IntelliFarm: A Unified AI-Driven Decision Support System for Crop Planning, Disease Detection, and Market Price Forecasting

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Abstract:
Modern agriculture faces challenges such as climate variability, crop diseases, and fluctuating market prices, making traditional experience-based farming less effective. This paper presents IntelliFarm+, an Artificial Intelligence (AI)-based decision support system designed to assist farmers in crop recommendation, crop disease detection, and crop price forecasting. The crop recommendation module utilizes a Random Forest classifier to suggest suitable crops based on soil and climatic conditions. Crop disease detection is performed using DenseNet-based Convolutional Neural Networks (CNNs) to identify diseases from leaf images. For market analysis, Long Short-Term Memory (LSTM) networks are employed to forecast crop prices using historical and recent market data. The system is implemented as a scalable web-based platform with a modular architecture, enabling real-time interaction and decision support. Experimental results demonstrate strong performance, with crop recommendation achieving 99.55% accuracy, disease detection reaching 95.05% for grape leaves and 90.67% for sugarcane leaves, and crop price forecasting attaining 80.4% accuracy with a 7.0% mean absolute percentage error. These findings indicate that IntelliFarm+ can effectively support precision agriculture by enabling informed, data-driven farming decisions.

Key Words: Smart Agriculture, Artificial Intelligence, Crop Recommendation, Crop Disease Detection, Crop Price Forecasting, Deep Learning, LSTM, Precision Agriculture.

I. Introduction

Agriculture is a vital sector that supports food security and economic development worldwide. Farmers must make critical decisions regarding crop selection, disease management, and market planning under uncertain conditions influenced by climate variability, soil characteristics, and fluctuating market prices. Traditional farming methods largely depend on experience and intuition, which may not effectively address these dynamic challenges [3], [10].

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have enabled data-driven approaches for improving agricultural decision-making. ML techniques have demonstrated success in crop recommendation by analyzing soil and climatic parameters [1], [2], [4], [5], while deep learning models have achieved high accuracy in crop disease detection through image-based leaf analysis [6], [8], [9]. Similarly, time-series forecasting methods have been applied to predict crop prices and support market-related decisions [3], [10].

However, most existing agricultural systems focus on individual tasks and lack integration of crop planning, disease diagnosis, and market forecasting within a unified framework [7]. To address this limitation, this paper proposes IntelliFarm+, an integrated AI-based decision support system that combines crop recommendation, crop disease detection, and crop price forecasting on a single platform. The system utilizes a Random Forest classifier for crop recommendation, DenseNet-based Convolutional Neural Networks (CNNs) for disease detection, and Long Short-Term Memory (LSTM) networks for price forecasting. By integrating agronomic, crop health, and market information, IntelliFarm+ supports accurate and data-driven decision-making for precision agriculture.

II. BACKGROUND

A. Crop Recommendation

Selecting the right crop is an important decision that directly affects agricultural productivity. Recent studies have applied machine learning techniques to recommend suitable crops based on soil nutrients, temperature, humidity, rainfall, and pH values [1], [2], [4], [5]. Algorithms such as Random Forest, Decision Trees, and Support Vector Machines have shown promising results in improving crop selection accuracy. However, most existing systems focus only on crop recommendation and do not consider crop health or market conditions during decision-making [1], [4].

B. Crop Disease Detection

Plant diseases can significantly reduce crop yield and quality. With advancements in deep learning, Convolutional Neural Networks (CNNs) have been widely used to detect diseases from leaf images [6]–[9]. Architectures such as DenseNet have achieved high accuracy in identifying diseases in crops like grape and sugarcane. Mobile and web-based solutions have also made disease diagnosis more accessible to farmers [7]. Despite their effectiveness, many disease detection systems are limited to specific crops and are not integrated with broader agricultural support systems [8].

C. Crop Price Forecasting

Market price fluctuations create uncertainty for farmers when selling their produce. Traditional forecasting methods often struggle to capture complex market trends and seasonal variations. Recent studies have shown that deep learning models, particularly Long Short-Term Memory (LSTM) networks, can effectively forecast crop prices using historical market data [3], [10]. However, most forecasting systems operate independently and are not linked with crop planning or disease management processes.

