FloraCheck: Pioneering for Leaf Disease Recognition

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Abstract

The major source of our economy, which is the agricultural sector, is seriously threatened by plant diseases. They negatively impact crops and the means of livelihood for farming communities. The need for automated solutions becomes evident when we consider how labor-intensive and error-prone traditional manual methods are for identifying illnesses. Our study FloraCheck investigates plant disease identification using the EfficientNetB3 model by using deep learning. We have chosen the PlantVillage dataset and implemented advanced image preprocessing techniques for effective model training. Existing approaches show differences in the data and models they use and often struggle with limitations such as dataset specificity and a lack of comprehensive generalization. FloraCheck is bridging these gaps by harnessing the power of EfficientNetB3 through transfer learning, ensuring adaptability to a diverse range of plant diseases. The model is refined through strategic construction involving batch normalization, regularization, dropout and a final classification layer. This ensures the development of a robust and adaptive framework for accurately detecting plant diseases. Our project has achieved an accuracy rate of 98.93%, signifying a considerable advancement in the automated detection of plant diseases.

Keywords

Plant disease recognition, CNN, transfer learning, plant village[1]

1. Introduction

In India, agriculture remains the backbone of the economy, with a substantial percentage of

the population engaged in farming activities. Especially in rural areas, agriculture is not merely

an occupation but a way of life. However, the agricultural sector stands as the major pillar of many economies worldwide, it provides sustenance, employment, and economic stability to millions of people out there. Unfortunately, plant disease poses a daunting challenge to this vital sector. These diseases not only threaten crop yields but also jeopardize food security and the livelihoods of farming communities. The urgency for efficient and automated solutions to detect and combat these diseases has never been more apparent.

Our research is propelled by the profound impact that plant diseases impose on agricultural productivity and food security. Traditional manual methods for disease identification are not only labor-intensive and time-consuming but also prone to errors. The need for automated systems that can precisely identify and diagnose plant diseases is evident given the scope and complexity of today's agricultural challenges. In an ever-changing global landscape, these kinds of systems are essential for maintaining crop health and maximizing agricultural output.

In response to these pressing challenges, our study sets to achieve several objectives. First and foremost, our goal is to create a reliable and effective automated system for the identification and treatment of plant diseases by employing cutting-edge deep learning techniques. Secondly, we seek to explore the effectiveness of transfer learning and advanced image preprocessing techniques in enhancing the accuracy and adaptability of the proposed system. Finally, we will evaluate the developed model's practical suitability for deployment in agricultural settings by assessing its performance using real-world datasets.

Our study presents several significant contributions to the field of plant disease detection and agricultural technology:

1. We present an innovative method for automated plant disease identification that makes use of deep learning, specifically the EfficientNetB3 model.
2. Through the integration of sophisticated image preprocessing techniques and transfer learning, we enhance the model's ability to precisely identify a wide range of plant diseases.
3. Through extensive experimentation and evaluation using the PlantVillage dataset, we demonstrate the efficacy and real-world applicability of the developed model in diverse agricultural scenarios.

Finally, the structure of our paper is as follows:

In Section 2, we have mentioned a comprehensive overview of relevant research work in the field of automated plant disease detection. Further in Section 3, focus has been laid on outlining the methodology implemented and technical approach adopted in our study, which includes data acquisition, data preprocessing, model construction, model training, and classification. Section 4, we present the results of our experiments, including classification model, performance metrics, comparative analysis and the limitations. It also does the analysis and discussion of the findings of our study, interprets the results, and highlights implications for agricultural practice. In Section 5, of the paper concludes with an overview encompassing our contributions, limitations, and prospects for future research endeavors. Finally, in Section 6, the References provide a concise list of all sources cited throughout the paper, facilitating further exploration of the topic and validation of the study's findings.

2. Literature Review

In [1], the key elements of CNN architecture, such as convolutional layers, ReLU activation, pooling layers, and dropout layers, were employed in the Caffe framework. In [2], CNN architecture was used with layers such as Convo2D, flatten, max, pooling etc. on the Plant Village dataset with accuracy of 88%. In [3], the five different architectures are compared which include VGG16, ResNet50, InceptionV3, InceptionResNet, and DenseNet169, achieving the best result from ResNet50.

