

FarmSense: AI-Enhanced Decision Support for

Farmers

Ratul Raj, SIES Graduate School of Technology, ratul.padmaraj.313@gmail.com Prachiti Gaikwad, SIES Graduate School of Technology, prachiti.814@gmail.com Dhruv Jethva, SIES Graduate School of Technology, dhruvjethva@hotmail.com

Sonal Patil, Assistant Professor, SIES Graduate School of Technology, sonalpatil606a@gmail.com

Rizwana Shaikh, Associate Professor, SIES Graduate School of Technology,

hellorizwana@gmail.com

Abstract: The agricultural sector in India faces persistent challenges, including unpredictable weather patterns, resource constraints, and limited access to expert guidance. This work aims to bridge these gaps by developing an intelligent, AI- powered assistant tailored to the needs of Indian farmers. Leveraging advanced technologies such as Large Language Models (LLMs), VectorDB, and Retrieval-Augmented Generation (RAG), the system provides personalized, real-time recommendations on crop management, weather analysis and market trends. The multilingual chat-based interface ensures accessibility for farmers across diverse regions, addressing barriers related to language and literacy. By integrating weather forecasts and predictive analytics, the assistant enables farmers to make informed decisions, enhancing productivity and sustainability.

Keywords — Agricultural AI, Generative AI, Large Language Models, Multilingual AI, RAG, VectorDB

I. INTRODUCTION

Agriculture forms the backbone of India's economy, establishing livelihoods for smallholder farmers in millions. Though it is a critical component of ensuring food security, the sector is beset with numerous challenges such as unpredictable weather and ineffective resource utilization. in End In addition to impacting productivity, these challenges have also threatened the sustainability of agricultural practices, hence compromising national food security. Technological interventions are progressively finding their way into agriculture, but much of what is available is too general, inaccessible to rural-based communities, or is not complemented by localized expertise. Smallholder farmers, especially those in remote areas, face barriers such as language diversity, limited technical literacy, and an inability to access reliable data and expert advice. Addressing these issues requires innovative, accessible, and scalable solutions that cater to farmers' specific needs. Artificial intelligence (AI) and large language models (LLMs) hold unprecedented possibilities for the agricultural revolution through the provision of real-time, personalized guidance to farmers. Research studies have touched upon considering the use of natural language processing (NLP), machine learning (ML), and deep

learning to develop interactive AI assistants capable of addressing a wide range of agricultural challenges, including crop management, price prediction, and climate analysis [1]. Traditional farming advisory services, often struggle to meet the growing demand for expert assistance, making AI-driven chatbots a promising alternative [2]-[3]. In regions like Nigeria, where extension agents are limited, a recent study found that ChatGPT-generated responses were preferred over human experts' responses in 78% of cases, with AI answers being rated six times higher in quality than those from agricultural officers. However, the same study also highlighted that AI chatbots still struggle with localized agronomic recommendations, such as optimal planting times and seed rates, underscoring the importance of fine-tuning AI models for specific agricultural conditions [4]. Future chatbot systems could incorporate reinforcement learning and generative AI models to enhance their ability to provide personalized, adaptive recommendations based on real-time environmental conditions [5]. Despite the advancements in chatbot technology, several challenges remain. One major issue reported was the lack of multilingual support, which limits accessibility for farmers in rural areas who primarily speak local dialects [6]. Some hybrid AI models combine ontology-based knowledge systems with machine learning algorithms like Word Shuffling and Jacquard Similarity to



improve chatbot query matching, particularly in rural farming communities with low internet access [7]. Many existing chatbot systems rely on static datasets and struggle to provide real-time updates on crucial agricultural factors such as market prices, weather forecasts, and future price prediction were limiting factors [8]. The work regarding growing need to integrate AI-driven chatbots with IoT devices, such as smart sensors and automated irrigation systems, to enable precision farming were reported [9]. ML-based chatbot surveys, emphasized that AI chatbots in agriculture must have transition from static, predefined responses to adaptive, real-time learning systems that evolve with climate conditions and market dynamics [10]. Additionally, AI-driven chatbots have been designed to offer 24/7 support in regional languages, making expert agricultural knowledge more accessible to farmers who may not be fluent in English [11]. Smart systems and artificial intelligence-driven chatbots were profoundly transforming the agricultural sector by providing datadriven, real-time information to support farmers' decision-Several studies have demonstrated making. the effectiveness of different AI models in enhancing chatbot capabilities. The text-based smart answering system in agriculture uses RNN implemented a recurrent neural network (RNN) model that answered farmers' queries [12]. Another research proposed an AI-based chatbot using the same NLP techniques to offer real-time farming advice and enhance decision-making precision [13]. The AI-based farmer's assistance chatbot utilized NLP techniques like TF-IDF vectorization and cosine similarity to improve the chatbot's ability to match user queries with relevant agricultural knowledge [14]. Beyond text-based responses, study have been explored multimodal AI approaches that integrate different data processing techniques to enhance chatbot functionality [15]. Another method of agricultural aid via chatbots, is using neural ranking models in an attempt to extract valuable scientific data from large studies, making the leap between scientific knowledge and real-world farming use. [17]. Beyond traditional advisory roles, AI chatbots were also revolutionizing farm-to-market Research on E-Agriculture chatbots has connectivity. introduced direct-to-consumer sales models, allowing farmers to sell their produce directly through social media Facebook Messenger, platforms like eliminating middlemen and ensuring better pricing transparency. While this model improves economic outcomes for farmers, it also demonstrates the wider potential of chatbots beyond information retrieval, moving into supply chain management and financial transactions [18]. The studies, also have demonstrated the scalability of AI-powered agricultural assistants, reaching over 15,000 farmers across multiple countries and processing more than 300,000 queries, highlighting how AI-driven chatbots could bridge the knowledge gap in smallholder farming communities [19].

