ijamrsd.com JAMRSD ISSN: 2583-6404
Journal of Advanced Multidisciplinary Research Studies and Development
Peer Reviewed Referred Journal Bi-monthly Open Access

REVIEW ON AI-DRIVEN SMART AGRICULTURE: AN INTEGRATED APPROACH FOR SOIL ANALYSIS, IRRIGATION, AND CROP-FERTILIZER RECOMMENDATIONS

Ms. Tamhane Vrushali Bhausaheb[1], Dr. Bere Sachin S.[2]

[1,2] Department of Computer Engineering, Dattakala Group of Institution Faculty of Engineering Swami-Chincholi Bhigwan.

Abstract

Machine learning (ML) can make use of agricultural data related to crop yield under varying soil nutrient levels, and climatic fluctuations to suggest appropriate crops or supplementary nutrients to achieve the highest possible production. The aim of this study was to evaluate the efficacy of five distinct ML models for a dataset sourced from the Kaggle repository to generate practical recommendations for crop selection or determination of required nutrient(s) in a given site. The datasets contain information on NPK, soil pH, and three climatic variables: temperature, rainfall, and humidity. The models namely Support vector machine, XGBoost, Random forest, KNN, and Decision Tree were trained using yields of individual data sets of 11 agricultural and 10 horti-cultural crops, as well as combined yield of both agri-horticultural crops. The results strongly suggest to evaluate individual data sets separately for each crop category rather than using combined the data sets of both categories for better predictions. Comparing the five ML models, the XGBoost demonstrated the highest level of accuracy. The precision rates of XGBoost for recommending agricultural crops, horticultural crops, and a combination of both were 99.09 % (AUC 1.0), 99.3 % (AUC 1.0), and 98.51 % (AUC 0.99), respectively. This non-intrusive method for generating crop recommendations in diverse environmental conditions holds the potential to provide valuable insights for the development of a user-friendly AI cloud-based interface. Such an interface would enable rapid decision-making for optimal fertilizer applications and the selection of suitable crops for cultivation at specific sites.

Keywords: Machine Learning, Deep Learning, Artificial Intelligence, XGBoost, Smart Agriculture, Precision Farming, Web Application Development.

► *Corresponding Author: Ms. Tamhane Vrushali Bhausaheb*

1. Introduction

Agriculture has always been one of the most vital sectors of human civilization, serving as the primary source of food and raw materials for industries. With the global population continuously rising, the demand for agricultural productivity has increased exponentially. However, conventional farming techniques often rely on farmers' intuition and past experiences rather than scientific data and modern technology. These traditional methods are inadequate in the face of today's unpredictable climatic conditions, soil degradation, and resource limitations.

To overcome these challenges, the agricultural sector is witnessing a revolutionary shift through the integration of Artificial Intelligence (AI), Machine Learning (ML), and Data Science. These technologies have enabled the concept of Smart Agriculture — a data-driven approach to farming that leverages sensors, data analytics, and intelligent algorithms to enhance productivity, efficiency, and sustainability.

Among various aspects of smart farming, crop recommendation plays a crucial role. The ability to select the most suitable crop for cultivation based on soil and weather conditions can significantly improve yield and reduce resource wastage. Farmers often struggle with identifying which crop to grow for a particular soil type or environmental condition. Factors such as soil nutrient composition (N, P, K values), temperature, and humidity are critical in determining the success of a crop.

This project proposes an AI-Driven Smart Agriculture System that uses Machine Learning—specifically, the XGBoost Classifier algorithm—to recommend the most appropriate crop based on soil nutrients (Nitrogen, Phosphorus, Potassium) and environmental parameters (temperature and humidity). The model is trained using a Kaggle Crop Recommendation Dataset, which contains real agricultural data linking soil and weather conditions to suitable crops.

Furthermore, a Flask-based web application has been developed to make the system user-friendly and easily accessible to farmers and agricultural consultants. The user can enter NPK values, temperature, and humidity through the web interface, and the system will provide the best crop recommendation instantly. The combination of machine learning and web technology offers an efficient, real-time solution for modern-day agriculture.

2. Literature Survey

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative technologies in the field of agriculture. The integration of these technologies enables intelligent decision-making, enhances productivity, and helps achieve sustainable farming practices. Numerous research works have focused on developing predictive systems that analyze soil and environmental data to recommend appropriate crops, fertilizers, and irrigation methods.

