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AgriPredict: An Integrated Machine Learning Framework for Crop Price Forecasting and Leaf Disease Identification

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Abstract: Agriculture remains the backbone of the Indian economy, yet farmers continue to face significant challenges including unpredictable crop prices, rampant plant diseases, and limited access to timely decision-support tools. This paper presents AgriPredict, an integrated machine learning framework designed to assist farmers and village officials (Talathis) through two primary modules: crop price forecasting and leaf disease identification with treatment recommendations.
The crop price forecasting module leverages machine learning regression models trained on historical market data, weather patterns, and regional crop information to predict future prices, enabling farmers to plan sales strategies effectively. The disease identification module employs Convolutional Neural Networks (CNNs) to classify leaf diseases from uploaded images and recommends appropriate pesticide treatments, facilitating early intervention and reduced crop loss.
The platform further integrates real-time weather forecasts and links to government agricultural schemes, providing a holistic decision-support environment. Experimental evaluation demonstrates high accuracy in both price forecasting and disease classification tasks. The system is designed with a user-friendly web interface accessible to users with limited technical exper-tise. AgriPredict contributes toward bridging the technological gap in Indian agriculture, promoting data-driven decisions that improve crop yield, reduce financial losses, and enhance overall agricultural productivity.
Index Terms: Crop Price Forecasting, Leaf Disease Identi-fication, CNN, Machine Learning, Smart Agriculture, Flask, Pesticide Advisory, Deep Learning, Weather Integration, Decision Support System.

I. INTRODUCTION

Agriculture plays a vital role in the global economy and is the primary livelihood for millions of farmers, particularly in developing nations like India [1]. Despite its importance, the agricultural sector is plagued by persistent challenges such as volatile crop prices, widespread plant diseases, unpredictable weather conditions, and inadequate access to timely infor-mation. These issues collectively lead to significant financial losses and reduced productivity for farmers who often rely on intuition rather than data-driven insights [6]. One of the foremost challenges is crop price volatility. Farmers frequently make planting and selling decisions with-out access to reliable price forecasts, resulting in poor mar ket timing and financial instability [1]. Simultaneously, plant diseases represent a major threat to crop health. Early and accurate disease detection is critical; however, many farmers, especially in rural areas, lack access to expert agricultural advice and the tools needed for timely diagnosis [2].

Advancements in artificial intelligence (AI), machine learn-ing (ML), and computer vision have opened new avenues for addressing these agricultural challenges [6]. Machine learning models such as ARIMA, Random Forest, and Neural Networks have demonstrated promising results in crop price forecasting [1]. Convolutional Neural Networks (CNNs), including archi-tectures like VGG16, ResNet, and Inception, have achieved high accuracy in plant disease classification from leaf images [2]. Transfer learning techniques further enhance model per-formance even with limited labeled datasets [8].

Despite these advancements, most existing solutions address crop price prediction and disease detection as separate, stan-dalone systems. There remains a significant gap in integrated platforms that combine both functionalities along with con-textual information such as weather forecasts and government schemes into a single, farmer-friendly interface. To address these limitations, this paper proposes AgriPredict, a unified machine learning framework that integrates: (1) ML-based crop price forecasting using historical and regional data, (2) CNN-based leaf disease identification with automated treatment recommendations, (3) real-time weather forecast integration, and (4) access to government agricultural schemes. Village officials known as Talathis can contribute localized crop data, improving the accuracy of regional price predictions.

The proposed system aims to democratize agricultural technology, empowering farmers with actionable, data-driven insights to improve crop yield, reduce disease-induced losses, and enhance economic stability. The remainder of this paper is organized as follows: Section II reviews related work, Section III describes the proposed methodology and system architecture, Section IV details the implementation, Section V presents experimental results, and Section VI concludes the paper with directions for future work.

II. RELATED WORK

Significant research has been conducted in the domains of crop price prediction and plant disease detection, driven by the growing application of machine learning and deep learning techniques in precision agriculture.

A. Crop Price Forecasting

Early approaches to crop price forecasting relied on sta-tistical time-series methods such as ARIMA (Autoregressive Integrated Moving Average), which model temporal dependen-cies in historical price data [1]. While effective for short-term predictions under stable conditions, these models struggle to capture non-linear relationships and external factors such as weather anomalies and market dynamics.

