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RESEARCH ARTICLE

Identification of Diseased Papaya Leaf through Transfer Learning

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Abstract

Background/Objectives: Papaya leaf being an excellent source of bioactive compounds plays a crucial role in the formulation of Ayurvedic remedies, irrespective of medicinal usage Papaya leaves are frequently affected by diseases which harm the crop and decrease its productivity. Hence, it urges for disease detection. **Methods/Statistical analysis:** Utilizing computer vision methods to detect diseases, presents a solution to the limitations of constant human supervision. The study introduces a transfer learning model built upon the Resnet-50 architecture to recognize and classify diseased papaya leaves. On a dataset of 2159 images, 1726 images are allocated for training, 213 for validation and 220 for testing. The classes we distinguish in our study include healthy leaves as well as those afflicted by anthracnose, bacterial spot, curl, and ringspots. **Findings:** The proposed model has been pre-trained and fine-tuned on this dataset, and when evaluated using a sample set of 220 images, it achieves an impressive accuracy rate of 87.95%. Notably, this model surpasses the performance of the base models, including CNN, VGG 16, Inception V3, ResNet-50, DenseNet 121, MobileNet V2, and EfficientNet B0 in the classification task. **Novelty/Applications:** This work emphasizes the practicality of the proposed approach in real-world applications and its importance in agriculture and disease management. It paves the way for significant revolutions in food security and contributes to environmental conservation and economic stability.

Keywords: CNN; Papaya Leaf Diseases Anthracnose; Bacterial Spot; Curl and Ring Spot; Transfer Learning

1 Introduction

Plants play a vital role in supporting human life by providing essential resources such as food, oxygen, nutrients, medications etc. The papaya, a horticultural crop with its therapeutic potential, holds a remarkable role in the medical field that encompass boosting platelet count for Dengue Fever victims, diabetes management, aiding digestion, relieving symptoms of Irritable Bowel Syndrome etc.[(1)]. However, papaya cultivation is susceptible to diseases as these crops are sensitive to environmental factors like flooding, soggy and strong winds. These factors not only diminish crop quality but also reduce the productivity of crop. Thus, effective management of these challenges is crucial for successful papaya cultivation. Precision agriculture, enabled by modern technology, is making significant advancements in disease identification on plant leaves and improving decision-making processes. Through the use of digital technologies, copious real-time data is collected, and machine learning algorithms are leveraged to make more cost-effective decisions. Nevertheless, there is still room for improvement, particularly in the development of decision-support systems capable of translating massive data into valuable recommendations.

The paper [2] highlights the flips and flops of CNN in detecting plant diseases. It focuses only on CNN and lacks the discussion about other machine learning methods and their empirical data to support its assertions. The paper [3] discusses the VGG16 training model to classify 38 different classes of plant diseases, achieved by an average accuracy of 94.8%. However, the dataset used in the study is limited to 38 different classes of plant diseases, which may not cover all possible diseases that can affect various plants. The proposed system was tested using a specific set of images, and its performance may vary when applied to different images or under different conditions. The paper [4] explores the random forest, k-means clustering, support vector classification, and convolutional neural networks (CNN) for papaya disease recognition with a dataset of 214 images. It is figured that CNN achieves the highest accuracy of 98.4%. This study is aimed to aid farmers in Bangladesh; however, the work is challenging as it needs technological literacy among farmers. The paper also disappoints in addressing algorithm accuracy variations due to variable lighting and image qualities. The authors in [5], due to the lack of readily available datasets, created a custom dataset of rice leaf diseases images captured by Motorola E4 Plus and Redmi 5A mobile cameras and used augmentation techniques and developed 1649 images. The model achieves a classification accuracy of 92.46% on 1509 images of rice leaves when transfer learning by fine-tuning a pre-trained VGG16 is applied. The original dataset used is small and gathered from a specific geographical area and the model performance hasn't been tested on a large-scale dataset. The research in [6], employees K-means clustering to group a dataset of potato leaves. A total of 10320 images were generated after data augmentation into three categories: early-blight, late-blight, and healthy leaves. In addition, Deep learning models like VGG16, VGG 19 and Resnet-50 are also used, where VGG16 achieved the highest accuracy of 97%. The accuracy of these models depends on the specific crop, disease, and the quality of the dataset. However, it falls off the line when detailed comparison is done with other techniques of Deep learning, which could limit the generalizability of their findings. In [7] a transfer learning with Inception V3 is applied on leaf image dataset of 54305 images for disease recognition, this method achieves a 95.8% of training precision rate and a 93% of test set precision rate, but the paper does not include fine-tuning and the other deep learning methods which may produce efficient performances. The authors of [8] used ResNet50 architecture on a dataset of 9470 images to identify and classify papaya leaf diseases, like Leaf Curl of Papaya and papaya mosaic, and achieved an average accuracy of 85.1%. However, the number of classes used was relatively small, which could limit the generalizability of the results. Additionally, the approach may not be effective in cases where the leaf image has a complex background or when the disease symptoms are not well-defined. The algorithm in [9] is based on a pre-trained densenet-121 model of the Keras library and implemented on Huges DP Plant-Village dataset wrapping 35,779 images to classify 29 different diseases across seven plant types, it achieves an accuracy of 98.23%. An average accuracy of 94.96% was achieved for 50 epochs with a learning rate of 0.002. The performance metrics could have improved if other pre-trained models with various epoch numbers are assisted. The paper [10] discusses the Raspberry Pi device for classifying papaya leaf diseases using a MobileNet architecture and transfer learning. This model identified diseases like Blackspot, Brown Spot, Powdery Mildew, Mealybug Infection on papaya leaves. The system tested 72 samples and attained an accuracy of 91.667% from a total of 1394 images. The accuracy could have been improved if the training samples are more, a power efficient CNN architecture is highly recommended for this embedded usage. The study [11] proposes an EfficientNet-based deep learning framework for identifying corn leaf diseases, which include 1306 Common Rust images, 574 Gray Leaf Spot images, 1146 Blight images, and 162 Healthy images, achieving an accuracy of 98.85%. However, a limited dataset will affect the generalization in diverse environmental conditions. The paper [12] addresses the significant issues caused by papaya diseases through CNN model using Keras API. A total 234 images in which 184 images are for training, 28 images for validations and 22 images are used for testing the model achieving a training accuracy of 91%. The primary goal of this research is to provide a solution for village farmers. But lags in justifying illiterate farmers who may not have knowledge in electronic gadgets and there is much scope of improvement by exploring more samples.

