Title: "Advances in Crop Recommendation: A Review of Adversarial Networks and Machine Learning Approaches".

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Declaration of Conflict of Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Abstract

Agriculture has a critical role in India's economy, serving as a backbone for the livelihood of up to 60% of the population. It accounts for approximately 17% of India's GDP, emphasizing its critical role in its development. However, suboptimal crop production often results from excessive or insufficient fertilizer use. Precision agriculture gives a result to this experiment by utilizing soil data collected from farms, expert insights, and soil testing lab results. Recommendation systems process these data inputs to provide accurate, site-specific crop suggestions, enhancing productivity and efficiency. To further improve crop yields and optimize inputs, this paper highlights various methods that can aid in developing advanced recommendation systems for smart farming.

Keywords: Crop Recommendation, Crop Yield Production, Machine Learning, Adversarial Network

Introduction

India's physical and cultural diversity is unparalleled, and agriculture remains the nation's backbone. Most families in India depend on agriculture or related professions for their livelihood. [1]. Despite being a leading producer of farmingthings, the country struggles with low farm productivity. Improving productivity ensures farmers earn more from the same land with less labor. Precision agriculture offers a promising solution. Precision farming involves applying the right amount of resources, such as water, fertilizers, and soil amendments, at the optimal time to maximize productivity and yields. However, not all precision agriculture systems deliver reliable results. To address this, extensive research is underway to develop precise and efficient models of crop prediction. [2].Techniques such as machine learning (ML), generative adversarial networks (GANs), artificial intelligence (AI), and neural networks have been widely applied ML methods model crop yield as a complex and nonlinear function of input factors like weather and soil conditions. Notably, studies have shown that Random Forest algorithms outperform traditional regression models in predicting crop production [3] .

Crop Recommendation Techniques

1. Generative Adversarial Network: GANs have gained important prominence in generative modeling due to their ability to create novel content. While some generative models focus solely on data generation, others can simultaneously estimate density functions, making GANs versatile tools for analyzing and synthesizing complex datasets. [4]. These models aim to learn the fundamental parameters of the underlying data distribution. This approach enablestheanalysis of data, abstraction of new insights, and the generation of synthetic data, transforming low-dimensional inputs into high-dimensional outputs. GANs have emerged as a leading class of generative models, leveraging the collaborative optimization of two neural networks with opposing objectives to achieve exceptional performance. A GAN [5] has the generator (G) and the discriminator (D) as two neural networks. The generator will produce artificial data points that are perceptually convincing, transforming random inputs from a low-dimensional source space into a high-dimensional target area. Meanwhile, the discriminator works to differentiate between genuine and synthetic data samples, creating a competitive dynamic that enhances the value of the generated outputs .

2. Machine Learning Techniques: A key advantage of ML techniques is their capacity to autonomously resolve complex problems by utilizing datasets from many potentially organized sources [6]. It offers a robust and adaptable framework that combines data-driven insights with expert knowledge, making it highly versatile across various domains[7]:

2.1 Decision Tree: Their classifiers utilize a grasping approach and fall under supervised learning algorithms. They employ a tree-like structure to represent features and class labels. By deriving decision rules from historical data, the main objective of a decision tree is to develop a model capable of predicting the class or value of target variables.Decision nodes and leaves are its two primary constituents. While leaves represent the final forecasts or results, they represent test conditions based on specific features. Each branch from a decision node represents a possible outcome of the test, directing the path toward the final prediction

2.2 Naive Bayes (NB): Support Vector Machine (SVM) is a supervised learning method used for classification and regression tasks. It represents training data as points within an n-dimensional space, where each feature corresponds to a specific coordinate.Using SVM, data is divided into discrete groups by optimizing the distance between them. The classification process involves identifying the optimal hyperplane that divides the classes with the widest possible gap .

2.3 Support Vector Machine (SVM): This approach is functional to both regression and classification problems. In SVM, training data points are represented in a space that is as far apart from one another as possible.

2.4 Logistic Regression (LR): The widely used numerical technique known as logistic regression models a binary dependent variable in its most simple form using a logistic function. It also comes in more sophisticated versions to deal with various situations.

3. Artificial Neural Networks (ANN)

ANNs are a core concept in ML, modeled after the arrangement and functioning of organic neural networks bythehuman central nervous system. As the brain of human consists of interrelated neurons, an artificial neural network is made up of numerous processing units (or "neurons") that are connected, enabling them to work together to process and learn from data[8].Artificial neurons (processing units) can handle large data, identify patterns, and make logical inferences.Typically, an ANNcomprisesthree layers: the input layer, the hidden layer, and the output layer .

