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Enhanced Agricultural Decision-Making: Machine Learning Approaches for Crop Prediction and Analysis in India

Sandeep Gupta[1,2], Abu Bakar Abdul Hamid[1], Tadiwa Elisha Nyamasvisva[3], Nitin Tyagi[4] , Vishal Jain[1,5], Ng Khai Mun[1], Danish Ather[6]

[1]Kuala Lumpur University of Science & Technology, Unipark Suria, Jalan Ikram-Uniten, Kajang, Selangor, Kuala Lumpur, Malaysia
[2]Department of Computer Science & Engineering, SSCSE,Sharda University, Plot no. 32, 34 KP –III, Greater Noida 201301(U.P.), India
[3]Faculty of Engineering Science and Technology, Kuala Lumpur University of Science & Technology, Unipark Suria, Jalan Ikram-Uniten, Kajang, Selangor, Kuala Lumpur, Malaysia
[4]Department of CSE and Allied Branches, Accurate Institute of Management and Technology, Greater Noida, U. P.-201306, India
[5]Department of Computer Science & Engineering, School of Engineering & Technology, Vivekananda Institute of Professional Studies-Technical Campus, New Delhi, India
[6]Amity University, Tashkent City, Street Labzak, Building-70, 100028, Uzbekistan

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ABSTRACT

This paper addresses the critical aspects of agriculture in the Indian economy and the challenges faced by this sector, including soil quality decline, unpredictable weather, and the need for efficient decision-making. It presents machine learning as a transformative approach for improved agricultural decision-making, enabling enhanced crop prediction and productivity. Machine learning (ML) algorithms are shown to effectively analyze vast datasets to generate predictive models that aid in crop selection optimization, disease outbreak prediction, and market fluctuation anticipation, thus leading to increased yields and profitability. Focusing on crop prediction, the paper discusses models leveraging historical data and advanced algorithms to forecast crop yields. Additionally, the application of machine learning in precision farming, such as optimizing fertilizer application, is explored. The paper uses a mixed-method approach on a dataset encompassing various crops and environmental parameters. In this paper the various techniques such as K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Decision Tree (DT) and Random Forest (RF) algorithms have been employed to demonstrate the utility of ML in the agricultural fields. The KNN at the value of K=4 and SVM with polynomial kernel resulted the accuracy of 0.982 and 0.989 respectively. Whereas DT and RT gave the results in terms of accuracy of 0.987 and 0.970 respectively. Overall, it can be said that all these techniques used in the present work showed the better accuracy for agricultural sustainability.

Corresponding Author:

Nitin Tyagi
Professor and Head
Department of Computer Science Engineering and Allied Branches
Accurate Institute of Management and Technology
Plot 49, Knowledge Park III, Greater Noida-201306, Uttar Pradesh, India
Email: nitinnitin8218@gmail.com

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1. INTRODUCTION

Agriculture plays a critical role in the Indian economy, contributing significantly to the nation's GDP and presuming livelihood for a vast majority of the population [1]. However, the sector faces numerous challenges, including declining soil quality, unpredictable weather patterns, and the need for more efficient decision-making processes [2]. To address these challenges, the application of ML in agriculture has emerged as a promising approach, offering opportunities for enhanced decision-making, improved crop prediction, and overall productivity enhancement as well as other predictive analysis [3-5].

ML algorithms have the potential to analyze large datasets, including historical crop yields, weather patterns, soil characteristics, and market prices, to develop predictive models that can assist farmers in making more informed decisions [6]. These models can help farmers optimize their crop selection, predict disease outbreaks, and anticipate market fluctuations, ultimately leading to increased yields and improved profitability [7].

One of the key areas where machine learning has been applied in agriculture is crop prediction and analysis. By leveraging historical data and advanced algorithms, researchers have developed frameworks that can precisely predict crop yields, allowing farmers to plan their planting and harvesting strategies more effectively. Additionally, ML techniques can be employed to analyze soil and environmental conditions, providing farmers with valuable insights into the suitability of specific crops for their land [2].

Despite the promising potential of ML in agriculture, its adoption in India has been relatively slow, with various challenges and barriers to overcome. These include the lack of comprehensive data, limited access to technology, and the need for capacity building among farmers and agricultural extension workers. To handle these challenges, a holistic approach is required, involving collaboration between policymakers, researchers, and the farming community to develop and implement effective ML -based solutions.

The application of ML in agriculture has been the area of extensive research, with numerous studies highlighting its potential benefits [8]. In a review of the literature on precision agriculture decision-making, researchers found that while traditional decision-making methods are still widely used in India, particularly by small and marginal-scale farmers, the adoption of ML -based approaches can significantly improve the efficiency and accuracy of agricultural decision-making [2]. One study that explored the use of ML for crop prediction focused on the development of a model to forecast the yields of major crops, such as rice, wheat, and maize [9]. The researchers used historical data on crop yields, weather patterns, and other relevant factors to train a ML algorithm, which was then able to provide precise predictions of future crop yields [10-16].

