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RESEARCH ARTICLE

An Intelligent LoRaWAN-Based IoT Device for Monitoring and Control Solutions in Smart Farming Through Anomaly Detection Integrated With Unsupervised Machine Learning

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ABSTRACT Smart farming, popularly called precision agriculture, refers to technologies like the Internet of Things (IoT), Artificial Intelligence (AI), and drones that are rapidly transforming age-old farming traditions. This paper investigates how smart farming technologies are revolutionizing the practice of agriculture, specifically focusing on monitoring and control solutions of IoT devices and LoRaWAN networked. Therefore, the implementation of IoT devices would give the farmer access to current readings when needed for making decisions and optimizing their resources on the most important parameters for agricultural activity. And this is where IoT devices come in, making possible precision agriculture techniques with lowered costs by customizing farming practice for each crop or section of land. It means that even the most remote farms will benefit from monitoring and control solutions within LoRaWAN networks. Moreover, low power with long-range wireless connectivity technology devised by LoRaWAN ensures communication and data analysis to be a reliable one within the system. It introduces an intelligent LoRaWAN-based IoT device for the monitoring and controlling solutions with the parameters of performance evaluation, experimental setup, and the dataset used for its analysis. This paper elaborates on anomaly detection through Isolation Forest and proves it for the identification of anomalies in data related to temperature and humidity. Predominantly, the study also indicates precision in the temperature variation prediction model through the use of the predictive model based on the linear regression and random forest algorithms. This improves smart farming practices developed for precision agriculture in terms of efficiency, productivity, and sustainability.

INDEX TERMS Monitoring and control, smart farming, LoRaWAN, machine learning, anomaly detection, prediction.

I. INTRODUCTION

Smart farming, or precision agriculture, changes the very way farmers work by turning it into the process of constant development and infusion of new technologies and data-driven practices that make farming better. It draws upon such components as the Internet of Things, Artificial Intelligence, drones, and sensors; together, they allow for the development of crops in much more effective and sustainable ways [1], [2], [3]. For instance, by using sensors, one can monitor soil moisture, temperature, and crop health. The data generated from these devices is then transmitted to computers that make

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use of artificial intelligence to analyze and advise the farmer on issues like irrigating crops and harvesting them. This kind of information aids in making better decisions and improving crops [4]. The main component of smart farming is the use of data in making decisions. Farmers accrue tons of data from the sensors and IoT devices on soil moisture, temperature, and weather conditions. They then extract that data into a computer, and have it run through AI algorithms so they can learn about crop performance or whether they have a pest to treat. This enables the farmer to make improved decisions and hence make use of fewer resources such as water and pesticides, hence gentle on the environment. The second most important application of smart farming involves the use of precision agriculture techniques. This is where farmers can use technologies to finely tune farming for a particular crop or part of their lands rather than uniformly treating crops. For example, it uses less water in wet land places; it saves water and reduces wastage. It will, therefore, help the farmer save money and be sustainable [5]. It further employs gadgets and mechanization to help farmers in the accomplishment of their jobs in a more effective way. For example, guided tractors by GPS and AI. It reflects that farmers save time on driving tractors and dedicate that time to other duties. Also, drones are used to take pictures of the fields above. This way, it will be easy for the farmers to see if they have any problems with the crops, like pests or diseases, so that they can fix them quickly [6], [7], [8].

IoT devices are very important in smart farming, through which monitoring and control solutions help farmers trace exactly what is happening on the farms in real time [9], [10], [11], [12], [13], [14], [15]. Such devices carry sensors and can connect to the internet, measuring things like moisture in the soil, temperature, and crop health. Data gets transferred to a computer, which farmers can access from anywhere [9], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28]. For example, they can know whether the crops need more water or if there is some pest that has to be taken care of. They are then able to make decisions just in time and are better able to take care of the crops. Another good aspect of the IoT devices is that they allow farmers to be able to carry out techniques on precision agriculture. In other words, it allows one to provide exactly the right amount of water or fertilizer to certain crops. For example, they use less water where the soil is already wet. Saving water means cutting down on waste. Therefore, IoT devices allow farmers to try and know in advance whether there is a problem with the crops, be it infestation or diseases [29]. This makes him act in advance before the crisis escalates. The other advantage of IoT devices is that they allow farmers to control everything on the farm from wherever they are. This, in turn, allows farmers to use their phones to switch on the irrigation system or engines of machines like drones. In doing so, time is saved, and farming is done efficiently.

Incorporating LoRaWAN networks into IoT devices for smart farming applications in monitoring and control solutions is a great stride forward in agricultural technology. LoRaWAN, standing for Long Range Wide Area Network technology, offers long-range, low-power wireless connectivity that is suitable for farms with much ground to cover while energy is at a premium [30], [31], [32], [33], [34]. That would, therefore, imply that farmers will be able to sprinkle IoT devices all over their farms, right up to locations where it's hard to get a signal from traditional networks. LoRaWAN networks would be very good for smart farming because they connect devices spread out over a large area, even in some of the remotest places where there's not much option for communication. That means that, through the IoT, farmers are currently able to keep a record of soil moisture, temperature, and the health of their crops for the whole farm. LoRaWAN will enable farmers to own a network of sensors and actuators that can communicate with each other and with computers. In this way, they will be able to see in real-time what is going on in the farm and take instant action [9], [35], [36], [37], [38], [39]. Another big plus for LoRaWAN is that it consumes very little power. This ensures a long life for IoT devices before new batteries need to be installed. This is also good for farms, where power can be untrustworthy or sparse. In addition, LoRaWAN devices are so low-power that they are very economical to run and environmentally friendly [40]. LoRaWAN is also capable of strong interference and does well in the worst environment: bad weather conditions, and dense forests [41]. It means that it will assist farmers in getting their important data in every corner of the farm, which other wireless technologies cannot do due to a poor signal [42], [43], [44], [45], [46].

The motivation of this research is the transformative effect that smart farming technologies, particularly IoT devices and LoRaWAN networks, have on agricultural practices. So, smart farming, or rather, the more common name for precision agriculture, invokes a sea change in the manner in which farmers do their work by turning to new technologies and data-driven methods for productivity, efficiency, and sustainability in growing crops. The power of IoT devices puts in real-time insights on certain aspects of farming operations—soil moisture level, temperature, humidity, and crop health. With such a large amount of data, the farmer is able to make reasonable decisions on how to optimize resource usage and reduce waste to enhance food production. IoT devices further enable methods for precision agriculture, which will assist a farmer by controlling his ways for the real needs of plants or a piece of land. Such tailoring results in saving costs, conserving resources, and thus environmental sustainability. Integration with LoRaWAN networks further enhances the capabilities of IoT devices in smart farming with long-range, low-power wireless connectivity. A farmer can deploy IoT devices for very large areas, including remote or rural locations with poor communication infrastructure. Wide coverage of LoRaWAN networks allows complete monitoring and control over agricultural parameters, ensuring proactive management of farm operations and intervening at the right time in cases of pest invasions or crop diseases. Apart from all these, LoRaWAN finds further application in agriculture because of its low power and strong connectivity. This assures effective communication between IoT devices and the central data platforms for flawless collection and analysis of data to aid in well-informed decision-making. The cost-effectiveness and environmentally friendly nature of LoRaWAN networks add further to the attractiveness for sustainability in smart farming applications. Given that, the study will look for practical implications and the possible benefit to be drawn from integrating LoRaWAN-based IoT devices into smart farming. Considering the effectiveness of such technologies in optimizing agricultural operations and improving crop yields, the current research study intends to give very valuable insight into decision-making and innovation within the domain of precision agriculture. The proposed study is based on a novel framework we developed for an IoT-based device that monitors and controls mechanical systems, which forms the foundation of our methodology [47]. To implement this concept, we integrated IoT sensors, LoRaWAN communication, and machine learning for smart farming applications. This framework is the foundation upon which we built our research, allowing us to develop an innovative approach to anomaly detection and predictive modeling in IoT-based agricultural systems.

