Smart Farming: IoT-Driven Crop Yield Prediction for Rice Cultivation

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***Abstract*—In recent years, the agricultural sector has faced challenges in achieving optimal crop yields due to complex environmental factors and limited access to data-driven decision-making tools. An innovative IoT-based approach to predict crop yields is presented, aiming to improve crop productivity for farmers. The system utilizes a network of IoT sensors, including DHT22 and rainfall sensors, to gather real-time data on temperature, humidity, and rainfall. Soil-integrated sensors are also used to monitor specific soil properties such as nitrogen, phosphorus, potassium, pH, electrical conductivity, humidity, and temperature. This data is sent to a web interface for live display and stored for predictive modeling. Several regression models—decision tree, random forest, ridge regression, and linear regression—were implemented to predict crop yields, with the random forest regression model achieving the highest accuracy and an error rate of 6.46 percent. The stacking model was also analyzed, but the random forest model's MAE and R^2 metrics proved superior, leading to its selection for deployment. A user-friendly web-based interface has been developed to enable farmers to interact with the system and predict crop yields effectively. This implementation smoothly integrates IoT technology with advanced data analytics, providing valuable insights to optimize agricultural practices, which in turn enhances food security and improves livelihoods.**

***Keywords*—IoT, crop yield prediction, machine learning algorithms, regression models, web-based interface, stacking**

I. Introduction

Agriculture is crucial in supporting the world's expanding population, providing the main source of livelihood for a large part of India's population and playing a key role in boosting food production [1]. With the increasing demand for food, farmers need to adopt better practices to improve productivity and reduce losses. Predicting and analyzing crop growth has become a critical part of modern agriculture with machine learning landing as an essential tool to help achieve these goals. As a rapidly advancing technology, machine learning improves precision and provides solutions to challenges in crop yield prediction within the agricultural sector [2]. Smart farming helps farmers improve yields while conserving essential resources like water, fertilizers, and energy. The main goal of smart agricultural systems is to enhance field productivity [3]. Over the years, smart farms have integrated a wide range of technologies into their operations such as sensing and monitoring tools, IoT sensors, data analytics, remote control systems, and big data storage alongside precision farming methods. These innovations are designed to enhance the farming efficiency and productivity. In smart farming, IoT is seen as a vital technology, mainly used to monitor agricultural factors and provide guidance for effective crop management [4]. IoT sensors play a crucial role by collecting real-time data on environmental factors like temperature, humidity and rainfall, which are then processed to generate accurate yield predictions. These sensors monitor parameters like rainfall, temperature, soil pH and other environmental conditions. The data collected helps in analyzing crop yields for upcoming seasons. IoT sensors like DHT22, pH, and rain sensors are used to monitor factors like rainfall, soil pH, and temperature, and the data they collect undergo processing and analysis. This highlights the importance of data cleaning and preprocessing when applying machine learning algorithms. Machine learning is a rapidly developing field that has the potential to transform the way crop yield is predicted and evaluated. By using statistical and mathematical models, machine learning algorithms can analyze data and make predictions allowing systems to enhance their accuracy over time without requiring explicit programming. These algorithms are used for tasks like predicting water needs and identifying pests based on agricultural requirements [5]. Regression models, such as the Random Forest Regressor, are applied to predict crop yield. These models were selected over classification models since the goal is to predict a continuous value. Linear Regression is used to estimate the amount of fertilizer required, taking into account soil parameters like pH, potassium, nitrogen, phosphorus, boron, zinc, carbon, and manganese as inputs [6].

However, deploying machine learning in agriculture comes with challenges, such as the high cost of sensors and technologies, the lack of data preparation, and the need for specialized skills to develop and maintain solutions. As precision farming becomes more widespread and farms collect more data, the advantages of using machine learning in agriculture will become clearer. It is worth noting that machine learning in agriculture is still developing, and more research is needed to fully unlock its potential. Nevertheless, the results so far are promising, and machine learning is likely to play an increasingly important role in agriculture. The primary focus is to create an IoT-based crop yield prediction system using machine learning algorithms. The aim is to forecast crop yield for future seasons by analyzing data from IoT sensors, such as DHT22, pH, and rain sensors. Various regression models, including Linear Regression, Decision Tree Regressor, Random Forest Regressor, and Ridge Regression, are employed, with the Random Forest Regressor showing the highest accuracy and being selected for prediction. To make the predictions accessible, a user-friendly website is developed. Data from the sensors is stored, and after one year, the average data is calculated and saved in a CSV file. Farmers can upload parameters such as the area and fertilizer values, and the model will predict the crop yield for the upcoming season.

