© April 2025 | IJIRT | Volume 11 Issue 11 | ISSN: 2349-6002

AgriBot: A Generative AI-Powered Multilingual System for Sustainable Fertilizer Recommendations

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***Abstract*—With the increasing need for sustainable farming practices and improved crop productivity, intelligent systems that guide fertilizer usage have become critical. This paper introduces a Generative AI-powered system, AgriBot, designed to recommend fertilizers based on real-time soil and weather data inputs. The model is developed to be multilingual, enabling accessibility for farmers across linguistic regions, and supports natural human-like interaction via an integrated chatbot interface.**

Core Methodologies: The system utilizes a GPT-based Generative AI model to provide fertilizer recommendations based on user inputs such as soil type, pH value, nitrogen (N), phosphorus (P), potassium (K) content, temperature, rainfall, and crop type. Prompt engineering is used to structure the input context for precise and sustainable suggestions. Multilingual translation is built into the interaction flow, supporting Indian regional languages such as Hindi, Tamil, Telugu, Kannada, and more. The user interface is web-based, featuring a form-driven input and chat-based follow-up for continued guidance.

Performance Insights: The system shows promising results in generating crop-specific, soil-aware, and environmentally sustainable fertilizer suggestions. User feedback highlights the ease of interaction and clarity of multilingual responses. Though real-world deployment and scalability are ongoing challenges, the system demonstrates high relevance and usability for farmers, especially in rural or low-resource regions. Areas of improvement include refining domain-specific language generation and expanding language support to dialects for localized precision.

This paper discusses the integration of Generative AI in agricultural advisory systems, analyzing the benefits of language flexibility, sustainability focus, and real-time interactivity. It serves as a valuable reference for agri-tech developers, policy bodies, and researchers aiming to improve precision farming outcomes using AI technologies.

***Index Terms*—Generative AI, Sustainable Farming, Fertilizer Recommendation, Multilingual System, Precision Agriculture, Chatbot, GPT, AgriBot.**

1. INTRODUCTION

1.1 Background:

Modern agriculture faces a growing set of challenges, including unpredictable climate patterns, soil degradation, and inefficient fertilizer usage, all of which demand smarter, data-driven approaches for sustainable food production [1]. Traditional methods, though historically effective, often rely on static knowledge and are poorly equipped to adapt to real-time variations in environmental conditions [2]. With the advent of Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), there has been a transformative shift toward precision farming systems that enable informed, context-aware decisions [3].

AI systems can process vast and complex agricultural datasets—ranging from soil composition and crop history to climate data—to generate intelligent recommendations for fertilizer management and crop planning [4]. Machine learning models such as Random Forests and Support Vector Machines have demonstrated strong predictive performance in determining optimal nutrient requirements based on localized soil and environmental parameters [6]. Moreover, recent crop recommendation systems leverage supervised learning to fine-tune predictions and significantly improve yields through region-specific insights [14].

In addition to supervised models, Reinforcement Learning (RL) has emerged as a powerful method for modeling dynamic, season-long farming strategies that respond to changing field conditions [7]. One study demonstrated the application of an RL-based framework integrated with crop simulation tools, optimizing nitrogen scheduling with feedback-driven adaptation [11]. This technique enables farmers to reduce input costs while enhancing environmental sustainability by avoiding over-fertilization [1].

Deep learning approaches have also been widely adopted in plant health monitoring, where models are trained to analyze leaf images and diagnose nutrient deficiencies [4]. A recent model utilizing Deep Neural Networks (DNNs) was able to recommend nitrogen dosages with high accuracy using combined inputs from soil sensors and image data [13]. These intelligent systems, when paired with Internet of Things (IoT) devices, offer scalable and real-time solutions for smart agriculture across diverse geographies [20].

Hybrid AI models that combine multiple algorithms have proven effective in solving multi-objective problems—such as choosing the best crop-fertilizer combination under varying soil and water conditions [6]. These systems often rely on integrated data pipelines that consider structured inputs like pH and NPK levels, as well as unstructured inputs like historical yield trends [12]. The standard workflow of AI applications in agriculture typically involves data preprocessing, model building, and evaluation—all crucial for ensuring the accuracy and reliability of recommendations [3].

