A Comprehensive Review on Data-Driven Approaches in Agriculture: Crop Selection, Fertilizer Optimization, and Disease Detection

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Abstract— **It is noticed that crop selection, optimization of fertilizers, and detection of diseases in plants have become critical problems to be addressed by data-centric methodologies and have emerged to revolutionize agriculture. The review article will discuss the latest developments in the above areas of concern, critically evaluating techniques and models used to improve precision agriculture through the application of machine learning and other related methods.**

Crop recommendation systems are essential for addressing environmental variability and enabling informed crop selection. A study [1] utilized methods such as Naïve Bayes, SVM, and K-Means Clustering with NLP in providing recommendations for the crops that will significantly be affected by the aftermaths of temperature, soil conditions, and water availability. Another analysis [20] of soil nutrients (NPK) and environmental parameters like rainfall, humidity, temperature is giving personalized crop suggestions. All of these enhance the decision-making and optimize the usage of resources towards sustainable farming.

Fertilizer recommendation systems are one of the essential systems for effective soil nutrient management and improved agricultural productivity. A research [6] uses NPK sensors and machine learning algorithms for cost-effective fertilizer recommendations, including soil analysis as well as data preprocessing. Another research [21] deals with nutrient prediction for crops like groundnuts using an advanced 1D-CNN model to classify macronutrient levels like (N, P, K) as low, medium, or high. This model has an accuracy of 99.78% and surpasses traditional methods such as SVM and Naïve Bayes. These advancements point to the role of machine learning in sustainable nutrient management.

Plant disease detection is a key to reducing crop losses and maintaining economic sustainability. Traditional methods are time-consuming and hence not suitable for large-scale application. One study [22] emphasizes machine learning and deep learning techniques with image processing methods such as segmentation and feature extraction for reliable disease diagnosis. Another study [23] uses a K-Nearest Neighbor (KNN)-based model with image preprocessing, feature extraction, and classification to identify leaf diseases efficiently. These developments show how machine learning has been used to improve the accuracy and scalability of plant disease detection systems.

Machine learning in crop recommendation systems optimizes resource use and promotes sustainability. Fertilizer recommendation systems with 1D-CNN models enhance nutrient management for balanced soil fertility. Image processing in plant disease detection improves diagnosis accuracy, reducing crop losses. These advancements boost sustainability and economic outcomes.

In conclusion, this review highlights data-driven approaches in precision agriculture for crop selection, fertilizer optimization, and disease detection. These technologies promise to increase food security and sustainability while facing environmental and economic challenges.

Keywords: Crop recommendation, fertilizer optimization, plant disease detection, machine learning, data-driven approaches, Naïve Bayes, Support Vector Machines (SVM), K-Means Clustering, Natural Language Processing (NLP), NPK sensors, 1D-CNN, image processing, segmentation, feature extraction, K-Nearest Neighbor (KNN)

INTRODUCTION

Data-driven technologies transform the agriculture industry since agriculture is very important for food security and economic stability globally. Precision agriculture is an integration of advanced computational techniques and machine learning in the multifaceted challenge of modern farming, including crop selection optimization, efficiency in fertilizer use, and improvement in plant disease management. It thus improves productivity by using data analytics and promoting sustainable practices that apply to varying environmental conditions.

Crop recommender systems have emerged as integral parts of informed decision support for agriculturalists. Crop recommender systems interpret important characteristics of soil, climate variables, and nutrient availability that support the optimal choice of crops. Bandara et al. [1] has shown how ML algorithms, such as Naïve Bayes, SVM and K-Means Clustering, integrated with NLP can be used to make crop suggestions using data about the environment, soil conditions, temperature, etc. Sharma et al. [2] described the use of classifiers like XGBoost, which has been proved to classify crops based on soil and weather patterns by having improved accuracy in crop predictions. These studies focus on the use of ML to enhance resource efficiency and sustainability in farming.

