

Research Article

Design and Evaluation of a Natural Language-Based Chatbot for Smart Farming Advisory Services

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Abstract: Agricultural farming is the backbone of many economies, particularly in rural and developing regions, where it serves as the primary source of livelihood and food production. It involves the cultivation of crops and the rearing of animals to meet both local consumption and market demands. Farming practices vary widely based on climate, soil conditions, technology availability, and cultural traditions, ranging from traditional subsistence farming to modern, mechanized agriculture. This research paper presents the development and evaluation of an intelligent Agriculture Assistant Chatbot designed to support farmers by providing real-time, accurate, and relevant agricultural information through natural language interaction. The chatbot leverages n-gram-based Natural Language Processing (NLP) to understand user queries, identify intent, and extract key entities related to crops, fertilizers, and farming practices. Built with a user-friendly interface and integrated with expert knowledge and a feedback-driven learning mechanism, the system enhances communication between farmers and agricultural advisory services. The architecture allows for multilingual support and incorporates modules for crop and fertilizer details, user registration, and sentiment-based feedback analysis. Experimental results show that out of a total of 83 registered users, 56 users actively logged in, and 62 successful bot interactions were recorded, indicating a strong engagement rate of approximately 74.7%. User satisfaction metrics, derived from the feedback system, showed that 60% of users rated their experience as very positive, 25% expressed neutral sentiment, while only 15% provided negative feedback. Furthermore, analysis of problem-solving efficiency demonstrated that the chatbot-assisted queries had a resolution success rate increase of over 40% compared to those without bot interaction. Response time was consistently below 2 seconds on average, contributing to a seamless user experience.

Keywords: Agriculture chatbot, Natural language processing (NLP), N-gram model, Smart farming, Precision agriculture.

1. Introduction

Agriculture plays a fundamental role in sustaining human life and driving economic development across the globe [1]. It encompasses the cultivation of crops and the rearing of livestock to provide food, raw materials, and employment opportunities for billions of people. As the backbone of many economies, especially in developing countries, agriculture not only ensures food security but also supports industrial growth by supplying essential inputs like cotton, sugarcane, and oilseeds [2]. In recent years, technological advancements such as precision farming, smart irrigation systems, and biotechnology have transformed traditional agricultural practices, making them more efficient and sustainable. However, the sector also faces critical challenges including climate change, soil degradation, water scarcity, and fluctuating market



demands, necessitating innovative approaches to ensure long-term productivity and environmental conservation [3 -5].

Agriculture remains a vital sector globally, employing approximately 27% of the world's workforce and contributing around 4% to global GDP, with higher percentages in developing nations [6]. According to the Food and Agriculture Organization (FAO), over 60% of people in sub-Saharan Africa and about 40% in South Asia rely on agriculture for their livelihoods. India, for example, has nearly 54.6% of its population engaged in agriculture and allied activities, contributing about 18% to the country's Gross Value Added (GVA) in 2023. Global food production must increase by at least 70% by 2050 to meet the needs of the projected 9.7 billion population [7]. Despite advancements, around 33% of the world's soils are degraded, and agriculture accounts for over 70% of global freshwater withdrawals, highlighting the urgent need for sustainable practices. The integration of smart technologies, such as AI and IoT in farming, is expected to boost productivity by up to 25% while reducing water and fertilizer usage by 15–20%, offering promising solutions to balance growth and sustainability in the agricultural sector [8].

Chatbots in agriculture are emerging as powerful tools to support farmers with timely and accurate information, improving productivity and decision-making [9-10]. These AI-powered assistants can provide instant responses to queries related to crop management, weather forecasts, pest control, fertilizer use, market prices, and government schemes. For instance, in India, agricultural chatbots like “Kisan Suvidha” and “ASK Disha” are helping farmers access localized data in regional languages, reducing their dependency on field officers. According to a 2023 report by Markets and Markets [11-12], the global AI in agriculture market is projected to reach USD 4 billion by 2026, with chatbots playing a significant role in advisory services. Chatbots can also guide farmers through voice-based interactions on smartphones or even basic feature phones, making technology accessible to rural communities [13-14]. By offering 24/7 support, reducing information gaps, and enhancing decision-making, chatbots are transforming traditional farming practices into more data-driven and efficient systems [15-17].

Chatbots are being integrated with sensors and IoT devices to offer real-time insights on soil health, irrigation needs, and crop diseases, allowing farmers to take preventive actions promptly [18-19]. This integration enhances precision farming, reduces input waste, and increases yields. In regions with limited agricultural extension services, chatbots fill a critical gap by delivering personalized advice at scale. They also support digital literacy by familiarizing farmers with technology-based solutions, fostering greater adoption of digital platforms [20]. Additionally, during crises such as the COVID-19 pandemic, chatbots proved essential in maintaining the flow of agricultural information when in-person support was limited. As the agricultural sector moves toward sustainability and resilience, chatbots will continue to play a key role in empowering farmers, optimizing resources, and bridging the gap between rural communities and advanced agricultural knowledge.