D. Research Gap

Although significant progress has been made in crop recommendation, disease detection, and price forecasting, these solutions are usually developed as separate applications [7]. Farmers require a unified system that can support decisions throughout the agricultural lifecycle. To address this gap, IntelliFarm+ integrates crop recommendation, crop disease detection, and crop price forecasting into a single AI-based platform, providing comprehensive and data-driven support for smart agriculture.

III. LITERATURE SURVEY

Recent studies have demonstrated the effectiveness of Artificial Intelligence (AI) and Machine Learning (ML) in crop recommendation systems. Karthik and Moduguri [1] developed a data-driven recommendation system using Explainable AI, while Badshah et al. [2] applied robust ML models for crop classification and yield prediction. Similarly, Bag et al. [4] and Kumar et al. [5] utilized soil and environmental parameters to recommend suitable crops with improved accuracy. These approaches help farmers make informed crop selection decisions but are generally limited to recommendation tasks.

Significant advancements have also been made in crop disease detection using deep learning techniques. Reddy et al. [6] proposed a mobile-based disease detection system, while Dighe et al. [7] developed a web-based platform for disease management. Joseph et al. [8] and Feng et al. [9] further improved disease classification accuracy using advanced deep learning architectures and real-time datasets. Although these systems effectively identify plant diseases, they primarily focus on disease diagnosis and are not integrated with other agricultural decision-support functions.

For agricultural market analysis, Chaitra and K. [3] and Sarangi et al. [10] explored machine learning techniques for crop price forecasting using historical market data. Their studies demonstrated the potential of predictive models in supporting farmers' marketing decisions. However, most existing solutions address crop recommendation, disease detection, and price forecasting as separate applications. To overcome this limitation, the proposed IntelliFarm+ system integrates these three functionalities into a unified AI-based platform, enabling comprehensive and data-driven decision support for precision agriculture.

IV. SYSTEM OVERVIEW

The system architecture represents the high-level structural design of the proposed IntelliFarm+ intelligent agricultural decision support system. It illustrates how users, artificial intelligence models, data sources, and software services are organized and interact to provide crop recommendation, crop disease detection, and crop price forecasting.

At the top of the architecture is the Farmer, who interacts with the system through the Web/Mobile User Interface. The interface serves as the primary access point, allowing users to enter soil and climatic information for crop recommendation, upload crop leaf images for disease detection, and request crop price forecasts. It provides a simple and user-friendly platform that can be accessed from different devices without requiring advanced technical knowledge.

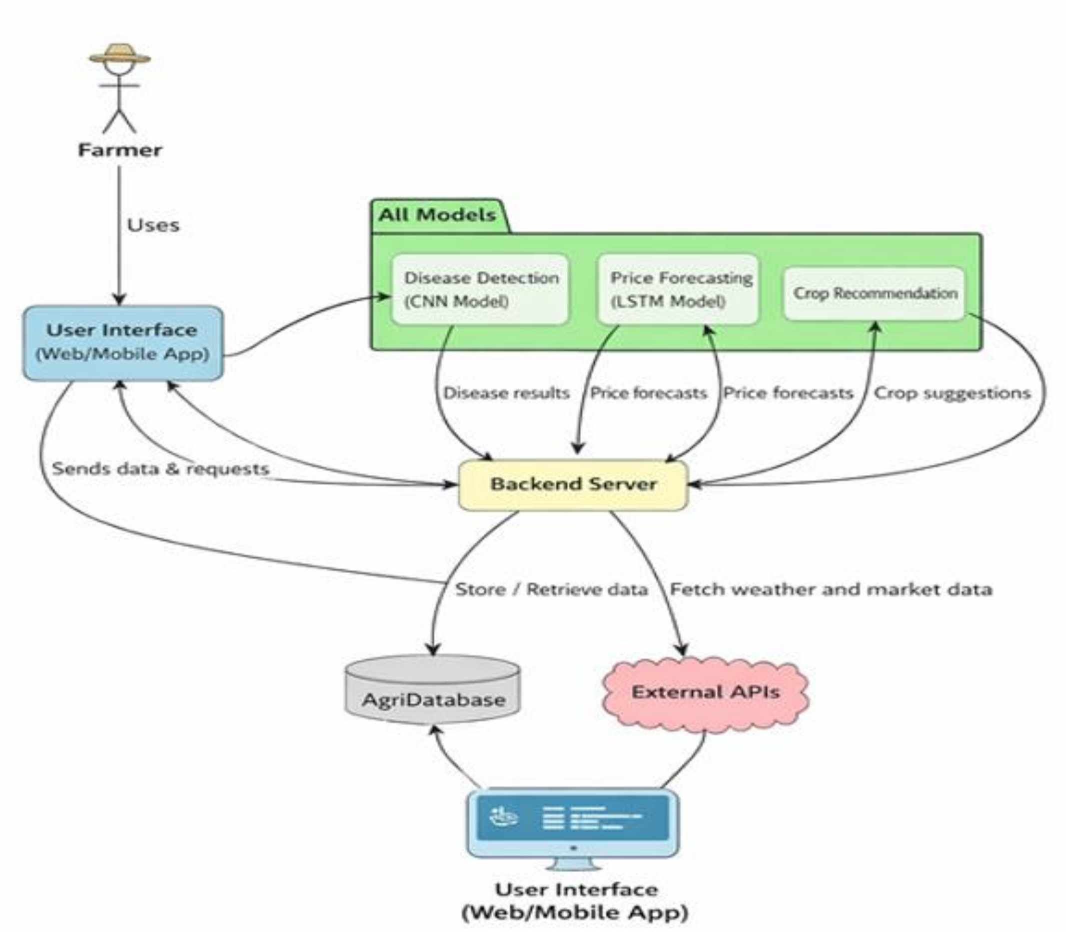
The user interface communicates with the system through the Backend Server, which acts as the central processing and control unit. The backend handles user requests, validates input data, manages communication between system components, and coordinates the execution of artificial intelligence models. It ensures efficient processing and real-time response generation.