The proposed work aims to develop an AI-powered assistant for farmers, offering personalized, real-time agricultural recommendations through a chat-based interface. This assistant will use advanced large language models (LLMs) to provide farmers with crucial information such as weather forecasts, future price prediction, and market trends, all tailored to their specific location and crop type. This work leverages modern technologies, including Generative AI, VectorDB, LangChain, and Retrieval-Augmented Generation (RAG), to develop a chat-based assistant. The system integrates real-time weather updates, crop-specific advisory services and disease predictions, and multilingual support to ensure inclusivity across diverse regions. The proposed AI assistant will address these issues by offering real-time, localized multilingual chat interface, ensuring farmers across diverse regions can easily access expert advice. This solution promises to enhance decisionmaking, optimize farming practices, and boost overall productivity, thereby improving farm outcomes. The proposed work is organized in three sections. The design methodology is described in second section, results are discussed in third section, the proposed work compared with literature in forth and the conclusion is presented fifth section.



II. SYSTEM DESIGN

The system aims to assist farmers by leveraging AIpowered analytics to improve decision-making in farming. It is structured in a hierarchical manner, with a core decision-making module leading to specialized insights. As in Fig:1 The key components of the system include agri metrics, smart harvesting, crop intel, smart climate, agri weather, agri price and agri trends. Agri Metrics is the primary module of the system and serves as its foundational component. It is designed to provide key farming insights, likely derived from AI models analyzing multiple data sources. The smart harvesting component allows farmers to select their crop and year for obtaining precision insights. It customizes recommendations based on user inputs. The crop intel component is framed to provide AI-powered insights for smarter farming, possibly covering, price prediction crop recommendations, climate analysis. The smart climate insights for better farming, likely including weather predictions, drought risk analysis, and rainfall forecasting is achieved by The smart climate insights for better farming, likely including weather predictions,

drought risk analysis, and rainfall forecasting by agri weather component. The agri price component offers smarter market insights for maximum profit, providing realtime price trends, demand forecasting, and best-selling strategies. The agri trends unlocks historical data to predict future trends, helping farmers anticipate market shifts and plan ahead. The system is designed with a structured decision-making process that optimizes response retrieval by leveraging OpenAI's vector storage and embeddings. The flow begins at the Interface (Streamlit), where a user submits a query. If the system is online, the next decision node checks whether the query has been previously asked. This is crucial for optimizing response time and reducing redundant computations. If the query has been previously stored, the system retrieves the corresponding response from the Vector Database and returns it to the user. If the query is new, it is forwarded to OpenAI, which processes the request and generates an appropriate response. This response undergoes vectorization and is stored in OpenAI Vector Storage, where embedding generation occurs. Embeddings play a significant role in improving search efficiency and response relevance, as they convert textual queries into high-dimensional numerical representations that facilitate quick and accurate retrieval. The processed embeddings are subsequently stored in the Vector Database (DB) for future retrieval. This database functions as a longterm memory, enabling the system to recognize previously asked queries efficiently. Additionally, a retrieve chat history mechanism ensures that users can access prior interactions, enhancing the conversational continuity and user experience.

This system's architecture effectively integrates machine learning-based retrieval with traditional database storage, leveraging OpenAI's language models and vector EA embeddings to improve accuracy and response time. The decision nodes and storage mechanisms ensure a balance between real-time processing and optimized retrieval, making the system both scalable and efficient. The flow of system shown in fig. 2 outlines a structured pipeline that minimizes redundant processing, enhances response efficiency, and leverages embeddings for intelligent query handling, thereby improving the overall user experience in conversational AI applications.