Main contributions of this research are highlighted as follows:

- The proposed study provides a comprehension of how IoT devices make farmers able to obtain momentary details of the most important agricultural parameters and consequently lead to informed decision-making and improved resource use. IoT technology makes farming operations more efficient, ultimately increasing crop yields and productivity.
- The study brings to light how IoT devices help to enhance precision farming techniques by giving farmers the liberty to customize their farming practices to the different needs of individual crops or sections of land. By means of tailoring based on real-time data, farmers are able to cut down their costs, save natural resources, and preserve the environment in the process of crop growth.
- Through the application of LoRaWAN networks in conjunction with IoT devices, the research provides an opportunity to enlarge the range of monitoring and control in smart farming. This also provides farmers the opportunity to install the IoT devices over vast geographical areas, including in remote or rural locations with limited communication infrastructure, which in turn provides them with the ability to manage farm operations in a proactive manner.
- The proposed research implemented two categories of analysis. Firstly, it performs anomaly detection using Isolation Forest to examine the relationship between temperature and humidity in IoT sensor data, distinguishing between normal observations and anomalies. Secondly, it carries out predictive modeling using Linear Regression and Random Forest.
- The research explores LoRaWAN-based IoT technology, and in doing so, it adds to the understanding of the cost-effectiveness and environmental benefits of smart farming applications. Resource conservation and the eco-friendly dimension of LoRaWAN networks make them a sustainable option for agricultural practice optimization.

The remaining part of this research work is organized as follows: Section II presents the literature review. Section III describes the system design and model. Section IV describe performance evaluation. Section V provides results and discussions. Finally, section VI concludes the article.

II. LITERATURE REVIEW

We review the related work in terms of smart farming, IoT devices for control and monitoring, and use of LoRaWAN in IoT based control and monitoring solutions.

The paper [48] presents a detailed exposition of smart farming as a union of technologies like sensors, the Internet of Things (IoT), and machine learning that are aimed at improving farm productivity. This part explains the development of sensor technology to detect water stress in plant leaves and the influence of climate on agricultural practices. This article also marks the communication protocol constraints and the power limitations of edge devices. The fact that innovations are necessary is shown through this. Web-based applications for the Internet of Things (IoT) like GeoFarmer are assessed for their role in farmers' knowledge sharing. Moreover, the study investigates the use of machine learning for diagnosis and seed morphology analysis, highlighting the game-changing role of IoT in fields like water management, pest mitigation, and agricultural data analytics. Lastly, it encourages the deepening of research into such frameworks as fog computing and the use of machine learning algorithms in new ways to meet the evolving problems in agriculture.

The research [49] explored how IoT technology is radically transforming the way various sectors, such as agriculture, operate. It shows the multi-functionality and range of the applications' fields, such as smart houses, traffic control, and urban infrastructure. The paper has an emphasis on agriculture, and it shows that IoT has contributed to improving the management of crops, allocating resources, being cost-effective, and overall agricultural efficiency. The IoT platform that is proposed uses a number of sensors to measure the air temperature, soil pH, moisture levels, humidity, and water quantity. The study applies empirical observations and surveys conducted within agricultural settings such as polyhouses to shed light on the penetration of new technologies in farming. The presented IoT architecture consists of sensor deployment, data transmission via Wi-Fi to a central server, and the usage of data for decision-making and prompt interventions based on real-time information.

The study in [50] explores the future of the Internet of Things (IoT) technology, which is playing a big role in the transformation of various sectors, including agriculture. It addresses the implementation of IoT-based technologies that aim at automation and monitoring farming processes with little human interference. The paper covers a detailed description of the technical components of IoT-driven smart farming, the network architecture, layers, topology, and protocols used in agricultural IoT networks. Next to that, the paper covers the integration of IoT-based agricultural systems with other technologies like cloud computing, big data storage, and analytics. The security issues that come with IoT agriculture are addressed, and data and systems should be protected from various threats. The article also lists smartphone-based and sensor-based applications designed for farm management, along with international regulatory frameworks that aim to standardize IoT-driven agricultural methods. In the end, it is the unanswered questions and limitations that are pinpointed in the space of IoT in agriculture. This paves the way for future research and innovation that will surely be a result of this growing field.

The study given in [42] presents a novel solution for smart farming using IoT technologies, accentuating a cost-effective and modular platform called ''LoRaWAN-based Smart Farming Modular IoT Architecture'' (LoRaFarM). The main goal of this platform is to make the collecting, monitoring, and utilizing of relevant agricultural data a straightforward process that will then contribute to more sustainable and environmentally friendly farming practices. Leveraging a central middleware, LoRaFarM allows for flexibility by means of both low-level modules that provide data from the farm and high-level modules that offer more advanced functionality to the farmer. The platform's effectiveness is shown by a real farm in Italy, which was used for the evaluation. The environmental data relevant for the growth of crops such as grapes and greenhouse vegetables was collected over a period of three months. Besides, the paper also has a visualization tool designed for the web that is in support of the LoRaFarM architecture and can be used to show the acquired data.

The most important component in ensuring the effectiveness and caliber of aquaculture is maintaining an ecological environment with clean water. Maintaining the quality of the water can prevent anomalous conditions from occurring and greatly increase the likelihood of food security in the future. By identifying abnormalities, it is possible to make sure that the aquaculture environment is kept up to date and suitable for fish farming. The use of machine learning techniques to identify anomalies in water quality data in aquaculture environments is the primary focus of [51]. Three machine learning anomaly detection methods are analyzed: isolation forest, local outlier factor, and K-Means clustering. Several sensor datasets from an actual IoT aquaculture system were used to perform extensive analysis of the techniques, with particular focus on the temperature, dissolved oxygen, and pH parameters. According to the evaluation analysis, the three aquaculture parameters can be anomalously detected using the K-Means and Isolation Forest anomaly detection methods, which demonstrate encouraging outcomes [51]. Isolation Forest is a well-known algorithm that uses a collection of odd trees known as isolation trees to define an anomaly score [52]. These are constructed using an incredibly quick and inexpensive random partitioning technique. The authors discover that the standard algorithm could be enhanced with respect to memory needs, latency, and performance; this is especially important in scenarios involving limited resources and in TinyML implementations on extremely constrained microprocessors.

