A Systematic Literature Review of Crop Recommendation Systems for Agriculture 4.0

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Abstract

Machine learning and data-driven methodologies are transforming crop recommendation systems (CRS) to enhance agricultural productivity and sustainability. These systems integrate advanced technologies, such as the Internet of Things (IoT), to provide customized crop selection and management recommendations that address challenges from population growth to climate change. Despite considerable progress, the literature highlights key limitations, particularly the reliance on region-specific data and issues related to data quality and availability. This review synthesizes current findings, identifies research gaps, and proposes future directions to improve CRS adaptability and robustness. The outcomes aim to advance ongoing research initiatives and support the development of more effective crop recommendation systems for diverse agricultural environments.

Keywords

Crop Recommendation Systems, Agriculture 4.0, Machine Learning, Internet of Things, Sustainability, Data-Driven Approaches

1. Introduction

The advent of Agriculture 4.0 marks a transformative era in the agricultural sector, characterized by the integration of advanced technologies, data analytics, and machine learning into traditional farming practices [1]. As global population growth and climate change present unprecedented challenges to food security, there is an urgent need for innovative solutions to enhance agricultural productivity and sustainability [2, 3]. Crop recommendation systems (CRS) have emerged as pivotal tools, leveraging data-driven methodologies to provide tailored recommendations for crop selection and management based on various environmental and agronomic factors.

Recent advancements in deep learning and machine learning techniques have significantly contributed to the progress of CRS research. These advancements are further complemented by developments in related fields, such as computer vision for automated agricultural monitoring, robot control for precision farming[4], and EEG-based classification[5, 6] techniques for understanding human-environment interaction [7, 8, 9, 10]. For instance, previous work on employing machine learning for computer vision tasks has demonstrated robust solutions for automating complex systems [11, 12]. Similarly, efforts in integrating deep learning with robot control have highlighted novel approaches to autonomous decision-making [13, 14, 15]. These contributions not only underline the potential of advanced AI methodologies but also suggest opportunities for their application in agriculture, including crop recommendation systems[16, 17]. To systematically explore the current state of CRS, this study employs a structured, four-step literature review methodology inspired by established frameworks. The first step involves gathering relevant literature from Scopus, the largest repository of peer-reviewed scientific publications, for the period from 2020 to 2024. The search was guided by predefined keywords and filtering criteria to ensure the quality and relevance of the selected studies. The following keyword combinations were used: "crop recommendation system," "crop selection system," and "machine learning in crop recommendation." Initial search results were refined to maintain consistency and focus by applying language filters (English only), excluding dissertations, and limiting the timeframe to studies published within the specified period. A total of 310 articles were retrieved, forming the basis for further analysis. The collected literature was analyzed descriptively to identify trends and patterns in the field, covering aspects such as the number of publications per year, types of publications, geographical distribution, citation analysis, and keyword trends. Subsequently, a subset of high-impact papers was selected from the 310 reviewed articles for deeper analysis. This selection was based on criteria such as citation frequency, contributions from diverse countries, and alignment with key themes like predictive modeling, optimization techniques, and region-specific recommendations. The focused analysis aimed to identify research gaps, novel approaches, and well-established methodologies.

The final step involves identifying key limitations in

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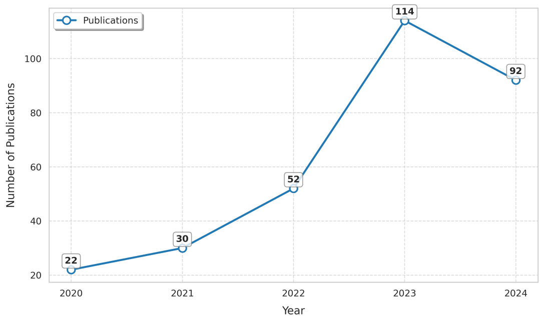

Figure 1: Annual distribution of publications on crop recommendation systems (2020–2024).

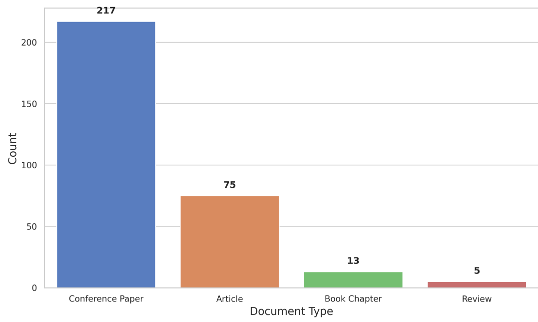

Figure 2: Distribution of publications by document type.

the current literature and proposing directions for future research. This section highlights the gaps and challenges faced by researchers in crop recommendation systems and outlines potential areas for advancement. By synthesizing key findings and identifying research gaps, this review seeks to support researchers and practitioners in enhancing the effectiveness and adoption of crop recommendation systems across diverse agricultural environments.

