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Adaptive sugarcane monitoring in Mojokerto using a hybrid-powered IoT multi-sensor system and machine learning

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ABSTRACT

This study develops a hybrid-powered internet of things (IoT) multi-sensor system integrated with machine learning (ML) for sugarcane monitoring in Mojokerto. Four sensors—soil moisture, pH, LM35 temperature, and light dependent resistor (LDR) light—are connected to an Arduino UNO R4 wireless fidelity Wi-Fi microcontroller. A hybrid power supply (mains electricity and solar panels) and dual data storage (real-time transmission to Google Sheets and local SD backup) ensure resilience and reliability under field conditions. Sensor data are normalized and smoothed prior to analysis using k-means clustering to map environmental states and a random forest (RF) classifier to predict crop health. Field validation demonstrates soil moisture as the most influential parameter, followed by temperature, pH, and light intensity. The RF model achieved 93.01% accuracy, 93.88% precision, 99.02% recall, and a 96.38% F1-score on held-out data. By combining hybrid power, multi-sensor integration, dual storage, and ML, the system provides robust, data-informed monitoring that supports timely irrigation and management decisions in sugarcane cultivation.

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1. INTRODUCTION

Sugarcane (*Saccharum officinarum L.*) is a carbohydrate-rich plant and the primary raw material for sugar production [1]. As one of Indonesia's key agricultural commodities, sugarcane plays a vital role in supporting economic growth and national food security [2]. Being a seasonal crop with an annual harvest cycle [3], sugarcane requires intensive care, and inadequate management can reduce both crop and sugar productivity [4], [5]. According to the Central Statistics Agency (BPS), Indonesia's sugar production declined from 2.23 million tons in 2019 to 2.12 million tons in 2020 [6]. More recently, sugar mills in East Java, including PG Gempolkrep Mojokerto, have experienced a decline in productivity during the 2023 milling season, which is commonly associated with limited availability of high-yielding varieties, suboptimal cultivation practices, and the absence of reliable environmental monitoring systems [7]–[9]. Key parameters influencing sugarcane yield include soil properties, water availability, air temperature, and light intensity [10].

Soil conditions are a critical parameter of the growing medium that determines plant suitability. Plants with fibrous and shallow roots require large amounts of water [11], [12] because they extract moisture rapidly from the soil [13], [14] whereas plants with taproots need less water [15], thereby improving drought tolerance [16] and reducing irrigation frequency [17]. Sugarcane has a relatively complex root system—

comprising shallow, supporting, and deep rope roots—that enables water absorption even under drought conditions, making it highly dependent on sufficient water throughout its growth cycle [18]. Soil conditions are influenced by soil type, moisture, and pH, all of which affect crop management. Soil moisture directly impacts sugarcane growth [19], [20] while soil pH, defined by hydrogen ion concentration, regulates nutrient availability and plant development [21], [22]. In addition, air temperature and light intensity are key environmental parameters. Temperature governs germination, vegetative growth, respiration, flowering, and yield [8], [23] while light plays a vital role in photosynthesis and sugar production [24]–[26]. Without continuous monitoring of these parameters, farmers face difficulties in maintaining optimal growth conditions, leading to reduced productivity.

Monitoring environmental conditions is therefore essential to ensure vigorous and healthy sugarcane growth. An environmental monitoring system that measures soil moisture, pH, temperature, and light, integrated with information technology, can simplify the process and meet farmers' needs. The integration of internet of things (IoT) and machine learning (ML) technologies offers great potential for developing optimal monitoring systems [27], [28]. IoT enables real-time acquisition of environmental data to support efficient farming operations, while ML analyzes patterns in plant conditions based on sensor inputs [29]–[32]. Previous studies have demonstrated IoT applications in agriculture, including hydroponic monitoring [33], ornamental plant irrigation [34], greenhouse irrigation [35], soil moisture monitoring in green beans [36], [37], pH and moisture monitoring in peanuts [38], chili growth monitoring [39], tomato height detection [40], corn irrigation [41], rice condition monitoring [42], corn protection from animal disturbances [43], warehouse environmental monitoring [44], [45] pest prediction in sugarcane [19], and soil moisture monitoring in sugarcane [19], [20]. However, most implementations remain limited to single-parameter sensing or specific crop contexts, and few have developed multi-sensor IoT systems with hybrid power supply and dual data storage, validated directly in sugarcane fields, and integrated with adaptive ML for health classification.

