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DISEASE DETECTION IN PLANTS USING TRANSFER LEARNING APPROACHES

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Article Info

Abstract

Food security completely relies on agriculture at the global level. Diseases of plants are a threat to crop yields which ultimately leads to economic loss and food insufficiency. With the boom of the technological revolution, traditional methods to detect diseases were left behind. Techniques from AI, computer vision, image processing, machine learning (ML), and deep learning (DL) were applied to automate processes and provide solutions quickly and labor-free. Transfer learning comes under the domain of machine learning, and can leverage pre-trained models on huge datasets, and acclimate them to certain tasks (detect plant disease). This research investigates the implications of the transfer learning (TL) approach in detecting plant diseases and getting better accuracy on larger datasets. The verdicts of this study have the potential to decrease the time and computational cost associated with model training and get more efficiency. This research used a dataset available on Kaggle named "plant disease recognition dataset".

Keywords: *Image Classification, Transfer Learning, Convolutional Neural Networks (CNNs), Deep Learning, Pre-trained Models, Fine-tuning, Layer-freezing, Plant Diseases.*

Introduction

Global sustenance is critically dependent on agriculture and significantly contributes to ensuring food security. However, the quality of crop yield poses a significant threat to plant diseases. This threat can further lead to food scarcity and economic downturns. Earlier, detecting plant diseases depended on manual methods, either by visual evaluation or by any expert physically examining them. However, they are labor and time-intensive approaches with the possibility of human error. Now in this technological era, disease detection systems have been updated too. They get advanced and automated with the intrusion of AI, image processing, and ML methods. TL comes under the domain of machine learning, as it can leverage pre-trained models on huge datasets, and acclimate them to certain tasks, for example "*detection of plant diseases*"[1].

Since deep learning became available, the field of image classification has changed dramatically, enabling extremely high levels of accuracy. In particular, Convolutional Neural Networks (CNNs) are DL models that have demonstrated exceptional effectiveness in various image classification tasks, ranging from recognizing ordinary objects to providing diagnostic information[2]. In any case, huge numbers of labeled data are typically required to train these models effectively. For various industries, such as medical services, agriculture, manufacturing, and the IT sector, obtaining big datasets is not feasible due to constraints including monetary feasibility, consumption of time, and data availability[3].

Nowadays, it is easy for various agricultural diseases in all stages of its growth to attack a plant and finally affect its overall health and productivity. These diseases could all be caused either by biotic factors or abiotic ones. Biotic factors include viruses, fungi, bacteria, mites, and slugs due to microbial infection while abiotic - water scarcity, high or low temperature, irradiation, and scant nutrition - restrict growth[4]. Sample images of diseased plant leaves, included in this work, were taken from the Plant Village dataset and other datasets to represent both diseased and healthy plants. The survey also focuses on some works related to plant disease detection and classification using computer vision-based techniques, starting from image acquisition to the leaf image dataset, image pre-processing, test and training and validation sets, further splitting of data, and methods of performance evaluation[5].

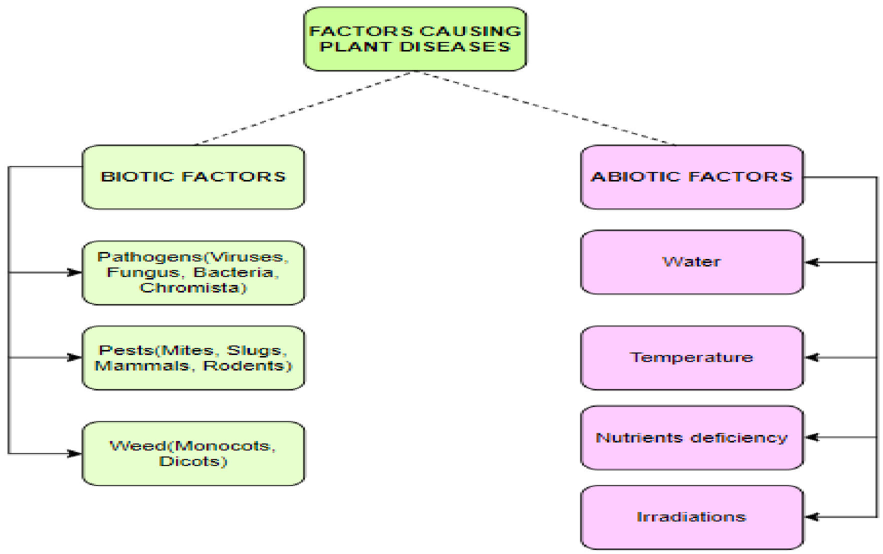


Figure 1. Causes of plant diseases

Fig. 1 and 2 represent the causes of plant diseases, and other images from different datasets for diseased and healthy plant leaves are included here for more details. Transfer learning is the act of taking a pre-trained neural network model and modifying it to fit a modified dataset by moving the features that were learned[6].

