



# CROP DISEASE DETECTION and SOLUTION PREDICTION USING CONVOLUTION NEURAL NETWORK

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**Abstract:** Crop diseases have grown significantly in recent years due to severe climate change and weakened crop immunity. This results in widespread crop destruction, lower cultivation, and ultimately financial loss for farmers. Recognizing the illness and treating it have become significant challenges due to the diversity of diseases growing quickly and farmers' lack of expertise. The texture and visual similarity of the leaves help determine the kind of illness. Therefore, the resolution to this issue lies in the use of deep learning to computer vision. In this study, a deep learning-based model using images of both well and ill crop leaves is proposed, and it is trained on a public dataset. The model accomplishes its goal by categorizing photos of leaves into categories according to the pattern of defect.

**Keywords:** crop image dataset, CNN, MobileNet, ResNet.

## I. INTRODUCTION

One significant advancement in the field of agriculture is the automated identification of plant diseases by the use of information from plant leaves. Furthermore, crop yield and quality are positively impacted by the timely and precise identification of plant diseases. Owing to the development of a vast array of crop products, even a pathologist or agriculturist may frequently be unable to recognize plant illnesses by looking at sick leaves. Visual inspection is the predominant mode of illness identification in the countryside of developing countries. It also has to be continuously observed by professionals. Farmers in isolated places might have to make a lengthy and costly trip to meet with an expert. With its high throughput, automated computational methods for diagnosing plant diseases and detection help agronomists and farmers and accuracy. To speak with the aforementioned issues, scholars have put forth some solutions. Plant diseases can be categorized by machine learning utilizing a range of feature set types. Deep-learning (DL)-based and conventional handcrafted feature sets are the most important often used among them. Effective feature extraction requires pre-processing, such as segmentation, color transformation, and image enhancement. After extracting features, different classifiers can be applied.

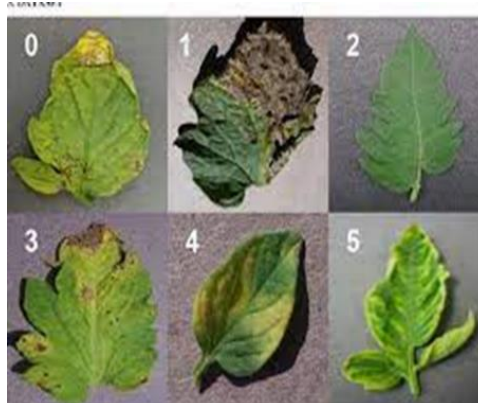


Fig. 1 Diseased Leaf



Plant diseases have a detrimental effect on the output of agriculture. Food insecurity will rise if plant diseases are not identified in a timely manner. Plant diseases are mostly prevented and controlled by early diagnosis, which is why agricultural production management and decision-making depend heavily on them. Plant disease identification has evolved into a critical issue in recent years. Plants with diseases typically have visible lesions or marks on their leaves, stems, blooms, or fruits. Typically, every illness or pest problem has a distinct outward pattern that may be utilized to identify anomalies in a certain way. Plant illnesses are typically primarily identified by looking at the leaves of the plants, as most disease signs can first be seen on the leaves. The majority of the time, on-site identification of fruit tree diseases and pests is carried out by forestry and agricultural specialists, or by farmers using their own experience. This approach is not only personal, but also hard, time-consuming, and ineffective. During the identification procedure, less experienced farmers could make poor decisions and use medications carelessly. Along with output and quality, pollution of the environment will lead to needless financial losses. Using image processing techniques to identify plant diseases has gained popularity as a resolution to these problems.

