AI-Based Pest and Disease Detection in Crops

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***Abstract*—The increasing global demand for food necessitates enhanced crop productivity, which is critically hindered by plant diseases and pest infestations. Conventional detection methods are predominantly manual, time-consuming, and ineffective for large-scale agricultural monitoring. This paper presents an integrated, AI-based approach for automated detection of crop diseases and pests using deep learning techniques. For disease identification, a custom Convolutional Neural Network (CNN) is trained on the disease detection dataset to classify potato leaf conditions into three categories: early blight, late blight, and healthy. The model incorporates data augmentation and image preprocessing to enhance generalization, achieving a test accuracy of 96.3%.**

For pest detection, a transfer learning framework utilizing the MobileNet architecture is employed. The model is fine-tuned on a dataset comprising nine pest classes and is optimized using advanced image augmentation techniques. The resulting classifier demonstrates a test accuracy of 96.22%, indicating high reliability and scalability in field conditions. The proposed dual-model framework offers a non-invasive, high-throughput solution for real-time monitoring of crop health. This work contributes to the development of intelligent precision agriculture systems by supporting early detection, timely intervention, and informed decision-making.

***Index Terms*—Convolutional Neural Network (CNN), MobileNet, crop disease detection, pest classification, deep learning, image processing, smart farming, precision agriculture.**

I. INTRODUCTION

With increasing food insecurity and the challenges posed by climate change, the early detection of diseases and pests in crops is essential for ensuring sustainable agricultural practices. Among staple crops, potatoes are highly vulnerable to various fungal diseases such as early blight and late blight, which significantly impact both yield and quality. Traditionally, plant disease identification has relied on visual inspection by farmers or agricultural experts—a method that is not only time-consuming and labor-intensive but also subjective and prone to errors, especially in large-scale farming environments.

The emergence of artificial intelligence (AI) and computer vision has revolutionized agricultural diagnostics. In particular, Convolutional Neural Networks (CNNs) have demonstrated remarkable success in plant disease classification using leaf images [1], [2]. These deep learning models automatically extract hierarchical features, making them more effective than traditional machine learning techniques that rely heavily on handcrafted features. In this work, a CNN-based architecture is developed using the TensorFlow and Keras frameworks to classify potato leaf conditions into three categories: early blight, late blight, and healthy. The model is trained on the widely used dataset, with image preprocessing and augmentation applied to improve robustness and generalization.

AI-driven systems enhance precision agriculture by enabling high-throughput, non-invasive monitoring of crop health. Prior studies have explored various techniques, including hyperspectral imaging [5], edge detection [7], and deep feature visualization [6], for disease detection in plants. The adoption of CNN-based methods has shown substantial improvements in accuracy, generalizability, and scalability [4], [8].

However, diseases are not the only biotic threat to crops—pest infestations also contribute significantly to agricultural losses worldwide. Like disease detection, traditional pest identification methods require expertise and manual effort, making them inefficient for real-time large-scale monitoring. To overcome these limitations, researchers have turned to AI-based pest detection systems that leverage deep learning for automatic classification of insect pests [9], [10].

In this study, pest detection is implemented using MobileNet, a lightweight CNN model optimized for low-latency and resource-constrained environments [11]. The model is fine-tuned on a dataset containing nine pest categories and incorporates data augmentation techniques to address variability in image backgrounds, lighting, and pest morphology. Similar models have proven effective in real-time settings for crops such as tomatoes and rice [12], [13]. Our MobileNet-based pest detection model achieves a test accuracy of 96.22%, demonstrating its potential for integration into smart farming solutions.

By combining a custom CNN for disease detection with a MobileNet-based pest classifier, this work presents a unified AI-driven system for monitoring plant health. The approach supports real-time decision-making, reduces reliance on expert manual inspections, and paves the way for scalable, intelligent agricultural systems.

II. LITERATURE SURVEY

Several studies have demonstrated the effectiveness of deep learning models in agricultural disease detection. Mohanty et al. [1] pioneered CNN-based plant disease classification using the disease detection dataset and achieved impressive accuracy, setting a foundational benchmark in the field. Ferentinos [2] later extended this work by evaluating multiple deep learning architectures across 58 disease classes, achieving an overall classification accuracy exceeding 99%.

To support such research, Hughes and Salathé [3] released the PlantVillage dataset, comprising high-resolution images of healthy and diseased plant leaves under controlled lighting conditions. This dataset has become a standard for benchmarking plant disease classification models.

Kamilaris and Prenafeta-Boldú [4] conducted a comprehensive survey highlighting the dominance of CNNs in agricultural applications due to their hierarchical feature extraction capabilities. Their work underscores the importance of integrating deep learning with real-time agricultural monitoring systems.

