# Intelligent Data-Driven Crop Recommendation Systems for Farmers: A Systematic Review and Classification

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## ABSTRACT

Agriculture plays an important role in the Philippines, but Filipino farmers' reliance on traditional practices due to limited access to scientific technology, services, and guidance leaves them vulnerable to poor crop choices, income loss, climate risks, and low yields. This research study proposes developing a reliable, accessible, and climate-resilient crop recommendation approach for farmers. The objective of the study is to identify trends, technological methods, and research gaps. A systematic review with meta-analysis and secondary data analysis of carefully selected published studies is used as the population sampling, rather than actual human beings. To classify crop recommendation systems and identify trends, limitations, and research gaps, data were extracted using a standardized extraction form, categorized, and analyzed using descriptive statistics, mode identification, cross-tabulation, and qualitative thematic analysis. Out of the twenty (20) published studies selected, soil and weather with soil nutrients, pH, moisture, and important field factors constantly influencing the right choices are identified as the crucial input parameters in this study. Common AI-based systems primarily use machine learning and deep learning, deployed via cloud-based architectures, and are organized into a taxonomy based on method, data inputs, and deployment. Reliance on internet connectivity, high hardware costs, and difficult explainability are the challenges found in this study. Furthermore, unexplored areas are conducive to system deployment and also include inadequate farmer-centered design, limited generalizability, limited field validation, and insufficient local datasets. Moreover, researchers recommended using low-cost modular sensors, hybrid cloud–edge or TinyML deployment, and locally representative datasets with field validation.

**Keywords:** Crop Recommendation System (CRS), Data-Driven System, Decision Support System (DSS), Internet of Things (IoT) and Machine Learning (ML)

## INTRODUCTION

Agriculture holds a significant role in society by providing raw materials, establishing jobs, and promoting economic growth in a country. In particular, in the Philippines, farmers are the keystone in the agricultural system. Traditionally, the profession focuses on cultivation, crop selection, and soil conservation; however, many farmers still rely on methods inherited from past experience rather than modern crop management (Ama et al., 2025).

Moreover, according to the Department of Agriculture (DA) reports from the Adaptation and Mitigation Initiative in Agriculture, the Philippines still lacks extension services and scientific advice, and studies are limited, resulting in most farmers choosing old practices based on what is familiar and known. Research from Catublian, Hinunangan, Southern Leyte, states that farmers mostly rely on traditional knowledge but also consider modern advancements and government-suggested practices, except for organic fertilizers (Ama et al., 2025).

Additionally, according to the Department of Agriculture, farmers face difficulties due to soil degradation and extreme weather conditions, leading to nutrient depletion and oversight issues. Moreover, frequent storms and disasters affect food security following intense weather events (Trần, 2024). At present, technological and informational gaps compound the problem, resulting in conflicts over the latest reliable price and demand information for crops (PhilSeed, 2023).

Furthermore, real-time data can be sensed, gathered, processed, and transmitted by IoAT devices to the intended devices. Monitoring and managing the environmental aspects of plants, soil, and crop yields, and improving productivity by analyzing data pertaining to soil factors are the factors of IoAT that ensure the farmers will overcome the issue of the supply-demand gap by providing environmental protection, high yields, and high return of money (Xu et al., 2022). In relation to the study's theory, data-driven crop recommendation relied on real-time field data from sensors and hardware devices to provide farmers with accurate, data-driven information about the field environment.

In addition, the Decision Support System (DSS) transforms various data inputs into useful information to support recommendations and assist farmers' decision-making. The DSS approach is a computer-based system that supports complex decision-making by integrating data management, analytical models, and user interaction. The data subsystem, the model subsystem, and the dialog or interface subsystem are the theory's three core components (Sprague & Carlson, 1982). In relation to this study, the DSS supports the reviewed systems based on their data inputs, decision logic, and deployment interfaces that are classified and analyzed. The DSS theory explains the agricultural data that are processed through analytical models to produce actionable recommendations for farmers. DSS theory provides a conceptual foundation for intelligent data-driven crop recommendation systems.

This research proposes an Intelligent Data-Driven Crop Recommendation System for Farmers: A Systematic Review and Classification, in response to the problem of poor crop choices, insufficient access to scientific guidance, and rising climate variability faced by Filipino farmers. In addition, a meta-analysis will be used to synthesize and assess findings from selected studies, aiming to integrate statistical results into new findings. This study aimed to support farmers in choosing appropriate crops by providing data-driven information from the research and studies conducted. The objective was to compare and analyze the gathered data, determine trends in previous studies regarding hardware use, data sources, modeling techniques, and farmer results used in crop recommendations.

