Utilitas Mathematica
ISSN 0315-3681 Volume 122, 2025

Disease Detection of Apple Leaf Using Machine Learning Techniques

Patiballa Subrahmanya Kasyap[1], Dr. Prasanth Yalla[2]

[1,2]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Guntur, Andhra Pradesh, India, 522302.

[1]kasyappatiballa@gmail.com, [2]prasanthyalla@gmail.com

ABSTRACT

Application of farming in sample and identification of diseased leaves is another area where farming can bring a revolution in terms of disease control through the use of machine learning. Building, in essence, works with loopholes with the aid of state-of-the-art computation to learn plant diseases through the depiction of pictures. This process integrates multiple stages, and one of the first is data acquisition: the necessary set of images of leaves of different access was collected, and the method of support SVM's would be a large space of diseased and non-diseased samples in comparison to the other classifiers. This implies that before getting into the AI model, the data is subjected to several processing steps that yield features suitable for the model. increase the extent of image detail of current objects of interest and acquire new sources for the current corpus. There are basically artificial neural network approaches here, and among these, convolutional neural networks (CNNs) are used most in the current time. This comes from the capacity to regulate and decide on the hierarchy attributes of the distinct pictures and patterns. Model selection reaches even the activity of comparing features of some algorithms to make the correct choice among the available ones, using criteria of efficacy, for instance, including accuracy and precision. In other words, there is a significantly large phase of checking the accuracy of the model in another dataset entirely different from the input data set, whose aim is to determine the generality and overall robustness of the model in any other data set.

Keywords:

Support Vector Machine (SVM), Convolutional Neural Network (CNN).

1. INTRODUCTION

Identification of the diseases that affect the leaves is relevant to understanding the general and particular state of plants and, therefore, crops. Many existing screening processes, including asymptomatic disease screenings, have significant levels of administration and high error rates because they rely on professional experience. To counter these challenges, this study puts forward a strategy that utilizes machine learning in both detection and categorization of the diseases in the leaves. From the presented results, it is evident that the proposed system is capable of distinguishing between different diseases from the images of the leaf by applying the principles of CNN's image analysis. Some of the important steps familiar to the technique are data acquisition, initial data preparation, feature extraction or acquisition, model training, and model evaluation. Besides that, to enhance the model's reliability, more samples of healthy and sick leaves were also gathered and included. Tasks such as scaling down the images, normalizing the images, or adding an augmentation process to the data are done in preprocessing to enhance the quality and quantity of the feed data. CNNs are used in feature extraction because of the effectiveness they portray in the identification of multi-scale structural patterns and textures in the image. It is also useful for preprocessing the given dataset before training the CNN model; one might employ such approaches as transfer learning and fine-tuning to boost the model's outcomes. Furthermore, during the testing phase, the informed model is passed through a distinct test set, and it performs fairly well in terms of correctly categorizing the illness. The results bring out the effectiveness of the assessed machine learning approach in diagnosing the cases of the aforesaid leaf illnesses, and such a type of method is advantageous in precision farming and early disease prevention.

2. LITERATURE SURVEY

[1] Melike Sardogan applied a range of machine learning-based technologies and sensors, the idea of "smart farming" is gaining momentum in today's agricultural sector. Recent polls show that 56% of the agriculture industry is experiencing significant losses as a result of illnesses that are developing on plant leaves. It is crucial for monitoring the spread of diseases and increase in agricultural production. To begin with, we must recognize the illness early on and take action to prevent its spread. In order to resolve this issue, we may thus apply specific algorithms to detect illness while on leave. The models of K-Nearest Neighbor (KNN), convolutional neural network (CNN), and support vector machine (SVM) are compared.