This study proposes a hybrid-powered IoT multi-sensor system integrating soil moisture, pH, LM35 temperature, and light dependent resistor (LDR) light sensors with an Arduino UNO R4 Wi-Fi microcontroller. To ensure resilience in field conditions, the system employs a hybrid power supply (mains electricity and solar panels) and dual data storage (real-time transmission to Google Sheets and local backup on SD card). Sensor data are preprocessed and analyzed using k-means clustering to map environmental conditions and a random forest (RF) classifier to classify sugarcane health status into healthy and unhealthy categories. Field validation in Mojokerto demonstrates the system's ability to capture dynamic environmental variations and provide accurate health predictions. By combining hybrid power, multi-sensor IoT integration, and adaptive ML, this research delivers a resilient monitoring solution tailored to local farming conditions. The system enables farmers to make timely decisions on irrigation and crop management, thereby improving productivity, supporting food security, and enhancing farmer welfare in Mojokerto and potentially other sugarcane-producing regions in Indonesia.

2. METHOD

The proposed sugarcane monitoring system integrates IoT sensors with ML to provide adaptive and efficient support for sugarcane farming. Automatic monitoring of key environmental parameters—soil moisture, pH, temperature, and light intensity—enables farmers to track crop conditions continuously and make timely decisions to improve productivity. The methodological framework of this study is illustrated in Figure 1, which outlines the sequential stages: literature review and needs analysis, system design, real-time sensor data collection, data conversion and preprocessing, ML analysis, and evaluation. This structured approach ensures that both technical and agricultural aspects are addressed comprehensively.

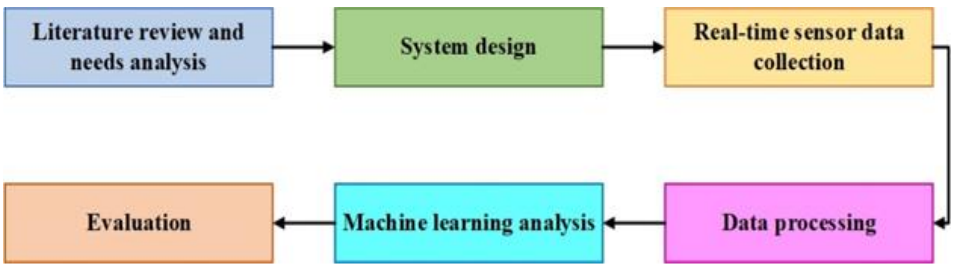

Figure 1. Research method flowchart

The initial stage involved a literature review and needs analysis to identify critical environmental factors influencing sugarcane growth, including soil moisture, soil pH, temperature, and light. Previous studies on crop monitoring systems using IoT sensors and ML were examined to establish the research gap and guide system development. Based on this analysis, the required components—Arduino UNO R4 Wi-Fi microcontroller, soil moisture sensor, pH sensor, LM35 temperature sensor, LDR sensor, hybrid power supply, and dual storage mechanism—were selected to ensure resilience, accuracy, and applicability in real field conditions.

2.1. System design

The sugarcane monitoring system was designed as a hybrid-powered IoT architecture to ensure resilience and reliability in field conditions. Four primary sensors—soil moisture, pH, LM35 temperature, and LDR light intensity—are integrated with an Arduino UNO R4 Wi-Fi microcontroller. The microcontroller functions as the central unit, acquiring sensor data, transmitting it wirelessly to Google Sheets for real-time monitoring, and storing backup data locally on an SD card. The analysis of component requirements in this study is shown in Table 1. This dual storage mechanism guarantees data availability even during connectivity disruptions, thereby supporting continuous monitoring in agricultural environments.