II. Related Work

Numerous studies have explored the application of data mining and predictive modeling techniques to enhance crop yield prediction and recommendation systems for improved agricultural productivity. These works focus on the importance of identifying critical factors influencing crop production and employ advanced machine learning algorithms to develop accurate predictive models. Building on these foundations, the project integrates IoT technology to enhance existing predictive models with more detailed and real-time data, leading to more accurate and timely recommendations for farmers. [7] conducts a systematic literature review focusing on the application of machine learning for crop yield prediction. The review involved a comprehensive search across multiple databases to identify relevant studies published between 2008 and 2018, selecting 50 studies for in-depth analysis. The review addresses research questions regarding machine learning algorithms, features used, evaluation parameters, and challenges in crop yield prediction. Key findings highlight the prevalence of algorithms such as Artificial Neural Networks and Support Vector Machines, common features like temperature and rainfall, and challenges related to data availability, feature selection, and model interpretability. Additionally, the review includes an analysis of deep learning-based studies, identifying techniques like Convolutional Neural Networks and Long Short-Term Memory networks. Overall, [7] provides a comprehensive overview of the current state of machine learning and deep learning for crop yield prediction, identifying research gaps and suggesting future directions. (Van Klompenburg, Thomas, Ayalew Kassahun, and Cagatay Catal, 2020). [8] reviews existing literature on simplified approaches to crop yield prediction, advanced regression techniques, and the utilization of large datasets. It emphasizes the need for practical and accessible prediction tools for Indian farmers and proposes a model that addresses these requirements. The contributions include employing advanced regression techniques like Kernel Ridge and utilizing a large dataset obtained from government repositories. Limitations include the lack of exploration of additional factors affecting crop yield prediction, a focus solely on Indian agriculture, and the absence of comparative analysis with existing models. Additionally, it offers a user-friendly web application interface for farmers. (Nishant, Potnuru Sai, Pinapa Sai Venkat, Bollu Lakshmi Avinash, and B. Jabber, 2020). [9] provides an overview of existing literature on crop classification systems in precision agriculture, emphasizing the necessity for advanced techniques to optimize crop selection and enhance production. It highlights the introduction of deep reinforcement learning as a promising solution to address challenges faced by farmers in selecting suitable crops based on soil conditions. The comparison of the proposed deep reinforcement learning system with conventional machine learning algorithms demonstrates its superiority in providing accurate site-specific crop recommendations. [9] also suggests future work to enhance the performance of the recommender system, emphasizing the importance of incorporating previous records and exploring optimization strategies. (Bouni, Mohamed, Badr Hssina, Khadija Douzi, and Samira Douzi, 2022). [10] provides an overview of existing literature on machine learning applications in agriculture, with a focus on improving planting, watering, and harvesting practices. It discusses how integrating IoT sensors, data analytics, and machine learning algorithms can enhance decision-making in agriculture. The experimental results demonstrate the high accuracy of machine learning algorithms in analyzing agricultural data. [10] concludes by emphasizing the potential of machine learning in optimizing crop production and reducing waste, while acknowledging the need to address challenges such as data preparation and sensor costs. (Elbasi, Ersin, Chamseddine Zaki, Ahmet E. Topcu, Wiem Abdelbaki, Aymen I. Zreikat, Elda Cina, Ahmed Shdefat, and Louai Saker, 2023). [11] reviews IoT-based systems for soil content analysis and crop yield prediction, focusing on the use of machine learning algorithms for soil classification and crop recommendation. The integration of IoT technology in agriculture allows real-time data collection on soil parameters, which machine learning models can analyze. Research has shown that algorithms such as Support Vector Machine and Decision Tree are effective in classifying soil types and recommending suitable crops, significantly improving crop yield predictions. Experimental results indicate that Decision Tree algorithms provide higher accuracy in crop prediction compared to Support Vector Machine. Real-world implementations of these IoT-based systems demonstrate their feasibility and advantages in enhancing agricultural productivity. However, there are challenges, including the need for further automated sensors, a broader range of algorithm comparisons, and consideration of long-term environmental impacts. Overall, IoT-based systems combined with machine learning algorithms hold great potential for optimizing soil analysis and crop yield prediction, helping farmers make better decisions and improving precision farming techniques. (Reshma, R., V. Sathiyavathi, T. Sindhu, K. Selvakumar, and L. SaiRamesh, 2020). [12] explores how data mining techniques are used to predict crop yields and recommend crops, emphasizing the integration of environmental and biotic factors like rainfall, temperature, soil pH, and salinity to improve prediction accuracy. Studies have used methods like K-means clustering to group regions with similar agricultural characteristics and have utilized machine learning models like linear regression, k-nearest neighbors, and neural networks for yield prediction. Model accuracy is typically evaluated using metrics like RMSE to ensure reliability. However, existing studies face limitations such as restricted geographical scope and the integration of additional factors such as soil nutrients and specific agricultural practices. Future research should aim to include more comprehensive datasets and translate clustering and prediction results into practical recommendations for farmers. (Ahamed, AT M. Shakil, Navid Tanzeem Mahmood, Nazmul Hossain, Mohammad Tanzir Kabir, Kallal Das, Faridur Rahman, and Rashedur M. Rahman, 2015).

