

# Crop Disease Prediction Using Image Processing

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## Abstract

*For any country in the world, its livelihood depends on agriculture. However, crop diseases affect the production and food supply of any country because we are unable to detect crop diseases. This paper presents a machine learning CNN (convolutional neural network) model, which uses images of crops to detect diseases. This model detects the diseases in the early stage and provides us with a solution to the crop diseases. It improves the crop yield and production and maintains the food supply. The method of image processing focuses on extracting features from the image, which helps for detection and classification of disease in the early stage only. This enhances the productivity of the crop. In this model, we provide images from the selected dataset, and then image preprocessing is performed. When the preprocessing is done, features of the crop, like shape, size, and color, are extracted. Then we provide the data for the model to train it, and then testing is performed to provide us with the precision, accuracy, and F-1 score. This model focuses on image processing and deep learning, making it an efficient tool. The combination of image processing and artificial intelligence enables fast disease prediction. This does not require expensive laboratory equipment. The main aim of the model is to help farmers with a timely disease diagnosis. Also, automatic systems like this improve crop management and improve productivity. In short, we can say that crop disease prediction using image processing gives us a cost-effective and reliable method for enhancing decision-making.*

**Keywords:** CNN (Convolutional neural network), crop disease prediction, deep learning, image processing, machine learning

## INTRODUCTION

Machine learning has emerged as a life-changing technology over the past few years, helping farmers make faster, data-driven, and more accurate decisions in real-time. Agriculture has always suffered losses due to crop diseases, which destroy a large portion of crops every year and negatively impact farmers' income, food supply, and the GDP of the country. The situation has become even more challenging due to climate change, which has increased the frequency and severity of crop diseases. Factors like soil, climate, and temperature then affect the growth of crops. The soil type and nourishment level of the soil tell how the crop will grow. If we do not check the soil type, then it affects crop growth and results in less production. After these conditions, if infection and pests destroy the crop, then it will affect the crop as well as the food supply for the local population. The methods that are present today to identify crop diseases depend mostly on human work. Farmers have to work manually to find the crop disease. These methods take a lot of time, which delays the identification of crop disease, reducing its production. Therefore, to address these problems, we are specifically focused on developing a new system that can identify crop disease in the early stage only and can provide a solution to the farmers without requiring manual labor [1–3].

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In this, we are developing a system that can identify the disease using an image. We have used the CNN (Convolutional Neural Network) along

with SVM (Support Vector Machine). Firstly, we will give an image as input, then it will preprocess the image, and then classify it. Classification will be done on the basis of features extracted using CNN [4–5].

## RELATED WORK

The study that are conducted in the field of crop disease production have brought significant and revolutionary changes to the field; however, every system has some drawbacks. Today, most methods require extensive manual labor, making it difficult for farmers to detect crop disease in the early stages. Here, machine learning and deep learning have come into prominent focus. These diverse and large datasets work on methods and help achieve higher overall accuracy; still, they show notable limitations in scalability and generalization. For example, Huang worked on an SPM model for feature extraction, but it has limited ability to adjust to complex field problems [6]. The research conducted on deep learning brought towards CNN model, such as the research conducted by Schmidhuber and Ferentinos [7].

Some researchers, like Too, L. and Nandini worked on several CNN architectures and brought image classification [8]. We have done the comparative analysis of related work on different research and their method which tells their key outcomes and their limitations in Table 1.

## Technologies Used

The technologies that we have used for this project, while working on it and conducting this research are shown in Table 2 & 3. These are:

