

# Plant Disease Detection Using Deep Learning

Aman Chandravanshi<sup>1</sup>, K Vaishnavi<sup>1</sup>, Ayush Singh Sachan<sup>1</sup>, Eman Kashyap<sup>1</sup>, Neetu Ahirwal<sup>2</sup>

<sup>1</sup>Student, Department of Computer Science Engineering, Shri Shankaracharya Technical Campus Bhilai, Chhattisgarh, India

<sup>2</sup>Assistant Professor, Department of Computer Science Engineering, Shri Shankaracharya Technical Campus Bhilai, Chhattisgarh, India

Corresponding Author: nahirwar13@gmail.com

**Abstract**— The impact of pests on plants and crops poses significant challenges to agricultural production worldwide. Traditional methods of disease detection, reliant on manual observation by farmers or professionals, are marred by time constraints, high costs, and inaccuracies. In this context, leveraging technological advancements, this study proposes a Disease Recognition Model utilizing leaf image classification to streamline the detection process. Central to our approach is the implementation of Convolutional Neural Networks (CNNs) for image processing, renowned for their effectiveness in pixel input analysis and image recognition tasks. By harnessing CNNs, we aim to develop a robust and efficient system capable of accurately identifying plant diseases from leaf images, thereby offering a promising avenue for optimizing agricultural practices and mitigating crop losses.

**Index Terms**— Deep learning, convolutional neural network (CNN).

## 1. Introduction

Agricultural production stands as one of humanity's oldest endeavors, providing sustenance and livelihoods worldwide. Its significance reverberates not only for human populations but also for the intricate ecosystems where plants serve as the cornerstone, providing essential resources like food and oxygen. In response to the imperative need for enhanced food production, governments and experts globally have undertaken substantial initiatives, yielding tangible successes. However, amidst these efforts, the specter of plant diseases looms large, threatening not just crop yields but also ecosystem stability. From bacterial to fungal infections, plant diseases manifest across various parts of the plant, influenced by multifaceted factors including climate and environmental conditions. The repercussions of such ailments ripple through communities, exacerbating food insecurity in regions already vulnerable to scarcity. Moreover, the omnipresent challenge of climate change further compounds these issues, altering the landscape of agricultural productivity.

Manuscript revised May 17, 2024; accepted May 18, 2024. Date of publication May 20, 2024.

This paper available online at [www.ijprse.com](http://www.ijprse.com)  
ISSN (Online): 2582-7898; SJIF: 5.59

Yet, amidst these challenges, strides in technology offer a beacon of hope. Automated disease detection tools, leveraging the power of deep learning and neural networks, promise rapid and accurate identification of plant ailments, revolutionizing agricultural practices. In particular, the utilization of Deep Convolutional Neural Networks (CNN) exemplifies this paradigm shift, enabling precise discrimination between healthy and infected plant tissues. Through the integration of cutting-edge technologies with traditional agricultural practices, the quest for sustainable food security takes on renewed vigor, heralding a future where innovation and expertise converge for the betterment of agriculture and society at large. The adoption of computerized disease detection systems will be advantageous to farmers. Results from this method can be used in small- and large-scale agricultural production. The fact that the problems are identified quickly and with precision is noteworthy. For these technologies to work, deep learning and neural networks are essential. This study uses a deep convolutional neural network to distinguish between healthy and diseased leaves and to diagnose disease in plants that are affected. The CNN model is made to work with both healthy and sick leaves; it is trained using photographs, and the input leaf determines the output.

## 2. Review Of Literature

Using a variety of machine learning techniques, K. Muthusannan and colleagues identified spot infections in leaves and classified them in accordance with the diseased leaf classifications. Using form and texture data collected from the affected leaf photo, FFNN (Feed Forward Neural Network), RBFN (Radial Basis Function Networks), and LVQ (Learning Vector Quantization) were used to identify unhealthy plant leaves. The simulation demonstrated the effectiveness of the suggested system. With the support of this work, a machine learning-based system for improving crop quality in the Indian economy can be developed [1].

