An Edge Assisted Internet of Things Model for Renewable Energy and Cost-Effective Greenhouse Crop Management

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Abstract – Improved greenhouse Crop Yields (CY) are now within reach due to the rise of "Smart Farming (SF)" based on the Internet of Things (IoT). The IoT presents a massive opportunity for precision farming, which has the potential to increase CY, optimize resource use, and decrease the environmental impact of agriculture. Kenya's climate challenges greenhouse CY, but this paper lays out an integrated model that works well for growing Capsicum there. A multi-layered system equipped with sensors allows for the real-time monitoring of critical Environmental Factors (EF) in the model. For faster responses and less dependence on distant cloud services, these sensors send data to a processing layer that acts as an intermediary and uses Edge Computing (EC) for data management and immediate action. The analytics layer successfully reads sensor data, predicts possible scenarios, and makes decisions using Random Forest (RF) algorithms to improve crop productivity and yield. Also, the framework's user-friendly interface integrates data display and control, enabling efficient human communication. Kenya's climate impedes the cultivation of horticultural crops. The current study demonstrates that a hybrid model using IoT + EC + RF substantially improves Capsicum growth. The research establishes a standard for SF operations by combining advanced data analytics with the IoT to demonstrate how to develop a sustainable and adaptive SF system. This research set the standard for SF production by proving how a dynamic SF environment can be developed by applying advanced analytics with IoT.

Keywords – Internet of Things, Edge Computing, Random Forest, Smart Farming, Greenhouse Management.

I. INTRODUCTION

Over the past few decades, there has been a noticeable shift in farming methods from traditional techniques to increasingly revolutionary approaches. The development of novel innovations and the interest in improved Smart Farming (SF) practices have triggered the advancement of agriculture: global population growth and growing food consumption pressure farmers to enhance crop quality and reduce food waste. Owing to technological advancement, farmers may now address these problems in person, implementing new tools and techniques to boost production while decreasing the consumption of resources [1]. SF and Precision Agriculture (PA) are the upcoming horizons of agricultural growth. These approaches enhance the use of PA and management by applying data-driven technology. Global Positioning System (GPS) routing, automation systems, sensors, robotics, Unmanned Aerial Vehicles (UAVs), computerized machinery, dynamic rate technologies, and specialized applications are all elements of PA's toolbox. This technique permits an accurate optimization of farming techniques to different farm situations, increasing the performance of resources such as water, fertilizer, and pesticides. [2-3].

A defined environment is most effectively demonstrated by greenhouse farming. In addition to preventing crops from extreme temperatures and maintaining them in an ideal condition for growth and development, it has the unique benefit of prolonging the period during which they grow. Crop Yield (CY), product quality, water consumption, and the application of pesticides may all be significantly enhanced with the use of greenhouses for cultivation. The capacity of these plants to grow produce throughout the year is an enormous advantage for maintaining an ongoing supply of nutritious foods and supplying demand for specific crops even when they don't belong in season. The positive aspects of greenhouse farming have been enhanced using the Internet of Things (IoT). Smart greenhouse settings may be refined with IoT sensors that monitor several environmental variables [4-5]. IoT tools improve plant conditions and CY by optimizing historically manually performed operations like cultivation, regulating temperatures, and fertilizer in the delivery process, thus decreasing labor costs and enhancing the precision with which resources are deployed.

The IoT systems for Greenhouse Crop Management (GCM) incorporate sensors, Edge Computing (EC) devices, and advanced data analysis as key components. This enables enhanced CY and optimizes the use of resources. Regional data processing reduces delay, enhances real-time decision-making, and lessens the need for remote cloud services, resulting in better energy effectiveness and environmental sustainability. There is a significant risk to the future sustainability of India's agricultural sector from variables such as global warming, higher atmospheric temperatures, and an overall lack of groundwater. Within the frequency spectrum of thermal infrared radiation released by the Earth's surface, the environment absorbs and releases electromagnetic radiation at a particular wavelength.

The recommended work aims to capitalize on the benefits of these advances while also addressing the problems with conventional GCM. Enhancing GCM effectiveness and productivity is a top priority due to the growing demand for environmentally friendly SF [6]. This attempt is motivated by a system that optimizes plant cultivation while mitigating resource consumption, environmental impact, and growing demand for food. The research proposal provides a four-layer approach to controlling capsicum greenhouses in Kenya that works synergistically to present a successful framework for GCM. At its core, the Sensing Layer continuously monitors crucial greenhouse parameters such as humidity and temperature through interconnected sensors. The Edge Layer rapidly analyzes data from different sensors, decreasing latency and allowing quick local decision-making. This has an immediate impact on environmental control. The Data Analytics Layer uses the Random Forest (RF) algorithm, recognized for its accuracy in predictive analytics, to determine the entire system's decisions. These results help to improve the environment so that Capsicum can grow to its fullest potential. The User Interface Layer improves network connections by providing an LCD dashboard. This panel provides an understandable overview of the greenhouse's state and enables human control over its several parts. This system achieves the necessary atmosphere control for optimal CY and efficient resource use.

The paper is organized in the following manner: Section 2 provides an existing literature evaluation, Section 3 discusses the proposed framework, Section 4 analyzes the model's deployment, and Section 5 summarizes the research results.

II. LITERATURE REVIEW

A few recent studies have concentrated on how to use the IoT in greenhouse farming. In order to improve the precision of humidity and temperature control, an IoT intelligent GCM was presented in [7] that uses clustering methods and a fuzzy adaptive PID controller. With the help of cloud-based data visualization and the integration of mobile apps, this technology represents a revolutionary step forward in SF.

