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Harnessing IoT and Data Analytics to Enhance Resource Efficiency and Crop Productivity in Smallholder Agriculture

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Abstract

This research focused on the development of a cost-effective IoT-enabled smart agriculture system meant to address the specific challenges that smallholder farmers are facing in Butaleja District (Uganda). The challenges included limited resources, dependence on traditional farming methods and vulnerability to climate change. The proposed system integrated low-cost IoT sensors to monitor critical environmental parameters such as soil moisture, temperature and weather conditions combined with cloud-based and offline edge analytics. It further provided real-time actionable insights to farmers via SMS (Short Message Service) and user-friendly platforms enabling improved irrigation management, optimized resource usage and enhanced crop productivity. Usability was prioritized through designing the system with the ability to operate in low-connectivity environments and ensuring ease of usage for farmers with minimal technical expertise. The system's design and functionality were validated through the execution of multiple simulations proving its ability to accurately monitor environmental parameters, predict when irrigation is to happen using a machine learning model ensuring efficient irrigation management. The simulation also highlighted the effectiveness of integrating SMS notifications and real-time analytics, ensuring accessibility for farmers with minimal technological expertise. By addressing the unique needs of smallholder farmers, the study offers a scalable, sustainable and impactful solution for transforming agriculture in resource-constrained regions with potential applications beyond Uganda. Future work is intended to explore scaling the system to diverse agricultural contexts, assessing its socio-economic impacts and integrating renewable energy solutions to enhance sustainability.

Keywords

IoT (Internet of Things), smart farming systems, smallholder farmers, resource efficiency, climate resilience, offline edge analytics, precision agriculture, low-cost technology, data-driven decision-making, irrigation optimization.

Introduction

Agriculture is the backbone of Uganda's economy employing approximately 70% of the labor force and contributing about a quarter of the nation's GDP (GAFSP 2024). Smallholder farmers that constitute most of the agricultural producers within the country play a critical role in ensuring food security and supporting rural livelihoods. However, they are faced with a lot of challenges including reliance on rainfall for farming, use of outdated farming practices and limited access to affordable technology and resources. In Butaleja District, these challenges are expounded due to the presence of poor soil quality, erratic rainfall patterns and a very low penetration of modern agricultural tools.

Approximately 90% of smallholder farmers in Butaleja depend on rain-fed agriculture leaving their livelihoods vulnerable to unpredictable weather patterns and prolonged droughts. Studies show that crop losses during severe droughts can reach 30–40% in Uganda and Butaleja is no exception. However, initiatives such as the Doho Rice Scheme provide irrigation to around 10,000 farmers and this accounts for less than 6% of the district's total arable land of 455 km² (Nantale 2024). The limited access to irrigation highlights the pressing need for more comprehensive and inclusive strategies to address the risks associated with climate change.

Traditional farming practices in the district are both inefficient and environmentally unsustainable leading to poor irrigation management, water wastage, soil degradation and persistently low crop yields. The lack of affordable, accurate and timely climate data further compounds these challenges leaving farmers unable to make informed decisions. The high cost and technical complexity of modern precision agriculture technologies also hinder their adoption preventing smallholder farmers from leveraging data-driven insights to optimize resource use and improve productivity. These challenges have led to heightened food insecurity, increased vulnerability to climate variability and limited opportunities for sustainable agricultural development.

To address these challenges, this research proposed the design, implementation and evaluation of an affordable IoT-enabled smart agriculture system tailored to the specific needs of smallholder farmers in Butaleja District. The system integrated low-cost IoT sensors for real-time monitoring of soil moisture, temperature and weather conditions combined with offline edge analytics and SMS-based notifications. With this approach, it ensures usability in low-connectivity environments and accessibility for farmers with minimal technical expertise empowering them to optimize irrigation, enhance resource efficiency and improve crop yields.

The primary objective of this research was to provide smallholder farmers with an innovative, cost-effective technological solution that improves their resilience to climate variability and promotes sustainable farming practices. This study is guided by the following research questions;

1. What are the critical design considerations for an IoT system tailored to the affordability, accessibility and literacy challenges of smallholder farmers in Butaleja District?
2. How can offline analytics and SMS-based communication enhance the usability of IoT systems in low-connectivity rural areas?
3. What is the impact of the proposed IoT-enabled system on resource efficiency, crop productivity and farmer decision-making?

To achieve its goals, the study focused on three specific objectives;

1. To investigate and identify requirements needed through performing an assessment of technological and contextual needs of smallholder farmers to inform the system design, ensuring it is both relevant to local conditions and user-friendly.
2. To design and build a robust IoT system solution that integrates offline analytics, low-cost sensors and SMS-based feedback, making it accessible, affordable and practical for farmers in rural Uganda.
3. To test and validate the proposed developed system. This will include a pilot in Butaleja District to evaluate its impact on productivity, resource efficiency and farmer adoption using the feedback to refine and optimize the system for broader implementation.

This study demonstrated significant potential for transforming smallholder agriculture in Uganda by improving resource efficiency, enhancing crop productivity and building climate resilience. The system's affordability and farmer-centric design addressed critical barriers to adopting modern agricultural technologies. Insights from this research informed policies and guided the scaling of IoT-based agricultural solutions across Uganda and other similar regions fostering sustainable agricultural development and food security.