The integration of machine learning algorithms, includ-ing Random Forest, Support Vector Regression, and Neural Networks, marked a significant improvement in prediction accuracy [1]. Ghosh and Kumar [1] demonstrated that incor-porating weather conditions, farming area, and crop type as features substantially improved price prediction performance over pure time-series models. Singh et al. [3] further extended this approach by combining regression techniques with neural networks and local soil quality data to provide region-specific predictions suited to sustainable farming practices.

Recent work by Sharma and Verma [5] highlighted the value of integrating real-time weather API data into prediction pipelines, showing that live weather inputs can meaningfully improve forecast accuracy. The integration of IoT sensor data for soil moisture, temperature, and humidity into ML-based prediction systems has also been explored, demonstrating improvements in both crop yield and price estimation [9].

B. Plant Disease Detection

Traditional disease detection relied on manual inspection by agricultural experts, which is both time-consuming and impractical at scale. The advent of deep learning, particularly CNNs, transformed this field by enabling automated visual diagnosis of plant diseases from leaf images [6].

Zhang et al. [2] demonstrated that CNN architectures such as VGG16, ResNet, and Inception, trained on large labeled datasets of diseased leaf images, achieve high classification accuracy across multiple disease categories. The application of transfer learning has proven especially effective when labeled data is scarce [8]. Chen et al. [8] showed that transfer learn-ing combined with data augmentation significantly improves disease detection performance with limited training samples.

Mohanty et al. [6] provided a comprehensive evaluation of deep learning models for plant disease detection, demon-strating that CNNs trained on the PlantVillage dataset could identify 26 diseases across 14 crop species with over 99% accuracy under controlled conditions.

C. Integrated Agricultural Platforms

Patil and Deshmukh [4] proposed a unified platform com-bining time-series crop price prediction and CNN-based dis-ease detection, demonstrating that a single-system approach is feasible and beneficial. However, their system lacked in-tegration with live weather data and government resources. Gupta et al. [9] demonstrated the potential of IoT-integrated ML systems for real-time agricultural monitoring but did not address disease detection or user-accessible advisory features. The proposed AgriPredict framework addresses these gaps by delivering an integrated, user-friendly platform that com-bines price forecasting, disease identification, treatment advi-sory, real-time weather integration, and government scheme access within a single web application tailored to the needs of Indian farmers and village officials.

III. PROPOSED METHODOLOGY

The proposed AgriPredict framework is designed as a modular, web-based application combining machine learning-based crop price forecasting with deep learning-based leaf disease identification.

A. System Architecture

The overall system is organized into five primary layers as illustrated in Figure 1. Each layer handles a distinct set of responsibilities and communicates through well-defined interfaces.