An innovative GCM system that can automatically track and manage essential variables such as sunlight, moisture in the soil, and carbon dioxide (CO2) has been demonstrated in the SF field [8]. Despite customizing the greenhouse atmosphere for specific plants, their studies demonstrated the possible uses of the IoT to improve GCM-enabling methods for organic farming via remote IoT features.

A smart GCM that is capable of controlling the surrounding environment via the use of sensor-based indicators has been developed [9]. By using ecological science to guarantee suitable developing situations, the study's tools were able to transmit data via the MQTT protocol, proving the accuracy and dependability of the IoT in monitoring in real time.

An optimization approach that balances EC with maintaining temperatures has been suggested by [10] to deal with Energy Consumption (EC) challenges in greenhouse production, resulting in high costs and EC. The success of the system they developed has been verified using a simulation tool, and it presents an optimistic approach to real energy efficiency in greenhouses.

Adaptive Particle Swarm Optimization with Artificial Neural Networks (APSO-ANN) has been examined in [11] as an innovative tool for ecologically conscious farming. A powerful Olive SF approach related to IoT technology was demonstrated by their framework, which constantly integrated new datasets to improve classification algorithms without restoring the system.

Finally, [12] developed an innovative GCM that democratizes plant cultivation by maintaining an environment suitable for numerous plants, accessible through a mobile application. Their approach, based on Raspberry Pi and Arduino, automates environmental control, illustrating the feasibility of IoT for users with varying levels of expertise in plant cultivation [13-15].

To optimize GCM and resource utilization, the implementation of IoT in SF requires improved control systems and continuous tracking to address precise environmental factor management, EC reduction, and environmentally conscious procedures. In order to enhance SF and PA practices, the present article examines numerous GCMs based on the IoT. This study investigates the platforms, focusing on adaptive controllers, clustering algorithms, real-time data transfer, energy optimization approaches, and user-friendly user interfaces.

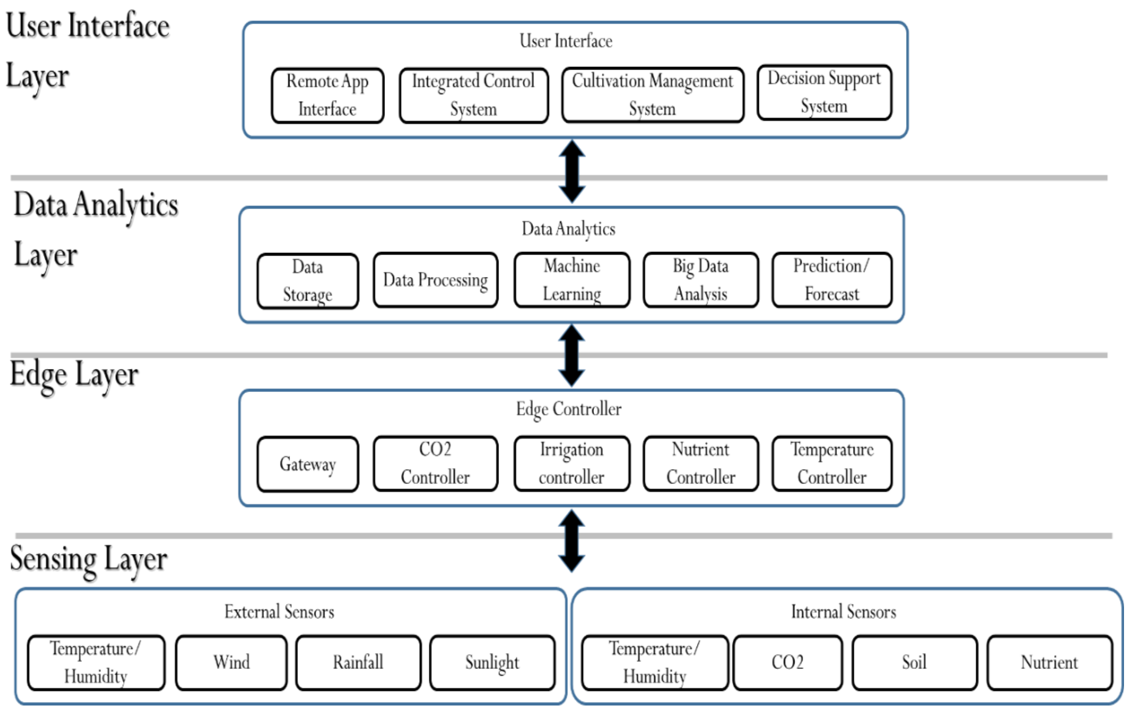

Fig 1. Proposed GCM System.

III. PROPOSED ARCHITECTURE

Fig 1 illustrates the projected model, organized into four distinct layers. The first layer, the sensing layer, is responsible for data collection. This is followed by the edge layer, which transmits the gathered data to the next tier and controls the edge devices. Data is received and processed on the third layer, known as data analytics. The user interface layer, positioned at the topmost level of the system, is accountable for rendering the data being processed accessible to end users.

Every element of this proposed design will be addressed thoroughly in the sections that follow:

Sensing Layer

In order to comprehend every variable controlling GCM and health, this layer is intended to gather a range of data inside and outside the greenhouse. This accurate sensing is performed so that the internal microenvironment of the greenhouse can be monitored and controlled for optimal GCM and that researchers are aware of how external factors could impact these circumstances.

Internal Sensing

The key objective of the greenhouse is to develop and maintain an optimal environment for crop development.
Several sensor categories are employed to accomplish this:

Temperature Sensors

These check if the greenhouse temperature is within the ideal range for different types of crops.

