



FERTI FORECAST: Identification of Fertilizer for Soil Based on NPK Levels using Machine Learning Algorithms

P.Darwin¹, B.Likitha², N. Mahendra Swamy², E.Charan Teja², N.David Son²

Department of ECE, Godavari Global University, Rajamahendravaram, INDIA.

Department of ECE, Godavari Institute of Engineering & Technology (A), Rajamahendravaram, INDIA.

To Cite this Article

P.Darwin, B.Likitha, N. Mahendra Swamy, E.Charan Teja & N.David Son (2026). FERTI FORECAST: Identification of Fertilizer for Soil Based on NPK Levels using Machine Learning Algorithms, 12(03), 138-147. <https://doi.org/10.5281/zenodo.18883421>

Article Info

Received: 28 January 2026; Revised: 26 February 2026; Accepted: 02 March 2026.

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KEYWORDS	ABSTRACT
Soil NPK Sensor, Fertilizer Recommendation, Machine Learning, Random Forest Classifier, IoT-based Agriculture, Soil Nutrient Analysis, Precision Farming, NodeMCU, Decision Tree, Real-time Monitoring.	Ferti Forecast is an AIoT-based fertilizer recommendation system that integrates IoT soil sensing with machine learning to deliver accurate, real-time nutrient advice for farmers. The system collects live Nitrogen, Phosphorus, and Potassium (NPK) values using an NPK soil sensor connected to a NodeMCU microcontroller, along with environmental parameters such as temperature and humidity. This data is processed using supervised machine learning algorithms—primarily Decision Tree and Random Forest classifiers—trained on real-world soil datasets. Random Forest demonstrated superior performance due to its ensemble learning capability and reduced overfitting, making it the preferred model for fertilizer prediction. The trained model is deployed using Python and Scikit-learn, enabling cloud-based or local inference for field-level decision-making. The recommended fertilizer is instantly displayed to the user through a web or hardware interface. By combining IoT monitoring with ML-driven analytics, the system minimizes excessive fertilizer use, supports sustainable agriculture, improves soil health, and provides farmer-friendly, low-cost decision support for enhanced crop productivity.

INTRODUCTION

Agriculture is the backbone of India’s economy, with a majority of the population depending on farming for livelihood. However, traditional farming practices often

rely on intuition, experience, and generalized recommendations, which results in improper fertilizer usage, soil degradation, reduced productivity, and increased financial burden on farmers. With increasing

climate variability, declining soil fertility, and the growing need for sustainable crop production, modern agriculture requires intelligent, data-driven solutions that can support farmers in making accurate decisions.

The rapid advancement of the Internet of Things (IoT) has transformed agricultural monitoring by enabling real-time measurement of soil and environmental conditions. Sensors deployed on farmlands can continuously track parameters such as soil nutrients, moisture, temperature, and humidity, allowing farmers to understand soil health more precisely. In parallel, advancements in Machine Learning (ML) provide powerful techniques for analyzing agricultural datasets and generating reliable predictions for crop planning, nutrient management, and fertilizer recommendations.

Ferti Forecast integrates IoT sensing with supervised ML algorithms to deliver real-time fertilizer recommendations based on the soil's NPK (Nitrogen, Phosphorus, Potassium) levels. An NPK sensor connected to a NodeMCU microcontroller collects nutrient values from the field and transmits them to a trained ML model. Among the tested models—including Decision Tree and Random Forest—the Random Forest classifier demonstrated higher accuracy and robustness, making it suitable for real-world deployment. The system provides instant, user-friendly fertilizer suggestions through a web or hardware interface, enabling farmers to optimize soil nutrient supply, reduce excess fertilizer usage, and improve crop yield sustainably.

By combining IoT, machine learning, and precision agriculture principles, the proposed system aims to empower farmers with intelligent decision-support tools that enhance productivity, reduce resource wastage, and promote long-term soil health management.

LITERATURE SURVEY

1. Crop Yield Prediction Using Machine Learning Algorithms

[Crop Yield Prediction Using Machine Learning Algorithms | IEEE Conference Publication | IEEE Xplore](#)

In India, farming is both a common and low-paying profession. By determining the best crop to cultivate, machine learning has the potential to revolutionize the agricultural industry and dramatically increase income. Predicting agricultural yield using various machine learning algorithms is the main emphasis of this article.

