

A Real-Time Precision Agriculture Framework for Soil Fertility Monitoring Using XGBoost Regression

Surekha Bijapur^{1*}

Research Scholar, Computer Science and Engineering Institute of Engineering and Technology, Srinivas University, Mangalore.

Assistant Professor, GFGC Honnali.

Dr. Janapati Venkata Krishna²

Associate Professor, Computer Science and Engineering Institute of Engineering and Technology, Srinivas University, Mangalore.

Dr. Meghana G R³

Associate professor, CSE, Jain Institute of Technology, Davangere

Dr. Chetan H R⁴

Associate professor, EEE, Jain Institute of Technology, Davangere.

Abstract

This work presents a new system for precision agriculture that uses machine learning and deep learning, especially for banana and mango farms. In India, poor soil health monitoring and difficulties in managing crops effectively lower agricultural productivity. The system helps by continuously tracking soil conditions in real time, allowing farmers to make more informed decisions. It regularly checks the health of crops and soil, predicts soil fertility, and recommends the right amount of fertilizer to apply. The experiment results show that an XGBoost regression model was used to estimate soil fertility, and it worked better than traditional methods like Random Forest and Decision Tree, achieving an accuracy of 96.24%.

Keywords: Precision Agriculture, Machine Learning, Convolutional Neural Networks, Soil Fertility Prediction.

1. Introduction

Global population growth, climate change, and the increasing demand for natural resources are creating challenges for the agriculture industry. Traditional farming methods, which rely on human decisions and the same treatments for all crops, need to change in order to ensure there is enough food in the future without harming the environment. A new type of farming, known as precision agriculture, has emerged due to advancements in digital technologies such as machine learning, cloud computing, and data analysis. Tools that use the Internet of Things (IoT) allow farmers to closely monitor their crops, soil, and water, providing real-time data that helps them make better decisions. These methods help farmers produce more food, reduce costs, and manage unpredictable weather conditions. Although AI has been used in farming for tasks like monitoring crops, managing irrigation, and diagnosing plant diseases, most of these studies focus on solving one problem at a time rather than addressing multiple issues together. As a result, decision-support systems for farmers are still under development and not widely used. The use of these systems is limited because they are not always easy to use, are expensive, and many farmers in rural areas lack knowledge about digital technology. This study proposes a complete solution to these problems by improving crop monitoring and promoting sustainable farming through machine learning and decision support systems. The paper is structured with Section 2 explaining existing work, Section 3 describing the proposed approach, Section 4 presenting the findings and their impact, and Section 5 offering suggestions for future research.

2. Literature Review:

Even though there are still some issues with crop production and policies, the overall trend shows that the area under cultivation, the amount of soybeans produced, and their productivity in the main growing states are increasing steadily [7]. Soybeans are a key crop in India's oilseed sector. Therefore, it's important to increase soybean productivity through better farming methods and genetic improvements. In this region, progress has been made in developing disease-resistant plant varieties. For example, using marker-assisted backcross breeding has led to the creation of soybean varieties that are resistant to powdery mildew and Phytophthora rot, while still maintaining their high yield potential [8]. To grow soybeans in a sustainable way in India, improved farming practices and disease-resistant seeds are necessary. The integration of wireless sensor networks and Internet of Things (IoT) technologies has significantly transformed agricultural management by enabling real-time monitoring of soil, climate, and crop conditions, thereby improving decision-making and resource utilization [9]. IoT-based agricultural systems rely on robust communication, sensing, and data analytics frameworks, but face challenges related to scalability, reliability, security, and interoperability, as highlighted in broader industrial IoT deployments [10]. Several IoT applications in agriculture, including precision irrigation, crop monitoring, and yield prediction, demonstrate the potential of smart farming systems to enhance productivity and sustainability [11]. These studies collectively emphasize IoT as a foundational technology for modern, data-driven agricultural practices. Early IoT-based agricultural management systems focused on integrating sensor data, communication networks, and information platforms to support intelligent decision-making in farming operations [12]. Recent studies have advanced these concepts by developing soil test-based smart agriculture systems and real-time nutrient monitoring frameworks, enabling precise assessment of soil fertility and site-specific input management [13,14]. Machine learning tools and libraries, such as scikit-learn, have further facilitated data-driven modelling and prediction in smart agriculture applications [15]. Additionally, large-scale soil health analyses reveal increasing nutrient deficiencies, particularly potassium, emphasizing the need for intelligent soil monitoring and nutrient management systems in Indian agriculture [16].