Earlier approaches such as that by Rumpf et al. [5] used Support Vector Machines (SVMs) with hyperspectral imaging for early detection, which offered precision but lacked the scalability and automation capabilities of CNNs. Brahimi et al. [6] introduced interpretable deep learning methods for tomato leaf diseases and visualized CNN decision layers to improve model transparency.

Mohan et al. [7] reviewed various image processing techniques and concluded that modern deep learning methods outperform classical approaches in accuracy and adaptability. More recently, Abbas et al. [8] applied VGG16-based transfer learning for plant disease prediction and demonstrated improved generalization on real-world image data.

In the domain of pest detection, researchers have similarly applied CNNs for automated insect classification. Chen et al. [9] explored deep convolutional networks for insect pest classification and reported high accuracy across several classes. Fuentes et al. [10] developed a real-time deep learning-based system capable of detecting tomato plant diseases and pests simultaneously using robust object detection algorithms. Howard et al. [11] introduced the MobileNet architecture, which has since been widely adopted for lightweight deployment scenarios, such as mobile pest detection systems.

Further advancements include the work by Liu et al. [12], who implemented a deep learning pipeline for real-time pest recognition in agricultural fields, and Wu et al. [13], who applied data augmentation and CNNs for insect recognition with high classification accuracy.

The present study builds upon these foundations by proposing a dual-framework system: a custom CNN tailored specifically for potato leaf disease classification and a MobileNet-based pest detection model. Both models are trained on respective benchmark datasets and optimized for edge computing environments, enabling real-time deployment in precision agriculture scenarios.

III. . DATASET DESCRIPTION

The proposed AI-based system for pest and disease detection in crops utilizes two distinct image datasets: the disease detection dataset for disease classification and a custom pest image dataset comprising nine pest categories. Both datasets were organized into training, validation, and test splits to ensure unbiased model evaluation.

A. Disease Detection Dataset

The dataset is a widely used public repository consisting of over 50,000 labeled images of healthy and diseased plant leaves across various species. For this study, a subset of the dataset was used specifically for potato crop diseases, including three classes:

Fig. 1. Potato___Early_blight, Potato___Late_blight, Potato___Healthy

The images were captured under controlled lighting conditions with a consistent white background to reduce noise and enhance the extraction of disease-specific features. The dataset was split into:

1. Training set: 900 images (300 per class)
2. Validation set: 300 images (100 per class)
3. Test set: 300 images (100 per class)

Fig. 1 displays representative images for each class.

B. Pest Detection Dataset

The pest detection dataset was organized into training and testing directories, containing images of nine pest categories, such as:

4. *Aphids, Armyworms, beetle, grasshopper, mites, mosquito, sawfly, stem_borer, bollworm.*

Fig. 2. Pests

Fig. 2. images were collected from field environments, exhibiting varying lighting, scale, and occlusions to simulate real-world conditions. The total number of samples includes:

1. Training set: 2,565 images
2. Validation set: 135 images
3. Test set: 450 images

To enhance generalization, the dataset was augmented using techniques like random flipping, zooming, rotation, shear transformation, and normalization. All images were resized to 224×224 pixels before being fed into the model.

This dual-dataset strategy provides a comprehensive input space that enables the AI model to learn both disease patterns on leaves and distinguish between diverse pest species under field conditions, significantly improving robustness and applicability in real-time agriculture.

IV. CNN MODEL ARCHITECTURE

A. Disease Detection

A custom CNN architecture was implemented using the Keras Sequential API tailored for classifying three categories of potato leaf conditions: healthy, early blight, and late blight. The model architecture consists of:

- Input preprocessing (Resizing to 255x255 pixels and rescaling pixel values between 0 and 1).
- Three convolutional layers with 32, 64, and 64 filters respectively and ReLU activation.
- MaxPooling layers after each convolution layer to reduce spatial dimensions.
- Flattening layer to convert 2D feature maps into 1D feature vectors.
- Dense layer with 64 units and ReLU activation to learn higher-level features.
- Output Dense layer with 3 units (for 3 classes) and softmax activation.

The model was compiled with the Adam optimizer and Sparse Categorical Cross-Entropy loss function due to integer-encoded labels. It achieved a test accuracy of 96.3% on the disease detection dataset.