Capturing images is the first step in Malvika Ranjan and colleagues' investigation on plant leaf disease detection. The segmentation findings are used to extract colour data, such as HSV characteristics, which are then used to train an artificial neural network (ANN) by choosing feature values that accurately distinguish between healthy and sick samples. Using

a combination of image data processing methods and ANN, the current study suggests a method for identifying cotton leaf illnesses early and reliably. [2]

The goal of Syafiqah Ishakais and associates' study was to categorise healthy or diseased leaves of artificial neural networks and image processing techniques for medical plants. An algorithm was utilized to extract features, segment the images, and alter contrast from leaf shots. The multilayer feed-forward neural networks, which comprise the multilayer perceptron and radial basis function RBF, were employed to analyse the results using artificial neural networks. The outcomes demonstrated that when it came to identifying healthy and ill leaves, the RBF network outperformed the MLP network. [3]

Deep Convolutional Neural Network Supported Identification of Crop Diseases by Plant Image Classification is a novel approach for building a crop diseases recognition model based on plant image classification and deep convolutional networks, as presented by Srdjan Sladojevic and colleagues. The unique training approach combined with the methodology used makes it possible to quickly and easily set up the system in practice. The constructed model not only recognizes crops from their environment but also distinguishes thirteen different plant diseases from healthy leaves. The paper goes into depth about every step required to deploy this disease recognition algorithm, starting with taking pictures to create a database that is assessed by specialists in agriculture. The experimental results on the developed model achieved precision between 91% and 98%, for separate class tests, on average 96.3%. [4]

To classify plant diseases, CNN and Modelling Adversarial Networks were utilized. Some, such as Emanuel Cortes Using a publicly available dataset of 86,147 pictures of healthy and sick plants, a deep neural network and semi-supervised algorithms were trained to differentiate crop species and disease status of 57 different classes. The unlabeled data experiment that worked well was called rs-net. It completed the training phase in less than 5 epochs, scoring more than 80% with a detection rate of  $1e-5$ . [5]

Identification and management of plant diseases Konstantinos P. Ferentinos and colleagues developed CNN models employing neural network models to do crop disease identification and diagnosis using simple leaf photos of healthy and diseased plants. An open collection of 87,848 images, comprising 25 different plant species in 58 different classes of [plant, sickness] pairs—including non-affected plants—was used to train the models. A number of model architectures were created, and the best-performing model achieved a 99.53 percent success rate. The model is a useful early detection tool due to its high success rate. [6]

In Soybeans, Crop Disease Detection Using CNS, Walleign, Serawork, and Other Studies This work presents the feasibility of using CNN for the diagnosis of crop diseases in images of leaves taken in their natural habitat The LeNet architecture is used in the construction of the model to achieve the classification of plant diseases in soybeans. 12,673 samples of

tested green photographs from four different types—including images of healthy leaves—were obtained from the PlantVillage collection. Unstructured conditions were used to take the pictures. The developed model achieves a 99.32% classification accuracy, proving that convolutional neural networks can successfully extract important features and identify plant diseases from images taken in the wild. [7].

A Deep Learning-Based Detection for Tomato Plant Disease and Pest Identification in Real-Time In this research, Alvaro Fuentes and colleagues examine three different types of detectors, which they refer to as "deep learning meta-architectures": the Area Convolutional Neural Network (R-FCN), the Single Action Multibox Detector (SSD), and the Faster Region-based CNNs (Faster R-CNN). Each of these meta-architectures is combined using "deep feature extractors" such as Residual Network and VGG net (ResNet). We demonstrate the performance of deep morpho and feature extractors, and we propose a method for both locally and globally enhancing the accuracy and lowering false positives during training through feature extraction and category labelling. We train and test our systems end-to-end on our large Tomato Diseases and Pests Dataset, which contains challenging images of diseases and pests, including several inter- and extra-class variations, such as infection status and location in the plant. [8]

This paper describes a method for precisely identifying illnesses in apple leaves. In order to detect apple leaf diseases, a deep CNN with an AlexNet-based architecture and a suitable quantity of infected images must be built. With the use of a database of 13,689 photos of unwell apple leaves, the suggested deep CNN model can identify four typical illnesses that affect apples. The proposed sickness detection model has an overall accuracy of 97.62 percent. Compared to the AlexNet model, the suggested model's parameters were reduced by 51,206,928, and the model's accuracy was improved by 10.83 percent using produced pathological images. [9]

