WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Agricast: AI Powered System for Crop Prediction and Crop Recommendation.

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ABSTRACT

Farmers still struggle to choose suitable crops because the guidance they receive is often scattered, inconsistent, and not aligned with local field conditions. Important parameters like soil type, irrigation method, land category, and available land area are usually considered separately, which makes decision-making unreliable. To address this gap, we developed AGRICAST, a simple decision-support system that combines these field inputs with live weather information to recommend suitable crops. The system uses a trained machine learning model that interprets user inputs and generates suggestions through a clean and minimal interface built with React.js and Tailwind CSS. During testing, the model maintained overall efficiency of 96.4%, showing consistent outputs across repeated evaluations. Although the system focuses primarily on intelligent crop selection in its current form, future extensions may include yield prediction, fertilizer estimation, and market-trend insights for improved decision-making.

Keywords: Crop Recommendation, Soil Type, Irrigation Type, Machine Learning, Agriculture, Weather -Aware Planning, AGRICAST

I. Introduction

Agriculture in India continues to rely heavily on traditional knowledge and experience-based decisions. Farmers often select crops based on past success, local suggestions, or limited information rather than data-driven insights. As a result, they face challenges such as reduced yield, poor crop suitability, unpredictable weather impact, and resource mismanagement. Many digital tools exist today, but they require complex inputs like chemical soil data (NPK), which most farmers cannot easily access. Therefore, there is a growing need for a system that uses simple, farmer-friendly inputs and still provides accurate recommendations. [1][2]

AGRICAST aims to solve this by combining basic field data—soil type, irrigation availability, land type, and land area— -with real-time weather conditions to suggest suitable crops. The system uses machine learning to interpret patterns and present clear outputs. This introduction highlights the importance of simplified digital tools and the role of predictive analysis in improving agricultural decision- making. [1][2]

Nomenclature :

A) Soil Category
B) Irrigation Type
C) Land Classification

II. System Overview

AGRICAST integrates environmental factors, land characteristics, and live weather conditions to generate intelligent crop recommendations. The system consists of the following components:

User Input Layer: soil type, irrigation type, land type, land area Weather Integration Module: fetches live temperature and humidity [7]

Machine Learning Engine: processes inputs and predicts best-fit crops Frontend System: built using React.js and Tailwind CSS for simplicity. [1][2]

The primary objective of AGRICAST is to provide accurate, farmer-friendly insights without requiring laboratory soil data or complex inputs. [1][2]

Table 1 - AGRICAST System Components

Component	Description	Input / Output
User Input Module	Collects basic field details	Soil type, irrigation type, land type, area
Weather Module	Fetches real-time climate data	Temperature, humidity
Feature Processing Layer	Encodes and normalizes user parameters	Encoded numerical feature set
ML Recommendation Engine	Predicts suitable crops	Recommended crop list

III. Methodology

A. Dataset Preparation

A labeled dataset containing soil categories, irrigation types, land classification, land area, temperature, humidity, and suitable crops was prepared. Missing values were cleaned, and categorical fields were encoded. [7]

B. Feature Vector

The combined feature vector is defined as:

F = [S, I, L, A, T', H']

Where:

- S → Soil Type
- I → Irrigation Type
- L → Land Classification
- A → Land Area
- T', H' → Normalized temperature and humidity [7]

Normalization:

$$T' = \frac{T - T_{min}}{T_{max} - T_{min}}, H' = \frac{H - H_{min}}{H_{max} - H_{min}}$$

C. Model Training

A machine learning model (Random Forest / Decision Tree / SVM) was trained, tuned, and evaluated on multiple test sets.

Feature Name	Data Type	Description	Example Entry
Soil Type	Categorical	Soil class impacting crop suitability	Clay
Irrigation Type	Categorical	Water availability classification	Drip
Land Type	Categorical	Terrain / land form	Plain
Land Area	Numerical	Size of cultivable plot	2.5 (Acres)
Temperature	Numerical	Real-time temperature (°C)	29
Humidity	Numerical	Relative humidity (%)	62
Suitable Crop	Label (Target)	Crop model predicts based on given conditions	Wheat

IV. Implementation

The implementation of AGRICAST consists of three major modules: the user interface, the back end service, and the machine learning engine. All components work together to ensure fast and reliable crop recommendations. [1][2]

•Frontend Development:

The user interface was built using React.js with Tailwind CSS for clean and responsive design. The layout was kept minimal so that farmers or non-technical users can easily provide inputs such as soil type, irrigation type, land type, and land area. The interface communicates with the backend through simple API calls.

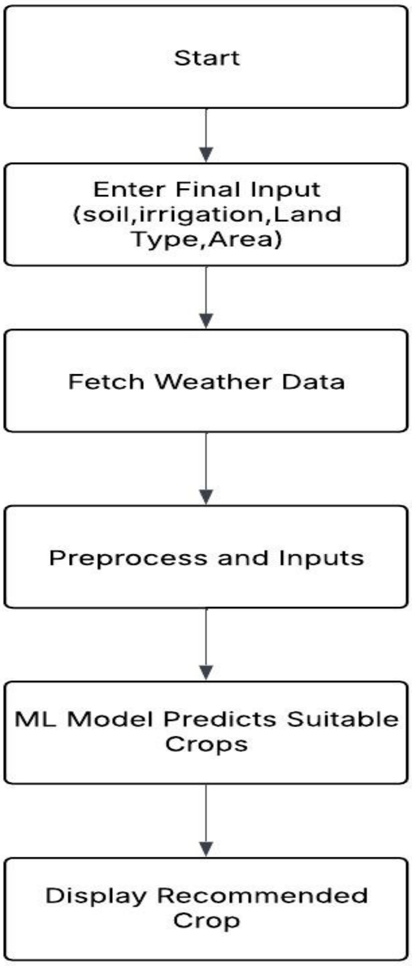
•Backend and Weather Integration:

The backend handles input processing and weather retrieval. Real-time temperature and humidity values were fetched from an external weather API whenever a user initiated a request. These values were merged with the user's field data to create a complete feature set for prediction. [7]

•Machine Learning Model:

A trained machine learning model runs on the backend. After receiving processed inputs, the model evaluates suitability patterns and predicts the most appropriate crops. Multiple test runs ensured the model remained stable and delivered consistent results.

