# A New Approach for Leaf Disease Detection using Multilayered Convolutional Neural Network

Vivek Shukla
*Department of Computer Science*
*National Institute of Technology*
Rourkela, Odisha, India
vivek987a@gmail.com

Sweta Rani
*Department of Computer Science*
*National Institute of Technology*
Rourkela, Odisha, India
swetarani1110@gmail.com

Ramesh Kumar Mohapatra
*Department of Computer Science*
*National Institute of Technology*
Rourkela, Odisha, India
mohapatrark@nitrkl.ac.in

***Abstract*—Leaf diseases reduce agricultural yield by 35% annually in India, where agriculture is the main sector. Manual detection of the type of disease present in leaves takes a long time since laboratories lack the necessary tools and expertise to recognise early leaf diseases. Diseases include early blight, late blight, black root, bacterial spot, mould leaf, healthy leaf, etc. Automated leaf disease detection systems are beneficial for spotting disease symptoms on plant leaves as soon as they appear, which helps to ease the time-consuming process of monitoring large agricultural farms. Recent advances in deep learning (DL) and computer vision models have highlighted the importance of developing autonomous leaf disease detection algorithms based on visual symptoms on leaves. The fundamental goal of the proposed model is to tackle the problem of leaf disease diagnosis using the most basic strategy while utilising the fewest computer resources to generate results comparable to state-of-the-art techniques. We used the multilayered architecture of convolutional neural networks (CNN) to identify and overcome leaf diseases. When compared to existing techniques, our proposed method can successfully train an image classification model to achieve 98.5% accuracy.**

***Index Terms*—Plant Leaf Disease Detection, Images Processing, CNN, Agriculture, Deep Learning**

## I. Introduction

Agriculture is the primary source of income for India's massive rural population. Agriculture is the principal source of income for 58% of the population. Raising the threshold in agriculture will very certainly raise it for rural residents. Numerous reports and studies, however, show that our Indian farmers continue to use old farming techniques and are unaware of contemporary equipment and strategies for battling leaf diseases. As a result, both the quality and quantity of agricultural products suffer. The demand for a reliable food supply develops in tandem with the world population. It is critical to producing food in a clean environment. This is possible in large quantities on a plantation with modern technologies. Pre-harvest and post-harvest planning, application of agricultural input resources such as fertilisers, early detection of pests and illnesses, and weed identification are just a couple of areas for image processing and computer vision in agriculture. Plants in the dataset include tomato, apple, blueberry, grape, peach, cherry, corn, orange, strawberry, pepper, squash, potato, raspberry, and soybean. The data set contains 18,345 training images and 3656 test images. Precision agriculture technology improves the agricultural industry. The optimal amount and timing of agricultural inputs are used after harvest. Precision agriculture makes use of tools such as Global Positioning System (GPS), remote sensing, and Geographic Information Systems (GIS). This method has enabled the secure collection, analysis, and deployment of field data. The field's spatial and temporal diversity indicates patterns, linkages, and the importance of this strategy. Fungi, viruses, bacteria, and certain nematodes are mainly responsible for the majority of leaf diseases. Leaf disease symptoms include a major change in the colour or the leaf's form, scabs, wilting, rust, blotches and mouldy coatings caused by the pathogen. For example, tomato powdery mildew first appears as light yellow patches on the leaves. The spots quickly fill with white spores, giving the leaves the appearance of being sprinkled using flour. The once-pale leaf segments turn black and shrink, becoming brittle and dry as the fungus infection worsens. Separating defective regions, extracting relevant features, and categorising the data using machine learning algorithms are all part of the pre-processing stages for computer vision-based modules for classifying leaf illnesses.

Training numerous spectral image inputs and defining their objectives are the main issues faced by CNN. With CNN classifier applications, classifying the variations from the provided input data has become even more difficult.

