Fruit Disease Detection Using Lightweight Transfer Learning Techniques

Anuradha S. Varal[1,2][a] and Shabnam F. Sayyad[1][b]
[1]*AISSMS College of Engineering, Pune, India*
[2]*AISSMS Institute of Information Technology, Pune, India*

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Abstract: Fruit disease identification is crucial and must be performed quickly to enhance the productivity of agriculture and reduce crop losses. In this context, fruit disease classification with CNN, powered by efficient transfer learning, is proposed. The pre-trained weights for both MobileNetV2 and VGG16 models are used; some of the initial layers are selectively frozen to create a trade-off between model performance and computational efficiency. This approach will allow us to retain critical features learned from large-scale datasets with reduced training loads on limited hardware. By optimizing the model, high classification accuracy can be achieved with a reduction in processing time and lower RAM consumption, which eventually will make the approach most suitable for deployment on devices with limited resources. To develop variability within the dataset and limit overfitting, augmentations like rotation, flipping, and zooming would be performed on the augmented data. Experimental sessions were carried out on a publicly available dataset of fruit disease images from several classes, showing healthy and diseased conditions. The results clearly describe how, among all, MobileNetV2 ensures the best trade-off between accuracy and efficiency for such applications in real time. Overall, this work showed a proper approach on how to conduct the detection of fruit diseases with lightweight transfer learning models and provided useful insights into implementing the technology for precision agriculture in resource-constrained settings.

1 INTRODUCTION

Due to the increase in the global population, demand for agricultural products has increased ever more and caused agriculture to bear a greater burden toward supporting sustainable development and ensuring food security around the world (Wang and Su, 2022). Agriculture is not only about economic stability, but it also plays an important role in being one of the major sources of food, income, and employment in most parts of the world (Eunice and Hemanth, 2022). Where the possibilities of expansion of agricultural land are limited, erosion of agricultural productivity has become the only feasible manner of meeting the demand. The more critical issues facing these productivity increases are the losses incurred by fruits due to the attack of diseases that always seriously affect its yield and quality (Dhaka, 2021). The early detection and treatment of diseases in fruits are very vital in reducing losses since they will prevent further results of infection and limit damage. Conventional methods of fruit disease detection and identification rely on expert observation by the naked eye. Though it is expected, most developing regions usually have experts in far-flung locations, and such expertise is costly in terms of time. Therefore, automated fruit disease detection has become very critical; it enables the early detection of the symptoms of a disease the moment they appear on the growing fruits. It indeed improves response times and provides expert-level analysis access and scalability, especially in resource-constrained settings.

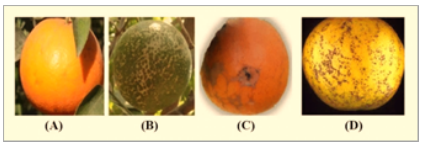

Figure 1: Healthy and infected Fruit images collected from dataset

Early detection of diseases in fruits and vegetables has been enabled lately by several machine learning, deep learning, and IoT-based approaches. Since agriculture today is intended towards its sustainable de-

[a] https://orcid.org/0000-0003-4435-4591
[b] https://orcid.org/0000-0001-8167-8451

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velopment, early disease identification should necessarily be intelligent technologically. Advanced imaging techniques and machine learning models are considered good data-driven frameworks in which a large number of variables have complex relations. In recent times, among them, much attention has been received by deep learning methods, mainly Convolutional Neural Networks and their variants for different complex agricultural challenges due to the fact that from images contextual information will be extracted with global descriptors, hence reduced missing values, minimized errors, and better characterization than any conventional method. Deep Transfer Learning has given disease detection a further boost by making possible tuned models for domain-specific datasets (Hasan, 2023). Also, sensor data generated and transmitted over IoT networks support remote monitoring of crops from agrarians. Cyber-agriculture methods, in turn, give a technological backbone for large-scale deployment. Integrating deep-learning algorithms has been a promising approach toward early detection of fruit diseases by making use of high-resolution imagery and automated analysis (Quy V.K., 2022). Thus, a review of the recent advances and challenges would help to collate the knowledge in detecting fruit and vegetable diseases. The study at hand considers these challenges by examining the potential of three lightweight transfer learning models, MobileNetV2, InceptionV3, and VGG16, for fruit disease detection.