Fertilizer recommendation systems are an important part of precision agriculture, emphasizing improved agricultural productivity by optimal management of soil nutrients. However, the traditional ways of processing soil nutrients are laborious and expensive, which limits their adoption, especially in poor resource sites. Subramanian [3] developed an FRT system, which includes IoT-based NPK sensors and machine learning-based algorithms for the analysis of soil data and thus provides optimal fertilizer prescriptions, which reduce cost and improve efficiency. Sharma et al. [4] further designed a better 1D-CNN model to classify the nutrient; at the same time, this model achieved an accuracy of 99.78%, which is above conventional approaches like SVM and Naïve Bayes. This progress demonstrates that fertilizer application and balanced soil fertility can be significantly improved by machine learning.

The identification of plant diseases, essential for reducing agricultural losses and ensuring economic sustainability, has also undergone significant transformation through the incorporation of image processing and machine learning methodologies. Conventional approaches to disease diagnosis, which frequently depend on manual examination, tend to be labor-intensive and unsuitable for extensive applications. Current research has illustrated the effectiveness of image-centric methods in facilitating the automation of disease detection. For example, Abbas et al. [5] utilized drone-enabled remote sensing technologies and machine learning algorithms to classify crop diseases accurately. Bharathi Raja and Rajendran [6] proposed a fine-tuned ensemble deep transfer network for the classification of banana plant diseases, thus demonstrating higher predictive accuracy and proving the applicability of such technologies in diverse agricultural environments.

This review article is an extensive look at data-oriented strategies within the agricultural sector, focusing on advancements in crop recommendation, fertilizer optimization, and the detection of plant diseases. It is through such assessments of methodologies, challenges, and real-world applications that the research emphasizes the role of machine learning in furthering sustainable agriculture. These technologies need to be integrated into platforms that are user-friendly and economically feasible to bridge the gap between research and practical application, particularly for smallholder farmers. Ultimately, these innovations are likely to contribute to enhanced food security, environmental sustainability, and economic resilience of agricultural communities.

LITERATURE REVIEW

In recent years, the integration of data-driven approaches using machine learning, artificial intelligence, and advanced computational techniques has brought about a paradigm shift in the agriculture sector. Precision agriculture has been coined as one of the leading transformative domains to help address important questions related to crop selection, fertilizer optimization, and plant disease detection. These advancements have improved the productivity of the lands, reduced the impact on the environment, and therefore promoted sustainable agriculture practices by optimizing the usage of resources.

This review emphasizes the recent research contributions that have shaped precision agriculture. Crop recommendation systems are presented in many studies in which ML algorithms such as Naïve Bayes, Support Vector Machines (SVM), K-Means Clustering, and XGBoost analyze critical environmental parameters to recommend suitable crops [1][2]. The system combines varied data types, such as soil type, weather conditions, and nutrient availability, in order to provide site-specific recommendations to farmers, enhancing decision-making.

Similarly, fertilizer recommendation systems have been advanced through the adoption of IoT-based sensors and ML techniques, enabling real-time soil nutrient analysis and cost-effective solutions. Subramanian [3] proposed a system using NPK sensors and ML models to give precise fertilizer recommendations, addressing some of the drawbacks of traditional soil testing. Sharma et al. [4] introduced an enhanced 1D-CNN model for the classification of nutrient levels with exceptional accuracy, which shows tremendous progress in fertilizer optimization technologies.

Another important application area is plant disease detection for precision agriculture, which has also received tremendous support from ML-driven improvements in image processing. In this regard, deep learning and drone-assisted remote sensing have revolutionized the early detection of plant diseases, enabling timely intervention. Abbas et al. [5] used drones integrated with image processing and ML algorithms for monitoring and diagnosis of plant diseases efficiently. In addition, Bharathi Raja and Rajendran [6] developed an optimal ensemble deep transfer network to classify banana plant diseases with a very high degree of accuracy. The innovations have led to considerable reduction in crop losses and enhanced scalability of plant health monitoring systems.

The following table summarizes the key research works, technologies used, and the unique contribution of each study. This comparative analysis provides a structured understanding of the advancement in precision agriculture and highlights potential avenues for future research.