The current research utilizes the knowledge gained from the aforementioned studies and understands the significance of Deep Learning in identifying diseased crop leaves for numerous datasets and notes down the respective metrics as per their datasets. The present study uses "BDPapayaLeaf" of Mendeley datasets [13] which are unique and encompass images of healthy as well as affected papaya leaves like Anthracnose, Bacterial Spot, Curl, and Ring Spot, also that are acquired with different poses, resolutions, lighting conditions, backgrounds, alignments and various environmental factors. Transfer learning by fine-tuning the Pre-trained models is used to examine the condition of leaves and finally, the best model is filtered based on the performance and resultant metrics. The objective of the work is to find the best transfer learning model that effectively classifies a leaf disease from the considered dataset.

2 Materials and Methods

The overall outline of the research is presented in [Figure 1].

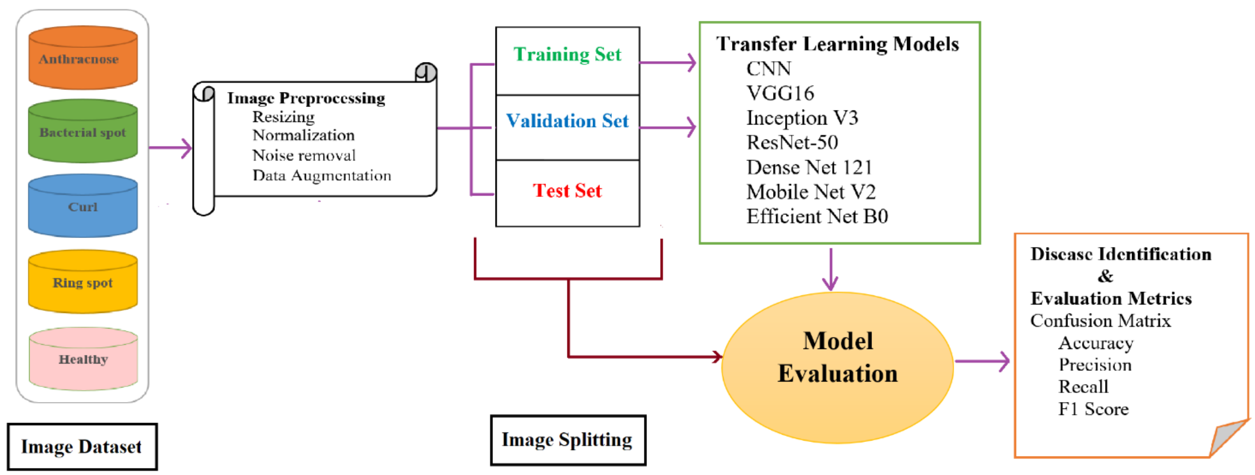

Fig 1. Methodology of work

2.1 Dataset Description

Image Acquisition: The system uses "BDPapayaLeaf: A annotation based image dataset of papaya leaf disease"[13] available in Mendeley datasets. The dataset contains images of papaya leaf diseases collected from Changao, Ashulia, Dhaka, Bangladesh areas. This dataset has 3 sub-directories such as Original Images, Annotations and Labels.

- 'Original Images' folder contains all the original jpg images of 2159 which are classified into five classes namely Anthracnose, Bacterial spot, Curl, Ring spot and Healthy.
- 'Annotations' folder holds annotation images in xml format.
- 'Labels' folder consists annotation images in txt format.

The dataset of 2159 images are partitioned into 80% for training, 10% for validation and the remaining for test data to aim for a decent performance of the proposed network.

There were several challenges addressed in the data collected which incorporate factors such as different poses, resolutions, lighting conditions, backgrounds, and alignment poor illumination. The details of the exact volume of images in the dataset for each class and the splitting of images are given in [Table 1] and sample images are presented in [Figure 2].

