical expertise, and computational infrastructure may be limited.

The main research question of this study is: Can an IoT-based rule-based control system improve the stability of temperature and relative-humidity in a vanilla processing environment compared to uncontrolled environmental conditions? The aims of this research were therefore to: a) characterize temperature and RH variations in a vanilla processing environment; b) assess spatial differences between monitoring zones; c) implement an IoT based rule-based environmental controller; d) quantify environmental stability before and after rule-based intervention; and e) develop a practical IoT architecture suitable for vanilla processing facilities in highland agricultural environments.

## 2. Materials and Methods

*2.1 Research Design*

The study was conducted in a vanilla processing environment in the Rembangan agricultural area, Arjasa District, Jember Regency, East Java, Indonesia, situated at approximately 536 m above sea level with ambient temperatures ranging from approximately 20–30 °C. The processing environment was monitored using an IoT-based environmental monitoring system consisting of three monitoring zones: Zone 1 (air inlet/entrance area), Zone 2 (central processing area), and Zone 3 (ventilation/outlet area), to identify spatial variations in temperature and relative humidity. The study was conducted in two operational phases: Phase I represented the baseline condition, during which environmental conditions were monitored without automatic ventilation control, while Phase II represented the rule-based control condition, during which the IoT system automatically operated the ventilation system according to predefined temperature and relative humidity thresholds. Environmental observations were conducted over 14 consecutive days, with data recorded at regular intervals and subsequently aggregated into hourly observations for analysis. The monitoring period consisted of 168 hourly observations during the baseline phase and 168 hourly observations during the rule-based control phase, resulting in a total of 336 observations used to characterize temporal and spatial environmental variations and evaluate changes following the implementation of the rule-based IoT control system.

*2.2 Material & Environmental Considerations*

The vanilla processing environment is characterized by variations in temperature and relative humidity that may affect both the processing conditions and the performance of the equipment used in the facility. High temperature, temperature fluctuations, and prolonged exposure to humid conditions can influence thermal stability, moisture resistance, dimensional stability, and corrosion resistance of materials and system components. Therefore, the environmental characteristics considered in this study and their corresponding material-related requirements are summarized in Table 1.

**Table 1.** Environmental Characteristics and Corresponding Material Requirements

| Environmental Characteristics | Material Considerations |
|---|---|
| High temperature | High thermal stability |
| High temperature fluctuations | Thermal fatigue resistance |
| High humidity | Moisture resistance |
| High humidity fluctuations | Dimensional stability |
| Humid environment | Corrosion resistance |

*2.3 System Architecture & Hardware Configuration*

The environmental monitoring and control system integrated DHT22-class digital temperature and RH sensors, ESP32 sensor nodes, Wi-Fi/MQTT communication protocols, an edge-based rule decision engine, and exhaust/ventilation fans (Maulana & Haryanti, 2025; Srimal et al., 2024). Similar IoT architecture implementations have proven effective for humidity and temperature regulation in food drying setups (Fissabillillah et al., 2025; Syamsiana et al., 2024). The sensors were distributed across three monitoring zones within the vanilla processing environment to capture spatial variations in temperature and relative humidity. Sensor readings were transmitted from the ESP32 nodes to the IoT gateway through the MQTT communication protocol, where environmental data were processed and the predefined rule-based control logic was executed locally. When the monitored environmental conditions exceeded the predefined thresholds, the system automatically activated the ventilation system, while the environmental measurements and control actuation states were recorded throughout the

monitoring period for subsequent analysis. The operational decision range for environmental monitoring was defined as 22 °C ≤ T ≤ 28 °C and 70% ≤ RH ≤ 85%.
The rule-based control logic was implemented as follows:

- Rule 1 (High Humidity): If RH ≥ 82%, then Fan = ON.
- Rule 2 (High Temperature): If T ≥ 29 °C, then Fan = ON.
- Rule 3 (Normalization/Hysteresis): If RH ≤ 78% AND T ≤ 27 °C, then Fan = OFF.

These predefined thresholds enabled the IoT system to automatically regulate the ventilation system according to the observed environmental conditions and support the maintenance of temperature and relative humidity within the targeted operating range.