Another study examined the potential of ML for precision agriculture, specifically in the context of fertilizer application. The researchers developed a model that could predict the optimal fertilizer application rates for different crop types and soil conditions, leading to more efficient resource utilization and reduced environmental impact [17-21]. Despite the growing body of research on the application of ML in agriculture, there are still significant challenges that need to be addressed. One key challenge is the limited availability of comprehensive and reliable data, which is essential for the development of accurate predictive models [22-26]. Additionally, the integration of ML -based solutions into existing agricultural practices and decision-making processes remains a significant hurdle, requiring substantial capacity building and training efforts.

In addition, the incorporation of ML -based solutions into existing agricultural practices and decision-making frameworks is still a major challenge that needs large-scale capacity building and training exercises. Hence, in the present work, different ML techniques like KNN, SVMs, DTs and RF algorithms have been utilized to show the effectiveness of ML in the agricultural fields for classification and prediction analysis.

2. METHOD

2.1 Dataset

Crop recommendation dataset is utilised for the analysis in this work [27]. This dataset contains information on the amount of nitrogen, phosphorus, and potassium in soil, as well as temperature, humidity, pH, and rainfall, and their impact on the growth of crops. Making recommendations for reaching ideal nutritional and environmental conditions to increase crop output can be done using the data. Dataset contains the records of 2200 samples of crops including rice, maize, kidney beans, chickpea, pigeon peas, mung bean, moth beans, black gram, pomegranate, lentil, banana, grapes, mango, watermelon, apple, muskmelon, orange, coconut, papaya, cotton, coffee and jute for the above-mentioned parameters (100 samples for each class).

The proposed study employs a multimethod approach, combining qualitative and quantitative data analysis, to investigate the potential of ML for enhanced agricultural decision-making in India. The following ML techniques are utilized for the analysis and prediction of the crop in India.

2.2 KNN Classifier

The KNN algorithm is one of the supervised ML techniques that can be used for both classification as well as regression tasks [28]. The KNN algorithm is particularly useful for predicting crop yields and other agricultural outcomes, as it can effectively capture complex nonlinear relationships in the data. The KNN algorithm detects the K closest neighbors, using one of the distance metrics (e.g. Euclidean distance), to a given data point. The majority vote or the mean of the K neighbors are then used to establish the class or value of the data item (refer Fig. 1). Using this method enables the algorithm to anticipate outcomes based on the local structure of the data and adjust to various patterns.

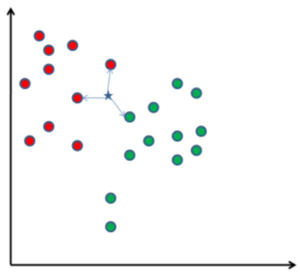

Figure 1. Example of KNN algorithms for classification with K=3.[28]

2.3 Support Vector Classifier

SVM is one of the supervised ML algorithms that may be utilized for classification as well as regression tasks [29]. SVMs have been successfully applied to various agricultural problems, including crop disease detection, yield prediction, and weed classification. The SVM algorithm's basic aim is to find the best hyperplane in an N-dimensional space, which can be utilized to classify data points into various feature space classes. The hyperplane attempts to maintain the largest feasible buffer within the nearest points of various classes. The count of features determines the dimension of the hyperplane. The hyperplane is essentially a line if there are just two input characteristics (refer to Figure 2).

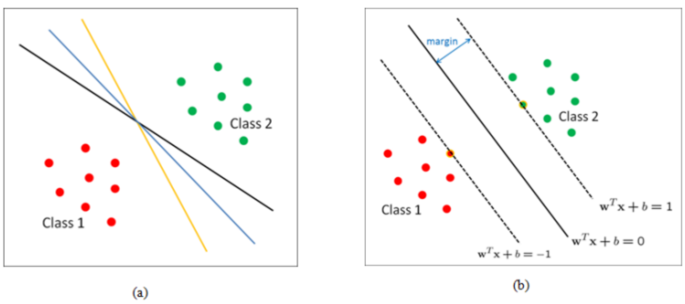

Figure 2. (a) Precedents for conceivable arrangements of the two-class characterization issue (directly distinguishable). (b) Illustration of the greatest edge[29]

2.4 Decision Tree Classifier

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DTs are a popular ML technique that can be utilized for both regression and classification problems [30]. DTs have been applied in many agricultural domains, including crop yield prediction, precision farming, and pest management. Tree-based prototypes are generally utilized as they are very straightforward and may be utilized for arrangement/relapse issues. The ordinary choice tree is a model that utilizes an arrangement of paired choice principles to process an objective esteem. At every hub in the choice tree, a particular property of the information test is tried. On the off chance that we think about the grouping issue, the choice tree orders new information tests by checking a characteristic at every hub at each progression, and picking the ensuing branch as indicated by the solid estimation of the property (refer Figure 3).

