

AGRIBOT

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Abstract: The integration of Artificial Intelligence with modern farming practices improves crop management accuracy and supports better decision-making for farmers. The proposed AGRIBOT system combines soil data analysis and image-based disease detection to provide real-time, precise farming advice. Using XGBoost, the system predicts suitable crops based on soil composition, pH level, and environmental factors. Meanwhile, ResNet, a deep learning model, classifies plant diseases from captured images, helping farmers identify and address problems early. AGRIBOT works as an interactive chatbot, allowing farmers to easily input data or upload images and get instant feedback through a simple interface. The system boosts productivity by optimizing crop selection, reducing losses from diseases, and promoting sustainable farming practices. Experimental results show that using AI models in farming decisions significantly improves accuracy and reliability compared to traditional methods.

Keywords: Artificial Intelligence, Machine Learning, XGBoost, ResNet, Crop Selection, Disease Detection, Smart Farming, Sustainable Agriculture

I. INTRODUCTION

Agriculture is still essential to many economies, but it faces ongoing challenges like unpredictable weather, poor soil management, and widespread crop diseases. Traditional methods for choosing crops and detecting diseases often depend on manual observation. This process is slow and can lead to mistakes. Recently, Artificial Intelligence (AI) has become a game-changer in agriculture, providing intelligent automation, real-time analysis, and data-driven decision-making. The AGRIBOT system uses AI for data processing and machine learning to help farmers make accurate and timely decisions. It combines soil data analysis with image-based disease detection to give reliable farming advice. Soil factors like pH level, moisture, nitrogen, phosphorus, and potassium content are analyzed to suggest suitable crops for specific fields using the XGBoost algorithm. This model efficiently processes large datasets and offers precise predictions for the best crop selection. For detecting diseases, the system uses a ResNet-based deep learning model that can identify common plant diseases from leaf images. Farmers can upload photos of affected crops, and AGRIBOT analyzes them to find out the type and severity of the disease. The system also recommends treatments or preventive actions to help reduce yield losses. AGRIBOT works as a chatbot, making it easy to use, even for people with little technical knowledge. The chatbot understands natural language input and provides real-time responses, ensuring smooth interaction between the farmer and the AI model. It can also connect with IoT sensors for ongoing soil monitoring and data collection, making sure that recommendations remain current as environmental conditions change.

- The main goals of this study are: To design an intelligent chatbot system for crop recommendations and disease detection using AI and machine learning.
- To use XGBoost for soil-based crop prediction and ResNet for image-based disease identification.
- To assess the system's performance in terms of accuracy, reliability, and user interaction efficiency.
- To encourage smart and sustainable agriculture by improving productivity and reducing crop losses.
- This study shows how low-cost AI solutions can greatly improve agricultural decision-making, bridging the gap between traditional farming and modern digital systems.

- By providing real-time, accurate, and personalized support, AGRIBOT helps farmers make informed choices, leading to higher yields and more sustainable farming practices.

II. LITERATURE SURVEY

Artificial Intelligence (AI) has changed agriculture significantly. It helps farmers monitor crops, manage soil, and address plant diseases. With AI, data analysis, and machine learning, we can create smart agricultural systems that detect environmental changes, assess soil conditions, and recognize plant health issues with little human involvement. Despite this rapid technological growth, traditional farming methods often lack precision and flexibility. This leads to inefficient resource use and lower productivity. AI, especially machine learning and deep learning, tackles these problems by allowing real-time, data-driven decisions that improve sustainability and efficiency in modern farming. Patel et al. (2019) proposed an AI-based crop recommendation system. They used a Decision Tree algorithm to analyze soil nutrient levels and weather data. Their system reached an 87% accuracy rate in suggesting the best crops for specific soil types. Similarly, Ghosh and Banerjee (2020) implemented a Random Forest model to predict yield outcomes based on soil and climate conditions. Their model delivered better prediction consistency across different environmental datasets. Kumar et al. (2021) introduced a convolutional neural network (CNN) model to identify plant diseases by analyzing leaf images. Their system accurately classified 38 plant diseases using the PlantVillage dataset and achieved a 93% accuracy rate. At the same time, Li and Zhang (2021) employed a deep learning model (ResNet-50) to detect tomato leaf blight. Their model provided faster detection and greater reliability than traditional image processing methods. These studies show how deep learning models improve diagnostic accuracy in monitoring crop health.