**Table 1.** Comparison of relate of work.

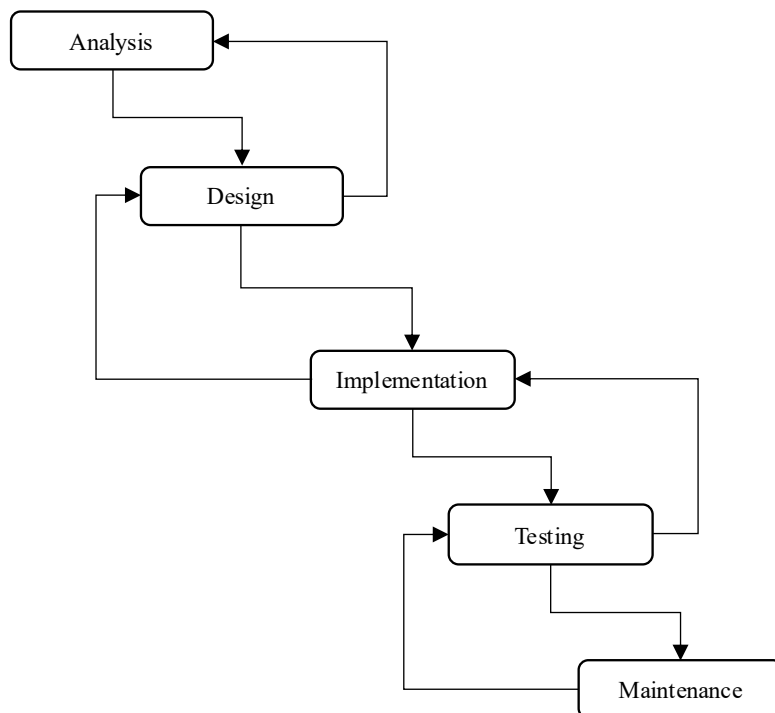
Ref.	Author(s)	Method	Key outcome	Limitation
[6]	Hughes & Salathe	PlantVillage Dataset	Enabled large-scale CNN training	Lab-based images
[15]	Ferentinos	CNN	High accuracy across crops	Requires a large dataset
[16]	Huang	SVM	Efficient for small datasets	Lower accuracy
[22]	Too et al.	Transfer Learning CNN	Improved accuracy with pre-trained models	Poor field generalization
[9]	Bhuyan et al.	Res4Net + CBAM	Better disease localization	High model complexity
[18]	Lu et al.	CNN (Field-based)	Works in real conditions	Sensitive to noise

**Table 2.** Software.

Software	Description
Operating System	Windows 10/11 or Ubuntu (Linux)
Programming Language	Python 3.x
Integrated Development Environment	VS Code
Panda and Numpy	Data manipulation and numerical calculation
OpenCV	Advance Image Preprocessing
Tensor/ Keras	Building, training, and deploying the CNN model
Lightning	For building User Interface

**Table 3.** Hardware.

Hardware	Description
Processor (CPU)	Intel Core i5
Storage	250 GB of free SSD Space
Graphics Processing Unit (GPU)	Cloud-based GPU access (Google Colab GPU)
Random Access Memory	Minimum 16 GB



**Figure 1.** Waterfall diagram of workflow steps.

### System Overview

This system overview defines the overall system architecture of the crop disease prediction system using image processing [9]. The complete workflow steps are shown in Figure 1 using a waterfall diagram.

Workflow Steps Consist of:

1. *Requirement analysis*: It understands the problem of crop disease prediction and the dataset required.
2. *System design*: It is used to design the architecture and select a suitable algorithm.
3. *Implementation*: This phase is used for developing, preprocessing, training, and predicting modules.
4. *Testing*: Used to specifically verify the accuracy and functionality of the components.
5. *Deployment*: This phase is required to create a user-friendly interface for real-time predictions.

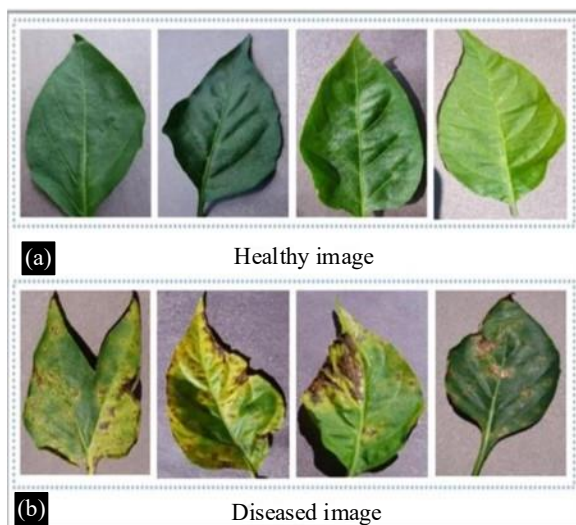
### The System Architecture Consists of The Following Steps:

#### *Image Acquisition*

This phase of data collection is used to collect the required data. In Figure 2, We have collected data for our model training from the Kaggle dataset platform, which is named as Plant Village dataset [10–11]. We have specifically chosen this repository because it has a large variety of images and provides us with a large variety of crops [12]. As these images are captured in a controlled laboratory environment, they provide a clean baseline for our CNN. This model is the core fundamental of our model.

#### *Image Preprocessing*

In Figure 3, The preprocessing layer is used to ensure that the images are prepared properly and standardized before given to the CNN. It resizes the image, normalizes the size and lighting, and then helps to reduce noise from the image as shown in Table 4. It is used to enhance image quality and model accuracy in crop disease detection [13]. Without this, the network might have inconsistent or noisy data as shown in Table 5.