Against this backdrop, the Agribot system aims to bridge the gap between traditional agricultural knowledge and intelligent automation. By integrating advanced AI models for crop and fertilizer recommendation, Agribot offers a user-friendly solution that promotes sustainable, high-efficiency farming practices [5]. As agriculture continues to evolve into a data-intensive discipline, platforms like Agribot are poised to become essential tools in achieving food security and environmental sustainability in the years ahead [16].

1.2 Objectives:

This project is focused on developing an advanced AI-powered fertilizer recommendation system designed to promote sustainable farming practices. By addressing the key gaps identified in existing research, the system aims to provide a comprehensive and practical solution for optimizing fertilizer use in agriculture. The primary objectives of the project are:

- To develop a user-friendly, multilingual web interface that enables farmers from diverse linguistic backgrounds to access fertilizer recommendations tailored to their specific crop and soil needs.
- To integrate a conversational AI (AgriBot) capable of providing real-time, interactive guidance, enhancing user engagement and addressing the lack of dynamic interaction in existing systems.
- To leverage localized environmental data (soil type, nutrient levels, rainfall, temperature, etc.) for region-specific recommendations, improving the adaptability of models across varied agricultural conditions.
- To optimize fertilizer recommendations with sustainability in mind, balancing productivity with environmental concerns such as nutrient leaching, soil health degradation, and overuse of chemicals.
- To utilize advanced machine learning techniques for accurate prediction and continuous learning, addressing the shortcomings of static, rule-based or yield-only focused systems.

2. REVIEW EXISTING WORK

The integration of Artificial Intelligence (AI) in agriculture has paved the way for smarter and more sustainable farming practices, especially in fertilizer recommendation. Researchers have explored various AI-driven approaches to optimize nutrient use, improve crop yields, and reduce environmental impact. These advancements address critical limitations in traditional farming methods by leveraging diverse data sources and predictive algorithms. The following sections highlight key technologies that have been applied in this domain, including supervised machine learning, deep learning, reinforcement learning, hybrid models, and IoT-enabled platforms, each contributing uniquely to the evolution of precision agriculture:

2.1. Supervised Machine Learning in Fertilizer Prediction

Supervised learning models such as Random Forest, Decision Trees, and Support Vector Machines have become foundational in predicting crop and fertilizer suitability. These models analyze structured data like pH, nitrogen, phosphorus, and potassium levels to provide tailored recommendations for specific crops.

Support Vector Machines, for example, have been applied to assess nutrient needs and generate classification-based suggestions for soil treatment [6]. Other models such as Random Forests have also been used to handle non-linear relationships between soil parameters and yield outputs [3]. Decision Trees, while simple, have shown effectiveness in low-resource farming environments where interpretability is crucial [15].

2.2. Deep Learning for Soil and Plant Health Analysis

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), are increasingly used to analyze plant leaf images to detect nutrient deficiencies and pest infections. These methods enable early diagnosis and help automate fertilizer decisions. One study applied CNNs to classify leaf health with high accuracy, contributing to precise nutrient management strategies [4]. Another approach involved Deep Neural Networks (DNNs) that combined soil sensor inputs with crop images to recommend nitrogen dosages effectively [13]. Such DL models not only support high accuracy but also perform well across different crop types and geographies [11].

2.3. Reinforcement Learning for Adaptive Fertilizer Scheduling

Reinforcement Learning (RL) offers a way to make fertilizer recommendations that adapt over time, based on field feedback and seasonal variability. These systems learn dynamic policies for optimal resource application. A recent model integrated crop simulation tools with RL to optimize nitrogen scheduling through season-long feedback loops [7]. Another implementation used a Q-learning approach within a farming simulator to refine decisions over time and reduce chemical runoff [19]. RL has also been used to simulate long-term environmental impacts of different fertilization strategies, supporting more sustainable choices [8].