The work in [9] introduces a tailored smart farming system designed to address the escalating challenges faced by the agricultural sector, coupled with the global surge in food demand. By leveraging the principles of real-time management and high automation levels, smart farming systems hold the potential to significantly enhance productivity, food safety, and overall efficiency throughout the agri-food supply chain. The presented system adopts a cost-effective, low-power, and wide-range wireless sensor network architecture, utilizing Internet of Things (IoT) and Long Range (LoRa) technologies. Integration of LoRa connectivity with existing Programmable Logic Controllers (PLCs), specifically the Simatic *IOT* 2040, enhances control over various processes, devices, and machinery commonly employed in industrial and farming contexts. Furthermore, the system features a newly developed web-based monitoring application hosted on a cloud server, facilitating data processing from the farm environment, and enabling remote visualization and control of all connected devices. To streamline communication with users, a Telegram bot is incorporated, enabling automated interactions via this mobile messaging platform. The proposed network structure has undergone rigorous testing, with a focus on evaluating path loss in the wireless LoRa communication medium, thereby validating its operational effectiveness and reliability.

III. SYSTEM DESIGN AND MODEL

In this research work we present an intelligent LoRaWAN-based IoT device for monitoring and control solutions in smart farming as shown in Figure 1. The proposed framework integrates the IoT device with LoRaWAN communication protocol and machine learning based intelligent mechanism for monitoring and control solutions in smart farming. It considers environmental factors for monitoring and provides intelligent mechanisms based on machine learning integrated solutions.

There are the following components of the proposed system.

A. SMART FARMING

Smart farming is a system of farming management that uses innovative technologies to determine the optimum way of producing more from a restricted number of resources while at the same time reducing pollution of the environment. Smart farming encompasses the application of diverse technologies such as the IoT, AI, robotics, and data analytics in real-time control, processing, and decision-making in several processes

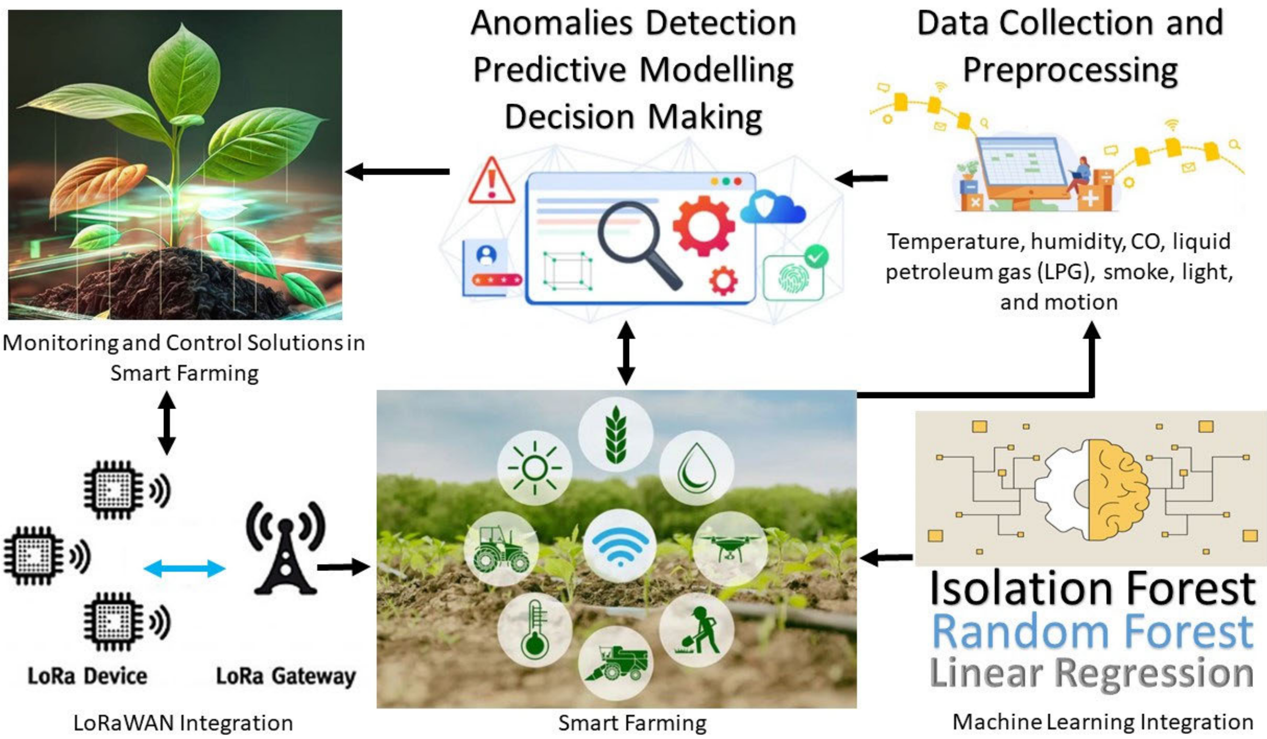

FIGURE 1. An intelligent LoRaWAN-based IoT device for monitoring and control solutions in smart farming.

in agriculture. These technologies give the capacity to track changes in the environment, such as soil quality, crop germination, and animal health, through a series of sensors that are sometimes mounted on the farm. This information is then analyzed by the AI algorithms, and the outcome is useful information and advice for farmers. Smart farming can be described as the application of automation technology such as self-driving tractors and drones in performing tasks such as planting, irrigation, fertilizing, and pest control, among others. Smart farming engages data analytics and automation to enable the farmers to manage the resources optimally, reduce the input costs, and enhance the yields in the long run, and all this is done while at the same time implementing sustainable and future-oriented measures as regards the environment and agriculture.

B. LoRaWAN INTEGRATION

LoRaWAN (long-range wide-area network) is a wireless network technology that enables IoT devices to communicate over a long distance. Some of these characteristics include low power consumption and extensive coverage that is suitable in smart farming applications, which consist of large networks over extensive farming regions. LoRaWAN works in the unlicensed frequency bands, and this makes the IoT device deployment cost-effective with little need for infrastructure. In the sphere of smart agriculture, LoRaWAN has numerous applications because it possesses one of the key characteristics, which is the ability to provide seamless communication between sensors, actuators, and other farm equipment at long range. For instance, sensors with LoRaWAN technology are used in extensive fields for monitoring the level of different parameters of the environment, such as moisture, temperature, humidity, and weather conditions. These sensors are constantly streaming data and transmitting it over the air to a gateway, which is like a translator so that the sensors can be integrated into the internet.

The LoRaWAN network can be used in smart farming in many areas, such as vineyards that employ the LoRaWAN network for monitoring soil humidity. The soil moisture sensors installed at strategic positions and developed on the LoRaWAN platform help the farmers to monitor the soil conditions and set up the irrigation schedules based on the obtained data. Thus, farmers can get high yields and quality of crops and water at the same time when the proper amount and time of water application is provided. An example is the use of LoRaWAN technology in the agriculture sector, especially to monitor livestock. As a result of the sensors installed with the help of LoRaWAN on the livestock, it is becoming possible to track location, temperature, and activity levels in real-time. It is then transferred wirelessly to a monitoring system, and farmers can then use it to monitor the health and wellbeing of the animals from a distance. For example, if the body temperature of a cow is higher than the threshold, a notification can go to the farmer's smartphone, which will enable him to intervene on time to prevent the cow from being sick. LoRaWAN technology can be linked with cloud-based platforms and data analytics tools to allow farmers to get useful information about their operations.