Mean absolute error is used to compare the results of these methods. By taking climate, rainfall, area, and other variables into account, machine learning algorithms will provide predictions that farmers may use to choose the crops that will produce the highest yields.

2 A Machine Learning Based Approach For Crop Yield Prediction And Fertilizer Recommendation

[A Machine Learning Based Approach For Crop Yield Prediction And Fertilizer Recommendation](#)

One common issue that farmers face is determining which crops are most suited to their specific soil and nutrient conditions. Soil samples must be sent to a lab for analysis in order to ascertain the soil quality; this procedure is laborious and costly. On top of that, picking the right fertilizer for the crop might be a challenge due to the wide variety of options. The goal of our research is to use machine learning and the internet of things to solve these problems. Thanks to the technology, farmers will have an easier time producing high-quality crops. Predicting future harvests from current data collected by sensors or user or farmer input is the main focus of this project's machine learning efforts. Based on the needs of the soil, it will also suggest fertilisers. In this case, two classifier models are used: Random Forest and Naïve Bayes. The forecasts made by machine learning algorithms will help farmers choose the most productive crops by considering factors like acreage, rainfall, temperature, and more. Hence, the system will use machine learning to suggest soil and crop-specific fertilizers and, given data on temperature, soil type, and nutrients, will forecast which crop would provide the maximum yield (more than 80%). Farmers will be able to boost their yields because to this.

3. Deep learning in ophthalmic image analysis: A task-driven review of segmentation, diagnosis, and progress prediction

[Deep learning in ophthalmic image analysis: A task-driven review of segmentation, diagnosis, and progress prediction - ScienceDirect](#)

One of the leading causes of blindness and visual impairment on a worldwide scale is ocular illness. In order to slow the course of illness, prompt diagnosis and accurate evaluation are crucial. Thanks to recent developments in medical imaging, sophisticated computer-aided diagnosis is now possible with the use of massive, high-quality ophthalmic datasets. Due to its

ability to acquire substantial features and allow end-to-end modeling, deep learning has taken the lead in this discipline. Extensive research has yielded significant advancements in the fields of architectural design and representation learning. On the other hand, the majority of reviews still sort the literature according to illness entities, which means that data types aren't systematically analyzed. When it comes to ophthalmic tasks, model architectures and learning paradigms change depending on the data. With data type serving as a lynchpin, we shift to a task-driven approach. Focusing on segmentation, diagnosis, and progression prediction are three ocular imaging key tasks. We go over the major obstacles and data characteristics for each job, and then we talk about ways to make the model fit the job and the data. Our mission is to aid in the development of deep learning systems for the detection of ocular diseases by offering both theoretical frameworks and concrete suggestions for improvement.

4. Leakage current mechanisms and leakage reduction techniques in deep-submicrometer CMOS circuits

[Leakage current mechanisms and leakage reduction techniques in deep-submicrometer CMOS circuits | IEEE Journals & Magazine | IEEE Xplore*](#)

With the decrease of threshold voltage, channel length, and gate oxide thickness, CMOS circuits are experiencing power dissipation due in large part to high leakage current in deep-submicrometer regimes. Therefore, for low-power applications in particular, it is crucial to identify and model various leakage components in order to estimate and reduce leakage power. The intrinsic leakage mechanisms of transistors are discussed in this study. These processes include gate oxide tunneling, drain-induced barrier lowering, weak inversion, and drain-induced leakage. In order to control the short-channel effects that occur during continuous scaling of complementary metal-oxide semiconductor (CMOS) devices, channel engineering methods such as halo doping and retrograde well are detailed. Finally, many circuit approaches are discussed in the study to lessen the power consumption caused by leakage.

