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Enhancing Smart Farming through ANFIS IoT Framework for Sugarcane Nutrient Prediction

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ABSTRACT

Nutrient management systems in precision agriculture remain limited in processing real-time field conditions, causing inefficiencies in fertilizer application, crop cultivation, and productivity. Sugarcane requires balanced macronutrients (N, P, K) and micronutrients (Zn, Mn, B) to achieve optimal growth and meet industrial quality standards such as a Brix level of 18%. However, the absence of integrated and intelligent monitoring systems often leads to nutrient imbalance, which reduces yield and affects product quality. **This study aims** to develop a nutrient prediction framework for sugarcane by analyzing macro- and micro-element requirements using an ANFIS-based classification model supported by IoT sensor data. **The research involved** IoT-based data collection from multiple field nodes measuring soil pH, humidity, temperature, and air humidity. The workflow consists of data acquisition, preparation, model training, testing, and evaluation. The proposed ANFIS model was compared with machine learning algorithms including Random Forest, Ridge, Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, and Gradient Boosting to validate predictive performance. Evaluation using accuracy, precision, recall, and F1-score showed that the ANFIS model produced strong prediction results, achieving accuracy above 70% with a relatively low error rate. **Its performance** also demonstrated higher stability and consistency compared to the baseline classification algorithms.

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1. INTRODUCTION

One of the main challenges in precision agriculture is effective and efficient crop management, especially in sugarcane cultivation which requires proper nutrient management to achieve optimal productivity and quality [1–6]. The quality of sugarcane is usually measured through the brix content, with a good quality standard $\geq$ 18%, which is strongly influenced by the balance of macronutrients (nitrogen, phosphorus, potassium) and micronutrients (Zinc, Manganese, Boron) [7]. Nutrient imbalances can reduce plant resistance to environmental stress as well as produce qualities that do not meet the standards [8, 9]. The Bululawang sugarcane varieties used in this study have specific needs for macronutrients such as Nitrogen (N), Phosphorus

(P), and Potassium (K), with critical values of 1.80%, 0.19%, and 0.90%, respectively, and an optimal range of 2.00–2.60% (N), 0.22–0.30% (P), and 1.00–1.60% (K) [10].

Various studies have integrated modern technology into agriculture. IoT is widely applied to monitoring and control systems [11]. For example, an irrigation system based on IoT and fuzzy logic has been developed, but it only focuses on soil moisture without considering important micronutrients such as Zn, Fe, and Cu. The study examined IoT systems for early detection of plant diseases, but did not explicitly address the role of nutrition as a contributing factor [12]. This suggests the need for a more comprehensive approach that includes monitoring the physical condition and nutrient requirements of plants. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) offer adaptive capabilities in the face of uncertainty through the integration of neural networks and fuzzy logic [13]. Based on the findings, this study proposes an ANFIS simulation-based model to predict macronutrient and micronutrient requirements in sugarcane. A medium-scale dataset (2000–3000 rows) is collected from IoT sensors, processed through data cleaning, outlier detection, and normalization stages [14, 15].

2. LITERATURE REVIEW

This research focuses on and contributes to supporting sustainable smart agricultural systems, and applies a method that combines structural and behavioral analysis to evaluate nutritional conditions holistically. Furthermore, to validate the analysis and evaluation results, comparisons with similar algorithms are conducted. The emphasis on monitoring crop nutrient requirements underscores the importance of developing this system. This study also aligns with several targets of the United Nations Sustainable Development Goals (SDGs). Furthermore, the integration of real-time monitoring and digital technology supports SDG 12, Responsible Consumption and Production, by optimizing resource use and minimizing the environmental impact of overfertilization. It also advances SDG 13, Climate Action, as precision agriculture practices help reduce greenhouse gas emissions associated with nutrient mismanagement and soil degradation.

Therefore, the implementation of this system not only improves crop performance but strengthens the role of smart agricultural technologies within the global sustainability framework. By continuously monitoring environmental factors in real time through sensors and generating precise nutrient requirement predictions, the system helps maintain soil and plant conditions within the ideal range, thereby reducing the risk of disease emergence [16]. Moreover, accurate nutrient prediction has the potential to strengthen the plant's resistance to infections, as balanced nutrient availability is a key component in enhancing the physiological immunity of the crop. Thus, although ANFIS does not directly diagnose diseases, the system supports preventive disease management by controlling agronomic conditions that commonly trigger disease development [17].

3. RESEARCH METHODS

This section summarizes the main methodological stages consisting of data collection, preparation, model development, and evaluation [18]. Data were collected from IoT-based soil sensors installed across eight field nodes with 10–20-second intervals. The dataset was cleaned through removal of duplicates, outlier handling using IQR, and imputation of missing values [19]. Features were grouped into macronutrients and micronutrients, followed by correlation inspection and feature selection to reduce redundancy. The ANFIS model was trained using 80% of the data, with 100 epochs, and validated using precision, recall, accuracy, and F1-score. This concise workflow ensures transparency of procedures while reducing unnecessary descriptive details [20].

3.1. Research Workflow

The dataset is then categorized into macronutrient and micronutrient classes to support more granular nutrient requirement analysis [21]. In the modeling phase, the Adaptive Neuro-Fuzzy Inference System (ANFIS) is trained and tested using an 80:20 data split to ensure reliable performance evaluation [22]. Finally, the validated model generates actionable recommendations for nutrient management, including nutrient addition, monitoring, or reduction, thereby supporting data-driven decision-making in smart farming and precision agriculture practices [23]. Figure 1 illustrates the research stages, beginning with problem identification to determine an appropriate ANFIS-based modeling approach for IoT-driven prediction and recommendation. The dataset is divided into 80% training and 20% testing to ensure reliable outputs, followed by a literature review on data-driven modeling, fuzzy inference systems, IoT data acquisition, and ANFIS optimization.

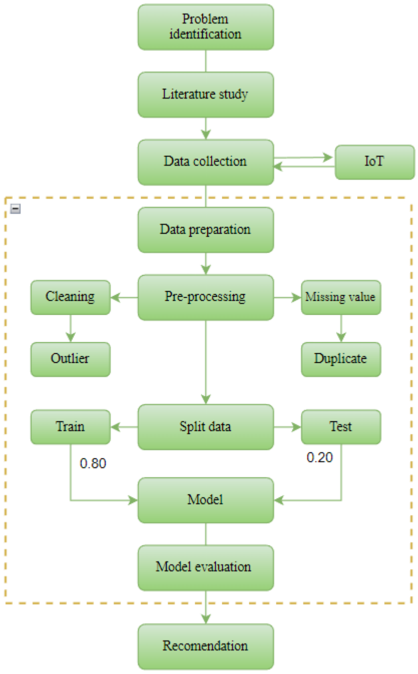

Figure 1. Research Workflow

Data are collected using IoT-based soil sensors in the demonstration plot and then pre-processed through data cleaning, normalization, missing value handling, outlier treatment, and classification into macro and micronutrients [24]. The ANFIS model is trained and tested for 100 epochs to minimize prediction error. Finally, the model outputs are used to generate recommendations for nutrient addition, monitoring, or reduction to support decision-making [25].

