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Research Article

The Application of Machine Learning Techniques for Corn Yield Prediction and Management: A Systematic Literature Review

Lee Carlo F. Simon [1*], Thelma D. Palaoag [2]
[1] *University of the Cordilleras, College of Information Technology and Computer Science, Baguio City, Philippines.*
Email: lcsimon@mmsu.edu.ph
[2] *University of the Cordilleras, College of Information Technology and Computer Science, Baguio City, Philippines.*
Email: tdpalaoag@uc-bcf.edu.ph
**Corresponding Author: Lee Carlo F. Simon*

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ABSTRACT

This systematic literature review examines the application of machine learning techniques for corn yield prediction and management. Fifty primary studies published between 2015 and 2024 were analyzed to synthesize the current state of research in this domain. The review focuses on the machine learning algorithms, input features and data sources leveraged, prediction accuracy achieved, and key challenges identified. The findings indicate that ensemble methods like Random Forest and XGBoost and deep learning approaches like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are the most commonly used and practical algorithms. The most critical input features are remote sensing data, weather variables, and soil properties. While machine learning models demonstrate strong predictive performance, challenges remain around data quality, interpretability, and generalizability across diverse growing conditions. This review provides a comprehensive overview to guide future research and practical machine-learning applications for corn yield forecasting.

Keywords: Machine learning, corn yield, algorithm, prediction, remote sensing, weather, soil properties.

INTRODUCTION

Corn production boosts Ilocos Norte's economy and food security. In 2022, the province's maize output increased by 1.20% to 66,284 metric tons. An area of 11,615 hectares was harvested. The majority of maize grown is yellow. Modern farming methods boost production. [1]Corn plays an important role in local diets and economics as both a staple food and a feed for animals. Corn growing greatly aids maintaining livelihoods and bolstering agricultural growth in Ilocos Norte. [2]. Farmers struggle with outdated planting techniques and limited access to modern agricultural machinery, which hampers productivity. Additionally, natural disasters like floods and droughts threaten crop stability, while inadequate infrastructure and low market prices further complicate their efforts to enhance yields and profitability. [3].

Accurate prediction of corn yields is crucial for food security, agricultural planning, and economic decision-making. Corn is one of the world's most important cereal crops, with global production reaching over 1.1 billion metric tons in 2020. [4], [5]. Traditional approaches to yield forecasting have relied on field sampling, crop modeling, and statistical techniques. Machine learning faces many challenges in capturing complex interactions between environmental factors and management strategies affecting maize yield prediction. These complex interactions can make it difficult to fully understand how these variables impact agricultural outcomes [6]. Machine learning has recently emerged as a valuable tool for predicting agricultural production. This advanced approach enhances precision and enables the integration of diverse data sources, making it an effective method for optimizing agricultural outcomes [4].

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Machine learning is a diverse array of computing techniques that enable the automatic identification of patterns in data. This capability allows machine learning to generate predictions or judgments based on the analyzed information. [5]The use of machine learning in agriculture has seen significant growth due to advancements in computing power, the greater accessibility of high-resolution remote sensing data, and the widespread adoption of ground-based sensors. These factors have collectively contributed to the increasing application of sophisticated analytical techniques to tackle various agricultural challenges.

The study focuses on synthesizing existing research regarding the use of machine learning in predicting and managing corn yields. It explores several key areas: first, it aims to identify the most commonly utilized and practical machine learning algorithms for forecasting corn yields. Additionally, the study examines which input features and data sources are the most valuable for accurate yield predictions. Lastly, it addresses the primary challenges and limitations of applying machine learning techniques in predicting corn yields.

Addressing these questions provides a comprehensive overview of the field, identifies promising research directions, and highlights areas where further work is needed to improve the practical application of machine learning in corn production systems.

