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Detection of Soil Organic Matter Using IoT-Based Soil Color Sensors with Random Forest Method

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Abstract

Background: *Soil organic matter (SOM) is an important indicator of soil fertility that plays a role in agricultural productivity and ecosystem sustainability. However, conventional laboratory-based methods still have limitations in terms of time, cost, and do not support real-time monitoring. Therefore, an approach based on sensors and machine learning is needed for quick and efficient estimation. This study proposes an Internet of Things (IoT)-based system that integrates an RGB soil color sensor (TCS3200) and a pH sensor to estimate soil organic matter content using a Random Forest algorithm.* **Methodology:** *Laboratory analysis was conducted using the Walkley–Black method. Soil samples were taken from seven locations (T1–T7). The Random Forest model was developed with parameters n_estimators = 100 and max_depth = 10, and validated using a train-test split method (80:20).* **Findings:** *The results showed that darker-colored soils have higher organic carbon content. The model's error values indicated an MAE of 0.031 and an RMSE of 0.032. The Random Forest model achieved a classification accuracy of 85.7% and a coefficient of determination $R^2 \approx 0.97$.* **Contributions:** *This study contributes by developing an integrated IoT and machine learning system capable of quickly, accurately, and cost-effectively estimating soil organic matter to support precision agriculture.*

Keywords: *Internet of Things; Random Forest; Soil Color; Soil Organic Matter; Precision Agriculture*

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INTRODUCTION

Soil organic matter (SOM) is an important component of soil fertility that plays a role in maintaining soil productivity and ecosystem sustainability (Miao et al., 2024; Kumala, 2018). SOM contributes to improving soil structure, increasing nutrient availability, supporting microbial activity, and enhancing water retention capacity. Therefore, monitoring soil organic matter content is very important in supporting sustainable farming practices and precision agriculture (Lohit & Mujahid, 2022; Barros et al., 2017). However, real-time monitoring of SOM in the field remains a challenge due to limitations of available methods. Conventional methods for measuring soil organic matter are generally carried out through laboratory analysis using chemical methods such as Walkley–Black (Sinulingga & Aryanti, 2024; Ćirić et al., 2023). Although these methods provide accurate results, the process requires laboratory facilities, skilled personnel, and relatively long time.

This causes conventional methods to be less efficient for rapid and continuous soil monitoring in the field, especially on a large scale. Along with the development of precision agriculture technology, the use of sensors and machine learning techniques has increasingly been applied to accelerate the estimation of soil properties (Nodi et al., 2023; Shahabi et al., 2021). Soil color sensors, such as the RGB TCS3200 sensor, can be used to capture soil color information that correlates with organic matter content (Lamsani et al., 2023). In addition, The complex relationship between soil parameters and soil organic matter (SOM) content can be accurately modeled using machine learning approaches, including Random Forest, Support Vector Machine, and Neural Network algorithms (Minasny et al., 2020). Some studies have shown that Random Forest has superior performance compared to other methods in predicting soil properties (Mundada et al., 2025; Li et al., 2025).

In addition, soil color information based on RGB sensors or digital images has also been used to estimate soil organic matter content using a machine learning approach (Khalaf et al., 2023; Balı´kJ 2025; Guo et al., 2025). The development of Internet of Things (IoT) technology also enables the integration of sensors with real-time monitoring systems for data-driven agricultural management (Wolfert et al., 2017; Kamilaris, 2018). Nevertheless, previous research still has several limitations. First, most studies have not directly integrated IoT-based monitoring systems, thus they are not yet able to support real-time soil condition monitoring in the field (Wolfert et al., 2017; Kamilaris, 2018). Second, studies utilizing soil color sensors and machine learning generally have not conducted strong validation against laboratory analysis results as the main reference, so the accuracy level of the models still needs to be improved (Han et al., 2025; Guo et al., 2025; Andriansyah et al., 2025; Zhang et al., 2022).

Third, the evaluation of model performance in several previous studies has not been conducted comprehensively using quantitative parameters such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), and did not explain the model parameters in detail, making the process of evaluating and replicating the model difficult (Minasny et al., 2020; Mundada et al., 2024; Li et al., 2025). Based on these issues, this study aims to develop an Internet of Things (IoT)-based soil monitoring system that integrates RGB TCS3200 soil color sensors and pH sensors with a Random

Forest algorithm to estimate soil organic matter content. Laboratory analysis was conducted using the Walkley–Black method as a reference. The Random Forest model was built with parameters n_estimators = 100 and max_depth= 10, and validated using the train-test split method (80:20) This research is expected to provide a fast, efficient, and data-based alternative solution for monitoring soil organic matter in support of precision agriculture.