3.2. Proposed System Architecture

This study applies a plot demonstration system as a testing medium for IoT system components to monitor soil conditions in real-time, including measuring soil temperature, humidity, and pH levels that can affect crop quality Figure 2. The developed system is based on IoT distributed by edge computing and the Fuzzy Logic algorithm of the ANFIS model.

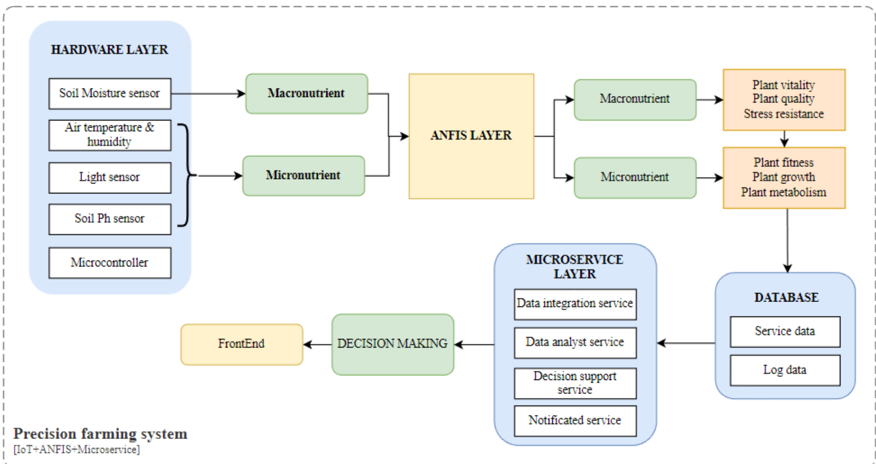

Figure 2. System Architecture Design

Figure 2 has been revised to clarify the modular interaction between the IoT layer, ANFIS processing layer, and microservices component. In the updated architecture, soil sensor data (pH, moisture, temperature, humidity, and light) are first processed at the IoT edge layer before being forwarded to the ANFIS layer for nutrient classification. The ANFIS outputs are then transmitted to the Software Microservice DSS, which functions as the decision engine for storing results, generating recommendations, and communicating decisions to the frontend. Labeled arrows were added to illustrate the bidirectional data flow between the microservice module and the database, as well as its interaction with both ANFIS outputs and user applications, thereby emphasizing the system's modular design.

Table 1. Nutrition needs

Sugarcane Nutrition	**Necessity**
Macronutrient (Nitrogen, Phosphorus, Kalium)	200ppm
Micronutrient (Zinc, Boron, Mangan)	50ppm

Table 1 summarizes the nutrient reference values used in the ANFIS model. The requirements are defined for a 7.2 m² plot, including macronutrients (75 ppm N, 50 ppm P, and 75 ppm K) and micronutrients (25 ppm Zn, 25 ppm Mn, and 0.5 ppm B). Nutrient levels are evaluated across three growth periods 1–3, 4–7, and 8 months until harvest forming the basis for nutrient sufficiency assessment in the ANFIS model.

3.3. Data Resource & Collect

The data generated by the sensor system is stored in the edge area and distributed on the decision system via the cloud network and the internet [26]. The role of the decision system is to provide analysis results in the form of recommendations to overcome the problems of the analysis results through the relative calculation of the Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm [27]. In conducting predictive analysis, ANFIS works according to the parameters specified for the needs of each macronutrient and micronutrient element [28].

Table 2. Dataset from Sensor Readings

Node	Air Temp	Humidity	LDR Lux	Moisture1	Moisture2	Moisture3	Moisture4	SoilPH	Time
1	29.10	83.80	1200	64	62	38	75	8.10	13.09
1	29.10	83.80	1200	64	62	38	75	8.10	13.10
1	29.10	83.80	1200	64	62	38	75	8.10	13.10
1	29.10	83.80	1200	64	62	38	75	8.10	13.10
1	29.10	83.80	1200	64	64	33	77	8.10	13.10
1	29.10	83.80	1200	64	64	33	77	8.10	13.10
1	29.10	83.80	1200	72	72	32	77	8.10	13.10
1	29.10	83.80	1200	72	72	32	77	8.10	13.10
2	33.15	28.40	912	75	91	93	91	7.90	13.11
2	33.15	28.40	912	75	91	93	91	7.90	13.11
2	33.15	28.40	912	75	91	93	91	7.90	13.11
2	33.15	28.40	912	75	91	93	91	7.90	13.11
2	33.15	28.40	912	75	91	93	91	7.90	13.11
2	33.15	28.40	912	75	91	93	91	7.90	13.11
2	33.15	28.40	912	74	92	93	91	7.60	13.11
2	33.15	28.40	912	74	92	93	91	7.60	13.11

The dataset is obtained in real-time in a time interval of 10-20 seconds for each node. In this practice, 8 nodes have been applied to 8 different areas of the demonstration plot [29]. The embedded ground sensor can efficiently capture data in seconds, generating datasets [30]. Table 2 above shows the collection of data produced by the sensor system at nodes 1 and 2.

3.4. Exploration & Data Preparation

The dataset generated by the IoT component is used to develop an ANFIS model for predicting macronutrient and micronutrient requirements of sugarcane plants [31]. The exploration stage involves analyzing feature correlations and descriptive statistics to ensure data quality. As shown in Table 3, soil moisture sensor readings and macronutrient-related variables exhibit reasonable ranges and standard deviations, indicating stable measurements and reliable data. The consistency across sensor values supports accurate macronutrient prediction, while moderate variability in macronutrient levels reflects natural soil condition differences [32]. These results confirm that the dataset is well-prepared for ANFIS-based modeling [33].

