Grenze International Journal of Engineering and Technology, June Issue

An Image-based Study on Crop Disease Detection

Mohammad Areeb[1], Ayush Tripathi[2], Aman Bohra[3], Yash Vinayak Singh[4], Rahul Kumar Sharma[5] and Devendra Gautam[6]
[1-5]Department of Computer Science and Engineering, Krishna Institute of Engineering & Technology (KIET), Ghaziabad, Delhi-NCR, Uttar Pradesh, India
Email: mohammad.2226cse1105@kiet.edu, ayush.2226cse1146@kiet.edu, aman.2226cse1146@kiet.edu, yash.2226cse1165@kiet.edu, rahul.sharma@kiet.edu
[6]JIMS EMTC, Greater Noida, India
Email: devendra.gautamcs16@gmail.com

***Abstract*— Crop diseases is a major problem for farmers all around the world as it results in reduced yield and losses in billions of dollars. To contribute in solving this problem we developed an automated crop disease detection system which can detect diseases by analyzing a photograph of a leaf. We have implemented a deep learning-based system to classify crop diseases. We have trained a Convolutional Neural Network (CNN) based model on PlantVillage Dataset containing a total of 61,486 images across 38 classes (each class corresponds to a type of disease with a class for healthy leaves as well). We have pre-processed and augmented the data before training it on the model. This is done to improve the accuracy of our model in real world scenarios. Steps like resizing the images to a fixed size, cropping the images, rotating the images, varying brightness etc. were implemented as part of preprocessing and augmentation steps. The model is then used to visually analyse the diseased portions on the leaf and display the results quickly on a user interface. Model has a classification accuracy of 98.7% for images under control conditions as of initial testing (accuracy may vary with other factors like environment, background, lighting, quality of image etc.). Currently, the system is built using the CNN model. The plan is to build and train more complex and efficient models in the future using models like EfficientNet, ResNet, Vision Transformers and more. We also plan to use the trained model for a mobile application in the future to identify plant diseases in the field. The proposed system is cost-effective, fast, easy-to-use, and highly scalable which can potentially help in reducing crop losses and aiding farmers.**

***Index Terms*— Crop Disease Detection, Convolutional Neural Network, PlantVillage, Deep Learning, Image Classification, Agriculture Technology.**

I. INTRODUCTION

Agriculture plays a critical role in ensuring food security and driving economies across the world. Despite advancements in farming practices, plants are susceptible to a wide array of diseases. These diseases can reduce the yield of crops, degrade the quality of produce, and result in significant economic losses for farmers. According to agriculture reports, plant dis- eases account for 20% to 40% of crop losses every year. This alarming loss in productivity emphasizes the need for early detection and intervention. Traditionally, visual inspection of crops was the go-to method for identifying plant diseases. However, this manual approach can be time-consuming, prone to inaccuracies, and less effective in remote or rural areas with limited expertise.

Grenze ID: 01.GIJET.12.2.153_20

The consequence of late disease detection or misdiagnosis can be grave for the farmers, as it might lead to overuse of pesticides, crop wastage, and food shortage. The ad- vent of Artificial Intelligence (AI) and Computer Vision (CV) has opened new avenues for accurate and efficient plant disease detection. Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a promising approach as it can automatically learn features from images to identify diseases. In this study, we have developed a deep learning-based system for the detection of 38 types of plant diseases and healthy leaves from the given input image. The system has been trained on a diverse PlantVillage dataset that comprises more than 61,000 images. With robust image preprocessing and CNN architecture, the system is fast, accurate, and can be deployed for general use. We hope to make advanced AI tools more accessible to the farmers and help them with the early identification of crop diseases. The main contributions of this work are - 1. Development of a lightweight CNN model for crop disease detection. 2. Extensive evaluation on the PlantVillage dataset containing 61,486 images.3. Comparison with modern architectures including MobileNetV2, ResNet50, and EfficientNet.