**Figure 2.** Some images from the dataset.

**Table 4.** Example of preprocessing effects.

Stage	Operation	Result
Original Image	Raw leaf image	Contains noise, uneven lighting
Normalized Image	Pixel values scaled to [0-1]	Smooth intensity distribution
Augmented Image	Rotated and flipped	Increases training samples
Final Output	Standardized 128*128 RCBimage	Ready for CNN input

**Table 5.** Comparison: raw vs. preprocessed images.

Aspect	Raw image	Preprocessed image
Size	Variable	Fixed (128*128)
Pixel Range	0-255	0-1
Background	Complex	Simplified
Noise	High	Reduced
Feature Clarity	Low	Enhanced

### Segmentation and Feature Extraction

As we know, this segmentation is used to apply the segmentation algorithm. It divide image pixel-by-pixel. This algorithm highlights the part of the leaf that is diseased or have infection.

Extraction of the feature in the leaf is done by the feature extraction layer. Its main work is to extracts feature from image of leaf like color, shape, and much.

### Classification

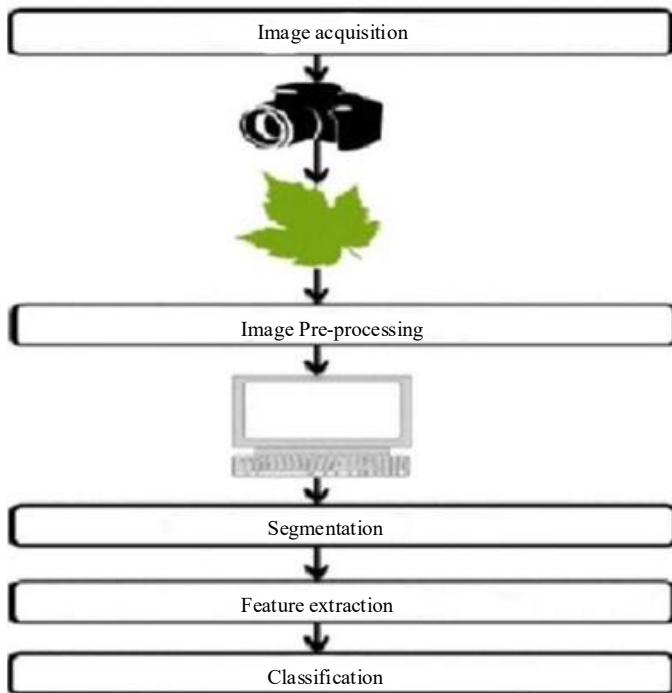
After everything is done, from feature extraction to segmentation, we classify the leaf as healthy or diseased. If the leaf is diseased, the system provides the specific disease and a solution to it.

### Performance

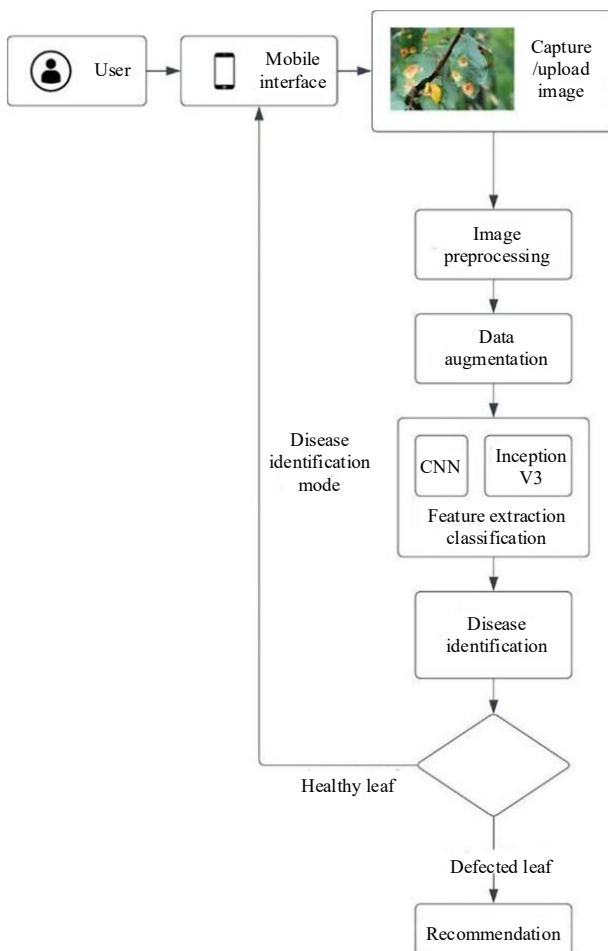
After everything is done, the performance is measured by precision, accuracy, and F-1 score. These help to identify how our model is working on the given data.