Several machine learning algorithms such as Decision Trees, Random Forest, Naïve Bayes, Support Vector Machines (SVM), and XGBoost have been explored in agricultural prediction systems. These models are trained on datasets containing parameters like Nitrogen (N), Phosphorus (P), Potassium (K), pH, temperature, humidity, and rainfall to determine the best crops for cultivation in specific conditions.

Researchers have demonstrated that AI-driven crop recommendation systems not only improve crop selection accuracy but also contribute to resource optimization by reducing fertilizer wastage, minimizing water usage, and improving soil health. The following section summarizes major works related to this study.

Author & Year	**Title / Research Focus**	**Methodology / Algorithm**	**Key Findings**	**Limitations**
Patel et al., (2020)	Crop Prediction using Machine Learning	Random Forest Classifier	Provided 94% accuracy in predicting suitable crops based on soil nutrients and temperature.	Did not include humidity or real-time weather data.

Sahu & Singh, (2021)	Smart Farming using IoT and ML	SVM & IoT Sensors	Integrated IoT sensors with ML to automate data collection and prediction.	Limited dataset and lack of deployment interface.
Gupta et al., (2022)	Crop Recommendation System using Decision Tree Algorithm	Decision Tree	Predicted suitable crops using NPK and rainfall data.	Low accuracy due to overfitting on training data.
Kumar et al., (2022)	AI-Based Agricultural Decision Support System	Naïve Bayes Classifier	Developed a mobile-based system for real-time crop recommendation.	System was limited to few soil types and regions.
Joshi et al., (2023)	Deep Learning in Smart Agriculture	ANN & CNN Models	Used neural networks for soil and crop classification achieving 96% accuracy.	Required high computational resources for training.
Reddy et al., (2023)	XGBoost-Based Crop Prediction	XGBoost Classifier	Achieved higher precision and recall compared to Random Forest.	Dataset imbalance affected rare crop predictions.
This Project (2025)	AI-Driven Smart Agriculture Using NPK, Temperature, and Humidity	XGBoost + Flask Web App	Provides accurate, real-time crop recommendations via web interface.	Currently limited to static input; future scope includes IoT integration.

3. Research Gap

Despite significant advancements in the application of machine learning (ML) in precision agriculture, most existing studies focus on generalized crop prediction or nutrient recommendation models that do not adequately differentiate between agricultural and horticultural crop categories. Furthermore, several prior works employ combined datasets, which often reduce prediction accuracy due to variations in nutrient and climatic requirements across crop types. Limited attention has been given to comparative performance analysis of multiple ML models using standardized datasets that include both soil (NPK, pH) and climatic (temperature, rainfall, humidity) features. Additionally, there is a lack of integration between predictive modeling and the development of user-friendly, cloud-based decision-support interfaces for farmers and agronomists.

This research addresses these gaps by systematically evaluating and comparing five ML algorithms—Support Vector Machine (SVM), XGBoost, Random Forest, K-Nearest Neighbors (KNN), and Decision Tree—using separate and combined datasets for agricultural and horticultural crops. The study also highlights the importance of dataset separation for improving model accuracy and provides insights toward the development of an AI-powered crop recommendation and fertilizer management system suitable for real-world deployment.

4. Methodology

4.1. Machine Learning Pipeline

A structured ML pipeline was implemented to ensure the reproducibility and scalability of the model.

Phases:

1. **Data Collection:**
Kaggle dataset containing soil nutrients and climatic conditions.
2. **Data Cleaning:**
Removal of missing values, outliers, and normalization.
3. **Feature Engineering:**
N, P, K, Temperature, and Humidity selected as key predictors.
4. **Model Selection:**
Compared algorithms (Random Forest, SVM, Logistic Regression, XGBoost) — selected XGBoost for best accuracy.
5. **Model Training & Tuning:**
Used GridSearchCV to optimize hyperparameters (learning_rate, max_depth, n_estimators).
6. **Model Evaluation:**
Accuracy, Precision, Recall, F1-score, and Confusion Matrix.
7. **Model Serialization:**
Saved using pickle for use in the web app.
8. **Deployment:**
Flask API integrated with frontend form for predictions.