5. A Comparative Study of Clustering Algorithms

[A Comparative Study of Clustering Algorithms | IEEE Conference Publication | IEEE Xplore](#)

Various domains rely on data analysis these days. Data clustering is a method for analyzing data that relies on

unsupervised learning to group data elements. There are a plethora of clustering methods available online. There are advantages and disadvantages to every algorithm. Consequently, some sets of clustering algorithms work better in certain contexts, while other sets of algorithms work better in others. Commonly used conventional algorithms are covered in this article. This work presents a thorough analysis and comparison of several clustering techniques. Using a wide range of criteria, we examine and contrast different clustering techniques in depth.

3. METHODOLOGY

a) Proposed Work:

The proposed work focuses on developing an AIoT-based fertilizer recommendation system that integrates real-time soil data collection with machine learning analytics to support precision agriculture. The system uses an NPK soil sensor connected to a NodeMCU microcontroller to measure Nitrogen, Phosphorus, and Potassium levels directly from the field, along with environmental parameters such as temperature and humidity. This data is transmitted wirelessly and preprocessed to remove noise, scale values, and prepare the dataset for model training. Supervised machine learning algorithms—specifically Decision Tree and Random Forest classifiers—are trained on labeled soil nutrient datasets to identify optimal fertilizer recommendations for different soil nutrient combinations. Random Forest, due to its ensemble learning and superior accuracy, forms the core prediction model of the system.

Once the model is trained and validated, it is deployed through a lightweight backend using Python, Flask, and Scikit-learn, enabling real-time inference either on the cloud or locally. The hardware module sends live soil data to the ML backend, which instantly predicts the most suitable fertilizer and displays it to the farmer through an LCD module or web interface. This proposed system minimizes manual decision-making, prevents overuse of fertilizers, reduces environmental impact, and improves crop productivity. By integrating IoT sensing, data-driven prediction, and user-friendly output delivery, the proposed work aims to build a reliable, low-cost, farmer-centric solution that enhances sustainability and supports data-backed farming practices across diverse agricultural conditions.

b) System Architecture:

The system architecture of Ferti Forecast integrates IoT hardware, machine learning models, and a user-friendly application layer to deliver real-time fertilizer recommendations. At the hardware level, an NPK soil sensor, soil moisture sensor, and temperature–humidity sensor are interfaced with a NodeMCU microcontroller. These sensors continuously capture essential soil parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), moisture, temperature, and humidity. The NodeMCU preprocesses this raw data and transmits it wirelessly to the backend using Wi-Fi. Additionally, external environmental information such as region-wise weather data can be fetched through APIs to improve accuracy. This continuous data flow ensures that the system receives reliable soil conditions in real time, forming the basis for accurate fertilizer prediction.

At the software level, the incoming sensor data is processed by a machine learning model deployed on a cloud server or local system. The architecture uses Random Forest as the primary prediction model due to its superior accuracy and robustness in handling noisy, nonlinear agricultural datasets. The backend processes the nutrient values, Applies the trained classifier, and generates the corresponding fertilizer recommendation. The output is then sent to a web application or LCD module, where farmers can instantly view the suggested fertilizer type suitable for their soil condition. This architecture ensures seamless integration of IoT sensing, ML analytics, and user interaction, enabling a scalable and efficient AIoT solution for precision agriculture.

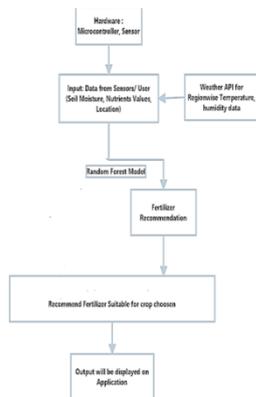


Fig.1. General Block diagram

c) Modules:

1. Sensor Data Acquisition Module

This module collects real-time soil nutrient information using NPK sensors, along with moisture, temperature,

and humidity sensors. The NodeMCU microcontroller reads these values and prepares them for transmission. It ensures accurate, continuous monitoring of soil conditions, forming the foundation for further analysis.

2. Data Transmission & IoT Communication Module

In this module, the NodeMCU transmits the collected sensor data to the backend server or local machine via Wi-Fi using HTTP or MQTT protocols. This module enables seamless IoT connectivity, ensuring that live field data reaches the machine learning model for prediction without manual intervention.