Table 1. Requirements for sugarcane monitoring system components

Components	Function
Arduino UNO R4 Wi-Fi	Read and receive data from sensors, send data to Google Sheets, save data to SD cards, process data, perform computations, and connect to the internet
Soil moisture sensor	Measure soil moisture
LM35 sensor	Measure ambient temperature
pH meter sensor	Measure soil pH
LDR sensor	Measure light intensity
Power supply	Convert AC power to DC power required by the Arduino and sensors. Provides power as needed and stabilizes voltage
Step down 12 to 5 V	Reduce voltage from 12V to 5V
Solar panel, battery, and solar charge controller (SCC)	Supply energy to the monitoring system
SD card	Store data from sensor readings and as a data backup medium
Google Sheets	Used as cloud-based data storage as an online database for sensor readings

The system's electrical power is supplied from two sources: mains voltage (State Electricity Company (PLN)) and solar panels. The voltage from PLN is stepped down to 12 V through a regulated power supply circuit, while the solar panel output is managed by a solar charge controller to produce a stable 12 V. A step-down converter then ensures a consistent 5 V supply for the microcontroller and sensors. This hybrid configuration enhances sustainability and reliability, allowing the system to operate seamlessly during grid interruptions and supporting deployment in rural areas. The overall design emphasizes modularity, enabling future scalability through the integration of additional sensors or components.

The design of the sugarcane monitoring system is shown in Figure 2. The system is designed with four main sensors, namely soil moisture sensor, pH sensor, LM35, and LDR, which are connected to the Arduino UNO R4 Wi-Fi microcontroller. The microcontroller functions to acquire data, send it to Google Sheets via a Wi-Fi network, and store backup data on an SD card. The energy source is supplied through a hybrid system (PLN and solar panels with a solar charge controller) so that the system continues to run even in the event of a power supply disruption.

2.2. Real-time sensor data collection

Real-time data collection is a critical process to ensure that variations in environmental conditions can be detected promptly and accurately. In this study, four parameters—soil moisture, soil pH, ambient temperature, and light intensity—were continuously monitored using integrated sensors connected to the Arduino UNO R4 Wi-Fi microcontroller. The microcontroller was programmed to acquire sensor readings at fixed intervals, thereby enabling continuous observation of sugarcane field conditions in Mojokerto. This approach ensures that dynamic changes in soil and climate factors are captured effectively to support adaptive crop management.

To guarantee data reliability, the system implements a dual storage mechanism. Sensor readings are transmitted wirelessly to Google Sheets for cloud-based monitoring and further analysis, while simultaneously stored locally on an SD card as a backup. This redundancy provides resilience against connectivity disruptions and safeguards data integrity in field conditions. The combination of real-time acquisition, cloud integration, and local backup enhances the robustness of the monitoring framework, ensuring that farmers and researchers can access accurate and uninterrupted datasets for decision-making and ML analysis.