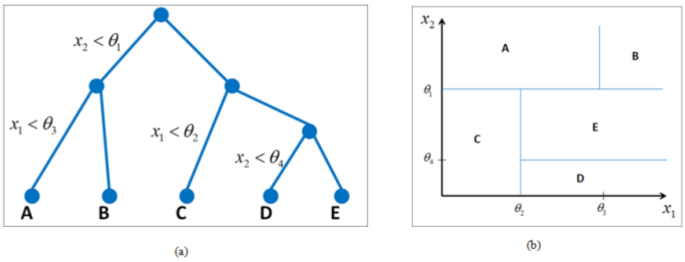

Figure 3. Example of Decision Tree Classification [30]

2.5 *Random Forest Classifier*

RF is an ensemble learning method that combines multiple decision trees to improve the overall predictive performance [31]. RFs have been widely used in agricultural applications, for example, as crop yield forecasting, soil property estimation, and pest/disease detection. During the training, it generates various DTs to measure a random subset of characteristics in every partition; a random subset of the dataset is utilized to construct every tree. As each tree is more variable as a result of the randomization, there are fewer occasions of overfitting, and the overall prediction outcome is enhanced. While predicting, the algorithm averages (for regression tasks) or votes (for classification tasks) the output of every tree. The findings of this cooperative prediction process, which is aided by the insights of various trees, are consistent and accurate. Regression as well as classification algorithms frequently employ RFs because of their propensity to handle complicated data, minimize.

3. RESULTS AND DISCUSSION

The conclusions from this research study will add to the body of literature on using machine learning for agriculture, particularly in the case of India. The models thus created for crop forecasting and planning for resources will show the usefulness of such technology in enhancing farm-level decision-making and overall productivity and sustainability.

3.1 *Distribution of temperature and pH*

Temperature and pH are the most important parameters that can influence processes significantly to an extent both of natural origin as well as man-made. Figure 4 reveals that the bell-shaped and symmetrical design of the distribution of temperature and pH signifies that although trials always produce values around the mean, they also deviate considerably from it on rare occasions. That these two indeed resemble each other is quite mind-boggling. The distribution of temperature and pH significantly impacts Indian crops, influencing their growth, yield, and geographical suitability. India's diverse agro-climatic zones experience varying temperature ranges and soil pH levels, affecting crop productivity.

3.2 *Effect of Rainfall*

The rainfall during the rainy season averages 120 mm, and the temperature is only slightly above 30°C. Rain changes the moisture content of soil, which further changes the pH of the soil. These are the crops that will likely be planted this year. Heavy rainfalls (>200 mm) and humidity of more than

80% are necessary for rice. It is no wonder that the East Coast of India grows most of the country's rice because it has an average annual rainfall of 220 mm. Because of its tropical origin and high humidity needs, coconuts are exported extensively from the country's coastal areas.

In India, the growth, distribution, and productivity of crops are highly dependent upon rainfall and its spatial distribution (refer Figure 5). The economy is fundamentally reliant on monsoon precipitation, which spatially and timely varies for different crops. The variability in rainfall patterns poses a great challenge for Indian agriculture and requires adaptive strategies for sustainable agricultural practices. Effective management of water resources has become essential due to the higher uncertainty coming from climate change.

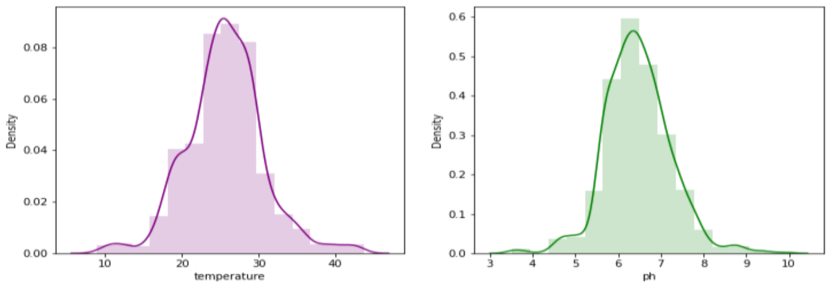

Figure 4. Distribution of pH and temperature in soil for Indian Crops

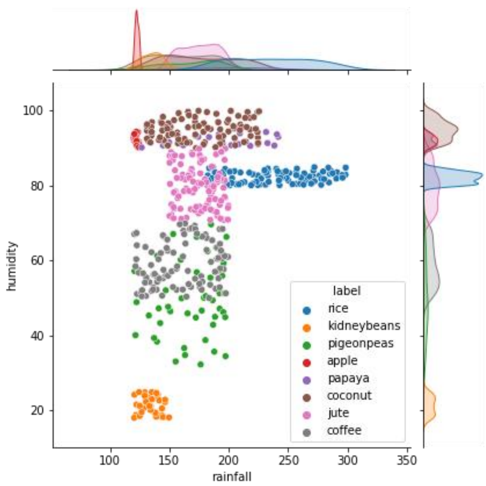

Figure 5. Effect of rainfall and temperature of crop yield for different crops in India

