[1]Snehal J. Banarase

[2]Suresh D. Shirbahadurkar

Enhancing Papaya Leaf Disease Detection with CNN and Transfer Learning Fusion for Precise Disease Diagnosis

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Abstract: - Papaya cultivation plays a vital role in global agriculture, providing a crucial source of nutrition and economic stability. However, the threat of diseases poses a significant challenge to papaya plant health. To address this challenge, we proposed an innovative approach for enhancing the detection of papaya leaf diseases using Convolutional Neural Networks (CNNs) and transfer learning fusion. Our proposed framework leverages the strengths of CNNs, known for their ability to extract intricate features from images, and the transfer learning approach combines these techniques to create a robust and efficient model for accurate papaya leaf disease diagnosis. Transfer learning approach with two pre-trained models: VGG-16 and ResNet-50 are taken to detect papaya leaf diseases. The training process involves utilizing a pre-trained model and fine-tuning it on a specific papaya leaf disease dataset. For experimentation, five different classes of papaya leaves such as Fresh Papaya Leaf, Papaya Black Spot, Papaya Leaf Curl, Papaya Ringspot, and Powdery Mildew of Papaya are considered. Experimental results demonstrate the effectiveness of our proposed approach in accurately identifying and classifying various papaya leaf diseases. The proposed model has received an accuracy of 99.79% using ResetNet-50 followed by CNN whose accuracy was 99.42% and VGG-16, whose accuracy was 98.25%. This fusion approach aims to create a robust and efficient model capable of distinguishing subtle patterns indicative of various papaya leaf diseases. This method not only improves the efficiency of disease detection but also demonstrates the adaptability of the model to various disease patterns. Our study contributes to the advancement of automated papaya leaf disease detection, providing a reliable and precise tool for early diagnosis. Overall, our approach offers a promising solution for improving papaya cultivation and ensuring a sustainable future for global agriculture.

Keywords: Transfer learning, Convolutional Neural Network, Papaya leaf disease detection, Agricultural innovation.

I. INTRODUCTION

Plant leaf disease identification is a global area for researchers. Papaya, a globally significant fruit crop, faces a significant challenge in sustainable cultivation due to various leaf diseases that can impact yield and quality. Accurate and early disease detection is crucial for effective disease management and crop protection. From a dietary point of view, papaya is in more demanding fruit because of its high nutritional value. Traditional methods of disease detection may be time-consuming and lack the precision needed for proactive intervention. So, it is important to include automation in farming for precise disease management. There are several methods to detect plant leaf diseases such as detection using GLCM (Gray-Level Co-Occurrence Matrix) feature extraction [4], ML (Machine Learning) based diseased classification, and DL (Deep Learning) based disease recognition. Classification of papaya leaf disease is carried out by checking the maturity status [1] of papaya, machine vision-based detection [2], and using recent advancements in technology, such as Convolutional Neural Networks (CNNs) [7] and transfer learning [10] have shown great promise in revolutionizing disease detection in agricultural settings. This study explores the application of a novel framework, which combines the strengths of CNNs and Transfer Learning to enhance the accuracy of papaya leaf disease diagnosis. CNNs are highly effective in image analysis [18], allowing for the extraction of intricate features from papaya leaf images. The incorporation of Transfer Learning enables [12-13] the transfer of knowledge gained from a pre-trained model to the specific task of papaya leaf disease detection.

The proposed framework has the potential to empower farmers with a proactive means to safeguard their papaya crops and mitigate the impact of diseases on yield and economic stability. The model has the potential to provide a reliable, automated, and precise tool for early papaya leaf disease diagnosis. This strategy leverages the pre-

[1] ZCOER, Narhe, S.P.P.U., Pune, Maharashtra, India

snehal.banarase1@gmail.com

[2] ZCOER, Narhe, S.P.P.U., Pune, Maharashtra, India

shirsd@gmail.com

*Correspondence: snehal.banarase1@gmail.com

trained model's captured knowledge to achieve high accuracy with limited labeled data, allowing our system to effectively identify papaya leaf diseases through subtle pattern recognition. By fine-tuning pre-trained models on a smaller dataset of papaya leaf images, Transfer Learning enables the development of accurate and robust disease detection models, particularly in agriculture where obtaining large, labeled datasets for specific crops can be challenging. The proposed framework is designed to contribute to the growing body of research in precision agriculture, providing a valuable tool for the detection and management of papaya leaf diseases.