In addition, data gathered via LoRaWAN sensors could be used to find out trends, patterns, and outliers in crop growth, soil health, or livestock behavior. Such information can be employed to make decisions based on data, for instance, by changing planting schedules, optimizing fertilizer applications, or using precision livestock management.

C. MACHINE LEARNING INTEGRATION

Machine learning implementation in smart farming brings a digital revolution to the agricultural sector through the use of data-driven insights to increase productivity, sustainability, and resource management. The machine learning algorithms are the basis for the analysis of the great amounts of data collected from the sensors, drones, and other IoT devices located in the field and on the farm. Smart farming systems can be executed well through the use of these algorithms, which will enable the prediction of crop yields, detection of anomalies such as diseases and pests, optimization of irrigation and fertilization schedules, and enhancement of livestock management practices.

Isolation Forest, a groundbreaking outlier detection algorithm, is best at detecting anomalies or irregularities in sensory IoT data. Isolation forests can be used in smart farming to detect abnormalities in environmental parameters, including temperature, humidity, and soil moisture. Through the identification of deviations from the normal patterns, Isolation Forest provides the farmers with the opportunity to quickly respond to problems like crop disease or machine failure, thereby minimizing losses and maximizing yields. Linear regression, which is a core statistical method, is used in smart farming to analyze trends and predict them. The linear regression models are able to analyze historical sensory IoT data in order to predict future developments in crop yields, soil fertility, or weather patterns. Through finding out the relationships between temperature, rainfall, and crop growth, linear regression provides farmers with an instrument to make informed decisions on the timing of planting, watering, and fertilizer application. Random Forest, an ensemble learning algorithm that is flexible and robust at the same time, is able to accurately predict data by combining several decision trees. Smart farming using Random Forest models can show crop yield, livestock health indicators, and soil fertility level predictions based on historical sensor data and environmental parameters. Through Random Forest's ability to forecast, farmers can strategize to utilize resources effectively, reduce input costs, and increase output while minimizing the risks associated with uncertainties in agriculture production.

D. MONITORING AND CONTROL SOLUTIONS IN SMART FARMING

Monitoring and Control Solutions in Smart Farming are wide-ranging technologies that enable the agricultural process to be improved through real-time data monitoring and analysis and automatic control mechanisms. These solutions take advantage of the innovation of technologies such as the Internet of Things (IoT), sensors, and machine learning algorithms to gather, analyze, and act on agricultural data, which is the ultimate way of increasing productivity, sustainability, and efficiency in farming operations. At the core of monitoring and control solutions in smart farming lies the integration of IoT devices and sensors, which pervade the agricultural landscape. These devices are installed in fields, greenhouses, and livestock facilities so as to collect a comprehensive data set that includes temperature, humidity, soil moisture, weather conditions, crop growth stages, and livestock health indicators. With a constant watch on these parameters, farmers will get important information about environmental conditions and the status of their crops and animals on an ongoing basis. Data analysis in smart farming is the area where machine learning algorithms are successfully applied to handle the huge volume of data from IoT devices and sensors. For the purpose of abnormality detection, algorithms like Isolation Forest are capable of identifying irregularities or outliers in the data, such as sudden changes in temperature or unexpected fluctuations in soil moisture levels, that may indicate the presence of pests, diseases, or malfunctioning equipment. Linear regression models could provide a forecast of future trends based on historical data, which would in turn help farmers make informed decisions about irrigation, fertilization, and crop management. Furthermore, the Random Forest models boast the ability to aggregate multiple decision trees together, which then enables farmers to predict crop yield, livestock health indicators, and soil fertility based on historical sensor data and environmental parameters.

By putting control mechanisms into smart farming systems, farmers can run many elements of the farming operation based on data insights that happen in real-time. With automatic irrigation systems that can regulate the watering frequency according to the soil moisture level, the watering will be perfect for crops while saving water resources. Also, automation of pest control systems can be used to track and react to pest infestations in real-time, which in turn decreases the need for human intervention and prevents crop losses. The internet of things (IoT) devices and sensors harvest agricultural data, which is then stored on cloud-based platforms along with other data analytics tools. This gives farmers the chance to have centralized access to agricultural data. These platforms empower farmers to look at, analyze, and interpret data trends, take data-driven decisions, and improve farming operations even from remote locations at any time. What is more, mobile applications and web-based interfaces are good tools for farmers to monitor and control agricultural operations from a distance, which in turn helps them to be more flexible and efficient in farm management.

E. ALGORITHMS FOR INTELLIGENT LoRaWAN-BASED IoT DEVICE FOR SMART FARMING

Algorithm 1 shows the working of the smart farming IoT device with LoRaWAN and machine learning integration. It is based on the combination of IoT sensors, LoRaWAN communication, and machine learning and it can help in increasing

Algorithm 1 Intelligent LoRaWAN-Based IoT Device for Smart Farming

1. ***Begin***
2. **Input:** Environmental sensor data (D): Soil moisture (S_m), Temperature (T), Humidity (H),
   Weather conditions (W), Crop growth (C_g), Livestock health indicators (L_h)
   Historical sensor data (H_D)
   Threshold values for anomalies (T_{ha})
3. **Output:** Predictions and recommendations for farming operations
   Alerts for anomalies
   Automated control actions
4. **Procedure: Intelligent LoRaWAN-Based IoT Device for Smart Farming**
5. **Deploy IoT Sensors:**
   - Sensor installations in fields, greenhouse, and livestock facilities.
   - $Sesnors = \{S1, S2, S3, \ldots, Sn\}$
6. **Environmental Data Collection:**
   - $Data\_env = \{soil\_moisture(t), temperature(t), humidity(t), weather(t)\}$
   - Periodically collect data at time intervals t
7. **Livestock Data Collection:**
   - $Data\_livestock = \{location(t), body\_temp(t), activity\_level(t)\}$
8. **Data Transmission Via LoRaWAN:**
   - Sensors send data to the central gateway using LoRaWAN protocol
   - $Data\_raw = Data\_env\ U\ Data\_livestock$
9. **Data Preprocessing:**
   - Remove noise and handle missing values
   - $Data\_clean = Preprocess\ (Data\_raw)$
10. **Data Storage:**
    - Save clean data to cloud-based platform
    - $Cloud\_storage = Store(Data\_clean)$
11. **Machine Learning Analysis:**
    - Train Isolation Forest model on historical sensor data
    - $IF\_model = Train\_Isolation\_Forest(Data\_hist)$
    - Detect anomalies in real-time data.
    - $Anomalies = IF\_model.predict(Data\_clean)$
12. **Predictive & Trend Analysis:**
    - Train Linear Regression model on historical data
    $$LR\_model = Train\_Linear\_Regression(Data\_hist)$$
    - Predict future trends
    $$Trends = LR\_model.predict(Data\_clean)$$
    - Train Random Forest model on historical data
    $$RF\_model = Train\_Random\_Forest(Data\_hist)$$
    - Predict outcomes such as crop yield and livestock health
    $$Predictions = RF\_model.predict(Data\_clean)$$
13. **Monitoring and Control Solutions:**
    - Analyze predictions and anomalies
    - Insights=Analyze (Trends, Predictions, Anomalies)
14. **Automate Control Mechanisms:**
    - Use insights to automate irrigation, fertilization, and pest control
    - $Control\_Commands = Generate\_Commands(Insights)$
    - Execute control commands.
    - $Execute(Control\_Commands)$
15. **Remote Monitoring and Management:**
    - Provide farmers with real-time monitoring through mobile apps and web interfaces
    - $Remote\_Access = Enable\_Remote\_Monitoring(Cloud\_storage)$
16. **end**

agricultural production and sustainability. The system is a network of sensors that are distributed on farms, greenhouses, and livestock houses. Sensors collect environmental and livestock data, which is transferred to the central gateway via