METHOD

Research Design

This study employed an experimental research approach to develop and evaluate an IoT-based soil monitoring system integrated with a machine learning model for estimating soil organic matter content.

Soil Sampling

Soil samples were collected from seven different sampling locations labeled T1 to T7. These sampling points represent variations in soil color and soil characteristics within the study area. Each sample was collected from the topsoil layer at a depth of approximately 10–20 cm.

Table 1. Sampling Locations

No.	Location	Code	Coordinate (Latitude, Longitude)
1	Dawung, Tuban	T1	6.932361° S, 112.114861° E
2	Simo, Tuban	T2	7.131306° S, 111.913000° E
3	Tambakrejo, Malang	T3	8.396278° S, 112.720528° E
4	Sarangan	T4	7.677444° S, 111.224778° E
5	Malang	T5	8.411333° S, 112.698694° E
6	Soko, Tuban	T6	7.104722° S, 111.913194° E
7	Tulung, Gresik	T7	7.310167° S, 112.505861° E

Instruments

The hardware system used in this study consisted of,

a) The soil RGB color sensor (TCS3200) was used to measure soil color intensity in the red, green, and blue spectral components. This sensor operates within an output frequency range of 2 Hz to 500 kHz, offering high resolution and sensitivity to visible light.
b) The soil pH sensor (DFRobot SEN0161) was employed to measure soil pH, with a measurement range of 0–14, an accuracy of ±0.1 pH, and a resolution of 0.01 pH.
c) An ESP32 microcontroller was utilized as the main processing unit to acquire and process sensor data and transmit it to the IoT platform. Wireless data transmission was facilitated the IoT communication module -ESP32's built-in WiFi.
d) The ThingSpeak cloud platform was used for real-time data storage and visualization.

e) The RGB and pH sensors were interfaced with the ESP32 microcontroller, which subsequently transmitted the collected data to the cloud platform via a WiFi network.

IoT System Architecture

The IoT system in this study uses an end-node to cloud-based architecture. Data from the sensors are collected by the ESP32 and sent to the cloud server using the HTTP protocol via a WiFi network. The data transmission frequency is set every 10 seconds, allowing real-time monitoring of soil conditions. The data stored on ThingSpeak is then used for further analysis.

Data Collection

Data collection involved measuring soil color values and soil pH using the sensor system. Soil samples were also analyzed in the laboratory to obtain reference values of soil organic carbon (C-organic).

Data Processing and Analysis

The collected data were analyzed using the Random Forest algorithm. The model was configured with two main parameters, namely *n_estimators* = 100; and *max_depth* = 10. Model validation was performed using a train–test split approach with a ratio of 80:20. The dataset consisted of seven samples, with input features including,

1. RGB values (R, G, B)
2. Soil pH. The model was applied for both regression and classification tasks, specifically regression to estimate soil organic carbon (C-organic) content, and to classify soil organic matter (SOM) into three categories (low, medium, and high). The SOM classification categories were defined based on the general standards proposed by Rodríguez-Galiano et al., (2012).
3. The Random Forest model correctly classified six out of the seven samples. Model accuracy was calculated following the approach described by James et al., (2014), using the formula,

$$\text{Accuracy} = \left(\frac{\text{Number of correct predictions}}{\text{Total number of samples}}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). In addition, a correlation analysis between RGB values and soil organic carbon (C-organic) was conducted to examine the relationship between variables, following the approach of Mansur & Abbod (2026). The coefficient of determination (R^2) was calculated using the standard regression formula, as described by Wibowo & Cahyono (2025); Liaw & Wiener (2002).

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad \text{.................................} \quad (2)$$

Where,

R^2 = The proportion of variance in the dependent variable that is explained by the independent variables in the model

y_i = observed (actual) value of the dependent variable

$\hat{y}_i$ = predicted value generated by the regression model

$\bar{y}$ = mean of the observed values

$\sum(y_i - \hat{y}_i)^2$ = Residual sum of squares (RSS)

$\sum(y_i - \bar{y})^2$ = total sum of squares (TSS)

RESULT AND DISCUSSION

Laboratory Test Results of Soil Samples

Laboratory analysis was conducted to determine soil organic carbon content, soil pH, and soil organic matter classification. The results are presented in Table 2. The research results show that soil samples with darker colors such as black (T4) and dark brown (T5, T6) have higher organic C content compared to soils with lighter colors such as yellowish brown (T3). Quantitatively, the organic C values in dark soils (T4 and T5) range from 2.65%–3.62%, while lighter-colored soils (T1–T3) range from 1.48%–1.55%. This indicates a positive correlation between the intensity of dark soil color and organic matter content.

