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Rule-Based IoT Decision Support System for Real-Time Chili Plant Growth Monitoring

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ABSTRACT

This study proposes a rule-based IoT decision support system for real-time chili plant growth monitoring. Its main contribution is an integrated framework for chili cultivation that combines plant growth indicators and environmental sensor data within a single transparent IF-THEN rule structure an integration not commonly addressed in prior chili-monitoring systems. The system integrates eight parameters stem height, branches, leaves, fruits, soil moisture, temperature, water volume, and soil pH collected from 100 plant samples and 704 repeated environmental sensor records over a single 14-week growing season. Classification is formalized as a maximum-severity decision over a knowledge base of eight rules: each rule carries a severity level, and a record receives the label of the most severe triggered rule (Less Optimal > Fairly Good > Optimal). Thresholds were set through a two-step calibration that combines established agronomic ranges for Capsicum annuum with empirical refinement against observed plant responses. The logic was validated against 100 expert-labeled records using a confusion matrix, achieving 96% overall accuracy (95% CI: 90.2–98.4%), a macro-average F1-score of 93.4%, and per-class F1-scores between 88.9% and 98.0%. Classification results show that 75% of records fell into the Less Optimal category, driven primarily by elevated temperature (mean 34.09°C) and acidic soil pH (mean 5.38). The system delivers interpretable, actionable decision support without complex machine learning infrastructure; its main limitation is that thresholds were calibrated on a single site and season, so external multi-site validation is required before broader deployment.

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1. INTRODUCTION

Chili (Capsicum annuum L.) is an important horticultural commodity because it is widely used as a food ingredient and has significant economic value for farmers. Chili productivity is strongly influenced by environmental conditions and plant growth characteristics such as soil moisture, temperature, soil pH, branching, leaf development, and fruit formation [1] [2] Improper cultivation conditions can reduce vegetative growth, delay fruit development, and increase the risk of plant stress.

In conventional cultivation, farmers commonly monitor chili plants by direct visual observation. This approach is simple but has several limitations, including delayed detection of environmental changes, subjective interpretation of plant growth, and difficulty in continuously recording plant data [3], [4]. Therefore, a technology-based monitoring system is required to help users observe plant conditions more accurately and consistently.

Internet of Things (IoT) technology can be applied in agriculture by integrating sensors, microcontrollers, databases, and monitoring dashboards [5] . Previous studies have shown that IoT can monitor chili microclimate, soil moisture, temperature, light intensity, rainfall, and irrigation conditions in real time, [6], [7], [8], [9], [10], [11]. The integration of IoT with artificial intelligence can transform raw sensor values into useful information for decision-making [12], [13], [14].

This research applies a rule-based system because it is transparent, lightweight, and suitable for prototype-scale agricultural monitoring [15], [16]. Beyond convenience, a rule-based formulation is mathematically preferable for this use case: it defines a deterministic, closed-form mapping from sensor inputs to condition labels with explicit, auditable decision boundaries; it requires no training data and therefore avoids the overfitting risk that data-hungry models face in the small-sample, single-season regime of a prototype study; and each record is classified in constant time, which suits low-power edge deployment. The rules are arranged in IF-THEN form by comparing sensor readings and growth indicators with predefined threshold values. Unlike black-box models, a rule-based system provides clear reasons for each classification result, making it easier for users to understand why a plant condition is categorized as Optimal, Fairly Good, or Less Optimal [17], [18] ; production-rule (IF-THEN) systems remain a core building block of explainable decision support precisely because they balance accuracy against interpretability [19].

Despite growing interest in agricultural monitoring, most existing systems for chili cultivation either rely on IoT dashboards without embedded decision logic or employ complex predictive models that lack interpretability for practical farm use. Approaches such as fuzzy logic [20], [21], multiple linear regression [22], and LSTM-based time-series forecasting [23] offer predictive capability but demand substantial computational resources and produce opaque outputs that are difficult for smallholder farmers to trust or act upon. Critically, few prior studies have proposed an integrated, transparent decision support system specifically for chili cultivation that simultaneously incorporates both plant growth indicators and environmental sensor data within a single rule-based framework. This gap is particularly acute in the Indonesian smallholder farming context, where real-time interpretable guidance is needed without access to high-performance computing infrastructure and where undetected soil pH acidity and heat stress are documented primary causes of yield loss.

This study addresses that gap by proposing a lightweight rule-based system with traceable IF-THEN logic that integrates plant growth data (stem height, branches, leaves, fruits) with environmental parameters (moisture, temperature, water volume, pH) to deliver explainable classification and actionable cultivation recommendations. The objective of this research is to design and evaluate a rule-based decision support system that integrates IoT sensor data with plant growth observations to provide real-time, interpretable monitoring for chili cultivation. The key contribution is an explainable classification framework combining eight growth and environmental parameters within a transparent IF-THEN rule structure, validated through confusion matrix analysis against expert-labeled ground truth, offering a practical alternative to computationally intensive approaches for small-scale smart farming.