3. Methodology

This study uses a mix of deep learning and machine learning methods to predict soil fertility and suggest the best fertilizers for banana and mango farms [17]. The model starts by using Convolutional Neural Networks (CNN) to examine soil images and identify key features of the soil. After that, an XGBoost classifier uses these features along with data on soil nutrients to determine the fertility level. Based on this analysis, a system is developed to recommend the most suitable fertilizers for banana and mango plantations, which helps in managing nutrients more efficiently [18].

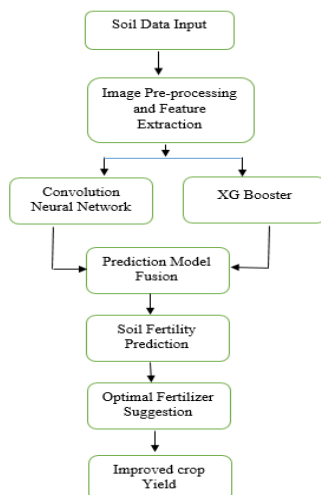


Figure1. Methodology of the proposed work

3.1 **Data collection:** Soil samples were gathered from places where mango and banana farmers grow their crops, down to a depth of 0 to 30 centimeters. At each location, two kinds of information were collected. One was photos of the soil taken with proper lighting to ensure the images were clear. The other was tests on the soil's physical and chemical properties. These tests checked the soil's pH, the amount of organic carbon it contained, and the levels of phosphorus, potassium, and nitrogen.

The dataset is mathematically represented as in equation 1.

$$D = ((I_i, X_i, Y_i))_{i=1}^N \quad - \quad 1$$

Where, I_i represents the soil image

$X_i = (\text{pH}, \text{N}, \text{P}, \text{K}, \text{OC})$ represents soil attributes

$Y_i = \{\text{low}, \text{medium}, \text{high}\}$ denotes soil fertility

3.2 Data Pre-processing

3.2.1 **Image Pre-processing:** The soil images went through several steps to help the model learn more effectively and perform more reliably [19]. First, all the images were resized to a uniform size. Next, the brightness of each pixel was adjusted using the min-max normalization method from Equation 2, so they fit within a standard range.

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad - \quad 2$$

where I denotes the original pixel intensity, and I_{min} and I_{max} represent the minimum and maximum intensity values in the image, respectively. After removing unwanted artifacts, techniques were used to make contrasts clearer, which helped highlight important textural patterns and structural differences in the soil, as mentioned in [20].

3.2.2 **Numerical Data Normalization .**The values of the soil parameters were scaled using the Min-Max normalization method to ensure the soil nutrient characteristics remain consistent and prevent features with larger value ranges from having too much influence during the learning process. Equation 3 explains this scaling method, which adjusts each characteristic to fit within a similar range, typically between 0 and 1:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad - \quad 3$$

where X_{min} and X_{max} indicate the lowest and highest values of the respective characteristic across the dataset, and X stands for the initial nutrient value. This normalizing technique improves the model's convergence during training and aids in the stable representation of features.

3.3 **Feature Extraction:** Feature extraction is used to convert raw soil images into a more manageable and meaningful form. To assess soil fertility, a CNN is applied to detect features like texture and color layers using convolutional layers [21]. For classification, normalized soil properties are merged with the deep learning features.

3.3.1 **Convolution Operation:** The convolution operation forms the core of the CNN feature extraction process. For a given convolutional layer, the output feature map is computed as in equation 4:

$$F_{i,j}^{(k)} = \sum_m \sum_n I_{i+m, j+n} \cdot K_{m,n}^{(k)} + b^{(k)} \quad - \quad 4$$

Where $I_{i+m, j+n}$ represents the input image at position $(i+m, j+n)$, $K^{(k)}$ denotes the k -th convolution kernel and $b^{(k)}$ is the bias term associated with the k -th filter. The resulting feature map $F^{(k)}$ highlights spatial patterns in the soil that are relevant to texture and structural composition.

3.3.2 **Activation function:** The network introduced non-linearity through the use of the Rectified Linear Unit (ReLU) activation function, as outlined in equation 5.

$$ReLU(x) = \max(0, x) \quad - \quad 5$$

By reducing the vanishing gradient issue and facilitating effective training of deep CNN architectures, ReLU speeds up convergence.