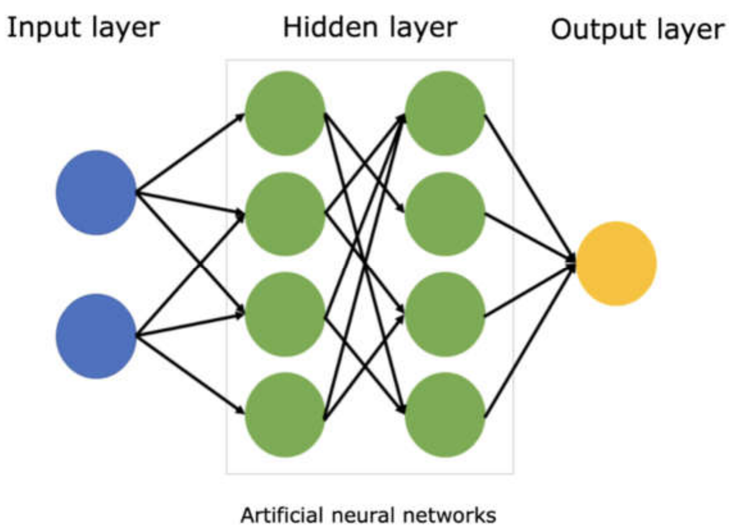

Fig.1. Artificial Neural Networks

3.1 Input Layer: An input will be provided in vector format, with each element representing a specific attribute. Along with the input, the desired output is also given to evaluate the accuracy of the neural network.

3.2 Hidden Layer: The hidden layer contains weights and thresholds that adjust the attributes. Two operations occur in this layer: first, the weights are multiplied by the attributes, and the results are summed. Next, a sigmoid function (explicitly used for binary inputs) is applied to the sum to generate the output.

3.3 Output Layer: In theoutput layer, the actual output is relatedto the desired output to assess the accurateness of the neural network. Feedback is sent to the hidden layer if there is a significant difference. This feedback triggers adjustments to the weights and attributes, refining the model to improve accuracy.

Literature Review

Tai et al. (2023)applied down sampling to transform raw data into additional weather features and then utilized a prediction model to capture more comprehensive weather patterns [9]. Kerdegari et al. (2019) employed semi-supervised GANs for pixel-wise arrangement of multispectral images. This model includes a generator that produces images to augment training data[10].Barth et al. (2017) envisioned that the comparison of synthetic and experiential images improves qualitatively and statistically when applied to the empirical world. They examined the effects of this conversion on morphology, color, and local texture [11]. Gopi and Karthikeyan (2023) used a Hybrid Moth Flame Optimization with Machine Learning (HMFO-ML) model to create a crop recommendation and yield prediction system . This approach effectively provides accurate and timely crop recommendations and yield forecasts [12].

Jadhav and Bhaladhare (2022) developed a smartphone app that connected farmers using GPS technology to assist with user identification and location tracking. Users could input the area and soil type for their farming activities, and ML algorithms helped determine the most cost-effectiveyield options based on the user's specifications[13].Gopi and Karthikeyan (2022) introduced an advancedapproach known as Multimodal Machine Learning-Based Crop Recommendation and Yield Prediction (MMML-CRYP). This approach primarily emphasizes two key procedures: crop recommendation and yield prediction[14].

Table 1: Detailed Summary of various crop recommendation techniques used by researchers