2. RESEARCH METHOD

2.1 System Materials and Dataset

This research used an engineering and experimental approach. The monitoring concept was designed as a prototype consisting of a sensing layer, data acquisition layer, database layer, web monitoring layer, and rule-based analysis. Data collection was conducted over a 14-week growing period from planting to early fruiting stage, under open-field conditions in Medan, North Sumatra, Indonesia. Measurements were recorded twice daily

(07:00 and 15:00 WIB) to capture diurnal temperature and moisture variation. Each record corresponds to one sensor reading at a given timestamp. Because readings were taken repeatedly at the same site throughout the growing period, the 704 environmental records constitute longitudinal (repeated) measurements rather than statistically independent samples. Descriptive statistics are therefore reported at the record level for monitoring purposes and are not treated as independent observations for inferential population estimation; the resulting temporal autocorrelation is acknowledged as a limitation of the present single-site design (see Section 3 and Conclusion). For missing-data handling, records containing non-numeric or missing values were removed during cleaning rather than imputed, yielding 704 valid records from the raw sensor log.

The dataset includes growth measurements from 100 plant samples for stem height, branches, and leaves, and 22 samples for fruit observation (fruit set begins at approximately week 8). Environmental sensor records comprise 704 valid rows after data cleaning. Sensor instruments used include a DHT22 temperature-humidity sensor (±0.5°C accuracy), a capacitive soil moisture sensor (±3% accuracy), a pH meter with 0.01 resolution, and a volumetric water flow sensor. All sensors were calibrated against reference instruments prior to deployment. Calibration was verified quantitatively by comparing each sensor against a calibrated reference instrument across its working range before data collection, confirming that readings tracked the reference within the rated accuracies stated above. Before analysis, the dataset was cleaned by checking non-numeric values, missing values, and inconsistent stem height formatting. Stem height was normalized into centimeter units.

2.2 Data Acquisition and Processing Flow

The proposed system begins with data collection from plant growth and environmental sensors. The data are stored in spreadsheet format and then processed for statistical analysis and rule-based classification. The processing stages include reading the dataset, validating numeric values, normalizing stem height, calculating descriptive statistics, applying IF-THEN rules, and producing plant condition labels. Fig. 1 illustrates the proposed system architecture integrating IoT technology with a rule-based artificial intelligence method for real-time chili plant growth monitoring. The architecture consists of five interconnected layers: (1) the sensing layer, which captures environmental parameters (soil moisture, temperature, water volume, pH) and plant growth indicators (stem height, number of branches, leaves, and fruits) using IoT sensors; (2) the data acquisition layer, responsible for collecting and transmitting sensor readings to the centralized database; (3) the database layer, which stores historical plant growth and environmental data in structured spreadsheet format; (4) the web monitoring layer, providing a user interface for visualization and real-time monitoring dashboard; and (5) the rule-based analysis layer, which applies predefined IF-THEN rules to classify plant conditions into three categories (Optimal, Fairly Good, Less Optimal) and generates cultivation recommendations. This layered architecture enables transparent, interpretable decision-making suitable for small-scale smart farming prototypes, where system explainability is prioritized over black-box machine learning approaches.

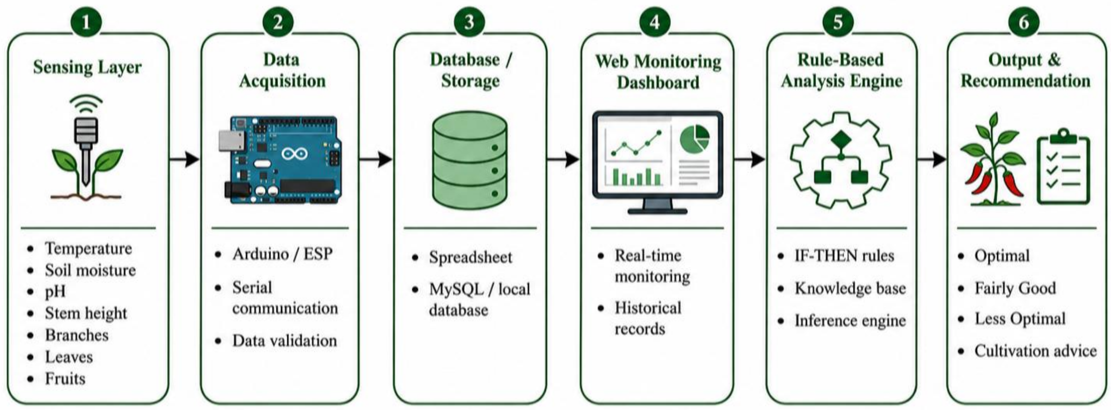

Figure 1. Proposed IoT and rule-based monitoring architecture for chili plant growth.

2.3 Rule-Based System Method

The artificial intelligence method used in this research is a rule-based system. This method uses predefined rules in the form of IF-THEN statements. The facts are obtained from sensor readings and plant growth variables, while the knowledge base contains threshold values for chili plant conditions. The inference engine compares each record with the rules and produces a classification result.

