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Smart Nutrition Monitoring: IoT-Based Rice Soil Health Classification Using Naive Bayes and Fuzzy Expert System

Abi Bayu Perkasa[1,*], Aisyah Faradila Fatah[1], Istikomah[1], Abdul Rafi[1], Rifa'a Aemelia Kartika[1], Aslam Syahid Majid[1]

[1] Mechatronics and Artificial Intelligence, Universitas Pendidikan Indonesia, Purwakarta, Indonesia
**Corresponding author email: abibayu83@upi.edu*

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ABSTRACT

The implementation of Machine Learning (ML) in precision agriculture often stops at probabilistic outputs without producing directly executable (actionable) agronomic guidance. In response to this functional gap, this study created an IoT proof of Concept (PoC) system architecture design that integrates Machine Learning with the Mamdani Fuzzy Expert System. To validate the software before entering the implementation phase, the system was trained and tested using 5000 synthetic datasets. This synthetic data was generated using a Multimodal Gaussian distribution to represent real-world conditions in the field (TDS, pH, humidity, and temperature). The evaluation results obtained proved that the Naive Bayes classification was very efficient for use in system architectures with minimal resources, with an accuracy of 96.65% and a latency of 0.054. In the final stage of the system, the Fuzzy Logic integration successfully produced output in the form of solutions and recommendations based on the values generated by the Machine Learning system. The integration of these three systems successfully became a unified, complete architectural system. This system has proven to be able to bridge the gap between the complexity of the system and the needs of farmers, and is ready to be implemented in the field using real-time data.

1. Introduction

Rice (Oryza sativa L.) is a strategic commodity because rice is the main food in Indonesia and will greatly determine the stability of national food security [1]. Even with a high level of domestic production, food security in Indonesia remains at risk because of regional production imbalances, land degradation and climate change (unstable supply), requiring rice importation [2], [3], [4]. In this context, rice import policies have been an important instrument to stabilize domestic prices and food supply, but recent empirical studies suggest that such policies may also put downward pressure on local grain prices with adverse effects on the profitability of farmers and local economies [5], [6]. At the regional scale, however, two cases of implementing intensive rice cultivation in Indonesian regions such as Citalang Village, Purwakarta Regency are still dominated by using conventional agronomic practices which are based on intuition and empirical experience. Decision-making, especially around stewardship and fertilizer management for land is often done qualitatively without quantitative assessment of soils on the ground. The absence of this systematic, data-based assessment has been realized to result in biased nutrient management and disproportionate use of chemical inputs, spreading ultimately over the faster degradation of land fertility [7], [8], [9].

The nutrient imbalance and the loss of long-term resilience of crop yields are caused by an extensive conventional agricultural practice, leading to soil degradation due to overuse of chemical fertilizer and improper land management [10], [11]. To tackle these problems, data-driven techniques, especially Machine Learning (ML) can support accurate and objective soil fertility diagnoses from sensor information [12]. Conventional soil–plant relationship modeling methods have several limitations that machine learning (ML) algorithms can overcome [13], [14]. Naive Bayes, in particular, is a great choice when it comes to low computational complexity and relatively fast and stable classification for datasets of medium size [15]. Since the outputs of ML are probability distributions rather than direct agronomic recommendations, Another approach is required to bridge the gap between analysis results and on-field actionable results [16].

In order to overcome this gap, Expert Systems which mimic human expert knowledge using rule-based inference are integrated with computationally precise ML results interpreting them for the specific application scenario of agricultural decision-making (e.g. fertilization, irrigation.) from Crop Management and Precision Agriculture perspective extending beyond conventional machine learning outputs [13], [17].

This integrated system uses the Internet of Things (IoT) to collect real-time environmental data (pH, moisture, temperature, and nutrients), being this information collected as a primary input [18], [19]. This research focuses on the evaluation of the Naive Bayes model classification and the effectiveness of the Expert System as a decision-making tool, even though IoT functions as a basic acquisition system.