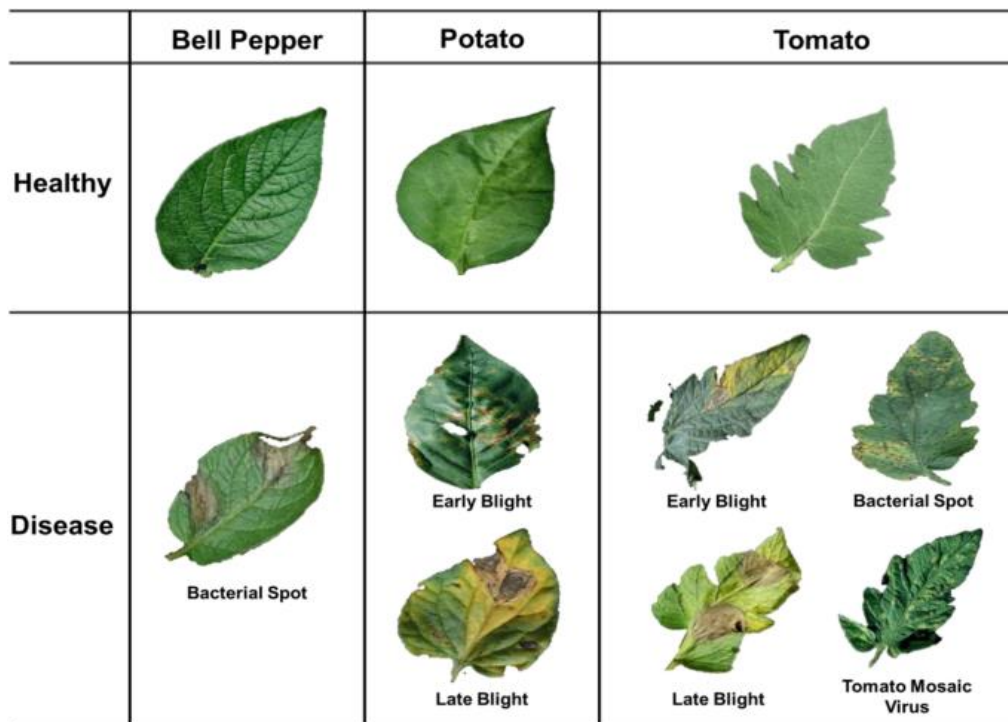


Fig. 2 Crop Diseased Detection

## II. LITERATURE REVIEW

1. Nilam Bhise et al. [1] They proposed the deep learning and Convolutional Neural Networks (CNNs) and Deep Learning (DL) CNN models Machine Learning, segmentation, pre-processing, extraction, identification, Implementation Methodologies are Dataset, Image Acquisition, Feature Extraction, illness identification and classification.
2. P. Aditya Maharnavar et al. [2] Developed Deep Convolutional Network model utilized in this uses an assortment of crop disease photos to provide quick and accurate automated detection. This utilizing neural networks for illness detection system convolution (CNN). We can identify crop disease using neural networks and digital image processing approaches.
3. Kowshik B et al. [3] Developed Crop disease identification and categorization have traditionally been accomplished by Machine Learning (ML) models; however, with current advancements in a subset of ML called Deep Learning (DL). Convolution Neural Network, deep learning Plant Disease Detection OpenCV. The goal of the suggested methodology is to produce a plant leaf disease detection strategy based on convolution neural networks.
4. Kinjal Vijaybhai et al. [4] Proposed the deep learning (DL) and Convolutional Neural Networks (CNNs) and CNN models Machine Learning, Deep Learning, Crop Disease, Agriculture, Image Detection optimizers leads to superior outcomes the grouping of illnesses that affect plants. To increase the efficacy of disease identification, traditional methods for machine learning (ML) have been implemented in agricultural operations.



5. Omkar. Kulkarni et al.[5] Utilizing the suggested neural network, the illness is identified in crop. The following steps are performed in order to implement the strategy: gathering the dataset, pre-processing the dataset, training of a convolutional neural network (CNN) model to determine the crop type, and CNN model training to detect disease in crop. They three different types of agriculture illnesses and five classes of crops were used to evaluate the suggested methodology.

6. M. Murk Chohan et al.[6] Developed CNNs (or) Convolution Neural Network (CNN) which is accustomed to find the disease in crop. They proposed a model based on deep learning called plant disease detector. The model is able to detect several diseases from plants using pictures of their leave[Methodology] Model for detecting plant diseases is developed using neural network.