[4] evaluates multiple deep learning models such as GoogleNet, ResNet101, ResNet50, InceptionV3, AlexNet, InceptionResNetV2, SqueezeNet, VGG16, VGG19. For object recognition, conventional techniques like LBP, HOG, colour features and GLCM for are also assessed. Bi-CNN employs pre-trained VGG and ResNet models for feature extraction followed by ADAM optimizer on Plant Village Dataset [5].

In [6], CNN is achieved through a re-parametrization method and a dynamic pruning gate to manage computational complexity, optimizing the feature extraction network. In [7], three classifiers LeafNet, SVM and MLP are evaluated to detect diseases in tea plants. LeafNet performed best with accuracy of 90.16%. In [8], the recognition of diseases in tomato leaves is done by S-CNN in which the model is trained using segmented images. In [9], on tomato, potato and pepper crops in the Plant Village dataset, CNN with image preprocessing is done and it achieves 98.029% of accuracy.

In [10], CNN incorporated a fully connected layer for classification, convolutional and pooling layer for feature extraction on approx. 35,000 images of Plant Village dataset. In [11], max pooling layers come after the convolutional layers, and the final layer includes an Adam optimizer and softmax activation to lower the loss function. In [12], using CNN with Raspberry Pi kit to anticipate crop diseases in advance. With a suggested activation function and two convolutional layers, it achieves 95% of system accuracy. Fertilizer optimization is aided by K-means clustering-based image segmentation.

In [13], convolution is used to identify patterns and edges, while pooling serves to reduce the image dimensions. CNN architectures which are applied simple CNN, VGG and InceptionV3. In [14], a diverse dataset is captured through various sensors. Subsequently, transfer learning is employed to leverage a pre-trained GoogLeNet CNN, facilitating detection and classification tasks. The dataset is expanded (XDB) through manual subdivision of images into smaller regions for optimal results.

In [15], The synthesis of three different CNN models (VGG-16, Google Net, ResNet 50) used with the application of two different classifiers (SVM and KNN). In [16], CNN is being used where the feature extraction is done by DWT, GLCM giving an accuracy of 98.12%. In [17], three approaches are used, a customized CNN, transfer learning with INCEPTIONv3, and visual transformers (small and large). Training involves Adam and RM-Sprop optimization, categorical cross-entropy loss, and callbacks and appropriate learning rates.

[18] explores ML and DL techniques, like random forest, SVM, and CNN like VGG-16, VGG-19, and Inception-V3, to accurately detect and classify citrus leaf diseases based on a manually curated dataset. (Evaluation involves area under the curve (AUC), precision, F1-

score, recall and accuracy, comparing the performance of ML and DL methods, with DL demonstrating higher overall effectiveness). [19] Utilizing the Plant Village dataset for supervised learning, applying pixel-based operations, and employing CNNs for image classification.

In [20], utilization of advanced deep learning meta-architectures including RFCN, SSD and Faster RCNN, SSD with Inception-v2 and the highest mean average precision (73.07%) was achieved and optimization with Adam significantly improves accuracy, particularly for specific disease classes. In [21], while the model is trained, its process has included 160 images of the papaya leaves. There are numerous machine learning algorithms, such as KNN, Naive Bayes, Random Forest, Support Vector Machine, CART, and Logistic Regression, these all have been applied. Out of which, random forest performed the best with an accuracy of 70.14%.

In [22], detection of plant infections relies on K Means clustering and GLCM technique. Accuracy achieved was 98.27%. In [23], through the introduction of a rice plant disease recognition system, the ML algorithms such as KNN, Logistic Regression, Naive Bayes and Decision Tree are introduced. The Decision Tree algorithm gave best results by achieving an accuracy of a perfect 97.9167%. This dataset consisted of three different disease classes wherein each class has 40 images.

