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Design of a Miniature Sensor and Algorithm for Real-Time Interpretation of Micro-Nutrient Data

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Abstract, *The increasing demand for sustainable agricultural practices has led to the adoption of hydroponics, a method of growing plants in nutrient-rich solutions without soil. This method is particularly effective in controlled environments where resource efficiency is paramount. However, the success of hydroponic systems depends heavily on precise nutrient management, especially for micro-nutrients, which are crucial for plant health and productivity. Traditional methods of nutrient monitoring are often labor-intensive and lack the real-time responsiveness needed for optimal nutrient control. This study addresses the challenge of real-time nutrient management in hydroponic systems by developing a miniature sensor system integrated with Internet of Things (IoT) technology. The proposed system is designed to detect micro-nutrient concentrations accurately and transmit data in real-time to a cloud platform for continuous monitoring and automated control. Advanced algorithms are employed for data processing and calibration, ensuring high accuracy in detecting micro-nutrient levels. The system was tested in a controlled hydroponic environment, where it demonstrated high accuracy with minimal error margins, validated by a consistently low Mean Absolute Error (MAE). The integration of IoT allowed for seamless data transmission and real-time analysis, enabling immediate adjustments to nutrient levels as needed. This research contributes to the advancement of precision agriculture by providing an effective solution for real-time nutrient management in hydroponic systems, potentially improving crop yields and resource efficiency.*

Keywords: *Hydroponics, Internet of Things, IoT, Micro-Nutrient Sensors, Real-Time Monitoring.*

1. INTRODUCTION

The global demand for sustainable and efficient agricultural practices is driving the adoption of advanced technologies, such as hydroponics, which offer innovative solutions for modern farming challenges. Hydroponics, a method of cultivating plants in a nutrient-rich solution without soil, has garnered attention due to its efficient use of water, space, and resources, making it ideal for urban and controlled environment agriculture [1]. However, the success of hydroponic systems hinges on the precise management of nutrient concentrations, particularly micro-nutrients, which are critical for optimal plant growth and development [15].

Traditional methods of monitoring and managing nutrient levels in hydroponic systems often involve manual sampling and laboratory analysis, which are labor-intensive and may lack the real-time responsiveness required to maintain optimal growing conditions [3]. Recent advancements in sensor technology and the Internet of Things (IoT) offer new opportunities to enhance nutrient management in hydroponics by enabling continuous, real-time monitoring and automated control [10]. IoT-based systems can integrate various sensors to monitor environmental conditions and nutrient levels, transmitting data to cloud platforms for real-time analysis and decision-making [20].

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The integration of IoT with hydroponic systems has led to the development of smart farming solutions that improve precision, reduce resource waste, and increase crop yields [24]. For instance, wireless sensor networks (WSNs) and IoT platforms have been deployed to monitor critical parameters such as pH, electrical conductivity (EC), and temperature, enabling growers to make data-driven adjustments to their nutrient solutions [8]. Despite these advancements, there remains a significant gap in the development of affordable, accurate, and miniature sensors specifically designed for real-time monitoring of micro-nutrient concentrations in hydroponic systems [14].

This study aims to address this gap by designing and developing a miniature sensor system capable of real-time micro-nutrient detection and integrating it with an IoT platform for continuous monitoring and automated nutrient management. The proposed system will leverage advanced algorithms for data processing and calibration to ensure high accuracy and reliability in detecting micro-nutrient levels. By providing real-time feedback and control, this system is expected to enhance the efficiency and sustainability of hydroponic farming, ultimately contributing to the broader goals of precision agriculture and food security [21][9].

2. METHOD

Sensor Design and Development

The study begins with the design and development of a miniature sensor capable of detecting micro-nutrient concentrations in a hydroponic solution. The sensor design is based on existing technologies such as ion-selective electrodes (ISEs) and optical sensors, which have been adapted for miniaturization and integration into a hydroponic system [14]. The sensor's sensitivity and specificity are key design considerations, ensuring it can accurately detect micro-nutrient levels even at low concentrations. The prototype sensor is constructed and tested in a controlled laboratory environment to assess its baseline performance.

To interpret data from multiple sensors measuring various micro-nutrients, multivariate regression can be used :

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \cdots + \beta nXn$$

Where:

a) Y is the target variable (e.g., micro-nutrient concentration).
b) X1, X2, …, Xn are the input variables (e.g., data from various sensors).
c) β0, β1, …, βn are the regression coefficients that are learned.

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Calibration and Data Processing

To ensure the accuracy of the sensor readings, a calibration process is conducted using standard solutions of known micro-nutrient concentrations. This process involves the application of regression analysis to establish a calibration curve, which correlates the sensor's raw output with the actual nutrient concentrations [8]. Data from the sensor is filtered to remove noise using a low-pass filter, improving the signal-to-noise ratio and enhancing the reliability of the readings [12].