2. Descriptive Analysis

This section provides a descriptive analysis of the reviewed literature, examining key aspects such as the yearly distribution of publications, types of publications, geographical trends, frequently used keywords, and the influence of notable studies through citation analysis.

2.1. Number of Publications per Year

The distribution of publications from 2020 to 2024 reveals a clear upward trend in research interest in crop recommendation systems. As shown in Figure 1, the field began with 22 publications in 2020 and grew steadily to 52 publications by 2022. A notable surge occurred in 2023, with 114 publications, likely due to advancements in machine learning, IoT, and smart agriculture. In 2024, the count slightly declined to 92 but remains significantly higher than in previous years, indicating sustained strong interest.

2.2. Types of Publications

The literature on crop recommendation systems includes conference papers, journal articles, book chapters, and reviews, each contributing unique perspectives. As shown in Figure 2, conference papers lead with 217 publications, reflecting a focus on recent innovations, while 75 journal articles offer in-depth, peer-reviewed research. There are also 13 book chapters providing specialized knowledge and 5 reviews summarizing trends and future directions. This distribution shows the field's dynamic nature and the role of conferences in quickly sharing findings.

2.3. Country of Research

This section describes the global distribution of research on crop recommendation systems, as shown in Figure 3. India leads with 249 publications, demonstrating a strong focus on agricultural technologies to address diverse climatic challenges. The United States (14) and Bangladesh (11) are also significant contributors, followed by Morocco (6), China (5), Egypt (5), and Sri Lanka (5), reflecting regional efforts to improve agricultural productivity. Other countries like Algeria, Iraq, and Italy, with fewer publications, indicate emerging interest. The involvement of nations from various continents, such as Australia, France, and Ethiopia, underscores the worldwide importance of this research, despite differences in research capacity and funding.

2.4. Citation Analysis

This section examines the influence of studies based on their citation counts over time. Figure 4 shows steady growth in both publications and citations from 2020 to 2024. The number of documents increased consistently, with a significant rise in 2023, surpassing 90 publications. Citations also grew sharply starting in 2022, and by 2024, they are expected to exceed 700, reflecting the growing impact of AI-driven crop recommendation systems. The surge in citations in 2023 indicates the influence of earlier foundational research, showing the increasing importance of AI in agriculture and interdisciplinary interest in crop recommendation systems.

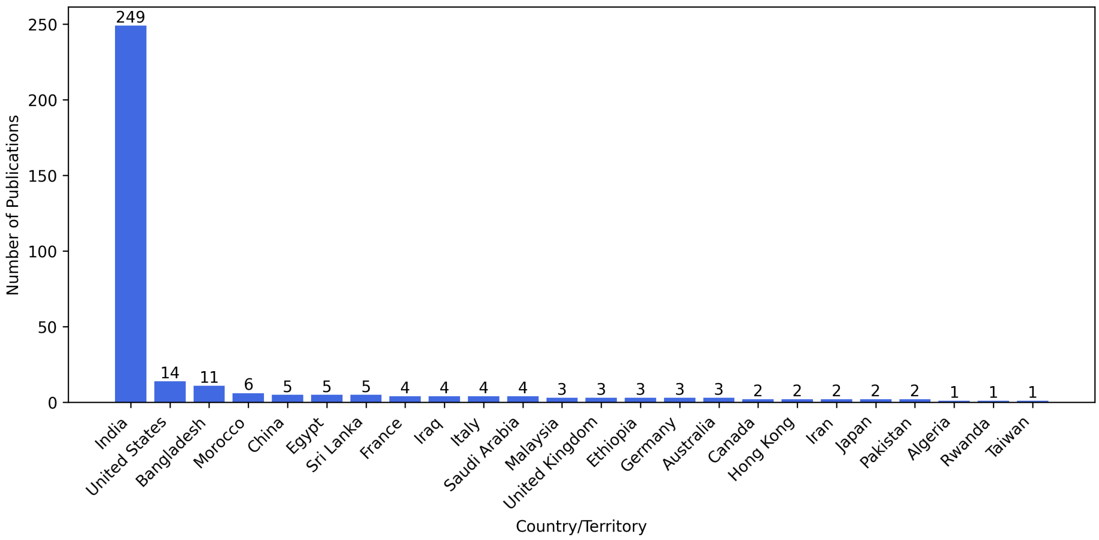

Figure 3: Geographical distribution of publications in crop recommendation systems.