Humidity Sensors

These are useful to sustain crop health and avoid diseases. They evaluate the moisture level of the atmosphere.

Soil Moisture Sensors

An essential tool for measuring the moisture in the soil while providing plants with precisely the proper quantity of water.

pH Sensors

Use to measure the pH or alkalinity of the soil, which impacts the supply of nutrients and how plants consume nutrients.

NPK Sensors
Soil tests like this show the percentage of plant essential factors like potassium, phosphorus, and nitrogen detected in the soil's composition.
External Sensing
The environmental circumstances of the greenhouse exterior may influence the one inside significantly.
Thus, it is necessary to use sensors to keep track of these external impacts:

External Temperature Sensors
The intention is to understand and predict how the temperature inside the greenhouse will respond to deviations in the air temperature outside.

External Humidity Sensors
These are used to find out how to control the humidity level within the greenhouse according to readings collected of the air around it and moisture levels.

Rainfall Sensors
Both inside and outside irrigation systems shed light on rainfall levels.

Wind Sensors
Collecting precise wind speed readings and direction is essential for greenhouse temperature control and air circulation.

Sunlight Sensors
Sensors play an important part in measuring the quantity of natural sunlight and regulating any LED lighting that may be needed inside the greenhouse.

The design provides a flexible and adaptable system capable of managing the greenhouse's in-house microclimate and its outside environmental factors by including internal and external sensors in the Sensing Layer. This encompassing sensing technique is essential if greenhouse agricultural systems are to be maintained effectively and effectively.

Edge Layer
The Sensing Layer has links to the more advanced data processing and analysis features via the edge layer. For the greenhouse system to function productively, in this instance, data analysis and rapid control actions are performed in real time. The control panels and gateway devices that make up this layer are responsible for various facets of the GCM.

Gateway Devices
They constitute the core of the Edge Layer. Their primary function is to act as communication hubs, processing data from internal and external sensors. In order to execute control actions internally or send the data to higher-level systems for processing, such devices complete the initial processing of the data, such as filtering and initial analysis. In addition to helping transmit data from the greenhouse to the cloud or local data centers, gateways additionally perform an essential role in securing the reliability and privacy of the data.

CO2 Controller
The ideal level of carbon dioxide in the greenhouse is set by the CO2 Controller. The photosynthesis process of plants utilizes CO2, and the level of CO2 has a direct impact on how plants grow and CY. In order to sustain optimal CO2 levels for the development of crops, this device constantly monitors and responds to data from CO2 sensors.

Irrigation Controller
This controller is responsible for the drip system in the greenhouse. The irrigation controller ensures that crops obtain a suitable quantity of water through data from moisture levels in the soil sensors. This eliminates either over- or under-watering. Aside from minimizing water waste, this approach of accurately regulating water use supports plants' robust growth.

Nutrient Controller
The Nutrient Controller is vital to soil-based cultivation and hydroponic gardening systems. To regulate the water's level of nutrients and substances, data from pH and NPK sensors are employed as an indication. In this manner, crops can be sure they are receiving the nutrients they require at an appropriate time for their particular growth phase.

Temperature Controller
This controller preserves the optimal range of temperatures for the greenhouse. Incorporating data from both internal and external temperature measurement devices regulates the HVAC. This provides a constantly ideal atmosphere for the development of plants, ignoring modifications to the external climate.

The Edge Layer's elements function together to develop a controlled, automatically adaptable, and productive greenhouse atmosphere. More accurate regulation of greenhouse conditions can be obtained by the Edge Layer's processing of the data analytics layer's output, significantly decreasing response times. The green design principles boost CY while enhancing the system's overall EC.

Data Analytics Layer

Stored, analyzed, and processed here are valuable findings from the enormous quantities of data the Sensing and Edge Layers collected. Its main tasks are data management, analysis, and Machine Learning (ML).

Data Storage

Protecting a chronological repository of collected data depends on this function. The capacity to store data for a longer time in a greenhouse makes it feasible to study correlations in factors like climate, crop development, and the use of resources. To ensure the confidentiality of data, its availability, and compliance with privacy laws, the selection of storage solutions—whether cloud-based or onsite—depends on the quantity of data, privacy concerns, and accessibility.

Data Processing

Data cleansing, the normalization process, and transformation are all phases in the processing and conversion process that must be performed for data storage in order to render it appropriate for analysis. There are two primary types of data analysis: batch processing, which analyzes enormous data sets at scheduled times, and accurate-time processing, which starts immediately after data is collected. In order to prepare the data for practical analysis, this phase is essential in eliminating noise, correcting errors, and cleaning the data.

ML

Findings, developments, and predictions in data processed have been rendered possible by this layer's ML algorithms. ML is employed for predictive analytics in the context of greenhouses to perform tasks like predicting crop development patterns, predicting when diseases will occur, and optimizing the use of resources. To determine when crops require more water or nutrients, an ML model could look at historical and current data. Determining the best times for planting and harvesting crops is merely one instance of how it may support DSS.

With the integrated Data Analytics Layer's elements, researchers can recognize the greenhouse environment and the agricultural product's life cycle from start to finish. The effectiveness, profitability, and environmental impact of greenhouse systems can be improved with their support in making intelligent choices. To make better, more data-informed decisions and more accurate predictions, statistics have grown more complicated with the incorporation of ML.

User Interface Layer

Turning complicated data and analytics into acceptable practical findings for end-users is the task of the User Interface Layer. Using this layer's user-centric layout, the entire system's features and data are simple to find. This methodology includes systematic decision-making, continuous control, and cultivation management.