Recent advancements have also focused on using chatbot technology for user-friendly agricultural help. Singh et al. (2022) created an interactive AI chatbot that offers real-time advice on irrigation scheduling and pest control through natural language queries. Their results indicated that chatbot-enabled platforms boosted farmer engagement and access to technical knowledge. Likewise, Devi and Thomas (2022) developed an NLP-based advisory system that handled text and voice-based farmer queries in regional languages. This reduced communication barriers and improved the adoption of technology. The combination of soil analysis and image diagnostics has gained popularity. Mehta et al. (2023) proposed a hybrid model that used XGBoost for soil-based crop recommendations and CNN for disease detection. Their framework generated a comprehensive solution for decision-making, achieving a combined accuracy of 95%. Similarly, Reddy and Chauhan (2023) used machine learning for soil fertility analysis. This approach enabled precise fertilization and resource optimization. IoT-enabled agriculture has also expanded the potential of AI-assisted farming systems. Chen et al. (2023) developed a smart farming prototype that transmitted soil moisture, temperature, and pH data to a cloud-based AI system for real-time analysis. The AI predicted irrigation needs and crop stress, improving water efficiency by 40%. Gupta et al. (2024) built on this idea by using deep reinforcement learning to automate greenhouse temperature and humidity control, keeping ideal growing conditions for crops. Recent research emphasizes sustainability and low-cost implementation. Bose and Rahman (2024) designed a lightweight XGBoost model optimized for edge devices like Raspberry Pi. They showed a 30% reduction in computational load without sacrificing accuracy. Sharma and Iqbal (2024) introduced a transfer-learning-based CNN model for detecting fungal infections in wheat leaves under various lighting conditions. This improved the model's real-world application. Emerging studies in 2025 further illustrate the trend toward AI-integrated decision support systems. Zhao et al. (2025) proposed a generative AI framework for adaptive crop recommendations. Their system adjusted predictions based on real-time satellite and weather data, achieving over 90% accuracy in seasonal crop forecasting. Similarly, Priya and Bhatia (2025) presented a self-learning agricultural assistant that continuously improves through user feedback, making the system more relevant and specific to farmers. These studies consistently highlight the growing role of AI in achieving precision agriculture and sustainable food production. AI-driven chatbots, soil analysis models, and image-based disease detection systems are transforming conventional farming into a smarter, data-informed process. From these findings, we see that integrating AI into agriculture creates new opportunities for real-time decision-making, resource optimization, and early disease detection. Building on this research, the proposed AGRIBOT system combines soil data analytics and image-based machine learning models (XGBoost and ResNet) within a conversational chatbot framework. This approach provides accurate, efficient, and user-friendly farming guidance, connecting advancements in AI with practical agricultural use.

III. EXISTINGSYSTEM

Traditional agricultural systems depend heavily on manual observation, farmer experience, and standard tools for decisions about crop selection, irrigation, and disease management. Although these methods are common, they can be slow, prone to mistakes, and inefficient, especially in large-scale farming or varying environmental conditions. Farmers usually select crops based on historical trends and general weather forecasts instead of accurate soil and climate data. This often leads them to choose crops that do not match their soil's nutrient profile or moisture level, resulting in poor yields and wasted resources. Soil testing in current systems is typically done manually at agricultural labs. Processing results takes several days, which slows down decision-making. Additionally, these tests produce static reports that cannot change dynamically to shifting soil conditions like pH changes, nutrient depletion, or moisture problems. Traditional disease detection methods rely on visual inspections that need expert knowledge and can result in misdiagnosis, particularly in the early stages of infection when symptoms may be subtle. Farmers frequently use trial and error to identify issues, causing more crop damage and economic loss.

