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PlantShield AI: An Integrated Deep Learning Framework for Intelligent Crop Pest and Disease Detection in Precision Agriculture

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Abstract: Agricultural productivity is under severe and growing threat from plant pests and diseases that cause significant crop losses worldwide, particularly inregions where farmers lack access to expert diagnostic support. This paper presents Plant Shield AI, a web-based intelligent system that leverages Convolutional Neural Networks (CNN) built on the MobileNet architecture to automatically detect and classify plant pathogens and crop pests from user-uploaded leaf images. The system is deployed via a Django web Framework and integrates a community profile module alongside dedicated pathogen detection and pest classification modules. Training was performed over 100 epochs using an augmented dataset with an 80:20 train-validation split. Experimental results demonstrate incremental accuracy improvement across epochs, validating the viability of the proposed deep learning pipeline. The platform aims to bridge the technological divide between modern AI capabilities and traditional farming practice, offering timely, data-driven, and actionable recommendations for sustainable crop management and improved food security.
Keywords: Convolutional Neural Network, MobileNet Architecture, Crop Disease Detection, Pest Classification, Deep Learning, Django, Precision Agriculture, Image Classification, PlantShield AI

I. INTRODUCTION

Agriculture forms the backbone of the global economy, providing food and livelihood for billions. However, plant diseases and pest infestations remain persistent challenges that silently erode crop yields, escalate production costs, and ultimately compromise food security at regional and global levels. Traditional disease identification methods depend heavily on the visual judgment of experienced agronomists—a resource that is neither scalable nor consistently available, particularly in rural farming communities of developing nations.

The emergence of deep learning, especially Convolutional Neural Networks (CNNs), has fundamentally transformed computer vision tasks including image-based plant disease recognition. CNNs automatically learn hierarchical visual representations—such as texture anomalies, discoloration patterns, and lesion morphologies—without requiring hand-crafted feature engineering. This makes them exceptionally well-suited for the complex, multi-class nature of agricultural disease classification.

This paper introduces PlantShield AI, a full-stack intelligent system that combines a MobileNet-based CNN backbone with a Django web interface to offer real-time crop pathogen detection and pest classification. The system accepts leaf images uploaded by users, processes them through a trained deep learning pipeline, and returns diagnostic results accompanied by actionable crop management recommendations.

II. RELATED WORK

Extensive research has been conducted on the application of machine learning and image processing techniques for plant disease identification. Padmavathy (2025) presented an AI-driven crop disease prediction framework that compared classification, detection, and segmentation networks, underscoring both the rapid progress of deep learning models and the challenges of deploying them in resource-limited agricultural settings. Magdum et al. (2023) demonstrated the effectiveness of neural network approaches over conventional machine learning techniques for rice pest identification, reducing the dependency on intensive manual crop surveillance. Kulkarni et al. (2022) proposed a computer vision system capable of detecting twenty distinct diseases across five commonly grown plant species, highlighting the potential of multi-class CNN models in practical agronomical contexts.

Subbarayudu and Kubendiran (2023) conducted a comprehensive comparative survey of ML and DL techniques for crop disease prediction, conclusively establishing that deep learning architectures yield higher classification accuracy compared to conventional approaches. Yadav et al. (2021) specifically explored Random Forest, Decision Tree, and Extreme Machine Learning algorithms for disease classification, producing benchmark results that inform architecture choices in the present work.

III. EXISTING SYSTEM

The existing system refers to the currently available methods and approaches used to address the problem domain. Traditional systems primarily rely on manual processes or basic computational techniques, which often lack scalability and efficiency. In many applications, rule-based models and conventional algorithms are employed to perform tasks such as data processing, classification, or prediction. In recent years, machine learning-based approaches have been introduced to improve performance. These systems utilize algorithms such as decision trees, support vector machines, and basic neural networks to analyze data and generate outputs. While these methods offer better accuracy compared to manual systems, they still depend heavily on feature engineering and structured data. Furthermore, many existing systems are designed for specific use cases and lack adaptability. They often operate in isolated environments without integration with real-time data sources, limiting their practical usability in dynamic scenarios.