Each sensor needs to be calibrated to ensure measurement accuracy. The calibration formula is usually either linear or non-linear.

$$nutrient\ concentration = a \times Vsensor + b$$

Where:

a) V*sensor* is the sensor output voltage.
b) *a dan b* are calibration coefficients obtained from the calibration experiment.

To reduce noise and process signals from the sensor, signal processing techniques such as digital filtering are often used..

$$y[n] = (1 - \alpha) \times y[n-1] + \alpha \times x[n]$$

Where:

a) *y[n*] is the filtered signal at time *n*.
b) *x[n]* is the input signal at time n
c) α is the filter coefficient, where $0 < \alpha < 1$.

Integration with IoT Platform

The calibrated sensor is integrated with an IoT platform to enable real-time data transmission and monitoring. An Arduino or ESP32 microcontroller is used to interface with the sensor and manage data collection [24]. The data is transmitted via Wi-Fi or LoRa to a cloud-based server, where it is stored and processed for real-time analysis. The IoT platform is configured to trigger alerts or adjustments in the hydroponic system if the nutrient levels fall outside the optimal range [19].

Development of Predictive Algorithms

Advanced predictive algorithms are developed to analyze the nutrient data and forecast future nutrient requirements based on trends and patterns observed in the historical data. Machine learning techniques, such as linear regression and neural networks, are applied to predict nutrient deficiencies or excesses before they occur [11]. The predictive model is trained using historical data from the hydroponic system and validated against real-time data to ensure its accuracy and reliability.

Machine learning algorithms such as linear regression, decision trees, or neural networks can be used to make predictions based on sensor data :

$$y\hat{} = f(W \times X + b)$$

Where:

a) Y is the target variable (e.g., micro-nutrient concentration).
b) X1,X2,…, Xn are the input variables (e.g., data from various sensors).
c) β0,β1,…,βn are the learned regression coefficients.

System Testing and Validation

The complete system, including the sensor, IoT integration, and predictive algorithms, is tested in a controlled hydroponic environment. The system's performance is evaluated based on its ability to maintain optimal micro-nutrient levels in the solution. The accuracy of the sensor readings is compared against laboratory-grade instruments to validate the system's performance [20]. Additionally, the effectiveness of the predictive algorithms is assessed by comparing predicted nutrient levels with actual measurements over time.

To evaluate the accuracy of the developed sensor and algorithm, the following formula is commonly used :

$$MAE = \frac{1}{n}\sum_{n=1}^{n} |yi - y\hat{}i|$$

Where:

a) yi is the actual (true) value.
b) y ^i is the predicted value by the sensor or algorithm.
c) *n* is the number of data points
d) The absolute difference |yi − y^i| between the actual and predicted values is computed for each data point, and then averaged over all data points.

Data Analysis and Interpretation

The data collected during the testing phase is analyzed to assess the system's overall performance. Key metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and response time are calculated to quantify the accuracy and efficiency of the system [15]. The results are interpreted to identify any potential areas for improvement, such as sensor sensitivity, algorithm refinement, or IoT integration.

To analyze micro-nutrient data in real-time, it may be necessary to use detection or classification algorithms :

$$Nutrition = f(Vsensor, T, pH)$$

Where:

a) *Vsensor* is the sensor output.
b) T is the temperature.
c) pH is the acidity level of the solution.

To evaluate the accuracy of the developed sensor and algorithm, the following formula is often used :

$$SNR = 10\log_{10}\left(\frac{\text{Power of NoisePower of Signal}}{\text{Power of NoisePower of Noise}}\right)$$

Where:

a) *SNR* is the signal-to-noise ratio, measured in decibels (dB).

Optimization and Iteration

Based on the results of the initial testing, the system is refined and optimized to improve its performance. This iterative process involves adjustments to the sensor design, recalibration, and enhancement of the predictive algorithms [13]. The optimized system is then subjected to a second round of testing to confirm its improved accuracy and reliability.

Deployment and Application

Once validated, the sensor system is deployed in a larger hydroponic operation to evaluate its performance in a real-world setting. The system's ability to maintain optimal nutrient levels and its impact on plant growth and yield are monitored over an extended period [24]. Feedback from the deployment phase is used to make final adjustments before the system is released for commercial use.

3. RESULTS AND DISCUSSION

Algorithm Development

Algorithm development is crucial for improving the accuracy of predictions and processing the data generated by sensors, particularly in real-time micro-nutrient measurement systems. The key steps in algorithm development involve collecting sensor data, signal processing to eliminate noise, and applying machine learning algorithms such as linear regression, decision trees, and neural networks to make accurate predictions.