The proposed system relies on two high-performance yet computationally efficient models, optimized by pre-trained weights and selective layer freezing to reach an effective classification with low consumption of memory and time. Further, these are used with data augmentation to give more robustness across a wide range of environmental conditions. Contribution towards precision agriculture: Incorporate scalability for disease detection for the sole aim of maximizing output to support sustainable agricultural practices in resource-constrained environmental setups. The contributions of this paper are:

- To Evaluate Lightweight Transfer Learning Models: Assess the effectiveness of MobileNetV2, InceptionV3, and VGG16 for fruit disease detection, focusing on their ability to achieve high accuracy with low computational demands.
- To Optimize Model Performance: Implement pre-trained weights and selective layer freezing to enhance the performance of the models, aiming to reduce training time and memory usage.
- To Implement Data Augmentation Strategies: Enhance model robustness and generalization by applying data augmentation techniques, ensuring reliable disease detection across diverse environmental conditions.

2 LITERATURE REVIEW

Ramazan Hadipour-Rokni et al.(Ramazan Hadipour-Rokni, 2023) studied CNNs for identifying the type and stage of citrus fruit diseases due to a certain type of pest infestation. Images of citrus fruits were captured before the infestation, at the beginning of the infection, and eight days after infection, amounting to 1,519 images in the dataset taken under highly illuminated natural conditions. The methods used pre-trained CNN models. The VGG-16 model optimized by SGDm showed the best performance in the accuracy of pest detection.

Gulzar Y et al.(Gulzar, 2023) proposed a modified architecture by adding a five-layer head to MobileNetV2, comprising special architecture. They developed the TL-MobileNetV2 model by reusing the pre-trained weights of MobileNetV2 and thus had a very impressive performance with an accuracy of 99%. Their work has pointed out that transfer learning and dropout strategies were quite necessary in enhancing the results and reducing overfitting for the fruit classification task.

Zia Ur Rehman et al.(Zia Ur Rehman, 2022) presented several high-resolution images from different diseases of leaves of citrus from various agricultural settings and used some pre-trained CNN architectures such as VGG16, ResNet50, and InceptionV3. Elaborate pre-processing methodologies, such as scaling, normalization, and increasing the data by augmentation, were used to make the model robust.

Ashok Kumar Saini et al.(Ashok Kumar Saini and Srivastava, 2022) explored transfer learning to identify and classify various diseases affecting the citrus variety of fruits, by employing a number of different pre-trained deep learning models. Their approach reduced the data and computational resource requirements to almost negligible while training on a rich dataset of images related to citrus fruits. These results confirm that these sophisticated methods help in disease control and, in turn, will help to keep crops healthy and improve the yield. This underlines the importance of the integration of AI techniques in agriculture regarding the successful identification of the disease at a faster pace.

W. Gómez-Flores et al.(W. Gómez-Flores and Varela-Fuente, 2022) compared some CNN architectures, like ResNet18, GoogLeNet, Inception-V3, AlexNet, VGG16, and VGG19, for the detection of Huanglongbing disease and other disorders in Citrus sinensis leaves. Results showed that their models were heavily reliant on the number of trainable parameters needed for HLB detection, even with a deeper architecture than VGG19 could achieve perfect sensitivity compared to Inception-V3.

Brown D et al.(Brown D, 2021) performed transfer learning with the MobileNetV2 model to identify fruit diseases, taking its inverted residuals and linear bottlenecks to perform effective feature extraction. Therefore, their work proved that MobileNetV2 could effectively recognize fruit diseases from captured images of natural agricultural environments with high accuracy and recorded an accuracy of 92%on a custom dataset of apple orchards.

Wang Y et al.(Wang, 2021) proposed, an on-field fruit disease diagnostics framework using a MobileNet architecture. Because of its lightweight nature, it is well suited for on-the-spot real-time testing on a mobile platform, with an accuracy of up to 92% and a unique Apple orchard dataset. This demonstrates the practical applicability of MobileNet in agriculture for farmers by providing an inexpensive way toward low-power modern devices.