### A. Motivation

The use of CNN in agriculture in recent years, its growing popularity and success in resolving multiple agricultural challenges, and the fact that there are currently numerous research projects employing CNN to discuss various agricultural topics are driving forces behind the research. Due to its remarkable result, CNN is perhaps the most well-known and widely used methodology in the agricultural field, and the fact that there are currently numerous research projects employing CNN to discuss various agricultural topics is the driving force behind the research. In terms of image analysis, the current study focuses on a specific branch of Deep Learning models and approaches because there aren't many studies of this type in agriculture, particularly with CNN use. As a result, it would be beneficial to offer and analyse essential information to assist researchers in conducting a more thorough examination.

### B. Research Contribution

In this study, deep convolutional networks are used to create a way to figure out what's wrong with a plant-based on how its leaves look. The suggested model is capable of detecting 38 distinct forms of plant diseases in different plant species by distinguishing plant leaves from their surroundings.

- To use the dataset available on Kaggle named "New Plant Disease Dataset" for leaf disease detection on different plants.
- To Propose an efficient model using CNN in order to detect the leaf disease.
- To achieve good accuracy using a multilayered CNN architecture.

## II. Related Work

Different sorts of literature have recommended various approaches and techniques for identifying leaf diseases in plants. The illnesses in tea leaves have been identified using a Support Vector Machine classifier. An important contributor to the economic development of countries such as India and Bangladesh is the manufacturing of tea. The authors [1] have dedicated their efforts to creating a model that can identify the most common tea leaf diseases. As a result, the country's output and rate of growth benefit. In order to categorise the various leaf diseases, machine learning methods have been used. The identification of leaf diseases [2] has been addressed by several authors who have employed KNN, Decision Tree, SVM, and neural networks. Identifying diseases in leaves This article focuses on three major leaf diseases: early black spot, late black spot, and black rot.

Understanding which parts of a leaf are diseased and which are healthy is the primary goal. There have been attempts to employ image processing methods for this purpose. Implementing classification and image analysis algorithms for leaf disease detection is the primary focus of this effort. In order to distinguish between healthy and diseased leaf photos, the SVM classification algorithm has been used. Neural Networks(NN) have been suggested by the authors [3] for the diagnosis and categorization of grape leaf diseases. The input for this system is a picture of a grape leaf. Green pixels are masked using thresholding. Noise cancellation is achieved by anisotropic diffusion. The grape leaf disease is then segmented using K-means clustering. The afflicted organ is identified by the use of neural networks. In [4], the authors presented a method for identifying leaf spots caused by illness using colour transforms. This research provides an analysis of how various colour spaces affect the identification of disease spots.

Comparisons are made between the HSI, CIELAB, and YCbCr colour spaces, and the CIELAB colour model is ultimately implemented through the A component. When smoothing a picture, the median filter is often used. Finally, the threshold is determined by applying the Otsu technique to the colour part of the image. The authors [5] established a rapid and thorough method for diagnosing and classifying leaf diseases. In this approach, the author [6] employs K-means clustering for NN and segmentation for classification using a texture feature set. Images of potato leaves have been classified as healthy or sick using the support vector machine classifier [7]. This research aims to provide a disease management tool that can automatically identify areas of potato leaves that have been impacted by early blight or late blight. The deep learning technique has been used for leaf disease identification by the authors [8].

The CNN and RNN methods detect several disease types in plants. A total of thirteen different leaf diseases may be identified and categorized automatically using this approach. There are 10 distinct illnesses that may be detected using CNN on roughly 500 photos of rice plant leaves. In this case, the author used cross-validation with a 10-fold sample size. Rice leaf diseases are described by the authors in [6]. Leaf disease detection segmentation has been studied in relation to preprocessing methods. Normal and sick leaves are separated using a histogram plot. Features of both form and colour are derived. The PCA approach [9] is used to extract shape features, while colour features are retrieved using colour-based grid moments. Every one of these strategies relies on some combination of texture, shape, and colour traits in order to extract relevant information. It's also difficult to say how many neurons the NN classifier uses, and training it requires a very limited sample.