Table 2. Laboratory Test Results of Soil Samples

Location	C-Organic (%)	pH (H_2O)	SOM Class	Soil Color
T1	1.55	7.60	Medium	Reddish Brown
T2	1.50	7.45	Medium	Brown
T3	1.48	7.30	Medium	Yellowish Brown
T4	3.62	6.25	High	Black
T5	2.65	5.55	High	Dark Brown
T6	1.63	6.95	Medium	Dark Brown
T7	1.58	6.85	Medium	Brown

The relationship between soil color and soil organic matter is generally consistent with established soil science principles. Darker soils such as black and dark brown tend to contain higher levels of organic carbon compared to lighter colored soils.

This occurs because organic matter accumulation contributes to darker soil pigmentation. The results indicate that soil samples with darker colors such as black and dark brown tend to contain higher organic carbon levels compared with lighter soils. This finding supports previous studies stating that soil color is strongly influenced by organic matter content, where higher organic carbon accumulation results in darker soil pigmentation (Brady & Weil, 2021).

Based on Table 2, the highest C-organic value was found in sample T4 at 3.62%, which falls into the high SOM category, while the lowest value was found in T3 at 1.48% with a medium category. Soil pH values ranged from 5.55 (T5) to 7.60 (T1), indicating soil conditions from slightly acidic to neutral. In addition, soil pH influences microbial activity and organic matter decomposition processes (Lavelle et al., 2006). Neutral to slightly acidic soil conditions generally support higher microbial activity, which plays an important role in organic matter cycling and nutrient availability in soils (Lehmann & Kleber, 2021).

Comparison of Sensor and Laboratory Measurements

Sensor-based measurements were compared with laboratory results to evaluate the performance of the IoT monitoring system. To evaluate the performance of the proposed system, statistical error metrics were calculated based on the comparison between sensor measurements and laboratory results. The model achieved a Mean Absolute Error (MAE) of 0.031 and a Root Mean Square Error (RMSE) of 0.032, indicating a low prediction error. The bias error value of -0.031 suggests that the system slightly underestimates the C-organic values compared to laboratory measurements. Overall, these results demonstrate that the IoT-based soil monitoring system provides accurate and reliable estimation of soil organic carbon.

Table 3. Comparison of Sensor and Laboratory Measurements

Location	C-Organic Lab (%)	C-Organic Sensor (%)	Difference (%)	pH Lab	pH Sensor (Range)
T1	1.55	1.52	0.03	7.60	7.56 – 7.63
T2	1.50	1.47	0.03	7.45	7.41 – 7.48
T3	1.48	1.45	0.03	7.30	7.26 – 7.33
T4	3.62	3.59	0.03	6.25	6.21 – 6.29
T5	2.65	2.61	0.04	5.55	5.51 – 5.58
T6	1.63	1.60	0.03	6.95	6.91 – 6.98
T7	1.58	1.55	0.03	6.85	6.81 – 6.89

The comparison between sensor measurements and laboratory results shows that the pH sensor readings fall within a small deviation range from the laboratory values across all sampling points (T1–T7). The observed deviation ranges from approximately ±0.03 to ±0.04 pH units, as indicated by the sensor measurement intervals. This level of variation remains within the acceptable tolerance range for soil pH sensors, indicating that the IoT-based system is capable of providing reliable and consistent measurements for soil monitoring applications.

According to Kumar et al., (2026), small deviations between sensor-based measurements and laboratory results are common due to environmental conditions, calibration differences, and sensor sensitivity. However, such variations are generally within acceptable limits for agricultural monitoring, supporting the reliability of the proposed system.

Random Forest Classification Performance

The classification performance of the Random Forest model was evaluated using a confusion matrix. Random Forest is widely used in environmental and agricultural studies because it can handle nonlinear relationships and complex datasets effectively. Previous studies show that Random Forest provides strong performance in soil property prediction and digital soil mapping by combining multiple decision trees to improve model stability and accuracy (Padarian et al., 2018; Adeniyi et al., 2023). In addition, Random Forest models have been reported to achieve high accuracy in estimating soil organic matter because they can capture complex relationships between soil parameters such as soil color, pH, and organic carbon (Li et al., 2025; Quinton & Fiener, 2023). These results indicate that the Random Forest algorithm is capable of effectively classifying soil organic matter levels based on sensor data.