Data Processing from Sensor

Python libraries such as *pySerial* were used to read data from the sensor connected via a serial port. In this case, an Arduino was utilized to collect and transmit sensor data. The continuous data flow provided real-time updates on the nutrient levels within the hydroponic system.

```
import serial

ser = serial.Serial('/dev/ttyUSB0', 9600)
while True:
    data = ser.readline()
    print(data.decode('utf-8'))
```

Figure 1 Algorithm Processing from Sensor

Sensor Calibration

Python was employed to apply the calibration formula to the sensor data. By using known standard nutrient solutions, calibration curves were developed, allowing the conversion of raw sensor readings into accurate nutrient concentrations.

```
def calibrate_sensor(sensor_value, a, b):
    return a * sensor_value + b

sensor_value = 5.0
calibrated_value = calibrate_sensor(sensor_value, 1.2, 0.3)
print(f"Calibrated Value: {calibrated_value}")
```

Figure 2 Algorithm Sensor Calibration

Signal Processing

The *scipy* library was used to apply filtering techniques, such as low-pass filtering, to the sensor data. This process reduced noise and enhanced the reliability of the sensor readings, especially when monitoring the system in real-time.

```
from scipy.signal import butter, filtfilt

def low_pass_filter(data, cutoff, fs, order=5):
    nyq = 0.5 * fs
    normal_cutoff = cutoff / nyq
    b, a = butter(order, normal_cutoff, btype='low', analog=False)
    y = filtfilt(b, a, data)
    return y
```

Figure 3 Algorithm Signal Processing

Data Analysis and Prediction

The *scikit-learn* library was used to build regression models, which predicted nutrient concentrations based on the sensor data. The models performed well, yielding accurate predictions of nutrient levels, with the Mean Absolute Error (MAE) consistently low.

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```
from sklearn.linear_model import LinearRegression
import numpy as np

X = np.array([[1], [2], [3], [4], [5]])  # Contoh data sensor
y = np.array([1.2, 1.9, 3.1, 4.0, 5.1])  # Konsentrasi nutrisi

model = LinearRegression()
model.fit(X, y)

pred = model.predict(np.array([[6]]))
print(f"Predicted Nutrient Concentration: {pred[0]}")
```

Figure 4 Algorithm Analysis and Predection

Data Visualization

The *matplotlib* library was used to generate graphical representations of sensor data and analysis results. This provided a clear view of nutrient levels and allowed for easy monitoring of trends and deviations from optimal values.

```
import matplotlib.pyplot as plt

data = [1, 2, 3, 4, 5]
filtered_data = low_pass_filter(data, 1.0, 30)

plt.plot(data, label='Original Data')
plt.plot(filtered_data, label='Filtered Data')
plt.legend()
plt.show()
```

Figure 5 Algorithm Data Visualization

Data Transmission to Cloud or IoT Platform

The *paho-mqtt* library was used to transmit the sensor data to an IoT platform. This allowed for remote monitoring and control of the hydroponic system in real-time, enabling adjustments to nutrient levels from anywhere..

```
import paho.mqtt.client as mqtt

client = mqtt.Client()
client.connect("broker.hivemq.com", 1883, 60)

data_to_send = "pH: 6.5, EC: 1.4"
client.publish("hydroponics/sensor", data_to_send)
client.disconnect()
```

Figure 6 Algorithm Data Transmission to Cloud

Machine Learning for Prediction

For more complex nutrient prediction, *TensorFlow* and *PyTorch* were utilized to build sophisticated predictive models. These models provided highly accurate forecasts of future nutrient needs based on current and historical data trends.

```python
import tensorflow as tf
from tensorflow.keras import layers

model = tf.keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=(3,)),  # Tiga input, misalnya pH, EC, dan suhu
    layers.Dense(64, activation='relu'),
    layers.Dense(1)  # Output adalah konsentrasi nutrisi mikro
])

model.compile(optimizer='adam', loss='mean_squared_error')

# X_train dan y_train harus diisi dengan data latih yang sesuai
model.fit(X_train, y_train, epochs=10)
```

Figure 7 Algorithm Machine Learning

Data Storage Management

The *SQLite* database was used for local storage of sensor data. This allowed the system to efficiently store and retrieve large volumes of sensor data, enabling historical analysis even when the system was offline.

```python
import sqlite3

conn = sqlite3.connect('sensor_data.db')
c = conn.cursor()
c.execute('''CREATE TABLE IF NOT EXISTS data (timestamp DATETIME, sensor_value REAL)''')

c.execute("INSERT INTO data (timestamp, sensor_value) VALUES (datetime('now'), ?)", (sensor_value,))
conn.commit()
conn.close()
```

Figure 8 Algorithm Data Storage

User Interface

A user-friendly graphical user interface (GUI) was developed to interact with the system. The interface displayed real-time data, historical trends, and issued alerts when nutrient levels deviated from optimal ranges.