In terms of classification, and accuracy, Support Vector Machines are superior to both Random Forest and Logistic Regression. A mechanism for automatically detecting early blight and late blight damage in plant leaves has been implemented in this study. To better identify leaf diseases, deep learning methods might be used. Different types of leaf diseases may be detected using CNN and RNN approaches. This approach may be used to automatically detect and categorize thirteen distinct leaf diseases. Ten distinct illnesses were identified in over 500 photos of rice plant leaves using CNN. In this case, the cross validation method has been used 10 times. Very few test photos are used in the report despite a large number of investigations. Approximately 15,000 leaves, both healthy and harmful, are considered. The presence of plant diseases in the leaf has been identified using three machine learning methods: random forest classifier, logistic regression, and support vector machine [10]. These models have been compared in depth with all algorithms.

## III. Background Details

One of the most widely used AI techniques today among researchers looking at automation and the Internet of Things is deep learning (DL). This is because of significant improvements in processing speed and data accessibility, which have enabled researchers in numerous domains to come to meaningful conclusions. CNN algorithms have developed to the point where they can understand images in a manner similar to that of human brains.

To begin with, DL systems need a tonne of high-quality data in order to properly learn and predict the future. Therefore, the initial stage in applying DL to image processing is to assess the images, followed by annotation and generalisation. To develop the model, used Convolutional Neural Network.

The methods for categorising images are listed in Table I.

TABLE I
DIFFERENT IMAGE PROCESSING TECHNIQUES

| Sr.No. | Techniques |
|---|---|
| 1 | Convolutional Neural Network (CNN) |
| 2 | Random Forest Classifier (RF) |
| 3 | K-Nearest Neighbors (KNN) |
| 4 | Probabilistic Neural Network (PNN) |
| 5 | Naive Bayes (NB) |
| 6 | Artificial Neural Network (ANN) |
| 7 | Support Vector Machine (SVM) |

### A. Deep Learning

A subset of machine learning entitled “deep learning” is fully supported by artificial neural networks. Deep learning is a type of human brain mimic because neural networks are built to resemble the human brain. Not everything has to be explicitly programmed into deep learning. The premise of deep learning is not new. It has been in existence for some time. We aren’t equipped with as much processing power or data as we previously did, therefore it’s more frequent now.

### B. Neural Network (NN)

Biological neural networks serve as the foundation for artificial neural networks. These systems do not use task-oriented rules; instead, they learn to perform tasks by being exposed to a variety of examples and facts. It is believed that the system, which is not pre-programmed with a pre-coded comprehension of such datasets, produces distinguishing characteristics from the data that is provided to it. Threshold logic computational models underpin neural networks. The foundations of neural networks are the study of the brain or the application of neural networks to artificial intelligence.

### C. Convolutional Neural Network (CNN)

CNN, or Convolutional neural network, is a subset of deep learning neural networks that are used to analyse ordered arrays of data, like photos. CNN is extremely good at recognising design elements in the input image, such as arcs, gradients, rings, or even faces and people.

## IV. PROPOSED WORK

The proposed model uses deep convolutional networks to develop a method for recognizing leaf diseases based on the classification of leaf images. Out of 14 different plants, the proposed model can identify 38 different types of leaf illnesses. Following the collection of the dataset, basic data analysis and feature extraction methods are applied. It helps us focus on the image’s most valuable elements while dismissing the rest. For feature extraction, a feature descriptor called the Histogram of Oriented Gradients (HOG) is used. The first step is to recognise the edges and orientation of pixels in an image. To do this, gradient and orientation are computed.

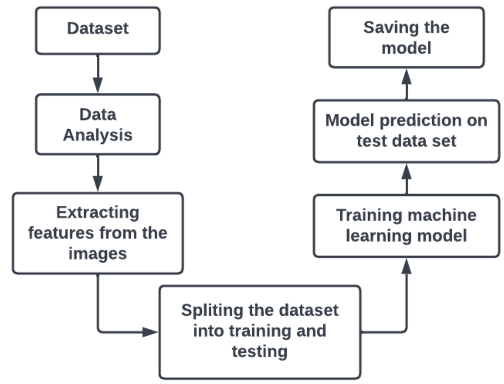


Fig. 1. Workflow of Model

A histogram must be used to plot the regions independently. HOG consists of the following actions: The first step is to read the image from the folder, and then the OpenCV library converts RGB images to grayscale. HOG is then taken from each image after it has been resized to a format that may be used. The NumPy array, which contains the images and titles, is then used to construct the array. Fig. 1 depicts the suggested model’s workflow.