Table 1. Overview of dataset classes and utilization

Serial No.	Class	Number of samples	Training samples	Validation samples	Test samples
1	Anthracnose	355	284	35	36
2	Bacterial Spot	458	366	45	47
3	Curl	585	468	58	59
4	Ring Spot	533	426	53	54
5	Healthy	228	182	22	24

Fig 2. Sample images of Anthracnose, Bacterial spot, Curl and Healthy and Ring spot [13]

- **Anthracnose**

Anthracnose is a fungal disease that affects papaya plants, including leaves and fruit. It is generally occurs to crop by various fungi such as *Colletotrichum* spp and *Glomerella* spp. The disease spreads during rainy, humid periods and can be transmitted from plant to plant via unsanitized tools. Symptoms include dark, sunken lesions with pinkish spore masses on leaves, leading to defoliation and reduced fruit quality. The lesions are sunken and can cause structural damage to leaves. In humid conditions, the fungus produces small, dark conidia on the lesions. Anthracnose can also infect papaya fruit, resulting in similar sunken lesions and reduced fruit quality, including postharvest decay.

- **Bacterial Leaf Spot**

Bacterial leaf spot on papaya is caused by various bacterial pathogens, including *Xanthomonas campestris* and *Pseudomonas caricae*. The disease results in small, water-soaked lesions on papaya leaves, initially surrounded by a yellow halo, which can expand and turn necrotic, affecting leaf health. Infected leaves may also curl and display yellowing, impacting overall plant health. In severe cases, the bacteria can infect stems and fruits, causing similar water-soaked lesions and fruit rot.

- **Papaya Leaf Curl Virus (PaLCuV)**

Papaya Leaf Curl Virus (PaLCuV) is a viral disease that shows severe impact on papaya plants in tropical and subtropical regions. It is transmitted primarily by white flies (*Bemisia tabaci*) which acquire and spread the virus. Infected plants display symptoms such as distorted, curled leaves, leaf yellowing, reduced size, and stunted growth. These symptoms impede photosynthesis, leading to poor growth and lower fruit yield, ultimately affecting the plant's overall health and productivity.

- **Healthy papaya leaves**

Healthy papaya leaves play a crucial role in the overall well-being of the papaya plant. It has a Green Color, Smooth Texture, Uniform Shape, No Spots or Lesions, Good Leaf Size, Strong Veins, Turgidity, No Signs of Disease or Pests, Good Leaf-to-Stem Ratio and Vibrant Growth. To maintain the leaves healthy, it is essential to provide the plant with proper care, including appropriate watering, fertilization and protection from diseases and pests. Regular monitoring and early intervention can help address any issue that may arise and ensure the continued health of the papaya plant.

- **Papaya Ringspot Virus (PRSV)**

Papaya ringspot, caused by Papaya Ringspot Virus (PRSV), is a significant viral disease in papaya plants. It is primarily spread by aphids that feed on infected papayas and then transmit the virus to healthy plants. PRSV displays distinctive symptoms, including ring-shaped lesions on papaya leaves, typically light yellow with a green halo. Infected leaves may become distorted, mottled, and exhibit curling. Moreover, the virus can affect fruit quality, leading to mottling, streaking, and reduced overall fruit quality. Severe PRSV infections may result in stunted papaya plant growth, compromising its health and fruit production.

The present study focuses on evaluation of the proposed model and Deep Learning algorithms as documented in existing literature for identifying and classifying papaya leaf diseases. Models are trained and assessed on the dataset after which a comparison is made through the resultant metrics and the best model is picked upon the accuracy and performance scores.

2.2 Model development

Convolutional neural networks (CNNs) of[14] are complex networks as depicted in [Figure 3], and are widely used for image classification tasks. They have proven to be highly effective in various computer vision tasks, including image classification, object detection, and segmentation.

Since 2019, the field of computer vision has seen continuous advancements and modifications in the existing architectures of CNN. For specific tasks or datasets, it is essential to experiment with different architectures and apply transfer learning to tailor the requirements of the problem at hand.

2.3 Transfer learning

Transfer learning is utilized to transfer knowledge, weights and features learned in one domain to another. Transfer learning is an efficient approach for leveraging a pre-trained deep neural network to solve a new or specific image classification task by using any of the base models of CNN.

Here is an explanation of how transfer learning works:

1. Pre-trained Base Models: The first step in transfer learning is to obtain any of the pre-trained base models that have already been trained on a vast dataset, typically containing a large variety of images from thousands of different categories. The Base models have learned to extract meaningful features from images.
2. Feature Extraction: The initial layers of Base models are responsible for low-level feature extraction like edges and textures, while deeper layers capture high-level features and object representations as shown in [Figure 3], these pre-trained layers have already learned to recognize many generic features from the original training data.
3. Fine-tuning: To adapt the base models, a new specific classification task is achieved by removing the original classification layers and replacing them with a new set of fully connected layers. These new layers are randomly initialized.
4. Training with New Data: The new classification layers are trained on our smaller dataset, using the existing pre-trained weights of base models as the starting point for our current classification problem. The lower layers, which capture generic features, are often frozen during fine-tuning to prevent them from changing. This is because these lower layers are useful for various tasks.
5. Transfer of Knowledge: Throughout the fine-tuning process, the network fine-tunes the higher-level features specific to the task while preserving the generic lower-level features. This transfer of knowledge from the pre-trained layers to our task can accelerate model's learning process, enabling quicker and more efficient training compared to starting from the scratch.
6. Improved Performance: By fine-tuning base models on any new data can lead to substantial enhancement in performance for image classification tasks. The current model, customized by adjusting neurons or layers during the classification phase, is now tailored to recognize features and patterns specific to our dataset.