Related works

The transformative potential of Internet of Things technologies in smallholder agriculture has been extensively explored particularly in addressing resource management, crop monitoring and irrigation efficiency in developing countries. For example, Doshi et al. developed a smart farming prototype that integrates agricultural sensors with a third-party cloud application for data display on farmers' smartphones (Doshi et al. 2019). Ayaz et al.

(2019) emphasized the role of wireless sensors and IoT devices in providing real-time insights to improve agricultural decision-making.

IoT applications in irrigation have demonstrated significant water-saving potential. Nigussie et al. proposed an IoT-based irrigation system in sub-Saharan Africa reducing water usage by 60% while maintaining or increasing crop yields through real-time monitoring of soil and weather conditions (Nigussie et al. 2020). Similarly, Dahane et al. (2022) implemented a low-cost IoT solution in Algeria reducing water consumption by 50% while sustaining productivity. These findings show the value of affordable IoT systems in water constrained regions.

Beyond irrigation, IoT applications extend to broader agricultural contexts. Bayih et al. implemented an IoT system for monitoring irrigation and fertilization in Ethiopia achieving improvements in crop yield, water efficiency and fertilizer use (Bayih et al. 2022). Maraveas et al. explored IoT systems in greenhouse environments emphasizing their potential to enhance resource use and crop quality while stressing affordability and reliability in their implementation (Maraveas and Bartzanas 2021). In Tanzania, Lufyagila et al. demonstrated how IoT-powered environmental monitoring in poultry houses improved animal productivity and health through low-cost sensors tracking temperature, humidity and air quality (Lufyagila et al. 2022).

Despite their promise, the widespread adoption of IoT in smallholder agriculture remains constrained by high costs, limited connectivity and technical complexity. Antony et al. (2020) identified the economic burden of IoT systems as a significant barrier for resource-limited farmers. Similarly, Haque et al. (2021) and Bera (2021). highlighted the need for secure, low-cost solutions, with Bera et al. proposing the use of blockchain and drones to enhance data security and precision farming (Haque et al. 2021, Basudeb et al. 2021). These studies highlight the importance of designing simple, affordable systems for smallholder farmers tailored to their unique socio-economic contexts.

The socio-economic implications of IoT adoption are equally important, for example, Quayson et al. emphasized the need for a supportive environment that includes access to technology, training and market incentives to ensure the success of IoT-based interventions (Quayson et al. 2020). Secondly, innovative technologies like voice-activated tools have also been explored with Katanga et al. demonstrating their potential to simplify IoT adoption for farmers with low literacy levels (Katangle, Kharade, Deosarkar, Kale, & Nalbalwar, 13–15 February 2020). Similarly, Bu and Wang 2019 introduced a smart IoT system integrated with deep learning to optimize water usage for crops (Bu and Wang 2019). Jiang et al. applied deep learning for apple fruit detection showcasing its potential for improving fruit sorting and handling (Jiang et al. 2021). Similarly, Bu et al. introduced a smart IoT system integrated with deep learning to optimize water usage for crops (Bu and Wang 2019).

Addressing gaps in affordability, scalability and contextual relevance remains critical for IoT success in smallholder agriculture. Incorporating offline functionality as proposed by Nigussie et al. (2020) and solar-powered IoT devices as highlighted by García et al.

(2018) can enhance usability in resource-limited settings. Building on these strengths, this study integrates offline edge analytics, SMS feedback and farmer-centric designs to contribute to the development of scalable and sustainable IoT solutions for smallholder agriculture in Uganda and similar regions.

System Design and Modeling

The system was designed using several key components. Low-cost IoT sensors were deployed including soil moisture sensors, temperature sensors and weather stations to measure rainfall and humidity. These sensors were designed to be rugged, energy-efficient and affordable to ensure their usability in rural environments with limited infrastructure. Wireless communication was enabled through low-power wide-area network (LPWAN) technologies such as LoRa WAN and NB-IoT which are cost-effective and well-suited for areas with limited mobile network coverage. A cloud-based analytics platform was developed to collect and process sensor data using predefined algorithms and agricultural expertise. This platform provided tailored recommendations on irrigation and farm management accessible through a mobile application, SMS service or web interface. Additionally, the system incorporated offline data analytics and edge devices to manage localized data processing in cases of limited connectivity ensuring functionality in all environments.

Pilot Testing and Farmer Engagement

A pilot project was implemented in selected communities within Butaleja District to test the system on real farms. The pilot involved 10–15 farms chosen in collaboration with local farmer cooperatives to ensure representation across diverse soil types and crop varieties. The pilot spanned six months covering both dry and wet seasons to evaluate the system's performance under varying climatic conditions. During the pilot testing, the system was tested for technical reliability, data accuracy and ease of use. Feedback from farmers was collected to refine the system's functionality and to align it with their needs. Training sessions were also provided to ensure farmers understood how to use the system and had the ability interpret its recommendations effectively.