Using deep learning, Prasanna Mohanty and associates created a deep convolutional neural network that can identify 26 diseases and 14 distinct crops. The training set model achieved an accuracy of 99.35 percent on a held-out test set, demonstrating the usefulness of this approach. When the model is tested on a set of photos obtained from reliable websites, meaning photos taken in different settings than those used for training, it still achieves an accuracy of 31.4%. While this accuracy is substantially greater than the one based on random selection 2.6%, a larger collection of training data is required to increase overall accuracy. [10].

Ashwin Dhakal and associates developed a model that comprises feature extraction, segmentation, and classification of gathered data to diagnose plant leaf diseases. designs on leaves. The four classifier labels used are Bacterial Spot, Late Blight, Yellow Leaf Curl Virus, and Healthy Leaf. The retrieved characteristics are fitted into the neural network using 20 epochs. There are several neural network-based topologies employed, and the most accurate one predicts plant disease with 98.59 percent accuracy. [11]

In 2015, S. Khirade and associates employed backpropagation neural networks (BPNN) and digital image processing techniques to address plant disease identification issues. The authors have devised many methods for recognising plant diseases using photos of leaves. They employed Otsu's thresholding, boundary detection, and spot detection algorithms to divide the contaminated leaf into segments. Then, in order to categorise plant illnesses, they extracted characteristics like colour, texture, morphology, edges, and so on. Plant diseases are classified or identified using the BPNN algorithm. [12]

Peyman Moghadam and associates demonstrated in 2017 the efficacy of hyperspectral imaging in the identification of plant diseases. The visible and near-infrared (VNIR) and short-wave infrared (SWIR) spectrums were used in this study. The authors used the k-means clustering method in the spectral domain for leaf segmentation. They proposed a novel method for removing the grid from hyperspectral images. In the VNIR spectral band, the accuracy of vegetation indices was 83%, while full-spectrum accuracy was 93%. Although the recommended method produced better accuracy, using a hyperspectral camera with 324 spectral bands is required, which makes the solution unaffordable. [13]

In 2019, Sharath D. M. and associates developed a Pomegranate plant Bacterial Blight detection method using characteristics such as colour, mean, homogeneity, SD, variance, correlation, entropy, and edges. The authors segmented the region of interest in the image using grab cut segmentation. The Canny edge detector was used to extract the photo's edges. The authors have been successful in creating a system that predicts the level of fruit infection.[14].

In 2020, Garima Shrestha and associates employed convolutional neural networks to detect plant diseases. Classifying 12 plant diseases, the authors achieved an accuracy of 88.80%. The 3000 RGB high-resolution photos in the collection were used for the experiments. This network has three blocks for the pooling layer and the convolutional layer. This eventually leads to the network becoming extremely costly. The model also has an unusually low F1 score of 0.12 because of the large number of incorrect negative predictions. [15]

### 3. Suggested System

Our goal is to create a neural network model that can classify images. This model will be used to identify plant leaf disease in real time using an image on a web browser that has Streamlit enabled. Fig. 1 shows the recognition and classification processes.

- Gathering data is the initial stage. The New Plant Diseases Dataset, which is extensively accessible, is what we are using. CrowdAI released this dataset.
- Pre-processing and Augmentation of the collected dataset is done using pre-processing and Image-data generator API by Keras.

