International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Deep Learning Based Approach for Plant Disease Detection and Cure Recommendation

Ms. Shrutika Jadhav[1], Mrs. Rajeshwari Rasal[2]

[1]SYMCA, [2]Assistant Professor

MCA Dept, Dr. D. Y. Patil Institute of Master of Computer Applications & Management, Akurdi, Pune-44, India

[1]shrutiijadhav12@gmail.com, [2]rajeshwarirasal44@gmail.com

ABSTRACT

One of the essential components of human civilization is agriculture. It helps the economy in addition to supplying food. Plant leaves or crops are vulnerable to different diseases during agricultural cultivation. The diseases halts the growth of their respective species. Early and precise detection and classification of the diseases may reduce the chance of additional damage to the plants. The detection and classification of these diseases have become serious problems. Farmers' typical way of predicting and classifying plant leaf diseases can be tedious and erroneous. Problems may arise when attempting to predict the types of diseases manually. The inability to detect and classify plant diseases quickly may result in the destruction of crop plants, resulting in a significant decrease in products. Farmers that use computerized image processing methods in their fields can reduce losses and increase productivity.

Numerous techniques have been adopted and applied in the detection and classification of plant diseases based on images of infected leaves or crops. Researchers have made significant progress in the detection and classification of diseases in the past by exploring various techniques. However, improvements are required as a result of reviews, new advancements, and discussions.

The use of technology can significantly increase crop production all around the world.

Previous research has determined the robustness of deep learning (DL) and machine learning (ML) techniques such as k-means clustering (KMC), naive Bayes (NB), feed-forward neural network (FFNN), support vector machine (SVM), k-nearest neighbor (KNN) classifier, fuzzy logic (FL), genetic algorithm (GA), artificial neural network (ANN), convolutional neural network (CNN), and so on. In this particular study deep learning and machine learning based techniques have been adopted.

CNNs are often the favored choice for image detection and classification due to their inherent capacity to autonomously acquire pertinent image features and grasp spatial hierarchies. Nevertheless, the selection between conventional ML and DL hinges upon the particular problem, the accessibility of data, and the computational capabilities accessible. Accordingly, in numerous advanced image detection and classification tasks, DL, mainly through CNNs, is preferred when ample data and computational resources are available and show good detection and classification effects on their datasets, but not on other datasets.

***Keywords*:** Convolutional Neural Networks, Plant Disease detection, Image acquisition, pre-processing, features extraction, classification, symptoms, neural network.

I. Introduction

Agriculture plays vital role in Indian economy. Agriculture contributes nearly 17-18% country GDP. Due to various factors, sometime yield of the agriculture is not as good as expected. The agriculture yield is affected by nature as well as disease. The challenges in agricultural field are seed selection, irrigation techniques, soil defects, weather condition and water treatment . The virus, fungi and bacteria causes the plant disease. It is another challenge in the agriculture field. If the plant diseases are not correctly and timely identified, then it will

lead to heavy loss in the yield of crops. The identification of plant disease needs experts and infrastructure. It is not available in all places. The computer aided identification plant disease identification helps the experts to find the disease accurately and timely manner. The machine techniques are used to identify, classify and predict the plant's disease. The traditional machine techniques such as Support Vector Machine, Decision Tree classification, Random forest, Naïve Bayes are used for plant disease classification and prediction. Nowadays convolutional neural networks are used for plant disease classification and prediction [2-4]. The most important sector of our Economy is Agriculture. Various types of disease damages the plant leaves and effects the production of crop there for Leaf disease detection is important. Regular maintenance of plant leaves is the profit in agricultural products. Farmers do not expertise in leaf disease so they producing lack of production. Leaf disease detection is important because profit and loss depend on production. So that here use deep learning techniques to detect apple, grape, corn ,potato, and tomato plant leaves diseases. That contains twenty-four types of leaf diseases and twenty-four thousand leaves images are used. Apple, grape, corn, potato, and tomato plant leaves which are categorized total 24 types of labels apple label namely: Apple scab, Black rot, apple rust, and healthy. Grape label namely: Black rot, Esca, healthy, and Leaf blight. Corn label namely: Corn Cercospora spot Gray spot, Corn rust, Corn healthy, Corn Northern Blight. Potato label namely: Early blight, healthy, and Late blight. Tomato label namely: bacterial spot, early blight, healthy, late blight, leaf mold, septoria leaf spot, spider mite, target sport, mosaic virus. The dataset consist of 31,119 images of apple, grape, potato and tomato, all Images are resized into 256 x 256,that images divided into two parts training and testing dataset.

The main contribution of the paper is to predict the plant disease using convolutional neural network. The CNN extracts the features from plant and it identifies the disease of the plant.

II. Literature survey

A significant amount of research has been dedicated to the detection of leaf diseases using image processing throughout history, and it remains a popular area for ongoing research. Recently, automatic crop disease detection using image processing and machine learning has gained substantial prominence.

P.Krithika et al. [9] conducted image pre-processing by resizing, enhancing contrast, and converting color spaces. They used K-Means clustering for segmentation and extracted features using the Gray-Level Co-occurrence Matrix (GLCM). Classification was performed using a multiclass Support Vector Machine (SVM). Similarly, R. Meena et al. [10] converted primary colors of leaves into the LAB* color space and used K-Means clustering for segmentation, followed by GLCM and SVM for feature extraction and classification.

Bharat et al. [12] used a digital camera for image acquisition and a median filter for image enhancement. They applied K-Means clustering for segmentation and SVM for classification. Pooja et al. [13] focused on segmenting the infected regions of leaves using K-Means clustering, Otsu's detection for converting RGB to HSI, and later segmentation using boundary and spot detection algorithms. Rukaiyya et al. pre-processed images by adjusting contrast and normalization, converting colors to YCBCR, and applying bi-level thresholding. They used GLCM and Hidden Markov Models (HMM) for feature extraction and classification.

Chaitali et al. employed image segmentation for background subtraction and used KNN, ANN, and SVM methods for classification. KNN classified samples based on the nearest distance between training and testing subjects [17]. Varun et al. [19] developed a model using extraction thresholding techniques and morphological operations, followed by multiclass SVM for classification. For segmentation, they analyzed the color and luminosity components in LAB* color space, using GLCM for feature extraction.

Vijai Singh et al. [19] used samples of plant leaves, capturing images with a digital camera. They segmented the green regions using a thresholding algorithm and employed a genetic algorithm for further segmentation. Color co-occurrence was used to extract useful features from segmented images, followed by Minimum Distance Criterion and SVM for classification, achieving an average accuracy of 97.6%.

Sa'ed Abed et al. [20] improved input sample quality through scaling and stretching processes, created an HIS model, and segmented it using combined Euclidean distance and K-Means clustering. They used GLCM and SVM for feature extraction and classification. Arya et al. [21,22] transformed input RGB images into HIS format and segmented components using Otsu's method. Nema et al. [23] analyzed 81 images in the Lab color space, used K-Means clustering for segmentation, and SVM for disease classification, recording statistical information like mean, median, mode, and standard deviation.

Vidyashree Kanbur et al. [24] developed a model for leaf disease detection using multiple descriptors, tested on a local leaf database, demonstrating superior performance, though it could benefit from testing on publicly available datasets. Pushpa et al. [25] used an Indices Based Histogram technique to segment unhealthy leaf regions, outperforming other segmentation methods like slice segmentation, polygon approximation, and mean-shift segmentation. Kaleem et al. [26] pre-processed images by resizing them to 300x300 pixels, removing background noise, enhancing brightness, and adjusting contrast. They used K-Means clustering for segmentation and extracted useful features using Statistical GLCM, followed by SVM classification of leaf disorders. In 2015, S. Khirade et al. addressed the problem of plant disease detection using digital image processing techniques and a back propagation neural network (BPNN) . They explored various techniques for detecting plant diseases from leaf images, implementing Otsu’s thresholding followed by boundary detection and spot detection algorithms to segment the infected parts of the leaf. They then extracted features such as color, texture, morphology, and edges for classification, using BPNN to identify the plant diseases.

Shiroop Madiwalar and Medha Wyawahare analyzed different image processing approaches for plant disease detection in their study . They focused on color and texture features, testing their algorithms on a dataset of 110 RGB images. Features for classification included the mean and standard deviation of RGB and YCbCr channels, GLCM features, and the mean and standard deviation of images convolved with a Gabor filter. A support vector machine classifier was used for classification. They concluded that GLCM features effectively detect normal leaves, while color and Gabor filter features are best for detecting anthracnose-affected leaves and leaf spots, achieving a highest accuracy of 83.34% with all features combined.

Peyman Moghadam et al. demonstrated the use of hyperspectral imaging for plant disease detection . They used visible and near-infrared (VNIR) and short-wave infrared (SWIR) spectrums, employing a k-means clustering algorithm in the spectral domain for leaf segmentation. They proposed a novel grid removal algorithm for hyperspectral images, achieving 83% accuracy with vegetation indices in the VNIR range and 93% accuracy with the full spectrum. However, their method requires a costly hyperspectral camera with 324 spectral bands.

Sharath D. M. et al. developed a bacterial blight detection system for pomegranate plants using features such as color, mean, homogeneity, standard deviation, variance, correlation, entropy, and edges . They implemented grab cut segmentation to segment the region of interest and used the Canny edge detector to extract edges. Their system successfully predicts the infection level in the fruit.

Garima Shrestha et al. deployed a convolutional neural network (CNN) to detect plant diseases, successfully classifying 12 diseases with 88.80% accuracy . They used a dataset of 3000 high-resolution RGB images, with a network comprising three blocks of convolution and pooling layers, making it computationally expensive. Despite its accuracy, the model had a low F1 score of 0.12 due to a high number of false negative predictions.

III. Methodology

3.1 Dataset

For this paper we have used public dataset for plant leaf disease detection called "PlantDoc: A Dataset for Visual Plant Disease Detection". The dataset consists 2,598 data points in total across 13 plant species and up to 17 classes of diseases. Some samples from the dataset are shown in Fig. 1.

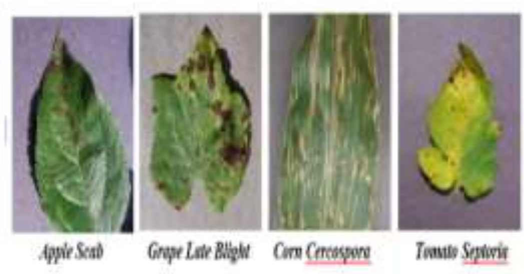


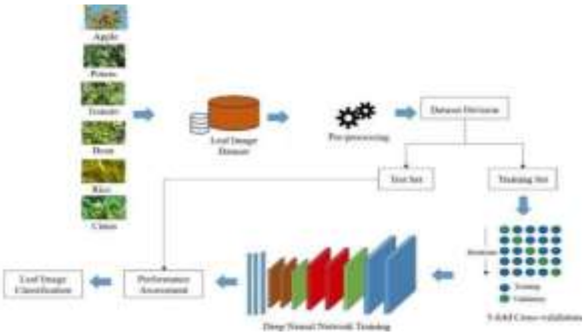
Fig. 1 Sample images from the dataset

3.2 Methodology :

To detect plant leaf diseases, the first step is to collect a dataset of images with both healthy and diseased leaves that accurately represent real-world scenarios. The collected images are preprocessed by removing noise and irrelevant information through techniques such as normalization and data augmentation. The selected model for this task is typically a Convolutional Neural Network (CNN). The dataset is then split into training, validation, and testing sets, and the model is trained on the training set while monitoring its performance on the validation set. After training, the model is evaluated on the testing set to measure its accuracy, precision, recall, and F1-score. If the model is not performing well, optimization techniques such as transfer learning or data augmentation can be used to improve its performance. Once the model is optimized, it can be deployed in a real-world scenario by integrating it into an application. This process involves a cyclical approach of data collection, preprocessing, model selection, training, evaluation, optimization, and deployment until the desired level of accuracy is achieved. The details are explained in the later Algorithms part.

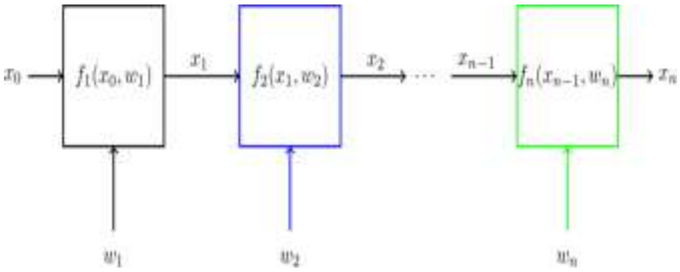
3.3. System Architecture:

Convolutional Neural Networks (CNNs) are widely adopted for analyzing and classifying digital images, especially in the field of plant leaf disease detection. These algorithms are designed to effectively capture and process image features through multiple layers of filters and nonlinear operations. The CNNs are proficient in handling large datasets and can dynamically learn new features from them in a supervised manner. By learning the important features from the input images, CNNs can make accurate predictions about the presence of diseases in plant leaves. Keras is a high-level API used to build and train deep neural networks for various machine learning tasks, including image processing. It offers a user-friendly interface for constructing complex neural network models by providing pre-built layers and modules. Keras is written in Python, which is a popular programming language in the field of machine learning. With Keras, developers can easily build deep neural networks, including CNNs, without having to worry about the low-level details of the underlying hardware and software. The system can use a predefined database of pesticides and their corresponding diseases to suggest the most effective treatment. The user can then choose to apply the recommended pesticide or seek further advice from a plant specialist. It is important to note that the use of pesticides should always be done with caution and in accordance with local regulations and guidelines. Overuse or misuse of pesticides can lead to adverse effects on the environment and human health.



1.Conv2D:

It is a 2D Convolution Layer, this layer creates a convolution kernel that's wind with layers input which helps produce a tensor of outputs.



2.Maxpooling:

Max pooling may be a pooling process that choose the very best element from the region of the feature map covered by the filter. Thus, the output after max-pooling level would be a feature map comprising the foremost important features of the previous feature map. [10].

3.Flatten:

In between the convolutional layer and therefore the fully connected layer, there is a 'Flatten' layer. Flattening transforms a two-dimensional matrix of features into a vector which will be fed into a totally connected neural network classifier.

4.Image Data Generator:

Image Data Generator quickly found out Python generators which will automatically turn image files on disk into batches of preprocessed tensors.

5.Epochs:

An epoch may be a term utilized in machine learning and indicates the amount of passes of the whole training dataset the machine learning algorithm has completed. Datasets are usually grouped into batches (especially when the quantity of knowledge is extremely large).

6.Validation Process:

Validation is mentioned because the process where a trained model is evaluated with a testing data set. The testing data set may be a separate portion of an equivalent data set from which the training set springs the most purpose of using the testing data set is to check the generalization ability of a trained model.

7. Testing Model:

The dataset is preprocessed like Image reshaping, resizing and conversion to an array form. Similar processing is additionally done on the test image. The dataset consisting of about 38 different plant leaf diseases is obtained, out of which any image is often used as a test image for the software.

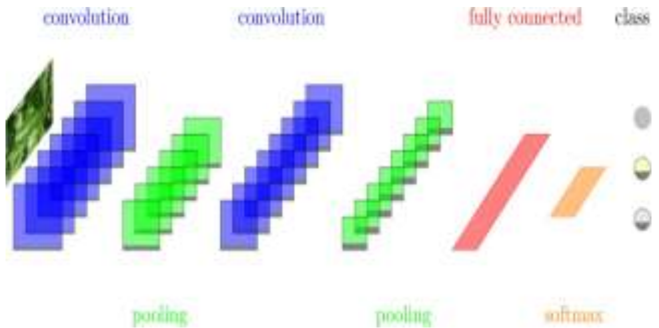
The train dataset is employed to coach the model (CNN) so that it can identify the test image and therefore the disease it is CNN has different layers that are Dense, Dropout, Activation, Flatten, Convolution2D, and maxpooling2d. After the model is trained successfully, the software can identify the disease if the plant species is contained within the dataset. After successful training and preprocessing, comparison of the test image and trained model takes place to predict the disease.

The testing is a dataset utilized to provide an impartial final design fit evaluation on the training set of data. In this stage, we use the groups that were trained in the previous step that was trained in CNN, and the features were extracted by learning the network when the data set passes from plant leaf diseases on this network, we used 13% of the data for testing.

8.Convolutional Neural Networks (CNNs), a type of multi-layer neural network, are specifically engineered to discern relationships within grid-structured inputs like images and textual data. The fundamental characteristic that distinguishes CNNs is the application of convolution operations across numerous intermediate layers. This convolution operation involves computing the dot product between a set of grid-based weights and a corresponding set of similarly

structured inputs. This mechanism enables CNNs to effectively extract relevant features and patterns from complex input data, facilitating tasks such as image recognition and natural

CNNs have become a staple in various fields such as healthcare, web services, and communication platforms due to their versatility in handling diverse data types like images, videos, audio, and text. They are extensively employed for tasks like image classification, segmentation, face recognition, and object detection.



10.Training and Fine Tuning of the Model:

1. Training:

The main aim is to design a system which is efficient and which provide disease name and pesticides name as fast as possible. For that purpose, we use two phases: 1st is training phase and 2nd is testing phase. In Ist phase: Image acquisition, Image Pre-processing and CNN based training. In 2nd phase Image acquisition, Image Pre-processing, Classification and disease identification and suggest appropriate remedies.

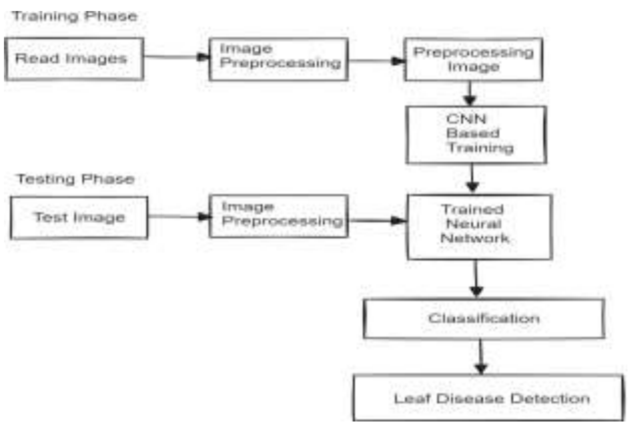
Training a network is a procedure of obtaining kernels in convolution layers and weights in fully connected layers that reduce differences on a training dataset between output predictions and specified ground truth labels. In our work, we used 87% of the data for training, through this stage so that the network that has been built learns by extracting features from plant leaf disease images to learn from these features for each image to be distinguished on its basis

A. Image Acquisition:

For training, an image is taken from a file on the system. To test the images of the plant leaves are captured as and when required and then transferred to a folder on the system for analysis.

B. Image Pre-Processing:

The image should be processed before sending to the algorithm for testing and training purposes. For that purpose, in this project image is scaled or resized into 50 x 50 dimensions. We used color images so that we don't need any color conversion techniques and that pre-processed images are directly passed to an algorithm for training and testing purposes.



3.Convolutional Neural Network:

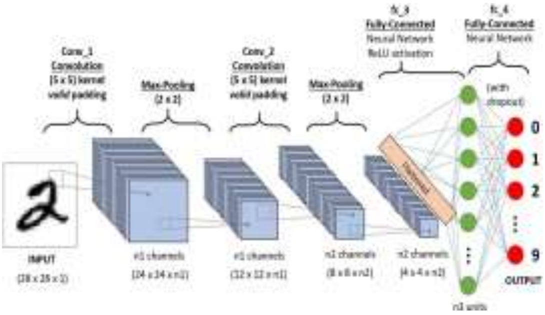
Once pre-processing is done, then CNN is used for training purposes and after that, we get a trained model. That CNN method is written with the help of tensor flow. By using this model, we classify the image that the system is getting after pre-processing of testing image. Then we get a particular disease name or status of a healthy leaf if there is no disease on that leaf. With the help of that disease name, we get the remedies that will help the farmer to take action to eradicate or decrease the effects of the disease.

4.Pooling Layer:

A pooling layer often follows a convolutional layer and can be utilized to depreciate the dimensions of feature maps and parameters of the network. Pooling layers are also invariant in interpretation, like convolutional layers because their calculations take into account neighboring pixels. The most widely used approaches are average pooling and max pooling In our research, we used a max-pooling layer.

5.Non-Linear Layer:

A non-linear transformation is applied to the input by the CNN, the object of which is to classify the features within per hidden layer. In CNN structure we use Rectified linear units (ReLU). Rectified linear units are commonly used as nonlinear transformations. This kind of layer executes a simple operation with a threshold where any input value smaller than zero is set to zero.



6. Detection for Plant leaf Diseases:

After the previous operations, plant species diseases are detected and classified according to three types of plant diseases, namely bacterial spots, late blight and yellow curl leaf virus.

7.Fine-Tuning the model:

Transfer Learning is a simple approach for re-purposing a pre-trained model to make predictions on a new dataset. The concept is straightforward. One utilizes the model's pre-trained feature extractor (convolutional base) and re-trains a new classifier to learn new weights for the new dataset. This is sometimes referred to as "freezing" the layers in the feature extractor, indicating that the pre-trained weights are loaded and not modified further during the training process. The theory is that the pre-trained model has learned valuable features for detecting many different object types. It is assumed that such features are general enough that only re-training the classifier portion of the network is necessary. This approach requires much less data and computational resources than training from scratch. Transfer learning allows one to quickly study how a pre-trained model can be customized for a new dataset. However, sometimes retraining the classifier isn't enough. This is where Fine-Tuning can be very beneficial.

3. Results and discussion

We have developed a flask based web application for detecting the plant disease Fig 2 shows the homepage of web application and Fig 3,4,5 shows the input images and their corresponding predictions made by our system. It shows that the system successfully detected the disease of leaf.

Fig.3. Home Page

Fig.4. Application Screen

Fig.5. Plant leaf image and sample output

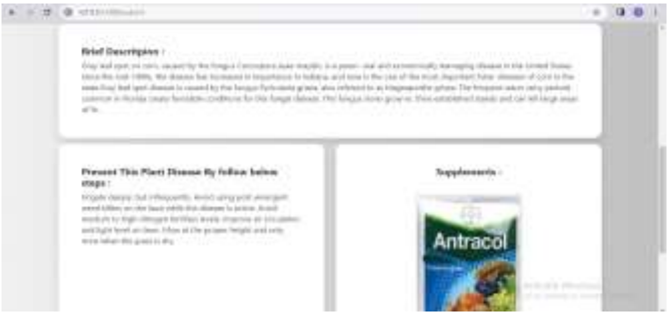


Fig.6. Sample Recommendation

4.Conclusion

We have successfully developed a computer vision based system for plant disease detection with average 93% accuracy. Also the proposed system is computationally efficient because of the deep learning and machine learning model

We can observe that our technique is accurate and efficient.

Also it won't require a specialized hardware, makes it cost effective solution

5.References

1. 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, doi: 10.1109/ICCUBEA.2015.153.

2. S. C. Madiwalar and M. V. Wyawahare, "Plant disease identification: A comparative study," 2017 International Conference on Data Management, Analytics and Innovation (ICDMAI), 2017, pp. 13-18, doi: 10.1109/ICDMAI.2017.8073478.

3. 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, doi:10.1109/DICTA.2017.8227476.

4. S. D.M., Akhilesh, S. A. Kumar, R. M.G. and P. C., "Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight," 2019 International Conference on Communication and Signal Processing (ICCSP), 2019, pp. 0645-0649, doi: 10.1109/ICCSP.2019.8698007.

5. G. Shrestha, Deepsikha, M. Das and N. Dey, "Plant Disease Detection Using CNN," 2020 IEEE Applied Signal Processing Conference (ASPCON), 2020, pp. 109-113, doi: 10.1109/ASPCON49795.2020.9276722.

6. Mohanty SP, Hughes DP and Salathé M (2016) Using Deep Learning for Image-Based Plant Disease Detection. Front. Plant Sci. 7:1419. doi: 10.3389/fpls.2016.01419

7. R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural Features for Image Classification," in IEEE Transactions on Systems, Man, and Cybernetics, vol. SMC-3, no. 6,pp. 610-621, Nov. 1973, doi: 10.1109/TSMC.1973.4309314.

8. Breiman, L. Random Forests. Machine Learning 45, 5–32 (2001). https://doi.org/10.1023/A:1010933404324

9.P Krithika, S Veni, Leaf disease detection on cucumber leaves using multiclass sup-port vector machine, in: IEEE International Conference on Wireless Communica-tions, Signal Processing and Networking, 2017, pp. 1276–1281.

10. R. Meena , "modern approach for plant leaf disease classification which depends on leaf image processing," IEEE International Conference on Computer Communication and Informatics (2017), pp. 12-16

11. R Prakash, G P Saraswathy, G Ramalakshmi, Detection of leaf diseases and classification using digital image processing, in: IEEE International Conference on Innovations in Information, Embedded and Communication Systems, 2017, pp. 1–4.

12. B Mishra, S Nema, M Lambert, S Nema, Recent technologies of leaf disease detection using image processing approach-review, in: IEEE International Conference on Innovations in Information, Embedded and Communication Systems, 2017, pp. 1–5.

13. C. Puttamadappa, B.D. Parameshachari, Demand side management of small scale loads in a smart grid using glow-worm swarm optimization technique, Microprocessors Microsyst. 71 (2019) 102886.

14.V Pooja, R Das, V Kanchana, Identification of plant leaf diseases using image processing techniques, in: IEEE International Conference on Technological Innovationsin ICT for Agriculture and Rural Development, 2017, pp. 130–133.

15 D.L. Vu, T.K. Nguyen, T.V. Nguyen, T.N. Nguyen, F. Massacci, P.H. Phung, HIT4Mal:hybrid image transformation for malware classification, Trans. Emerging Telecom-mun. Technol. 31 (11) (2020) e3789.

16 R P Shaikh, S A Dhole, Citrus Leaf Unhealthy Region Detection by using Image Pro-cessing Technique, in: IEEE International Conference on Electronics, Communication and Aerospace Technology, 2017, pp. 420–423.

17. K. Yu, L. Lin, M. Alazab, L. Tan, B. Gu, Deep learning-based traffic safety solution for a mixture of autonomous and manual vehicles in a 5G-enabled intelligent transportation system, IEEE Trans. Intell. Transp. Syst. 22 (7) (2020) 4337–4347.

18. Chaitali G Dhaware, K H Wanjale, A modern approach for plant leaf disease classification which depends on leaf image processing, in: IEEE International Conferenceon Computer Communication and Informatics, 2017, pp. 12–16.

19. J.P. Nayak, K. Anitha, B.D. Parameshachari, R. Banu, P. Rashmi, PCB Fault detection using Image processing, IOP Conference Series: Materials Science and Engineering, 225, IOP Publishing, 2017.

20.R P Narmadha, G Arulvadivu, Detection and measurement of paddy leaf disease symptoms using image processing, in: IEEE International Conference on Computer Communication and Informatics, 2017, pp. 1–4.

21. C.H. Nguyen, T.L. Pham, T.N. Nguyen, C.H. Ho, T.A. Nguyen, The linguistic summarization and the interpretability, scalability of fuzzy representations of multi level semantic structures of word-domains, Microprocessors Microsyst. 81 (2021)

103641.

22.V Gupta, N Sengar, M Dutta, C Travieso, J Alonso, Automated segmentation of powdery mildew disease from cherry leaves using image processing, in: IEEE International Conference and Workshop on Bioinspired Intelligence, 2017, pp. 1–4.

23. K. Yu, L. Tan, L. Lin, X. Cheng, Z. Yi, T. Sato, in: Deep-learning-empowered breast cancer auxiliary diagnosis for 5GB remote E-health, 28, IEEE Wireless Communications, 2021, pp. 54–61.

24. Vijai Singh, A.K. Misra, Detection of plant leaf diseases using image segmentation and soft computing techniques, Inf. Process. Agricult. 4 (1) (2017) 41–49.

25. S Abed, A Esmaeel, A novel approach to classify and detect bean diseases based on image processing, in: IEEE Symposium on Computer Applications & Industrial Electronics, 2018, pp. 297–302.

26.S.M. Nagashetti, S. Biradar, S.D. Dambal, C.G. Raghavendra, B.D. Parameshachari, Detection of disease in Bombyx Mori Silkworm by using image analysis approach, in: 2021 IEEE Mysore Sub Section International Conference (MysuruCon), IEEE, 2021, pp. 440–444.

27. M Arya, K Anjali, D Unni, Detection of unhealthy plant leaves Using image processing and genetic algorithm with Arduino, in: IEEE International Conference on Power, Signals, Control and Computation, 2018, pp. 1–5.

28. G. Chandrasekaran, T.N. Nguyen, D Hemanth, Multimodal sentimental analysis for social media applications: A comprehensive review, Wiley Interdisciplinary Rev. 11 (5) (2021) e1415.

29. S Hossain, R Mou, M Hasan, S Chakraborty, A Razzak, Recognition and detection of tea leaf's diseases using support vector machine, IEEE Int. Colloquium Signal Process. Appl. (2018) 150–154.

30. J. Zhang, K. Yu, Z. Wen, X. Qi, A.K. Paul, 3D reconstruction for motion blurred images using deep learning-based intelligent systems, CMC-Comput. Mater. Continua66 (2) (2021) 2087–2104. 309