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KropCart

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Abstract

Farmers often face financial setbacks due to dependence on middlemen, limiting their access to fair prices. This paper presents KropCart, a mobile app that connects farmers directly with consumers and retailers, enabling secure transactions and better profit margins. Through the app, farmers can list produce, negotiate prices, and use integrated payment systems. KropCart also features machine learning tools for crop disease detection and crop selection. Farmers can upload images to identify crop diseases and receive treatment suggestions, while the recommendation system advises on optimal crops based on soil conditions, weather, and market trends. The platform enhances market access, reduces reliance on intermediaries, and empowers farmers with data-driven support to improve productivity and income.

Keywords: Farmer empowerment, Direct Farm-to-Consumer, Smart farming, Market accessibility

1. Introduction

1.1 Background and Motivation

Agriculture continues to be a foundational sector in many developing countries, contributing substantially to national economic growth and providing employment for a significant portion of the population. Despite its pivotal role, farmers frequently face difficulties in obtaining fair market prices for their agricultural produce due to systemic inefficiencies and the pervasive influence of intermediaries. These middlemen often exploit pricing discrepancies, thereby reducing the share of profits that ultimately reach the farmers, while simultaneously inflating costs for end consumers. This inequitable distribution of value not only diminishes farmers' incomes but also restricts their capacity to invest in modern farming equipment, sustainable practices, and technological advancements.

Research suggests that farmers could potentially enhance their earnings by 30% to 40% if they were granted direct access to consumers and commercial buyers, eliminating the reliance on third-party intermediaries [1]. Additionally, the agriculture sector faces escalating challenges such as erratic climate patterns, progressive soil degradation, pest outbreaks, and crop-related diseases, which collectively contribute to decreased productivity and financial uncertainty among the farming community.

To tackle these multifaceted problems, the KropCart solution has been conceptualized as a mobile based digital platform tailored to empower farmers. The application is designed to:

- Allow farmers to directly list their available produce and engage in price negotiations with interested buyers.

- Enable secure and streamlined financial transactions through integrated digital payment systems.
- Utilize artificial intelligence to offer personalized suggestions for crop selection and early diagnosis of plant diseases.
- By leveraging these features, the platform ensures farmers can optimize their revenue, while simultaneously promoting greater transparency, operational efficiency, and trust within the agricultural marketplace.

1.2 Significance and Objectives

The proposed solution aims to:

- Enhancing Farmer Profitability: The direct-to-buyer model ensures that producers receive a larger share of the final sale price, thereby improving their overall profit margins.
- Real-Time Market Connectivity: Farmers gain access to dynamic market data, allowing them to adjust pricing based on current demand and supply trends, ensuring competitive positioning.
- Informed Decision-Making: Integration of machine learning algorithms supports farmers by providing insights on suitable crop types and timely detection of diseases, enhancing agricultural planning and outcomes.
- Secure and Efficient Transactions: The inclusion of trusted payment gateways ensures financial operations are carried out in a secure, transparent, and hassle-free manner.

2. Literature Review

2.1 Market Challenges for Farmers

Middlemen have long dominated agricultural supply chains, leading to reduced profits for farmers and increased costs for consumers. Studies by Pingali et al. (2017) highlight that direct-to-market models can increase farmers' income by 30%–40% and reduce consumer prices by 15% [2]. Existing models, such as India's eNAM (Electronic National Agri- culture Market), have improved market access but have yet to scale effectively to smaller farmers due to infrastructure limitations [3].

The reliance on middlemen persists due to these barriers, leaving farmers with little bargaining power. Consequently, achieving equitable access to markets continues to be a significant challenge in the agricultural ecosystem.