TABULAR DESCRIPTION OF TECHNOLOGY USED AND THEIR ACCURACY

Technology Used	Accuracy
Decision Tree	85.91%
Naive Bayes Classifier	99.55%
Random Forest	99.31%

K- Nearest Neighbour	98.86%
Support Vector Machine	99.31%
XG Boost	99.51%
Logistic Regression	98.63%
Deep Learning Model	94.50%
Plant Disease Detection (CNN)	97.90%

COMPARISON TABLE BASED ON SURVEYS

S. NO	Authors	Methodology	**Technology Used**	**Key Features**
1.	Pradeepa Bandara et al.	Crop Recommendation using Naïve Bayes, SVM, K-Meansand NLP	Naïve Bayes, SVM, K-Mean Clustering, NLP	Analyzes environmental factors (temperature, soil conditions, water) for crop suggestions. Improves resource optimization and decision-making.
2.	Mahesh V. Korde et al.	Personalized Crop Suggestion based on Soil Nutrients and Environmental Data	Machine Learning, Data Analytics	Utilizes soil nutrients (NPK), rainfall, temperature for recommending crops. Improves resource utilization and sustainability.
3.	Kanaga Suba Raja Subramanian	Fertilizer Recommendation with NPK Sensors and ML Algorithms	NPK Sensors, Machine Learning	Uses soil analysis and data preprocessing for cost-effective fertilizer recommendation. Enhances soil fertility and sustainability.
4.	Sivasankaran S et al.	Fertilizer Optimization with 1D-CNN for Nutrient Classification	1D Convolutional Neural Network (1D-CNN)	Classifies macronutrient levels (N, P, K) as low, medium, or high with high accuracy (99.78%).
5.	S. Suganya et al.	Plant Disease Detection with Image Processing and Classification Techniques	Image Processing, Deep Learning (CNN, KNN)	Identifies plant diseases through image preprocessing, feature extraction, and classification. Reduces crop losses and improves economic outcomes.
6.	Gurunathan V et al.	Disease Diagnosis with KNN-based Model and Feature Extraction	K-Nearest Neighbor (KNN), Image Processing	Uses image preprocessing and feature extraction for efficient leaf disease detection. Increases diagnosis accuracy and scalability.
7	Bandara et al. [1]	Crop Recommendation System using NLP	Naïve Bayes, SVM, K-Means, NLP	Site-specific crop recommendation based on soil and environmental parameters.
8	Bharathi Raja & Rajendran [6]	Efficient Banana Plant Disease Classification	Ensemble Deep Transfer Network	High prediction accuracy and scalability for banana plant disease classification.
9	Abbas et al. [5]	Drones in Plant Disease Assessment	Drone Remote Sensing, ML	Early and efficient plant disease detection over large areas using drones.

RESEARCH GAPS

While there have been some significant developments in crop recommendation, fertilizer optimization, and plant disease detection, many research gaps still exist. Filling these gaps is very important for increasing the scalability, applicability, and sustainability of precision agriculture technologies.

1. **Lack of Integrated Platforms for Unified Solutions** While considerable strides have been made in developing the individual systems of crop recommendation, fertilizer optimization, and plant disease detection, the lack of integrated platforms is still a big limitation. All-inclusive systems that could merge these functionalities would offer farmers a holistic solution to deal with multiple agricultural challenges. For instance, crop selection recommendation combined with real-time nutrient management and disease detection could lead to better decision-making and reduced operational complexity.

2. **Scalability and Adaptability to Diverse Conditions** Many of the current systems are crop-, dataset-, or region-specific, hence their generality is restricted. For example, Subramanian's fertilizer recommendation system ([3]) and Sharma et al.'s crop-specific nutrient analysis ([4]) are confined to specific crops and geographical contexts. Similarly, the disease detection models, like the drone-based ones in Abbas et al. ([5]), perform exemplarily under localized conditions but lack the ability to scale up globally. Future research ought to focus on developing adaptable models that can accommodate diverse datasets and real-time inputs to accommodate regional variability of soil, climate, and crop conditions ([8], [9]).

3. **Limited Real-Time Implementation**

   Real-time data integration remains a challenge in precision agriculture systems. Most of the current models are based on static datasets or pre-processed data. For example, while Abbas et al. [5] used drones in disease detection, the offline image analysis restricts real-time interventions. Similarly, Kushwaha and Bhattacharya [14] proposed the Agro algorithm for crop yield prediction using big data, but its implementation in real-time farming scenarios remains unexplored. It is important to develop systems that can ingest and process real-time streams of data from IoT sensors, drones, and satellite imagery for immediate and actionable insights.