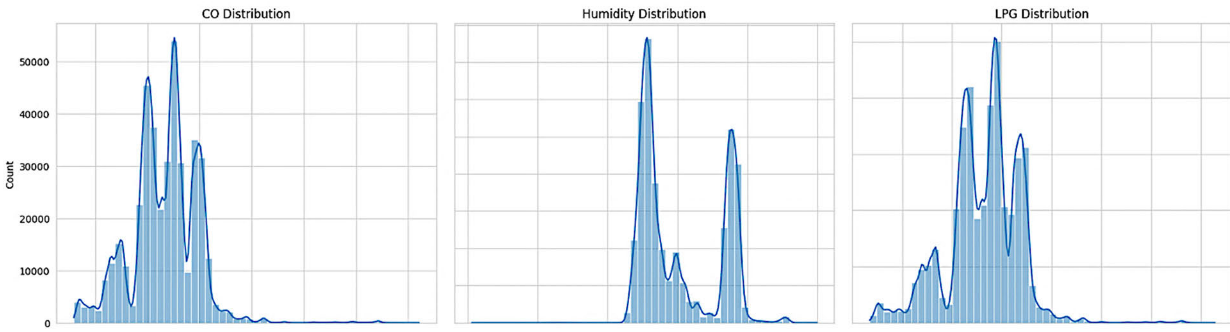

FIGURE 2. CO, humidity and LPG distribution.

LoRaWAN. This data undergoes pre-processing to remove the noise and handle the missing values, and then it is stored on a cloud-based platform. Among the machine learning models, isolation forest, linear regression, and random forest are used to detect anomalies, forecast the future, and provide predictive analytics, respectively. These models provide the system with actionable recommendations that automated control systems enable, such as irrigation, fertilization, and pest control; therefore, labor is saved and resources are used more efficiently. On the other hand, the system can be fully managed via mobile and web interfaces that allow farmers to make the right decisions at the farm. This integrated architecture takes advantage of AI and IoT as tools to increase effectiveness, reduce input costs, and maintain sustainable farming operations. Therefore, farmers will be equipped with data-based insights and automated solutions.

IV. PERFORMANCE EVALUATION

In this research work we present an intelligent LoRaWAN-based IoT device for monitoring and control solutions.

A. PERFORMANCE EVALUATION PARAMETERS

The study to be conducted adopts a wide-ranging performance evaluation parameter array to conduct a thorough analysis of IoT sensor data. First, the scatter plots were used to visually examine the link between temperature (in °C) and humidity (in%), which allowed for the identification of normal observations and anomalies. These visualizations made it possible to spot the anomalies, which were characterized by obvious deviations from expected patterns, and they were analyzed carefully. Consequently, line charts were used to determine the trends in the time series of temperature readings, with the anomalies being marked as exceptions in the data stream over time. Statistic metrics like mean, median, and STD have been computed for both normal and anomalous conditions. These values provide a deep understanding of the data scale and the magnitude of the deviations. The next step is the application of predictive modeling techniques that use mean square error (MSE) and R^2 parameters to thoroughly assess the accuracy and predictability of the used models. Through applying cross-validation techniques, the robustness and reliability of the predictive models were assessed by comparing models across different data subsets, which facilitated the decision-making process and selection of the model. The performance evaluation parameters are integrated into the study. The proposed study aims to provide a complete picture of sensor data from IoT, which helps to detect anomalies, the application of predictive modeling, and data-driven decision-making in IoT system management.

B. EXPERIMENTAL SETUP

The experiments were performed by implementing Isolation Forest [53] model for anomaly detection, while Linear Regression [54] and Random Forest [55], [56] for predictive modelling. All experiments are implemented in Python on a GPU based environment with 2.11 GHz CPU and 16 GB of RAM. Predefined machine learning packages and libraries including Pandas, Numpy, Seaborn, Sklearn, LabelEncoder, OneHoTencoding and Matplotlib have been implemented.

C. DATASET

In order to evaluate the working of proposed framework, Environmental Sensor Telemetry Data [57], a publicly available dataset on a Kaggle website has been used. The dataset comprises environmental sensor telemetry data collected from three identical custom-built sensor arrays, each connected to a Raspberry Pi device. These sensor arrays were deployed in different physical locations with varying environmental conditions. The dataset includes readings from seven different sensors: temperature, humidity, carbon monoxide (CO), liquid petroleum gas (LPG), smoke, light, and motion. There are total 405,184 rows in the dataset. Each sensor array collected readings at regular intervals and published them as MQTT messages. The message payload includes sensor readings, device ID, and timestamp. For instance, a payload might contain data such as CO concentration, humidity level, light detection status, LPG concentration, motion detection status, smoke concentration, and temperature. The dataset consists of nine columns: timestamp (ts), unique device ID (device), CO concentration (co), humidity level (humidity), light detection status (light), LPG concentration (lpg), motion detection status (motion), smoke concentration (smoke), and temperature (temp). Timestamps are in epoch format, and

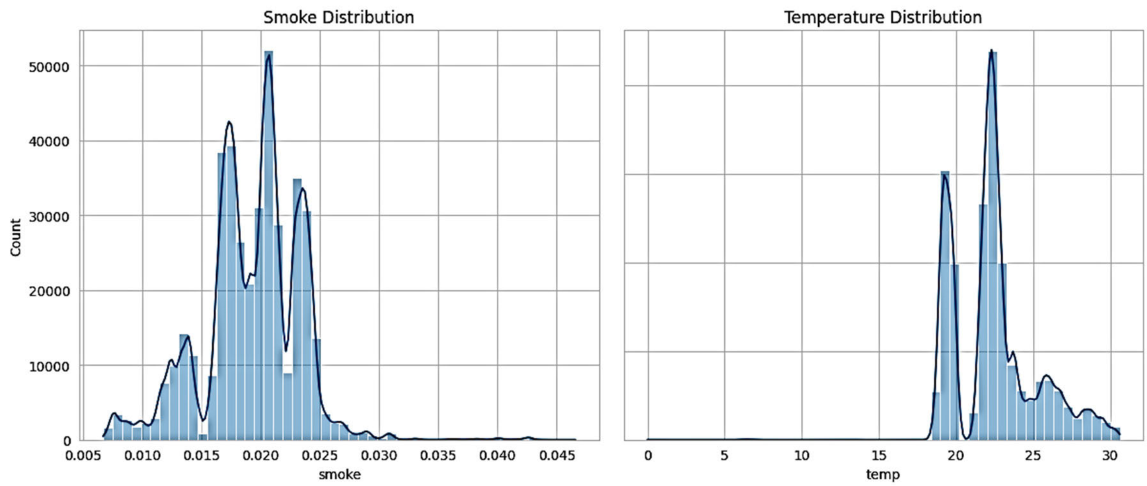

FIGURE 3. Smoke and temperature distribution.