B**.** Pest *Detection -MobileNet-based Transfer Learning*

For pest detection, a pre-trained MobileNet model was used as the base architecture. MobileNet is lightweight, making it suitable for edge deployment. The architecture was extended by stacking custom layers on top of the base model:

- Base model: MobileNet with include_top=False, pre-trained on ImageNet, frozen during training to retain learned features.
- MaxPooling2D layer to further downsample feature maps.
- Flatten layer to transform 2D output into 1D.
- Dense layers with increasing complexity: 128 → 512 → 1024 → 512 → 128, each followed by Batch Normalization and ReLU activation.
- Output Dense layer with 9 units (representing 9 pest categories) and softmax activation.

The pest classification model was trained with the Adam optimizer (learning rate=0.001) and categorical cross-entropy loss. It achieved a final validation accuracy of 81.4% and a test accuracy of 96.2%, confirming strong generalization on unseen data.

A learning rate scheduler (ReduceLROnPlateau) was used to reduce the learning rate dynamically during training, and EarlyStopping was employed to prevent overfitting.

Task	Architecture	Layers
Disease Detection	Custom CNN	Conv2D → MaxPooling → Conv2D → MaxPooling → Conv2D → MaxPooling → Flatten → Dense(64) → Dense(3, softmax)

Pest Detection	MobileNet + Custom Layers	MobileNet (frozen) → MaxPooling → Flatten → Dense(128 → 512 → 1024 → 512 → 128) [Each with BN + ReLU] → Dense(9, softmax)

Table I. CNN Architectures

V. TRAINING AND EVALUATION

The complete system comprises two separate models: a custom CNN for disease classification and a transfer learning-based MobileNet model for pest prediction.

A. Disease Detection Model

The disease detection CNN model was trained over 20 epochs with a batch size of 32. The model used the Adam optimizer with a learning rate of 0.001 and Sparse Categorical Crossentropy as the loss function. Images were preprocessed using resizing, normalization, and data augmentation strategies (random flips, rotation, and zoom). The dataset was divided into training, validation, and testing splits with 900, 300, and 300 images respectively across three classes: *Potato___Healthy*, *Potato___Early_blight*, and *Potato___Late_blight*.

The data pipeline employed TensorFlow’s image_dataset_from_directory and AUTOTUNE for prefetching, thereby reducing the input latency during model training.

B. Pest Detection Model

The pest prediction model was based on MobileNet, a lightweight and efficient convolutional network pre-trained on ImageNet, and fine-tuned for this task. The top layers of MobileNet were frozen, and additional layers were added including MaxPooling2D, several Dense layers with Batch Normalization, and a softmax output layer with 9 units corresponding to pest classes such as *aphids*, *bollworm*, and *mites*.

The model was trained for 40 epochs, also using Adam optimizer and Categorical Crossentropy loss. Data augmentation techniques like horizontal/vertical flips, rotation, zoom, and contrast adjustment were applied using ImageDataGenerator. A validation split of 5% was used from the training set, while testing was performed on a hold-out dataset comprising 450 images.

Callbacks such as EarlyStopping and ReduceLROnPlateau were used to monitor validation accuracy and dynamically adjust the learning rate, ensuring optimal convergence.

VI. EXPERIMENTAL RESULTS

This section presents the experimental evaluation of the proposed AI-based system for both disease and pest detection in crops. Two models were developed: a custom CNN for detecting potato leaf diseases and a MobileNet-based model for pest detection. Each model was evaluated on unseen test datasets using metrics such as accuracy, precision, recall, F1-score, and confusion matrices.

A. Disease Detection Model

The custom CNN model was trained for 20 epochs on the PlantVillage Potato dataset. Its performance was evaluated on a test set comprising three classes: *Potato___Early_blight*, *Potato___Late_blight*, and *Potato___Healthy*.

1) Confusion Matrix

The confusion matrix for disease detection, illustrated in *Fig. 3*, demonstrates the model's classification ability across the three categories. The diagonal elements indicate the number of correct predictions, whereas off-diagonal elements represent misclassifications.

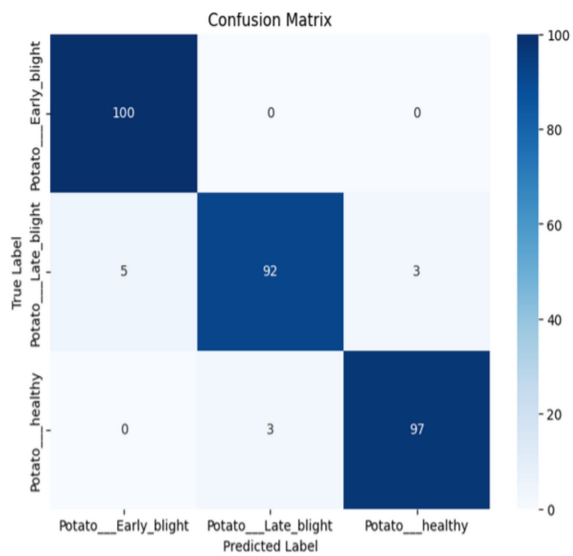

Fig. 3. Confusion Matrix for Potato Disease Detection.