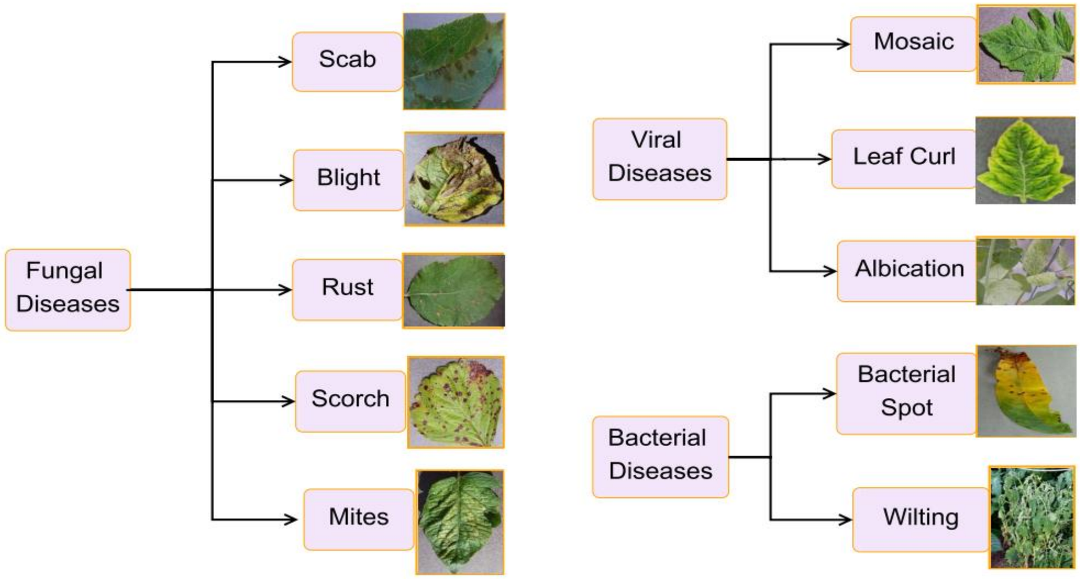


Figure 2. Various biotic infections

Using a TL approach, image classification can be improved on small datasets. There are many advantages and drawbacks to using TL approaches with small datasets. The main problem is to improve the transfer learning approach to concurrently reduce the cost of computing, increase precision, and improve efficiency. Furthermore, the accuracy and generalizability of previously trained and optimized models and techniques are adversely impacted when applied to small datasets[7][8].

Other industries, such as manufacturing, IT, and agriculture, may face similar issues and only be classified through image classification. The procedure of transfer learning involves first training a model on a situation that is identical to the unsolvable issue—either on a similar sample or an entirely distinct sample, and then applying the model to an unfamiliar assignment. The bottom layers of the CNN identify common patterns (such as lines and edges), the middle filters identify object portions, and the upper layers identify the entire object made up of various forms and angles[9]. There is a clear need for in-depth research that critically evaluates how different pre-trained models, fine-tuning methods, and layer-freezing techniques influence the performance of image classification tasks, particularly when limited data is available. Previous literature is mostly focused on traditional machine learning approaches, which are time-consuming and labor-intensive, and there can be human error too [10].

This study's primary goal is to look into the applications of transfer learning methodologies to enhance image classification performance when working with small datasets. The specific objectives include:

1. Compiling and getting ready for evaluation of the dataset.
2. Evaluating the effects of different fine-tuning techniques and pre-trained models within CNN frameworks on the accuracy and generalizability.
3. Determining the most effective TL strategies, that apply to different industries, including agriculture.
4. Lowering the time and computational load associated with training DL models on sparse data.

This research is crucial for industries struggling with data scarcity since it provides workable ways to use deep learning techniques properly. As Andrew Ng aptly stated, "Transfer learning will be the next driver of ML success," and this study positions itself at the forefront of that advancement.

LITERATURE REVIEW

In recent years, numerous studies have highlighted the growing prominence of transfer learning across various applications[11]. Researchers have consistently demonstrated that transfer learning can significantly enhance model performance and reduce training time by utilizing knowledge from pre-trained models[12]. While much of the research has concentrated on applying transfer learning to large datasets, there has been limited focus on optimizing these approaches for small datasets. This gap underscores the need for further exploration in adapting transfer learning techniques to handle smaller data environments effectively[13].

Transfer learning emerges as a powerful strategy to address challenges in scenarios with limited data[14]. It enables the adaptation of pre-trained models, which have already learned general features from extensive datasets like ImageNet, to new tasks that involve sparse data[15]. The authors review past research in plant disease detection, highlighting traditional computer vision methods such as feature extraction, image segmentation, and SVMs, as well as DL approaches using Convolutional Neural Networks (CNNs) like Alex Net, Google Net, and VGG Net[16]. The effectiveness of these techniques has varied and is primarily dependent on the quantity and quality of the dataset. Transfer learning has gained significant traction in recent years, emerging as a pivotal technique in various machine learning applications[17]. The value of transfer learning is particularly evident when the new task is constrained by limited data, enabling the model to draw on the knowledge acquired from larger, pre-existing datasets[5].