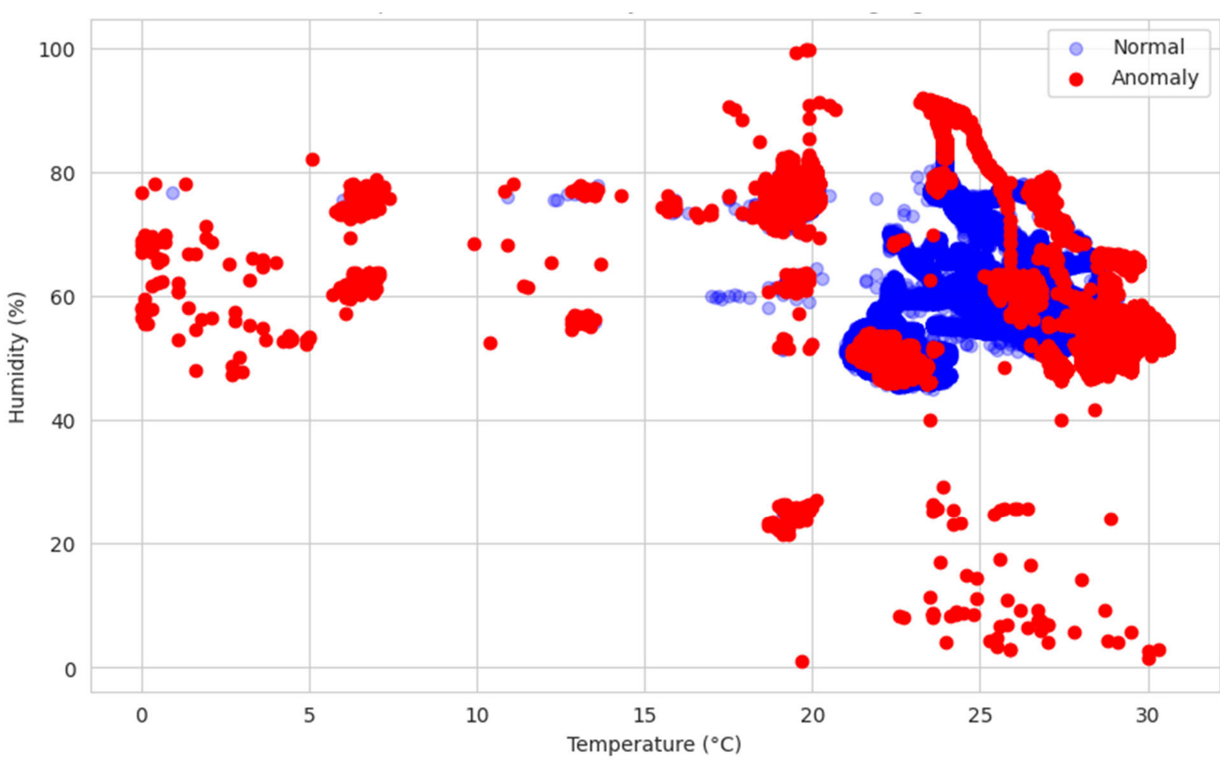

FIGURE 4. Temperature vs. humidity with anomaly highlighted.

units for sensor readings vary (e.g., ppm for CO and LPG, percentage for humidity, and Fahrenheit for temperature). This dataset is valuable for analyzing environmental conditions and detecting anomalies or patterns in sensor data across different locations. Figures 2 and 3 show the distribution of CO, humidity, LPG, smoke, and temperature.

V. RESULTS AND DISCUSSIONS

A. ANOMALY DETECTION THROUGH ISOLATION FOREST

We selected Isolation Forest for anomaly detection because, compared to other methods, it is highly effective for anomaly detection, especially for IoT sensor data [58]. Isolation Forest is fast, scalable, and does not make any assumptions about the data distribution, making it suitable for several types of sensory data [59]. It performs well with large numbers of features and is inherently designed to separate normal and anomalous points clearly [60]. This is demonstrated in our study, where temperature and humidity anomalies are detected and presented in scatter and line graphs. Box plots show higher variability and extreme readings during anomalies, further illustrating why Isolation Forest is adept at identifying such conditions in environmental metrics.

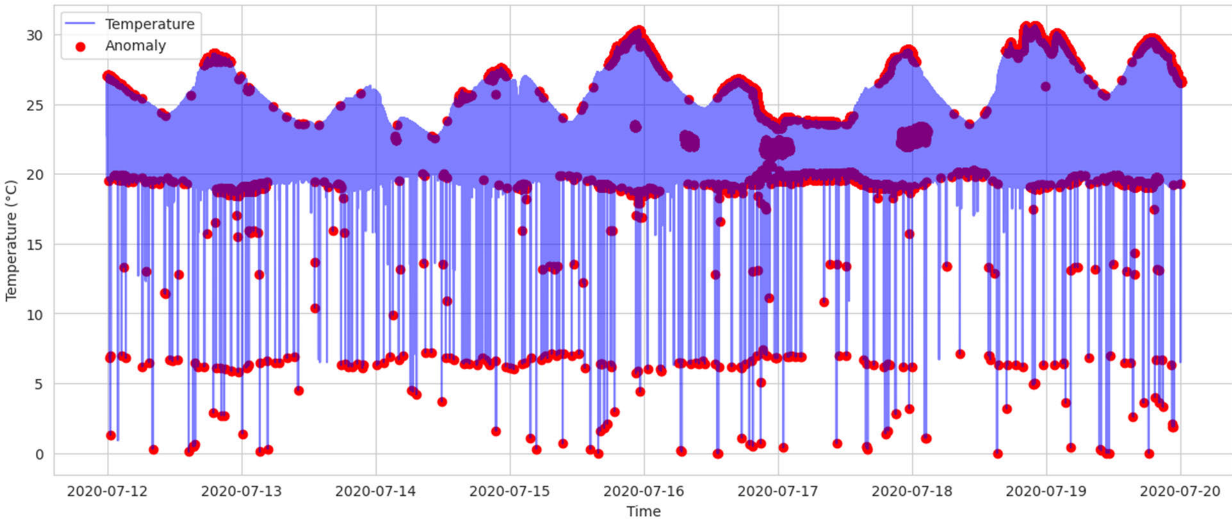

FIGURE 5. Temperature readings over time with anomalies highlighted.

TABLE 1. Normal mean, median, and std vs. anomaly mean, median, and std.