The main parameters used in rule-based classification are temperature, soil moisture, soil pH, and water volume. Growth indicators such as stem height, number of branches, leaves, and fruits are used to support discussion of plant development. The rules are designed to classify the condition into three categories: Optimal, Fairly Good, and Less Optimal.

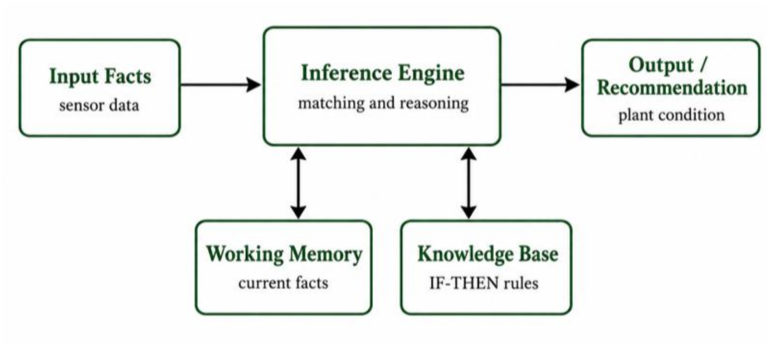

Figure 2. General architecture of a rule-based system.

Figure 2 presents the fundamental architecture of a rule-based system adapted for chili plant monitoring. The architecture comprises three core components: (1) the knowledge base, containing domain-specific rules formulated as IF-THEN statements with predefined threshold values for environmental parameters (e.g., optimal temperature range, soil moisture levels, pH ranges, and water volume requirements for chili cultivation); (2) the inference engine, which processes incoming sensor data (facts) by matching them against the rules in the knowledge base and executing logical reasoning to determine plant condition classifications; and (3) the working memory, temporarily storing current sensor readings and intermediate inference results during the classification process. This classical AI architecture provides transparency and traceability, allowing users to understand precisely why a particular classification was assigned, which is essential for building trust in agricultural decision support systems where farmers need clear explanations rather than opaque predictions.

Figure 3 depicts the operational flowchart of the rule-based classification system for chili plant condition assessment. The process begins with data input from environmental sensors (temperature, soil moisture, pH, water volume) and proceeds through a sequential decision tree structure. Each sensor parameter is evaluated against predefined optimal thresholds: temperature (24–30°C), soil moisture (50–70%), soil pH (5.5–7.0), and water volume (180–220 mL). The system employs a hierarchical IF-THEN logic where all four conditions must be simultaneously satisfied to classify the environment as "Optimal." If one or more parameters fall outside the optimal range but remain within acceptable limits, the condition is classified as "Fairly Good." When parameters significantly deviate from acceptable ranges, the system classifies the condition as "Less Optimal" and generates specific recommendations for corrective actions (e.g., irrigation adjustment, pH correction, temperature regulation). This deterministic flowchart ensures consistent, repeatable classifications and provides clear audit trails for decision-making, making it particularly suitable for prototype-scale agricultural monitoring systems where interpretability and farmer trust are prioritized.

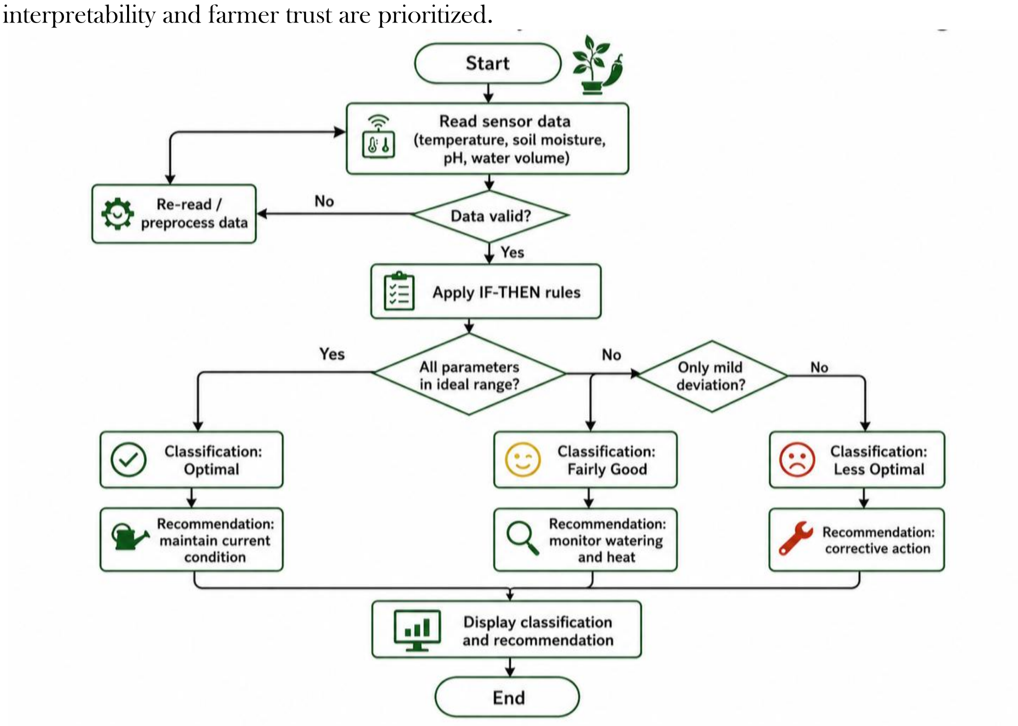

Figure 3. Flowchart of the rule-based system for chili plant monitoring.

