Grenze International Journal of Engineering and Technology, June Issue

A Survey on AI-Agent Architectures for Smart Agriculture: Crop Recommendation and Market Forecasting

Pramod M. Mathapati[1], Vijay S. Rajpurohit[2] and Sanjeev S. Sannakki[3]
[1-3]Department of Computer Science, K.L. S Gogte Institute of Technology, Affiliated with Visvesvaraya Technological University, Belagavi-590018, Karnataka, India
Email: pramodmathapati64@gmail.com, vijaysr2k@yahoo.com, sannakkisanjeev@yahoo.co.in

***Abstract*— The integration of Artificial Intelligence (AI) agents into smart agriculture promises transformative improvements in productivity, risk management, and market access. This survey systematically reviews AI-agent architectures applied to agriculture, focusing on crop recommendation, weather forecasting, and market price prediction. Following the PRISMA 2020 framework, we examine 65 studies published between 2018 and 2025, emphasizing reproducibility, critical evaluation, and practical implementation considerations. We discuss regional applicability to Karnataka, India, highlighting datasets, policy linkages, and linguistic diversity. The survey identifies key research gaps, including explainability, multilingual support, heterogeneous data integration, and agent orchestration. Furthermore, we propose the AgroSage architecture, a modular multi-agent system integrating CropAgent, WeatherAgent, and MarketAgent, and outline a validation plan encompassing simulation and field deployment. The survey concludes with a roadmap for advancing AI-based smart agriculture, emphasizing scalable, context-aware, and farmer-centric solutions.**

***Keywords*— Artificial Intelligence Agent, Crop Recommendation, Weather Forecasting, Market Price Prediction, Multi-Agent System, AgroSage, Karnataka Agriculture.**

I. INTRODUCTION

Agriculture is a cornerstone of India's economy, supporting over half of the population and contributing substantially to GDP. Despite its importance, the sector faces persistent challenges, including fragmented land holdings, unpredictable weather, pest and disease outbreaks, and volatile commodity prices. Traditional agricultural advisories are often generic, static, and poorly aligned with local conditions, limiting their effectiveness. Artificial Intelligence (AI) agents—autonomous software capable of perceiving environments, reasoning, and acting—offer a promising solution by integrating data from soil, weather, and markets to provide timely, context-aware recommendations.

Multi-agent architectures, comprising specialized CropAgents, WeatherAgents, and MarketAgents coordinated by a central orchestrator, have emerged to manage the complexity of agricultural decision-making. CropAgents analyze soil and historical yield data to recommend suitable crops, WeatherAgents forecast climatic conditions using advanced time-series models, and MarketAgents predict price trends to guide economic decisions. By coordinating these agents, integrated systems can provide holistic and adaptive guidance to farmers.

Grenze ID: 01.GIJET.12.2.81_21

This survey addresses the gaps in existing research by reviewing AI-agent architectures in agriculture, critically evaluating prior systems, proposing a detailed agent taxonomy, and outlining practical implementation considerations. Emphasis is placed on regional applicability to Karnataka, India, where agro-climatic diversity, soil heterogeneity, and linguistic differences influence adoption. The survey also introduces the AgroSage framework with a validation plan, contributing toward scalable, context-aware AI systems for smart agriculture.

II. Survey Methodology

To ensure reproducibility and comprehensiveness, the literature survey was conducted using a structured search across major databases including IEEE Xplore, Scopus, SpringerLink, ACM Digital Library, PubMed, and Google Scholar. The search spanned publications from 2018 to 2025 and employed keywords such as "AI agents in agriculture," "multi-agent farming systems," "crop recommendation machine learning," "market forecasting LSTM or ARIMA," "precision agriculture IoT," and "agriculture chatbot multilingual." Only peer-reviewed journals, conference papers, and high-quality technical reports were included, whereas hardware-only implementations and non-peer-reviewed sources were excluded. The PRISMA 2020 framework guided the screening and selection process, resulting in the inclusion of 65 studies that met the criteria for relevance and quality.

