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Intelligent Multimodal Decision Support Systems for Smart Agriculture: A Comprehensive Survey, Taxonomy, and Research Directions

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Abstract—the conventional Artificial intelligence (AI) is revolutionizing modern agriculture in terms of intelligent soil analysis, crop recommendation and plant disease detection systems. Although each module performs well in its prediction task, the current deterministic solutions focus on execution isolation and lack of holistic agricultural decision support. In this survey, we provide a systematic and critical review of AI-based agricultural systems with focus on multimodal learning and explainable AI. We give a taxonomy of current methods, comparisons between the models research, identification of research gaps and architectural information for unified decision support systems. The results underscore the need of integrated, scalable and interpretability capital sable in multi-modal systems for sustainable smart agriculture.
Index Terms—Smart Agriculture, Common modal learning, Crop Recommendation, Soil Classification, Plant Disease Detection, Explainable AI.

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I. INTRODUCTION

Insatiable demands for sustainable food production, climate resilience and precision agriculture have pushed for fast uptake of artificial intelligence (AI) in the field of agriculture. AI-centric systems have shown potentially useful results in soil fertility prediction, crop recommendation and disease diagnosis. Nevertheless, the current studies mainly concentrated on single tasks rather than systematic agricultural intelligence.

Decisions in the agro landscape around the world, evolve under a scenario of soil patterns, environmental variables and plant health relationships. This calls for the development of a multimodal decision support system in which structured soil data, visual soil classification and plant disease detection are integrated into one single computational framework.

This work provides an in-depth overview of the recent developments, as well as architectural and deployment limitations in state-of-the-art AI driven agricultural systems.

II. SURVEY METHODOLOGY

To guarantee adequate coverage as well as analysis, this review adopts a structured review process. The review process consisted of the following four stages: Findings Literature search Screening Appraisal Eligibility Final included studies.

A. Literature Sources and Search Strategy

We obtained studies from the main academic databases such as IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, and Google Scholar. Search terms were used in a combination of the following:

- "AI in agriculture"
- "soil classification using machine learning"
- "crop recommendation system"
- "plant disease detection deep learning"
- "multimodal learning in agriculture"
- "explainable AI for agriculture"

The review was mainly based on studies published from2016 and 2025 focusing on recent works from 2022 to present time (2022) in order to reflect the current trend of multimodal and explainable agricultural intelligence.

B. Inclusion and Exclusion Criteria

The following inclusion criteria were applied:

- Peer-reviewed journal articles and high-impact conference papers
- Submissions on machine learning, or deep learning mechanism studies

- Analyses of the soil, crop recommendation or disease detection.

Exclusion criteria included:

- Purely conceptual papers without implementation
- Studies unrelated to agricultural intelligence
- Duplicate or redundant publications

C. Screening and Selection Process

(Initial literature searches were derived from a pool of more than 80 publications through the use of keywords.) Following the abstract-level evaluation, 40 studies were selected concerning relevance and technical depth. A third sample of influential works to characterize was taken for further comparative analysis.

D. Evaluation Framework

Each selected study was evaluated based on the following parameters:

- Type of data utilized (i.e., structured, image-based, or multimodal)
- Machine learning or deep learning architecture
- Level of integration across agricultural tasks
- Use of explainable AI mechanisms
- Deployment feasibility and scalability

This organized assessment made it possible to identify common architectural patterns, points of integration, and future research directions in the field of AI-driven smart agriculture.

III. TAXONOMY OF AI IN AGRICULTURE

AI-based agricultural systems can be categorized into four major groups:

1) Soil Analysis Systems
2) Crop Recommendation Systems
3) Plant Disease Detection Systems
4) Multimodal Explainable Systems

IV. AI-BASED SOIL INTELLIGENCE SYSTEMS

Soil health evaluation is an essential part of agricultural options, as it impacts crop range for production, potential measures of harvest yield and farming that are nutrient based. Artificial intelligence methods have also been applied extensively to increase the accuracy and automation of soil analysis.