Lopez R et al.(Lopez, 2021) explored the Xception model for diagnosing fruit diseases through transfer learning using the Fruit360 dataset and obtained accuracy as high as 90%. The efficiency of depthwise separable convolutions of the model makes it effective for classifying images on a large scale, which is very intentional in agricultural applications that aim to yield a high degree of accuracy with limited computational effort.

The ResNeXt model was proposed by Zhang Y et al. (Zhang, 2021), performing fruit disease detection in an apple orchard using transfer learning. The ResNeXt model was trained using a proprietary dataset and gave an accuracy of 92%, along with good robustness against changes in the orchard conditions. Its modular architecture is enhancing its generalization and feature extraction, thereby improving disease control practices.

Park J et al.(Park, 2021), in the year 2021, proposed an SE-ResNet model which could manage an accuracy of 95% while considering the Fruit360 dataset. The incorporation of squeeze-and-excitation blocks in this model allowed the model to capture more channel dependencies and thus always upgraded its performance on fruit disease recognition. This supports the relevance of the SE-ResNet model for reliable identification of diseases.

Lee H et al.(Lee, 2020) conducted research into the use of the ResNet50 model for disease diagnosis in fruits, which ultimately demonstrated an efficient detection performance using deep residual learning for feature extraction. Because of these deep architectures and skip connections, ResNet50 is able to achieve 94% accuracy on the PlantVillage dataset and proves to be a reliable option for timely disease diagnosis. It also points out that, in general, the most important role of transfer learning is to reduce the training time by improving model performance.

Gupta R et al.(Gupta, 2020) (2020) studied transfer learning with the NASNet model for the identification of fruit diseases. The NASNet model achieved an accuracy of 96% on PlantVillage by structuring itself to adapt exactly to the peculiarities of the dataset. It is evident from this work that advanced neural architecture search significantly improves the performance and efficiency of NASNet and hence is viable for use even on challenges of image classification problems that improve agriculture-based disease management.

Recently, Y. Nagaraju et al.(Y. Nagaraju and Stalin, 2020) applied the optimized VGG-16 network in 2020 for the classification of eight types of apple and grape leaf diseases. Fine-tuning a new output layer of the model, while retaining original layers from VGG-16, reduced training parameters by 98.9%.

Pan F et al.(YPan F, 2023) created a lightweight channel authentication technique utilizing frequency-domain feature extraction in order to differentiate between authorized and unauthorized transmitters in agricultural wireless networks, A dataset of common smart agriculture scenarios with both indoor and outdoor communication channels was gathered for the study. When compared to existing ViT models, their modified FDFE-MobileViT model showed better convergence speed, accuracy, and performance.

Yan Zhang et al.(Yan Zhang, 2024) introduced TinySegformer, model for edge computing and agricultural pest identification. TinySegformer achieves great precision and accuracy in semantic segmentation tasks by combining Transformers with neural networks. The lightweight design of the model, which uses quantization and sparse attention methods, fits the processing and storage constraints of edge devices. TinySegformer beats well-known models like DeepLab, SegNet, and UNet when tested on both public and self-gathered datasets.

Siyu Quan et al.(Siyu Quan, 2024) presented a dataset of crop diseases derived from actual field situations in order to train and validate models and improve generality in crop disease detection research. Through the use of partial and point-wise convolutions in place of conventional deep convolution, the model preserves performance while lowering computational complexity.

Sahil Verma et al. (Sahil Verma, 2023) presented a lightweight convolutional neural network to detect illnesses in wheat, rice, and corn. The model achieves higher accuracy than models such as VGG16, VGG19, ResNet50, MobileNetV2, and others by utilizing convolution layers of different sizes to detect infections across different locations.

3 PROPOSED METHODOLOGY

Proposed methodology initiates with the very preliminary collection of a dataset comprising images of healthy and diseased fruits. Pre-processing involves resizing all images to a constant dimension, normalizing to keep the pixel value range consistent throughout the image, and converting color space of images if required. Further, pre-processing is followed by the use of data augmentation techniques that include rotations, flips, and zooms in order to increase variety in the dataset for better feature extraction. The dataset is then split into a train-test split. Later, lightweight models such as MobileNetV2 and VGG16 were used with transfer learning by using their pre-trained weights. The models will be strong in classifying fruit diseases while optimizing for efficiency and resource constraints. Figure 2: Proposed system architecture.