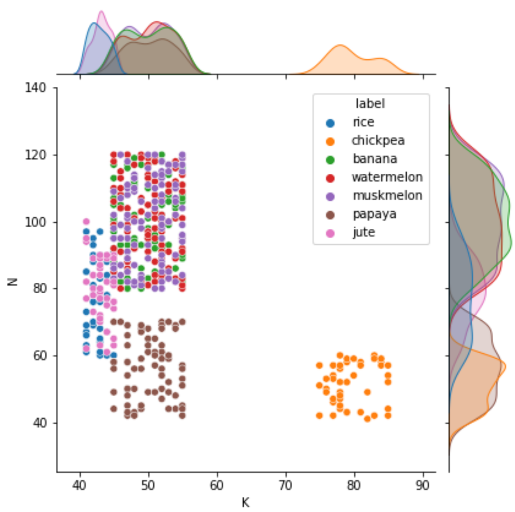

Figure 6. Effect of Nitrogen and Potassium (in kg/ha) of crop yields

3.3 Effect of Nitrogen and Potassium (in kg/ha)

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Nitrogen and potassium are fundamental macronutrients that significantly impact Indian crops in areas of growth, development, and productivity. Their impact is dependent on the type of soil, species of crops, weather, and method of application. Applying balanced and efficient nitrogen and potassium use is essential in supporting sustainable crop productivity, quality, and soil health in Indian agriculture. There needs to be integrated nutrient systems alongside precision farming with farmer education to improve agricultural sustainability and food supply security in India. The mean contents of nitrogen (N) and potassium (K), both over 50 kg/ha, are related in Figure 6. Nutritional value in the meal is directly affected by these soil factors. Highly nutritional fruits typically possess uniform potassium levels.

3.4 Effect of pH and Potassium (in kg/ha)

Low pH can also make it harder for the soil to keep providing potassium to plants, which can raise the demand for additional fertilizer applications or liming to readjust the soil pH. Aluminum toxicity can also arise at low pH, which can result in less root growth and less water and nutrient uptake. Figure 7 illustrates that ph levels are crucial for soil. Stability in the range of 6 to 7 is preferred.

The optimization of soil fertility, crop yields, and agricultural productivity relies on the impact of pH and potassium (K) levels on Indian crops. Both factors impact nutrient absorption, root growth, and plant vitality. Soil pH (which indicates level of acidity or alkalinity) will impact the solubility of minerals, the activity of, the life forms in the soil and plant growth. Potassium is a macro nutrient which serves a purpose in enzyme activation, water control and resistance to diseases. The Indian K-deficient soils, especially in mechanized farming regions (like the Punjab, Haryana, and UP), are in dire need of potassium due to rampant depletion. Integrated soil testing and area-specific nutrient management aid precision farming—crop yield improves significantly when pH is regulated between 6 and 7.5. Potassium is important for the sustenance of crop yield, quality, and stress tolerance—or India's crops. Through pH and potassium moderation, India's farmers can maximize agricultural output, especially for in-demand crops like rice, wheat, and horticultural produce, plunging them into surplus.

3.5 Effect of Rainfall, humidity and Phosphorus (in kg/ha)

The availability of crops might be decreased by heavy rainfall that removes vital nutrients from the soil. Pollution of the land and water can be caused by excess nitrogen and phosphorus. Agronomists may assist farmers in modifying fertilizer applications for the best crop development by examining soil samples. Another intriguing investigation in Figure 8 shows that when it rains a lot (over 150 mm), the phosphorus levels are very different.

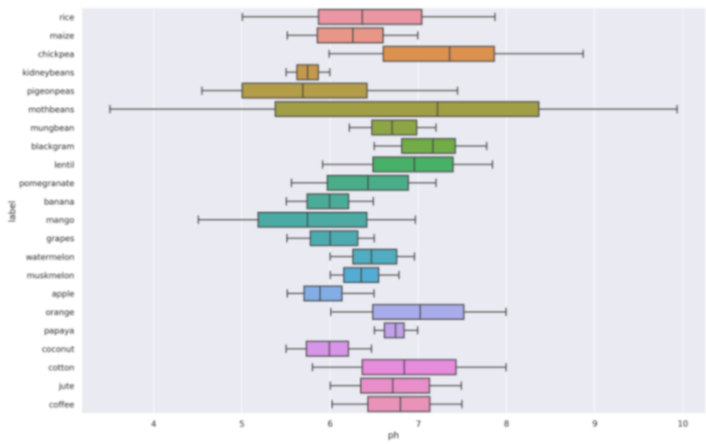

Figure 7. Effect of pH on crop yield. It is indicated that a pH value between 6 and 7 is desirable for good production of the crop