A. Structured Soil Nutrient-Based Approaches

Currently, most of the AI-based soil systems in the early stage depend on laboratory-based structured measurements of nitrogen (N), phosphorous (P), potassium (K), pH, organic carbon and percentage moisture. Supervised machine learning algorithms such as Random Forest, Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Artificial Neural Networks (ANN) are commonly employed to predict soil fertility or recommend crops.

Random Forest models are most commonly used for their resistance to overfitting and to account for nonlinear relationship between soil parameters. Nevertheless, such models rely heavily on reliable laboratory measurements which may not always be available in rural farming areas.

B. Image-Based Soil Classification Using Deep Learning

Recent developments examine soil type classification methods using field images, by computer vision approaches. Convolutional Neural Networks (CNNs), such as ResNet and MobileNet structures, have been developed to classify the soil texture and category based on images taken in measure.

Soil analysis using image provides an economical alternative to the lab test as well as quick in field evaluation. Yet, data diversity in terms of datasets, light conditions and texture heterogeneity still constitute a bottleneck that may partly disrupt the generalization performance across geographic regions.

C. Feature Engineering and Hybrid Models

Some reports incorporate environmental factors like rainfall, temperature, and humidity together with soil's nutrient attributes to improve the reliability of prediction. Hybrid ensemble algorithms such as those employing decision trees and neural networks (NNs) have achieved higher accuracy for modeling soil fertility predictions.

Even so, many of the hybrid systems continue to work within single-task scenarios without interacting with monitoring of plant health and detection of crop diseases.

D. Limitations and Research Observations

Based on the surveyed literature, the following limitations are observed:

- Dependence on laboratory-based soil nutrient testing
- Limited large-scale image-based soil datasets
- Minimal integration with disease monitoring systems
- Lack of explainability mechanisms in soil prediction models
- Poor generalization across diverse agro-climatic zones

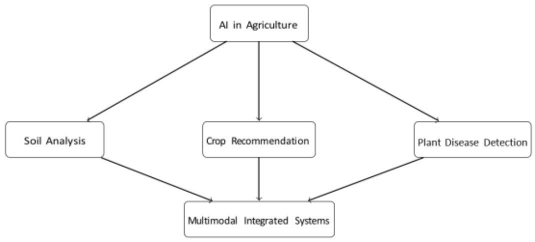

Figure.1.Taxonomy of AI-Based Agricultural Intelligence Systems

These limitations highlight the necessity of transitioning from isolated soil intelligence modules toward integrated multimodal frameworks capable of combining structured metrics and visual analysis for comprehensive agricultural decision support.

V. CROP RECOMMENDATION SYSTEMS

Recommendation Systems on Crops are designed to help farmers to choose crops according soil, climates and surroundings. Such systems are based on supervised machine learning algorithms and they are developed by training structured agricultural datasets.

A. Machine Learning-Based Crop Recommendation

Traditional crop recommendation models utilize soil nutrient parameters (N, P, K), pH values, rainfall, temperature, and humidity as input features. Commonly employed algorithms include Decision Trees, Random Forest, Naive Bayes, Support Vector Machines (SVM), and Multi-Layer Perceptrons (MLP).

Among these, Random Forest and Gradient Boosting models have demonstrated strong performance due to their ability to capture nonlinear relationships and handle feature interactions effectively. Ensemble methods often outperform

Single model approaches, particularly in heterogeneous agricultural datasets.

However, these systems typically assume static environmental conditions and may not account for dynamic crop health variations or disease risks.

B. Deep Learning and Hybrid Approaches

Recent studies utilize deep neural networks to capture intricate interrelationships between soil nutrients and environmental variables. Hybrid models between neural network and rule based systems have been also experimented to make the classifier more interpretable.

Despite better prediction performance, a majority of the current deep learning crop recommendation systems still count on the huge and balanced datasets, which are not always accessible in agriculture specific regions.

C. Explainable AI in Crop Recommendation

Explainable AI (XAI) techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable ModelAgnostic Explanations) have recently been integrated into crop recommendation systems to enhance transparency.

Explainability is particularly critical in agriculture, where farmers require understandable justifications for recommendations. Systems like AgroXAI demonstrate that interpretability mechanisms can improve user trust and adoption rates.

