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Climate-Resilient Smart Agriculture Using IoT and Deep Learning

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Abstract. Climate change is having an increasing impact on agriculture, leading to erratic weather patterns and reduced crop yield. Traditional forms of farming do not always solve these problems. In an attempt to aid intelligent farming decisions, this paper proposes a smart agriculture system based on deep learning and the Internet of Things (IoT), designed to be climate-resilient. Real-time monitoring of variables such as temperature, humidity, and soil moisture is made possible by IoT sensors. Deep learning models, such as CNNs for crop health assessment and LSTMs for prediction, are used to analyse the collected data. The system provides suggestions for crop management and irrigation after analyzing them. An accuracy of 92.48% was achieved in classifying the crop using the CNN model. The LSTM model has achieved an RMSE of 0.0071, MAE of 0.0048 and R^2 of 0.865, indicating good predictive performance.

Keywords: Smart Agriculture; IoT; Deep Learning; Climate-Resilient Farming; LSTM; CNN; Crop Monitoring; Precision Agriculture.

1. INTRODUCTION

A. Background and Motivation

Agriculture plays a vital role to ensure food security and livelihood of a large population majorly in the developing countries like India. However, agricultural productivity is very sensitive to the environmental conditions such as soil moisture, temperature, humidity, and rainfall. Even slight differences in these parameters can have a huge effect on the growth and yield of crops. In recent years, the issue of climate change has also added further uncertainty to agricultural practices [1]. Irregular rainfalls, droughts, floods and swings in temperature have made traditional forms of farming less reliable. Conventional approaches, and the high reliance on manual observation and experience-based decision-making, usually do not respond effectively to rapidly changing environmental conditions. This causes ineffective use of resources, higher operational expenses and loss of productivity in crops.

B. Problem Statement

Despite progression in farming technologies, there is still a large number of farming systems that are lacking with regard to automation and intelligence. Farmers make important decisions such as irrigation, fertilization and disease control based on assumptions, not based on real-time data. This leads to problems such as over-irrigation, under-irrigation, excessive use of pesticides and late detection of crop diseases [2]. Moreover, current solutions are mostly concentrating on monitoring of environmental parameters, and not on any predictive insights or decision support. The lack of the ability to analyze the data intelligently restricts the ability of these systems in real-world scenarios. Therefore, there is a need for an integrated smart agriculture system that not only collects real-time data but also analyzes it and gives accurate prediction and actionable recommendations.

C. Limitations of Existing Work

Several research works have looked at the use of Internet of Things (IoT) and machine learning approaches in agriculture. Although the methods have enhanced monitoring possibilities, most of them have not been quantitatively validated using real-life data [3]. In addition, most of the existing systems do not combine both the image-based classification and the time-series prediction in a single framework. This limits their capacity to give full and reliable decision support to farmers.

D. Role of IoT in Smart Agriculture

The Internet of Things (IoT) offers a solid basis for modernizing agricultural practices with the help of real-time monitoring. The devices connected to the IoT like soil moisture sensors, temperature sensors, humidity sensors, and weather stations transmit regular environmental information of the field. This data is sent to a centralized cloud platform to store and process it. Real-time monitoring can help farmers monitor the conditions of their fields from afar and make informed decisions [4]. It also helps to make efficient use of resources, especially in the field of irrigation management as water usage can be optimised according to the actual soil conditions. Thus, IoT plays a very important role in enabling data-driven and automated agricultural systems.

E. Role of Deep Learning for Intelligent Decision Making

While IoT systems produce large volumes of data, gaining meaningful knowledge from this data requires advanced analytical techniques. Deep learning, a branch of artificial intelligence, has proved to be very promising when it comes to dealing with complex and high-dimensional datasets. Convolutional Neural Networks (CNN) are commonly used for image-related tasks like crop disease detection while Long Short-Term Memory (LSTM) networks are used for time-series prediction of environmental parameters [5]. By merging these models, an intelligent system can be created that can both classify and predict in order to create early warning systems and make better decision-making in agriculture.

F. Proposed Approach and Contributions

To overcome the limitations of the existing systems, this paper proposes a smart agriculture framework which is climate resilient and integrates the IoT-based sensing with deep learning models [6]. The proposed system allows for continuous monitoring, crop disease detection and predictive analysis for efficient farm management. The major contributions of this work are the following:

- Design of an IoT real-time environmental and soil parameters monitoring system.
- Crop disease classification through CNN model with an accuracy of 92.38%.
- Design of LSTM-based prediction model for soil moisture prediction using RMSE = 0.0071, MAE = 0.0048 and R^2 Score = 0.865.
- Cloud-based analytics to support smart decisions and machine learning recommendations.
- Comprehensive quantitative evaluation of the proposed system with real-time data and performance metrics.