In [24], this paper's primary objective was to suggest enhancements to the existing machine-learning based classification methods which are for plant disease detection, supported by a comparison of the KNN classifier and SVM classifier. The outcomes demonstrated that the suggested algorithm has achieved a good accuracy of 98.56%, which also surpassed the 97.6% accuracy of the old/existing system. In [25], the suggested approach detects the plant diseases with an average accuracy of 93% by using the Random Forest Classifier as well as the digital Image processing technique.

In [26], Transfer learning is implemented with five pre-trained deep neural network architectures: VGG16, DenseNet169, InceptionV3, ResNet50, and Xception. Following model training, images representing different corn diseases from various datasets are employed as test data to evaluate the models' generalization capabilities. The DenseNet169 model demonstrated superior performance. The highest generalization accuracy of 81.60% was achieved when training the DenseNet169 model using (RGBA) images from the CD&S corn disease dataset, with backgrounds removed. In [27], the study compares 4 deep neural models such as fasterRCNN, EfficientDET, YoloV5 and YoloV6. Amongst all, YoloV5 model, which was trained with 93% accuracy on pre-trained hyper parameters, produced the best result. [28] achieves a detection accuracy of 98.26% by using the EfficientNetV2 model for cardamom plant disease detection and the U2-Net for background removal.

[29] employs transfer learning with six different CNN architectures, including VGG16, InceptionV3, Xception, Resnet50, MobileNet, and DenseNet121, for multi-class classification of plant diseases using 11,333 images from the PlantVillage dataset, with DenseNet121 achieving the highest accuracy at 95.48%. [30] proposes a rice plant disease

diagnosis method using DenseNet169-MLP, combining DenseNet169 as a feature extractor and a multilayer perceptron for classification along with fuzzy c-means (FCM) based segmentation for identifying diseased portions, achieving an accuracy of 97.68%. [31] uses a hyperparameter-optimized Deep Convolutional Neural Network with data augmentation to achieve an accuracy of 98.41%.
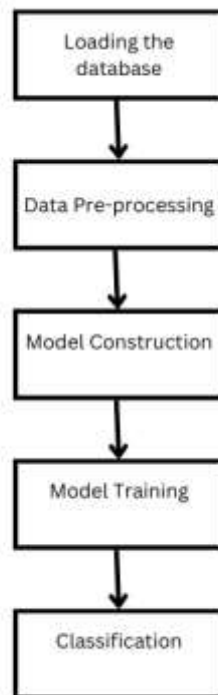
3. Methodology

Figure 1: Schematic overview of proposed methodology.

3.1. Data Acquisition

We have opted for the PlantVillage dataset, a compilation of images encompassing diverse plant species and diseases. Originally comprising 38 labelled classes, we refined the dataset to 25 classes. This curation, focused on specific plant species and diseases, establishes a controlled framework for the purpose of recognizing and classifying plant diseases. The resulting dataset, presented in Table 1, optimizes precision by concentrating on classes crucial to our research.

Table 1. Details of our dataset

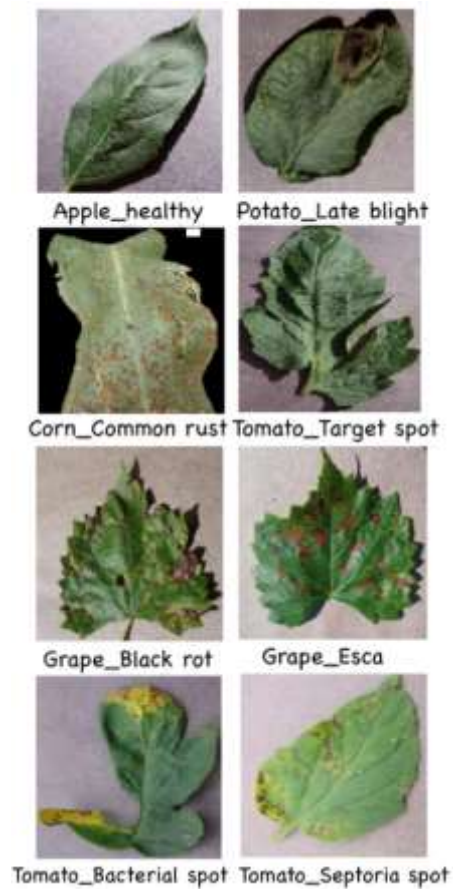| Details	Count
Number of images	31407
Number of unique plant species	5
Number of distinct plant diseases represented	25

Figure 2: Sample images from Plant Village dataset.