II. LITERATURE REVIEW

Papaya, a tropical fruit crop of great nutritional value and economic importance, faces challenges in sustainable cultivation due to various leaf diseases. In several studies, we found that ML [5-6] and DL [7-9] models have performed very well in plant leaf disease recognition and classification Traditional methods of disease detection in agriculture are often time-consuming and prone to human error. However, the integration of advanced technologies, such as Convolutional Neural Networks (CNNs), Transfer Learning [10-13], as well as deep CNN [14-18] holds great promise for automating and enhancing the accuracy of leaf disease detection and classification. Transfer Learning, a technique that leverages knowledge gained from pre-trained models on large datasets addresses the challenge of limited labeled data in specific domains. Researchers have also done great work in identifying leaf diseases such as tomato [16], potato[19], pomegranate[20], grapes[23], apple [24-25], and cucumber[37-38]. A systematic review and comparative study of DL models for plant leaf disease identification and classification are presented in well manner [26-31]. CNNs have shown remarkable capabilities in image analysis tasks, effectively extracting intricate features and patterns from visual data. In the realm of plant pathology, CNNs have proven successful in identifying and classifying diseases across different crops by analyzing images of leaves. The hierarchical feature extraction abilities of CNNs make them particularly well-suited for detecting the subtle visual cues indicative of leaf disease recognition. Advanced computing with lightweight CNN model MobileNetV2 is carried out for real-time apple leaf disease identification and classification [33-34] and has achieved good accuracy. Multiple CNNs also provide a good option for plant leaf disease detection. Several techniques such as Deep residual network [36], global pooling [38], Ensemble learning [39], and 3D deep learning [40] are used vastly in plant leaf disease classification.

Transfer learning is also used in the medical field for medical imaging [12-13], breast cancer detection [14], Alzheimer’s detection [41], and intro retention [42]. High-performing deep neural networks have made this field more promising for researchers. Several studies have demonstrated the potential of CNNs and Transfer Learning in plant disease detection, achieving notable success in crops such as tomatoes, apples, cucumbers, and grapes. However, there is a lack of research on the application of these technologies to papaya leaf disease detection in leaf as well as fruit, which this study aims to address with the introduction of a novel approach that integrates CNN and Transfer Learning for automated papaya leaf disease detection. By leveraging the knowledge gained from other related datasets, Transfer Learning can improve the accuracy of papaya leaf disease detection. In summary, the integration of CNNs and Transfer Learning offers a promising solution for automating and enhancing the precision of papaya leaf disease detection, ensuring the sustainability of this important tropical fruit crop.

III. MATERIAL & METHODS

This section describes the research methods used to build and evaluate model performance. The necessary information like the method chosen to acquire the dataset has been explained i.e., data preparation techniques, data analyzing techniques, etc. Also, it highlights the details of the selection of DL models to address papaya leaf disease recognition and classification.

3.1 Data Acquisition and Pre-processing

The CNN model and transfer learning model were evaluated and trained on the papaya leaves dataset with the aim of identifying and classifying papaya leaf diseases. A total of 700 images are used for a healthy and diseased category of leaves. The dataset used here is openly and freely available, which is created by referring to images from a plant village dataset. To evaluate the model performance 90% of the dataset is used for training and the remaining 10% is used for testing. Table 1 shows image distribution among five classes of papaya leaf used for training purposes. Data pre-processing and augmentation are applied using Image Data Generator. All input images are resized to 224×224. The dataset is taken under different environmental conditions and various light conditions. The created dataset is then undergoes with pre-processing which removes noise and gives more precise images. Data augmentation is necessary to enhance the quality and quantity of images to increase data diversity for the training set. Data augmentation techniques include rotation (45), height and width shift (0.01), horizontal and vertical flip (false), etc.

Table 1 Papaya Leaf Dataset

Leaf Class	**No. of Images**
Fresh Papaya Leaf	41
Papaya Black Spot	56
Papaya Leaf Curl	45
Papaya Ring spot	122
Powdery Mildew of Papaya	86
Total Number of Images	**350**

The proposed model has been evaluated on five different classes of papaya leaf i.e., Fresh Papaya Leaf, Papaya Black Spot, Papaya Leaf Curl, Papaya Ringspot, and Powdery Mildew of Papaya. Sample images for Papaya Leaf Classes are as shown in Figure 1.

(a) (b) (c) (d) (e)

Figure 1 Sample Images: (a) Fresh Papaya Leaf, (b) Papaya Black Spot, (c) Papaya Leaf Curl, (d)Papaya Ring spot, and (e) Powdery Mildew of Papaya

3.2 Experimental Setup

All the proposed models CNN, VGG-16, and ResNet-50 are trained and tested on a system D4A50CDE-A6BC-452F-8696-07951E7A7BF0 using Keras, Scitkit-learn, and OpenCV libraries. Python is used as a primary language for coding. The training and testing of all models were implemented using the TensorFlow framework. All experimentation is carried out on a system with Intel core i5-1235 U, 64-bit operating system, x64-based processor 16GB RAM.