## THEORETICAL FRAMEWORK

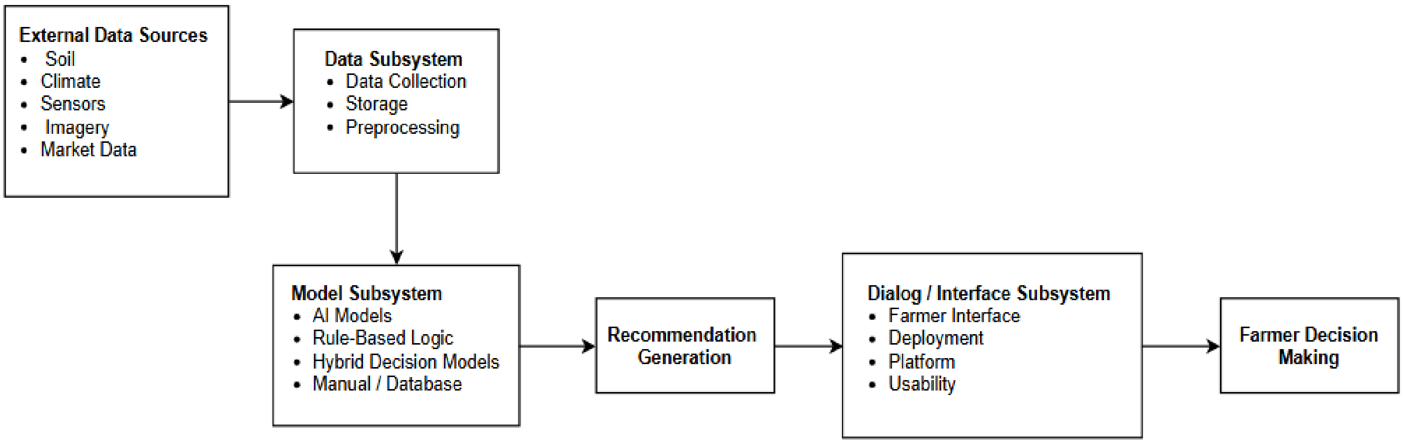


**Figure 1. Theoretical Framework**

The Decision Support System (DSS) theory presents a foundational framework for evaluating systems that transform raw data collected from studies into a useful recommendation system for farmers' crop decision-making. The theory that explains the integration of data, analytical models, and user interaction mechanisms is the role of computer-based systems in facilitating complex and semi-structured decision-making, as stated by Sprague and Carlson (1982) and Power (2002). Gathering different types of raw data on soil characteristics, climatic conditions, sensor readings, and remote sensing imagery collected from agricultural settings is being evaluated using analytical or artificial intelligence models to provide crop-related recommendations, implemented through intelligent crop recommendation systems that serve as decision support systems. For synthesizing the literature and interpreting trends in intelligent data-driven crop recommendation systems, the DSS theory offers a systematic approach and is employed in the study's theoretical framework that serves as a foundation in organizing and comparing existing crop recommendation systems' results based on the gathered data sources, modeling approaches, and deployment interfaces, rather than using and testing causal relationship frameworks.