3.2. Data Preprocessing

Before model construction, thorough data pre-processing procedures were conducted to guarantee the quality and relevance of the dataset.

- Dataset Stratification: A stratified split was implemented to guarantee that classes were fairly represented in the test, validation, and training sets
- Image Processing and Augmentation: We implemented image augmentation techniques of horizontal flipping, rotation, zooming, brightness adjustments, and

shifts to enhance robustness of our dataset and a scaling function to normalize pixel values. To balance efficiency and information preservation, we resize the images to (224, 224) pixels, aligning with the EfficientNetB3 architecture, which utilizes three color channels (RGB).

- Batch Size Selection: For both training and testing, we chose a batch of 40. This action aimed to achieve equilibrium between computational efficiency and model convergence.

3.3. Model Construction

Once the data was pre-processed, we constructed the model architecture.

- Transfer Learning with EfficientNetB3: We have utilized transfer learning with the EfficientNetB3 architecture as our base model for the construction of the image classification model. The model's pre-training on the ImageNet dataset motivated this choice, enabling it to capture complex image features. To tailor the base model to our specific classification task, we added these supplementary layers.
- Incorporating Batch Normalization: For the purpose of stabilizing and accelerating the training process, we incorporated batch normalization. This enabled us to normalize the input of each layer preventing internal covariate shift and promoting more streamlined model learning.
- Dense layer with regularization: A dense layer with Rectifier activation was introduced to capture complex patterns in the data. In order to reduce overfitting, L2 weight regularization was applied to the layer to promote resilient learning.
- Dropout for generalization: To enhance model generalization, a dropout layer with rate of 0.45 was implemented. This layer randomly deactivated neurons during training, to avoid overdependence of models on specific nodes and improving overall performance.
- Final Classification Layer: The model's concluding layer consists of a dense layer employing softmax activation, providing probabilities for each class in the classification task. This layer is crucial for generating predictions and determining the likelihood for each class.
- Model Compilation: The model that has been compiled makes use of the Adamax optimizer with a step size of 0.001. Choosing categorical cross-entropy as the loss function was in line with our goal of training for accuracy.

3.4. Model Training

With the model architecture in place, we trained the model using specific parameters and evaluated its performance.

1. Training parameters:
   - Epochs: The model underwent training for a total of five epochs.
   - Verbose Setting (Verbosity): The training progress was displayed with verbosity set to 1, for real time updates on metrics like loss and accuracy.
2. Validation for performance evaluation: To gauge the performance of our model and confirm that it can be extended to unfamiliar data, a validation dataset was employed during the training process. After each epoch, the model was evaluated

on this independent dataset, providing insights into its capacity to extrapolate beyond the provided training dataset.

3.5. Classification

The classification process determines whether a plant leaf from the Plant Village Dataset is contaminated or not. It further distinguishes the class of plant infection and recognizes the specific plant variety.

4. Result and Analysis

- **Classification Model**

    We have distributed our dataset into 80% training set, 10% validation set and 10% testing set. We prepared a classification report that provides a detailed assessment of the plant disease recognition system's performance across various diseases affecting plants.

    Table 2. Classification Report

Class	Precision	Recall	F1-Score
Apple__Apple_scab	1.00	1.00	1.00
Apple__Black_rot	1.00	1.00	1.00
Apple_Cedar_apple_rust	1.00	1.00	1.00
Apple__healthy	1.00	1.00	1.00
Corn_(maize)__Cercospora_leaf_ spot Gray_leaf_spot	0.93	0.81	0.87
Corn_(maize)__Common_rust	0.99	1.00	1.00
Corn_(maize)__Northern_Leaf_Bl ight	0.90	0.96	0.93
Corn_(maize)__healthy	1.00	1.00	1.00
Grape__Black_rot	1.00	1.00	1.00
Grape__Esca_(Black_Measles)	1.00	1.00	1.00
Grape__Leaf_blight_(Isariopsis_L eaf_spot)	1.00	1.00	1.00
Grape__healthy	1.00	1.00	1.00
Potato__Early_blight	1.00	1.00	1.00
Potato__Late_blight	1.00	1.00	1.00
Potato__healthy	1.00	1.00	1.00
Tomato___Bacterial_spot	1.00	1.00	1.00
Tomato___Early_blight	0.95	0.99	0.97
Tomato___Late_blight	0.99	0.99	0.99
Tomato___Leaf_Mold	0.94	0.99	0.96
Tomato___Septoria_leaf_spot	0.99	0.99	0.99
Tomato___Spider_mites Two-spotted_spider_mite	1.00	0.96	0.98
Tomato___Target_Spot	1.00	0.95	0.97
Tomato__Tomato_Yellow_Leaf_ Curl_Virus	1.00	1.00	1.00
Tomato___Tomato_mosaic_virus	0.97	1.00	0.99
Tomato__healthy	0.97	1.00	0.98

- **Performance Metrics**

```
Epoch 1/5
635/635 [==============================] - 6744s 11s/step - loss: 4.2516 - accuracy: 0.8982 - val_loss: 1.5203 - val_accuracy: 0.9827
Epoch 2/5
635/635 [==============================] - 481s 757ms/step - loss: 0.8754 - accuracy: 0.9789 - val_loss: 0.4454 - val_accuracy: 0.9921
Epoch 3/5
635/635 [==============================] - 482s 759ms/step - loss: 0.4182 - accuracy: 0.9874 - val_loss: 0.3193 - val_accuracy: 0.9912
Epoch 4/5
635/635 [==============================] - 480s 756ms/step - loss: 0.3324 - accuracy: 0.9899 - val_loss: 0.2750 - val_accuracy: 0.9921
Epoch 5/5
635/635 [==============================] - 480s 756ms/step - loss: 0.2842 - accuracy: 0.9926 - val_loss: 0.2595 - val_accuracy: 0.9924
```

The training process of the model unfolded over five epochs, revealing significant progress in both training and validation accuracies. Commencing with a notably high accuracy of 89.82% and loss of 4.2516, the model exhibited a remarkable learning curve, culminating in an accuracy of 99.26% and a substantially reduced loss of 0.2842 by the final epoch. Such progression signifies the model's adeptness at capturing intricate patterns within the dataset.

Finally, our plant disease recognition model achieves an accuracy of 98.93% on the test dataset following the model's performance evaluation.

Table 3. Performance Metrix

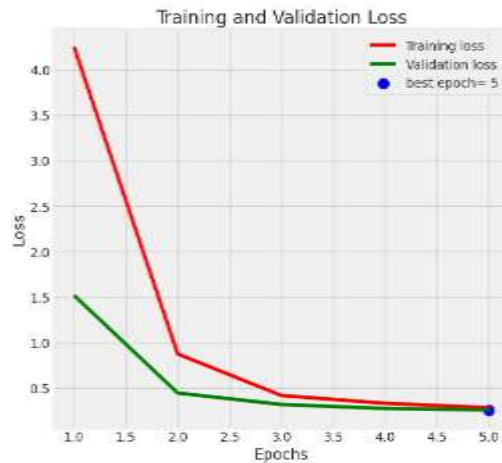|	Accuracy	Loss
Train	0.9937	0.2407
Valid	0.9913	0.2649
Test	0.9893	0.2604

Figure 3: Graph of loss during training and validation across epochs.
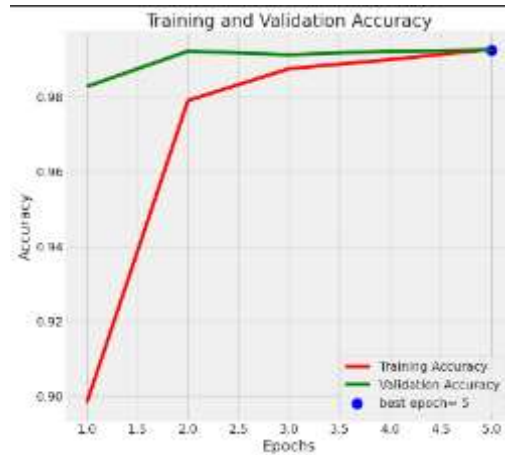
Figure 4: Graph of accuracy during training and validation across epochs.