Integrated Control System

Users can manually control the greenhouse's relative humidity, temperature, CO2 levels, and sunlight via the Integrated Control System or allow the device to adapt to shifting conditions based on sensor data. For GCM, the Cultivation Management System is beneficial for scheduling, tracking, and monitoring development and health. Planting and harvesting times, development stages, and nutrient forms and quantities are all components of this procedure.

Decision Support System (DSS)

The key component of the framework, the User Interface Layer, uses ML and data analytics to help with decisions. It can make recommendations based on past information, current state, and predictive modeling. The DSS could, for example, propose when to plant or harvest crops, predict when pests will strike, or direct the proper use of resources to achieve the highest yields while limiting the negative environmental effects. GCM can use this framework to assist people in generating decisions based on information.

The User Interface Layer integrates the system's complex analytics and data processing into the greenhouse's routine duties. It enables control and monitoring, supports transforming data into useful information, and reinforces strategic DSS with an easily accessible and user-friendly interface. This layer is essential to maximize the benefits of cutting-edge analytics and IoT technologies in the practical GCM.

Study Area

A suitable location for research for the previous model would be a capsicum farm in Kenya's Naivasha geographic area. Naivasha State provides an appropriate and feasible context for this research due to its pleasant weather and history as an agricultural powerhouse.

(a) (b)

Fig 2. Capsicum Cultivation A) Greenhouse, B) Open-Field.

Capsicum Farm in Naivasha, Kenya

Capsicums grow in Naivasha's moderately temperate environmental conditions, which provide approximately an adequate amount of direct sunlight, moderate rainfall, and suitable temperatures. Production is possible year-round, yields are higher, and nutritional value is improved due to the farm's use of regulated greenhouse conditions for optimal development. However, a more environmentally friendly and balanced approach to SF is open-field cultivation, which involves growing capsicums in their natural environment **Fig 2 (a)** and **(b).** The technique provides unique challenges regarding development dynamics compared to greenhouse cultivation because it relies on local climate and seasonal changes. While the soil and weather are suitable for open-field cultivation in Naivasha, farmers must be adaptive to deal with the unpredictability of their surroundings.

This capsicum farm in Naivasha demonstrates a dynamic and constantly evolving use for the SF environment. Integrating cutting-edge GCM and traditional open-field farming techniques provides a perfect experiment for using an IoT-based agricultural system to improve CY, efficiency, and lifespan in many different farming conditions. Numerous capsicum varieties and local climate factors impact the overall recommendations for the Capsicum plant, which are laid out in **Table 1**.

Table 1. At Different Growth Stages, Capsicum Needs

Growth Stage	Temperature (°C)	Humidity (%)	Soil Moisture (%)	pH	Light (Hours/Day)
Seed Germination (0-14 days)	22 - 25	60 - 70	40 - 50	6.0 - 6.8	14 - 16
Seedling (15-42 days)	20 - 22	60 - 70	50 - 60	6.0 - 6.8	14 - 16
Vegetative Growth (43-103 days)	18 - 22	50 - 60	60 - 70	6.0 - 7.0	14 - 16
Flowering (104-124 days)	18 - 20	40 - 50	70 - 80	6.5 - 7.0	12 - 14
Fruit Development (125-195 days)	20 - 22	40 - 50	70 - 80	6.5 - 7.0	12 - 14
Ripening (196-225 days)	18 - 20	40 - 50	60 - 70	6.0 - 6.8	12 - 14

Integration of the Proposed Architecture

In order to include the recommended GCM in an indoor capsicum farm, several types of sensors are set up to monitor and regulate the environmental factors.

The sensors that were used in the present investigation are explained below:

Temperature and Humidity Sensor

The DHT11 is an energy-efficient sensor **Fig 3**, operating within a voltage range of 3.5 V to 5.5 V. It's notable for its low power consumption, using only 0.3 *mA* during active measurement and 60 *uA* in standby mode. Using serial data output, the sensor accurately measures temperatures from 0°C to 50°C and humidity from 20% to 90%. The 16-bit resolution provides accurate temperature and humidity reports of ±1°C and ±1%, respectively. The DHT11 excels at monitoring vital environmental conditions in the capsicum greenhouse, providing accurate data for GCM.

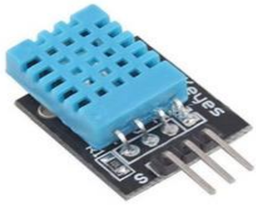

Fig 3. DHT11 Temperature and Humidity Sensor.

PH Sensor

The E201-C BNC Electrode pH Sensor **Fig 4** is an energy-efficient option for soil pH measurement in greenhouse settings, operating at a 5-0.2 V voltage range and 5-10 mA current. The pH test range is 0–14, and it detects water temperatures from 0–80°C with high precision. With an initial stabilization interval of 60 seconds and a response time of less than 5 seconds, the sensor provides precise and on-time results. Designed to handle the variable temperatures of a capsicum greenhouse, it features a low EC of a maximum of 0.5 W, can operate from -10 to +50°C, and can support moisture levels up to 95% RH. There are four M3 mounting holes and analog output on a tiny device that measures 42x32x20 mm, which makes it simple to integrate into prior systems for farming.

Fig 4. E201-C BNC Electrode pH Sensor.

Soil Moisture Sensor

The sensor for soil moisture associated with SKU: SEN0114 **Fig 5** can be used in greenhouses; it requires an electrical power source of either 3.3 or 5 volts and gives a signal voltage value between 0 and 4.2 volts. It has a simple three-wire interface that requires only 35 mA of current, allowing it to be installed entirely. Suitable for accurate irrigation management in capsicum cultivation, this small (60×20×5mm) moisture sensor precisely measures moisture in the soil levels from 0 to 300 for dry ground, 300 to 700 for humid soil, and 700 to 950 when submerged in water.