III. Dataset

The dataset for the study was sourced from Kaggle and included variables such as rainfall, temperature, soil pH, and cultivated area, which are key factors influencing crop yield. Initially, datasets were gathered from various government agriculture websites, but they were insufficient and lacked the necessary parameters for analysis. After struggling to find the ideal dataset after searching through various sources, a dataset that was accurate and more suitable than others was ultimately selected from Kaggle and used for training the model. The dataset was cleaned by removing null values and outliers, followed by feature selection to focus on the most relevant variables. The data was divided into 80 percent for training and 20 percent for testing, ensuring that the machine learning models were both accurate and reliable. The analysis focused on rice cultivation in India for several reasons:

1) Rice is commonly cultivated throughout India.
2) India's varied climatic conditions make it perfect for rice cultivation.
3) The large dataset from India enabled more in-depth testing and validation of the model.

By selecting only essential features and concentrating on a specific crop and region, we aimed to develop a strong model that aligns with local agricultural conditions. This focus improved the model's practical relevance and accuracy.

IV. Input Variables

From the extensive dataset, a few significant variables were selected based on their impact on crop yield. The chosen variables were:

1) Rainfall: The average annual rainfall was derived from monthly data. Rainfall plays a crucial role in influencing soil moisture. Generally, higher annual rainfall results in improved crop yields.

2) Temperature: Average temperature was included as a key factor due to its strong impact on crop growth and development. Annual temperature data was gathered to ensure accurate predictions.

3) pH: Soil pH was considered because it indicates the acidity of the soil, which plays a crucial role in microbial activity—an essential factor for crop growth. By using average pH values, we aimed to improve the accuracy of our predictions.

4) Area: The cultivated area was included as an input variable, with the understanding that a larger area typically results in a higher crop yield. The area was measured in hectares.

Other numerical input variables, such as nutrients like Nitrogen, phosphorus, and potassium, were excluded from the analysis as they did not produce a proper heatmap for correlation analysis. This step was crucial to ensure that only the most relevant and impactful variables were used in the predictive model.