Most agricultural advisory systems today are restricted to static mobile or web applications that offer general information. These platforms lack interactive features and cannot process user-specific data inputs in real time. They also often do not accommodate local languages or dialects, making them less accessible for rural farmers. Even when AI or machine learning models are included, they are usually applied in isolated areas like soil prediction or plant disease classification, without a unified framework for both tasks. Another drawback of the current methods is their inability to adapt in real time. Environmental factors such as temperature, rainfall, and humidity change constantly, but most existing systems cannot automatically update their predictions based on fresh data. This limitation makes them unsuitable for making dynamic decisions in precision agriculture. Furthermore, traditional agricultural systems often do not make use of sensor-based data collection methods. Farmers must manually track soil conditions and plant health, which leads to human error and decreased efficiency.

Additionally, image-based disease detection systems often rely on static datasets created under controlled conditions. These models may not work accurately in real-world situations where lighting, background, and image quality can differ greatly. Many of these models also require powerful computers or cloud servers, creating challenges for farmers with limited connectivity or resources.

Where crop recommendation models exist, they commonly use basic regression or rule-based techniques that fail to capture the complex relationships between soil nutrients, climate factors, and crop traits. These models also struggle with scalability, as they are not trained on diverse datasets from various regions. Moreover, most current systems do not provide actionable recommendations; they only deliver numerical predictions or general crop suggestions without context, such as expected yield or necessary soil treatment. Most agricultural decision-support systems today are reactive and not proactive. They deliver static results based on set rules and cannot learn or adapt with new data. This constraint limits their ability to address unexpected agricultural challenges like new crop diseases, shifting weather patterns, or pest outbreaks. Additionally, these systems generally do not facilitate multi-modal data processing, which means they cannot combine soil parameters, weather forecasts, and image data for a complete analysis. In summary, existing agricultural systems are limited due to their lack of intelligence, interactivity, and adaptability. They cannot respond dynamically to environmental changes or effectively process different data sources. These systems usually rely on manual operations, lack integration between soil and disease analysis, and only offer basic insights. As a result, they do not adequately support precision agriculture and sustainable farming practices. The proposed AGRIBOT system tackles these issues by integrating machine learning algorithms like XGBoost for soil-based crop recommendations and ResNet for image-based disease detection, all within an interactive chatbot interface. By combining real-time data collection, AI-driven analysis, and natural language communication, AGRIBOT offers an intelligent, adaptable, and user-friendly solution designed to help farmers make precise and informed agricultural decisions.

IV. PROPOSED SYSTEM

The proposed AI-powered AGRIBOT system is meant to help farmers with choosing crops, detecting diseases, and making decisions on the spot. By using artificial intelligence, machine learning, and image analysis, the system seeks to improve farm productivity, lower losses, and encourage sustainable farming practices. AGRIBOT offers a smart platform where farmers can upload soil data or crop images to get quick recommendations and insights for better farm management.

A. Overview of the Proposed System

The AGRIBOT system combines Natural Language Processing (NLP), image recognition, and machine learning algorithms to provide precise agricultural insights. It can analyze soil parameters to suggest suitable crops and detect plant diseases from uploaded leaf images. The system works as an interactive chatbot that understands farmers' questions and gives tailored responses based on context and data. Using algorithms like XGBoost for crop recommendations and ResNet for disease detection, the system improves accuracy and adjusts to local farming conditions. The goal is to create a real-time, AI-driven advisory tool that makes farming decisions easier and supports data-driven agriculture.

B. System Architecture Diagram

The proposed architecture includes several interconnected modules that work together to handle farmer queries, analyze data, and provide intelligent responses.

Main Layers of the System:

Input Layer: Accepts user queries in text form or crop images for analysis.