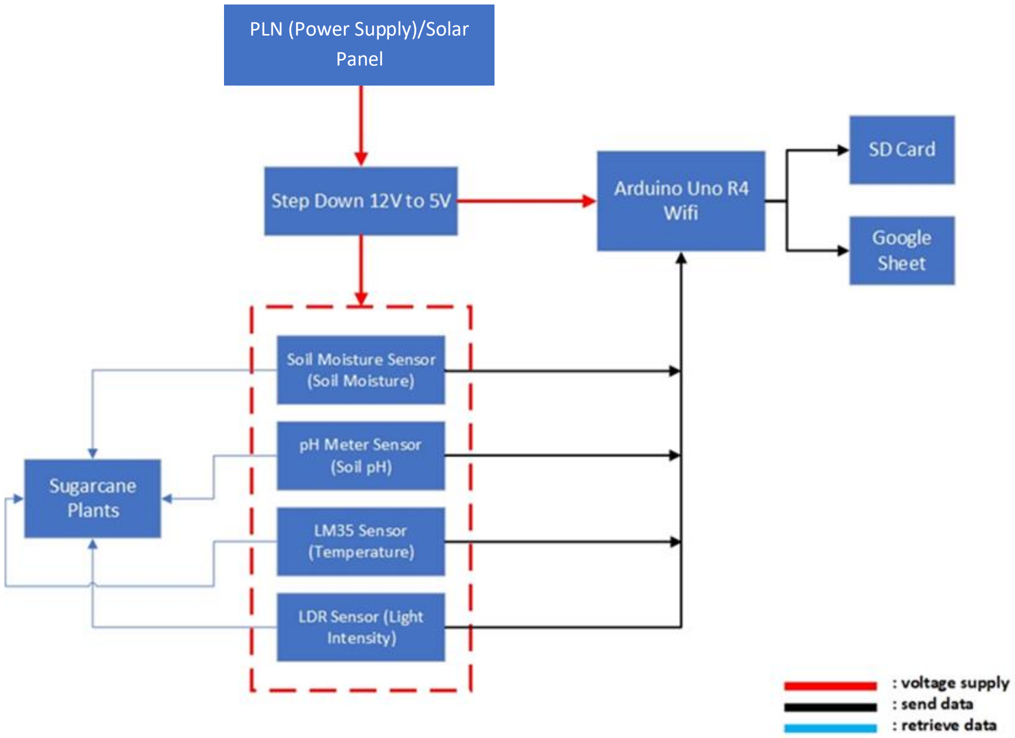

Figure 2. Sugarcane monitoring system design

2.2.1. Analog-to-digital converter to voltage conversion

All analog sensors are first converted from analog-to-digital converter (ADC) values to voltage [46]–[48] with (1).

$$V = \frac{ADC}{4095} \times Vref, Vref \approx 5{,}0\ V \quad (1)$$

2.2.2. Soil moisture sensor

The soil moisture sensor works on the principle of electrical conductivity, which measures soil resistance that is inversely proportional to water content. The sensor is usually wired as a voltage divider, producing an ADC value that can be converted into a voltage. The ADC value is mapped linearly between two calibration points, namely wet and dry. *ADC_wet* is the reading when the medium is very wet (value =900), *ADC_dry* is the reading when the medium is very dry (value =3000) [49]–[51] with (2) [52].

$$Moisture(\%) = clamp\left(\frac{ADC - ADCwet}{ADC_{\_dry} - ADC\_wet}\ x\ 100{,}0{,}100\right) \quad (2)$$

2.2.3. pH sensor

The pH sensor has a voltage of 2.5 V at pH 7 with a slope of approximately 0.18 V/pH at 25° [53] using (3).

$$pH = 7.0 + \frac{VpH7 - V}{S}, VpH7 \approx 2{,}5\ V, S \approx 0{,}18V/pH \quad (3)$$

2.2.4. LM35 temperature sensor

The LM35 sensor has a linear sensitivity of 10 mV/°C, so the temperature is calculated from the reading voltage [54] using (4).

$$V\_°C = V \times 100 \quad (4)$$

2.2.5. Light dependent resistor sensor

The LDR sensor works based on the principle of resistance change in response to light intensity. The brighter the light hitting the LDR surface, the lower the resistance value, while in dark conditions, the resistance becomes very high. To read this change in resistance, a voltage divider circuit with a fixed resistor Rf is used, so that the output voltage V can be calculated using the voltage divider law, and Vcc is the source voltage. The LDR resistance as (5).

$$R\_LDR = \frac{V\,Rf}{Vcc - V} \tag{5}$$

The relationship between LDR resistance and light intensity is non-linear, with A and γ being calibration constants. This equation shows that light intensity (lux) is inversely proportional to LDR resistance in the form of a power. The lux value equation is written as (6) [55].

$$lux \approx \left(\frac{A}{RLDR}\right)^{\frac{1}{y}} \tag{6}$$

2.3. Data conversion and preprocessing

Sensor outputs were initially obtained as analog signals and converted into digital values by the Arduino UNO R4 Wi-Fi microcontroller. Each sensor reading was then transformed into meaningful physical units through calibration equations. Soil moisture values were mapped linearly between wet and dry calibration points [49]–[52], while soil pH was calculated based on voltage slope and reference calibration [53]. The LM35 sensor provided temperature readings in degrees Celsius [54], and LDR resistance values were translated into light intensity (lux) using calibration constants [55]. This conversion process ensured that raw sensor data could be interpreted consistently and accurately for subsequent analysis.