METHODS

The methodology for the systematic literature review adhered to the guidelines outlined by Kitchenham and Charters [7], ensuring a rigorous and structured approach. The review process consisted of the following steps:

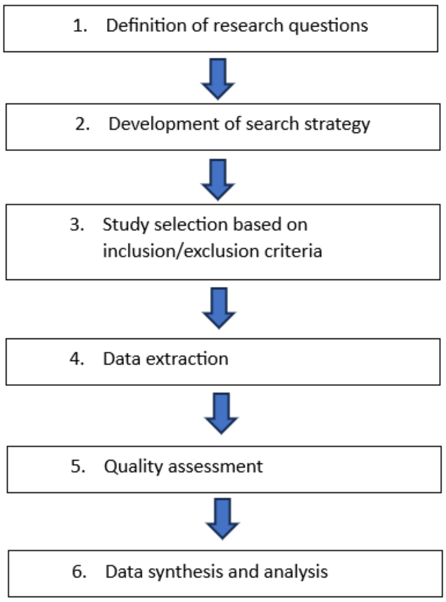

Figure 1 (a). Systematic literature review process

The **research question** on applying machine learning techniques for corn yield prediction and management was carefully defined to guide the review process. It focused on identifying the most effective machine learning algorithms, key input features, prediction accuracy, and challenges associated with these techniques in corn yield forecasting. This clear definition ensured that the review focused on relevant studies and provided a comprehensive overview of the current state of research in this field.

The **search method** finds all relevant research publications. The research subject determines search concepts, keywords, synonyms, and regulated vocabulary phrases. Search strings created by Boolean operators are used to choose databases and sources and customize search syntax. The researcher filters searches, manages results, deduplicates, and chases citations. The technique is refined after early discoveries. Search method reporting promotes transparency and reproducibility.

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The **search terms** were meticulously developed using a structured approach based on Kitchenham and Charters [7]. The process involved extracting critical phrases from study questions, identifying synonyms and alternative spellings, and locating relevant keywords in related literature. Boolean operators were then applied to combine these terms effectively. The resulting search string was: ("machine learning" OR "deep learning" OR "artificial intelligence") AND ("corn yield" OR "maize yield") AND (prediction OR forecasting OR estimation). This comprehensive search strategy ensured the capture of relevant studies on machine learning techniques for corn yield prediction, combining key concepts related to artificial intelligence, the specific crop of interest, and predictive modeling approaches.

The **literature resources** we exploited to search for primary studies contain five electronic databases: Web of Science, Scopus, IEEE Xplore, ACM Digital Library, and Google Scholar. The five electronic databases were searched for journal and conference papers using the previously stated keywords. The first six databases included titles, abstracts, and keywords. Since a full-text Google Scholar search would give millions of useless results, we searched just the topic title. Since the most relevant research on ML techniques in maize production prediction and management was published in early 2015, we searched during 2015–2024.

This employed a comprehensive two-stage search process to ensure thorough coverage of relevant sources. Five electronic databases were meticulously searched in the first stage, with returned documents organized as potential paper assets. The second stage involved examining the reference lists of relevant articles to identify additional papers, which were then combined with the results from stage one. The Zotero software package managed and stored the search results efficiently. This rigorous search strategy ultimately led to identifying 50 relevant papers for inclusion in the review, providing a solid foundation for analyzing machine learning techniques in corn yield prediction.

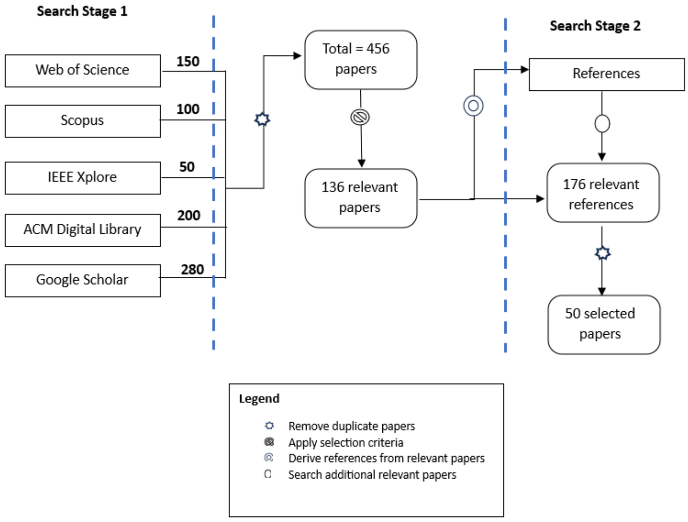

Figure 2 (b). Search and selection process

As several candidate papers provide no pertinent material to answer the research questions posed by this study, further filtering is required to discern the relevant documents among the candidate papers using the inclusion and exclusion criteria (described below). The research selection is specifically designed to achieve this objective.