Data Collection and Analysis

Data Collection

The data collection process relied on the IoT-enabled system's integration with various low-cost sensors for real-time monitoring. Soil moisture sensors were placed strategically across pilot farms to monitor soil water content at 15-minute intervals. The data was analyzed to provide irrigation recommendations tailored to the specific moisture needs of crops ensuring optimal irrigation while preventing over or under watering. Temperature sensors, deployed in both the air and soil monitored conditions affecting crop growth. This data was incorporated into predictive models to forecast stress conditions and provide early warnings. Humidity sensors measured relative humidity aiding and supporting irrigation management by providing evapotranspiration insights. Rainfall sensors measured precipitation amounts and intensity informing decisions on supplementary irrigation and contributing to long-term water management strategies. Light intensity sensors measured solar radiation to evaluate crop light adequacy and guide shading or repositioning recommendations where needed.

Frequency of Data Collection

Sensor data was collected every 15 minutes, providing granular insights into environmental conditions. Aggregated summaries were transmitted to the cloud or edge devices hourly to optimize storage and processing efficiency.

Data Analysis

Quantitative and qualitative approaches were used to analyze the collected data. Quantitative analysis relied on descriptive statistics to identify trends and anomalies in sensor readings such as soil moisture, temperature and humidity. Predictive models such as regression analysis estimated the impact of environmental factors on crop yields. Qualitative analysis involved semi-structured interviews and surveys to gather farmer feedback on the system's usability, benefits and challenges. Responses were coded and analyzed using pattern-based techniques to identify recurring themes and insights.

Integrated Analysis

The findings from quantitative and qualitative analysis were triangulated to provide a holistic assessment of the system's performance and its acceptance among farmers. Correlation analysis explored relationships between environmental data, system usage and reported outcomes, further validating the system's impact.

Proposed IoT model

The proposed IoT model incorporates as shown in Fig. 1 utilises low level sensors to measure environmental parameters which are then transferred to a central processing unit to perform desired analytics and eventually the data is sent to the cloud for permanent at predefined intervals of 1 hour. This model was simulated in PROTEUS software (Labcenter Electronics 2025).

Components used and their corresponding configuration in the simulation

Rain Sensor

Fig. 2 shows a rain sensor that was used for the detection of rain during the simulation. It was connected to the digital GPIO25 of the Raspberry Pi microcontroller. On its test pin, a logic state was added to its test pin to enable the simulation of rainfall. 0 signifying no rain while 1 indicating the presence of rain.

A soil Moisture Sensor is shown in Fig. 3 *.*

This was used for measuring soil moisture to determine whether the soil needs irrigation. It was configured in the following way.

The ground pin was connected to ground, its power pin connected to 5V dc power supply and its analog pin output connected to channel 0 of theMCP3208 ADC for reading via the Raspberry Pie. The output pin was connected through a 27μH inductor in series with a 1000μF 12V capacitor and output picked from the point between the inductor and the capacitor which was fed to the ADC.

Water Pump (Relay Controlled).

The water pump shown in Fig. 4 was controlled via a relay connected to a GPIO18 pin of the microcontroller (Raspberry Pi) to have the ability of driving it.

It only powers based on the soil moisture lever and the rain status.

A Raspberry Pi (Model 3 or Similar) is shown in Fig. 5*.*

This acts as the central controller. It interfaces with the soil moisture sensor, rain sensor, relay, GSM module and other components used in the simulation. It also communicates with the MCP3208 ADC to read analog values since it has no analog pins. It has been programmed to handle communications (SMS & Email sending), perform offline analytics and control the sensors and actuators used in the simulation.

MCP3208 ADC (Analog-to-Digital Converter).

This was incorporated to enable the conversion of analog signals (e.g., from the soil moisture sensor) to digital values for the Raspberry Pi. It is composed of multiple channels (CH0 – CH7) used for different sensors.

During the simulation as shown in Fig. 6, the temperature sensor was connected to CH0, the soil moisture sensor to CH1 and the humidity sensor to CH2 respectively.

The GSM Module.

The GSM Module (SIM900D) shown in In Fig. 7 was incorporated to enable the sending of SMS alerts (i.e., when irrigation starts / ends or soil moisture is low). It communicates with the Raspberry Pi over UART (TX and RX pins).

Potentiometers (RV1, RV2, RV3).

Simulate variable environmental conditions, such as soil moisture and humidity. These were connected to different ADC channels to provide adjustable input.

LED (Status Indicator).

This was used to indicate the system's status (i.e.., whether the pump is active or idle).

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Power Supply.

These were used to provide the necessary voltage levels (5V and 3.3V) for the Raspberry Pi, sensors and other components used in the simulation.

Irrigation Model Development

The developed model leverages environmental parameters such as soil moisture, air temperature and air humidity to predict whether the water pump should be activated (ON) or deactivated (OFF). A Random Forest Classifier was employed for this task due to its robust performance in handling tabular data and non-linear relationships.

Dataset Description

The dataset that was used to train the model contained observations with four key attributes;

1. *Soil Moisture:* The percentage of moisture content in the soil.
2. *Temperature:* The ambient air temperature in degrees Celsius.
3. *Air Humidity:* The relative humidity in percentage.
4. *Pump Data:* The target variable, indicating the status of the water pump (0 = OFF, 1 = ON).