The systematic approach involved identification, removal of duplicates, title and abstract screening, full-text eligibility assessment, and final inclusion for analysis. This structured methodology ensures that the survey is both reproducible and representative of the current state of research on AI-agent systems in agriculture. The resulting dataset provides a basis for critical comparison and synthesis of existing approaches, highlighting trends, strengths, and limitations across different applications.

III. Literature Review and Critical Evaluation

AI-agent systems in agriculture have evolved from simple rule-based models to complex, data-driven, multi-agent frameworks. Early systems, such as MyAgriAI, applied supervised machine learning techniques like Random Forests to recommend crops based on historical data. While accurate in controlled datasets, these systems lacked integration with IoT-based sensors and real-time adaptability. AgriGuide extended the paradigm by incorporating Natural Language Processing (NLP)-based voice assistants in regional languages, thereby enhancing accessibility for low-literacy farmers. However, it remained limited to crop recommendation and did not include market forecasting or comprehensive environmental modeling.

Agri Assist leveraged ensemble learning techniques to improve crop recommendation accuracy. Although the system demonstrated robust predictive performance under static datasets, it did not support real-time data integration or cross-domain coordination. More recent efforts, such as Kazmi et al.'s Smart Farming Assistant (2025), integrated IoT sensors for real-time environmental monitoring, showcasing significant improvement in responsiveness and adaptive recommendations. Nonetheless, market prediction capabilities were not addressed, and validation was restricted to laboratory simulations. The proposed AgroSage framework aims to overcome these limitations by conceptualizing a modular multi-agent system in which CropAgent, WeatherAgent, and MarketAgent operate in coordination under a central orchestrator. While the conceptual model is promising, practical validation remains a gap across the literature.

Across these systems, recurring limitations include fragmentation, lack of benchmarking, limited real-world deployment, and insufficient support for multilingual interaction and heterogeneous data integration. The need for a holistic, integrated approach is evident, motivating the development of frameworks like AgroSage that unify multiple decision domains within a single, adaptive architecture.

IV. AI Agents in Smart Agriculture

AI agents in smart agriculture work together in a multi-agent system, where each agent has a distinct role but contributes to a common goal. The CropAgent focuses on agronomic decision-making by analyzing soil properties (pH, conductivity, nutrients), historical crop performance, and environmental factors. It provides tailored recommendations on planting schedules, crop rotation, and fertilization, improving both yield and sustainability. The WeatherAgent supports these decisions through advanced forecasting models like LSTM and GRU, predicting rainfall, temperature, and humidity. These insights help in irrigation planning, pest control, and reducing risks from climate variability. The MarketAgent addresses the economic side by forecasting commodity prices and market trends using methods such as ARIMA, Support Vector Regression, and Random Forests. It guides farmers on the best timing and channels for selling produce, minimizing losses from price fluctuations.

Overseeing them all, the MasterAgent integrates the outputs, resolves conflicts, and ensures consistent, holistic recommendations that are aligned with local farming conditions. This coordinated approach enhances productivity, resilience, and profitability in agriculture.