4. **Data Quality, Accessibility and Regional Representation** Effectiveness in machine learning systems is strongly dependent on data availability and quality. Works such as Sharma et al. [2] and Ramesh & Vardhan [7] make use of soil and weather datasets but often lack representation of underrepresented crops or regions. Additionally, new tools, such as the lightweight CNN model in Akbar et al. [17], are very accurate in identifying diseases of the peach leaf but suffer from overfitting due to the specificity of their datasets. There needs to be an emphasis on creating large, diverse datasets that include several varieties of crops, soil types, and climatic conditions for inclusivity.

5. **Accessible to Small-Scale Farmers** Although these advanced models—like the ensemble deep transfer network [6] and IoT-based nutrient optimization [3]—hold great accuracy, their usability remains out of reach for small-scale farmers due to constraints in resources and costs. Likewise, the drone-based systems of Abbas et al. [5] can demand large capital investments, potentially limiting their uptake by smallholders. Future work ought to center on affordable hardware and software solutions with friendly interfaces so that precision agriculture becomes democratized.

6. **Sustainability and Environmental Impact** Few indeed discuss the ecological consequences of such technologies. For example, though Subramanian ([3]) and Sharma et al. ([4]) put forth optimized fertilizer application, no long-term possibilities of soil degradation or water pollution due to its incorrect implementation are considered. Likewise, while Bharathi Raja and Rajendran ([6]) concentrate on disease diagnosis, they do not measure the ecological impact of excessive pesticide use arising from wrongly diagnosed conditions. Sustainability metrics, including carbon footprint reduction and resource conservation, need to be included in the analysis so that such technologies will help advocate good environmental stewardship of farms.

7. **Validation and Benchmarking in Real-World Scenarios** While many of the proposed models show high accuracy in controlled environments, most of them still lack validation in real-world agricultural settings. For instance, promising results are shown in lab conditions for the enhanced 1D-CNN model [4] and the LWNet CNN model [17], but these need extensive field testing to establish their robustness and reliability. Moreover, standardized benchmarking frameworks will be required to compare models on similar datasets and conditions in order to point out the best solution.

By addressing these gaps, precision agriculture technologies can become more inclusive, scalable, and environmentally sustainable, contributing to global food security and economic resilience.

PROPOSED METHODOLOGY

Although much advancement has been made with regard to systems in crop recommendation, fertilizer optimization, and plant disease detection, more work is required for designing integrated, scalable agricultural solutions. This chapter distills the methods from current works on the considered domains of high technological value to develop an overall system toward holistic precision agriculture.

Crop recommendation systems have been developed to provide site-specific and personalized suggestions based on environmental and soil parameters. For instance, Bukhari et al. [7] presented a machine learning-based computational method using Decision Trees (DT) and ensemble techniques such as Bagging DT for recommending suitable crops. The study utilized features such as rainfall, temperature, and soil composition to achieve high classification accuracy, thus showing the potential of ensemble learning for crop selection.

Another innovative approach by Kushwaha and Bhattacharya [14] utilized big data processing on the Hadoop platform to analyze weather data and soil types for crop prediction. Their "Agro Algorithm" established suitability predictions for different crops, focusing on scalability and handling large datasets effectively. These methodologies emphasize the role of robust computational frameworks in improving crop selection.

Optimization of soil fertility with data-driven approaches is one of the essential methods for making farming highly sustainable. Subramanian et al. [9] came up with a fertilizer recommendation system, which included PCA for feature extraction and regression models for nutrient analysis. The described system ensures meaningful recommendations of required nutrients in the soil through minimum resource wastage.

Similarly, Palaniraj et al. [11] suggested a hybrid model which combined the analysis of soil nutrient with weather APIs for fertilizer optimization. Using the data for the deficiency of macronutrients (N, P, K) and climatic conditions, the model recommended improvements in the health of soil and crop yield. These studies establish the joint use of environmental and nutrient data as essential for effective fertilizer management.