In Fig. 8, the dataset was imported using the pandas library to facilitate data manipulation and exploration and the details for full implementation are available in the attached jupyter notebook Suppl. material 2 with the corresponding dataset as a CSV file attached as Suppl. material 3.

Data preprocessing followed next, this involved the separation of the *features* (input variables) and the *target* (output variable).

Features (X): Soil Moisture, Temperature and Air Humidity.

Target (y): Pump Data. This process is illustrated in Fig. 9

As shown in Fig. 10, the data was then split into training (80%) and testing (20%) subsets using the train_test_split function from the sklearn.model_selection module. This ensures that the model's performance is evaluated on unseen data, avoiding overfitting.

In Fig. 11, the Random Forest Classifier was then chosen as the machine learning model. This algorithm operates by constructing a multitude of decision trees during training and outputting the class that is the mode of the predictions made by the individual trees. It is particularly effective for handling datasets with a mix of numerical and categorical features and has built-in mechanisms for handling overfitting.

The model was trained on the training data (X_train, y_train) using the fit() method from the sklearn.ensemble.RandomForestClassifier module.

The trained model was then evaluated on the test data (X_test). Predictions were generated using the predict() method and the model's accuracy was computed using the accuracy_score function from the sklearn.metrics module as shown in Fig. 12 .

The accuracy score provides a quantitative measure of the model's performance, calculated as the ratio of correct predictions to the total number of predictions.

The Random Forest Classifier achieved a classification accuracy of 99.83%" on the test data, demonstrating its capability to predict water pump status based on environmental parameters effectively.

To facilitate future use of the trained model without retraining, the model was saved to the disk using the joblib library as illustrated in Fig. 13. It was the trained model that was used during the simulation to trigger the irrigation based on the environmental parameters obtained from the sensor readings. However, this serialized version of the model can be loaded and deployed in real-world applications.

System Architecture

The proposed system adopted a three-tier network architecture designed to optimize irrigation management for smallholder farmers. This architecture includes the perception layer, network layer and application layer each responsible for distinct functions in the system's operation.

The perception layer is comprised with distributed IoT devices i.e. soil moisture sensors, temperature sensors, rainfall gauges and light intensity sensors. These sensors collect real-time data on key environmental parameters critical for determining crop water requirements. Additionally, humidity sensors monitor microclimate conditions around the crops while rainfall sensors measure the quantity and intensity of precipitation. This layer ensures comprehensive monitoring of soil, crop and environmental conditions.

The network layer enables seamless communication between the perception layer and the data processing components of the system. Low-power wireless communication modules such as LoRaWAN or NB-IoT are employed to ensure efficient and reliable data transmission even in rural areas with limited mobile network coverage. These technologies minimize energy consumption while maintaining efficient communication over long distances addressing the challenges of rural connectivity.

The application layer is responsible for data processing, decision-making and system control. Unlike traditional IoT architectures that rely heavily on cloud-based processing, the proposed system integrates local data processing capabilities through edge devices. This approach reduces dependence on broadband connectivity and mitigates the costs associated with remote computing infrastructure. The localized data processing component performs intelligent analysis using predefined algorithms and crop-specific requirements enabling accurate predictions of water needs and effective irrigation scheduling. Supplementary inputs such as regional weather data, expert knowledge of crop & soil characteristics and indigenous knowledge from farmers are incorporated into the decision-making process to enhance accuracy and relevance.

The inclusion of feedback from farmers is a critical aspect of the architecture. By integrating their observations and insights, the system ensured better resource usage, adaptability to local conditions and improved acceptance within the community. Irrigation reports generated by the system provided valuable insights to agricultural experts enabling them to better understand the interplay of crop and soil characteristics under the irrigation scheme.

This system architecture in Fig. 14 leveraged the collaboration of IoT devices, localized data processing and wireless communication technologies to deliver a scalable, cost-effective and context-specific solutions for smart irrigation management in resource-constrained rural environments.

Components and technologies for the architecture

Simulation Software Used

Proteus Software is adopted for the simulation of this project. This is because its freely available and well suited for simulation with a vast amount of sensor libraries and documentation for them.

Things speak cloud was used for data storage and visualization coupled with data analytics

A couple of libraries were used during the simulation of the system as detailed in Table 1, these included the following.

Sensors and Actuators

The system utilized an array of sensors and actuators to monitor environmental conditions and manage irrigation. Table 2 provides thier outline and corresponding functions.

Connectivity technologies

The system employed low-power, wide-area network (LPWAN) technologies to enable robust communication in rural settings with limited connectivity. The key technologies used are summerized in Table 3.

Data processor and controller

The core data processing and control unit of the system was built around the Raspberry Pi microcontroller which served multiple critical functions. It was responsible for data integration, collecting and processing information from various sensors to monitor environmental conditions. Local analytics were performed using edge computing capabilities reducing reliance on cloud connectivity and ensuring functionality in low-connectivity areas. The system also incorporated machine learning models such as those implemented with scikit-learn to predict crop water requirements accurately. Additionally, the microcontroller managed actuation control by operating devices like the water pump based on real-time sensor data and analysis. As a communication hub, the Raspberry Pi facilitated data transmission to the cloud using HTTP requests and interfaced with the ThingSpeak platform for data visualization, analysis and storage ensuring comprehensive system functionality and accessibility.