The backend is connected to three core AI modules grouped under the AI Models Layer. The Crop Recommendation Model uses a Random Forest classifier to analyze soil nutrients and environmental conditions and suggest the most suitable crops[1]. The Disease Detection Model employs DenseNet-based Convolutional Neural Networks (CNNs) to identify crop diseases from uploaded leaf images[5]. The Price Forecasting Model utilizes Long Short-Term Memory (LSTM) networks to analyze historical market trends and predict future crop prices[8]. The prediction results generated by these models are returned to the backend server for further processing.

Connected to the backend is the AgriDatabase, which stores agricultural records, user requests, model outputs, and historical information required for system operation. This database supports data management, retrieval, and long-term storage of agricultural information. The backend also interacts with External APIs to obtain weather conditions, market prices, and other real-time agricultural data required for accurate recommendations and forecasting.

Finally, the processed outputs are delivered back to the Web/Mobile User Interface, where farmers can view crop recommendations, disease diagnosis results, and crop price forecasts in an understandable format. Overall, the architecture follows a modular and scalable design in which the user interface handles interaction, the backend manages system operations, the AI models perform intelligent analysis, the database stores information, and external APIs provide real-time agricultural data. This structure enables reliable, efficient, and data-driven decision-making for precision agriculture applications.

Figure 1.1: System Architecture



Technology Suite Used:
The IntelliFarm+ system is developed using a modern technology stack to ensure efficient performance, scalability, and reliable decision support.

- **Frontend:** React.js and Bootstrap are used to create a responsive and user-friendly web interface.
- **Backend:** Flask (Python) handles API services, user requests, data processing, and communication between system components.
- **Machine Learning:** Scikit-learn is used to implement the Random Forest model for crop recommendation.
- **Deep Learning:** TensorFlow supports DenseNet-based CNN models for crop disease detection and LSTM models for crop price forecasting.
- **Database:** SQLite is used for storing user information, agricultural data, and prediction records.
- **Authentication:** JSON Web Tokens (JWT) provide secure user authentication and access control.

This technology stack enables IntelliFarm+ to provide accurate, scalable, and real-time agricultural decision support.

V. METHODOLOGY

The proposed IntelliFarm+ system follows an integrated Artificial Intelligence (AI) framework that combines crop recommendation, crop disease detection, and crop price forecasting within a single platform. The objective of the system is to assist farmers in making informed decisions throughout the agricultural lifecycle by utilizing soil information, crop health data, and market trends.