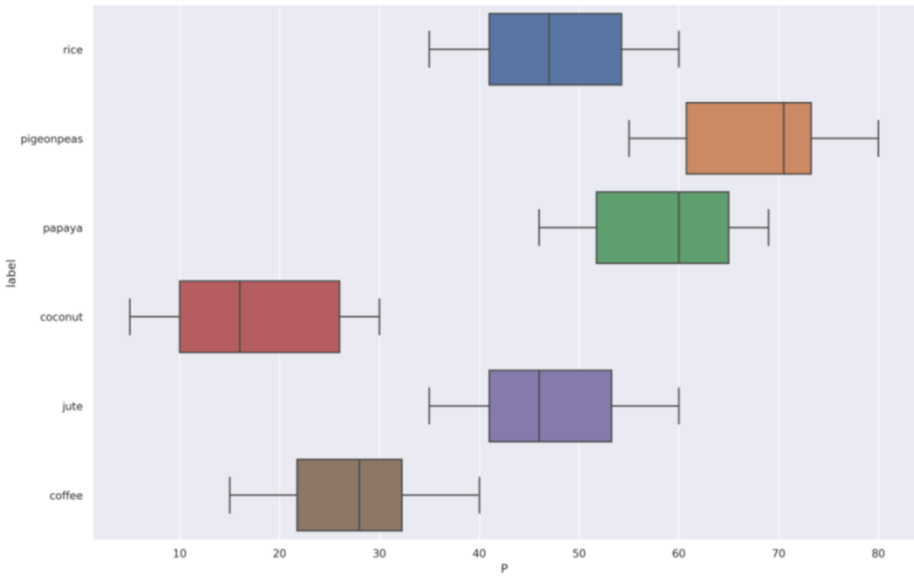

Figure 8. Effect of P (in Kg/ha) during heavy rainfall

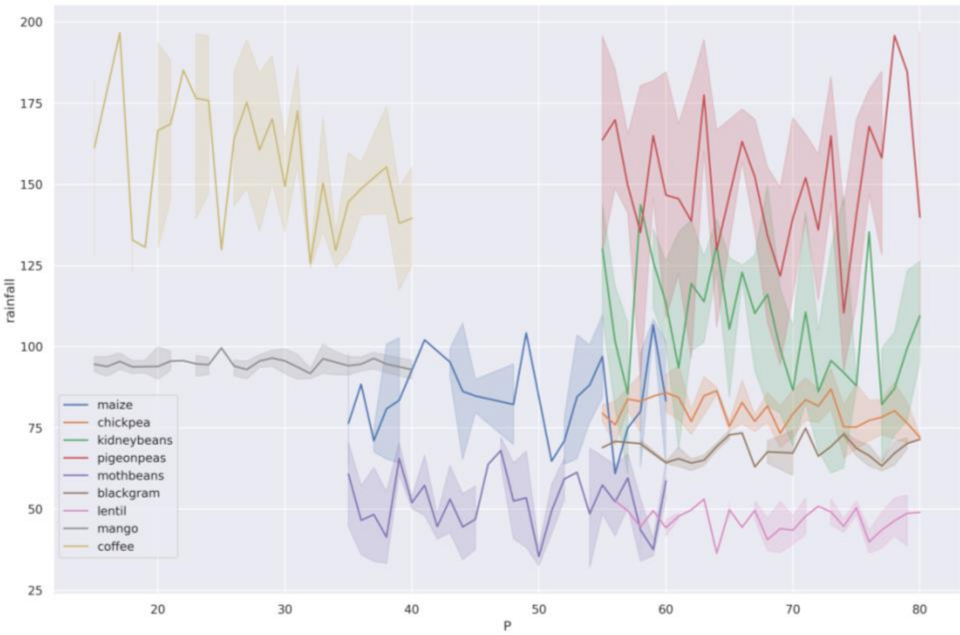

Figure 9. Effect of Rainfall and amount of P (kg/ha) on soil and crop yield

Nearly the same phosphorus levels (between 14 and 25) are needed for six crops when the humidity is below 65. These crops might be planted based just on the quantity of rain predicted over the next few weeks (refer to Figure 9). The availability of crops might be decreased by heavy rainfall that removes vital nutrients from the soil. Pollution of the land and water can be caused by excess nitrogen and phosphorus. Agronomists may assist farmers in modifying fertilizer applications for the best crop development by examining soil samples.

3.6 Correlation of Parameters

Visualization of feature correlations is shown in Figure 10. We can observe the strong correlation between potassium and phosphorus levels. It can be observed that soil pH, organic carbon, and salinity directly affect nutrient availability, rainfall and temperature determine crop selection, balanced fertilization & irrigation are crucial for yield sustainability. By analyzing these correlations, farmers and policymakers can optimize crop selection, nutrient management, and water use for higher productivity in Indian agriculture.

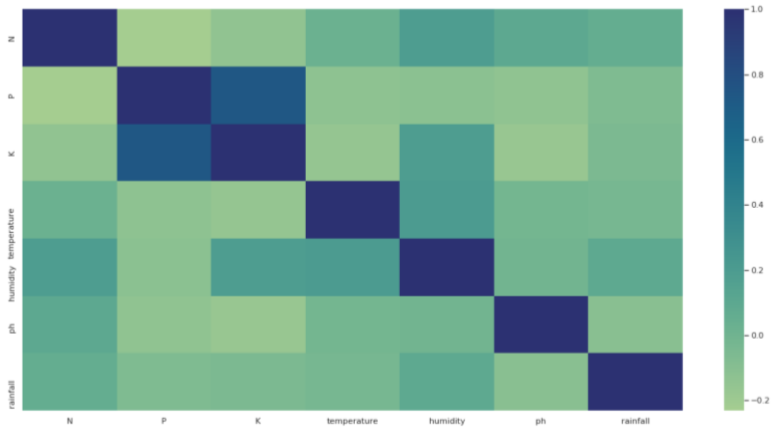

Figure 10. Correlation of different parameters on soil as well as crop classification

3.7 *KNN Classifier for Crop Prediction*

The KNN algorithm has emerged as a practical tool for crop prediction in India, leveraging historical and real-time agricultural data to guide farming decisions. The algorithm identifies patterns by comparing current conditions with historical datasets, classifying crops based on the k most similar cases (neighbors). The KNN approach demonstrates particular promise for smallholder farms, providing low-tech compatible solutions while laying the groundwork for advanced precision agriculture systems. Using the KNN algorithm for crop prediction with a default value of K gives a score of 97.81%. See Figure 11, which illustrates the confusion matrix of the KNN algorithm's output.