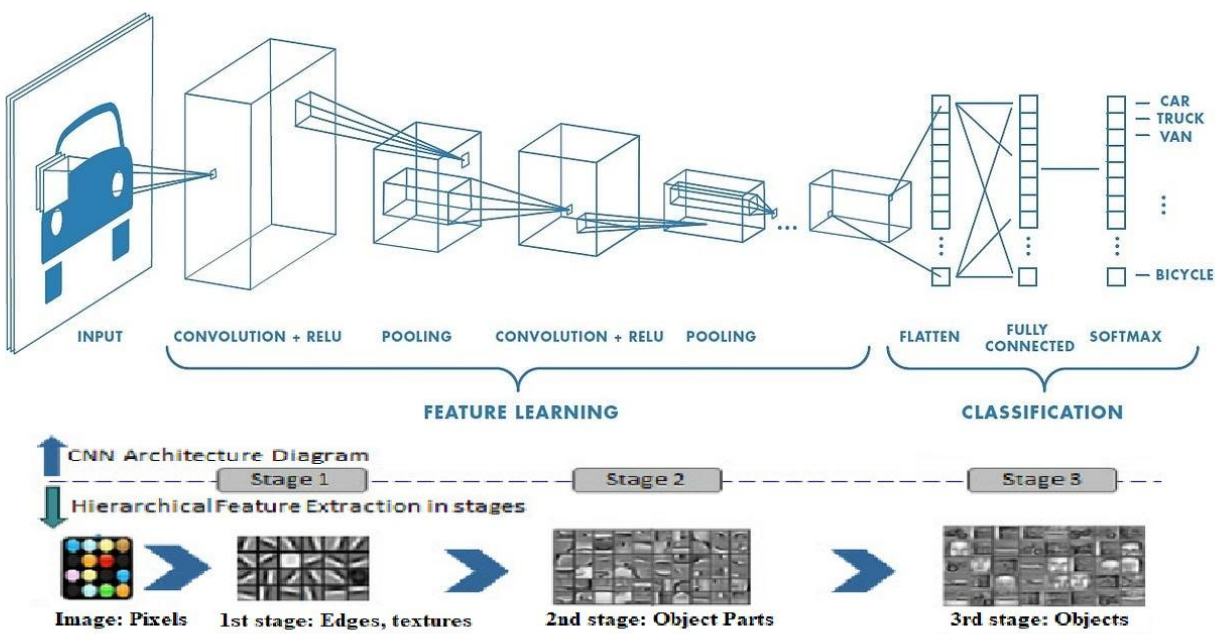

Fig 3. CNN architecture [15,16]

The present research employs transfer learning, utilizing pre-trained models trained on large-scale datasets such as ImageNet, COCO, CIFAR, etc., as the initial point. These models are then fine-tuned for the specific task at hand. Leveraging the knowledge embedded in pre-trained models not only saves time and resources but often yields superior results compared to training a deep neural network from scratch.

Furthermore, a comparative study is conducted by experimenting with various pre-trained models, including CNN[2,4], VGG16[5], Inception Net V3[7], ResNet-50[8], DenseNet 121[9], MobileNet V2[10], and EfficientNet B0[11]. The next section discusses the significance of ResNet-50 architecture and why it is a preferable choice in many Deep Learning applications.

2.4 ResNet-50 Architecture

Among the pre-trained models, ResNet-50 stands out as a preferred choice for numerous deep learning applications and is also adopted in the present study. The selection of ResNet-50 over alternatives like VGG and Inception is attributed to its innovative approach in addressing the vanishing gradient problem. ResNet-50 introduces a distinctive architectural concept known as residual learning, facilitated by skip connections. These connections enable a direct flow of information between layers, effectively mitigating the vanishing gradient issue during backpropagation.

The unique feature of skip connections allows gradients to bypass certain layers, ensuring smoother optimization and training of deep neural networks. This architectural innovation proves crucial, especially in tasks such as leaf disease classification, where the capability to capture intricate features through deep networks is paramount. While variants like VGG and Inception offer value, the empirical success of ResNet-50 in handling the vanishing gradient problem positions it as a robust choice. ResNet-50 strikes a balance between depth and computational efficiency, making it widely used for various computer vision tasks, including image classification.

