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AI-Based Multi-Parameter Decision System For Crop Recommendation And Disease Prediction

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Abstract- Agriculture is one of the most important sectors for food security and economic stability worldwide. Current methods in crop selection and disease diagnosis tend to rely on expertise that may not always deliver optimal results without real-time data analytics. The following review will cover the state of the art related to crop recommendation systems and crop disease prediction models enabled through advancements in AI and ML. It examines a range of approaches regarding how soil, weather, and disease data are integrated and identifies the dominant gaps in current research. Building on these findings, this work will introduce an integrated multi-parameter AI-enabled decision support system that can synthesize information on soil properties, weather forecasts, disease susceptibility, and economics toward intelligent crop recommendations.

Keywords- CNN, Crop Recommendation, Decision Support System, Deep Learning, Disease Prediction, Machine Learning, Precision Agriculture, Random Forest, Soil Analysis, Weather Forecasting, XGBoost.

I. INTRODUCTION

Agricultural activities have faced various challenges, including nutrient imbalance in the soil, changing weather patterns, and the rising incidence of plant diseases [1, 2]. For instance, conventional methods have relied on experience and patterns of weather change for selecting crops and controlling plant diseases. This, however, has led to poor decision-making, resulting in low yields and economic losses [1]. The emergence of AI and ML technologies, on the other hand, have provided a new and promising solution for solving problems in precision agriculture [3]. The technologies have enabled the analysis of complex interactions between soil, climate, disease, and economic factors, thereby ensuring accurate decision-making [5]. Although current technologies have shown high accuracy, they have largely concentrated on specific tasks, such as recommending crops and identifying plant diseases [4]. As such, there is a need for a comprehensive and integrated system that ensures the use of multiple parameters for decision-making.

Traditionally, farmers have relied on crop selection and disease management based on ancestral knowledge, intuition, and local practices. Such methods may have worked well in the past but today are usually too weak in view of present-day challenges in agriculture [4]. Soil nutrient deficiencies, fluctuating climatic conditions, and new plant diseases require solutions that are dynamic, data-driven, and precise [1],[16].

A. Motivation

Agriculture inherently relies on multiple interdependent factors, including soil fertility, seasonal variations, rainfall patterns, crop diseases, and market demand. Farmers, particularly in developing countries, rarely have access to advanced tools for real-time analysis of such heterogeneous parameters. Decision support in agriculture has typically been domain-specific--for instance, crop recommendations based on soil and weather conditions, or disease detection from leaf images. Though effective within their narrow scope, these approaches do not provide a holistic approach to decision-making.

B. Problem Statement

The integration of soil analysis, weather forecasting, and disease prediction is not part of existing agricultural decision systems in a unified AI-based framework; hence, the recommendations given to farmers will be incomplete and suboptimal.

II. LITERATURE REVIEW

Kavitha et al. (2020) suggested a crop recommendation system based on machine learning techniques using soil nutrient and weather data [1]. The suggested crop recommendation system showed the effectiveness of the crop recommendation process in comparison to the traditional crop recommendation process. However, the crop recommendation model mainly focuses on crop recommendation based on agronomic parameters and lacks the consideration of critical parameters like crop diseases and market trends.

Harsha and Varun (2021**)** applied the Random Forest algorithm to predict suitable crops based on soil attributes, temperature, and rainf all data [2]. While the model achieved high prediction accuracy, it was limited to static datasets and lacked integration with real- time data sources such as weather APIs [2]. However, the approach relies on static datasets and lacks integration with real-time data sources such as weather APIs, which limits its adaptability to dynamic agricultural environments.

Patil et al. 2023 proposed an IoT-based framework of crop recommendation utilizing soil sensors and weather forecasting services [3]. This system provided real-time recommendations with better efficiency in decision-making. But it did not consider any risk associated with crop diseases or profitability aspects [3]. Nevertheless, it does not consider crop disease risks or economic profitability, which are critical for practical agricultural decision support.