Author Name	**Year**	**Title of Paper**	**Crop Recommendation Technique used**	**Reference**
Tai et al.	2023	"Using Time-Series Generative Adversarial Networks to Synthesize Sensing Data for Pest Incidence Forecasting on Sustainable Agriculture"	time-series generative adversarial network (TimeGAN)	[9]
Kerdegari et al.	2019	"Smart Monitoring of Crops using Generative Adversarial Networks"	semi-supervised generative adversarial networks (GAN)	[10]
Barth et al.	2017	"Optimising Realism of Synthetic Agricultural Images using Cycle Generative Adversarial Networks"	Cycle-GAN	[11]
Gopi and Karthikeyan	2023	"Effectiveness of Crop Recommendation and Yield Prediction using Hybrid Moth Flame Optimization with Machine Learning"	Hybrid Moth Flame Optimization with Machine Learning (HMFO-ML)	[12]
Jadhav and Bhaladhare	2022	"A Machine Learning Based Crop Recommendation System: A Survey"	Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), Multivariate Linear Network (MLN)	[13]
Gopi and Karthikeyan	2022	"Multimodal Machine Learning Based Crop Recommendation and Yield Prediction Model"	Multimodal Machine Learning Based Crop Recommendation and Yield Prediction (MMML-CRYP)	[14]
Patel et al.	2021	"Crop Recommendation System using Machine Learning"	Decision Tree (DT), Support Vector Machine (SVM), Logistic Regression (LR), and Gaussian Naïve Bayes (GNB)	[15]
Pande et al.	2021	"Crop Recommender System Using Machine Learning Approach"	Machine Learning algorithms such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), Multivariate Linear Regression (MLR), and K-Nearest Neighbour (KNN)	[16]

Klompenburga et al.	2020	“Crop yield prediction using machine learning: A systematic literature review”	Deep Learning Algorithms	[17]
Reddy and Kumar	2021	“Crop Yield Prediction using Machine Learning Algorithm”	ML techniques	[18]
Doshi et al.	2018	“AgroConsultant: Intelligent Crop Recommendation System Using Machine Learning Algorithm”	AgroConsultant	[19]
D. N. and Choudhary	2022	“An artificial intelligence solution for crop recommendation”	Deep Neural Network Model	[20]
Sharma and Tripathi	2022	“A systematic review of meta-heuristic algorithms in IoT based application”	Meta-heuristic Algorithms and IoT	[21]
Chauhan et al.	2021	“Metaheuristic approaches to design and address multi-echelon sugarcane closed-loop supply chain network”	H-GASA, a hybrid of Genetic Algorithm with Simulated Annealing, H-KASA, a hybrid of Keshtel Algorithm with Simulated Annealing, and H-RDASA, a hybrid of Red Deer Algorithm	[22]
Gomaa and Abd El-Latif	2023	“Early Prediction of Plant Diseases using CNN and GANs”	Convolutional Neural Network (CNN) model and GAN	[23]
Priyadharshini A et al.	2021	“Intelligent Crop Recommendation System using Machine Learning”	Precision Agriculture	[24]
Sagan et al.	2021	“Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning”	2D and 3D deep residual network architectures	[25]
Patel and Patel et al.	2020	“A state-of-the-art survey on recommendation system and prospective extensions”	Pest Control Techniques	[26]
Bandara et al.	2020	“Crop Recommendation System”	Machine learning techniques such as Naive Bayes (Multinomial) and Support Vector Machine (SVM)	[27]
Saranya and Nagarajan	2020	“Efficient agricultural yield prediction using metaheuristic optimized artificial neural network using Hadoop framework”	Neural Network	[28]

Mishra et al.	2016	"Applications of Machine Learning Techniques in Agricultural Crop Production: A Review Paper"	Machine Learning Techniques	[29]
Bai et al.	2024	"A Conditional Generative Adversarial Networks-Augmented Case-Based Reasoning Framework for Crop Yield Predictions with Time-Series Remote Sensing Data"	Conditional Generative Adversarial Networks-augmented Case-Based Reasoning Framework (CGANa-CBR)	[30]

By forecasting which crops will flourish based on soil nutrients, rainfall, pH, and humidity, "Patel et al. (2021) help farmers select the best crops for particular environments. They used various ML models, such as GNB, LR, DT, and SVM [15]. Pande et al. (2021) suggest a user-friendly crop forecast method for farmers. Through a smartphone application, this solution provides farmers with connectivity. While the user-supplied details about the type of soil and area, the app used GPS to control the user's location. Based on the user's input, machine learning algorithms subsequently forecasted crop yields or suggested the most lucrative crops [16]. Klompenburga et al. (2020) showed a detailedassessment of selected readings, analyzing the features used and offering recommendations for future study [17]. Reddy and Kumar (2021) studied various ML techniques applied to crop production estimation and provided an in-depth analysis of their precision [18].The Agro Consultant is an intelligent system presented by Doshi et al. (2018), which is designed to help farmers in India by considering aspects corresponding to the seeding season, geographical location, soil characteristics, rainfall, and temperature[19].