Fig 5. SEN0114 Soil Moisture Sensor.

Nutrient Sensor

Built for application in agricultural environments, the JXBS-3001-NPK-RS sensor **Fig 6** functions on a 9.24V electrical supply. With a range of 0–1999 mg/kg (ml/l), it precisely measures NPK levels, which makes it suitable for precise nutrient management in greenhouse soils. The sensor's automated temperature compensation (ATC) enables it to function accurately in a range of temperatures, from 5-45°C (41-133°F), **subject** to outside conditions. Accurate nutrient data can be collected with its 1mg/kg (ml/l) level and ±2% F.S. precision. The sensor outputs data via RS485 signal, with an additional 0-10V output option, making it compatible with various control and monitoring systems. This focus on NPK measurement makes it an essential tool for optimizing fertilizer application and ensuring healthy capsicum growth.

Fig 6. JXBS-3001-NPK-RS Sensor.

The sensor layer of the system is centered around the ATmega328 microcontroller ESP8266 Wi-Fi module and is powered by a tps563201 drive. The ATmega328 **Fig 6 (a)** is a versatile 8-bit microcontroller with 32 KB ISP Flash memory, 2 KB SRAM, 1 KB EEPROM, various I/O lines, and communication interfaces like USART, SPI, and a two-wire serial interface. It also includes a 6-channel 10-bit A/D converter and operates between 1.8-5.5 volts. The ESP8266 module **Fig 6 (b)**, running on a 32-bit RISC processor at 80 MHz, offers substantial memory (32 KiB instruction RAM and 80 KiB user-data RAM), supports up to 16 MiB external flash, and features IEEE 802.11 b/g/n Wi-Fi, multiple GPIO pins, and interfaces like SPI, I²C, and UART. Together, these components facilitate robust data collection and wireless transmission in the greenhouse management system.

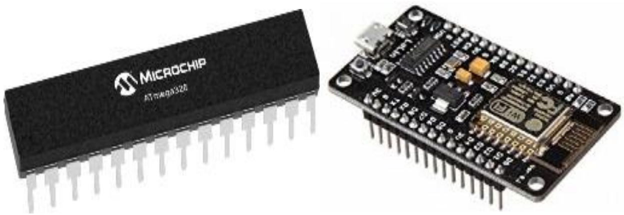

Fig 6. a) Atmega328 Microcontroller B) ESP8266 Wi-Fi Module.

The edge layer of the system is constructed using the ATmega328 microcontroller, integrated with the ESP8266 Wi-Fi module and the SX1278 LoRa Module Ra-02 **Fig 7** for wireless communication, all powered by the tps563201 power module. The ESP8266 provides robust Wi-Fi connectivity, while the SX1278 LoRa Module, operating at 433MHz and based on SEMTECH’s SX1278 wireless transceiver, is pivotal for long-range communication up to 10,000 meters. It utilizes advanced LoRa spread spectrum technology, offering significant anti-jamming capabilities and low power consumption with air wake-up functionality. The SX1278 module stands out for its high sensitivity (-148 dBm) and power output (+20 dBm), ensuring long transmission distances and high reliability. This integration of Wi-Fi and LoRa technologies, coupled with the efficient power management of the tps563201 module, makes the edge layer highly capable of handling long-distance, low-power, and reliable communication in diverse and challenging agricultural environments.

Fig 7. SX1278 LoRa Module.

The edge devices in the system are designed to receive sensor data from the sensor layer and then forward this data to the data analytics layer. Once they receive analyzed insights and decision directions from the analytics layer, these devices effectively control the greenhouse's water, fertilizer, and cooling systems. To facilitate this, the edge devices are equipped with specific components like solenoid valves, flow sensors, and air and pad systems, ensuring a controlled and optimized environment for capsicum cultivation.

The A3-7IRU-ZZN0 Solenoid Valve **Fig 8 (a)** and YF-S201 Flow Sensor are used in this work to manage irrigation and environmental control. The solenoid valve, designed to control air, water, oil, and gas flow, is a directly driven, normally closed valve with a 16 mm flow bore, operating within a temperature range of -5 to 80°C and a pressure range of 0-10 kg/cm². AC220V powers it and has a brass body. The YF-S201 Flow Sensor **Fig 8 (b)**, operating on 5~18V, measures water flow rates from 1 to 30 L/min with an accuracy of ±10%. It functions effectively in temperatures from -25 to +80°C and can handle water pressures up to 2.0 MPa. These components are integral for precision control in greenhouse irrigation and environment management.

Fig 8. a) A3-7IRU-ZZN0 Solenoid Valve, b) YF-S201 Flow Sensor, and c) Celdek Evaporative Cooling Pad System.

The Celdek Evaporative Cooling Pad System ensures that an optimal environment within the greenhouse is made more accessible **Fig 8 (c).** It depends on the evaporative cooling method, which consists of flowing water through unique feminine hygiene products, for its operation. Crops like capsicum thrive in the atmosphere that flows through these Celdek pads as they become more excellent and humid. Because it regulates humidity and temperature, this control system is invaluable in dry, hot climates. The Celdek system is prominent for its success and lifespan; it generates an atmosphere that eliminates plant trouble, supporting proper development and higher CY. Enhancing energy efficiency and region control and integrating them is essential for contemporary GCM.