Mohanty et al. (2016**)** demonstrated one of the earliest uses of Convolutional Neural Networks (CNN) for detecting plant diseases using the PlantVillage dataset [6]. The model achieved more than 95% accuracy in classifying diseased and healthy leaves, proving the potential of deep learning in agriculture. However, the dataset was collected under controlled conditions, limiting the model's applicability to real-world farming environments.

Ferentinos (2018) furthered the CNN-based plant disease detection with deeper architectures and larger datasets [7].

The study achieved very high accuracy across multiple crops and diseases but remained very computationally intensive and not easily adaptable for resource-constrained devices like mobile phones [7]. However, the model is computationally intensive and not suitable for deployment on resource-constrained devices such as smartphones.

Singh et al. (2021) developed a lightweight CNN model optimized for smartphones to enable real-time crop diseaseprediction. Their system made disease detection more accessible to farmers but remained limited to image-based predictions without integrating soil or economic factors [8]. However, the system remains limited to image-based predictions and does not integrate soil, weather, or economic factors for comprehensive decision-making.

Li et al. (2023) proposed an ensemble learning framework that combined CNN with Support Vector Machines (SVM) to enhance plant disease detection. Their model improved robustness and accuracy compared to standalone CNNs. However, the work focused only on disease detection, leaving out other aspects of decision-making [9].

Zhang et al. (2022) integrated soil nutrient data and weather information to provide recommendations for crops. Although their model performed better than single-factor systems, it did not include any aspects of disease prediction or profitability evaluation [10]**.** However, it does not consider the prediction of diseases and economic evaluation**.**

Patra et al. (2023) developed a multi-parameter model on yield prediction, taking into consideration soil and market data [11]. Though the system improved from solely single-domain approaches, it did not take into account the critical factor of plant disease risk for accurate decision-making [11]. However, it does not consider plant disease risks, which is important for effective agricultural decision-making.

Jha et al.(2019) presented an intelligent decision support system for crop management that would incorporate AI techniques to help a farmer make decisions [12]. While comprehensive, it did not integrate economic profitability and real-time disease analysis. the system does not integrate real-time disease prediction or economic profitability, reducing its effectiveness in practical deployment.

Sharma et al. (2022) presented a multi-factor crop recommendation framework for region-specific advice through consideration of soil and climatic data. However, this enhanced the local adaptability of the system but failed to give holistic decision support since it is designed to ignore disease and market-driven parameters [4]. the system does not integrate real-time disease prediction or economic profitability, reducing its effectiveness in practical deployment.

Forkan Uddin Ahmed et al. (2024) A Machine Learning Approach for Crop Yield and Disease Prediction Integrating Soil Nutrition and Weather Factors arXiv [16]. This paper aims to build an intelligent decision support system in Bangladesh capable of not only recommending the best crops in terms of yield but also predicting disease risk. Datasets combining soil condition, agro-meteorological, weather data, and disease incidence were used. The modeintegrates several real-world parameters and shows how the combination of these data sources outperforms models that focus on just soil or just weather.

Improved Deep Learning Model to Effectively Detect Crop Pests and Diseases-Illnesses (J. Imaging 2024, MDPI) This work is based on an improved ResNet34 model for the detection of crop pests and diseases. Herein, indistinct features of diseases, a few training samples, and high class imbalance are particularly discussed. Their modifications, including feature fusion and better loss functions, led to improved accuracy in detecting those on several datasets, which has made the model more useful in reality. However, these models are still computationally expensive and are only useful for disease detection, without fully incorporating other important parameters in agriculture such as soil conditions and market conditions.

