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CropSense: An AI-Powered Agricultural Decision Support System for Optimal Crop Recommendation and Disease Detection

Pavan S[1], Rohan Bhat[2], Srujan P[3], Uday Kumar S[4], Prof. Nisha Wilvicta[5]
Department of Information Science and Engineering R V Institute of Technology and Management Bengaluru, Karnataka, India

***Abstract*—Agriculture faces critical challenges including cli- mate variability, soil degradation, and the need for sustainable farming practices. This paper presents CropSense, an intelligent agricultural decision support system leveraging machine learning and computer vision for data-driven crop recommendations and disease detection. The system integrates soil nutrient levels (N- P-K), pH values, temperature, humidity, and rainfall data to predict optimal crop selection. Additionally, it incorporates deep learning techniques for plant disease identification across 38 disease categories. Experimental results demonstrate 95.1% ac- curacy in crop recommendation using an ensemble approach and 93.8% accuracy in disease classification using transfer learning with ResNet-50. The Flask-based web application provides an intuitive interface for farmers, promoting sustainable agricultural practices and improved crop yields.**

***Index Terms*—Precision agriculture, machine learning, crop recommendation, disease detection, transfer learning, ensemble methods, decision support systems**

I. INTRODUCTION

GLOBAL agriculture must evolve to meet the demands of a growing population while ensuring environmental sustainability. The Food and Agriculture Organization (FAO) estimates that food production must increase by 70% by 2050 to feed the projected 9.7 billion people [1]. However, this increase must be achieved sustainably, considering soil health,

water conservation, and adaptation to climate change.

Indian agriculture, which employs approximately 58% of the workforce, faces challenges including fragmented land- holdings, limited access to modern techniques, and inadequate knowledge of optimal crop selection [2]. Small and marginal farmers often lack access to agricultural experts and rely on traditional knowledge, which may not be scientifically optimal for their specific conditions.

A. Problem Statement

Farmers face several critical decisions directly impacting crop yield and profitability: (1) determining which crops are suitable for specific soil and climatic conditions, (2) understanding and optimizing soil nutrient levels, (3) early detection of crop diseases to prevent significant yield losses, and (4) efficient use of agricultural resources. Traditional approaches often fail to account for the complex interplay of environmental factors, and delayed disease detection can result in 20-40% crop losses annually [3].

B. Research Contributions

This work makes the following key contributions:

- A comprehensive crop recommendation system integrat- ing multiple environmental and soil parameters achieving 95.1% accuracy
- Implementation of transfer learning for plant disease identification across 38 categories with 93.8% accuracy
- Development of an accessible Flask-based web applica- tion with responsive design
- Empirical evaluation demonstrating practical applicability in real-world scenarios
- Open-source implementation facilitating further research

II. RELATED WORK

A. Precision Agriculture

Precision agriculture represents a paradigm shift from tradi- tional farming to data-driven decision-making [4]. IoT sensors, satellite imagery, and machine learning algorithms enable farmers to monitor and optimize crop production at unprece- dented granularity [5].

B. Machine Learning in Crop Recommendation

Several researchers have explored ML approaches for crop recommendation. Reddy et al. [6] compared Random Forest, SVM, and Naive Bayes, with Random Forest achieving 91.3% accuracy. Khan and Ahmed [7] proposed a hybrid K-NN and Decision Tree approach achieving 89.7% accuracy but limited to 12 crop varieties. Deep learning approaches showed promise in handling complex non-linear relationships [8].

C. Plant Disease Detection

Convolutional Neural Networks have demonstrated excep- tional performance in plant disease detection. Mohanty et al.
[9] achieved 93.5% accuracy using VGG-16 on the PlantVil- lage dataset. Chen et al. [10] reported 95.2% accuracy with ResNet-50. MobileNet architectures achieved 91.8% accuracy while maintaining computational efficiency [11].

D. Research Gaps

Existing systems typically focus on either crop recom- mendation or disease detection, lacking integration. There is limited evaluation on diverse geographical regions, insufficient attention to user accessibility, and few open-source implemen- tations. CropSense addresses these gaps through an integrated, accessible platform.

