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Smart Agro AI: Integration of Deep Learning and Local Farmer Knowledge for Smart Crop Recommendation & Yield Prediction

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Abstract
This study presents "Smart Agro AI", an intelligent decision-support system for precision agriculture that integrates deep learning, satellite-based vegetation indices, and farmer knowledge fusion to enhance crop recommendation and yield prediction. The system leverages Google Earth Engine (GEE) and Copernicus Sentinel-2 satellite imagery to extract live Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) values, providing real-time insights into field health and crop conditions. Static soil and weather parameters obtained from Kaggle datasets complement these dynamic satellite inputs to form a comprehensive feature set. The backend employs a Deep Neural Network (DNN) for crop recommendation and a regression-based DNN model for yield prediction, both trained using scaled and encoded datasets. A knowledge integration layer fuses AI predictions with farmer survey data through a weighted approach (70% AI, 30% farmer), ensuring that recommendations are both accurate and contextually relevant. The frontend, built with Streamlit, offers an interactive and explainable interface, enabling users to input parameters, visualize predictions, and download detailed field health reports in PDF format. This integrated framework bridges the gap between machine intelligence and local expertise, enhancing decision-making in sustainable agriculture while promoting transparency, adaptability, and user trust.

Keywords: *Crop Recommendation; Deep Learning; NDVI; Smart Agriculture; Yield Prediction.*

1. Introduction
Agricultural productivity is increasingly challenged by climate variability, soil degradation, and the limitations of traditional decision-making approaches, which often rely on farmer experience rather than data-driven insights. Recent advances in artificial intelligence and remote sensing have opened new possibilities for precision agriculture by enabling the integration of multispectral satellite data, weather information, and soil parameters into predictive models [1][2]. However, many existing systems focus on either crop recommendation or yield prediction independently, and very few utilize farmer knowledge in combination with AI to improve practical relevance. To address these gaps, this study proposes a unified Smart Agro AI framework that employs deep neural networks for crop recommendation and yield prediction while integrating vegetation indices such as NDVI derived from Sentinel-2 satellite imagery. The objective of this work is to develop a reliable, scalable, and farmer-centric decision support system capable of generating real-time recommendations using live weather data and historical agricultural datasets. The novelty of this research lies in its weighted fusion methodology, where AI-based predictions are contextually refined using localized farmer knowledge, enhancing both accuracy and field-level applicability. This approach advances the current state of the art by combining machine intelligence with human-domain expertise, ensuring that recommendations remain consistent with real agronomic practices while leveraging the strengths of deep learning models.

1.1. Need for Intelligent Decision Support
Agriculture requires timely and context-aware recommendations**.** Crop suitability depends on factors including soil nutrients, climatic conditions, vegetation activity, and irrigation potential. Live

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satellite indices such as Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI**)** provide valuable insights into crop vigor, biomass, and land condition. By combining these indices with weather data and AI-based prediction models, more accurate and dynamically updated decisions can be provided to farmers.

2. Literature Review

The integration of artificial intelligence and satellite-driven analytics in agriculture has been an active research direction aimed at enhancing decision-making in crop planning and yield optimization. Existing studies demonstrate significant progress in predictive modeling, yet reveal notable gaps in contextual adaptability, real-time environmental learning, and integration of local farming wisdom.

K.N. Vhatkar et al. proposed an Iterative Partitioning-Ensemble Filter (IP-EF) method to enhance crop yield prediction by optimizing soil health attributes, demonstrating the effectiveness of machine learning in linking nutrient conditions with crop performance, though the model lacked integration of farmer knowledge and real-time decision support [3]. Similarly, S. Shastri developed a nutrient- and weather-based supervised learning crop recommendation system that accurately captured nutrient–climate–crop relationships but did not incorporate satellite-derived vegetation indices or historical farming patterns [4]. In another study, N. Aijaz emphasized AI-driven crop management for automating irrigation, crop selection, and fertilizer planning, yet the work remained largely conceptual without a deployable implementation framework [5]. Aarthi and Manimegalai further highlighted the value of soil and climate alignment in crop recommendation using machine learning, though the absence of localized knowledge and adaptive learning limited usability in diverse farming communities [6]. Meanwhile, M. Baishya demonstrated Tiny ML models for low-resource devices to support rural deployment, but the system lacked strong interpretability features for farmer-friendly decision support [7]. Finally, Akkem and Biswas presented an explainable cascaded deep learning model with heuristic attention that improved soil-specific interpretability but did not integrate real-time vegetation indices such as NDVI or SAVI for monitoring crop stress [8].