7. S. Shreya et al.[7] Proposed Machine Learning, CNN, Image Segmentation, Feature Extraction, Automatic disease Recognition, Classification to determine which illnesses are present in crop Considering the pictureleaves and They proposed plant disease is an instantaneous prediction method that employs plant images as input and Methodologies are Leaf image dataset, Image processing, Image Segmentation and Feature Extraction, Classification based on CNN.

8. Gargi Sharma et al.[8] Proposed Deep Learning, CNN. They employed convolutional and classical neural networks as deep learning techniques. Generative Adversarial Network, Neural Networks with Recurrent Architectures Recurrent Neural Networks (RNN). Deep learning, a machine learning technology can be employed to achieve this goal. An artificial neural network will always have: Information layer, Hidden layer, Output layer.

### III. PROPOSED METHODOLOGY

**CNN:** A type Convolutional Neural Networks, a class of deep learning methods Networks (CNNs) was created for processing and analyzing visual data, including pictures and videos. They have proven to be extremely successful at jobs like object detection and picture categorization, as well as picture segmentation. Here's an explanation of CNN algorithm in 300 words:

#### **CNNs consist of several key components:**

**Convolutional Layers:** These layers are the heart of CNNs. They apply a collection of scalable filters (kernels) to the picture input. Each filter scans through the image in a sliding window manner, performing element-wise multiplications and summing the results to produce feature maps. These feature maps depict several patterns, such as edges, textures, and shapes, at various scales.

**Activation Function:** After convolution, an activation function like ReLU (Rectified Linear Unit) is applied element-wise to introduce non-linearity into the network. This helps CNNs learn complex relationships in the data.

**Pooling Layers:** The feature maps' the dimensions of space are decreased via pooling layers by down-sampling. Max pooling, for instance, selects the maximum value in a local region, effectively keeping the most crucial data while decreasing computational complexity.

**Fully Connected Layers:** usually follow a number of pooling and convolutional layers in CNNs layers. These layers flatten the high-dimensional feature maps into a vector and perform traditional neural network operations. It is their duty to forecast the future according to the attributes that have been retrieved.

The training procedure of a CNN involves:

**Forward Propagation:** During training, input data is fed forward through the network. Predictions are made, and the error comparing the expected and actual labels is computed applying a loss function (for example classification, cross-entropy, tasks).

**Backpropagation:** The error is then propagated backward utilizing gradient descent optimization across the network techniques. This process adjusts the mass of the filters and completely linked layers to reduce the error.

**Training Iterations:** The network goes through many iterations, adjusting the weights to strengthen its ability to recognize patterns and characteristics in the data. This continues until the loss converges to a minimum.



**MOBILENET:**

MobileNet is a compact deep learning model developed for efficient and fast neural network inference on mobile and edge gadgets with constrained processing power. Developed by Google researchers in 2017, MobileNet aims to balance computing efficiency and accuracy, which makes it ideal for tasks like object identification and picture classification on mobile platforms.

The key innovation in Mobile Net resides in its use of depth wise independent convolutions. Traditional convolutions apply a single filter to all input channels, leading to a high computational cost. In contrast, Two phases make up depth-wise separable convolutions: depth-wise convolutions, which apply a separate filter to each input channel, and pointwise convolutions, which combine the outputs of the depth-wise convolutions using 1x1 convolutions. This separation significantly reduces the quantity of parameters and computations while preserving model accuracy.

MobileNet is configurable, allowing users to choose the model size according to their computational constraints. The parameter called the "width multiplier" scales the number of channels in each layer, affecting the trade-off between accuracy and model size. The architecture also includes techniques such as global depthwise separable convolutions, linear bottlenecks, and a lightweight classifier to further optimize efficiency. As a result, MobileNet has become a popular choice for on-device machine learning applications, enabling tasks like image recognition to be performed locally on smartphones and other edge gadgets with constrained processing power.

**IV. IMPLEMENTATION**

**System:**

- Create Dataset:  
The dataset containing images of disease prediction are to be classified is split the test size into the training and testing dataset of 30-20%.
- Pre-processing:  
Resizing and reshaping the images into appropriate format to instruct our model.
- Training:  
The pre-processed training dataset should be used. employed in training our model.
- Classification:  
Our model's output is displayed as images are with either disease or normal

**User:**

- Upload Image  
The user has to upload an image, which needs to be classified.
- View Results  
User views the classified image results.

