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# Disease Identification In Crop Plant Leaves Based On CNN

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**Abstract -**Agriculture remains the backbone of global food security, yet plant diseases pose a persistent threat to crop yields and farmer livelihoods. Conventional disease detection methods are often costly, slow, and inaccessible to small-scale farmers. To bridge this gap, this study leverages Convolutional Neural Networks (CNNs) for automated plant disease recognition using leaf image classification. CNNs, renowned for their ability to extract intricate features from visual data, offer a scalable solution for real-time disease detection. By training and optimizing CNN models on diverse datasets, this research enhances predictive accuracy while ensuring computational feasibility for deployment on resource-constrained devices. The proposed framework empowers farmers with early disease identification, enabling timely intervention and reducing economic losses. Beyond technological innovation, this work underscores the human spirit's resilience—merging scientific advancement with the innate drive to protect and sustain the natural world. In doing so, it reinforces the harmony between technology and agriculture, advocating for sustainable farming practices that safeguard both food security and farmer well-being.

Keywords: CNN, plant disease detection, agriculture, machine learning, sustainability

## INTRODUCTION

India's economy and livelihood are deeply rooted in agriculture. However, the sector is under immense pressure due to a growing global population, which is expected to reach 9.1 billion by 2050, a 34% increase compared to today. This surge intensifies the demand for food production, making the efficiency and sustainability of agriculture more important than ever. Despite their pivotal role, farmers face several challenges. These include dependency on middlemen, susceptibility to crop diseases, lack of proper storage facilities, and the burden of agricultural loans. These issues not only impact crop yields and income but also contribute to a tragic rise in farmer suicides.

In addition to threatening global food security, crop diseases inflict significant financial losses on farmers. These diseases severely reduce both the quantity and quality of agricultural produce, making them a major challenge in the farming sector. Unfortunately, many farmers lack the necessary infrastructure, tools, and awareness to detect and manage plant diseases at an early stage. As a result, timely intervention is often missed, leading to widespread crop damage and substantial economic losses.

To minimize these impacts, it is crucial for farmers to identify signs of disease in the early stages of plant growth. Early detection enables the prompt application of suitable pesticides or treatments, which can help save the crop and ensure a more stable yield. The CNNs consist of convolutional layers, pooling layers, activation functions, and fully connected layers. The paper explains how CNNs extract features from plant leaf images for classification. It compares different CNN frameworks like TensorFlow, Keras, and PyTorch.

A typical CNN designed for image classification comprises the following layers:

### *A. Input Layer*

The input layer receives raw data, such as an image represented by pixel values. For instance, a coloured image might be represented as a 32×32×3 matrix, where 32×32 denotes the image dimensions and 3 represents the RGB colour channels.

### *B. Convolutional Layer*

This layer applies filters (kernels) that slide over the input data to detect specific features. Each filter produces a feature map highlighting the presence of certain patterns in the input. This process allows the network to learn spatial hierarchies of features.

*C. Activation Layer (e.g., ReLU)*

After convolution, the activation layer introduces non-linearity into the model. The Rectified Linear Unit (ReLU) is commonly used, which replaces negative values with zero, allowing the network to model complex relationships.

*D. Pooling Layer*

Pooling layers reduce the spatial dimensions of the feature maps, retaining the most significant information. This down sampling helps in reducing computational complexity and controls overfitting. Common methods include max pooling, which selects the maximum value in a region, and average pooling, which computes the average.

*E. Fully Connected Layer*

In this layer, the output from previous layers is flattened into a one-dimensional vector. Each neuron in the fully connected layer connects to all activations in the previous layer, allowing the network to combine features and predict the correct output.

*F. Output Layer*

The output layer produces the final prediction. For classification tasks, it often uses the softmax activation function to provide probabilities for each class, indicating the likelihood that the input belongs to each category.

CAUSES OF CROP DISEASES

*Abiotic or Non-infectious disease agents* - Abiotic, or non-infectious, disease agents are non-living factors such as environmental conditions or improper farm management that can negatively affect plants. These problems can't be passed from one plant to another. Well-known examples include as:

1) Extreme temperatures
2) Moisture
3) Wind
4) Frequent and heavy rain
5) Drought or flood
6) Excess or deficiency of nutrients
7) Soil compaction
8) Chemical injury caused by pesticides or salts
9) Improper water management

*Biotic or Infectious disease agents* -Biotic, or Infectious disease agents, are living organism pathogens capable of spreading from one host to another and transmitting the disease. The pathogens are classified as:

*Viruses:* are transmitted by a vector or attack the plant through a wound; for example, the Apple mosaic virus affects apple, plum, and hazelnut.