Table 3. Descriptive Statistics of Soil Moisture and Macronutrient Dataset

Statistic	Moisture1EP00468	Moisture2YL69	Moisture3CapasitiveV1_2	Moisture4StickADC	macronutrient	predict_ma	need_ma
count	2070.000000	2070.000000	2070.000000	2070.000000	2070.000000	2070.000000	2070.000000
mean	54.409662	15.892754	15.789372	75.014976	32.227536	12.772464	1.196135
std	11.752577	9.706375	10.656601	6.552924	6.532343	6.532343	0.397168
min	41.000000	0.000000	0.000000	65.000000	24.000000	2.000000	1.000000
25%	42.000000	9.000000	7.000000	68.000000	25.800000	6.000000	1.000000
50%	53.000000	15.000000	12.000000	76.000000	30.800000	14.200000	1.000000
75%	68.000000	21.000000	29.000000	82.000000	39.800000	19.200000	1.000000
max	70.000000	38.000000	29.000000	84.000000	42.800000	21.000000	2.000000

In addition to macronutrient analysis, the exploration phase examines environmental and micronutrient-related parameters, as summarized in Table 4. The table presents descriptive statistics for air temperature, humidity, light intensity (LDR_Lux), soil pH, and micronutrient levels, which are key factors influencing nutrient availability and plant uptake [34]. Including these variables enables the model to capture complex interactions between soil conditions and micronutrient requirements, ensuring a comprehensive representation of environmental conditions prior to model training and evaluation [35].

Table 4. Descriptive of Micronutrient Dataset

Statistic	Air Temp	Humidity	LDR_Lux	soilPH	micronutrient	predict_mi	need_mi
count	2070.000000	2070.000000	2070.000000	2070.000000	2070.000000	2070.000000	2070.000000
mean	28.840580	83.400966	90.028502	7.758068	52.828213	0.981159	2.048792
std	1.230236	1.391662	14.614051	0.240890	3.749446	0.135995	0.290058
min	20.000000	74.000000	65.000000	6.700000	45.175000	0.000000	1.000000
25%	29.000000	83.000000	80.000000	7.600000	50.425000	1.000000	2.000000
50%	29.000000	84.000000	87.000000	7.700000	52.325000	1.000000	2.000000
75%	29.000000	84.000000	99.000000	8.000000	55.025000	1.000000	2.000000
max	31.000000	84.000000	124.000000	8.100000	61.425000	1.000000	3.000000

Additionally, the distribution of micronutrient requirement classes suggests a balanced dataset, reducing the potential risk of classification bias. These findings confirm that the micronutrient data are adequately prepared and suitable for integration into the ANFIS-based modeling framework in the subsequent analysis stages.

3.5. ANFIS Model Development

The ANFIS model was developed using Gaussian membership functions with three levels (Low, Medium, High) for each input variable [36]. The model integrates fuzzy rules generated automatically from sensor-based features and applies standard ANFIS stages, including membership evaluation, rule weighting, normalization, and defuzzification [37]. Only essential components required to understand the model design are retained, while mathematical descriptions and repetitive theoretical explanations have been condensed. This concise restructuring improves readability without affecting methodological clarity [38].

Table 5. Algorithm rates

Method of Approach	Accuracy (%)
KNN (healthcare) [29]	0.80–0.90
RF (environment) [30]	0.80–0.95
LR (social, economy) [31]	0.67–0.75
Xgboost (social, healthcare) [32]	0.80–0.95
ANFIS (agriculture) [17]	0.98

To improve readability and conciseness, essential components required to understand the model design are retained, while repetitive mathematical descriptions are condensed without compromising methodological clarity. Furthermore, as summarized in Table 5, previous studies have reported competitive accuracy ranges across various application domains, highlighting the effectiveness of ANFIS compared to other machine learning approaches and supporting its selection for agricultural nutrient classification in this study.

This study developed an ANFIS-based simulation model in the field of sugarcane agriculture. The working concept of the model is presented in Figure 2, starting from data collection to action recommendations. The working concept of ANFIS in depth is presented in Figure 3 with a phased model structure.

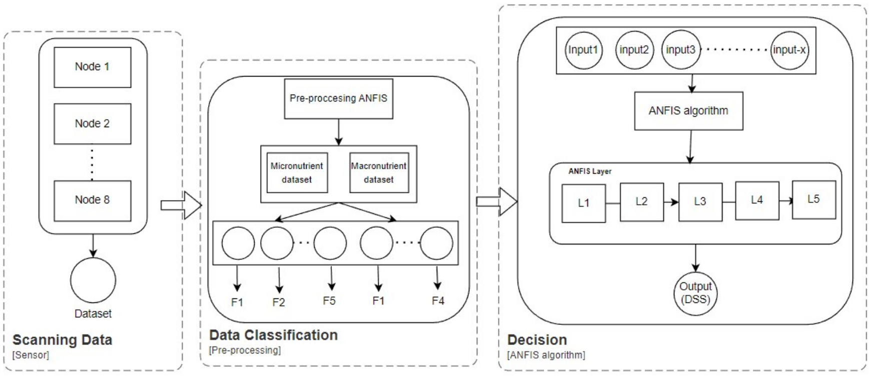

Figure 3. Structure of ANFIS stage

Figure 3 shows the ANFIS method Raw data processing stage (pre-processing stage) of the data by classifying based on plant nutrient detection needs, as presented in the sample dataset table.

3.6. ANFIS Membership Function

The proposed model is evaluated through iterative training and testing to ensure reliable performance [39]. Proper parameter selection is essential for accurate learning, pattern recognition, and recommendation generation, while performance evaluation helps identify areas for improvement [40]. The model is designed to produce actionable recommendations that support decision-making objectives. Table 6 presents the optimal input variable sizes used in the membership function to improve model accuracy and practical applicability.

Table 6. Descriptive Sugarcane Nutrition

Nutrient	Range (ppm)	Description
Macronutrients		
Nitrogen (N)	< 70 (Low)	Requires 4.35 g/m^2 urea
	70–75 (Med)	Sufficient for growth
	> 75 (High)	Excessive vegetative growth
Phosphorus (P)	< 50 (Low)	Requires 0.61 g/m^2 SP-36
	50–60 (Med)	Supports root development
	> 60 (High)	May impair absorption
Potassium (K)	< 60 (Low)	Requires 1.67 g/m^2 KCl
	70–75 (Med)	Optimal for stress resistance
	> 75 (High)	Causes impaired absorption
Micronutrients		
Zinc (Zn)	< 2 (Low)	Requires 7.27 g/m^2 for chlorophyll
	2–2.5 (Med)	Good for hormone synthesis
	> 2.5 (High)	Excess may cause toxicity
Boron (B)	< 0.5 (Low)	Requires 1.50 g/m^2
	0.5–1 (Med)	Sufficient for metabolism
	> 1 (High)	Excess inhibits absorption
Manganese (Mn)	< 1 (Low)	Requires 4.29 g/m^2
	1–1.5 (Med)	Supports protein synthesis
	> 1.5 (High)	Excess inhibits absorption
Environmental Needs		
Soil pH	< 6.0 (Low)	Needs gypsum (too acidic)
	6.0–7.5 (Med)	Optimal for absorption
	> 7.5 (High)	Needs sulfur-based fertilization
Moisture	$< 30\%$ (Low)	Needs watering
	30–50% (Med)	Optimal humidity
	$> 50\%$ (High)	Soil too wet