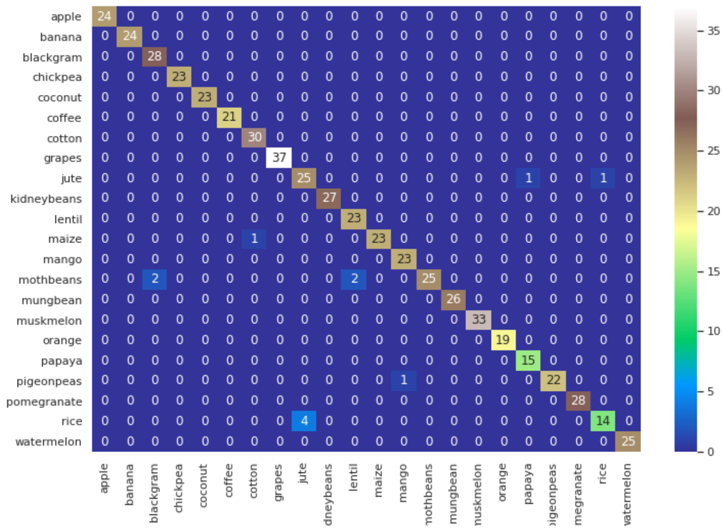

Figure 11: Plot of confusion matrix for KNN algorithm for classification of crop on the crop recommendation dataset.

3.8 *Classification using SVM*

SVM is a powerful supervised machine learning algorithm used for classification and regression tasks. In agriculture, SVM can effectively classify crops based on soil parameters, climatic conditions, and satellite/remote sensing data. Table 1 indicates that it is noteworthy to notice that although fine-tuning the linear kernel adds computation and can sometimes be wasteful, it also still produces good results. The accuracy of the poly kernel can be increased by tuning some parameters, but this could lead to very aggressive overfitting. RBF performs better than the linear kernel in results. Poly kernel has a slight advantage so far.

Table 1. Accuracy of SVC for different Kernels utilized for data analysis

Kernel	***Accuracy (in %)***
Linear	97.45
RBF	98.72
Polynomial	98.90

While using the Grid Search method, the best accuracy score obtained is 98.66% with hyper-arameters C = 1.0 and Gamma = 0.001.

3.9 Classifying using DT

DT algorithms are widely used in India for classifying crops based on various environmental, soil, and climatic factors. Their interpretability and ability to handle both categorical and numerical data make them especially useful in the agricultural context. DTs are being integrated into autonomous crop prediction systems and mobile advisory platforms, making advanced analytics accessible even to smallholder farmers. Decision Tree classifiers have become essential tools for classifying and recommending crops in India, offering transparent, data-driven support for agricultural decision-making and resource optimization. The important characteristics that DTs take into account are shown in Figure 12. The score obtained from the decision tree algorithm is 98.72%.

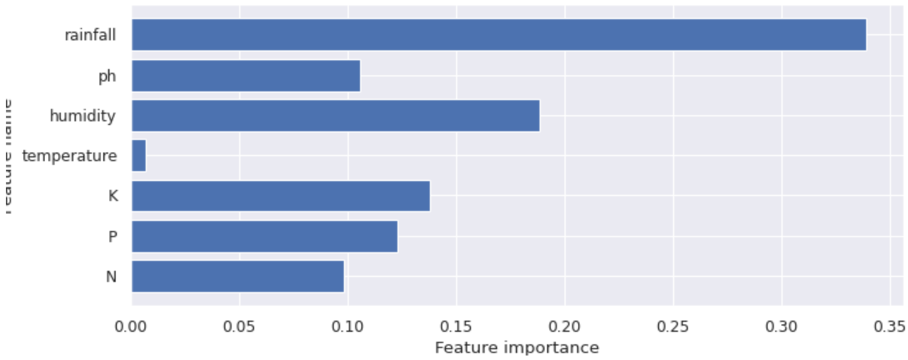

Figure 12. Importance of parameters utilized for DT algorithms

3.10 Classification using RF

RF is a robust and widely adopted machine learning algorithm for classifying Indian crops, supporting both field-level decision-making and large-scale agricultural analysis. RF classifiers are proving highly effective for Indian crop classification, offering accuracy, adaptability, and actionable insights for both farmers and policymakers. Their integration into digital advisory platforms and precision agriculture systems is driving smarter, data-driven agricultural practices across India.The score for RF algorithm while using the crop recommendation dataset obtained are 97% accuracy for Training dataset as well as 97% for Test dataset. Table 2 shows the classification report of RF algorithm for the crop recommendation dataset.

