LoRaWAN Hybrid Approach for IoT-Based Smart Farming Using Environmental Data and Machine Learning

Shaikh Navid Ahmed[1], Gazi Tawsif Turabi[2], Abu Talha[3], Md Harun-Ur-Raiyan[4], and Md. Motaharul Islam[5]
Department of CSE, United International University, Dhaka, Bangladesh
{sahmed201052, gturabi201467, atalha201043, mraiyan201066}@bscse.uiu.ac.bd, motaharul@cse.uiu.ac.bd

***Abstract*—The integration of LoRaWAN technology with smart farming practices offers a powerful solution for sustainable agriculture and efficient environmental monitoring. In this study, we propose a hybrid approach that combines LoRaWAN communication with energy-efficient techniques to enhance agricultural productivity and reduce resource consumption. Our system leverages sensor nodes deployed across the farm to collect real-time data on soil moisture, temperature, humidity, and other relevant parameters. These data are transmitted via LoRaWAN to a central gateway, where a Machine Learning-based decision-making system processes the data. This system enables farmers to make informed decisions about irrigation, fertilization, and pest control by analyzing the collected data. Additionally, we explore energy harvesting methods to power these sensor nodes, ensuring long-term operation without frequent battery replacements. By optimizing energy consumption and leveraging LoRaWAN's long-range capabilities, our approach contributes to sustainable agriculture and effective environmental monitoring. Furthermore, the integration of Machine Learning enhances decision-making, allowing for automated and more efficient resource management, and advancing smart farming practices.**

***Keywords*—LoRaWAN, Smart farming, IoT, Sustainable energy.**

I. Introduction

In recent years the adoption of Internet of Things (IoT)-related technologies in sectors focused on smart farming & agriculture has increased significantly. The use of smart agricultural techniques has grown essentially as the world's food demand grows and environmental concerns become more serious. For sustainable agriculture to continue energy-efficient methods and innovative communication technologies must be combined. To increase agricultural production and reduce resource consumption, a hybrid method is proposed in this research that explores the potential connections between LoRaWAN technology and smart farming.

Known for its long-range and low-power features, LoRaWAN technology is used to build a strong communication network across agricultural fields. Real-time data on vital factors including soil moisture, temperature, and humidity are gathered on the farm by placing sensor nodes throughout. These sensor nodes use LoRaWAN to send data to a central gateway, ensuring reliable and efficient communication over long distances while consuming a small amount of energy.

At the central gateway, a machine learning-based decision-making system analyzes the collected data. Using data analysis, this system provides helpful guidance on fertilization and watering. The system can predict optimal resource management plans using machine learning algorithms, which improves decision-making and helps change field conditions.

Our proposed solution is to optimize energy usage while using LoRaWAN's long-range capabilities and to create a hardware and software Eco-system to provide smart resource management and environmental monitoring in agriculture. The Eco-system enables smart farming practices that increase the efficiency and sustainability of agricultural operations by combining machine learning with real-time data collection. The end-user and stakeholders will be benefited with ease of information processing and farm management along with plug-and-play like operation with different farming hardware modules and management software providing data analysis and decision making using machine learning models.

This paper's significant contributions are as follows:

- We have implemented and designed energy-saving methods with LoRaWAN to enable effective agricultural communication. The use of improvised algorithms in end-device firmware focused on saving energy of node devices will significantly improve the sensor nodes' and agricultural devices' performance. But also reduce human intervention to change power sources or maintenance in the long run, saving time and energy.
- We have applied machine learning to make data-driven resource management decisions to enhance the decision-making process for farmers, particularly in determining the optimal fertilizer to use. Our method greatly increases the efficiency and precision of these choices by incorporating machine learning predictions, which raises crop yield overall. This innovative approach simplifies and speeds up the decision-making process, enabling farmers to react to crop needs more quickly and efficiently. In addition, the usage of data-driven insights results in an agricultural system that is more productive and efficient by optimizing resource utilization, minimizing waste, and promoting more sustainable farming practices.
- We have put energy harvesting techniques into use to power sensor nodes, ensuring sustainable and long-term operation. Sensor nodes in crop-fields on in agricultural infrastructures will be equipped with renewable energy source or cells, which will allow them the minimize

energy draw from primary energy cells (eg. Battery) and will make the sensor nodes sustainable and occur less human or manual intervention in the long run.

- We have designed a hardware and software Eco-system to seamlessly operate the nodes and devices with the central gateway and the management software to assist user with farming operation automation and data analysis.

  The main structure of this study, In Section 1, an energy-efficient farming system is introduced as a way of addressing farming issues. To maximize farming methods, the study offers a LoRaWAN Hybrid Approach for IoT-based Smart Farming that makes use of machine learning and environmental data. Section 2 provides a discussion of studies relevant to our research topic. we examined the current literature and methodologies used in smart farming, IoT-based solutions, and environmental data integration for agricultural practices. Table 1 presents a detailed analysis of the research gaps highlighting areas where further innovation is needed. In Phase 3, we conducted a comparative analysis between two machine learning models for the task of fertilizer type prediction it highlights the importance of selecting the right algorithm based on the characteristics of the dataset.