### *2.4 Sensor Specification, Sampling, and Data Quality*

Temperature and relative humidity were measured using DHT22-class sensors with a manufacturer-rated accuracy of ±0.5 °C for temperature and ±2–5% for relative humidity, with a resolution of 0.1 °C and 0.1% RH. The sensors were connected to ESP32 nodes and deployed across the three monitoring zones within the vanilla processing facility. Environmental measurements were recorded every 5 minutes and aggregated into hourly mean values for statistical analysis, then transmitted to the IoT gateway through the MQTT protocol with Quality of Service (QoS) level 1. Before the monitoring period, the sensors were checked and calibrated against a reference thermo-hygrometer using a two-point offset correction procedure. Data quality was monitored throughout the observation period, and missing readings caused by temporary communication interruptions were identified by the IoT gateway. Short gaps of two consecutive hours or less were treated using linear interpolation, whereas longer gaps were excluded from the corresponding hourly analysis to avoid introducing excessive estimation bias. The final dataset consisted of valid environmental observations collected during the baseline and rule-based control phases.

### *2.5 Statistical Analysis*

Environmental data collected during the baseline and rule-based control phases were analyzed to evaluate changes in temperature and relative humidity following the implementation of the IoT-based control system. Zone-level sensor readings were aggregated into hourly environmental observations for each monitoring phase, and descriptive statistics including mean, standard deviation, minimum, and maximum values were calculated for temperature and relative humidity. The distribution of the observed data was assessed using the Shapiro–Wilk test, followed by comparative statistical analysis to evaluate differences in environmental conditions between the baseline and rule-based control phases. A non-parametric analysis was also conducted as an additional robustness check, while effect sizes were calculated to quantify the magnitude of differences between the two operational conditions. Environmental performance was further evaluated by calculating the proportion of observations that simultaneously satisfied the predefined operating range of 22–28 °C for temperature and 70–85% for relative humidity, while spatial differences among the three monitoring zones were examined using descriptive comparisons of environmental conditions during each operational phase. All analyses were performed using Python 3.11 with pandas 2.x and SciPy 1.x, with a significance level of $\alpha = 0.05$.

## 3. Results and Discussion

### *3.1 Data Collection & Descriptive Analysis*

A total of 336 hourly environmental observations were collected during the monitoring period across the baseline and rule-based control phases. Temperature and relative humidity measurements were obtained through the IoT-based monitoring system deployed across the three monitoring zones of the vanilla processing environment. The collected observations were aggregated and analyzed to describe the environmental characteristics of the processing facility and evaluate changes following the implementation of the rule-based ventilation control system. The descriptive statistics of temperature and relative humidity for both operational phases are presented in Table 2.

**Table 2.** Descriptive Statistics of Environmental Conditions

| Phase | Variable | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|---|
| **Baseline** | Temperature (°C) | 23.99 | 1.86 | 20.46 | 29.15 |
| **Baseline** | RH (%) | 82.63 | 6.90 | 66.92 | 97.40 |
| **Rule-based** | Temperature (°C) | 23.96 | 1.47 | 21.16 | 28.80 |
| **Rule-based** | RH (%) | 80.30 | 4.79 | 70.72 | 90.70 |

Rule-based intervention exerted a dominant effect on relative humidity compared to temperature. Mean temperature shifted slightly (23.99 °C → 23.96 °C, $p = 0.593$), whereas mean RH dropped significantly (82.63% → 80.30%, $p < 0.001$). A paired-samples t-test (Shapiro-Wilk-confirmed normal differences) was used for both variables: temperature, $t(167) = 0.24$, $p = 0.808$, Cohen's $d = 0.02$ (negligible effect); RH, $t(167) = 4.89$, $p < 0.001$, Cohen's $d = 0.38$ (small-to-moderate effect). Relative humidity showed improved stability, with the standard deviation decreasing from 6.90 to 4.79 percentage points. These results agree with observations in environmental control systems where the active ventilation is mainly intended for moisture removal (Elleres, 2023; Khawashi et al., 2024). A comparison of the hourly temperature and relative humidity profiles between the baseline and rule-based phases is presented in Figure 1.