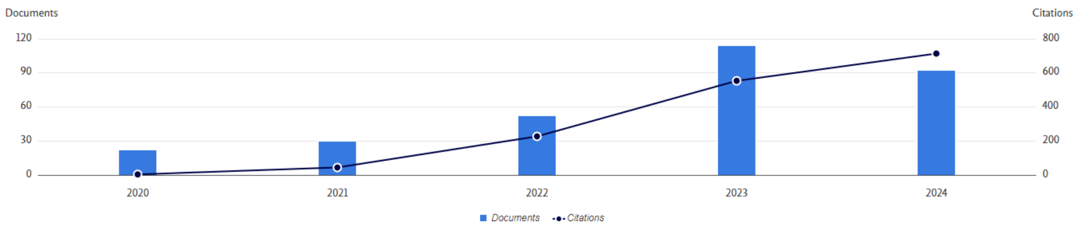

Figure 4: Citation analysis of documents and citations from 2020 to 2024.

2.5. Keyword Analysis

This section provides a keyword analysis, as shown in Figure 5, illustrating key themes and trends in crop recommendation system research. Prominent keywords such as "crops," "crop recommendation," "crop selection," and "learning systems" reflect the core focus on using AI to optimize crop decisions. Terms like "Internet of Things (IoT)," "precision farming," and "machine learning" demonstrate the integration of data-driven technologies into agriculture to improve efficiency and sustainability.

Other clusters, including "soil conditions," "fertilizers," and "agricultural productivity," emphasize the importance of environmental and resource management in developing crop recommendation models. Keywords like "decision trees," "support vector regression," and "genetic algorithms" reveal the variety of machine learning techniques applied in this field.

Interdisciplinary themes, such as "economics," "logistics," and "food supply," show the broader socioeconomic dimensions of the research. Additionally, keywords like "climate conditions," "weather prediction," and "soil moisture" highlight the focus on external factors influencing agricultural decision-making. This analysis reflects the merging of AI, environmental science, and agricultural economics in advancing crop recommendation systems.

3. Related Works

This section reviews key studies defining the state-of-the-art in crop recommendation, illustrating advancements from foundational predictive models to more sophisticated approaches.

Bhat et al. [18] propose a hybrid model combining Gradient Boosted Regression Trees (GBRT) and deep learning, optimized via Bayesian techniques, achieving an F1-score of 1.0 by leveraging 1,148 soil data points on