Table 2: Classification report of Random Forest algorithm

Crop	**Precision**	**Recall**	**F1 score**	**Support**
watermelon	1.000	1.000	1.000	25
rice	0.842	0.889	0.865	18
pomegranate	1.000	1.000	1.000	28
pigeonpeas	1.000	1.000	1.000	23
papaya	1.000	1.000	1.000	15
orange	1.000	1.000	1.000	19
muskmelon	1.000	1.000	1.000	33
mungbean	1.000	1.000	1.000	26
mothbeans	1.000	0.655	0.792	29
mango	1.000	1.000	1.000	23
maze	1.000	1.000	1.000	24
lentil	0.920	1.000	0.958	23
kidneybeans	1.000	1.000	1.000	27
jute	0.923	0.889	0.906	27
grapes	1.000	1.000	1.000	37
cotton	1.000	1.000	1.000	30
coffee	1.000	1.000	1.000	23
coconut	1.000	1.000	1.000	23

Crop	Precision	Recall	F1 score	Support
chickpea	1.000	1.000	1.000	23
blackgram	0.778	1.000	0.875	28
banana	1.000	1.000	1.000	24
apple	1.000	1.000	1.000	24

4. CONCLUSION

The use of ML algorithms in Indian agriculture is already proving to enhance decision-making processes, operational productivity, and overall sustainability. As the study has proven, crop and resource allocation forecasting solutions based on ML algorithms can improve the security of food, resource optimization, and the overall sustainability and resilience of the agri-food system. The comparison results of various ML algorithms, including KNN with 0.982 accuracy, SVMs with a polynomial kernel at 0.989, DT at 0.987, and Regression Trees at 0.970, showcase the effectiveness of these approaches for crop yield prediction. These ML methods, as with all other methods tested in this study, improved the accuracy of predictions, emphasizing the importance of these methods for agricultural operations. In summary, the incorporation of machine learning algorithms, including KNN, SVM, DT, and RF into Indian agriculture holds a revolutionary potential to enhance crop yield prediction, facilitate data-driven decision-making, and enhance sustainability, thus opening up the doorway for a resilient, technology-based agricultural ecosystem capable of surviving climatic challenges and addressing the food security needs of an expanding population.

Current yield-prediction models suffer from several intertwined limitations. They rely too narrowly on climatic and remote-sensing data while neglecting crucial socio-economic and management factors. Data inconsistencies arise because yield records seldom align with shifting administrative boundaries, and historical datasets fail to capture recent changes such as emerging pests, rainfall shifts, and new technologies. As a result, models trained in one area often perform poorly elsewhere due to local variations in soil, weather, and farming practices. Efforts to include more variables risk overfitting, producing complex “black box” outputs that offer little practical guidance. Moreover, these models are rarely integrated into operational early-warning or advisory systems, limiting their visibility to farmers. Communication challenges, limited infrastructure, and scalability constraints further hinder real-world impact and the expansion of predictive tools nationwide.

Future research in machine learning–based crop yield prediction should focus on integrating real-time IoT and satellite data for dynamic monitoring of crops, soil, and weather to enable instant decision-making. Localization and customization of models for different agro-climatic zones and crop types are essential to improve accuracy and relevance. User-friendly mobile applications and web platforms can bridge the technological gap for smallholder farmers by offering accessible yield forecasts and recommendations. Efforts must also prioritize cost reduction and accessibility, ensuring that advanced analytics benefit even marginal farmers. Incorporating deep learning and ensemble methods can enhance model precision for complex agricultural challenges such as pest and disease management. Collaboration among policymakers, educational institutions, and the private sector is crucial for building farmer capacity and ensuring sustainable adoption, while continuous assessment of socio-economic and environmental impacts will help balance productivity gains with ecological preservation. As outlined, machine learning has the potential to substantially alter the agricultural landscape in India, fueled by the country's intense research and innovation activities aimed at removing obstacles and creating pathways for sustainable development and food security.

REFERENCES

[1] Daware, T., Ramteke, P., Shaikh, U., & Bharne, S. (2022, January 1). Crop Guidance and Farmer’s Friend – Smart Farming using Machine Learning. EDP Sciences, 44, 03021-03021. https://doi.org/10.1051/itmconf/20224403021
[2] Bhimanpallewar, R., & Rao, M N. (2021, October 13). Precision in Agriculture Decision Making Based on Machine Learning. IntechOpen. https://doi.org/10.5772/intechopen.98787
[3] Gupta, S., Tyagi, N., Jain, M., Singh, S., & Saraswat, K. K. (2023). Role of Computer-Based Intelligence for Prognosticating Social Wellbeing and Identifying Frailty and Drawbacks. In Computational Intelligence in Analytics and Information Systems (pp. 149-159). Apple Academic Press.

[4] Tyagi, N., Gupta, S., Srivastava, A. P., & Awasthi, S. (2018). Analysis and review of extraordinary machine learning approaches. International Journal of Engineering and Technology (UAE), 7(4.39 Special Issue 39), 915-920.

[5] Tyagi, N., Gupta, S., Singh, S., & Saraswat, K. K. (2020). Deep Learning Autoencoder for Single Specimen Face Remembrance. Journal of Computational and Theoretical Nanoscience, 17(9), 3907-3914.