Here is the description of the ResNet-50 architecture:

- Input Layer: The network takes a colored image as input, typically with dimensions of 224x224 pixels (though this can be adjusted to match your dataset).
- Initial Convolution Layer: The input image goes through an initial convolution layer with 7x7 filters to extract basic features. This is followed by batch normalization and a ReLU (Rectified Linear Unit) activation function.
- Max Pooling Layer: After the initial convolution, a max-pooling layer is applied to reduce the spatial dimensions of the feature maps.
- Residual Blocks: ResNet-50 consists of multiple residual blocks. These blocks are the key innovation of ResNet and are designed to make it easier to train very deep networks. Each residual block contains a set of convolutional layers and shortcut connections (skip connections). The convolutional layers within a block are responsible for learning the residual mapping (the difference between the input and output of the block). The skip connection allows the output of one layer to bypass one or more intermediate layers and be added directly to the output of a later layer. The skip connection mitigates the vanishing gradient problem, making it feasible to train extremely deep networks.
- Bottleneck Architecture: ResNet-50 uses a "bottleneck" architecture in each residual block. It consists of three convolutional layers: 1x1, 3x3 and 1x1. The 1x1 convolutional layers are responsible for reducing and then increasing the dimensions, thus acting as bottlenecks in terms of computational complexity. These bottleneck layers help in reducing the number of parameters, making the network more efficient while maintaining performance.
- Fully Connected Layer: At the end of the network, there is a global average pooling layer, which reduces the spatial dimensions of the feature maps to a single vector. This is followed by a fully connected layer of two units with 512, 256 neurons in each carried over to a softmax activation function for classification.
- Output Layer: The output layer produces a probability distribution over the different classes in the classification task. The number of neurons in this layer is equal to the number of classes that is five as shown in [Figure 4].

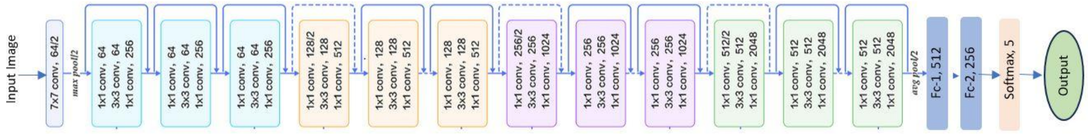

Fig 4. ResNet-50 Architecture fine-tuned the last two layers with 512 and 256 neurons in the Dense FC Layer and 5 neurons in the Softmax Layer as the output [17]

ResNet-50 is a standard variant, there are also deeper versions of ResNet, such as ResNet-101 and ResNet-152, for even more demanding tasks.

2.5 Metrics for Evaluation

The table depicted in [Figure 5] is a confusion matrix utilized to assess the effectiveness of a classification model by presenting the counts of predicted and actual values.

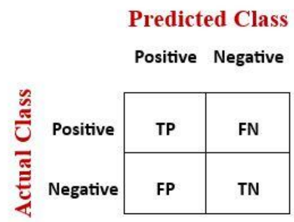

Fig 5. Confusion Matrix

In this matrix, ”TN” represents True Negative, indicating the accurate classification of negative examples. Conversely, ”TP” stands for True Positive, denoting the correct classification of positive examples. The term ”FP” corresponds to False Positive, representing the number of actual negative examples incorrectly classified as positive. On the other hand, ”FN” signifies False Negative, representing the instances where actual positive examples are inaccurately classified as negative.

- **Accuracy:** Accuracy is a measure of how well a model is performing in terms of correctly classifying instances from the total number of instances. Higher accuracy indicates that the model is making more correct predictions and is a common metric used for classification tasks. In the imbalanced datasets, higher accuracy can be misleading, which is calculated using Equation (1).

$$Accuracy = \frac{TN+TP}{TP+TN+FP+FN} \tag{1}$$

- **Precision:** It represents the ratio of true positive predictions to all the positive predictions made by the model. High precision exemplifies that the model makes few false positive errors, and is formulated as given in Equation (2).

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

- **Recall:** It measures a model’s ability to identify all relevant instances. It represents the ratio of true positive predictions to all actual positive instances in the dataset. High recall means that the model is good at capturing all positive instances. Formula for Recall is depicted in Equation (3).

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

- **F1 Score** is a single metric that combines precision and recall to provide a balanced assessment of a model’s performance. Equation (4) used to calculate the F1 Score.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

3 Results and Discussion

The objective of this study is to identify an effective recognition and classification model for papaya leaf diseases. Our dataset consists of 2159 images, of which 1726 are assigned for training, 213 for validation, and 220 for testing purposes.

The proposed model, based on transfer learning with ResNet-50, incorporates customizations to the classification layers. Specifically, the FC1, FC2 and softmax layers are tailored with 512, 256 and 5 neurons, respectively, to facilitate the identification of different classes of diseased papaya leaves. Additionally, fine-tuning is also exercised on several pre-trained models, including CNN[2,4] VGG16[5] VGG19[6], Inception V3[7], ResNet-50[8], DenseNet 121[9], MobileNet V2[10], and EfficientNet B0[11].

These fine-tuned base models are applied to the dataset[13], and each undergoes training for a maximum of 100 epochs, this decision is based on the observation that accuracy reaches a plateau, and the loss no longer decreases on both the training and validation datasets. Throughout the experiment, the Adam Optimizer is utilized with a learning rate of 0.001, and the experiments are conducted on Google Colab. [Figure 6] illustrates the training and validation accuracies and losses of the models, while [Figure 7] provides a summary of the accuracy results for the implemented models.