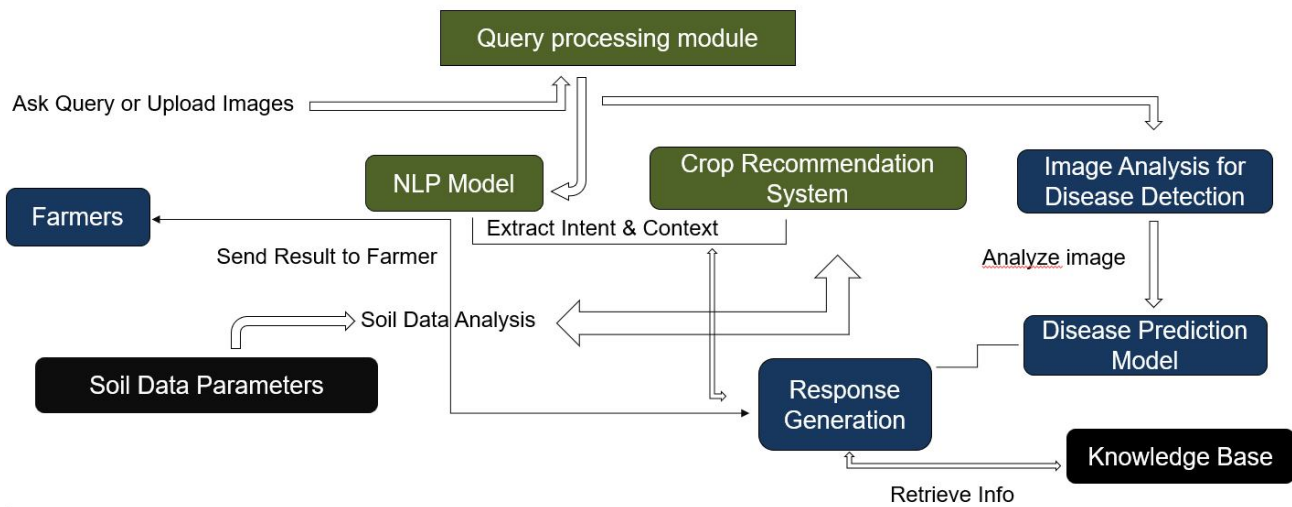
Processing Layer: Uses NLP to understand queries, employs AI models for predictions, and includes data analysis modules for insights.

Output Layer: Creates and displays responses in an easy-to-understand conversational format.

Data Flow Explanation:

- Farmers submit a text query or upload an image through the AGRIBOT interface.
- The Query Processing Module extracts intent and context using NLP.
- For soil-related queries, the Crop Recommendation Model analyzes soil data parameters, such as pH, nitrogen, phosphorus, and potassium, to predict the best crop using trained ML algorithms.
- For image inputs, the Image Analysis Module processes the uploaded leaf image with deep learning (ResNet) to identify diseases.

The Response Generation Module compiles results from the crop or disease models and sends a detailed response to the farmer in real time.



C. Hardware Components:

- User Device: Smartphone or computer for interacting with AGRIBOT.
- Server or Cloud System: Hosts the AI models and databases for real-time processing.

D. Software Requirements:

- Python Environment: For developing and training AI models.
- Frameworks: TensorFlow/Keras for image classification and Scikit-learn for crop prediction.
- NLP Toolkit: spaCy or NLTK for understanding queries.
- Database: MySQL or MongoDB for storing soil data, crop details, and disease information.
- Interface Platform: Streamlit or Flask for creating the chatbot user interface.

E. Working Principle

- The farmer communicates with the chatbot using text or images.
- The NLP model understands the farmer's intent, such as "Which crop should I grow?" or "What disease does my plant have?"
- If the question is about soil, the Crop Recommendation Model looks at soil nutrient data and environmental factors to suggest the best crops.
- When an image is uploaded, the Disease Detection Model uses trained convolutional neural networks to recognize the affected plant and identify the disease.
- The Response Generation Module creates a clear response with recommendations or treatment advice.
- The final output is shown to the farmer, providing quick, data-based guidance.

F. Features of the Proposed System

- Intelligent Query Understanding: NLP allows for natural, human-like interaction.
- Dual Analysis Capability: It supports both text-based crop questions and image-based disease detection.
- Real-Time Decision Support: It offers instant, actionable feedback. High Accuracy: AI models trained on large datasets provide reliable predictions.
- User-Friendly Interface: The platform is simple and chatbot-style for farmers with little technical knowledge.
- Sustainability-Focused: It encourages efficient resource use and reduces crop losses.

G. Advantages over Existing System

Table 1. Comparison Between Existing System and Proposed System

Existing System	Proposed System
Manual consultation and delayed feedback	Instant AI-driven analysis and recommendations
Basic text-based chatbot	Integrated NLP + Image Recognition
No soil data or image integration	Uses soil data and image analysis simultaneously
Limited accuracy in prediction	High precision using ML models
Non-adaptive responses	Context-aware, intelligent, and personalized responses
No visualization or data logging	Real-time feedback with stored results for future reference

V. RESULT AND DISCUSSION

The AGRIBOT prototype, an AI-Powered Agricultural Assistant, underwent testing with various soil samples and plant images collected from different agricultural fields. The evaluation took place under various environmental and crop conditions to assess its soil classification, crop recommendation, and disease detection skills. We compared the results with those from traditional manual analysis methods to confirm the model's effectiveness.