A number of recent studies have looked at data-driven approaches to soil and crop management. For example, recent implementation of IoT-based Machine Learning models such as Support Vector Machines, and Random Forests have shown high accuracy in soil fertility prediction [20]. However, these models usually require high computational resources, so are less suitable for low-cost edge deployment in rural areas such as Citalang Village. Alternatively, Naive Bayes has been recognized as an efficient and stable algorithm for classification of environmental sensor data [21]. Most existing studies using Naive Bayes, although computationally efficient, only go as far as providing probabilistic classification outputs, leaving a critical gap in translating the diagnostic results into actionable agronomic steps for farmers. [22].

On the other hand Fuzzy Logic for Expert Systems has been used to determine the appropriate fertilizer dosage based on rules set by experts [23]. However, this system has weaknesses, it is highly dependent on manual input of parameters or data, does not have the ability to provide output in real time and continuously. Therefore, IoT integration with data analysis and Machine Learning is needed to significantly improve the accuracy and efficiency of soil monitoring and land management recommendations [24], [25], [26], [27].

To address these shortcomings, we propose a system that combines real-time IoT data acquisition with a two-stage approach. In the first stage, for soil health classification, we use the Naive Bayes algorithm due to its low latency and lightweight nature. In the second stage, to transform the probabilistic model output into fertilizer recommendations, we integrate a Fuzzy Expert System. This approach can bridge the gap between algorithm complexity and farmer needs, supporting sustainable agriculture.

This research will focus on a Proof of Concept (PoC) due to the complexity of direct field data collection, which is time-consuming. Alternatively, to test the Naive Bayes algorithm across various risks, we use synthetic data. This testing is essential to ensure software readiness before being deployed with IoT. Specifically, this research aims to design, build, and validate the integration of an IoT system architecture with Naive Bayes and an Expert System for soil health classification, using agricultural parameters for testing in rice fields in Citalang Village, Purwakarta Regency. This approach is expected to improve the accuracy of soil condition diagnosis, optimize fertilizer efficiency, and support data-driven rice productivity.

2. Methods

In this study, we used a top-down methodology, developing the system from a general vision to specific components, thus requiring a structured framework. To facilitate management, the system was broken down into several modules (IoT system architecture, machine learning classification, and expert system modules). These modules were designed and implemented sequentially until they became a complete system. The top-down methodology is fundamental because it allows for a logical and systematic organization of the design process. This ensures that each stage aligns with specific objectives: architectural stability, low transmission latency, and reliability of the Decision Support System for precision agriculture. The application of this methodology at each stage of the project is explained below.

2.1. IoT System Architecture

The development of this system prototype began with a Top-Down methodology approach. At the high-level design stage, the system is required to be able to monitor soil parameter conditions precisely with a low transmission latency level. To meet the criteria of reliability and cost efficiency, the hardware design is realized as shown in Figure 1. The system control center uses an ESP32 microcontroller connected to a 16-bit ADC module (ADS1115) to increase the resolution and accuracy of analog signal readings from the sensor. This system integrates a series of physical sensors, including a soil pH sensor, Capacitive Soil Moisture, DHT (Temperature and Humidity) sensor, and a rainfall detector sensor. This circuit is also equipped with local actuators in the form of a buzzer and LED for early-warning functions, all of which are powered by an 18650 Li-ion battery configuration through a step-down converter module.

To facilitate systematic risk management and testing, the system's communication architecture is decomposed into three interconnected functional layers (Figure 2). At the basic level, the Perception and Processing Layer (Edge Acquisition Module) is responsible for acquiring microclimate parameters from sensors while autonomously controlling local actuators. The data is then routed by the Network and Cloud Layer (Transmission Module) via an HTTP-based Wi-Fi network for real-time transmission and storage into the Firebase cloud database. At the highest level, the Application Layer (Logic and Interface Module), a web dashboard, is responsible for capturing and visualizing this data, while also processing it using integrated Machine Learning and Expert System algorithms to extract information into accurate agronomic decisions.