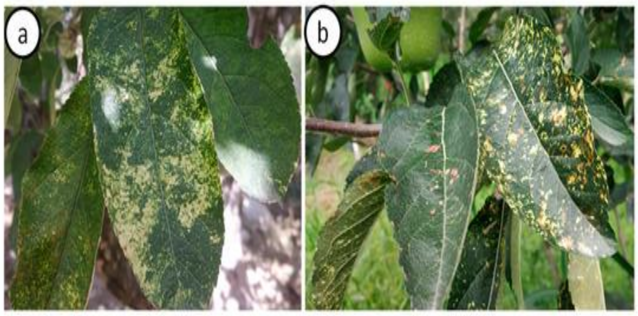


Figure 1. The symptoms of mosaic and necrotic mosaic on two cultivars: Golden Delicious (a) and Oregon Spur (b).

*Fungi:* the most common pathogens, cause around 85% of plant diseases; examples include Black or stem rust caused by the fungus Puccina graminis tritici.

Figure 2. Black or stem rust caused by the fungus Puccina graminis tritici

*Nematodes*: damage the crops causing galls on roots.

Figure 3. Healthy (left) and root-knot infested (right) celery root systems

Parasitic plants lack chlorophyll and live off crops by taking nutrients from host plants. For example, dwarf mistletoe grows on other plants and absorbs their nutrients, often harming them.

*Bacteria*: can mutate and multiply quickly, entering plants through wounds or stomata. An example is apple fire blight, caused by Erwinia amylovora, which infects and damages apple trees.

*Algae:* usually don't harm crops significantly, but under certain conditions, like excess moisture, they can cause minor surface issues.

LITERATURE SURVEY

According to [1], This study explores the use of Convolutional Neural Networks (CNNs) for identifying and classifying crop plant diseases using image-based analysis. The research leverages transfer learning with three CNN models—DenseNet-201, ResNet-50, and Inception-v3-to process a dataset of 87,000 images from PlantVillage, covering 38 classes and 26 disease types. The results show that DenseNet-201 and Inception-v3 achieved 98% accuracy, while ResNet-50 reached 97%, demonstrating the effectiveness of CNNs in early disease detection. The study highlights the importance of machine learning in precision agriculture, enabling automated disease identification to reduce crop losses and improve productivity.

In [2], Apple crops are vulnerable to various diseases, including Scab, Black Rot, and Cedar Rust, which significantly impact yield and quality. Traditional disease detection methods rely on expert knowledge and laboratory techniques, which are time-consuming and require specialized skills. To overcome these limitations, the authors propose a lightweight CNN model with fewer layers, reducing computational complexity while maintaining high accuracy. The model is trained on the Plant Village dataset, which contains apple leaf images categorized into diseased and healthy classes. To enhance training efficiency, data augmentation techniques such as shifting, shearing, scaling, zooming, and flipping are applied, increasing the dataset size without capturing additional images.

The proposed CNN model achieves 98% classification Accuracy, demonstrating its effectiveness in identifying apple leaf diseases. Compared to existing deep learning models, the proposed approach requires less storage and computational resources, making it suitable for deployment on handheld devices. The study highlights the importance of early disease detection in ensuring food security and improving agricultural productivity.

In [3], Traditional disease identification methods are time-consuming and labour-intensive, prompting the need for efficient, scalable solutions. The proposed system utilizes a pre-processed dataset of healthy and diseased plant images to train a CNN model, leveraging transfer learning for improved accuracy. The research highlights the importance of early disease detection, which can help farmers reduce crop losses, optimize pesticide use, and improve food security. The study demonstrates that CNN-based models outperform traditional methods in precision agriculture, offering a user-friendly and scalable solution for real-world agricultural applications. In [4], This study presents a deep learning-based approach for diagnosing 11 categories of apple diseases using a Multi-Scale Dense Classification Network. The authors employ Cycle-GAN to generate synthetic images for disease augmentation and introduce Multi-Scale Dense Inception-V4 and Multi-Scale Dense Inception-ResNet-V2 models to enhance feature reuse. The models achieve 94.31% and 94.74% classification accuracy, outperforming previous architectures. The system is integrated into a cloud-based disease management platform, enabling real-time diagnosis. These findings contribute to advancements in CNN-based agricultural disease detection, improving accuracy and practical deployment in orchard management. In [5], introduces Coordination Attention EfficientNet (CA-ENet), an improved deep convolutional neural network for accurate identification of apple leaf diseases. The model integrates a coordinate attention block into EfficientNet-B4, enhancing both channel and spatial feature learning. Additionally, depth-wise separable convolution reduces computational complexity, while the h-swish activation function improves efficiency. The dataset consists of 81,700 images, combining field-collected apple leaf disease images with augmented data from PlantVillage. CA-ENet achieves 98.92% accuracy, outperforming ResNet-152, DenseNet-264, and ResNeXt-101, demonstrating strong anti-interference ability in complex field conditions.