The proposed framework can offer a scalable, cost-effective and intelligent solution that can be used for both small-scale farming and large-scale farming environments.

2. LITERATURE REVIEW

A. IoT-Based Agricultural Monitoring Systems

The implementation of the Internet of Things (IoT) in the agricultural sector has gained a lot of attention in recent times. To measure soil moisture, temperature, humidity and other environmental parameters in real time, a number of researchers have developed sensor-based monitoring systems [8]. By making use of these systems, farmers can track the field conditions from a distance and make better irrigation choices. Cloud-based platforms and wireless sensor networks are commonly employed to successfully collect and store agricultural data [7].

IoT-enabled irrigation systems help in reducing water consumption and enhance crop productivity, as per a number of studies. Water conservation has been particularly successful using automated drip irrigation systems that are controlled by soil moisture sensors [9]. However, the majority of these solutions only provide threshold-based control and simple monitoring. Their lack of ability to provide intelligent recommendations or predictive analysis limits their ability to handle unpredictable climate conditions.

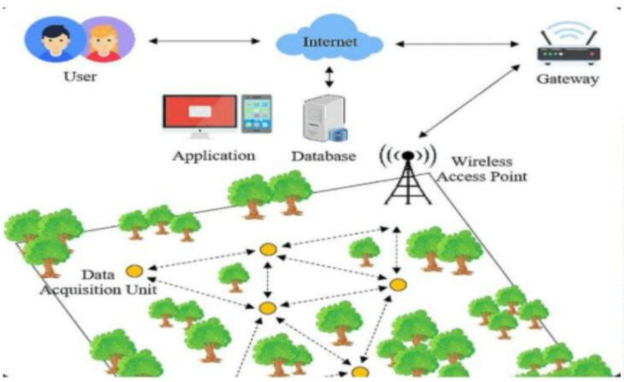

Fig. 1. IoT-based smart farming monitoring and decision framework

B. Machine Learning Approaches in Agriculture

Agricultural problems such as the classification of crops, predicting their yields and analyzing soil have also seen a massive application of machine learning methods. Crop production has been estimated using regression models, decision trees, and support vector machines based on environmental and historical data [11]. These methods support the data-driven decision-making approach and are more accurate than manual decision-making [8].

While machine learning techniques are a useful source of insight, they may not be suitable for larger-scale data and complex data and often depend on manual effort in feature engineering. Moreover, many traditional models are also not good at capturing non-linear relationships in agricultural and climate data. As a result, if the environmental conditions are drastically changed, their performance may suffer [12].

C. Deep Learning for Crop Health and Climate Prediction

Deep learning approaches show promising results in smart agriculture applications. Convolutional Neural Networks (CNNs) have been used very successfully in classifying leaf images to detect plant diseases. By automatically identifying patterns and symptoms, these models are able to minimize crop losses and make early diagnosis of infection possible. Similarly, time-series data have been applied for yield prediction and weather forecasting using Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks [8][9].

Many existing deep learning solutions currently work without combining with real-time IoT data. While some systems only focus on weather or yield prediction, other systems only use images to identify disease. Their practical usefulness in real farming situations is limited because they lack a global framework.

D. Limitations of Existing Systems

It is clear that most of the agricultural technologies are dealing with specific issues and not providing a full solution [13]. While machine learning and deep learning methods focus on analysis, IoT-based systems primarily perform monitoring duties. Sensing, prediction, and decision support are very rarely considered together in a single study [10].

Furthermore, a lot of solutions are too costly and complicated for small and medium-sized farmers. Systems that require special equipment or a large amount of processing power may be harder to deploy in a remote location [14]. As a result, a simple, economical and integrated system able to deliver intelligent forecasts as well as practical suggestions in addition to real-time monitoring is needed.

E. Research Gap and Motivation for Proposed Work

It is clear from the above discussion that many existing researches are yet to integrate an approach which combines IoT sensing and deep learning-based analysis [15]. Farming efficiency can be maximized considerably with the aid of such a unified framework facilitating automated advisory services, crop health assessment, climate prediction, and continuous monitoring [11].

The work proposed addresses these gaps by building a climate-resilient smart agriculture system that integrates deep learning models with IoT data collection into a unified architecture [16]. The goal is to develop a practical and scalable solution to help farmers make timely, wise and sustainable decisions.