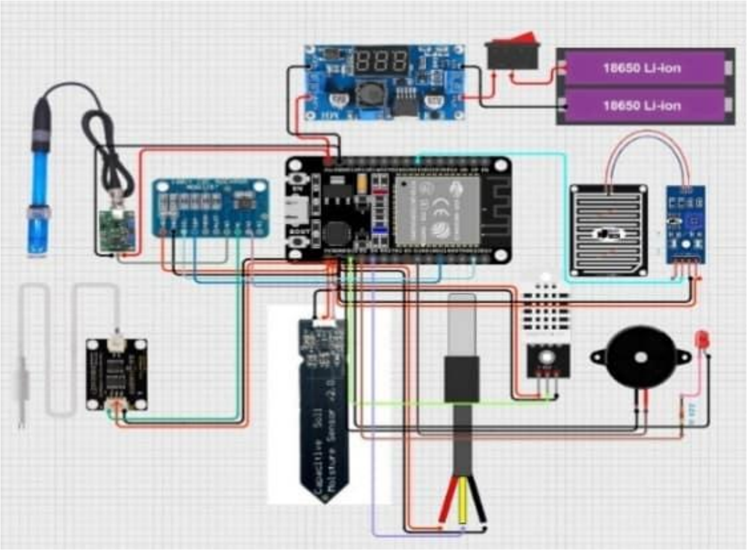

Figure 1: Hardware wiring diagram.

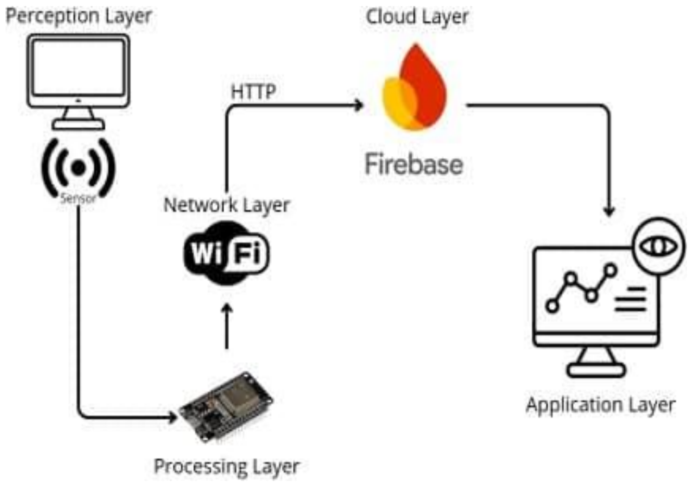

Figure 2: Multi-Layer architecture of smart nutrition monitoring system.

2.2. Synthetic Data Generation

Considering that this research is oriented towards the prototype and proof of concept (Proof of Concept) of an integrated intelligent system architecture, the initial evaluation of the Machine Learning module is focused on the use of synthetic data totaling 5,000 samples. The use of synthetic datasets is essential in the IoT pre-design stage to overcome the limitations of initial data acquisition [28]. This simulation approach allows for comprehensive stress-testing of algorithms in detecting sensor anomalies, while eliminating the burden of mass hardware implementation costs in the field [29]. This data generation process is not carried out using pure randomization, but rather applies a random sampling method with a Gaussian Multimodal Distribution (Gaussian Mixture) approach. This approach is used to model sub-populations of soil condition classes separately (healthy and anomalous), while simulating the characteristics of noise and natural environmental fluctuations that are the basic properties of physical sensor devices in open areas [30], [31].