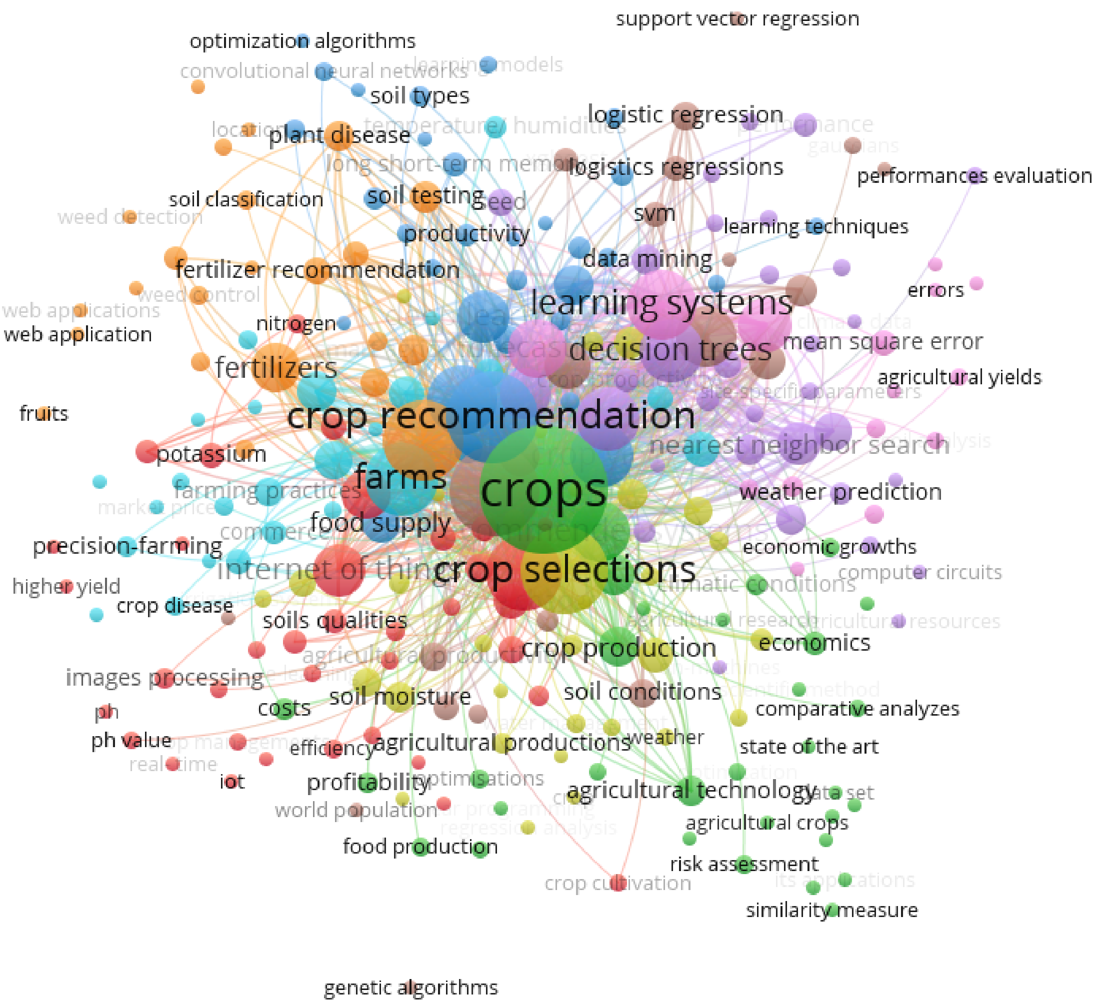

Figure 5: Keyword network analysis highlighting key themes in crop recommendation research.

nitrogen, organic carbon, and pH.

Motamedi et al. [19] build on this by introducing an ensemble model that integrates Fine Gaussian Support Vector Machine (FGSVM) and Bayesian Optimized Ensemble Decision Trees (BOEDT). Their system, which employs Principal Component Analysis (PCA), achieves accuracy rates exceeding 99%, demonstrating the effectiveness of nutrient-specific data.

Bouni et al. [20] apply Random Forest, K-Nearest Neighbors (KNN), and Deep Reinforcement Learning (DRL) to enhance scalability in crop recommendations, indicating DRL's adaptability to larger datasets. Similarly, Gottemukkala et al. [21] leverage IoT integration for real-time soil analysis, achieving high accuracy in crop recommendations.

[22] presents a cloud-based system utilizing deep learning to select suitable crops based on soil health metrics, achieving a 98.62% accuracy rate. The User-friendly AIoT-Based Crop Recommendation (UACR) system by [23] gathers environmental data automatically, streamlining user interaction to promote smart agriculture.

Mahale et al. [24] develop a decision-support system for Indian agriculture using Random Forest, XGBoost, and Support Vector Machine (SVM)[25, 26, 27], achieving a 91.88% accuracy rate by integrating meteorological and soil data.