The primary interface is user interface, developed by using streamlit, which provides a simple, intuitive chatbased interaction model for farmers. The system supports multiple Indian languages to overcome linguistic barriers. When a user submits a query, the system first checks if it has been previously asked. If so, it retrieves the response from a Vector Database, reducing redundant API calls. If it is a new query, it is processed using OpenAI's LLMs. The generated response is then stored for future reference. The system utilizes OpenAI's vector storage for efficient data retrieval. The text is converted into embeddings using advanced AI models, which are then stored in a VectorDB. This allows for fast and relevant retrieval of information. By using external weather forecast APIs and existing market trend APIs, the system provides timely information that assists farmers in making good decisions.Predictive analytics is used to recommend optimal sowing and harvesting periods. One of the major challenges in implementing AI-based solutions for Indian farmers is language diversity. The system supports multiple Indian languages using fine-tuned LLMs, enabling seamless communication for users in different regions.



Fig. 2: System flow diagram

Batch processing is essential for handling large datasets efficiently, ensuring that the data is processed in manageable chunks instead of all at once:

$$B = \{R_i \mid i = k, k+1, \dots, k+batchsize\}$$
(1)

where: *B* is a batch of rows,

Ri represents an individual row,

k is the starting index of each batch.

Total number of batches:

$$N_B = \frac{N}{BatchSize}$$
(2)

Text Embedding should convert structured information into a vector space that can be employed in similarity search or in machine learning applications:



$$T = format(Y, A, V, U, I, E, D)$$
(3)

where: *T* is the formatted text,

Y, *A*, *V*, *U*, *I*, *E*, *D* represent the Year, Area, Value, Unit, Item, Element, and Domain fields of the row, respectively.

Sentence Transformer Embedding:

$$E_T = f(T) \tag{4}$$

where: E_T is the resulting embedding vector, f is the embedding function.

Inserting the processed data into AstraDB after batch processing is key:

$$C \leftarrow C \cup B \tag{5}$$

where: C is the AstraDB collection,

B is the batch of documents being inserted.

III. RESULT ANALYSIS

The proposed AI-powered assistant has been tested across multiple scenarios, including crop selection, year selection, and market trend analysis. The multilingual capabilities significantly improved user engagement and adoption, especially in rural areas. Key findings include:

- Reduction in Information Gaps Farmers gained access to real-time, expert-level guidance tailored to their specific needs.
- Improved Decision-Making AI-generated intelligence optimized resource allocation, reducing costs and enhancing yields.
- Improved Accessibility The multilingual interface removed language barriers, allowing more farmers to benefit from AI-driven recommendations.
- Scalability The architecture supports large-scale deployment, ensuring that more users can access the service without performance degradation.





FarmAssist is an AI-powered agricultural chatbot that provides real-time insights, market impact analysis, and data-driven recommendations with AstraDB integration, NLP-based smart query handling, and multilingual support, it helps farmers, researchers, and agribusinesses make informed decisions and predict future trends. It uses OpenAI key for multilingual support, enabling seamless language translation and region-specific query responses, ensuring accurate and accessible agricultural insights.

🞯 गेहूँ की खेती कैसे करे	
--------------------------	--

👩 गेहूँ की खेती करने के लिए आपको कुछ मुख्य चरणों का पालन करना होगा। यहाँ पर गेहूँ की खेती के लिए विस्तृत प्रक्रिया दी गई है:

1. भूमि चयन और तैयारी:

- भूमि का चयन: अच्छे जल निकासी और उपजाऊ मिट्टी वाले क्षेत्र का चयन करें।
- जुताई: खेत की अच्छी तरह जुताई करें ताकि मिट्टी में हवा और नमी का संचार हो सके। • खुदाई: खेत की खुदाई करें और मिट्टी को अच्छे से पलटें।
- 0.0.0.

2. मिट्टी की जांच: 🗠

pH स्तर: गेहूँ के लिए मिट्टी का pH 6.0 से 7.5 के बीच होना चाहिए।
 नाइट्रोजन, फास्फोरस, और पोटाश: मिट्टी की कमी के अनुसार उर्वरक का प्रयोग करें।