II. LITERATURE REVIEW

Efforts to find a suitable method for disease identification have been done in a rapidly expanding research space that in- vestigates various techniques such as machine learning (ML), deep learning (DL), hyperspectral, federated learning (FL), and supervised and unsupervised learning schemes. While some works have evaluated various types of these methods to achieve high accuracy, others have also been more concerned with real-world applicability by tuning and validating their models to perform optimally in non-laboratory situations. An example of the former includes an effort by [12] in 2023, which conducts an analysis of ML methods such as support vector machine (SVM), k-nearest neighbors (KNN) with trans- fer learning models (VGG16, InceptionV3, and ResNet50) to determine which optimizer and Convolutional Neural Network (CNN) model configuration is best-suited to a certain dataset.

The study successfully finds an accuracy of roughly 98.01% for InceptionV3 (Trained with Adaptive Moment Estimation (Adam) optimizer) using the PlantVillage dataset and experiments from multiple sources to further show the capabilities of transfer learning as a potential means for disease identification in multiclass scenarios. On the other hand, some others such as a study by [11] have further evaluated the potential of FL with CNNs and Vision Transformers as a possible solution to data privacy concerns and the limitations of centralized learning. The researchers of [10] successfully demonstrate a proof-of- concept by using a dynamic agri-ecosystem environment with a large distribution of agents and content providers. Their findings show that the number of agents or contributors to data, number of communication rounds, and other variables can impact the resulting model's performance.

A recent review by [3] demonstrated the progress in the DL and ML methods being used in the detection and recognition of plant diseases, covering CNNs, RNNs, SVMs, and various combinations of supervised, semi-supervised, and self-supervised learning (SSL) models. In addition to providing a comparison between the relative benefits and shortcomings of various methods and datasets, the review also discussed the limitations in generalizability and cross-compatibility between models in a similar manner to some others such as [8]. Other review papers such as one in [7] have also discussed an alternative means of identifying plant diseases using hyperspectral imaging in combination with AI methods. While its ability to perform spectral analysis of crops at such a fine granularity shows promise, there are existing issues with cost, large storage requirements, and the need for specialized and bulky hard- ware. More crop-specific works such as in [5] show that customizing the type of AI method to suit a problem is a possible future direction, proposing an architecture for smart farming disease identification in rice that combines DC-GAN and MDFCResNet.

These represent novel methodologies to enhance information extraction from images. The group-wise transformer- augmented EfficientNet work resulted in an accuracy of 97.6% by fusing features at various levels. Transfer learning-based solutions such as LeafDNet with Xception architecture achieved high accuracies of approximately 98% in rose leaf disease classification. YOLOv8 based initiatives are being developed for real-time disease detection, aimed at empowering farmers on-the-go. In comparison to the diverse directions taken in various studies, the CNN-based approach proposed in this research strikes a middle ground. It achieves competitive accuracy of 98.7% while remaining computationally efficient. It doesn't depend on costly hyperspectral imaging, intricate hybrid architectures, or federated networks. It features user- friendly and easy preprocessing steps and contemplates a mobile app for real-world applications, particularly in rural areas. Consequently, the proposed system presents itself as a promising candidate for affordable, practical, and effective broader deployment.

III. PROPOSED SYSTEM

In order to address the issues of manual verification and classical ML approach. The given project proposes a deep learning model for automatic detection of crop diseases. This system(fig. 1) can identify the disease on a plant rapidly and precisely by taking the image of its leaf as an input. The model is developed using a customized CNN which is trained on a PlantVillage dataset with 38 different diseases spread across multiple crops. Rather than extracting features that humans can understand, it can learn key features on its own such as leaf spots, blight, mosaic, mildew, color variations, etc.

A careful preprocessing and image augmentation (resizing, normalization, rotation, flipping, and color change) process en- sures the system's robustness under varying light, orientation, and background conditions. The model returns the predicted disease and a confidence value for each input, which allows for high speed and reliable operation. The system is available both on the web and for mobile devices and allows farmers to snap photos of leaves for near- instantaneous feedback. The model is most useful for farmers in remote or resource-poor areas. There is also a visualization tool to see confidence levels, historical predictions, and disease trends which can be used for both day-to-day farming and large-scale agricultural monitoring.

