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Original Article

AgroIntel: An AI-Powered Crop Planning and Profit Optimization System for Sustainable Farming

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Abstract

Agriculture is increasingly affected by climate vari- ability, soil degradation, fluctuating market prices, rising labor costs, and uncertainty in water availability. Traditional crop selection methods are often based on past practice or intuition and therefore may not adapt well to current environmental and economic conditions. This paper presents AgroIntel, an AI- powered agricultural decision support system that recommends suitable and profitable crops by integrating three years of historical data related to soil, weather, cultivation cost, yield, and market conditions. The proposed framework performs crop suitability analysis, cultivation cost estimation, yield prediction, profit forecasting, crop failure risk assessment, and intercropping recommendation within a single pipeline. In addition, the system reports a Natural Farming Suitability Score to support low-input and environmentally responsible cultivation. A farmer-friendly output layer presents ranked crop options, crop calendars, visual summaries, and knowledge tables for practical field use. The results indicate that the proposed system can improve crop selection quality, reduce cultivation risk, and support sustainable farm planning.

Introduction

Agriculture remains central to food security and rural liveli- hoods, yet farming decisions are becoming more difficult because of erratic rainfall, climate change, soil degradation, water stress, volatile input costs, and unstable market prices [1–3,10]. Under such conditions, crop selection is no longer a simple seasonal choice; it is a multi-factor decision that must jointly consider agronomic suitability, expected productivity, cultivation cost, and market return.

In many farming regions, crop selection still depends on local convention, seasonal intuition, or prior experience. Al- though such practices are useful in stable environments, they may fail when weather behavior changes or input and output prices fluctuate sharply. As a result, farmers may cultivate unsuitable crops, overuse water and chemical inputs, incur high labor costs, or face profit losses after harvest. Prior research has shown that machine learning and data-driven agriculture can substantially improve prediction and farm decision quality when soil, climate, and management data are integrated effectively [4–7].

This paper presents AgroIntel, an integrated decision support framework for crop planning and profit optimization. The system uses historical agricultural records and current farm conditions to identify suitable crops and intercropping combi- nations, estimate cultivation cost, predict yield and profit, as- sess crop failure risk, and present actionable recommendations. The main goal is to move from generic agricultural advice to farm-level, data-driven decision support.

Problem Statement and Objectives

Farmers often do not have access to intelligent decision support tools that combine soil conditions, weather conditions, cultivation costs, expected yield, and market profitability in one analysis. Existing advisory approaches frequently provide broad seasonal suggestions but do not offer farm-specific ranking of crop options. They also tend to omit labor cost, weeding cost, risk of crop failure, and sustainability-oriented guidance.

The objective of the proposed work is therefore to design a practical and scalable agricultural decision support system that: 1) recommends crops and intercropping options suited to local soil and climate conditions, 2) forecasts cultivation cost, expected yield, and likely profit, 3) evaluates crop failure risk,

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and 4) promotes more sustainable and natural-farming-aligned choices through understandable farmer-facing reports.

Related Work

Artificial intelligence and machine learning are increasingly used in agriculture for crop classification, disease detection, yield prediction, irrigation management, and decision support [1,2,20]. Review studies have shown that modern agri- cultural intelligence systems can benefit from the joint use of historical farm records, weather information, and sensor data [3,7]. However, many existing studies focus on a single problem such as yield prediction or classification, instead of end-to-end crop planning.

Recent literature on crop-yield forecasting reports strong performance from random forests, gradient boosting methods, and deep neural models [9,13,14]. Systematic reviews also indicate that input diversity, data quality, and local adaptation are critical to model reliability [4,8]. In addition, smart farming and IoT-enabled precision agriculture have expanded the availability of farm-level observations, especially for irri- gation and environmental monitoring [5,6]. Process-based crop modeling frameworks such as DSSAT remain influential for simulation and agronomic analysis, but data-driven systems are often easier to adapt for practical advisory applications that must integrate economics and recommendation ranking [12]. Despite these advances, several limitations remain. Many systems recommend only one crop, ignore cultivation cost and profit estimation, do not explicitly quantify crop-failure risk, and provide limited support for sustainable or natural farming practices. These gaps motivate the proposed framework, which unifies agronomic suitability, economic prediction, risk assessment, intercropping support, and farmer-friendly reporting.