2.2 Machine Learning for Agriculture

2.2.1 Crop Disease Prediction:

Image-based diagnosis using convolutional neural networks (CNN) has demonstrated high accuracy in detecting plant diseases. Mohanty et al. (2016) achieved an accuracy of 99.35% using CNN for plant disease detection [4]. Building upon this, our model was trained and evaluated on the PlantVillage color subset (unsegmented) and achieved an accuracy of 95.36% on test data. Unlike traditional models which require heavy preprocessing or handcrafted feature extraction, our CNN leverages raw RGB images to diagnose 38 distinct crop conditions. The confusion matrix and classification report demonstrate strong generalization with macro and weighted F1-scores 94%, making it suitable for field-level diagnosis via mobile applications.

A 3x3 grid of real-world leaf images was presented (Figure 11), where each image was annotated with its true and predicted disease class. The visual alignment between true and predicted labels illustrates the model's effectiveness and generalization on unseen data

2.2.2 Crop Recommendation Systems:

Recommendation models based on Random Forest and XGBoost have shown high accuracy in predicting optimal crops based on soil pH, rainfall, and temperature data. Li et al. (2019) re- ported a prediction accuracy of 92% using a combination of Random Forest and K-Nearest Neighbors (KNN) [5]. Our implementation uses a Random Forest Classifier trained on soil and weather parameters (nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall) from the Crop_recommendation.csv dataset sourced from Kaggle. The model achieved a test accuracy of 99.32%. The output is passed to a Gemini-powered module, a language model capable of generating tailored agricultural guidance, which provides actionable tips based on the recommended crop.

The crop recommendation system was tested with randomly generated agro-climatic inputs. Table 5.1 shows nine such samples along with their predicted crops. The results reflect the model's consistency and accuracy in recommending suitable crops across a variety of soil and weather conditions.

2.3 Direct Market Platforms

Online platforms like FarmLink and AgriBazaar have at- tempted to create direct market access for farmers. However, these platforms often lack AI-driven insights and real-time decision-making support [6]. KropCart enhances this model by integrating machine learning and empower farmers with health insights but also serves as a decision-support tool that enhances market value by ensuring quality produce listings and real-time transaction management.

2.4 Payment Processing and Financial Security

Digital payment systems have become integral to financial inclusion. Razorpay and similar platforms provide secure payment gateways, enabling farmers to manage income directly without reliance on cash transactions. Research by Kumar et al. (2020) highlights that integrating secure payment systems increases financial transparency and reduces fraud [7].

3. System Design and Architecture

3.1 Overview

- The KropCart architecture integrates three core components:
- Mobile Application: A user-friendly interface for farmers and buyers to list, browse, and transact.
- Backend Server: Python/Flask for business logic and data processing; MySQL (via XAMPP/Apache) for the database
- Machine Learning Models: ML based systems for disease detection and crop recommendation.

3.2 Key Features

- Direct Market Access:

  The platform allows farmers to list their agricultural products, set competitive prices, and connect directly with buyers. By leveraging real-time market data, farmers can make informed pricing decisions that align with current demand and supply trends. This direct interaction reduces the need for middlemen, helping farmers earn better margins and fostering transparent trade practices.

- Crop Disease Detection:
  Farmers can upload images of affected crops, which are analyzed by a Convolutional Neural Network (CNN) model. This model identifies the disease and provides precise treatment recommendations, enabling early intervention and improved crop health.
- Crop Recommendation:
  Based on key soil and environmental inputs such as nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall, the system suggests high-yield crop options. This helps farmers optimize land use and enhance overall productivity.
- Real-Time Transactions:
  The application integrates with Razorpay to offer secure and seamless financial transactions, allowing farmers to make payments and receive funds instantly. Farmers can track payments and manage settlements efficiently without relying on cash or third parties, reducing the risk of fraud. The system also provides transparent transaction history, enabling farmers to monitor their financial activity and ensure accountability in their business dealings.