3. Data Pre-processing Module

This module handles cleaning, scaling, and organizing the incoming soil data. It removes noise, checks for missing or inconsistent values, and ensures the data is in the correct format for the ML classifier. Proper preprocessing helps increase the accuracy and reliability of the fertilizer prediction system.

4. Machine Learning Model Module

This module runs the trained ML model—primarily the Random Forest classifier—to predict the most suitable fertilizer based on NPK values and environmental factors. It loads the trained dataset, performs classification, and generates an optimized fertilizer recommendation for the given soil condition.

5. Fertilizer Recommendation Engine

This module converts the ML output into meaningful fertilizer suggestions that farmers can understand easily. Based on nutrient deficiency patterns detected by the model, it recommends balanced fertilizers such as nitrogen-rich, phosphorus-rich, or potassium-rich formulations.

6. Front-End User Interface Module

This module displays the prediction results to the user via a web application or LCD display. It provides a simple and intuitive interface where farmers can view real-time soil readings and instantly see the recommended fertilizer, enhancing usability and decision-making.

7. Backend API & Integration Module

This module acts as the bridge between IoT hardware, ML model, and the user interface. It uses Python, Flask, and REST APIs to receive data, trigger predictions, and send the results to the UI. It ensures smooth system integration and efficient handling of user queries and responses.

8. Data Storage Module

This module stores historical soil data, predictions, and sensor logs in a structured database. The stored data can be used for retraining models, generating reports, and analyzing long-term soil health patterns.

D) Components Used and Description:

i. Arduino Uno (ATmega328P Microcontroller)

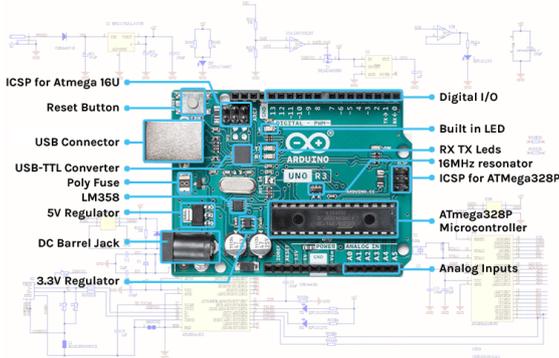


Fig 2 Arduino Uno

The Arduino Uno is the primary microcontroller board used for interfacing sensors, processing signals, and transmitting readings. It operates on the ATmega328P chip and contains 14 digital I/O pins, 6 analog input pins, USB connectivity, and built-in voltage regulators. In this project, Arduino Uno is used to read soil sensor values (NPK, moisture, temperature) and forward the processed data to the NodeMCU for wireless communication.

ii. NodeMCU (ESP8266 Wi-Fi Module)



Fig 3 NodeMCU

NodeMCU acts as the communication controller, enabling Wi-Fi-based transmission of real-time NPK and environmental data to the ML backend. With built-in ESP8266 Wi-Fi capabilities, it sends sensor readings to a cloud or local API where the Random Forest model performs predictions. Its low cost, low power usage, and

ease of integration make it ideal for IoT-based smart agriculture systems.

iii. Soil NPK Sensor



Fig 4 Soil NPK Sensor

The Soil NPK sensor measures three essential nutrients—Nitrogen (N), Phosphorus (P), and Potassium (K)—which directly influence fertilizer needs. The sensor uses Modbus-RTU (RS485) communication, allowing stable and long-distance data transfer. It provides accurate nutrient values that become key input for the Random Forest fertilizer recommendation model.

iv. Soil Moisture Sensor



fig5 Soil Moisture Sensor

This sensor detects the water content present in the soil, helping determine whether soil conditions are suitable for nutrient absorption. Moisture levels influence fertilizer selection and help the system avoid recommending fertilizers when soil is too dry or too wet, ensuring safer and more effective soil management.

v. Temperature & Humidity Sensor (DHT11/DHT22)

