RESEARCH PAPER

AgriGenius: Smart IoT & AI-Powered Agriculture Monitoring and Recommendation System

Aryaveer Singh[1], Shikha Chaudhary[2*], Amit Kumar Bairwa[3]
[1]Department of Information Technology
Email: Aryaveer.singh0902@gmail.com
[2*]Department of Information Technology, Manipal University Jaipur, India
Email: shikha.chaudhary@jaipur.manipal.edu
[3]Department of AIML, Manipal University Jaipur, India
Email: amit.bairwa@jaipur.manipal.edu

Received: 25th Aug, 2026 | Revised: 1st Sep, 2026 | Accepted: 5th Sep, 2026 | Available Online: 11th Sep, 2026

Abstract—Agriculture is the backbone of society and plays a prominent role in economic stability, especially in developing nations. Traditional farming practices often suffer due to a lack of real-time information, which fails to fulfil needs due to the increasing demand. This paper suggests AgriGenius as an IoT-Agriculture monitoring system with machine learning (ML) algorithms to improve farming skills to make informed or reactive decisions in real time. The system can now provide smart recommendations for crop selection and fertilizer usage based on real-time data. The AgriGenius system can monitor soil moisture, temperature, humidity, and nutrient levels of the soil in real time, and provide accurate recommendations for irrigation and fertilizer injections based on each farm's specific environment and state. AgriGenius is more accurate in its prediction as a whole since it enhanced the feature selection processes and the preprocessing of data approaches. The IoT adoption provides real-time details from IoT sensors, and the use of Light Gradient Boosting Machine (LightGBM) provides AgriGenius the capability to change drastically based upon environmental conditions, and thereby provide farmers with flexible recommendations. In reference to model performance, the accuracy of the crop recommendation model is 94-95% , while the fertilizer recommendation model achieved 99.36% accuracy, which greatly exceeded older models examined in the literature.

Index Terms—IoT in Agriculture; Agriculture 4.0; Farmer Adoption; Artificial Intelligence Technique; LightGBM; Agricultural Innovation; Fertilizer; Sustainable Agriculture; Crop Yield.

How to cite this article: Aryaveer Singh1 Shikha Chaudhary2* Amit Kumar Bairwa3. AgriGenius: Smart IoT & AI-Powered Agriculture Monitoring and Recommendation System. Int J Drug Deliv Technol. 2026;16(82s):1183-1189. DOI: 10.25258/ijddt.16.82s.131.

INTRODUCTION

Agriculture is the foundation of society, which influences social well-being, public health, and sustainable development, while providing access to food, livelihoods, and economic stability. Agriculture has progressed from manual labor to mechanization, and today it is undergoing a new transformation driven by digital technologies. This latest evolution of agriculture, labeled Agriculture 4.0, combines emerging technologies with traditional farming, illustrating a significant transition to improved agricultural efficiency, profitability, and environmental sustainability. Technological advancements such as precision farming, drones, and smart irrigation enhance crop yield, conserve resources, and improve the overall wellbeing of society by ensuring food security and rural development. The involvement of the Internet of Things (IoT) in agriculture is an innovative step that brings technology closer to the farmer to make farming smarter and more efficient [1].

Real-time data is collected with the connected IOT devices and sensors that help farmers to monitor fields and to improve farming decisions. This also helps farmers to save water, reduce waste, and grow healthier crops to increase productivity and sustainability.