The methodology begins with the Data Collection Stage, where datasets are acquired from publicly available Kaggle repositories and external agricultural sources. For the crop recommendation module, a structured dataset containing soil and climatic parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), temperature, humidity, pH, and rainfall is used [1]. These parameters are commonly employed in precision agriculture for determining crop suitability [2]. For crop disease detection, two image datasets are utilized: the Niphad Grape Leaf Disease Dataset (NGLD) containing images of Downy Mildew, Bacterial Rot, Powdery Mildew, and Healthy leaves, and a Sugarcane Disease Dataset consisting of Healthy, Mosaic, Red Rot, Rust, and Yellow Disease classes. For crop price forecasting, a historical market price dataset containing multi-year crop price records is used to capture long-term market behavior and seasonal trends. In addition, real-time weather and market information are collected through external APIs to improve prediction reliability.

After data acquisition, the collected information undergoes a Data Preprocessing Stage. Structured agricultural data is cleaned, normalized, and formatted to remove inconsistencies and missing values. Disease images are resized and normalized before training[1],[2],[5],[7],. To improve model generalization and reduce overfitting, image augmentation techniques such as rotation, flipping, and scaling are applied. Historical market price records are transformed into sequential time-series datasets suitable for forecasting. The processed datasets are then divided into training, validation, and testing subsets to evaluate model performance on unseen data.

The preprocessed data is supplied to three independent AI modules. The Crop Recommendation Module employs a Random Forest classifier that analyzes soil nutrients and environmental conditions to recommend the most suitable crop for cultivation[1]. The model learns complex relationships between soil properties, climate variables, and crop suitability, enabling accurate recommendations under varying agricultural conditions[3][4]. The Crop Disease Detection Module utilizes DenseNet-based Convolutional Neural Networks (CNNs) to automatically identify diseases from uploaded leaf images. The dense connectivity structure of DenseNet facilitates efficient feature reuse and improves disease classification accuracy. The Crop Price Forecasting Module uses a Long Short-Term Memory (LSTM) network to learn temporal dependencies from historical market data and generate future crop price predictions[9][10].
The outputs generated by these AI models are managed by the Backend Server, which acts as the central control unit of the system. The backend coordinates communication between modules, stores prediction records in the AgriDatabase, and retrieves real-time weather and market information through external APIs. Finally, the prediction results are delivered through the Web/Mobile Interface, where farmers can view crop recommendations, disease diagnosis results with confidence scores, and future market price forecasts.

Overall, the proposed methodology integrates structured agricultural data analysis, image-based disease diagnosis, and time-series forecasting into a unified decision-support framework. This integrated approach enables farmers to make accurate, timely, and data-driven decisions, thereby supporting sustainable and precision agriculture practices.