To improve data quality, several preprocessing techniques were applied before ML analysis. All sensor readings were normalized to a uniform scale to eliminate bias caused by differing measurement ranges. Noise reduction was performed using the exponential moving average (EMA) method [56], which smooths fluctuations while preserving underlying trends. Missing or erroneous data points were handled through error detection and correction procedures to maintain dataset integrity. The EMA smoothing process is expressed mathematically as (7).

$$T_{EMA[k]} = \alpha T[k] + (1 - \alpha) T_{EMA[k-1]},\ 0 < \alpha < 1 \tag{7}$$

Where $T[k]$ represents the current sensor reading, $T\_EMA[k]$ is the smoothed value at time step k, and α is the smoothing factor. These preprocessing steps ensured that the input dataset was reliable, consistent, and suitable for clustering and classification tasks in subsequent stages.

2.4. Machine learning analysis

ML was employed to analyze sensor data and provide adaptive insights into sugarcane growth conditions. Two algorithms were selected: k-means clustering and RF classification. K-means clustering was used to group sensor readings into natural clusters, representing distinct environmental conditions in the sugarcane field. This unsupervised approach allowed the identification of patterns in soil moisture, pH, temperature, and light intensity without prior labelling, thereby supporting exploratory analysis of environmental variability.

The RF classifier was then applied to categorize sugarcane health status into healthy and unhealthy conditions. RF was chosen due to its robustness against noise and outliers, as well as its ability to reduce overfitting through ensemble learning. The classifier utilized multiple decision trees, with majority voting determining the final prediction. Feature importance analysis was conducted to identify the most influential parameters, confirming soil moisture as the dominant factor, followed by temperature, pH, and light intensity. This combination of clustering and classification provided a comprehensive framework for adaptive monitoring, enabling farmers to receive actionable information based on real-time sensor data.

2.5. Evaluation

The performance of the proposed monitoring system was evaluated through both functional validation and ML assessment. Functional validation ensured that all sensors operated correctly in field conditions, with data successfully transmitted to Google Sheets and stored locally on the SD card. The hybrid power supply was tested under varying conditions to confirm uninterrupted operation during grid outages, while dual storage was verified to guarantee data reliability.

For ML evaluation, the predictive capability of the RF classifier was assessed using standard metrics: accuracy, precision, recall, and F1-score. These metrics provided a comprehensive view of model performance, balancing correctness, sensitivity, and robustness. In addition, feature importance analysis was conducted to identify the most influential environmental parameters affecting sugarcane health classification. Results consistently highlighted soil moisture as the dominant factor, followed by temperature, pH, and light intensity. This evaluation confirmed that the system not only functions reliably in real-world conditions but also delivers meaningful insights for adaptive sugarcane monitoring.

3. RESULTS AND DISCUSSION

3.1. System implementation outcomes

The hybrid-powered IoT monitoring system was successfully implemented in sugarcane fields in Mojokerto. All four sensors—soil moisture, pH, LM35 temperature, and LDR light intensity—operated reliably under real field conditions. Data acquisition was conducted at five-minute intervals, with sensor readings transmitted wirelessly to Google Sheets and simultaneously stored on an SD card. The dual storage mechanism proved effective in maintaining data integrity, ensuring that no information was lost during temporary connectivity disruptions. The hybrid power supply, combining mains electricity and solar panels, enabled continuous operation even during grid outages, validating the system's resilience in rural agricultural environments.

3.2. Sensor data behavior

Trend graph of soil, pH, temperature, and light sensor data is shown in Figure 3. The collected data revealed clear variations in environmental parameters across different times of day and weather conditions. Soil moisture levels fluctuated significantly depending on irrigation schedules and rainfall, while pH values remained relatively stable within the optimal range for sugarcane growth. Temperature readings showed diurnal patterns, with peaks during midday and declines at night. Light intensity data captured by the LDR sensor correlated strongly with sunlight exposure, confirming the sensor's effectiveness in monitoring photosynthetic conditions. These results highlight the importance of continuous monitoring to capture dynamic environmental changes that directly affect sugarcane productivity.