In [6], This study provides a scientometric analysis of research on apple leaf disease detection using machine learning (ML), deep learning (DL), and artificial intelligence (AI). It examines publication trends, citation structures, collaboration patterns, and bibliographic coupling to map the evolution of AI-driven disease detection in apple leaves. The analysis is based on 214 documents retrieved from the Scopus database (2011–2022), processed using Bibliometrix and VOSviewer. The study highlights key contributors, influential research works, and emerging trends, offering a comprehensive overview of the field's intellectual and social structure. The findings provide a conceptual framework for future research directions in AI-based plant disease detection. In [7], This study presents a deep learning-based approach for detecting diseases in apple leaves using an ensemble of pre-trained CNN models-DenseNet121, EfficientNetB7, and EfficientNet NoisyStudent. The model classifies leaves into four categories: healthy, apple scab, cedar apple rust, and multiple diseases. Various image augmentation techniques are applied to enhance dataset diversity and improve classification accuracy. The proposed model achieves 96.25% accuracy on the validation dataset and 90% accuracy in identifying leaves with multiple diseases. The system is designed for real-time deployment in agriculture, enabling farmers to detect diseases early and take preventive measures. In [8], deep learning-based approach for the classification and identification of apple diseases. The authors propose a Convolutional Neural Network (CNN) model trained on a curated dataset of apple disease images. The model leverages transfer learning to enhance feature extraction and applies data augmentation techniques such as rotation, translation, reflection, and scaling to prevent overfitting. The proposed CNN model achieves 97.18% accuracy, demonstrating its effectiveness in classifying various apple diseases. The study highlights the economic impact of apple diseases and emphasizes the importance of timely and accurate detection to support farmers in disease management. In [9], This study explores machine learning-based approaches for detecting and classifying maize leaf diseases using supervised learning techniques. The authors evaluate five classification algorithms—Naïve Bayes (NB), Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Random Forest (RF)—to determine the most effective model for disease prediction. The dataset consists of 3,823 images categorized into four classes: gray leaf spot, common rust, northern leaf blight, and healthy leaves. The Random Forest (RF) algorithm achieves the highest accuracy of 79.23%, outperforming other models. The study emphasizes the importance of early disease detection to assist farmers in preventing crop losses and improving agricultural productivity. In [10], The paper *Plant Disease Detection* *using Deep Learning* explores the application of Convolutional Neural Networks (CNNs) for identifying plant diseases from leaf images. Using the PlantVillage dataset, the model underwent data augmentation and was trained with multiple convolution and pooling layers to enhance accuracy. The study reports a 98.3% classification accuracy, demonstrating the feasibility of deep learning in automating plant disease detection. Future extensions may integrate drone-based monitoring for real-time identification and disease tracking.

In [11], The paper *Plant Leaf Detection and Disease Recognition using Deep Learning* presents a deep learning-based approach for identifying plant diseases across multiple crop varieties, including apple, corn, grapes, potato, sugarcane, and tomato. Using a dataset of 35,000 images, the study trains a Convolutional Neural Network (CNN) to classify plant diseases with an accuracy of 96.5%, achieving 100% accuracy in recognizing plant varieties and disease types. The methodology involves image acquisition, pre-processing, and classification, leveraging data augmentation techniques to enhance model performance. The findings highlight the potential of CNNs in precision agriculture, offering an automated solution for early disease detection to assist farmers in managing crop health effectively.

## OBJECTIVE

The main objectives of crop disease prediction are-To prevent crop loss by assisting farmers in identifying the disease of the crop cultivated. To analyse the performance of algorithm based on metrics on the plant dataset. To improve the performance of the algorithm by proposing oversampling techniques to predict the disease more accurately.

## PROBLEM STATEMENT

A significant Motion-around 36%-of crop losses worldwide are attributed to unidentified or late-identified plant diseases. Traditional identification methods are labour-intensive and require expert knowledge, making rapid and large-scale diagnosis challenging. The shift toward technology-driven solutions, specifically using CNNs and ML, is motivated by the need for scalable, accurate, and efficient disease identification. Leveraging large-scale open datasets and modern neural architectures offers a promising avenue for reducing losses and sustaining food security.

