CAPSTONE PROJECT

AI AGENT FOR SMART FARMING ADVICE

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OUTLINE

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PROBLEM STATEMENT

An AI Agent for Smart Farming Advice, powered by RAG (Retrieval-Augmented

Generation), supports small-scale farmers by delivering real-time, localized agricultural guidance.

It retrieves trusted data on weather forecasts, soil conditions, crop recommendations, pest control

measures, and current market prices from agricultural departments, meteorological sources, and agritech platforms.



PROPOSED SOLUTION

- The proposed system aims to address the challenge of predicting which are the best crops that can be grown on a particular area. This involves leveraging AI and Retrieval-Augmented Generation (RAG) techniques to provide accurate, real-time agricultural guidance to small-scale farmers.. The solution will consist of the following components:
- Data Collection:
 - Gather historical data on weather and soil condition, including time, date, location, and other relevant factors.
 - Utilize real-time data sources, such as weather conditions, market prices, and soil conditions, to enhance prediction accuracy.
- Data Preprocessing:
 - Clean and preprocess agricultural data to handle missing values, outliers, and inconsistencies
 - Feature engineering to extract key factors affecting crop choice, soil health, and market trends...
- Agentic Al Logic:
 - Implemented a Retrieval-Augmented Generation (RAG) based AI agent that retrieves relevant agricultural data and generates contextual answers to farmer queries, incorporating factors like weather, soil conditions, crop seasonality, and market trends to ensure accurate and localized guidance..
- Deployment:
 - Developed a user-friendly interface or application that provides real-time predictions for best crop recommended at different locations.
 - Deployed the AI agent on a scalable and reliable platform like IBM Cloud, ensuring efficient server infrastructure, low response time, and easy accessibility for farmers across devices and regions.
- Evaluation:
 - Evaluated the AI agent's performance using relevance and user feedback metrics, and continuously fine-tune the system based on farmer interactions and real-time monitoring to improve response accuracy and usefulness.
 - Result:



SYSTEM APPROACH

System Requirement: Access to agricultural databases, weather APIs, soil data, market prices, and language translation tools.

Libraries/Tools Required: Google, Weather, Webcrawler, Wikipedia Search, watsonx.ai.studio, watsonx.ai.runtime, IBM Granite, IBM Cloud SDKs.



ALGORITHM & DEPLOYMENT

Algorithm Selection:

The chosen Al architecture is Retrieval-Augmented Generation (RAG), which combines the power of information retrieval with natural language generation. It is ideal for this problem as it enables the system to fetch accurate, real-time agricultural data (like weather, soil, and market rates) and generate contextual, language-friendly responses to farmer queries. This ensures that the advice is both data-driven and easy to understand, making it highly effective for grassroots-level smart farming support.

Data Input:

The input features for the RAG-based Al agent include real-time and historical data such as weather conditions, soil health reports, crop calendars, pest alerts, and mandi (market) prices. Additionally, user queries in local languages are processed to extract context and intent, enabling the system to retrieve the most relevant agricultural information for accurate and personalized recommendations.

Training Process:

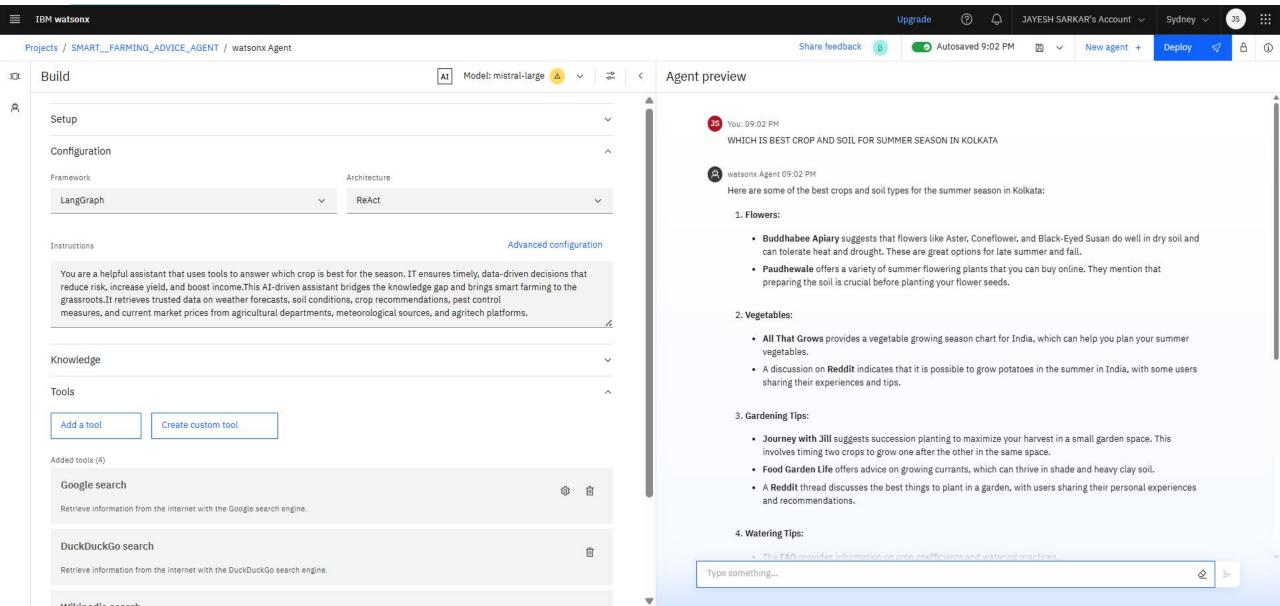
The AI agent leverages pre-trained language models fine-tuned on agricultural datasets, FAQs, and government advisories. Instead of traditional training, it uses retrieval mechanisms to fetch relevant documents in real time. Key considerations include curating high-quality domain-specific data, optimizing retrieval accuracy, and periodically updating the knowledge base to ensure the system remains relevant and context-aware.