### User Interface

User Interface is a platform that acts as an interaction point between the system and the end user. In this, the user uploads an image, and then it provides them with the disease, and then provides the required solution for the crop disease that is predicted [14–17].



**Figure 3.** Architecture overview diagram.



**Figure 4.** Working of the model.

**Table 6.** Model performance.

Metric	Description	Result
Accuracy	Correct Prediction/ Total Images	0.95
Precision	Positive Predictions/ Total Predicted positives	0.94
Recall	True positives/actual positives	0.94
Inference Time	Time per Prediction	Approx 2 sec (CPU)

These are the main functions used in this model. The data collection involves collecting data from Kaggle, image preprocessing to enhance quality, segmentation for highlighting diseased parts, feature extraction to extract features, and then classification to classify images as diseased or healthy [18–20]. After classification, we give recommendations for disease images as shown in Figure 4.

## RESULT AND DISCUSSION

The proposed system has worked on all the images provided during the training and testing phases for proper validation of the system. The model performance is done on the data of the PlantVillage Dataset from Kaggle. The Table shows its Precision, accuracy, recall, and Inference time.

Till now, crop disease prediction highly depended on methods like SIFT or ORB. These models are great as they do not require thousands of images, but still, they fail to understand the bigger picture. This is where our Convolutional Neural Network (CNN) based model comes into focus. This model is trained on a large amount of images with different types of sizes, shapes, and textures, making it highly accurate and able to easily work on any new data. This will help farmers to easily detect the diseases at early stages, improving crop yield [21–23].

## CONCLUSION AND FUTURE STUDIES

It is true that the advancements in the field of AI and ML have brought significant changes around the world. Now it is easier to detect crop diseases faster and more easily in the early stage than any human. Still, there is a huge gap in developing countries like India, where the equipment needed, like cameras and high-quality mobile phones, is expensive.

Everything works perfectly on the laboratory data, but for field data, we get blurry images, overlapping, and many more issues. This model removes all these issues using image preprocessing. But still, climate change alters the rules, and it becomes tough to segment the features and detect diseases easily.

Our model mostly focuses on working on real-time data and can work easily with any kind of images, and tends to work on the field images. We have trained it with a large variety of images that help our model to work on field data.

Considering the prospects, the biggest problem is to create a system that captures and works on the real-time images under every circumstance, with harsh sunlight, shifting shadows, and overlapping. Future research needs to focus on developing a system that can work on real-time data. It can deal with lighting problems and climate change problems easily. Climate change does not alter the course to identify diseases. Thus, we have to focus on developing a web application that can easily overcome these issues in the future.

## REFERENCES

1. Gupta D, Ahlawat A. Usability feature selection via MBBAT: A novel approach. In: Gupta D, editor. *Journal of Computational Science*. 1st edition. Amsterdam, Netherlands: Elsevier; 2017. pp. 195–203.
2. Nandhini M, Kala KU, Thangadarshini M, Verma SM. Deep learning model of sequential image classifier for crop disease detection in plantain tree cultivation. In: Nandhini M, editor. *Computers and Electronics in Agriculture*. 1st edition. Amsterdam, Netherlands: Elsevier; 2022. pp. 106915–106920.