### A. Steps

1) The images are loaded, their size is downsized to 128 × 128 (256 × 256 images take longer to process), and then they are turned into tensors.
2) 30% of the overall dataset is used to create a validation dataset, and 70% is used for the training dataset.
3) Data loading with batches.
4) Combination of Multilayered CNN architecture is used to train the model.
5) Model development and evaluation using test data.

### B. Data Preparation

Data preparation is used to clean, standardize, and enrich the raw image to make it ready for training the model. When data is acquired in the form of images, it should be ensured that there are enough features for the learning model to be correctly taught and trained. Generally, more data always yields better outcomes. The leaf image of the plant is clipped in order to isolate the affected regions, and the image is then smoothed. Each image then goes through image preprocessing techniques. In order to improve image quality, preprocessing is applied to a collection of images that are in various dimensions. Both unwanted distortion and background noise are suppressed by it. This image is first downsized to 128 × 128, after which thresholding is carried out to extract all green colour components.

### C. Understanding The Data

The dataset referred to as ”New Plant Diseases Dataset” could be accessed at https://www.kaggle.com/vipoooool/new-plant-diseases-dataset. This dataset was obtained from Kaggle.

When data is gathered in the form of images, it's important to make sure there are enough features so that the trained model can be properly taught and trained. 87,867 images are gathered to build the dataset requisite to apply the model. Only 22,001 of the 87,867 images are used to test and train the model. There are images of various healthy and diseased crop leaves, as shown in Fig. 2. A train and valid directory are created by dividing the dataset. The folders present in the train directory are as follows:

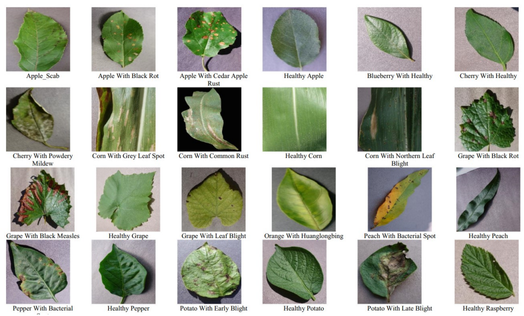

Fig. 2. Sample Images of New Plant Diseases Dataset

Tomato_Target_Spot, Corn_(maize)_healthy, Tomato_Bacterial_spot, Strawberry_healthy, Blueberry_healthy, Tomato_Tomato_mosaic_virus, Strawberry_Leaf_scorch, Tomato_Leaf_Mold, Potato_healthy, Grape_Esca_(Black_Measles), etc.

Number of Unique Plants present in the dataset: 14

Unique Plants: ['Strawberry', 'Blueberry', 'Potato', 'Pepper', 'Apple', 'Tomato', 'Peach', 'Soybean', 'Grape', 'Squash', 'Corn', 'Cherry', 'Raspberry', 'Orange']

To process images more quickly, a batch of the dataset is created. As long as it fits in memory, the batch size of 64 images is chosen according to the need of the model. For quicker processing of the images, a batch of the dataset has been created as shown in Fig. 3. Once the directory structure has been verified, the dataset is established and images of size 128 × 128 are loaded as PyTorch tensors. Applying transform to the images in the directory allows us to load them as Pytorch tensors. The test dataset will be created in the valid folder, while the training and validation datasets will be created in the train folder.

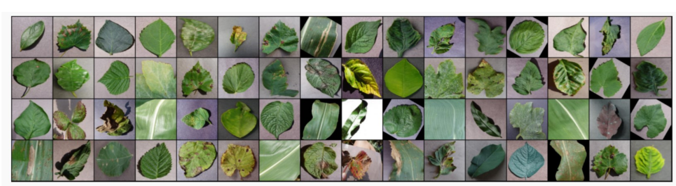

Fig. 3. Batch of Images

### D. Visualizing a single image

By putting data in a visual context and trying to understand it, data visualisation studies patterns, trends, and connections that might not otherwise be noticeable. Fig. 4 illustrates how the image was permuted so that the pixel image became reversed.