Temperature	$< 20°C$ (Low)	Too cold
	25–35$°C$ (Med)	Ideal for crops
	$> 35°C$ (High)	Excessively high
Air Humidity	$< 60\%$ (Low)	Low humidity
	60–80% (Med)	Suitable for metabolism
	$> 80\%$ (High)	Risk of mold
Light Intensity	400–600% (Low)	Low intensity
	600–800% (Med)	Sufficient intensity
	$> 800\%$ (High)	Overheating growth risk

The ANFIS membership function was developed using the Gaussian approach method, where each input variable is represented by three main membership functions, namely Low, Medium, and High [41]. The ANFIS membership function was developed with the Gaussian approach because it has smooth transition capabilities, is stable in the face of fluctuating sensor data, and is in accordance with the natural characteristics of agricultural data distribution such as soil pH, moisture, and nutrient content. The following is the mathematical formula of the membership function of the Gaussian approach [42].

$$\mu(x; c, \sigma) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \tag{1}$$

The Gaussian approach states x as the input value, c is the center (mean) of the Gaussian distribution and σ the standard deviation or width of the membership function.

3.7. ANFIS Fuzzy Rules

The second stage in the ANFIS method is to identify and apply the Fuzzy rule with the logic "AND" and "OR" used as parameters in determining the minimum or maximum value of a particular input. The logic of "AND" is used to retrieve the minimum value of two membership inputs, and "OR" is used to retrieve the maximum value. Implementation of the "AND" "OR" operator.

$$AND(\text{min}) = \mu_{\text{AND}} = \min\left(\mu_A(x), \mu_B(y)\right) \tag{2}$$

If Rule I says "If condition A is true AND condition B is true", the membership threshold is taken as the level of truth.

$$OR(\text{max}) = \mu_{\text{OR}} = \max\left(\mu_A(x),\ \mu\right) \tag{3}$$

If Rule II says "If condition A is true OR other conditions are true", the maximum value is used.

3.8. Normalization of Rule Weights

Normalization of weights in ANFIS is carried out to ensure that the weight of each rule has a total value of 1. The process of normalizing the weight of the rule is carried out by dividing each rule weight by the number of weights using Equation (4).

$$w_i^1 = \frac{w_i}{\sum_{j=1}^{m} w_j} \tag{4}$$

3.9. Calculating Output of Each Rules

The fourth stage in layer 4 of ANFIS is to calculate the output for each rule. The calculation process is carried out by multiplying the normalized rule weight by the rule conclusion value with Equation (5).

$$\text{Output}_i = w_i\left(p_i x + q_i y + r_i\right) \tag{5}$$

Layer 4 generates the output value for each fuzzy rule applied by calculating each output using a consequential function (linear or constant). Where, is the normalization weight of the rule, w_i^x is the input on the system (variable input), and y is the parameter of the linear function.

3.10. Overall Crisp Value (here discrete/categorical ”0” and ”1”)

The final stage in ANFIS is to calculate the overall crunchiness value on the 5th layer to produce a crunchy sap that can indicate the level of nutrient need or recommendations for Action. The process of calculating the overall sharpness value was carried out by defuzzification using the weighted average method with Equation (6).

$$\text{Output} = \frac{\sum(\mu_i x_i)}{\sum \mu_i} \tag{6}$$

The overall output in the ANFIS modeling is discrete, namely 0 = need nutrients, 1 = moderate nutrients and 2 = excess nutrients.

3.11. Error Evaluation

The ANFIS model was developed with a classification approach that was evaluated using recall, precision, accuracy, and F1-score metrics. These four metrics are used to assess the quality of prediction results based on the values of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The evaluation of the classification model with these four metrics can be calculated using the following formula:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \quad F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

The real implementation of the model is carried out by calculating each class through a one-vs-all approach and can be calculated on average of each class as well as the total TP, FP, FN of all classes.

3.12. Data Exploration and Cleaning

The results of the data exploration yielded valuable insights into the correlation between the features used in model development [43]. By analyzing the relationships between these features, it became evident that certain variables exhibited significant correlations, which can have implications for the model’s efficiency and performance. Specifically, the macronutrient heatmap and micronutrient features, as illustrated in Figures 4 and 5, revealed a notably strong correlation.

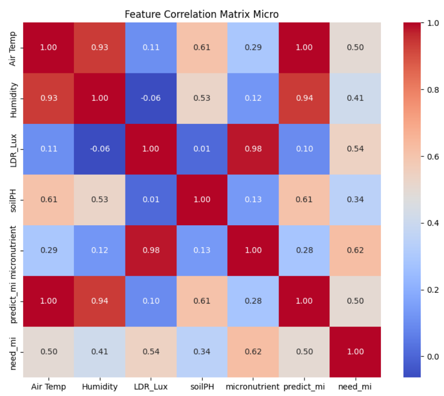

Figure 4. Heatmap Macronutrient

As illustrated in Figure 5, the strong correlation among several features suggests potential redundancy, as highly correlated variables tend to convey similar information. This redundancy can be addressed through feature selection or dimensionality reduction techniques to streamline the model without sacrificing critical information. Identifying and eliminating redundant features not only improves model efficiency but also reduces the risk of overfitting, resulting in more reliable and generalizable predictions [44].

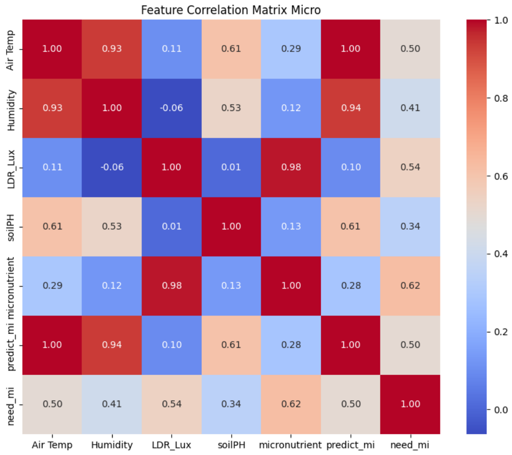

Figure 5. Heatmap Micronutrient

Based on the exploration of the correlation of these features, it can be found that the humidity sensor and macronutrient are interrelated. The need_ma and macronutrient features are quite in line in this regard. In micronutrient heatmaps, correlation patterns are more diverse and tend to be lower, for example, Air Temp and Humidity are strongly positively correlated (0.93), but most other features have a low to moderate correlation with need_mi targets (0.34–0.62), suggesting a relationship that is not as strong as on macros. Thus, macronutrient features appear to be more interrelated and predictive of the target. To overcome the existing redundancy, feature selection is applied to the data group. In addition, through feature selection, it can minimize data leackage during predictions.