II. LITERATURE REVIEW

The integration of IoT with AI-driven analytics for precision agriculture is examined to describe how machine learning (ML) models, cloud services, and Internet of Things (IoT) sensors enable real-time crop health, temperature, and soil moisture monitoring. The study highlights the value of wireless sensor networks (WSN) and cloud-based analytics for agricultural improvement by comparing and evaluating different IoT architectures and processing methods [2]. IOT and AI based precision farming efficiently manages soil while drastically lowering water consumption [3]. Crop disease identification using CNN for agricultural image analysis is applied to identify infected crops with the accuracy of over 90%, demonstrating AI's potential in early pest detection to prevent significant crop damage [4]. An organised IoT and Machine Learning for Crop Monitoring and Precision Farming to assess soil nutrient profiles and predict the best times for planting, the authors test ML techniques such as Random Forest, K-Nearest Neighbours, and Artificial Neural Networks. They conclude that combining ML with IoT sensor data greatly improves the effectiveness of agricultural decision-making [5]. Realtime data processing are made possible by edge AI computing combined with IoT hardware, which lessens reliance on the cloud. The results emphasise the benefits of edge-based deep learning models, such as increased effectiveness and lower bandwidth usage [6]. Neural network models used for agricultural security monitoring are assess, to guarantee safe and reliable data transfer. It investigates Long Short-Term Memory (LSTM) and Generative Adversarial Networks

(GANs) for identifying irregularities in IoT agricultural networks [7].

III. METHODOLOGY AND FRAMEWORK

This system is the deployment of a large network of IoT sensors located across the agricultural field. These sensors are required to provide real-time data on variables that influence crop productivity as presented in Figure 1. The YL-69 sensor [8] is used to record soil moisture levels, while the NPK sensors [9] [10] are used to record the nutrient content in the soil. The DHT22 [11] sensor is used to continuously monitor and record the surrounding temperature and humidity. After being gathered, the data is wirelessly transferred via technologies like LoRa and Wi-Fi, depending on farm size and network accessibility [12] [2] [13]. After that, data is transferred to a local edge computing device or cloud-based platform, where it is arranged, stored, and made easily accessible for analysis. With the help of this infrastructure, stakeholders can remotely monitor their fields in real time and obtain immediate insights into the environmental conditions. Now, machine learning methods are applied to analyze the obtained data. Random Forest, XGBoost, and other predictive algorithms will analyse both historical and up-to-the-minute data to accurately forecast irrigation requirements and to determine optimum fertilizer quantities [14] [15] [16].

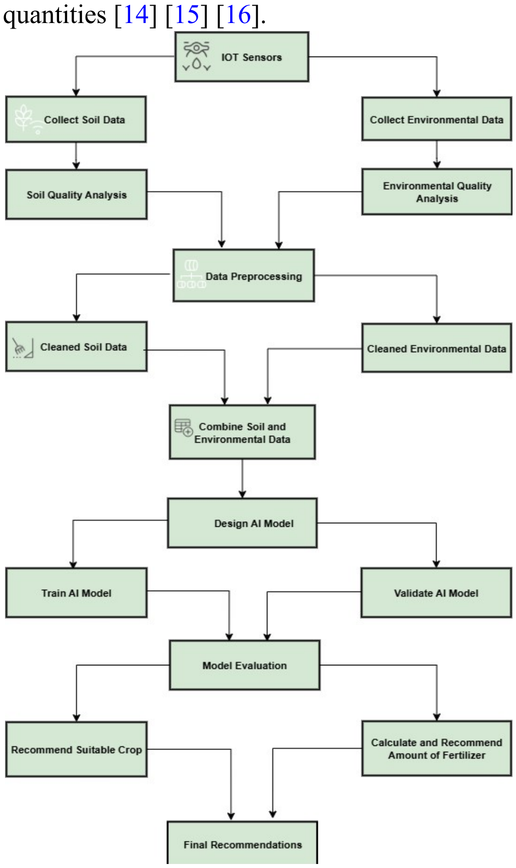

Fig. 1: Methodology diagram for precision farming using IOT and machine learning techniques

To ensure minimal water waste, smart irrigation systems, for instance, are integrated with the platform to automatically water the crops based on real-time soil moisture levels [17] [18] [19]. Additionally, fertilizer application is automated, which enables the accurate delivery of nutrients where and when they are needed, improving plant growth while preventing overuse. Farmers can effectively prevent yield loss by implementing timely pest control measures through image processing for early disease detection [20].