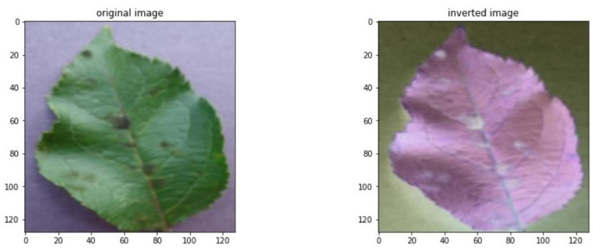


Fig. 4. Single image visualization

### E. Building the CNN Model Architecture

The proposed model has been implemented using multilayered CNN architecture. Initially, a base image classification class is defined that has features for each batch of data training and data validation. This will save us from repeatedly developing these routines and allow us to build multiple CNN models. For training, the model batch of images is used shown in Fig. 5. A CNN architecture is created by inheriting the basic class.

CNN architecture provided for this model is given below:

- Building a multilayer CNN model from scratch using Conv2D
- Relu and Maxpool 2D and Linear Layers.

Data loading into a GPU device and model creation: For fast processing of the images, the data must be loaded from the CPU to the GPU. Computing on a CPU will be exceedingly time consuming due to the size of the data.

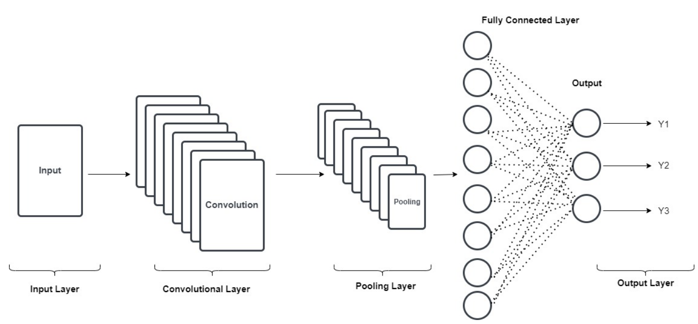


Fig. 5. CNN Architecture

## V. Results and Discussion

To determine how well the suggested method worked, our model ran a number of tests utilising databases of photos of both healthy and diseased tomato leaves. The leaves with various diseases are quite similar to one another, which makes disease identification and classification difficult for this study. Because of this similarity, certain leaves may be folded into the incorrect groups. The accuracy of the model on test data is 98.5%.