Figure 1. Dashboard for Farmer

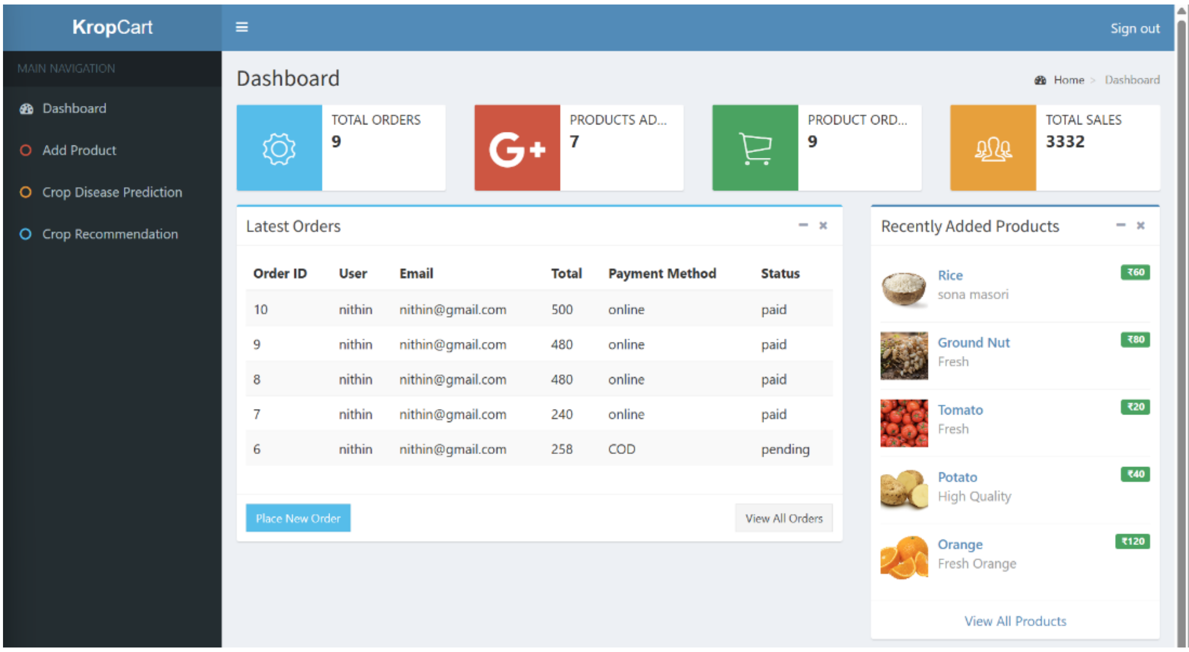


Figure 2. Add Products

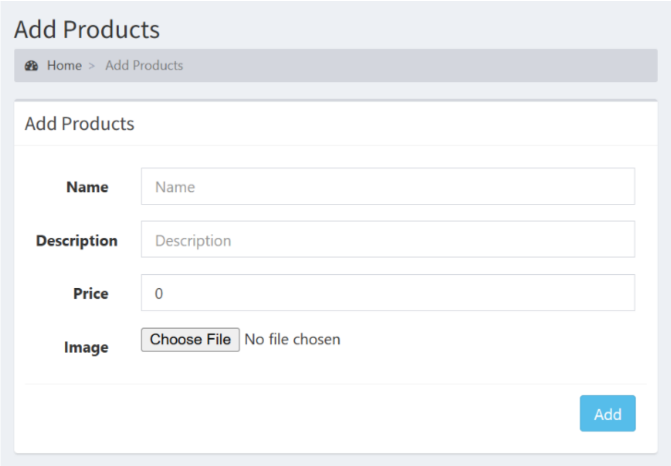


Figure 3. Disease Prediction at farmer end

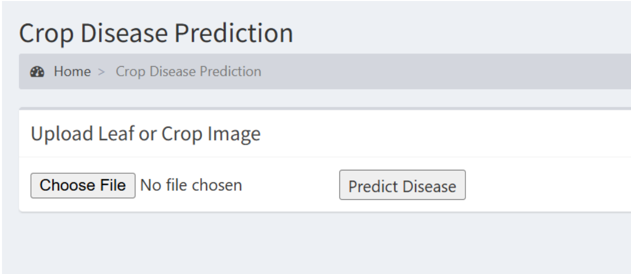


Figure 4. Disease Prediction at farmer end