3.3 Performance Measures

To analyze the model performance, individual CNN models are trained by providing different classes of papaya leaf datasets. In evaluating the model performance, statistical parameters play an important role. Accuracy, Precision, Recall, and F1-score evaluate the model performance. These parameters are mentioned in equation (1) to (4). Based on true positive and true negative values ‘Accuracy’ finds correctly classified values. ‘Precision’ indicates how often the model is correct based on all positive values. ‘Recall’ provides the model's predicted frequency; i.e., how the model predicts the correct positive values. The harmonic mean of Recall and Precision is represented by ‘F1 Score’. These measures are important to tell how well the model is trained also how precisely the model can recognize and distinguish different classes of papaya leaf.

$$\text{Accuracy: } A = (TP+TN)/TP+TN+FP+FN \quad (1)$$

$$\text{Precision: } P = TP / (TP + FP) \quad (2)$$

$$\text{Recall: } R = TP / (TP + FN) \quad (3)$$

F1 Score: F1 = 2*P*R / (P+R) (4)

Where; TP, FP, TN, and FN are true positive, false positive, true negative, and false negative resp.

3.4 Model Selection

To form an automated plant leaf diagnosis system CNN architectures are trained and assessed. In this work, two architectures of CNN were tested to get more precise results for papaya leaf disease management. The models are VGG-16, and ResetNet-50, used primarily for classification and recognition.

3.4.1 CNN Models

A deep learning model called a convolutional neural network (CNN) is used to process and analyze visual data, especially images. It performs exceptionally well on object detection, image categorization, and image recognition. Figure 2 shows the basic architecture of CNN is shown in Figure 2. It has convolutional layers, pooling layers, and fully connected layers.

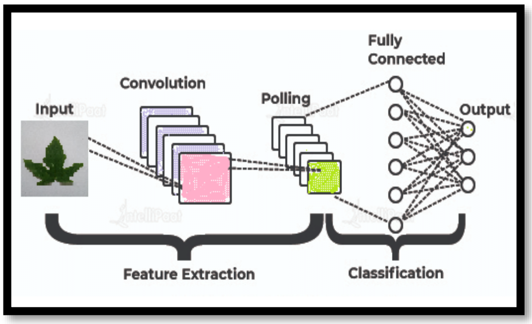


Figure 2 Basic CNN Model Architecture

Features are extracted from input images by using convolutional layers. The input volume's spatial dimensions are down-sampled through the use of pooling layers. Rectified Linear Unit (ReLU) and other activation functions like sigmoid are used to add non-linearity to the model. ReLU is frequently used to give a network non-linearity and the ability to learn intricate relationships. The information is flattened and sent through one or more fully connected layers after features are extracted from the input using convolutional and pooling layers. These layers use the learned features to make global decisions about the input. To avoid overfitting, dropout is used. It is a regularization technique that CNNs frequently employ. During training, it randomly removes a predetermined percentage of neurons, pushing the network to rely on alternative learning pathways. Cross-entropy loss is a popular loss function for classification applications. Reducing this loss is the main objective of training. During training, optimization methods like Stochastic Gradient Descent (SGD) and its variations (such as Adam and RMSprop) are frequently employed to update the model parameters. CNNs have proven to be remarkably effective in a wide range of computer vision applications.

3.4.2 VGG-16

A convolutional neural network architecture called VGG-16, or Visual Geometry Group 16, is intended for image classification as shown in Figure 3. It was created by the University of Oxford's Visual Geometry Group. The network is called "16" because it consists of 03 fully connected layers and 13 convolutional layers, a total of 16 layers. With 16 weight layers, VGG-16 has a deep design that sets it apart.

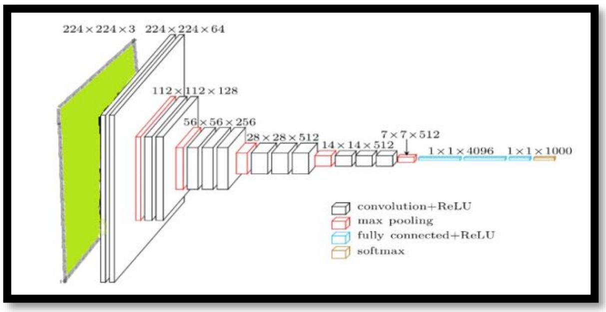


Figure 3 VGG-16 Model Architecture

The network is capable of learning complex hierarchical characteristics from input photos thanks to its deep stack of convolutional layers. The network architecture shows; primarily made up of convolutional layers, max-pooling layers, and fully connected layers. Its depth is influenced by the convolutional and pooling layer's repetitive pattern. Over the network, VGG-16 only makes use of 3x3 convolutional filters. Selecting tiny filter sizes lowers the number of parameters and enables the network to learn more intricate features. A Softmax activation function used in the final layer provides probabilities for the predicted classes.