**Conceptual Framework**

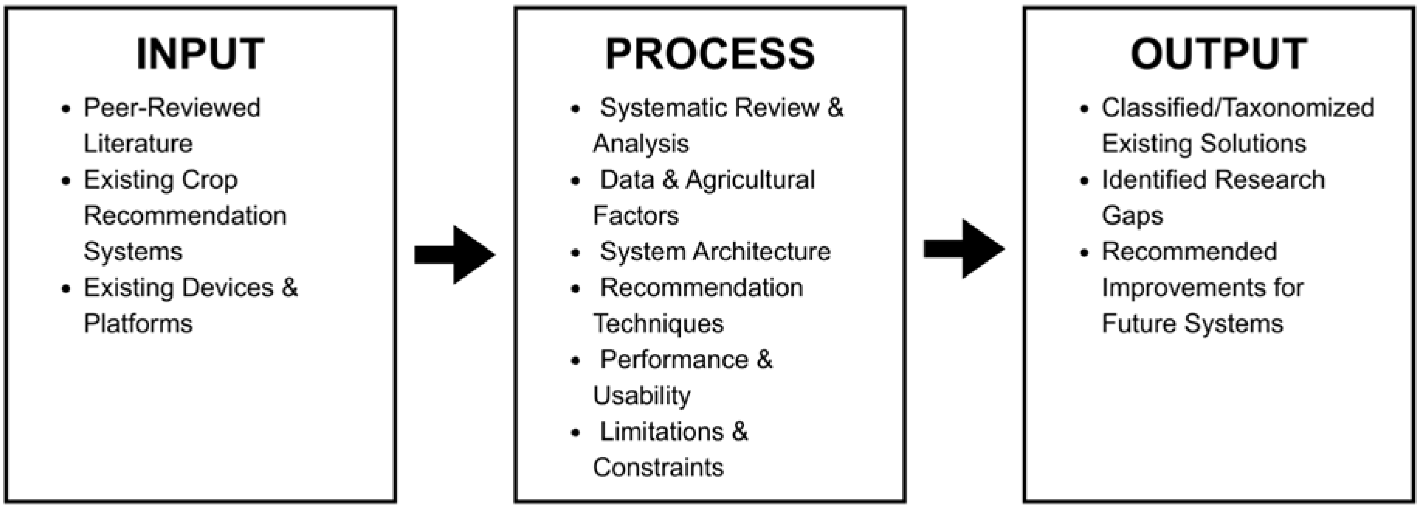


**Figure 2. Conceptual Framework**

The input process includes peer-reviewed literature, existing crop recommendation systems, and devices and platforms documented in the collected studies. The systematic review and analysis of these inputs by examining agricultural and environmental data factors, system architecture, and recommendation techniques, performance and usability, and reported limitations and constraints are what the process method ensures to evaluate the data. The classified and taxonomized existing system solutions, identified research gaps, and recommended improvements for future data-driven crop recommendation systems are utilized in the framework's output segment.

**Research Objective**

1. To identify and prioritize key agricultural elements that determine crop suitability for Filipino farming contexts.
2. To collect, compare, and classify existing crop recommendation systems to show what solution types have been developed, categorized by method, architecture, or approach.
3. To analyze recurring limitations, barriers, and research gaps found in the related literature, such as data scarcity, lack of local calibration, explainability, cost, connectivity, and usability.
4. To synthesize actionable, practical research recommendations based on the review and to guide the development of improved crop recommendation systems that are adoptable by farmers.

## METHODOLOGY

**Research Approach**

This study uses a systematic review, secondary data analysis (SDA), and meta-analysis to examine intelligent, data-driven crop recommendation systems. The systematic review method was selected to clarify, ensure transparency, and make the search, assessment, and synthesis of relevant literature reproducible.

To reduce bias in this literature review, the PRISMA 2020 guidelines were followed and adapted for this method. These guidelines helped ensure clarity during the identification, screening, and inclusion of studies.

**Search Strategy and Data Sources**

The researcher carried out a systematic literature search using several academic databases, such as (1) Google Scholar, (2) IEEE Xplore, (3) ScienceDirect, and (4) SpringerLink

The researcher used the following keywords in our search:

- "crop recommendation system,"
- "precision agriculture,"
- "machine learning in agriculture,"
- "IoT-based farming,"
- "smart agriculture systems,"
- "data-driven agriculture."

The researcher applied search filters using Boolean operators such as AND and OR. Only studies published from 2015 to 2026 were included to focus on recent advances in agricultural technology.

**Inclusion and Exclusion Criteria**

To ensure clarity and consistency in the study selection process, specific inclusion and exclusion criteria were established. Studies were included if they focused on crop recommendation systems that used artificial intelligence, the Internet of Things, or other data-driven approaches. Eligible sources comprised peer-reviewed journal articles, conference papers, and reputable academic theses that detailed their methodologies, system designs, or evaluation outcomes. Only publications written in English were considered to maintain consistency in analysis.

The researcher excluded studies that did not provide sufficient technical or methodological detail, as this made it difficult to assess their value. The researcher also excluded papers that were purely conceptual and did not include implementation, experiments, or evaluation. Duplicate studies were removed to prevent bias, and we excluded studies that were not directly related to agriculture or crop recommendation systems.

**Study Selection Process**

Study selection was conducted in a systematic four-stage screening process:

1. Identification - the first search results were retrieved from targeted databases.
2. Screening - irrelevant studies were excluded based on title/abstract review.
3. Eligibility Assessment - Full-text articles were assessed against the inclusion and exclusion criteria.
4. Final Inclusion - Twenty (20) of these were selected for the detailed study.

This process is conducted to ensure reproducibility and minimize selection bias in the review.