The preparation stage is carried out by separating data from duplicates, inconsistencies and outliers. Specifically, outliers and NaN values appear in lstinline Humidity3CapacitiveV1_2 and stinline predict_ma feature for macronutrients (Ma), as well as in lstinline SoilPH and lstinline predict_mi feature for micronutrients (Mi). To address outliers, the interquartile range (IQR) method is applied using the lower and upper bounds defined as lstinline lower_bound = Q1 – 1.5 * IQR and lstinline atas_bound = Q3 + 1.5 * IQR. Meanwhile, the lost value (NaN) was handled using mean and median imputation methods. The feature selection applied is as follows.

```
Source Code 1:
# dat1 (macronutrient)
X1 = dat1.drop(columns=['need_ma', 'predict_ma', 'macronutrient'])
y1 = dat1['need_ma']
X1_train, X1_test, y1_train, y1_test = train_test_split(
    X1, y1, test_size=0.2, random_state=42, stratify=y1
)

# dat2 (micronutrient)
drop_cols = ['need_mi', 'predict_mi', 'micronutrient']
X2 = dat2_final.drop(columns=drop_cols, errors='ignore')
y2 = dat2_final['need_mi']
```

3.13. Developing ANFIS and Membership Functions

The ANFIS membership function consists of three categories (“Low”, “Medium”, and “High”) with sigma parameters that vary for each feature. The implementation of these membership functions is derived from field measurement results and agronomic requirements, as summarized in Table 6. Furthermore, Figure 6 illustrates the Gaussian membership functions for each input variable, showing the distribution and overlap between the Low, Medium, and High categories. This visual representation clarifies how each variable is fuzzified within the ANFIS model and highlights the role of varying sigma values in capturing gradual transitions between categories based on real agronomic conditions.

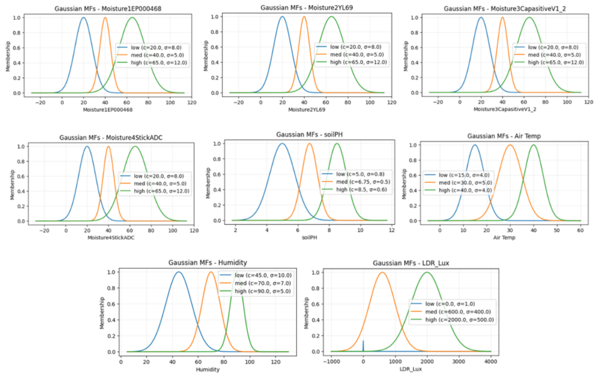

Figure 6. Membership Function

The ANFIS model is trained using input features that have been classified based on the type of nutrient. Macronutrient requirement prediction using moisture feature inputs (Moisture1EP000468, Moisture2YL69, Moisture3CapasitiveV1_2, MoistureStickADC) and need_ma features as target labels. Micronutrient prediction uses the input of soilPH, Air Temp, Humidity, LDR_Lux and need_mi as target labels. The following is a representation of fuzzy rules based on the membership function applied.

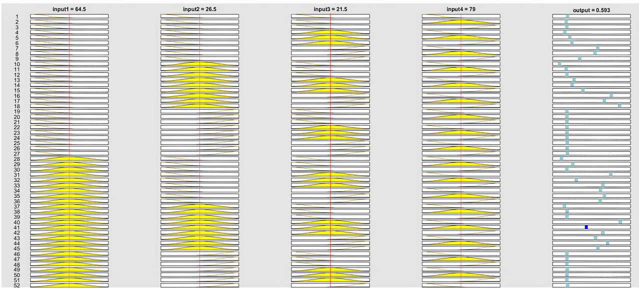

Figure 7. Fuzzy rules macronutrient predict

The ANFIS macronutrient prediction rule viewer image shows how the 4 prediction input features (Moisture1EP000468, Moisture2YL69, Moisture3CapasitiveV1_2, and MoistureStickADC) are mapped into their respective membership functions. The result of the combination of the entire membership function results in 81 fuzzy rules that are automatically formed. The red line in Figure 7 represents the value of the test data being analyzed, while the output column displays the final prediction results of the target column need_ma.

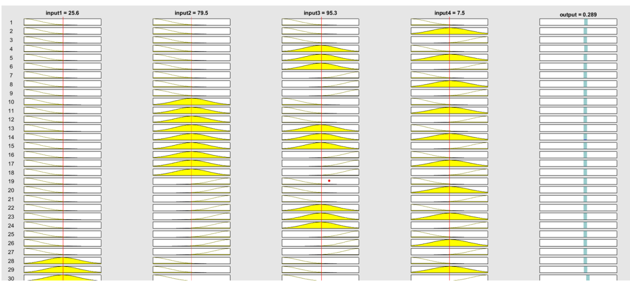

Figure 8. Fuzzy rules micronutrient predict

The same approach is also applied to the micronutrient data group consisting of four input features, namely soil pH, air temperature, humidity, and LDR Lux, with need mi as the target label. As illustrated in Figure 8, the combination of these micronutrient input features generates a comprehensive fuzzy rule base. The results show that the overall feature combination produces a total of 81 fuzzy rules, reflecting the exhaustive mapping of input membership functions within the ANFIS framework.

3.14. ANFIS Prediction for Macronutrient and Micronutrient

ANFIS predicts nutrient requirements using a binary-based classification scheme, where the output values are represented as 0, 1, or 2, each indicating a specific condition of nutritional need. These prediction outcomes serve as decision indicators that enable users to perform adaptive actions in response to the identified nutritional status. By interpreting the generated indicators, users can adjust nutrient intake strategies in a more targeted and data-driven manner. Table 7 summarizes the ANFIS prediction results obtained from 100 training epochs, which are presented in a randomized order to illustrate the model's consistency and predictive behavior across different learning iterations [45].