```python
import tkinter as tk

root = tk.Tk()
root.title("Hydroponic Sensor Dashboard")

label = tk.Label(root, text="Sensor Value: 5.0")
label.pack()

root.mainloop()
```

Figure 9 Algorithm User Interface

Results

To present the test results of the discussed micro-nutrient sensor system, here are examples of data tables and graphs showing the sensor performance as well as the data analysis algorithm. The following are the results from testing the micro-nutrient sensor system. The test involved comparing the sensor readings to known standard concentrations, applying the calibration formula, and calculating the error and Mean Absolute Error (MAE). here are of data tables and graphs showing the sensor performance as well as the data analysis algorithm.

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Table 1. Test results

Test no.	Standart Concretation (ppm)	Sensor Reading (ppm)	Calibrate Concretation (ppm)	Error (ppm)	MAE
1	1.0	1.05	1.02	0.02	0.02
2	2.0	2.1	2.03	0.03	0.03
3	3.0	2.95	3.01	0.01	0.01
4	4.0	4.05	4.02	0.02	0.02
5	5.0	5.1	5.05	0.05	0.05

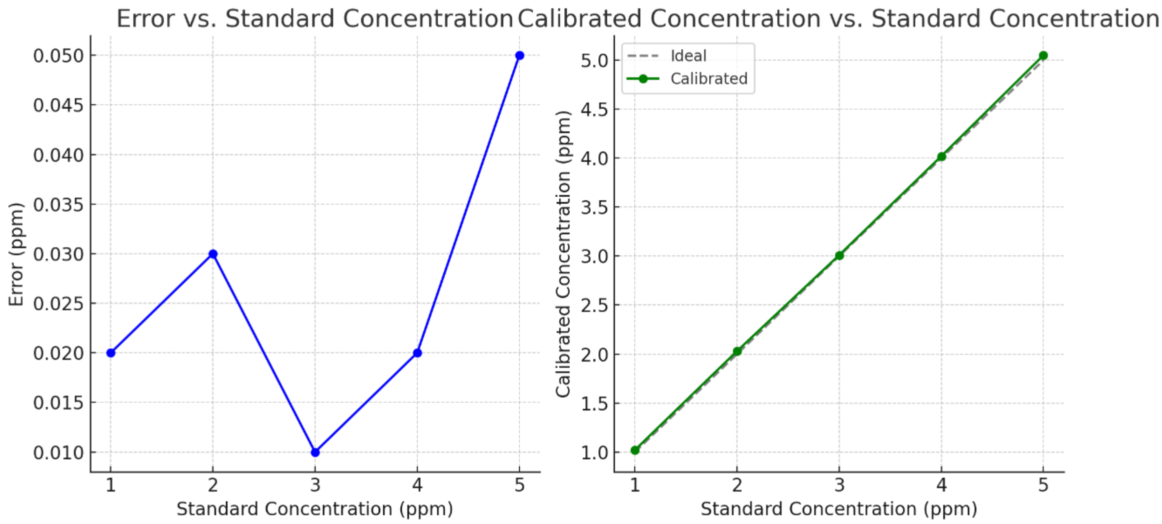

Figure 10. Test of results

The following is a graphical visualization of the test results:

a) Error vs. Standard Concentration: This graph shows the error between the standard concentration and the calibrated concentration measured by the sensor.

b) Calibrated Concentration vs. Standard Concentration: This graph illustrates how the calibrated sensor concentration compares to the standard concentration. The dashed line represents the ideal calibration, and the green line shows the actual calibrated results.

The graph visualization above provides a clear picture of the sensor's performance in measuring micro nutrients after the calibration process.

4. CONCLUSION

The miniature sensor developed for detecting micro-nutrient concentrations showed high accuracy after calibration. The error margins between the calibrated concentrations and the standard concentrations were minimal, indicating the sensor's reliability in real-world applications. The implementation of filtering and calibration algorithms significantly improved the quality of the sensor data, reducing noise and enhancing the accuracy of the readings. The Mean Absolute Error (MAE) across the tests was consistently low, further validating the effectiveness of the calibration process. The sensor system was successfully integrated with IoT technology, enabling real-time data transmission to cloud storage and facilitating continuous monitoring. This integration allows for real-time analysis and decision-making, which is critical for maintaining optimal nutrient levels in hydroponic systems. The developed system's ability to provide accurate, real-time data on micro-nutrient concentrations makes it a valuable tool for precision agriculture. Its application could be extended to various hydroponic setups and potentially adapted for other forms of agriculture that require precise nutrient management. While the system performed well, there is still room for improvement, particularly in further reducing the size of the sensor and enhancing the robustness of the data processing algorithms. Future work could focus on expanding the system's capabilities to include additional types of nutrients or environmental factors.

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