To guarantee modularity, scalability, and robustness, the system is organised into several architectural layers. The IoT sensor layer, which is in charge of ongoing data collection, serves as the basis [21]. The data transmission layer sits on top of this, ensuring dependable communication between the processing units and sensors. All machine learning calculations are handled by the data analysis and processing layer, which, depending on infrastructure capabilities, can be carried out on the cloud or through edge computing. The automation layer is in charge of carrying out decisions on the ground, like turning on pumps or distributing fertilizer. Lastly, farmers can enjoy a smooth and engaging experience thanks to the user interface layer. The system is intended to improve agriculture in measurable ways with this end-to-end framework. It is anticipated to use less fertiliser and water, near about 30% less, and an increase in crop yield by about 20% by recommending the suitable crop on the basis of soil and environmental conditions. In addition to modernising farming methods, this integrated approach gives farmers access to real-time, datadriven tools that improve sustainability and productivity.

A. Model Overview and Data Processing

To evaluate the performance of the machine learning and IoT-based intelligent agricultural recommendation system, the model was implemented using Python libraries and trained and tested on the dataset. This dataset includes essential parameters like temperature, rainfall, humidity, pH levels etc., all of which are key indicators for monitoring and improving agricultural conditions. Using this simulated data allowed us to develop, test, and refine our system ; it effectively served the purpose of demonstrating how the system would behave in a real-world scenario.

Two fundamental models for machine learning were created. The first forecasts the ideal crop based on variables like rainfall, temperature, humidity, pH level, phosphorus (P), potassium (K), and nitrogen (N). The dataset includes a variety of field scenarios mapped to particular crops that are known to do well in those situations. By taking the crop type, soil type, and any nutrient deficiencies found, the second model suggests the right fertilizers. Categorical and numerical features found in the input data were converted using methods like label encoding and one-hot encoding to make them appropriate for machine learning models [22].

B. Exploratory Data Analysis (EDA)

Exploratory data analysis (EDA) is an important initial step to uncover the inherent patterns, relationships, and trends of the data. In this section, the EDA of the agricultural dataset is performed to identify certain features that illustrate useful patterns for development of predictive models for crop types and irrigation management. *1) Feature Classification*

The dataset analyzed in this study has a number of features that were categorized according to the data type as well as their role in the analysis.

Numerical Features (12): There are a total of 12 numerical features in the dataset which are important to assess the environmental conditions and other soil conditions that decide the tactics of farmers. These features include: - temperature as ambient temperature in degrees Celsius. - humidity as relative humidity in percent. - water level as the moisture content of the soil. - N, P, K, as nitrogen, phosphorus, and potassium levels in the soil, which are nutrients affecting plant growth. In addition to these, there are six binary actuator states representing onoff states of farm management devices such as pumps for irrigation, fans, etc. The binary actuator features show interesting aspects of the status of the system operations and how they relate to environmental variables.

Categorical Features (1): There is one categorical variable: date, which allows us to see and analyse patterns in temporal aspects of environmental variables and actuator responses.

2) Trend Analysis

Missing measuring opportunities, identifying trends is considerably affected by your environmental conditions over time; using daily averages will allow you to observe the general dynamics and behaviors of a complex system under different situations. For trend observations we monitored:

- Temperature (degree C). Temperature trends provide indications of seasons of the year, and their implications to plant growth and possible need for irrigation.
- Humidity (%). Regardless of the data we will collect for potential evapo-transpiration and the impact to irrigation, the humidity percentage is a critical metric to continue to track with consideration to estimated evapo-transpiration.
- Water Level (%). Percentage indications of soil moisture available is a critical measure for when to initiate irrigation.
- Soil Nutrients (N, P, K). The nutrient values can provide an understanding of soil fertility, an important factor in assessing crop ability and indicating if manure or fertilization is needed.

By monitoring the daily average values we can determine trends of the environmental conditions over time while reasoning the association of the farming operations and surrounding environment.