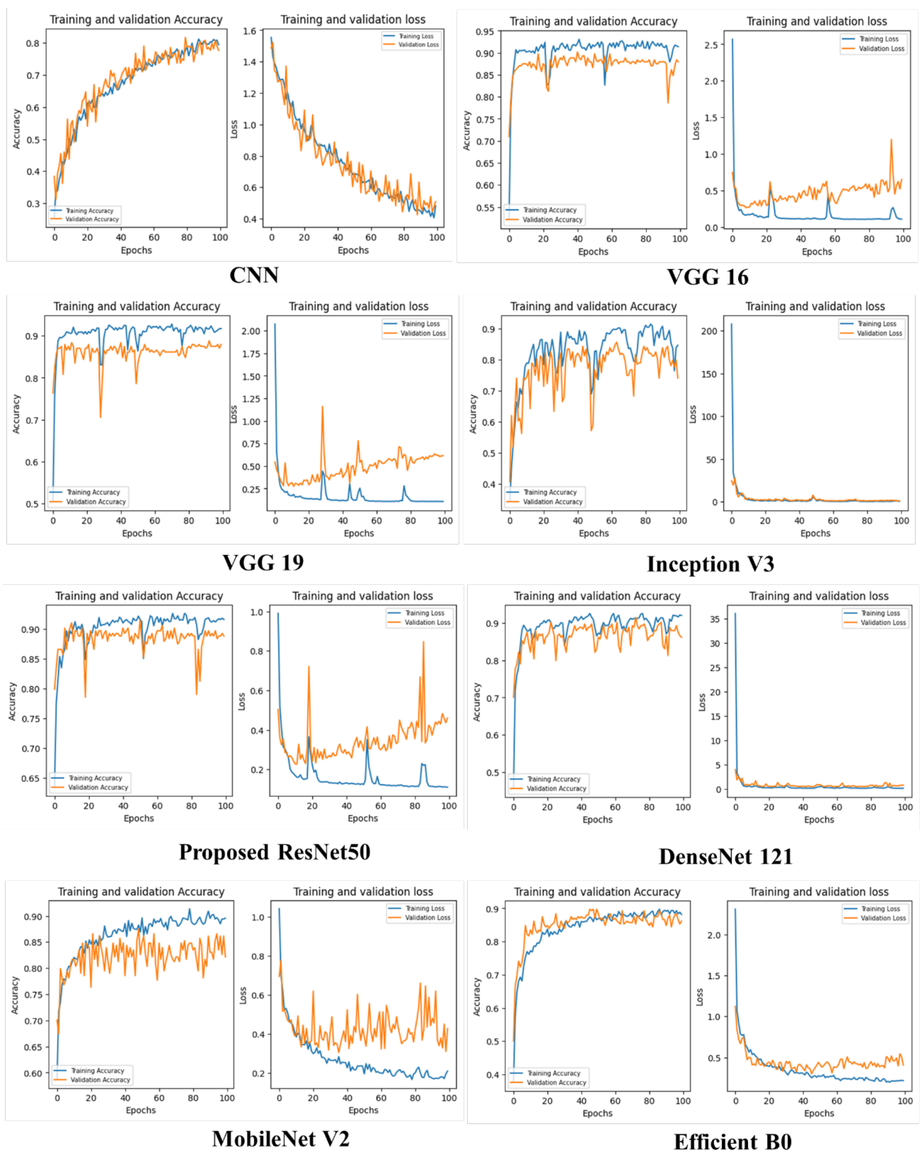

Fig 6. Training and Validation accuracies and loss curves of Base Models of CNN

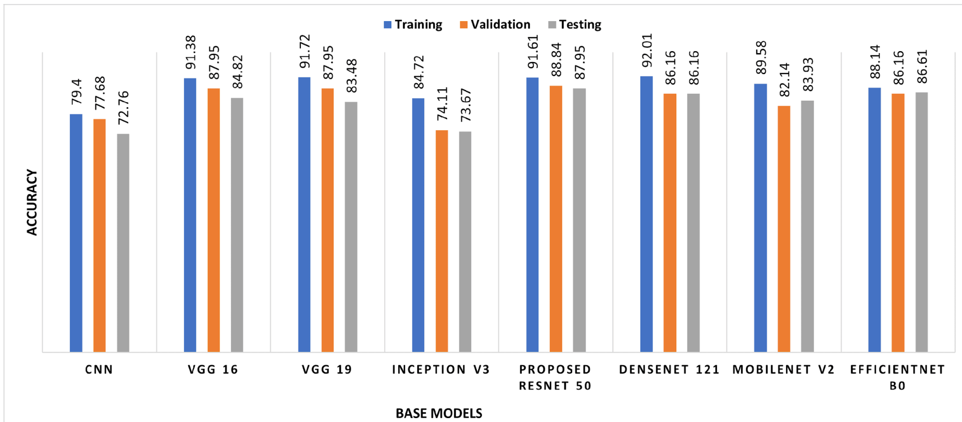

Fig 7. Training, validation and Test accuracies of Fine-tuned models

The confusion matrix of each fine-tuned transfer learning model of CNN is provided in [Figure 8]. The performance metrics such as accuracy, precision, recall and F1-scorefor each model are tabulated in [Table 2], These metrics are calibrated using TP, TN, FP and FN values obtained from the respective confusion matrix.