Fig. 3 depicts the operational flowchart of the rule-based classification system. Each environmental record is evaluated sequentially against four parameters: temperature, soil moisture, soil pH, and water volume. The system uses a hierarchical priority structure: temperature is evaluated first because it is the most directly observable stress factor for chili plants. If temperature falls within the optimal range (24–30°C), moisture is evaluated next, followed by pH, and finally water volume. Classification outputs ("Optimal," "Fairly Good," or "Less Optimal") and corresponding recommendations are produced based on the combination of parameter states. In cases where multiple parameters simultaneously violate thresholds, the most severe violation determines the final classification label; for example, a record with both R3 (critical heat stress) and R6 (acidic pH) is classified as Less Optimal based on the highest-priority rule.

To formalize the classification logic, let each environmental record be represented as a vector $x = (T, M, P, V)$, where T is temperature (°C), M is soil moisture (%), P is soil pH, and V is water volume (mL). The knowledge base defines eight rule predicates over x: R1 (Optimal) holds when $(24 \le T \le 30) \land (50 \le M \le 70) \land (5.5 \le P \le 7.0) \land (180 \le V \le 220)$; R2: $30 < T \le 35$; R3: $T > 35$; R4: $M < 40$; R5: $M > 80$; R6: $P < 5.5$; R7: $P > 7.0$; and R8: $V < 180 \lor V > 220$. Each rule is assigned a severity level $s \in \{0, 1, 2\}$, where $s = 0$ denotes Optimal, $s = 1$ denotes Fairly Good, and $s = 2$ denotes Less Optimal. The critical rules ($s = 2$) are {R3, R4, R6}, the warning rules ($s = 1$) are {R2, R5, R7, R8}, and R1 ($s = 0$) requires simultaneous satisfaction of all four core ranges.

Let $\Phi(x)$ denote the set of rules triggered by record x. The final class label is determined by the maximum-severity rule, $C(x)$ = arg max over $r \in \Phi(x)$ of $s(r)$, with the convention that $C(x)$ = Optimal only when no warning or critical rule fires (i.e., $\Phi(x) \subseteq \{R1\}$). This max-severity precedence makes the rule ordering explicit and deterministic: a record satisfying both R3 (critical heat stress) and R6 (acidic pH) is labeled Less Optimal because $s(R3) = s(R6) = 2$ dominates any lower-severity match, which resolves the case described above without sequential ambiguity. The threshold constants in R1–R8 were not chosen arbitrarily; each was initialized from agronomic literature for Capsicum annuum under tropical conditions and then refined against observed plant responses during the experimental period, as detailed in the two-step calibration procedure below.

The classification procedure is summarized as pseudocode in Algorithm 1, which makes the decision logic fully reproducible. The early-return structure realizes the maximum-severity precedence: critical rules are tested first, then warning rules, and the Optimal label is assigned only when all four parameters lie within their optimal ranges (R1). Line 9 explicitly handles borderline records that fall outside the optimal envelope yet trigger no critical or warning rule, assigning them too Fairly Good.

Algorithm 1. Rule-based classification by maximum-severity precedence

```
Input:  record x = (T, M, P, V)   // temperature, moisture, pH, water volume
Output: class label C in {Optimal, Fairly Good, Less Optimal}
1:  if (T > 35) or (M < 40) or (P < 5.5) then        // critical R3, R4, R6
2:      return "Less Optimal"
3:  if (30 < T <= 35) or (M > 80) or (P > 7.0)
          or (V < 180) or (V > 220) then          // warning R2, R5, R7, R8
4:      return "Fairly Good"
5:  if (24 <= T <= 30) and (50 <= M <= 70)
          and (5.5 <= P <= 7.0) and (180 <= V <= 220) then   // rule R1
6:      return "Optimal"
7:  return "Fairly Good"   // outside optimal envelope, no rule triggered
```