A. Limitations of Existing System

Despite advancements, the existing systems suffer from several key limitations:

1) Low Accuracy and Generalization — Traditional and basic machine learning models often fail to generalize well on unseen data, leading to reduced prediction accuracy.
2) High Dependency on Manual Effort — Many systems require extensive manual intervention, including data preprocessing, feature selection, and parameter tuning.
3) Limited Scalability — Existing approaches may not handle large-scale or real-time data efficiently, making them unsuitable for modern applications involving big data.
4) Poor Handling of Complex Data — Conventional systems struggle with unstructured data such as text, images, or audio, limiting their effectiveness in real-world scenarios.
5) Lack of Adaptability — Most systems are static and cannot adapt to changing environments or evolving data patterns without retraining.
6) Computational Inefficiency — Some models require high computational resources while still not delivering optimal performance.
7) Data Imbalance Issues — Existing methods often perform poorly on imbalanced datasets, leading to biased results.

IV. SYSTEM ARCHITECTURE AND DESIGN

PlantShield AI is structured around a three-tier web architecture comprising a presentation layer (HTML/CSS/JavaScript frontend), a business logic layer (Django backend in Python), and a data persistence layer (SQLite3 database). The deep learning inference engine is embedded within the Django backend and is invoked upon image submission. The end-to-end data flow proceeds as follows: (1) agricultural image datasets are harvested from publicly available repositories; (2) raw images undergo preprocessing including resizing to 224×224 pixels, pixel normalization, and augmentation; (3) the processed data is partitioned into training (80%) and validation (20%) subsets; (4) the MobileNet-based CNN model is trained and the best-performing checkpoint is saved; (5) the finalized model is integrated with the Django application; and (6) users interact through the web portal to upload images and receive diagnostic outputs.

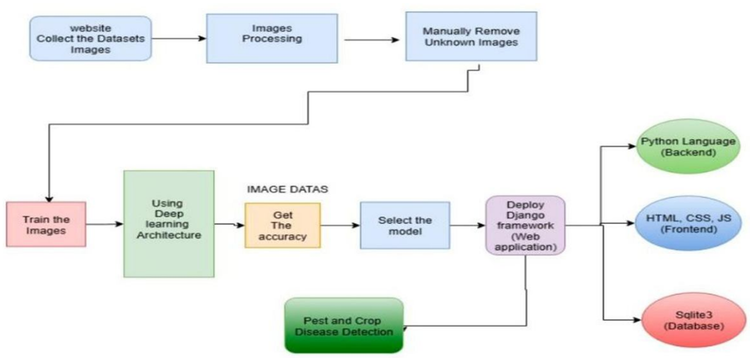

Fig. 1. System Architecture and Data Flow Diagram

V. METHODOLOGY

A. Dataset and Preprocessing

The training corpus comprises crop leaf images spanning multiple pathogen classes including fungal diseases (brown rot, leaf blight), bacterial infections, and healthy control samples. Data augmentation strategies—including horizontal flipping, shear transformation (range 0.2), and zoom variation (range 0.2)—were applied using Keras Image Data Generator to artificially expand the dataset and reduce overfitting risk. All images were rescaled by 1/255 to normalize pixel intensities to the [0, 1] range.

Sample images of plant diseases used in training are shown below:

Stem Lesions

Brown Rot (Leaves)

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Crown Gall (Pine)

Crown Gall (Roots)

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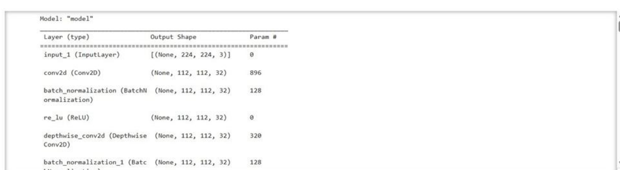
Stem Lesions / Bud Growth

Fig. 2. Sample Plant Disease Images Used for Training

B. *MobileNet Architecture*

MobileNet was selected as the backbone due to its computationally efficient design based on depthwise separable convolutions, which significantly reduce the parameter count compared to standard convolutional architectures while maintaining competitive classification accuracy. The network begins with a standard Conv2D layer (32 filters, 3×3 kernel, stride 2) followed by batch normalization and ReLU activation. Subsequent blocks employ depthwise convolutions followed by pointwise projections, progressively increasing channel depth while halving spatial resolution. The model accepts input tensors of shape (None, 224, 224, 3), and a GlobalAveragePooling2D layer aggregates spatial features before the final Dense classification head with softmax activation.



Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
conv2d (Conv2D)	(None, 112, 112, 32)	896
batch_normalization (BatchNormalization)	(None, 112, 112, 32)	128
re_lu (ReLU)	(None, 112, 112, 32)	0
depthwise_conv2d (DepthwiseConv2D)	(None, 112, 112, 32)	320
batch_normalization_1 (BatchNormalization)	(None, 112, 112, 32)	128

Fig. 3. MobileNet Model Architecture Summary

C. *Training Configuration*

Training was conducted over 100 epochs using the Adam optimizer with categorical cross-entropy loss. Model Checkpoint callbacks preserved the best model weights based on validation accuracy, while EarlyStopping callbacks were employed to prevent unnecessary computation. The model was developed using TensorFlow 2.9.3 and Keras within an Anaconda environment on Python 3.9.

VI. SYSTEM MODULES

The PlantShield AI web application consists of five core operational modules:

1) Pathogen Detection Module: Accepts crop leaf images and applies the trained CNN to classify the type of pathogen present, reporting the disease category and associated confidence.
2) Pest Classification Module: Enables identification of pest species from uploaded images, assisting farmers in selecting targeted interventions and reducing broad-spectrum pesticide usage.

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3) User Authentication Module: Provides secure registration and login functionality, storing user credentials and profile data in the SQLite3 backend.
4) Community Profiles Module: Displays a community directory of registered users, supporting collaborative knowledge sharing among agricultural stakeholders.
5) Database Module: Maintains structured records of user profiles, uploaded images, and diagnostic histories for longitudinal crop health monitoring.

VII. RESULTS AND DISCUSSION

The PlantShield AI system was successfully implemented and tested across all core modules. The web interface provides intuitive navigation for user registration, login, image-based analysis, and community interaction.

```
Epoch 1/100
9/9 [==============================] - ETA: 0s - loss: 2.7241 - accuracy: 0.0938 - precision: 0.2222
Epoch 1: accuracy improved from -inf to 0.09375, saving model to MOBILENET.h5
9/9 [==============================] - 113s 12s/step - loss: 2.7241 - accuracy: 0.0938 - precision: 0.2222 - val_loss: 2.4821 - val_accuracy: 0.0833 - va
l_precision: 0.0000e+00
Epoch 2/100
9/9 [==============================] - ETA: 0s - loss: 2.6038 - accuracy: 0.1007 - precision: 0.0000e+00
Epoch 2: accuracy improved from 0.09375 to 0.10069, saving model to MOBILENET.h5
9/9 [==============================] - 69s 8s/step - loss: 2.6038 - accuracy: 0.1007 - precision: 0.0000e+00 - val_loss: 2.5012 - val_accuracy: 0.0764 -
val_precision: 0.0000e+00
Epoch 3/100
9/9 [==============================] - ETA: 0s - loss: 2.4476 - accuracy: 0.1285 - precision: 0.0000e+00
Epoch 3: accuracy improved from 0.10069 to 0.12847, saving model to MOBILENET.h5
9/9 [==============================] - 59s 7s/step - loss: 2.4476 - accuracy: 0.1285 - precision: 0.0000e+00 - val_loss: 2.5219 - val_accuracy: 0.0694 -
val_precision: 0.0000e+00
Epoch 4/100
9/9 [==============================] - ETA: 0s - loss: 2.4068 - accuracy: 0.1397 - precision: 0.0000e+00
Epoch 4: accuracy improved from 0.12847 to 0.13971, saving model to MOBILENET.h5
9/9 [==============================] - 51s 6s/step - loss: 2.4068 - accuracy: 0.1397 - precision: 0.0000e+00 - val_loss: 2.5617 - val_accuracy: 0.0903 -
val_precision: 0.0000e+00
Epoch 5/100
9/9 [==============================] - ETA: 0s - loss: 2.4569 - accuracy: 0.1667 - precision: 0.3846
Epoch 5: accuracy improved from 0.13971 to 0.16667, saving model to MOBILENET.h5
9/9 [==============================] - 53s 6s/step - loss: 2.4569 - accuracy: 0.1667 - precision: 0.3846 - val_loss: 2.6140 - val_accuracy: 0.0729 - val_
precision: 0.0000e+00
Epoch 6/100
9/9 [==============================] - ETA: 0s - loss: 2.4080 - accuracy: 0.1944 - precision: 0.1429
Epoch 6: accuracy improved from 0.16667 to 0.19444, saving model to MOBILENET.h5
9/9 [==============================] - 49s 5s/step - loss: 2.4080 - accuracy: 0.1944 - precision: 0.1429 - val_loss: 2.7200 - val_accuracy: 0.0903 - val_
precision: 0.0000e+00
Epoch 7/100
9/9 [==============================] - ETA: 0s - loss: 2.3946 - accuracy: 0.1701 - precision: 0.1000

]: history.history.keys()
```