Table 2. Metrics illustration of Fine-tuned Pre-trained CNN models.

	CNN	VGG16	VGG 19	Inception V3	DenseNet 121	MobileNet V2	EfficientNet B0	Proposed ResNet50
Accuracy (%)	72.76	84.82	83.48	73.67	86.16	83.93	86.61	87.95
Precision (%)								
Anthracnose	88.23	92.31	88.89	92.31	92.45	96.15	95.83	100
Bacterial Spot	48.57	77.5	76.92	78.26	72.5	63.79	67.21	73.01
Curl	90.47	70.67	70.67	0.53	80.59	83.02	93.75	87.75
Healthy	68	100	96.43	100	95.65	91.67	91.67	93.55
Ring Spot	80.55	98.15	96.36	92	95.12	94.59	93.02	96.49
Recall (%)								
Anthracnose	88.23	100	100	100	96.08	98.04	90.19	100
Bacterial Spot	73.91	56.36	0.54	32.73	63.04	80.43	89.13	83.64
Curl	59.37	88.33	88.33	91.67	84.37	68.75	70.31	71.67
Healthy	77.27	100	93.1	75.86	100	100	100	100
Ring Spot	70.73	94.64	94.64	82.14	95.13	85.36	97.56	98.21
F1 (%)								
Anthracnose	88.23	96	94.11	96	94.23	97.8	92.93	100
Bacterial Spot	58.62	65.26	63.83	46.15	67.44	71.15	76.63	77.96
Curl	71.69	78.51	78.51	67.48	82.44	75.21	80.35	78.89
Healthy	72.34	100	94.74	86.27	97.78	95.65	95.65	96.67
Ring Spot	75.32	96.36	95.49	86.79	95.12	89.74	95.23	97.34
Parameters (M)	0.21	16.91	16.91	37.88	33.69	0.79	0.79	1.18