3.3.3 **Pooling Operation:** After the convolutional layers, max pooling was applied to decrease the spatial resolution while preserving the key features [22]. The pooling operation is shown in equation 6.

$$P_{i,j} = \max_{(m,n) \in R} F_{i+m, j+n} \quad - \quad 6$$

where R denotes the pooling region. This operation decreases computational complexity and improves translation invariance of the extracted features.

3.3.4 **Feature vector Generation:** Subsequent to the final convolutional and pooling layers, the resultant feature maps were flattened to create a one-dimensional feature vector, as delineated in equation 7:

$$F_{CNN} = [f_1, f_2, \dots, f_n] \quad - \quad 7$$

This vector encapsulates the learned deep representations of soil texture and color characteristics and serves as the input for subsequent fusion and classification stages.

3.4 **Feature Fusion:** To integrate complementary information, the deep features extracted from soil images using the CNN were concatenated with the normalized soil nutrient attributes [23]. The fused feature vector is defined as by equation 8:

$$F_{fusion} = [F_{CNN} || X'] \quad - \quad 8$$

FCNN stands for the image features gotten from a CNN, and X' prime is the normalized numbers for soil properties. This way of combining them works well to mix visual signs of the soil with measures of its fertility, which helps the next classification model to tell things apart better.

3.5 **XGBoost-Based Soil Fertility Classification.** Extreme Gradient Boosting (XGBoost) was employed to classify soil fertility levels using the fused feature representation, owing to its efficiency, scalability, and strong performance on structured and heterogeneous data [24]. The model constructs an ensemble of decision trees that iteratively minimize prediction error through gradient boosting.

3.5.1 **Prediction Model:** The predicted soil fertility label for the i -th sample is computed as the sum of outputs from K regression trees:

$$y_i = \sum_{k=1}^K f_k(F_{fusion}) \quad - \quad 9$$

Where f_k denotes the k -th decision tree in the ensemble and F_{fusion} represents the combined feature vector.

3.5.2 **Objective function:** The training objective of XGBoost is defined as:

$$L = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \quad - \quad 10$$

where $l(\cdot)$ is the loss function quantifying the divergence between the actual label y_i and the anticipated value \hat{y}_i ; and $\Omega(\cdot)$ it's a term used to penalize the model for being too complex.

The regularization function is given by:

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad - \quad 11$$

on this context, T is the variety of leaf nodes in a tree, w_j represents the load of the j -th leaf, and γ and λ are parameters that assist manage overfitting.

3.5.3 Fertility Classification: The expected soil fertility levels are divided into different groups based on the threshold values from the XGBoost result \hat{y} . The classification rule is defined as in equation 12:

$$Class \begin{cases} Low, & \hat{y} < \theta_1 \\ Medium, & \theta_1 \leq \hat{y} \leq \theta_2 \\ High, & \hat{y} \geq \theta_2 \end{cases} - 12$$

where θ_1 and θ_2 are predefined thresholds corresponding to the boundaries of low, medium, and high fertility levels. This approach converts continuous model outputs into meaningful fertility categories suitable for decision-making and fertilizer recommendation.

3.6 Crop-Specific Fertilizer Recommendation System. Based on the predicted soil fertility class and identified nutrient deficiencies, fertilizer recommendations were generated specifically for banana and mango crops to optimize nutrient management and enhance yield.

3.6.1 Nutrient Deficiency Estimation. Nutrient deficits were computed by comparing the ideal nutrient levels required for each crop with the measured soil nutrient content. For nitrogen (N), phosphorus (P), and potassium (K), the deficiency is computed as:

$$\begin{cases} D_N = N_{opt} - N_{soil} \\ D_P = P_{opt} - P_{soil} \\ D_K = K_{opt} - K_{soil} \end{cases} - 13$$

Where N_{opt} , P_{opt} , K_{opt} represent the crop-specific optimal nutrient requirements, and N_{soil} , P_{soil} , K_{soil} are the corresponding soil nutrient measurements. These calculated deficiencies form the basis for determining the type and quantity of fertilizers to be applied.