II. LITERATURE REVIEW

A. LoRaWAN & IoT

Codeluppi et al. developed the LoRaFarm modular IoT architecture for smart farming, demonstrating its effectiveness in scalable, customized data collection and environmental monitoring to optimize crop and greenhouse conditions [1]. Kadusic et al. analysis of LPWAN technologies highlights that Sigfox, LoRaWAN, and NB-IoT are the leading solutions in the IoT market, each offering unique advantages and limitations in terms of scalability, bandwidth, data rate, coverage, power consumption, and security for smart IoT applications [2] . Rebeiro et. al. proposed an analysis of LoRa and NB-IoT to show that LoRa offers better coverage in urban environments. NB-IoT uses directional antennas and provides superior coverage in rural areas using sub-GHz frequencies [3]. Marini et al. compared LoRaWAN and NB-IoT for LPWAN applications, finding NB-IoT better in range and reliability due to directional antennas, while LoRaWAN outperforms in energy efficiency but is more sensitive to interference and latency [4]. Ballerini et al. compared LoRaWAN and NB-IoT in an industrial IoT context, showing LoRaWAN's lower energy consumption for latency-sensitive communications and NB-IoT's efficient energy use with buffering, offering insights into optimal use cases for each technology [5]. Islam et. al. proposed LoRawan smart farming with a range of over 10 kilometers and a low power usage of 15.36 mAh per day, LoRaWAN is ideal for smart farming since it allows for distant, energy-efficient monitoring and control without the need for LTE or other backup networks [6]. Haxhibeqiri et al. demonstrated that LoRa, with its long-range, low-power, and low-bit-rate capabilities, effectively supports large-scale, low-bandwidth industrial IoT applications by providing extensive coverage and accommodating up to 6000 nodes with a single gateway [7]. Cheong et al. highlighted how IoT applications benefit from LoRaWAN as it consumes less power and provides long-range connectivity. He also discussed the three device classes of LoRaWAN and compared their energy consumption and battery life [8].

Ismail et. al. discussed LPWAN technologies to overcome the restrictions of existing networks to provide long-range, low-power communication, they also present issues related to spectrum management, coexistence, mobility, and security [9]. Polonelli et al. proposed a paper where he mentioned a low-cost low-power sensor for Structural Health Monitoring(SHM) systems to measure and track cracks in concrete and other materials. He combined the sensor with a microprocessor which is LoRaWAN. The tests highlighted that it provides $1\mu m$ accuracy and the lifetime is over 10 years [10]. Augustin et al. found that in LoRa, the chirp spread spectrum modulation and high receiver sensitivity offer less interference and can offer network coverage up to 3 km in a suburban area with dense residential dwellings [11]. Castro Tomé et al. discussed LoRa technology in smart electricity grids, highlighting how interference affects communication reliability and comparing time-based versus event-based sampling for more efficient data transmission [12]. Ballerini et. al. compared the performance of NB-IoT with LoRaWAN, indicating that LoRaWAN achieves 10× lower energy consumption for the same payloads, supporting longer device lifetimes and energy-efficient operation. In contrast, NB-IoT's transmission energy is unaffected by payload length [13].

Venkatesan et al. proposed IoT's rapid growth, comparing its technologies and communication features while identifying challenges such as the need for service-oriented approaches and middleware architectures, and suggesting IoT gateways to enhance data handling and application integration [14]. Davcev, et al. presented a model of an IoT agricultural system that utilizes LoRaWAN for data transmission from the sensor nodes to cloud services and The Things Network platform that implements LoRaWAN's backend services [15] . Muhammad Ayaz et al. analyze the potential applications of IoT and wireless sensors in agriculture and the difficulties in combining new technology with conventional farming methods. In addition to discussing how IoT technology may support farmers throughout the agricultural cycle and cover different sensors [23].

B. Machine Learning

Leo Breiman et al. proposed an algorithm of Random Forest that provides adaptability against noise and variable important assessment by combining tree predictors to produce converged generalization error [29]. Archana Kumaravel et al. proposed a system to focus on soil macronutrients (NPK), pH, electrical conductivity, and temperature to provide suitable crop suggestions. Using a voting-based ensemble classifier algorithm, the system achieves an accuracy of 92% in suggesting appropriate crops [17]. S. Veenadhari et al. created a study method of "Crop Advisor," an intuitive web tool to forecast how climate elements will affect crop output. The program mainly used the C4.5 algorithm [18]. Devdatta A Bondre et al. proposed a study that indicates crop yield prediction using machine learning techniques. The system uses machine learning algorithms, specifically Support Vector Machine and Random Forest, to predict crop yield based on historical data [19]. Musanase et al. present an innovative approach to precision farming combining ML and the IoT to optimize crop productivity and resource use [20].

Abhinav Sharma et al. offer a solution driven by ML and the IoT focusing on predicting soil parameters, crop yield prediction, disease and weed detection, species detection, computer vision for crop image classification and quality assessment, livestock production enhancement, and intelligent irrigation and harvesting techniques to reduce labor [21]. Yogesh R. Shahare et al. provide a technique that uses soil chemical data to categorize soil levels. Classification and regression methods employed to predict soil levels and using a random forest algorithm achieved 93% training accuracy and 83% testing accuracy [22]. Pandith et al. proposed machine learning techniques for predicting mustard crop yield based on soil nutrient analysis, concluding that KNN and ANN outperform other methods in accuracy, recall, precision, and specificity [24]. Kumar T G. et al. proposed machine learning to analyze soil properties, grading soils based on nutrients like EC, pH, and OC, and recommending suitable crops. It finds that Random Forest offers the highest accuracy for crop prediction compared to other classification algorithms [25].