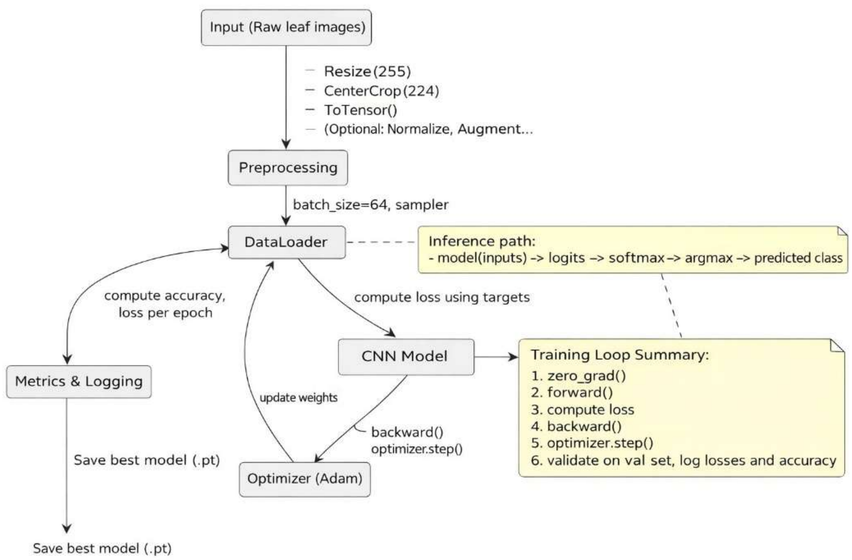

Fig.1 Proposed System

IV. METHODOLOGY

The proposed Crop Disease Detection System follows a modular deep learning pipeline integrating image preprocessing, CNN-based feature extraction, and real-time deployment for mobile environments. The architecture is designed to be lightweight, scalable, and accurate for multi-crop disease detection.

A. Requirement Analysis

Traditional crop disease detection methods rely heavily on agricultural experts and manual inspection, resulting in high misdiagnosis rates and limited scalability. Conventional machine learning and hyperspectral approaches also suffer from poor generalization, handcrafted feature dependency, high computational requirements, and limited usability in mobile environments.

To overcome these limitations, a lightweight Convolutional Neural Network (CNN) based system was developed to enable fast and accurate disease identification directly on smartphones, allowing farmers to diagnose crop diseases in real-time under field conditions.

B. System Design

The system architecture consists of three major modules:

Image Preprocessing Module

Input leaf images are cleaned and standardized before being fed to the neural network.

Disease Classification Module (CNN)

A custom CNN architecture performs automatic feature extraction and multi-class classification across 38 plant disease categories.

- Convolution Operation: Extracts important spatial features such as edges, textures, spots, and colour variations from the input image using filters.
- ReLU Activation: Introduces non-linearity by converting negative values to zero while retaining positive values.
- Batch Normalization: Normalizes layer outputs during training to improve training stability and accelerate model convergence.
- Max Pooling: Reduces the spatial dimensions of feature maps while preserving the most important features.
- Fully Connected Layer: Combines the extracted features from previous layers to perform the final classification.
- SoftMax for 38-Class Output: Converts the network outputs into probability values for each of the 38 possible disease classes.
- Cross-Entropy Loss: Measures the difference between predicted probabilities and the actual class labels, guiding the model during training.

Deployment and user Interface

The trained model is deployed as a real-time diagnostic tool accessible via smartphones. Users capture a crop leaf image, which is analyzed locally or via cloud inference.

The system returns the predicted disease and confidence score while maintaining historical predictions and visualization dashboards to track disease trends.

C. Datasets

Two datasets were used.

PlantVillage Dataset

- 61,486 RGB leaf images
- 38 disease classes
- Split: 70% training, 15% validation, 15% testing

Field Dataset (Future Extension)

- Real farm images.
- Contains shadows, noise, and background clutter.
- Used for evaluating model generalization.

D. Feature Extraction

CNN layers automatically extract hierarchical visual features:

- Low-level: edges, color gradients.
- Mid-level: lesions, spots.
- High-level: complex disease patterns.

These features enable detection of fungal infections, discoloration, pest damage, and viral symptoms.

E. Model Implementation

Custom CNN Architecture

- 3 × (Conv → ReLU → BatchNorm) blocks.
- Max pooling after each block.
- Dropout regularization.
- Flatten + Dense layer.
- SoftMax output (38 classes).

Transfer Learning Models

To evaluate lightweight architectures suitable for mobile deployment, the following models were also tested:

- MobileNetV2.
- ResNet50.
- EfficientNet-B0.