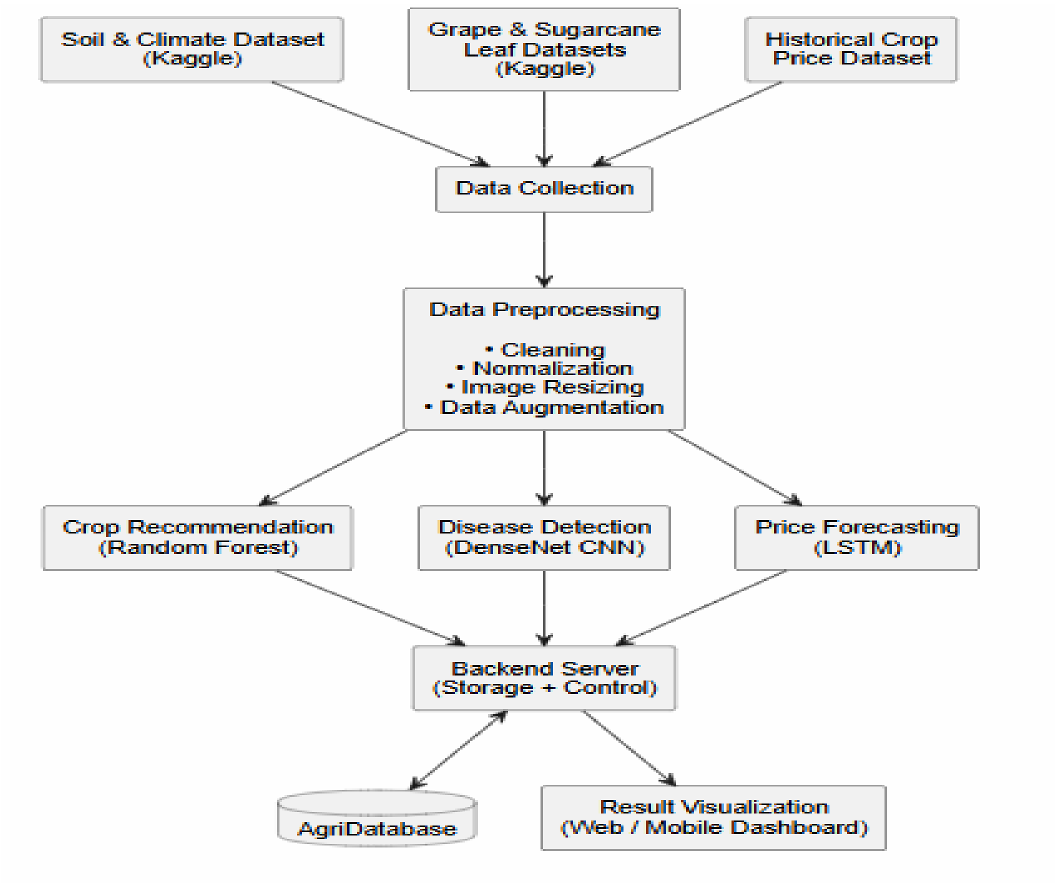


Figure 1.2: System Flow

VI. MATHEMATICAL MODEL OF THE SYSTEM

The proposed IntelliFarm+ system is designed as an integrated agricultural decision support framework that utilizes soil parameters, climatic conditions, crop leaf images, and historical market data to generate crop recommendations, disease predictions, and crop price forecasts. The system combines machine learning, deep learning, and time-series forecasting techniques to support precision agriculture.

1. System Representation

The complete IntelliFarm+ system can be represented as:

S = {I, M, O} …………. (1)

Where:

- **S** = IntelliFarm+ System
- **I** = Input Set
- **M** = Set of AI Models
- **O** = Output Set

2. Input Set

The system receives three different types of agricultural inputs:

I = {Xs, Xi, Xt} ………(2)

Where:

- **Xs** = Soil and climatic parameters
- **Xi** = Crop leaf image
- **Xt** = Historical crop price data

The soil and climatic feature vector is represented as:

$$\mathbf{Xs = \{N, P, K, T, H, pH, R\}} \quad \ldots\ldots\ldots(3)$$

Where:

- **N** = Nitrogen content
- **P** = Phosphorus content
- **K** = Potassium content
- **T** = Temperature (°C)
- **H** = Relative Humidity (%)
- **pH** = Soil pH value
- **R** = Rainfall (mm)

The historical crop price sequence is represented as:

$$\mathbf{Xt = \{p_1, p_2, p_3, ..., p_t\}} \quad \ldots\ldots\ldots\ldots(4)$$

where $\mathbf{p_t}$ denotes the market price at time **t**.

3. Data Preprocessing Function

Before model execution, the collected data is preprocessed to improve data quality and model performance.

$$\mathbf{Xp = fpre(I)} \quad \ldots\ldots\ldots\ldots..(5)$$

Where:

- **fpre** = preprocessing function
- **Xp** = processed input data

The preprocessing stage includes:

- Missing value handling
- Feature normalization
- Image resizing and augmentation
- Time-series sequence generation

4. Crop Recommendation Model

Crop recommendation is formulated as a supervised multi-class classification problem.

The recommendation function is defined as:

$$\mathbf{Rc = fRF(Xs)} \quad \ldots\ldots\ldots\ldots.(6)$$

Where:

- **fRF** = Random Forest classifier
- **Rc** = Recommended crop class

The Random Forest model learns the relationship between soil nutrients, climatic conditions, and crop suitability. The predicted crop is obtained as:

$$\mathbf{Rc = arg\ max\ P(Ci \mid Xs)} \quad \ldots\ldots\ldots\ldots.(7)$$

Where:

- **Ci** = ith crop category
- **P(Ci | Xs)** = probability of crop Ci given input conditions

5. Crop Disease Detection Model

The crop disease detection module uses a **DenseNet-based CNN** to classify diseases from crop leaf images.

$$\mathbf{Dd = fCNN(Xi)} \quad \ldots\ldots\ldots\ldots\ldots(8)$$

Where:

- **Xi** = Input leaf image
- **fCNN** = DenseNet CNN model
- **Dd** = Predicted disease class

The final disease probability is calculated using Softmax:

$$P(y_i) = e^{z_i} / \Sigma(e^{z_j}) \quad \text{……………(9)}$$

The disease class with the highest probability is selected as the final prediction.