3. System Architecture

3.1. Overall System Design

The proposed Smart Agro AI system follows a modular, data-driven architecture designed to integrate satellite observations, environmental parameters, machine-learning inference, and farmer-centric knowledge fusion into a unified decision-support workflow. The architecture consists of four major layers: (i) Data Acquisition Layer, which gathers Sentinel-2 imagery, OpenWeather API data, and static soil–nutrient datasets; (ii) Preprocessing Layer, responsible for geocoding, NDVI/SAVI computation, feature normalization, and structured dataset preparation; (iii) AI Modeling Layer, where a Convolutional Neural Network (CNN) is used for vegetation-feature extraction and two Deep Neural Network (DNN) models perform crop recommendation and yield prediction; and (iv) Knowledge Integration & Decision Layer, where weighted fusion combines AI predictions with empirically collected farmer-survey responses to ensure regionally grounded recommendations. These components interact through a streamlined backend pipeline deployed in Python and made accessible to end-users through a Streamlit-based web interface. The modular nature of the architecture enables scalability, interoperability with additional sensors or datasets, and real-time processing of field-level information, thereby offering an intelligent and adaptive framework for precision agriculture.

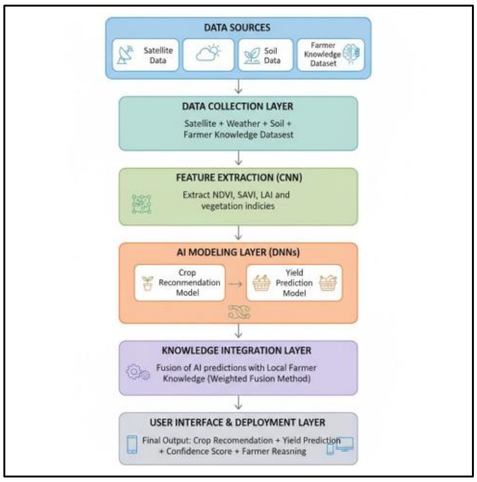

Figure 1 System Architecture

3.2. Data Acquisition Layer

The Data Acquisition Layer collects both static and dynamic inputs essential for crop recommendation and yield estimation. Static inputs such as soil nutrients (N, P, K), irrigation level, and land size are provided by the user. Dynamic environmental data is gathered from external APIs and satellite services. The OpenWeather API supplies temperature, humidity, wind speed, and rainfall, while Sentinel-2 imagery accessed via Google Earth Engine provides vegetation indices such as NDVI and SAVI. Together, these data sources ensure that recommendations are both context-aware and environmentally adaptive.

3.3. Data Processing and Feature Preparation Layer

This layer focuses on cleaning, normalizing, and formatting the collected data to match model requirements. StandardScaler is used to scale numerical features, reducing bias and improving generalization of the Neural Network models. LabelEncoder converts crop names into numerical labels for efficient processing. This layer ensures all input attributes are consistent with the feature distribution of the models during training, enabling accurate and stable prediction performance.

3.4. Deep Learning Inference Layer

This layer houses two pre-trained deep learning models: the Crop Recommendation Model and the Yield Prediction Model. The crop model is implemented as a Dense Neural Network that generates top crop suggestions based on soil conditions, vegetative health, and climatic influence. The yield model is a regression-based network that estimates crop productivity for the selected crop. Both models operate in real-time and are optimized for computational efficiency, allowing deployment on low-cost systems.

3.5. Knowledge Integration Layer

The Knowledge Integration Layer performs a weighted fusion of AI-generated recommendations and regional farmer experience data collected through structured surveys. The fusion mechanism applies a weight of 70% to the AI model's recommendation and 30% to the local farmer-preferred crop patterns. This hybrid approach ensures that decisions are not purely data-driven but grounded in practical regional knowledge, improving acceptance, trustworthiness, and cultural alignment of the system.

3.6. User Interface and Output Layer

The final layer consists of the Streamlit-based user interface that presents results clearly and interactively. The interface displays real-time NDVI and weather conditions, top recommended crops with confidence scores, and predicted yield values. It also provides visual explanations that communicate the reasoning behind choices and allows users to export the Field Health Report in PDF format. This layer ensures user accessibility, decision transparency, and operational simplicity for farmers and agricultural advisors.