Table 1
Comparison of Crop Recommendation Systems in Related Works

Study	Methodology	Data Sources	Key Findings	Limitations
[20]	Deep Reinforcement Learning (DRL) with ML algorithms (Random Tree, Naive Bayes, KNN, SVM) for crop classification	Soil quality, crop yield, temperature, moisture, rainfall, humidity	DRL outperforms traditional ML algorithms by improving crop selection and yield efficiency.	Limited geographic scope; instability in algorithm performance due to inconsistent spatial/temporal data.
[28]	Random Forest Classifier for crop selection and LSTM RNN for weather prediction	Weather data, soil parameters (pH, moisture, nutrients)	Achieves 97.235% accuracy in crop selection, effective in predicting resource needs and sowing time.	Focused on Telangana region; challenges in scaling to other areas.
[29]	IoT-based system using Improved Distribution-based Chicken Swarm Optimization (IDCSO) and Weight-based LSTM (WLSTM) for precision farming	Soil characteristics, weather data (rainfall, temperature, soil moisture)	Achieved faster execution and better precision for crop recommendation; real-time data from IoT sensors improves decision-making.	Geographic limitations; small dataset size may impact generalization.
[30]	Neural networks for crop recommendation combined with rule-based fertilizer recommendations	Soil nutrients (N, P, K), pH levels, weather data	Achieves 97% accuracy in crop and fertilizer recommendation; focuses on smallholder farms.	Limited scalability to larger regions; focused on smallholder farms in Rwanda.
[18]	GBRT-based hybrid DNN surrogate models optimized with Bayesian techniques for crop recommendation	Soil physical and chemical features (sand, silt, clay, pH, EC, SOC, N, P, K)	Achieved an F1-Score of 1.0 with high accuracy for soil suitability classification.	Small and unbalanced soil dataset; limited correlation studies for soil indexing.
[31]	Web-based crop recommendation system using Random Forest and Decision Tree algorithms	Soil quality, environmental data (temperature, rainfall)	Random Forest showed the best performance in crop recommendation; effective for Moroccan agriculture.	Lacks validation on a large scale; limited geographic scope.
[32]	Hybrid model of Enhanced Long Short-Term Memory (ELSTM) and ARIMA for yield prediction and crop recommendation based on environmental factors.	Soil nutrients (NPK), rainfall, production history, temperature, humidity, price.	85% accuracy in crop yield prediction; ELSTM outperformed Naive Bayes and Decision Tree models.	Geographic limitation to Indian districts; potential inaccuracies in historical data due to missing values.
[21]	Real-time data collection with NPK sensors and analysis using KNN for crop recommendation	Soil nutrient levels (NPK)	High accuracy (99.67%) in real-time crop recommendations based on soil conditions.	Limited to specific NPK sensor data; field trials required for broader validation.
[33]	Ensemble-based crop recommendation system with optimization techniques, including Moth Flame Optimization (MFO)	Soil characteristics, weather data	Achieved 99.32% accuracy using ensemble techniques, particularly MFO for crop selection optimization.	Limited to specific crops in Indian agriculture.
[34]	Voting classifier combining multiple ML models (Random Forest, KNN, Decision Trees) for crop recommendation	Soil characteristics, temperature, humidity, N, P, K, pH	High accuracy (99.31%) through ensemble learning, improving crop recommendations.	Geographic limitations; model not tested on broader environmental factors.
[35]	Optimized Multilayer Perceptron integrated with Crop Yield Prediction (CYP) and Crop Price Prediction (CPP) for ROI-based recommendations	Soil fertility, climate data, market price data	Recommends crops based on financial profitability using ROI analysis; integrates market and agricultural data.	Assumes stable market conditions; regional focus (Maharashtra); data collection challenges.
[19]	Bayesian-optimized ensemble decision trees combined with PCA for dimensionality reduction and multi-class classification	Soil nutrient levels (nitrogen, phosphorus, potassium), environmental variables (temperature, humidity, pH, rainfall)	99.5% accuracy in multi-class crop prediction across 22 crops; effective dimensionality reduction using PCA.	Potential overfitting due to hyper-parameter tuning; generalization issues for unseen data.
[36]	IoT sensors integrated with Arduino for real-time crop monitoring and automation	Soil moisture, temperature, nutrient levels	Improved crop yields through real-time monitoring and automated decisions based on environmental data.	Expensive IoT infrastructure; complex system maintenance required.
[37]	IoT-enabled ML models (Decision Trees, KNN, Random Forest) for real-time crop recommendation	Soil nutrients, pH, temperature, humidity, rainfall data	Decision Tree model achieved 99.2% accuracy, enhancing crop productivity.	Limited regional focus (Somalia); dependency on stable IoT infrastructure.
[24]	Random Forest and LSTM algorithms with expectation-maximization for missing data handling	Weather data, crop yield data (2001–2022)	Achieves 92% accuracy in predicting crop yields; LSTM predicts 3-month weather patterns.	Regional limitation (Maharashtra); scalability challenges for other regions.
[38]	IoT-based smart irrigation system with machine learning (Random Forest) for real-time crop recommendation and automated irrigation.	IoT sensor data: soil moisture, pH, NPK levels, temperature, humidity.	RF achieved 98% accuracy in crop recommendations; improved water usage and crop yield.	Sensor data accuracy may fluctuate; limited to areas with deployed sensors; lacks extensive geographic validation.

Addressing uncertainty, [39] applies a Bayesian Belief Network (BBN) to adjust crop selection based on local conditions, while [40] proposes a cluster-based system for crop grouping, optimizing machine learning performance.

In Rwanda, Musanase et al. [30] achieve a 99% training accuracy with neural network models. Kiruthika et al. [29] present a Weighted Long Short-Term Memory (WLSTM) model, reaching 98.35% accuracy by combining nutrient data with seasonal patterns.