[2] Barenya Bikash Hazarika undertook a comprehensive study on this topic between 2010 and 2022 and found that researchers are frequently using multispectral or hyperspectral imaging to look into agricultural illnesses. Deep learning (DL) and machine learning (ML) models are used to classify different leaf diseases. We have developed a workflow framework for assisting researchers in this field. Support vector machines (SVM), Random Forest, and multiple twin SVM (MTSVM) are popular machine learning (ML) models for predicting leaf disease, while convolutional neural networks (CNN), visual geometry group (VGG), ResNet (RNet), GoogLeNet, deep CNN (DCNN), back propagation neural networks (BPNN), DenseNet (DNet), LeafNet (LN), and LeNet are popular deep learning models used for leaf disease detection. It is clear from using these deep learning models that CNN, VGG, and ResNet are some of the best models for identifying illnesses in leaves. Typically, criteria like accuracy, precision, and F1 score are employed to assess the algorithm's performance.

[3] Partha Sarathi S established an approach to recognize ailments in banana plant leaves automatically. Convolutional Neural Networks (CNN) have proven to be a useful tool for studying plant disease detection and classification; however, CNN is not able to reliably record the posture and orientation of objects due to inherent constraints in the max pooling layer. In view of these shortcomings, they adopted a unique paradigm called the Capsule Network (CapsNet). With a 95% test accuracy, the constructed model recognized black sigatoka, healthy leaves, and banana bacterial wilt. In terms of rotation invariance, it fared better than ResNet50, LeNet5, and built a trained CNN

model from scratch. Nevertheless, the suggested model has been surpassed by the test dataset using the ResNet50 architecture without any rotation.

[4] Kushal M U and Nikitha M used leaf maladies may be recognized via feature extraction techniques like as template matching, thresholding, blob extraction, Hough transformation, and generalized histogram of oriented gradients (HoG) transformation, among others. It might be complicated to obtain data from a leaf image if the illness shows erratic patterns of presence. Commonly used feature extraction techniques may be used to extract several components of the sick leaf picture, such as the background leaf image, the damaged leaf area, and the leaf's green section. The range of forms, patterns, and colors makes it difficult to identify leaf disease in a shot. One instance where traditional approaches are inadequate is the identification of leaf diseases. Another type of issue is weather that is both sunny and overcast.These difficulties make it difficult to identify various diseases in leaf photos.

[5] Grabka et al. put out the hypothesis that fungi can work as endophytes to protect against species other than insects, including bacteria, nematodes, viruses, fungi, and mites. It has been observed that in the agricultural sectors of some countries, reduced plant productivity is causing food insecurity. Thus, several plant diseases diminish the quantity and quality of essential commodities including wood, fruits, vegetables, flowers, leaves, and blooms. Early detection of leaf disease limits the disease's spread by assisting farmers in identifying the many disease types present in damaged plants. It has been shown in recent years that the use of machine learning algorithms improves the accuracy of leaf disease diagnosis. Support vector machines (SVM), k closest neighbor (KNN), artificial neural networks (ANN), convolutional neural networks (CNN), deep neural networks (DCNN), and other machine learning (ML) and deep learning (DL) classification algorithms have been employed to analyze leaf detection.

3. METHODOLOGY

3.1 Model building :

While forming the CNN model for the identification of leaf diseases, the following are some of the points that need to be considered with the aim of making the process easier: The ‘function’ in penetration learning models mostly involves CNNs, where received information is translated into an image that is then distinguished. However, prior to commencing with establishing a basic CNN, there is a need to pre-register its attributes and the layouts of the incorporated components, that is, layers and nodes. Section I of the above work has pointed out that there is normally more than one convolution layer that extracts the feature independently; the mentioned pooling layers and the normal fully connected layer are mainly used to make the decision. Finally, each convolutional layer also takes an image, and the latter is then passed through a succession of convolutional layers that help detect features like edges, texture, or patterns in general that have a link to disease in some way. For this reason, these pooling layers are advantageous in the generalization feature process since they also reduce this parameter while increasing the computation at the same time. The set of such photo images of leaves of plants of a given type is a matrix that includes objects, the training set of which is composed of a matrix array of categories. This was also the case with backpropagation occurring in both of them as a form of optimizer, as was the case with stochastic gradients.