Results and Discussion

The data collected from the simulations was transmitted to the ThingSpeak (MathWorks 2025) cloud platform for secure, long-term storage and advanced visualizations. ThingSpeak, a widely used Internet of Things (IoT) analytics platform, enabled efficient real-time data monitoring, storage and processing. This facilitated the generation of dynamic visual representations, such as graphs and charts, which provided insightful trends and patterns in soil moisture, air temperature and humidity levels over time.

These visualizations illustrated in Fig. 15 offered critical information for data-driven decision-making in irrigation management.

In addition to cloud integration, a Graphical User Interface (GUI) was developed to enhance user accessibility and system interaction. This interface was designed to be intuitive, user-friendly and compatible with a range of smart devices, including smartphones, tablets and personal computers. By leveraging web technologies, the GUI enabled farmers to remotely monitor farm parameters and irrigation system status in real-time via an internet connection. The system displayed essential metrics such as current soil moisture levels, ambient temperature, air humidity and pump status, empowering users to make informed decisions about irrigation scheduling and water usage.

To ensure robustness and scalability, the platform incorporated a secure data transmission protocol using HTTP with API keys for authentication when sending data to ThingSpeak. The GUI's design emphasized responsiveness and adaptability, allowing seamless interaction across devices of varying screen sizes. The system also supported integration with predictive analytics models, such as the trained Random Forest classifier, for forecasting irrigation needs based on environmental conditions.

This implementation bridges the gap between IoT technology and agricultural practices, promoting sustainable water management and improving crop yield. By combining real-time monitoring, cloud computing and user-centric design, the system provides a comprehensive solution for modern precision agriculture. Fig. 16 shows the developed web system.

For farmers that have no access to smart devices, SMS notifications were employed to enable their consistent update of the farm’s parameters over time as illustrated in Fig. 17.

In addition to SMS notifications, the system was configured to send email alerts to inform farmers of key events such as the activation or deactivation of the irrigation pump. This dual-channel communication mechanism was designed to ensure redundancy and reliability in the notification process. In cases where SMS delivery might fail due to network issues or other unforeseen circumstances, email notifications served as a backup to guarantee that the farmer remained informed.

The email notifications provided detailed updates on the farm's operational status, enhancing situational awareness and allowing farmers to respond promptly to changes in the system. These notifications also included timestamped records of events, offering a log for future reference and analysis.

By implementing this integrated notification system, the platform addressed potential communication gaps and strengthened the reliability of farm monitoring. The combination of real-time data access through the GUI, cloud-based storage via ThingSpeak and proactive alerts via SMS and email creates a robust system that supports effective farm management.

In conclusion, this comprehensive system optimizes the use of farm resources, minimizes water wastage and promotes sustainable agricultural practices. It empowers farmers with actionable insights and ensures that they remain informed under all circumstances, contributing to improved productivity and resource efficiency.

Analysis

In comparison to traditional methods, the IoT model achieves the following;

1. *Increased Agricultural Productivity:* By using real-time data to agricultural processes, farmers can expect improved crop yields and reduced crop loss.
2. *Efficient Resource Management:* The system will help farmers optimize water usage reducing waste and conserving this vital resource in the face of erratic rainfall patterns.
3. *Enhanced Farmer Capacity:* Through training and engagement, smallholder farmers will develop skills in using IoT technologies and data-driven decision-making, fostering long-term sustainability.
4. *Scalability:* The system will be designed to be replicable in other districts of Uganda and potentially other East African countries helping to scale its impact across the region.

Challenges

During the simulation of the proposed system, several challenges were encountered. One significant difficulty was the configuration of sensors within the simulation software. Physical usage of IoT sensors would have been more straightforward given prior experience but the simulation process proved cumbersome. Additionally, obtaining libraries for various sensors posed another challenge as Proteus software lacked many components by default requiring effort to source and integrate them from external sources.

Conclusions

This study investigated the potential of IoT-enabled smart agriculture systems to address key challenges faced by smallholder farmers in Butaleja District, Uganda. By integrating low-cost IoT sensors, wireless communication technologies and offline edge analytics, the proposed system provides real-time, data-driven insights for optimizing irrigation, improving resource efficiency and enhancing crop productivity. The research demonstrated the feasibility of implementing affordable, context-specific technological solutions that can empower smallholder farmers to adapt to climate variability and improve their agricultural outcomes.

The findings of this study have significant practical implications. First, the system offers a scalable solution for efficient water management in regions where irrigation infrastructure is limited, contributing to reduced water wastage and increased resilience to drought. Secondly, the incorporation of offline edge analytics addresses the challenge of unreliable internet connectivity enabling consistent decision-making even in remote rural areas. Thirdly, the farmer-centric design coupled with simplified user interfaces and localized training programs ensures broad accessibility and encourages adoption among farmers with limited technological proficiency.