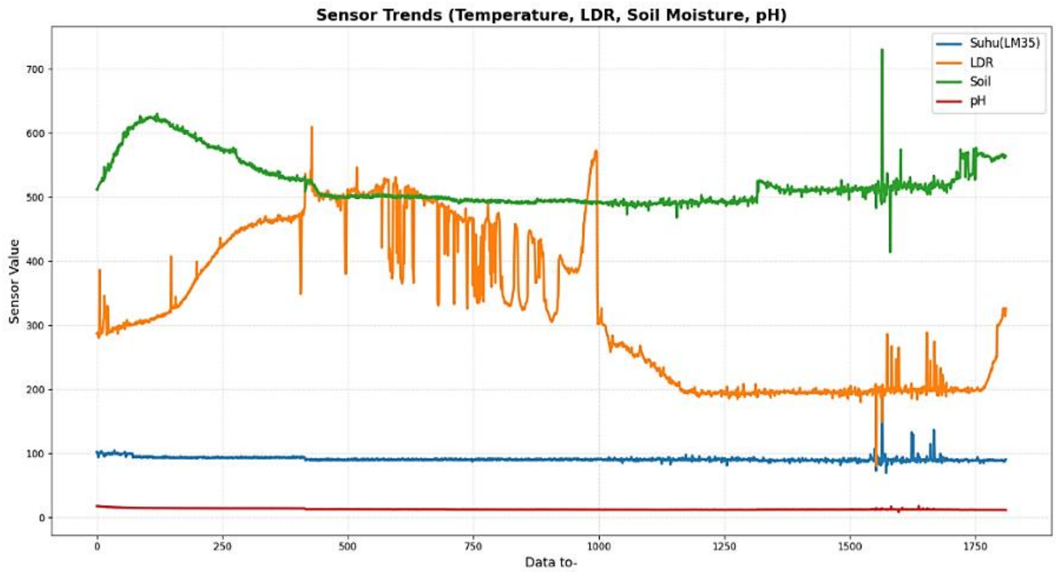

Figure 3. Trend graph of soil, pH, temperature, and light sensor data

3.3. Data preprocessing results

Raw sensor data were successfully converted into meaningful physical units through calibration equations. Soil moisture was expressed as percentage values, pH readings were mapped to acidity levels, LM35 outputs were converted into degrees Celsius, and LDR resistance values were translated into lux. Preprocessing techniques—normalization, smoothing using the EMA, and error handling—significantly improved data quality. The normalization graph from the sensor is shown in Figure 4, and the EMA sensor graph results are shown in Figure 5. The EMA method reduced noise while preserving underlying trends, ensuring that the dataset was consistent and reliable for ML analysis.