3.2 Disease detection :

Picture capture is the first step of the image processing pipeline, whose objective is to produce a high-quality image that would be suitable for additional processing stages. At this stage, a host of tools—digital cameras, scanners, and specialized sensors—make the task of image capture possible. Kaggle is used here for collecting a huge amount of data. The resolution and clarity of the image hence impact significantly on the effectiveness of the other remaining image processing steps. A well-lit scene with clarity, free of any form of distortion or aberration, will certainly ensure a quality photograph. Many factors are at play in this, ranging from lighting to camera settings and ambient circumstances.

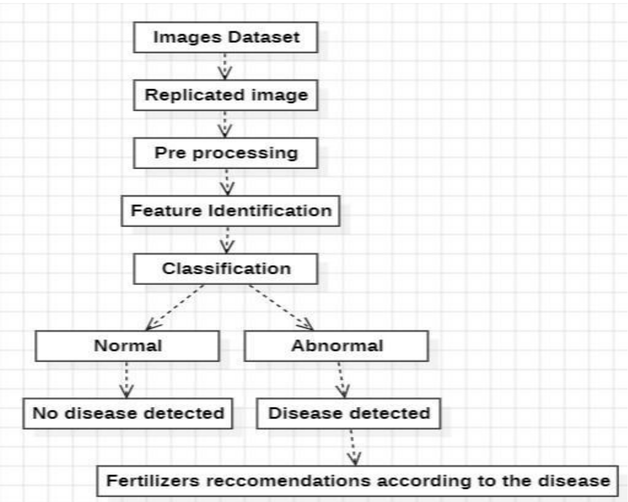

Figure 1 : Flow chart of leaf disease detection

3.3 Convolutional Neural Network :

CNN is one kind of deep neural network. As indicated in Figure 2, the CNN model has been constructed with an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer. The images are fed as an input to the developed model to precisely identify the sickness of the plant. The convolution layer will extract the features of the given image. The pooling layer calculates feature values based on the features obtained. Convolution and pooling can be boosted further depending on how complex the images are to get more information. Finally, a completely connected layer encompasses the prior output of layers into a single vector, which is then fed in as input for the layer that comes after it. Finally, the output layer is used to classify plant diseases.

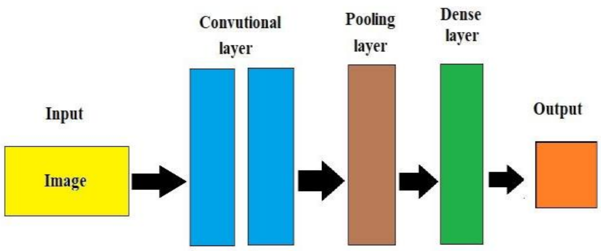

Figure 2 : CNN Model

3.4 Fertilizer recommendation system :

In addition, with optical leaf disease recognition technology that involves a fertilizer recommendation system, it could optimize agricultural practices. The technology works with high accuracy since it detects diseases by analyzing images of the plant leaves and combining machine learning with image processing techniques. The approach considers nutrient deficiencies or disorders with respect to a specific identified ailment. This information is used to formulate personalized fertilizer recommendations based on the individual requirements of plants. Since this provides the plants with the capacity to fight disease and ensure healthy growth, demand for broad-band fertilizers is reduced while crop productivity is increased. This focused approach reduces the environmental impact of excessive application of fertilizers while improving plant health and productivity.

4. DATASET

It contains photographs of apple leaves at different stages of health and those suffering from some common diseases. Cedar rust, black rot, and apple scab are three of the most common diseases that can be found in these datasets. High-resolution photos are normally taken under different conditions to ensure the model is trained accurately. To supervise learning, each image in the dataset is annotated to indicate whether it represents a healthy or unhealthy leaf. There are three key divisions of the dataset: training, validation, and testing. While training a machine learning model, this division is, therefore, important because one can only allow the model to learn on the training set, tune parameters on the validation set, and finally test on the test set with the objective of proving that it works and is generalizable. Due to the subset of photos kept in folders with class labels like "Apple_scab," "Apple_black_rot," and "Apple_cedar_rust," it becomes easier to maintain and retrieve the data.