3) Correlation Analysis

Correlation analysis is important for exploring the relationship between different environmental parameters. The Pearson correlation matrix, seen in Table Iindicates the strength and direction of linear relations between the variables :

TABLE I: Correlation Matrix

	Temp	**Humidity**	**N**	**P**	**K**
Temperature	1.00	-0.14	0.02	0.01	0.01
Humidity	-0.14	1.00	-0.35	-0.35	-0.35
N	0.02	-0.35	1.00	0.99	0.99
P	0.01	-0.35	0.99	1.00	0.99
K	0.01	-0.35	0.99	0.99	1.00

Several significant findings are highlighted by the correlation matrix: A Pearson correlation coefficient of roughly 0.99 indicates a strong positive correlation between the soil nutrients (N, P, and K). This implies that these nutrients are frequently applied at the same time and that there is a close relationship between their soil levels. All soil nutrients exhibit a moderately negative correlation with humidity, suggesting that higher soil evaporation rates may be the cause of the tendency for nutrient concentrations to decline as humidity rises. As expected, there seems to be little relationship between temperature and soil nutrients because moisture and soil chemistry have a greater direct impact on nutrient levels than temperature alone.

4) Pairwise Relationships

Pairplots and heatmaps were developed in order to better understand the connections between feature pairs. We can identify both linear and non-linear dependencies between the variables thanks to these visualisations.

The near-perfect correlation between nitrogen (N), phosphorus (P), and potassium (K), with values near 0.99, is one important finding from these analyses. This suggests that these nutrients frequently coexist in comparable amounts, and that treatments that alter one are probably going to affect the others. In the pairplot, these relationships were visually confirmed as the nutrients ranged closely together with respect to the various points of data.

C. Recommendation System using LightGBM

The LightGBM framework, a gradient boosting method renowned for its effectiveness and speed, particularly when working with large-scale tabular data, is used in both models [?]. It is ideal for agricultural recommendation systems due to its innate capacity to manage overfitting and multi-class classification. LightGBM operates on the principle of gradient boosting decision trees, adopting a leaf-wise tree growth strategy by selecting the leaf with the maximum loss reduction at each step to improve accuracy. Each subsequent decision tree tries to correct the residuals of the preceding model by minimizing a loss function using gradient descent as shown in Eq. ??.

$$G_t(x) = G_{(t-1)}(x) + \eta . H_t(x) \tag{1}$$

Here $G_t(x)$ is the ensemble model, $H_t(x)$ is the decision tree (base learner), η is the learning rate over t iterations. In precision farming, the role of the AI model is to support data-driven decision making based on data collected through sensors to recommend the most suitable crop for the farm and the amount of fertilizer based on soil health and environmental conditions. For the crop recommendation model, LightGBM works as a multi-class classification and learns to predict the most suitable crop by providing ranked probabilities for various crops. Whereas, for the fertilizer recommendation model, it is treated as one classification task and one regression task by recommending the suitable fertilizers and predicting the required quantity of each fertilizer respectively.

D. Model Training and Evaluation

Besides the non-availability of real-time sensor data, to ensure the reliability of our results, strong validation techniques were embedded to ensure the robustness of the model training process. This helped us to monitor performance, reduce overfitting, and maintain accuracy, even though the data wasn't collected in real time. In detail, the evaluation of model performance was done using stratified K-fold cross-validation with five folds, where the dataset is split into five folds and the model is trained and tested k times. This has the effect of increasing evaluation accuracy, as it ensures that there is a similar distribution of classes in all training and validation splits, making it more representative of real-world behaviour.

In each fold, the training set consisted of 80% of the data, and the validation set 20%. This was done over 5-folds, and the diverging metrics from those evaluations were averaged, to provide a holistic metric for overall model performance.

The hyperparameters of the LightGBM model were optimised to achieve the maximum generalisation while mitigating overfitting. Key hyperparameters included:

- learning_rate = 0.035
- max_depth = 6
- num_leaves = 26
- reg_alpha = 0.3, reg_lambda = 0.3 for L1 and L2 regularization
- n_estimators = 190

Early stopping was applied to halt training if validation performance plateaued, preventing overfitting.