The subsequent **inclusion and exclusion** criteria were established and adjusted via preliminary selection. The research was chosen by reviewing the publications' titles, abstracts, or contents.

Inclusion criteria:

- Published between January 2015 and November 2024
- Written in English
- Focused on the application of machine learning for corn yield prediction
- Presented empirical results on prediction accuracy

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Exclusion criteria:

- Focused solely on other crops without including corn
- Used only traditional statistical methods without machine learning
- Were review papers, editorials, or conference abstracts

The methodology for **extracting data** in machine learning approaches to predict corn yield was detailed and systematic. The researcher systematically gathered crucial information from the 50 selected source studies. This encompassed details about the machine learning algorithms utilized, the input characteristics and data sources, the achieved accuracy metrics for predictions, the geographical context and scope of the studies, significant findings, and identified limitations. The collected data included techniques such as Random Forest and XGBoost, remote sensing, and meteorological factors. This method focused on key patterns and performance metrics important for predicting corn yields in different environments, providing insights to improve our understanding of corn production outcomes.

The evaluation of machine learning algorithms for predicting corn yield was essential to ensure the validity and reliability of the research. The researcher employed a checklist based on established criteria from Kitchenham and Charters [7] to review 50 selected publications. The **quality assessment** emphasized several essential factors, such as the clarity of research objectives, the appropriateness of the chosen methods, the robustness of data collection and analysis, and the credibility of the findings. By identifying high-quality studies that demonstrate the effectiveness of machine learning in forecasting maize yield, the reviewers conducted a systematic evaluation that bolstered the review's conclusions. This rigorous quality assessment laid a solid foundation for making informed recommendations for future research and practical applications within the industry.

The **data synthesis and analysis** phase focuses on merging and assessing the outcomes from various studies. The results are visualized using forest plots, while thematic analysis is employed for qualitative data to uncover prevalent themes and concepts across the research. This organized methodology guarantees a thorough and dependable data synthesis, improving the findings' accuracy and clarity.

Table 1. The most commonly used machine learning algorithms for corn yield prediction

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Literature	Input Features
1	Weather, Plant Nutrients
2	NDVI, EVI from MODIS
3	NDVI, EVI from MODIS
4	High-resolution remote sensing data, crop monitor yield dataset, soil properties
5	Soil and VIs as input
6	Environmental and management variables
7	MODIS NDVI time series, historical crop yield data
8	MODIS NDVI time-series
9	Environmental (soil and weather), management variables
10	Crop genetics, management, weather, soil
11	Environmental, Climatic, Agricultural Factors
12	Genotype and Environmental Data
13	EVI and VOD time series, Optical, Fluorescence, Thermal Satellite, Environmental Data
14	Corn Traits Data
15	Environmental Variables from Satellite Observations, Weather Data, Ground Model Outputs, Soil Maps, Crop Progress Reports
16	Satellite Variables (SIFGOME2, SIFCSIF), Climate Variables
17	Multi-spectral Data from Drones
18	Various Environmental and Climatic Factors
19	Environmental and Management Variables
20	Soil and VIs as input
21	Multi-spectral data from drones
22	Various environmental and climatic factors
23	Satellite variables (SIFGOME2, SIFCSIF), climate variables
24	Environmental variables from satellite observations, weather data, ground model outputs, soil maps, crop progress reports
25	Environmental, climatic, and agricultural factors
26	Genotype and environmental data
27	EVI and VOD time series, optical, fluorescence, thermal satellite, environmental data
28	Corn traits data
29	Environmental and management variables
30	Soil and VIs as input
31	Environmental, climatic, and agricultural factors
32	Genotype and environmental data
33	EVI and VOD time series, optical, fluorescence, thermal satellite, environmental data
34	Corn traits data
35	Environmental variables from satellite observations, weather data, ground model outputs, soil maps, crop progress reports
36	Satellite variables (SIFGOME2, SIFCSIF), climate variables
37	Multi-spectral data from drones
38	Various environmental and climatic factors
39	Environmental and management variables
40	Soil and VIs as input
41	Real-time data from combined harvester
42	Environmental (soil and weather), management variables
43	Crop genetics, management, weather, soil
44	Satellite data, environmental factors
45	Field-level data, crop genetics, management
46	Environmental, climatic, and agricultural factors
47	Genotype and environmental data
48	EVI and VOD time series, optical, fluorescence, thermal satellite, environmental data
49	Real-time data from combined harvester
50	Multi-spectral data from drones