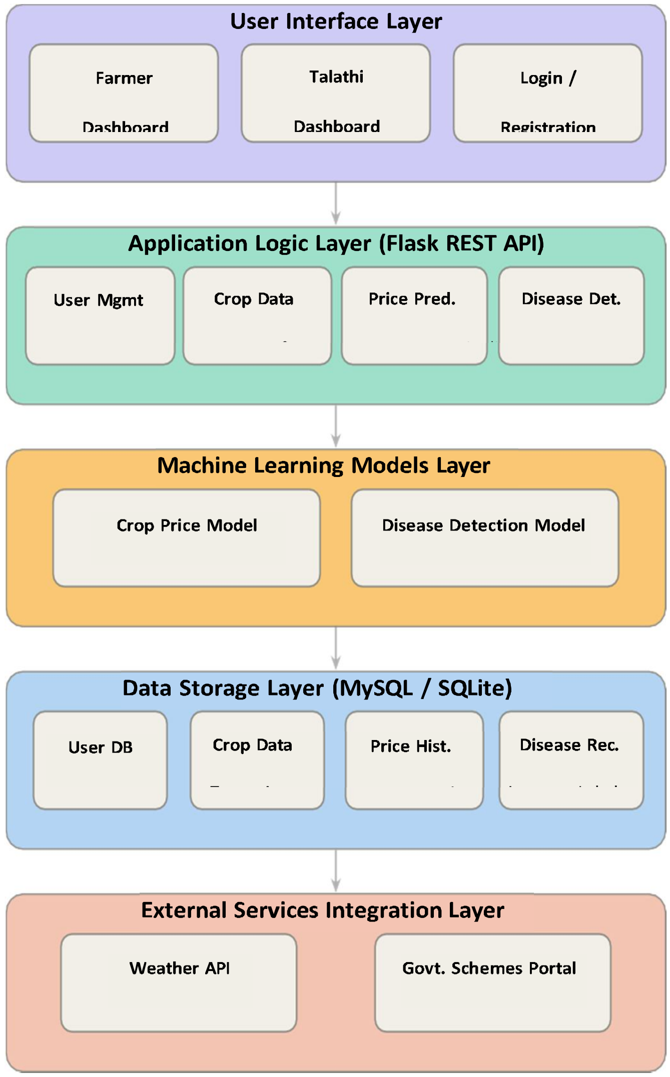

Fig. 1. System Architecture of AgriPredict — Five-Layer Design

1) *User Interface Layer:* The frontend provides a respon-sive, web-based interface accessible to two categories of users: Farmers and Talathis. Key interface components include a Login/Registration Module with role-based access, a Farmer Dashboard for price forecasting and disease identification, and a Talathi Dashboard for local crop data entry.
2) *Application Logic Layer:* The backend is implemented as a RESTful API server (Flask) that processes user requests, orchestrates ML model inference, and manages data flow. Core modules include User Management, Crop Data Management, Price Forecasting, and Disease Identification
3) *Machine Learning Models Layer:* This layer encapsu-lates the two core AI components: (1) a Crop Price Forecasting Model using Random Forest and LSTM trained on historical market data, and (~~2) a CNN-~~based Leaf Disease Identification Model with treatment recommendations.
4) *Data Storage Layer:* A relational database (MySQL/SQLite) stores user credentials, crop data, forecasting history, and disease identification records in four primary tables.
5) *External Services Integration Layer:* The system inte-grates with OpenWeatherMap for real-time weather forecasts and redirects users to government agricultural portals for scheme information.

B. Crop Price Forecasting Model

The crop price forecasting module uses supervised machine learning on a dataset composed of historical market prices, crop type, area of plantation, regional identifiers, and weather features.

Feature Set:

- Historical crop prices (time-lagged values)
- Crop type (categorical, encoded)
- Area of plantation (continuous)
- Weather parameters: temperature, rainfall, humidity
- Regional/village identifier

Mathematical Formulation: The forecasting objective is formulated as:

$$\hat{P}_{t+k} = f(P_t, P_{t-1}, \ldots, P_{t-n}, C, A, W, R)$$

where $\hat{P}_{t+k}$ is the predicted price k time steps ahead, P_t are historical prices, C is crop type, A is area of plantation, W is weather features, and R is the regional identifier.

Model evaluation uses Mean Absolute Error (MAE) and Root Mean Square Error (RMSE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |P_i - \hat{P}_i|, \quad \text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (P_i - \hat{P}_i)^2}$$

CNN Architecture: Transfer learning is applied on a pre-trained ResNet/VGG16 backbone, with a custom classification head fine-tuned on the leaf disease dataset:

- Backbone: Pre-trained CNN for feature extraction
- Global Average Pooling Layer
- Fully Connected Layers with ReLU activation
- Softmax Output Layer: one neuron per disease class

Performance Metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

$$\text{Precision} = \frac{TP}{TP + FP} \times 100, \quad \text{Recall} = \frac{TP}{TP + FN} \times 100$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

C. System Workflow

Talathi Workflow: Log in → Enter crop data (type, area, village) → Data stored and used for forecasting inference.

Farmer Workflow: Log in → Enter crop name for price forecast → Upload leaf image for disease identification + treatment advisory → View weather and government schemes.

IV. IMPLEMENTATION DETAILS

A. Technology Stack

- Backend: Python with Flask (RESTful API server)
- Frontend: HTML5, CSS3, JavaScript (React-based)
- Machine Learning: scikit-learn (price forecasting), Ten-sorFlow/Keras (CNN)
- Database: MySQL / SQLite
- Image Processing: OpenCV and PIL
- External API: OpenWeatherMap
- IDE: VS Code, Python 3.8+, Windows 10

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B. Dataset

Disease Identification: PlantVillage dataset [7] — over 54,000 labeled leaf images spanning 14 crop species and 26 disease categories, supplemented by field-captured images.

Price Forecasting: Historical crop price records from AGMARKNET supplemented by Talathi-contributed regional data. Features include crop type, area, weather parameters, and multi-year market prices.