In the Literature Grounding stage, the generated data parameters are strictly calibrated based on the agronomic threshold of rice plants to be equivalent to the inference rules (rule-based) in the Fuzzy Expert System. The value of the degree of acidity (pH) of the soil is simulated with an ideal range of 6.5 to 8.5, considering that values that are persistently below this limit trigger toxicity and inhibit nutrient absorption [32], [33]. Next, the concentration of Total Dissolved Solids (TDS), which represents the accumulation of dissolved nutrient ions in the soil solution, is configured at an ideal limit of 450 – 2,000 ppm. Simulation of TDS numbers far exceeding 2,000 ppm is intentionally generated to detect extreme salinity levels due to inorganic fertilizer residues that damage the soil structure of rice fields [34]. The last parameter, soil moisture, is simulated to fluctuate Gaussianically within the ideal range of the vegetative phase, namely 33% – 90%. This soil moisture parameters were taken from a study related to rice plants [35]. By adjusting these value limits, the dataset can be divided into four target classes, namely healthy, nutrient deficient, acidic, and dry. This aims to produce an evaluation matrix based on real conditions in agricultural ecosystems.

2.3. Dataset Composition, Labeling, and ML Parameter Configuration

To conduct load testing in this PoC system, the evaluation process used a synthetic dataset consisting of 5,000 data samples. The IoT sensor reading data generation process was continuous, with a sampling frequency of every hour over a simulated multi-season period. To ensure an unbiased evaluation model, the class distribution was evenly split.

A total of 5,000 samples were divided proportionally into four classes: Healthy (25%), Nutritionally Deficient (25%), Acidic (25%), and Dry (25%), resulting in 1,250 data samples per class. The data labeling procedure was carried out algorithmically using predetermined agronomic thresholds based on the Literature Grounding stage. For example, data with a TDS value of <450 ppm was labeled 'Nutrient Deficient', while samples with soil moisture <33% were labeled 'Dry' (see figure 3).

Histogram visualization shows that the data generation process successfully formed a multivariate bimodal distribution. This multi-peak formation represents a clear segmentation between optimal (healthy) land parameter boundaries and environmental anomaly conditions (acidic, dry, and nutrient deficient), resulting in an ideal feature variance for training the algorithm.

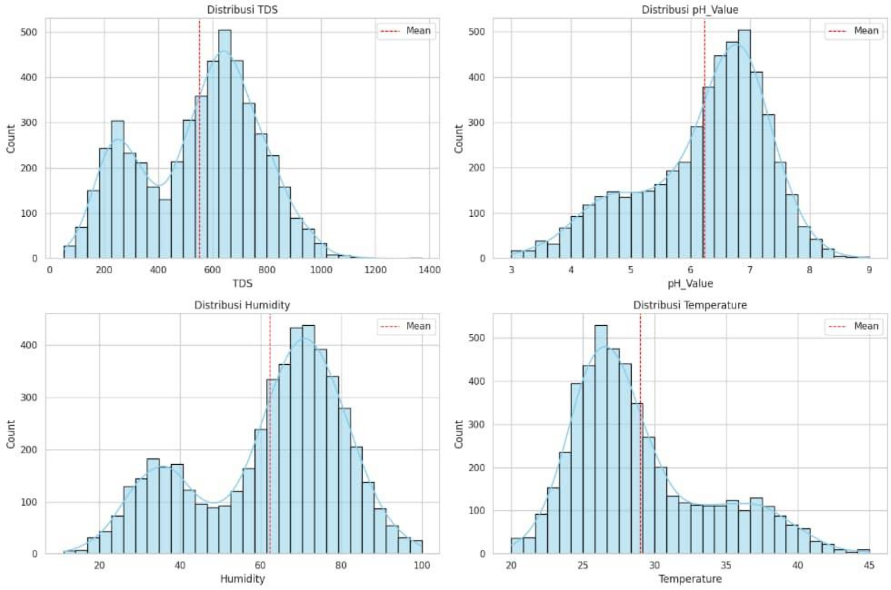

Figure 3: Histogram visualization.

2.4. Machine Learning Modeling

For the Machine Learning configuration, the dataset was partitioned using 5-Fold Stratified Cross-Validation, Sending a well-allocated training and testing allocation, for 80% training (4,000 samples) and 20% testing (1,000 samples) allocation in each iteration, maintaining a balanced class ratio. To provide a proper assessment, model performance is evaluated using several metrics, namely accuracy, precision, recall, and F1 score.