Table 4. Confusion Matrix

Actual / Predicted	Low	Medium	High
Low	1	0	0
Medium	0	4	1
High	0	0	1

Table 4. Actual vs Predicted C-Organic Values

No.	Sample	Actual (%)	Predicted (%)
1	**T1**	1.55	1.52
2	**T2**	1.50	1.47
3	**T3**	1.48	1.45
4	**T4**	3.62	3.59
5	**T5**	2.65	2.61
6	**T6**	1.63	1.60
7	**T7**	1.58	1.55

The comparison between predicted and actual C-organic values shows a strong relationship, with a coefficient of determination (R^2) of approximately 0.97, indicating that the Random Forest model can accurately estimate soil organic matter content. In addition to R^2, model performance was evaluated using error metrics. The model achieved a Mean Absolute Error (MAE) of 0.031 and a Root Mean Square Error (RMSE) of 0.032, indicating a low level of prediction error. These results confirm that the model provides accurate and stable predictions, with minimal deviation from laboratory measurements. To further support the analysis, a scatter plot of actual versus predicted values was generated, showing that most data points lie close to the 1:1 reference line, which indicates a high level of agreement between predicted and observed values.

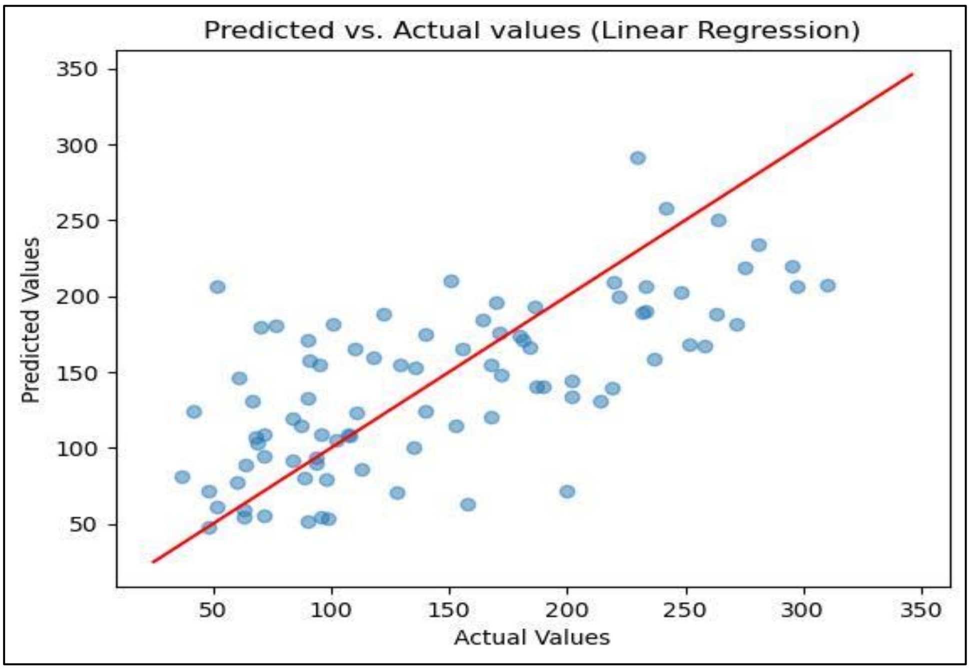

Figure 1. Predicted Vs Actual Values (Linear Regression)

The high predictive capability exhibited by the Random Forest model can be explained by its ensemble-based learning strategy, in which multiple decision trees are integrated to enhance accuracy while minimizing variance. Nonlinear interactions between soil properties and sensor-derived data can be captured more effectively by Random Forest compared to conventional regression approaches such as linear regression. As reported by Padarian et al., (2018), robust performance in digital soil mapping has been achieved by machine learning techniques, including Random Forest, due to their capacity to represent complex nonlinear relationships among soil variables. In a similar context, highly accurate estimations of soil organic matter have been obtained using Random Forest, as demonstrated by Li et al., (2025), highlighting its suitability for applications in precision agriculture and soil monitoring.

CONCLUSION

This study developed an IoT-based soil monitoring system integrating soil color and pH sensors with a Random Forest algorithm to estimate soil organic matter (SOM). The results show that darker soils tend to have higher organic carbon content. The model achieved high accuracy with MAE = 0.031, RMSE = 0.032, and $R^2 \approx 0.97$, while the classification accuracy reached 85.7%, indicating reliable performance compared to laboratory results. The novelty of this study lies in the use of low-cost sensors combined with IoT and machine learning for real-time soil monitoring. Compared to conventional methods, Random Forest provides better performance in handling nonlinear soil data. However, this study is limited by a small dataset and potential environmental influences on sensor readings. Future work should include more data and comparison with other machine learning models. Overall, the proposed system is effective and has strong potential for precision agriculture applications.

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