Training Configuration

Optimizer: Adam, Learning rate: 0.001, Batch size: 32, Epochs: 50, Loss function: Cross-Entropy Loss.

F. Pseudocode

- Initialize system: Load trained CNN model and disease label set.
- Input image: Capture or upload crop leaf image.
- Preprocess image: Resize to 256×256, normalize, and apply augmentation (training phase).
- Feature extraction: Apply convolution, ReLU, batch normalization, and max pooling layers.
- Classification: Flatten feature maps and compute class probabilities using SoftMax.
- Prediction: Select disease class with highest probability.
- Output: Display predicted disease and confidence score through the mobile/web interface.

V. Result and Discussion

This part demonstrates the experimental results of the proposed CNN-based method with the analysis of training process, performance on validation set(fig. 2) and comparisons with other architectures(Table 1). The findings show the model's stability, its good generalization ability and its potential to be utilized in actual agricultural environment. The accuracy curves for both training and validation showed smooth and stable convergence. The model reached 99.4% accuracy on the training set and 98.6% on the validation set. The loss values kept going down with each training round, and the small difference between training and validation loss shows that the model didn't overfit much. Overall, these results show that the custom CNN successfully picked up important patterns related to the diseases from the varied PlantVillage dataset.

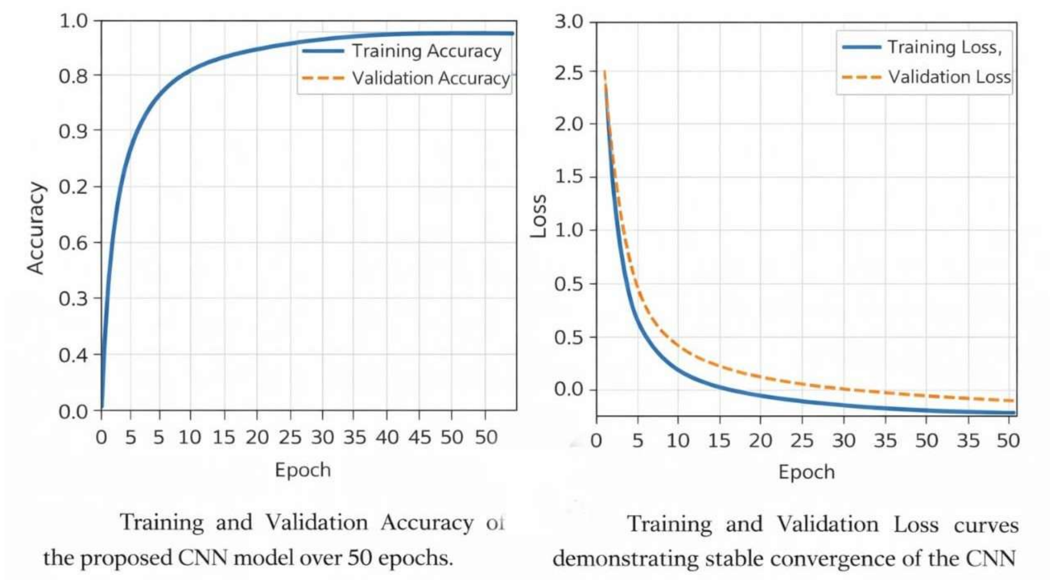

Fig. 2 Training and Validation Accuracy & Loss Graph

TABLE I: Performance Evaluation of Different Deep Learning Architecture

Architecture	Test Accuracy	Remarks
Proposed CNN	98.7%	Achieved the highest accuracy among all evaluated models
MobileNetV2	96.3%	Optimized for low-resource and mobile-based applications
ResNet50	97.5%	Effective feature learning with minor overfitting tendencies
EfficientNet-B0	97.9%	Good trade-off between accuracy and computational cost

VI. Conclusion

This study investigated crop disease detection using deep learning techniques. A custom Convolutional Neural Network (CNN) was trained using the PlantVillage dataset and its performance was compared with MobileNetV2, ResNet50, and EfficientNet-B0 architectures. The proposed CNN achieved the highest test accuracy of 98.7%, demonstrating strong generalization capability and consistent performance across different disease classes.