Tremendous strides have been taken in the field of plant disease detection through image-based machine learning techniques. Dolatabadian et al. [15] have presented a review on the application of high-resolution imaging technology combined with advanced ML algorithms such as CNN to identify minute visible signs of crop diseases. The integration of multispectral imaging with AI-based analytics significantly accelerated the rate of diagnosis with increased accuracy.

Besides, Abbas et al. [16] have applied drones that integrate intelligent sensors for monitoring plant health. Some of the features like edge detection and histogram equalization have been included in ML models to classify the diseases of the plants at an initial stage. This drone-assisted remote sensing approach has shown its scalability towards large fields so that timely interventions in agricultural sectors are facilitated.

INTEGRATED SYSTEM

Although various improvements are visible on individual systems, no coupled integrated platform of crop recommendation and fertilizer optimization along with disease detection exists. A major portion of the existing systems works separately and fails to provide any overall agricultural solutions in an integrated platform:

- Crop recommendation models [7][14] were primarily based on environmental and soil characteristics but did not account for nutrient optimization or disease.
- Fertilizer recommendation frameworks [9][11] optimize soil nutrient management but lack inputs from disease detection systems.
- Drought detection systems are image-based, and soil and climatic data are not involved in a more holistic decision-making process [15][16].

Future research will be on interoperability among these systems. For instance, integrating drone-based disease detection [16] with real-time soil nutrient analysis [9] and big data-powered crop prediction [14] will create unified platforms that can address multiple challenges at once. These systems will equip farmers with actionable insights at every stage of agricultural decision-making and foster sustainable and productive farming practices.

DATABASE USED

Out[5]:

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice
5	69	37	42	23.058049	83.370118	7.073454	251.055000	rice
6	69	55	38	22.708838	82.639414	5.700806	271.324860	rice
7	94	53	40	20.277744	82.894086	5.718627	241.974195	rice
8	89	54	38	24.515881	83.535216	6.685346	230.446236	rice
9	68	58	38	23.223974	83.033227	6.336254	221.209196	rice

Figure 1. Sample Dataset for Crop Recommendation

Figure 2. Classification of Crop Disease Dataset

Figure 3. Object Detection of Crop Disease

Good quality, diverse, and well-curated datasets in crop recommendation and fertilizer optimization systems ensure effective crop disease detection. They allow machine learning and deep learning models to extract patterns and produce correct predictions toward making an effective recommendation to the farmer. The details of the dataset applied in the crop recommendation and disease detection system in the reviewed studies above follow.

For the recommendation of crops, datasets on the parameters of soil, climatic conditions, and information regarding crop productivity are required. Bukhari et al. [7] utilized the dataset consisting of soil nutrients, including Nitrogen, Phosphorus, and Potassium, pH levels, and environmental factors such as rainfall, temperature, and humidity. Crop productivity data for rice, maize, and wheat were also considered in the dataset so that the analysis is holistic and site-specific crop recommendations are feasible.

Sharma et al. [2] have applied a dataset that focuses on soil types, different geographical regions and climatic variability along with advanced classifiers such as XGBoost to improve the accuracy of crop recommendations for various types of crops. These datasets highlight the importance of including diverse parameters to account for regional variability in soil and environmental conditions and guarantee reproducibility, reliability, robustness, and scalability of the results.

Modern plant disease detection systems use image datasets to provide examples of the healthy and diseased plants. Abbas et al. [16] have made use of the drone-captured datasets that contain high-resolution images of different crops. The datasets were annotated with the disease symptoms such as discoloration, lesions, and wilting found on the leaves. Remote sensing combined with machine learning models allowed large-scale monitoring of diseases and early detection.

In a similar manner, Dolatabadian et al. [15] used the dataset of images of diseased plants where detailed classes of diseases such as rust, blight, or mildew have been used during the annotation process. The developed dataset was also useful in constructing CNN models with high accuracy to identify subtle visual cues of infection by the pathogen.

Akbar et al. [17] have specifically designed a dataset of more than 10,000 images related to peach leaf diseases along with their respective labels marked as healthy or infected due to bacteriosis. The preprocessing steps involved removal of noise, enhancement, and augmentation of the images. Such a dataset would strongly advocate the use of disease-specific classification problems with targeted datasets.