Data Analytics Using RF

The preprocessing step of sensor data plays a role in the Data Analytics stage of the GCM, particularly for its subsequent evaluation using RF algorithms. When data is prepared correctly, the ensemble learning method RF is highly used in classification and regression tasks. To ensure the RF model is as precise as feasible, the primary phase in preliminary processing is to clean the sensor data to eliminate noise or unnecessary data. Key measurements such as temperature, soil moisture, humidity, and levels of nutrients must be inspected for anomalies. The following phase uses standardization or normalization techniques to ensure that all the sensor data has an identical scale. While RF algorithms are not concerned significantly about data size, it is still an excellent idea to standardize the data so that various data types remain coherent.

A further significant step in preliminary processing is Feature Selection (FS), which requires identifying and selecting appropriate features that impact the crop's development and health. Because they impact the model's prediction accuracy, FS is essential for RF. Soil moisture, nutrient levels, and temperature in the environment are all essential factors that might serve as predictors in this scenario. Finally, the appropriate RF processing of the data was finished. This involves inventing new features that might give the model additional information or converting statistical formats from classification data. To make accurate predictions and decisions about GCM, it is essential first to preprocess the data so that the RF algorithm can identify patterns and developments.

For many types of data analysis tasks, such as FS, classification, and regression, RF—a secure and adaptable ML—works considered in a GCM. After training, this model develops several decision trees, which it applies to identify the type of classification it experiences frequently or to determine an average prediction for regression.

Key Aspects of RF in Greenhouse Data Analysis:

Ensemble Learning

When addressing large datasets, RF can help avoid bias by integrating the predictions from different ML.

Handling Multifaceted Data

The data extracted from greenhouses is heterogeneous and non-linear. Crop environmental factor evaluation is an excellent match for RF due to the complicated relationship of its factors.

Feature Importance Analysis

According to the RF's potential to evaluate moisture in the soil, relative humidity, and the outside temperature, modeling accuracy is substantially improved. With that information, researchers can identify the most essential factors affecting health and CY.

Versatility with Data Types

RF analyzes data that is simultaneously statistical and classified. The data from greenhouses, including soil pH and temperature tests, are suitable for this adaptable sensor.

High Accuracy and Noise Resistance

With the support of decision tree standard deviations, RF reaches outstanding accuracy and resilience. It enables it to control noise in practical problems and sensor data efficiently.

User-Friendly and Interpretable

Deep Neural Networks (DNNs) are more complicated and complex to comprehend and operate with than RF. Because of this, models are suitable for use in the agricultural sector, where the model's accuracy is as important as the decisions made.

Dynamic Adaptability

If updated with fresh data, greenhouse RF can adjust to changing crop development patterns and environmental changes in the climate.

Improved DSS and productivity in greenhouses result from using the RF model as a predictive and analytical tool for GCM. This model improves at processing complex data sets while maintaining accuracy, adaptability, and accessibility.

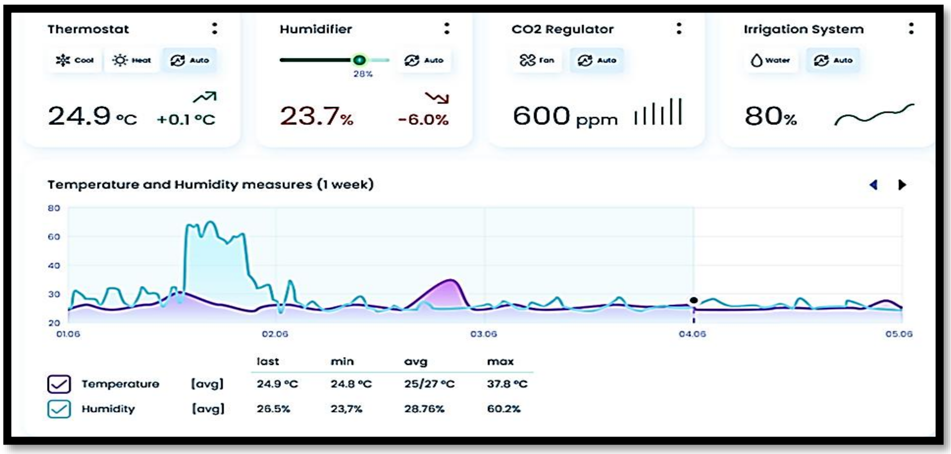

Fig 9. Dashboard of the GCM.

User Interface Layer

The GCM's state-of-the-art interfaces indicate the present greenhouse gas emissions. This console acts as a dashboard, displaying real-time updates from all sensors and control devices to control environmental parameters and components like temperature and humidity sensors, soil moisture meters, and automated irrigation systems **Fig 9**. Users can adjust irrigation system settings and nutrient delivery rates for optimal crop care using the console's advanced manual adjustment features. Graphs and color-coded alerts make the control system console easy to use for non-technical users. It uses predictive analytics and decision support for proactive GCM.

IV. IMPLEMENTATION ANALYSIS

The analysis of the graphs **Fig 10** and **Fig 11** provided for a greenhouse environment over 24 hours reveals critical insights into the climate control system's performance, particularly concerning temperature and humidity management, as well as irrigation practices for capsicum cultivation in Kenya during September.