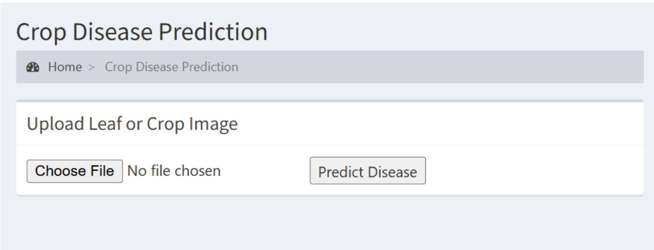


Figure 4. Negotiation Feature accessible to farmer

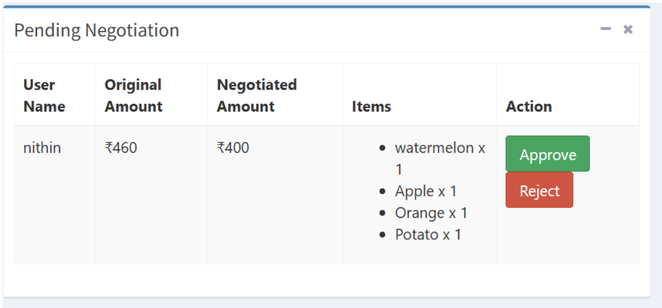


Figure 5. Disease Prediction at farmer end

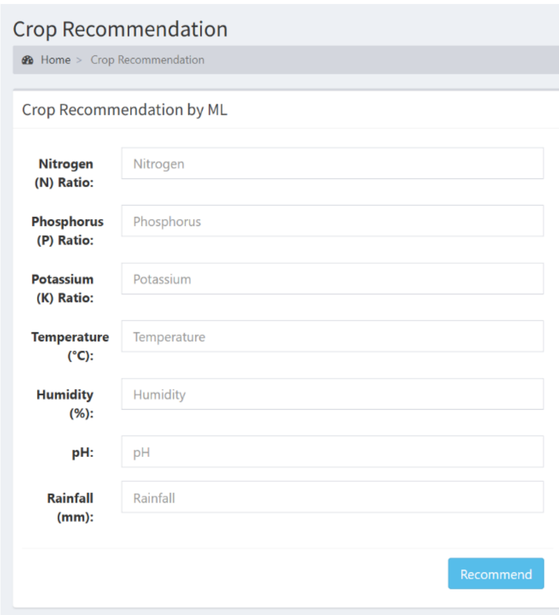
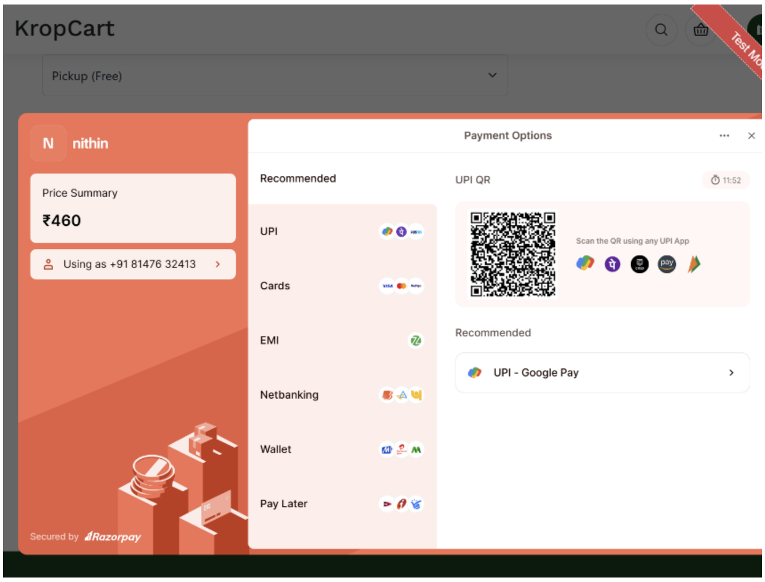