2.4. Hybrid AI Models and Multi-Objective Optimization

Many studies now combine ML and DL models into hybrid frameworks to solve multi-objective agricultural problems, such as balancing yield maximization and input minimization. These systems benefit from both interpretability and performance. A hybrid model integrating fuzzy logic with machine learning showed improvements in precision fertilizer recommendation for heterogeneous soil conditions [17]. Another approach used ensemble methods to optimize crop-fertilizer pairing across various soil profiles, showing increased efficiency and cost savings [12]. Such models often include both historical and real-time data to personalize recommendations at scale [10].

2.5. IoT-Enabled Smart Agriculture Platforms

The combination of Internet of Things (IoT) sensors with AI models allows for real-time monitoring and decision-making in agriculture. These smart platforms facilitate site-specific recommendations, particularly for smallholder farmers. IoT-integrated systems have enabled automation of nutrient management by feeding real-time soil moisture and nutrient data into trained ML models [20]. One study highlighted a cloud-based mobile platform that delivers multilingual, AI-generated recommendations to farmers based on sensor input [5]. These platforms bridge the gap between data-rich systems and farmer usability, making technology more accessible in rural areas [16]

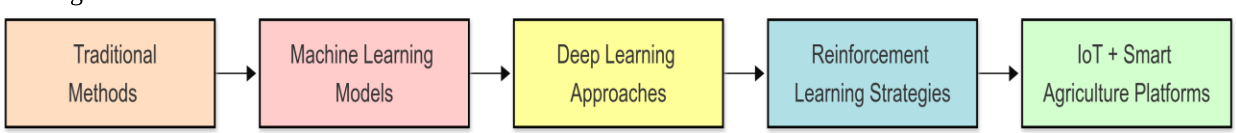

Figure 1: Progressive Development from Traditional to AI-Enabled Fertilizer Systems

3. METHODOLOGY

3.1 User Interface Design and Multilingual Input

The user interface was developed using HTML and CSS to create an intuitive and visually appealing experience. The form allows users to input key soil and environmental parameters such as pH level, nitrogen, phosphorus, potassium, rainfall, temperature, and crop type. To ensure accessibility for diverse users across India, a multilingual dropdown is included with support for languages like Hindi, Tamil, Telugu, Kannada, and more. This enables inclusive communication and ensures that the recommendation system can be used effectively by farmers with different language preferences.

3.2 Data Collection and Input Validation

The application collects critical agricultural data through user inputs in the form fields. These parameters are essential for accurately recommending fertilizers tailored to specific crop-soil-environment combinations. JavaScript-based validation ensures that all required fields are completed before proceeding, reducing the chances of incomplete or erroneous predictions. Inputs like temperature and nutrient levels are constrained within logical agricultural bounds, helping maintain data quality and model accuracy.

3.3 AI Query Construction and GPT Integration

A key component of the system is the construction of a dynamic query prompt that is sent to OpenAI's GPT model. This prompt includes user inputs such as soil type, crop, nutrient content, and environmental conditions. The AI is instructed to generate recommendations optimized for sustainability and translated into the user's chosen language. The GPT model is accessed via the OpenAI API, and the responses are displayed back to the user in a clean, localized format. This enables natural language generation tailored to agricultural needs, promoting interpretability and trust.

