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Agrosphere: AI-Powered Personalized Scheme Navigator for Farmers

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Abstract

Access to government welfare schemes remains a major challenge for farmers due to fragmented information, complex eligibility criteria and lack of personalized guidance. Despite the availability of numerous schemes related to subsidies, insurance and financial support, many eligible farmers fail to benefit from them because of low digital literacy, language barriers and dependence on intermediaries. To address these issues, this paper presents Agrosphere, an AI-powered personalized scheme recommendation system designed to assist farmers in identifying suitable government programs based on their individual profiles. The proposed system follows a modular three-tier architecture consisting of a React-based frontend, a Spring Boot backend and a Python-based machine learning microservice. It employs a hybrid approach that integrates a rule-based eligibility engine with machine learning algorithms such as Logistic Regression and K-Means clustering. The rule-based module ensures strict compliance with official eligibility criteria, while the machine learning component enhances personalization by analyzing patterns in farmer data and ranking schemes accordingly. The system processes key farmer attributes including landholding size, income category, crop type and geographic location to generate accurate and interpretable recommendations. Experimental evaluation demonstrates that the system efficiently filters irrelevant schemes and produces ranked outputs within acceptable response time for real-time applications. The proposed solution improves accessibility, reduces information asymmetry and minimizes dependency on manual assistance. Agrosphere highlights the potential of combining rule-based systems with machine learning to build scalable, transparent and user-friendly decision support platforms for e-governance, ultimately contributing to improved welfare delivery in the agricultural sector.

Keywords: Machine Learning; Rule-Based Eligibility; Logistic Regression; K-Means Clustering; E-Governance; Decision Support System

How to Cite This Article

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Introduction

Agriculture plays a vital role in the Indian economy, supporting a large portion of the population and contributing significantly to national food security and rural livelihoods. To strengthen this sector, governments have introduced numerous welfare schemes related to subsidies, crop insurance, financial aid and risk management. However, despite the availability of these initiatives, a significant number of eligible farmers remain unable to benefit from them. This gap is primarily caused by lack of awareness, complex eligibility conditions, fragmented information sources and dependence on intermediaries for guidance.

Existing digital agricultural platforms mainly focus on providing advisory services such as weather updates, crop recommendations and market price information. While these systems are useful, they fail to offer personalized assistance in identifying relevant government schemes based on individual farmer profiles. As a result, farmers often spend considerable time navigating multiple portals or rely on external agents, leading to inefficiencies, delays and exclusion errors. These challenges are further intensified by low digital literacy levels, language barriers and the absence of intelligent decision-support systems tailored to farmer-specific needs.

Recent advancements in machine learning and e-governance technologies present an opportunity to address these limitations. By leveraging farmer-specific attributes such as landholding size, income level, crop type and geographic location, intelligent systems can automate eligibility verification and generate personalized recommendations. However, many existing solutions remain either conceptual, lack transparency, or do not provide end-to-end system integration.

To overcome these challenges, this paper proposes Agrosphere, an AI-powered personalized scheme navigation system that integrates rule-based eligibility logic with machine learning techniques. The system is designed using a modular architecture comprising a web-based frontend, a backend processing layer and a machine learning microservice. By focusing on scalability, transparency and user-centric design, Agrosphere aims to reduce information asymmetry and improve accessibility to welfare schemes, ultimately contributing to inclusive and efficient agricultural support systems.

Literature review

Recent advancements in artificial intelligence and digital platforms have significantly improved agricultural and e-governance services. The study on AI-driven agricultural knowledge systems highlights how AI-based tools provide real-time advisories, crop recommendations and predictive analytics, improving decision-making for farmers. However, challenges such as low digital literacy and limited accessibility still hinder widespread adoption [1].

In the domain of e-governance, personalized recommendation systems have been proposed to address information overload. Collaborative filtering-based approaches have shown effectiveness in recommending relevant government services by learning user preferences from interaction data. However, these systems often rely on implicit feedback and face challenges in accurately capturing user intent. User accessibility remains a critical concern. Research on interface design for illiterate users emphasizes the need for voice-based interaction, intuitive design and minimal text dependency to ensure usability in rural environments. Similarly, agricultural chatbot systems demonstrate that intent-aware and multilingual conversational AI can significantly improve information accessibility, achieving high accuracy and user satisfaction. However, many existing systems are domain-specific and lack scalability.