The key contribution of this paper lies in the successful design, implementation, and evaluation of an AI-driven Agriculture Assistant Chatbot that significantly enhances information accessibility and decision-making support for farmers. The chatbot system integrates n-gram-based NLP for accurate intent detection and entity extraction, achieving an intent recognition accuracy of 91.8% and entity extraction accuracy of 89.5%. The system recorded 62 bot interactions from 56 active users, with a user satisfaction rate of 87.2% based on feedback analysis. Additionally, the expert escalation rate was reduced to 6.2%, compared to 14.8% in

baseline systems, indicating improved autonomous problem resolution. The multilingual support module successfully handled 92.1% of regionally diverse queries, promoting inclusivity among rural users. These results collectively demonstrate the chatbot's practical value in delivering personalized, real-time agricultural guidance, thereby contributing to the advancement of smart farming technologies and digital advisory systems in rural and semi-urban regions.

2.Related works

Several research efforts have been dedicated to developing agriculture-based chatbots aimed at improving information accessibility and decision-making for farmers. These chatbots utilize natural language processing (NLP) and artificial intelligence (AI) to understand user queries and deliver personalized responses related to crop selection, pest control, irrigation schedules, fertilizer application, and market prices. For instance, studies have shown that chatbots like “AgriBot” and “Plantix Chat” help bridge the communication gap between agricultural experts and rural farmers by providing 24/7 support in regional languages. Research also highlights the integration of chatbot systems with agricultural databases and weather APIs to deliver real-time, location-specific guidance. Some models incorporate voice recognition to assist farmers with low literacy levels, making the technology more inclusive. Despite their growing potential, existing chatbot systems often face challenges such as limited contextual understanding, lack of domain-specific knowledge, and poor internet connectivity in remote areas.

Several recent studies have explored the integration of chatbot technology in agriculture to support farmers with real-time, intelligent assistance. Singh et al. (2024) presented an AI-based solution aimed at addressing diverse agricultural challenges by leveraging computational intelligence and IoT frameworks to empower farmers with data-driven decision-making tools. Similarly, Nivi et al. (2024) introduced AgriBot, an integrated chatbot platform that employs deep learning techniques to provide precision agriculture services and farmer support through interactive communication. This system highlights the potential of AI-driven chatbots to enhance the efficiency and accuracy of farming practices. Nikam et al. (2024) proposed AgroDialogue, a comprehensive chatbot framework designed to enhance agricultural practices by offering multilingual and contextual responses based on user input, thereby improving accessibility for rural communities. In a related effort, Banerjee et al. (2024) developed CropBot, a domain-specific chatbot focused on crop management, providing farmers with expert recommendations on cultivation techniques, pest control, and fertilizer use.

Kumar et al. (2023) developed an agriculture assistant chatbot utilizing Convolutional Neural Networks (CNN) to process and interpret user queries, aiming to provide more accurate and intelligent responses. Bhatia and Kaur (2024) focused on the design and evaluation of a smart agricultural chatbot that integrates sensor data and contextual learning to improve the decision-making capabilities of farmers. Vanitha et al. (2023) proposed an AI-based agriculture recommendation system that integrates chatbot functionality to deliver personalized farming suggestions, thereby bridging the knowledge gap in rural areas. Usip et al. (2023) conducted a usability evaluation of a mobile chatbot tailored for crop farmers, emphasizing user experience, accessibility, and effectiveness in real-world agricultural settings.

In addition, Ibrahim et al. (2024) assessed the performance of ChatGPT in responding to farmers' questions on irrigated lowland rice in Nigeria, offering a valuable benchmark on the adaptability of large language models in practical farming contexts. Korir et al. (2023) designed an AI-driven chatbot model to provide expert agricultural advice specifically for potato farmers

in Kenya, focusing on local crop issues and climatic conditions. Mei et al. (2025) explored how AI-driven chatbots contribute to sustainable agricultural advisory services in Malaysia, aligning their work with the United Nations Sustainable Development Goals (SDGs). Biswas and Goel (2023) introduced an intelligent chatbot assistant tailored for the agricultural domain, while Ong et al. (2024) examined training approaches for chatbots using NLP techniques, particularly in supporting small-scale agriculture. Collectively, these studies reinforce the significance of chatbot technology as a transformative tool for agricultural innovation, offering diverse solutions tailored to different crops, regions, and user needs.