3.4.3 ResNet-50

In 2015 ResNet-50 was introduced by Microsoft Research, a 50-layer deep CNN architecture. ResNet stands for residual network, which uses residual connection or skip connection. Residual networks bypass the information to certain layers in the network. For object detection and image classification ResNet is very useful.

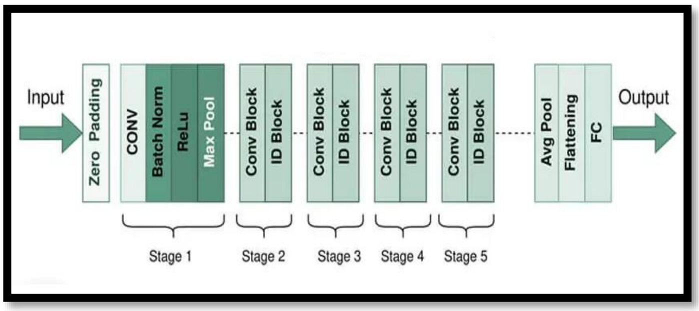


Figure 4 ResNet-50 Model Architecture

For classification purposes we have used the Keras ResNet-50 model as shown in Figure 4; because it can classify the images with greater accuracy than any other residual network. ResNet-50 helps in reducing vanishing gradient problems that may occur while working with huge datasets or training very deep neural networks. In architecture 50 layers include; convolutional layers, residual blocks, and fully connected layers. To achieve depth architecture, multiple residual blocks are stacked. Large datasets like ImageNet often use pre-trained versions of ResNet-50 which is widely available. For various computer vision tasks, transfer learning using pre-trained models is popular where the learned features from ImageNet can be fine-tuned for a specific task.

IV. PROPOSED METHODOLOGY

Figure 5 shows the proposed model for Papaya leaf disease identification and classification. The first step is to collect a dataset; the referred dataset is from the plant village dataset and the Kaggle dataset. The dataset is taken under different environmental conditions and various light conditions. Initially, all the selected input image datasets undergo pre-processing which removes noise and gives more precise images. Data augmentation is necessary to enhance the quality and quantity of images to increase data diversity for the training set.

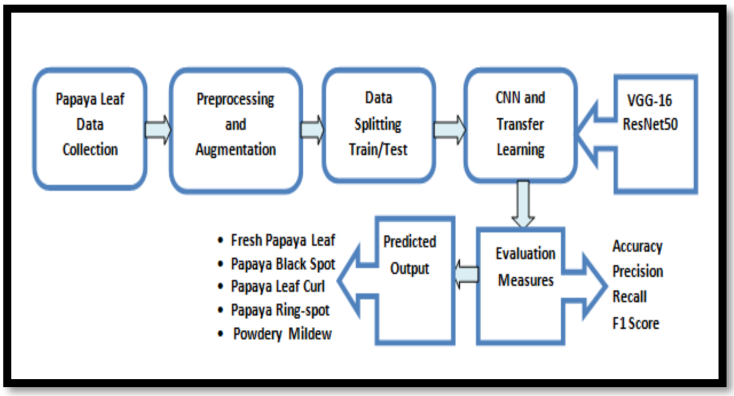


Figure 5 Proposed Model for Papaya leaf disease identification and classification

To train the model, it is necessary to divide the selected dataset into two categories i.e. training and testing datasets. The percentage for training data is 90% to that of test data is 10%. First of all, the model is trained with the CNN model. A total of 60 epochs are considered to train the model.
The overall loss and accuracies for training and validation using the CNN model are mentioned in Table 2. The model undergoes with transfer learning technique using VGG-16 and ResNet50 models. A total of 60 epochs are taken for training. The learning rate taken throughout the training for this papaya leaf model was 0.0001. The overall loss and accuracies for training and validation are mentioned in Table 3 for the VGG-16 model and ResNet-50 is represented in Table 4. The performance measures we have used here are Accuracy, Precision, Recall, and F1-score. The proposed papaya leaf model can efficiently recognize and classify a total of five classes of papaya leaf.

V. RESULT AND DISCUSSION

This section describes how well the model has performed during the training and testing period. The techniques used for training are a fusion of CNN and transfer learning with VGG-16 and residual network ResNet-50.
Table 2 shows the CNN model performance; the model is trained for 60 numbers of epochs. During training, it was observed that at the beginning the performance was poor but it improved after the 30th epoch and the model achieved an accuracy of 97.66% at the 40th epoch and got the best accuracy of 99.42% at the 50th epoch with validation loss of 1.4512.