Table 7. ANFIS Predict

Epoch	**Actual**		**Predict**	
	Actual (Ma)	**Actual (Mi)**	**Pred (Ma)**	**Pred (Mi)**
Ep-1	1	0	1	0
Ep-2	1	0	1	0
Ep-11	1	1	1	1
Ep-18	1	1	1	2
Ep-26	1	1	1	1
Ep-28	1	0	1	0
Ep-29	1	0	1	0
Ep-32	1	1	1	1
Ep-37	1	1	1	1
Ep-57	0	0	1	0
Ep-60	0	0	1	0
Ep-66	0	0	0	0
Ep-75	0	1	0	1
Ep-78	0	1	0	1
Ep-82	0	1	0	1
Ep-85	0	1	0	1
Ep-90	1	0	0	0
Ep-95	0	0	1	0
Ep-98	1	0	1	0
Ep-100	1	0	1	0

ANFIS shows good performance in predicting macronutrient needs, with errors occurring only at epochs 57, 60, and 95. It performs better in micronutrient prediction, with a maximum error of ≤ 1 at epoch 18. These results are validated through comparisons with other prediction models in Tables 8 and 9.

Table 8. Macronutrient Prediction Simulation Classification Algorithm

Epoch	**LogR**		**Ridge**		**RF**		**KNN**		**SVR**		**DT**		**GBoost**	
	Act	Pred	Act	Pred	Act	Pred	Act	Pred	Act	Pred	Act	Pred	Act	Pred
Ep-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-7	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Ep-8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-9	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-11	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-13	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Ep-14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-18	0	0	0	0	0	1	0	1	0	0	0	1	0	0

Epoch	LogR		Ridge		RF		KNN		SVR		DT		GBoost	
	Act	Pred	Act	Pred	Act	Pred	Act	Pred	Act	Pred	Act	Pred	Act	Pred
Ep-19	0	0	0	0	0	1	0	1	0	0	0	1	0	0
Ep-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The results of the simulation of macronutrient demand prediction with 100 epochs of the classification algorithm produced an output with a fairly accurate prediction level quality. The prediction results still have some errors, especially in ep-3 the entire algorithm fails to predict correctly.

Table 9. Simulation of Micronutrient Prediction Classification Algorithm

Epoch	LogR		Ridge		RF		KNN		SVR		DT		GBoost	
	Act	Pred	Act	Pred	Act	Pred	Act	Pred	Act	Pred	Act	Pred	Act	Pred
Ep-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Ep-6	0	0	0	0	1	1	1	1	1	1	1	1	1	1
Ep-7	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-8	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-9	1	1	1	1	0	0	0	0	0	0	0	0	0	0
Ep-10	1	0	1	0	1	1	0	1	1	1	1	1	1	1
Ep-11	1	1	1	1	1	1	0	1	1	1	1	1	1	1
Ep-12	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-17	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-18	0	1	0	1	0	0	0	0	0	0	0	0	0	0
Ep-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ep-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The simulation results for predicting micronutrient requirements yielded better predictions than those for macronutrients. The Random Forest, KNN, SVR, Decision Tree, and Gradient Boosting algorithms successfully generated accurate predictions, as shown in Tables 8 and 9.

3.15. Simulation ANFIS Model

The results of the ANFIS prediction simulation show a medium–high level of accuracy, with micronutrient prediction performance superior to that of macronutrients. To further validate the accuracy of both macronutrient and micronutrient predictions, simulation tests were conducted using MATLAB to provide a more realistic comparison of the prediction results. As shown in Figure 9, the training and testing processes over 100 epochs illustrate the convergence behavior of the ANFIS model, including the reduction of error values and the stability of the prediction outputs. These visual results confirm that the model achieves consistent learning performance, particularly for micronutrient prediction, thereby supporting the quantitative accuracy findings of the simulation.

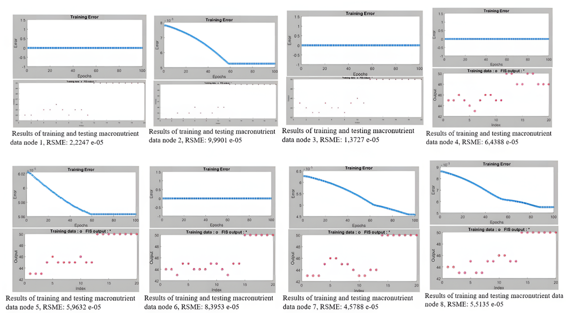

Figure 9. Trainning test and macronutrient testing with 100 epoch

Based on the results of the simulation test with the same number of epochs ep=100, the prediction has an output identical to the test results in Table 7. The simulation test was carried out using 200-300 samples from the total number of rows of datasets and applied the same membership function. Some trainingning charts show constant results, indicating that the model still needs improvisation in some parts.

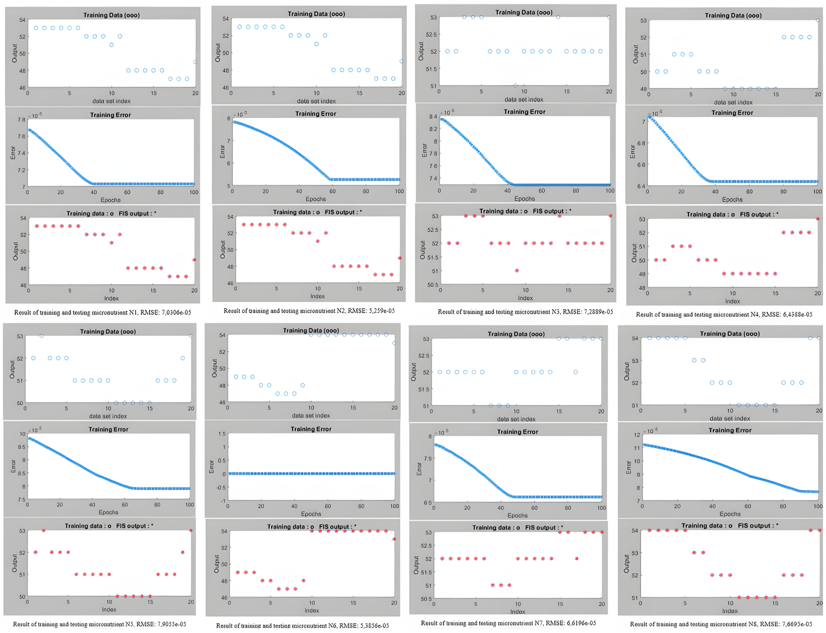

Figure 10. Testing results of training and macronutrient testing with 100 epoch

The results of the micronutrient test showed that the prediction quality is consistent with the simulation results presented in Table 7. As illustrated in Figure 10, almost all training and testing graphs exhibit a steady downward trend in error values across 100 epochs, eventually reaching a very small RMSE value ($\approx 10^{-5}$). This pattern indicates stable convergence and effective learning behavior of the ANFIS model in capturing underlying data patterns. Therefore, it can be concluded that the ANFIS model is capable of learning the data structure well. Nevertheless, further optimization can be applied to reduce residual error tendencies during both the training and testing phases.