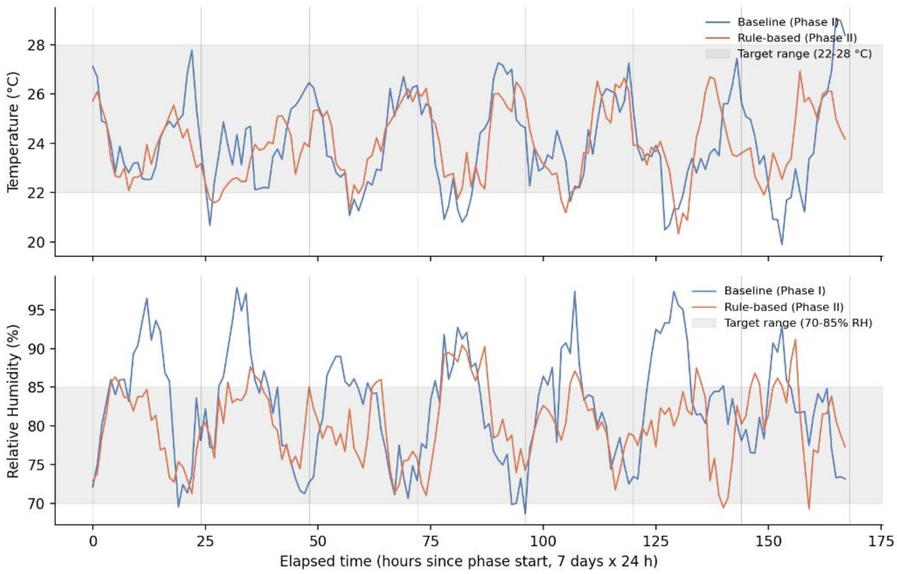


**Figure 1.** Hourly Time-Series of Temperature and RH

Figure 1 presents a dual time-series plot depicting the hourly trajectories of temperature and relative humidity across both operational phases. The baseline series (blue) exhibits several sharp RH spikes exceeding 90%, and in some cases approaching 98%, that recur roughly every 24–30 hours, consistent with diurnal humidity buildup left uncorrected in the absence of automated ventilation. The rule-based series (orange) shows visibly dampened excursions, with RH more consistently contained near or within the 70–85% band, though it still deviates outside the range during certain periods. Temperature trajectories in both phases follow a similar diurnal pattern and overlap closely for much of the observation window, reinforcing that the controller's intervention is more evident in humidity than in temperature dynamics. A comparison of the overall distributions of temperature and RH values between the two phases is presented in Figure 2.

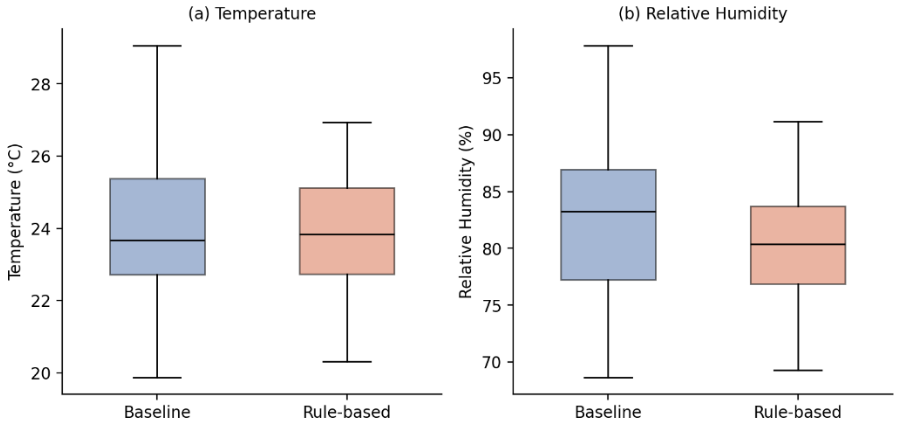


**Figure 2.** Distribution Comparison via Boxplots

Figure 2 displays boxplots summarizing the overall distribution of temperature and relative humidity values across both phases. For temperature (panel a), the median and interquartile range are similar between baseline and rule-based conditions, with only a slightly narrower spread and lower upper whisker under rule-based control. For RH (panel b), the rule-based phase shows a clearly lower median (around 80% versus 83% at baseline) and a narrower interquartile range (77–84% versus 77–87%), along with a reduced upper whisker. This distributional narrowing indicates that the rule-based strategy not only shifted the central tendency of RH downward but also reduced its overall variability, which is consistent with more stable and predictable humidity conditions during the rule-based phase.