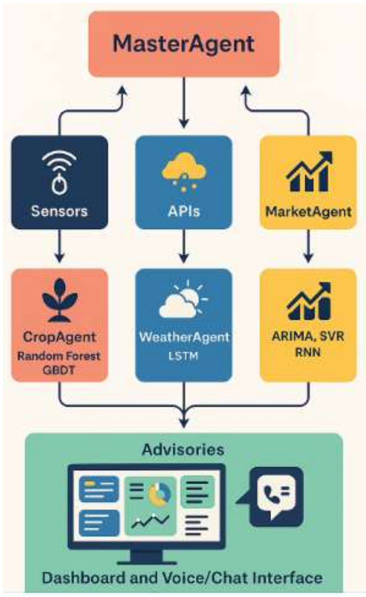

Fig 1. Proposed Architecture or AI Agents

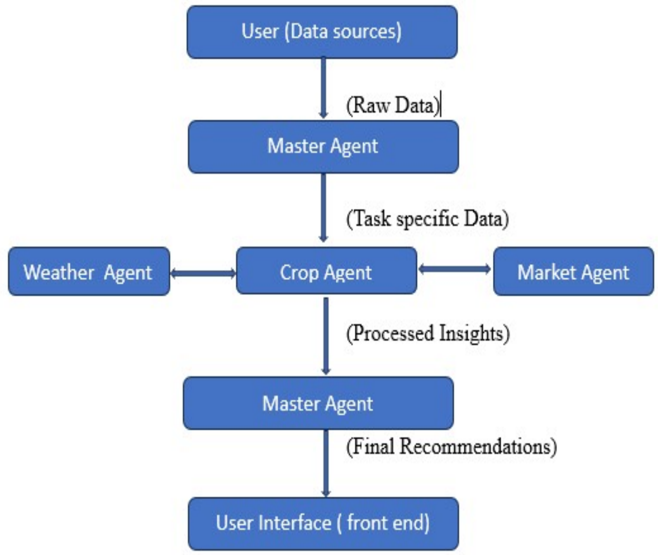

Fig 2. System Dataflow Diaram

V. Multi-Agent Architectures and Implementation Considerations

Multi-agent architectures in smart agriculture are designed for adaptability and integration, with specialized agents handling soil, weather, and market data while synchronizing their outputs into coherent recommendations. Frameworks such as JADE and Mesa enable distributed and simulation-based development, while communication is managed through brokers like Apache Kafka or RabbitMQ, ensuring smooth data flow from heterogeneous sources. A key challenge lies in data fusion, where sensor readings, historical records, and predictive models must be combined to balance agronomic, climatic, and economic needs. These systems also need to address latency, as farmers often require near real-time decision support. To remain effective, they incorporate adaptive learning pipelines that update predictive models in response to shifting weather patterns and market fluctuations. Privacy and security are safeguarded through methods like Federated Learning, which allows collaborative model training without exposing sensitive farmer data. Integration with external APIs and standard protocols ensures interoperability and reliability. Overall, successful deployment depends on harmonizing technical sophistication, operational efficiency, and ease of use for farmers.

VI. Regional Relevance: Karnataka, India

Karnataka's diverse agro-climatic zones, ranging from semi-arid to humid tropical regions, offer a compelling case for deploying AI-agent systems in agriculture. Regional datasets such as Agmarknet mandi price records, e-NAM trading data, and APMC datasets from data.gov.in provide valuable inputs for CropAgent, WeatherAgent, and MarketAgent. Unique challenges in Karnataka include rainfall variability, soil heterogeneity, and the need for multilingual advisory systems to accommodate Kannada-speaking farmers. Policy frameworks such as the Pradhan Mantri Fasal Bima Yojana (PMFBY) and networks of Krishi Vigyan Kendras (KVKs) provide opportunities for practical implementation and validation of AI-agent systems, ensuring that technology solutions are both locally relevant and scalable.

VII. Proposed Prototype and Validation Plan for AgroSage

The AgroSage architecture is validated through a two-phase approach encompassing both simulation and field deployment. In the simulation phase, platforms such as Mesa or JADE are used to model the CropAgent, WeatherAgent, and MarketAgent, incorporating datasets from Agmarknet, soil surveys, and Indian Meteorological Department APIs. Evaluation metrics include RMSE for market forecasts, F1-score for crop classification, latency for responsiveness, and simulated improvements in farmer profitability.

The field deployment phase involves collaborating with selected farmer groups in Karnataka over a complete cropping season. The evaluation focuses on adoption rates, usability, trust in AI-generated recommendations, and feedback on multilingual interfaces. This two-stage validation ensures that the system is both technically robust and practically relevant, providing a comprehensive assessment of its effectiveness in real-world conditions.