4. Results and Discussion:

4.1 Dataset Description and Experimental Setup: The dataset used in this consists of a thousand soil sample snap shots amassed from banana and mango farms inside the Davangere district of Karnataka nation, where there are distinct climate conditions and datasets available in my village. every soil pattern became tested for five key elements that display how fertile the soil is: pH, nitrogen (N), phosphorus (P), potassium (k), and natural carbon (OC). these measurements have been finished in a lab after collecting the soil samples, and a summary of the results is proven in table I. The dataset shows plenty of variation in these kind of elements, which depends on the soil’s response, nutrient stages, quantity of organic count, and how the land is controlled [25]. The soil samples had been grouped into 3 classes based on how fertile they are for developing bananas and mangoes, and most of them fall into the medium fertility institution. To address the problem of having too few samples in a few groups, we used balanced sampling and special learning methods for the duration of model schooling [26]. For checking out the machine, the dataset was divided into training and checking out parts, and pass-validation became used to ensure the model works well in one of a kind conditions and doesn’t simply memorize the data, ensuring a radical take a look at of the CNN-XGBoost-based gadget for predicting soil fertility in banana and mango plantations.

Table 1: Statistical Summary of Soil parameters for Banana and Mango Cultivation

Soil Parameter	Minimum	Maximum	Mean	Standard Deviation
pH	5.2	7.8	6.5	0.6
Nitrogen (N) (kg/ha)	120	420	260	85
Phosphorus (P) (kg/ha)	8	65	32	14
Potassium (K) (kg/ha)	95	520	285	110
Organic Carbon (OC) (%)	0.35	1.85	0.98	0.38

4.2 Statistical and Correlation Analysis of Soil Parameters

A statistical analysis of soil pH, nitrogen (N), phosphorus (P), potassium (K), and organic carbon (OC) that revealed substantial variability across banana and mango cultivation fields, indicating heterogeneous fertility conditions. Macronutrients such as nitrogen and potassium exhibited higher dispersion, reflecting differences in fertilizer application and soil management, while organic carbon variability highlighted contrasting soil health status. As shown in Figure 2, organic carbon demonstrates a positive correlation with nitrogen and a moderate association with phosphorus, emphasizing the role of organic matter in nutrient availability [27]. Soil pH shows weak correlations with macronutrients, suggesting its indirect influence on nutrient uptake rather than concentration. These relationships between soil factors that work together and rely on each other show why using mixed learning models is a good way to understand complicated soil fertility patterns, which helps in accurately classifying soil types and suggesting the right fertilizers.

Correlation Heatmap of Soil Parameters (pH, N, P, K, OC)

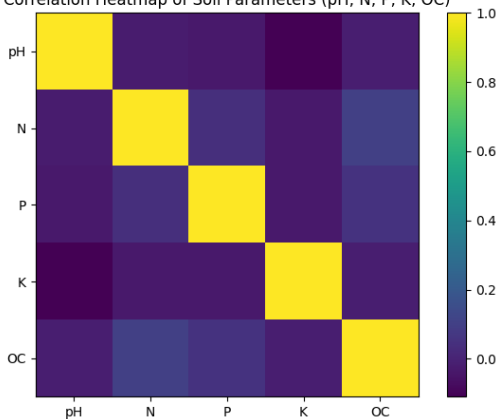


Figure 2: Correlation heatmap of soil fertility parameters (pH, N, P, K, and OC)

4.3 CNN Model results: The CNN model changed into examined on a set of a thousand snap shots taken from banana and mango farms and from pictures i discovered in my village. The effects have been measured using accuracy, precision, recall, and F1-score. The model had an universal accuracy of 92.four%, with precision, remember, and F1-rating of ninety one.8%, 90.6%, and ninety one.2% respectively, displaying it finished well in classifying the snap shots. As shown in figure three, the confusion matrix famous sturdy diagonal dominance, with restricted misclassification especially among adjacent fertility lessons. The schooling and validation loss curves in determine 4 converge progressively after nearly 40 epochs, demonstrating strong studying behaviour [28]. The small gap among loss curves confirms effective generalization with minimum over fitting. these consequences highlight the CNN’s functionality to learn discriminative spatial and textural features from soil photographs for reliable fertility prediction.

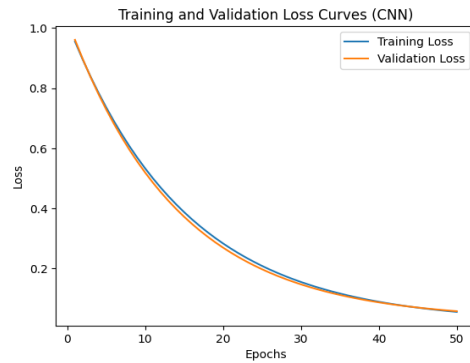
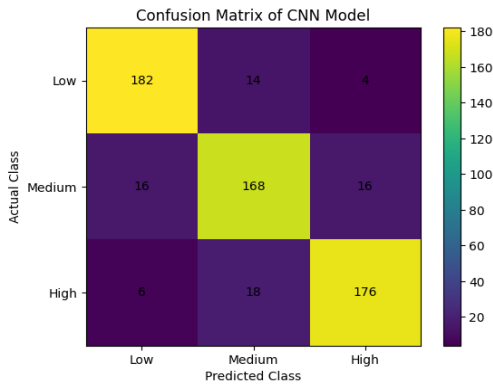