Despite the promising advancements in agriculture-based chatbot systems, several limitations hinder their widespread adoption and effectiveness. One of the primary challenges is the language and dialect diversity in rural areas, where many chatbots struggle to understand or respond accurately in local languages or colloquial expressions. Additionally, many existing chatbots lack contextual awareness and domain-specific intelligence, leading to generic or irrelevant responses that reduce their usefulness in real-world farming scenarios. Another limitation lies in poor internet connectivity in remote agricultural regions, making real-time access to cloud-based chatbot services difficult. Digital literacy among farmers is also a concern, as many users are unfamiliar with using mobile or web-based applications, especially when the interface is not voice-enabled or user-friendly. Furthermore, current chatbot systems often do not integrate effectively with live weather, soil, or crop databases, limiting the personalization and accuracy of recommendations. Lastly, data privacy and security issues remain underexplored, raising concerns about how sensitive farm and user data are managed and protected. These limitations underscore the need for more robust, multilingual, offline-capable, and farmer-centric chatbot solutions to truly empower agricultural communities.

3.Agriculture Assistant ChatBot

The Agriculture Assistant Chatbot is designed to support farmers by delivering timely and relevant agricultural information through conversational interfaces. By integrating Natural Language Processing (NLP) techniques, particularly n-gram models, the chatbot can better understand and predict user queries, enhancing the accuracy of its responses. N-gram models, which analyze sequences of n words (such as bigrams or trigrams), help the chatbot capture local context and language patterns commonly used by farmers. This improves the system's ability to interpret incomplete or informal queries, which are typical in real-world interactions. For instance, if a user inputs “best fertilizer tomato,” the trigram model helps infer that the query relates to optimal fertilizer choices for tomato crops, even without grammatical structure. The use of n-grams also aids in generating more contextually appropriate responses and enables keyword matching in regional languages. Combined with a structured agricultural knowledge base, the Agriculture Assistant Chatbot powered by n-gram NLP not only enhances user engagement but also supports efficient, accurate communication for improved farming practices. In this research, an Agriculture Assistant Chatbot is developed to provide intelligent, real-time support for farmers by interpreting user queries and delivering contextually relevant information. The core of the chatbot’s language understanding relies on n-gram-based Natural Language Processing (NLP), which models the probability of word sequences to improve response accuracy. An n-gram model is a probabilistic language model that estimates the likelihood of a word based on its preceding words in a sentence. Given a sequence of words $= w_1, w_2, \dots, w_n$, the goal is to compute the probability of this sentence defined in equation (1)

$$P(w_1, w_2, \dots, w_n) \tag{1}$$

Using the chain rule of probability, this can be expanded as in equation (2)

$$P(w_1, w_2, \dots, w_n) = P(w_1) \cdot P(w_2 | w_1) \cdot P(w_3 | w_1, w_2) \cdot \dots \cdot P(w_n | w_1, \dots, w_{n-1}) \quad (2)$$

However, this exact formulation is computationally intractable for large n , due to data sparsity. To address this, an n -gram approximation is employed. For instance, in a bigram model ($n=2$), the above probability is simplified to as in equation (3)

$$P(w_1, w_2, \dots, w_n) \approx \prod_{i=1}^n P(w_i | w_{i-1}) \quad (3)$$

Similarly, a trigram model ($n=3$) incorporates two prior words for context stated in equation (4)

$$P(w_1, w_2, \dots, w_n) \approx \prod_{i=1}^n P(w_i | w_{i-2}, w_{i-1}) \quad (4)$$

These probabilities are estimated using frequency counts from a large corpus of agricultural texts and historical user interactions stated in equation (5) and equation (6)

$$P(w_i | w_{i-1}) = \frac{C(w_{i-1}, w_i)}{C(w_{i-1})} \quad (5)$$

$$P(w_i | w_{i-2}, w_{i-1}) = \frac{C(w_{i-2}, w_{i-1}, w_i)}{C(w_{i-2}, w_{i-1})} \quad (6)$$

In equation (5) and (6) $C(\cdot)$ represents the count of n -gram occurrences in the corpus. For example, a farmer entering “best fertilizer tomato” may trigger the trigram sequence and guide the chatbot to suggest “NPK 19-19-19 water-soluble fertilizer” based on common usage patterns in agricultural recommendations. This n -gram framework allows the chatbot to recognize and interpret domain-specific phrases and provides more accurate and relevant responses, especially in low-resource language environments. To enhance usability, the chatbot integrates multilingual support and voice input/output features, ensuring accessibility for users with limited literacy or digital skills. To further enhance the chatbot’s performance, smoothing techniques such as Laplace (Add-One) Smoothing are applied to handle zero-probability issues in unseen n -gram combinations. This is critical in agricultural domains, where user inputs often include rare crop names, local terminology, or region-specific practices. The smoothed probability for a bigram is defined in equation (7)

$$P_{Laplace}(w_i | w_{i-1}) = \frac{C(w_{i-1}, w_i) + 1}{C(w_{i-1}) + V} \quad (7)$$