## A. Result analysis of proposed model

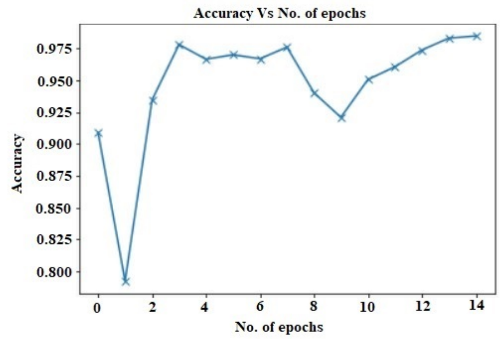


Fig. 6. Accuracy of model after applying CNN architecture

## B. Prediction on some single image of dataset

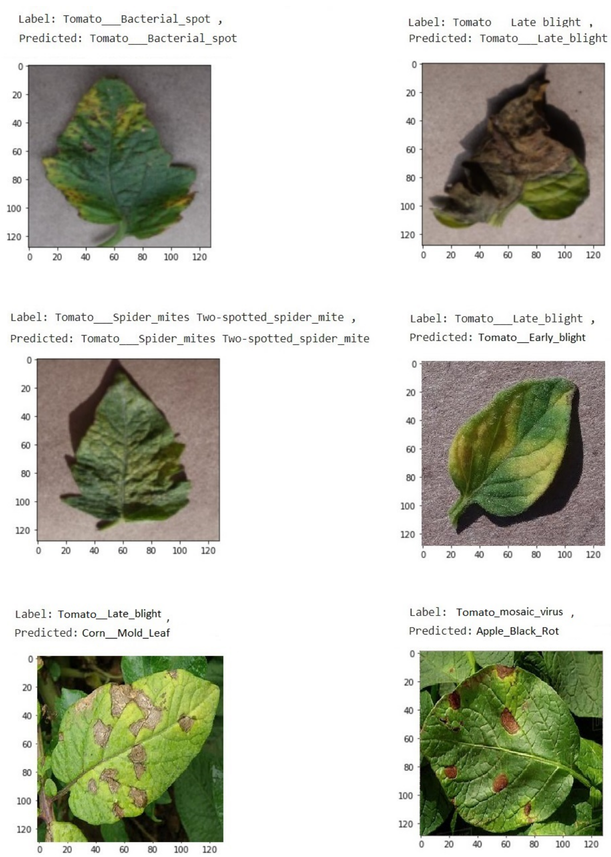


Fig. 7. Prediction on test dataset

The above Fig. 7 shows the prediction of our model. In the figure, the label means the actual name of the leaf and the predicted means the output of our model. Some of the prediction and label name is not matching.

## VI. Conclusion and Future Direction

In this proposed model, a multilayered Convolutional Neural Network architecture is used for the classification and detection of different leaf diseases provided in the given dataset. The collection is comprised of 22,001 pictures of various types of leaves. Each image in the dataset has had a distinct input matrix developed for its R, G, and B channels. These matrices have also been constructed. This model is capable of effectively training an image classification model with multilayered CNN architectures, as demonstrated by the model's test accuracy of 98.5%.

The majority of the studies used CNN techniques, and also underlined that pre-training models, rather than creating new models from starting with leaf image datasets, can quickly enhance performance accuracy, especially if there is enough data for each class to train the models. However, a critical future impact would be the development of extremely efficient detection algorithms using vast datasets containing various plant leaf diseases. Requiring large generalised datasets would assist to balance out the class imbalance. In future, image localization techniques can be used in order to pinpoint the precise location of the leaf's damaged portion. To put this model into action, a Flask application programming interface (API) might be constructed.

## References

[1] Newlin Shebiah Russel and Arivazhagan Selvaraj. Leaf species and disease classification using multiscale parallel deep CNN architecture. *Neural Computing and Applications*, 34:19217–19237, 2022.

[2] Heba Al-Hiary, Sulieman Bani-Ahmad, M Reyalat, Malik Braik, and Zainab Alrahamneh. Fast and accurate detection and classification of plant diseases. *International Journal of Computer Applications*, 17:31–38, 2011.

[3] Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk, and Darko Stefanovic. Deep neural networks based recognition of plant diseases by leaf image classification. *Computational intelligence and neuroscience*, 2016.

[4] R Chavan, A Deoghare, R Dugar, and P Karad. Iot based solution for grape disease prediction using convolutional neural network and farm monitoring. *International Journal of Scientific Research and Engineering Development*, 2019.

[5] T Suman and T Dhruvakumar. Classification of paddy leaf diseases using shape and color features. *IJEEE*, 7:239–250, 2015.

[6] Jayme Garcia Arnal Barbedo. Digital image processing techniques for detecting, quantifying and classifying plant diseases. *SpringerPlus*, 2:1–12, 2013.

[7] Changjian Zhou, Sihan Zhou, Jinge Xing, and Jia Song. Tomato leaf disease identification by restructured deep residual dense network. *IEEE Access*, 9:28822–28831, 2021.

[8] Archana Chaudhary, Savita Kolhe, and Raj Kamal. An improved random forest classifier for multi-class classification. *Information Processing in Agriculture*, 3:215–222, 2016.

[9] Anisha Kumari, Satya Prakash Sahoo, Ranjan Kumar Behera, and Bibhudatta Sahoo. Supervised machine learning for link prediction using path-based similarity features. In *2020 IEEE 17th India Council International Conference (INDICON)*, pages 1–7. IEEE, 2020.

[10] Ananda S Paymode, Shyamsundar P Magar, and Vandana B Malode. Tomato leaf disease detection and classification using convolution neural network. In *2021 International Conference on Emerging Smart Computing and Informatics (ESCI)*, pages 564–570. IEEE, 2021.