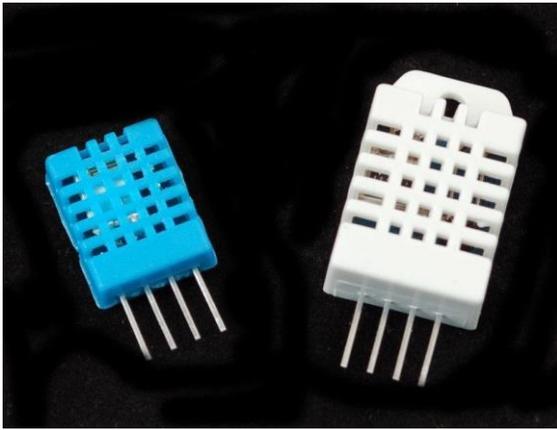


Fig 6 Temperature & Humidity Sensor

Temperature and humidity data are essential for understanding environmental conditions that affect soil nutrient availability. This sensor provides real-time atmospheric readings which are combined with NPK data to improve the model's prediction accuracy. These values are processed alongside soil parameters to generate precise fertilizer recommendations.

vi. RS485 to TTL Converter (MAX485 Module)

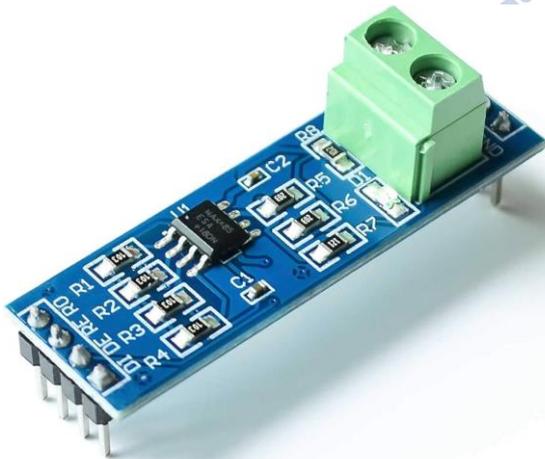


fig 7

RS485 to TTL Converter (MAX485 Module)

Since the NPK sensor communicates using the RS485 Modbus-RTU protocol, it cannot directly interface with Arduino. The MAX485 module converts RS485 signals to TTL serial signals, enabling smooth communication between the NPK sensor and Arduino Uno. This ensures stable long-distance data transfer without signal loss.

vii. LCD Display (16x2 or I2C LCD)



fig8.

LCD Display (16x2 or I2C LCD)

The LCD display module is used to show real-time fertilizer recommendations directly in the field. Once the ML model predicts the required fertilizer type, the output is conveyed to the farmer via this compact display. It ensures usability even in rural areas with limited smartphone or internet access.

viii. Power Supply



fig 9

Power Supply

A 5V–12V DC power adapter is used to supply regulated power to Arduino and sensors. Various jumper wires and a breadboard are used to establish connections between sensors, modules, and microcontrollers. Stable and noise-free electrical connections are essential for accurate data acquisition.

e) Algorithms:

1. Naïve Bayes Classifier

Naïve Bayes is a probabilistic machine learning algorithm based on Bayes' Theorem. It assumes that all input features (N, P, K, temperature, humidity) are independent of each other, making it simple and computationally efficient. In the project, Naïve Bayes was initially tested to classify soil nutrient patterns and predict appropriate fertilizer types. Although it performs well with small datasets and provides fast predictions,

its accuracy in this application was lower due to the dependency relationship among soil features, making it less suitable compared to more robust tree-based models.

2. Logistic Regression

Logistic Regression is a supervised classification algorithm that predicts the probability of a given class—here, the fertilizer type—based on soil inputs. It maps input values to a probability curve using a sigmoid function. In the fertilizer recommendation system, Logistic Regression was evaluated for distinguishing nutrient categories based on soil NPK levels. However, due to nonlinear relationships present in agricultural datasets and multiple fertilizer classes, its performance was limited compared to ensemble methods like Random Forest.

3. Decision Tree Classifier

The Decision Tree algorithm constructs a tree-like model of decisions, where each internal node splits data based on the most informative feature, such as Nitrogen or Phosphorus levels. In this project, the Decision Tree classifier was used to classify fertilizer requirements by learning patterns from the dataset. It is easy to interpret and efficient for medium-sized datasets. However, standalone decision trees can overfit and show reduced generalizability when applied to diverse soil samples. Still, they formed the foundational model for improving accuracy through ensemble methods.