To help farmers, D. N. and Choudhary (2022) suggested combining deep learning and IoT. The model considers several soil factors for soil fertility evaluation, like pH, moisture content, nitrogen, phosphorus, and potassium.They used a deep neural network model to predict the finest crop for the specified soil conditions [20].Anorganized assessment of meta-heuristic algorithms used in the creation of Internet of Things applications was provided by Sharma and Tripathi (2022). [21]. To tackle complex problems, Chauhan et al. (2021) presented three hybrid metaheuristic algorithms: H-GASA, H-KASA,and H-RDASA, which combines the Red Deer Algorithm and Simulated Annealing. According to the study, H-RDASA performs better in medium &large-sized situations, whereas H-KASA isnoticeably good for small-sized situations[22] .

Gomaa and Abd El-Latif (2021) employed a deep-learning model using real-time images to detect plant infections before severe disease symptoms appeared. The model was applied at various life stages of tomato plants infected with Tomato Mosaic Virus (TMV) [23]. Priyadharshini A et al. (2021) put up a plan to assist farmers in crop selection by considering variables, including the time of year for planting, the type of soil, and the location. Furthermore, by utilizing contemporary agricultural technologies, the system incorporates precision agriculture. [24]. Sagan et al. (2021) investigated the function of in-season multitemporal images in grain yield forecasting and created deep learning via theraw imagery method for field-scale yield prediction. [25].Patel and Patel et al. (2020) reviewed various types of recommendation systems and their application areas [26]. An integrative model uses Arduino microcontrollers to gather environmental data. Bandara et al. (2020) have reported that the system is accurate and efficient in recommending crops for specific lands by using ML techniques [27] .

To optimize weights and enhance performance, Saranya and Nagarajan (2020) used a neural network for prediction and suggested alearning technique on population-based incremental [28].Research on the applicability of ML techniques in agricultural crop production was reviewed by Mishra et al. (2016) [29]. Bai et al. (2024) utilized the CGANa-CBR model to generate remote-sensing images of farmland, which were then used to supplement real images missing harvest period data, facilitating data augmentation [30].

Conclusion

After reviewing numerous studies, we conclude that further study is needed in farming to advancethe accuracy of crop recommendations & yield predictions. Generative Adversarial Networks (GANs) hold significant potential in generative modeling and its applications across various domains. This review highlights applications that can enhance crop recommendation systems. We have explored different crop recommendation methods, and it is clear that ML techniques have made rapid advancements over the past era. Those advancements are expected to continue, offering more lucrative and completedatasets alongside increasingly refined algorithms to improve crop and environmental state estimation and decision-making.

References

[1]Dighe, D., Joshi, H., Katkar, A., Patil, S., & Kokate, S. (2018). Survey of crop recommendation systems. *IRJET*, *5*, 476-481.

[2] Rajak, R. K., Pawar, A., Pendke, M., Shinde, P., Rathod, S., & Devare, A. (2017). Crop recommendation system to maximize crop yield using machine learning technique. *International Research Journal of Engineering and Technology*, *4*(12), 950-953.

[3] Jyothika, P., Ramana, K. V., & Narayana, C. L. (2021). Crop Recommendation System To Maximize Crop Yield Using Deep Neural Network. *Journal of Engineering Sciences*, *12*(11).

[4] Rizvi, S. K. J., Azad, M. A., & Fraz, M. M. (2021). Spectrum of advancements and developments in multidisciplinary domains for generative adversarial networks (GANs). *Archives of Computational Methods in Engineering*, *28*(7), 4503-4521.

[5] Förster, A., Behley, J., Behmann, J., & Roscher, R. (2019, July). Hyperspectral plant disease forecasting using generative adversarial networks. In *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium* (pp. 1793-1796). IEEE.

[6] Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and electronics in agriculture*, *151*, 61-69.

[7] Gosai, D., Raval, C., Nayak, R., Jayswal, H., & Patel, A. (2021). Crop recommendation system using machine learning. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *7*(3), 558-569.

[8] Banavlikar, T., Mahir, A., Budukh, M., & Dhodapkar, S. (2018). Crop recommendation system using Neural Networks. *International Research Journal of Engineering and Technology (IRJET)*, *5*(5), 1475-1480.

[9] Tai, C. Y., Wang, W. J., & Huang, Y. M. (2023). Using time-series generative adversarial networks to synthesize sensing data for pest incidence forecasting on sustainable agriculture. *Sustainability*, *15*(10), 7834.