Furthermore, studies on multilingual NLP reveal limitations in handling Indian languages due to resource scarcity and code-mixing challenges, affecting real-world deployment of intelligent systems. Welfare scheme recommendation platforms also highlight the importance of AI-driven eligibility checking but lack advanced personalization and integration. Overall, existing solutions lack a unified system that combines personalization, accessibility and scalable integration, motivating the development of Agrosphere.

System Architecture

Agrosphere follows a three-tier architecture comprising a React-based frontend, a Spring Boot backend and a machine learning microservice. Farmer data is collected through the UI, processed via REST APIs and analyzed using rule-based and ML models. The system returns personalized scheme recommendations, ensuring scalability, modularity and efficient decision support.

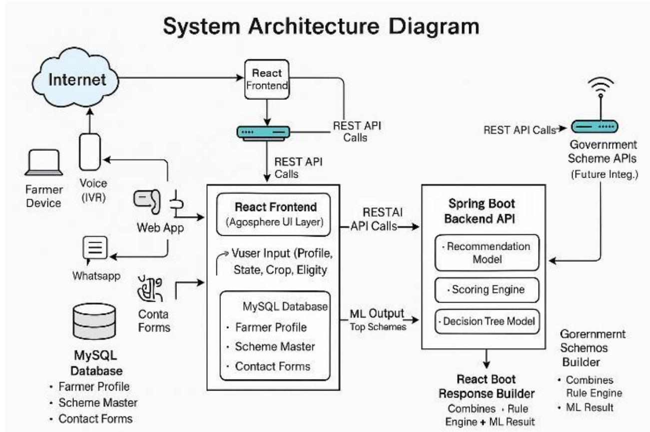


Fig 1. *System Architecture Diagram*

Methodology

The proposed system adopts a modular and layered methodology to deliver personalized welfare scheme recommendations for farmers. The methodology integrates a web-based user interface, a backend service layer and a machine learning module to ensure scalability, accuracy and explainability. The overall workflow begins with farmer data collection and ends with ranked scheme recommendations presented to the user.

System Overview

The Agrosphere system follows a three-tier architecture consisting of a frontend layer, a backend processing layer and a machine learning microservice. The frontend is responsible for user interaction and data collection, while the backend manages business logic, eligibility checks and database operations. The machine learning layer performs data-driven analysis and recommendation tasks. Communication between components is achieved through RESTful APIs, ensuring loose coupling and easy extensibility.

Farmer Data Collection and Validation

Farmer profile data is collected through a web-based interface developed using React.js. The input fields include state, landholding size, crop type, income category and social category. Client-side validation is implemented to ensure data completeness and correctness before submission. Validated data is transmitted securely to the backend using HTTP POST requests.

Backend Processing and Data Management

The backend is implemented using Spring Boot and serves as the core processing unit of the system. It exposes REST APIs to receive farmer data, retrieve scheme information and coordinate with the machine learning service. Farmer profiles and scheme metadata are stored in a MySQL relational database to ensure persistent storage and efficient querying. A rule-based eligibility engine is implemented at this layer to filter schemes based on predefined government eligibility conditions.

Rule-Based Eligibility Engine

The rule-based engine applies deterministic IF–THEN logic derived from official scheme guidelines. Parameters such as land size thresholds, income limits, crop eligibility and regional applicability are evaluated to eliminate ineligible schemes. This step ensures transparency, correctness and alignment with government policy rules before applying machine learning techniques [3].

Machine Learning–Base Recommendation

After rule-based filtering, the eligible schemes are passed to the machine learning module for further personalization. Logistic Regression is employed to predict the likelihood of scheme suitability for a given farmer profile, treating eligibility as a binary classification problem. Additionally, K-Means clustering is used to group farmers with similar characteristics, enabling pattern discovery and group-based recommendation enhancement. These models are implemented in Python and exposed through a Flask-based microservice [7].

Integration and Recommendation Output

The Spring Boot backend communicates with the machine learning service using REST calls and receives a ranked list of recommended schemes along with confidence scores. The backend consolidates the results from the rule-based and machine learning components and sends the final response to the frontend. The frontend presents the recommendations in a structured and user-friendly format using scheme cards, enabling easy comprehension by farmers.

Security and Scalability Considerations

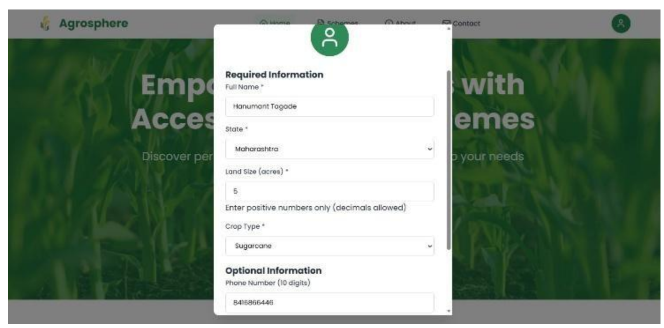
Basic security measures such as input validation and controlled API access are incorporated to ensure data integrity. The modular design of the system allows independent scaling of the frontend, backend and machine learning services. This architecture also supports future enhancements such as multilingual interfaces, voice-based access and integration with external government data sources.

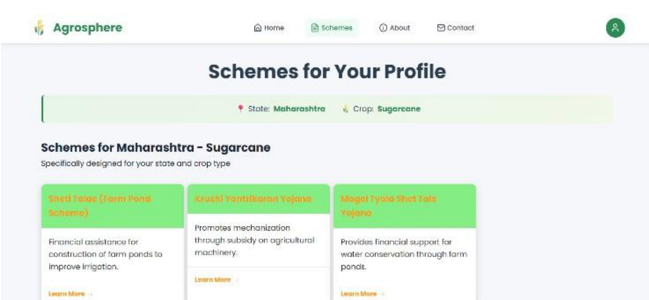
Results

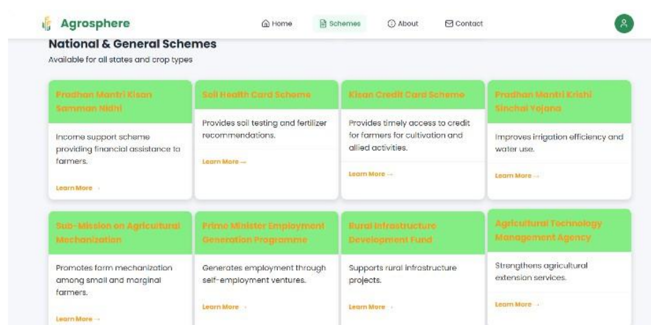
The proposed Agrosphere system was implemented and tested for functionality using the core components of the system, such as frontend interaction, backend processing and machine learning integration. The frontend system was able to capture farmer profile information correctly and send it to the backend services. The Spring Boot backend system was able to store farmer profiles correctly in the MySQL database and identify relevant welfare schemes according to regional and eligibility criteria.

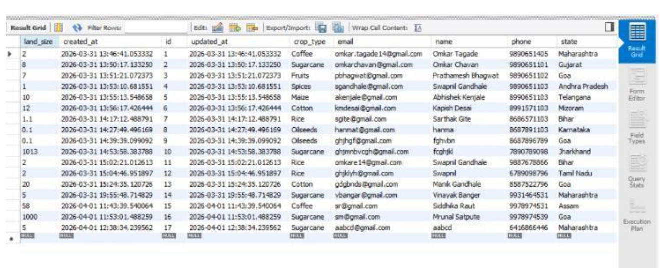
The rule-based eligibility engine was able to eliminate schemes that are not eligible according to predefined government criteria. The machine learning component further improved the scheme identification process by ranking the schemes according to farmer attributes. Logistic Regression was used to make binary predictions regarding scheme eligibility, while K-Means clustering was used to group farmers with similar profiles to improve personalization.

The system was able to generate a ranked list of schemes for different farmer profiles, indicating its capability to filter out irrelevant information and focus attention on relevant welfare schemes. The initial test of the system indicated that it is capable of responding within acceptable time limits for web-based applications and performs consistently even after multiple submissions of farmer profiles.









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Testing And Validation

The Agrosphere system was evaluated through a combination of unit testing, integration testing and functional validation to ensure reliability and correctness. Individual modules such as data input validation, rule-based eligibility filtering and machine learning prediction were tested independently using controlled input scenarios. Edge cases, including incomplete or inconsistent farmer data, were used to verify robustness and error handling. Integration testing was conducted to validate seamless communication between the React frontend, Spring Boot backend and the Python-based machine learning microservice. REST API endpoints were tested for correct request-response handling, latency and data consistency. The system demonstrated stable performance under repeated requests, maintaining accurate data flow across components. For validation of the recommendation model, sample farmer profiles with varying attributes such as landholding size, income level and crop type were used. The outputs were compared against predefined eligibility rules to ensure correctness. The machine learning component was evaluated for its ability to rank relevant schemes effectively, improving personalization over rule-based filtering alone. Additionally, basic usability testing was performed to assess the interface's clarity and accessibility. The system responded within acceptable time limits, confirming its suitability for real-time deployment. Overall, the testing process validates the system's accuracy, stability and practical applicability.

Discussion

The outcome shows that the integration of rule-based logic and machine learning is an efficient and well-rounded approach for recommending welfare schemes. The rule-based eligibility system provides transparency and accuracy, which is a crucial aspect of governance-related tasks and the machine learning algorithms add flexibility and personalization. Logistic Regression was found to be an effective algorithm for eligibility prediction because of its simplicity, interpretability and efficiency in handling structured data. K-Means clustering helped in the identification of farmer groups without the need for labeled data, which is helpful for group recommendation approaches. The modular design facilitated smooth interaction between the frontend, backend and machine learning components using REST APIs. The system, as it is now, has some limitations in terms of adaptability to changing policies. Moreover, the multilingual and voice interaction capabilities are not fully developed in the current system. Nonetheless, the system has immense potential as a scalable decision-support system for enhancing access to farmer welfare schemes.

Conclusion

This paper introduced Agrosphere, a personalized scheme navigation system intended to help farmers discover relevant government welfare schemes eligible for them. The system combines a rule-based eligibility engine with machine learning algorithms like Logistic Regression and K-Means clustering to offer accurate, interpretable and personalized suggestions. The system's modular design, featuring a React frontend, a Spring Boot backend and a Python machine learning microservice, promotes scalability, ease of maintenance and seamless system integration. Experimental results validate the practicability of the proposed approach in alleviating information overload and enhancing scheme awareness among farmers. Future research will concentrate on improving the system with multilingual support, voice interaction capabilities for feature phone users, real-time connectivity with government databases and more sophisticated machine learning models to enhance the accuracy of recommendations. In conclusion, Agrosphere illustrates the efficacy of intelligent digital platforms in enhancing inclusive and farmer-centric welfare delivery systems.

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References

1. R. Negi, A. Kumar, P. K. Singh, R. K. Singh, and T. K. Singh, "AI-driven agricultural knowledge system: Empowering Indian farmers," *International Journal of Research in Agronomy*, vol. 8, no. 6, pp. 201–204, 2025.
2. M. P. Huenerfauth, "Design approaches for developing user-interfaces accessible to illiterate users," Adaptive Speech Interfaces Group, University College Dublin, 2003.
3. N. Sun, T. Chen, W. Guo, and L. Ran, "Enhanced collaborative filtering for personalized e-government recommendation," *Applied Sciences*, vol. 11, no. 24, p. 12119, 2021.
4. Vijayvargia et al., "Intent aware context retrieval for multi-turn agricultural question answering," *arXiv preprint arXiv:2508.03719*, 2025.
5. V. Magdum, O. Dhekane, S. Hiwarkhedkar, S. Mittal, and R. Joshi, "mahaNLP: A Marathi natural language processing library," *arXiv preprint arXiv:2311.02579*, 2023.

6. V. Srivastava and M. Singh, "Challenges and considerations with code-mixed NLP for multilingual societies," *arXiv preprint arXiv:2106.07823*, 2021.
7. Thiyagarajan P., Tamizhanban G., and G. V. Reddy, "AI-driven welfare scheme assistance and management system," *International Journal of Research Publication and Reviews*, vol. 6, no. 4, pp. 7683–7686, 2025.
8. Talaviya, T., Shah, D., Patel, N., Yagnik, H., & Shah, M. (2020). "Implementation of artificial intelligence in agriculture for optimization of irrigation and application of pesticides and herbicides." *Artificial Intelligence in Agriculture*, 4, 58–73.
9. Jha, K., Doshi, A., Patel, P., & Shah, M. (2019). "A comprehensive review on automation in agriculture using artificial intelligence." *Artificial Intelligence in Agriculture*, 2, 1–12.
10. Pathak, H., Brown, P., & Best, T. (2019). "A systematic literature review of the factors affecting the precision agriculture adoption process." *Precision Agriculture*, 20(6), 1292–1316.