Fig. 4. Training Log Output (Epochs 1–7)

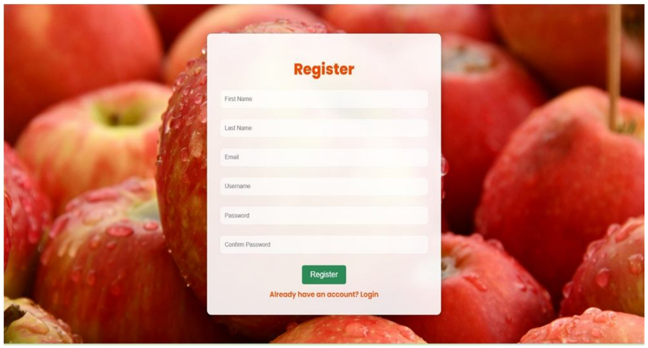

Fig. 5. User Registration Page

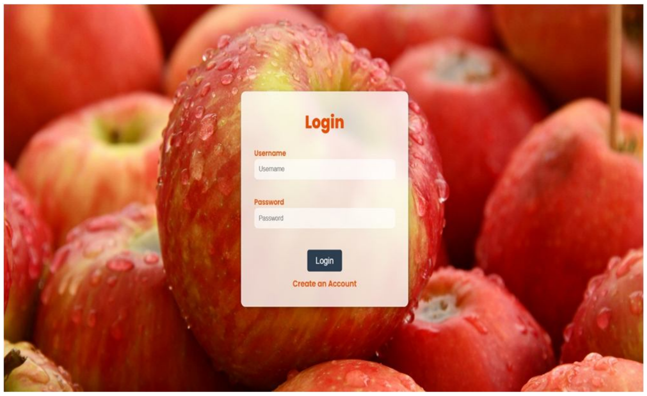

Fig. 6. User Login Page

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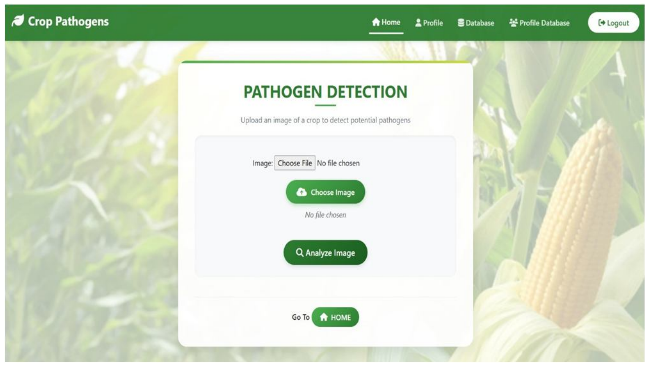