### 3.2 Environmental Stability Evaluation

The proportion of observations simultaneously satisfying 22 ≤ T ≤ 28 °C and 70 ≤ RH ≤ 85% increased from 57.7% (97/168) during baseline to 76.2% (128/168) under rule-based control, representing an 18.5 percentage point increase (a 32.1% relative improvement). Precise microclimate stabilization through targeted control strategies has similarly been shown to optimize drying parameters for high-value agricultural commodities (Pratama et al., 2025; Yu et al., 2024). A comparison of the proportions of observations falling within the operational target range between the baseline and rule-based phases is presented in Figure 3.

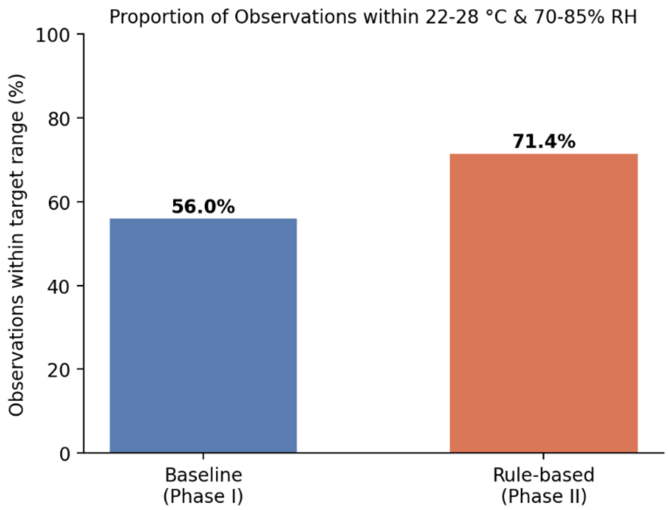


**Figure 3.** Proportion of Observations within Target Range

Figure 3 quantifies control performance through a bar chart comparing target-range compliance between the baseline and rule-based phases. The proportion of compliant observations rose from 56.0% during the baseline phase to 71.4% during the rule-based phase, an absolute increase of 15.4 percentage points. This single summary statistic provides a direct, interpretable measure of how much more consistently the environment stayed within the desired range once the rule-based ventilation control was activated.

### 3.3 Spatial Characterization & Multi-Zone Modeling

Spatial representation across the three zones was formulated as ($E(t)=\{T_1,T_2,T_3,RH_1,RH_2,RH_3\}$). Zone-level statistics (Table 3) indicate that the three zones had comparable baseline relative humidity (RH) levels (82.5–82.8%), although the reduction under rule-based control varied spatially. Zone 3 (outlet/ventilation) exhibited the largest RH decrease, from 82.53% to 79.10% (($\Delta$=3.43) pp), along with the greatest reduction in RH variability (SD 7.13 to 4.29), consistent with its direct exposure to actuated airflow. Zone 1 (inlet) showed the smallest RH reduction (82.75% to 80.96%, ($\Delta$=1.79) pp), while Zone 2 (central processing) showed an intermediate reduction (82.61% to 80.84%, ($\Delta$=1.77) pp). Meanwhile, mean temperature remained similar across all zones in both phases (23.9–24.0°C), suggesting that the rule-based controller primarily influenced humidity rather than temperature at the zone level. These spatial gradients are consistent with multi-zone environmental management principles reported in indoor and laboratory microclimate control studies (Marques & Pitarma, 2019a, 2019b; Zhou, 2025). A comparison of average temperature and relative humidity per zone between the baseline and rule-based phases is presented in Table 3 and Figure 4.

**Table 3.** Zone-Level Descriptive Statistics of Temperature and Relative Humidity by Phase

| Zone | Phase | Temperature (°C), mean ± SD | RH (%), mean ± SD |
|---|---|---|---|
| Zone 1 (inlet) | Baseline | 23.96 ± 1.92 | 82.75 ± 6.94 |
| Zone 1 (inlet) | Rule-based | 24.00 ± 1.50 | 80.96 ± 5.33 |
| Zone 2 (central) | Baseline | 23.98 ± 1.86 | 82.61 ± 6.88 |
| Zone 2 (central) | Rule-based | 24.00 ± 1.46 | 80.84 ± 5.18 |
| Zone 3 (outlet/ventilation) | Baseline | 24.03 ± 1.86 | 82.53 ± 7.13 |
| Zone 3 (outlet/ventilation) | Rule-based | 23.88 ± 1.52 | 79.10 ± 4.29 |