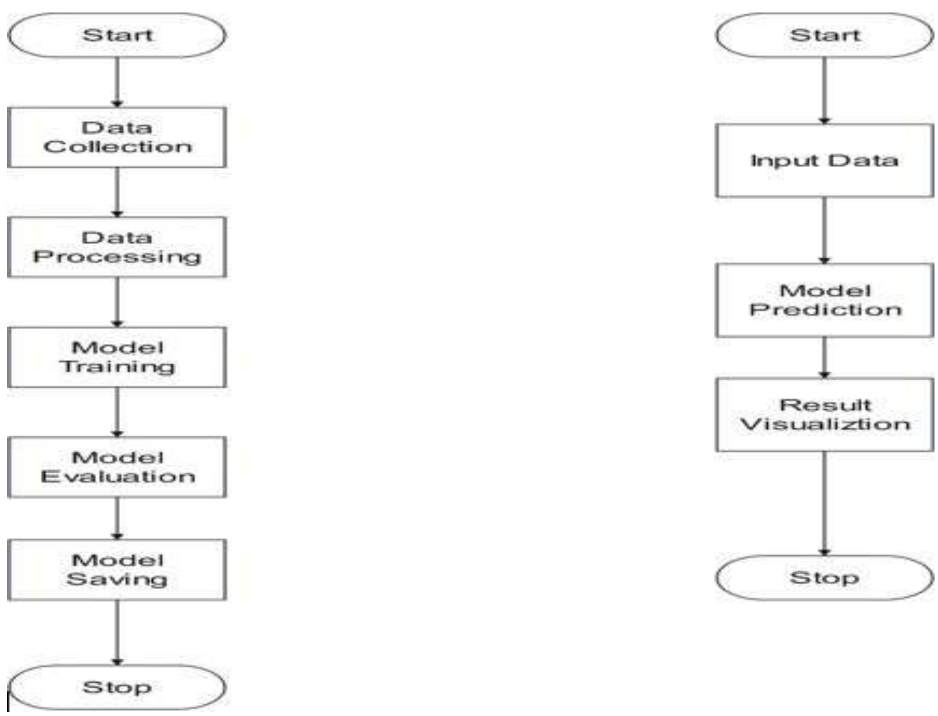


Fig 4.1 Flowchart

4.2. Flask Web Application Development
The Flask framework was used to create the web interface for user interaction.
Key Features:
1. Input form for N, P, K, temperature, humidity.
2. Backend API to process inputs and return predictions.
3. HTML/CSS-based interface with responsive design.
4. Real-time prediction results displayed instantly.

4.3. Model Evaluation Methodology
Metrics used:
1. **Accuracy** = (TP + TN) / (TP + TN + FP + FN)
2. **Precision** = TP / (TP + FP)
3. **Recall** = TP / (TP + FN)
4. **F1-score** = 2 × (Precision × Recall) / (Precision + Recall)
5. **Confusion Matrix** to visualize prediction distribution.

5. Architecture

The AI-Driven Smart Agriculture System is designed as a modular, scalable, and intelligent framework for forecasting the most appropriate crop by analyzing environmental and soil conditions. The architecture of this system combines machine learning (XGBoost Classifier) with a Flask web interface, allowing real-time predictions using data from users or sensors.
The system is structured into four layers.
Data Input Layer: Receives inputs from users or IoT sensors for N, P, K, temperature, and humidity. Processing Layer – Manages data preprocessing and utilizes the trained XGBoost model to produce predictions.
Application Layer: Operates the Flask backend, which processes requests, interacts with the model, and facilitates communication between the interface and prediction logic.
Presentation Layer: Offers the user interface for data entry and displays the suggested crop along with the results.