Table 1. Core input attributes used by agrointel

Group	Attributes
Soil	Soil pH, soil moisture, location-specific land condition
Weather	Rainfall, temperature, humidity, seasonal context
Economics	Seed cost, labor cost, irrigation cost, weeding cost, market price
Production	Historical crop yield, crop duration, water requirement
Farmer Input	Season, water availability, field condition, pre-ferred cropping choice

Table 2. Crop failure risk interpretation

Risk Level	Interpretation Basis
Low	Stable weather pattern, adequate water, and consistent historical yield
Moderate	Partial uncertainty in rainfall, water supply, or historical yield variability
High	High weather fluctuation, water scarcity, or unstable past performance

IV. PROPOSED METHODOLOGY

The proposed methodology follows a structured pipeline similar to the reasoning process used by agricultural experts. Historical agricultural data are first collected, then cleaned and normalized, and finally processed using machine learning models and rule-based crop knowledge. The output is a ranked list of suitable crops with decision-support explanations.

Data Acquisition

The system uses three years of historical agricultural information. The collected attributes include crop yield, market price, rainfall, temperature, humidity, soil pH, soil moisture, labor cost, seed cost, irrigation cost, and weeding cost. The historical layer is combined with current farmer inputs such as land location, season, available water, and present soil condition. In practical deployment, such information can be collected through agricultural records, soil test reports, weather services, market databases, and sensor-assisted farm monitoring [3,5, 19].

Data Preprocessing

Raw agricultural data may contain missing values, noisy measurements, duplicated entries, and scale inconsistencies. Therefore, preprocessing is applied before prediction. Missing values are handled using interpolation or statistical imputation, duplicated records are removed, and noisy fields are smoothed where required. Feature normalization is then performed so that model inputs remain numerically stable across diverse variable ranges. This stage is important because prediction quality in agricultural datasets is highly sensitive to input consistency and representativeness [4,8].

Crop Suitability Analysis

Crop suitability analysis compares farmer-provided conditions with crop requirements stored in a knowledge base. For each crop, the system checks compatibility with soil pH, water availability, climate conditions, and seasonal feasibility. Only crops satisfying these minimum suitability constraints are passed to subsequent economic prediction stages. The same knowledge layer is also used to identify intercropping options by examining complementarity in crop duration, nutrient demand, and environmental compatibility.

Cost, Yield, and Profit Prediction

Once candidate crops are shortlisted, the system estimates cultivation cost using historical cost data adjusted to current conditions. The cost model considers labor, seed, irrigation, and weeding components. The yield model uses historical yield trends together with soil and weather attributes to es- timate expected production. Profit is then computed as

$$\hat{P}_c = \hat{Y}_c \times M_c - \hat{C}_c, \quad (1)$$

where $\hat{P}_c$ is the predicted profit for crop c, $\hat{Y}_c$ is the predicted yield, M_c is the expected market price, and $\hat{C}_c$ is the estimated cultivation cost. Tree-based methods such as random forests and gradient boosting are suitable for these prediction tasks because they can handle non-linear relationships and mixed agricultural features [9,16–18].

Risk Assessment

The framework also evaluates the probability of crop failure using weather variability, water scarcity, and yield instability. Each crop is assigned to a qualitative risk class that can be interpreted easily by farmers.

Recommendation and Ranking

The final recommendation stage ranks all suitable crops using anticipated profit, water-use efficiency, labor burden, risk level, and natural-farming suitability. Instead of presenting one isolated prediction, the system produces a decision set that helps

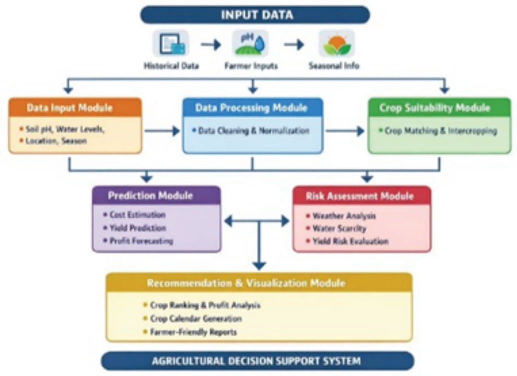

Fig. 1. System architecture of the proposed agricultural decision support system.

the farmer compare alternatives. It also generates crop calendars and knowledge tables so that recommendations can be translated into practical action.