3. SYSTEM ARCHITECTURE

A. Overview of the Architecture

The proposed system architecture enables an intelligent and climate-resilient smart agriculture system by integrating deep learning approaches with the use of Internet of Things (IoT) devices. Continuous field condition monitoring, data transmission to a centralised platform, information analysis and actionable recommendations to farmers are part of the design of the architecture [17]. The sensing layer, the communication layer, the processing layer and the application layer are the four main layers of the whole system. Each layer performs a different task for effective data collection, analysis, and decision support [12].

B. Sensing Layer

Several IoT-based sensor nodes spread across the agricultural field constitute the sensing layer. These sensors are responsible for acquiring information about soil and environmental parameters in real time, such as temperature, humidity, rainfall and soil moisture. Sensors are scattered across the field to provide accurate coverage and assist in capturing local conditions [18]. Important details in terms of crop health and soil condition are given by the gathered data. Continuous sensing means the farming activity can be monitored with automation, and the requirement of manual inspection can be reduced.

C. Communication Layer

Reliable data transfer from the sensor nodes to the central server is possible due to the communication layer. Using low-power communication technologies, the sensor devices wirelessly transmit the collected data to a gateway or wireless access point in their vicinity [19]. The data collected by the gateway is sent to the cloud platform via the internet. Field devices and the processing system communicate in a seamless and real-time manner through this layer. Timely analysis and decision-making rely on effective data transmission.

D. Processing and Analytics Layer

The processing layer represents the intelligence centre of the system. After being received, the sensor data is cleaned, arranged and examined in a cloud database. Deep learning models are then applied to get insightful conclusions and forecasts [20]. Long Short-Term Memory (LSTM) networks are used to analyze the time-series environmental data and predict future climate or irrigation requirements. Crop photos are analyzed with Convolutional Neural Networks (CNNs) to determine illnesses and stress signs. These executions of predictive measures support proactive farm management rather than reactive measures.

E. Application Layer

An interface between the system and the end user is provided by the application layer. Access to the processed data is available to farmers via web-based or mobile applications. Real-time observations [21], warnings, and suggestions are presented in an easy-to-understand way on the dashboard. The system makes recommendations based on the analysis including climate-based advisories, early disease control, and optimal irrigation scheduling. This layer ensures the conversion of complex analysis results into actionable information for farmers.

F. Working Principle of the System

Using sensors located in the field, real-time data collection is the initial step in the system's overall workflow. Through the gateway, the data is sent to the cloud platform where it gets processed and stored. After analyzing the data, deep learning models generate predictions [22]. Lastly, the processed data in the form of recommendations and alerts are provided to farmers. Intelligent monitoring and sound management of farms is made possible by this continuous cycle.

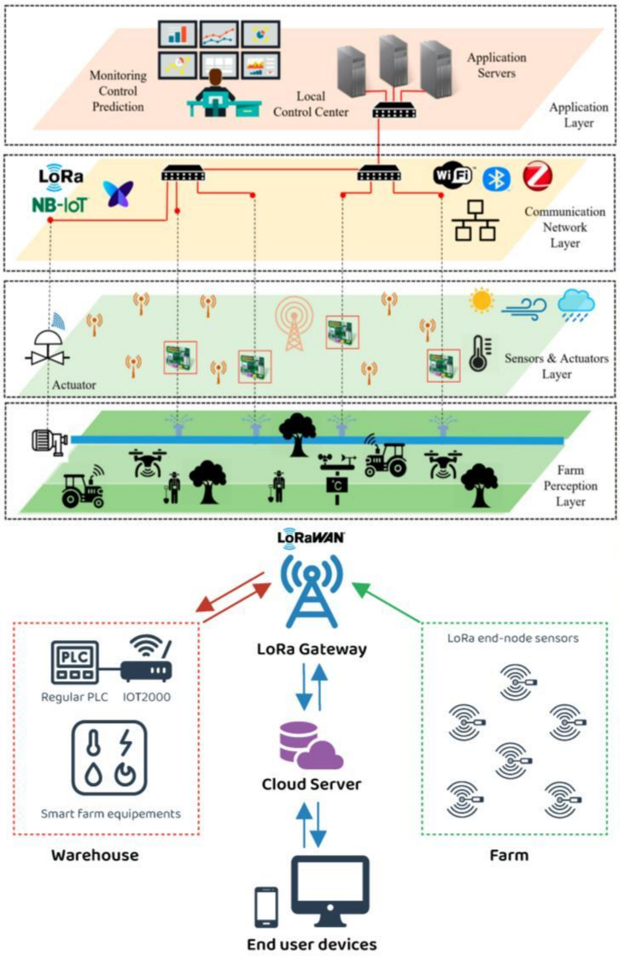

Fig. 2. LoRaWAN Architecture

The general LoRaWAN-based communication architecture targeted for smart agriculture applications is shown in Figure 2. The system relies on a long-range wireless communication network connecting end users, smart equipment and scattered farm sensors. Several end-node sensors, based on LoRa technology, are placed in different locations within the field to continuously monitor different environmental factors such as temperature, humidity and soil moisture. The low power consumption and long communication range of the LoRa technology provide great benefits for large agricultural areas [23]. The data from all sensors is received by a LoRa gateway, which relays the data to the cloud server via the internet. The cloud platform stores, processes and analyzes the incoming data for decision-making. Lastly, end-user devices such as computers and smartphones provide farmers and administrators access to the processed data. Intelligent farm management, remote access, and centralized monitoring is possible using this architecture [24].