V. Methodology

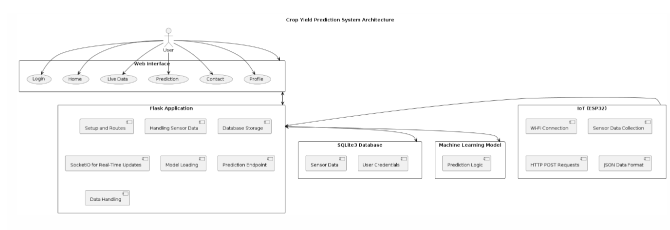

Fig. 1. Architecture of the proposed system

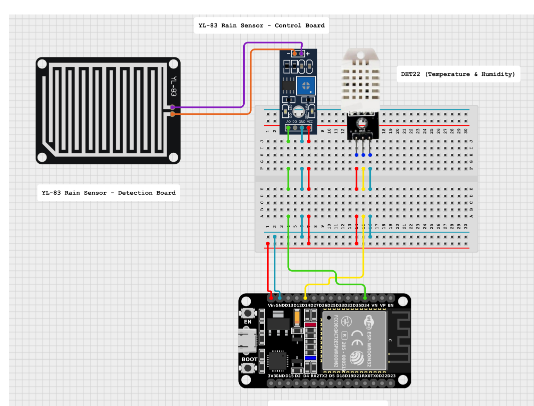

Fig. 2. Tinkercad Model of Circuit

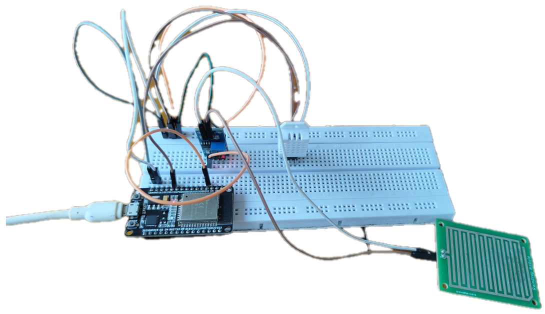

Fig. 3. Image of the connected physical circuit

A. Hardware

To successfully deploy an IoT-based system for monitoring efficient crop yield, a simple circuit model, as shown in Figure 3, was adopted. The model included:

- DHT22 Sensor
- Rain Sensor
- pH Sensor
- ESP-WROOM-32
- Breadboard

1) IoT Sensors:

a) DHT22 Sensor: Monitors temperature and humidity. This sensor provides accurate and reliable data necessary for understanding environmental conditions affecting crop growth.

b) Rain Sensor: Measures rainfall. This is crucial for assessing soil moisture levels and predicting crop yield.

c) pH Sensor: Although essential for monitoring soil pH levels, the local unavailability of this sensor due to limited distribution channels prevented its integration into the system. Suppliers were only accessible outside the region.

An alternative method involves using a soil pH probe and meter, which requires creating a soil slurry and measuring the pH. However, this approach is impractical for continuous, real-time monitoring due to the need for constant soil sampling and record maintenance.

As a result, the implementation proceeded without including data from the soil pH sensor.

The DHT22 sensor, which measures both temperature and humidity, along with the rain sensor for detecting rainfall, were selected due to their accuracy and real-time data provision, which are essential for predicting crop yields. Their affordability also makes them a good choice for prototyping. Although these sensors work well for demonstration purposes, advanced sensors would be necessary for large-scale field deployments to guarantee thorough and precise data collection.

2) Hardware Components:

a) Breadboard: Provides a platform for building and testing the circuit without soldering.

b) Jumper Wires: Connect the sensors and other components on the breadboard to the ESP-WROOM-32.

c) ESP-WROOM-32: Acts as the main microcontroller for the system. It manages sensor integration, establishes Wi-Fi connectivity, and sends sensor data to the Flask server through HTTP POST requests. Environmental data is stored in an SQLite3 database, ensuring continuous updates on current conditions.

The required code for programming the microcontroller was developed using the Arduino IDE software.

3) Data Transmission and Real-Time Updates:

a) Data Transmission and Storage: The system displays sensor data on the website in real-time, updating every second. Data is stored hourly, with daily, weekly, monthly, and yearly averages computed and saved in a separate dataset for long-term analysis. Initially, a Kaggle dataset with yearly averages was used to kick-start the predictions.

b) Real-Time Updates: To keep the web interface continuously updated without manual refreshing, the system employs Socket.IO for real-time communication between the server and clients. This feature provides immediate insights into environmental conditions affecting crop yields, improving decision-making processes.

B. Software

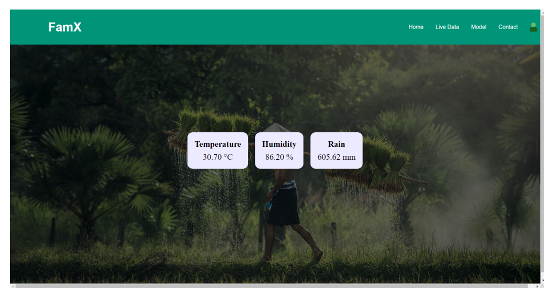

Fig. 4. Real-time data displaying page

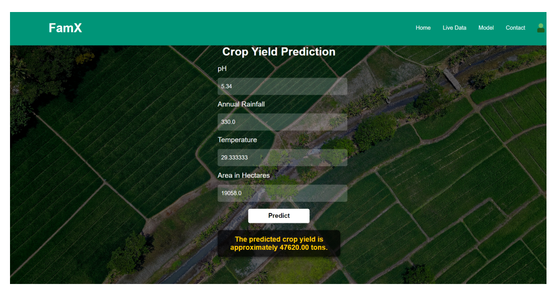

Fig. 5. Crop yield prediction page

1) Website:

a) Development Framework: Flask was used for developing the backend of the website, providing a lightweight and flexible framework for integrating the prediction model.