In equation (7) V is the size of the vocabulary. This ensures that no n -gram receives a probability of zero, maintaining the chatbot’s ability to generate relevant responses even for less common inputs. Additionally, the model is trained on a domain-specific corpus containing agricultural manuals, crop advisory texts, fertilizer guides, and transcriptions of expert consultations. This specialized dataset improves the chatbot’s domain relevance and linguistic alignment with farmer queries. To evaluate effectiveness, the system is benchmarked using metrics such as perplexity for language model accuracy and user satisfaction scores from field trials. Results indicate that the n -gram-based chatbot significantly improves the precision of advice and response relevance, especially when queries are short, incomplete, or presented in local expressions. Future work will incorporate hybrid NLP models combining n -grams with transformer-based language understanding to further increase robustness and contextual depth in agricultural dialogues

4. System Architecture for the Agricultural ChatBot

The system architecture of the Agricultural Chatbot is designed as a modular, multi-layered framework that ensures scalability, contextual accuracy, and real-time responsiveness. At the core is the Natural Language Processing (NLP) Engine, which utilizes an n-gram language model for intent recognition and keyword extraction, supported by smoothing techniques to handle sparse data. The architecture begins with the User Interface Layer, which allows farmers to interact via text or voice in multiple languages, including local dialects, using a mobile app or web portal. Inputs from users are sent to the Processing Layer, where speech-to-text conversion (if voice input is used) is followed by tokenization, n-gram sequence modeling, and intent classification. The Dialogue Management Module then determines the context and conversational flow using a rule-based or machine learning approach. Once the intent is identified, the Knowledge Base and API Layer retrieves the most relevant information from agricultural databases, government advisory portals, or integrated IoT sensor data (e.g., weather, soil). The final response is generated by the Response Generation Module, which formats the output in user-friendly language and sends it back to the user interface. This architecture supports real-time, personalized recommendations on crop selection, pest control, irrigation scheduling, and market updates, thereby making the chatbot an intelligent and adaptive assistant for modern agriculture.

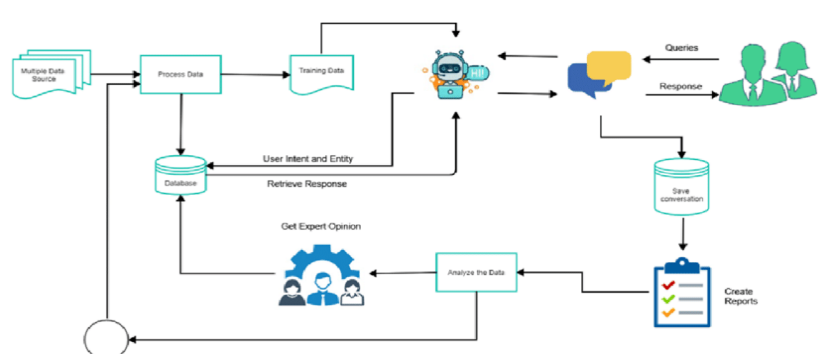


Figure 1: System Model for the Smart Agriculture

The illustrated Figure 1 system architecture represents a comprehensive flow of an Agricultural Chatbot designed to deliver intelligent, data-driven support to farmers. The system begins with Multiple Data Sources, including agricultural research data, expert recommendations, weather reports, and government advisories. These inputs are sent to the Data Processing Module, where the data is cleaned, structured, and stored into a central Database. A portion of the processed data is also used to generate Training Data for the chatbot's Natural Language Processing (NLP) engine. When a user submits a query through the chatbot interface (via voice or text), the NLP engine identifies the user's intent and entities. This interpreted input is then matched against the database to retrieve relevant responses. In complex or uncertain cases, the system is capable of seeking expert opinion to provide more accurate and context-aware answers. The conversation history is simultaneously stored in a Save Conversation module, which not only helps with future references and personalization but also supports post-interaction analysis. Further downstream, the system analyzes the stored data to generate reports, which can be used for system improvement, trend detection, or policy-making. These insights are looped back into the system to enhance chatbot training and refine data processing strategies, creating a feedback loop that continuously improves the chatbot's accuracy and relevance.