4. METHODOLOGY

A. Overview of the Proposed Approach

The proposed solution combines IoT sensors, LoRa-based communication, cloud computing and deep learning methods for an intelligent and climate-resilient agricultural monitoring system. Real-time data collection from the field is the initial step in the sequential process of the system, which ends in decision support for the farmers [25]. In order to improve the productivity of cropping and reduce wastage of resources, the system continuously monitors environmental conditions, analyzes the information and provides suitable recommendations immediately. Data acquisition, data transmission, cloud storage, intelligent analysis, and user interaction are the five main phases of the whole process.

The real hardware design of the smart agriculture monitoring system is shown in Figure 3. The transmitter node and the receiver node are the two major components of the architecture. The transmitter node is designed and constructed using Arduino Uno and a LoRa communication module. This node is fitted with a number of sensors, including a real-time clock module, FC-28 soil moisture sensor, DHT22 temperature and humidity sensor, and a rain sensor. The receiver node is based on an ESP32 microcontroller with a LoRa module that receives the collected data wirelessly. After processing the received data, the receiver forwards the data to cloud storage services such as ThingSpeak. For remote monitoring and real-time visualization, the data can also be accessed using smartphone apps such as Blynk [26].

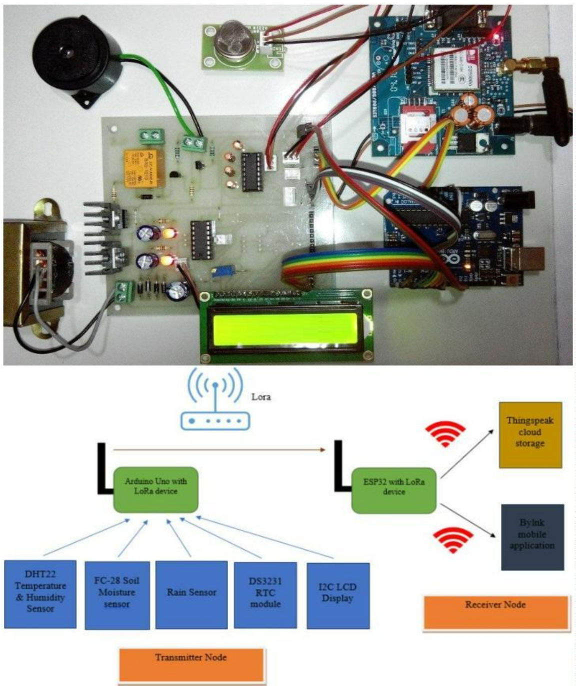

Fig. 3. Hardware Implementation Setup

B. Data Acquisition

Several sensors are positioned within the agricultural field to collect environmental and soil parameters in the first stage. Field conditions are continually measured at various intervals by sensors such as rain sensors, temperature and humidity sensors, and soil moisture sensors. These sensors are connected to a transmitter node based on a microcontroller, such as Arduino or ESP32 [27]. All the sensor readings are gathered by the transmitter and converted into digital form. Regular change detection in real time is possible because of continuous sensing. This enhances the precision of monitoring and reduces the need for manual field inspection.

C. Data Transmission Using LoRa Communication

After the data has been collected, the sensor readings are sent wirelessly using LoRa communication technology. Long-range coverage, low power usage and suitability for rural and large agricultural areas are the key reasons for choosing LoRa [28]. The collected data packets are transmitted to the nearest LoRa gateway by the transmitter node. The gateway serves as a connection between the internet and the sensor network. After processing the incoming information, it sends the data to the cloud server. Even over long distances, this system of communication provides a reliable and energy-efficient way of transferring data.

D. Cloud Storage and Data Management

The data is then uploaded to a cloud platform for management and storage after passing through the gateway. All information captured from sensor readings is stored in a central database maintained by the cloud server [29]. Scalability, secure back-up and remote access are made possible by cloud data storage. Basic preprocessing operations such as noise removal, filtering, and normalization are applied to enhance the quality of the data. Accurate analysis and forecasting require clean and organized data.