Table 1 presents the evaluation and comparison results of several machine learning algorithms. Compared to other algorithms, Naive Bayes demonstrated the best performance, with an accuracy of 96.67%, a recall of 96.65%, and an F1 score of 96.64%. Furthermore, this algorithm also recorded the fastest speed, demonstrating Naive Bayes' ability to classify soil conditions using several interrelated parameters.

Table 1: Model training results with 5-fold stratified cross validation

No	Models	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (%)	Time (s)
1	Naive Bayes	96.65	96.64	96.67	96.65	0.540
2	Support Vector Machine	96.42	96.42	96.44	96.42	1.173
3	Random Forest	96.18	96.17	96.20	96.18	4.928
4	K-Nearest Neighbors	95.78	95.77	95.81	95.78	0.988
5	XGBoost	95.52	95.52	95.55	95.52	1.297
6	Decision Tree	93.40	93.40	93.44	93.40	1.499

With high precision and recall values, the Naive Bayes model demonstrates its ability to minimize errors in the classification process, including false positives and false negatives. These results indicate that Naive Bayes is a suitable model for implementation in IoT systems. Therefore, Naive Bayes was chosen as the primary model in this study and integrated with an Expert System to generate accurate and easily implemented agronomic recommendations for farmers.

2.5. Rule-Based Expert System

The knowledge base was built using 54 production rules in the form of IF–THEN structures that map combinations of input variables to specific technical decisions. Each rule was validated by domain experts and assigned a Certainty Factor (CF) value ranging from 0.4 to 1.0 to represent the level of confidence associated with the resulting recommendation. This approach has proven effective in improving diagnostic accuracy in agricultural expert systems [36]. The inference flow is designed to prioritize critical conditions. For example, when the system detects rainfall conditions (Rain = 1), it automatically triggers a rule to suspend all fertilization activities to prevent operational cost inefficiencies and nutrient loss due to leaching [37].

This study applies the Mamdani Fuzzy Logic method to address environmental conditions when determining irrigation and fertilizer doses. The process consists of three main stages, namely Fuzzification, which aims to map sensor input values to linguistic variables, using the MIN application at the Rule Evaluation stage and Defuzzification using the Centroid method to produce accurate output values. The application of the Mamdani algorithm to rice irrigation systems has proven effective based on plant needs and can significantly increase water use efficiency compared to conventional irrigation methods [38].

Table 2: Soil condition classification.

Input	Condition	Value
TDS (Nutrient/Fertilizer) Soil pH	Starving	< 450 ppm
	Optimal	450 - 2000 ppm
	Toxic	> 2000 ppm
Soil Moisture	Acidic	< 6,5
	Ideal	6.5 - 8.5
	Alkaline	> 8.5
Rain TDS (Nutrient/Fertilizer)	Dry	< 33%
	Moist (Moist)	33% - 90%
	Wet (Stagnant)	> 90%
Soil pH	Sunny (No Rain)	0
	Rain	1

Each sensor input variable (TDS, pH, moisture, and temperature) is mapped into membership function curves to determine its degree of membership (table 2). For example, the soil pH variable is represented using trapezoidal and triangular membership functions, which divide soil conditions into three linguistic sets: *acidic*, *neutral*, and *alkaline*. This mapping enables the system to effectively handle uncertainty when sensor values fall within transition regions. For instance, a soil pH value of 6.44 can simultaneously belong to both the *acidic* and *neutral* sets with different degrees of membership under fuzzy logic principles.

2.6. Integration of Machine Learning and Expert Systems

The system was developed using an integrated platform architecture that separates the workflow between automated monitoring and simulation-based decision-making. The Machine Learning module (Naive Bayes) is directly connected to IoT sensors to perform real-time land condition classification without user intervention. In contrast, the Expert System module is designed as a Decision Support System (DSS) that operates based on manual user input. Farmers or users can enter soil parameter values (such as pH or TDS levels) into the system interface to simulate specific conditions and obtain precise fertilizer and irrigation recommendations.