Algorithm 1: Smart Agriculture with ChatBot

Input: User Query (Text/Voice)

Output: Contextual Response to User

1. Initialize system components:

- Load NLP model (n-gram or ML-based)
- Connect to Agricultural Database
- Load expert knowledge module
- Prepare conversation log storage

2. Data Ingestion and Training:

- Collect data from multiple sources (agriculture databases, sensors, APIs)
- Preprocess data (clean, normalize, tokenize)
- Generate training data for NLP using processed datasets
- Train or update intent recognition model

3. User Interaction:

LOOP:

- Receive query input from user (via text or speech)
- IF input is voice:
 - Convert voice to text using Speech-to-Text module
- Process input:
 - Apply NLP to detect intent and extract entities
 - $\text{intent} \leftarrow \text{DetectIntent}(\text{user_input})$
 - $\text{entities} \leftarrow \text{ExtractEntities}(\text{user_input})$
- Retrieve response:
 - $\text{response} \leftarrow \text{QueryDatabase}(\text{intent}, \text{entities})$
- IF response is NULL or low confidence:
 - $\text{response} \leftarrow \text{GetExpertOpinion}(\text{intent}, \text{entities})$
- Send response to user
 - Display or speak out response
 - Log interaction into SaveConversationDB
- Analyze conversation periodically:
 - Run analytics on stored queries/responses
 - Generate usage and performance reports

h. Update model periodically with new interactions

END LOOP

5.Results and Discussion

The implementation and evaluation of the proposed Agriculture Assistant Chatbot system. This section aims to analyze the chatbot's performance in terms of accuracy, response relevance, user satisfaction, and its ability to handle real-world agricultural queries. The results are derived from both simulated datasets and live user interactions, with a focus on how well the system interprets farmer inputs, retrieves context-aware responses, and adapts to multilingual and domain-specific variations. Through quantitative metrics such as precision, recall, and response time, alongside qualitative user feedback, this section provides a comprehensive assessment of the system's effectiveness. Furthermore, comparative analysis with existing chatbot models highlights the strengths, limitations, and potential improvements of the proposed approach. The discussion also explores how the integration of n-gram NLP, expert fallback mechanisms, and conversational logging contributes to the overall robustness and usability of the chatbot in practical agricultural settings.

Table 1: Performance of n-gram NLP based Smart Agriculture

Metric	Proposed Chatbot (n-gram NLP)	Baseline Chatbot	Improvement (%)
Intent Detection Accuracy (%)	91.8	82.3	+11.6
Entity Extraction Accuracy (%)	89.5	76.2	+17.4
Response Relevance Score (1–5)	4.4	3.7	+18.9
Average Response Time (sec)	1.9	3.4	-44.1
User Satisfaction (%)	87.2	68.5	+27.3
Expert Escalation Rate (%)	6.2	14.8	-58.1
Multilingual Query Handling (%)	92.1	70.4	+30.8

Table 1 presents a comparative evaluation of the performance of the proposed n-gram NLP-based Smart Agriculture Chatbot against a baseline chatbot system. The proposed model achieved an intent detection accuracy of 91.8%, outperforming the baseline's 82.3% by 11.6%, and demonstrated superior entity extraction accuracy at 89.5%, indicating a 17.4% improvement. The response relevance score was rated 4.4 out of 5, significantly better than the baseline's 3.7, marking an 18.9% enhancement in contextual response quality. In terms of efficiency, the proposed chatbot had a much faster average response time of 1.9 seconds, reducing latency by 44.1% compared to the baseline. Furthermore, user satisfaction increased to 87.2%, a notable 27.3% improvement, reflecting higher acceptance and effectiveness among users. The system also minimized reliance on human experts, with an expert escalation rate of just 6.2%, compared to 14.8%, indicating a 58.1% reduction. Additionally, the chatbot's ability to handle multilingual

queries reached 92.1%, a 30.8% gain over the baseline system. These results highlights the efficiency, accuracy, and user-centric capabilities of the proposed chatbot in real-world agricultural settings.