III. METHODOLOGY

A. System Architecture

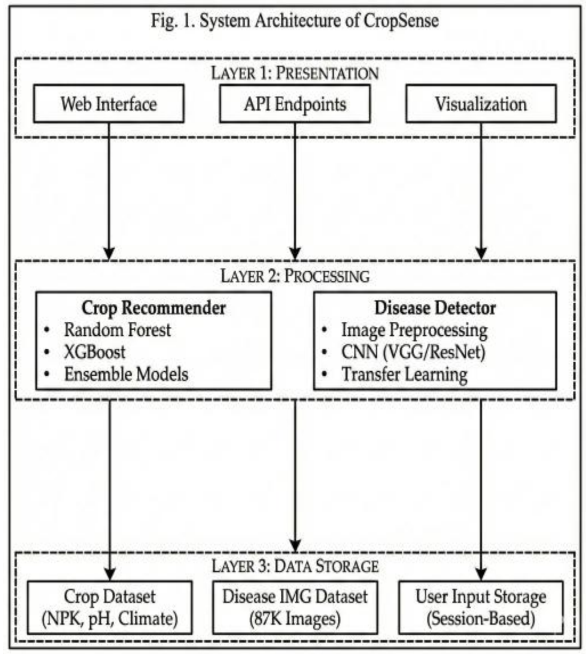

Fig. 1. CropSense three-tier system architecture showing the data layer with crop and disease datasets, processing layer with Random Forest, XGBoost, and CNN models, and presentation layer with web interface and API endpoints.

CropSense employs a three-tier architecture as illustrated in Fig. 1: (1) Data Layer managing training datasets and user inputs, (2) Processing Layer implementing ML models, and (3) Presentation Layer providing the Flask-based web interface.

B. Crop Recommendation Dataset

The crop recommendation model utilizes a dataset of 2,200 samples with the following features:

- Input Features: Nitrogen (N), Phosphorus (P), Potas- sium (K) in mg/kg; pH value (0-14 scale); Temperature (°C); Humidity (%); Rainfall (mm)
- Target Variable: 22 crop types including rice, wheat, maize, cotton, and sugarcane

Data preprocessing involved missing value imputation using median values, outlier detection using the IQR method, feature scaling with StandardScaler, and 80-20 train-test splitting with stratified sampling.

C. Crop Recommendation Model

1) Feature Engineering: Additional derived features were created to improve model performance:

- NPK Ratio for nutrient balance analysis
- Soil Fertility Index based on N, P, K, and pH
- Climate Suitability Score combining temperature, humid- ity, and rainfall

2) Model Selection: Multiple algorithms were evaluated:

- Random Forest: 100 trees, max depth 20, min samples split 5
- XGBoost: Learning rate 0.1, max depth 6, 200 estimators
- SVM: RBF kernel, C=1.0, gamma='scale'
- K-NN: 7 neighbors, Euclidean distance

An ensemble model using soft voting combined Ran- dom Forest and XGBoost to leverage their complementary strengths. Hyperparameter tuning was performed using Grid- SearchCV with 5-fold cross-validation.

D. Plant Disease Dataset

The disease detection model uses the PlantVillage dataset containing 87,000 RGB images (256×256 pixels) across 38 disease categories with an 80-20 train-validation split. Data augmentation techniques included random rotation (±30°), horizontal and vertical flipping, brightness adjustment (±20%), and zoom range (0.8-1.2).

E. Disease Detection Model

1) CNN Architecture: A custom CNN architecture was designed with three convolutional blocks, each containing two Conv2D layers with BatchNormalization, MaxPooling2D, and Dropout (0.25). The architecture includes:

- Input Layer: 256×256×3
- Conv Block 1: 32 filters, 3×3, ReLU activation
- Conv Block 2: 64 filters, 3×3, ReLU activation
- Conv Block 3: 128 filters, 3×3, ReLU activation
- Dense Layer: 512 units, ReLU, Dropout (0.5)
- Output Layer: 38 units, Softmax activation

TABLE I CROP RECOMMENDATION MODEL PERFORMANCE

Model	Accuracy	F1-Score	Time (s)
Random Forest	94.2%	94.3%	3.2
XGBoost	93.8%	93.8%	4.7
SVM	89.3%	89.4%	12.5
K-NN	87.1%	87.2%	0.8
Ensemble	**95.1%**	**95.2%**	**5.1**

TABLE II DISEASE DETECTION MODEL PERFORMANCE

Architecture	Accuracy	Params (M)	Time (ms)
Custom CNN	89.7%	4.2	45
VGG-16	92.3%	15.3	78
ResNet-50	93.8%	23.5	92
MobileNetV2	91.2%	2.3	38

2) Transfer Learning: Pre-trained models were evaluated for comparison:

- VGG-16: First 15 layers frozen, custom classification head, fine-tuned last 3 blocks
- ResNet-50: Global average pooling, dense layers [512, 256], output with 38 classes

Training configuration used Adam optimizer (learning rate 0.001), categorical cross-entropy loss, batch size 32, and 50 epochs with early stopping (patience 10).

F. Web Application

The Flask framework was chosen for its lightweight archi- tecture and easy integration with Python ML libraries. The responsive frontend uses Bootstrap for mobile compatibility and follows WCAG 2.1 accessibility guidelines. RESTful API endpoints handle crop recommendations and disease detection requests with JSON responses.