Prediction Process:

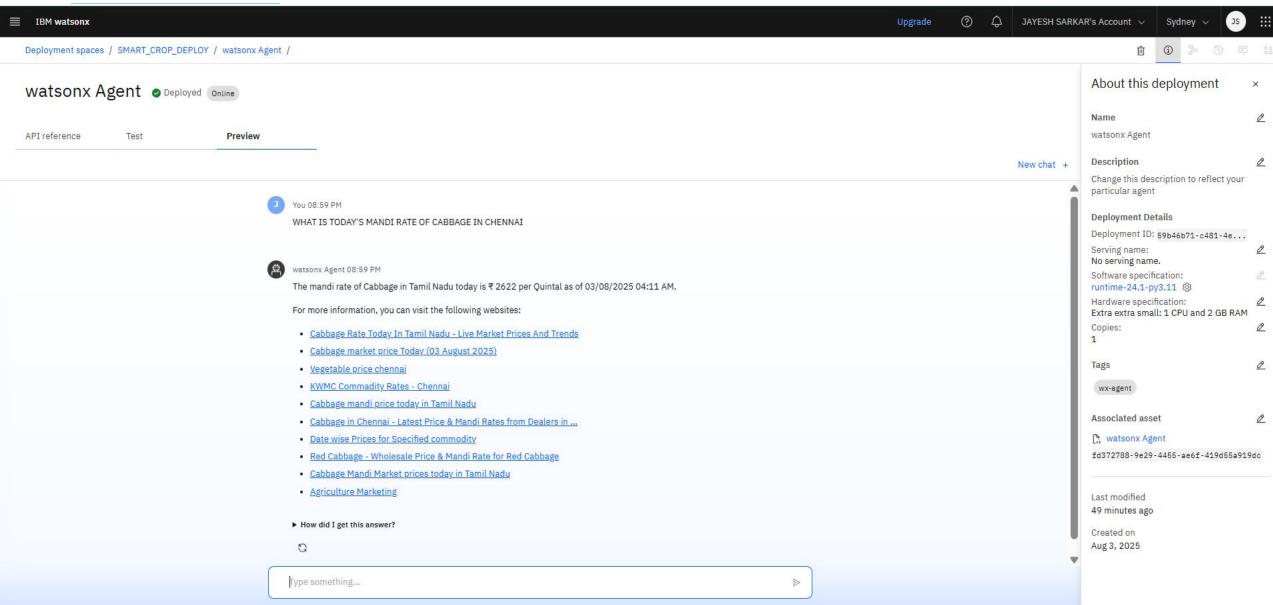
The Al agent does not make traditional predictions but dynamically generates responses by retrieving and synthesizing relevant data in real-time. When a farmer submits a query, the system uses live inputs such as current weather, soil reports, pest updates, and mandi prices. These inputs guide the retrieval process to fetch the most contextually appropriate information, which is then used by the RAG model to generate accurate and personalized advice instantly.



RESULT



RESULT



CONCLUSION

The Al-powered smart farming assistant has proven effective in delivering real-time, localized, and relevant agricultural advice to small-scale farmers. By integrating RAG architecture with trusted data sources and local language support, the system bridges the knowledge gap at the grassroots level. Challenges faced include ensuring data consistency across sources, handling regional language nuances, and maintaining system responsiveness in low-connectivity areas. Future improvements include adding voice interfaces and offline capabilities. Accurate and timely information empowers farmers to make better decisions, ultimately enhancing yield, reducing risk, and improving income stability.



FUTURE SCOPE

Potential enhancements for the Al-powered farming system include integrating more diverse and region-specific data sources such as satellite imagery, IoT sensor data from farms, and hyper-local weather updates. The retrieval mechanism and generation model can be further optimized for faster and more context-aware responses. Expansion to multiple regions with support for various local dialects and crops will increase accessibility. Emerging technologies like edge computing can enable offline advisory services in remote areas, while advanced Al techniques such as multimodal learning and federated learning can further personalize and secure the farming advice.



REFERENCES

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According to the Adobe Learning Manager system of record

Completion date: 25 Jul 2025 (GMT)

Learning hours: 20 mins

THANK YOU