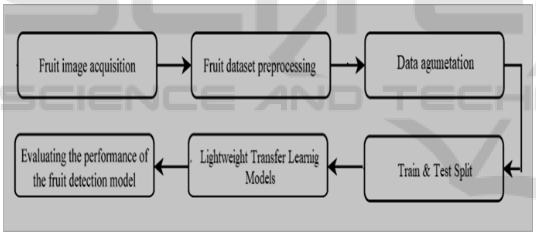

Figure 2: Proposed Fruit Disease Detection Model Flow

Detailed description of each phase for fruit disease classification:

- **Data Collection:** Any machine learning model first needs the collection of a dataset containing a very diverse number of images of both healthy and diseased fruits. Publicly available datasets include the Fruit Disease dataset.
- **Pre-processing:** In this phase, the collected images undergo several pre-processing steps to prepare them for effective model training:

  -Image Resizing: Images are resized into 224x224 pixels to ensure uniformity across the dataset.

  -Color Conversion: Depending on the requirements of the pre-trained models, images may be converted to a specific color space (e.g., RGB, grayscale). This ensures compatibility with the input specifications of the chosen models.
- **Data Augmentation:** Data augmentation expand the dataset and improve the model's robustness. This phase includes:

  -Rotations: Randomly rotating images helps the model learn invariant features and makes it less sensitive to the orientation of the fruit.

  -Flips: Horizontal and vertical flipping can enhance the diversity of the dataset, allowing the model to generalize better.

  -Zooms: Randomly zooming in or out on images can help the model learn features at different scales, improving its ability to recognize diseases regardless of the fruit's size in the image.

  These techniques effectively counteract overfitting by introducing variability into the training set, ensuring the model learns to identify diseases under different conditions.
- **Train-Test Split:** The dataset then undergoes some pre-processing and augmentation, before splitting into training and testing sets; this is often done in an 80-20 split. This way, the model can learn from a large quantity of data while reserving portions to test its performance objectively.
- **Transfer Learning and Lightweight Models:** In this phase, lightweight models such as MobileNetV2, InceptionV3 and VGG16 are employed using TL techniques. This involves:

  -Utilizing Pre-trained Weights: Models that have been pre-trained on large datasets (e.g., ImageNet) are fine-tuned on the fruit disease dataset. This allows the models to leverage learned features from previous tasks, significantly improving performance while requiring less training data.

  -Selective Freezing of Layers: Certain initial layers of the pre-trained model are frozen, while the final layers are retrained on the new dataset. This helps retain critical features while adapting the model to the specific task of fruit disease classification.
- **Performance Evaluation:** Finally, the performance of the models is evaluated using several metrics, including:

  -Accuracy and Loss Curves: Visualizations of the model's accuracy and loss over epochs during training help assess the learning process and detect potential overfitting or underfitting issues.

  This comprehensive methodology ensures robust and efficient classification of fruit diseases, paving the way for practical applications in precision agriculture, particularly in resource-constrained settings.

4 ALGORITHMS

4.1 MobileNet V2

MobileNetV2 is a lightweight CNN suitable for mobile and embedded vision applications. It is an improved version of its original architecture, which Google introduced in 2018. Efficiency: With respect to efficiency, MobileNetV2 has been designed to be highly efficient for both computation and low memory while maintaining high accuracy.

- **Architecture:** MobileNetV2 employs an inverted residual structure that enhances efficiency. This structure includes two main components:

  -Depthwise Separable Convolutions: MobileNetV2 replaces standard convolutions with depthwise separable convolutions, dividing the convolution process into a depthwise convolution and pointwise convolution.

  -Inverted Residual Blocks: These blocks consist of a lightweight depthwise separable convolution followed by linear bottlenecks. This structure allows for more efficient computation and helps preserve spatial information.

- **Activation Function:** Normally, MobileNetV2 used the ReLU6 activation function, which is some sort of modification from the ReLU function where its maximum output is limited to 6. The latter was supposed to weaken the outlier's effect and helpful for quantization.

- **Pre-processing:** The input images for MobileNetV2 should be resized to 224×224 pixels, while the pixel values are often normalized.