[10] Kerdegari, H., Razaak, M., Argyriou, V., & Remagnino, P. (2019). Smart monitoring of crops using generative adversarial networks. In *Computer Analysis of Images and Patterns: 18th International Conference, CAIP 2019, Salerno, Italy, September 3–5, 2019, Proceedings, Part I 18* (pp. 554-563). Springer International Publishing.

[11] Barth, R., IJsselmuiden, J. M. M., Hemming, J., & van Henten, E. J. (2017). Optimising realism of synthetic agricultural images using cycle generative adversarial networks. In *Proceedings of the IEEE IROS workshop on Agricultural Robotics* (pp. 18-22).

[12] Gopi, S. R., & Karthikeyan, M. (2023). Effectiveness of Crop Recommendation and Yield Prediction using Hybrid Moth Flame Optimization with Machine Learning. *Engineering, Technology & Applied Science Research*, *13*(4), 11360-11365.

[13] Jadhav, R., & Bhaladhare, P. (2022). A machine learning based crop recommendation system: a survey. *Journal of Algebraic Statistics*, *13*(1), 426-430.

[14] Gopi, P. S. S., & Karthikeyan, M. (2023). Multimodal machine learning based crop recommendation and yield prediction model. *Intell Autom Soft Comput*, *36*(1), 313-326.

[15] Patel, M., Anurag. R., & Rane, A. (2023). Crop Recommendation System using Machine Learning.

[16] Pande, S. M., Ramesh, P. K., Anmol, A., Aishwarya, B. R., Rohilla, K., & SHAURYA, K. (2021, April). Crop recommender system using machine learning approach. In *2021 5th international conference on computing methodologies and communication (ICCMC)* (pp. 1066-1071). IEEE.

[17] 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.

[18] 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.

[19] Doshi, Z., Nadkarni, S., Agrawal, R., & Shah, N. (2018, August). AgroConsultant: intelligent crop recommendation system using machine learning algorithms. In *2018 fourth international conference on computing communication control and automation (ICCUBEA)* (pp. 1-6). IEEE.

[20] Varshitha, D. N., & Choudhary, S. (2022). An artificial intelligence solution for crop recommendation. *Indonesian Journal of Electrical Engineering and Computer Science*, *25*(3), 1688-1695.

[21] Sharma, V., & Tripathi, A. K. (2022). A systematic review of meta-heuristic algorithms in IoT based application. *Array*, *14*, 100164.

[22] Chouhan, V. K., Khan, S. H., & Hajiaghaei-Keshteli, M. (2021). Metaheuristic approaches to design and address multi-echelon sugarcane closed-loop supply chain network. *Soft Computing*, *25*(16), 11377-11404.

[23] Gomaa, A. A., & Abd El-Latif, Y. M. (2021). Early prediction of plant diseases using CNN and GANs. *International Journal of Advanced Computer Science and Applications*, *12*(5).

[24] Priyadharshini, A., Chakraborty, S., Kumar, A., & Pooniwala, O. R. (2021, April). Intelligent crop recommendation system using machine learning. In *2021 5th international conference on computing methodologies and communication (ICCMC)* (pp. 843-848). IEEE.

[25] Sagan, V., Maimaitijiang, M., Bhadra, S., Maimaitiyiming, M., Brown, D. R., Sidike, P., & Fritschi, F. B. (2021). Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning. *ISPRS journal of photogrammetry and remote sensing*, *174*, 265-281.

[26] Patel, K., & Patel, H. B. (2020). A state-of-the-art survey on recommendation system and prospective extensions. *Computers and Electronics in Agriculture*, *178*, 105779.

[27] Bandara, P., Weerasooriya, T., Ruchirawya, T., Nanayakkara, W., Dimantha, M., & Pabasara, M. (2020). Crop recommendation system. *International Journal of Computer Applications*, *975*, 8887.

[28] Saranya, C. P., & Nagarajan, N. (2020). Efficient agricultural yield prediction using metaheuristic optimized artificial neural network using Hadoop framework. *Soft Computing-A Fusion of Foundations, Methodologies & Applications*, *24*(16).

[29] Mishra, S., Mishra, D., & Santra, G. H. (2016). Applications of machine learning techniques in agricultural crop production: a review paper. *Indian J. Sci. Technol*, *9*(38), 1-14.

[30] Bai, Y., Chen, D., & Zhang, Z. (2024). A Conditional Generative Adversarial Networks-Augmented Case-Based Reasoning Framework for Crop Yield Predictions with Time-Series Remote Sensing Data.