C. Gap analysis

In Table II-C, We present a gap analysis of past works in which we have found scope for improvement by implementing a hybrid methodology. Our proposed approach specifically includes Machine learning data automation for decision-making and energy sustainability to overcome the shortcomings of current technology. We have improved the system's ability to predict and optimize agricultural results by introducing machine-learning approaches for predictive data analysis. Our system now contains supercapacitors for improved power supply to sensor nodes to improve energy sustainability. This development reduces possible problems related to energy supply ensuring long-term dependable functioning. Also by merging energy sustainability and machine learning our method closes a gap in the literature and builds a strong hybrid system that provides full support for sustainable agricultural methods.

III. The Proposed Methodology

A. Phase 1: Sensor Node

*1) **Solar Energy Harvesting Cell**:* Sensor nodes are typically deployed in agricultural fields. To extend their operational period and minimize human intervention, we propose using a solar panel to charge both primary and auxiliary power sources. The solar panel should be compact enough to fit on the sensor node. However, smaller solar panels generate less current. For instance, a 90x90 mm solar panel can produce a maximum of 200mA under optimal conditions. In reality, the solar cell won't always operate at peak efficiency. While the solar energy harvesting cell won't fully charge the power cells, it will decrease the frequency of manual recharging required for the sensor nodes.

*2) **Power Management Unit**:* The Power Management Unit (PMU) is what we are proposing to develop inside each sensor node, which will be capable of monitoring the primary and the secondary power source charge state and switch between the primary (Supercapacitor) and the auxiliary power source, which is the Energy storage unit (Sodium Ion Battery). PMU delivers power to the power distribution board which is responsible for powering each component in the sensor node by providing the required voltages. PMU will be monitoring the battery voltage and sending the battery voltage level to the central microcontroller unit in the sensor node over UART communication. In extreme weather conditions when renewable energy sources aren't available, the PMU will detect it by measuring the current from the solar energy cell. Then the sensor node will utilize the auxiliary power source. The power management unit will be able to send out manual diagnostic requests to the end user by sending a message to the local server in case of sensor or auxiliary power failure.

*3) **Energy Storage Unit**:* Sodium-ion batteries offer a cost-effective and environmentally friendly alternative to lithium-ion batteries. They provide a stable voltage output and have lower energy density compared to lithium-ion batteries, but much safer. Less environmental effects and lower costs make them suitable for long-term deployment in agricultural fields. The sodium-ion battery will be charged by the solar panel and serve as the auxiliary power source when solar energy is insufficient. Its ability to operate efficiently in various environmental conditions ensures the reliable performance of the sensor node, reducing the need for frequent maintenance and manual recharging.

*4) **Supercapacitor Bank**:* Supercapacitors are widely used for rapid charging and discharging for powering small electronic devices. We are integrating a supercapacitor bank to buffer power between the solar panel and the battery, leveraging its rapid charging properties. This setup ensures that energy harvested from the solar panel is quickly stored and subsequently delivered to the sodium-ion battery as needed. This will help smooth out fluctuations in the power supply, providing a more consistent energy flow to the sensor node. Additionally, the supercapacitor's ability to endure numerous charge-discharge cycles without significant degradation further extends the lifespan of the power management system.

*5) **Microcontroller Unit**:* For the central microcontroller unit, we have chosen the ATmega328p VQFN (Very-Thin-Profile Quad Flat No-Lead Package) microcontroller chip. This features a 20MHz 8-bit processor. This microcontroller also supports various communication interfaces, such as USART and SPI, which are required to communicate with the PMU and the Sensor modules attached to the sensor node, making it highly versatile for this application. The VQFN package is particularly advantageous for compact designs due to its small footprint and excellent thermal performance. This makes the

Author	Contribution	Limitations	Methodology
Schreck et al. [2023] [26]	This study presents the development and evaluation of LoRaFarM, a low-cost, modular IoT platform based on LoRaWAN for smart farming. Collecting environmental data over three months to optimize farm management and improve sustainability.	The proposed system has limitations on AI-driven automation techniques for predictive data analysis	A web-based visualization tool was used to validate the data and the effectiveness of the LoRaFarM architecture.
Boonyopakorn et al. [2020] [27]	This study proposed an environment monitoring system using a LoRaWAN Network to collect real-time weather and humidity data, which will be interpreted and displayed via a web application.	The proposed system has limitations in energy sustainability as it does not utilize supercapacitors for better power delivery leading to potential issues with long-term and reliable operation of sensor nodes.	The proposed method involves deploying sensor nodes across the target area to collect real-time environmental data.
Arshad et al. [2022] [28]	The study proposes a smart Decision Support System for agriculture, integrating IoT sensors via LoRa for sustainable farming practices, enhancing crop yield.	Absence of energy-efficient architecture and renewable energy usage and machine learning integration.	Utilizing LoRa for long-range data transmission and an Android application for remote monitoring.
Marini et al. [2022] [4]	This study compares LoRaWAN and NB-IoT, two key LPWAN technologies for IoT applications, evaluating their features and performance to guide technology selection.	The primary limitation of NB-IoT is the variability in coverage, affecting reliability in dense urban or remote areas.	Employing quantitative methods to compare performance metrics like coverage range, data rate, latency, scalability, energy efficiency, and regulatory considerations.
Kadusic et al. [2022] [2]	This paper compares Sigfox, LoRaWAN, and NB-IoT, focusing on their scalability, bandwidth, data rate, coverage, power consumption, and security for IoT applications.	The limitations of Sigfox and NB-IoT are highlighted in terms of scalability, coverage, and power consumption.	A method for scalability, bandwidth, data speed, coverage, power efficiency, and security of NB-IoT, LoRaWAN, Sigfox for IoT.

