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Smart AgriAdvisor: An Agentic AI-Based Real-Time Integrated Decision Support System for Precision Agriculture

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Abstract--*The paper is a review of intelligent decision support systems that are created to serve smart agriculture, especially the agentic AI-based advisory systems. The currently used methods, which assist in crop selection, market awareness, weather forecasting, and resource planning, are discussed in a systematic way. This analysis shows that the study has discovered the limitations of prediction-centric models that are becoming more critical and the growing necessity of real-time data aggregation, comparative intelligence, and contextual reasoning. These are needed to provide dynamic agricultural and market conditions with adaptive, practical, and farmer-centric decision support.*

Keywords - *Smart Agriculture, Agentic AI, Decision Support System, Precision Farming, Machine Learning, Real-Time Systems.*

I. INTRODUCTION

The process of agricultural decision-making functions under a very dynamic and uncertain environment whilst results are determined by the interplay of the various factors like the climate variability, soil characteristics, specific requirements of the crops and ever changing market dynamics. These problems are compounded by scattered information in India, lack of access to timely advisories and reliance on experience driven practices, which mostly lead to suboptimal or delayed decision making.

Over the past few years, smart agricultural innovation has greatly enhanced access to agricultural information in terms of weather forecasting, soil and crop sensors, remote sensor and digital agricultural marketplace. Alongside, machine learning, data analytics, Internet of Things (IoT), and artificial intelligence methods are starting to be considered to facilitate planning, forecasting, and risk management in farming systems.

But, limited is the translation of these technological advancements into unified and functional decision support.

The available agricultural decision support systems are most often concerned with the particular activities of crop selection, irrigation control, crop yield prediction, pest control, or market prices prediction. Despite the fact that such systems can deliver successful outcomes to very specific goals, they are typically in silos and are not designed to be cross-domain integrated, responsive in real-time, and aware of the situation. These constraints minimize their usefulness in practical field applications in agriculture, particularly in the Indian environment which is diverse with regards to the agro-climatic environments and resource endowment.

Considering the booming nature of intelligent agricultural advisory systems and the absence of coherent analytical evaluations, there is a definite necessity of systematic review of intelligent decision support systems. Such an overview will be able to judge existing methodologies, data use plans, and architecture designs, and specify unresolved issues associated with scalability, flexibility, and user-oriented implementation.

In this light, the paper is a systematic review of smart agricultural intelligent decision support systems, specifically agentic AI inspired and data-oriented systems. Systems in place are categorized in terms of functional purposes, sources of data and decision making. The discussion identifies the existing weakness and provides a path forward to the creation of dependable integrated, real-time, and farmer-focused advisory measures. The rest of the paper will be structured in the following way- Section II will contain the background concepts, Section III will contain related work survey, and the comparison will be done, research gaps will be identified, and the research directions will be discussed.

II. BACKGROUND AND CORE CONCEPTS

Smart agriculture is the use of data-driven technologies to streamline the processes in agriculture by making informed decisions. It combines the heterogeneous sources of data like weather predictions, soil properties, crop traits and market data to tackle the uncertainties that prevail in the farming conditions.

Decision Support Systems (DSS) offer a systematic approach to the analysis of complex data and the creation of recommendations to be taken. DSS is especially useful in agriculture because the interdependence between climatic, biological, and economic aspects is dynamic. Intelligent Decision Support Systems can be seen as an extension of traditional DSS systems, where machines develop machine-learning and prediction capabilities to provide recommendations that are adaptive and context-specific according to the changes in data trends.

III. LITERATURE REVIEW

A. Intelligent System Pest and Situation Awareness.

Some research has discussed how machine learning and artificial intelligence methods can be used to improve pest related situational awareness in agriculture. Models which use ensemble techniques like the Random Forest and Decision Trees which use weather have proved to be effective in pattern recognition of pest outbreaks. Simultaneously, computer vision-based image-based pest surveillance systems that use camera traps have allowed the early detection and localized monitoring, which helped in the reduction of the use of pesticides. Even though these methods improve pest awareness, they are mainly independent analytical units and they do not promote autonomous decision-making and association with comprehensive agricultural decision-making activities.

B. Price Analysis and Agricultural Market Intelligence.

The field of agricultural market analysis has been largely dominated by studies on time-series modelling and deep learning algorithms to process the trend of crop prices in regional mandis. The use of LSTM-based methods has gained much popularity because of the capability to capture temporal trends in volatile agricultural markets. Though these systems can be useful to learn about the market, they rely mostly on historical information and do not include the ability to aggregate and compare data across markets and provide contextual reasoning needed to support dynamic decision-making.