**Data Collection Instruments**

A Standardized Extraction Form (SEF) was developed to promote consistency and accuracy in data collection across all included studies. The development and application of the SEF were guided by existing recommendations for data collection and systematic reviews (Page et al., 2021; Higgins et al., 2019) and by methodological guidance for designing and pilot testing data extraction forms (Büchter et al., 2020). The SEF comprised the following categories:

1. Bibliographic information, including author, year, and country
2. System classification, such as AI-based, rule-based, or hybrid systems
3. Types of data inputs, including soil, weather, imagery, and economic data
4. Hardware components, such as sensors and microcontrollers
5. Modeling techniques, including machine learning (ML), deep learning (DL), and rule-based approaches

6. Evaluation metrics and methods for validation
7. Deployment platforms, such as cloud, mobile, edge, or dedicated hardware
8. Reported limitations and identified research gaps

**Data Gathering Procedure**

Each selected study underwent a systematic review using a structured, standardized approach to ensure consistency, accuracy, and transparency in data extraction. A Standardized Extraction Form (SEF) was employed to collect relevant information, including bibliographic details, system classification, data inputs, hardware components, modeling techniques, deployment strategies, evaluation methods, and reported limitations. The extracted data were encoded into a structured dataset, such as a spreadsheet, to promote uniformity, facilitate cross-study comparison, and support subsequent quantitative and qualitative analyses.

To minimize bias and enhance reliability, data extraction utilized predefined categories and consistent coding schemes. Key terminologies, including algorithm types (such as machine learning and deep learning), system classifications (such as AI-based, rule-based, and hybrid), and data input types (such as soil parameters and weather data), were standardized across all entries to ensure comparability. When data were incomplete, ambiguous, or inconsistently reported, verification was performed through cross-checking with the original source. If information remained unclear or unverifiable, it was excluded from the dataset to preserve data integrity.

Qualitative observations were systematically recorded alongside quantitative data. These included reported system limitations, usability concerns, implementation challenges, and research gaps identified in each study. The qualitative data were analyzed and grouped into thematic categories through coding to identify recurring patterns and trends. This integrated approach to quantitative and qualitative data gathering provided a comprehensive and rigorous foundation for the classification, analysis, and synthesis of intelligent data-driven crop recommendation systems.

**Data Processing and Analysis**

The collected data were analyzed using both quantitative and qualitative techniques to achieve a comprehensive and systematic interpretation of the findings. Descriptive frequency analysis was initially employed to quantify the occurrence of specific features, including the use of artificial intelligence, sensor types, and deployment platforms, across the selected studies. This approach yielded a quantitative overview of trends and patterns within existing crop recommendation systems. Additionally, mode identification was used to determine the most prevalent characteristics within each category, such as commonly used data inputs, modeling approaches, and deployment methods.

To further examine relationships between key variables, cross-tabulation analysis was conducted. This method facilitated the exploration of associations between system classification and other attributes, such as data inputs and deployment strategies, thereby providing deeper insights into the interconnections among system components. Furthermore, qualitative thematic analysis was applied to textual data extracted from the studies, with particular attention to recurring themes related to system limitations, research gaps, and implementation challenges. These themes were identified through a systematic coding process and subsequently grouped into higher-level categories to support interpretation.

The integration of these quantitative and qualitative analytical techniques constitutes a mixed-method approach that enhances both the depth and reliability of the findings. This approach ensures a more robust classification and evaluation of intelligent data-driven crop recommendation systems.

**Ethical Consideration**

This study uses data from publicly available academic sources. All sources are properly cited and credited. No human participants were involved, and the research is intended only for academic purposes.

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## RESULTS AND DISCUSSION

**Table 1. System Classification Frequency Table**

| System Classification | Frequency (n) | Percentage (%) |
| --- | --- | --- |
| AI – Based | 18 | 90% |
| Rule – Based | 5 | 25% |

The results show that eighteen (18) studies integrated AI-based systems (90%), indicating the prevalent use of Artificial Intelligence in crop recommendation systems. On the other hand, five (5) studies implemented rule-based systems (25%), which are based on predefined rules and logic in recommending crops. Moreover, other studies utilized a combination of AI-based and rule-based mechanisms, and these studies are counted in both categories, showing the use of both intelligent algorithms and pre-defined rules in crop recommendation systems. Thus, the findings indicate that AI-based crop recommendation systems are more widely used than rule-based methods, but are often used together in hybrid systems.