Table 2 CNN Model Performance

No. of Epochs	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
10	2.2260	0.6374	2.3886	0.3
20	1.7328	0.7135	1.7243	0.85
30	1.4081	0.8363	1.8761	0.2
40	1.1294	0.9766	1.4608	0.6
50	0.9633	0.9942	1.4512	0.6
60	0.9037	0.9064	1.8706	0.2

As the dataset used here is limited, so transfer learning approach is used to achieve the best accuracies. Table 3 gives the VGG-16 model performance; 60 numbers of epochs are used for training. During training it is observed that from the beginning itself, the model has performed very well; it has achieved an accuracy of 88.30% at the 10th epoch. At each stage, model accuracy had been improved. After the 30th epoch model achieved an accuracy of 97.66% and at the 40th epoch VGG-16 got the best accuracy of 98.25% with a loss of 1.7646. Again, at the 50th epoch, the accuracy has dropped by almost 0.0059.

Table 3 VGG-16 Model Performance

No. of Epochs	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
10	2.0565	0.8830	7.6397	0.20
20	1.9097	0.9649	7.5580	0.2
30	1.7884	0.9766	7.4809	0.2
40	1.7646	0.9825	7.4527	0.20
50	1.8337	0.9766	7.5233	0.20
60	1.9093	0.9649	7.5573	0.20

Table 4 represents how well the papaya leaf diseases are recognized and classified after applying the residual network ResNet-50 model; here also 60 numbers of epochs are used for training. During training it is observed that, from the beginning itself the model performed very well; at the very epoch model has received an improved accuracy. At the 40th epoch, the model achieved an accuracy of 97.97% and at the 50th epoch, ResNet-50 had got best accuracy of 99.79% with a loss of 3.5432 during training. After the 50th epoch the accuracy has dropped by a value of almost 0.0086 i.e. accuracy has dropped to 98.93%.

Table 4 ResNet- 50 Model Performance

No. of Epochs	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
10	6.3958	0.8397	6.3788	0.5577
20	5.7789	0.9231	5.5670	0.9327
30	5.3518	0.9594	5.3940	0.7885
40	5.0040	0.9797	4.9539	0.9135
50	3.5432	0.9979	3.7776	0.8846
60	3.4497	0.9893	4.0197	0.9135

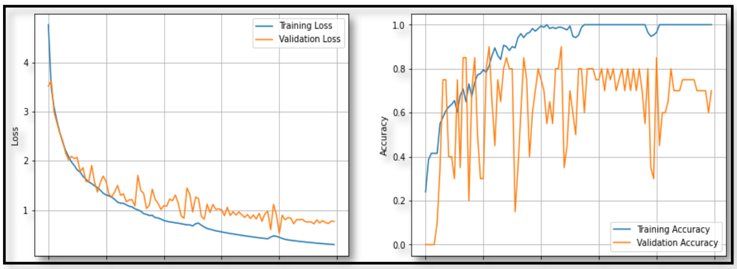
Table 5 represents the overall model performance. All three models have achieved the best possible accuracy for papaya leaf disease detection. ResNet-50 model has achieved the best accuracy of 99.57%. Also, VGG-16 has reached 98.25% accuracy followed by the CNN model which has achieved an accuracy of 96.24%

Table 5 Overall Model Performance

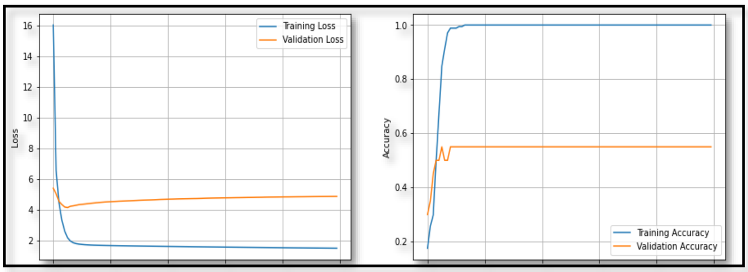
Model	Learning Rate	Optimizer	Predicted Accuracy (%)
CNN	0.0001	Adam	99.42%
VGG-16	0.0001	Adam	98.25%
ResNet50	0.0001	Adam	99.79%

While training CNN models, accuracy and loss are critical to evaluate. These parameters highly show how well the model learns from the training data. The training process usually involves iterative optimization of the model and weights using the training data. In addition, a validation dataset is used to evaluate the performance of the model on unseen data during training.

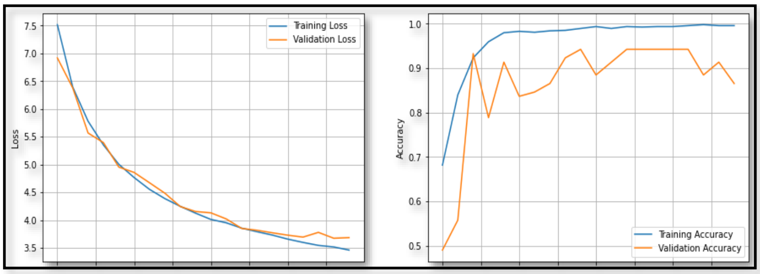
Figure 8 shows Accuracy and Loss during training and validation for different models. Numbers of epochs are represented on the x-axis and accuracies and losses are represented on the y-axis. CNN model got the best accuracy of 99.42% at the 40th epoch, with decreasing training loss. It is seen that the ResNet-50 model has achieved the best training accuracy as well as validation accuracy with decreasing validation loss. For VGG-16 the performance was good from the initial stage of training itself. High training accuracy indicates that the model learns from the training data and makes accurate predictions. Validation accuracy measures the model's performance on a particular set of validation data that it doesn't see during training. Validation accuracy helps to assess the general ability of the model. The training loss is a training error. Again, it is a quantitative measure of the difference between the predicted values and the actual entries in the training set. Validation loss measures the difference between predicted and actual tags in the validation dataset. During each epoch, decreasing validation loss is desirable. Similar to training loss, the goal is to minimize validation loss.



(a)



(b)



(c)

Figure 8 Accuracy and Loss during Training and Validation for different models

(a)CNN (b) VGG-16 (c) ResNet-50

By observing these results, it is clear that the proposed model with CNN and transfer learning fusion are more efficient in distinguishing diverse classes of papaya leaf than the existing model. This is a significant step in precision agriculture, enabling timely and targeted interventions to mitigate the impact of diseases on papaya crops.

VI. CONCLUSION AND FUTURE SCOPE

In the domain of papaya leaf disease detection, the application of deep learning models, specifically Convolutional Neural Networks (CNN), VGG-16, and ResNet-50 has proven to be highly effective for disease classification. The study aimed to leverage the capabilities of these models to enhance accuracy and efficiency in identifying various diseases affecting papaya crops. The implementation of CNN and Transfer Learning, a powerful approach in deep learning, for precise papaya leaf disease diagnosis has shown promising results in advancing the field of automated plant disease detection. Through the utilization of deep learning techniques, we have achieved significant improvements in accuracy and efficiency compared to traditional methods.

This fusion of CNN and transfer learning has enhanced the model's ability to generalize and adapt to the intricacies of papaya leaf diseases, even in the presence of limited labeled data. The experiments and evaluations conducted on diverse datasets have showcased the robustness and reliability of the proposed methodology. After experimentation, the CNN model has an accuracy of 99.42% followed by VGG-16 with an accuracy of 98.25%.

Out of all these models, the ResNet-50 model has achieved the best accuracy of 99.57% with minimum loss. In summary, the study demonstrates the efficiency of CNN, VGG-16, and ResNet-50 in the realm of papaya leaf disease detection. The models not only offer high accuracy but also provide a foundation for future research in optimizing and tailoring these architectures for specific agricultural contexts.

There are several avenues for future research and improvements such as the diverse samples dataset collection and exploring different fine-tuning strategies for transfer learning. Adapting and deploying the model for real-time disease detection.

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REFERENCES

[1] S. K. Behera, A. K. Rath, P. K. Sethy, "Maturity status classification of papaya fruits based on machine learning and transfer learning approach," Information Processing in Agriculture, Elsevier, 2020.
[2] Md. Tarek Habib, Anup Majumder, A.Z.M. Jakaria, "Machine vision based papaya disease recognition," Journal of King Saud University Computer and Information Sciences, Elsevier, 2018.
[3] Wahyuni Eka Sari, Yulia Ery Kurniawati, Paulus Insap Santosa, "Papaya Disease Detection Using Fuzzy Naïve Bayes Classifier," ISIRTI, 42-47, 2020.
[4] "Papaya Diseases Detection Using GLCM Feature Extraction and Hyperparameter Tuning of ML Approach," 145–148, 2023, doi: 10.1007/978-981-19-7874-6_12.
[5] Md. Ashiqul Islam, Md. Shahriar Islam, "Machine Learning Based Image Classification of Papaya Disease Recognition," ICECA ISBN: 978-1-7281-6386-4, 2020.
[6] Hafiz Tayyab Rauf, Basharat Ali Saleem, M. Ikram Ullah Lali, "A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning," Elsevier, 2018, https://doi.org/10.1016/j.dib.2019.104340.
[7] H.-C. Shin, H.R. Roth, M. Gao, L. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura, R.M. Summers, S. Hoo-Chang, "Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning," IEEE Trans. Med Imaging, vol. 35, 2016, pp. 1285–1298, doi: 10.1109/TMI.2016.2528162.
[8] M.H. Saleem, J. Potgieter, K.M. Arif, "Plant disease detection and classification by deep learning," Plants, vol. 8, no. 11, MDPI AG, Nov. 01, 2019, doi: 10.3390/plants8110468.
[9] M. Brahimi, M. Arsenovic, S. Laraba, S. Sladojevic, K. Boukhalfa, A. Moussaoui, "Primitive Interaction Design. Deep Learning for Plant Diseases: Detection and Saliency Map Visualization," Springer Science and Business Media LLC, 2018, pp. 93–117.
[10] J. Chen, J. Chen, D. Zhang, Y. Sun, Y. Nanehkaran, "Using deep transfer learning for image-based plant disease identification," Comput. Electron. Agric., 2020, vol. 173, pp. 105393, doi: 10.1016/j.compag.2020.105393.
[11] M. Turkoglu, D. Hanbay, "Leaf-based plant species recognition based on improved local binary pattern and extreme learning machine," Phys. A Stat. Mech. Its Appl., 2019, vol. 527, pp. 121297, doi: 10.1016/j.physa.2019.121297.
[12] M. Raghu, C. Zhang, J. Kleinberg, S. Bengio, "Transfusion: Understanding transfer learning for medical imaging," Adv. Neural Inf. Process. Syst., 2019, pp. 3347–3357.
[13] L. Alzubaidi, M.A. Fadhel, O. Al-Shamma, J. Zhang, J. Santamaría, Y. Duan, S.R. Oleiwi, "Towards a Better Understanding of Transfer Learning for Medical Imaging: A Case Study," Appl. Sci., 2020, vol. 10, pp. 4523, doi: 10.3390/app10134523.
[14] L. Alzubaidi, O. Al-Shamma, M.A. Fadhel, L. Farhan, J. Zhang, Y. Duan, "Optimizing the Performance of Breast Cancer Classification by Employing the Same Domain Transfer Learning from Hybrid Deep Convolutional Neural Network Model," Electronics, 2020, vol. 9, pp. 445, doi: 10.3390/electronics9030445.
[15] J.G.A. Barbedo, "Factors influencing the use of deep learning for plant disease recognition," Biosyst. Eng., 2018, vol. 172, pp. 84–91, doi: 10.1016/j.biosystemseng.2018.05.013.
[16] H.A. Atabay, "Deep residual learning for tomato plant leaf disease identification," J. Theor. Appl. Inf. Technol., 2017, vol. 95, pp. 6800–6808.
[17] S.H. Lee, H. Goëau, P. Bonnet, A. Joly, "New perspectives on plant disease characterization based on deep learning," Comput. Electron. Agric., 2020, vol. 170, pp. 105220, doi: 10.1016/j.compag.2020.105220.
[18] P. Sharma, Y.P.S. Berwal, W. Ghai, "Performance analysis of deep learning CNN models for disease detection in plants using image segmentation," Inf. Process. Agric., 2019, doi: 10.1016/j.inpa.2019.11.001.
[19] M. Islam, A. Dinh, K. Wahid, P. Bhowmik, "Detection of potato diseases using image segmentation and multiclass support vector machine," Proceedings of the 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, Canada.
[20] S.S. Sannakki, V.S. Rajpurohit, V.B. Nargund, "SVM-DSD: SVM Based Diagnostic System for the Detection of Pomegranate Leaf Diseases," in Proceedings of the International Conference on Advances in Computing, M.A.R.S. Kumar and T. Kumar, Eds., Kochi, Kerala, India, 29–31 August 2013, New Delhi, India: Springer, 2013.
[21] K. Tian, J. Li, J. Zeng, A. Evans, L. Zhang, "Segmentation of tomato leaf images based on adaptive clustering number of K-means algorithm," Comput. Electron. Agric., vol. 165, 2019, pp. 104962, doi: 10.1016/j.compag.2019.104962.

[22] M. Arsenovic, M. Karanovic, S. Sladojevic, A. Anderla, D. Stefanovic, "Solving Current Limitations of Deep Learning Based Approaches for Plant Disease Detection," Symmetry, vol. 11, 2019, pp. 939, doi: 10.3390/sym11070939.

[23] Adeel, M.A. Khan, M. Sharif, F. Azam, J.H. Shah, T. Umer, S. Wan, "Diagnosis and recognition of grape leaf diseases: An automated system based on a novel saliency approach and canonical correlation analysis based multiple features fusion," Sustain. Comput. Inform. Syst., vol. 24, 2019, pp. 100349, doi: 10.1016/j.suscom.2019.08.002.