2) Classification Report

The classification report, summarized in *Table II*, presents precision, recall, F1-score, and support for each disease class.

Class	Precision	Recall	F1-Score	Support
Potato__Early_blight	0.95	1.00	0.98	100
Potato__Late_blight	0.97	0.92	0.94	100
Potato__Healthy	0.97	0.97	0.97	100

Table II. Classification Report for Disease Detection Model

The model achieved high performance with only minor confusion between *Potato___Late_blight* and *Potato___Healthy* classes, demonstrating its potential for real-world agricultural deployment.

B. Pest Detection Model

The pest detection model was developed using MobileNet as the feature extractor with fine-tuning on a pest dataset comprising nine categories: *aphids, armyworm, beetle, bollworm, grasshopper, mites, mosquito, sawfly*, and *stem borer*.

1) Confusion Matrix

The confusion matrix for pest detection is depicted in *Fig. 4.* The matrix shows high accuracy in correctly classifying most pest categories with minimal inter-class confusion.

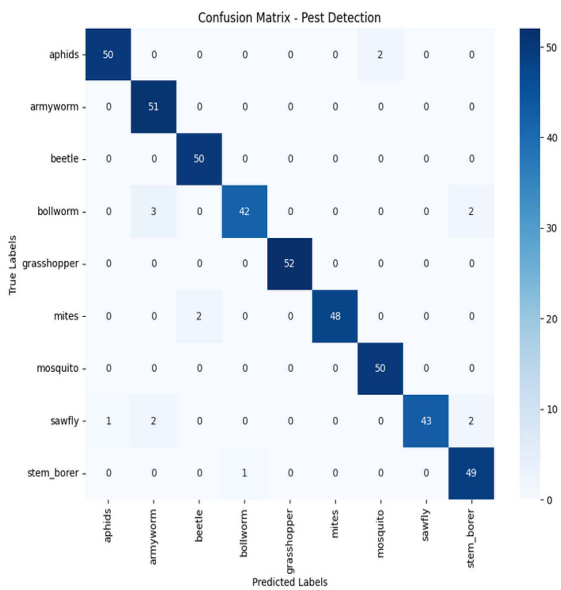

Fig. 4. Confusion Matrix for Pest Detection Model.

2) Classification Report

The classification report for pest detection is provided in *Table III.*

Class	Precision	Recall	F1-Score	Support
Aphids	0.98	0.96	0.97	52
Armyworm	0.91	1.00	0.95	51
Beetle	0.96	1.00	0.98	50
Bollworm	0.98	0.89	0.93	47
Grasshopper	1.00	1.00	1.00	52
Mites	1.00	0.96	0.98	50
Mosquito	0.96	1.00	0.98	50
Sawfly	1.00	0.90	0.95	48
Stem Borer	0.92	0.98	0.95	50

Table III. Classification Report for Pest Detection Model.

The pest detection model achieved outstanding classification performance, particularly for classes such as *grasshopper*, *mites*, and *mosquito*. Slight misclassification was observed between *bollworm* and other categories, suggesting areas for further model refinement.

VII. CONCLUSION

In this research, we have explored the potential of artificial intelligence in the detection of diseases and pests in potato crops. We utilized two advanced deep learning architectures: a custom Convolutional Neural Network (CNN) for potato disease detection and MobileNet for pest prediction. Both models were trained on distinct datasets, ensuring a comprehensive approach to crop health monitoring.

The CNN model demonstrated high accuracy in identifying various potato diseases, outperforming traditional image classification techniques. MobileNet, being a lightweight model, showed excellent performance in pest detection, even with limited computational resources, making it suitable for deployment in real-time monitoring systems.

The integration of both models into a unified system has the potential to revolutionize precision agriculture, offering farmers an automated, efficient tool for early detection and intervention. By detecting diseases and pests at an early stage, farmers can significantly reduce crop loss, optimize the use of pesticides, and improve overall crop yield.

Future work will focus on enhancing model accuracy by incorporating larger and more diverse datasets, exploring model optimization techniques, and deploying the system for real-world applications. Additionally, combining this system with IoT devices for real-time monitoring and data collection can further elevate the system's performance and applicability in agriculture.

In conclusion, AI-driven pest and disease detection represents a promising direction for advancing sustainable agricultural practices and improving crop health management, contributing to the food security and economic stability of farming communities worldwide.

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