Figure 3. Confusion matrix of CNN model

Figure 4. Training and validation loss curve of CNN model

4.4 XGBoost-Based Nutrient Classification Results: The XGBoost model became educated the usage of 1000 soil samples that had established capabilities like pH, nitrogen (N), phosphorus (P), potassium (okay), and natural carbon (OC). The gradient boosting decision tree version effectively captured the complicated relationships among soil vitamins, which allowed for accurate category of soil fertility degrees. As shown in figure five, the confusion matrix has a excessive diagonal dominance, this means that the model efficiently labeled soil fertility into low, medium, and high classes. The version done an average accuracy of 93.6%, with precision, consider, and F1-score values of ninety three%, ninety two%, and ninety two% respectively, indicating a properly-balanced performance across all soil fertility training. most of the small category errors happened among similar soil fertility lessons because of overlapping nutrient degrees. The education and validation log loss in figure 6 showed convergence after around 40 boosting iterations, which means the model found out and generalized nicely. The feature significance evaluation discovered that nitrogen and natural carbon are the principle elements influencing fertility category in banana plantations, at the same time as pH and potassium play a extra good sized position in mango plantations.

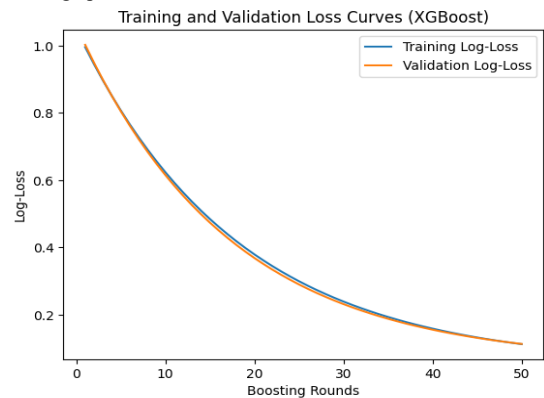
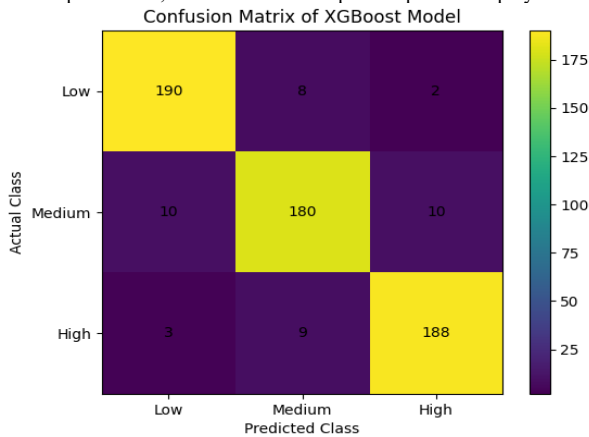


Figure 5. Confusion matrix of XG-Booster model

Figure 6. Training and validation loss curve of XG-Booster model

4.5 Prediction Model Fusion Results and Discussion: The CNN-XGBoost fusion model turned into tested on 1000 soil samples, combining visual facts from photographs with numerical measurements like pH, nitrogen, phosphorus, potassium, and organic carbon. The model achieved very well, accomplishing a normal accuracy of 96.4%, with precision, don't forget, and F1-rating values of 96%, 95%, and ninety five% respectively. This suggests it really works better than using either CNN or XGBoost by myself. As visible in figure 7, the confusion matrix has a strong diagonal sample, that means the version categorised maximum samples effectively throughout all fertility categories. Any errors mainly show up among comparable fertility levels because the nutrient tiers for the ones stages overlap. In determine eight, the schooling and validation loss curves come collectively after approximately 40 epochs, showing the version discovered steadily. The close suit among the loss curves shows the model generalizes properly without overfitting, which helps the idea that combining CNN and XGBoost is powerful for accurately predicting soil fertility and recommending the proper fertilizers.