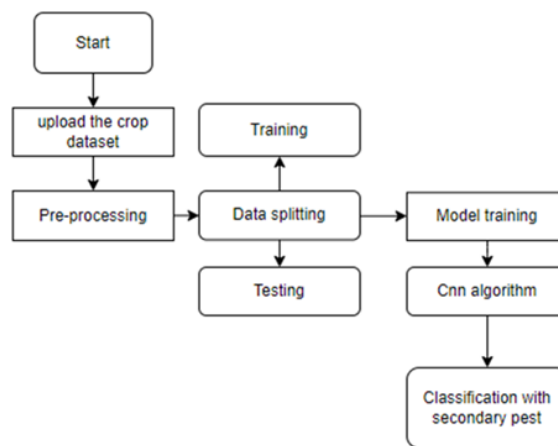


Fig. 3 Flow Chart



## V. RESULTS AND DISCUSSIONS

Deep learning-based identification of crop diseases involves training computer algorithms to recognize patterns in images of crops impacted by various diseases. Deep learning models, Convolutional neural networks, for example (CNNs), are taught using big datasets that include pictures of both well and ill crops. While in instruction, the model learns to identify distinguishing features or patterns associated with different diseases, enabling it to categorize fresh pictures accurately. Once trained, the A mode of deep learning may deployed to analyze images of crops in real-time. Farmers or agronomists can simply take photos of their crops using a smartphone or other imaging device, and the mode of deep learning has the capacity for swiftly assess whether the plants are healthy or afflicted with a disease. This technology gives farmers access to timely and accurate information, allowing them to take proactive measures arranged to stop the dissemination of diseases, optimize resource allocation, and ultimately improve yields of crops and food security.

Crop utilizing deep learning in illness detection involves using sophisticated algorithms to analyze images of crops and identify signs of illnesses or vermin. This process typically begins by collecting photos of both well-being and illness crops are employed to instruct a deep learning model. The model learns to recognize patterns and features in these images that discern between well and ill plants. Once trained, the model can analyze new images of plants and accurately detect if any diseases are present. This technology offers farmers a fast and reliable way to monitor the health of their crops, allowing them to take prompt action to stop the transmission of illnesses and minimize crop losses. In-depth education for identifying crop diseases simplifies the task for farmers by automating the procedure for identifying diseased plants. Instead of manually inspecting each plant, farmers can simply take pictures of their crops using a smartphone or drone and utilize the deep learning framework. to quickly assess their health. This Technology has the ability to revolutionize agriculture by making it possible to detect illnesses early, decreasing the requirement for chemical pesticides, and ultimately improving crop yields. Additionally, it empowers farmers with accessible tools to decide on a crop in an informed manner management, leading to more sustainable and efficient farming practices.