[24] P. Jiang, Y. Chen, B. Liu, D. He, C. Liang, "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks," IEEE Access, vol. 7, 2019, pp. 59069–59080, doi: 10.1109/ACCESS.2019.2914929.

[25] B. Liu, Y. Zhang, "Identification of Apple Leaf Diseases based on DCNN," doi:10.3390/sym10010011.

[26] E.C. Too, L. Yujian, S. Njuki, L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," Comput. Electron. Agric., vol. 161, Jun. 2019, pp. 272–279, doi: 10.1016/j.compag.2018.03.032.

[27] A.F. Fuentes, S. Yoon, J. Lee, D.S. Park, "High-performance deep neural network-based tomato plant diseases and pests diagnosis system with a refinement filter bank," Front Plant Sci, vol. 9, Aug. 2018, doi: 10.3389/fpls.2018.01162.

[28] M. Nagaraju, P. Chawla, "Systematic review of deep learning techniques in plant disease detection," International Journal of System Assurance Engineering and Management, vol. 11, no. 3, Jun. 2020, pp. 547–560, doi: 10.1007/s13198-020-00972-1.

[29] K.P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Comput. Electron. Agric, vol. 145, Feb. 2018, pp. 311–318, doi: 10.1016/j.compag.2018.01.009.

[30] G. Geetharamani, A.P. J., "Identification of plant leaf diseases using a nine-layer deep convolutional neural network," Computers and Electrical Engineering, vol. 76, Jun. 2019, pp. 323–338, doi: 10.1016/j.compeleceng.2019.04.011.

[31] M. Snehal, J. Banarase, S.D. Shirbahadurkar, "A Review on Plant Leaf Diseases Detection and Classification," 2021.

[32] C. Bi, J. Wang, Y. Duan, B. Fu, J.R. Kang, Y. Shi, "MobileNet Based Apple Leaf Diseases Identification," Mobile Networks and Applications, vol. 27, no. 1, Feb. 2022, pp. 172–180, doi: 10.1007/s11036-020-01640-1.

[33] Snehal J.B., Suresh D.S., “OrchardGuard: Deep Learning powered apple leaf disease detection with MobileNetV2 model”, J. Integr. Sci. Technol., 2024, 12(4), 799

[34] L. Li, B. Wang, Y. Li, H. Yang, "Diagnosis and Mobile Application of Apple Leaf Disease Degree Based on a Small-Sample Dataset," Plants, vol. 12, no. 4, Feb. 2023, doi: 10.3390/plants12040786.

[35] M. Ji, L. Zhang, Q. Wu, "Automatic grape leaf diseases identification via United Model based on multiple convolutional neural networks," Information Processing in Agriculture, vol. 7, no. 3, Sep. 2020, pp. 418–426, doi: 10.1016/j.inpa.2019.10.003.

[36] V. Bodhwani, D.P. Acharya, U. Bodhwani, "Deep residual networks for plant identification," in Elsevier B.V., 2019, pp. 186–194, doi: 10.1016/j.procs.2019.05.042.

[37] J. Ma, K. Du, F. Zheng, L. Zhang, Z. Gong, Z. Sun, "A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network," *Comput. Electron.

[38] S. Zhang, S. Zhang, C. Zhang, X. Wang, Y. Shi, "Cucumber leaf disease identification with global pooling dilated convolutional neural network," Comput. Electron. Agric, vol. 162, Jul. 2019, pp. 422–430, doi: 10.1016/j.compag.2019.03.012.

[39] Yousuf and U. Khan, "Ensemble Classifier for Plant Disease Detection," International Journal of Computer Science and Mobile Computing, vol. 10, no. 1, Jan. 2021, pp. 14–22, doi: 10.47760/ijcsmc.2021.v10i01.003.

[40] K. Balasubramanian, S. Jones, A.K. Singh, S. Sarkar, A. Singh, B. Ganapathysubramanian, "Plant disease identification using explainable 3D deep learning on hyperspectral images," Plant Methods, vol. 15, no. 1, Aug. 2019, doi: 10.1186/s13007-019-0479-8.

[41] S.S. Bamber, T. Vishvakarma, "Medical image classification for Alzheimer’s using a deep learning approach," Journal of Engineering and Applied Science, vol. 70, no. 1, Dec. 2023, doi: 10.1186/s44147-023-00211-x, Volume 64, 2022, 103063, ISSN 2214-2126.

[42] Z. Wu, J. Zheng, J. Liu, C. Lin, H.D. Li, "DeepRetention: A Deep Learning Approach for Intron Retention Detection," Big Data Mining and Analytics, vol. 6, no. 2, Jun. 2023, pp. 115–126, doi: 10.26599/BDMA.2022.9020023.