"An Integrated AI-Based Crop Prediction and Advisory Platform for Precision Agriculture"

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ABSTRACT

Agriculture is an area where a small difference in information can affect a farmer's decision about what to grow, how to manage a crop and whether an expected return is realistic. Farmers may have useful experience, but information about soil conditions, weather, crop diseases, expected yield and market prices is not always available in one place. Contract farming creates an additional information problem because farmers and contractors may not always have the same information when discussing prices and terms. SmartCrop AI is proposed as a practical digital platform that brings these requirements together. The system combines machine-learning based crop and yield prediction, soil-suitability assessment, an AI advisory component, simulated IoT data, mandi-price information and farmer-oriented reporting. Random Forest and Gradient Boosting are used in the prototype for prediction and suitability scoring, while an LLM-based Kisan Mitra component is intended to explain results in natural language. The design is based on findings from five related studies covering contract farming, IoT-based crop recommendation, AI advisory, sustainability assessment and yield-demand based crop recommendation. The present work focuses on the system design and prototype architecture; real-field sensor validation and large-scale farmer testing are considered future work.
Keywords: Precision Agriculture, Crop Recommendation, Machine Learning, Artificial Intelligence, IoT, Random Forest, Yield Prediction, Contract Farming, Mandi Market Intelligence, AI Advisor.

I. INTRODUCTION

Farmers often make cultivation decisions using experience, local advice and information from previous seasons. This can work well in familiar conditions, but it becomes difficult when soil conditions, weather, market prices or crop diseases change. The problem is not only a lack of data; it is also the difficulty of bringing different types of information together in a form that is easy to use.

Earlier research has approached this problem from different directions. Agent-based simulation has been used to study how farmers and contractors behave under different contract conditions [1]. IoT and machine-learning systems have used soil and environmental information for real-time crop recommendations [2]. AI advisory systems have combined machine learning with language models and market prices [3]. Other work has examined sustainability in contract-farming supply chains [4], while crop recommendation research has considered both expected yield and market demand [5].

These studies are useful individually, but they do not provide one farmer-facing platform containing all of these capabilities. SmartCrop AI is therefore proposed as an integrated prototype. Its purpose is not to claim that one model can solve every agricultural problem, but to provide a common place where field information, prediction, advice and market information can be viewed together.

II. LITERATURE REVIEW

The literature used for this research was taken mainly from the five studies reviewed in the first paper. The role of each study in the present work is clearly indicated below.

A. Agent-Based Simulation of Contract Rice Farming – 2017

The first study models farmers and contractors as agents. Their decisions are influenced by trust and cost-benefit considerations, allowing researchers to examine possible changes in contract conditions before implementing them in the field [1]. This study is used in SmartCrop AI mainly for the contract-farming perspective. It supports the idea that a digital agricultural platform should not consider crop production alone, but should also recognize the relationship and information gap between farmers and contractors. The original study is limited by its single regional setting and does not include weather, live market data, sensing or AI prediction [1].

B. IoT-driven Machine Learning for Crop Recommendation – 2026

The second study combines IoT inputs with machine-learning classifiers for crop recommendation. It compares EGNB, Random Forest, Bagging and Decision Tree models and reports EGNB as the best performer with 99.55% accuracy [2]. The important idea used in SmartCrop AI is the connection between field measurements and machine learning. The first paper also notes that the NPK values used for training in that study were simulated, so performance with real sensor noise still requires validation [2]. This limitation directly supports the decision to describe the IoT part of SmartCrop AI as a prototype and not as a completed field deployment.

C. AI-Driven Smart Crop Recommendation and Advisory Framework – 2025

The third study combines conventional machine-learning models with an LLM API for advisory text. It also uses live market prices to estimate profit and suggest alternatives and reports 87% recommendation accuracy [3]. SmartCrop AI uses the same broad idea of combining prediction with an AI advisory layer. The concept of presenting technical information in natural language is reflected in the Kisan Mitra assistant. The first paper identifies dependence on reliable input data and internet access as limitations and also notes that the reviewed system does not include IoT sensing or a contract-farming component [3].