[6] Priya, R., & Ramesh, D. (2020, December 1). ML based sustainable precision agriculture: A future generation perspective. Elsevier BV, 28, 100439-100439. https://doi.org/10.1016/j.suscom.2020.100439

[7] Gaddam, A., Malla, S., Dasari, S., Darapaneni, N., & Shukla, M K. (2022, January 1). Creating an Optimal Portfolio of Crops Using Price Forecasting to Increase ROI for Indian Farmers. Cornell University. https://doi.org/10.48550/arxiv.2211.01951

[8] Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2021, January 1). Machine Learning Applications for Precision Agriculture: A Comprehensive Review. Institute of Electrical and Electronics Engineers, 9, 4843-4873. https://doi.org/10.1109/access.2020.3048415

[9] Van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. Computers and Electronics in Agriculture, 177, 105709.

[10] Elbasi, E., Zaki, C., Topcu, A. E., Abdelbaki, W., Zreikat, A. I., Cina, E., ... & Saker, L. (2023). Crop prediction model using machine learning algorithms. *Applied Sciences*, *13*(16), 9288.

[11] Nigam, A., Garg, S., Agrawal, A., & Agrawal, P. (2019, November). Crop yield prediction using machine learning algorithms. In 2019 Fifth International Conference on Image Information Processing (ICIIP) (pp. 125-130). IEEE.

[12] Rashid, M., Bari, B. S., Yusup, Y., Kamaruddin, M. A., & Khan, N. (2021). A comprehensive review of crop yield prediction using machine learning approaches with special emphasis on palm oil yield prediction. *IEEE access*, *9*, 63406-63439.

[13] Reddy, D. J., & Kumar, M. R. (2021, May). Crop yield prediction using machine learning algorithm. In *2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 1466-1470). IEEE.

[14] Agarwal, S., & Tarar, S. (2021). A hybrid approach for crop yield prediction using machine learning and deep learning algorithms. In *Journal of Physics: Conference Series* (Vol. 1714, No. 1, p. 012012). IOP Publishing.

[15] PS, M. G. (2019). Performance evaluation of best feature subsets for crop yield prediction using machine learning algorithms. *Applied Artificial Intelligence*, *33*(7), 621-642.

[16] Gupta, S., Geetha, A., Sankaran, K. S., Zamani, A. S., Ritonga, M., Raj, R., ... & Mohammed, H. S. (2022). Machine learning-and feature selection-enabled framework for accurate crop yield prediction. *Journal of Food Quality*, *2022*, 1-7.

[17] Ahmed, U., Lin, J. C. W., Srivastava, G., & Djenouri, Y. (2021). A nutrient recommendation system for soil fertilization based on evolutionary computation. *Computers and Electronics in Agriculture*, *189*, 106407.

[18] Mengel, K. (1983). Responses of various crop species and cultivars to fertilizer application. *Plant and soil*, *72*, 305-319.

[19] Hao, T., Zhu, Q., Zeng, M., Shen, J., Shi, X., Liu, X., ... & de Vries, W. (2020). Impacts of nitrogen fertilizer type and application rate on soil acidification rate under a wheat-maize double cropping system. *Journal of environmental management*, *270*, 110888.

[20] Ye, Q., Zhang, H., Wei, H., Zhang, Y., Wang, B., Xia, K., ... & Xu, K. (2007). Effects of nitrogen fertilizer on nitrogen use efficiency and yield of rice under different soil conditions. *Frontiers of Agriculture in China*, *1*, 30-36.

[21] Cao, P., Lu, C., & Yu, Z. (2018). Historical nitrogen fertilizer use in agricultural ecosystems of the contiguous United States during 1850–2015: application rate, timing, and fertilizer types. *Earth System Science Data*, *10*(2), 969-984.

[22] Khan, M. A., Khan, R., & Ansari, M. A. (Eds.). (2022). *Application of Machine Learning in Agriculture*. Academic Press.

[23] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, *18*(8), 2674.

[24] Mishra, S., Mishra, D., & Santra, G. H. (2016). Applications of machine learning techniques in agricultural crop production: a review paper. *Indian Journal of Science and Technology*.

[25] Medar, R., Rajpurohit, V. S., & Shweta, S. (2019, March). Crop yield prediction using machine learning techniques. In *2019 IEEE 5th international conference for convergence in technology (I2CT)* (pp. 1-5). IEEE.

[26] Gunjan, V. K., Kumar, S., Ansari, M. D., & Vijayalata, Y. (2022). Prediction of agriculture yields using machine learning algorithms. In *Proceedings of the 2nd International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications: ICMISC 2021* (pp. 17-26). Springer Singapore.

[27] Crop Recommendation Dataset (available at https://www.kaggle.com/datasets/aksahaha/crop-recommendation)

[28] An, Y., Xu, M., & Chen, S. (2019). Classification method of teaching resources based on improved KNN algorithm. International Journal of Emerging Technologies in Learning (Online), 14(4), 73.

[29] Xu, Y., Zomer, S., & Brereton, R. G. (2006). Support vector machines: a recent method for classification in chemometrics. Critical Reviews in Analytical Chemistry, 36(3-4), 177-188.

[30] Priyam, A., Abhijeeta, G. R., Rathee, A., & Srivastava, S. (2013). Comparative analysis of decision tree classification algorithms. International Journal of current engineering and technology, 3(2), 334-337.

[31] Speiser, J. L., Miller, M. E., Tooze, J., & Ip, E. (2019). A comparison of random forest variable selection methods for classification prediction modeling. Expert systems with applications, 134, 93-101.