This functional separation aims to ensure that users do not rely solely on sensor data, which may be subject to fluctuations, but can also perform cross-validation by inputting manually measured field data. Such an approach enhances the reliability of the recommended actions and supports more accurate and informed decision-making in land management practices.

3. Results and Discussion

3.1. Machine Learning Implementation

The implementation results showed that the Naive Bayes model effectively classified four soil conditions (healthy, nutrient-deficient, acidic, and dry) with a cumulative average accuracy of 96.65%. Confusion Matrix analysis (Figure 4) on 1,000 samples validated this with an accuracy rate of 95.7%. The algorithm had high precision in identifying extreme conditions, with a negligible false negative rate. Misclassification only occurred at the decision boundary between acidic and healthy soils. This overlap is reasonable and anticipated, given the use of synthetic Gaussian noise at a pH threshold of 6.5 to represent actual sensor readings in the field.

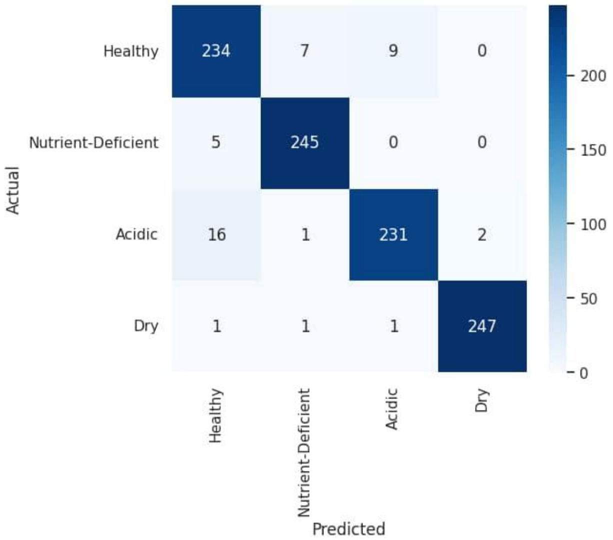

Figure 4: Confusion matrix.

In the context of this PoC, one of the key advantages of utilizing Naive Bayes, despite these minor boundary overlaps, is its computational efficiency. The algorithm's conditional independence assumption enables rapid convergence, providing fast and stable classification performance with minimal processing latency compared to computationally heavy models. These findings scientifically validate that the proposed software architecture is highly feasible and fully capable of processing real-time, continuous data streams once the physical IoT sensors are massively integrated into the actual agricultural fields.

3.2. Fuzzy Logic Implementation

The implementation of fuzzy logic in this system is designed to map continuous environmental sensor inputs into crisp decision outputs. This process involves representing each input variable through appropriate membership functions and conducting computational simulations to validate the accuracy of the system's decision-making mechanism. To verify the correctness of the constructed inference logic, a case simulation under extreme environmental conditions specifically acidic and dry soil was performed using the following test input data: TDS of 3 ppm, soil pH of 6.44, soil moisture of 16%, and clear weather conditions. The manual calculation process was carried out through the following stages:

3.2.1. TDS Variable

$$\mu\, Starving\ (X) = \begin{cases} 1 & X \leq 400 \\ \dfrac{500 - X}{500 - 400}, & 400 < X < 500 \\ 0 & X \geq 500 \end{cases} \tag{1}$$

$$\mu\, Ideal\ (X) = \begin{cases} 0 & X \leq 400 \\ \dfrac{X - 400}{500 - 400} & 400 < X \leq 500 \\ 1, & 500 < X \leq 1900 \\ \dfrac{2000 - X}{100} & 1900 < X \leq 2100 \\ 0 & X \geq 2100 \end{cases} \tag{2}$$

$$\mu\, Toxic\ (X) = \begin{cases} 0 & X \leq 1900 \\ \dfrac{X - 1900}{2100 - 1900}, & 1900 < X \leq 2100 \\ 1 & X \geq 2100 \end{cases} \tag{3}$$