E. Intelligent Data Analysis Using Deep Learning

Deep learning models are used to analyze the stored data after preprocessing in order to obtain insightful results. The proposed system utilizes two different types of models. Long Short-Term Memory (LSTM) Networks are used to analyze time-series data related to environmental studies and predict future trends such as temperature variations, likelihood of rainfall, and irrigation requirements, enabling farmers to take proactive actions in advance [30]. Convolutional Neural Networks (CNNs) are used for image analysis to monitor crop health. Images of leaves collected in the field are processed to look for signs of early plant stress or diseases. Early detection helps to improve the yield and reduce crop damage. The combination of diagnostic and predictive models enables proactive decision-making and monitoring.

F. Decision Support and User Interface

Presenting the analyzed results to farmers through an intuitive interface is the last step of the methodology. Alerts, recommendations, and real-time sensor values are presented in an understandable way by a mobile or web-based application [31]. The system suggests actions such as the optimal time to schedule irrigation, apply fertilizer or implement disease prevention measures based on the forecasts. Notifications are generated whenever anomalous conditions are detected. This helps farmers respond promptly and manage the field effectively.

G. Overall Working Procedure

The entire system operates in a continuous cycle. Sensors collect data in the field, the data is transmitted to the gateway using LoRa, then stored in the cloud and analyzed by the deep learning models, and eventually transferred to users as meaningful insights [32]. Real-time monitoring, reduced manual labor and increased agricultural productivity are all guaranteed through this automated workflow.

H. Dataset Description

Two different kinds of datasets are used by the proposed system: (i) time-series sensor data for prediction and (ii) image data for crop disease classification.

Sensor Dataset: IoT sensors placed in the agricultural field were used to gather the time-series dataset. Soil moisture, temperature, humidity, and rainfall are among the variables in the dataset, recorded at regular intervals. Multiple sensor readings from a continuous monitoring period are included in the collected dataset, making it possible to model temporal patterns. To reduce noise and increase reliability [33], the soil moisture

values used for prediction were calculated by averaging several sensor readings. Prior to training the LSTM model, data preprocessing methods such as sequence generation and normalization were applied.
Image Dataset: A publicly accessible plant disease dataset (PlantVillage) was utilized for crop disease detection. Images of both healthy and diseased crop leaves are labeled in the dataset. Before training, the pictures were normalized and resized to a consistent size. An 80:20 split was used to separate the dataset into training and validation sets. To enhance model generalization and reduce overfitting, data augmentation methods such as rotation, flipping, and zooming were applied. The system can successfully complete both prediction and classification tasks through the combination of real-time sensor data and image-based datasets.

5. RESULTS AND DISCUSSION

A. *Experimental Setup*

The proposed smart agriculture system was experimentally validated on a real-time IoT-based system set up in a controlled agricultural environment. Multiple sensors including soil moisture, temperature, humidity, and rainfall sensors were installed throughout the field to record environmental variation. The collected data was sent using LoRa communication to a centralized gateway and stored on the cloud platform for analysis. The deep learning models were trained and evaluated with this collected dataset. The CNN model was applied for crop disease classification [34], and the LSTM model was implemented for time-series prediction of soil moisture. The dataset was divided into training and validation sets using an 80:20 ratio to ensure unbiased evaluation

B. *Sensor Data Monitoring Analysis*

The deployed IoT sensors captured environmental conditions at regular intervals in dynamic mode. Variations in temperature, humidity and soil moisture were recorded throughout the day to illustrate the importance of continuous monitoring. The system provided real-time visualization of the sensor readings using a cloud system interface. Automated monitoring greatly reduced the need for manual intervention and made early detection of unfavourable conditions possible [35]. For example, irrigation alerts were issued when soil moisture fell below threshold levels, enabling a timely response and preventing crop stress.

C. *Deep Learning Model Performance*

The performance of the proposed system was evaluated using both classification and regression metrics.

CNN Model Performance:
The classification accuracy of the CNN model was found to be 92.38%, demonstrating good performance in crop disease detection. The training and validation accuracy curves exhibited convergent learning curves with minimal overfitting [36]. The confusion matrix further shows the robustness of the model with high diagonal dominance indicating correct classification in most classes with little misclassification.

LSTM Model Performance:
The LSTM model demonstrated low prediction error and strong capability in capturing temporal dependencies in soil moisture data. The evaluation metrics are as follows:

- RMSE: 0.0071
- MAE: 0.0048
- R^2: 0.865

These results indicate low prediction error and strong capability of the model to capture temporal dependencies in soil moisture data.