D. Sustainability Assessment of Contract Farming Supply Chain – 2020

The fourth study evaluates a broiler-chicken contract-farming supply chain using Rap-Poultry, MDS, leverage analysis, Monte-Carlo methods and Delphi techniques [4]. It considers economic, social and environmental dimensions and identifies weak points in the supply chain. This study is used in the present paper to broaden the meaning of agricultural decision support beyond crop prediction. SmartCrop AI currently does not implement a full sustainability assessment; instead, sustainability is identified as an important future extension. The original study is also limited by its sample and stakeholder coverage [4].

E. Crop Advisor: Intelligent Crop Recommendation System – 2025

The fifth study combines Random Forest yield prediction with ARIMA-based demand forecasting and benchmarks other machine-learning methods [5]. The approach is useful because it considers expected production and demand rather than looking only at crop suitability. SmartCrop AI uses this idea in its market-intelligence view, where mandi or MSP-referenced prices can be considered together with yield estimates. The reviewed study mainly uses Maharashtra data and a limited crop set and does not include IoT, conversational advisory or contract-farming features [5].

III. RESEARCH GAP

The main gap found from the reviewed papers is not the absence of machine-learning algorithms. Instead, the gap is that the useful capabilities are separated across different systems. Contract-farming research focuses on trust, behavior and sustainability [1], [4]. IoT and machine-learning research focuses on field data and crop recommendation [2]. AI advisory work adds natural-language support and market information [3], while yield-demand research connects production estimates with demand [5].

SmartCrop AI addresses this practical gap by bringing these ideas into one platform. The proposed system accepts soil and environmental information, produces model-based outputs, provides AI-assisted advice, presents market information and stores farmer-facing records. Contract and sustainability features are not claimed to be fully solved; they remain limited or planned extensions.

IV. RESULTS AND DISCUSSION

SmartCrop AI is designed as a full-stack agricultural decision-support platform. The prototype uses a React/TypeScript frontend and a Python Flask backend. The main services include machine-learning prediction, an LLM-based advisory component, simulated IoT telemetry, mandi-rate information, reports and administration.

A. Data Collection

The system accepts NPK, pH, temperature, humidity and rainfall information through user forms or simulated IoT nodes. This follows the field-data concept discussed in the IoT-based crop recommendation study [2]. Pandas and NumPy are used for data cleaning, normalization, unit handling, missing-value treatment and outlier processing.

B. Machine Learning Module

The prototype uses a Random Forest Regressor for orange (mandarin) and cotton yield prediction and a Gradient Boosting Regressor for soil-suitability scoring. Standard Scaler is used for feature normalization and trained models are stored for later use. The choice of Random Forest is also consistent with the approaches discussed in the crop recommendation and yield-prediction literature [2], [5].

C. AI Advisory Module

The Kisan Mitra component uses an LLM API to provide natural-language agricultural guidance. The aim is to make model outputs easier to understand instead of showing only a numerical result. This part of the system is directly motivated by the AI advisory framework reviewed in the first paper [3]. The prototype also supports leaf-image based disease or pest diagnosis.

D. IoT Module

The current IoT layer is simulated using an ESP32-oriented setup. It represents soil moisture, NPK and environmental telemetry and includes actuator endpoints for functions such as irrigation control. This is based on the sensing direction discussed in the IoT-driven ML study [2]. Since the first paper specifically notes the need for validation with real sensor data, SmartCrop AI treats real hardware deployment as future work.

E. Market and Contract View

The mandi module keeps market and MSP-referenced price information and uses it with yield estimates for profit estimation. This follows the market-aware recommendation idea discussed in [3] and the yield-demand perspective discussed in [5]. The contract-farming perspective is informed by [1], where trust and cost-benefit considerations are important. In the current prototype, contract support is indirect and mainly based on shared information rather than a complete negotiation or behavioural model.

F. Reports and Administration

Prediction and diagnostic results can be saved and exported as reports. The administrative area supports alerts, user management and audit logs. JWT-based authentication and separate access flows are included in the prototype design.