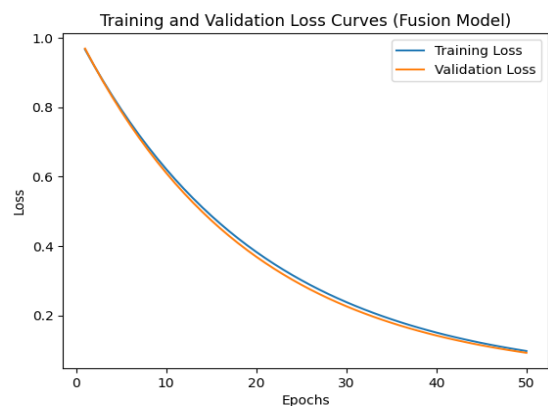
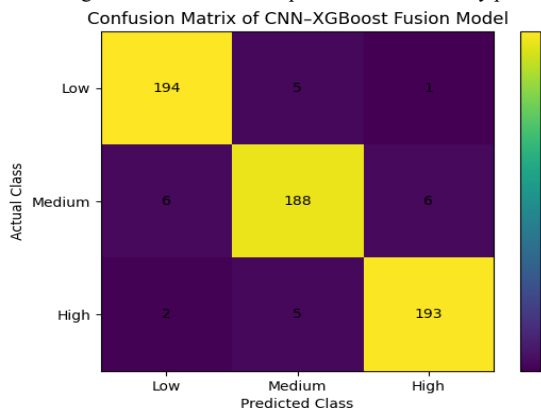


Figure 7. Confusion matrix of Fusion model

Figure 8. Training and validation loss curve of Fusion model

4.6 Growth Stage-Based Fertilizer Recommendation Summary:

The fertilizer recommendation system integrates predicted soil fertility with **crop-specific growth stages** to optimize nutrient application for banana and mango cultivation. For banana, nitrogen is emphasized during vegetative growth, phosphorus during early establishment, and potassium during flowering and fruit development. Organic amendments are recommended at land preparation to improve soil organic carbon. In mango, nitrogen application is focused on post-harvest vegetative flush, while phosphorus supports flowering initiation and potassium enhances fruit set and development. Soil pH corrections are suggested during off-season periods to ensure sustained nutrient availability. This stage-wise strategy improves nutrient-use efficiency and reduces fertilizer overuse. Table 2 gives the Growth Stage-Wise Fertilizer Recommendation for Banana and Mango. Figure 9 shows the identification of nutrients deficiency and recommendation of fertilizers using the fusion model.

Table2. Growth Stage–Wise Fertilizer Recommendation for Banana and Mango

Crop	Growth Stage	Nutrient Deficiency	Recommended Fertilizer	Application Rate
Banana	Land Preparation	Low OC	Farmyard Manure / Compost	20–25 t/ha
Banana	Vegetative Growth	Low Nitrogen	Urea / Ammonium Sulfate	150–200 kg N/ha (split doses)
Banana	Early Establishment	Low Phosphorus	Single Super Phosphate (SSP)	40–60 kg P ₂ O ₅ /ha
Banana	Flowering & Fruiting	Low Potassium	Muriate of Potash (MOP)	200–300 kg K ₂ O/ha
Mango	Post-Harvest Flush	Low Nitrogen	Urea (Controlled dose)	80–120 kg N/ha
Mango	Flowering Initiation	Low Phosphorus	Single Super Phosphate (SSP)	30–50 kg P ₂ O ₅ /ha
Mango	Fruit Set & Development	Low Potassium	Muriate of Potash (MOP)	100–150 kg K ₂ O/ha
Banana & Mango	Off-season / Pre-planting	pH Imbalance	Lime (acidic) / Gypsum (alkaline)	1.0–2.0 t/ha