Future research will explore the real-world deployment and validation of the proposed system across diverse agricultural contexts and crop types. Additionally, long-term assessments of the socio-economic and environmental impacts of IoT adoption in smallholder agriculture will provide deeper insights into its scalability and sustainability. Further investigations into integrating renewable energy sources such as solar power, with IoT devices will enhance the system's energy efficiency and operational sustainability. Through these future directions, this research aims to contribute to the development of sustainable, precision agriculture practices, advancing food security and rural livelihoods.

Funding program

The research received no external funding

Ethics and security

This study followed ethical guidelines for research involving human participants. Informed consent was obtained, ensuring participants were fully aware of the study's purpose, procedures, and their right to withdraw at any time.

To safeguard data privacy and security, all collected information was de-identified and stored in a secure, access-controlled environment, preventing unauthorized access. The study complied with Uganda's Data Protection and Privacy Act (2019) and international best practices in research ethics.

The researchers **declare no conflict of interest**, and all procedures were conducted transparently and ethically.

Conflicts of interest

The authors have declared that no competing interests exist.

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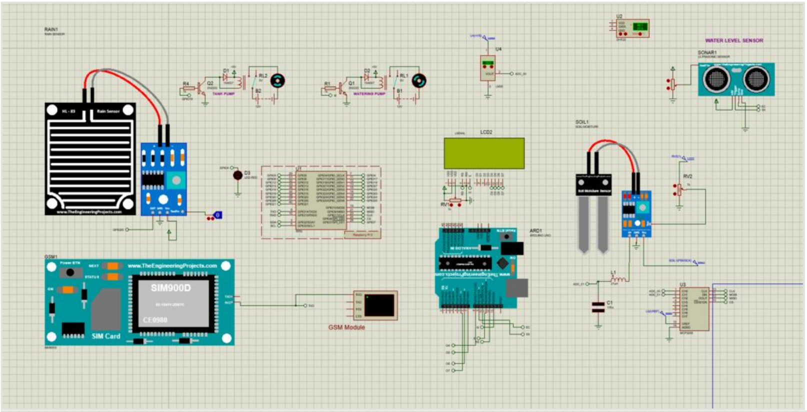

Figure 1.

Simulation of an IoT-Based Model in PROTEUS software: Integrating Sensors, a Microcontroller and Communication Modules.

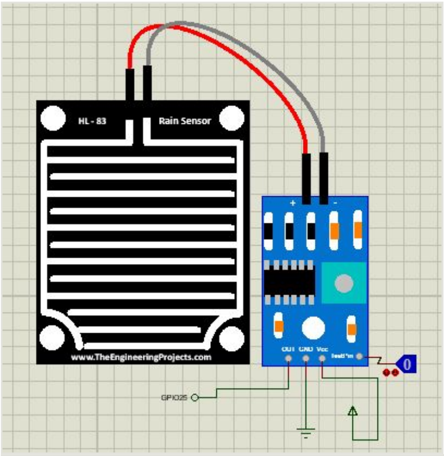

Figure 2.

Rain Sensor: Integrated with the Raspberry Pi for Real-Time Rainfall Detection.

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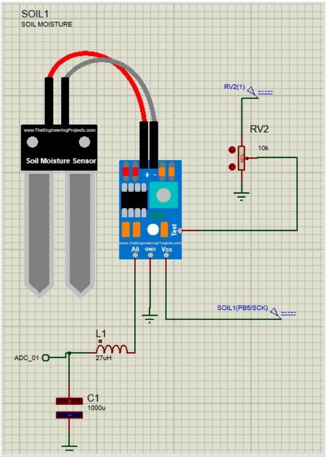

Figure 3.

Soil Moisture Sensor: Used for Monitoring Soil Water Levels for Efficient Irrigation.

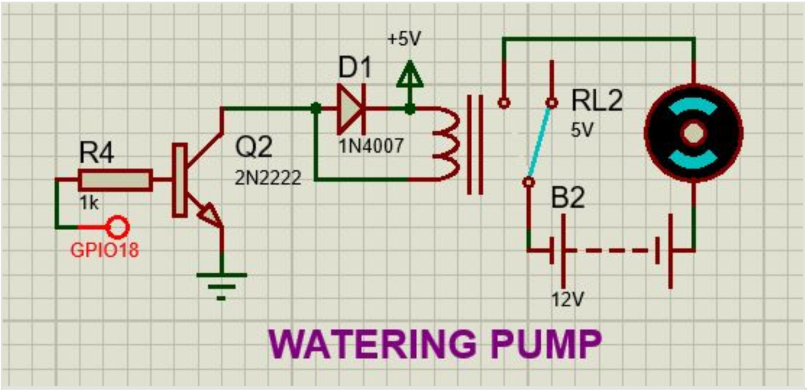

Figure 4.

Watering Pump: IoT-Controlled System for Smart Irrigation.