The threshold values were derived through a two-step calibration process. Concretely, the two steps can be reproduced as follows. Step 1 (initialization): each parameter range was initialized from established agronomic literature on Capsicum annuum under tropical conditions optimal temperature 24–30°C, soil moisture 50–70%, and soil pH 5.5–7.0 [1], [2] while the water-volume range was initialized from the irrigation system's measured flow rate. Step 2 (empirical refinement): for each threshold, the boundary was set to the sensor value at which the associated observable symptom became consistently present across the monitored plants leaf curling above 30°C and acute wilting above 35°C for the temperature bounds; wilting onset matched against moisture-recovery curves for the moisture bounds; visible nutrient-deficiency indicators for the pH lower bound; and the flow range (180–220 mL per irrigation event) that maintained root-zone moisture replenishment for the volume bounds. Once refined, the thresholds R1–R8 were frozen, after which every record is classified deterministically by Algorithm 1 with no further tuning; the mapping from raw sensor values to class label is therefore fully reproducible from the reported threshold constants alone. The residual subjectivity in Step 2 where symptom onset was judged by expert visual assessment rather than by a numeric optimization is acknowledged as a limitation. A fully automated calibration that selects each threshold by maximizing agreement with expert labels on a held-out calibration split is identified as the natural next step toward an entirely data-driven, reproducible protocol.

Formally, calibration fixes a single threshold vector $\Theta = (\theta_T^{lo}, \theta_T^{hi}, \theta_M^{lo}, \theta_M^{hi}, \theta_P^{lo}, \theta_P^{hi}, \theta_V^{lo}, \theta_V^{hi}) = (24, 30, 50, 70, 5.5, 7.0, 180, 220)$, so that each parameter axis is partitioned into an optimal interval $[\theta^{lo}, \theta^{hi}]$ and its complementary stress region. For a parameter with value v, the boundary indicator $g(v) = 1[v < \theta^{lo}] \lor 1[v > \theta^{hi}]$ determines whether the associated rule fires, and the severity of the deviation (warning vs. critical) is fixed by which side of which bound is crossed, as tabulated in Table 1. The class label is then the deterministic composition $C(x) = f(\Theta, x)$ evaluated by Algorithm 1. Because Θ is reported explicitly and f is fixed, every label is reproducible from the raw sensor vector x alone, without access to the original dataset; the only element that reflects authors' judgment is the numerical choice of Θ in the empirical-refinement step, which is precisely the calibration limitation stated above and the target of the proposed automated threshold selection.

Table 1. Rule-Based Knowledge Base For Chili Plant Monitoring

Rule	Condition	Output	Recommendation
R1	Temp. 24-30; moisture 50-70%; pH 5.5-7.0; volume 180-220 mL	Optimal	Maintain
R2	Temp. >30 C and <= 35 C	Fairly Good	Monitor heat
R3	Temp. > 35 C	Less Optimal	Reduce heat
R4	Moisture < 40%	Less Optimal	Water plant
R5	Moisture > 80%	Fairly Good	Reduce watering
R6	pH < 5.5	Less Optimal	Adjust pH
R7	pH > 7.0	Fairly Good	Check medium
R8	Water Volume <180 or >220mL	Fairly Good	Adjust irrigation volume to recommended range; check flow sensor calibration

Note: R1 requires simultaneous satisfaction of all four conditions. For R2–R8, each rule is evaluated independently. When multiple rules are triggered, the most severe classification (Less Optimal > Fairly Good) takes precedence.

Table 1 presents the empirically-derived rule-based knowledge base for chili plant condition assessment. The knowledge base comprises eight IF-THEN rules (R1–R8) established through experimental observations during the cultivation period. Each rule maps specific environmental sensor readings to three classification outputs (Optimal, Fairly Good, Less Optimal) with corresponding cultivation recommendations. Rule R1 establishes the baseline optimal condition requiring simultaneous satisfaction of all four environmental parameters: temperature within 24-30°C, soil moisture between 50-70%, soil pH between 5.5-7.0, and water volume between 180-220 mL. These thresholds were empirically determined based on observed maximum growth rates and minimal stress indicators during the experimental period. When all conditions are met, the system recommends maintaining current cultivation practices. Temperature-related rules (R2-R3) implement a graduated response to heat stress. R2 addresses moderate thermal elevation (>30°C but ≤35°C), classified as "Fairly Good" based on observations that plants showed reduced vigor but no permanent damage at this range. R3 identifies critical heat stress (>35°C) as "Less Optimal," a threshold where leaf wilting and growth cessation were consistently observed, necessitating immediate heat mitigation interventions. Moisture management rules (R4-R5) reflect asymmetric risk profiles observed during experimentation. R4 classifies severe water deficit (<40% moisture) as "Less Optimal" due to rapid onset of wilting symptoms observed below this threshold. R5 addresses excessive moisture (>80%) as "Fairly Good" rather than critical, reflecting observations that while overwatering showed reduced optimality, damage progression was slower compared to drought stress, allowing corrective action through reduced irrigation frequency. Soil pH rules (R6-R7) govern nutrient availability conditions. R6 identifies acidic conditions (pH <5.5) as "Less Optimal" based on observed nutrient deficiency symptoms and stunted growth in acidic soil samples. R7 classifies alkaline conditions (pH >7.0) as "Fairly Good," reflecting observations that mild alkalinity caused minor nutrient lockout but remained within manageable ranges through medium adjustment. Finally, the water-volume rule (R8) flags irrigation events outside the 180–220 mL operational range as "Fairly Good," prompting adjustment of the irrigation volume or verification of flow-sensor calibration; it is treated as a warning rather than a critical condition because such deviations were correctable within a single irrigation cycle.