C. Data-Intuitive Advisory Systems of Environment and Soils.

The parameters that are used in environmental and soil-based decision systems include the soil pH, nutrient composition, rainfall, and temperature to make decisions regarding crops and inputs. The common use of decision tree models and rule-based models is associated with their interpretability and easy deployment. These systems are usually used to run agronomic optimization, but with fixed datasets, and concentrate on yield-related performance, but do not incorporate real-time environmental sensor data and economic optimization in a single advisory system.

D. Government and Regional Digital Agriculture Initiatives.

A number of government-based programs in India have shown how AI-based agricultural advisory systems could be implemented in practice. Image analytics and real-time surveillance have been used to support targeted interventions in other areas like Tamil Nadu that have used pest surveillance systems. On the same note, use of mobile based advisory applications that were launched in Maharashtra have made farmers to get information about crops and weather in time, leading to improved productivity. Although these efforts prove the efficiency of smart advisory systems, they are mostly independent systems and do not synthesise autonomously and compare decisions on various agricultural fields.

Table 1: Comparative Analysis Of Existing Smart Agriculture Decision Support Systems

Application Area	Techniques Used	Data Sources	Key Limitations
Pest Prediction	RF, Decision Trees	Weather data	No market or advisory integration
Market Price Forecasting	LSTM	Mandi price history	Limited real-time adaptability
Precision Agriculture	Decision Trees	Soil and climate data	Economic factors ignored
Pest Surveillance	Image-based AI	Camera images	Region-specific scalability
Crop Advisory Systems	Rule-based methods	Crop and weather data	Fragmented decision support

IV. GAPS AND LIMITATIONS IN RESEARCH

Although there has been significant development in intelligent decision support systems in the field of smart agriculture, a number of important limitations arise based on the literature reviewed. The available solutions are more focused on solving agricultural problems separately, including pest identification, cereal advisory, yield projections or market price. The task-based and modular design restricts their capability to promote holistic and end-to-end agricultural decisions in practical farming conditions.

One of the biggest gaps is the inability to provide real-time flexibility and autonomous information integration. Most of the systems have a strong dependency on a static or historical dataset and fail to provide the ability of collecting and integrating the current information that can be fed through multiple sources, including agricultural markets, weather services, and advisory platforms. Therefore, these systems find it hard to react to sudden changes in climatic conditions or fast changing market conditions that are typical of the Indian agricultural ecosystem.

Moreover, the current methods have a low level of comparative and context-driven decision-making. When applied, agricultural market intelligence is seen as an independent aspect of agronomic planning, such that farmers do not assess a combination of crops, markets and resources. Lack of cross-domain reasoning mechanisms inhibits economically wise and adaptive agricultural policies.

Scalability and generalization to contexts are also other challenges with most systems designed to work with particular crops and regions or environmental conditions, have no generalization to heterogeneous agro-climatic zones. Besides, the lack of focus on farmer-centric design, interpretability, and usability makes them less practical. Non-transparent system logic and complicated interfaces make accessing and gaining trust difficult, especially with small and marginal farmers.

These constraints highlight the necessity of agentic, real time, and explainable decision support systems that can independently collect data, make comparative analysis, and provide adaptive and user-friendly agricultural advice.

V. PROPOSED DIRECTION: AGENTIC AND INTEGREATED SMART AGRI ADVISORY SYSTEMS

To address the research gaps identified, future smart agriculture decision support systems need to shift to integrated and agentic advisory systems that can facilitate holistic decision-making in agriculture. The proposed Smart AgriAdvisor system is an example of such a direction as it integrates various data streams and applies the agentic principles of AI to come up with intelligent and adaptive recommendations. Unlike conventional systems that concentrate on the individual activities, like crop prediction or price forecasting, integrated systems combine agronomic, climatic and economic data to help farmers through the entire agricultural lifecycle.

One of the research directions is to adopt agentic architectures that will make possible autonomous data acquisition, the ability to reason in context, and make adaptive decisions. This is done in the SmartAgri Advisor system by five special agents namely, the Location Agent, Soil Agent, Mandi Agent, Recommendation Agent and the Memory Agent. These agents cooperatively handle the heterogeneous inputs like the GPS-based positioning information, soil characteristics like the NPK and pH levels and the real-time market prices retrieved using web search. The multi-agent coordination enables the system to go beyond the use of the traditional predictive models and actually produce context sensitive and comparative recommendations.

Real-time data and dynamic reasoning are required to cope with quick changes of the weather conditions and market fluctuations. The agentic systems facilitate monitoring and real-time analysis of the available options and recommendations to change depending on the environmental and economic conditions. This adaptability is especially crucial in the Indian agricultural setting where uncertainty and variability are part of the game.