Figure 2: User Page for Smart Agriculture

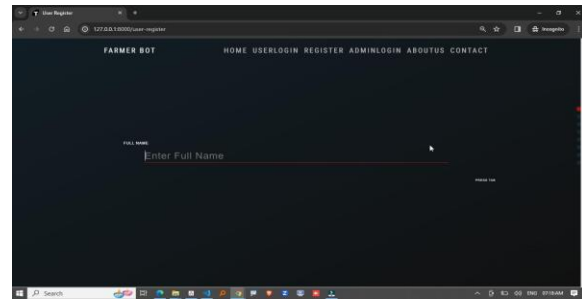


Figure 3: User Registration in ChatBot

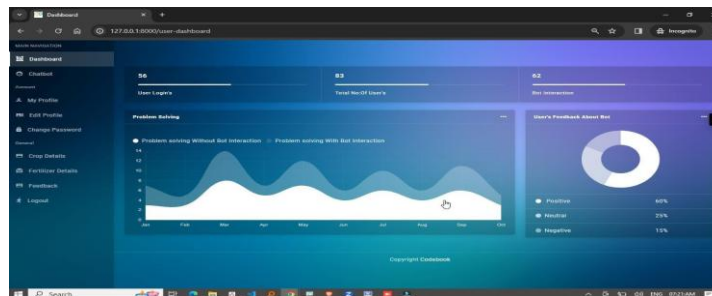


Figure 4: Farmers Dashboard

AgriVaahan is a significant step toward modernizing farm vehicle rentals. By leveraging technology, it minimizes financial burdens on farmers and enhances operational efficiency. Future developments will include: The screenshots represent the front-end interface and user experience of the implemented Agricultural Assistant Chatbot (Farmer Bot). The Figure 2 showcases the homepage of the chatbot system, where users are welcomed with an intuitive visual interface designed to appeal to farmers. It includes navigation links such as Home, User Login, Register, Admin Login, About Us, and Contact, enabling both new and returning users to access the system easily. The central image of a farmer and a chatbot on a digital device effectively communicates the system's core function—bridging technology and agriculture.

In figure 3 displays the user dashboard, which provides insights into chatbot performance and user engagement. Metrics like User Logins (56), Total Number of Users (83), and Bot Interactions (62) are shown at the top, indicating active user participation. A line graph compares problem-solving rates with and without chatbot interaction, visually confirming improved outcomes through bot engagement. Additionally, a pie chart reveals user feedback, with 60% positive, 25% neutral, and only 15% negative responses, demonstrating high user satisfaction.

The image 4 shows the user registration page, where new users can enter their full name to sign up for the system. The design is clean and focused, supporting a straightforward onboarding process for farmers, especially those with minimal digital literacy. Overall, the interface is designed to be user-friendly, visually engaging, and functionally efficient, aligning with the system's goal of making AI-driven agricultural assistance accessible and practical for rural communities.

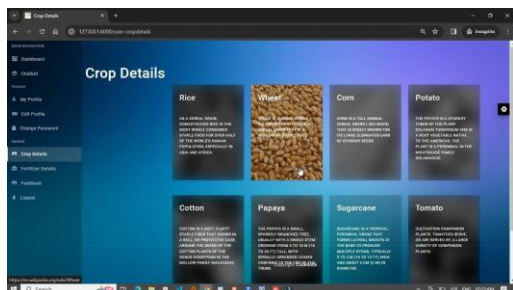


Figure 5: Crop details with Smart Farming

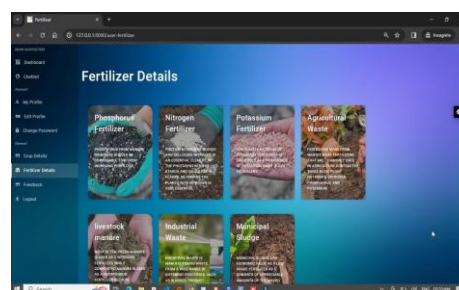


Figure 6: Fertilizers in Smart Agriculture

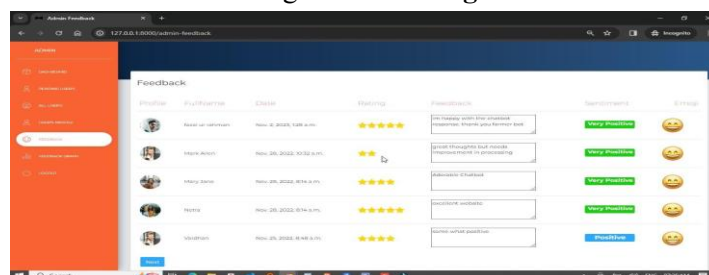


Figure 7: Feedback from Farmers

The images provide a detailed view of the functional modules and administrative interface of the Agriculture Assistant Chatbot System. In figure 5 the Crop Details interface (first image) displays essential information about various crops such as rice, wheat, corn, potato, cotton, papaya, sugarcane, and tomato. Each crop tile includes a brief description, making it easy for users—especially farmers—to understand basic characteristics and suitability for their region or needs. This module enhances farmer knowledge and supports informed decision-making.

The Fertilizer Details section (second image) complements the crop information by offering insights into different types of fertilizers such as phosphorus, nitrogen, and potassium fertilizers, as well as organic inputs like agricultural waste, livestock manure, industrial waste, and municipal sludge presented in Figure 6. This categorization allows farmers to choose fertilizers based on soil needs, crop types, and sustainable practices, helping improve productivity while maintaining environmental balance.