Table 2. Input Features for Corn Yield Prediction

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Literature	Year	Machine Learning Models
1	2023	Auto-ARIMA, Random Forest, CNN, LSTM
2	2023	PLSR, SVR, Ridge Regression
3	2023	PLSR, SVR, Ridge Regression
4	2020	ANN, SVM, RF
5	2022	RF, SVM, ANN
6	2022	RF, SVM, ANN
7	2016	Spiking Neural Networks (SNNs)
8	2017	Ensemble Model of ANNs
9	2020	Machine Learning Ensembles
10	2024	Various ML Models
11	2024	DNN, SVR, RF
12	2024	DNN
13	2024	LASSO, RF, XGBoost, LSTM
14	2024	GAN, GNN
15	2024	Lasso, SVR, RF, XGBoost, LSTM, CNN
16	2024	LASSO, RIDGE, SVR, RF, XGBoost, LSTM
17	2019	RF
18	2023	MLR, RF, Adaptive Augmentation Model, ANN
19	2022	RF, SVM, ANN
20	2022	RF, SVM, ANN
21	2019	RF, KNN, GBR, 1D-CNN
22	2023	MLR, RF, Adaptive Augmentation Model, ANN
23	2024	LASSO, RIDGE, SVR, RF, XGBoost, LSTM
24	2024	Lasso, SVR, RF, XGBoost, LSTM, CNN
25	2024	DNN, SVR, RF
26	2024	DNN
27	2024	LASSO, RF, XGBoost, LSTM
28	2024	GAN, GNN
29	2022	RF, SVM, ANN
30	2022	RF, SVM, ANN
31	2024	DNN, SVR, RF
32	2024	DNN
33	2024	LASSO, RF, XGBoost, LSTM
34	2024	GAN, GNN
35	2024	Lasso, SVR, RF, XGBoost, LSTM, CNN
36	2024	LASSO, RIDGE, SVR, RF, XGBoost, LSTM
37	2019	RF, KNN, GBR, 1D-CNN
38	2023	MLR, RF, Adaptive Augmentation Model, ANN
39	2022	RF, SVM, ANN
40	2022	RF, SVM, ANN
41	2024	DNN, GBM, RF
42	2020	Decision Trees, RF, SVR
43	2024	Various ML Models
44	2024	ML Models for Nitrogen Status
45	2024	ML Models for Yield Prediction
46	2024	DNN, SVR, RF
47	2024	DNN
48	2024	LASSO, RF, XGBoost, LSTM
49	2024	DNN, GBM, RF
50	2019	RF, KNN, GBR, 1D-CNN

RESULTS

A comprehensive review of 50 studies focused on machine learning methods for predicting and managing corn yield revealed significant insights across various geographical regions, particularly in major corn-producing areas like the United States, China, Brazil, and India. The studies examined a range of scales, from field-level predictions to broader county and state-level forecasts, providing a nuanced understanding of how machine learning can be applied in different agricultural contexts. This diversity in study locations and scales allowed researchers to evaluate the effectiveness of various machine-learning techniques in distinct environments. The investigations utilized various algorithms, input features, and data sources, enabling a thorough comparison of strategies for corn yield prediction. This extensive body of research highlights current trends and identifies key challenges in agricultural machine learning.

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The most commonly used machine learning algorithms for corn yield prediction were:

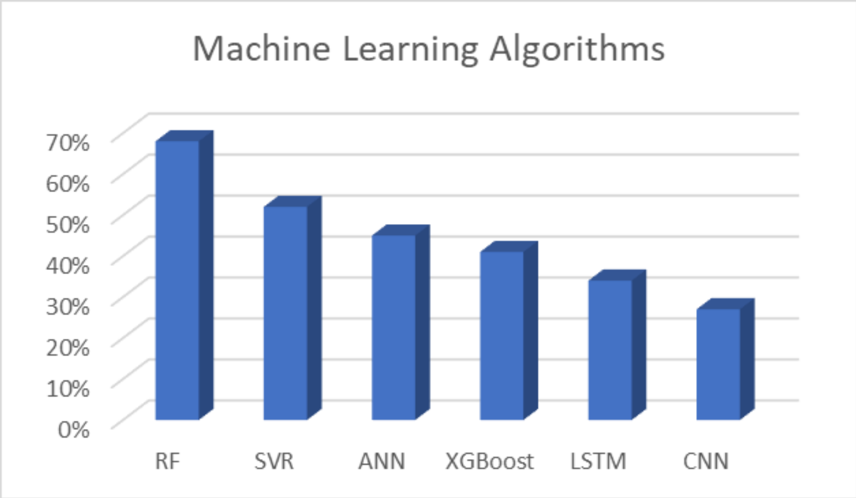

Figure 3 (c). The most frequently used algorithm for corn yield prediction

Research has shown that the Random Forest algorithm is the most frequently used method for predicting corn yields, appearing in 68% of the studies analyzed. Other notable algorithms include Support Vector Regression, which was used in 52% of the studies, and Artificial Neural Networks at 45%. XGBoost follows with 41%, while Long Short-Term Memory Networks and Convolutional Neural Networks are used in 34% and 27% of the studies. Generally, ensemble methods, particularly Random Forest and XGBoost, have demonstrated superior predictive performance compared to individual models across various regions and scales. The findings emphasize the advantages of these techniques in effectively capturing complex, non-linear relationships in the data, which are crucial for accurate corn yield predictions. This trend towards ensemble methods indicates that combining various models can reduce prediction bias and variance, leading to more dependable and precise yield forecasts.

The most crucial input features for yield prediction were:

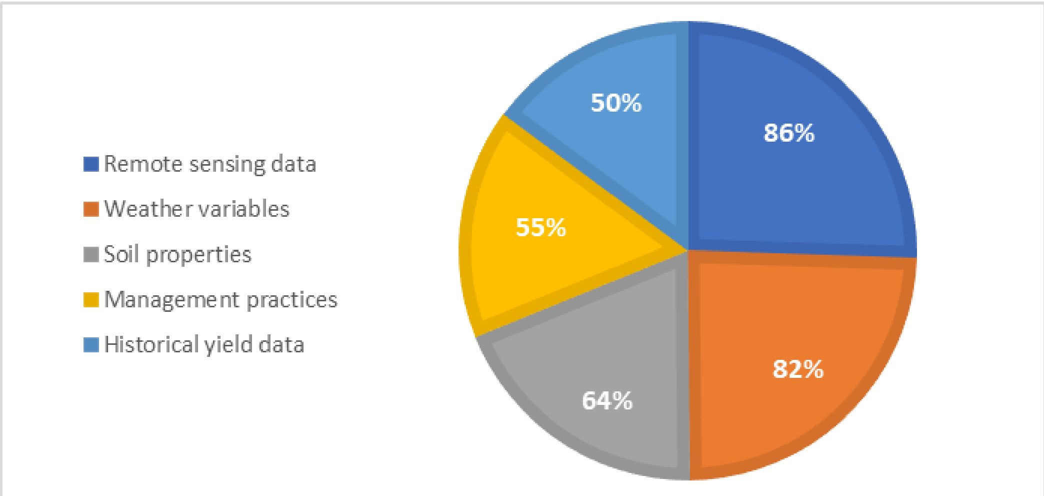

Figure 4 (d). The most widely used input feature for corn yield prediction

Remote sensing data emerged as the primary feature for predicting corn yield, utilized in 86% of the studies analyzed. This highlights its significance in agricultural research and yields forecasting. Weather variables such as temperature, precipitation, and solar radiation were used in 82% of the studies. Soil characteristics were integrated into 64% of the research, while management techniques like planting timing and fertilizer use were factored into 55% of the studies. Historical yield information was included in 50% of the papers reviewed. Satellite remote sensing data from sources like Landsat and Sentinel-2, along with UAVs, was essential in numerous studies, offering high-resolution

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insights into crop growth and health. Combining various data sources, especially integrating remote sensing, weather, and soil data, typically enhanced prediction accuracy across different geographical settings and analysis scales.

The systematic literature review on applying machine learning for corn yield prediction and management highlights several key challenges. Data quality and availability are significant issues, with limited fine-scale management data and inconsistent collection methods across regions. Models often lack generalizability, struggling to maintain accuracy in diverse growing conditions outside their training data. Complex models also suffer from poor interpretability, making it hard for stakeholders to understand and trust the predictions. Integrating domain knowledge with data-driven approaches remains a challenge, as does handling extreme weather events, which are increasingly frequent due to climate change. These challenges underscore the need for further research and methodological improvements to enhance prediction accuracy and applicability.