- **Comparison Analysis of Performance with Related Studies**

We compared our results with several existing research papers to contextualize the success of our method. Following is the comparison evaluation of performance with existing research papers.

Our approach, concentrating on 25 carefully selected classes, distinguishes itself from studies like [14], which employed a more diverse dataset captured through numerous different sensors widely available. The deliberate emphasis on specificity enhances the precision of disease classification in our model. The stratified split, image processing, and augmentation techniques contributed to the robustness of our dataset.

In comparison to [10], which utilized CNN with a fully connected layer for classification and convolutional and pooling layers for feature extraction, our preprocessing techniques align with the specific requirements of the EfficientNetB3 architecture, ensuring efficiency and preservation of information. Leveraging transfer learning with EfficientNetB3, we introduced batch normalization, densely connected layers with regularization, and dropout for generalization.

Compared to [17], which explored multiple approaches including a customized CNN and transfer learning, our use of EfficientNetB3 with tailored modifications ensures an effective balance between complexity and accuracy. Using categorical cross-entropy as the loss function, five epochs were conducted during the training phase at a learning rate of 0.001.

In comparison to [6], where a reparameterization method and dynamic pruning gate were used to manage computational complexity. Our approach achieves competitive accuracy without resorting to complex computational optimization techniques.

Our model achieved an outstanding accuracy of 98.93% surpassing the performance of [20], wherein deep learning meta-architectures with a mean average precision of 73.07% attained the highest score. The specificity of our model in detecting diverse plant diseases across various species is reflected in the precision, recall, and F1-score metrics, as illustrated in our classification report.

So, our research showcases competitive performance when compared to existing research papers. The specificity and efficiency of our approach position it as a noteworthy contribution to the field of plant disease detection and classification.
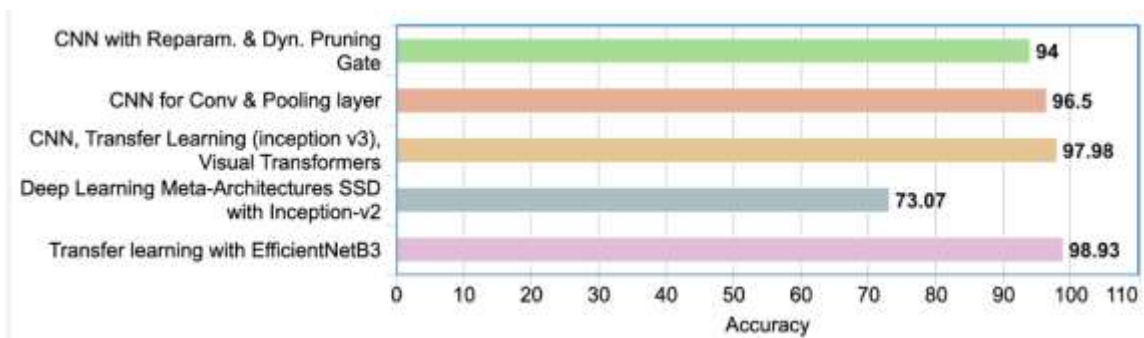

Figure 5: Comparison of performance with different studies

- **Limitations**

While our project has made significant strides, it is crucial to acknowledge areas where can continue to grow and improve.

1. Larger dataset: The project acknowledges that the model's performance is contingent on the size and diversity of the dataset. For the model to be even more effective at generalizing to a wider variety of plant diseases, a bigger dataset might be needed.
2. Additional factors: One aspect worth noting is our model's current focus on visual cues in images, leaving out contextual information such as soil conditions or weather patterns. Integrating these factors could provide a more comprehensive analysis of plant health.
3. Real-time updates: The project does not explicitly address real-time or frequent updates. Changes in the dataset or emerging diseases may necessitate periodic model updates for sustained effectiveness. Periodic updates could be necessary to keep the model relevant and effective.