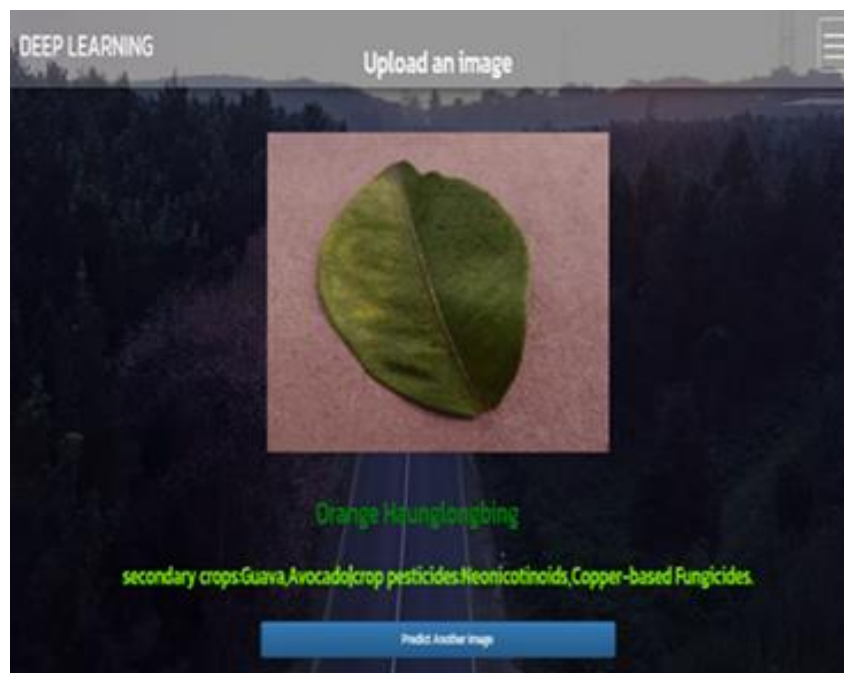


Fig. 4 Result of the leaf

## VI. FUTURE SCOPE

- To use deep learning for crop disease detection which involves developing a system with precise identification and classification plant disease in crops by analyzing images of leaves, and improving crop yields.
- In this we use several leaf varieties to determine the disease.
- It offers main benefits in agriculture, such as improving crop yield, reducing pesticide use and minimizing crop damage.



Detecting leaf damage via deep learning and machine learning (ML) techniques involves creating algorithms that use photos to precisely diagnose and categorize plant illnesses of leaves. This approach leverages the capabilities of neural networks and ML models to analyze visual patterns, enabling early detection and timely intervention for plant diseases. It offers significant benefits in agriculture, such as improving crop yield, reducing pesticide use, and aiding in sustainable farming practices. This technology is particularly crucial for monitoring large crop areas and for farmers who might not have expert knowledge in plant pathology.

## VII. CONCLUSION

In conclusion, Using Convolutional Neural Networks (CNNs) to identify agricultural diseases has demonstrated remarkable efficacy. The model effectively identifies and classifies diseases, enabling timely intervention to mitigate agricultural losses. Through the incorporation of CNNs, precision in disease prediction has improved, supporting farmers in making knowledgeable crop decisions management. The synergy of technology and agriculture holds promise for sustainable farming practices, emphasizing the potential for advanced technologies to revolutionize crop disease management and ensure global food security.

## REFERENCES

- [1]. Nilam Bhise, Ms. Shreya Kathet, Mast. Sagar Jaiswar, Prof. Amarja Adgaonkar "Crop Disease Detection Using Machine Learning " International Research Journal of Engineering and Technology , vol. 07, no. 07, pp. 2924-2929, 2020.
- [2]. Aditya Maharnavar, Tejal Lengare, Prachi Gunjal, Pallavi Sonawane, Prof. Ekta Patel "Crop Disease Detection Using Deep Learning," International Journal Of Research Publications, vol. 04, no. 05, pp. 5108-5110, 2023.
- [3]. Kowshik B, Savitha V, Nimosh madhav, M,Karpagaam, G,Sangeetha K "Plant Disease Detection Using Deep Learning," International Research Journal, vol. 03, no. 03, pp. 30-33, 2021.
- [4]. Kalpdrum Passi, Chakresh Kumar jain, Kinjal Vijaybhai Deputy, "Crop Disease Detection Using Deep Learning Techniques on Images," Journal of Computer Science, vol. 19, no. 12, pp. 1439- 1448, 2023.
- [5]. Omkar. Kulkarni, "Crop Disease Detection Using Deep Learning", Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), pp.1-5, 2018.
- [6]. Murk Chohan, Saif Hassan Katper, Adil Khan, Muhammad Saleem Mahar "Crop Diseases Detection Using Deep Learning. "International Journal of Recent Technology and Engineering (IJRTE), vol. 09, no. 01, pp. 909-914, 2020.
- [7]. S. Shreya , P. Likitha, G. Saicharan , Dr. Shruti Bhargava Choubey "Plant Disease Detection Using Deep Learning, "International Journal Of Creative Research And Thoughts, vol. 11, no. 05, pp. 754- 760, 2023.
- [8]. Gargi Sharma and Gourav Shrivastava "Crop Diseases prediction Using Deep Learning Techniques". Ictact Journal on Data Science and Machine Learning. vol. 03, no. 02, pp. 312-315, 2022.