Metrics \ Factors	Temperature	Humidity
Normal Mean	22.334528	59.403039
Normal Median	22.300000	53.500000
Normal STD	2.262846	10.829191
Anomaly Mean	23.086464	66.381481
Anomaly Median	22.100000	73.099998
Anomaly STD	4.271426	12.303579

In Isolation Forest, anomaly scores are assigned to each data point to reflect how isolated it is from the rest of the data. To determine the threshold for anomalies, we analyze the distribution of these scores and set the threshold based on the 95th percentile. This approach helps control the sensitivity of the detection system by ensuring that only the highest anomaly scores are classified as anomalies. We used cross-validation to fine-tune the threshold, optimizing it to balance false positives and false negatives effectively.

The scatter plot visualized in Figure 4 shows the relationship between temperature (in °C) and humidity (%) for IoT sensor data, with the distinction between normal observations and anomalies. The blue points represent normal data, showing typical temperature and humidity readings, while the red points indicate anomalies—data points that deviate significantly from the common patterns. The plot reveals that most anomalies occur at higher humidity levels across various temperatures, suggesting potential issues or unusual conditions captured by the sensors. This visualization helps in quickly identifying and focusing on areas where the sensor readings do not follow the expected trends, which is important for further investigation and decision-making in IoT systems management.

The line chart shown in Figure 5 illustrates temperature readings over time, superimposed with highlighted anomalies. The continuous blue line represents the temperature data, varying over time, depicted against a specific timeline. The red dots pinpoint anomalies, identified as significant deviations from typical temperature patterns. The chart effectively shows both the daily fluctuations in temperature and the instances where the readings are unusual. The frequency and placement of anomalies may suggest specific trends or external factors affecting the temperature, making it a useful tool for monitoring and further analysis to identify the causes of such anomalies in an IoT environment. This visualization can help in diagnosing system issues, predicting potential failures, or detecting environmental changes that may impact the sensor readings.

Table 1 shows the values of normal mean, median, and std vs. anomaly mean, median, and std. The results are further depicted from Figure 5 as box plots of temperature and humidity. The analysis of the dataset reveals substantial disparities between normal and anomalous environmental conditions, particularly concerning temperature and humidity metrics derived from Isolation Forest. In normal circumstances, the mean temperature hovers around 22.33°C, while during anomalies, it slightly elevates to approximately 23.09°C. Similarly, the mean humidity experiences an increase from approximately 59.40% in normal conditions to about 66.38% during anomalies, indicating heightened

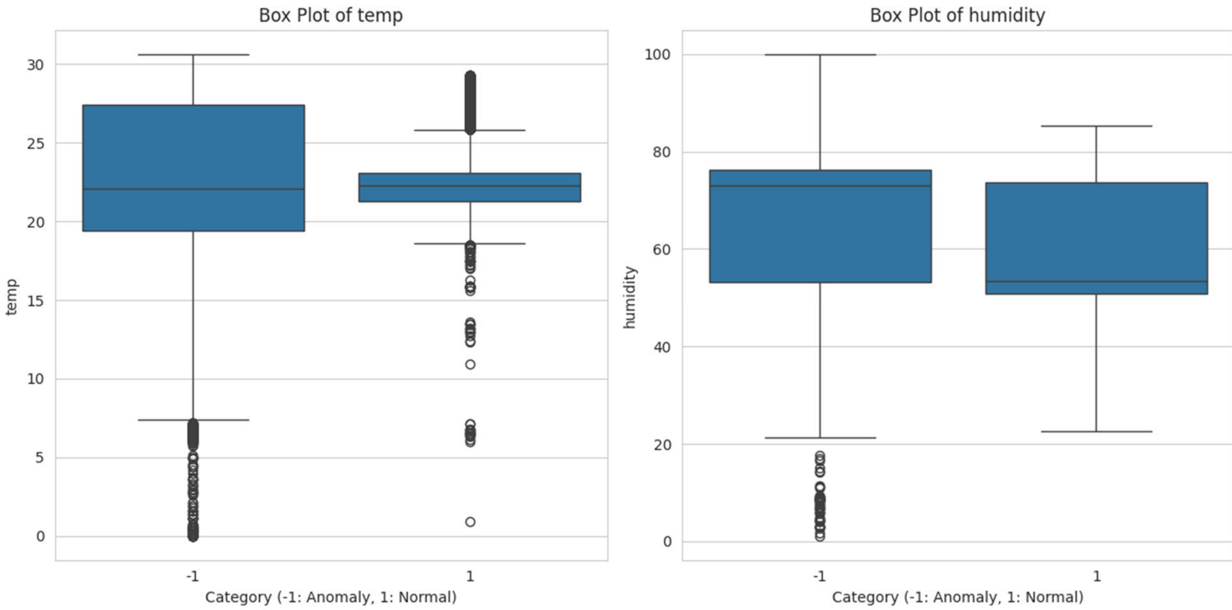

FIGURE 6. Box plots of temperature and humidity.

humidity levels during anomalous events. While anomalies induce fluctuations in mean temperature, the median temperature remains relatively stable at around 22.10°C, contrasting the more pronounced shift observed in median humidity levels from 53.50% under normal conditions to 73.10% during anomalies.

Further analysis of standard deviations reveals a greater variability and dispersion in temperature readings during anomalous events, with the standard deviation increasing from 2.26°C in normal conditions to 4.27°C during anomalies. The standard deviation of humidity also experiences an escalation during anomalies, rising from 10.83% under normal conditions to 12.30% during anomalous situations. Visual representation through box plots as reflected from Figure 6, reinforces these findings, illustrating a broader spread of temperature and humidity values during anomalies compared to normal conditions. Anomalies are characterized by higher mean values, increased variability, and more extreme readings, highlighting the efficacy of Isolation Forest in discriminating between normal and anomalous environmental conditions based on temperature and humidity readings.

Isolation Forest has proven to be highly reliable due to its robust design and efficiency in handling high-dimensional data. It does not rely on any assumptions about data distribution, making it versatile for various datasets [61], [62]. Its ability to isolate anomalies by partitioning data points ensures a clear distinction between normal and anomalous observations. We validated the reliability of our system through extensive testing and cross-validation on IoT sensor data, which showed consistent performance in identifying anomalies. The statistical analyses and visualizations, including scatter plots, line charts, and box plots, further confirm the robustness and reliability of the Isolation Forest method in our application.

B. PREDICTIVE MODELLING THROUGH LINEAR REGRESSION AND RANDOM FOREST

We used Linear Regression to predict future trends in environmental data. Linear Regression is a simple yet powerful model that helps us understand the relationship between dependent and independent variables. By training this model on historical sensor data, we can make continuous predictions about future temperature and humidity levels, providing valuable insights for decision-making. To enhance the accuracy and robustness of our predictions, we also used the Random Forest algorithm. Random Forest is an ensemble learning method that builds multiple decision trees and merges them to obtain a more accurate and stable prediction. This algorithm is particularly effective in handling non-linear relationships and interactions between variables, making it suitable for predicting outcomes such as crop yield and livestock health based on sensor data.