Dataset Name	Data Type	Size	Disease Types	Source/Remarks
PlantVillage Dataset	RGB Images	~54,000 images	Multiple plant diseases	Widely used benchmark for DL models
Multispectral Data	Multispectral Images	Varies	Hyperspectral analysis	High precision in detecting disease areas
Banana Leaf Dataset	RGB Images	~5,000 images	Black sigatoka, wilt	Used for CapsNet-based disease detection
Custom Leaf Dataset (Hazarika, 2022)	Hyperspectral Images	Varies	General leaf diseases	Used to study hyperspectral imaging impact

Figure 3 : Dataset description

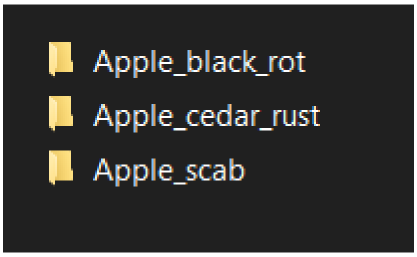

Figure 4 : Dataset folder

Comparative Table:

Model	Type	Advantages	Limitations	Performance Metrics	Remarks
K-Nearest Neighbor (KNN)	ML	Simple to implement, effective for small datasets	Computationally intensive for large datasets	Accuracy: Moderate	Used for basic leaf disease detection
Support Vector Machine (SVM)	ML	Effective in high-dimensional spaces	Poor scalability with large datasets	Precision: High	Popular for traditional ML-based classification
Convolutional Neural Network (CNN)	DL	Automatic feature extraction, robust for image analysis	Struggles with rotation invariance	Accuracy: High	Often used for general leaf disease detection
ResNet	DL	Handles vanishing gradients, deep architecture	May require large computational resources	Accuracy: Very High	Superior to traditional CNN in many cases
Capsule Network (CapsNet)	DL	Captures object orientation, rotation invariance	Computationally expensive	Test Accuracy: 95%	Outperformed ResNet50 in rotation invariance
Random Forest	ML	Handles non-linear relationships well, interpretable results	Prone to overfitting with noisy data	Accuracy: Moderate to High	Suitable for smaller datasets
DenseNet (DNet)	DL	Efficient parameter usage, avoids redundancy	High computational demands	Accuracy: Very High	Suitable for complex disease classification

5. RESULTS

We trained our convolutional neural network model and got better accuracy with a low error rate. Now, the model can say which type of disease the leaf has. The model will provide three types of outputs. They are actual outcomes, predicted outcomes, and recommendations. If our model has a good accuracy rate, our actual outcome and the predicted outcome will be the same. Here, the fertilizer recommendation is based on the disease that inflicts the leaf. For the 3 types of diseases, we took 3 fertilizers: micronutrients, compost and organic matter, and silicon supplements. The well-balanced score of 96% confirms the robustness of the model against the classification task. Very important is that it underlines the feasibility of custom CNN models in leaf disease detection and their huge potential to bring improvements in the envisioned fields of precision agriculture.

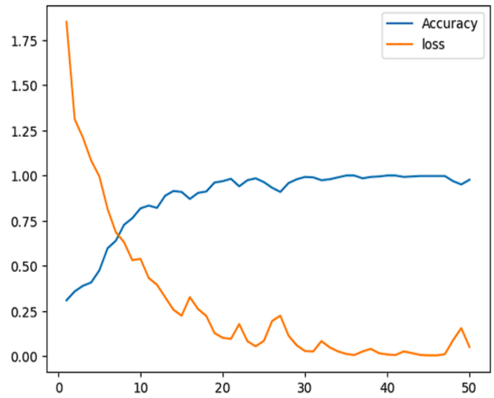

Figure 4 : Graphical representation of accuracy

6. ALGORITHM :

Input:

- Images of leaves (I) captured using multispectral or hyperspectral imaging.
- Pretrained weights for deep learning models (if applicable).
- Feature extraction parameters (color, texture, shape, etc.).