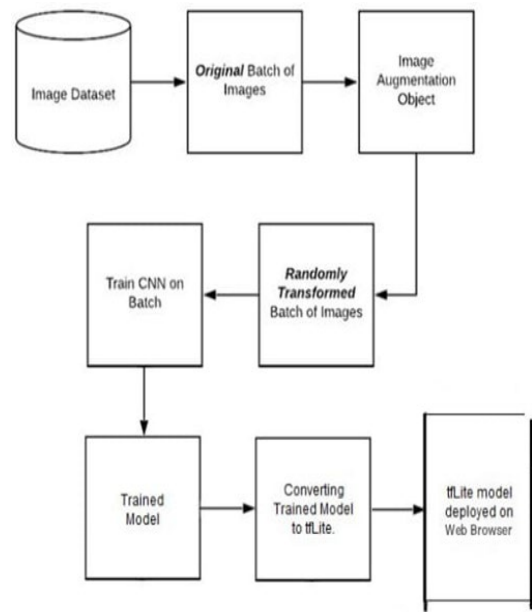


Fig.1. Block Diagram for the Suggested System

- Building CNN Model for classification of various plant diseases.
- Developed model will be deployed on the Web Browser with help of Stream lit.

### 4. Integration In Neural Network Design

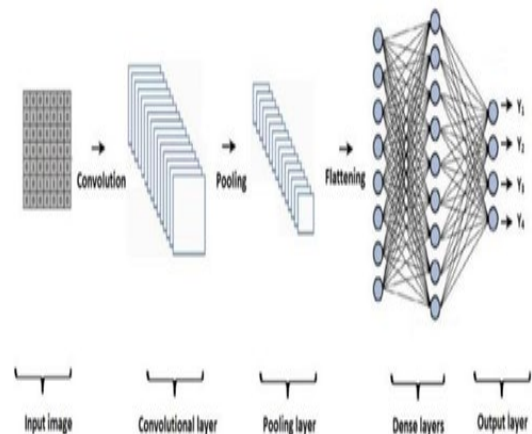


Fig.2. CNN'S Architecture

The three layers of a convolutional neural network are the fully connected layer, the pooling layer, and the convolutional layer. The combined layers are shown in Fig 2.

#### A. Layer of Convolution

Convolutional layer: creates an activation map by applying a filter to scan many pixels at once in the image. Figure 3 illustrates how the convolution layer functions internally.

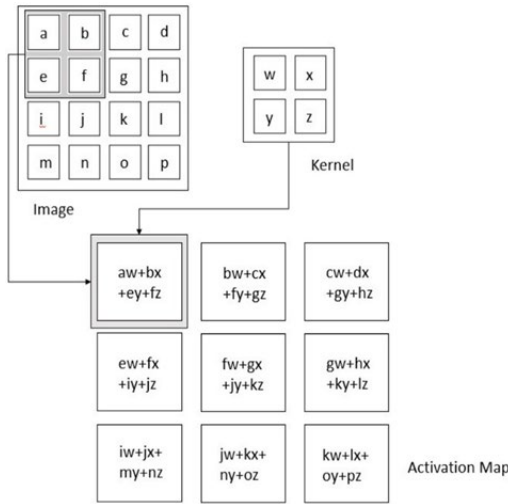


Fig.3. Layer of Convolution

Our CNN model has been pre-trained and is well-versed on the form, colour, and structure of an image. A deep neural network called CNN was trained on hundreds of images with difficult categorization issues.

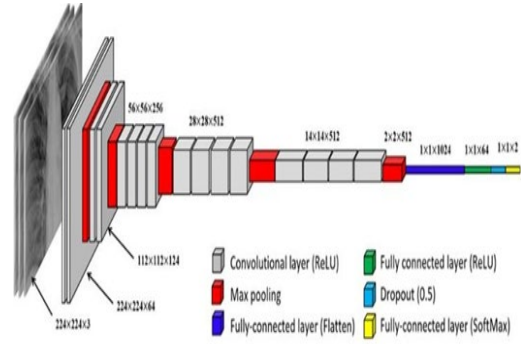


Fig.6. Layers of CNN

**B. Layer of Pooling**

The pooling layer makes better use of storage space by reducing the volume of data produced by the convolutional layer. Figure 4 illustrates how the pooling layer functions inside

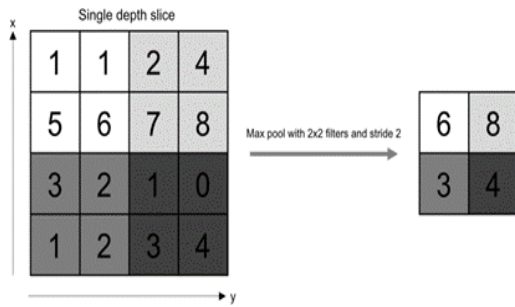


Fig.4. Layer of pooling

**C. Fully Connected Convolution Layer**

Fully linked input layer: The output of the layers before it is "flattened" into a single vector, which serves as the input for the layer after it. In order to predict the correct label,

The first fully connected layer applies weights to the inputs from the feature analysis. The fully connected output layer provides the final probability for every label.