We predicted the performance through mean square error (MSE) and r-squared parameters for random forest and linear regression, the results are shown in Table 2. The MSE metric measures the average squared difference between the estimated values and the actual value. An MSE of 1.449 for Linear Regression suggests that, on average, the model's predictions deviate from the actual temperatures by about the square root of this value, which is approximately 1.20 degrees. The lower the MSE, the better, as it indicates a closer fit to the data. The R-squared value of 0.799 for Linear Regression indicates that approximately 79.9% of the variance in the dependent variable (temperature) is predictable from the independent variables. An R^2 score close

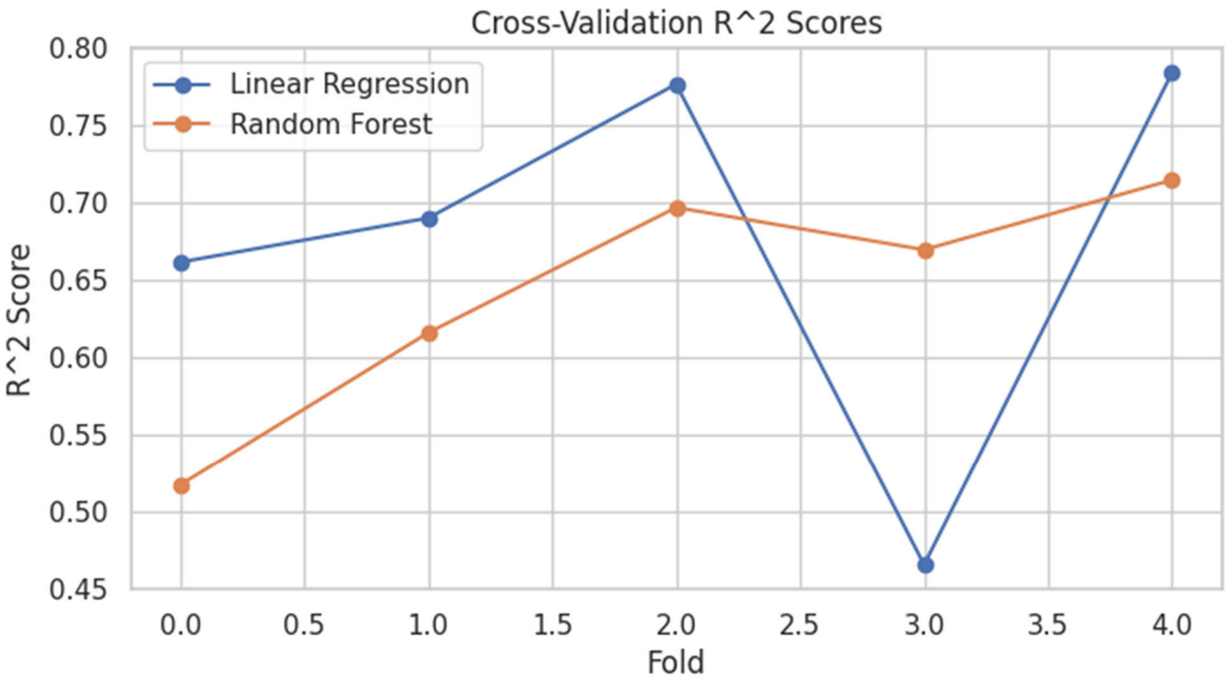

FIGURE 7. Comparative analysis of linear regression and random forest models through cross-validation.

TABLE 2. MSE and R^2 for random forest and linear regression.

Metrics \ Models	Linear Regression	Random Forest
MSE	1.4490572908241728	0.16159989204668784
R^2	0.7998763231417185	0.9776820662778001

to 1 indicates a strong correlation between the actual and predicted values, so 0.80 is quite good for many practical applications, especially for a first attempt. The MSE has significantly decreased from 1.449 in the linear regression model to 0.162 in the Random Forest model. This reduction indicates that the average squared difference between the estimated values and what was observed is much smaller, suggesting a tighter fit to the data. The *R^2 score* has improved from 0.800 to 0.978, meaning that the model now explains about 97.8% of the variance in the temperature data, compared to 80% with linear regression. This indicates a very high level of predictive accuracy.

The chart shown through Figure 7 illustrates the R^2 scores derived from cross-validation procedures for Linear Regression and Random Forest regression models. R^2, or the coefficient of determination, gauges the proportion of variability in the dependent variable predicted by the independent variables. These scores are pivotal in assessing model performance across diverse data subsets. Examining the trends across five folds of cross-validation, Linear Regression starts with a commendable R^2 score of approximately 0.75 in the initial fold and sustains a relatively steady performance throughout, concluding near 0.75 in the fifth fold. Conversely, Random Forest initiates with a lower R^2 score around 0.55, undergoing fluctuations in performance. It ascends until the third fold, peaking slightly above 0.75, sharply declines in the fourth fold to around 0.50, and then rebounds to approximately 0.70 in the final fold. The graph indicates that Linear Regression demonstrates more uniform performance across data subsets, whereas Random Forest exhibits greater variability, potentially reflecting sensitivity to data splits or influential outlier points. Understanding these traces is important for assessing model stability and can inform refinement or model selection based on consistency and predictive reliability.

VI. CONCLUSION

The incorporation of IoT devices and LoRaWAN networks in agricultural technology is the first step in the modern farming revolution, which is the main solution for contemporary farming. We have seen in our study how the application of IoT-based monitoring and control solutions in agriculture has multiple dimensions and practical implications. Real-time data insights and precision agriculture methods enable farmers to accomplish this by increasing resource efficiency, improving productivity, and lessening environmental degradation. Through the use of IoT devices based on LoRaWAN intelligent technology, farmers are able to get complete information about important agricultural parameters such as soil moisture, temperature, humidity, and crop health. This wealth of data provides a base for conscious decision-making, and farmers can now adjust their agricultural practices to the exact requirements of a particular crop or area of land. Precision agriculture methods, like variable-rate irrigation and specific fertilization, allow farmers to enhance resource efficiency and reduce waste in the process, thereby leading to environmental sustainability. Furthermore, the low-consumption, long-range wireless communication offered by LoRaWAN technology allows for seamless communication and data transmission across large geographical areas with no problems, even in remote or rural areas with poor infrastructure. The statistical analysis highlights the accuracy of Isolation Forest in anomaly detection by demonstrating a discernible rise in mean and variability during anomalies. When comparing Random Forest to Linear Regression in predictive modeling, Random Forest shows a significant improvement in predictive accuracy as shown by lower MSE and higher R^2 values. The research validates the predictive power of Random Forest for temperature data modeling in an IoT context, as well as the dependability and efficiency of Isolation Forest for anomaly detection.

Further research entails the fusion of state-of-the-art machine learning and time series analysis techniques for the higher-quality discovery of anomalies and the prediction of the future. Exploring emerging technologies, such as blockchain and edge computing, could further enhance the security, reliability, and efficiency of smart farming systems. In essence, smart farming has the potential to revolutionize global food production, promote sustainability, and ensure food security for future generations. By addressing current challenges and embracing technological innovation, smart farming will continue to evolve as a cornerstone of modern agriculture, driving efficiency, productivity, and environmental stewardship in the years to come.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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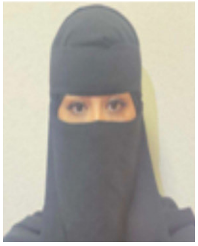

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