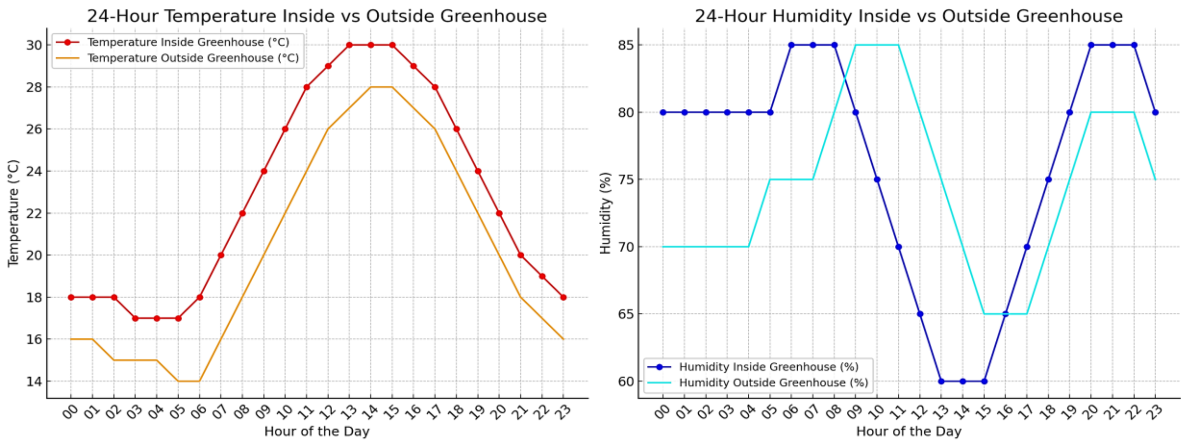

Fig 10. a) Temperature Measurement B) Humidity Measurement.

The temperature graph **Fig 10 (a)** indicates a stable internal greenhouse environment, with temperatures ideal for capsicum plant growth. Inside temperatures start at 18°C in the early hours, gradually increasing to a peak of 30°C during the midday before tapering off in the evening.

Despite the outside variations in temperature, which have a more evident daily cycle, this regulated temperature range is maintained. Additionally, the greenhouse's temperature control system has effectively minimized the impact of outside factors, such as warmer peak temperatures and more relaxed night temperatures, consequently maintaining an atmosphere good for capsicum growth. A controlled increase in internal humidity levels in the early morning hours is shown in the humidity histogram **Fig 10 (b)**, which is probably caused by routine watering or rainfall impacts. For capsicum plants to avoid becoming turgid and ensure photosynthesis and transpiration are productive, the humidity inside the greenhouse must be much greater than outside all day. The dip in external humidity during midday suggests an increase in temperature, which is well-managed within the greenhouse to prevent excessive plant transpiration stress.

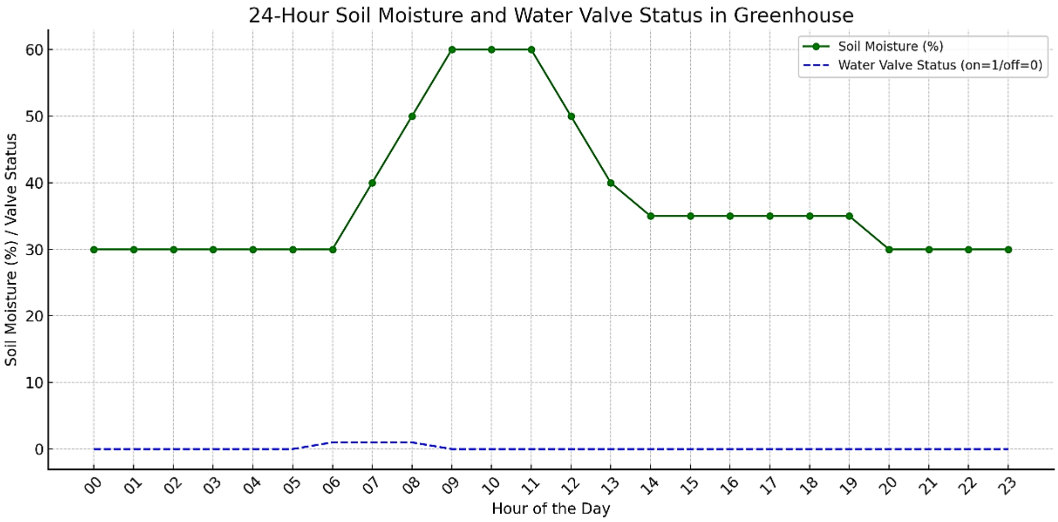

Fig 11. Soil Moisture and Water Valve Status.

The soil moisture and water valve status graph **Fig 11** demonstrates an irrigation event between 06:00 and 08:00, where the soil moisture level rises sharply from 30% to 60% before gradually decreasing as the plants utilize the water. The water valve status indicates that the irrigation system is automated, turning on when soil moisture drops to a certain threshold, ensuring that the capsicum plants have adequate water supply without the risk of waterlogging. The climate control and irrigation systems effectively maintain the greenhouse conditions within the optimal ranges for capsicum cultivation. The precision in temperature and humidity regulation, alongside timely irrigation, suggests that the greenhouse management system is well-tuned to the needs of the crop and the local Kenyan climate in September. This balance is crucial for the capsicum plants' health and maximizing yield and resource efficiency.