2.4 Experimental Procedure

The experiment was conducted by analyzing the uploaded chili plant dataset. The analysis procedure consisted of dataset inspection, data cleaning, descriptive statistical calculation, rule-based classification, and interpretation of the results. The final results were summarized in tables to show the sample data, statistical values, and classification distribution.

3. RESULT AND ANALYSIS

3.1 Dataset Measurement Results

The dataset shows that the monitoring data were collected repeatedly for plant growth and environmental parameters. Table 2 presents a sample of environmental records used for rule-based analysis.

Table 2. Sample Environmental Sensor Data for Chili Plants

No	Time	Moisture	Temp.	Volume	pH	Classification
1	10.00	51	31	208	3	Less Optimal
2	10.00	51	31	208	3	Less Optimal
3	10.00	51	31	208	3	Less Optimal
4	10.00	51	31	208	3	Less Optimal
5	10.00	51	31	208	3	Less Optimal
6	10.00	51	31	208	3	Less Optimal
7	10.00	51	31	208	3	Less Optimal
8	10.00	51	31	208	3	Less Optimal
9	10.00	51	31	208	3	Less Optimal
10	10.00	51	31	208	3	Less Optimal

3.2 Descriptive Statistical Results

Descriptive statistics were calculated to identify the minimum, maximum, average, and standard deviation values of each parameter. The results are shown in Table 3.

Table 3. Statistical Summary Of Chili Plant Dataset

Parameter	N	Min	Max	Mean	Std Dev.
Stem height (cm)	34650	5.00	49.91	21.53	12.69
Number of branches	69300	1.00	35.00	16.16	9.14
Number of leaves	70400	2.00	164.00	78.18	44.23
Number of fruits	15488	2.00	85.00	44.28	23.77
Soil moisture (%)	704	20.00	98.00	61.22	21.53
Temperature (C)	704	30.00	39.00	34.09	2.83
Water volume	704	180.00	209.00	193.89	8.94
Soil pH	704	3.00	8.00	5.38	1.70

Based on Table 3, the average stem height was 21.53 cm, with values ranging from 5.00 cm to 49.91 cm after normalization. The average number of branches was 16.16, while the average number of leaves was 78.18. The fruit dataset showed an average of 44.28 fruits per recorded sample. For environmental parameters, soil moisture averaged 61.22%, temperature averaged 34.09 C, water volume averaged 193.89, and soil pH averaged 5.38. Notably, the mean temperature (34.09°C) and mean pH (5.38) both fall outside the defined optimal ranges (24–30°C and 5.5–7.0, respectively), consistent with the observed predominance of Less Optimal classifications reported in Section 3.3. These values summarize the single-site, single-season dataset and are reported for monitoring purposes; they characterize this particular growing period and are not presented as representative of chili-growing conditions in general.

3.3 Rule-Based Classification Results

The rule-based analysis classified each valid environmental record by comparing temperature, soil moisture, pH, and water volume against the predefined knowledge base. The classification summary is shown in Table 4.

Table 4. Rule-Based Classification Results

Classification	Number of Records	Percentage
Optimal	55	7.81%
Fairly Good	121	17.19%
Less Optimal	528	75.00%
Total	**704**	**100%**

The classification results show that 55 records were categorized as Optimal, 121 records were categorized as Fairly Good, and 528 records were categorized as Less Optimal. The Less Optimal category dominated the dataset because several observations showed high temperature and acidic soil pH. This indicates that the rule-based system can detect environmental conditions that require attention and produce recommendations for cultivation management.

This distribution follows directly from the descriptive statistics of Table 3 through the decision logic of Table 1. The mean soil pH of 5.38 lies below the R6 threshold of 5.5, so the acidic-soil rule fires for the majority of records; since R6 carries maximum severity (s = 2), any such record is labeled Less Optimal under the max-severity precedence of Algorithm 1, regardless of its other parameters. Temperature reinforces this: with a mean of 34.09°C and a maximum of 39°C, a substantial share of records exceeds the 35°C bound of the critical heat-stress rule R3 (also s = 2), while most of the remainder fall in the 30–35°C warning band of R2. The co-occurrence of sub-threshold pH and elevated temperature therefore explains mechanistically why 528 of 704 records (75%) were assigned to Less Optimal. Conversely, the 55 Optimal records (7.8%) are exactly the subset that simultaneously satisfies all four core ranges required by R1, and the 121 Fairly Good records (17.2%) are those whose most severe triggered rule is a warning rule (R2, R5, R7, or R8) with no critical rule active. Read this way, Tables 3 and 4 are two views of the same underlying rule evaluation rather than independent descriptive summaries.