Rani et al. [28] explore various models with weather and soil datasets over six years, achieving robust accuracy. Janrao et al. [35] similarly use regression techniques to forecast crop yield and prices, achieving high regression accuracy.

Numerous studies, including those by [41] and [42], highlight IoT's role in real-time data collection, achieving accuracies of 99.14% and 99.55%, benefiting smallholder farmers. Abdullahi et al. [37] and Mancer et al. [34] achieve 99.2% and 99.31% accuracy, respectively, using localized data and ensemble techniques.

Ensemble methods are further advanced by [43], achieving 99% classification accuracy, while [33] applies Moth Flame Optimization (MFO) to enhance ensemble model performance, reaching 99.32% accuracy.

To provide a comprehensive analysis, the following works will be examined in a comparative table (Table 3).

Table 3 compares crop recommendation studies across diverse regions, including India, Morocco, Taiwan, and Rwanda, each tailored to specific local conditions. This geographic focus, however, limits broader applicability, as models trained on region-specific data may not perform well in other areas. Methodologies range from traditional machine learning models to advanced deep learning and optimization techniques, such as Neural Networks, LSTM, and Bayesian optimization, with recent studies incorporating IoT sensors for real-time monitoring. Advanced models generally show higher accuracy, often exceeding 97%, with deep learning and ensemble methods achieving the best results. While data sources include soil nutrients, weather data, and IoT sensor information, dependence on specific regional data and sensor technology impacts scalability. Findings emphasize the potential of these systems but underscore challenges in adapting models for varied agricultural environments.

4. Limitations and Future Research Directions

Limitations: A key limitation is the reliance on region-specific data, which restricts the generalizability of models. Many systems are finely tuned to local conditions, such as specific soil types, climate variables, and crop varieties, making it difficult to apply them across diverse geographic regions. Additionally, data availability and quality remain barriers; most models depend on detailed parameters like soil nutrients, climate data, and historical crop data, which are often inconsistent or unavailable in certain rural or developing regions. This lack of reliable, high-quality data can significantly affect model performance.

Another challenge is the dependency on advanced technologies, including IoT for real-time data collection, which, while enhancing model precision, requires significant investment in infrastructure. This reliance may limit the usability of models in areas without such resources. Furthermore, complex methodologies, such as deep learning and ensemble techniques, demand high computational power, which can be infeasible for small farms or regions with limited technology. Compounding this issue is the lack of interpretability in many advanced models, leading to a lack of trust among stakeholders. When the reasoning behind AI-based recommendations is not transparent, farmers and decision-makers may hesitate to adopt these systems, as they struggle to understand and verify the AI's predictions.

Future Research Directions: To overcome these limitations, future research should prioritize the development of more generalizable models that can adapt across regions with minimal adjustments. Techniques like transfer learning or domain adaptation could enable these models to be applied successfully in diverse agricultural settings. Furthermore, enhancing data sources by integrating satellite imagery, remote sensing, and publicly available climate data can reduce the dependency on localized data, making models more adaptable and scalable.

Improving data quality and accessibility will also be vital. In addition, future models should focus on being lightweight and cost-effective, performing efficiently without extensive computational resources—benefiting smallholder farmers in resource-limited settings.

Another promising direction is the enhancement of model interpretability. By building transparency into complex algorithms, researchers can make these models more trustworthy and comprehensible, fostering greater acceptance and adoption. Additionally, designing models with expandability in mind will ensure that systems can evolve to accommodate new data types, crops, and environmental conditions, extending their relevance over time. Finally, integrating blockchain technology could address data security and traceability concerns, making sure that the data used is tamper-proof and transparent. Addressing these limitations and advancing research in these areas will result in crop recommendation systems that are more robust, scalable, and accessible, effectively meeting the diverse and evolving needs of global agriculture.

5. Conclusion

This review examines the advancements in crop recommendation systems driven by machine learning and IoT, demonstrating the potential to improve crop selection based on soil, climate, and environmental factors. Despite progress, challenges remain, such as reliance on region-specific data and the need for high-quality inputs and IoT infrastructure, limiting scalability across regions. Future research should focus on developing more generalizable and explainable models, leveraging transfer learning and remote sensing data to enhance adaptability. Addressing these issues will make crop recommendation systems more robust, accessible, and supportive of agricultural sustainability globally.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT, Grammarly in order to: Grammar and spelling check, Paraphrase and reword. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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