TABLE I
GAP ANALYSIS OF EXISTING WORKS

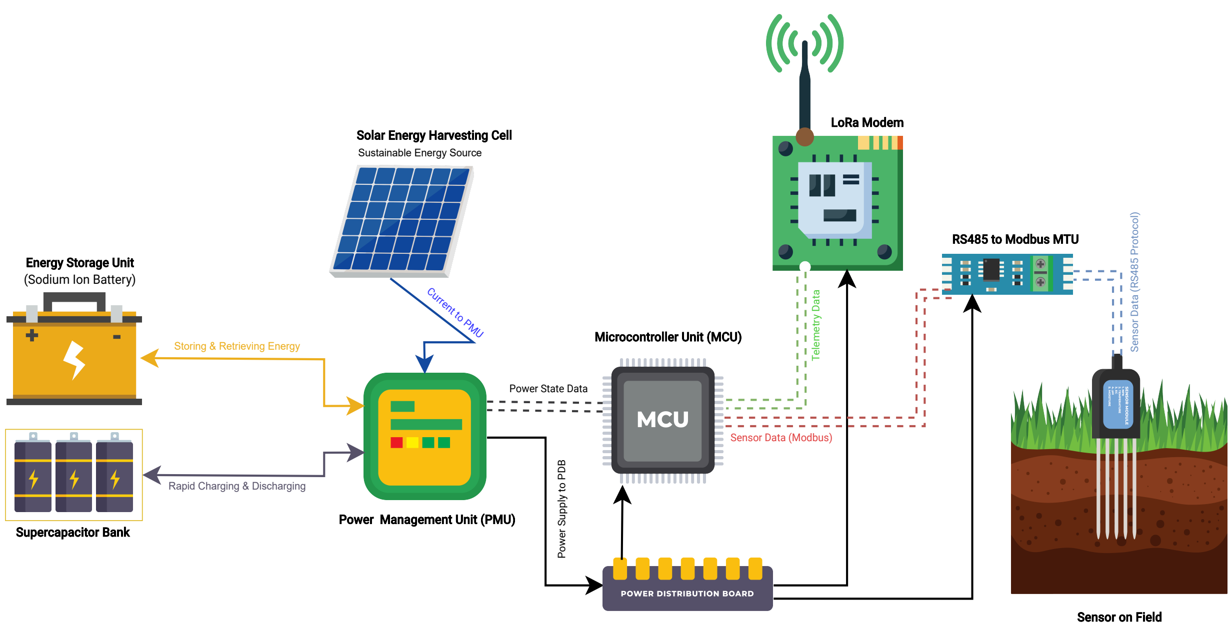

Fig. 1. Proposed Architecture

ATmega328P VQFN ideal for space-constrained applications like sensor nodes in agricultural fields, where reliable performance and efficient power management are crucial.

*6) **LoRa Modem**:* The sensor nodes will incorporate the LoRa SX1278 module operating in the 433 MHz band. LoRa modules are available in various frequency ranges, with 433 MHz, 915 MHz, and 868 MHz being the most common. The selected 433 MHz band is well-suited for long-range communication in agricultural fields. The LoRa module operates at 3.3V, supplied by a linear voltage regulator on the Power Distribution Board, ensuring stable power delivery. Communication between the microcontroller and the LoRa module is facilitated via the SPI protocol, enabling efficient and reliable data transfer. This integration ensures robust wireless connectivity and optimal performance of the sensor nodes in monitoring and managing agricultural environments.

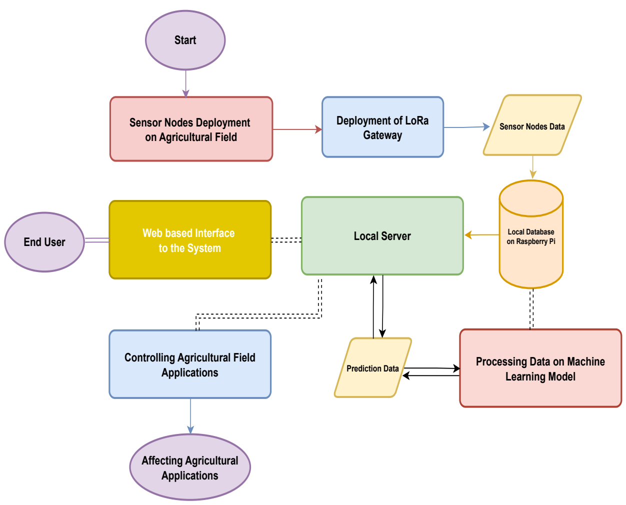

Fig. 2. System Deployment Diagram

*7) **Sensor Module**:* We have chosen the 7-in-1 NPK sensor which is a versatile and comprehensive sensor module designed for precision agriculture. It measures the critical soil nutrients Nitrogen (N), Phosphorus (P), and Potassium (K), along with four other essential soil parameters: soil moisture, temperature, pH, electrical conductivity (EC), and organic matter. By providing real-time, accurate readings over RS485 protocol, the 7-in-1 NPK sensor helps in monitoring nutrient levels, ensuring balanced fertilization, and enhancing crop yield and quality. It is robust in design because of the sealed enclosure and stainless steel sensor probes which allow it to work in extreme environmental conditions.