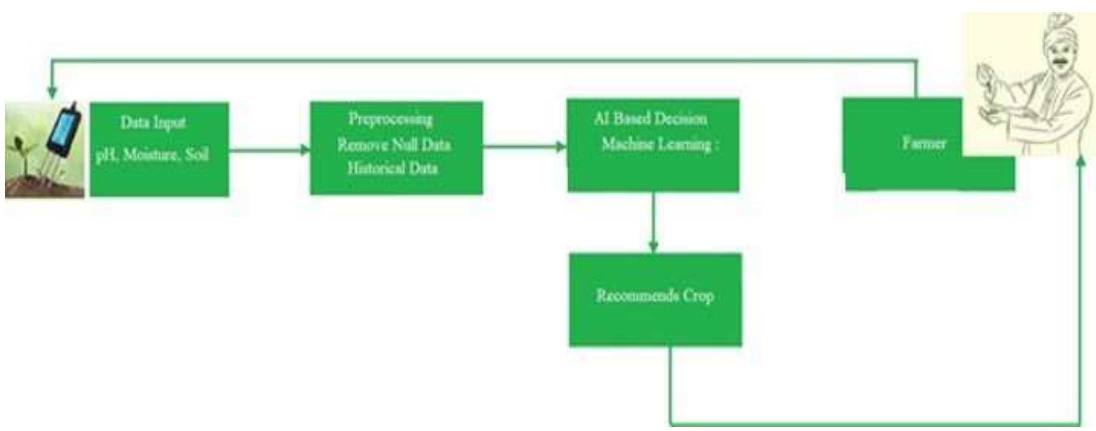


Fig.5.1 System Architecture

Algorithm
1. Input:
Dataset $D = \{(x_i, y_i)\}$, where

$x_i = [N, P, K, Temperature, Humidity]$(features)
y_i= Crop label.

2. Initialize the Model:

Start with an initial prediction $\hat{y}_i^{(0)} = 0$.

3. For each iteration (tree) $t = 1,2,\ldots,T$:

a. Compute the gradient and Hessian of the loss function with respect to predictions:

$$g_i = \frac{\partial L(y_i, \hat{y}_i^{(t-1)})}{\partial \hat{y}_i^{(t-1)}}, h_i = \frac{\partial^2 L(y_i, \hat{y}_i^{(t-1)})}{\partial (\hat{y}_i^{(t-1)})^2}$$

b. Fit a regression tree $f_t(x)$on the computed gradients $g_i$and h_i.

c. Compute the leaf weights $w_j$for each terminal node using:

$$w_j = -\frac{\sum_{i \in I_j} \quad g_i}{\sum_{i \in I_j} \quad h_i + \lambda}$$

where I_j= set of samples in leaf j, and λ= regularization parameter.

d. Update the predictions:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i)$$

where η= learning rate.

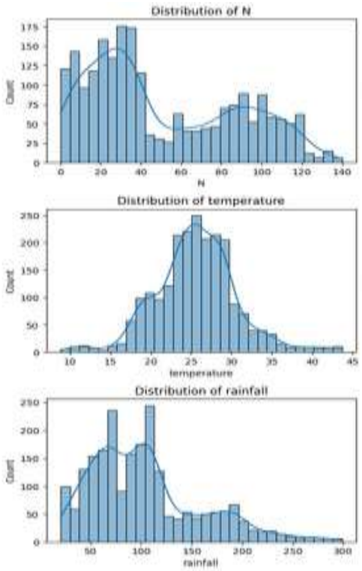
4. Final Prediction:

$$\hat{y}_i = \sum_{t=1}^{T} \quad \eta f_t(x_i)$$

The label corresponding to the highest probability is returned as the recommended crop.

6. Result & Discussion

This section evaluates the performance of various smart farming recommendations by focusing on four key datatypes: weather conditions, soil properties, fertilizer details, and crop information. These core element significantly influence agricultural outcomes. The models were developed using Python on a standard Windows 10 setup equipped with an Intel Core i5 processor, 8 GB RAM, and a 256 GB SSD— sufficiently powerful to manage and process large volumes of data efficiently.