telesson and these about any institutes



ettings			Deploy
eferred Language		🧿 পাট চাৰের পদ্ধকি	
lutomatic	~		
Rođel		👩 পাঁট চাম্বের পদ্মতি সম্পর্কে বিস্তারিত তথ্য নিচে দেওয়া যদো:	
iPT-4o mini	~	১. জমির প্রস্তুতি	
sativity (Temperature)		 জ্ঞামি নির্বাচন: পাটের জন্য উর্বর ৬ জলনিকাশি ভাল এমন জমি নির্বাচন করুন। 	
		• স্কমি চাম্ব: প্রথমে ডেমি ডেলোচাবে চাম করুন এবং আগাছা পরিষ্কার করুন। ডেমি যদি কাঁদা হয় তাহলে তা শুকাতে দিন।	
10	1.00	 সার প্রয়োগ: ভয়িতে জৈব সার (যেমন গোবর) এবং এনপিকে সার (Ntrogen, Phosphorus, Potassium) প্রয়োগ করন। 	
s Response Length 100		২. বীজ বপন	
9	4808	 বীজ নির্বাচন: উচ্চ ফলনশীল পাটের জাত বেছে নিন। সধারণত ১০-১২ কেজি বীজ প্রতি একর জমিতে যথে?। 	
cation (Optional)		 ৰপন পদ্ধতি: গাংটর বীজ সাধারণত এর্জিন মে মাসে বগন করা হয়। বীজগুলো ২-০ সেন্টিমিটার গভীরে বগন করন। 	
ion/State		৩. ডাল ব্যবস্থাপনা	
olkata		. אונה מושאה החולה היונה אינה אינה היה היה היה אינה אינה אינה	
Reset Conversation		• আল দেও জয় সাওের জন্য সময় জেলে হাজেল, নিয়ার করে আজ বাদের সার এবং চাল্ল সভালের সময় জান বেন দেওে নিয়ন্ত্র আ নিষ্ঠিত করুল, তবে জলাবন্ধান্ত এড়িয়ে চলুন।	
		Ask me anything about agriculture	>

Fig. 5: Answering queries in local languages

Farm Assist leverages OpenAI's multilingual capabilities to answer queries in local languages, tailoring responses based on the specified region. It ensures precise, region-specific insights with controlled data length and creativity, making agricultural knowledge accessible to all.

erred Language		Deploy	/ 1
utomatic	×		
odel		give the crops grown in the region	
PT-4o mini	v	Mahamatan kaine diana neinduna kata meneratuka miti ning dianing menekana ania.	
tivity (Temperature)	0.70	Animashita, being a unverse agricultural scale, supports the culturation or various crops deseu on its climate and soil conditions. Here are some major crops grown in the region:	
0 Response Length 80	1.00	Cereals: Paddy (Rice): Grown mainly in the Konkan region. Wheat: Cultivated in the northern and central parts.	
	4000	 Jowar (Sorghum): A staple in many areas, especially during the Kharit season. Bajra (Pearl Millet): Grown in dry regions. 	
ation (Optional)		2. Pulses:	
on/State		• Tur (Pigeon Pea): Commonly grown in the Vidarbha region.	
harastra		 Gram (Chickpea): Grown in various narts during the Rabi season. 	
		Ask me anything about agriculture	
eset Conversation			



It is an intelligent GenAI-driven agricultural chatbot that delivers region-specific, multilingual insights using OpenAI's API. It dynamically adjusts response length and creativity based on user preferences, ensuring precise and actionable recommendations for farmers, researchers, and agribusinesses.



Preferred Language		Deploy	
Automatic	*		
Al Model		🌀 অঞ্চলে ডাল চাষের জন্য আবহাওয়ার পারান্থাত তৈরি করুন	
GPT-40 mini	~		
Creativity (Temperature)		তাল চাম্বের জন্য west Bengal-এ আবহাওয়ার পারাহার্ড বেশ গুরুত্বপূর্ণ। এখানো কন্মু মূল পায়েন্ট রয়েছে যা আপনাকে সাহায্য করকে:	
0.	.79		
8.80	1.00	 মৌসুম: ভাল চাম্বের ছন্য সাঠক সময় হলো ব্রবি মৌসুম (নল্ডেম্বর থেকে ফেব্রুয়ার)। এই সময়ের মধ্যে তাপমাত্রো ২০°C থেকে ২৫°C হওয়া উচিত। 	
Max Response Length		2. বৃষ্টিপাত : ডাল চাম্বের জন্য অভিরিন্ত জল দাঁডিয়ে থাকা উচিত নয়। তাই, বর্ষার সময় জ্রেন থেকে	
		সেপ্টেম্বর) ডামি ভালোভাবে গ্রন্থত করা উচিত এবং অতিরিন্ধ ডাল নিদ্ধাশনের বাবস্থা থাকতে হবে।	
100	4899	 মাটির অবস্থান: ভাল চাষের জন্য দোআঁশ মার্টি সবচেয়ে উপযোগী। মার্টিভে জেব পদার্থ এবং পৃষ্টির 	
Location (Optional)		অভাব না থাকলে তালো ফলন পাওয়া যায়।	
Region/State		 তাপমার্রা: সন্ধা এবং রাতের তাপমারা ১০°৫ এর নিচে না পড়লে ডালো হয়। তাপমারা যুব বেশি হলে সম্পর্ক বিশেষ করের করের বিশেষ বিশেষ বিশেষ করের বিশেষ বিশেষ সম্পর্ক বিশেষ ব সম্পর্ক বিশেষ বিশেষ	
West Bengal		(୧୦୦୮, ଅନ ଓ ୩୮.୫) ଆଟେନ ମାହେନ କ୍ରୀକ୍ଥ ବାବାଣଙ୍କ ୧୯୫ ୩୮.୫।	
		Ask me anything about agriculture	
Reset Conversation			

Fig. 7: Climatic condition of the region

It provides real-time climatic conditions for a specified region, delivering insights in the local language using OpenAI's API key and multilingual support. By integrating regional weather data, it provides accurate information of temperature, rainfall, humidity, and other climatic factors of importance, which allow the farmers to make appropriate agricultural decisions.