B. Phase 2: Gateway

The proposed LoRa-based sensor nodes can broadcast data packets over a LoRaWAN network, transmitting soil nutrition and environmental data from agricultural fields or farms. These LoRa sensor nodes can also act as trigger modules for automated actions in the field and function as watchdogs. All these applications require communication through a network established by a LoRa Gateway. LoRa Gateways capture and broadcast LoRa packets, interfacing the data with consumer networking protocols like Ethernet or Wi-Fi to relay it to

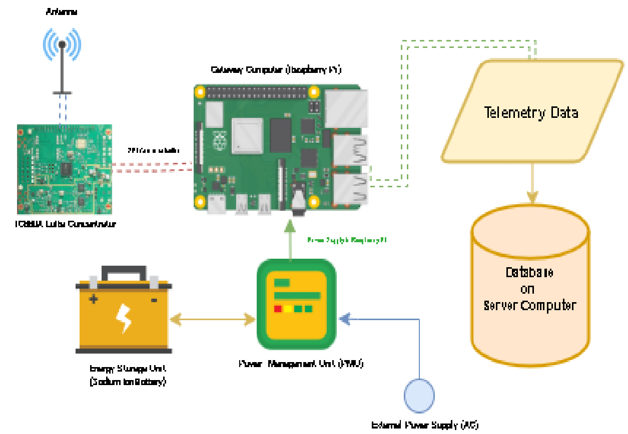

Fig. 3. Gateway Diagram

a server or the cloud for processing. To make the gateway module mobile and compact, we are proposing to build the system on a Raspberry Pi with a LoRa Hat. Raspberry Pi offers a cost-effective, low-power, and highly portable computing platform, ideal for deploying in remote agricultural environments where space, power, and mobility are critical factors. By adding a LoRa Hat, the Raspberry Pi can function as a fully operational LoRa gateway, capable of receiving and transmitting LoRa packets from sensor nodes scattered across the field or deployed in other applications. Additionally, the Raspberry Pi provides the flexibility to integrate other essential components to interface with other systems, such as GPS modules for geolocation, 4G/5G dongles for cellular connectivity, or external storage for data logging. In our proposed system architecture, This Raspberry Pi should also work as a central server for IoT-based agricultural devices monitoring and control, managing and collecting data, and data analysis using our machine learning models for local decision-making, which will not only let farmers help decide the future workflow but also to control smart farming devices. This combination enables the gateway to operate independently in remote areas without relying on fixed infrastructure for network access like Ethernet or Wi-Fi. With its compact form factor, the entire system can be easily mounted in weatherproof enclosures and powered by batteries or solar panels, ensuring continuous operation in rugged outdoor conditions. By leveraging Raspberry Pi's computing capabilities, the system can also perform edge processing, filtering unnecessary data locally before transmitting relevant information to the cloud, which can save bandwidth and reduce latency.

*1) **Central Computing Unit for Gateway**:* The Raspberry Pi 4 Model B is a high-performance single-board computer consisting of a 64-bit Quad Core ARM Cortex-A72 CPU, clocking at 1.5 GHz. There are multiple variants for RAM, but for our system proposal, running the LoRa gateway, machine learning models and the local web server will require a lot of memory and processing power too. We are recommending the

8GB of LPDDR4 3200 MHz SDRAM variant for this purpose. In terms of connectivity, the Raspberry Pi 4 Model B includes true Gigabit Ethernet for high-speed networking, along with dual-band 802.11ac Wi-Fi and Bluetooth 5.0, providing both wired and wireless communication options for the system users. For Gateway device external peripheral connectivity, like data logging storage, this single board computer offers a USB 3.0 port for faster USB communication. The GPIO header has a 40-pin configuration, offering access to SPI, I2C, UART, PWM, and other standard communication interfaces for hardware. Power input is handled via a USB-C connector, ensuring stable operation even with high power demands in scale with the Raspberry Pi 4 Model B. For this, it is easier to operate in areas with limited access to electricity and can be powered by renewable energy sources.

*2) **LoRa Transiever:**:* To give the Raspberry Pi the capability to communicate with the LoRa nodes, we are going to use a LoRa Hat. LoRa Hat is a 40-pin standard module to works with Raspberry Pi to let this single-board computer talk in LoRa. This Hat will communicate with the computer on SPI protocol. But the hat does support UART protocol which is available via a CH340 USB Serial converter which will let the user use this hat directly with USB Serial. It also has a voltage level shifter chip called 74HC125V which lets the LoRa hat talk with devices with higher voltage levels without damaging itself. And this hat supports auto multi-level repeating. This allows the module to automatically retransmit data at multiple levels, which increases the reliability of data transmission over long distances. LoRa Hat is not an ideal solution for developing a LoRa gateway. There are industrial solutions for LoRa gateways that are expensive and more reliable than this consumer-grade solution.

C. Phase 3: Algorithms

*1) **Random Forest**:* The Random Forest algorithm is an effective and adaptable machine learning method for both regression and classification applications. Using bootstrapping to create different subsets of the original data, each produced by random sampling with replacement, it builds multiple decision trees during training. At every split, a random subset of features is taken to build each decision tree, which then grows to its maximum depth without pruning. All of the trees' results are combined to create the final prediction majority voting is used for classification by using an ensemble technique, overfitting is reduced, prediction accuracy is improved, and insights into feature value can be gathered [29].

$$\hat{f}(x) = \frac{1}{B}\sum_{b=1}^{B} f_b(x)$$

Represents the average of a set of functions $f_b(x)$ evaluated at a point x. Here's a breakdown of the components: $\hat{f}(x)$ is the resulting averaged function value at point x. B is the total number of functions being averaged. $f_b(x)$ denotes each individual function in the set of B functions.