3.2.2. pH Variable

$$\mu\, Acidic\ (X) = \begin{cases} 1 & X \leq 6 \\ \dfrac{7 - X}{7 - 6}, & 6 < X \leq 7 \\ 0 & X \geq 7 \end{cases} \tag{4}$$

$$\mu\, Neutral\ (X) = \begin{cases} 0 & X \leq 6 \\ \dfrac{X - 6}{7 - 6} & 6 < X \leq 7 \\ 1, & 7 < X \leq 8 \\ \dfrac{9 - X}{9 - X} & 8 < X \leq 9 \\ 0 & X \geq 9 \end{cases} \tag{5}$$

$$\mu\, Alkaline\ (X) = \begin{cases} 0 & X \leq 8 \\ \dfrac{X - 8}{9 - 8}, & 8 < X \leq 9 \\ 1 & X \geq 9 \end{cases} \tag{6}$$

3.2.3. Humidity Variable

$$\mu\, Dry\ (X) = \begin{cases} 1 & X \leq 28 \\ \dfrac{38 - X}{9 - 8}, & 28 < X < 38 \\ 0 & X \geq 38 \end{cases} \tag{7}$$

$$\mu\, Moist\ (X) = \begin{cases} 0 & X \leq 28 \\ \dfrac{X - 28}{38 - 28} & 28 < X \leq 38 \\ 1, & 38 < X \leq 85 \\ \dfrac{95 - X}{95 - 85} & 85 < X < 95 \\ 0 & X \geq 95 \end{cases} \tag{8}$$

$$\mu\, Wet\ (X) = \begin{cases} 0 & X \leq 85 \\ \dfrac{X - 8}{9 - 8}, & 85 < X \leq 95 \\ 1 & X \geq 95 \end{cases} \tag{9}$$

3.2.4. Rain Variable

$$\mu\ Sunny\ (X) = \begin{cases} 1, & if\ X = 0(Sunny) \\ 0, & if\ X = 1(Rain) \end{cases} \tag{10}$$

$$\mu\ Rain\ (X) = \begin{cases} 0, & if\ X = 0(Sunny) \\ 1, & if\ X = 1(Rain) \end{cases} \tag{11}$$

3.3. System Integration Implementation (Dashboard)

During the integration of the three systems, we created a web dashboard as an information monitoring center that displays the results of data analysis generated by IoT devices. The monitoring system and IoT devices were implemented directly at the research site, a rice field in Citalang Village, Purwakarta Regency. The main page presents users with a real-time land condition data monitoring panel integrated with Machine Learning and Fuzzy Logic.

To validate system reliability, a data comparison was conducted between the IoT system readings and standard commercial handheld meters. Table 3 shows a sample of the comparison data. The results indicate that the deviation level is very minimal, with an average percentage error below 5%. Likewise, other parameters each recorded very small differences, namely 0.06; 5 ppm; 2%; and 0.2°C compared to the reference measuring instrument. This level of precision, with a status of "Accurate" to "Excellent," proves that the sensor calibration, particularly through the use of the ADS1115 module, has succeeded in achieving readings very close to standard values.

Table 3: Comparison of measurement results: IoT System vs. Standard Tool.

Parameter	Standard Tool Value	IoT System Value	Difference (Error)	Status
Soil pH	6.50	6.44	0.06	Accurate
TDS (ppm)	450	445	5	Accurate
Moisture (%)	60%	58%	2%	Good
Water Temperature (°C)	28.5	28.3	0.2	Excellent

Status Perangkat: OFFLINE

Kering

Input Realtime: Nutrisi (TDS):3 | pH:6.44248 | Tanah:16% | Suhu:26.0°C

PH: 6.44248 pH masam

NUTRISI (TDS): 3 ppm kurang

KELEMBABAN TANAH: 16 % kering

CURAH HUJAN: 0 mm cerah

Figure 5: Real-time dashboard monitoring and classification.