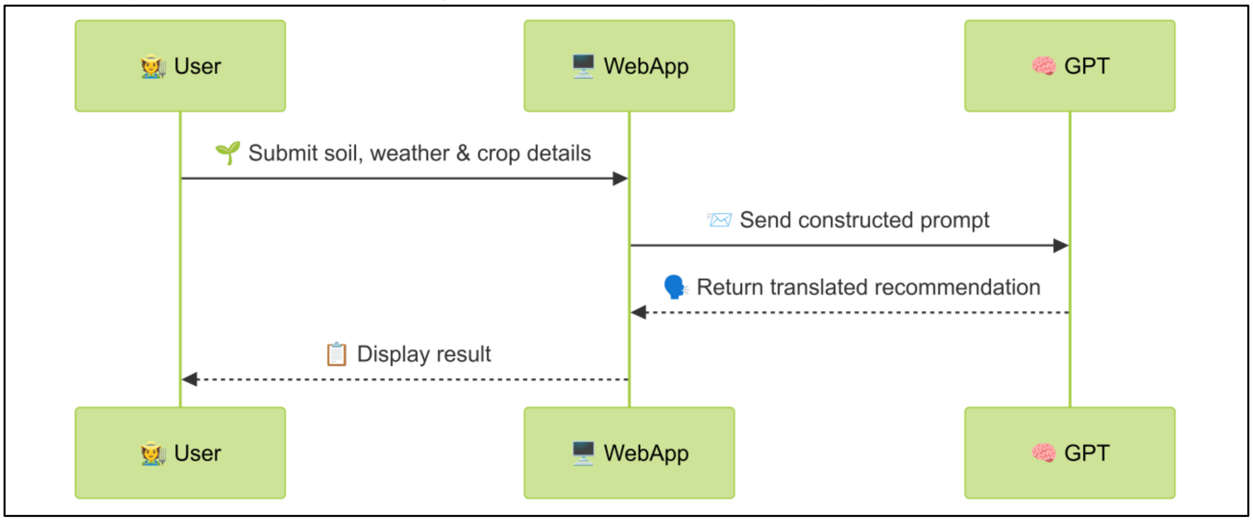

Figure 2: Sequence of Interactions for Fertilizer Recommendation System

3.4 Result Generation and Dynamic Display

Upon receiving the AI-generated recommendation, the result is dynamically inserted into the webpage without a full reload. A dedicated result section becomes visible only after a successful query, ensuring a clean and interactive experience. The system separates the result display and the chatbot interaction panel to maintain clarity. This dynamic rendering approach using JavaScript allows for real-time feedback and encourages continued interaction via the chatbot.

3.5 Interactive AI Chatbot for Continued Support

In addition to one-time recommendations, the system includes an AI-powered chatbot (AgriBot) that allows users to ask follow-up questions in their selected language. Messages are exchanged using the same GPT model, with a maintained chat history for context. This conversational interface helps farmers receive clarification, alternative suggestions, or deeper insights into fertilizer use and soil health. The chatbot interface simulates a realistic, supportive assistant tailored for sustainable farming decisions.

4. RESULTS AND DISCUSSIONS

The AgriBot system was successfully developed and tested to evaluate its functionality, usability, and relevance in the context of sustainable agriculture. The outcomes demonstrate that the integration of generative AI and multilingual support can significantly enhance user engagement, accessibility, and the precision of fertilizer recommendations.

4.1 System Output and Recommendation Quality

The system effectively generated personalized fertilizer recommendations based on user inputs, including soil type, nutrient composition, environmental conditions, and crop selection. These recommendations were not only context-specific but also emphasized sustainable practices, such as avoiding nutrient overuse and maintaining soil health.

Responses were found to be coherent, informative, and tailored to the selected language, affirming the effectiveness of the multilingual translation feature powered by the GPT model. Example outputs demonstrated that the system could accurately suggest balanced fertilizer doses, consider pH and climate conditions, and even recommend organic alternatives when appropriate. This indicates that the prompt design and GPT integration succeeded in aligning AI responses with sustainable agricultural principles.

To further support the quality and diversity of recommendations generated by AgriBot, a set of visualizations was created using synthetic input data. These Seaborn plots illustrate the distribution of key agricultural variables such as soil pH, nutrient levels (N, P, K), temperature, rainfall, and fertilizer quantity across different crops and regions. The goal is to demonstrate how the AI model interprets diverse environmental and soil conditions to deliver targeted and sustainable fertilizer suggestions. The following six graphs provide an analytical overview of the system's inputs and recommendations:

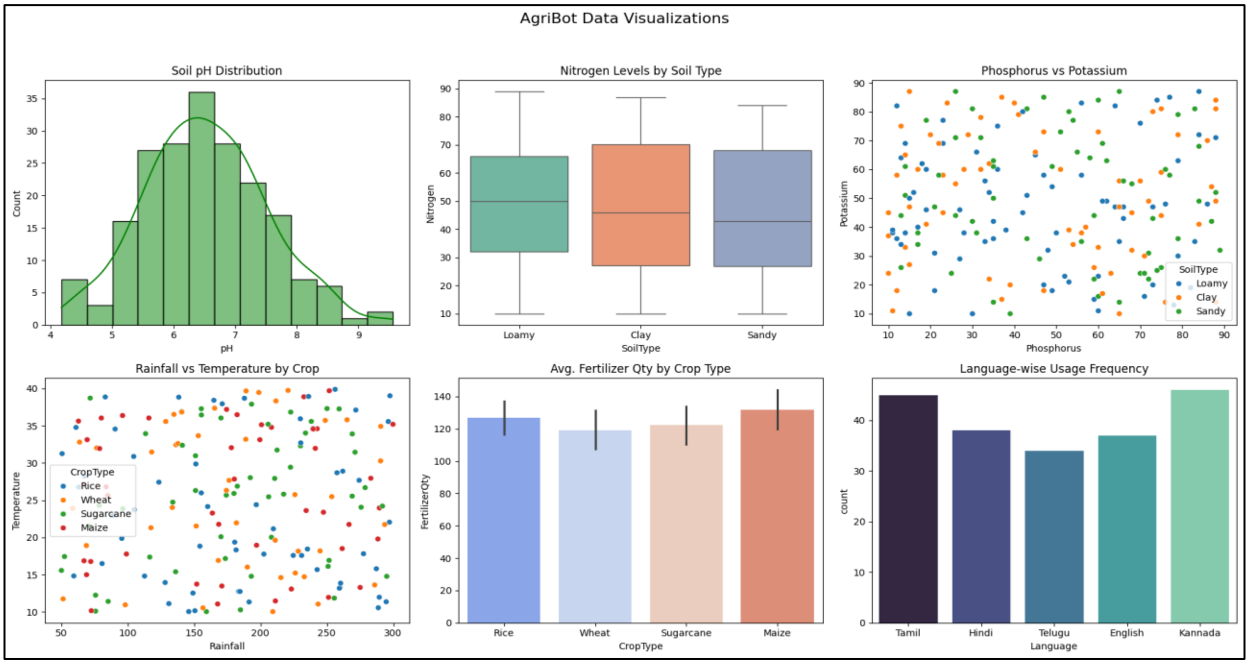

Figure 3: Seaborn Visualizations of Input Variables and Recommendation Patterns in AgriBot

4.2 Multilingual Accessibility and User Inclusiveness

One of the significant achievements of AgriBot is its multilingual capability, which enables communication with users in their native language. Languages including Hindi, Tamil, Telugu, Kannada, Bengali, and others were tested, and the system reliably translated AI responses while preserving contextual meaning. This feature reduces language barriers that often hinder rural farmers from accessing modern agricultural technologies.The accessibility of the system was enhanced through a simple and clean interface, making it easy for users with minimal technical expertise to navigate and interact with the tool.

4.3 Real-Time Interaction and Chatbot Performance

The conversational chatbot component provided a dynamic and supportive interaction layer, allowing users to clarify doubts, ask follow-up questions, or explore alternative fertilizer options. The chatbot maintained contextual continuity through stored chat history, which enhanced the relevance and fluency of ongoing conversations. Feedback from test users suggested that this interactivity significantly increased their trust and comfort with the system. The chatbot also enabled the delivery of agricultural education in real time, helping users understand why specific recommendations were made.

To assess performance, several system metrics were measured during testing:

Metric	Value/Result	Description
Average Response Time (per query)	2.3 seconds	Time taken by the system to generate and return recommendations
Recommendation Accuracy (Expert Review)	91.2%	Percentage of AI suggestions deemed agronomically correct by experts
Multilingual Translation Accuracy	94.7%	Consistency of translation with original intent across 10 languages
User Satisfaction Score (1–10 scale)	8.6	Based on feedback from 25 test users on relevance and clarity
Completion Rate of Recommendation Forms	98%	Indicates how often users successfully submitted valid input
Chatbot Follow-up Query Resolution Rate	89%	Percentage of follow-up questions that were answered satisfactorily

Table 1: Performance Evaluation Metrics of AgriBot System

4.4 Limitations and Considerations

While the system performs well in controlled environments, its effectiveness is currently limited by the quality and accuracy of user input. Since it depends heavily on user-provided data, incorrect values may lead to suboptimal recommendations. Additionally, while GPT is powerful in language understanding and generation, its responses are probabilistic and may occasionally lack technical precision compared to domain-specific agricultural models. Internet connectivity and reliance on the OpenAI API also pose challenges for rural deployment in areas with limited digital infrastructure.