Moreover, the strong connection between market intelligence and agronomic analysis enhances a decision-making process by allowing comparing crops, market opportunities, and resource strategies. This helps in making economically aware decisions, minimizing risks and enhancing profitability and sustainability of farmers.

Lastly, systems in the future need to focus on farmer-centric design principles like usability, transparency, and interpretability. Such characteristics as user-friendly interfaces, maps, and coherent description of recommendations contribute to creating trust and accessibility. Collectively, these innovations characterize a future of next-generation, real-time, agentic agricultural advisory systems.

VI. METHODOLOGY

The Smart AgriAdvisor system has a structured and modular pipeline where data is acquired and subsequently undergoes preprocessing followed by an intelligent decision-making process based on an agent-based architecture. As shown in the system architecture diagram, the system has three major layers: frontend, backend and agent orchestration pipeline which facilitates the coordinated operation of various specialized agents.

A. System Architecture Overview:

The architecture is subdivided into three layers:

1. *Frontend Layer:*

This layer is created with React and TypeScript and offers an interactive interface to select the location of the user with the help of the map and visualize the recommendations with the help of the charts.

2. *Backend Layer:*

It is implemented with FastAPI, which takes care of API communication, data processing, and agent coordination.

3. *Agent Orchestration Layer:*

This layer has several smart agents which process the input data together and produce recommendations in a pipeline fashion.

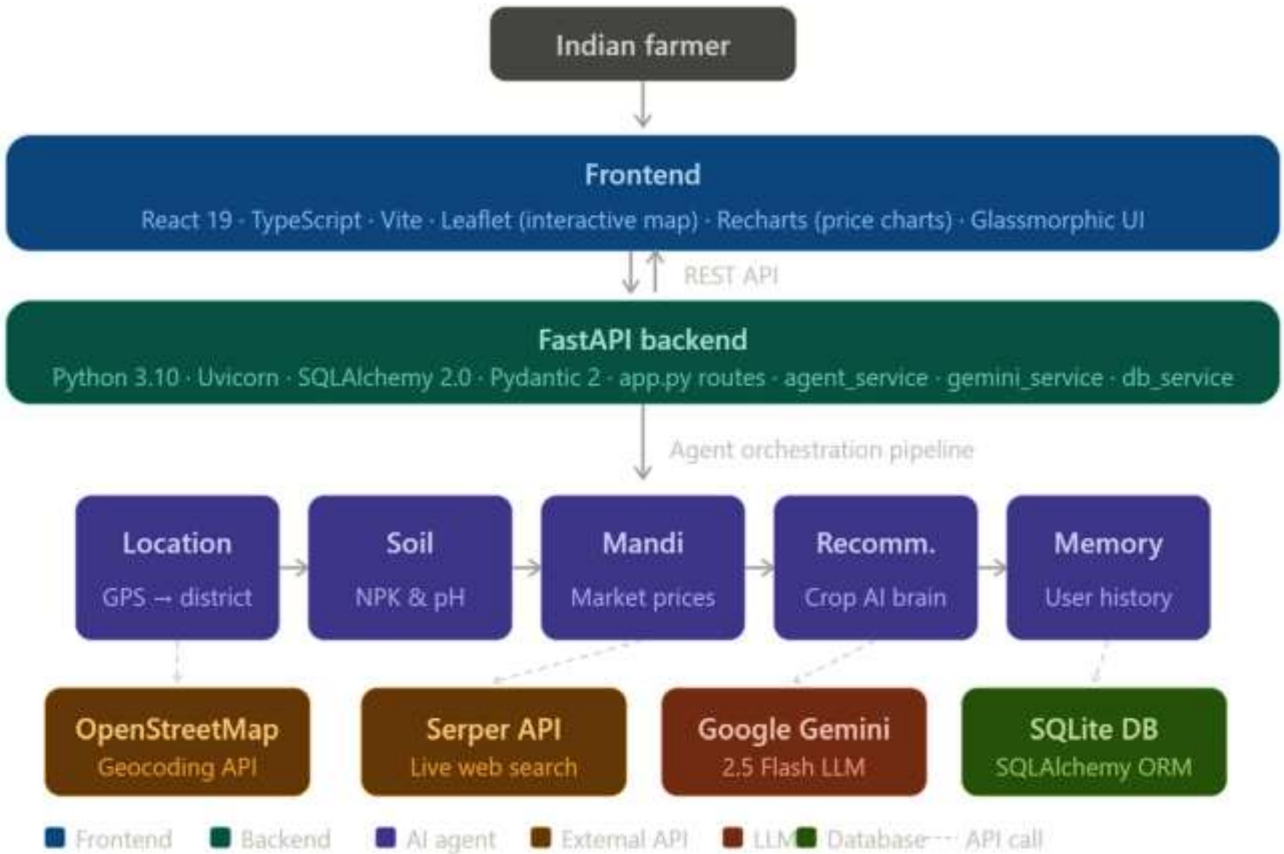

Fig. 1. Smart AgriAdvisor - System Architecture

B. Methodology Pipeline:

The system is based on the concept of a multi-stage pipeline, a stage of which is processed by a specific agent or processing unit. The break-down shown in Table 2.