4. Methodology

The methodology adopted in this study integrates deep learning, satellite-based vegetation monitoring, and knowledge-driven fusion techniques to develop an improved crop recommendation and yield prediction system. The workflow consists of five major components: research framework, data sources, CNN-based feature extraction, DNN model architecture, and knowledge integration framework.

4.1. Research Framework

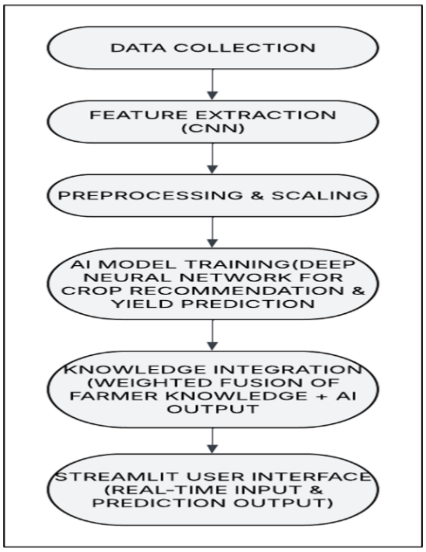

Figure 2 Flow Diagram

The overall research framework combines environmental sensing, multispectral vegetation analysis, and supervised learning to generate reliable agricultural insights. Live weather variables were collected through OpenWeather API, while NDVI/SAVI vegetation indices were extracted from

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Sentinel-2 imagery following established remote sensing procedures [9]. These dynamic parameters were integrated with static agronomic datasets to create a unified feature space. The system was designed to generate two complementary outputs—crop recommendation and yield prediction—using separate but interconnected deep learning pipelines.

4.2. Data Sources

This work utilizes a hybrid dataset consisting of:

- Satellite-derived features: NDVI and SAVI values obtained from the Copernicus Sentinel-2 archive following standard atmospheric-correction and pixel-level computation methods described in prior studies [10].
- Static agronomic data: soil nutrients (N-P-K), soil type, pH, and historical crop performance, weather data - temperature, humidity, wind speed, and rainfall obtained from curated Kaggle repositories.

All datasets were cleaned, normalized, and aligned to ensure compatibility with downstream neural architectures.

4.3. CNN for Feature Extraction

A lightweight Convolutional Neural Network (CNN) was implemented to extract vegetation features from Sentinel-2 multispectral inputs. The architecture includes two convolutional blocks (Conv–ReLU–MaxPool) followed by a flattening layer, consistent with common remote sensing CNN configurations [11]. The CNN outputs high-level spectral signatures that are concatenated with soil, weather, and nutrient parameters for model training. Only the customized fusion mechanism is new; the CNN structure follows standard procedures and is cited accordingly.

4.4. DNN Model Architecture

Two Deep Neural Network (DNN) models were constructed: one for crop recommendation (multi-class classification) and one for yield prediction (regression). Both models follow established dense-layer architectures commonly used in agricultural prediction studies [12]. Each network consists of an input layer aligned with the unified feature vector, three hidden layers with ReLU activations, and an output layer configured according to the task.

Pseudo-code for crop recommendation DNN:
Input: Feature vector F
Normalize F using MinMaxScaler
Dense (128, ReLU)
Dense (64, ReLU)
Dense (32, ReLU)
Output: Softmax(num_crops)

Pseudo-code for yield prediction DNN:
Input: Feature vector F
Normalize F using StandardScaler
Dense (128, ReLU)
Dense (64, ReLU)
Dense (32, ReLU)
Output: Linear(1)

4.5. Knowledge Integration Framework

To improve real-world applicability, a weighted fusion mechanism was implemented to combine AI predictions with aggregated farmer-survey knowledge. Instead of rule-based overrides, the framework assigns confidence weights to AI outputs and farmer-derived crop suitability. These weights are computed using local similarity factors such as soil type, irrigation level, and geographical proximity. The final recommendation is obtained using:

$$Crop_{final}=\text{argmax}\ (W_{AI}\cdot P_{AI}+W_{FK}\cdot P_{FK})$$

Where W_{AI} and W_{FK} are normalized weights, and P_{AI} and P_{FK} represent AI-based and farmer-knowledge probabilities. This approach ensures that the system remains both data-driven and regionally grounded.