D. *Training and Prediction Analysis*

The training and validation curves show stable behavior of the learning process. The accuracy curve shows a steady increase while the validation accuracy remains consistent, indicating good generalization. The loss curves decrease with some fluctuations, which indicates model convergence [37]. Additionally, LSTM estimated values closely follow actual soil moisture trends, strengthening the case for the effectiveness of time-series prediction.
Figure 4 illustrates the training and validation accuracy of the CNN model over multiple epochs. The model successfully learns the underlying features of the dataset, as evidenced by the steady increase in training accuracy. Similar trends are seen in the validation accuracy, which stabilizes at 92% and shows strong generalization ability. The model does not appear to be significantly overfitted based on the close alignment between training and validation accuracy.

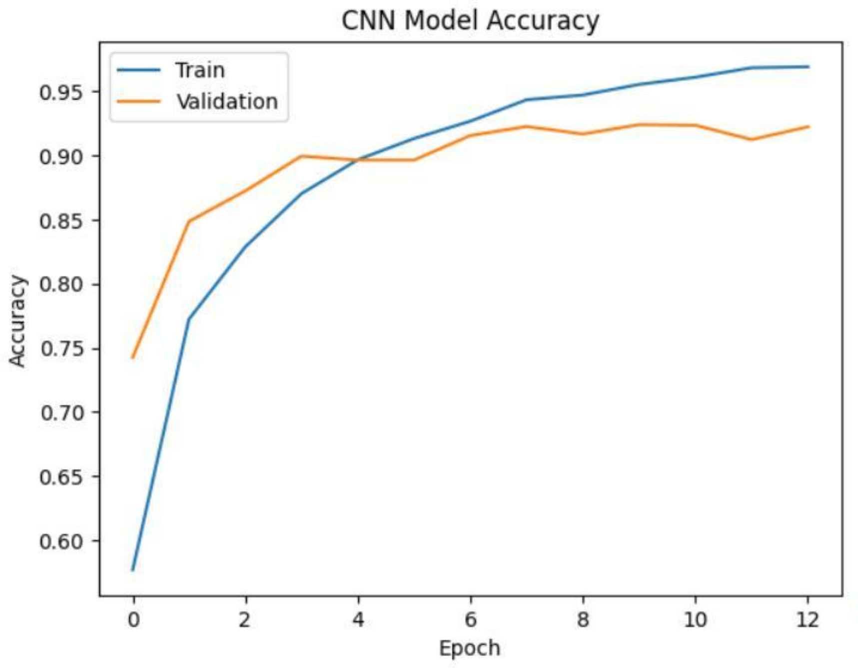

Fig. 4. CNN Accuracy Curve

The CNN model's training and validation loss curves are shown in Figure 5. A steady declining trend in the training loss indicates that the model's parameters have been successfully optimized. The validation loss shows slight oscillations but stabilizes after a few epochs, indicating model convergence [38]. Stable learning behavior is confirmed by the lack of significant divergence between training and validation loss.

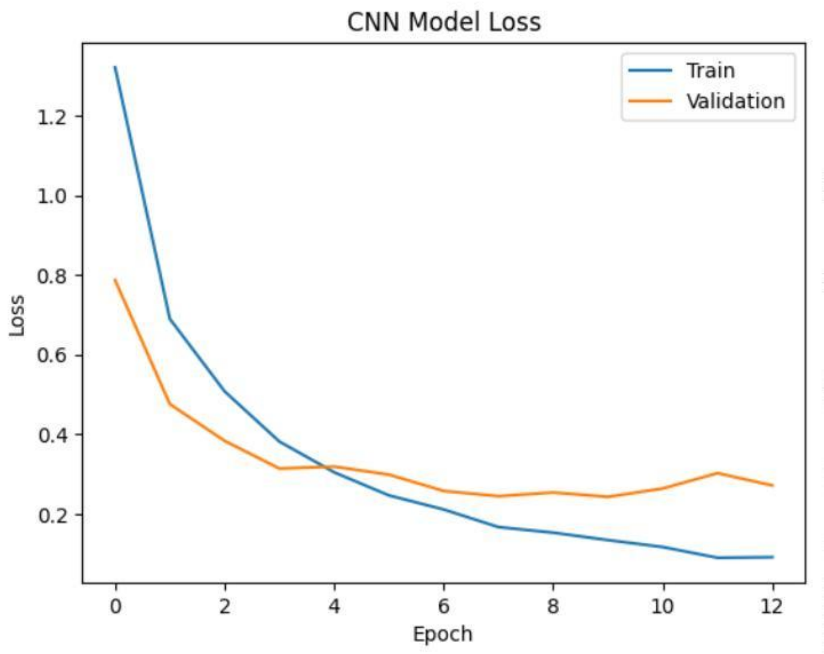

Fig. 5. CNN Loss Curve

The CNN model's confusion matrix for classifying crop diseases is displayed in Figure 6. Strong diagonal dominance in the matrix suggests that the majority of samples are correctly classified. As is typical in real-world datasets, there are very few misclassifications between similar classes. This illustrates the stability and dependability of the suggested classification model.