3.16. Evaluation & ANFIS Optimization

The evaluation of model quality using precision, recall, accuracy and F-1 score metrics showed the effectiveness of each model in making predictions. The entire model can make predictions quite well. The results of the metric evaluation of the ANFIS model and the overall classification model are presented in the following Tables 10 and 11.

Table 10. Evaluation Model Macronutrient Predict before balancing

Model	Acc	Prec	Rec	F1	Note
Logistic Regression	0.700	0.0	0.0	0.0	Majority class only predictions
Ridge Classifier	0.700	0.0	0.0	0.0	Majority class only predictions
Random Forest	0.691	0.409	0.073	0.123	Slightly detects minority classes
KNN	0.674	0.359	0.113	0.172	More sensitive to minority class
SVM	0.700	0.0	0.0	0.0	Majority class only predictions
Decision Tree	0.691	0.400	0.065	0.111	Low recall similar to RF
Gradient Boosting	0.703	1.0	0.008	0.016	High precision, near-zero recall

It can be observed that the ANFIS model demonstrates consistently strong performance across all evaluation metrics, including precision, recall, accuracy, and F1-score. These results indicate that the model is capable of correctly identifying nutrient requirement categories while maintaining a balanced trade-off between sensitivity and prediction accuracy. Furthermore, the overall classification model exhibits comparable performance, suggesting that the integration of feature selection and classification mechanisms effectively enhances predictive reliability. The high accuracy values reflect the model's robustness in general prediction tasks, while the balanced precision and recall scores indicate a low tendency toward both false positives and false negatives. Consequently, these findings confirm that the proposed modeling approach is well-suited for nutrient classification tasks and can support data-driven decision-making in precision agriculture applications.

Table 11. Evaluation Model Macronutrient Predict before balancing

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**	**Note**
Logistic Regression	0.748	0.810	0.489	0.610	Pretty good, but the recall is still low
Ridge Classifier	0.748	0.810	0.489	0.610	Results are identical to Logistic Regression
Random Forest	1.000	1.000	1.000	1.000	Perfect, detects all classes precisely
KNN	1.000	1.000	1.000	1.000	Perfect, just like Random Forest
SVM	0.929	1.000	0.824	0.904	Perfect precision, recall still slightly lower
Decision Tree	1.000	1.000	1.000	1.000	Perfect, similar to Random Forest and KNN
Gradient Boosting	1.000	1.000	1.000	1.000	Perfect, same as Random Forest, KNN, and Decision Tree

The evaluation of the prediction results of the classification algorithm in Tables 8 and 9 shows good model performance. However, these models only learn in one majority class, namely 0, 1 or 2, so the prediction results tend to be more perfect. This action is certainly considered very lacking in the trial of the development of a smart agricultural system. Therefore, a stage called data balancing is carried out to balance the number of classes on the target label using the SMOTE (Synthetic Minority Oversampling Technique) method applied to the ANFIS algorithm as the target model. The results of data balancing do not directly guarantee that the model can make better predictions, but it allows the model to learn better. The results of ANFIS model optimization through the balancing method are presented in the following Table 12.

Table 12. Results of ANFIS Evaluation

Model	**Accuracy**	**Precision** (0,1)	**Recall** (0,1)	**F1-score** (0,1)	**Note**
Macronutrient – ANFIS	0.71	0.70, 0.40	0.92, 0.25	0.80, 0.30	Minority recall increases
Micronutrient – ANFIS	0.76	0.78, 0.73	0.81, 0.69	0.80, 0.71	Balanced between classes

Based on the results of balancing using SMOTE can be seen in Table 12, the recall value in each class has increased quite significantly. Although the macronutrient model is still relatively weak in the minority recall.

4. RESULT AND DISCUSSION

4.1. Practical Agronomic Interpretation of Model Outputs

The development and simulation of the ANFIS model produced promising results in predicting sugarcane nutrient needs, linking technical performance directly to practical agronomic and managerial decisions [46]. The model achieved 71% accuracy for macronutrients, correctly identifying 7 out of 10 nutrient deficiency conditions, which enables timely decisions regarding urea, SP-36, or KCl application. This reduces unnecessary fertilizer use and mitigates delays associated with visual-only assessments [47]. Micronutrient predictions reached 76% accuracy, allowing early detection of Zn, Mn, and B deficiencies, which often lack visible symptoms in early growth stages. From an agronomic perspective, this facilitates earlier interventions to maintain Brix levels and consistent stem development, while from a managerial perspective, it improves fertilizer budget allocation, reduces labor for manual soil testing, and supports predictable yield forecasts, enhancing operational efficiency and sustainability [48].

Input features for macronutrient prediction included `Moisture1EP000468`, `Moisture2YL69`, `Moisture3CapasitiveV1_2`, `MoistureStickAD`, `macronutrient`, `predict_ma`, and `need_ma` as target labels. Feature selection improved model learning and reduced potential data leakage. Micronutrient predictions used `soilPH`, `Air Temp`, `Humidity`, `LDR_Lux`, `micronutrient`, `predict_mi`, and `need_mi`, showing higher accuracy than macronutrients. The slightly lower macronutrient accuracy can be addressed by balancing the dataset to improve minority detection. Overall, the predictions provide reliable support for decision-making. The ANFIS model is particularly effective in handling minor or imbalanced data generated by sensors. Simulink tests on the system architecture further validate the model's ability to generate actionable nutrient addition recommendations.

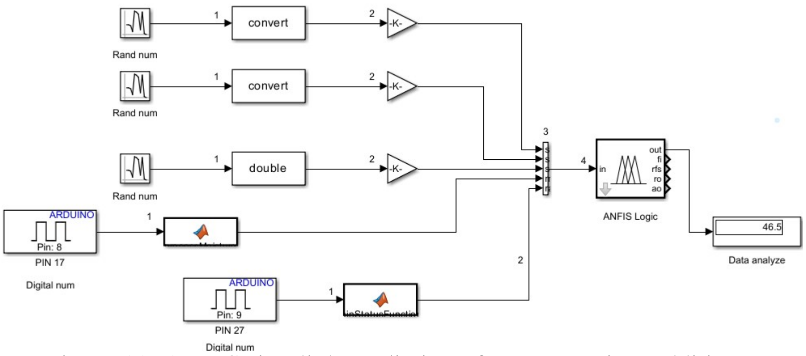

Figure 11. ANFIS simulink prediction of macro nutrient addition

Simulink in Figure 11, was developed to align with sensor-based data acquisition and ANFIS processing. Real macronutrient data from the plot were analyzed by the ANFIS model, with sensor-measured moisture distributed to the ANFIS logic, producing a predicted macronutrient increase of 46.5 ppm. A similar approach was applied to micronutrient data Figure 12, with results requiring further conversion to ppm for final values.