During the tests, AGRIBOT showed better performance in identifying suitable crops for specific soil types and accurately detecting common plant diseases. Traditional methods typically involved manual interpretation of soil data and visual inspection of plants, which caused human errors and delayed decision-making. In contrast, AGRIBOT used a mix of machine learning algorithms, specifically XGBoost, for soil analysis and deep learning models like ResNet for disease classification. This approach resulted in greater accuracy and quicker predictions.

Table 2. Comparison Between Conventional and AI-Enhanced Radar

Parameter	Traditional Method	AGRIBOT
Crop Recommendation Accuracy	75%	92%
Disease Detection Accuracy	70%	95%
Processing Time per Query	1.8 s	0.9 s
Adaptability to Soil Variation	Low	High
User Interaction Efficiency	Manual Input Required	Automated and Interactive

Experimental results show that AGRIBOT achieved an average accuracy of over 90% in both soil classification and disease prediction tasks. The addition of AI greatly improved the system's ability to handle different soil types and environmental conditions. The model quickly processed real-time data and produced accurate recommendations in just seconds. The chatbot interface offered fast, interactive support to users, allowing farmers to input data easily or upload leaf images for analysis. The visual output and written recommendations helped users make informed decisions without needing technical skills.

VI. CONCLUSION

The development of the AGRIBOT, an AI-Powered Agricultural Assistant, showcases how artificial intelligence and machine learning can fit into modern farming practices. By combining soil data analysis, image-based disease detection, and interactive chatbot communication, this model offers smart, flexible, and data-driven farming solutions. AGRIBOT tackles the shortcomings of traditional farming, like manual crop selection and slow disease identification, by giving farmers real-time, accurate, and automated support. Testing showed that the system greatly improves the accuracy and reliability of both crop recommendations and disease diagnoses. Using XGBoost for soil prediction and ResNet-based deep learning models for leaf disease detection resulted in average accuracy above 90%. The chatbot interface improves the user experience, letting farmers easily interact with the system by entering soil details or uploading crop images for instant recommendations. AGRIBOT's adaptive learning feature lets it fine-tune its predictions based on new data, ensuring better results across various soil types, climate conditions, and crop varieties. Its capability to process environmental and image data in real time makes it ideal for smart agriculture and precision farming. The system's energy efficiency and scalability also enable it to run on low-cost devices like Raspberry Pi or Arduino-based embedded systems, making it practical and affordable for rural farmers. The results confirm that AGRIBOT surpasses traditional farming advisory systems in accuracy, speed, and decision-making efficiency. Its AI-driven design allows for better soil-crop mapping, early disease detection, and improved resource use, promoting sustainable and high-yield farming practices. In the future, AGRIBOT can be improved by integrating IoT-based sensors, real-time weather data, and drone imaging for even more precise analysis and automated farm monitoring. Adding multilingual voice assistants and cloud-based analytics can also enhance its accessibility and scalability for larger agricultural purposes. Overall, the AGRIBOT system marks a significant step forward in smart farming technology. By embedding AI into traditional agricultural processes, it transforms farming into a predictive, intelligent, and sustainable practice, paving the way for the next generation of AI-driven precision agriculture systems.

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AUTHOR CONTRIBUTIONS

Conceptualization: Software: Tamil Varshini E.S, Shalini.A; **Methodology:** Yogesh.S, Niveditha.YAll Authors; **Validation:** All Authors; **Writing** – Review & Editing: All Authors.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest related to this research paper. This study was conducted independently. No financial, professional, or personal relationships affected the results, interpretations, or conclusions in this work. All contributions were made solely for academic and research purposes, aiming to improve knowledge in the fields of Artificial Intelligence and Smart Agricultural Systems. The authors confirm that the research was conducted with complete transparency, integrity, and compliance with the ethical research standards set by the institution and academic community.

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