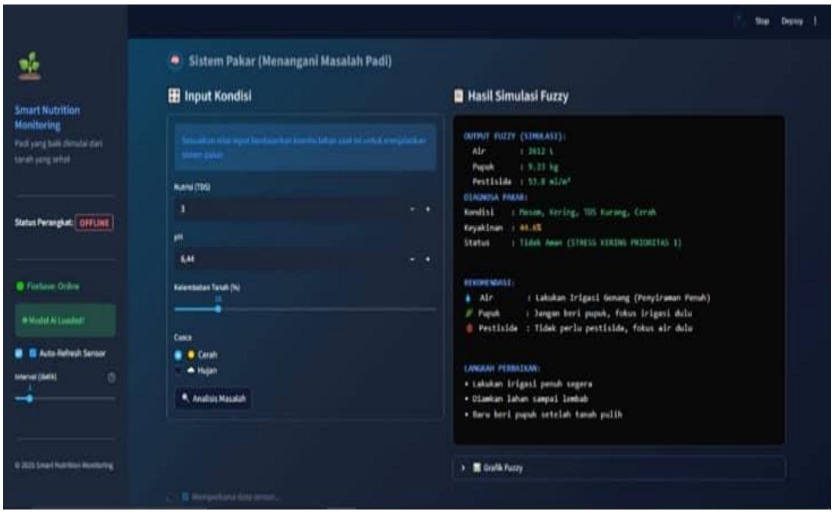

Figure 6: Real-time dashboard expert system.

The Machine Learning module processes real-time data sent by IoT sensors, including TDS, soil pH, temperature, and humidity. The soil condition classification system uses the Naive Bayes algorithm, which automatically sends classification results, such as the "dry" indicator in Figure 5. At this implementation stage, the Machine Learning classification process is still being tested using dummy data for system classification validation.

Unlike machine learning classification, the expert system module utilizes manual input, allowing users to manually enter data for simulations (figure 6). Users can input manual field measurements to validate sensor accuracy or store the likelihood of specific soil conditions to obtain appropriate fertilizer and irrigation dosage recommendations. This functional separation aims to enable farmers to act as validators in the decision-making process. Thus, land management decisions are supported by expert system recommendations, eliminating the need for direct reliance on machine learning classification, which is subject to potential errors.

4. Conclusion and Suggestions

4.1. Conclusion

This study successfully designed and validated a Proof of Concept (PoC) for an integrated smart agriculture architecture that combines the Internet of Things (IoT), a Naive Bayes Machine Learning model, and a Mamdani Fuzzy Logic-based Expert System. Through computational load testing using 5,000 synthetic dataset samples generated through a multimodal Gaussian distribution, the system accurately located environmental noise sensors across TDS, soil pH, moisture, and temperature parameters, demonstrating excellent throughput. The Naive Bayes algorithm proved highly efficient, achieving 96.65% classification accuracy with very low delivery latency (0.054 seconds), making it well-suited for resource-constrained edge computing environments.

Furthermore, the integration of the classification output with a rule-based Expert System effectively bridges the gap between probabilistic algorithms and practical agriculture. The system successfully translated complex multivariable anomalies (such as nutrient deficiencies or moisture stress) into explicit and actionable agronomic recommendations, including precise adjustments to irrigation and fertilization protocols. Ultimately, this PoC validates that the proposed software architecture is computationally robust and fully prepared to handle continuous real-time data streams for future physical deployments.

4.2. Suggestion

This research currently focuses on a Proof of Concept that successfully integrates a system and has been implemented in the rice fields of Citalang Village, Purwakarta Regency. However, the process still uses dummy data. Future studies should shift to the application of data according to field data. Long-term sensor data collection is highly recommended to enable the implementation of weather-resistant devices and validation of results with real harvests. In addition, the addition of NPK sensors to IoT devices can be done to obtain a knowledge base and Expert System. Finally, the development of a web-based dashboard can be expanded to a mobile application that will increase effectiveness and mobility for farmers.

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