**Table 2. Reported Data Input Frequency Table**

| Reported Data Inputs | Frequency (n) | Percentage (%) |
| --- | --- | --- |
| Soil Parameters | 19 | 95% |
| Weather Data | 16 | 80% |
| Geographical Data | 4 | 20% |
| Imagery | 1 | 5% |
| Economic Data | 1 | 5% |

The results show that nineteen (19) studies integrated Soil Parameters (95%), indicating that soil parameters such as NPK, pH level, and moisture are most utilized and relevant in crop recommendation systems for data inputs. On the other hand, weather data are used in sixteen (16) studies (80%), geographical data are used in four (4) studies (40%), while imagery and economic data were used in only one (1) study (5%). Various studies used multiple parameters and therefore counted as more than one category. Thus, findings indicate that soil parameters are the most significant data inputs for crop recommendation systems.

**Table 3. Utilized Microcontroller Frequency Table**

| Microcontroller | Frequency (n) | Percentage (%) |
| --- | --- | --- |
| ESP 8286 | 3 | 15% |
| Arduino UNO | 2 | 10% |
| Arduino NANO | 1 | 5% |
| ESP 32 | 1 | 5% |
| Raspberry pi 3 | 1 | 5% |
| Raspberry pi 5 | 1 | 5% |
| Raspberry pi 4b | 1 | 5% |

The results show that ESP8266 is the most used microcontroller, appearing in three (3) studies (15%). On the other hand, Arduino UNO is used in two (2) studies (10%), while Arduino NANO, ESP32, Raspberry Pi 3; Raspberry Pi 5, and Raspberry Pi 4b were each used in only one (1) study (5%). Additionally, only the studies that mentioned the use of microcontrollers were counted in the categories. Thus, the findings indicate that the ESP8266 is the most integrated microcontroller, but both the ESP and Arduino boards are commonly used in crop recommendation systems.

**Table 4. Utilized Sensors Frequency Table**

| Sensor | Frequency (n) | Percentage (%) |
|---|---|---|
| Soil Moisture Sensor | 6 | 30% |
| Soil NPK Sensor | 6 | 30% |
| Soil Ph Level Sensor | 5 | 25% |
| Temperature Sensor | 5 | 25% |
| Humidity Sensor | 3 | 15% |
| Rainfall Sensor | 2 | 10% |
| LDR Sensor | 1 | 5% |
| TDS Sensor | 1 | 5% |

The results show that soil sensors, such as soil moisture and soil NPK, were the most frequently used, both appearing in six (6) studies (30%). On the other hand, Soil pH, and temperature sensor were utilized in five (5) studies (25%), while humidity sensors appear in three (3) studies (15%), rainfall sensors in two (2) studies (10%), while LDR and TDS sensors are integrated only in one (1) study (5%). Thus, the findings indicate that soil sensors (moisture, NPK, pH) are the most commonly integrated, followed by environmental sensors (temperature, humidity), in crop recommendation systems.

**Table 5. Modeling/ Decision Logic Frequency Table**

| Modeling/Decision Logic | Frequency (n) | Percentage (%) |
|---|---|---|
| Machine Learning | 10 | 50% |
| Deep Learning | 8 | 40% |
| Rule-Based | 2 | 10% |

The results show the machine learning approach as the most frequently used, appearing in ten (10) studies (50%). On the other hand, deep learning was utilized in eight (8) studies (40%), while the rule-based approach appeared in two (2) studies (10%). Moreover, deep learning is treated as a distinct field, even though it's a subcategory of machine learning, to highlight studies that utilize neural networks. Thus, the findings indicate that data-driven approaches, especially machine learning and advanced deep learning, are more commonly used than pure rule-based decision logic in crop recommendation systems.

**Table 6. Deployment Frequency Table**

| Deployment | Frequency (n) | Percentage (%) |
|---|---|---|
| Cloud | 11 | 55% |
| None | 6 | 30% |
| Hardware Device | 6 | 30% |
| Web | 3 | 15% |
| Mobile | 3 | 15% |
| Blockchain | 1 | 5% |
| TinyML | 1 | 5% |

The results show that cloud-based deployment is the most common, appearing in eleven (11) studies (55%). On the other hand, hardware device utilization and systems with no clearly specified deployment appeared in six (6) studies (30%), while web and mobile-based interfaces were used in three (3) studies (15%). Moreover, blockchain and TinyML implementation only appeared in one (1) study (5%). Various studies integrated multiple deployment methods and, therefore, counted in more than one category. Thus, the findings indicate that cloud-based deployment is the most widely used approach, but it is often combined with other approaches in hybrid implementations of crop recommendation systems.