b) Frontend: Built using HTML, CSS, and JavaScript to ensure a user-friendly interface.

Users log into the website using their credentials. Once authenticated, they are redirected to a homepage displaying real-time data from the IoT system, as shown in Figure 4. The website features a "Model" option, allowing users to enter values such as yearly average temperature, rainfall, pH, and area to predict the total crop yield, as shown in Figure 5.

The website serves as an interface for users to interact with the prediction model and view real-time data. It provides a platform for farmers and other stakeholders to input necessary data and obtain predictions about crop yield, aiding informed decision-making.

2) Arduino IDE: Used for programming the IoT sensors to ensure accurate data collection and transmission.

3) Database: SQLite3 stores user data such as username and password. IoT sensor data (temperature, rainfall, pH) is stored in hourly, daily, monthly, and yearly tables within the SQLite3 database, with data being inserted, averaged, and updated accordingly. This ensures secure and organized data management, crucial for accurate predictions.

Upon logging in, users are authenticated against the SQLite3 database. Valid users are redirected to the homepage, displaying real-time data from the IoT sensors. In the menu bar, the "Model" option allows users to enter values for yearly average temperature, rainfall, pH, and area to predict total crop yield. The data collected from sensors over a year will automatically populate these fields for ease of use. Clicking the "Predict" button sends the input data to a prediction model created in Jupyter and integrated into the Flask backend. The model processes the data and displays the predicted crop yield on the website. Users can log out from the "Profile" option, ending their session securely.

C. Model

1) Preprocessing:

a) Data Cleaning and Preparation: The dataset collected from Kaggle was cleaned and preprocessed to ensure accuracy. This involved removing inconsistencies and outliers, such as null values and blank values.

b) Selection of Input Variables: The study focused on the most relevant input variables, including temperature, rainfall, pH, and area, stored as 'x' variables, with crop yield stored as the 'y' variable. Other numerical input variables, such as nutrients like nitrogen, phosphorous, and potassium, were excluded due to poor correlation as indicated by heatmap analysis.

c) Data Splitting: The dataset was split into training and testing sets with an 80:20 ratio. Specifically, 80 percent of the dataset was allocated for training the model, leaving 20 percent reserved for testing.

SNo	Method	MAE	R^2
0	Linear Regression	40775.716722	0.787515
1	Ridge Regression	40775.714422	0.787515
2	Decision Tree Regressor	24920.817778	0.886809
3	Random Forest Regressor	19226.712641	0.935356

TABLE I
REGRESSION MODELS.

SNo	Method	MAE	R^2
0	Final Estimator-Decision Treee Regressor	29051.805048	0.850105
1	Final Estimator-Random Forest Regressor	23320.729664	0.907889
2	Final Estimator-Ridge Regression	19223.758966	0.936532
3	Final Estimator-Linear Regressor	19314.699371	0.936887

TABLE II
STACKING OF MODELS

2) Random Forest Regressor: The random forest regressor, as detailed in Table 1, was chosen for its ability to capture non-linear relationships, essential for managing complex interactions between environmental factors like temperature, rainfall, and soil pH. It also reduces overfitting by averaging multiple decision trees, making it robust against noisy data. IoT sensors collect real-time data on temperature, rainfall, and soil pH. The data is cleaned, normalized, and key features are selected to ensure accuracy. Regression models like Random Forest are trained on historical data, learning relationships between environmental factors and crop yield. Farmers input real-time data into a web interface, and the model generates crop yield predictions based on its learned patterns. In terms of performance, Random Forest achieved the lowest Mean Absolute Error (MAE) and highest R^2, outperforming other models in predicting crop yield. Regression models were selected over classification models since crop yield is a continuous value, not a categorical output.