IV. IMPLEMENTATION AND RESULT

In an ideal scenario, this paper would have been implemented by real-time data collected directly from IoT devices and sensors deployed in an actual farming environment. However, due to limitations of resources and the nonavailability of a physical setup during this phase, implementing the real-time hardware system was not feasible. To move ahead with the research and to evaluate our model, we opted for a publicly available dataset that closely mimics the kind of data realworld sensors would provide [23]. The model was trained to recommend crops and the appropriate amount of fertilizer on the basis of soil data and environmental data. For each of the models, we had approximately 94% and 99% crossvalidation accuracy. For each class, we calculated additional metrics, F1-score, precision, and recall. All of these values were less than 1.0 in each class which verifies that we had reasonable generalisation and not overfitting.

1) Crop Recommendation Model

The model effectively recommends crops that complement the current environmental conditions by integrating the various parameters, thus optimising the potential yield. With an average accuracy of roughly 94–95%, the model performs well, highlighting the significance of employing high-quality features and meticulous data preprocessing. Compared to the accuracy attained in certain comparable studies, this performance is noticeably better.

Confusion metric and feature importance graphs were used for a detailed illustration of how and why we were making predictions, and which features contributed the most to those predictions. The confusion matrix for the crop recommendation model is presented in Figure 2. Strong diagonal alignment indicates excellent model performance with only minor classwise confusion. The values like 99 or 100 show that the true class was predicted with nearly 99% accuracy.

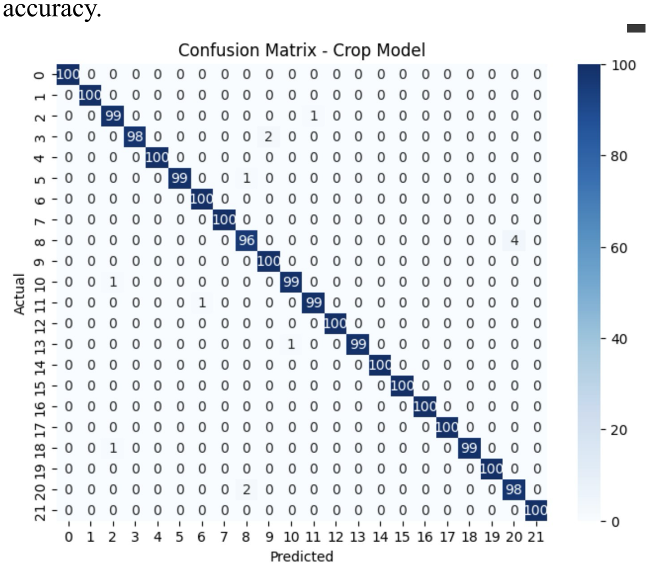

Fig. 2: Crop Model Confusion Matrix

The Humidity and rainfall rank highest in influencing the model's crop selection, followed closely by phosphorus, potassium, and nitrogen levels, as shown in Figure 3 for selecting the right crop for farmers based on environmental and soil data for the crop recommendation dataset.

2) Fertilizer Recommendation Model

The second model adds soil and crop types as features in fertilizer recommendations. This enables suggestions of fertilizers that are not only appropriate for the specific soil conditions but also biologically appropriate conditions of the selected crop. Demonstrating a few misclassifications, the model has shown a strong capacity to recommend fertilizer. Our model includes contextual elements, such as crop and soil type, to provide a better-rounded prediction and is more accurate than alternative methods in the literature, for example, Liao et al. [24], who considered only nutrient content.

The fertilizer recommendation model to suggest an appropriate amount of fertilizer, Phosphorus has the highest Model) influence on fertilizer recommendation decisions, followed by nitrogen and potassium as shown in Figure 4.