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**Table 7. Mode of each Category Table**

| Category | Most Frequent Attribute | Frequency (n) |
|---|---|---|
| System Classification | AI-Based | 19 |
| Reported Data Inputs | Soil Parameters | 19 |
| Deployment | Cloud | 11 |
| Modeling /Decision Logic | Deep Learning | 10 |
| Sensors | Soil Moisture/Soil Ph Level Sensors | 5 |
| Microcontrollers | ESP | 3 |

The results show the mode of each category to indicate the most common signifying dominance by frequency of occurrence in the reviewed studies. Furthermore, AI-based systems are the most frequent system classification appearing in nineteen (19) studies. Additionally, the use of soil parameters for data inputs, and soil-related sensing for sensors appeared in nineteen (19) and five (5) studies, respectively, while ESP boards dominate as the most used microcontroller, appearing in three (3) studies (15%). Moreover, deep learning is the most utilized modelling and decision logic, appearing in ten (10) studies. Lastly, deployment through cloud-based implementation appeared in eleven (11) studies. Thus, the findings indicate a current trend toward implementing AI-based, cloud-deployed systems that rely primarily on soil parameters, supported by ESP microcontrollers and soil-monitoring sensors, and that utilize deep learning in crop recommendation systems.

**Table 8. Cross Tabulation of System Classification and Reported Data Inputs**

| | System Classification | |
|---|---|---|
| Reported Data Inputs | AI-Based | Rule-Based |
| Soil Parameters | 19 | 5 |
| Weather Data | 15 | 4 |
| Geographical Data | 5 | 0 |
| Imagery | 1 | 0 |
| Economic Data | 1 | 0 |

The results show the relationship between system classification and the data inputs used, as shown in the cross-tabulation. In AI-Based systems, eighteen (18) utilized soil parameters, fifteen (15) used weather data, five (5) incorporated geographical data, and one (1) included imagery and economic data. On the other hand, Rule-Based systems show five (5) utilizing soil parameters, four (4) using weather data, one (1) incorporating geographical data, and none using imagery or economic data. The tabulation exceeds twenty (20) since some studies utilize both AI-Based and Rule-Based approaches, and multiple data inputs. Thus, the findings indicate that both system classifications primarily rely on soil data, whereas AI-based systems use a wider range of data inputs for crop recommendation.

**Table 9. Cross Tabulation of System Classification and Deployment**

| | System Classification | |
|---|---|---|
| Deployment | AI-Based | Rule-Based |
| Cloud | 11 | 2 |
| None | 6 | 2 |
| Hardware Device | 6 | 1 |
| Web | 3 | 0 |
| Mobile | 3 | 1 |
| Blockchain | 1 | 0 |
| TinyML | 1 | 0 |

The results show the relationship between system classification and deployment methods using cross-tabulation. In AI-Based systems, six (6) had no specific deployment, eleven (11) were deployed on cloud platforms, three (3) on web and mobile, six (6) on hardware devices, and one (1) each on blockchain and TinyML. On the other hand, Rule-Based systems show two (2) with no deployment, two (2) in the cloud, one (1) on mobile and hardware, and none on the web, blockchain, or TinyML. Thus, findings of the cross tabulation indicate the comparison of deployment patterns relative to the used system classification, showing that AI-Based systems rely primarily on cloud deployment, incorporating web, mobile, and hardware for flexibility in interface and architecture, while Rule-Based systems use fewer deployment methods and focus only on cloud and hardware interface for crop recommendation systems.

**Thematic Analysis of Reported Limitations**

The implementation and adoption constraints noted across all crop recommendation systems under investigation are summarized in this thematic analysis. Recurring limiting statements were classified into higher-level themes using the qualitative fields extracted from the standardized extraction form. If a topic had a direct impact on the system's viability, was limited by datasets, and had few data coverage or practical implementation for farmers, it was classified as a limitation.

**Data and Dataset Limitations**

There were 29 instances of constraints on dataset quality and availability in numerous research studies. Data imbalance and model risks were also noted, including "class imbalance/small class support," "potential overfitting," and "possible overfitting (100% train accuracy)." Several studies also highlighted that "system performance depends heavily on quantity and quality of data," that "models are prone to errors when data is insufficient or not representative," and that "model correctness depends on training data quality." Common problems included "limited dataset size and diversity," "static dataset," and "small/augmented dataset.