Crop Recommendation with Fertilizer Suggestion and Disease Detection TEC AC This project involves three integrations: crop recommendation, fertilizer suggestion, and disease detection. Environmental data such as temperature, humidity, soil moisture, and nutrient levels are gathered through IoT sensors. After that, the data goes for processing in order to recommend what kind of crop to plant and what fertilizer to use, while image analysis is used for the detection of diseases. It is closer to a multi-parameter system, though parts like economic trade-offs or seasonal shifts are less emphasized. However, these models do not fully incorporate important parameters such as economic trade-offs and market conditions, and seasonal variability.

Machine Learning Assisted Recommendations on Agricultural & Horticultural Crops Farming in India with Respect to NPK, Soil pH, and Three Climatic Variables ScienceDirect This research article assesses different ML models such as Random Forest, etc. for crop recommendation on the basis of NPK, Soil pH, and climatic factors. This research is aimed at the situation in India, attempting to identify what crops are most advisable after being provided with certain inputs of soil quality, etc. This supports the thesis that a combination of multiple factors is useful, but has not delved deep into economic markets. However, these models do not fully incorporate important parameters such as economic trade-offs and market conditions, and seasonal variability.

Optimized Recurrent Neural Network-Based Early Diagnosis of Crop Pest and Diseases in Agriculture (Discover Computing, 2024)This proposal focuses on developing a pest/disease diagnosis system for crops that is optimized and utilizes recurrent neural networks to identify these from leaf images, thereby providing an early diagnosis. The methods are optimized, ensuring faster identification, particularly for data identified with a time series, such as changes that occur daily. The strengths are that it provides an early diagnosis, but the weakness is that the solution is dependent on images, with a few extra factors. However, they are largely dependent on image/time series inputs and lack integration with crop recommendation systems and economic analysis.

Machine Learning and Deep Learning for Crop Disease Diagnosis: Performance Analysis and Review (Ngugi, Akinyelu, Ezugwu, 2024) MDPI This is a survey paper that reviews a variety of ML & DL approaches (SVM, RF, CNNs such as VGG, ResNet, DenseNet) used for crop disease diagnosis problems. It specifically mentions the difficulties of imbalanced datasets, variability in climatic conditions, noisy images, etc. Even though it doesn't address the problem of crop recommendation, it might throw some light on which disease diagnosis models are better, which might be used for disease prediction models in your system.

However, they do not address the integration of disease prediction with crop recommendation and economic decision-making frameworks.

Mohan ty et al. (2016). The researchers managed to show the efficiency of convolutional neural networks (CNNs) in plant disease classification with high accuracy, which used the PlantVillage dataset. It is a pioneering work in plant disease identification via images. However, the dataset was collected under controlled conditions, which limits the model's applicability to real-world agricultural environments.

Sladojević et al. (2016) Proposed a deep learning solution for automated disease recognition in plants from leaf images. The CNN solution has a high potential to replace human disease diagnosis. The gap: The number of considered plant diseases and crops is limited, scalability is not tested on a regional scale. However, the study is limited in scalability in the sense that it only considers a limited number of crops and diseases and does not assess the performance on a large regional scale.

PlantVillage Dataset (Hughes & Salathé, 2015) Offers a collection of more than 50,000 leaf images labeled with multiple crops and disease categories. Highly regarded benchmark dataset within the domain of plant pathology and AI research. However, it does not consider real-world variability such as lighting conditions and environmental noise, making it less effective in real-world applications.

Kaggle Crop Recommendation Dataset (2020, community dataset) Provides soil factors (N, P, K, pH) and climatic attributes (temperature, rainfall, humidity) for supervised crop recommendation tasks. Often used in ML modeling, such as Random Forests, XGBoost. Problem with existing solutions: The datasets used are generic; hence, the applicability is limited to a certain location. However, it is a generic dataset and is independent of the region.

Kumari et al(2024) Applied Random Forest and Gradient Boosting approaches for crop recommendation, based on soil nutrient attributes as well as weather factors. Obtained high accuracies for recommending crops to farmers. Limitations: The approach considered only agronomic suitability, but did not consider economic and disease risk factors. However, the method only considers the agronomic suitability without considering the risks of diseases and economic factors, which are essential in making informed decisions.