Preprocessing:

- Resize all images to a uniform size (W×H):

I′=Resize(I,W,H)

Convert images to grayscale or appropriate color channels for analysis (C):

I″=ConvertColor(I′,C)

Apply noise reduction using Gaussian filtering:
Ifiltered = GaussianFilter(I″,σ)

Feature Extraction:

- Histogram of Oriented Gradients (HoG): Compute gradients and orientations for disease regions:

Model-Based Classification:

- Traditional ML Models:

  Support Vector Machine (SVM):

  Train an SVM with extracted features:

$$\min \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}\xi_i$$

Subject to:

$$y_i(w^T\phi(x_i)+b) \geq 1-\xi_i,\ \xi_i \geq 0$$

K-Nearest Neighbors (KNN):

Predict disease type based on nearest feature vectors:

$$d(i,j) = \sqrt{\sum_{k=1}^{n}(x_{ik}-x_{jk})^2}$$

Deep Learning Models:

- Convolutional Neural Networks (CNN):

Utilize layers for automatic feature learning:

$$\text{Output} = f\left(W * X + b\right)$$

Train CNN with backpropagation:

$$L = -\sum_i y_i \log(\hat{y}_i)$$

Capsule Networks (CapsNet):

Incorporate spatial hierarchies for rotation invariance:

$$u_j = \text{Routing}(\sum_i c_{ij}W_{ij}u_i)$$

Evaluation Metrics:

- Compute performance metrics such as accuracy (A), precision (P), and F1 score (F1):

$$A = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN} + \mathrm{TN}}$$

$$P = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \quad F1 = \frac{2 \cdot P \cdot R}{P + R}$$

Output:

- Predicted disease label (D).

Post Processing:

- Highlight diseased regions on the image:

$$I_{\text{highlighted}} = \mathrm{Overlay}(B, I_{\text{original}})$$

7. MODEL TRAINING

For the image processing or machine learning tasks, there will be some important libraries which need to be imported. The tools required for managing data, displaying outcomes and creating models are provided by the libraries. To construct picture datasets for training and testing, the Python code imports the 'image_dataset_from_directory' function from the Keras library. Here we will get the information about the total number of classes, files and how many files will be used under training and how many will be used under validation. Now the class names should be justified. In the model training process, we will train the model by giving the respective dataset. For the apple leaf, we took 3 types of diseases which are Apple_scab, Apple_black_rot, Apple_cedar_rust. These were the three classes. Here comes the demonstration of how to Read and Display a Photo Below is the example of how to read and display a photo with the help of Matplotlib and OpenCV packages: These images in the beginning of the process are loaded from the file location specified using OpenCV's cv2. imread() function. However, as pictures as expected in Matplotlib are in RGB from Red, Green Blue respectively, while OpenCV images are in BGR from Blue, Green Red respectively the code first converts the image to RGB format by using cv2. cvtColor(). Subsequently for visualization Matplotlib is used for displaying the resultant image after color conversion. First of all, a figure of the needed size, for instance 3x3 inches, is drawn with the assistance of the plt. after calculating with the figure() function; then the RGB picture is obtained using plt. imshow(). Last but not the least, the title is placed on the image using plt. title("Apple scab"), and the axis labels are disabled by plt. axis('off'). The fundamental step of training a machine learning model with help of the framework such as TensorFlow or Keras. The below mentioned command actually kicks off the training process in which the model learns from the training data sample; train_ds. The fit() function is the method that is responsible for the training and takes the data and the labels in the form of train_ds and gradually updates the internal parameters of the model in the form of weights and biases till it obtains minimum errors. The training process will be set to 50 epochs, which means that the model will go through the data set 50 times trying to fine-tune its results. The outcome of this process is saved in the history variable, which is a History object that holds the specifics of the training performance such as the loss and accuracy of each epoch. The former information is useful for assessing how well the model is learning in the process and might help to adjust it.