Select what you'd like to know

0	Area harvested: Total land area used for cultivation (hectares)
\bigcirc	Yield: Production per unit of land (hg/ha)
\bigcirc	Production: Total quantity produced (tonnes)
\bigcirc	Producing Animals/Slaughtered: Available inventory (tonnes)
\bigcirc	Stocks: Current stock available (tonnes)
_	

- Yield/Carcass Weight: Weight of carcass produced per unit of animal (kg)
- O Milk Animals: Total number of milk-producing animals (head)

○ Laying: Total number of laying hens (head)

Continue

Restart Application

Fig. 8: Select Your Agricultural Metric (Agri Metrics)

Module allows users to retrieve key agricultural metrics, including area harvested, yield, total production, livestock inventory, stock availability, carcass weight, and poultry/milk animal counts. Integrated with real-time data sources, it provides precise, region-specific insights for n Engine informed decision-making in farming.

Hey there! I see you're interested in the area harvested. Could you please see for various categories like cereals, pulses, fruits, and more. Once you choose specific crop you're curious about!	lect a crop category? We have data e a category, let me know which
Select specific crop	
Cassava, fresh	~
Select the year	
2023	~
View Data	
Restart Application	

Fig. 9: Enter Your Query for Precise Agricultural Insights (Smart Harvest)

The query input module allows users to enter specific agricultural queries, which are processed to retrieve relevant data from a AstraDB and connected to Open Api key. Upon receiving a query, the system dynamically fetches, filters, and processes the data based on the selected metrics.

lect specific crop	
Cassava, fresh	
Cassava, fresh	
Peas, green	
Chillies and peppers, dry (Capsicum spp., Pimenta spp.),, raw	
Sorghum	
Tea leaves	
Coffee, green	
Nutmeg, mace, cardamoms, raw	

This module dynamically fetches crop names and related metrics from AstraDB, ensuring accurate and realtime agricultural insights. Users can select different metrics and the system retrieves the corresponding crop data from the connected database.

Hey there! I see you're interested in the area harvested. Could you categories like cereals, pulses, fruits, and more. Once you choose	please select a crop category? We have data for various a category, let me know which specific crop you're curious a
Select specific crop	
Cassava, fresh	
Select the year	
2023	
1960	
1961	
1962	
1963	
1964	
1965	
1966	

Fig. 11: Track Crop Data Across Years (1960-2023)

For each specified crop, the system dynamically retrieves available years (1960-2023) from AstraDB, enabling real-time access to historical agricultural data. This ensures accurate trend analysis and informed decisionmaking.

vear		ltem	Element	Display Value	Status
D	2023	Cassava, fresh	Area harvested	166,000.00 ha	Official figure
Local Back			Parking 1		
alue (ha)			Status		
66 00	00 00		Off	icial figure	
,	0.00		011	ierar ingare	
L Date Mr.	ther Analysis	Price Predictions H	istorical Trends		
eo bata we	Aner Monyais				
eo bata we	And Sharyas				
eo pata we	And Sharyad				
Search Web	for Addition	al Data			
Search Web	for Addition	al Data			
Search Web	for Addition	al Data	Tech	Forent Matric	
Search Web	for Addition	al Data	Try D	ifferent Metric	
Search Web Start New S	for Addition	al Data	Try D	ifferent Metric	

rig. 12: Analysing Data

Farmer Analysis Dashboard dynamically retrieves agricultural data from AstraDB, leveraging OpenAI for multilingual insights. It intersects with web information, price forecasts, weather data, and past trends, offering realtime, AI-based decision-making for farmers and agricultural businesses.



Web Search Results ∞ 1. Global Production Context

- Global Area Harvested: Cassava is primarily cultivated in tropical regions, with an estimated global area harvested of approximately 30 million hectares in 2023. This is consistent with previous years, indicating stability in cultivation practices.
- Major Producing Regions: The largest producers of cassava are:
- Africa: Nigeria remains the world's largest producer, accounting for about 20% of global production, followed by the Democratic Republic of Congo and Ghana.
- Asia: Thailand and Indonesia are significant contributors, with Thailand being the largest exporter.
- Latin America: Brazil and Colombia also play a crucial role in cassava production.
- Changes from Previous Years: The area harvested in Nigeria has seen a slight increase of about 5%
 Fig. 13: Agri Web Insights

It fetches real-time agricultural data from World Bank's API, uses OpenAI for AI-driven summaries, and leverages Redis Cloud as a cache manager for faster data retrieval and reduced API latency, ensuring seamless access to global agricultural insights.