*2) **Naïve Bayes**:* For classification problems, the probabilistic machine learning approach Naïve Bayes is applied. It simplifies the probabilistic calculation by assuming that every feature is conditionally independent where the class is given [30]. It determines which class has the highest probability by applying Bayes' theorem to compute the next probability of each class given the input features. Large datasets with high dimensional feature spaces can be handled by naive Bayes classifiers, which are also highly scalable.

$$P(y|X) = \frac{P(X_1, X_2, ..., X_n|y) \cdot P(y)}{P(X_1, X_2, ..., X_n)}$$

Represents Bayes' Theorem, which is used to update the probability of a hypothesis y given observed data X. Here's a breakdown of the components: $P(y \mid X)$ is the posterior probability of the hypothesis y given the data X. $P(X_1, X_2, \ldots, X_n \mid y)$ which represents the probability of observing the data $X_1, X_2, \ldots, X_n$ given the hypothesis y. $P(y)$ is the prior probability of the hypothesis y before observing the data. $P(X_1, X_2, \ldots, X_n)$ which is the total probability of observing the data $X_1, X_2, \ldots, X_n$ under all possible hypotheses.

IV. Performance Evaluation

A. Dataset

The dataset that we gathered for our model came from Kaggle. This dataset includes several important agricultural factors and is mostly concerned with fertilizer-type prediction. We have divided the data into multiple classes to improve analysis and prediction accuracy. The dataset in particular has 6 different types of soil classes that help in understanding the characteristics of the soil and its compatibility with various crops. Types of Crops such as consist of 11 distinct crop classes reflecting the variety of crops taken from the dataset. There are 7 classes of fertilizers, showing the different types of fertilizers and how they are applied. Our program can accurately predict the best fertilizer for a certain crop and soil type using this large dataset, which helps farmers make well-informed decisions.

B. Result and Discussion

In this study, we implemented and compared two machine learning algorithms to evaluate their effectiveness in predicting fertilizer types. The primary objective was to determine which algorithm could provide the most accurate predictions, thereby offering a reliable tool for real-world agricultural decision-making. Our analysis revealed that the Naive Bayes algorithm outperformed the other model, achieving an impressive accuracy rate of 99%. This high level of accuracy demonstrates the potential of Naive Bayes in practical applications, where precise fertilizer recommendations are crucial for optimizing crop yield and resource management. The comparative analysis underscores the importance of selecting the right algorithm for specific agricultural tasks, as it directly impacts the decision-making process and overall productivity.

We have measured the performance of the Random Forest Algorithm using precision, recall, f1-score, and accuracy. Additionally, we have calculated the macro average and weighted average of those metrics to better understand the correctness of the model. Table 2 depicts the effectiveness of the Random forest Algorithm in accurately getting the fertilizer prediction. We experiment on 7 different classes that are shown in the first column of Table 2. We have obtained 96% accuracy for the Model and 93% for the Dataset, which not only highlights the model's strong performance in correctly predicting the fertilizer type but also indicates the system's efficiency in real-world applications. Moreover, our model illustrates strong precision, recall, and F1-score metrics, with values of 94%, 90%, and 90%, respectively for macro-average, and 95%, 93%, and 92%, respectively for weighted average.

Class	Precision	Recall	f1-score
10-26-26	1.00	0.33	0.50
14-35-14	0.83	1.00	0.91
14-35-14	0.75	1.00	0.86
20-20	1.00	1.00	1.00
28-28	1.00	1.00	1.00
DAP	1.00	1.00	1.00
Urea	1.00	1.00	1.00
Macro Avg	0.94	0.90	0.90
Weighted Avg	0.95	0.93	0.92
Accuracy			0.93

TABLE II
RESULTS FOR FERTILIZER PREDICTION USING RANDOM FOREST.

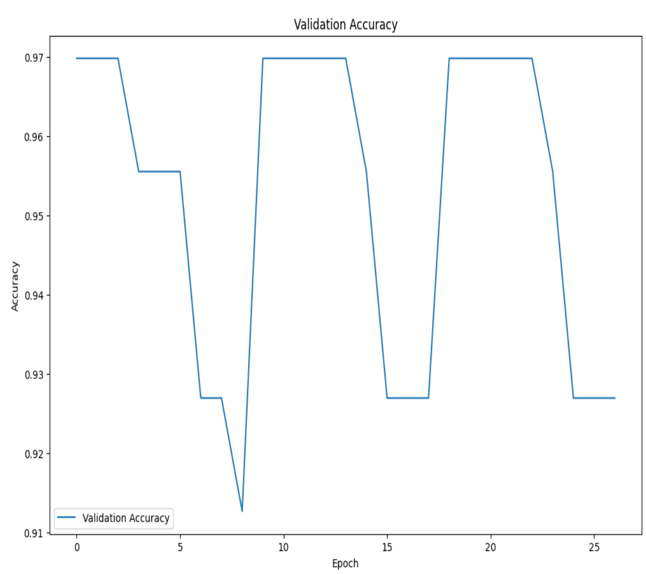

Fig. 4. Validation accuracy graph for Random Forest

In Figure 4 the validation accuracy of Random Forest over several epochs is shown in the graph above. The curve shows the differences in validation accuracy across testing, with phases of decrease and recovery following an initial high accuracy of almost 97%. In particular, accuracy has a sudden reduction at some points but recovers in the next epoch, stabilizing at 91% in the final stages of validation. Overall, the validation accuracy remains within a high range despite these oscillations, demonstrating the model's effectiveness in predicting unobserved data.

We have analyzed the Naive Bayes Algorithm's performance in terms of accuracy, recall, f1-score, and precision. To better analyze the accuracy of the model, we have also computed the weighted average and macro average of those metrics. The accuracy of the fertilizer forecast obtained by the Naive Bayes Algorithm is shown in Table 3. We run tests on the 7 classes indicated in Table 3's first column. Our results show that the model performs well in accurately predicting the type of fertilizer, with 98% accuracy for the Model and 99% accuracy for the Dataset.