While much individual progress has been made in crop recommendation and disease detection datasets, their integration into one framework remains glaringly lacking. The current datasets specialize on either the soil and environmental data for crop recommendation ([7], [14]) or on image-based data for disease detection ([15], [16], [17]). Much work needs to be invested in building extensive datasets that encompass both of these domains in order to build systems that will make more integrated recommendations regarding healthiness of soils and the incidence of diseases.

Modern precision agriculture systems, with such diverse datasets, are well set to tackle key challenges in crop selection and disease management to achieve scalable and actionable solutions that promote productivity and sustainability.

CONCLUSION

Agriculture remains the backbone of food security and stability worldwide, hence its challenges in terms of resource optimization, climate variability, and sustainability practices adoption need innovative solutions. This review highlights the transformative role of data-driven approaches in three critical domains: crop recommendation, fertilizer optimization, and plant disease detection in precision agriculture.

The performance of crop recommendation systems is demonstrated through machine learning techniques, including Decision Trees (DT), XGBoost, and clustering algorithms, in the analysis of environmental conditions, soil characteristics, and nutrient profiles for specific crop recommendations [7] [14]. Similarly, fertilizer optimization has been taken to new heights using IoT-based NPK sensors coupled with advanced models like enhanced 1D-CNN, enabling precise nutrient management and better yields while protecting soil health [3] [4] [9]. Plant disease detection has seen significant improvement through deep learning methodologies, including CNNs and drone-assisted image processing systems, to enable accurate large-scale disease identification for early interventions [15] [16] [17].

While some progress has been achieved in each of these areas, the existing systems usually work in isolation and are limited to particular aspects of agricultural management. Therefore, their overall impact is limited, and the potential for integrated insights that can be leveraged by farmers remains unfulfilled. For example, crop recommendation systems do not consider real-time disease monitoring, while fertilizer optimization models rarely take into account dynamic environmental factors or disease outbreaks. Another major limitation comes from the poor quality and limited availability of datasets, mainly for underrepresented regions and crop types. The cost and accessibility of these technologies further limit adoption by small-scale farmers in resource-constrained settings [11], [17].

Such development should focus on integrated platforms where crop recommendation, fertilizer optimization, and plant disease detection are well-coordinated in one framework. Systems like this would take advantage of real-time data streams from IoT devices, drones, and satellite imagery integrated with advanced analytics and user-friendly interfaces that make the information actionable. Further, attempts at democratizing such technologies, through low-cost hardware, open-access datasets, and community-driven models, will go a long way in ensuring these solutions are within the reach of smallholder farmers.

Overcoming these barriers, integrated data-driven agricultural systems have the potential to revolutionize farming practices to achieve sustainability, resource efficiency, and economic resilience. These holistic solutions will give farmers the tools to make educated decisions, guiding them toward reducing environmental impact while improving productivity in an ever-changing agricultural ecosystem. This comprehensive approach is perhaps one of the most important steps toward ensuring food security around the globe and fostering sustainable development in the agricultural sector.

FUTURE SCOPE

Future prospects for data-driven agriculture include an integrated platform of crop recommendation, fertilizer optimization, and plant disease detection. The integrated system would have real-time data from IoT devices, drones, and satellite imagery. Such adaptive and context-aware decision-making will have potential in various agricultural areas. For instance, a combined soil nutrient analysis [9], disease monitoring [16], and weather-based forecasting [15] will bring comprehensive solutions for precision farming.

Scalability and affordability will be the key factors to make it adoptable, especially among small-scale farmers. Low-cost IoT sensors [3], lightweight ML models like LWNet [17], and streamlined mobile interfaces will help close the gap between the high-end technology and the reality of using it. Community-driven data platforms will also bring such technologies within easy reach.

Sustainability must also be a core focus, with systems evaluating the environmental impacts of fertilizer and pesticide use to minimize soil degradation and water pollution. AI-driven tools integrated with high-resolution satellite imagery [16] and drone-based systems [15] can further enhance resource efficiency and productivity.

These advancements promise to revolutionize precision agriculture, enabling farmers to make informed decisions, reduce resource wastage, and ensure food security amidst global challenges like climate change and population growth.

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