6. Crop Price Forecasting Model

Crop price forecasting is formulated as a time-series prediction problem.

Given historical prices:

$$X_t = \{p_1, p_2, p_3, \ldots, p_t\} \quad \text{…………..(10)}$$

the LSTM forecasting function is defined as:

$$P_f(t+1) = f_{LSTM}(X_t) \quad \text{…………..(11)}$$

Where:

- **fLSTM** = LSTM forecasting model
- **Pf(t+1)** = Predicted crop price for the next time step

The LSTM model captures seasonal variations, market fluctuations, and long-term dependencies from historical agricultural price data.

7. Output Set

The final output generated by IntelliFarm+ is:

$$O = \{R_c, D_d, P_f\} \quad \text{…………….(12)}$$

Where:

- **Rc** = Recommended Crop
- **Dd** = Detected Disease
- **Pf** = Forecasted Crop Price

8. Decision Support Function

The overall decision support function of IntelliFarm+ can be represented as:

$$O = F(X_s, X_i, X_t) \quad \text{…………….(13)}$$

Where **F** represents the integrated AI framework consisting of Random Forest, DenseNet CNN, and LSTM models. Thus, IntelliFarm+ transforms agricultural, image, and market data into actionable recommendations that support crop planning, disease management, and market decision-making for precision agriculture.

VII. EXPERIMENTAL RESULTS

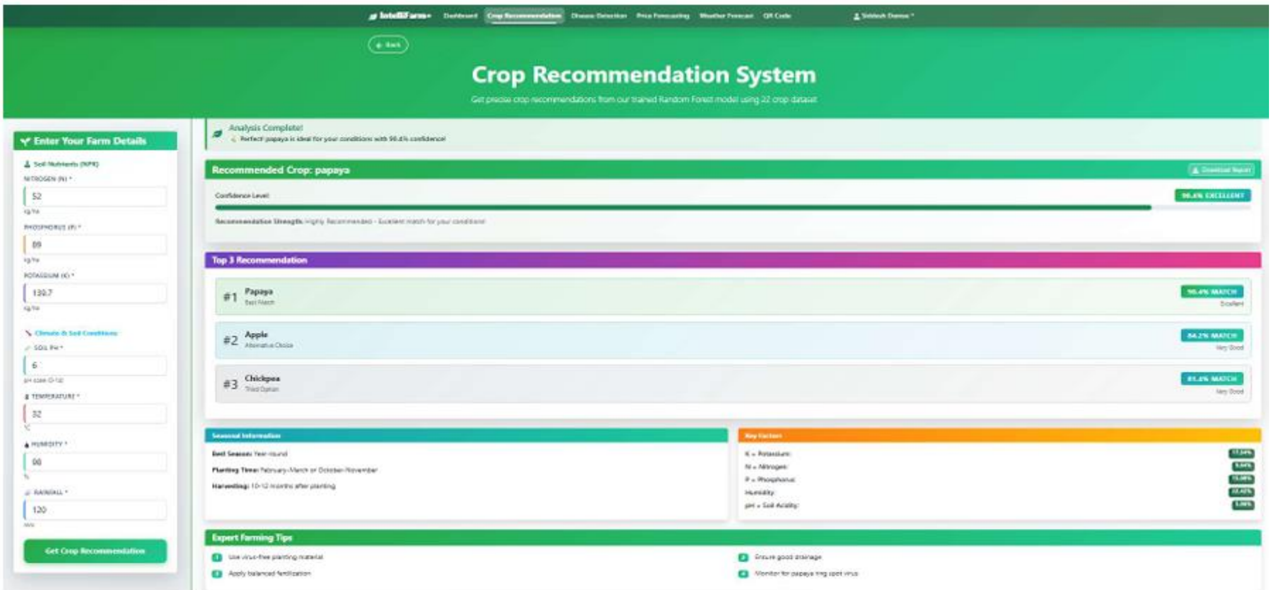
Module/ Algorithm	Accuracy Metric
Module 1. Crop Recommendation	
Algorithms:	
i. Naive Bayes	99.23% Acc
ii. Random Forest	99.55% Acc
iii. SVM	98.40% Acc
iv. KNN	97.41% Acc
v. Decision Tree	97.95% Acc
vi. Logistic Regression	97.23% Acc
Module 2. Crop Disease Detection	
Algorithms: **Crop Name: Grape**	
i. CNN	89.01% Acc
ii. VGG 16	86.45% Acc
iii. ResNet50V2	91.94% Acc
iv. DenseNet201	95.50% Acc
Algoritms: **Crop Name: Sugarcane**	