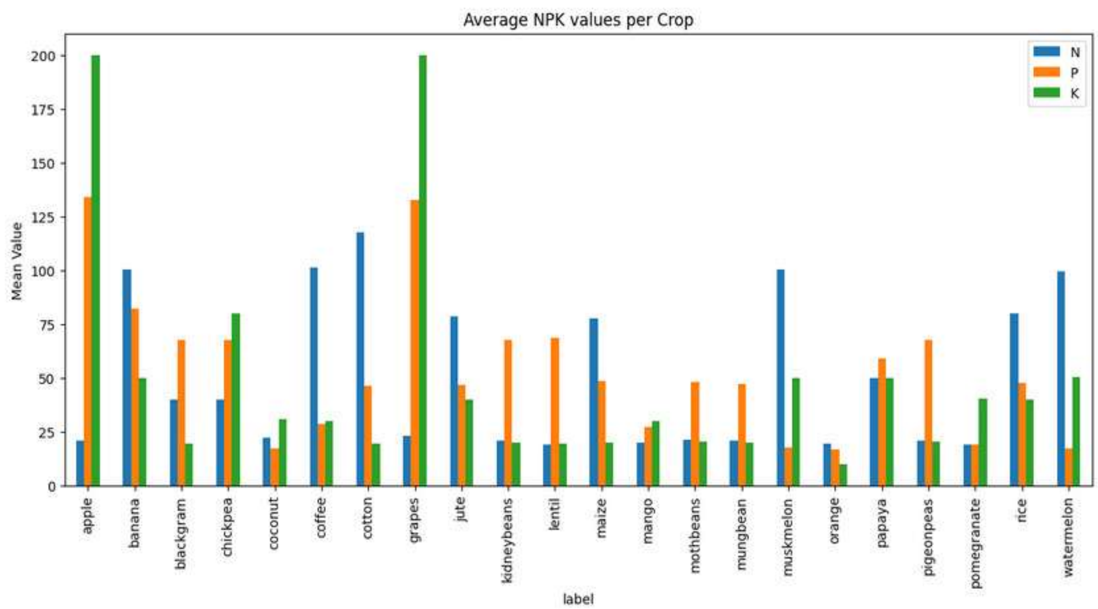


Fig. Dataset used for crop recommendation containing key soil and climatic parameters.

7. Conclusion

Precision agriculture has emerged as a transformative approach in the agricultural sector. The present study has made a significant contribution to this field by utilizing machine learning-based modeling to provide precise information on the suitability of agricultural or horticultural crops based on prevailing nutrient, climatic and soil pH variables. It is widely recognized that insufficient nutrient supply can have a detrimental impact on crop yield and may even lead to a decline in the soil's inherent capacity to sustain future crop cultivation. The agronomic requirements of agricultural crops vary from those of horticultural crops, particularly in terms of their nutrient needs (primarily NPK) and sensitivity to climatic factors. Hence, it is important to construct individual models for each class separately, as we have shown in our study. Based on the results of the study, it is recommended to use specifically trained models for individual crop classes in order to provide efficient, rapid, and more accurate cropping suggestions. The results of our study provide a useful reference for farmers in rural areas, as they can benefit from crop recommendations based on our findings, thus avoiding the need for trial-and-error farming. Moreover, the outcomes of our study can be utilized to design a user-friendly tool for a crop recommendation system that optimizes crop yield by taking into account the prevailing local environmental conditions. By offering more precise and accurate suggestions for crop selection and cultivation, it is possible to assist farmers in enhancing their productivity and efficiency, which can ultimately result in increased profitability and food security. Despite the huge implications of the study, it should be noted that the authors in the present study used public dataset, more datasets across the globe could have resulted in more pragmatic findings from which the wider community could harvest the benefit. Therefore. It is recommended to set more experiments in the field in wider environmental conditions to generate quality data for modelling using various ML algorithms.

References

1. S.W. Wang, W.K. Lee, Y. Son, An assessment of climate change impacts and adaptation in South Asian agriculture, Int. J. Clim. Chang. Strateg. Manag. 9 (2017) 517–534, https://doi.org/10.1108/IJCCSM-05-2016-0069.

2. K.K. Verma, X.P. Song, A. Joshi, D.D. Tian, V.D. Rajput, M. Singh, J. Arora, T. Minkina, Y.R. Li, Recent trends in nano-fertilizers for sustainable agriculture under climate change for global food security, Nanomaterials 12 (2022) 1–25, https://doi.org/10.3390/nano12010173.

3. X. Liu, Y. Xu, S. Sun, X. Zhao, P. Wu, Y. Wang, What is the potential to improve food security by restructuring crops in Northwest China? J. Clean. Prod. 378 (2022) 134620 https://doi.org/10.1016/J.JCLEPRO.2022.134620.

4. A. Bouguettaya, H. Zarzour, A. Kechida, A.M. Taberkit, Deep learning techniques to classify agricultural crops through UAV imagery: a review, Neural Comput. Appl. 34 (2022) 9511–9536, https://doi.org/10.1007/S00521-022-07104-9, 2022 3412.

5. United Nations, World Population Prospects 2019, 2019. New York, https://population.un.org/wpp/Download/Standard/Population/.

6. W.H. Meyers, N. Kalaitzandonakes, W.H. Meyers, N. Kalaitzandonakes, World population, Food Growth, and Food Security Challenges 15 (2015) 161–177, https://doi.org/10.1108/S1574-871520.