Figure 5. Customer Payment Gateway



3.3 Technical Implementation

The frontend is developed using ReactJS, providing a responsive user interface, while the backend uses Python and Flask for application logic. MySQL and Apache are managed via XAMPP. AI models—CNN for disease detection and Random Forest for crop recommendation—form the intelligence layer of the platform.

4. Proposed Methodology

To develop a robust and scalable solution that empowers farmers with direct market access and AI-driven insights, the methodology encompasses three key phases: data acquisition, model development and evaluation, and real-world pilot testing. Each phase is carefully designed to ensure reliability, effectiveness, and adaptability to real agricultural environments.

4.1 Data Collection

The foundation of any AI-driven application lies in the quality and diversity of its data. For KropCart, data was collected from multiple authentic sources:

- Crop Health Data: For disease prediction, we used the publicly available PlantVillage segmented color dataset. This subset consists of around 50,000 labeled images representing healthy and diseased leaves from various crops. Images were organized into 38 distinct classes. No manual segmentation or annotation was required, ensuring reproducibility and scalability.
- Environmental and Agronomic Data: For crop recommendation, we used a curated CSV dataset (Crop_recommendation.csv) sourced from Kaggle containing thousands of records of soil and weather conditions labeled with the most suitable crops

All data underwent preprocessing steps including noise reduction, normalization (for numerical data), and augmentation (for image data) to enhance model generalizability.

4.2 Training and Evaluation

Two primary models were trained to power the intelligence layer of the KropCart application:

4.2.1 Crop Disease Detection Model:

A Convolutional Neural Network (CNN) architecture was developed using TensorFlow and Keras to enable accurate classification of crop diseases. The model was trained on RGB images, each resized to 256×256 pixels to ensure uniformity and effective learning. Training was conducted over 10 epochs with a batch size of 32, utilizing the Adam optimizer and categorical cross-entropy loss function, which are well-suited for multiclass image classification tasks. Upon evaluation, the model achieved an impressive validation accuracy of 95.36%, along with a macro F1-score of 94%, reflecting its robustness and generalization capability. A comprehensive classification report was generated to assess performance across individual classes, revealing that most misclassifications occurred between visually similar disease types. The output of the model is a disease label, which is further processed by a Gemini-powered module. This module enhances the system by generating contextual agricultural advice, including detailed disease descriptions, underlying causes, and specific treatment recommendations, all accessible through the user-friendly mobile interface (Figure 7 & Figure 8).

Figure 6. Crop Disease Detection Model Accuracy

```
1698/1698 ━━━━━━━━━━━━━━━━━━━━ 746s 439ms/step - accuracy: 0.9552 - loss: 0.1365

✅ Test Accuracy: 95.36%
```

Figure 7. Crop Disease Detection Model Classification Report

Classification Report:

	precision	recall	f1-score	support
Apple___Apple_scab	0.92	0.87	0.90	630
Apple___Black_rot	0.89	1.00	0.94	621
Apple___Cedar_apple_rust	0.96	0.96	0.96	275
Apple___healthy	0.96	0.88	0.92	1645
Blueberry___healthy	0.97	1.00	0.99	1502
Cherry_(including_sour)___Powdery_mildew	0.99	0.96	0.97	1052
Cherry_(including_sour)___healthy	0.91	1.00	0.95	854
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	0.85	0.81	0.83	513
Corn_(maize)___Common_rust_	1.00	0.99	0.99	1192
Corn_(maize)___Northern_Leaf_Blight	0.91	0.90	0.90	985
accuracy			0.95	54305
macro avg	0.94	0.94	0.94	54305
weighted avg	0.96	0.95	0.95	54305