Class	Precision	Recall	f1-score
10-26-26	1.00	0.33	0.50
14-35-14	1.00	1.00	0.91
14-35-14	1.00	1.00	0.86
20-20	1.00	1.00	1.00
28-28	1.00	0.93	0.96
DAP	0.93	1.00	0.96
Urea	1.00	1.00	1.00
Macro Avg	0.99	0.99	0.99
Weighted Avg	0.99	0.99	0.99
Accuracy			0.99

TABLE III
RESULTS FOR FERTILIZER PREDICTION USING NAÏVE BAYES.

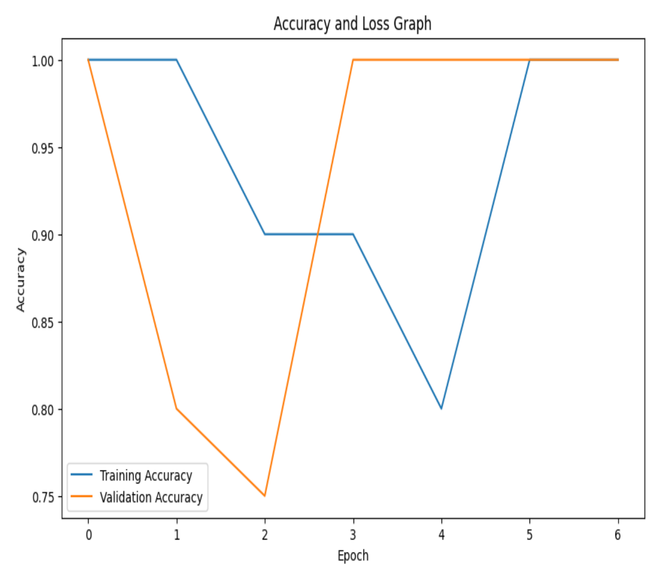

Fig. 5. Trainning & Validation accuracy graph for Naïve Bayes

In Figure 5 training and validation accuracy are visually displayed over several epochs with oscillations right before stabilization. The training accuracy is represented by the blue line, which starts high and decreases at epoch 4 in the learning process. On the other hand validation accuracy shown by the orange line gradually rises until epoch 5 at which point it reaches a stable peak of 100%.

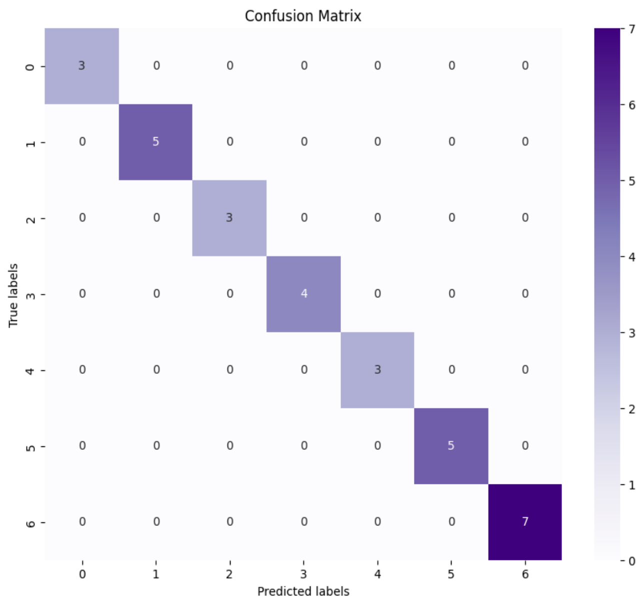

Fig. 6. Confusion Matrix of Naïve Bayes

V. Conclusion

Smart farming techniques combined with LoRaWAN technology present an effective solution for environmental monitoring and sustainable agriculture. In this work, we suggest a hybrid strategy to improve agricultural output and cut resource usage. It combines LoRaWAN communication with energy-efficient methods. Our system uses sensor nodes placed across the farm to gather data in real time on temperature, humidity, soil moisture content, and other essential factors. These data are sent over LoRaWAN to a central gateway, where they are processed by a machine learning based decision making system. Through data analysis, this system helps farmers make knowledgeable decisions about pest control, fertilization, and irrigation. In our study, we utilized the Naive Bayes method and achieved a 98% accuracy. An analysis was conducted by comparing this high training of accuracy with the Random Forest method. The results demonstrate that Naive Bayes offers reliable performance and serves as a strong predictive model in our context, providing a robust solution for accurate classification. To power these sensor nodes and ensure long-term operation without regular battery replacements, we also investigate energy harvesting techniques.

References

[1] Codeluppi, Gaia, et al. "LoRaFarM: A LoRaWAN-based smart farming modular IoT architecture." Sensors 20.7 (2020): 2028.

[2] Kadusic, Esad, et al. "The factors for choosing among NB-IoT, LoRaWAN, and Sigfox radio communication technologies for IoT networking." 2022 International Conference on Connected Systems & Intelligence (CSI). IEEE, 2022.

[3] Ribeiro, Lucas Eduardo, et al. "Comparison between LoRa and NB-IoT coverage in urban and rural Southern Brazil regions." Annals of Telecommunications 75 (2020): 755-766.

[4] Marini, Riccardo, et al. "Low-power wide-area networks: Comparison of LoRaWAN and NB-IoT performance." IEEE Internet of Things Journal 9.21 (2022): 21051-21063.