However, existing XAI-supported systems are mainly restricted to well-structured input features without involving multimodal signals like soil image or plant disease detection.

D. Limitations and Observations

The drawbacks of the literature survey are:

- Reliance on applications of inorganic fertilizer as soil nutrient inputs
- Those real-time plant health cues are not filtering into the root-soil interface as much needed.
- No integration with disease surveillance systems
- Regional dataset bias and its impact on generalization
- Lack of validation of deployment in rural settings

These implications suggest the next generation of CMS should not be limited to structured data but combined with visual and health signals in a unified multimodal framework.

VI. DEEP LEARNING FOR PLANT DISEASE DETECTION

Plant diseases significantly impact agricultural productivity and food security Rapid and accurate diagnosis is critical to reduce yield losses and target control strategies. In recent years, the performance of automated plant disease classification has been particularly impressive with deep learning methods especially Convolutional Neural Networks (CNNs).

A. CNN-Based Disease Classification

General CNNs like AlexNet, VGGNet, ResNet, DenseNet and Efficient- Net have been extensively used in leaf-based disease detec tion works. Of these, ResNet architectures in particular are effective because of the residual connections that help to alleviate vanishing gradient problems and make it possible to train a deeper network.

Transfer learning methods are widely applied in practice to utilize pre-trained models on large image datasets, which can greatly save the requirement of plenty of agricultural images. Application of pre-trained networks can achieve high classification accuracy for several crop types.

B. Public Datasets and Generalization Challenges

The PlantVillage dataset has been still the most popular benchmark in plant disease detection. Although it includes a large collection of labeled samples, the majority of images are taken in a controlled laboratory setup with relatively homogeneous backgrounds.

Therefore, models learned upon those datasets alone may not be able to cope with images collected in the field from actual environment with varying lighting conditions, background noise, occlusions, etc. Domain gap between lab and field settings is still a strong source of generalization error.

C. Advanced Techniques and Improvements

New research into attention mechanisms, ensemble CNNs and vision transformer-based models have been a few primary voices for improving robustness classification. Some of the methods involve solving data augmentation and synthetic creation in order to overcome lower generalization capability of models.

Nevertheless, most of disease detection systems today are implemented as separate diagnostic tools and they are not integrated to a bigger context like decision support systems in agriculture.

D. Deployment and Practical Limitations

However, deep learning models have the following limitations practice:

- Low latency and high computational demands for edge processing
- Light and environment sensitivity
- Integration with soil and crop technology recommendations is restricted
- Lack of interpretability in most CNN based models
- Data imbalance namely between classes of diseases

These challenges suggest that plant disease detection cannot be treated as a standalone classification task, but instead incorporated into an overall agricultural decision support system.

VII. DATASETS AND BENCHMARKING CHALLENGES

Performance of AI-based agriculture systems highly depends on availability, quality and diversity of data. While model architectures have moved forward leaps and bounds, it still cannot overcome the bottleneck of dataset-related constraints to a reliable deployment of agricultural intelligence systems.

A. Structured Agricultural Datasets

Most crop recommendation, and soil fertility prediction study are based on structured datasets that contain values of NPK nutrients, pH, rainfall, temperature, humidity and of statistics pertaining to the crop yield. Such datasets are more often collected through official agricultural surveys or lab analyses on soils.

Structured data sets can provide for effective supervised learning, but they tend to be multiple home and temporally limited. Models that are trained using regional datasets may not be able to generalize well when used in different agro-climatic zones.

B. Image-Based Plant and Soil Datasets

Image datasets play a crucial role in soil classification and plant disease detection tasks. Public datasets such as PlantVillage have facilitated rapid advancements in deep learning based disease recognition.

However, most available image datasets are captured under controlled conditions, lacking the environmental variability encountered in real agricultural fields. Variations in illumination, background clutter, occlusions, and camera quality introduce domain shifts that negatively impact model performance during real-world deployment.

C. Multimodal Dataset Scarcity

An important difficulty to overcome in AI research in agriculture is the lack of large-scale multimodal datasets that integrate soil measurements, climate attributes and imagery of plant species in a single dataset. The majority of studies independently address one modality, thereby restricting the comparison against an integrated approach.