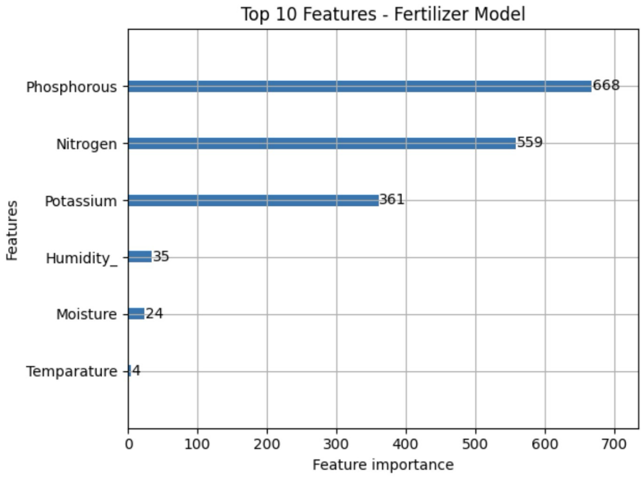

Fig. 4: Feature importance plot (Fertilizer Recommendation Model)

The model demonstrates strong generalization with high accuracy across all fertilizer categories, as in Figure 5. The few misclassifications observed fall within acceptable error thresholds

.

3) Validation and Cross-Validation

Both models were validated using a 5-fold stratified crossvalidation technique to guarantee robustness and prevent overfitting. This approach further improved the reliability of the performance estimates by guaranteeing that the class distributions of fertilizers and crops were dispersed equally between the training and test sets. This approach works especially well for agricultural datasets, which frequently have imbalances where specific crop or fertilizer types are over-represented.

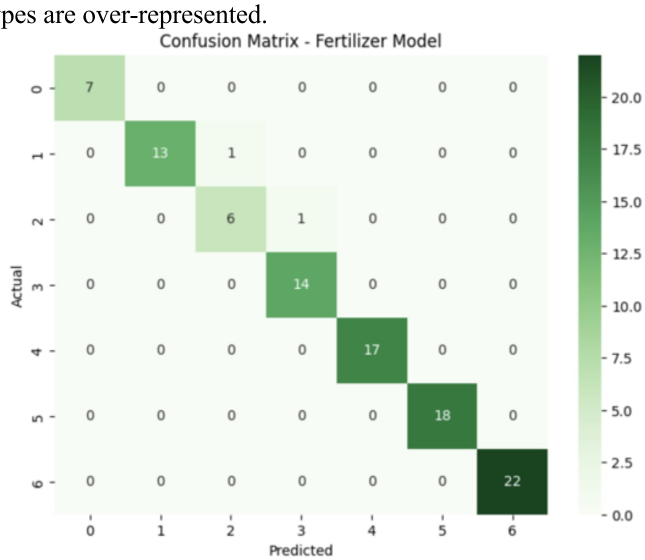

Fig. 5: Fertilizer Model Confusion Matrix

The table II summarizes the performance results of the two machine learning models used in this project: the Crop Recommendation Model and the Fertilizer Recommendation Model. The performance is evaluated based on key metrics, including accuracy, precision, and recall, obtained through a 5-fold cross-validation procedure:

Fold Accuracy: This metric displays the model's accuracy at each 5-fold cross-validation fold. The accuracy of fertilizer Recommendation Model is 99.36%, and the Crop Recommendation Model of 94.74%.

TABLE II: Model Performance Results

Metric	Fold Accuracy	Average Cross-Validation Accuracy	Precision	Recall
KNN [25]	95.68%	-	0.9629	0.9568
SVM [25]	96.82%	-	0.9715	0.9682
Crop Recommendation Model	94.74%	97.95%	0.99	0.98
Fertilizer Recommendation Model	99.36%	99.36%	0.99	0.99

Precision: Precision quantifies the percentage of recommendations that are accurate among all recommendations. The precision of both models was very near to 1.00, indicating that the models' recommendations were nearly perfect. Recall: Out of all potential true positive cases, recall shows the percentage of true positives (correct recommendations). Both models were successful in identifying every potential crop and fertilizer, as evidenced by their high recall values (0.98 for the crop model and 0.99 for the fertilizer model). These findings show that while both models exhibit remarkable performance, the fertilizer Recommendation Model exhibits marginally higher overall accuracy and consistency. The models are offering useful, trustworthy suggestions for crop and fertilizer selection, as further evidenced by the high precision and recall values. The overall outcome of the integrated model using these two models is shown in Table III.