7. Shoukat fiza, M. Awais, M. Khalid, Asad Sohail, The role of genetically-modified (GM) crops in food security, Life Sci. J. 19 (2022) 26–30, https://doi.org/ 10.7537/marslsj190222.04.

8. G. Clarkson, P. Dorward, S. Poskitt, R.D. Stern, D. Nyirongo, K. Fara, J.M. Gathenya, C.G. Staub, A. Trotman, G. Nsengiyumva, F. Torgbor, D. Giraldo, Stimulating small-scale farmer innovation and adaptation with participatory integrated climate services for agriculture (PICSA): lessons from successful implementation in africa, Latin America, the caribbean and South Asia, Clim. Serv. 26 (2022) 100298, https://doi.org/10.1016/J.CLISER.2022.100298.

9. R. Islam, R. Ahmed, B. Dey, S. Haque, S. Aktar, M.S. Bhuiyan, M.S. Arif, M.A. Habib Ador, M.M. Ul Haque, N. Saha, Salinity hazard drives the alteration of occupation, land use and ecosystem service in the coastal areas: evidence from the south-western coastal region of Bangladesh, Heliyon 9 (2023) e18512, https://doi.org/10.1016/j.heliyon.2023.e18512.

10. B. Dey, M. Masum Ul Haque, R. Khatun, R. Ahmed, Comparative performance of four CNN-based deep learning variants in detecting Hispa pest, two fungal diseases, and NPK deficiency

symptoms of rice (Oryza sativa), Comput. Electron. Agric. 202 (2022) 107340, https://doi.org/10.1016/j.compag.2022.107340.

11. J.-H. Chen, J.-T. Wu, C. Young, The Combined Use of Chemical, Organic Fertilizers And/or Biofertilizer for Crop Growth and Soil Fertility, 2007, https://doi. org/10.30058/SE.200706.0001.
12. M.A. Saleque, M.J. Abedin, N.I. Bhuiyan, S.K. Zaman, G.M. Panaullah, Long-term effects of inorganic and organic fertilizer sources on yield and nutrient accumulation of lowland rice, Field Crops Res. 86 (2004) 53–65, https://doi.org/10.1016/S0378-4290(03)00119-9.
13. D. Batool, M. Shahbaz, H. Shahzad Asif, K. Shaukat, T.M. Alam, I.A. Hameed, Z. Ramzan, A. Waheed, H. Aljuaid, S. Luo, A hybrid approach to tea crop yield prediction using simulation models and machine learning, Plants 11 (2022) 1925, https://doi.org/10.3390/PLANTS11151925, 2022, Vol. 11, Page 1925.
14. H. Burdett, C. Wellen, Statistical and machine learning methods for crop yield prediction in the context of precision agriculture, Precis. Agric. 23 (2022) 1553–1574, https://doi.org/10.1007/s11119-022-09897-0.
15. S. Fei, M.A. Hassan, Y. Xiao, X. Su, Z. Chen, Q. Cheng, F. Duan, R. Chen, Y. Ma, UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat, Precis. Agric. (2022) 1–26, https://doi.org/10.1007/s11119-022-09938-8.
16. D. Paudel, H. Boogaard, A. de Wit, M. van der Velde, M. Claverie, L. Nisini, S. Janssen, S. Osinga, I.N. Athanasiadis, Machine learning for regional crop yield forecasting in Europe, Field Crops Res. 276 (2022) 108377, https://doi.org/10.1016/J.FCR.2021.108377.
17. A. Nihar, N.R. Patel, A. Danodia, Machine-learning-based regional yield forecasting for sugarcane crop in Uttar Pradesh, India, J. Indian Soc. Remote Sens. 50 (2022) 1519–1530, https://doi.org/10.1007/S12524-022-01549-0.
18. R. Tufail, A. Ahmad, M.A. Javed, S.R. Ahmad, A machine learning approach for accurate crop type mapping using combined SAR and optical time series data, Adv. Sp. Res. 69 (2022) 331–346, https://doi.org/10.1016/J.ASR.2021.09.019.
19. O.P. Duke, T. Alabi, N. Neeti, J. Adewopo, Comparison of UAV and SAR performance for Crop type classification using machine learning algorithms: a case study of humid forest ecology experimental research site of West Africa, Https://Doi.Org/10.1080/01431161.2022.2109444. 43 (2022) 4259–4286. https:// doi.org/10.1080/01431161.2022.2109444.
20. S. Nandhini, K. Ashokkumar, Machine learning technique for crop disease prediction through crop leaf image, Appl. Math. Inf. Sci. 16 (2022) 149–158, https:// doi.org/10.18576/amis/160202.
21. M. Sharif, M.A. Khan, Z. Iqbal, M.F. Azam, M.I.U. Lali, M.Y. Javed, Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection, Comput. Electron. Agric. 150 (2018) 220–234, https://doi.org/10.1016/J.COMPAG.2018.04.023.
22. E.C. Too, L. Yujian, S. Njuki, L. Yingchun, A comparative study of fine-tuning deep learning models for plant disease identification, Comput. Electron. Agric. 161 (2019) 272–279, https://doi.org/10.1016/j.compag.2018.03.032.
23. J. Chen, D. Zhang, A. Zeb, Y.A. Nanehkaran, Identification of rice plant diseases using lightweight attention networks, Expert Syst. Appl. 169 (2021), https:// doi.org/10.1016/J.ESWA.2020.114514.
24. H. Chu, C. Zhang, M. Wang, M. Gouda, X. Wei, Y. He, Y. Liu, Hyperspectral imaging with shallow convolutional neural networks (SCNN) predicts the early herbicide stress in wheat cultivars, J. Hazard Mater. 421 (2022) 126706, https://doi.org/10.1016/j.jhazmat.2021.126706.