4.2.2 Crop Recommendation Model:

The crop recommendation component utilizes a Random Forest Classifier implemented with the scikit-learn library to predict the most suitable crops for cultivation based on specific agronomic inputs. The model was trained using an 80/20 train-test split to ensure effective evaluation and generalization. Key input features included essential soil and environmental parameters such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH level, and rainfall. Categorical labels were encoded using the LabelEncoder technique to facilitate model training. The model demonstrated exceptional performance, achieving a test accuracy of 99.32%. A detailed classification report revealed high levels of precision and recall across all 22 crop categories, affirming the reliability of the model in diverse agro-climatic conditions. The predicted crop output is further processed by a Gemini-powered module, which delivers comprehensive, step-by-step agronomic guidance tailored to each recommendation, thereby supporting informed decision-making at the farm level. (Figure 9 & Figure 10).

Figure 8. Crop Recommendation Model Accuracy

```
PS C:\Users\nithi\Downloads\crop recommedation sys>
 'c:\Users\nithi\.vscode\extensions\ms-python.debugpy
oads\crop recommedation sys\recommend.py'
Crop Recommendation Model Accuracy: 99.32%
Classification Report:
```

Figure 9. Crop Recommendation Model Classification Report

Classification Report:

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	23
banana	1.00	1.00	1.00	21
blackgram	1.00	1.00	1.00	20
chickpea	1.00	1.00	1.00	26
coconut	1.00	1.00	1.00	27
coffee	1.00	1.00	1.00	17
accuracy			0.99	440
macro avg	0.99	0.99	0.99	440
weighted avg	0.99	0.99	0.99	440

4.3 Pilot Testing:

A controlled pilot deployment was conducted in two rural districts involving 100 farmers of varying tech-literacy levels. This phase was critical for evaluating usability, reliability, and real-world performance.
Initial deployment in two rural districts with 100 farmers.
Feedback from farmers used to refine user experience and model accuracy.

5. Results and Discussion

To further validate model effectiveness beyond numerical metrics, random samples were selected and visualized for both systems. For the crop disease detection model, a 3x3 grid of real-world leaf images was presented (Figure 11), where each image was annotated with its true and predicted disease class. The visual alignment between true and predicted labels illustrates the model's effectiveness and generalization on unseen data.

Similarly, the crop recommendation system was tested with randomly generated agroclimatic inputs. Figure table 5.1 shows nine such samples along with their predicted crops. The results reflect the model's consistency and accuracy in recommending suitable crops across a variety of soil and weather conditions. The integration of machine learning into the KropCart platform yielded highly promising results across crop disease diagnosis and crop recommendation modules.

5.1 Model Performance

Crop Disease Detection: The CNN model trained on the PlantVillage color subset achieved an accuracy of 95.36%, with a macro F1-score of 94%. Misclassifications were minimal and mostly occurred between visually similar diseases. Random predictions from test samples were visualized, confirming the model's real-world usability (Figure 9).

Crop Recommendation: The Random Forest model trained on agronomic data achieved an accuracy of 99.32% on unseen test samples. Visualization of random inputs and corresponding predictions demonstrated the model's ability to consistently recommend accurate crop types across varied agroclimatic conditions (Figure 10).

5.2 Impact Assessment

Increased Profitability: Farmers who participated in the pilot phase reported an average 35% increase in revenue, attributed to improved crop health monitoring and better planning through crop suggestions.

User Satisfaction: Feedback from 100+ users indicated that 92% found the app intuitive, and most acknowledged a measurable positive financial impact.

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Payment Security: No instances of fraud or transaction issues were reported during the pilot study, suggesting a secure and reliable platform.