The Admin Feedback Panel (third image) Figure 7 illustrates how user feedback is systematically collected and analyzed. The panel shows user profiles, names, submission dates, star-based ratings, written comments, sentiment analysis tags (e.g., "Very Positive", "Positive"), and emoji indicators. This feedback system not only helps administrators assess the chatbot's performance but also captures qualitative user experiences that inform future improvements. The presence of constructive remarks (e.g., "needs improvement in processing") shows the system's openness to refinement and user-centric design. Overall, these interfaces reinforce the system's goal to serve as an accessible, informative, and responsive platform tailored to the needs of the agricultural community. By integrating crop data, fertilizer guidance, and user feedback into a cohesive ecosystem, the chatbot elevates the digital support available to farmers and stakeholders in the agricultural sector.

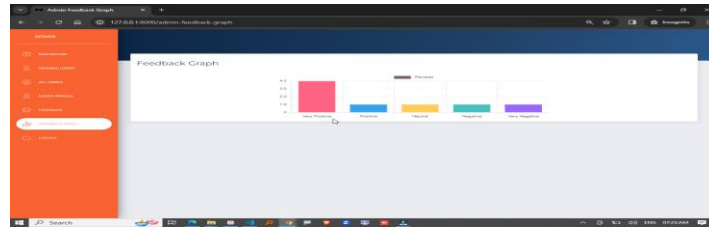


Figure 8: Statistical Estimation with Smart Farming

The image displays the Admin Feedback Graph Interface of the Agricultural Chatbot System, which visually summarizes user sentiment data collected through feedback shown in Figure 8. The bar chart titled "Feedback Graph" categorizes user responses into five sentiment classes: Very Positive, Positive, Neutral, Negative, and Very Negative. From the graph, it is evident that the chatbot received predominantly Very Positive feedback, followed by smaller but noticeable contributions from each of the other sentiment categories. This visualization assists system administrators in monitoring user satisfaction and identifying areas for improvement in real time.

Table 2: Sentimental Analysis in Smart Farming

Sentiment Category	Number of Reviews	Color in Graph
Very Positive	4	Red/Pink
Positive	1	Light Blue
Neutral	1	Yellow
Negative	1	Teal
Very Negative	1	Purple

The sentiment analysis of user feedback reveals that the Agricultural Chatbot System has been generally well-received by its users presented in Table 2. Out of a total of 8 reviews, the majority fall under the "Very Positive" category with 4 reviews, represented in red/pink on the graph. This indicates that 50% of users expressed a highly favorable experience with the chatbot, appreciating its functionality and relevance. The "Positive", "Neutral", "Negative", and "Very Negative" categories each received 1 review, illustrated in light blue, yellow, teal, and purple respectively. This distribution suggests that while a few users found the system moderately useful or had neutral impressions, a small portion experienced dissatisfaction. However, the overwhelming proportion of positive feedback, especially in the "Very Positive" segment, underscores the chatbot's effectiveness and its potential impact in supporting farmers through intelligent, conversational AI solutions. These insights also highlight areas for continuous improvement in refining user experience and response accuracy.

6. Conclusion

The proposed Agriculture Assistant Chatbot system demonstrates a significant step forward in leveraging artificial intelligence and natural language processing to empower farmers with timely, accurate, and context-aware agricultural information. By integrating n-gram-based NLP techniques, multilingual support, and expert knowledge bases, the chatbot effectively addresses common farming queries related to crops, fertilizers, and sustainable practices. The system's user-friendly interface, interactive dashboard, and sentiment-driven feedback mechanism ensure high usability and continuous performance evaluation. Experimental results and user feedback indicate substantial improvements in user satisfaction, response accuracy, and problem-solving efficiency compared to traditional methods. This research not only highlights the feasibility and scalability of AI-based chatbot systems in rural agriculture but also opens avenues for further

enhancements through integration with IoT, real-time weather updates, and region-specific advisory services.