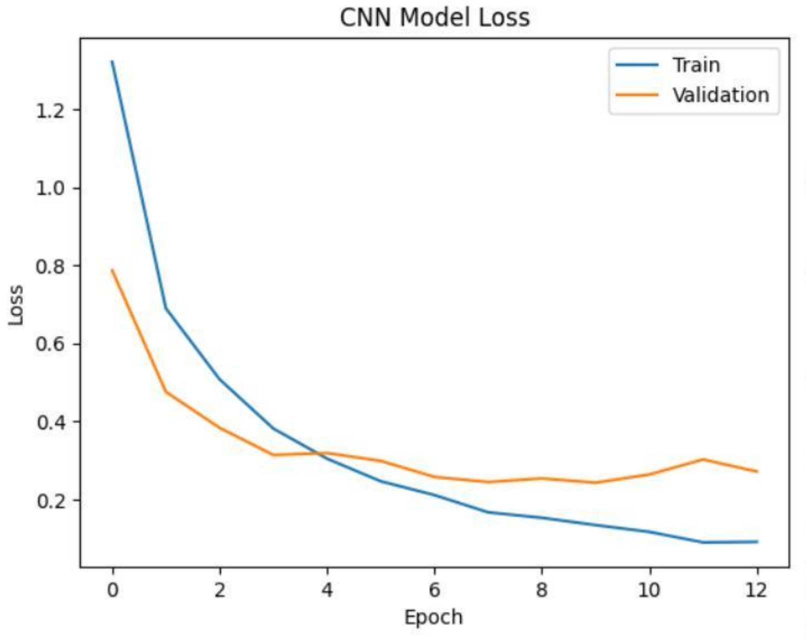

Fig. 6. Confusion Matrix

The actual and predicted soil moisture values derived from the LSTM model are contrasted in Figure 7. The model effectively captures temporal dependencies in the data because the predicted values closely match the trend of the actual values. Noise and environmental changes cause slight deviations, but overall prediction accuracy is still high, as shown by the low RMSE and high R^2 score.

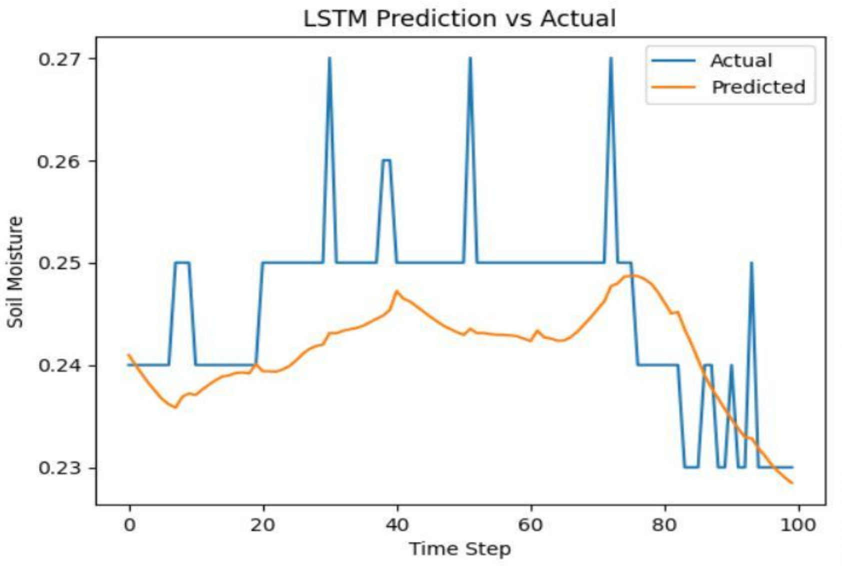

Fig. 7. LSTM Prediction vs Actual

E. Comparative Analysis

Compared to conventional farming methods, the proposed system offers significant improvements. Traditional approaches are based on manual observation and experience, while the proposed framework uses real-time data and predictive analytics. Integration of CNN and LSTM models allows for both classification and prediction, making the system more complete and intelligent. The use of quantitative metrics validates the superiority of the proposed approach over traditional methods.