[5] Ballerini, Massimo, et al. "NB-IoT versus LoRaWAN: An experimental evaluation for industrial applications." IEEE Transactions on Industrial Informatics 16.12 (2020): 7802-7811.

[6] Islam, Nahina, Biplob Ray, and Faezeh Pasandideh. "IoT based smart farming: Are the LPWAN technologies suitable for remote communication?." 2020 IEEE international conference on smart internet of things (SmartIoT). IEEE, 2020.

[7] Haxhibeqiri, Jetmir, et al. "LoRa indoor coverage and performance in an industrial environment: Case study." 2017 22nd IEEE international conference on emerging technologies and factory automation (ETFA). IEEE, 2017.

[8] San Cheong, Phui, et al. "Comparison of LoRaWAN classes and their power consumption." 2017 IEEE symposium on communications and vehicular technology (SCVT). IEEE, 2017.

[9] Ismail, Dali, Mahbubur Rahman, and Abusayeed Saifullah. "Low-power wide-area networks: opportunities, challenges, and directions." Proceedings of the Workshop Program of the 19th International Conference on Distributed Computing and Networking. 2018.

[10] Polonelli, Tommaso, et al. "An accurate low-cost Crackmeter with LoRaWAN communication and energy harvesting capability." 2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA). Vol. 1. IEEE, 2018.

[11] Augustin, Aloÿs, et al. "A study of LoRa: Long range & low power networks for the internet of things." Sensors 16.9 (2016): 1466.

[12] de Castro Tomé, Mauricio, Pedro HJ Nardelli, and Hirley Alves. "Long-range low-power wireless networks and sampling strategies in electricity metering." IEEE Transactions on Industrial Electronics 66.2 (2018): 1629-1637.

[13] Ballerini, Massimo, et al. "Experimental evaluation on NB-IoT and LoRaWAN for industrial and IoT applications." 2019 IEEE 17th International Conference on Industrial Informatics (INDIN). Vol. 1. IEEE, 2019.

[14] Venkatesan, V. Prasanna, C. Punitha Devi, and M. Sivaranjani. "Design of a smart gateway solution based on the exploration of specific challenges in IoT." 2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC). IEEE, 2017.

[15] Davcev, Danco, et al. "IoT agriculture system based on LoRaWAN." 2018 14th IEEE International Workshop on Factory Communication Systems (WFCS). IEEE, 2018.

[16] Breiman, Leo. "Random forests." Machine learning 45 (2001): 5-32.

[17] Archana, K., and K. G. Saranya. "Crop yield prediction, forecasting and fertilizer recommendation using voting based ensemble classifier." SSRG Int. J. Comput. Sci. Eng 7.5 (2020): 1-4.

[18] Veenadhari, S., Bharat Misra, and C. D. Singh. "Machine learning approach for forecasting crop yield based on climatic parameters." 2014 International Conference on Computer Communication and Informatics. IEEE, 2014.

[19] Bondre, Devdatta A., and Santosh Mahagaonkar. "Prediction of crop yield and fertilizer recommendation using machine learning algorithms." International Journal of Engineering Applied Sciences and Technology 4.5 (2019): 371-376.

[20] Musanase, Christine, et al. "Data-driven analysis and machine learning-based crop and fertilizer recommendation system for revolutionizing farming practices." Agriculture 13.11 (2023): 2141.

[21] Sharma, Abhinav, et al. "Machine learning applications for precision agriculture: A comprehensive review." IEEE Access 9 (2020): 4843-4873.

[22] Shahare, Yogesh R., et al. "ASUR: Agriculture Soil Fertility Assessment Using Random Forest Classifier and Regressor." Procedia Computer Science 235 (2024): 1732-1741.

[23] Ayaz, Muhammad, et al. "Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk." IEEE access 7 (2019): 129551-129583.

[24] Pandith, Vaishali, et al. "Performance evaluation of machine learning techniques for mustard crop yield prediction from soil analysis." Journal of scientific research 64.2 (2020): 394-398.

[25] Keerthan Kumar, T. G., C. and Shubha, and S. A. Sushma. "Random forest algorithm for soil fertility prediction and grading using machine learning." Int. J. Innov. Technol. Explor. Eng 9 (2019): 1301-1304.

[26] Schreck, Adam. The Application of Lorawan as an Internet of Things Tool to Promote Data Collection in Agriculture. MS thesis. Purdue University, 2023.

[27] Boonyopakorn, Pongsarun, and Thanamate Thongna. "Environment monitoring system through LoRaWAN for smart agriculture." 2020-

5th International Conference on Information Technology (InCIT). IEEE, 2020.
[28] Arshad, Jehangir, et al. ”Implementation of a LoRaWAN based smart agriculture decision support system for optimum crop yield.” Sustainability 14.2 (2022): 827.
[29] Breiman, Leo. ”Random forests.” Machine learning 45 (2001): 5-32.
[30] Webb, Geoffrey I., Eamonn Keogh, and Risto Miikkulainen. ”Naïve Bayes.” Encyclopedia of machine learning 15.1 (2010): 713-714.
[31] Rahman, Syed Ishtiak, et al. ”Green IoT-Based Automated Door Hydroponics Farming System.” International Conference on IoT Based Control Networks and Intelligent Systems. Singapore: Springer Nature Singapore, 2023.
[32] Anwar, Wahid, et al. ”IoT-Based Decision Making of Irrigation and Fertilizer Management for Marginal Farmers in Bangladesh.” The Fourth Industrial Revolution and Beyond: Select Proceedings of IC4IR+. Singapore: Springer Nature Singapore, 2023. 673-682.