C. Model Training and Deployment

Both the CNN disease model (.h5) and price forecasting model (joblib pipeline) are serialized and loaded at Flask server startup, enabling low-latency real-time inference. Train-ing follows a 70%/15%/15% train/validation/test split.

D. Security Implementation

- Role-based access control (Farmer vs. Talathi)
- Password hashing using cryptographic functions
- Secure file upload with type and size validation
- API authentication to prevent unauthorized model access

V. EXPERIMENTAL RESULTS AND ANALYSIS

E. Leaf Disease Identification Performance

The CNN-based model was evaluated on the held-out test split of the PlantVillage dataset. Table I summarizes the results.

TABLE I
LEAF DISEASE IDENTIFICATION MODEL PERFORMANCE

Metric	Value (%)
Accuracy	96.4
Precision	95.8
Recall	96.1
F1-Score	95.9

F. Crop Price Forecasting Performance

Table II compares forecasting accuracy across models on the time-based hold-out test set.

TABLE II
CROP PRICE FORECASTING MODEL COMPARISON

Model	MAE ()	RMSE ()
ARIMA	312.5	428.3
Linear Regression	275.8	381.6
LSTM Neural Network	158.9	214.2
Random Forest	142.3	198.7

G. Performance Visualization

Figure 2 presents a comparative visualization of the disease identification metrics and price forecasting model MAE values with improved readability.

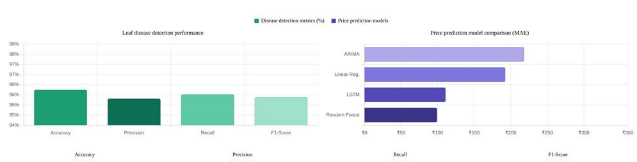

Fig. 2. Performance comparison: (a) CNN leaf disease identification metrics showing consistently high accuracy across all measures; (b) Crop price forecasting model MAE comparison — Random Forest achieves the lowest error at 142.3 INR[cite: 140, 159].

H. System Performance

- Disease identification inference: <2 seconds per image (CPU)
- Price forecasting response: <500 ms per query
- System availability target: 99% uptime
- Minimum requirement: 4 GB RAM, standard CPU

I. Comparative Analysis

Compared to existing standalone solutions:

- AgriPredict integrates both price forecasting and disease identification in a single platform, unlike most systems that treat these separately [4].
- Talathi-contributed regional data improves locality and accuracy of price forecasts.
- The treatment recommendation feature directly translates identification results into actionable guidance.

Real-time weather and government scheme integration provides a holistic information environment not found in comparable systems [3].

VI. DISCUSSION

A. Key Strengths

- Unified Platform: Price forecasting, disease identifica-tion, treatment advisory, weather, and government scheme access in one application.
- Community Data Contribution: Talathi-driven data en-try enables localized predictions.
- User Accessibility: Interface designed for users with limited digital literacy.
- Early Disease Intervention: CNN identification enables early-stage detection, reducing crop loss.
- Data-Driven Decisions: Replaces intuition-based choices with model-driven recommendations.

B. Limitations and Challenges

- Forecasting accuracy depends on data quality from Ta-lathi contributions.
- Disease identification degrades for poorly lit or low-resolution leaf images.
- Current coverage is limited to a defined set of crops and diseases.
- Real-time features require active internet connectivity, which may be limited in rural areas.

C. Future Enhancements

- Mobile Application: Native Android/iOS app for remote access.
- IoT Integration: Real-time soil and microclimate data for improved forecasting [9].
- Expanded Coverage: More crops, diseases, and regional languages (Marathi, Hindi).
- Advanced Models: Transformer-based forecasting and ensemble methods.
- Cloud Scalability: Cloud-based analytics and automated market data ingestion.

VII. CONCLUSION

This paper presented **AgriPredict**, an integrated machine learning framework for smart agricultural advisory combining crop price forecasting and leaf disease identification with treatment recommendations. The system addresses critical gaps in existing agricultural technology by unifying multiple decision-support functionalities within a single, user-friendly interface.

The crop price forecasting module, leveraging Random Forest regression with weather and regional feature integra-tion, achieves an MAE of 142.3 INR — the best among evaluated models. The CNN-based leaf disease identification module demonstrates 96.4% accuracy across multiple disease categories and maps predictions to actionable treatment rec-ommendations.