**Infrastructure and Implementation Constraints**

With 23 instances, a number of research documented technical implementation and system infrastructure hurdles. These include dependence on hardware and connectivity (e.g., “dependence on sensor accuracy and calibration,” “sensor setup and maintenance,” and “initial hardware investment needed”); connectivity constraints (e.g., “Wi-Fi connectivity is needed for real-time data transmission,” “data collection dependent on IoT connectivity,” and “dependence on smartphone availability and internet/cloud”); and other constraints (e.g., “compute and communication costs,” “computational resources for neural training,” and “implementation/tuning complexity."

**Real-World Implementation and Validation Limitations**

Making 26 appearances. Limited system deployment and validation in actual agricultural settings was another recurrent theme. Other obstacles included "limited real-world validation," "no field testing or farmer trials," and "no hardware or edge deployment plan." Some studies also lacked evaluation details, such as "no quantitative predictive performance metrics provided," "no quantitative accuracy comparison with ML models," and "missing reproducibility details." A number of studies reported "limited geographic scope," "geographical testing limited to Rayagada district," or "geographic scope limited to Bangladesh."

**Table 10. Thematic Analysis of Reported Limitations**

| Themes | Frequency (n) |
|---|---|
| Data and Dataset Limitation | 29 |
| Infrastructure and Implementation Limitation | 23 |
| Real-World Implementation and Validation Limitations | 26 |

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### Thematic Analysis for Reported Research Gaps

The research gaps mentioned in the analyzed studies of crop recommendation systems are summarized in this thematic analysis. Repeating gaps were classified and categorized into themes using the qualitative fields extracted in the standardized extraction form. If a research gap mentioned Dataset expansion, explored or used more advanced modeling, or suggested a better explainable/usable device, it was identified as a gap.

### Data Coverage and Dataset Expansion

Research gaps related to increasing the number and diversity of datasets were found in 18 studies. Larger, more comprehensive datasets, "expand data collection & coverage," and the "need for larger, diverse, and real-world datasets" are among the suggested improvements. Other studies suggested different contexts for the parameters, such as "region-specific agricultural and climate data" and "environmental & geographic variables."Other gaps include "expand geographic coverage/dataset size" and "geographic generalization," which highlight the need for more extensive and representative agricultural datasets.

### Modeling and Algorithm Development

At 16 occurrences, several studies highlighted gaps in the development and evaluation of advanced modeling techniques. These include the need for “more advanced AI models,” “additional ML approaches,” and “hybrid or ensemble XAI-enhanced models.” Other suggested improvements include “temporal modeling,” “feature engineering,” and “handle overfitting better,” “improve classifier performance,” and “improve robustness & generalization.” Since most studies have approached crop recommendation systems using machine learning, including deep learning, these gaps indicate opportunities to improve prediction accuracy and modeling capabilities.

### Explainability and Usability

Limitations in system usability and transparency were mentioned in the studies 11 times. Interpretability is crucial for farmers' trust, according to research highlighting the need for "explainable AI (XAI)" and "explainable recommendations." Some gaps include "policy-level agricultural decision support integration" and "conduct a survey among farmers," underscoring the need for more user-friendly and accessible crop recommendation systems. Other recommended improvements include "farmer-centered usability evaluation," "mobile application integration," and "develop a mobile application that integrates proposed models."

**Table 11. Thematic Analysis of Research Gaps**

| Themes | Frequency (n) |
|---|---|
| Data Coverage and Dataset Expansion | 18 |
| Modeling and Algorithm Development | 16 |
| Explainability and Usability | 11 |

## CONCLUSION

One of the most important agricultural factors is soil parameters, occurring in nineteen (19) studies (95%), followed by weather parameters in sixteen (16) studies (80%). The less common parameters include Geographical, image, and economic parameters, as NPK values, pH, moisture, and major meteorological factors are considered the most important inputs for crop recommendation. Appearing in eighteen (18) studies (90%), AI systems are the most prevalent in crop recommendation system approaches, while the rule-based systems are less frequent, appearing in five (5) studies (25%). Machine learning is the most widely used for modeling and decision logic (10 studies, 50%), followed by deep learning (8 studies, 40%), while rule-based logic is less frequently used (2 studies, 10%). For architecture, one of most widely used (11 studies, 55%) is cloud computing, followed by hardware or embedded systems with no deployment (6 studies each, 30%), while web and mobile platforms are less frequent (3 studies each, 15%), and blockchain and TinyML are less frequent (1 study each, 5%). Recurring implementation barriers are data and dataset limitations (29 instances); infrastructure and implementation constraints (23 instances); and real-world and validation limitations (26 instances). This imposes constraints on real-world usability and on the likelihood that it will be engineered into a system. The major gaps in the research involve a lack of coverage of datasets and data being stated (18 studies, 90%), and a lack of use of more advanced models or algorithms for machine learning approaches (16 studies, 80%). Lastly, explainability and usability of the system itself (11 studies, 55%). The systems should be designed to be much more explainable and farmer-centric that can improve trust and usability, does it include creating larger, more diverse and local datasets that has been conducted in multi-site field trials and validation, model interpretability should be improved along with uncertainty quantification, and also the underutilized inputs such as images and economic data, and lastly opening benchmarks to improve comparability and generability of the system.