Figure 5 illustrates how a fully connected layer operates inside.

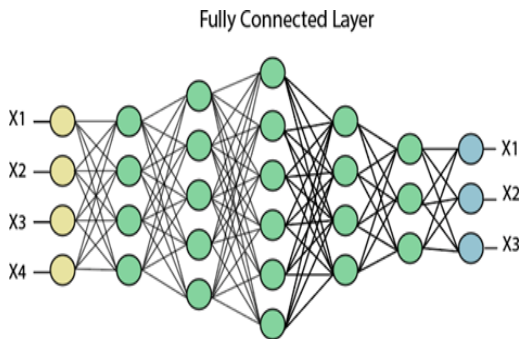


Fig.5. Fully Connected Convolution Layer

**5. Result**

With early halting, a 95% accuracy rate was attained during the model's 10-epoch training process. The training and validation accuracy visualization is shown in Figure 7. Figure 8 displays the outcome of identifying and detecting a tomato plant leaf. A healthy potato plant leaf is on the bottom, while a sick, diseased plant leaf is on top. Figure 9 illustrates what happens when a potato plant is found and identified. A sick, infected plant leaf is at the top, while a healthy plant leaf is at the bottom.

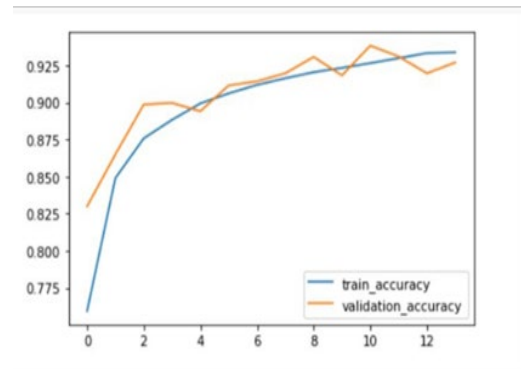


Fig.7. Validation versus Training

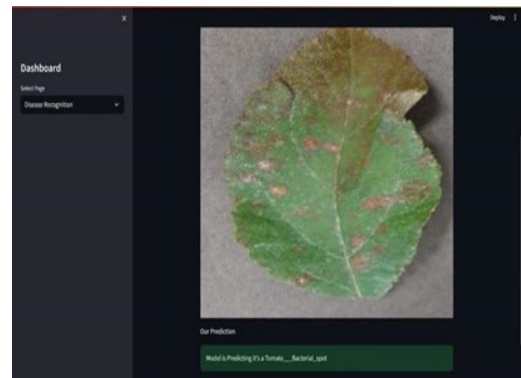


Fig.8. outcome of identifying and detecting a Tomato leaf.



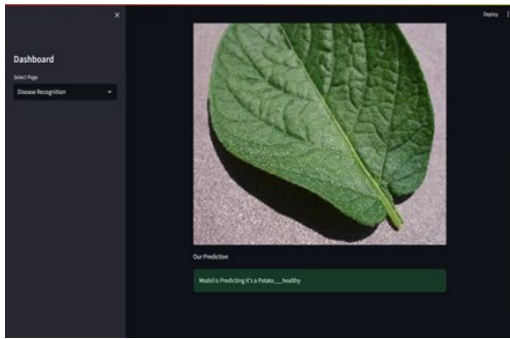


Fig. 9. outcome of identifying and detecting a potato leaf.

## 6. Conclusion

In conclusion, our efforts in developing disease classification techniques for plant leaf detection have yielded promising outcomes. Through the creation of a deep learning model, we have automated plant leaf disease identification and categorization across a diverse range of species, including tomato, Potato, Apple and others. Testing our model on 38 classes of plants has showcased its versatility and accuracy in disease identification.