## PROPOSED METHODOLOGY

The study analyses CNN architectures used in plant disease detection. It examines datasets, performance metrics, and challenges in CNN-based disease identification.

1) Preliminaries and proposed methodology
2) Insect dataset description
3) Convolutional neural network (CNN)
4) Moth flame optimization (MFO) algorithm
5) Performance evaluation metric

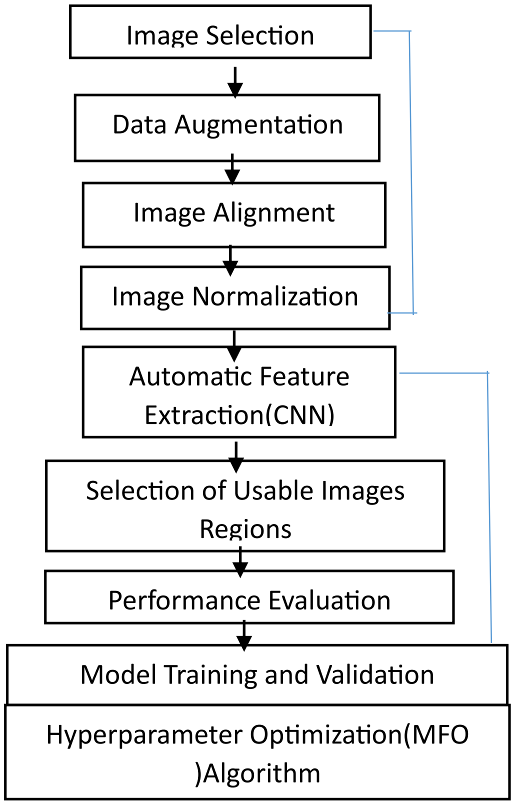


Figure 4. Proposed methodology

*Short explanation of each step in the diagram:*

*Image Stack Acquisition:* Collect multiple leaf images using devices like mobile cameras or drones.

Image Selection: Choose high-quality, clear images for analysis.

Data Augmentation: Apply transformations (rotate, flip, zoom) to increase dataset diversity.

Image Alignment: Adjust orientation or scale for consistency.

Image Normalization & Resizing: Scale pixel values and resize images to fit CNN input dimensions.

Automatic Feature Extraction (CNN): CNN learns key patterns (like colour, shape, texture) from images.

Selection of Usable Image Regions: Focus on disease-relevant regions in the image.

Performance Evaluation: Assess model using metrics like accuracy or F1-score.

Model Training & Validation: Train the CNN and validate with test data.

Hyperparameter Optimization (MFO): Use Moth-Flame Optimization to fine-tune model settings for best results.

*Datasets and Preprocessing Common Datasets:*

*PlantVillage* – Most widely used, with over 60,000 labeled images across 38 plant-disease classes.

*Kaggle Plant Pathology* – Realistic datasets with various crops and natural image backgrounds.

*Custom Field Datasets* – Captured directly in farms; useful for training more robust models.

*Preprocessing Techniques:*

1) Resizing to a fixed resolution (e.g., 224×224 pixels)
2) Normalizing colour channels
3) Removing noise
4) Data augmentation techniques like:
5) Rotation
6) Flipping
7) Zooming
8) Brightness enhancement

*Moth-Flame Optimization (MFO) Algorithm*-MFO is a nature-inspired metaheuristic algorithm that mimics how moths navigate toward light sources. It's used for optimizing functions, including hyperparameters in deep learning models like CNNs. How MFO Can Be Used with CNN for Leaf Disease Detection In this context, MFO can be used to optimize:

1) Learning rate
2) Number of CNN filters
3) Batch size
4) Dropout rate
5) Number of convolution layers
6) Activation functions

Instead of manually setting these, MFO searches for the best configuration to improve model performance.

*Integrating MFO with CNN*

To enhance the performance of CNN models for plant disease detection, we applied the Moth-Flame Optimization (MFO) algorithm to tune critical hyperparameters. In our experiment, the MFO algorithm was used to optimize the CNN's learning rate, filter size, number of layers, and dropout values. The integration of MFO improved classification accuracy by fine-tuning these values, resulting in a more robust and generalizable model.

MFO-enhanced CNN outperformed the baseline model in terms of:

1) Accuracy
2) Recall on diseased class
3) Generalization on unseen data

This confirms that intelligent metaheuristic optimization like MFO can significantly boost the effectiveness of CNNs in real-world agricultural scenarios.