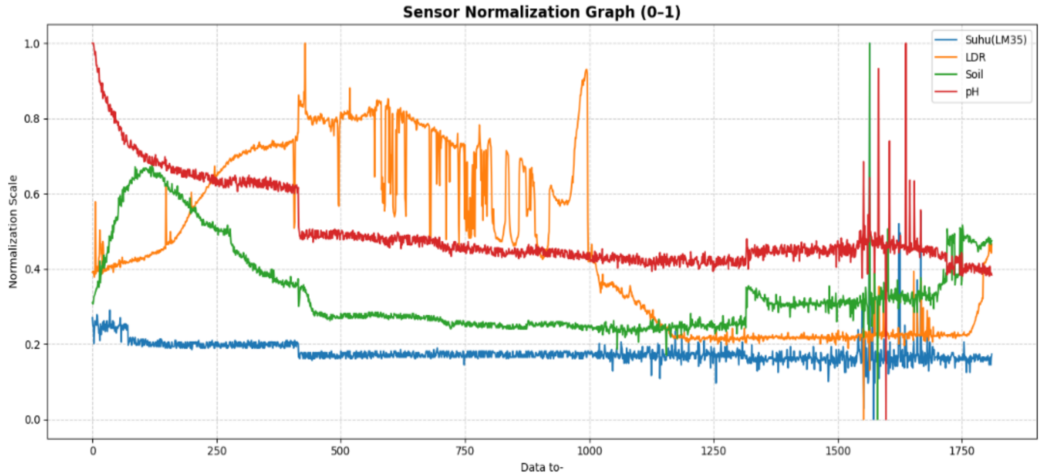

Figure 4. Sensor data normalization graph

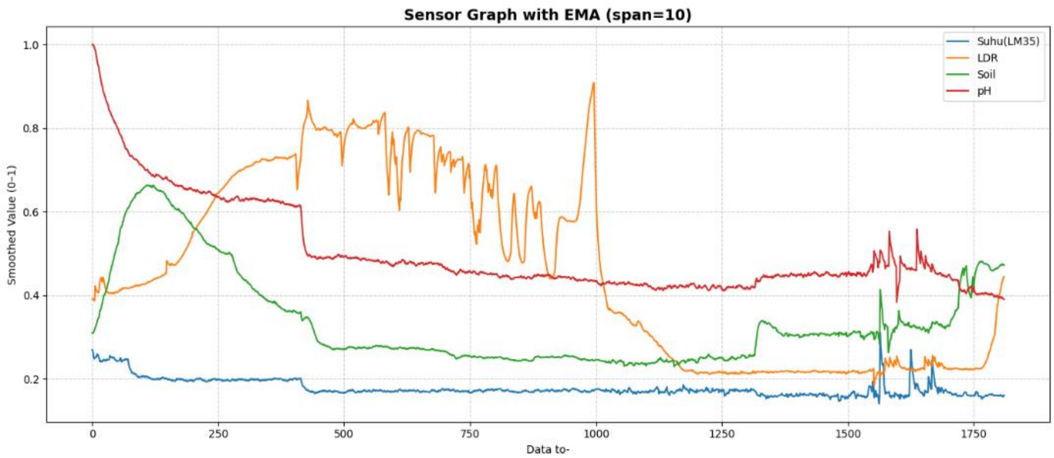

Figure 5. The EMA graph for smoothing sensor data

3.4. Machine learning analysis

The preprocessed dataset was analyzed using k-means clustering and RF classification. K-means clustering grouped sensor readings into distinct clusters, representing favorable and unfavorable environmental conditions for sugarcane growth. Figure 6 shows the k-means algorithm with the x-axis representing temperature and the y-axis representing humidity. K-means clustering produces three clusters, namely cluster 0 (purple), cluster 1 (blue), and cluster 2 (yellow). The purple cluster is mostly found in low humidity (around 0.25–0.35) with relatively low temperatures (0.15–0.20). This can be interpreted as the condition of plants in a dry state or under water stress. This indicates that the sugarcane tends to be unhealthy or at risk of drought. The blue cluster is found more in high humidity (0.50–0.65) with moderate temperatures (0.20–0.25). These conditions are close to optimal for sugarcane growth and are thought to be healthy, as high humidity supports nutrient absorption and stable temperatures. The yellow cluster is spread across moderate humidity (0.35–0.50) with varying temperatures (0.15–0.30). This is likely a transitional condition, which could be healthy or unhealthy depending on other factors. This indicates a mixed zone, where the sugarcane could still be healthy if other supporting factors are present, such as stable soil pH and sufficient light intensity. The RF classification results with the x-axis being temperature (around 0.15–0.30) and the y-axis being humidity (around 0.30–0.65) are shown in Figure 7. The RF prediction results for sugarcane conditions are blue for cluster 0 (unhealthy) and red for cluster 1 (healthy). Based on humidity, there are three conditions: low humidity (0.28–0.35) shows a tendency for more blue dots (unhealthy). Medium humidity (0.35–0.50) shows a mixture of healthy and unhealthy (vulnerable/transition zone). High humidity (0.50–0.65) indicates a predominance of red (healthy). Furthermore, the role of temperature shows that the temperature range (0.15–0.30) is not very wide, so its effect on classification is not as significant as humidity. However, at higher temperatures (>0.25), healthy points (red) are more dominant if humidity is also high. The RF classifier achieved high predictive performance, with accuracy exceeding 90%, supported by balanced precision, recall, and F1-score values. The classification results provided actionable insights by distinguishing between healthy and unhealthy sugarcane states, enabling farmers to make informed decisions regarding irrigation and crop management.