VIII. Explainability and Future Opportunities

The adoption of AI-agent systems in agriculture is closely linked to transparency and interpretability. Farmers are more likely to trust recommendations when the underlying reasoning is understandable, highlighting the importance of explainable AI techniques.

References

[1] G. Gupta and S. K. Pal, “Applications of AI in Precision Agriculture,” Discover Agriculture, vol. 3, p. 61, 2025.

[2] S. Dalwai et al., “LEAFSCAN: AI Assistant for Farmers,” International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 5, no. 11, Nov. 2023.

[3] D. Gupta et al., “MyAgriAI: An AI-Powered Web-Based Farming Solution,” International Journal of Research Publication and Reviews (IJRPR), vol. 6, no. 3, pp. 5355–5359, Mar. 2025.

[4] T. Palepu et al., “AgriGuide: AI-Powered Voice Assistant,” International Research Journal, 2025.

[5] P. D. Reddy et al., “Agri Assist: AI Integrated Farmer Assistant,” Procedia Computer Science, vol. 258, pp. 3510–3522, 2025.

[6] M. Kazmi et al., “Smart Farming Assistant Using AI and IoT,” Journal of Emerging Technologies and Innovative Research (JETIR), vol. 12, no. 4, 2025.

[7] A. Kumar et al., “Multi-Agent Based Agriculture Expert System,” NeuroQuantology, vol. 20, no. 12, pp. 4095–4101, 2022.

[8] S. Krishnan, “AI Agents: Architecture and Applications,” International Journal of Computer Applications (IJCA), 2025.

[9] B. Kisliuk et al., “AI in Current and Future Agriculture,” KI - Künstliche Intelligenz, vol. 37, pp. 117–132, 2023.

[10] M. Javaid, A. Haleem, I. H. Khan, and R. Suman, “Understanding the potential applications of artificial intelligence in agriculture sector,” Advanced Agrochem, vol. 2, no. 1, pp. 15–30, 2023.

[11] D. Gosai, C. Raval, R. Nayak, H. Jayswal, and A. Patel, “Crop recommendation system using machine learning,” Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol., vol. 7, no. 3, pp. 558–569, 2021.

[12] V. Aggarwal, A. Jain, H. Khatter, and K. Gupta, "Evolution of Chatbots for Smart Assistance," no. 10, pp. 77–83, 2019

[13] B. Borah, D. Pathak, P. Sarmah, B. Som, and S. Nandi, “Survey of text-based chatbot in perspective of recent technologies,” in Computational Intelligence, Communications, and Business Analytics: Proc. 2nd Int. Conf. CICBA 2018, Kalyani, India, Jul. 27–28, 2018, Revised Selected Papers, Part II, vol. 2, Springer, 2019, pp. 84–96.

[14] J. Khanna, J. Sadavarte, and M. Sankhe, “Krushi – the farmer chatbot,” in Proc. 2021 Int. Conf. Communication Information and Computing Technology (ICCICT), IEEE, 2021, pp. 1–6.

[15] M. Kalimuthu, P. Vaishnavi, and M. Kishore, “Crop prediction using machine learning,” in Proc. 2020 3rd Int. Conf. Smart Systems and Inventive Technology (ICSSIT), IEEE, 2020, pp. 926–932.

[16] Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. PLoS Med. 2021.

[17] Kisliuk B., et al., 'AI in Current and Future Agriculture,' KI - Künstliche Intelligenz, 2023

[18] ter Hoeven E., Kwakkel J., Kazil J., 'Mesa 3: Agent-based modeling with Python,' JOSS, 2025.

[19] Agmarknet, Government of India. https://agmarknet.gov.in

[20] Indian Meteorological Department. https://mausam.imd.gov.in