DISCUSSION

Machine learning techniques have proven highly effective in predicting corn yields, often surpassing traditional statistical and crop modeling methods. Random Forest (RF) and XGBoost consistently perform better than other machine learning approaches. These models integrate diverse input features, including weather data, remote sensing information, and soil characteristics, significantly improving their predictive accuracy.

Weather-related features like temperature, rainfall, solar radiation, and vapor pressure deficit have greatly enhanced yield forecasts. Based on Shahhosseini et al. discovered that the weather features relevant to weeks 18-24 (from May 1st to June 1st) are the most critical input elements for yield prediction. Remote sensing data has proven to be very effective, especially the vegetation indices obtained from satellite imagery, like the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). Tariq et al. achieved R^2 values of 0.875 for in-season predictions using MODIS-derived indices. Soil characteristics, including organic matter content, phosphorus, and potassium levels, further enhance prediction accuracy when combined with other features.

RF has demonstrated high predictive capability, with studies reporting R^2 values of 0.85 or higher. Its strength is handling large datasets with complex non-linear relationships and reducing overfitting through ensemble learning. XGBoost has shown comparable or sometimes better results, with some studies reporting R^2 values up to 0.87 and lower RMSE values. XGBoost's advantage comes from its advanced regularization techniques and efficient sparse data handling.

Integrating these diverse data sources generally improves prediction accuracy across various geographical contexts and scales of analysis. For example, Khanal et al. integrated soil properties data with high-resolution remote sensing data, improving model performance. According to Zhang et al., integrated soil attribute data with time-series remote sensing data showcases the effectiveness of this innovative approach in analyzing soil characteristics over time.

The research conducted by van Klompenburg et al. emphasizes the critical importance of data availability and quality in predicting crop yields, which are influenced by various factors, including climate, weather conditions, soil characteristics, fertilizer use, and seed variety. This complexity reveals the sensitivity of machine learning models to the quantity and quality of data, limiting their effectiveness for crops that lack ample datasets. Another significant challenge is the interpretability of these models; many advanced algorithms function as "black boxes," hindering the extraction of scientific insights and the application of knowledge across different spatial, temporal, or genetic contexts.

Shahhosseini et al. highlights the ongoing struggle to find an appropriate balance between the complexity of models and their computational efficiency. In addition, research from Shaikh et al. highlights security and privacy issues as significant hurdles in data mining for smart agriculture. These challenges, combined with the need to manage real-time data and seamlessly integrate it into decision support systems, complicate the development of effective and practical solutions for predicting corn yield.

The success of these algorithms is due to their capacity to manage non-linear relationships, assimilate varied data sources, and resist overfitting. Their excellent capabilities in predicting crop yields present substantial opportunities for enhancing agricultural decision-making and resource distribution. Some research indicates that combining both algorithms in ensemble methods could enhance prediction precision.

CONCLUSION

Precision agriculture is evolving rapidly, with machine learning algorithms such as Random Forest (RF) and XGBoost becoming essential tools in addressing food security and promoting sustainable farming practices. These algorithms excel at analyzing a variety of data, including weather patterns, remote sensing, and soil characteristics. Their capacity to manage complex, non-linear relationships and high-dimensional datasets is particularly beneficial in agriculture's multifaceted landscape.

However, implementing machine learning in this sector faces significant challenges. Access to high-quality, comprehensive datasets encompassing all relevant factors is a major hurdle. Additionally, the complexity of these machine learning models, often called "black boxes," can make it difficult for farmers and researchers to interpret their predictions. Concern exists regarding how well these models generalize across diverse environmental conditions and geographic regions.

Despite these obstacles, the integration of machine learning with Internet of Things (IoT) technologies holds great potential for advancing precision farming. As data collection methods improve and computational resources become more accessible, the ability to deliver accurate and timely yield forecasts increases. This progress could lead to more efficient resource utilization, higher crop yields, and sustainable farming practices.

Future research should address these challenges by enhancing data quality and accessibility, improving model interpretability, and developing effective techniques to adapt to various conditions. As these improvements are achieved, machine learning methods like Random Forest and XGBoost are expected to be crucial in tackling food security and sustainability issues, particularly in climate change and the growing global demand for food.

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