The experimental results show that the model is effective for real-time farming. The strong predictive accuracy and positive impact on field operations highlight the real potential of smart agriculture solutions. This AI and IoT-based approach not only addresses key challenges in modern farming but also supports sustainable practices. By offering a scalable and adaptable solution, it can be tailored to various agricultural environments and local needs, enabling farmers to make informed decisions and sustainably improve productivity.

TABLE III: System Performance Outcomes

Metric	Achieved Value	Improvement
Water usage reduction	˜30%	Compared to manual irrigation

Fertilizer saving	˜28%	Based on historical usage
Crop yield improvement	˜20%	On selected test plots

V. CONCLUSION

The paper offers a IOT and AI based model for precision farming, with a particular focus on crop and fertilizer recommendations, by creating two reliable models using the LightGBM framework. Strict data processing methods, including label encoding, data shuffling, feature engineering, and careful cleaning, were used to optimise the input data quality so that the models could generalise well in various agricultural contexts. The results indicate that the model is highly reliable, a precision of 0.99 means that nearly all predictions made by the model are accurate, while a recall close to 1.00 shows that it successfully detects almost all actual cases from the dataset. Such high precision and recall values confirm the robustness of the system, making it well-suited for real-time farming decisions where both accuracy and sensitivity are critical. The model has successfully reduced the water consumption by 30% , fertilizer by 28% and improved the crop yield by 20% by selecting apprpriate crop as per the environment and soil.

REFERENCES

[1] K. Sharma and S. K. Shivandu, "Integrating artificial intelligence and internet of things (iot) for enhanced crop monitoring and management in precision agriculture," *Sensors International*, vol. 5, p. 100292, 2024.

[2] P. P. Jayaraman *et al.*, "Internet of things platform for smart farming: Experiences and lessons learnt," *Sensors*, vol. 16, no. 11, p. 1884, 2016.

[3] A. Baggio, "Wireless sensor networks in precision agriculture," *ACM Workshop on Real-World Wireless Sensor Networks*, pp. 50–60, 2009.

[4] A. Fernandez *et al.*, "Cnn-based strategies for disease detection and crop prediction in precision agriculture," *Computers and Electronics in Agriculture*, vol. 155, pp. 41–49, 2018.

[5] A. Kamilaris and F. X. Prenafeta-Boldu, "A review of the use of con-´ volutional neural networks in agriculture," *The Journal of Agricultural Science*, vol. 156, no. 3.

[6] K. G. Liakos *et al.*, "Machine learning in agriculture: A review," *Sensors*, vol. 18, no. 8, p. 2674, 2018.

[7] "Artificial neural networks in agriculture, the core of artificial intelligence: What, when, and why," *Computers and Electronics in Agriculture*, vol. 230, p. 109938, 2025.

[8] W. Y. Tan, Y. L. Then, Y. L. Lew, and F. S. Tay, "Newly calibrated analytical models for soil moisture content and ph value by low-cost yl-69 hygrometer sensor," *Measurement*, vol. 134, pp. 166–178, 2019.

[9] P. Musa, H. Sugeru, and E. P. Wibowo, "Wireless sensor networks for precision agriculture: A review of npk sensor implementations," *Sensors*, vol. 24, no. 1, p. 51, 2023.

[10] M. Masrie, M. S. A. Rosman, R. Sam, and Z. Janin, "Detection of nitrogen, phosphorus, and potassium (npk) nutrients of soil using optical transducer," in *2017 IEEE 4th international conference on smart instrumentation, measurement and application (ICSIMA)*. IEEE, 2017, pp. 1–4.