4. Random Forest Classifier

Random Forest is the primary algorithm used in this project due to its superior accuracy and robustness. It is an ensemble of multiple decision trees, each trained on random subsets of the dataset and features. The final prediction is obtained through majority voting, making the model less prone to overfitting and more reliable for real-world agricultural data. In Ferti Forecast, Random Forest delivered the highest accuracy among all tested algorithms, making it ideal for predicting fertilizer requirements from NPK, temperature, and humidity values. Its ability to generalize effectively across varying soil conditions is why it was selected as the final model for deployment.

EXPERIMENTAL RESULTS

The experimental results were obtained by training and testing multiple supervised machine learning algorithms—Naïve Bayes, Logistic Regression, Decision

Tree, and Random Forest—on a soil nutrient dataset containing N, P, K, temperature, and humidity values. Each model was trained using balanced data to avoid bias and variance issues, ensuring reliable prediction performance. During evaluation, the Random Forest classifier consistently achieved the highest accuracy due to its ensemble learning approach, which reduces overfitting and improves generalization across diverse soil conditions. Decision Tree and Logistic Regression produced moderate accuracy, while Naïve Bayes performed lower because of its independence assumptions, which do not hold well for correlated soil features.

After finalizing the Random Forest model, real-time sensor data was tested using the IoT setup consisting of the NPK sensor, moisture sensor, and NodeMCU. The live soil readings were processed and sent to the deployed ML model, which successfully predicted the appropriate fertilizer corresponding to the nutrient deficiencies detected. The system demonstrated stable performance, fast prediction response, and accurate recommendations under varying soil conditions. The results confirm that integrating IoT-based sensing with machine learning significantly improves fertilizer decision-making, reduces manual effort, and supports sustainable agricultural practices.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

$$\text{Accuracy} = \frac{TP + TN}{(TP + TN + FP + FN)}$$

$$\text{Accuracy} = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. The formula is used to calculate precision:

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Recall: The ability of a model to identify all pertinent instances of a class is assessed by machine learning recall. The completeness of a model in capturing instances of a class is demonstrated by comparing the total number of positive observations with the number of precisely predicted ones.

$$Recall = \frac{TP}{(FN + TP)}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$F1 - Score = 2 * \frac{(Precision * Recall)}{((Precision + Recall))}$$

mAP: Assessing the level of quality Precision on Average (MAP). The position on the list and the number of pertinent recommendations are taken into account. The Mean Absolute Precision (MAP) at K is the sum of all users' or enquiries' Average Precision (AP) at K.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

$AP_k =$ the AP of class k
 $n =$ the number of classes



Fig.9 Project kit



Fig.10. results

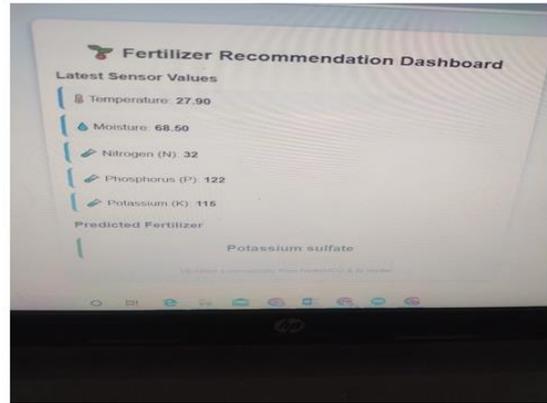


Fig.11. fertilizer recommended dashboard

CONCLUSION

The proposed Ferti Forecast system successfully demonstrates how the integration of IoT sensing and machine learning can significantly improve fertilizer decision-making in agriculture. By utilizing real-time NPK, moisture, temperature, and humidity data, the system accurately identifies soil nutrient deficiencies and recommends appropriate fertilizers using a Random Forest classifier, which proved to be the most reliable among all tested algorithms. The IoT-ML pipeline minimizes manual dependency, reduces excessive fertilizer usage, enhances soil health, and supports sustainable farming practices. Overall, the system provides a low-cost, scalable, and farmer-friendly solution that strengthens precision agriculture and highlights the potential of AIoT technologies in improving agricultural productivity and long-term soil management.