Current	Weather	Conditions

Temperatur 33.2° 7-Day I	°℃ Forecast ∞	Humi 13	3%		wind Speed 2.23 m/s	
	date	temp_min	temp_max	humidity	description	rain_prob
0	2025-03-26	24.31	34.26	52	clear sky	c
1	2025-03-27	21.67	34.67	44	clear sky	(
2	2025-03-28	21.71	34.93	46	clear sky	(
3	2025-03-29	23.53	36.54	32	overcast clouds	C
4	2025-03-30	23.96	37.68	48	overcast clouds	(
5	2025-03-31	23.77	34.03	15	scattered clouds	(

🖶 Al Recommendations

```
Weather Impact Analysis for Cassava - Seedling Growth Stage
```

```
Current Conditions:
```

Temperature: 33.2°C
Humidity: 13%

Wind Speed: 2.23 m/s
Conditions: Clear sky

Fig. 14: Agri Weather Analysis

Insights connect to a Weather API and agriculture databases to provide real-time weather conditions, forecasts, and AI-driven crop growth analysis. It delivers region-specific agricultural insights, helping farmers optimize planting and growth strategies based on climate conditions.

Prediction Summary

Expected decreasing trend with 40.99% change over the next 2 years

Model Confidence

86.77%

Predicted Values

	Year	Predicted Value
0	2,024	130,288.42
1	2,025	76,880.84

Fig. 15: Agri Price Prediction

It leverages Linear Regression with trend and cyclical features to forecast crop prices for the next two years. It provides model confidence scores to indicate prediction reliability, ensuring AI-driven market insights for smarter agricultural decision-making.

Also, it analyses 7 years of historical crop data to track growth trends, maximum increases, and declines. It provides trend visualizations and calculates the overall percentage change, helping farmers and stakeholders make data-driven agricultural decisions.

Historical Trends

	Time Range	- 2023		Average 179,125.0	0	Peak 1	4,000.0)0
listori	cal Dat	а						± < ;
	Ye	ear		Value		Unit		
	0		2,016	204,000.00		ha		
	1		2,017	199,000.00		ha		
	2		2,018	173,000.00		ha		
	3		2,019	163,000.00		ha		
	4		2,020	173,000.00		ha		
	5		2,021	183,000.00		ha		
0,000 0,000 0,000 0,000 0,000								
10,000	160 20165	20170 20	175 20180 2015	5 20100 20105	2 020 0 2 020 5	2.021.0 2	021.5 2.022.0	2.022.5. 2.02
Trend	Analy	sis	11.3 2,010.0 2,010	23 Yurayo Yoraya	2,020.0 2,020.3	2,021.0 2,	021.5 2,022.0	2,022.3 2,02

Fig. 16: Agri Historical Trends

The performance analysis of the system is listed in table 1. The examination is done on different agri metrics of harvested area, yield, total quantity produced, available inventory, stocks, weight of carcass produced per unit of animal (kg), total number of milk-producing animals, total number of laying hens across crop name, year, price prediction, location, agri weather analysis and agri historical trend.

IV. COMPARISON WITH LITERATURE

The proposed system utilizes large language models chatbot with Astra DB database for efficient data storage and multilingual support. It enables advanced queries, offers real-time farm-related information, and offers contextually sensitive suggestions for intelligent farming. The accuracy is used as performance metric for assessment. The proposed system provides accuracy of 94%. The FarmSense work is compared with the existing systems in briefly listed in table 2.



Table 1: Performance Analysis

Agri Metrics	Crop Names	Year	Agri Price Prediction	Location	Agri Weather Analysis	Agri Historical Tends
Area harvested: Total land area used for cultivation (hectares)	Cassava, fresh	2023	76,880.24	Satara	Temp:33.64°C Humidity:17%	-38,000.00 -18.63%
Yield: Production per unit of land (hg/ha)	Sesame seed	2022	848.5	Kolkata	Temp:31.96°C Humidity: 48%	133.50 33.95%
Production: Total quantity produced (tonnes)	Cashew nuts, in shell	2018	1153141.82	Kokan, Maharsatra	Temp: 2.67°C Humidity: 95%	111,000.00 16.54%
Producing Animals/Slaughtered: Available inventory (tonnes)	Meat of chickens, fresh or chilled	2023	2798676.28	Jammu and Kashmir	Temp:17.46°C Humidity: 28%	570,802.00 23.50%
Stocks: Current stock available (tonnes)	Buffalo	2020	111387517.98	Satara	Temp: 33.64°C Humidity: 17%	1,688,496.00 1.53%
Yield/Carcass Weight: Weight of carcass produced per unit of animal (kg)	Meat of goat, fresh or chilled	1999	232.86	Udupi, Karnataka	Temp: 33.26°C Humidity: 47%	29.00 26.13%
Milk Animals: Total number of milk- producing animals (head)	Raw milk of camel	2023	46833.77	Rajasthan	Temp: 33.42°C Humidity: 11%	-956.00 -1.98%
Laying: Total number of laying hens (head)	Hen eggs in shell, fresh	2023	693668.89	Kolhapur	Temp: 37.17°C Humidity: 17%	287,223.00 75.06%