V. SYSTEM ARCHITECTURE

The architecture is organized into four layers: Presentation Layer, Application Layer, Service Layer and Data Layer. The Presentation Layer provides the farmer and administrator dashboards. The Application Layer contains Flask REST routes. The Service Layer contains machine-learning, AI, data-processing and visualization services. The Data Layer uses SQLite with SQL Alchemy to store users, alerts, mandi rates, IoT nodes, reports and audit logs.

PRESENTATION LAYER

React + TypeScript	Role-Based Access

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APPLICATION LAYER

Flask REST API	Authentication & Authorization JWT

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SERVICE LAYER

Data Processing	ML Prediction Engine	AI Advisory and Disease Diagnosis	IoT Telemetry	Market Intelligence	Alerts, Reports and Visualization
Pandas + NumPy	Random Forest + Gradient Boosting	LLM API + Leaf Image	Simulated ESP32	Mandi / MSP Rates	

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DATA LAYER

SQLite Database SQL Alchemy	Users • Alerts • Mandi Rates IoT Nodes • Reports • Audit Logs

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System Flow

Farmer/Admin Input + Simulated IoT + Leaf Photograph → Pandas/NumPy preprocessing → Random Forest / Gradient Boosting → LLM advisory & disease diagnosis → Mandi/MSP + yield for profit estimation → Dashboard, reports and administration.

Figure 1: Proposed SmartCrop AI Architecture

IV. RESULT AND DISCUSSION

The proposed system provides a single place to work with agricultural inputs, predictions, advice and market information. Its expected benefit is mainly organizational and decision-support oriented. Instead of checking separate sources for soil information, crop prediction, market prices and advisory guidance, the farmer can view these components through one interface.

The literature also shows why caution is necessary when interpreting performance. The reviewed IoT study reports 99.55% accuracy for its best classifier, while the AI advisory study reports 87% recommendation accuracy [2], [3]. These values cannot be directly transferred to SmartCrop AI because datasets, crops, regions and experimental conditions are different. The present prototype therefore does not claim a new accuracy value or field superiority.

The system also has clear current limitations. IoT data are simulated, real sensor noise has not been evaluated, and large-scale testing with farmers has not been reported. The contract-farming and sustainability parts are also not implemented as complete analytical modules.

These limitations are important because the first paper emphasizes real-world validation, sensor quality, regional coverage and data freshness as practical issues.

VII. CAPABILITY COMPARISION

Capability	Studies [1], [4]	Studies [2], [3], [5]	Smart Crop AI
ML yield/suitability prediction	Limited /No	Yes	Yes
IoT telemetry	No	Yes/ Partial	Yes, simulated
AI advisory	No	Yes	Yes
Market information	No	Yes/Partial	Yes
Contract-farming view	Yes	No	Indirect
Sustainability assessment	Yes	No	Future extension
Reports/administration	No	No	Yes

The comparison is capability-based, not an accuracy benchmark. This distinction is important because the reviewed studies use different datasets and experimental settings.

VIII. CONCLUSION

SmartCrop AI is proposed as an integrated platform for agricultural decision support. The system brings together ideas found separately in the reviewed literature: contract-farming behaviour and trust [1], IoT-based machine-learning recommendation [2], LLM-based advisory and market-aware decision support [3], sustainability assessment [4], and yield-demand based crop selection [5].

The prototype uses machine learning, AI advisory, simulated IoT telemetry, mandi-price information and reporting to make agricultural information easier to access in one place. However, it should be treated as a prototype rather than a field-proven system. Real sensor data, farmer testing and broader regional validation are required before making strong claims about performance or impact.

IX.FUTURE SCOPE

- Replace simulated IoT values with calibrated real-field sensor data.
- Test the system with farmers and evaluate usability and recommendation quality.
- Add live weather, satellite and wider regional data.
- Increase the number of supported crops and regions.
- Add an explicit contract-farming trust, behaviour and negotiation model based on [1].
- Add a formal economic, social and environmental sustainability assessment based on the approach discussed in [4].
- Improve and validate image-based crop disease/pest diagnosis using real field images.
- Provide multilingual and mobile-friendly access for rural users.

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