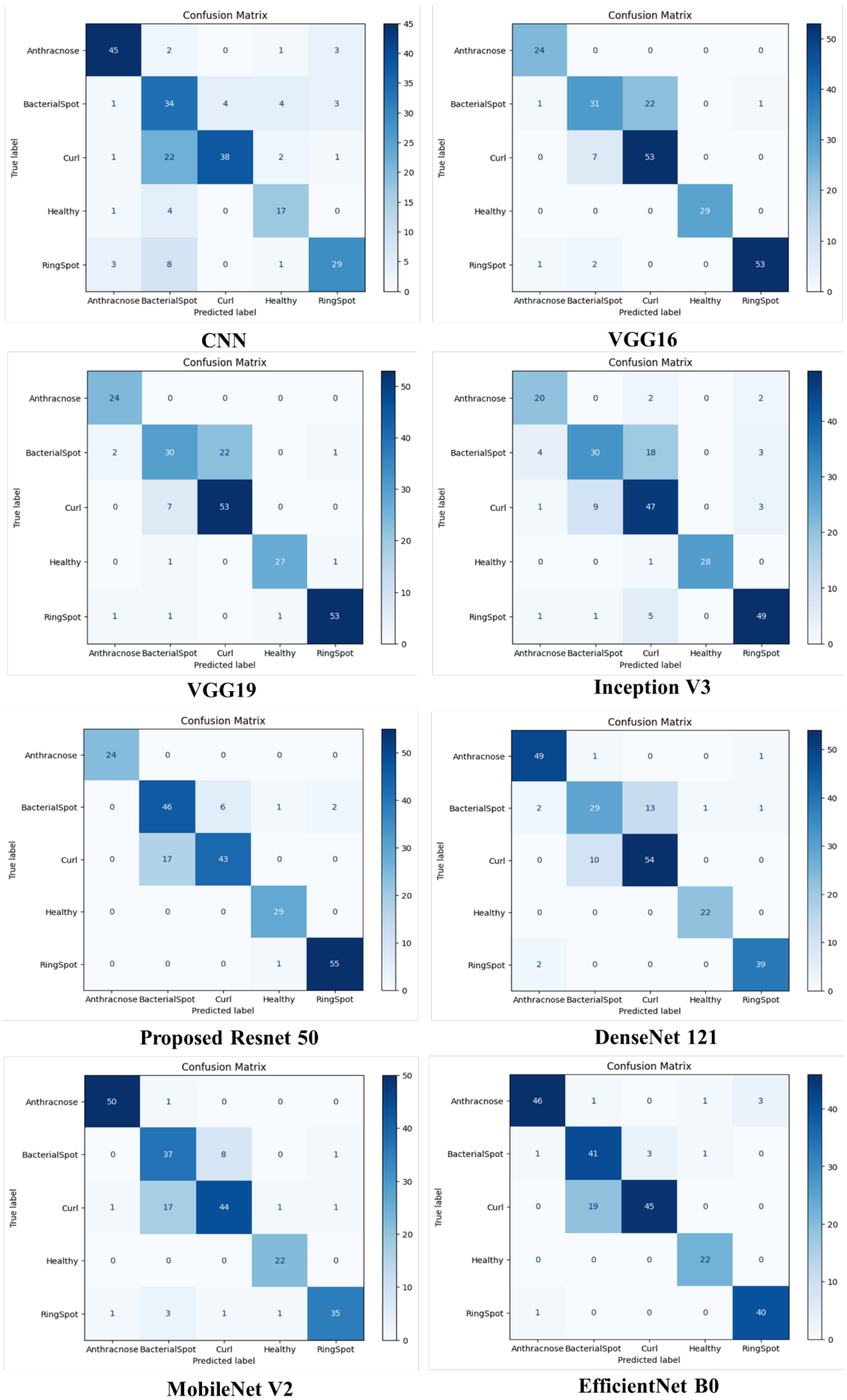

Fig 8. Confusion matrix of CNN base models implemented in the work

With reference to [Table 2], The table offers a comprehensive assessment of various convolutional neural network (CNN) architectures, including VGG16, VGG19, Inception V3, DenseNet 121, MobileNet V2, EfficientNet B0, and a customized ResNet50, in the context of classifying leaf diseases. Notably, the customized ResNet50 model excels in accuracy, achieving an impressive 87.95%, demonstrating its ability to correctly categorize healthy and diseased papaya leaves. In contrast, other architectures like basic CNN, VGG16, VGG19, Inception V3, DenseNet 121, MobileNet V2, and EfficientNet B0 exhibits 72.76%, 84.82%, 83.48%, 73.67%, 86.16%, 83.93%, and 86.61%, respectively. Furthermore, the F1 score, which balances precision and recall, highlights overall effectiveness of each model. Once again, ResNet50 stands out, achieving the highest F1 scores for Anthracnose, Bacterial Spot, Curl, Healthy, and Ring Spot. These results underline the model's balanced performance in terms of correctly identifying positives while minimizing false positives and false negatives. Regarding computational efficiency, the number of parameters in millions (M) provides insights into model complexity. ResNet50, with 1.18 million parameters, strikes a reasonable balance between complexity and performance, outperforming models like VGG16, VGG19, Inception V3, DenseNet 121, MobileNet V2, and EfficientNet B0 while maintaining efficiency. This ResNet-50 model with transfer learning achieved an impressive recognition performance with an accuracy of 91.61% in training and 87.95% in the test dataset. These results surpass the outcomes obtained by other models used in previous studies.

Unlike previous studies[4,5,10–12] which relied on limited datasets collected from specific geographical areas or augmented datasets, our study leverages the "BDPapayaLeaf" dataset. The dataset offers a more extensive and diverse collection of papaya leaf images, encompassing various diseases and environmental conditions, this diversity provides a more realistic representation of real-world challenges.

The proposed model in this study harnesses the capabilities of transfer learning, allowing it to capture intricate features and patterns within the papaya leaf images, ultimately enhancing its classification accuracy. In contrast, earlier studies[3,7,9] employed simpler models potentially missed the advancements offered by more sophisticated models like ResNet. Additionally, our proposed model has been tested on a broader range of papaya leaf diseases, avoiding limitations with a small number of classes[6]. This broader scope ensures that the model's applicability extends to a wider array of disease types, making it crucial for practical use in agriculture.

The application of a transfer learning with a well-established architecture like ResNet-50, coupled with the diverse "BDPapayaLeaf" dataset, leads to enhanced accuracy and generalizability compared to certain prior studies[8]. This approach empowers the model to address challenges associated with variable lighting and image qualities, complex backgrounds, and undefined disease symptoms. These were limitations identified in some of the earlier research endeavors[8].

4 Conclusion

Early detection of leaf diseases is important for Optimizing crop yields, and leveraging computer vision techniques offers a solution to challenges associated with continuous human surveillance. This article focuses on detecting and classifying papaya leaf diseases using the Mendeley dataset, encompassing categories like anthracnose, bacterial spoot, curl, and ring spot in both healthy and diseased papaya leaves. To evaluate the effectiveness of the proposed model, transfer learning was applied to several pre-trained convolutional neural network models, including the basic CNN, VGG16, VGG19, Inception V3, ResNet50, DenseNet121, MobileNet V2, and EfficientNet B0. On a dataset of 1726 training images, 213 validation images, and 220 testing images, recorded accuracies of 72.76%, 84.82%, 83.48%, 73.67%, 85.1%, 86.16%, 83.93%, and 86.61%, respectively.

Notably, the fine-tuned transfer learning model based on ResNet50 emerged as the top performer, attaining an impressive accuracy rate of 87.95%. This outcome serves as a compelling demonstration of its ability to accurately distinguish between healthy and diseased papaya leaves. This study underscores the practicality of the approach in real-world agricultural applications, particularly in predicting crop disease.

Future studies could prioritize the utilization of data augmentation techniques with the aim of balancing the number of images in each class within the dataset. This approach may further enhance testing accuracy.

5 Acknowledgment

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