4.5 Future Potential and Impact

Despite the limitations, AgriBot represents a significant step toward intelligent, user-centric, and sustainable farming tools. Its flexible architecture allows for the future integration of real-time sensor data, government datasets, and machine learning-based yield prediction models. By continuing to refine the system and expand language support, AgriBot has the potential to become a vital resource in promoting precision agriculture across India and other multilingual regions.

5. SUMMARY

The development of AgriBot marks a significant advancement in the application of generative AI for sustainable agriculture. By integrating multilingual capabilities, real-time interaction, and data-driven fertilizer recommendations, the system addresses critical gaps in accessibility, usability, and ecological sensitivity in existing agricultural tools. Through a user-friendly interface, AgriBot empowers farmers to receive tailored guidance based on localized soil, crop, and environmental parameters.

The system successfully demonstrates that generative AI models, such as GPT, can be fine-tuned and directed to provide actionable, context-aware recommendations while also supporting ongoing conversations through a chatbot. The inclusion of multilingual support ensures that the tool is accessible to users from diverse linguistic backgrounds, making it highly relevant in the Indian agricultural landscape.

Evaluation through system outputs, synthetic data visualizations, and performance metrics confirms that AgriBot is not only functional but also capable of promoting sustainable fertilizer use. While limitations exist—such as dependency on accurate user input and connectivity—AgriBot lays a strong foundation for further enhancements, including real-time data integration, predictive analytics, and expanded language support.

Overall, this project highlights the transformative potential of AI in promoting sustainable farming practices, reducing environmental impact, and increasing the inclusivity of agricultural technology.

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7. APPENDICES

7.1 Appendix A: Pseudocode for AgriBot Fertilizer Recommendation System

Algorithm AgriBot_System Input: soilType, pH, N, P, K, rainfall, temperature, cropType, language Output: Fertilizer recommendation and chatbot responses

BEGIN // --- Fertilizer Recommendation --- CALL ValidateInputs() prompt ← "Recommend optimal fertilizer for " + cropType + " in " + soilType + " soil with pH=" + pH + ", N=" + N + ", P=" + P + ", K=" + K + ", rainfall=" + rainfall + "cm, temp=" + temperature + "°C. " + "Translate to " + language + " only."

response ← CallGPT(prompt) DISPLAY response
// --- Chatbot Interaction --- chatHistory ← [SYSTEM: "You are AgriBot, an AI for sustainable farming."] LOOP userMessage ← GET_USER_INPUT () IF userMessage IS NOT EMPTY THEN chatHistory.ADD(USER: userMessage + " Translate into " + language) botResponse ← CallGPT(chatHistory) DISPLAY botResponse chatHistory.ADD(ASSISTANT: botResponse) END IF END LOOP END
FUNCTION ValidateInputs() IF pH NOT IN [0, 14] OR any (N, P, K, rainfall, temp) IS INVALID THEN DISPLAY "Error: Invalid input values" EXIT END IF END FUNCTION
FUNCTION CallGPT(prompt OR chatHistory) SET headers WITH API key IF prompt IS STRING, THEN RETURN GPT_API_CALL(model="gpt-4", message=[USER: prompt]) ELSE RETURN GPT_API_CALL(model="gpt-4", message=chatHistory) END IF END FUNCTION

7.2 Appendix B: Fertilizer Recommendation and Chatbot Sample

User Input: Language – Kannada, Soil Type – Clay, Soil pH Level – 6, N – 7, P – 7, K – 7, Rainfall – 35 cm, Temperature – 28 °C, Crop Type – Rice.