Mandal et al(2023) Analyzed ML disease forecasting models with humidity, rainfall, and temperatures as parameters. Illustrated the role of time-series data in disease forecasting.Gap: Did not integrate disease forecasts with visual symptom detection models. However, the study fails to incorporate methods of visual detection of diseases, thus making the prediction of diseases incomplete.

Zhang et al. (2024) Proposed a deep learning solution that integrates phenotypic properties, environment, and image attributes for yield prediction tasks. Illustrated that multimodal learning enhances prediction performance when compared to single-modality learning. Unexplored Problem Area: Interpretability, adaptation, and regional specific. However, challenges such as interpretability, regional adaptability, and scalability are not addressed.

Gupta et al. (2024) Employed ARIMA models and a hybrid XGBoost technique for crop price predictions. The findings from the research showed that hybrids are better than statistical models in volatile markets. However, it does not incorporate agricultural variables such as soil conditions or diseases, making it less effective in facilitating a holistic decision for crop planning.

Lundberg & Lee (2017) (SHAPframework) Proposed SHAP (SHapley Additive exPlanations), a generalized technique for explaining predictions. Widely used in agriculture for tabular data. Gap: Should be modified for farmer-friendly interpretation, going beyond the existing plots. It needs further modifications to facilitate simple and understandable descriptions beyond the use of complex graphical plots, making it less useful in a real-world context.

Selvaraju et al. (2017) (Grad-CAM) Proposed Gradient-weighted Class Activation Mapping (Grad-CAM), a visual explanation technique for CNN predictions. Employed in a plant disease diagnosis application to emphasize infection areas on leaves. Gap: Heat maps cannot be used alone by farmers without a text description. However, the use of heat maps alone does not provide a clear explanation for the farmers, making it less practical in a real-world context.

Tan & Le (2019) - EfficientNet Proposed highly efficient CNN models that reach high accuracy with a reduced number of parameters. Existing research utilizes the modified version of "EfficientNet-Lite" models for mobile agricultural disease diagnosis. The gap in existing research is that the models are not extensively tested in rural conditions with limited internet connectivity. However, their use has not been thoroughly validated in a rural context where internet access and computational power are limited.

Rangarajan et al. (2025) presented a review of domain adaptation techniques for plant disease recognition. It has shown that fine-tuning and adversarial training improve performance in the real world with fewer labeled local samples. This provides a clear gap: few-shot learning practical pipelines are underdeveloped in resource- limited agricultural settings. However, the practical applications of the few-shot learning pipeline are not well developed, especially in an agriculture environment where resources are limited.

Chaudhary et al. (2024) had proposed an integrated IoT-based crop management system that integrates soil sensors and machine learning models to predict yield. Prototype validated on a small-scale farm; gap: did not include disease risk modeling or economic profitability layers. However, the system does not include disease risk prediction and economic profitability analysis. Therefore, it is not effective as a comprehensive decision system.

Kaur&Singh (2025) Highlighted the need for explainable and interpretable AI as key to the adoption of AI in agriculture by farmers. Suggested SHAP and Grad-CAM explanations combined, for practical deployment Gap: Did not include empirical testing on usability of explanations with real farmers. However, the study does not validate the empirical evidence of how farmers perceive the explanations provided by the system.

Sharma et al (2025) Highlighted socio-technical challenges in AI adoption among smallholder farmers,including trust, data ownership, and usability. Gap: Few systems evaluate how recommendations are perceived and acted upon by farmers in real conditions. the advice and information are true and accurate at the time of publication. However, the system does not assess the practical implementation of the AI-based recommendations by the farmers, Recently, a research paper was presented in 2024, suggesting a hybrid deep learning model based on VGG-16 architecture with improvements in the model,

including batch normalization and ELU activation functions, for crop disease detection. The model reported high accuracy in detecting crop diseases, i.e., 98.89%. However, this approach only deals with crop disease detection based on images and does not consider other crop parameters, including soil and economic conditions.[23]
Afzal et al. presented a crop recommendation system based on machine learning, considering soil parameters to enhance crop yield. The authors used ensemble learning techniques, achieving high accuracy in crop prediction. However, this model only deals with crop parameters and does not consider crop disease detection.[24]
Recent developments in this field, introduced in 2025, include multimodal AI systems, such as "AgriDoctor," which utilize images and natural language processing for intelligent crop disease detection. This allows for interactive and knowledge-based decision-making.[25]