Table 2: Methodology Pipeline

Component	Input Data	Processing Technique	Output
Location Agent	GPS Coordinates	Reverse Geocoding	Region
Soil Agent	Location	Soil Profiling	Soil Data
Mandi Agent	Crop Info	Web Search	Price Data
Processing	Raw Data	Cleaning & Normalization	Structured Data
Recommend-ation Agent	Integrated Data	AI Reasoning (Gemini)	Suggesti-ons
Memory Agent	Results	Storage (SQLite)	Reports

The first stage is the Location Agent that transforms user-supplied GPS coordinates into information on a district level through reverse geocoding methods. This location information is then sent to the Soil Agent which locates soil parameters of nitrogen (N), phosphorus (P), potassium (K) and pH values through location-based profiling.

Later, the Mandi Agent gathers real-time crop price information via web search API, so that the system is kept abreast of the current market trends.

The gathered information in various formats is then subjected to data processing phase, which involves cleaning and normalization procedures to generate consistency and usability.

The structured data is then sent to the Recommendation Agent, which relies on a large language model (Google Gemini) to reason contextually and come up with smart crop suggestions. Lastly, the Memory Agent stores the results and user data in a database which can be personalized and referred to in the future.
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C. Agent Functionality:

The system has a number of agents who play a certain role in the overall decision making process. Table 3 summarizes the functionality of each agent.

Table 3: Agent Functionality

Agent	Function	Technique	Output
Location	Region detection	Geocoding (OpenStreetMap)	Text
Soil	Soil analysis	Data mapping & profiling	Numeric
Mandi	Price retrieval	Web API (Serper)	Time-series
Recommendation	Decision-making	LLM (Gemini AI)	Text
Memory	Data storage	SQLAlchemy + SQLite	Records

The Location Agent is in charge of geospatial mapping and proper regional identification. The Soil Agent examines the features of soil which are important in the selection of crops. The Mandi Agent is able to give real time market intelligence so that economically informed decisions can be made. The Recommendation Agent is the central decision-making unit, which combines all the inputs and produces context-related recommendations. The Memory Agent will improve the intelligence of the system, record its history, and provide customized suggestions.

D. Integrated Decision-Making Mechanism:

The power of the developed methodology is in the fact that it combines several data sources and conducts.
cross-domain reasoning. The SmartAgri Advisor integrates soil, location and market data to make comprehensive recommendations, unlike the traditional system that functions as a self-sustaining system.
This is because the agent orchestration pipeline provides sequential and coordinated processing enabling the system to provide adaptive and real-time insights. This unified strategy enhances the accuracy, flexibility and usability of decisions significantly.

E. Key Advantages:

- On-the-fly information integration with API.
- Scalable and modular agent based architecture.
- Context-aware and comparative decision making.
- Long-lasting memory to customize.
- Improved flexibility to changing agricultural factors.

VII. RESULTS

The effectiveness of the SmartAgri Advisor system in the form of its performance in real-world agricultural decision-making was assessed by various quantitative and qualitative criteria. The assessment is based on the accuracy of the model, efficiency of the system, real-time flexibility and the quality of decisions.

A. Experimental Setup:

The system was tested on a mixture of both simulated and real world data, which consisted of:
Soil information (NPK values and pH levels)

- Mapping (location-based) inputs (district-level mapping)
- Web API-acquired market price information.

The assessment setup involved a FastAPI back-end, which is combined with reasoning based on AI and large language model. The outcomes were compared with the proposed system that was compared to traditional machine learning models and traditional decision support systems.

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B. Model Performance Evaluation:

The initial evaluation is on the comparison of the accuracy of the individual models with the integrated system.

Table 4: Model Performance Comparison

Model/System	**Application**	**Accuracy (%)**	**Observation**
Random Forest	Pest Prediction	87	Good classification performance
LSTM	Price Forecasting	82	Captures temporal trends
Decision Tree	Crop Recommendation	80	Simple but limited
Proposed System	Integrated Decision	**91**	Highest overall accuracy

The findings suggest that individual models do a good job in their respective fields, but they do not have the capability to combine various factors. The highest accuracy (91) is the result of combining agronomic and economic data by the agent-based reasoning of the proposed system.