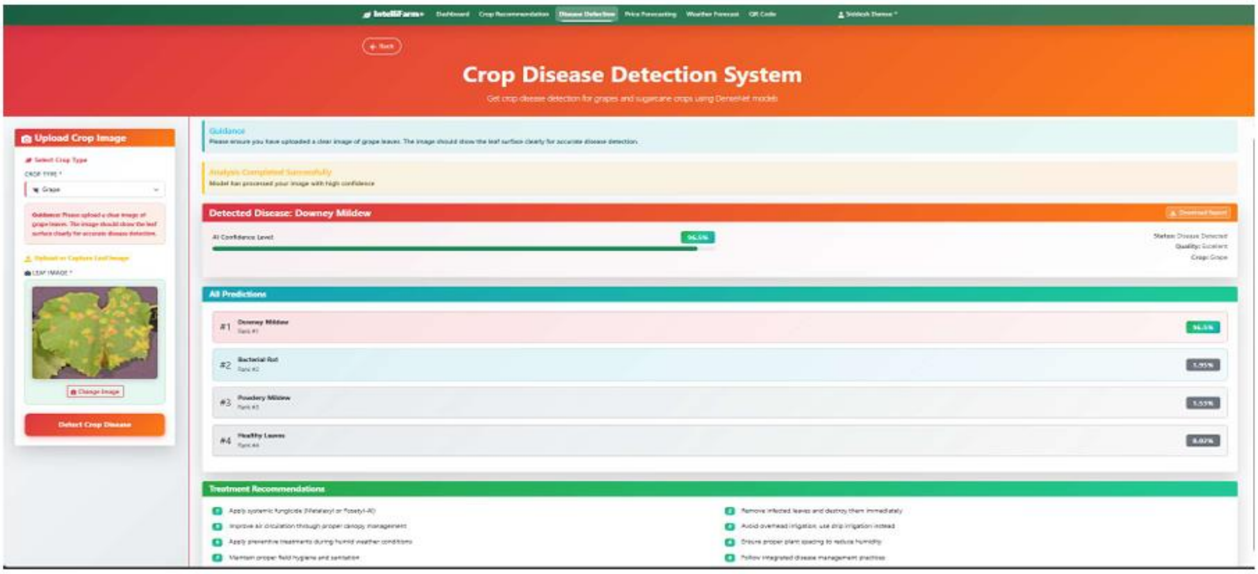
i. CNN	78.50% Acc
ii. MobileNetV2	85.31% Acc
iii. DenseNet121	91.67% Acc
Module 3. Crop Price Prediction/Forecast	
Algorithms:	
i. Linear Regression	High Error
ii. ARIMA	Moderate error
iii. LSTM	6.0% MAPE