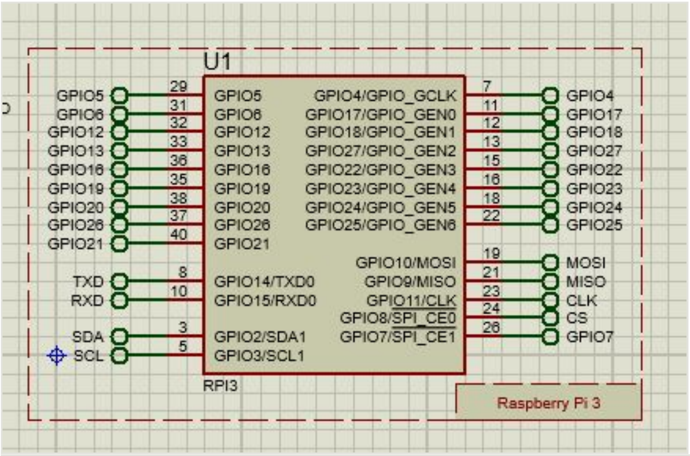

Figure 5.

Raspberry Pi: A Microcontroller for IoT-Based Automation and Control.

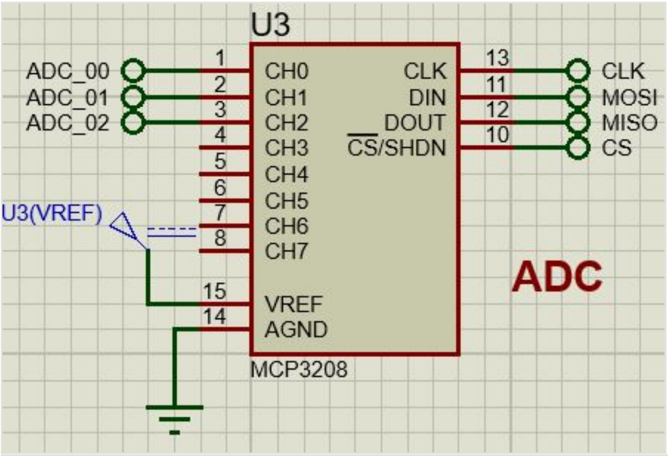

Figure 6.

MCP3208 ADC: 8-Channel 12-Bit Analog-to-Digital Converter for Accurate Signal Conversion.

Figure 7.

SIM900D GSM Module integrated for cellular communication and SMS alert functionality.

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```
import pandas as pd
# Load the dataset
data = pd.read_csv('Soil Moisture, Air Temperature and humidity, and Water Motor onoff Monitor data.csv')
```

Figure 8.

Loading the training dataset using the pandas library in Python for preprocessing and analysis.

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```
# Features: Soil Moisture, Temperature, Air Humidity
X = data[['Soil Moisture', 'Temperature', 'Air Humidity']]

# Target: Pump Data (0 = OFF, 1 = ON)
y = data['Pump Data']
```

Figure 9.

Selection of input features (X) and target variable (y) from the dataset during the data preprocessing stage.

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```
from sklearn.model_selection import train_test_split
#spliiting data into testing and training data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Figure 10.

Split of data into training and test data sets.

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```python
from sklearn.ensemble import RandomForestClassifier
# training  the model
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
```

Figure 11.

Training the Random Forest Classifier using the selected features and target variable.

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```
from sklearn.metrics import accuracy_score
#testing the model accuracy
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy * 100:.2f}%")
```

Figure 12.

Evaluating model accuracy using the accuracy_score function from the sklearn.metrics module.