The lack of standardized multimodal datasets also discourages the fair comparison between different fusion architectures and integration strategies.

D. Benchmarking and Evaluation Limitations

In this context, AI performance evaluation typically concentrates on accuracy-based metrics without addressing possible deployment constraints peculiar to agriculture situations. The traditional metrics, such as classification accuracy and F1score, might not cover the complete characteristics in robustness, interpretability and scalability.

Also, heterogeneous splits across datasets make it difficult to compare results from different studies.

Open Issues: The absence of benchmarking standard that is universally accepted.

E. Dataset Bias and Domain Shift

Imbalance in image-level classes, seasonal bias and crop-specific skewness. Diseases datasets might present common pathologies over them and on the other hand rare but extremely important diseases.

The domain shift between training and deployment conditions has a crucial effect on model reliability, highlighting the relevance of domain adaptation, data augmentation and lifelong learning methods in agricultural AI systems.

VIII. MULTIMODAL INTEGRATION STRATEGIES IN SMART AGRICULTURE

Agricultural decision-making inherently involves heterogeneous data sources, including structured soil metrics, climatic variables, and visual plant health indicators. Multimodal learning aims to integrate these diverse data modalities into a unified predictive framework to improve robustness and contextual awareness.

A. Motivation for Multimodal Integration

Systems that use a single modality tend to lack context. For instance, if a crop recommendation model is formulated based on soil nutrients only, it does not take into account disease occurrences at the time. Similarly, a disease detection model does not take potential soil for re-planting into account.

Multimodal integration aims to mitigate these issues by combining multiple information sources, thereby increasing decision certainty and decreasing uncertainty.

B. Fusion Strategies

Multimodal learning strategies can be categorized into three major approaches:

1) Early Fusion (Feature-Level Integration): In early fusion, features extracted from different modalities are concatenated into a unified feature vector before model training. For instance, soil nutrient metrics can be combined with image derived features from a CNN before being fed into a classifier.

While early fusion enables joint feature learning, it may suffer from dimensional imbalance and modality dominance, where one modality overpowers others.

2) Intermediate Fusion (Representation-Level Integration): Intermediate fusion involves learning modality-specific representations first and then merging them at hidden layers. For example, soil features may be processed through a fully connected network, while leaf images are processed via CNN layers before integration at a shared latent space.

This approach allows balanced feature abstraction and has shown improved performance in heterogeneous data environments.

3) Late Fusion (Decision-Level Integration): In late fusion, individual models generate independent predictions, which are then aggregated using voting mechanisms or weighted averaging.

For example:

$$Yfinal = w1\,Ysoil + w2\,Ycrop + w3\,Ydisease$$

where w_i represents modality-specific weights.

Late fusion offers flexibility and modularity, making it suitable for real-world deployment where independent systems may already exist.

C. Comparative Analysis of Fusion Approaches

- Joint optimization is possible with early fusion, but takes vast aligned databases.
- Intermediate fusion balance between abstraction and interpretability.
- Late fusion offers modularization of deployment as well as scale.

For agricultural applications where datasets are often collected independently, late fusion is frequently more practical.

D. Implications for Integrated Agricultural Systems

The literature indicates that most agricultural AI systems lack true multimodal fusion. Soil analysis, crop recommendation, and disease detection modules are typically developed and evaluated independently.

An effective integrated framework should:

- Keep modality-specific learning pipelines
- Consider explainability in terms of both local and global levels
- Incremental model updates are supported
- Developing harmonized ad-vice outputs for farmers.

This kind of integration can be used for the enriched contextual intelligence and improved the more robust agricultural decision.

IX. COMPARATIVE ANALYSIS

TABLE I
COMPARISON OF SURVEYED SYSTEMS

Reference	Soil	Crop	Disease	Multimodal
Afzal (2025)	Yes	Yes	No	No
AgroXAI (2024)	Structured	Yes	No	Limited
Gunasekaran (2025)	Yes	Yes	No	No
Upadhyay (2025)	No	No	Yes	No

The analysis indicates a significant gap in unified multimodal integration.