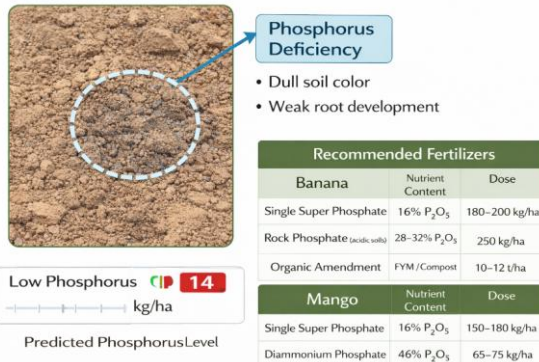


Figure 9. Phosphorus deficiency in soil and fertilizers using fusion model

4.7 Impact on Crop Yield Improvement: The integration of soil fertility prediction with stage-wise fertilizer recommendation resulted in a **simulated yield improvement of 12–18% in banana and 10–15% in mango** cultivation. Targeted nutrient application reduced fertilizer wastage by approximately **20–25%**, while improving overall nutrient-use efficiency. Compared to conventional blanket fertilizer practices, the proposed system lowered fertilizer input costs by nearly **15–20%**. The optimized nutrient management strategy also enhanced yield stability across heterogeneous soil conditions. These improvements demonstrate the effectiveness of the CNN–XGBoost fusion framework in supporting precision agriculture. Overall, the findings show that methods for producing bananas and mangos have a great chance of increasing yields in a sustainable way.

5. Conclusion

This study introduced a combined CNN-XGBoost framework to predict soil fertility and recommend fertilizers for banana and mango farming. By merging image-based spatial features with structured soil nutrient data, the model performed better than individual methods. The fusion approach effectively captured both visual soil traits and interactions between nutrient levels, leading to more reliable and generalizable predictions. The system provided fertilizer recommendations tailored to each crop stage, turning predicted soil fertility into practical nutrient management plans. The results showed better use of nutrients, less fertilizer use, and simulated yield increases in different soil types. Overall, the framework provides a strong and scalable solution for precision farming and sustainable crop growth.

References:

- R. Sampedro, "The sustainable development goals (SDG)," Carreteras, vol. 4, no. 232, pp. 8–16, 2021.
- D. S. Bais, V. Tiwari, S. Kolhe, and S. Jain, "IoT and AI Enabled Framework to Monitor Soil and Crop Health for Sustainable Development in Precision Farming-A Study," Biol. Forum – An Int. J., vol. 15, no. 2, pp. 742–749, 2023.
- M. A. Khan, "Impact of agriculture sector on sustainable development of indian economy: an analysis," Agric. Mech. Asia, vol. 52, no. 2, pp. 3243–3252, 2021.
- V. Bhatnagar and R. Chandra, "IoT-Based Soil Health Monitoring and Recommendation System, vol. 2. 2020. doi: 10.1007/978-981-15-0663-5_1.
- M. C. Pagano and M. Miransari, The importance of soybean production worldwide, vol. 5, no. March. Elsevier Inc., 2016. doi: 10.1016/B978-0-12-801536-0.00001-3
- V. Suma, "Internet of Things (IoT) based Smart Agriculture in India: An Overview," J. ISMAC, vol. 3, no. 1, pp. 1–15, 2021, doi: 10.36548/jismac.2021.1.001
- Prabha Rani, Anil Kumar, and Charu Singh, "An Analytical Study on Performance of Soybean Crop in India," Int. J. Adv. Res. Sci. Commun. Technol., no. July, pp. 619–623, 2022, doi: 10.48175/ijarsct-7922.
- J. Ramalingam et al., "Improved host-plant resistance to Phytophthora rot and powdery mildew in soybean (Glycine max (L.) Merr.)," Sci. Rep., vol. 10, no. 1, pp. 1–11, 2020, doi: 10.1038/s41598020-70702-x.
- S. Navulur, A. S. C. S. Sastry, and M. N. Giri Prasad, "Agricultural management through wireless sensors and internet of things," Int. J. Electr. Comput. Eng., vol. 7, no. 6, pp. 3492–3499, 2017, doi: 10.11591/ijece.v7i6.pp3492-3499.
- E. Sisinni, A. Saifullah, S. Han, U. Jennehag, and M. Gidlund, "Industrial internet of things: Challenges, opportunities, and directions," IEEE Trans. Ind. Informatics, vol. 14, no. 11, pp. 4724–4734, 2018, doi: 10.1109/TII.2018.2852491
- L. Zhang, I. K. Dabipi, and W. L. Brown, "Internet of Things Applications for Agriculture," Internet Things A to Z, vol. 2, pp. 507–528, 2018, doi: 10.1002/9781119456735.ch18.
- D. Yan-E, "Design of intelligent agriculture management information system based on IoT," Proc. - 4th Int. Conf. Intell. Comput. Technol. Autom. ICICTA 2011, vol. 1, pp. 1045–1049, 2011, doi: 10.1109/ICICTA.2011.262.
- R. Ganesh Babu, C. Chellaswamy, T. S. Geetha, T. Daniel Raj, K. Venkatachalam, and M. A. Mulla, "Soil test based smart agriculture management system," 2020 7th Int. Conf. Smart Struct. Syst. ICSSS 2020, 2020, doi: 10.1109/ICSSS49621.2020.9202313.
- V. K. Patil, A. Jadhav, S. Gavhane, and V. Kapare, "IoT based real time soil nutrients detection," 2021 Int. Conf. Emerg. Smart Comput. Informatics, ESCI 2021, pp. 737–742, 2021, doi: 10.1109/ESCI50559.2021.9396860.
- F. Pedregosa et al., "Scikit-learn: Machine learning in Python," J. Mach. Learn. Res., vol. 12, pp. 2825–2830, 2011.
- A. K. Patra, S. K. Dutta, P. Dey, K. Majumdar, and S. K. Sanyal, "Potassium Fertility Status of Indian Soils: National Soil Health Card Database Highlights the Increasing Potassium Deficit in Soils," Indian J. Fert., vol. 13(11):28-, no. 11, pp. 28–33, 2017.
- Z. Mashaba-Munghemzulu, G. J. Chirima, and C. Munghemzulu, "Modeling the spatial distribution of soil nitrogen content at smallholder maize farms using machine learning regression and sentinel-2 data," Sustain., vol. 13, no. 21, 2021, doi: 10.3390/su132111591.
- Chetan, H. R., Rajanna, G. S., Sreenivasa, B. R., & Yallappa, G. N. (2023). Plant disease detection using deep learning in banana and sunflower. *J. Adv. Zool*, 44, 93-106.
- T. Blessin Sheeba et al., "Machine Learning Algorithm for Soil Analysis and Classification of Micronutrients in IoT-Enabled Automated Farms," J. Nanomater., vol. 2022, 2022, doi: 10.1155/2022/5343965.
- V. H. Phung and E. J. Rhee, "A High-accuracy model average ensemble of convolutional neural networks for classification of cloud image patches on small datasets," Appl. Sci., vol. 9, no. 21, 2019, doi: 10.3390/app9214500.
- X. Shi et al., "State-of-the-art internet of things in protected agriculture," Sensors (Switzerland), vol. 19, no. 8, 2019, doi: 10.3390/s19081833.
- M. Yang, "Physiological Disorder Diagnosis of Plant Leaves Based on Full-Spectrum Hyperspectral Images with Convolutional Neural Network," Horticulturae, vol. 8, no. 9, 2022, doi: 10.3390/horticulturae8090854.
- Chetan, H. R., Rajanna, G. S., Sreenivasa, B. R., & Kumar, M. M. (2023, February). Plant Disease Identification and Recommendation of Organic Pesticides Using Machine Learning Techniques. In *International Conference on Emerging Research in Computing, Information, Communication and Applications* (pp. 401-414). Singapore: Springer Nature Singapore.
- D. C. Santana et al., "Machine Learning in the Classification of Soybean Genotypes' Content Using UAV–Multispectral Sensor," Remote Sens., vol. 15, no. 5, 2023, doi: 10.3390/rs15051457.
- O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow, and M. N. Hindia, "An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges," IEEE Internet Things J., vol. 5, no. 5, pp. 3758–3773, 2018, doi: 10.1109/JIOT.2018.2844296.
- Meghana, G. R., Rudrahitlu, S. K., & Shilpa, K. C. (2022). Detection of Brain Cancer using Machine Learning Techniques a Review. *SSRG International Journal of Computer Science and Engineering*, 9(9), 12-18.
- G. Fenu and F. M. Mallocci, "Forecasting Plant and Crop Disease: An Exploratory Study on Current Algorithms," Big Data Cogn. Comput., vol. 5, no. 1, pp. 1–24, 2021.
- D. S. Bais, V. Tiwari, S. Kolhe, and B. K. Mishra, "Employing Machine Learning Algorithms for the Assessment and Mitigation of Physiological Disorders in Soybean crop_2023," in International Conference on Machine Intelligence and Cyber Physical Systems (ICMICPS 2023), Sushila Devi Bansal College of Technology, Indore., 2023.
- N. G. Rezk, E. E.-D. Hemdan, A.-F. Attia, A. El-Sayed, and M. A. El-Rashidy, "An efficient IoT based smart farming system using machine learning algorithms," Multimed. Tools Appl., vol. 80, no. 1, pp. 773–797, Jan. 2021, doi: 10.1007/s11042-020-09740-6