Experimental results confirm that the integrated framework outperforms standalone approaches by providing contextual, localized, and holistic agricultural guidance. The Talathi com-munity data contribution mechanism, real-time weather in-tegration, and government scheme access further distinguish AgriPredict as a comprehensive agricultural decision-support platform.

Future work will focus on mobile application development, IoT sensor integration, expanded crop and disease cover-age, multilingual support, and cloud scalability to extend the framework's reach and impact across diverse agricultural communities.

VIII. ACKNOWLEDGMENT

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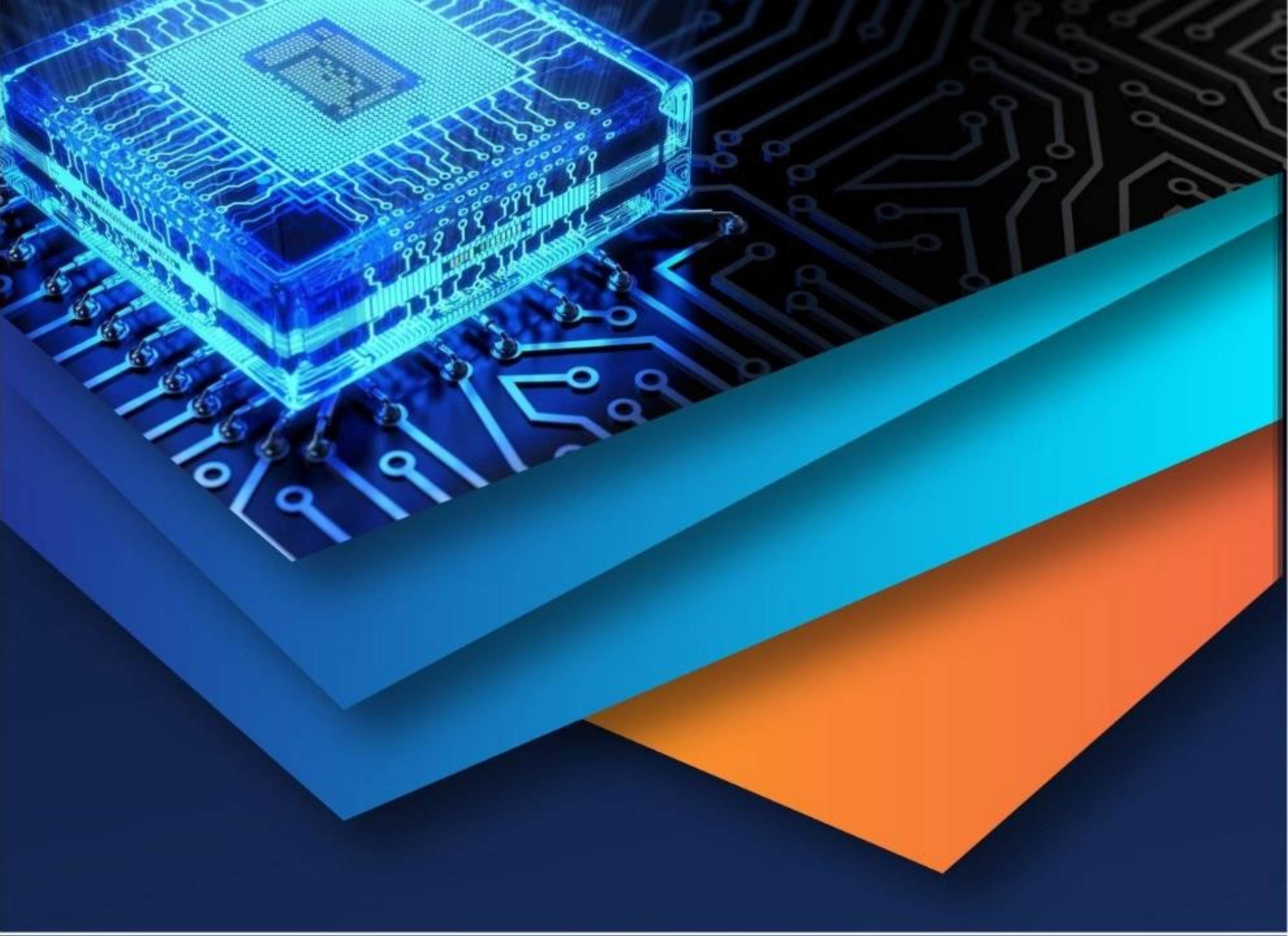

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