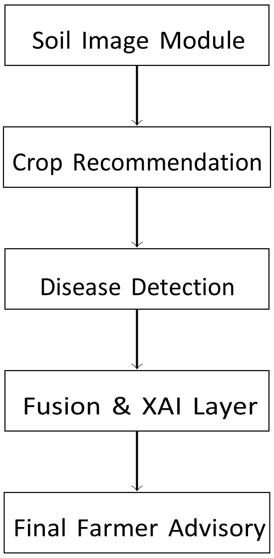

Fig. 2. Conceptual Multimodal Decision Support Architecture

X. PERFORMANCE EVALUATION METRICS

Performance evaluation plays a critical role in assessing the reliability and applicability of AI-driven agricultural systems. Due to the diversity of tasks involved—classification, regression, and decision support— multiple evaluation metrics are required to comprehensively analyze system performance.

A. Classification Metrics

Classification metrics are commonly used in soil type prediction and plant disease detection tasks. The most frequently adopted metrics include accuracy, precision, recall, and F1score.

Accuracy provides an overall measure of correct predictions; however, it may be misleading in the presence of class imbalance. Precision and recall offer better insights into false-positive and false-negative trade-offs, particularly in disease detection scenarios where misclassification may lead to severe crop loss.

The F1-score balances precision and recall and is widely used to evaluate robustness in multi-class classification problems.

B. Regression Metrics

Regression metrics are typically applied in crop yield prediction and soil fertility estimation tasks. Commonly used measures include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

RMSE penalizes larger errors more heavily, making it suitable for evaluating yield estimation models, whereas MAE provides a more interpretable measure of average prediction deviation.

C. Model Robustness and Generalization

Because agricultural systems are prone to variability in environmental conditions, it is critical to evaluate robustness. Crossvalidation and/or hold out testing for different regions/seasons are commonly used to evaluate generalization performance.

However, some of the previous works in the literature transmit results over only a few data splits which may not be specially relevant to real application scenarios.

D. Explainability and Trust Metrics

More importantly than accuracy, interpretability is a key requirement in agricultural decision support systems. Explainability metrics measure how clear and consistent the model explanations are produced by XAI methods (e.g. , SHAP or GradCAM).

Although explainability is typically evaluated qualitatively, recent work has underscored the importance of quantitative trust metrics that capture user confidence and decision consistency.

E. Deployment-Oriented Metrics

Deploying practical agriculture systems should also consider deployment limitations in terms of inference latency, computational cost and memory. In the context of edge deployment, lightweight models suitable for resource constrained deployments will be needed.

Although such metrics are important, deployment-oriented measures often tend to be not reported in the agricultural AI literature addressing the aspect of future work toward standardization.

XI. RESEARCH GAPS AND OPEN CHALLENGES

However, despite significant success in AI-based farming systems, there are still a number of important research challenges to be solved. This section summarizes the main limitations found in a review of literature and discusses open challenges which inspire further research.

A. Fragmentation of Agricultural Intelligence Systems

The majority of previous works only consider single agricultural tasks, such as soil analysis, crop recommendation or disease detection. These pieces are frequently designed separately from one another, leading to disconnected decision-making channels.

The absence of global frameworks does not allow contextual reasoning, as in the output of one block is used to influence and localize decision on another.

B. Limited Multimodal Integration

While multimodal learning is gaining more attention in other application domains, it is not popular yet in the field of agriculture. There are few studies that combine soil indicators, environmental information and visual plant health assessment in an integrated framework.

There is no standard multimodal benchmarking dataset or fusion benchmarks, which limit the ability to systematically evaluate and compare integrated models.

C. Dependence on Laboratory-Based Inputs

A large segment of AI for agricultural systems is based on lab-generated soil nutrient testing. Although reliable, such methods are generally expensive, time consuming and inaccessible to small farmers.

It is this reliance that restricts the degree of scalability, and demonstrates a requirement for alternative methods such as image-based soil classification and low-cost sensing.