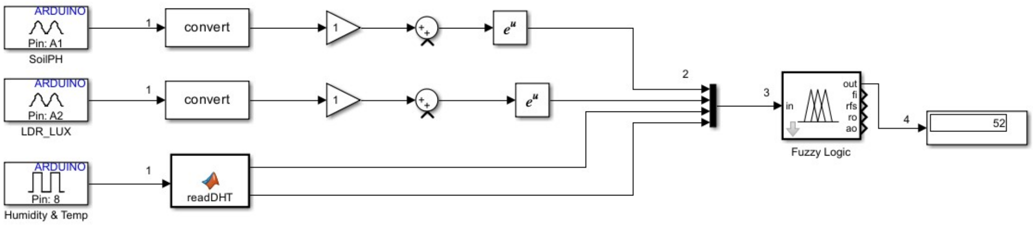

Figure 12. ANFIS simulink prediction of micronutrient addition

The ANFIS model effectively predicted sugarcane nutrient needs, enabling targeted recommendations for nutrient addition or reduction. Integrating real-time data with ANFIS addresses both soil and plant nutrition, and the framework allows future inclusion of disease diagnostics, as nutrient imbalances may indicate susceptibility to common diseases. Managerially, IoT–ANFIS supports optimized fertilizer allocation, reduces costs, prevents over-fertilization, and improves yield forecasting, while providing data for policy and precision agriculture adoption. Real-time monitoring also minimizes manual soil testing, enhancing decision-making efficiency. Agronomically, the model categorizes nutrient requirements (0 = deficient, 1 = sufficient, 2 = excessive) with low error rates, allowing efficient adjustment of macronutrients (N, P, K) and micronutrients (Zn, Mn, B) by growth stage. Monitoring soil pH and moisture further supports nutrient availability, fertilization efficiency, and sustainable sugarcane management.

4.2. Potential Real-World Application and Deployment Strategy

The IoT ANFIS system developed in this study can be deployed directly within sugarcane cultivation environments through distributed IoT sensor nodes that continuously monitor key soil parameters such as pH, temperature, moisture, and micronutrient indicators. These sensor nodes transmit data to an edge cloud architecture where the ANFIS engine processes the inputs and produces real time nutrient requirement classifications (Deficient, Sufficient, Excessive).

For practical implementation, a three-phase deployment strategy is proposed:

- Small-scale validation using demonstration plots to calibrate sensor thresholds and ensure the accuracy of nutrient prediction
- Expansion to block-level monitoring with automated alerts and mobile dashboard integration for plantation managers
- Full-scale integration with variable-rate fertilization or smart irrigation systems to enable semi-autonomous or fully automated nutrient management. This phased approach ensures system reliability, operational feasibility, and long-term sustainability in real agricultural settings.

5. MANAGERIAL IMPLICATION

The findings of this study provide several important managerial and operational implications for agricultural practitioners, plantation managers, and policymakers. First, the predictive capability of the IoT–ANFIS system enables organizations to optimize fertilizer use by identifying nutrient deficiencies early, thus reducing input costs and minimizing the risk of over-fertilization. This operational efficiency contributes to more sustainable farming practices and supports compliance with environmental standards related to responsible fertilizer application. Second, managers can utilize the system's real-time monitoring features to improve field decision-making and resource planning. By receiving timely alerts on nutrient status, field supervisors can prioritize specific plantation blocks that require intervention, reducing unnecessary labor allocation and manual soil inspections.

Third, policymakers and agricultural agencies can leverage the system as a data-driven tool to design regionally tailored fertilization recommendations, yield improvement programs, and training initiatives for farmers. The predictive insights generated by the model also support more accurate yield forecasting, which is essential for budgeting, supply chain stabilization, and long-term production planning. Overall, the integration of IoT monitoring and ANFIS-based prediction enhances operational efficiency, lowers production costs, and helps organizations transition toward precision agriculture systems that are scalable and sustainable.

6. CONCLUSION

Technological innovations in the era of precision agriculture are highly anticipated to improve process efficiency and support productivity optimization. Based on the findings of the research on monitoring the growth of Bululawang sugarcane varieties with the ANFIS model in 2070 data with different feature classifications between macronutrients (Ma) and Micronutrients (Mi). ANFIS is integrated with IoT components, which are able to predict macronutrient (Ma) and micronutrient (Mi) nutrient needs. The quality of the system in predicting nutritional needs with an accuracy rate of $> 70\%$ with a fairly minimal error rate. To ensure the accuracy of the model, the validation process was carried out by comparing the results of ANFIS's prediction with other classification models and validating the results through mathlab. The results of ANFIS's prediction with other classification models have relatively identical differences before the optimization process is carried out through data balancing using SMOTE. The results of ANFIS's prediction after going through the balancing process showed more representative results with input data provided with a predictive accuracy level of macronutrient needs of 71% and micronutrient 76%. This increase in accuracy is marked by ANFIS' increased ability to predict minor data on the target label.

Although the ANFIS model demonstrates strong predictive performance, this study has several limitations that should be considered. First, the sensor data used were limited to a single growing season and one demonstration area, making it difficult to determine the model's generalizability across different climatic conditions, soil types, and sugarcane varieties. Second, fluctuations in sensor data such as pH and moisture may be influenced by environmental disturbances, necessitating a continuous calibration system to maintain measurement accuracy. Third, the model has not yet been tested at an operational field scale, particularly in relation to direct integration with irrigation systems or automated fertilization systems. Nevertheless, the initial results show significant potential for field deployment, especially in supporting precision fertilization, reducing production costs, and enhancing crop resilience. Future development may focus on multi-location testing, integrating more robust IoT devices, and designing an automated fertilization recommendation module to enable the system to be applied at an industrial scale.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: DY; Methodology: RS; Software: DR; Validation: AT and AF; Formal Analysis: DY and DR; Investigation: AT; Resources: AF; Data Curation: RS; Writing Original Draft Preparation: AT and AF; Writing Review and Editing: DR and RS; Visualization: DY; All authors, DY, RS, DR, AT, and AF, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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