When using a machine learning model, we can be required to illustrate the outcomes expected by the model on a part of the testing data. Firstly, a large plotting area is generated using Matplotlib as the library. We are going to layout nine images using 3 * 3 matrix markings. Then it obtains a batch of images and their associated labels in the test dataset of one batch_size. This operation includes and gets the image as well as the ground truth of the first nine images of this batch in addition to the predicted label. This prediction is made based on the image that has been passed through the model and then returns the actual label with which it is compared. In this manner, both the given actual label and the appearing predicted label for every subplot in the grid can be properly classified and compared. Although the axes are usually helpful in understanding the data, in this case, they are switched off to allow us to view only the images. Then the whole figure is presented when all the images along with predictions are depicted so that the viewer has a clear imagery of how the model is actually working on the given test dataset. This comes in handy to see how frequently the model is likely to make mistakes or correctly classify the patterns, which shows us what further finetuning is required during the evaluation stage. Then it is supposed to show the results obtained with a given test dataset, namely a set of images for which the model has made a prediction and given treatment recommendations. The code begins by showing an array of certain plant diseases, most of which correspond to recommended treatments like "Apple_black_rot: Silicon supplements" and "Apple_scab: Compost and organic matter." It then goes on to open a plot window with Matplotlib and loops through the first batch of nine images from the test dataset, building a 3X3 image plot out of these. It then takes the real label of each image, obtains a disease from the model, and finally seeks out the recommendation from the dictionary. A given subplot in a grid informs about the name of the ground truth and the predicted disease, followed by the suggested treatment. The layout of the model is changed to be more readable, then it adds the final figure which includes an easily understandable figure about the modeling and some practical advice from the modeling. It turned out that this approach allowed a user to estimate model accuracy and gather information at the same time, which is very convenient for using an ML model in such applications as early detection of diseases for agricultural crops, for example.

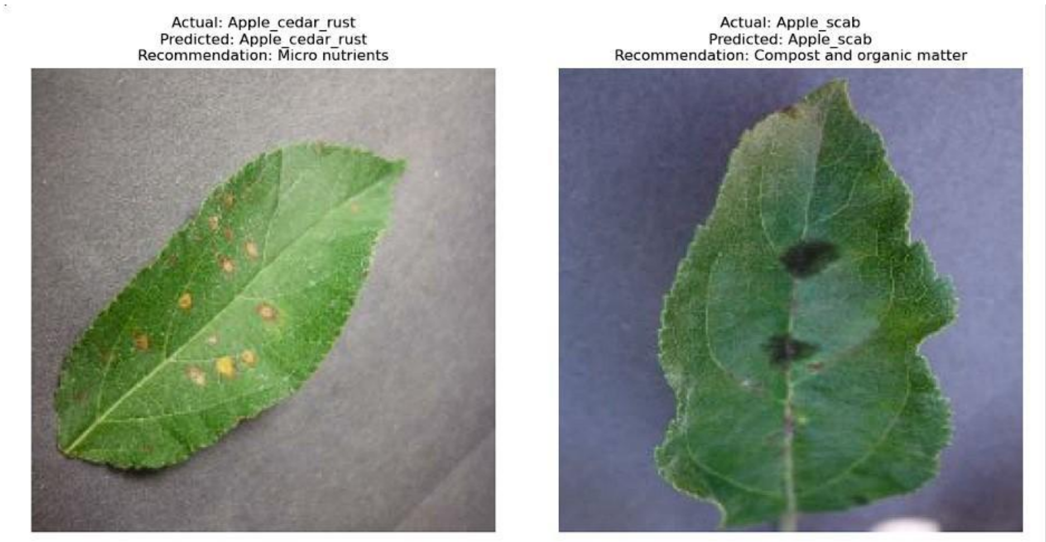

Figure 8 : Output

8. CONCLUSION

Consequently, the comparison of actual and projected labels showed that this model reasonably accurately and successfully detects a number of apple leaf illnesses. Its practical utility is improved through the addition of an interpretability layer, providing targeted therapy suggestions based on the expected illness. What makes it more valuable is the high accuracy of the system in disease detection and giving practical recommendations, therefore very resourceful to farmers and gardeners seeking intervention measures for efficient management and curing of apple leaf diseases. More testing and refinement are therefore advised for the sake of increasing spectra of diseases that might be detected and increasing the accuracy of the predictions. The hybridization of machine learning methodologies with leaf recognition has resulted in a manifold rise in automation and accuracy within botanical and allied fields. Moreover, as the datasets keep on growing and technology advances, the scalability and accuracy in leaf identification algorithms grow, opening new avenues for environmental care and sustainable development.