4.2 VGG16

VGG16 is a CNN architecture. It is known for simplicity in addition to effectiveness for the Image Classification tasks.

- **Architecture:** VGG16 consists of 16 weight layers, which include:

  - 13 convolutional layers

  - 5 max-pooling layers

  - 3 fully connected layers (also referred to as dense layers) at the end.

  Max-pooling layers are employed after convolutional layers to reduce the spatial dimensions of the feature maps and to downsample the input, allowing for a reduction in computational load while retaining important information.

- **Activation Function:** ReLU stands as an activation function after each convolutional layer in VGG16. It helps the model to learn complex patterns through this non-linearity.

- **Depth and Complexity:** Considering VGG16, a depth of 16 layers lets it learn a rich hierarchy from low-level edges and textures to high-level concepts such as shape and object.

- **Fully Connected Layers:** The feature maps after convolution and pooling are flattened and fed to the three fully connected layers.

- **Pre-processing:** The input images to VGG16 are resized to 224×224 pixels and normalized-mean subtraction is performed.

4.3 Inception V3

GoogLeNet, also referred to as the Inception Network, is a CNN computational architecture presented by Google in 2014. The Inception architecture leverages multiscale features together with effectively using computing resources.

- **Architecture:** The core innovation of the Inception architecture is the Inception module, which allows the model to learn features at various scales. Each module contains multiple parallel convolutional filters of different sizes (1x1, 3x3, 5x5) and a pooling operation (typically max pooling).

- **1x1 Convolutions:** The use of 1x1 convolutions serves several purposes:

  – Dimensionality reduction: They reduce the number of input channels before applying larger convolutions (3x3, 5x5), which helps decrease the computational burden.

  – Feature extraction: They allow the model to learn complex features without increasing the number of parameters significantly.

- **Auxiliary Classifiers:** To combat the vanishing gradient problem and improve gradient flow, the original Inception model introduced auxiliary classifiers. These are additional branches in the architecture that act as regularizers, providing additional gradients during training.

- **Global Average Pooling:** Inception uses global average pooling, which reduces the feature map to a single value. This approach decreases the number of parameters and helps mitigate overfitting.

5 RESULTS ANALYSIS

5.1 Performance Parameters

Several performance metrics are used to assess the effectiveness of fruit disease classification algorithms. Below are key performance parameters along with their formulas:

Table 1: PERFORMANCE PARAMETERS

Parameter	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1-Score	$\frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$

Where;
TP = True Positives (correctly predicted positive cases)
TN = True Negatives (correctly predicted negative cases)
FP = False Positives (incorrectly predicted positive cases)
FN= False Negatives (incorrectly predicted negative cases)

5.2 Results

Results depict a significant improvement in metrics performance for the lightweight MobileNetV2 model, showing its efficiency in this application. MobileNetV2 achieved the highest among others in terms of performance and efficiency as 95% accuracy. This remarkable accuracy indicates that MobileNetV2 is successful in identifying the most relevant features within the dataset, which it does with a small computational cost, making it a good candidate to be put into practice in resource-constrained environments. Overall, results confirm the advantages of applying lightweight transfer learning models, particularly MobileNetV2, for high classification accuracy and ensuring operational efficiency. This progress brings very nice insights into the implementation of precision agriculture technologies, proving that effective fruit disease detection might not demand computationally expensive resources.

Figure 3, Figure 4 and Figure 5 shows the accuracy and loss curve of Lightweight MobileNet Model, Lightweight Inception Model and Lightweight VGG16 model.