Fig. 7. Pathogen Detection Module

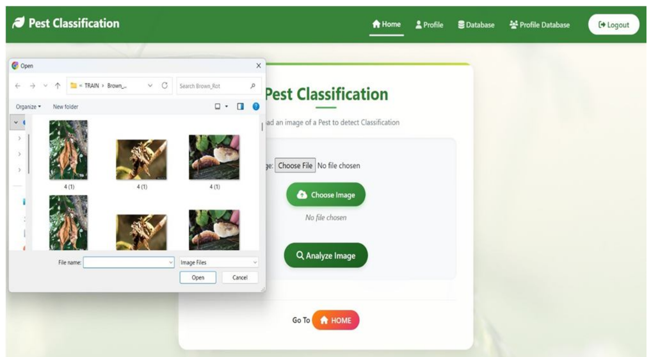

Fig. 8. Pest Classification Module

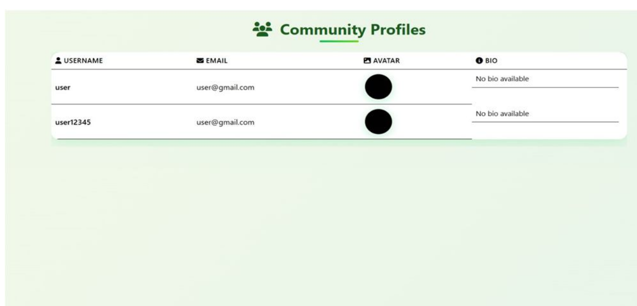

Fig. 9. Community Profiles Page

Figure 10 illustrates the model accuracy curve plotted over 50 epochs. The graph reveals the characteristic oscillatory behaviour typical of models trained on limited batches per epoch (9 steps/epoch), with local accuracy peaks reaching up to 11.72% at epoch 20. Training logs confirm steady epoch-wise improvement in the best-saved model checkpoint, with validation accuracy rising from 8.33% at epoch 1 to 9.03% at epoch 6. These results reflect an early training phase; convergence and substantially higher accuracy are anticipated with extended training, larger datasets, and fine-tuned hyperparameters.

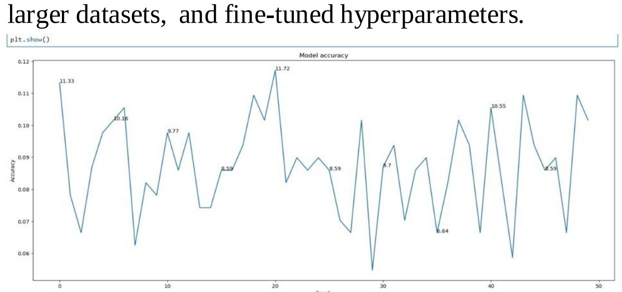

Fig. 10. Model Accuracy Graph (50 Epochs)

The MobileNet architecture summary confirms an input layer of shape (None, 224, 224, 3), an initial Conv2D layer producing (None, 112, 112, 32) feature maps with 896 parameters, followed by batch normalization and a depthwise Conv2D layer with 320 parameters. The lightweight parameter footprint validates MobileNet's suitability for deployment on resource-constrained hardware.

VIII. CONCLUSION AND FUTURE WORK

This paper has presented PlantShield AI, an end-to-end intelligent web system for crop pest and disease detection using a MobileNet-based CNN pipeline. The system successfully integrates deep learning inference with a scalable Django web framework, offering farmers and agricultural workers an accessible tool for real-time plant health diagnostics. The platform's modular architecture—encompassing pathogen detection, pest classification, user management, and community interaction—positions it as a comprehensive agricultural intelligence portal rather than a single-purpose classifier.

Future enhancements will focus on expanding the training dataset to encompass a wider variety of crop species and disease categories, integrating IoT environmental sensors for contextual disease forecasting, developing a mobile application for on-field use, and incorporating multilingual interfaces to broaden accessibility across diverse agricultural communities globally.

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