D. Generalization and Deployment Challenges

The performance of many published models was based on controlled experimental conditions, and the efficacy in field settings is not guaranteed. Environmental diversity, regional variety and seasonal transformation add domain shifts which enormously impact the reliability of model.

In addition, deployment issues such as computation overhead, energy consumption and connectivity constraints are often neglected.

E. Explainability and Farmer Trust

While high prediction performances are pursued, interpretability and user confidence are frequently considered second afterthoughts. Black-box decision systems may also be subject to challenge from farmers who need interpretable reasons for recommendations.

Explainable AI (XAI) mechanisms are required to enhance understanding, assist in supporting decision-making based upon them and promote their adoption.

F. Evaluation and Benchmarking Limitations

With varying typical approaches in evaluation protocol, dataset split as well as performance measure among different studies, the reproducibility and fair comparison of experiments are not guaranteed. Lack of common standards is stunting development of reliable AI in agriculture.

To address these obstacles there is a need for community-driven work on standardizing the dataset and making as much of the evaluation process transparent to support reproducible research.

XII. RELEVANCE TO INTEGRATED MULTIMODAL AGRICULTURAL SYSTEMS

The review of the literature presents an evident gap for integrated decision-support systems that can aggregate diversified sources of farm-related information. The result of this survey indeed motivates the creation of comprehensive multimodal systems covering soil analysis, crop recommendation and plant disease detection in a unified pipeline.

A. Soil Intelligence as a Foundational Module

Soil characteristics form the basis of agricultural planning and crop selection. While most surveyed systems rely on laboratory-based soil nutrient analysis, recent advancements in image-based soil classification demonstrate the feasibility of low-cost, in-field soil assessment.

Integrating deep learning-based soil image analysis with traditional soil metrics enhances robustness, particularly in regions where laboratory testing infrastructure is limited.

B. Crop Recommendation Driven by Multisource Inputs

Crop recommendation systems benefit significantly from enriched contextual information. Instead of relying solely on static soil and climate features, multimodal systems can incorporate soil classification outputs and environmental indicators to generate more informed recommendations.

This integration enables adaptive crop planning that responds to both long-term soil conditions and short-term environmental variations.

C. Disease Detection as a Feedback Mechanism

Plant disease detection blocks deliver real time important insights about crop health. Instead of being direct diagnosis systems themselves, the prediction results can be used as feedback signals in one integrated decision system.

In combination with disease detection responses, crop recommendation logic can suggest risk mitigation practices, rotation plans and alternative crop options.

D. Unified Decision Fusion and Explainability

In a multimodal integrated system, a fusion layer that integrates information from individual modules into a unified advisory response is needed. Late fusion approaches are especially appealing since they are modular and can be applied in various contexts.

The inclusion of explainable AI methods at this point in the prediction provides interpretability of decisions by robustly identifying what soil properties, crop attributes, or disease signals drive final predictions.

E. Advantages of Integrated Multimodal Systems

The integrated multimodal system is superior to the isolated agricultural AI (Internet of things) as follows:

- Improved robustness of decisions based on awareness of context
- Less dependence on expensive laboratory testing
- Better adaptation to real-world agriculture variabilities
- Enhanced farmer trust with explainable recommendations
- Adaptable in wide range of agro-climatic zones

Such benefits make the integrated multimodal decision support system a promising way to the future smart agriculture.

XIII. FUTURE RESEARCH DIRECTIONS

Future systems should emphasize:

- Lightweight multimodal architectures
- Federated learning on mobile devices farms
- Explainable AI adoption
- Optimizing edge deployment
- Standardized multimodal datasets

XIV. CONCLUSION

Recent progress of artificial intelligence (AI) in smart agriculture particularly for soil intelligence, crop recommendation, plant disease detection, and multi-modal integration was surveyed. The analysis shows that although each AI module performs well individually, they cannot make real agricultural decisions in practice when deployed isolated. Synthesizing from the literature, challenges of datasets and evaluations are presented, gaps in integration emphasized and the significance of integrated soil data and image base explainable multimodal decision support system to be developed is highlighted. Future efforts should focus on scalable multimodal frameworks, validation of real world deployment and transparent decision-making needed to promote resilient farmer-centric agriculture.

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