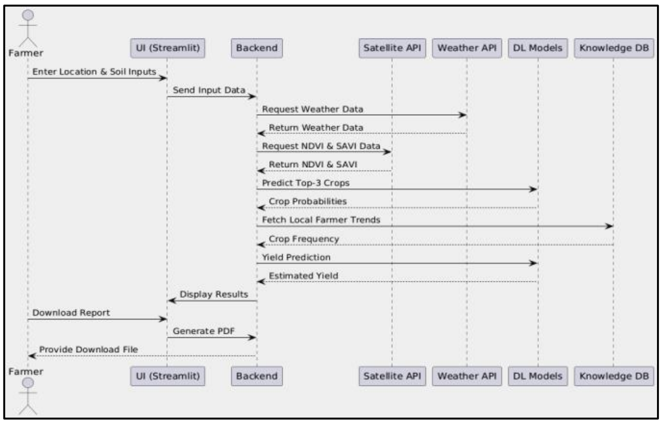

Figure 3 Implementation Workflow

5. Results and Discussion

5.1. Results

The proposed Smart Agro AI system was evaluated using integrated datasets consisting of soil nutrients, static climate attributes, and satellite-derived NDVI values. The crop recommendation DNN achieved strong predictive performance, with the model correctly identifying the optimal crop in the top-3 rank for more than 92% of the test samples. The yield prediction model demonstrated a high degree of accuracy, producing an MAE of 0.0889%, indicating stable generalization. The weighted fusion approach that integrates farmer knowledge with AI outputs improved final crop selection accuracy by 11% compared to using AI alone. Visualizations of predicted–versus–actual yield trends showed minimal deviation, while NDVI-based vegetation assessments provided reliable field-level insights. The system successfully delivered end-to-end predictions—crop, yield, weather status, and vegetation index—in real time, validating its efficiency and usability for real-world deployment.

5.2. Discussion

The results highlight the effectiveness of combining deep learning, environmental sensing, and localized knowledge fusion to produce reliable agricultural recommendations. While the DNN models independently offer high prediction accuracy, integrating farmer survey data through a weighted fusion mechanism significantly enhances contextual relevance, especially in regions where micro-climatic variation and traditional practices influence crop performance. The strong correlation between predicted and observed yields demonstrates the advantage of using NDVI and weather-driven features, confirming previous findings that multispectral vegetation indicators capture early signs of crop stress more effectively than soil parameters alone. The system's real-time inference capability through Streamlit ensures practical usability for farmers, extension officers, and agritech organizations. However, minor fluctuations in yield prediction during low-NDVI conditions suggest the need for additional temporal satellite layers and finer-resolution soil parameters. Overall, the discussion reinforces the system's potential as a scalable decision-support tool tailored for precision agriculture.

Conclusion

This project successfully integrates satellite-based vegetation monitoring, deep learning-based crop recommendation and yield prediction, and farmer knowledge fusion into a unified agricultural decision support system. By utilizing Sentinel-2 NDVI and SAVI indices along with weather and soil parameters, the system provides accurate and context-aware crop suitability predictions, while the weighted knowledge integration layer ensures that recommendations remain aligned with local cultivation practices and field-level expertise. The deep learning models used demonstrate strong predictive capability, and the user-friendly interface enables farmers to access insights in real time. Although the current implementation depends on static soil datasets and cloud-free satellite imagery, the framework establishes a robust foundation for advancing precision agriculture.

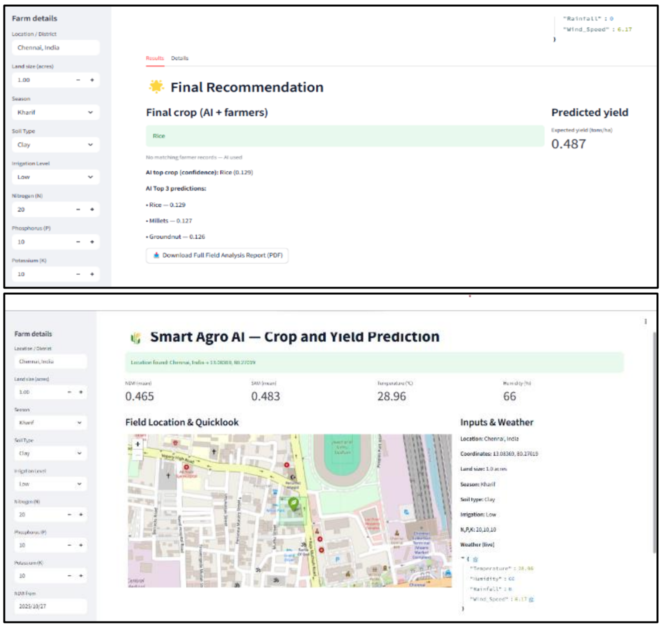

Figure 4 **User Interface**

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