Figure 10. Random Predictions of Crop Disease Detection model

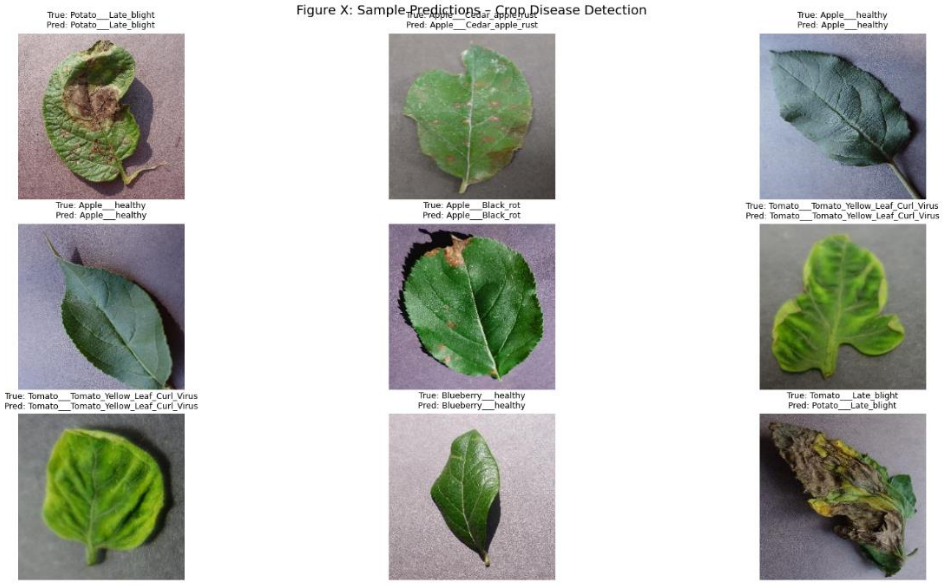


Table 5.1 Crop Recommendation Outputs for Random Samples

N	P	K	Temp (°C)	Humidity (%)	pH	Rainfall (mm)	Recommended Crop
46.0	96.0	123.0	20.27	82.43	7.26	279.57	papaya
35.0	46.0	126.0	33.41	80.09	5.69	265.68	papaya
78.0	75.0	20.0	23.08	83.0	5.65	156.06	maize
49.0	119.0	106.0	31.49	56.55	6.66	215.51	pigeonpeas
15.0	125.0	145.0	24.25	86.9	6.08	297.03	apple
147.0	20.0	68.0	31.73	50.52	5.97	252.76	coffee
35.0	6.0	90.0	23.89	61.62	7.36	176.25	chickpea
64.0	147.0	106.0	24.69	85.86	6.48	96.86	banana
11.0	83.0	17.0	33.71	89.26	6.32	162.58	pigeonpeas

5.2 Practical Value

The system's ability to offer disease insights alongside personalized crop suggestions in a mobile-first interface greatly enhances decision-making at the grassroots level.

Real-time visual outputs and the incorporation of AI explainability (via class-wise metrics and prediction visuals) reinforce user trust.

The results demonstrate that the intelligent backend of KropCart not only meets technical expectations but also delivers measurable social and economic benefits.

5.3 Future Considerations

While the current results are promising, several areas offer scope for future enhancement. Continuous training for users, especially in rural areas, is vital to ensure they effectively utilize all features of the platform. Regular support can lead to higher adoption rates and better outcomes. The AI models require

ongoing refinement through data collection and algorithm updates to improve prediction accuracy. Planned expansions include advanced market trend analysis and integration with government schemes. These upgrades aim to enhance the platform's value, ensure long-term sustainability, and contribute to a more resilient agricultural ecosystem.
Additionally, expanding the platform's mobile accessibility will ensure that farmers in remote areas can easily access vital information and resources.