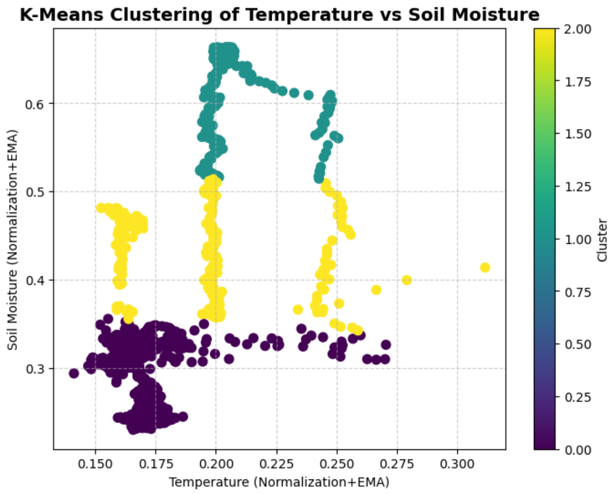

Figure 6. K-means clustering results from humidity and temperature data

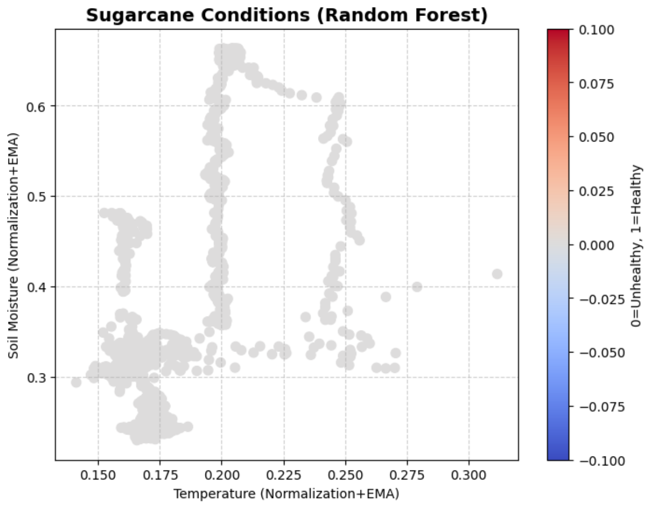

Figure 7. RF classification

3.5. Feature importance and insights

Feature importance analysis revealed that soil moisture was the most influential parameter in determining sugarcane health, followed by temperature, pH, and light intensity. This finding aligns with agronomic knowledge that water availability is the dominant factor affecting sugarcane productivity. Temperature and pH contributed to secondary variations, while light intensity played a supporting role in photosynthesis and sugar accumulation. These insights confirm the relevance of multi-sensor monitoring and emphasize the need for adaptive management strategies in sugarcane farming.

3.6. Comparative discussion

Compared to previous studies that focused on single-parameter sensing or specific crop contexts [33]–[38], [39]–[43], the proposed system offers a more comprehensive and resilient framework. The integration of multi-sensor IoT monitoring, hybrid power supply, dual storage, and ML analysis represents a significant advancement in agricultural technology. This system not only ensures reliable data acquisition under challenging field conditions but also provides predictive analytics to support decision-making. The results demonstrate the potential of IoT and ML technologies to improve sugarcane productivity, strengthen food security, and enhance farmer welfare in Mojokerto and other sugarcane-producing regions.

4. CONCLUSION

This work demonstrates a hybrid-powered IoT multi-sensor monitoring system integrated with ML for sugarcane fields in Mojokerto. The architecture—combining soil moisture, pH, temperature, and light sensing with an Arduino UNO R4 Wi-Fi microcontroller, hybrid power (mains and solar), and dual storage (Google Sheets and SD card)—operated reliably under real field conditions. ML analysis using k-means and RF provided data-informed insights into environmental variability and crop health, with soil moisture identified as the most influential factor. The RF model achieved 93.01% accuracy, 93.88% precision, 99.02% recall, and a 96.38% F1-score on held-out data. These results support the potential of multi-sensor monitoring and predictive analytics to guide timely irrigation and management decisions. This study is limited to a single-site deployment and a finite observation window; future work will extend validation across seasons and locations, add sensors (e.g., electrical conductivity), improve calibration robustness, and integrate closed-loop actuation for irrigation control. Overall, the proposed system offers a resilient, scalable framework that can be adapted to broader agricultural contexts, contributing to improved productivity and farmer welfare in sugarcane-producing regions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Oktavia Citra Resmi Rachmawati		✓			✓	✓	✓	✓		✓	✓	✓		
Tole Sutikno		✓		✓	✓		✓			✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SS], upon reasonable request.

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