Table 2: Compari<mark>son</mark> with Literature

Ref.	Paper Title	Methodology	Accuracy	Limitations
[2]	Agribot: A Generative Neural Network for Agriculture(Arora et al. (2020))	Agribot is a GNN- and NLP-based artificial intelligence chatbot that helps farmers make decisions on crop selection, weather, pests, and market conditions through interactive question-answering.	70%	Limited Real-time Adaptability Data Dependency
[3]	AgriBot - An Interactive Interface (Sawant et al.)	NLP chatbot using the assistance of AI to support farmers.language queries, understands context, and gives farming recommendations using pre-trained models.	78%	Language barriers, dependency on training data
[7]	Machine Learning-Based Mobile Chatbot for Farmers (Usip et al.)	Machine learning and NLP-based mobile chatbot to assist farmers. text-based queries, learns from users, and optimizes responses for better adaptability.	85%	Struggles with dialects
[19]	Output Sentence Generation for QA Systems(Yamada & Arakawa (2013))	The proposed research prescribes an SMT methodology to produce well-defined, contextually appropriate responses in QA systems in an effort to enhance NLP interactions.	74%	Accuracy depends on the quality of training data, with errors in intricate queries.
[23]	AgriBot: Agricultural QA System (Jain et al.)	NLP question-answering system for agriculture based on machine learning and deep learning to process farmer questions and generate context-sensitive answers.	86%	Struggles with nuanced queries
[25]	Crop Yield Prediction Using ML (Medar et al.)	Machine learning to predict crop outputs from historical data, soil characteristics, and weather patterns through supervised models to give more precise data to help farmers	75.55%	Sensitive to input quality
[26]	A Survey on Chatbot Systems for Agriculture(Niranjan et al. (2019))	AI chatbots in agriculture are presented based on their NLP approach, response strategies, and the integration of the agricultural database to help farmers.	78%	Challenges include language barriers, data dependency, and real-time adaptability issues.
Proposed System	FarmSense: AI-Enhanced Decision Support for Farmers	LLM chatbot with Astra DB for efficient data storage and multilingual support. It enables advanced queries, offers real-time farm-related information, and offers contextually sensitive suggestions for intelligent farming.	94%	



V. CONCLUSION

This work explored the development of an AI-powered agricultural assistant that integrates real-time weather analysis, crop recommendations, historical data visualization, and price forecasting within a multilingual Streamlit application. The assistant leverages GPT-based language models for query interpretation, Linear Regression for price prediction, Redis for fast caching, AstraDB for scalable storage, and Deep Translator for multilingual accessibility. The model achieved a high accuracy of 94%, demonstrating strong reliability. These findings confirm that the integration of advanced AI models with traditional machine learning and modern data platforms can significantly improve agricultural insights and decision-making.

REFERENCES

- Vajinepalli Sai Harsha Vardhan, Parsi Anurag, and Richa Sharma, "Rule-Based Chatbot," International Research Journal of Modernization in Engineering Technology and Science, vol. 4, issue 5, May 2022. e-ISSN: 2582-5208.
- [2] Pravinkrishnan K., Prabavathy Balasundaram, and Lekshmi Kalinathan, An Overview of Chatbots Using ML Algorithms in Agricultural Domain. International Journal of Computer Applications Volume 184 – No.11, May 2022, ISSN:-0975 – 8887.
- [3] Divya Sawant, Anchal Jaiswal, Jyoti Singh, and Payal Shah, "AgriBot - An Intelligent Interactive Interface to Assist Farmers in Agricultural Activities," IEEE Bombay Section Signature Conference (IBSSC), 2019.
- [4] 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, 2024.
- [5] V. Himabindu, V. Anantha Krishna, M. Aishwarya, K. Sri Sindhu, K. Vijaya Laxmi, and A. Jabeen, "Agricultural Helper Chatbot," BioGecko, vol. 12, issue 3, 2023. ISSN: 2230-5807.
- [6] H. Zhu et al., "Foundation Models in Smart Agriculture: Basics, Opportunities, and Challenges," arXiv preprint, vol. 9, issue 6, pp. 761-767, August 2023. ISSN: 2278-0181.
- [7] P. U. Usip, E. N. Udo, D. E. Asuquo, and O. R. James, "A Machine Learning-Based Mobile Chatbot for Crop Farmers," EGETC 2022 Conference, Mexico, 2022, pp. 1–8.
- [8] N. Singh et al., "Generative AI Like ChatGPT in Blockchain Federated Learning: Use Cases, Opportunities, and Future," arXiv preprint, vol. 9, issue 5, pp. 1190-1192, July 2024. ISSN: 2278-0181.
- [9] J. Abou Jaoude and R. Saade, "Blockchain Technology in Smart Agriculture and Food Supply Chain," arXiv preprint, vol. 8, issue 4, pp. 1190-1192, September 2018. ISSN: 2278-0181.
- [10] P. K. Pravinkrishnan, P. Balasundaram, and L. Kalinathan, "An Overview of Chatbots Using ML Algorithms in Agricultural Domain," International Journal of Computer Applications, vol. 184, no. 11, pp. 15–16, May 2022.
- [11] Susheel Gounder, Mahaleppa Patil, Vishal Rokade, and Nikita More, "Agrobot: An Agricultural Advancement to Enable Smart Farm Services Using NLP," JETIR, vol. 8, issue 7. ISSN: 2349-5162.
- [12] Raji Sukumar, Hemalatha, Sarin, and Rose Mary C. A., "Text-Based Smart Answering System in Agriculture Using RNN," Techtern Pvt Ltd.