5. Conclusion

Our plant disease recognition system has accomplished prominent results using the plant village dataset when evaluated. The model has achieved test accuracy of 98.93% which shows that the model is highly trained at classifying the different classes of plant diseases accurately. We have also provided a comprehensive classification report containing evaluation parameters such as positive prediction value, sensitivity, and F-measure of different plant disease classes which again declares the efficiency of the model. In this paperwork, transfer learning has been employed with EfficientNetB3, integrated image preprocessing techniques, applied batch normalization, used ReLU activation and dropout layers making sure the model remains efficient and robust in all kinds of situations. In order to efficiently train and test the model, we have divided the dataset in strategic ways. Also, image augmentation is incorporated to enhance model's robustness. The data is fed into the model by dividing it into batches. These techniques contribute to enhancing the efficacy of the model and capability to identify the different plant diseases precisely.

6. References

[1] Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk, Darko Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," Computational Intelligence and Neuroscience, vol. 2016, Article ID 3289801, 11 pages, 2016. https://doi.org/10.1155/2016/3289801

[2] Srivastava, Prakanshu & Mishra, Kritika & Awasthi, Vibhav & Sahu, Vivek & Pal, Pawan Kumar. (2021). PLANT DISEASE DETECTION USING CONVOLUTIONAL NEURAL NETWORK. International Journal of Advanced Research. 09. 691-698. 10.21474/IJAR01/12346.

[3] A. Sagar and D. Jacob, "On using transfer learning for plant disease detection," BioRxiv, pp. 1–8, 2021.

[4] TÜRKOĞLU, MUAMMER and HANBAY, DAVUT (2019) "Plant disease and pest detection using deep learning-based features," Turkish Journal of Electrical Engineering and Computer Sciences: Vol. 27: No. 3, Article 6. https://doi.org/10.3906/elk-1809-181

[5] D. Srinivasa Rao, R. Babu Ch, V. Sravan Kiran, N. Rajasekhar, K. Srinivas et al., "Plant disease classification using deep bilinear cnn," Intelligent Automation & Soft Computing, vol. 31, no.1, pp. 161–176, 2022.

[6] Liu, Y.; Liu, J.; Cheng, W.; Chen, Z.; Zhou, J.; Cheng, H.; Lv, C. A High-Precision Plant Disease Detection Method Based on a Dynamic Pruning Gate Friendly to Low-Computing Platforms. Plants 2023, 12, 2073. https://doi.org/10.3390/plants12112073

[7] Chen, J.; Liu, Q.; Gao, L. Visual Tea Leaf Disease Recognition Using a Convolutional Neural Network Model. Symmetry 2019, 11, 343. https://doi.org/10.3390/sym11030343

[8] Sharma, P.; Berwal, Y.P.S.; Ghai, W. Performance analysis of deep learning CNN models for disease detection in plants using image segmentation. Inf. Process. Agric. 2020, 7, 566–574.

[9] M. A. Jasim and J. M. AL-Tuwaijari, "Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques," 2020 International Conference on Computer Science and Software Engineering (CSASE), Duhok, Iraq, 2020, pp. 259-265, doi: 10.1109/CSASE48920.2020.9142097.

[10] S. V. Militante, B. D. Gerardo and N. V. Dionisio, "Plant Leaf Detection and Disease Recognition using Deep Learning," 2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE), Yunlin, Taiwan, 2019, pp. 579-582, doi: 10.1109/ECICE47484.2019.8942686.

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

[12] S. Y. Yadhav, T. Senthilkumar, S. Jayanthy and J. J. A. Kovilpillai, "Plant Disease Detection and Classification using CNN Model with Optimized Activation Function," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 564-569, doi: 10.1109/ICESC48915.2020.9155815.

[13] Chohan M, Khan A, Katper S, Mahar M (2020) Plant disease detection using deep learning. Int J Recent Technol Eng 9(1):909–914

[14] Barbedo JG. Plant disease identification from individual lesions and spots using deep learning. Biosyst Eng. 2019;180:96–107.

[15] Mohameth, F. , Bingcai, C. and Sada, K. (2020) Plant Disease Detection with Deep Learning and Feature Extraction Using Plant Village. Journal of Computer and Communications, 8, 10-22. doi: 10.4236/jcc.2020.86002.

[16] S. Ashok, G. Kishore, V. Rajesh, S. Suchitra, S. G. G. Sophia and B. Pavithra, "Tomato Leaf Disease Detection Using Deep Learning Techniques," 2020 5th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2020, pp. 979-983, doi: 10.1109/ICCES48766.2020.9137986.

[17] E. Hirani, V. Magotra, J. Jain and P. Bide, "Plant Disease Detection Using Deep Learning," 2021 6th International Conference for Convergence in Technology (I2CT), Maharashtra, India, 2021, pp. 1-4, doi: 10.1109/I2CT51068.2021.9417910.

[18] R. Sujatha, J. M. Chatterjee, N. Jhanjhi, and S. N. Brohi, "Performance of deep learning vs machine learning in plant leaf disease detection," Microprocessors and Microsystems, vol. 80, p. 103615, 2021.

[19] Panchal, A.V.; Patel, S.C.; Bagyalakshmi, K.; Kumar, P.; Khan, I.R.; Soni, M. Image-based Plant Diseases Detection using Deep Learning. Mater. Today Proc. 2021.

[20] Saleem, M.H.; Khanchi, S.; Potgieter, J.; Arif, K.M. Image-Based Plant Disease Identification by Deep Learning Meta-Architectures. Plants 2020, 9, 1451. https://doi.org/10.3390/plants9111451

[21] S. Ramesh et al., "Plant Disease Detection Using Machine Learning," 2018 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C), Bangalore, India, 2018, pp. 41-45, doi: 10.1109/ICDI3C.2018.00017.

[22] Dr. Sridhathan C"Plant Infection Detection Using Image Processing."International Journal Of Modern Engineering Research (IJMER), vol. 08, no. 07, 2018, pp.13-16.

[23] K. Ahmed, T. R. Shahidi, S. M. Irfanul Alam and S. Momen, "Rice Leaf Disease Detection Using Machine Learning Techniques," 2019 International Conference on Sustainable Technologies for Industry 4.0 (STI), Dhaka, Bangladesh, 2019, pp. 1-5, doi: 10.1109/STI47673.2019.9068096.

[24] 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.

[25] Kulkarni, P.; Karwande, A.; Kolhe, T.; Kamble, S.; Joshi, A.; Wyawahare, M. Plant disease detection using image processing and machine learning. arXiv 2021, arXiv:2106.10698.

[26] A. Ahmad, A. E. Gamal and D. Saraswat, "Toward Generalization of Deep Learning-Based Plant Disease Identification Under Controlled and Field Conditions," in IEEE Access, vol. 11, pp. 9042-9057, 2023, doi: 10.1109/ACCESS.2023.3240100

[27] Khalid, M.; Sarfraz, M.S.; Iqbal, U.; Aftab, M.U.; Niedbała, G.; Rauf, H.T. Real-Time Plant Health Detection Using Deep Convolutional Neural Networks. Agriculture 2023, 13, 510. https://doi.org/10.3390/agriculture13020510

[28] S. C. K., J. C. D. and N. Patil, "Cardamom Plant Disease Detection Approach Using EfficientNetV2," in IEEE Access, vol. 10, pp. 789-804, 2022, doi: 10.1109/ACCESS.2021.3138920.

[29] Sumalatha, G.; Rao, S.K.; Singothu, J.R. Transfer Learning-Based Plant Disease Detection; IJIEMR: Lucknow, India, 2021; Volume 10.

[30] R. P. Narmadha, N. Sengottaiyan and R. J. Kavitha, "Deep transfer learning based rice plant disease detection model," Intelligent Automation & Soft Computing, vol. 31, no.2, pp. 1257–1271, 2022.

[31] Pandian, J.A.; Kanchanadevi, K.; Kumar, V.D.; Jasińska, E.; Goňo, R.; Leonowicz, Z.; Jasiński, M. A Five Convolutional Layer Deep Convolutional Neural Network for Plant Leaf

Disease Detection. Electronics 2022, 11, 1266. https://doi.org/10.3390/electronics11081266