[11] I. Singh, V. Kumar, T. Aarthy, T. Akilan, V. Sharma *et al.*, "Realtime monitoring and surveillance in hazardous environments using iotenabled robotics," in *2024 1st International Conference on Advances in Computing, Communication and Networking (ICAC2N)*. IEEE, 2024, pp. 1093–1097.

[12] L. Aldhaheri, N. Alshehhi, I. I. J. Manzil, R. A. Khalil, S. Javaid,
N. Saeed, and M.-S. Alouini, "Lora communication for agriculture 4.0: Opportunities, challenges, and future directions," *IEEE Internet of Things Journal*, 2024.

[13] H. Muthukrishnan, A. Jeevanantham, B. Sunita, S. Najeerabanu, and V. Yasuvanth, "Performance analysis of wi-fi and lora technology and its implementation in farm monitoring system," in *IOP Conference Series: Materials Science and Engineering*, vol. 1055, no. 1. IOP Publishing, 2021, p. 012051.

[14] D. T. Santosh, N. Anuradha, M. Kolukuluri, G. Gupta, M. K. Pathak, V. G. Krishnan, and A. Raghuvanshi, "Development of iot based intelligent irrigation system using particle swarm optimization and xgboost techniques," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 3, pp. 1927–1934, 2024.

[15] K. V. S. Bhai, S. M. Ahmad, K. Y. N. Gupta, C. Jyothi, and M. Yunus, "Forecasting the environment factors for optimal plant growth using xgboost," in *2024 2nd International Conference on Sustainable Computing and Smart Systems (ICSCSS)*. IEEE, 2024, pp. 71–78.

[16] A. O. Ok, O. Akar, and O. Gungor, "Evaluation of random forest method for agricultural crop classification," *European Journal of Remote Sensing*, vol. 45, no. 1, pp. 421–432, 2012.

[17] K. Obaideen, B. A. Yousef, M. N. AlMallahi, Y. C. Tan, M. Mahmoud, H. Jaber, and M. Ramadan, "An overview of smart irrigation systems using iot," *Energy Nexus*, vol. 7, p. 100124, 2022.

[18] J. Karpagam, I. I. Merlin, P. Bavithra, and J. Kousalya, "Smart irrigation system using iot," in *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*. IEEE, 2020, pp. 1292–1295.

[19] M. A. Ragab, M. M. Badreldeen, A. Sedhom, and W. M. Mamdouh, "Iot based smart irrigation system," *International Journal of Industry and Sustainable Development*, vol. 3, no. 1, pp. 76–86, 2022.

[20] S. K. Pilli, B. Nallathambi, S. J. George, and V. Diwanji, "eagrobot—a robot for early crop disease detection using image processing," in *2015 2nd international conference on electronics and communication systems (ICECS)*. IEEE, 2015, pp. 1684–1689.

[21] F. Bing, "The research of iot of agriculture based on three layers architecture," in *2016 2nd International*

Conference on Cloud Computing and Internet of Things (CCIOT). IEEE, 2016, pp. 162–165.

[22] A. G, "Fertilizer prediction,"https://www.kaggle.com/datasets/ gdabhishek/fertilizer-prediction, Nov. 2019, accessed: 2025-05-08.

[23] V. Nalluri, "Crop recommendation data," https://www.kaggle.com/ datasets/varshitanalluri/crop-recommendation-dataset/data, n.d., accessed: 2025-05-08.

[24] R. Liao, S. Zhang, X. Zhang, M. Wang, H. Wu, and L. Zhangzhong, "Development of smart irrigation systems based on real-time soil moisture data in a greenhouse: Proof of concept," *Agricultural Water Management*, vol. 245, p. 106632, 2021.

[25] B. N. Mohapatra and V. Kale, "Crop recommendation system using machine learning," *ITEGAM-JETIA*, vol. 10, no. 48, pp. 63–68, 2024.