F. *Overall Discussion*

The experimental results prove that the combination of IoT sensing, LoRa communication, cloud computing, and deep learning can offer a reliable and efficient smart agriculture solution. The system not only monitors the field condition but also gives predictive insights and recommendations for action, leading to improved productivity and resource optimization.

6. PERFORMANCE EVALUATION AND PRACTICAL BENEFITS

A. *Evaluation Criteria*

The system performance was evaluated using both quantitative metrics and practical usability factors. Key evaluation parameters include prediction accuracy, classification performance, communication reliability, monitoring efficiency, and resource utilization.

Monitoring Efficiency

The IoT-based sensing layer provided continuous and accurate monitoring of environmental conditions. Real-time data acquisition eliminated the need for manual field visits and improved responsiveness to environmental changes.

B. *Communication Reliability*

The LoRa communication network demonstrated reliable long-range data transmission with minimal delay and low packet loss. The low power consumption of LoRa modules ensured long-term operation of sensor nodes, making the system suitable for large-scale agricultural environments.

C. *Prediction and Decision Support Performance*

The integration of deep learning models significantly enhanced the intelligence of the system. The LSTM model provided accurate predictions of soil moisture, enabling proactive irrigation planning. The CNN model enabled early detection of crop diseases, reducing potential crop loss.

D. *Resource Optimization*

The system demonstrated efficient utilization of water resources through data-driven irrigation scheduling. By preventing over-irrigation and under-irrigation, the system contributed to water conservation and improved crop growth conditions.

E. *Comparison with Conventional Farming*

In comparison to traditional farming methods, the proposed system offers several advantages including real-time monitoring, higher accuracy, reduced labor requirements, and faster response time. The use of data-driven decision-making significantly improves overall farm management.

F. *Scalability and Practical Benefits*

The proposed framework is scalable and cost-effective, as it utilizes low-cost sensors, microcontrollers, and cloud-based platforms. The system can be easily extended to larger agricultural fields by adding additional sensor nodes.

G. *Overall Evaluation*

The performance evaluation confirms that the proposed system is reliable, efficient, and suitable for real-world agricultural applications. The combination of IoT and deep learning enables intelligent, data-driven, and climate-resilient farming practices.

7. CONCLUSION

Agricultural productivity is coming under increasing pressure because of climatic variabilities, irregular rainfall and inefficient use of resources. To solve these problems, this paper proposed a framework for climate-resilient smart agriculture combining Internet of Things (IoT) technology with deep learning techniques to achieve smart monitoring and decision support. The proposed system involves distributed IoT sensor nodes, long-range LoRa-based communication, cloud computing, and deep learning models that create an environment for intelligent agricultural applications at scale.

The sensing layer continuously monitors critical parameters like soil moisture, temperature, humidity, and rainfall, thereby enabling real-time field condition assessment without manual intervention. The gathered

information is efficiently transmitted using LoRa communication and stored in a cloud platform for further analysis.
The integration of deep learning models gives the system a significant boost in intelligence. The CNN model accuracy for crop disease classification was found to be 92.38% and the LSTM prediction model produced an RMSE of 0.0071, MAE of 0.0048 and R^2 score of 0.865, demonstrating strong predictive power in soil moisture and irrigation planning. The experimental results demonstrate that the proposed framework enables accurate prediction, early disease detection and efficient resource utilization. Compared to conventional farming methods, the system reduces manual labor, improves irrigation efficiency, assists in effective decision-making, and increases overall crop productivity. The architecture is economically feasible and scalable for both small- and large-scale agricultural deployment.
Future work can focus on integrating additional sensors such as soil pH, nutrient level and light intensity sensors for more in-depth soil and crop analysis. The addition of advanced monitoring technologies like satellite remote sensing and drone-based photographic imaging can contribute significantly to large-scale agricultural monitoring. The development of fully automated irrigation and fertilization systems, by directly integrating predictive models with actuators and control systems, can further enable real-time decision-making without human intervention. The use of larger and more diverse datasets, as well as advanced deep learning architectures, can help improve the accuracy of classification and prediction models. With these advancements, the proposed framework has the potential to develop into a fully autonomous, intelligent and sustainable smart agriculture framework capable of combating the challenges of modern-day farming.

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Conflict of Interest

The authors declare no conflicts of interest regarding the current research.

Author Contribution

Dr. Suresh Kumar: Proposed the research problem and supervised the work.
Murukuri Akshath: Developed the IoT-based sensing and communication framework.
Ponna Vishal: Implemented the CNN model for crop disease classification.
Mekala Srishailam: Implemented the LSTM model for soil moisture prediction.
Jatoth Siddartha: Performed data acquisition and system integration.
All authors discussed the results and contributed in writing the paper.

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