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```
import joblib
#saving the model
joblib.dump(model, 'irrigation_model.pkl')
print("Model saved as 'irrigation_model.pkl'")
```

Figure 13.

Saving the trained model using the joblib library for future use.

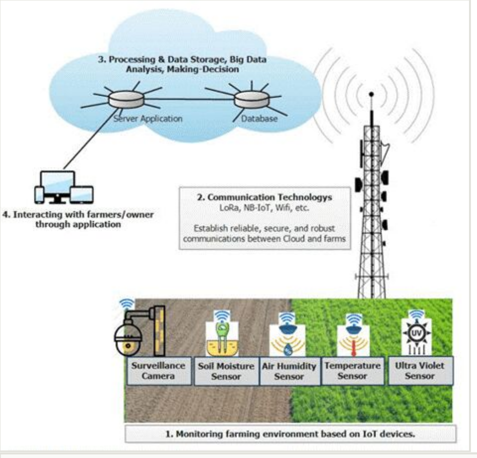

Figure 14.

IoT-based smart irrigation architecture illustrating sensor integration, data communication, processing and user interaction flow.

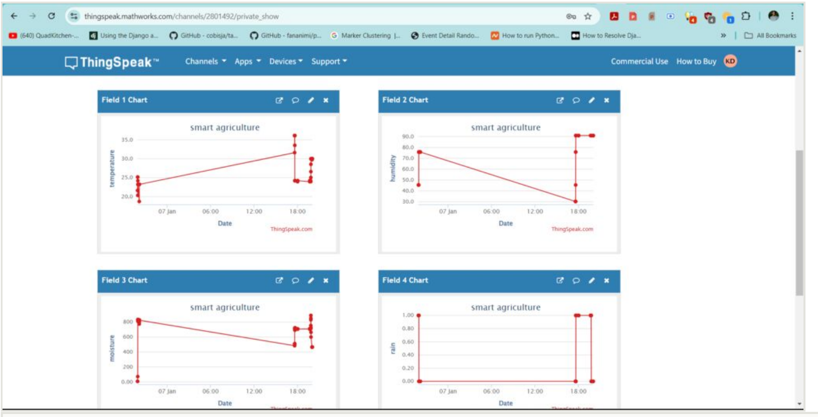

Figure 15.

Real-time data visualization dashboards generated using ThingSpeak for monitoring agricultural metrics.

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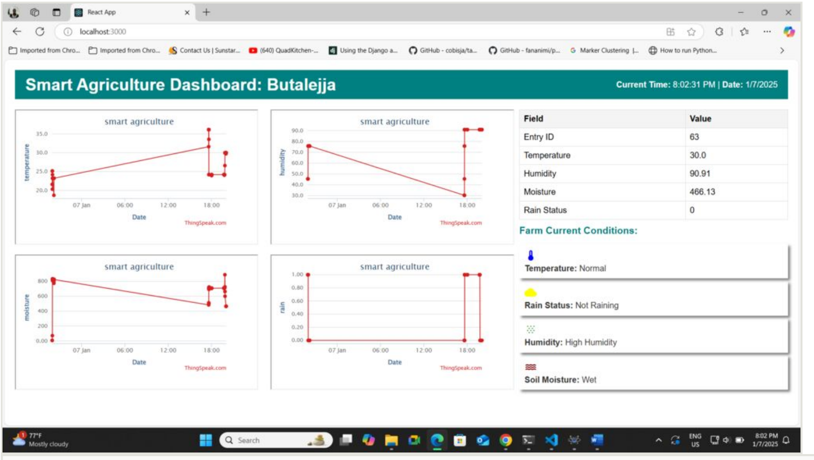

Figure 16.

Web-based system dashboard developed for the IoT irrigation simulation displaying real-time environmental metrics such as soil moisture, air temperature, humidity and pump status.

Figure 17.

SMS alert transmission using the SIM900D GSM module displaying real-time irrigation and environmental updates sent to farmers via an AT command interface.

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Table 1.

Libraries used, Suppl. material 1 outlines all the necessary libraries required for program execution.

Name	**Usage**
Pandas	Data manipulation and analysis, working with structured data.
scikit-learn	Machine learning algorithms for classification, regression, etc.
sockets	Network communication using TCP/UDP protocols.
pio	Controlling GPIO pins (e.g., on Raspberry Pi) for hardware interaction.
requests	Sending HTTP requests to interact with web APIs.
spidev	SPI communication with peripherals like sensors and displays.
time	Time manipulation, delays and performance measurement.
joblib	Model serialization and lightweight pipelining.

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Table 2.

Components used.

Sensor/Actuator	**Function**
Soil Moisture Sensors shown in Fig. 3	Measure water content in the soil to determine irrigation needs.
Temperature Sensors in Fig. 1	Monitor air and soil temperatures to detect stress conditions and forecast environmental impacts.
Humidity Sensors shown in Fig. 1	Record relative humidity to assess risks of fungal or bacterial diseases and adjust irrigation schedules.
Rainfall Sensors illustrated in Fig. 2	Measure the intensity and amount of precipitation to inform supplementary irrigation decisions.
Light Intensity Sensors illusrated in Fig. 1	Track solar radiation to evaluate light adequacy and suggest shading or repositioning strategies.
Water Pump (Actuator) shown in Fig. 4	Controlled via relays to regulate irrigation based on sensor data. Operates

Table 3.

Connectivity Technologies.

Technology	Function
Lora WAN	Provides long-range & low-power wireless communication ideal for transmitting sensor data across large farm areas.
NB-IoT	Enabled low-bandwidth, energy-efficient data transmission in areas with sparse cellular network coverage.
Wi-Fi	Facilitates localized data transmission in areas with stable internet connectivity for seamless cloud integration.
GSM	Allows data transmission and SMS notifications ensuring communication in areas with GSM network coverage.

Supplementary materials

Suppl. material 1: requirements file

Authors: Kinyonyi David Hope
Data type: text
Brief description: A text file containing the libraries that were installed in Python
Download file (2.23 kb)

Suppl. material 2: Irrigation Control Model Based on Soil Moisture, Temperature and Humidity

Authors: Kinyonyi David Hope
Data type: Text(Python Code)
Brief description: This Python script implements a machine learning model to automate irrigation decisions based on sensor data inputs (Soil Moisture, Temperature, and Air Humidity). It uses a Random Forest Classifier trained on historical data to predict whether the irrigation pump should be ON or OFF. The script includes data loading, preprocessing, model training, accuracy evaluation and model export as a .pkl file
Download file (1.08 kb)

Suppl. material 3: Sensor Dataset for Soil Moisture, Temperature, Humidity and Irrigation Pump Monitoring

Authors: Kinyonyi David Hope
Data type: Text
Brief description: This dataset contains environmental sensor readings collected for monitoring irrigation conditions on smallholder farms. It includes attributes such as Soil Moisture (%), Air Temperature (°C) and Air Humidity (%) along with a binary indicator showing the irrigation pump status (0 = OFF, 1 = ON). The data was used to train the machine learning model that automates irrigation decisions based on environmental conditions.
Download file (113.34 kb)