- [13] Patha Druva, Nelki Sainithin, Muppa Manisai, and K. Sreelatha, "AI-Based Farmer's Assistance Chatbot," IJRASET, vol. 11, issue 5. ISSN: 2321-9653.
- [14] A. Vyshnavi et al., "Chatbot Enhanced by Artificial Intelligence for the Advancement of Agricultural Producers," IJCRT, vol. 12, issue 11, 2024. ISSN: 2320-2882.
- [15] K. Venkat Reddy et al., "Agriculture Assistant Chatbot," IJISRT, vol. 9, issue 5, 2024. ISSN: 2456-2165.
- [16] Pravinkrishnan K. et al., "An Overview of Chatbots Using ML Algorithms in Agricultural Domain," IJCA, vol. 184, issue 11, 2022. ISSN: 0975-8887.
- [17] Bevan Koopman et al., "AgAsk: An Agent to Help Answer Farmers' Questions from Scientific Documents," International Journal on Digital Libraries, 2024.
- [18] N. Singh, J. Wang'ombe, N. Okanga, T. Zelenska, J. Repishti, J. G. K., S. Mishra, R. Manokaran, V. Singh, M. I. Rafiq, R. Gandhi, and A. Nambi, "Farmer.Chat: Scaling AI-Powered Agricultural Services for Smallholder Farmers," arXiv:2409.08916v2 [cs.ET] 8th Oct 2024
- [19] Yamada, T., Arakawa, T.: A study on output sentence generation method for question answering using statistical machine translation. In: 2013 13th International Conference on Control, Automation and Systems (ICCAS 2013), pp. 1199-1202. IEEE, Gwangju, South Korea (Oct 2013).
- [20] H. Zhu et al., "Harnessing Large Vision and Language Models in Agriculture: A Review," arXiv preprint, vol. 9, issue 6, pp. 761-767, July 2024. ISSN: 2278-0181.
- [21] A. Sharma et al., "Blockchain and AI in Precision Agriculture: Benefits, Use Cases, and Challenges," arXiv preprint, ISSN: 2278-0181.
- [22] Sumit Kumar Dam, Yu Qiao, Choong Seon Hong, and Chaoning Zhang, "A Complete Survey on LLM-Based AI Chatbot," IEEE, June 2024. DOI: 10.13140/RG.2.2.19901.27368.
- [23] Jain, N., Jain, P., Kayal, P., Sahit, J., Pachpande, S., Choudhari, J.: AgriBot: agriculture-specific question answer system. IndiaRxiv (June 2019).
- [24] Arora, B., Chaudhary, DS., Satsangi, M., Yadav, M., Singh, L., Sudhish, PS.: Agribot: a natural language generative neural networks engine for agricultural applications. In: 2020 In-ternational Conference on Contemporary Computing and Applications (IC3A), pp. 28-33. IEEE, Lucknow, India (Feb 2020).
- [25] Medar, R., Rajpurohit, VS., Shweta, S.: Crop yield prediction using machine learning techniques. In: 2019 IEEE 5th International Conference for Convergence in Technology (I2CT), pp. 1-5. IEEE, Mumbai, India (Mar 2019).
- [26] Niranjan, PY., Rajpurohit, VS., Malgi, R.: A survey on chat-bot system for agriculture do-main. In: 2019 1st International Conference on Advances in Information Technology (ICAIT), pp. 99-103. IEEE, Chikmagalur, India (Jul 2019).
- [27] U. Kiruthika, V. Balaji, S. K. S. Raja, and C. J. Raman, "E-Agriculture for Direct Marketing of Food Crops Using Chatbots," 2020 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS)