Enhancing Smallholder Agriculture through AI-Based Crop Advisory and Contract Farming Automation

Narendra Kolte1, Pranav Pawar2, Mohit Suradkar3, Sahil Wadafale4 , Prof. S. H. Thengil
1Department of Information Technology, Sinhgad College of Engineering, Pune- 41
2Department of Information Technology, Sinhgad College of Engineering, Pune- 41
3Department of Information Technology, Sinhgad College of Engineering, Pune- 41
4Department of Information Technology, Sinhgad College of Engineering, Pune- 41

---***---

Abstract **:** The Smart Farming Assistant is an Artificial Intelligence (AI)-driven platform designed to empower small and marginal farmers by offering intelligent crop advisory, contract farming opportunities, and real-time farm management support. The system utilizes soil testing reports and AI-based analysis, handled by the **Crop Prediction Module**, to recommend the most suitable crops and generate personalized farm schedules covering all stages from sowing to harvesting. A crucial element is the **Contract Farming Module**, which enables farmers to view and apply for contracts published by agro-based companies, ensuring assured markets and fair pricing. The platform also integrates the **Government Scheme Information Module**, real-time market intelligence, and provides an offline mode for users in low-connectivity rural areas. By focusing on digital intelligence, market access, and structured financial mechanisms, the Smart Farming Assistant bridges the gap between traditional farming and modern digital agriculture, enhancing profitability, efficiency, and sustainability for farmers

***Key Words*:** AI, Contract Farming, Crop Advisory, Smart Farming, Small Farmers; Sustainability; Broiler Chicken; Agent-based simulation; Agricultural supply chain; Household income; Rice cultivation; High ecological value standard.

1. INTRODUCTION

The agricultural sector faces pervasive challenges, particularly for small and marginal farmers who struggle with limited capital, high input costs, production risks, and difficulties accessing reliable, high-value markets. The Smart Farming Assistant platform addresses these constraints by providing a robust, AI-driven, digital solution focused on increasing profitability, efficiency, and sustainability.

The platform offers core services including intelligent crop advisory, secure market integration, and comprehensive farm management support. The system architecture is compartmentalized into seven major modules, but its core functionality is centred on the Crop Prediction Module, the Contract Farming Module, and the Government Scheme Information Module.

The integration of the Contract Farming Module is especially critical, as contract farming is recognized globally as a mechanism for vertical coordination that can provide smallholders with access to inputs, technology, and guaranteed output markets. However, the efficacy of contract farming hinges on addressing risks related to coordination, breaches, and transparency. By digitising this process, the Smart Farming Assistant provides a structured environment to manage these contractual relationships and promote stability.

2. LITERATURE SURVEY

The existing literature extensively explores the dynamics, impacts, and challenges of contract farming (CF), providing a crucial context for the platform's primary modules.

Contract Farming Scope and Impact

CF is broadly defined as vertical coordination that specifies market obligations (e.g., volume, quality, price) and often involves input provision and production control. Research distinguishes between **formal contracts** (e.g., large companies and producers) and **less formal credit agreements** (traders and farmers). Informal contracts, which concern locally consumed crops and are based on close social ties, might play a **more important role in agrarian transformation in Africa** than formal contracts by large companies.

CF has been associated with **substantially higher total household incomes**. However, the pathway to income gain differs significantly depending on the contract type:

• **Simple Marketing Contracts (MC):** These specify output conditions (price, quantity, timing). In the Ghana oil palm sector, MCs were associated with **higher off-farm wage and self-employment income** (up to 54% higher). This suggests that farmers reallocate labour time saved (e.g., from reduced post-harvest handling) to off-farm activities, as credit constraints often persist under MCs.

• **Resource-Providing Contracts (RPC):** These address credit market failures by additionally offering in-kind credits for investment and maintenance. In Ghana's oil palm sector, RPCs were associated with **much higher farm incomes** (110% higher total farm income), due to enabling investment in larger areas and intensified production. RPCs are effective for farmers aiming to overcome credit and technology constraints and focus on increasing farm production.

Trust, Breach, and Risk

The success of contracts in volatile markets depends heavily on **economic incentives (monetary profit)** and **trust**. Studies focusing on contract rice farming in the Mekong Delta (MKD) found early schemes failed due to frequent **unilateral breaches** by both parties, driven by spot market price fluctuations. When spot market prices increase, farmers may side-sell; conversely, large buyers may delay purchases to manipulate prices. Agent-

Based Simulation (ABS) models confirmed that when farmers have no fear of losing a contract, they opportunistically side-sell. Furthermore, breaching incidents by contractors can lead to a **reduction of the trust base-level** towards that contractor among neighboring farmers, hindering future contract success.

Technology Adoption and Sustainability

Contract farming has an **evident positive influence on farmers' choice of green, smart agriculture technologies**, such as in modern rice cultivation in China. CF provides standardized production processes, technical guidance, and training. Research using gradual regression methods found that the **high ecological value standard** plays a **completely mediating role** in promoting the adoption of green, smart technologies. This adoption is further strengthened when the farmer's income from cultivation is high, as greater economic accumulation enables them to bear operational and technological risks.

Sustainability assessments, such as those in the Indonesian broiler chicken supply chain using the Rap-Poultry method, indicate that contract farming supply chains often reach a **"moderate sustainable" status**. Key sensitive indicators affecting sustainability include pollution of chicken manure, frequency of technical guidance, and the price of Day Old Chickens (DOC) and feed.

3. OVERVIEW

3.1. Objective

The main objective of the Smart Farming Assistant is to provide an AI-driven digital tool to support small farmers by providing intelligent crop advisory, securing market access through digital contracts, and offering real-time farm management support to enhance **profitability, efficiency, and sustainability**.

3.2. Core Components

The platform is designed with seven major modules, with the following three emphasized as main areas of functionality:

i. Crop Prediction Module: This module provides personalized guidance throughout the crop lifecycle, generating schedules and recommendations based on soil data.

ii. Contract Farming Module: This critical module facilitates collaboration between farmers and organizations, ensuring assured market access and fair pricing.

iii. Government Scheme Information Module: This module provides informational access, allowing farmers to view eligible schemes and related requirements.

3.3. Working Principle

The system operates based on data-driven intelligence and management:

• **Data Input:** The Farmer class records essential attributes, including farmSize, location, and languagePreference. Each farmer is linked to a **1–1 SoilData record**, which captures metrics like soilType, phLevel, and nutrientLevels.

• **AI Processing:** The soil data is cleaned and preprocessed by the DataPipeline class (part of the **AI/ML Backend Module**) and feeds the CropPredictionModel.

• **Advisory Output:** The model output generates a **1–1 CropRecommendation** which lists recommendedCrops and a confidenceScore. Based on the crop selected, the FarmSchedule class generates personalized tasks (e.g., irrigation, fertilization, pest control alerts).

• **Contract Management:** The Company class can **post multiple contracts** (1–* relationship). Farmers can apply to multiple contracts (1–* relationship), and contract execution is tracked digitally via ContractProgress reports.

3.4. Accessibility and Innovation

While designed as a digital platform, the system incorporates features to enhance usability for all farmers:

• **Accessibility:** The platform is built for accessibility and inclusivity, allowing users to interact effortlessly.

• **Connectivity:** The **Offline Data Manager** is crucial for users in low-connectivity regions. It caches key data (Crop, Contract, Weather) locally and synchronizes when the device is online (1–1 composition relationship).

• **Real-time Data:** The **External API Integration Module** incorporates real-time information, including localized weather forecasts (WeatherService) and **mandi prices per quintal** (MarketPriceService).

3.5. Social and Technological Impact

The platform facilitates key transformation processes:

• **Market Security:** The Contract Farming Module provides assured markets and transparency by allowing companies to review progress and approve harvests digitally.

• **Technological Adoption:** By providing structured guidance and market incentives through contracts, the platform encourages the sustainable utilization of agricultural resources such as water and land, promoting a positive ecological circulation.

• **Government Support:** The **Government Scheme Information Module** allows farmers to view eligible schemes, including eligibilityCriteria and benefits (view-only 1–* relationship).

4. METHODOLOGY

The project methodology integrates quantitative research principles drawn from academic studies of contract farming with a detailed blueprint for system development (System Architecture).

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 11 | Nov - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

4.1. Academic Methodologies

The complex dynamics of contract farming relationships are evaluated using sophisticated statistical and simulation techniques:

Sustainability Metrics (Rap-Poultry Analysis)

To measure and compare the sustainable performance of supply chains (e.g., broiler chicken production), the **Rapid Appraisal for Poultry (Rap-Poultry)** method is used, based on the **Triple Bottom Line (TBL)** concept (Economic, Social, Environmental).

• **Process:** This method uses **Multidimensional Scaling (MDS)** to calculate the sustainability index, categorized as "not sustainable" (0-25%) up to "good sustainable" (>75-100%).

• **Validation:** The **S-stress value** must be less than 0.25, and the **R2** value should approach 1.00 for the model to have a good fit.

• **Sensitive Indicators: Leverage analysis** computes the **Root Mean Square (RMS)** value to identify indicators whose change has the greatest effect on the overall sustainability index (sensitive indicators).

• **Consensus:** The **Delphi method** is used to reach expert consensus on the causes of sensitive indicators and propose recommendations.

Behavioural Modelling (Agent-Based Simulation)

Agent-Based Simulation (ABS) is used to model the decision-making of contracting parties (farmers and contractors), particularly concerning opportunistic behaviours.

• **Decision Factors:** Agent decisions are based on preference rankings expressed as scores. The score calculation uses a Cobb-Douglas functional form combining **utility (mapped from profit)** and **adaptive trust**.

• **Trust Dynamics:** Trust is calculated using an equation that accounts for the trust base-level, the number of successful trades, and a trust factor parameter. If a farmer breaches a contract, the contractor sets their trust base to 0 and the number of trades to 1. Crucially, a breached farmer may communicate with adjacent farmers, reducing the **trust base-level of neighboring farmers** toward the untrustworthy contractor.

Causal Analysis (Gradual Regression Method)

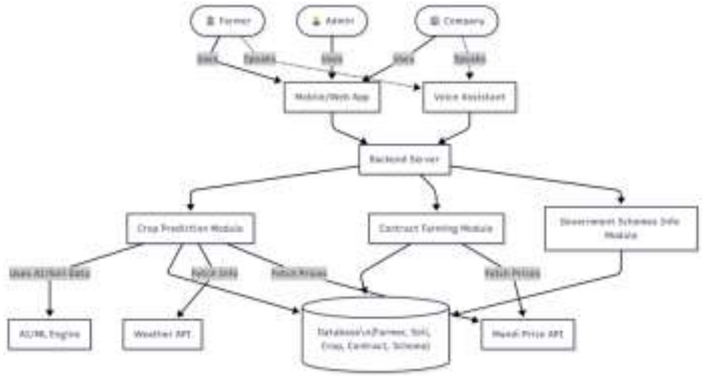
To analyze the mechanism of how CF influences farmers' adoption of green, smart agriculture technologies, a **gradual regression method** (referencing Baron's method) is used to check for mediating and moderating effects.

• **Mediation:** Regression models determine if CF has an overall positive effect ($\alpha 1$) on technology choice, and if the mediating variable (the **high ecological value standard**) is significantly affected by CF ($\beta 1$) and subsequently affects the technology choice ($\gamma 1$). The result of the analysis showed the high ecological value standard plays a **completely mediating role**.

• **Moderation:** An interaction term is added to determine if the effect of the mediating variable on technology choice is influenced by a moderating variable (e.g., **income from rice cultivation**). The results showed that high cultivation income **strengthens the positive relationship** between the high ecological value standard and technology adoption.

4.2. System Architecture

The architecture of the Smart Farming Assistant is segmented into seven modules, ensuring compartmentalization and efficient management of farmer data, intelligence generation, and market coordination. The system relies on key classes and defined relationships to manage its functionality.



1. Crop Prediction Module (Core Advisory)

This main module handles personalized guidance using data inputs.

• **Farmer Class:** Attributes include farmerId, name, phoneNumber, languagePreference (Marathi / Hindi / English), location, farmSize, and soilDataSource. Methods include register() and viewCropPrediction().

• **SoilData Class:** Stores inputs such as soilType, phLevel, nutrientLevels, and moistureLevel.

• **CropRecommendation Class:** Stores recommendedCrops and confidenceScore. Recommendation generation **depends on ML model output**.

• **FarmSchedule Class:** Generates personalized tasks for irrigation, fertilization, and pest control alerts, tied to specific startDate and endDate.

• **Relationships: Farmer 1 — 1 SoilData**; **SoilData 1 — 1 CropRecommendation**; **Farmer 1 — * FarmSchedule**.

2. Contract Farming Module (Core Market Access)

This module facilitates secure digital collaboration and market assurance.

• **Company Class:** Attributes include companyId, industryType, and address. Methods allow the company to postContract(), reviewProgress(), and approveHarvest().

• **Contract Class:** Tracks specifics such as cropType, pricePerUnit, quantity, and status ("Active", "Pending", or "Completed").

• **ContractProgress Class:** Records execution reports, including reportDate, status, remarks, and images.

• **Relationships: Company 1 — * Contract** (A company can post multiple contracts); **Farmer 1 — * Contract** (A farmer can apply to multiple contracts); **Contract 1 — * ContractProgress** (Each contract can have multiple progress reports).

3. Government Scheme Information Module

This module provides informational access to relevant governmental support programs.

• **GovtScheme Class:** Attributes include name, eligibilityCriteria, benefits, and documentsRequired.

• **Relationship: Farmer 1 — * GovtScheme (view-only)**.

4. AI/ML Backend Module (Intelligence Core)

This module provides the computational engine for advisory services.

• **CropPredictionModel Class:** Contains model details like modelVersion and accuracy. Methods include trainModel() and predictCropSuitability(soilData).

• **DataPipeline Class:** Manages the data lifecycle, including collectData(), cleanData(), and storeInDB().

• **Relationships: DataPipeline feeds CropPredictionModel** (ML model is trained via cleaned and preprocessed soil data). **CropRecommendation uses CropPredictionModel** (Recommendations are generated using the ML model).

5. Offline Data Manager

This crucial component ensures the platform's utility in low-connectivity areas.

• **OfflineDataManager Class:** Manages local caching, storing dataType ("Crop", "Contract", "Weather", etc.) and lastSyncedAt.

• **Relationship: Farmer 1 — 1 OfflineDataManager (composition)**. Each farmer has a local instance for caching key data and performing synchronization when online.

6. External API Integration Module

This module facilitates real-time data integration.

• **WeatherService Class:** Fetches localized forecasts (temperature, humidity, rainProbability). Method: sendWeatherAlert().

• **MarketPriceService Class:** Fetches real-time **mandi prices per quintal** for specific crops and locations.

• **Integration: MarketPriceService → Farmer (view-only)**.

5. CONCLUSION

Conclusion

The Smart Farming Assistant is a sophisticated digital solution that successfully leverages AI for predictive advisory and structures market engagement through the **Contract Farming Module**. By using personalized **Crop Prediction** based on SoilData and integrating the **Government Scheme Module**, the platform delivers essential support for small farmers. The system architecture, supported by the **AI/ML Backend** and **Offline Data Manager**, ensures both data intelligence and accessibility.

Academic context confirms the platform's value proposition: structured CF is associated with **substantially higher total household incomes**. The design of the contract is critical; resource-providing mechanisms (analogous to digital credit/input assurance) lead to greater farm intensification, while marketing contracts can free up labour for off-farm income. Furthermore, research demonstrates that CF significantly promotes the adoption of **green, smart agriculture technologies**, with the **high ecological value standard playing a complete mediating role** in this process.

Future Scope

Future development and research should focus on extending the scope and validating the platform's impact within a broader context:

1. **Sustainable Supply Chain Expansion:** Future study should improve the measurement of sustainability by including actors often excluded from current assessments, specifically **consumers and governments**, to gain a more complete view of the broiler chicken supply chain.

2. **Model Validation and Policy Evaluation:** The Agent-Based Model developed for the Mekong Delta rice supply chain can serve as a basis for future work to evaluate the performance of supportive schemes (e.g., the "Large-Scale Sample Field" model). This would assess how different policies and supporting services from various actors can maintain a sustainable contract farming model.

3. **Causal Verification of Contract Design:** Additional research using **experimental set-ups** is required to verify the associations identified between different contract types (like MC vs. RPC) and livelihood outcomes, enabling stronger causal conclusions.

REFERENCES

1. Veldwisch, G. J., & Woodhouse, P. (2022). Formal and informal contract farming in Mozambique: Socially embedded relations of agricultural intensification. *Journal of Agrarian Change*, 22(1), 162–178.
2. Susanty, A., Puspitasari, N. B., Purwaningsih, R., & Siregar, A. R. R. (2020). Sustainability assessment of contract farming broiler chicken supply chain using RAP-Poultry. *International Journal of Supply Chain Management*, 9(4), 1–10.
3. Nguyen Khanh, H., Chiong, R., Chica, M., & Middleton, R. H. (2017). Agent-based simulation of contract rice farming in the Mekong Delta, Vietnam. *Asia Pacific Symposium on Intelligent and Evolutionary Systems (IES)*.
4. Ruml, A., Ragasa, C., & Qaim, M. (2022). Contract farming, contract design, and smallholder livelihoods. *Australian Journal of Agricultural and Resource Economics*, 66(1), 24–43.
5. Chen, J., & Zhou, H. (2023). The role of contract farming in green smart agricultural technology adoption. *Sustainability*, 15(10600), 1–20.
6. Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, 92(5), 1644–1655.

7. Wen, Z., Fan, X., Ye, B., & Chen, Y. (2016). Characteristics of mediation effect size and appropriateness of mediation testing. *Acta Psychologica Sinica*, 48(4), 431–441.
8. Poulton, C., Dorward, A., & Kydd, J. (1998). The revival of smallholder cash crops in Africa: Public and private roles in the provision of finance. *Journal of International Development*, 10(1), 85–103.
9. White, B., Borras, S. M., Hall, R., Scoones, I., & Wolford, W. (2012). The new enclosures: Critical perspectives on corporate land deals. *Journal of Peasant Studies*, 39(3–4), 619–647.
10. Oya, C. (2012). Contract farming in sub-Saharan Africa: A survey of approaches, debates, and issues. *Journal of Agrarian Change*, 12(1), 1–33.
11. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.
12. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90.
13. Singh, A., & Misra, S. (2023). AI-powered crop prediction models using soil and weather parameters: A comprehensive survey. *International Journal of Agricultural Technology*, 19(3), 501–520.