## RECOMMENDATION

To address these limitations, the study recommends the development of more practical and accessible solutions. Future systems should incorporate low-cost modular sensors to enable affordable data collection directly from the field. The integration of hybrid cloud–edge computing or TinyML deployment is also suggested to reduce reliance on continuous internet connectivity while maintaining efficient system performance. Moreover, the researchers emphasize the importance of developing locally representative agricultural datasets and conducting extensive field validation to ensure that the recommendations are accurate and applicable to specific farming conditions. Overall, the study contributes meaningful insights toward the development of climate-resilient, accessible, and farmer-friendly crop recommendation systems that can enhance agricultural productivity and sustainability in the Philippines.

## REFERENCES

1. Ama, N. A., Apdo, R. L., Baclayon, E. K., Boctot, J., Degorio, M. J., Demiao, A., Jason, R. J., Lacbanes, M. R., Malaki, K., & Nuñez, E. (2025). Assessing the relationship between farmer's perception to agricultural practices, risk management and sustainability. https://doi.org/10.21203/rs.3.rs-6893174/v1
2. Braun, V., & Clarke, V. (2006). Using Thematic Analysis in Psychology. Qualitative Research in Psychology, 3, 77–101. Scientific Research Publishing. https://www.scirp.org/reference/referencespapers?referenceid=1596232
3. Büchter, R. B., Weise, A., & Pieper, D. (2020). Development, testing and use of data extraction forms in systematic reviews: A review of methodological guidance. BMC Medical Research Methodology, 20(1), 1–14. https://bmcmedresmethodol.biomedcentral.com/articles/10.1186/s12874-020-01143-3
4. Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive Sampling: Complex or Simple? Research Case Examples. Journal of Research in Nursing, 25(8), 652–661. https://doi.org/10.1177/1744987120927206
5. Cooksey, R. W. (2020). Descriptive Statistics for Summarising Data. Illustrating Statistical Procedures: Finding Meaning in Quantitative Data, 1(1), 61–139. https://doi.org/10.1007/978-981-15-2537-7_5
6. Cross-Tabulation Analysis: A Researcher's Guide – Qualtrics. (2018). Qualtrics. https://www.qualtrics.com/articles/strategy-research/cross-tabulation/
7. Department of Agriculture. (n.d.). Climate-resilient agriculture (CRA) considerations. https://amia.da.gov.ph/wp-content/uploads/2025/01/Annex-2.-Full-version-of-the-CRA-country-profile.pdf
8. Harrod, T. (2023, September 25). Research Guides: Study Design 101: Meta-Analysis. Guides.himmelfarb.gwu.edu. https://guides.himmelfarb.gwu.edu/studydesign101/metaanalysis
9. National University of Singapore. (2023). What is a systematic review? https://medicine.nus.edu.sg/rsu/service/systematic-review/what-is-a-systematic-review/
10. Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., & McGuinness, L. A. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. British Medical Journal, 372(160). https://doi.org/10.1136/bmj.n160

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue III March 2026

11. PhilSEED. (2023, May 18). Top 5 challenges faced by Filipino farmers today. https://www.philseed.org/post/top-5-challenges-faced-by-filipino-farmers-today
12. Sprague, R. H., & Carlson, E. D. (1982). Building effective decision support systems. Prentice-Hall. Retrieved January 16, 2026 from https://books.google.com/books/about/Building_Effective_Decision_Support_Syst.html?id=89_sPTAmkVsC
13. Trần, M. H. (2024, September 22). Smallholder farmers' challenges and opportunities: Implications for agricultural production, environment and f. HAPRI. https://www.hapri.org/post/smallholder-farmers-challenges-and-opportunities-implications-for-agricultural-production-environ
14. Xu, J., Gu, B., & Tian, G. (2022). Review of agricultural IoT technology. Artificial Intelligence in Agriculture, 6. https://doi.org/10.1016/j.aiia.2022.01.001