To further enhance prediction accuracy, stacking regression was employed, as shown in Table 2. Stacking involves combining multiple regression models to improve overall performance by leveraging the strengths of different models. Various regression models, including Linear Regression, Ridge Regression, Random Forest Regression, and Decision Tree Regressor, were selected as base models. Each base model was trained on the same dataset and generated predictions on the test dataset. These predictions were used as inputs for the final meta-model, which combined Decision Tree Regressor, Ridge Regressor, Linear Regressor, and Random Forest Regressor as final estimators. The meta-model learns to address and correct errors from the base models to refine final predictions.

To further enhance the model's precision and reduce inaccuracies, various techniques were used. Parameters, such as tree depth and the number of trees in the Random Forest, were fine-tuned to optimize performance and reduce errors. This helps the model balance between underfitting and overfitting. Moreover, to reduce variance and improve prediction accuracy, models like Random Forest were used to combine multiple decision trees.

3) ML-IoT Integration: Our system leverages IoT and Machine Learning to improve crop yield predictions. IoT sensors send data to the backend via the ESP32 microcontroller, where it's stored and processed. Flask works with the database to create a new yearly average dataset from this data. This dataset is then used in machine learning models like the Random Forest Regressor, with Flask handling model integration. By using Pickle, the trained model is saved and loaded for real-time predictions. Farmers can input live data or tweak settings through a web interface, allowing the system to update predictions continuously based on both historical and current data. This ensures accurate and timely insights that adjust to environmental changes.

VI. Results

The performance of the four individual regression models from Table 1 was compared with the four stacking models from Table 2. The evaluation metrics used were Mean Absolute Error (MAE) and R^2 score. The stacking models, which combine predictions from multiple models, demonstrated improved prediction accuracy over individual models. The stacking approach resulted in a lower MAE and a higher R^2 score compared to standalone models, indicating enhanced predictive performance and better generalization to new data. Among the eight models compared, the Random Forest Regressor achieved the lowest MAE and an R^2 score close to one, showcasing its effective use of strengths from other models for superior predictive accuracy.

IoT sensors were deployed in the field to collect real-time data on temperature, pH, and rainfall. This data is continuously stored in a database and used to calculate yearly averages. These averaged values are added to a newly created CSV file for more accurate future model predictions.

Due to the lack of historical data, an external dataset from Kaggle was used. This dataset was split into training and testing sets, with 80 percent allocated for training and 20 percent for testing. The Random Forest Regressor model was trained on this data, and its performance was evaluated through the website interface using test dataset values. The model consistently predicted the correct yield, confirming its reliability.

The website, developed with Flask for the backend and HTML, CSS, and JavaScript for the frontend, allows users to input values for yearly average temperature, rainfall, pH, and area to predict crop yield. As pH was included in the dataset used for model development, users can input the pH value on the website. Users can log in to view real-time sensor data and obtain predictions, providing actionable insights for optimizing farming practices. This system demonstrates the practical application of IoT technology and data analytics in enhancing agricultural productivity and decision-making.

VII. Future Works

During the project, significant challenges were faced, primarily related to data acquisition. Finding a high-quality dataset specific to agriculture proved difficult, with available datasets often lacking accuracy and essential features. Due to the unavailability of comprehensive datasets, the decision was made to store data collected from IoT sensors in a database and generate yearly average values, which were appended to a new CSV file. This file will be used for future predictions, aiming to improve the accuracy of the models over time. Despite the absence of soil pH sensor data, the implementation continued, focusing on other environmental factors such as temperature and rainfall to predict crop yields effectively. While soil pH monitoring remains a valuable aspect of agriculture, its absence underscores the need for improved accessibility to such sensors in the region.

Future work will focus on integrating soil sensors to gather vital data on soil temperature, moisture, humidity, pH, nitrogen, phosphorus, potassium, and electrical conductivity. Currently, the sensors (DHT22) can only measure atmospheric temperature and humidity. Incorporating soil sensors will allow for a more comprehensive study of the soil and obtain accurate values, thereby creating a dataset that enhances the accuracy and efficiency of predictions. Additionally, these sensors can monitor soil moisture levels. If the moisture falls below a certain threshold, an automated system can activate a water pump to maintain optimal moisture levels in the soil. Image recognition technology will also be used to detect crop diseases and suggest appropriate pesticides. This comprehensive approach will significantly enhance crop management and yield.