Results are shown in Figure 6, comparing all the models tested in this work. From these results, it can be noticed that, among all models, the light version of MobileNetV2 reached the highest accuracy

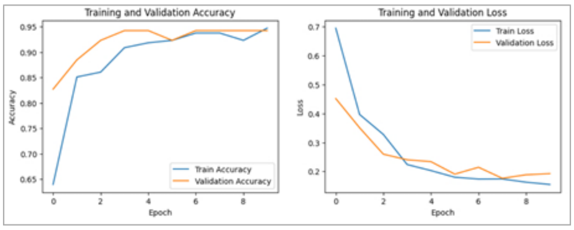

Figure 3: Accuracy and Loss Curve of Lightweight MobileNet V2 Model

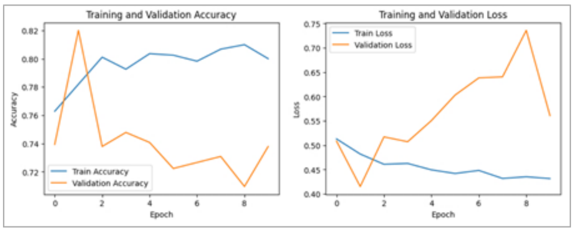

Figure 4: Accuracy and Loss Curve of Lightweight Inception V3 Model

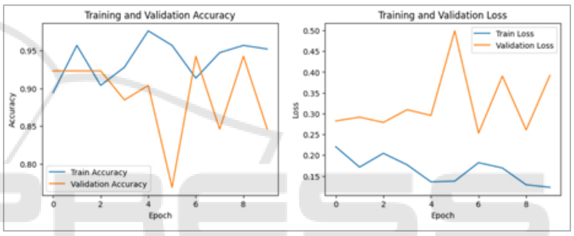

Figure 5: Accuracy and Loss Curve of Lightweight VGG16 Model

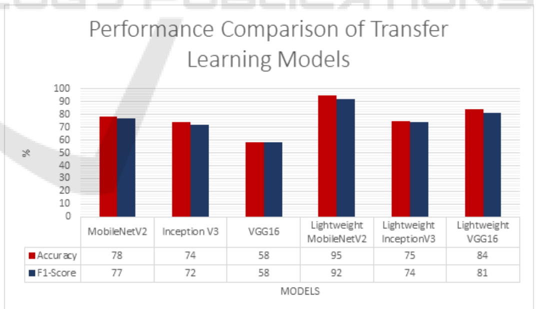

Figure 6: Performance Comparison of Transfer Learning Models

and F1-score. The MobileNetV2 model reached an incredible 95% in accuracy, beating even the best classical transfer learning models. This success is attributed to its neat architecture: it allows for effective feature extraction while saving computations, hence making a model feasible in resource-constrained settings. Conclusions: The results confirm capability for a lightweight transfer learning model, such as MobileNetV2, in advancing agricultural applications to provide farmers with timely and accurate fruit disease detection without relying on high-end computing resources.

5.3 Computational Benefits

Lightweight models like MobileNetV2, Lightweight InceptionV3, and Lightweight VGG16 offer significant computational benefits over regular models. These models also provide faster inference with lower latency, enabling real-time processing on resource-constrained devices. Their lower computational overhead and efficient use of resources reduce power consumption. Additionally, lightweight models are more scalable and easier to optimize for mobile and embedded systems, supporting hardware accelerators like DSPs, GPUs, and NPUs. This makes them well-suited for edge computing and real-time applications. Below Table shows the parameters comparison of traditional transfer learning models and proposed lightweight transfer learning model.

Table 2: MODEL PARAMETERS COMPARISON

Models	**Traditional (Params)**	**Lightweight (Params)**
VGG16	˜138M	˜16M
MobileNet V2	˜3.4M	˜2.9M
Inception V3	˜23.8M	˜6M

6 CONCLUSION

This research addresses the importance of rapid and precise fruit disease detection, whose essence is paramount, as it enhances agricultural productivity by reducing crop loss. By using light-weight transfer learning with pre-trained models, effective classification models with a good balance between accuracy and computational efficiency were developed using MobileNetV2 and VGG16. Therefore, subsequent to this, our approach in this paper consists of rigorous steps of preprocessing, effective augmentation strategies, and judicious model performance evaluation performance in terms of various metrics such as precision, accuracy, recall, and F1-score. Notably, the lightweight MobileNetV2 model stood out with the highest accuracy of 95%, thus representing superiority against traditional transfer learning methods. It is crystal clear from the comparative analysis that lightweight models achieved higher accuracy and F1 scores with MobileNets, hence, can make a robust solution for deployable real-time applications in resource-constrained agricultural settings. These results add valuably to the insights on implementing technologies in precision agriculture that finally help farmers in effective disease management and improvement of overall fruit health.

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