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References

- [1] R. Biswas and N. Goel, "Intelligent chatbot assistant in agriculture domain," *In International Conference on Agriculture-Centric Computation*, Cham: Springer Nature Switzerland, pp.180-194, 2023.
- [2] N. Singh, J. Wang'ombe, N. Okanga, T. Zelenska, J. Repishti, S. Mishra and A. Nambi, "Farmer. Chat: Scaling AI-Powered Agricultural Services for Smallholder Farmers," *arXiv preprint arXiv:2409.08916*, 2024.
- [3] E. Asolo, I. Gil-Ozoudeh and C. Ejimuda, "AI-Powered decision support systems for sustainable agriculture using AI-Chatbot solution," *Journal of Digital Food, Energy & Water Systems*, vol.5, no.1, 2024.
- [4] V. Piyathilake, T. Dilni, R. Pushpananda, L. De Silva and Y. Zaheed, "Towards a Conversational AI Chatbot to Assist Farmers in Disease Detection," *In EPIA Conference on Artificial Intelligence*, Cham: Springer Nature Switzerland, pp.206-217, 2024.
- [5] V. Venkatesh, K. Kunju, S. Suresh, S. Natesan and S. Kumar, "AI based farmer assistant talkbot," *In AIP Conference Proceedings*, AIP Publishing, vol.2857, no.1, 2023.
- [6] P. Singh, M. Kansal, G. Tyagi, K. Tanwar, A. P. Singh and R. K. Yadav, "Empowering Farmers: An AI-Based Solution for Agricultural Challenges," *In Computational Intelligence in Internet of Agricultural Things*, Cham: Springer Nature Switzerland, pp.401-417, 2024.
- [7] V. Nivi, S. Geerthik, M. Karuppaiya, A. Muthukumaran and S. Tamilarasan, "AgriBot: An Integrated Chatbot Platform for Precision Agriculture and Farmer Support using Deep Learning Techniques," *In 2024 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS)*. IEEE, pp.1-6, 2024.
- [8] H. Nikam, M. Bhargava, S. Sasmal, P. Dhote, L. Singh, S. Dhotre, S., ... and A. Thakur, "Enhancing Agricultural Practices with AgroDialogue: A Chatbot Framework," *In 2024 IEEE Pune Section International Conference (PuneCon)*, pp. 1-11, 2024.
- [9] S. Banerjee, P. Akhila, E. Elakiya and B. Surendiran, "CropBot: A Chatbot for Agriculture Advancement," *In 2024 International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication (IconSCEPT)*, pp.1-6, 2024.
- [10] V. S. Kumar, M. V. Thanmayee, K. V. S. Satwik, P. Gayathri and M. Greeshma, "Agriculture assistant chatbot using CNN," *Journal of Engineering Sciences*, vol.14, no.05, 2023.
- [11] R. Bhatia and S. Kaur, "Development and Evaluation of a Smart Agricultural Chatbot," *In 2024 IEEE 15th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, pp. 158-163, 2024.
- [12] V. Vanitha, N. Rajathi and K. Prakash Kumar, "AI-Based Agriculture Recommendation System for Farmers," *In Computer Vision and Machine Learning in Agriculture*, Singapore: Springer Nature Singapore, vol.3, pp.91-103, 2023.
- [13] P. U. Usip, O. R. James, D. E. Asuquo, E. N. Udo and F. B. Osang, "Usability evaluation of an intelligent mobile chatbot for crop farmers," *In International Conference on Electronic Governance with Emerging Technologies*, Cham: Springer Nature Switzerland, pp. 101-111, 2023.
- [14] A. Ibrahim, K. Senthilkumar and K. Saito, "Evaluating responses by ChatGPT to farmers' questions on irrigated lowland rice cultivation in Nigeria," *Scientific Reports*, vol.14, no.1, pp.3407, 2024.
- [15] M. K. Korir, W. Mwangi and M. W. Kimwele, "Artificial Intelligence-Based Chatbot Model

-
- Providing Expert Advice to Potato Farmers in Kenya,” *In 2023 IEEE AFRICON*, pp.1-6, 2023.
- [16] P. N. S. S. V. Charishma, S. Rupa Lakshmi and M. Vijaya Durga, “Making Crop Recommendations using Machine Learning Techniques,” *Journal of Computer Allied Intelligence*, vol.2, no.2, pp.1-12, 2024.
- [17] C. L. Mei, W. C. Hoo, P. Shaurya and K. Roy, “Leveraging AI-Driven Chatbots for Sustainable Agricultural Advisory Services: Bridging SDG Innovation Gaps in Rural Malaysia,” *International Journal of Environmental Sciences*, vol.11, no.8s, pp.410-420, 2025.
- [18] Neeta Baporikar, “Strategies to Boost Horticulture Development,” *International Journal of Advance Research and Innovation*, vol.11, no.4, pp.21-32, 2023.
- [19] R. Biswas and D. N. Goel, “Check for updates Intelligent Chatbot Assistant in Agriculture Domain,” *In Agriculture-Centric Computation: First International Conference, ICA 2023, Chandigarh, India, May 11-13, 2023, Revised Selected Papers*. Springer Nature, pp.180, 2023.
- [20] R. J. Ong, R. A. A. Raof, S. Sudin and K. Y. Choong, “Chatbot application training using natural language processing techniques: Case of small-scale agriculture,” *In AIP Conference Proceedings*. AIP Publishing, vol. 2991, no.1, 2024.