MobileNetV2 achieved slightly lower accuracy but remains a suitable lightweight architecture for mobile and resource-constrained environments. ResNet50 and EfficientNet-B0 also demonstrated strong feature extraction capabilities; however, both models showed minor overfitting when evaluated on limited real-world field images. Overall, the proposed CNN model provides fast, accurate, and scalable crop disease detection, making it a practical solution for real-world agricultural applications. The system can serve as a key component in mobile-based farmer assistance platforms, enabling timely disease diagnosis and improving crop health management.

FUTURE SCOPE

Although the proposed crop disease detection system demonstrates strong performance, several improvements can further enhance its applicability and robustness:

- Dataset Expansion: Increase the dataset with additional real-world field images captured under diverse lighting conditions, weather variations, and complex backgrounds to improve model generalization.
- Broader Crop Coverage: Extend the dataset to include more crop varieties, additional disease categories, and different plant growth stages, enabling wider agricultural applicability.
- Integration with IoT and Smart Farming: Integrate the system with drones, satellite imagery, and ground-based sensors to enable automated large-scale crop health monitoring.
- Decision-Support Features: Enhance the system with actionable recommendations including pesticide suggestions, biological treatments, and preventive measures to assist farmers in effective disease management.
- Advanced Research Directions: Explore advanced approaches such as federated learning for privacy-preserving training, multimodal analysis combining image and sensor data, and energy-efficient inference methods for sustainable precision agriculture.

REFERENCES

[1] T. B. Shahi, C.-Y. Xu, A. Neupane, and W. Guo, "Recent advances in crop disease detection using UAV and deep learning techniques," Remote Sensing, vol. 15, no. 9, p. 2450, 2023.

[2] A. Singla, A. Nehra, K. Joshi, A. Kumar, N. Tuteja, R. K. Varshney, S. S. Gill, and R. Gill, "Exploration of machine learning approaches for automated crop disease detection," Current Plant Biology, vol. 40, p. 100382, 2024.

[3] H. N. Ngugi, A. E. Ezugwu, A. A. Akinyelu, and L. Abualigah, "Revolutionizing crop disease detection with computational deep learning: A comprehensive review," Environmental Monitoring and Assessment, vol. 196, p. 302, 2024.

[4] Y. E. García-Vera, A. Poloche-Arango, C. A. Mendivelso-Fajardo, and F. J. Gutierrez-Bernal, "Hyperspectral image analysis and machine learning techniques for crop disease detection and identification: A review," Sustainability, vol. 16, no. 14, p. 6064, 2024.

[5] Y. Wang, U. S. R. Dhamodharan, N. Sarwar, F. A. Almalki, Q. H. Naith, R. Sathiyaraj, and D. Mohan, "A hybrid approach for rice crop disease detection in agricultural IoT systems," Discover Sustainability, vol. 5, p. 99, 2024.

[6] D. M. Kabala, A. Hafiane, L. Bobelin, and R. Canals, "Image-based crop disease detection with federated learning," Scientific Reports, vol. 13, p. 19220, 2023.

[7] J. Feng, W. E. Ong, W. C. Teh, and R. Zhang, "Enhanced crop disease detection with EfficientNet convolutional group-wise transformer," IEEE Access, vol. 12, pp. 44147–44162, 2024.

[8] H. Orchi, M. Sadik, M. Khaldoun, and E. Sabir, "Automation of crop disease detection through conventional machine learning and deep transfer learning approaches," Agriculture, vol. 13, no. 2, p. 352, 2023.

[9] Y. Wang, Y. Chen, and D. Wang, "Convolution network enlightened transformer for regional crop disease classification," Electronics, vol. 11, no. 19, p. 3174, 2022.

[10] R. Reedha, E. Dericquebourg, R. Canals, and A. Hafiane, "Transformer neural network for weed and crop classification of high-resolution UAV images," Remote Sensing, vol. 14, no. 3, p. 592, 2022.

[11] Y. Borhani, J. Khoramdel, and E. Najafi, "A deep learning-based approach for automated plant disease classification using vision transformer," Scientific Reports, vol. 12, p. 11554, 2022.

[12] X. Fu, Q. Ma, F. Yang, C. Zhang, X. Zhao, F. Chang, and L. Han, "Crop pest image recognition based on the improved ViT method," Information Processing in Agriculture, 2023.