Table 2. Comparison of Performance

Algorithm	Prediction Accuracy (%)	Energy Consumption
FA-C	89	0.567
APSO-ANN	90.5	0.687
RF	94	0.262

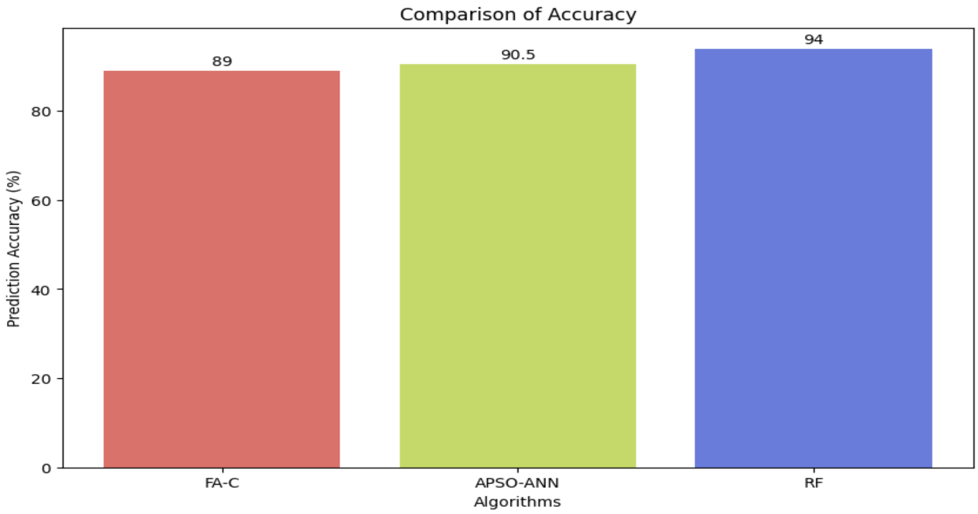

Fig 12. Comparison of Accuracy.

Table 2 analyzes the prediction accuracy and EC of three algorithms (RF, FA-C, and APSO-ANN), and the findings demonstrate the following: With a prediction accuracy of 94%, the RF algorithm superiors the other two algorithms. In second place, with a prediction accuracy of 90.5%, APSO-ANN is closely following RF but superior to FA-C, which comes finally with an accuracy of 89%.

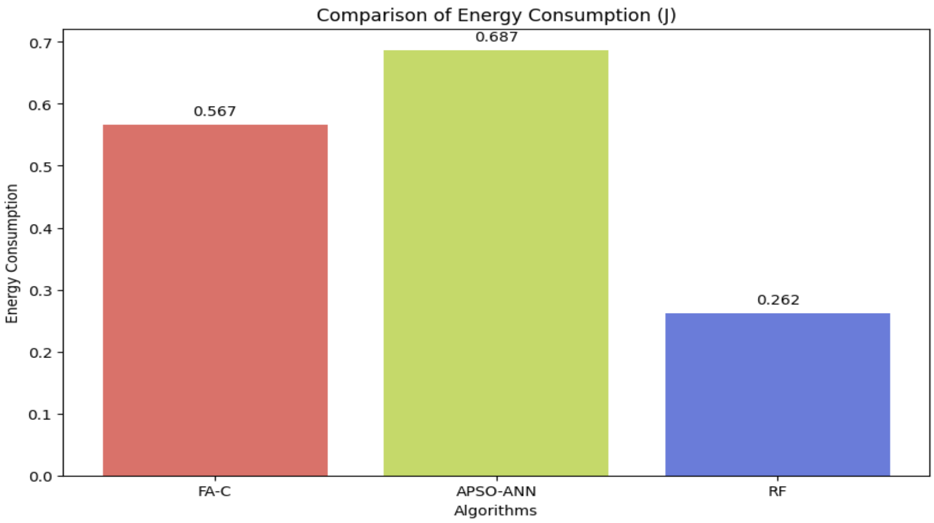

Fig 13. Comparison of EC.

Among the algorithms investigated, RF has the highest EC at 0.262, thus being probably the most efficient. With an EC of 0.567, FA-C improves RF but drops low APSO-ANN. The highest EC, at 0.687, was achieved by APSO-ANN, which has an approximate high accuracy. **Fig 12** illustrates the prediction accuracy, and **Fig 13** provides the EC of the algorithms, which can be evaluated graphically. When comparing algorithms, RF represents the best solution due to its low EC and high accuracy.

V. CONCLUSION AND FUTURE WORK

At the end of introducing an IoT-based Greenhouse Crop Management (GCM) system, there has been tremendous promise in enhancing the productivity and lifespan of capsicum production in Kenya. Smart Farming (SF) innovations are demonstrated by the system's multilayer design incorporating real-time data acquisition, intelligent analytics, and user-centered control. The model enhances Crop Yields (CY) and Decision-Making Systems (DMS) through the use of Edge Computing (EC) and ML, specifically the RF, to provide accurate, data-driven conclusions. By reducing problems to entry according to a farmer's level of knowledge in the field, the user interface renders SF technology more functional in practical problems in agricultural conditions.

A significant development could be the introduction of IoT and intelligent data analysis into SF; this could set benchmarks for other areas with similar agricultural histories, boosting the global trend toward food safety and sustainable farming.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Nabeel S Alsharafa, Sudhakar Sengan, Santhi Sri T, Arivazhagan D, Saravanan V and Rahmaan K; **Methodology:** Arivazhagan D, Saravanan V and Rahmaan K; **Software:** Sudhakar Sengan, Santhi Sri T and Arivazhagan D; **Data Curation:** Nabeel S Alsharafa, Sudhakar Sengan and Santhi Sri T; **Writing- Original Draft Preparation:** Sudhakar Sengan, Santhi Sri T and Arivazhagan D; **Visualization:** Arivazhagan D, Saravanan V and Rahmaan K; **Investigation:** Nabeel S Alsharafa, Sudhakar Sengan and Santhi Sri T; **Supervision:** Arivazhagan D, Saravanan V and Rahmaan K; **Validation:** Nabeel S Alsharafa, Sudhakar Sengan and Santhi Sri T; **Writing- Reviewing and Editing:** Nabeel S Alsharafa, Sudhakar Sengan, Santhi Sri T and Arivazhagan D; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests

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