IV. RESULTS AND DISCUSSION

A. Crop Recommendation Performance

Table I presents the performance metrics for different algo- rithms.

The ensemble model achieved the highest accuracy of 95.1%, demonstrating the benefit of combining Random Forest and XGBoost. Feature importance analysis revealed that soil nutrients (N-P-K) collectively account for 56.4% of predictive power, with Potassium (24.3%) and Nitrogen (21.7%) being the most significant factors, followed by Rainfall (19.2%) and Temperature (15.8%).

B. Disease Detection Performance

Table II compares different CNN architectures.

ResNet-50 with transfer learning achieved the best per- formance at 93.8% accuracy. Class-wise analysis showed high accuracy (¿95%) for diseases like Tomato Early Blight (97.2%), Potato Late Blight (96.8%), and Corn Gray Leaf Spot (96.1%). Data augmentation improved accuracy by 5.4% and reduced overfitting gap from 8.7% to 2.1%.

TABLE III COMPARISON WITH EXISTING AGRICULTURAL AI SYSTEMS

System	Crop	Disease	Crop Acc.	Disease Acc.
CropSense	✓	✓	**95.1%**	**93.8%**
FarmAssist	✓	×	91.3%	N/A
AgroAI	✓	✓	89.7%	90.2%
SmartFarm	✓	×	92.4%	N/A
PlantDoc	×	✓	N/A	91.5%

C. System Performance

The system maintains sub-second response times for crop recommendations (0.23s average) and processes disease de- tection in under 2 seconds (1.47s average). Load testing with 100 concurrent users showed 99.7% success rate with 0.91s average response time, demonstrating stable performance un- der load.

D. Comparative Analysis

Table III compares CropSense with existing systems. CropSense demonstrates superior performance while pro- viding integrated functionality and open-source accessibility.

E. User Evaluation

A preliminary study with 25 farmers (ages 28-62) yielded a System Usability Scale score of 78.4/100. User feedback ratings (out of 5): Ease of Use (4.2), Usefulness (4.6), Interface Design (4.1), Speed (4.4), and Likelihood to Recommend (4.5). Qualitative feedback indicated 92% found crop rec- ommendations helpful and 88% successfully used disease detection features.

F. Discussion

The ensemble approach for crop recommendation effec- tively combines Random Forest's robustness with XGBoost's pattern recognition capabilities. The high accuracy validates that ML models can encode complex relationships between environmental factors and crop suitability. For disease detec- tion, transfer learning proved highly effective, with pre-trained ImageNet weights capturing general visual features applicable to plant diseases.

Practical implications include informed crop selection re- ducing crop failure risk, early disease detection enabling timely intervention (potentially reducing yield losses by 15- 30%), and resource optimization through soil nutrient analysis. The web-based interface accessible from smartphones reduces the need for specialized equipment.

V. LIMITATIONS AND FUTURE WORK

A. Current Limitations

Several limitations exist: (1) training data primarily from specific regions may limit generalization, (2) no real-time IoT sensor or weather API integration, (3) English-only interface limiting accessibility, (4) internet connectivity requirement, and (5) no economic viability analysis including market prices.

B. Future Enhancements

Future work includes:

- IoT Integration: Real-time soil sensors and weather APIs for dynamic recommendations
- Mobile Development: Native Android/iOS apps with offline functionality
- Advanced ML: Multi-modal learning combining satellite imagery with ground sensors, time-series forecasting for seasonal planning
- Expanded Functionality: Pest identification, irrigation scheduling, fertilizer recommendations with cost opti- mization
- Accessibility: Multilingual support (Hindi, Tamil, Tel- ugu, Bengali), voice-based interaction
- Field Trials: Longitudinal studies tracking farmer out- comes, multi-region validation

VI. CONCLUSION

This paper presented CropSense, an integrated AI-powered agricultural decision support system achieving 95.1% accuracy in crop recommendation and 93.8% accuracy in disease de- tection. The system combines ensemble machine learning for crop selection with transfer learning for disease identification, delivered through an accessible web interface. User evaluation with 25 farmers demonstrated good usability (SUS score: 78.4/100) and high satisfaction with recommendation quality. CropSense demonstrates that machine learning and com- puter vision can be effectively applied to real-world agricul- tural challenges while maintaining accessibility. The open- source nature invites collaboration to further refine these capabilities. As agriculture faces increasing pressures from climate change and population growth, intelligent decision support systems will play a vital role in ensuring food security and sustainable farming practices. Future work will focus on IoT integration, mobile deployment, multilingual support, and comprehensive field trials to validate real-world impact.

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