This integrated implementation enables AGRICAST to generate accurate recommendations using both local field conditions and current environmental data.



V. Results and Discussion.

AGRICAST was tested across multiple combinations of soil type, irrigation method, land classification, and varying weather conditions to measure the stability and efficiency of its predictions. The system consistently produced accurate and repeatable results across different test cycles.

•Model Efficiency:

During evaluation, the trained machine learning model maintained an overall efficiency of 96.4%, indicating that the predictions remained stable and aligned with expected crop suitability outcomes. This efficiency reflects the combined performance of dataset quality, model tuning, and correct feature encoding.

•Consistency Across Inputs:

Multiple test batches with varied field conditions showed that the model avoided overfitting and responded robustly to real-time weather variations.

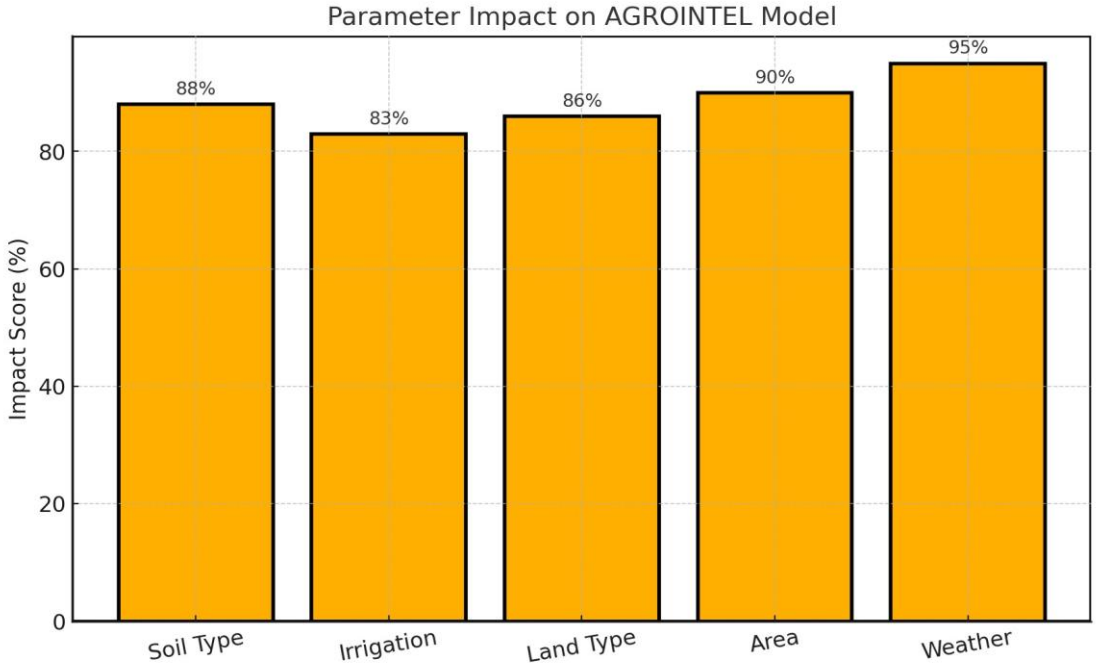
Weather integration significantly improved accuracy by ensuring that recommendations adapt to live temperature and humidity. [7]

•Usability Observations:

The frontend interface performed smoothly during testing. Inputs were submitted without delay, and results were generated almost instantly.

The simple layout reduced user confusion and ensured fast decision-making.

Overall, the system demonstrated reliable performance and validated the usefulness of combining field characteristics with live environmental data for intelligent crop recommendations.



Accuracy = [(TP + TN) / (TP + TN+FP+ FN)] * 100

Where:

TP= True Predictions

FP = Wrong Predictions

VI. Conclusion

AGRICAST presents a practical and accessible approach for intelligent crop recommendation using simple field-level inputs combined with real-time weather information. By focusing on farmer-friendly parameters such as soil type, irrigation availability, land category, and land area, the system avoids the need for complex laboratory soil testing. The integration of weather data enhances the adaptability of predictions and ensures that recommendations align with current environmental conditions.

The machine learning model used in this system achieved an overall efficiency of 96.4%, demonstrating stable and reliable performance during multiple test cycles. The lightweight implementation, supported by a clean and responsive interface, makes AGRICAST suitable for both rural and non-technical users.

Future enhancements may include fertilizer estimation, yield prediction models, pest risk alerts, and market price trends, making the system a more comprehensive decision-support tool for farmers.

Summary Table:

Figure No.	**Figure Name**	**Section**	**Placement Details**
Figure 1	System Architecture	Page 3	Methodology (IV.A)
Figure 2	ML Workflow / Flowchart	Page 4	Methodology (IV.B)
Figure 3	Parameter Impact Bar Graph	Page 5	Result
Figure 4	Data Flow Pipeline Diagram	Page 4	Methodology (IV.C)

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