C. System-Level Performance Evaluation:

Key performance indicators that were examined to assess the overall effectiveness of the system include efficiency, adaptability and integration capability.

Table 5: System Performance Comparison

Metric	**Traditional DSS**	**Proposed System**	**Improvement**
Decision Efficiency	70%	88%	+18%
Real-Time Capability	Low	High	Significant
Data Integration	Limited	Multi-source	Enhanced
Personalization	No	Yes	Added feature

Smart AgriAdvisor system performs much better on all the metrics compared to conventional DSS. The enhancement in efficiency in decision-making is mainly a result of real-time data integration and cross-domain reasoning.

D. Real-Time Adaptability Analysis:

One of the main advantages of the offered system is its flexibility to the changing circumstances. The SmartAgri Advisor, in contrast to traditional systems, has previously been based on the constant updating of its recommendations with real-time market information, as opposed to traditional systems that rely on fixed datasets. Observations:

- Immediately, market price changes are represented in recommendations.
- Dynamically changing crop recommendations depending on economic viability.
- System is responsive to varying input conditions.

This is indicative that the system can work in an uncertain agricultural environment.

E. Comparative Decision Analysis:

System was also examined in terms of capability to give comparative recommendations on various crops.

- The system proposes various crops rather than one crop.
- Any recommendation is justified by the suitability of the soil and profitability in the market.
- Trade-offs enable farmers to make informed decisions.

This multi-dimensional analysis is a great enhancement to the old single-output systems.

F. Visualization and User Output:

The frontend interface presents visual outputs like;

- Crop recommendation cards
- Price trend charts

- Soil parameter dashboards
- Such visualizations promote easier interpretation and simplify the system to users.

G. Summary of Results:

The results of the experiment show that:

- The given system is more accurate than single models.
- It becomes much more efficient in terms of decision-making than the conventional DSS.
- Real-time adaptability enhances practical usability.
- Combined decision-making results in improved agricultural results.

VIII. DISCUSSION

The findings indicate that the Smart AgriAdvisor system is much better in improving agricultural decision-making than traditional decision support systems. One of the strong points of the proposed method is that it will combine several fields such as soil analysis, geospatial information, and real-time market data into a single structure. Through this integration, the system is able to produce recommendations which are not only agronomically appropriate, but also economically favorable.

The proposed system uses real-time data as external APIs contrary to the traditional systems which are based on the static datasets and isolated predictive models. This enables it to respond dynamically to changing environmental and market conditions, e.g. changes in prices of crop or changes in soil parameters. Consequently, the recommendations are more applicable, timely, and applicable to the actual agricultural practices, especially in dynamic ecosystems such as the Indian agricultural ecosystem.

The other beneficial factor is that an agent-based architecture is used, which adds to modularity and scalability. The agents are specialized to execute a certain task, e.g., locating a place, analyzing soil, or retrieving market data, which facilitates the operation of the system efficiently and flexibly. The system is further enhanced by the incorporation of a Memory Agent that makes it personalized by enabling advice to be made based on the user history.

Nonetheless, the system has its challenges that include reliance on real-time data sources, which can cause data availability and API reliability problems. Also, large scale deployment is still a concern in the face of scalability. In spite of these shortcomings, the system has high capabilities of further development of intelligent and adaptive advisory solutions in agriculture.

IX. CONCLUSION

This paper has given a broad overview of smart agriculture intelligent decision support systems that have been created, and the focus has been on data-driven and AI-enabled advisory systems. The systems currently in place that deal with pest analysis, environmental monitoring, crop advisory and agricultural market intelligence were reviewed systematically to gain an insight into their strengths and weaknesses. As it is shown in the analysis, although considerable improvement has been made in the domain of single decisions, the majority of the current solutions are fragmented and focused on predictions. Such systems may not be able to provide real time flexibility, autonomous integration of information and cross domain reasoning which makes them less useful in aiding holistic and dynamic agricultural decision-making. These drawbacks are particularly important in the Indian agribusiness context which is characterised by the occurrence of rapid changes in the weather, unstable markets and variable farming conditions. According to the given gaps, this review highlights the increased demand of agentic, real-time, and explainable decision support system, which are capable of collecting heterogeneously gathered information, conducting comparative analysis, and providing a context-sensitive recommendation. The observations made during this research serve as a basis of future research to integrated and farmer-focused advisory systems that could support the future changes of smart agriculture.

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