TABLE I. COMPARATIVE ANALYSIS

Study	**Method Used**	**Parameters Considered**	**Limitations**
Bhargavi et al. (2023)	ML	Soil, Weather	No disease prediction
Senapaty et al. (2024)	Classification ML	Soil, Climate	No economic factors
XAI-based Model (2024)	Explainable AI	Soil, Weather	No disease integration
Patel et al. (2025)	RF, SVM, NN	Soil, Climate	No decision support
Integrated ML System (2025)	Multi-ML	Soil, Weather, Yield	No full integration
Proposed System	RF + XGBoost + CNN	Soil + Weather + Disease + Market	Fully integrated

al., Anand et al., and mobile-based CNN models by Singh et al.
Yet, most solutions are experimental or dataset-specific, and there is a lack of large-scale validation under diverse agricultural environments.

E. **No Analysis of Economic Factors**

The profitability and market trending usually get ignored in most of the. systems. Even those that include yield prediction (Patra et al. 2023) do not incorporate dynamic pricing and fluctuations in demand that directly affect farmer decision-making.

F. **Recent Partial Integration Efforts**

Some of the recent works (Ahmed et al. 2024; Crop Recommendation with Fertilizer Suggestion 2024) try to integrate crop recommendation, fertilizer advice, and disease detection.
However, these methods remain incomplete because they elide either economic feasibility or long-term seasonal adaptability

III. GAP ANALYSIS

A. **Single-Domain Focus**

Most of the works, like Kavitha et al. 2020; Harsha & Varun 2021; Patil et al., 2023 solely concern crop recommendation based on soil and climatic parameters.
While effective in pinpointing potential crops, they disregard disease risks and profitability, which will be crucial for any practical adoption.

B. **Isolated Disease Prediction**

Deep learning-based approaches using CNN and ensemble methods have shown highly accurate results in plant disease detection, including Mohanty et al. 2016; Ferentinos 2018; Singh et al. 2021; Li et al. 2023.
However, these systems are stand-alone and do not relate disease outcomes to crop management decisions or economic input.

C. **Poor Integration of Parameters**

A few studies tried to develop multi-parameter systems, incorporating data from soil, weather, or market. These systems still lack the incorporation of disease susceptibility and real-time environmental changes into decision- making.

***D.* Scalability and Real-World Deployment**

Access through IoT-based systems was enhanced by Patil et

IV. OBJECTIVES

- To analyze existing research on crop recommendation, plant disease prediction, and decision support systems in agriculture.
- To identify the gaps in existing methodologies in order to address a lack of cohesion between soil characteristics, meteorology information, resistance to diseases, and economical elements.
- To suggest a comprehensive AI-powered multi-parametric decision-support system which integrates analysis of soil, forecasting, diseases, and profit analysis under a unified platform.
- The goal is to develop an architecture for a system that facilitates, in real time, data analysis and recommendations to farmers.
- The assessment of the relevant algorithms can be performed for algorithms such as Random Forest, XGBoost, CNN, and Ensemble learning, which can be used in different modules of a proposed.
- The purpose of illustrating the benefits of a system to be incorporated in this project in terms of increased crop production, reduced exposure to diseases, and profit-making.
- Comprehensive Review: In attempt to comprehensively evaluate current methodologies in AI and machine learning used in crop recommendation, disease modeling, and agricultural decision support systems
- Gap Identification: In order to better understand the weaknesses within the current state of the art, specifically the failure to examine soil, weather, disease, and profitability together.
- Multi-Parameter Integration: To emphasize the need for an AI-based common framework that integrates soil nutrients, environmental factors, plant health status, and market trends into one system.