25. P. Bhatt, S. Sarangi, S. Pappula, Comparison of CNN models for application in crop health assessment with participatory sensing, GHTC 2017 - IEEE Glob. Humanit. Technol. Conf. Proc. (2017) 1–7, https://doi.org/10.1109/GHTC.2017.8239295, 2017-January.
26. P.R. Sai Sankar, S.D.p.s Ramakrishna, M.M. Venkata Rakesh, P. Raja, V.T. Hoang, C. Szczepanski, Intelligent health assessment system for paddy crop using CNN, 2021 3rd, Int. Conf. Signal Process. Commun. ICPSC 2021 (2021) 382–387, https://doi.org/10.1109/ICSPC51351.2021.9451644.
27. N. Kaur, Devendran, S. Verma, Kavita, N.Z. Jhanjhi, De-noising diseased plant leaf image, in: 2022 2nd Int. Conf. Comput. Inf. Technol., IEEE, Tabuk, Saudi Arabia, 2022, pp. 130–137, https://doi.org/10.1109/ICCIT52419.2022.9711604.
28. Z. Doshi, S. Nadkarni, R. Agrawal, N. Shah, AgroConsultant: intelligent crop recommendation system using machine learning algorithms, Proc. - 2018 4th Int. Conf. Comput. Commun. Control Autom. ICCUBEA (2018), https://doi.org/10.1109/ICCUBEA.2018.8697349, 2018.
29. V.C. Waikar, S.Y. Thorat, A.A. Ghute, P.P. Rajput, M.S. Shinde, Crop prediction based on soil classification using machine learning with classifier ensembling, Int. Res. J. Eng. Technol. 7 (2020) 4857–4861. www.irjet.net. (Accessed 23 December 2022).
30. A. Dubois, F. Teytaud, S. Verel, Short term soil moisture forecasts for potato crop farming: a machine learning approach, Comput. Electron. Agric. 180 (2021) 105902, https://doi.org/10.1016/J.COMPAG.2020.105902.
31. M.U. Ahmed, I. Hussain, Prediction of wheat production using machine learning algorithms in northern areas of Pakistan, Telecomm. Policy. 46 (2022) 102370, https://doi.org/10.1016/J.TELPOL.2022.102370.
32. K. Bakthavatchalam, B. Karthik, V. Thiruvengadam, S. Muthal, D. Jose, K. Kotecha, V. Varadarajan, IoT framework for measurement and precision agriculture: predicting the crop using machine learning algorithms, Technol. 10 (2022) 13, https://doi.org/10.3390/TECHNOLOGIES10010013, 2022, Vol. 10, Page 13.
33. R.K. Rajak, A. Pawar, M. Pendke, P. Shinde, S. Rathod, A. Devare, Crop Recommendation System to Maximize Crop Yield Using Machine Learning Technique, Academia.Edu., 2017. https://www.academia.edu/download/55495855/IRJET-V4I12179.pdf. (Accessed 23 December 2022).
34. N.H. Kulkarni, G.N. Srinivasan, B.M. Sagar, N.K. Cauvery, Improving crop productivity through A crop recommendation system using ensembling technique, Proc. 2018 3rd Int. Conf. Comput. Syst. Inf. Technol. Sustain. Solut. CSITSS (2018) 114–119, https://doi.org/10.1109/CSITSS.2018.8768790, 2018.
35. D. Modi, A.V. Sutagundar, V. Yalavigi, A. Aravatagimath, Crop recommendation using machine learning algorithm, in: 2021 5th Int. Conf. Inf. Syst. Comput. Networks, 2021, https://doi.org/10.1109/ISCON52037.2021.9702392. ISCON 2021.
36. P. Parameswari, N. Rajathi, K.J. Harshanaa, Machine learning approaches for crop recommendation, in: 2021 Int. Conf. Adv. Electr. Electron. Commun. Comput. Autom. ICAECA 2021, 2021, https://doi.org/10.1109/ICAECA52838.2021.9675480.
37. R.K. Rajak, A. Pawar, M. Pendke, P. Shinde, S. Rathod, A. Devare, Crop recommendation system to maximize crop yield using machine learning technique, Int. Res. J. Eng. Technol. 4 (2017) 950–953. www.irjet.net. (Accessed 23 December 2022).
38. G. Suresh, D.A.S. Kumar, D.S. Lekashri, D.R. Manikandan, C.-O. Head, Efficient crop yield recommendation system using machine learning for digital farming, Int. J. Mod. Agric. 10 (2021)