Integrated Decision Support Framework

The core contribution of the proposed work is the integration of agronomic, economic, and environmental reasoning into one decision support framework. Rather than depending on a single input parameter, the system jointly evaluates soil condition, water availability, weather pattern, crop requirement, expected cost, expected yield, profit potential, and risk exposure. This integrated view is important because a crop that is agronomically feasible may still be economically weak, while a profitable crop may be too risky under uncertain rainfall.

The system also introduces a Natural Farming Suitability Score as an additional sustainability-oriented output. This score is intended to indicate how well a crop aligns with low-input and environmentally responsible cultivation under the observed local conditions. In practical terms, it helps the recommendation engine prefer crop choices that are not only profitable but also more compatible with resource conservation and lower chemical dependence.

System Architecture

The proposed architecture is modular so that individual components can be updated or scaled independently. Figure 1 presents the complete structure extracted from the source document.

The Data Input Module collects both historical records and current farmer inputs. The Data Processing Module cleans, normalizes, and prepares the data for model use. The Crop Suitability Module filters crops and intercropping combinations based on agronomic constraints. The Prediction Module estimates cost, yield, and profit. The Risk Assessment Module evaluates weather, water, and yield uncertainty. Finally, the Recommendation and Visualization Module ranks the candidate crops and presents farmer-friendly outputs.

Results and Performance Analysis

The source paper reports that the proposed system was evaluated using historical agricultural data and that the integrated recommendation strategy improves decision quality compared with conventional crop-selection practice. The results emphasize three practical outcomes: more accurate identification of suitable crops, more informed cost–profit estimation, and better avoidance of high-risk choices under uncertain environmental conditions.

Figure 2 reproduces the performance chart from the source document. Visual inspection indicates that the system performs strongly across all major dimensions, with cost prediction accuracy, yield prediction accuracy, profit prediction accuracy, crop selection accuracy, and risk reduction effectiveness all remaining above the 80% level. Crop selection accuracy appears to be the strongest component among the reported measures.

These outcomes are consistent with the broader literature, which shows that agricultural prediction systems become more useful when agronomic variables are combined with economic and environmental context instead of being modeled in isolation [2,4,13,14]. In particular, the proposed framework is valuable because it converts prediction outputs into ranked crop recommendations that farmers can use directly.

Discussion

The main strength of the proposed framework lies in its unified treatment of agronomic suitability, economic fore- casting, and sustainability. The architecture does not stop at predicting yield; it extends the decision process to cultivation cost, market-linked profit, intercropping, and crop failure risk. This makes the system more practical than advisory tools that provide only generic regional suggestions.

A second strength is interpretability at the application level. Farmers may not need to understand model internals, but they do need to understand why one crop is recommended over another. By presenting risk labels, crop calendars, and knowledge tables together with ranked outputs, the framework improves usability for non-technical users.

The current system can be further strengthened through live weather feeds, real-time sensor integration, and region- specific market forecasting. Future work may also explore deeper explainability, larger multi-region datasets, and hybrid modeling that combines process-based agricultural simulation with machine learning [12], [20]. Nevertheless, even in its current form, the framework provides a meaningful bridge between agricultural data and practical farm-level decision support.

Conclusion

This paper presents an IEEE-formatted version of the proposed AgroIntel research work on AI-powered crop planning and profit optimization. The system integrates crop suitability analysis, cultivation cost estimation, yield prediction, profit forecasting, crop failure risk assessment, and natural-farming-oriented recommendation into a single decision support framework. By analyzing historical soil, weather, cost, yield, and market data together with current farm inputs, the framework helps farmers select crops more scientifically and sustainably. The proposed approach improves crop selection quality, supports profit-aware planning, and reduces cultivation risk. Its modular architecture also makes it suitable for future integration with IoT sensors, cloud services, and real-time agricultural advisories. As a result, AgroIntel can serve as a practical foundation for intelligent and sustainable farming support systems.

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