V. SYSTEM ARCHITECTURE

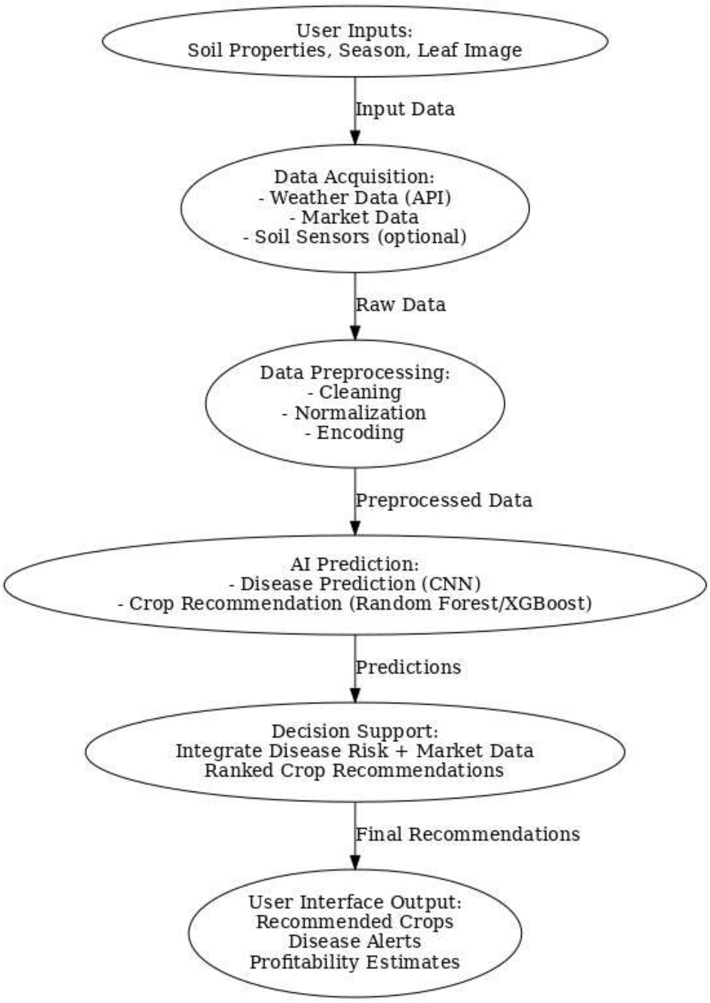

Fig. 1. System Architecture Flow

V. METHODOLOGY

A. Description of System Architecture

The proposed system merges different parameters in agriculture such as soil characteristics, climatic conditions, weather forecasting, plant diseases, and market information into a single AI-powered model. The methodology is described below

1. User Input

The input parameters given by farmers include soil characteristics such as NPK values and pH level, organic carbon content, and optionally upload images of crop leaves to identify diseases. This will make sure both crop health and nutritional status of soil are considered.

2. Data Acquisition

- External datasets are acquired in real time by considering the following:
- Weather Data through APIs (Temperature, Rainfall, Humidity,
- Market Data (Crop Prices & Demand Trends)
- IoT/Soil Sensors (Moisture, EC, Micro- Nutrients) With such a combination, both environmental factors available in wheat fields and other.

3. Data Preprocessing

- The raw data obtained from sensor inputs, APIs, and user inputs undergo
- Cleaning: Deleting inconsistent, missing, and noisy data entries.
- Normalization: Normalizing or scaling numeric variables for machine learning Encoding Exception: The mapping of categorical inputs such as soils and crop names into a format interpretable by a computer.