FUTURE SCOPE

The Ferti Forecast system can be significantly enhanced in the future by integrating advanced technologies to broaden its effectiveness and real-world impact. One major enhancement is the incorporation of cloud-based platforms, enabling large-scale storage and real-time analysis of soil and environmental data. This would support continuous model updates and remote monitoring for farmers across different regions. Another promising extension is the integration of blockchain technology to securely store agricultural data, ensuring transparency and traceability in fertilizer usage, crop health history, and farming practices.

Additionally, the system can be improved using advanced artificial intelligence techniques, such as deep learning, to better capture complex patterns in soil behavior, weather fluctuations, and crop nutrient needs. Developing a dedicated mobile application would allow farmers to receive instant fertilizer recommendations, weather alerts, and soil health reports directly on their smartphones. Incorporating geospatial analysis and satellite data can further refine predictions by linking soil conditions with climatic and topographical factors. With these enhancements, the system can evolve into a comprehensive precision agriculture platform that empowers farmers with smarter, faster, and more sustainable decision-making tools.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

- [1] Aruvansh Nigam, Saksham Garg, Archit Agrawal "Crop Yield Prediction using ML Algorithms", International Journal of Engineering Research & Technology (IJERT), 2019.
- [2] R. Kaur and S. K. Soni, "A review of crop prediction models and remote sensing- based approaches for crop yield forecasting," International Journal of Agricultural and Environmental Information Systems, vol. 8, no. 1, pp. 1-22, 2017.
- [3] R. Garg, P. Jain, and R. K. Jain, "Crop yield prediction using machine learning algorithms: A review," Journal of Agricultural Science and Technology, vol. 21, no. 3, pp. 501-516, 2019.
- [4] S. Saha, S. Ghosh, and M. Pal, "A review on machine learning approaches for crop yield prediction," International Journal of Computer Applications, vol. 182, no. 27, pp. 23-30, 2018.
- [5] D. Kumar, A. Kumar, and S. Kumar, "Crop yield prediction using machine learning techniques: A review," Journal of King Saud University-Computer and Information Sciences, vol. 30, no. 2, pp. 163-178, 2018.
- [6] N. Dubey and D. Kumar, "A survey of machine learning techniques for crop yield prediction," International Journal of Computer Sciences and Engineering, vol. 7, no. 4, pp. 416-423, 2019.
- [7] S. K. Roy, S. C. Paul, M. S. Islam, and M. A. Hasan, "Crop yield prediction using machine learning algorithms: A comprehensive review," IEEE Access, vol. 7, pp. 78907-78926, 2019.
- [8] P. Patil, A. Shinde, and M. Kadam, "A survey on crop yield prediction using data mining techniques," International Journal of Advanced Research in Computer Science, vol. 8, no. 1, pp. 421-425, 2017.
- [9] S. Kumar, M. R. Gupta, and M. S. Bhatia, "Crop yield prediction using machine learning algorithms: A comprehensive review," International Journal of Computer Applications, vol. 179, no. 6, pp. 1-6, 2018.
- [10] M. Kamble, D. Kumar, and P. Kumar, "A review on crop yield prediction using machine learning techniques," International Journal of Advanced Research in Computer Science and Software Engineering, vol. 7, no. 4, pp. 260-267, 2017.
- [11] H. Yu and S. Liu, "A survey on crop yield prediction models and methods," Journal of Northeast Agricultural University, vol. 25, no. 1, pp. 1-10, 2018.
- [12] H. Ma, X. Zhang, Y. Ma, and Y. Wang, "A survey on crop yield prediction based on deep learning," in 2018 IEEE International Conference on Big Data and Smart Computing (BigComp), Shanghai, China, 2018, pp. 335-340.
- [13] S. T. K. Das and S. S. Mohanty, "Prediction of crop yield using machine learning techniques: A review," International Journal of Agricultural and Environmental Information Systems, vol. 10, no. 3, pp. 1-16, 2019.
- [14] V. N. Nguyen, Q. N. Nguyen, and T. N. Huynh, "A comparative study of machine learning algorithms for crop yield prediction," in 2020 International Conference on Advanced Technologies for Communications (ATC).
- [15] S. R. Singh, A. Singh, and V. P. Singh, "Crop yield prediction using machine learning: A review," Journal of Big Data, vol. 6, no. 1, pp. 1-27, 2019.
- [16] D. K. Pal and B. Datta, "Crop yield prediction: A review," Journal of Agrometeorology, vol. 16, no. 2, pp. 121-130, 2014.
- [17] S. Kumar, N. Kumar, and D. Kumar, "Crop yield prediction using machine learning algorithms: A comprehensive review," in 2018 IEEE 4th International Conference on Computational Intelligence and Communication Networks (CICN), pp. 68-72.
- [18] N. K. Gupta and V. G. S. Kumar, "Crop yield prediction using machine learning algorithms: A review," in 2018 International Conference on Smart Computing and Informatics (SCI), pp. 647-652.
- [19] R. Dubey and S. Jain, "A review of crop yield prediction models and methods," Journal of Engineering Science and Technology, vol. 13, no. 9, pp. 2720-2737, 2018.
- [20] A. Sahay and P. N. V. N. N. Murthy, "Crop yield prediction using machine learning: A review," in 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), pp. 1-6.
- [21] S. G. S. Saini, S. S. Rajput, and S. S. Khillare, "Crop yield prediction using data mining techniques: A review," in 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), pp. 1953-1957.
- [22] M. Manasa, S. S. Kumar, and A. Kumar, "A review on crop yield prediction using machine learning techniques," in 2018 International Conference on Computing, Power and Communication Technologies (GUCON), pp. 901-905.
- [23] P. N. Shinde, S. K. Mahajan, and R. P. Gohad, "A review on crop yield prediction using data mining techniques," in 2018 International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques (ICEECCOT), pp. 1-5.
- [24] S. K. Singh, R. Singh, and S. Gupta, "A review on crop yield prediction using machine learning algorithms," in 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), pp. 433-437.
- [25] T. H. Shroff and D. R. Patel, "A review on crop yield prediction using machine learning techniques," in 2019 International Conference on Intelligent Sustainable Systems (ICISS), pp. 1167-1171.