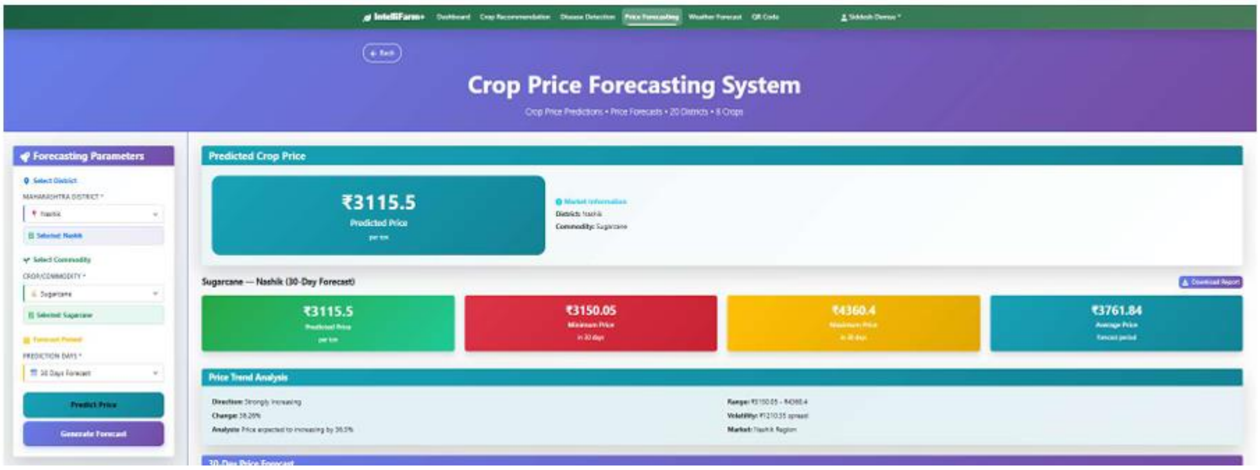
Table 1: Modules Performance Comparison

The final models in **IntelliFarm+** were selected based on their accuracy, robustness, and suitability for agricultural applications. **Random Forest** was chosen for crop recommendation due to its high accuracy and ability to handle complex relationships between soil and climatic parameters. For crop disease detection, **DenseNet201** achieved the best performance for grape leaf diseases, while **DenseNet121** provided an effective balance between accuracy and computational efficiency for sugarcane disease detection. In crop price forecasting, the **LSTM** model outperformed traditional methods by effectively capturing seasonal patterns and non-linear market trends. Together, these models provide an accurate, reliable, and scalable solution for integrated agricultural decision support.

VII. SYSTEM RESULTS







VIII. LIMITATION AND FUTURE WORK

Although IntelliFarm+ achieves high accuracy in crop recommendation, disease detection, and price forecasting, certain limitations remain. The system relies mainly on publicly available datasets and historical records, which may not fully represent rare agricultural conditions or sudden market fluctuations. Currently, the disease detection module supports only grape and sugarcane crops, and its performance may be affected by variations in image quality and field conditions. In addition, the crop recommendation model depends on a fixed set of soil and climatic parameters, while the price forecasting model primarily relies on historical market trends.

Future work will focus on expanding disease detection to a wider range of crops by incorporating larger and more diverse datasets. The crop recommendation and forecasting modules can be further enhanced through the integration of additional agricultural and market-related factors. These improvements will increase the accuracy, scalability, and practical applicability of IntelliFarm+, making it a more comprehensive decision support system for precision agriculture.

IX. CONCLUSION

Agriculture is becoming increasingly data-driven, and farmers require intelligent tools to make timely and informed decisions. This paper presented IntelliFarm+, an integrated Artificial Intelligence (AI)-based decision support system that combines crop recommendation, crop disease detection, and crop price forecasting within a single platform. By utilizing a Random Forest classifier for crop recommendation, DenseNet-based Convolutional Neural Networks (CNNs) for disease detection, and Long Short-Term

Memory (LSTM) networks for price forecasting, the system provides comprehensive support across multiple stages of the agricultural lifecycle.

The experimental results demonstrate that IntelliFarm+ can effectively analyze soil and climatic conditions, identify crop diseases from leaf images, and forecast future crop prices with reliable accuracy. The integration of these functionalities into a unified web-based platform simplifies decision-making and enables farmers to access valuable insights through a single interface. This reduces dependency on traditional experience-based practices and promotes more efficient and informed agricultural planning.

Overall, IntelliFarm+ highlights the practical potential of combining machine learning, deep learning, and time-series forecasting techniques to address real-world agricultural challenges. The proposed system contributes toward precision agriculture by improving productivity, supporting better resource utilization, and enabling data-driven farming decisions. With further enhancements and broader dataset coverage, IntelliFarm+ can serve as a scalable and effective solution for modern smart agriculture applications.

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