4. AI Prediction Models

- Disease Prediction: A convolutional neural network is used to predict diseases when a leaf image is uploaded.
- Crop Recommendation: Random Forest/ XGBoost algorithms assess information related to soil, weather, and season to recommend suitable crops.

5. Decision Support System:

The predictions produced by the models will be incorporated in a Decision Support System which provides a complete view of:

- Integrating crop suitability with disease risk levels.
- Integrating market information to prioritize crops based on profit potential.

6. Output of User

- The system offers a farmer-friendly
- Recommended crops based on existing soils and present season.
- Detected diseases with level of severity and treatment available.
- Profitability forecasts using present market prices.

This protects farmers from receiving misleading information.

7. Database

A variety of datasets can be used for research purposes in crop recommendations and disease forecasting. They include Kaggle Crop Recommendation Dataset and Indian Soil Health Card Database, which can be used for crop recommendations and have parameters such as soil nutrients (NPK, pH, and organic carbon content) and climatic parameters. Other datasets include image datasets used in plant disease identification, which are Plant Village Leaf Dataset (50,000+ images) and PlantDoc datasets with real-world field images, and AI Challenger Crop Disease Dataset. Weather parameters can be obtained from Open Weather Map API, Indian Meteorology Department, or NOAA Climate Data Online. Other parameters for economical analysis include Agmark Net and FAOStat datasets, which contain crop market price trade statistics.

B. Purpose of Study

The main objective of this research work is to design and develop an AI-Based Multi-Parameter Decision Support System to enable farmers to make well-informed decisions in agriculture. Contrary to most solutions available in literature, which either primarily focus on crop identification or crop disease prediction, this research will work towards incorporating factors such as soil information, climatic parameters, crop susceptibility, and market viability into a single platform. With the aid of machine learning algorithms such as Random Forest, XGBoost, and CNN, this will prove to be an efficient way of making decisions in real-time, with a focus on providing a complete and accurate perspective to upcoming crop selection decisions to allow farmers to predict potential disease risks, and maximize profit, thus ensuring a contribution for a smarter and more reliable precision agriculture. therefore ensuring enhanced security through proactive and automatic monitoring.

VII. COMPARATIVE ANALYSIS

The existing AI-based systems for agriculture have limited capabilities, such as focusing on single-domain issues. For instance, there is a focus on recommending crops and disease detection. The application of Random Forest and Support Vector Machine algorithms is significant for crop recommendation due to their ability to handle structured data. The application of these algorithms is limited due to their inability to handle dynamic changes. The application of Convolutional Neural Network algorithms is significant for plant disease detection due to its high accuracy. The application of these algorithms is limited due to their inability to handle decision-making.

The existing AI-based systems have shown significant capabilities, such as integrating multiple parameters such as soil and weather for predicting crops. The application of these algorithms shows significant performance compared to existing methods. The application of these algorithms is limited due to their inability to handle critical parameters such as disease susceptibility, economic profitability, and dynamic changes.

VI. CONCLUSION

Agriculture is a complex domain influenced by varied factors including soil fertility, climatic conditions, seasonal variations, plant diseases, and market dynamics. The traditional approaches towards the selection of crops and management of diseases are insufficient to meet new emerging challenges of the twenty-first century like climate change, resource constraints, and newly emerging plant pathogens. The available AI-driven decision support systems have accomplished partial success in individual domains—like crop recommendation, disease detection, or yield prediction—but they mostly operate in silos and fail to offer holistic decision support to farmers. This survey thus indicates a clear research gap in integrating soil analysis, weather forecasting, disease susceptibility, and economic profitability into a single framework. The proposed AI- Based Multi-Parameter Decision Support System will account for this limitation by unifying multiple data sources and making use of machine learning and deep learning algorithms to come up with comprehensive recommendations. Such a system can enable Farmers will get real-time, data- driven, and profitable decisions that will have a positive impact on increasing crop yield, reducing risks, and contributing to sustainable precision agriculture.

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