- [26] A. Mukherjee, S. K. Bandyopadhyay, and T. K. Basu, "Crop yield prediction using machine learning: A review," in 2020 International Conference on Computational Intelligence in Data Science (ICCIDS), pp. 1-5.
- [27] P. Singh and P. Kharya, "A review of crop yield prediction models and techniques," International Journal of Research in Engineering, Science and Management, vol. 3, no. 3, pp. 12-16, 2020.
- [28] V. Pandya and S. Goyal, "A comprehensive review on crop yield prediction using machine learning," in 2021 International Conference on Inventive Systems and Control (ICISC), pp. 1757-1762.
- [29] H. B. Kumar, V. Singh, and A. Kumar, "A review on crop yield prediction using machine learning techniques," in 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), pp. 114-119.
- [30] S. S. Saini, S. S. Khillare, and S. S. Rajput, "A review on crop yield prediction using machine learning and data mining techniques," in 2018 2nd International Conference on Advances in Electronics, Computers and Communications (ICAIECC), pp. 1-5.
- [31] M. Bajgai, D. Grgicak-Mannion, and A. Mukherjee, "A comprehensive review of crop yield prediction using machine learning methods," Journal of Agricultural Informatics, vol. 12, no. 2, pp. 1-25, 2021.
- [32] M. Sharma, N. Mishra, and N. Singh, "A survey on crop yield prediction using machine learning techniques," in 2020 7th International Conference on Signal Processing and Integrated Networks (SPIN), pp. 348-352.
- [33] D. Liu, J. Zhang, and J. Sun, "Crop yield prediction using machine learning: A review," Journal of Physics: Conference Series, vol. 1634, no. 1, p. 012050, 2020.
- [34] S. Gupta, S. Kumar, and S. S. Iyengar, "A review on crop yield prediction using machine learning," in 2018 IEEE 2nd International Conference on Inventive Systems and Control (ICISC), pp. 1006-1010.