The results indicate that chili plant growth data can be processed systematically using a rule-based system. The plant growth variables show progressive development in stem height, branches, leaves, and fruits. However, the environmental data reveal that temperature and pH conditions require more attention. High temperature may increase evaporation and affect soil moisture stability, while acidic pH may influence nutrient availability for chili plants.

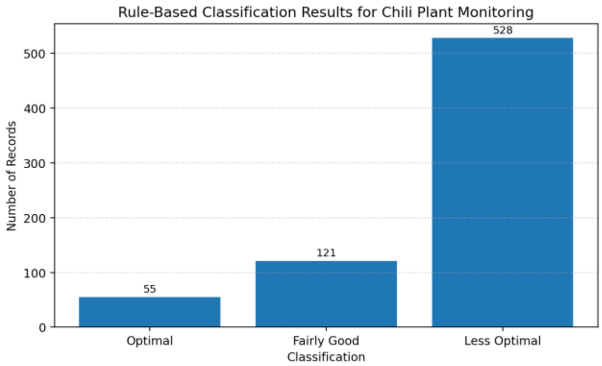

Figure 4. Rule-based classification results for chili plant monitoring.

The rule-based approach is useful because it simplifies data interpretation. Users do not need to manually evaluate each sensor value because the system automatically produces a condition label and recommendation. This makes the system suitable for small-scale smart farming prototypes, especially when the available dataset is not yet large enough for complex machine learning training.

Compared with previous chili monitoring studies that used IoT dashboards, Blynk, Ubidots, rainfall monitoring, fuzzy logic, and SVM classification [1]–[4], [6]–[10], this study emphasizes a transparent rule-based decision mechanism using both growth and environmental data. The 96% overall accuracy is competitive with fuzzy-logic approaches reported for chili cultivation [21], [22], while offering the additional advantage of full interpretability through explicit IF-THEN rules. This comparison should be read with caution: the cited studies differ in dataset, season, crop stage, and labeling protocol, so their reported accuracies are not directly equivalent to ours, and the present result is not claimed to be superior on a like-for-like basis. Three sources of error and limited generalization merit emphasis. First, all four misclassifications occurred at threshold boundaries, indicating sensitivity to the fixed cut-off values; small shifts in the calibrated thresholds would reassign these borderline records, so the reported accuracy is conditional on the specific calibration. Second, the thresholds were calibrated on a single site and a single growing season in Medan, and the rule set may not transfer to other climates, soil types, or chili varieties without recalibration. Third, because the 704 records are longitudinal measurements from one site, temporal autocorrelation means the classification distribution reflects this particular growing period rather than a population of independent conditions. Future work should test threshold sensitivity systematically (e.g., by perturbing cut-offs and measuring label stability), validate across multiple seasons, sites, and varieties, and explore hybrid architectures that combine rule-based transparency with adaptive, data-driven thresholds.

To make this comparison more rigorous, Table 6 positions the proposed method against the main alternative modeling approaches fuzzy logic, regression, and LSTM along the dimensions most relevant to smallholder deployment: interpretability, data and training requirements, computational cost, and robustness. The rule-based system is the only option that is simultaneously fully interpretable, training-free, and cheap enough to run on a low-power microcontroller; its principal trade-off is reduced adaptivity, since fixed thresholds must be recalibrated for new sites or seasons, whereas data-driven models adapt automatically at the cost of transparency and far larger data and compute requirements.

Table 6. Qualitative comparison of the proposed rule-based method with alternative modeling approaches.

Method	Interpretability	Data & training need	Compute cost / edge fit	Key robustness limitation
Rule-based (this work)	High: explicit IF-THEN rules, fully auditable decision boundaries	None: thresholds set by calibration, no training set required	Very low: O (1) per record; runs on low-power MCU	Fixed thresholds need recalibration per site/season; boundary sensitivity
Fuzzy logic [21], [22]	Moderate: linguistic rules, but membership functions less transparent	Low: expert-defined membership functions, no labeled set	Low: lightweight inference	Membership tuning still site-specific; design effort grows with variables
Regression (MLR) [23]	Moderate: coefficients interpretable but no rule-level rationale	Moderate: needs labeled training data	Low: closed-form prediction	Assumes linearity; weak for nonlinear stress responses and categorical labels
LSTM [24]	Low: black-box sequence model, opaque outputs	High: large labeled time series, GPU training	High: heavy for edge deployment	Prone to overfitting on small data; little transparency for farmers