9. REFERENCES

1. Chittabarni Sarkar, Deepak Gupta, Umesh Gupta, Barenya Bikash Hazarika,Leaf disease detection using machine learning and deep learning: Review and challenges, 2023,Applied Soft Computing,Volume 145,2023,110534, ISSN 1568-4946

2. M. Sebastian, S. M S and C. M. Antony, "Apple Leaf Disease Detection: Machine Learning & Deep Learning Techniques," 2023 Intelligent Computing and Control for Engineering and Business Systems (ICCEBS), Chennai, India, 2023, pp. 1-5, doi: 10.1109/ICCEBS58601.2023.10449037.

3. S. M. Jaisakthi, P. Mirunalini, D. Thenmozhi and Vatsala, "Grape Leaf Disease Identification using Machine Learning Techniques," 2019 International Conference on Computational Intelligence in Data Science

(ICCIDS), Chennai, India, 2019, pp. 1-6, doi: 10.1109/ICCIDS.2019.8862084.

4. Huang, Zhaohua, et al. "Grape leaf disease detection and classification using machine learning." *2020 international conferences on internet of things (iThings) and IEEE green computing and communications (GreenCom) and IEEE cyber, physical and social computing (CPSCom) and IEEE smart data (SmartData) and IEEE congress on Cybermatics (Cybermatics)*. IEEE, poi:10.1109/iThings-GreenCom-CPSCom-SmartData-Cybermatics50389.2020.00150.

5. K. Prabavathy, M. Bharath, K. Sanjay Ratnam, N. S. S. R. Reddy and M. S. Reddy, "Plant Leaf Disease Detection using Machine Learning," 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 2023, pp. 378-382, doi: 10.1109/ICAAIC56838.2023.10140367.

6. A. S. Tulshan and N. Raul, "Plant Leaf Disease Detection using Machine Learning," 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kanpur, India, 2019, pp. 1-6, doi: 10.1109/ICCCNT45670.2019.8944556.

7. P. Chaitanya Reddy, R. M. S. Chandra, P. Vadiraj, M. Ayyappa Reddy, T. R. Mahesh and G. SindhuMadhuri, "Detection of Plant Leaf-based Diseases Using Machine Learning Approach," *2021 IEEE International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS)*, Bangalore, India, 2021, pp. 1-4, doi: 10.1109/CSITSS54238.2021.9683020.

8. P.C Reddy, R. M. S. Chandra, P. Vadiraj, M.A Reddy, T. R. Mahesh and G.S Madhuri, "Detection of Plant Leaf-based Diseases Using Machine Learning Approach", 2021 IEEE (CSIT SS).

9. D. Varshney, B. Babukhanwala, J. Khan and D. Saxena, "Plant Disease Detection Using Machine Learning Techniques", 2022 3rd (INCET).

10. S. Pawar, S. Shedge, N. Panigrahi, A. P. Jyoti, P. Thorave and S. Sayyad, "Leaf Disease Detection of Multiple Plants Using Deep Learning," 2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON), Faridabad, India, 2022, pp. 241-245, doi: 10.1109/COM-IT-CON54601.2022.9850899.

11. T. Priya Radhika Devi, R. Mohan, T. Ragupathi, S. Prasanna, K. Madhan and R. Ananthi, "Leaf Disease Detection Using Machine Learning Algorithm," 2023 Eighth International Conference on Science Technology Engineering and Mathematics (ICONSTEM), Chennai, India, 2023, pp. 1-5, doi: 10.1109/ICONSTEM56934.2023.10142564.

12. Aneel Narayanapur, Pavankumar Naik, Priya B Kori, Naseem Kalaburgi, Rubiya I, Madhu M, “Leaf Disease Detection of Agricultural plant Using Image Processing “, 2020 IJSRCSEIT | Volume 6 | Issue 3 | ISSN : 2456-3307, DOI : https://doi.org/10.32628/IJSRCSEIT.