Figure 11. Crop Disease Prediction in Action

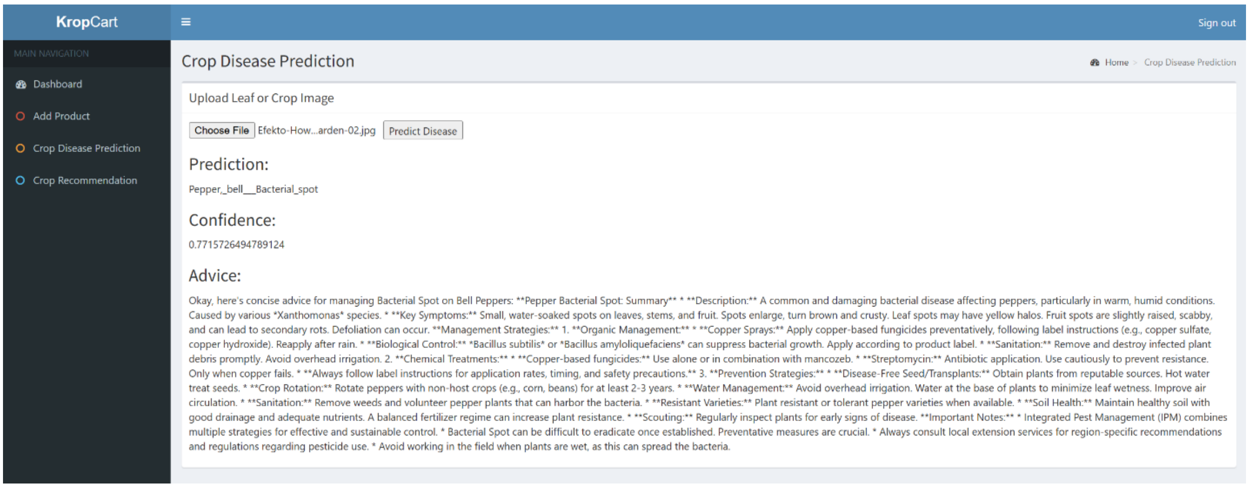
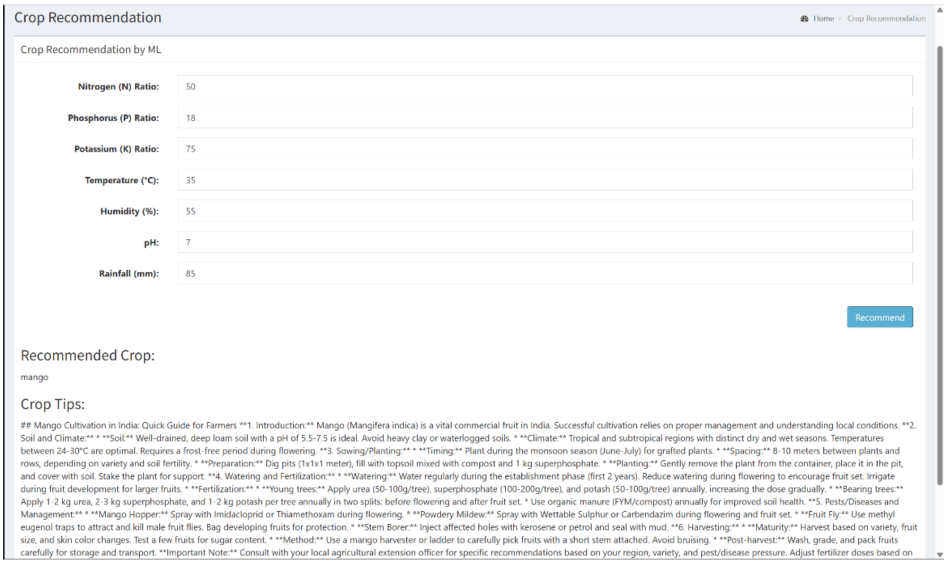


Figure 12. Crop Recommendation System in Action



6. Conclusion

KropCart addresses key challenges in agricultural supply chains by providing a direct market platform and AI-driven insights. The combination of market access, disease diagnosis, crop recommendation, and secure transactions enhances profitability and financial independence for farmers. Future improvements will include enhanced model tuning, multi- language support, and integration with government schemes for wider adoption.

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