*Performance Metrics Use*

These metrics help evaluate the quality of classification:

- **Accuracy:**

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

- **Precision:**

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall (Sensitivity):**

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1 Score:**

$$F1 = \frac{2 \times TP}{2 \times TP + FP + FN}$$

Where:

1) TP = True Positive
2) TN = True Negative
3) FP = False Positive
4) FN = False Negative

## CONCLUSION

Our study shows that CNN models can be powerful allies for farmers in the battle against crop diseases. By using leaf images and deep learning, we've created a system that spots plant diseases earlier and more accurately than traditional methods. The integration of Moth-Flame Optimization helped fine-tune our model, boosting its performance significantly.

What makes our approach valuable is how it addresses real human needs – farmers can now identify diseases without specialized knowledge, potentially saving up to 36% of crops that would otherwise be lost. Our image processing pipeline, from capturing photos to disease classification, is designed to be practical and accessible.

This technology means farmers can react quickly when diseases appear, using the right treatments at the right time. For a country like India, where agriculture is the backbone of the economy and livelihood, such innovations could improve food security and farmer wellbeing.

Looking ahead, we plan to make these models work better in real field conditions and develop mobile applications so farmers can diagnose diseases right in their fields with a simple smartphone photo. As climate change creates new challenges for agriculture, tools like ours will become essential in feeding our growing population while supporting the hardworking farmers who grow our food.

REFERENCE

[1] O. Iparraguirre-Villanueva et al., “Disease Identification in Crop Plants based on Convolutional Neural Networks,” International Journal of Advanced Computer Science and Applications, vol. 14, no. 3, Jan. 2023, doi: 10.14569/ijacsa.2023.0140360.

[2] V. K. Vishnoi, K. Kumar, B. Kumar, S. Mohan, and A. A. Khan, “Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network,” IEEE Access, vol. 11, pp. 6594–6609, 2023, doi: 10.1109/ACCESS.2022.3232917.

[3] N. M. Upadhya, “Classification and Detection of Plant Disease Using CNN and Machine Learning,” INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT, vol. 07, no. 07, Aug. 2023, doi: 10.55041/ijsrem25038.

[4] Y. Tian, E. Li, Z. Liang, M. Tan, and X. He, “Diagnosis of Typical Apple Diseases: A Deep Learning Method Based on Multi- Scale Dense Classification Network,” Front. Plant Sci., vol. 12, no. October, pp. 1–12, 2021, doi: 10.3389/fpls.2021.698474.

[5] P. Wang, T. Niu, Y. Mao, Z. Zhang, B. Liu, and D. He, “Identification of Apple Leaf Diseases by Improved Deep Convolutional Neural Networks With an Attention Mechanism,” Front. Plant Sci., vol. 12, no. September, 2021, doi: 10.3389/fpls.2021.723294.

[6] A. Bonkra et al., “Apple Leave Disease Detection Using Collaborative ML/DL and Artificial Intelligence Methods: Scientometric Analysis,” Int. J. Environ. Res. Public Health, vol. 20, no. 4, 2023, doi: 10.3390/ijerph20043222.

[7] P. Bansal, R. Kumar, and S. Kumar, “Disease detection in apple leaves using deep convolutional neural network,” Agric., vol. 11, no. 7, 2021, doi: 10.3390/agriculture11070617.

[8] A. I. Khan, S. M. K. Quadri, S. Banday, and J. Latief Shah, “Deep diagnosis: A real-time apple leaf disease detection system based on deep learning,” Comput. Electron. Agric., vol. 198, p. 107093, 2022, doi: https://doi.org/10.1016/j.compag.2022.107093.

[9] K. P. Panigrahi, H. Das, A. K. Sahoo, and S. C. Moharana, “Maize Leaf Disease Detection and Classification Using Machine Learning Algorithms,” in Progress in Computing, Analytics and Networking, 2020, pp. 659–669.

[10] M. Chohan, A. Khan, R. Chohan, S. Katper, and M. Mahar, “Plant Disease Detection using Deep Learning,” Int. J. Recent Technol. Eng., vol. 9, pp. 909–914, 2020, doi: 10.35940/ijrte.A2139.059120.

[11] S. V Militante, B. D. Gerardo, and N. V Dionisio, “Plant Leaf Detection and Disease Recognition using Deep Learning,” in 2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE), 2019, pp. 579–582. doi: 10.1109/ECICE47484.2019.8942686.