906–914. http://modern-journals.com/index.php/ijma/article/view/688. (Accessed 23 December 2022).
39. Kaggle. https://www.kaggle.com/, 2022. (Accessed 25 December 2022).
40. ICFA, Indian Chamber of Food and Agriculture, 2022. https://www.icfa.org.in/. (Accessed 25 December 2022).
41. Y. Hua, F. Li, S. Yang, Application of support vector machine model based on machine learning in art teaching, Wireless Commun. Mobile Comput. 2022 (2022), https://doi.org/10.1155/2022/7954589.
42. B. Dey, K.A.M. Abir, R. Ahmed, M.A. Salam, M. Redowan, M.D. Miah, M.A. Iqbal, Monitoring groundwater potential dynamics of north-eastern Bengal Basin in Bangladesh using AHP-Machine learning approaches, Ecol. Indicat. 154 (2023) 110886, https://doi.org/10.1016/j.ecolind.2023.110886.
43. B. Dey, R. Ahmed, J. Ferdous, M.M.U. Haque, R. Khatun, F.E. Hasan, S.N. Uddin, Automated plant species identification from the stomata images using deep neural network: a study of selected mangrove and freshwater swamp forest tree species of Bangladesh, Ecol. Inform. 75 (2023) 102128, https://doi.org/ 10.1016/J.ECOINF.2023.102128.
44. P.S.S. Gopi, M. Karthikeyan, Red fox optimization with ensemble recurrent neural network for crop recommendation and yield prediction model, Multimed. Tool. Appl. (2023) 1–21, https://doi.org/10.1007/S11042-023-16113-2.
45. T. Swathi, S. Sudha, Crop classification and prediction based on soil nutrition using machine learning methods, Int. J. Inf. Technol. 15 (2023) 2951–2960, https://doi.org/10.1007/S41870-023-01345-0.
46. S.G. Kundu, A. Ghosh, A. Kundu, G. G P, a ml-ai enabled ensemble model for predicting agricultural yield, Cogent Food Agric. 8 (2022), https://doi.org/ 10.1080/23311932.2022.2085717.
47. S.H. Ewaid, S.A. Abed, A. Chabuk, N. Al-Ansari, Water footprint of rice in Iraq, IOP Conf. Ser. Earth Environ. Sci. 722 (2021) 012008, https://doi.org/10.1088/ 1755-1315/722/1/012008.
48. C.S. Murthy, M.K. Poddar, K.K. Choudhary, P. Srikanth, V. Pandey, S. Ramasubramanian, G.S. Kumar, Remote sensing based crop insurance for jute (Corchorus olitorius) crop in India, Remote Sens. Appl. Soc. Environ. 26 (2022) 100717, https://doi.org/10.1016/j.rsase.2022.100717.
49. V. Sridevi, V. Chellamuthu, Impact of weather on rice – a review, Int. J. Appl. Res. 1 (2015) 825–831.