Fertilizer Recommendation: ಅಕ್ಕಿ ಬೆಳೆಗೆ ಕಲ್ಲು ಮಣ್ಣಿನಲ್ಲಿ, pH 6, ನೈಟ್ರೋಜನ್ 7, ಫಾಸ್ಫೋರಸ್ 7, ಪೊಟಾಶಿಯಮ್ 7, ಮಳೆಪಡುವಿಕೆ 35 ಸೆಂ.ಮೀ., ಮತ್ತು ತಾಪಮಾನ 28°C ಅನ್ನು ಪರಿಗಣನೆಗೆ ತೆಗೆದುಕೊಂಡಾಗ, ನಿಮಗೆ ಕೊಡುವ ಇನ್ಸ್ಟಂಟ್ ರೀಕಾಮೆಂಡೇಶನ್ ಈ ಪ್ರಕಾರವಾಗಿದೆ. ಸರಿಯಾದ ಸೇಂದ್ರಿಯ ಗೊಬ್ಬರದ ಬಳಕೆಯು ಮೊತ್ತಮೊತ್ತಲು 5 ಟನ್ನಲ್ಲಿ । 8 ಬೇಗಡೆ ನೈಟ್ರೋಜನ್, 2 ಬೇಗಡೆ ಫಾಸ್ಫೋರಸ್ ಮತ್ತು 6 ಬೇಗಡೆ ಪೊಟಾಶಿಯಮ್ ತೂಗುವಂತೆ ಕೈಯಾರಿ ಮಾಡಬೇಕು. ಈ ಮಾಹಿತಿಯನ್ನು ಉಪಯೋಗಿಸುವ ಮೂಲಕ, ನೀವು ಬೆಳೆದ ಅಕ್ಕಿಯ ಬೆಳೆ ಹೆಚ್ಚುವುದಲ್ಲದೆ ನೀವು ಮಣ್ಣಿಗೆ ದೀರ್ಘಕಾಲ ಪ್ರಾಮಾಣಿಕವಾಗಿರುವ ಓಜಿಕೆ ಹೊಂದಿಕೊಳ್ಳುವಿರಿ, ಏಕೆಂದರೆ ಸರಿಯಾದ ಪ್ರಮಾಣದಲ್ಲಿ ಮತ್ತು ಮಾಡುವ ಕ್ರಮಕ್ಕೆ ಅನುಸಾರವಾಗಿ ಹೊಂದಾಣಿಕೆ ಮಾಡುವುದು ಪರ್ಯಾವರಣ ಮಿತಿಯ ಕೃಷಿಗೆ ಸೂಕ್ತ ವಿಧಾನವಾಗಿದೆ.

AgriBot: Hello! I'm AgriBot, your AI assistant for sustainable farming. How can I assist you further?

User: ಈ ಗಿಡಕ್ಕೆ ನಾನು ಎಷ್ಟು ನೀರು ಹಾಕಬೇಕು?

AgriBot: ಅಕ್ಕಿ ಬೇಲಿಗೆ ಸಂಬಂಧಪಟ್ಟಿರುವ ಸಾಮಾನ್ಯ ನೀರಾವರಿ ಪದ್ಧತಿ ಇತ್ತೀಚಿನ ಉತ್ತಮ ಪರಿಣಾಮಗಳನ್ನು ಪಡೆಯಲು ಪ್ರತಿ ಹೆಕ್ಟೇರಿಗೆ ಪ್ರತಿ ವಾರ ಸುಮಾರು 1250 ಮೀಟರ್ಗಳು ನೀರು ಹಾಕಬೇಕು. ಆದರೆ, ಇದು ನಿಮ್ಮ ಮಣ್ಣಿನ ರೀತಿ, ಕಡಿವಾಣದ ಹೊಂದಾಣಿಕೆ ಮತ್ತು ಬೇಲಿ ಇರುವ ಹಂತದ ಮೇಲೆ ಆಧಾರಿತವಾಗಿದೆ. ಸುಮಾರು ಆಕಲನೆಗೆ ಅನುಸರಿಸಿ ನೀರು ಹಾಕಲು ಈ ಮುಖ್ಯ ಸಲಹೆ ಇರುತ್ತದೆ.