13. U. P. Singh, S. S. Chouhan, S. Jain and S. Jain, "Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease," in *IEEE Access*, vol. 7, pp. 43721-43729, 2019, doi: 10.1109/ACCESS.2019.2907383
14. P. A. Dias, A. Tabb and H. Medeiros, "Multispecies Fruit Flower Detection Using a Refined Semantic Segmentation Network," in *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 3003-3010, Oct. 2018, doi: 10.1109/LRA.2018.2849498.
15. P. Lottes, J. Behley, A. Milioto and C. Stachniss, "Fully Convolutional Networks With Sequential Information for Robust Crop and Weed Detection in Precision Farming," in *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 2870-2877, Oct. 2018, doi: 10.1109/LRA.2018.2846289.
16. P. Bansal, R. Kumar and S. Kumar, "Disease detection in apple leaves using deep convolutional neural network", *Agriculture*, vol. 11, no. 7, pp. 617, 2021.
17. K. Sangeetha, P. Rima, P. Kumar and S. Preethees, "Apple leaf disease detection using deep learning", *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 1063-1067, 2022.
18. Simranjeet kaur, Geetanjali Babbar and Gagandeep, "Image Processing and Classification A Method for Plant Disease Detection", *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 9S, pp. 868-871, July 2019.
19. A. Bonkra, P. K. Bhatt, J. Rosak-Szyrocka, K. Muduli, L. Pilař, A. Kaur, et al., "Apple leave disease detection using collaborative ml/dl and artificial intelligence methods: Scientometric analysis", *International journal of environmental research and public health*, vol. 20, no. 4, pp. 3222, 2023.
20. J. U. M. Akbar, S. Fauzi Kamarulzaman and E. H. Tusher, "Plant Stem Disease Detection Using Machine Learning Approaches*," *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Delhi, India, 2023, pp. 1-8, doi: 10.1109/ICCCNT56998.2023.10307074.
21. S. M. Jaisakthi, P. Mirunalini, D. Thenmozhi and Vatsala, "Grape Leaf Disease Identification using Machine Learning Techniques", *Computational Intelligence*, Jan. 2019, [online] Available: https://doi.org/10.1109/iccids.2019.8862084.
22. J. Kotwal, R. Kashyap and S. Pathan, "Agricultural plant diseases identification: From traditional approach to deep learning", *Materials Today: Proceedings*, vol. 80, pp. 344-356, 2023.
23. K. Sahu, T. Saraswat, A. Singhal and G. Langer, "CNN Based Disease Detection in Apple Leaf via Transfer Learning", *2023*

24. *International Conference on Computational Intelligence Communication Technology and Networking (CICTN)*, pp. 447-451, 2023.
25. C. Sarkar, D. Gupta, U. Gupta and B. B. Hazarika, "Leaf disease detection using machine learning and deep learning: Review and challenges", *Applied Soft Computing*, pp. 110534, 2023.
26. J. U. M. Akbar, S. Fauzi Kamarulzaman and E. H. Tusher, "Plant Stem Disease Detection Using Machine Learning Approaches*," *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Delhi, India, 2023, pp. 1-8, doi: 10.1109/ICCCNT56998.2023.10307074.
27. S. Singh, I. Gupta, S. Gupta, D. Koundal, S. Aljahdali, S. Mahajan, et al., "Deep learning based automated detection of diseases from Apple leaf images", *Computers Materials & Continua*, vol. 71, no. 1, 2022.
28. A. I. Khan, S. Quadri and S. Banday, "Deep learning for apple diseases: classification and identification", *International Journal of Computational Intelligence Studies*, vol. 10, no. 1, pp. 1-12, 2021.
29. Davinder Singh, Naman Jain, Pranjali Jain, Pratik Kayal, Sudhakar Kumawat and Nipun Batra, "PlantDoc: A Dataset for Visual Plant Disease Detection", *CoDs COMAD Hyderabad*, January 2020.
30. I. Ahmed and P. K. Yadav, "Plant disease detection using machine learning approaches", *Expert Systems*, vol. 40, no. 5, pp. e13136, 2023.