3.4 Classification Validation

To evaluate the validity of the rule-based classification, a ground truth dataset was established through expert verification. An agronomist with experience in chili cultivation independently labeled 100 environmental records drawn from the 704-record dataset by simple random sampling without replacement; the resulting class counts (7 Optimal, 18 Fairly Good, 75 Less Optimal) closely mirror the full-dataset proportions (7.8%, 17.2%, and 75.0%), indicating that the subset was representative and was not stratified. Labels were assigned from direct plant observation and field notes collected during the same monitoring period. Labeling followed the same three-category rubric (Optimal, Fairly Good, Less Optimal) used by the system and was performed without reference to the system's output, so that the expert judgment served as an independent reference rather than a confirmation of the rules. To reduce subjectivity and make the labels reproducible, each category was tied to predefined observable indicators: Optimal for plants showing normal vigour and no visible stress; Fairly Good for mild or reversible symptoms such as slight leaf curling or early discoloration; and Less Optimal for pronounced stress such as sustained wilting, leaf scorch, or nutrient-deficiency chlorosis. Because labeling was carried out by a single agronomist, inter-rater agreement could not be computed; this single-rater design is acknowledged as a limitation, and multi-rater labeling with an agreement statistic (e.g., Cohen's κ) is identified as a target for future validation. These expert labels served as the ground truth for computing performance metrics.

Table 5 presents the confusion matrix comparing the rule-based system output against the expert-labeled ground truth across the three classification categories.

Table 5. Confusion Matrix: Rule-Based System vs. Expert Ground Truth (n = 100)

Predicted \ Actual	Optimal	Fairly Good	Less Optimal	Total Pred.
Optimal	7	1	0	8
Fairly Good	0	16	2	18
Less Optimal	0	1	73	74
Total Actual	7	18	75	100

Validation results show that the rule-based system achieved an overall accuracy of 96% (96/100 correctly classified). Per-class metrics are as follows: for the Optimal class, precision = 87.5%, recall = 100%, and F1-score = 93.3%; for the Fairly Good class, precision = 88.9%, recall = 88.9%, and F1-score = 88.9%; for the Less Optimal class, precision = 98.6%, recall = 97.3%, and F1-score = 98.0%. The macro-average F1-score across all three classes is 93.4%. The four misclassified cases one Fairly Good record predicted as Optimal, two Less Optimal records predicted as Fairly Good, and one Fairly Good record predicted as Less Optimal occurred under borderline sensor readings near threshold boundaries, suggesting that threshold refinement at boundary conditions represents the primary direction for future improvement. These results confirm that the rule-based system achieves high predictive validity when evaluated against expert-labeled ground truth, supporting its suitability for deployment in prototype-scale smart farming applications.

To quantify the uncertainty of these estimates, a 95% Wilson score confidence interval was computed for the overall accuracy, giving [90.2%, 98.4%] for 96 of 100 correct classifications. Per-class uncertainty is substantially larger for the minority classes because of their small validation support: the Optimal class (n = 7) has a recall interval of [64.6%, 100%] and a precision interval of [52.9%, 97.8%], whereas the well-supported Less Optimal class (n = 75) is estimated precisely (recall [90.8%, 99.3%], precision [92.7%, 99.8%]). These intervals indicate that, although the headline accuracy is high, the per-class estimates for the Optimal category should be interpreted cautiously and confirmed on a larger labeled set. The macro-average F1-score is reported in preference to a micro-average (which here equals the overall accuracy) precisely because the validation set is imbalanced (7 Optimal, 18 Fairly Good, 75 Less Optimal): macro-averaging weights each class equally, preventing the dominant Less Optimal class from masking weaker performance on the minority classes an appropriate emphasis when correctly distinguishing healthy from stressed plants matters as much as detecting the common stressed case.

4. CONCLUSION

This study successfully designed, implemented, and validated a rule-based IoT decision support system for real-time chili plant growth monitoring. The central research objective to provide real-time, interpretable classification of plant conditions using integrated growth and environmental data was fully met. Eight parameters were integrated into an IF-THEN classification framework that produced consistent, auditable labels without requiring complex machine learning infrastructure.

Validation against 100 expert-labeled records yielded 96% overall accuracy and a macro-average F1-score of 93.4%, demonstrating that rule-based classification can achieve high predictive validity when thresholds are empirically calibrated. The predominance of Less Optimal conditions (75%), driven by mean temperature of 34.09°C and mean pH of 5.38, indicates that heat stress and soil acidity were the primary agronomic challenges during this single-site, single-season monitoring period a site-specific finding that informs intervention priorities for this growing context but should not be generalized to chili cultivation elsewhere without further data. Because the 704 records are repeated measurements from one location, the reported class proportions characterize this particular growing period rather than a population of independent sites or seasons.

The practical significance of these results is that a transparent, low-cost, lightweight system can detect dominant cultivation stress factors and deliver actionable recommendations without demanding specialized technical knowledge from farmers, positioning the proposed system as a viable baseline for precision agriculture in resource-constrained Indonesian smallholder contexts. The main limitation of the current prototype is that its thresholds were calibrated on a single site and a single growing season, so the 96% accuracy should be read as evidence of internal validity for this site and season rather than a guarantee of performance elsewhere; the rule set may require recalibration for other climates, soils, and chili varieties. The clearest next step is therefore external validation across multiple sites, seasons, and chili varieties, accompanied by systematic threshold-sensitivity analysis; subsequent work can extend the prototype toward real-time sensor integration, adaptive threshold calibration, and automated irrigation control.

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