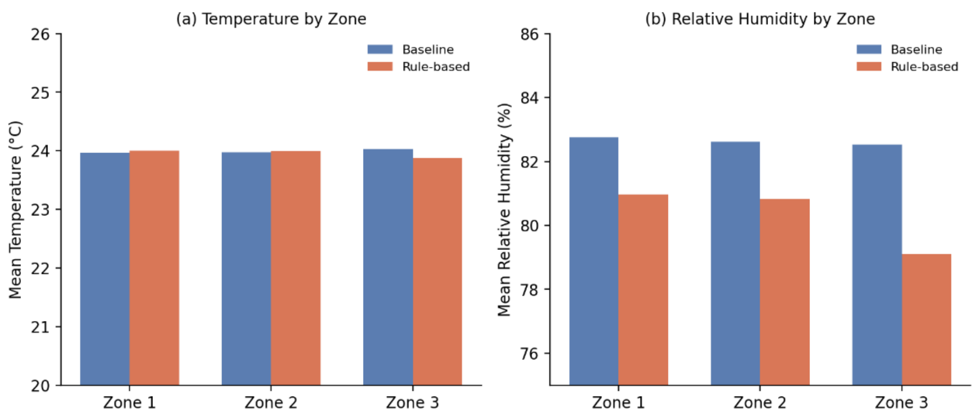


**Figure 4.** Temperature and RH by Zone

Figure 4 presents a grouped bar chart comparing mean temperature and relative humidity across the three monitoring zones for both phases. Mean temperature remains nearly identical across zones and phases (23.9–24.0°C), with only a marginal decrease in Zone 3 under rule-based control. In contrast, mean RH decreases in all three zones under rule-based control, but the magnitude is uneven: the reduction is smallest in Zone 1 (inlet), intermediate in Zone 2 (central), and largest in Zone 3 (outlet/ventilation), where RH drops from roughly 82.5% to 79.0%. This pattern indicates that the rule-based controller's effect is concentrated on humidity regulation rather than temperature, and that this effect is spatially graded, being strongest near the ventilation outlet.

### 3.4 System Architecture and Operational Resilience

The implementation of local edge-based control on the ESP32 gateway enabled the IoT system to process environmental data and execute predefined rules directly within the processing environment, reducing dependence on continuous cloud connectivity and allowing the ventilation control mechanism to continue operating locally during temporary network interruptions. Compared with computationally intensive machine learning or deep learning approaches, the implemented rule-based control provided a lightweight alternative for environmental management by requiring relatively low computational resources, offering transparent decision logic, and allowing deployment on affordable embedded hardware. These characteristics are particularly relevant for agricultural processing environments where internet connectivity, computational infrastructure, and technical resources may be limited, making the implemented architecture a practical approach for continuous environmental monitoring and automated ventilation control in vanilla post-harvest processing facilities.

## 4. Conclusions

This study demonstrated the application of an IoT-based rule-based approach for monitoring and controlling temperature and relative humidity in a vanilla post-harvest processing environment. Environmental observations collected through the deployed IoT monitoring system showed that the implementation of the rule-based ventilation strategy had a greater effect on relative humidity than on temperature. The implementation resulted in a significant reduction in relative humidity and reduced its variability during the rule-based control phase. In addition, the proportion of environmental observations simultaneously meeting the predefined operating range of 22–28 °C and 70–85% RH increased from 57.7% during the baseline condition to 76.2% during the rule-based control condition. The edge-based architecture enabled local environmental monitoring and automated control using lightweight computational resources, demonstrating the potential of rule-based IoT systems as a practical and interpretable approach for improving environmental management in vanilla post-harvest processing facilities.

Future research should extend the monitoring duration across different seasonal conditions and incorporate additional environmental variables, multi-stage ventilation control, sensor fault detection, and energy consumption analysis. Further studies involving multiple processing facilities would also strengthen the generalizability of the proposed approach and provide a broader understanding of the effectiveness of IoT-based environmental control under different processing and environmental conditions.

### Data Availability Statement

The environmental dataset used in this study was collected through field observations using the IoT-based monitoring system deployed in the vanilla processing environment in Rembangan, Jember, East Java, Indonesia. The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to data management and research collaboration considerations.

### Ethics and Research Integrity Statement

No human or animal subjects were involved in this study.

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