3. Jain R, Gupta D, Khanna A. Usability feature optimization using MWOA. In: Gupta D, editor. Proceedings of the International Conference on Innovative Computing and Communication (ICICC). 2nd edition. New York, USA: Springer; 2018. pp. 1–10.
4. Yadav PK, et al. Citrus disease detection using convolution neural network generated features and Softmax classifier on hyperspectral image data. In: Yadav PK, editor. Frontiers in Plant Science. 1st edition. Lausanne, Switzerland: Frontiers Media; 2022. pp. 1043712–1043718.
5. Schmidhuber J. Deep learning in neural networks: An overview. In: Schmidhuber J, editor. Neural Networks. 1st edition. Lugano, Switzerland: IDSIA; 2015. pp. 85–117.
6. Hughes DP, Salathé M. An open access repository of images on plant health to enable the development of mobile disease diagnostics. In: Hughes DP, editor. arXiv preprint arXiv:1511.08060. 1st edition. University Park, USA: Pennsylvania State University; 2015. pp. 1–10.
7. Patnaik A, Gupta D. Unique identification system. In: Patnaik A, editor. International Journal of Computer Applications. 1st edition. New York, USA: IJCA; 2010. pp. 16–28.
8. Goyal L, Sharma CM, Singh A, Singh PK. Leaf and spike wheat disease detection and classification using an improved deep convolutional architecture. In: Goyal L, editor. Informatics in Medicine Unlocked. 1st edition. Amsterdam, Netherlands: Elsevier; 2021. pp. 100642–100648.
9. Bhuyan P, Singh PK, Das SK. Res4Net-CBAM: A deep CNN with convolution block attention module for tea leaf disease diagnosis. In: Bhuyan P, editor. Multimedia Tools and Applications. 1st edition. Berlin, Germany: Springer; 2023. pp. 48925–48947.
10. Prathyusha G, Reddy V. Leaf-based plant disease detection using deep learning. In: Reddy V, editor. Journal of Emerging Technologies and Innovative Research. 1st edition. Ahmedabad, India: JETIR; 2021. pp. 47–51.
11. Gaikwad D, Sonone A, Patil S, Limbole S, Jain N. Crop disease detection system using deep learning method. In: Gaikwad D, editor. SAMRIDDHI: Journal of Physical Sciences, Engineering, and Technology. 1st edition. New Delhi, India: S.M.S; 2022. pp. 291–295.
12. Dyrmann M, Karstoft H, Midtby HS. Plant species classification using deep convolutional neural network. In: Dyrmann M, editor. Biosystems Engineering. 1st edition. Amsterdam, Netherlands: Elsevier; 2016. pp. 72–80.
13. Almási AD, Woźniak S, Cristea V, Leblebici Y, Engbersen T. Review of advances in neural networks: Neural design technology stack. In: Almási AD, editor. Neurocomputing. 1st edition. Amsterdam, Netherlands: Elsevier; 2016. pp. 31–41.
14. Barré P, Stöver BC, Müller KF, Steinhage V. LeafNet: A computer vision system for automatic plant species identification. In: Barré P, editor. Ecological Informatics. 1st edition. Amsterdam, Netherlands: Elsevier; 2017. pp. 50–56.
15. Ferentinos KP. Deep learning models for plant disease detection and diagnosis. In: Ferentinos KP, editor. Computers and Electronics in Agriculture. 1st edition. Amsterdam, Netherlands: Elsevier; 2018. pp. 311–318.
16. Huang T, Yang R, Huang W, Huang Y, Qiao X. Detecting sugarcane borer diseases using support vector machine. In: Huang T, editor. Information Processing in Agriculture. 1st edition. Amsterdam, Netherlands: Elsevier; 2018. pp. 74–82.
17. Ioffe S, Szegedy C. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In: Ioffe S, editor. Proceedings of the 32nd International Conference on Machine Learning (ICML). 1st edition. Lille, France: ICML; 2015. pp. 448–456.
18. Lu J, Hu J, Zhao G, Mei F, Zhang C. An in-field automatic wheat disease diagnosis system. In: Lu J, editor. Computers and Electronics in Agriculture. 1st edition. Amsterdam, Netherlands: Elsevier; 2017. pp. 369–379.
19. Liou CY, Cheng WC, Liou JW, Liou DR. Autoencoder for words. In: Liou CY, editor. Neurocomputing. 1st edition. Amsterdam, Netherlands: Elsevier; 2014. pp. 84–96.
20. Mahmud M, Kaiser MS, Hussain A, Vassanelli S. Applications of deep learning and reinforcement learning to biological data. In: Mahmud M, editor. IEEE Transactions on Neural Networks and Learning Systems. 1st edition. New York, USA: IEEE; 2018. pp. 2063–2079.

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21. Shin HC, et al. Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. In: Shin HC, editor. *IEEE Transactions on Medical Imaging*. 1st edition. New York, USA: IEEE; 2016. pp. 1285–1298.
  22. Too EC, Yujian L, Njuki S, Yingchun L. A comparative study of fine-tuning deep learning models for plant disease identification. In: Too EC, editor. *Computers and Electronics in Agriculture*. 1st edition. Amsterdam, Netherlands: Elsevier; 2019. pp. 272–279.
  23. Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture: A survey. In: Kamilaris A, editor. *Computers and Electronics in Agriculture*. 1st edition. Amsterdam, Netherlands: Elsevier; 2018. pp. 70–90.