Our approach leveraged the image data generator API by Keras, enabling efficient image processing tasks, and the implementation of the CNN model further enhanced the predictive capabilities of our system. Moreover, successfully deploying these models on a Web Browser represents a significant milestone, bringing the benefits of our research directly to users.

Our efforts towards disease detection through our Android app are ongoing. We are dedicated to constantly improving the accuracy of the app and the model it uses. By embracing new technology and methodologies, we aim to make our detection system even more effective and user-friendly. Looking ahead, we envision our work contributing to the broader efforts in safeguarding global crop production and ensuring food security.

Through collaboration and innovation, we are poised to make meaningful strides in the identification of plant diseases and management, ultimately contributing to a more resilient and sustainable agricultural future.

## References

- [1]. Diseased plant leaves using Neural Network Algorithms K. Muthukannan<sup>1</sup>, P. Latha<sup>2</sup>, R. Pon Selvi<sup>1</sup> and P. Nishal<sup>1</sup>  
<sup>1</sup>Department of ECE, Einstein College of Engineering, Anna University, Tirunelveli, India <sup>2</sup>Department of CSE, Government College of Engineering, Anna University, Tirunelveli, India ARPN Journal of Engineering and Applied Sciences, VOL. 10, NO. 4, MARCH 2015, ISSN 1819-6608.
- [2]. Ranjan, Malvika, and others "Detection and classification of leaf disease using artificial neural network." International Journal of Technical Research and Applications 3.3 (2015): 331-333.
- [3]. Ishak, Syafiqah, and others. "Leaf disease classification using artificial neural network." Jurnal Teknologi 77.17 (2015).
- [4]. Sladojevic, Srdjan, and others. "Deep neural networks-based recognition of plant diseases by leaf image classification." Computational intelligence and neuroscience 2016 (2016).
- [5]. Cortes, Emanuel. "Plant disease classification using convolutional networks and generative adversarial networks." (2017).
- [6]. Walleign, Serawork, Mihai Polceanu, and Cedric Buche. "Soybean plant disease identification using convolutional neural network." The thirty-first international flairs conference. 2018.
- [7]. Fuentes, Alvaro, and others. "A robust deep-learning-based detector for real-time tomato plant diseases and pests' recognition." Sensors 17.9(2017): 2022.
- [8]. Liu, Peide, Tahir Mahmood, and Qaisar Khan. "Multi-attribute decision making based on prioritized aggregation operator under hesitant intuitionistic fuzzy linguistic environment." Symmetry 9.11 (2017): 270.
- [9]. Mohanty, Sharada P., David P. Hughes, and Marcel Salath'e. "Using deep learning for image-based plant disease detection." Frontiers in plant science 7 (2016): 1419.
- [10]. Dhakal, Ashwin, and Subarna Shakya. "Image-based plant disease detection with deep learning." International Journal of Computer Trends and Technology 61.1 (2018): 26-29.
- [11]. Ramcharan, Amanda, et al. "Deep learning for image-based cassava disease detection." Frontiers in plant science 8 (2017): 1852.
- [12]. S. D. Khirade and A. B. Patil, "Plant Disease Detection Using Image Processing," 2015 International Conference on Computing Communication Control and Automation, 2015, pp. 768-771.
- [13]. P. Moghadam, D. Ward, E. Goan, S. Jayawardena, P. Sikka and E. Hernandez, "Plant Disease Detection Using Hyperspectral Imaging," 2017, International Conference on Digital Image Computing: Techniques and Applications (DICTA), 2017, pp. 1-8.
- [14]. Sharath, D. M., et al. "Image-based plant disease detection in pomegranate plant for bacterial blight." 2019 international conference on communication and signal processing (ICCSPP). IEEE, 2019.
- [15]. Shrestha, G., and M. Deepsikha. "Das, and N. Dey, "." Plant Disease Detection Using CNN," 2020 IEEE Applied Signal Processing Conference (ASPCON). 2020.