VIII. Conclusion

The incorporation of IoT technology, data analytics, and machine learning presents a promising solution for enhancing agricultural productivity and decision-making, ultimately leading to improved food security and livelihoods. This approach surpasses traditional agricultural practices by providing real-time data and insights, allowing for more precise and efficient resource management. Future work will focus on enhancing model accuracy by accumulating more comprehensive datasets and integrating additional sensors to capture a wider range of environmental factors. Overall, this study emphasizes the revolutionary potential of IoT and data-driven methodologies in agriculture, highlighting the importance of continued research and innovation in this field.

References

[1] Swetha, Tiramareddy Manasa, Tekkali Yogitha, Manche Kuruba Sai Hitha, Puppala Syamanthika, S. S. Poorna, and K. Anuraj. "Iot based water management system for crops using conventional machine learning techniques." In 2021 12th international conference on computing communication and networking technologies (ICCCNT), pp. 1-4. IEEE, 2021.

[2] Bhanu, K. N., H. J. Jasmine, and H. S. Mahadevaswamy. "Machine learning implementation in IoT based intelligent system for agriculture." In 2020 International Conference for Emerging Technology (INCET), pp. 1-5. IEEE, 2020.

[3] Varman, S. Aruul Mozhi, Arvind Ram Baskaran, S. Aravindh, and E. Prabhu. "Deep learning and IoT for smart agriculture using WSN." In 2017 ieee international conference on computational intelligence and computing research (ICCIC), pp. 1-6. IEEE, 2017.

[4] Rekha, P., Venkata Prasanna Rangan, Maneesha V. Ramesh, and K. V. Nibi. "High yield groundnut agronomy: An IoT based precision farming framework." In 2017 IEEE Global Humanitarian Technology Conference (GHTC), pp. 1-5. IEEE, 2017.

[5] Mathi, Senthilkumar, R. Akshaya, and K. Sreejith. "An Internet of Things-based Efficient Solution for Smart Farming." Procedia Computer Science 218 (2023): 2806-2819.

[6] Lekshmi, Gs, and P. Rekha. "AI Based IoT Framework for Soil Analysis and Fertilization Recommendation for Smart Coconut Farming." In 2022 8th International Conference on Signal Processing and Communication (ICSC), pp. 26-31. IEEE, 2022.

[7] Van Klompenburg, Thomas, Ayalew Kassahun, and Cagatay Catal. ”Crop yield prediction using machine learning: A systematic literature review.” Computers and Electronics in Agriculture 177 (2020): 105709.

[8] Nishant, Potnuru Sai, Pinapa Sai Venkat, Bollu Lakshmi Avinash, and B. Jabber. ”Crop yield prediction based on Indian agriculture using machine learning.” In 2020 international conference for emerging technology (INCET), pp. 1-4. IEEE, 2020.

[9] Bouni, Mohamed, Badr Hssina, Khadija Douzi, and Samira Douzi. ”Towards an Efficient Recommender Systems in Smart Agriculture: A deep reinforcement learning approach.” Procedia Computer Science 203 (2022): 825-830.

[10] Elbasi, Ersin, Chamseddine Zaki, Ahmet E. Topcu, Wiem Abdelbaki, Aymen I. Zreikat, Elda Cina, Ahmed Shdefat, and Louai Saker. ”Crop prediction model using machine learning algorithms.” Applied Sciences 13, no. 16 (2023): 9288.

[11] Reshma, R., V. Sathiyavathi, T. Sindhu, K. Selvakumar, and L. SaiRamesh. ”IoT based classification techniques for soil content analysis and crop yield prediction.” In 2020 fourth international conference on I-SMAC (IoT in social, mobile, analytics and cloud)(I-SMAC), pp. 156-160. IEEE, 2020.

[12] Ahamed, AT M. Shakil, Navid Tanzeem Mahmood, Nazmul Hossain, Mohammad Tanzir Kabir, Kallal Das, Faridur Rahman, and Rashedur M. Rahman. ”Applying data mining techniques to predict annual yield of major crops and recommend planting different crops in different districts in Bangladesh.” In 2015 IEEE/ACIS 16th International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD), pp. 1-6. IEEE, 2015.