Numerous transfer learning strategies, including feature-based transfer learning, fine-tuning transfer learning, and multi-task learning, have been covered in a study[18]. The transfer learning method was investigated in a different study using fifteen different convolutional neural network models, such as VGG, Inception, dense net, etc. [19]. Due to their fine-tuned models and greatest precision when using the transfer learning strategy, Inception and VGG fared exceptionally well[20]. Research reflects an upward trend in plant leaf and crop disease detection and classification studies. This indicates growing interest and a rise in the application of technologies, machine learning, and computer vision, toward agricultural problems[11]. While pathological diagnosis in the plant world has now become of vital importance with efficiency, research continues. Hence, more effective and efficient techniques regarding the detection and classification of diseases featuring crops come into existence with increased accuracy [4].

Some deep learning-based solutions have been proposed for real-time insect detection and identification in soybean crops, as indicated in [21]. In the study, several transfer learning models were evaluated to check on the feasibility and accuracy of the method in identifying and detecting the insects. The proposed method reached an accuracy of 98.75% with YoloV5, 97% with InceptionV3, and 97% with a CNN. Of those, YoloV5, which had the best performance, ran at 53 fps and was thus suitable for real-time detection[22]. A dataset of crop insects was also collected after several image captures using different devices. This approach greatly reduced the workload for producers, simplified the process, and furthered better results[14] [23].

The authors of [24] , presented a CNN-based model for the detection and classification of diseases in tomato leaves using a public dataset. Additional images were collected from some local farms. GANs were applied to avoid overfitting problems by generating synthetic samples with appearances similar to the training samples. The performance was excellent for the proposed model, with accuracy above 99% on both training and test datasets related to the detection and classification of diseases in tomato leaves. The authors of [25] applied the "Plant Village" dataset to classify four bacterial, two viral, two mold, and one mite infection for a total of 12 crop species. In addition, there were images of healthy leaves (unaffected). Predictive models with machine learning methods such as Support Vector Machines (SVMs), grey-level co-occurrence matrices (GLCMs), and CNNs were developed. Besides, the improvement of the classification methods within AI favored the advances in backpropagation inside artificial neural networks. A KMC operation was, therefore, conducted on real-time images of the leaves concerning disease detection[21] [26].

The proposed model has recorded high accuracy rates of 99% for rice crops, 98% for apples, and between 94% and 97% for tomato crops. Later, in the case of this multi-class problem, precision, recall, and F-measure were calculated for each symptom pool being considered to represent a class. These results prove that this model proves to be very effective in the detection and classification of various types of plant diseases with very good accuracy across different types of crop species[27].

Farmers usually face a helpless situation while protecting crops because they cannot identify the plant diseases correctly. Biomedicine is one of the attractive segments toward plant disease identification[28]. At present, there is no trustworthy and effective method except image processing techniques for plant leaf image-based disease diagnosis. This technique provides a fast and correct way of detecting different types of diseases within plants. Promotion of farmers' activities should go in a friendly direction: providing quick and effective means by which they can diagnose plant diseases both correctly and speedily, thus protecting the crop better and saving time[29].

It seems that transfer learning was a useful tactic to address these issues. Transfer learning enables the adaptation of pre-trained models to new tasks involving sparse data. These models have already acquired generic features from large datasets (such as ImageNet) [30]. A large dataset (labeled) and a wide range of computational and memory are the two essential steps for fully training a CNN. According to the author of another study [31] an alternate strategy with the same goal is transfer learning. In his investigation, he employed three models: Resnet, VGG Net, and Alex net [32]. Numerous writers have utilized empirical methodology in their investigations, primarily relying on trial and error to identify genuine transfer learning approaches[33]. These methods' main problems are their poor generalizability and lack of study comparability [34].

Title/Year	Classifier	Accuracy	Gaps/limitations
An effective disease detection approach for corn plants based on vgg16 TL model (2019)	VGG16	92.7%	Need diversity in the dataset
A deep learning approach to grape leaves disease classification (2020)	CNN	98.5%	Need to address environmental conditions, diversity in the dataset
Detection and classification of tomato leaf disease using deep learning (2021)	ResNet-50	97%	Need to address more diseases
Plant disease detection using CNN and GAN based data augmentation (2021)	CNN, GAN	97.7%	There should be increased computational power, focus on quality of augmented data

A comparative analysis of DL-techniques for plant disease detection (2023)	CNN, Res Net, VGG	Best one is 97%	Comparative in nature, but does not give deep insights
Multi-class plant disease detection using advanced CNN architectures and multi scale feature extraction (2023)	CNN	98%	Need diversity in dataset, high computational cost
Efficient deep learning techniques for the detection and classification of plant diseases (2023)	Efficient Net	97%	Need to get accuracy on large datasets
Comprehensive analysis of DL-model for recognizing plant diseases in diverse environments (2024)	CNN	94%	Require data diversity

In conclusion, there are still a lot of obstacles to overcome even though transfer learning provides effective ways to deal with data deficits, especially in challenging domains like image classification[35]. Therefore, the review of the related works shows that there is a research gap in special techniques comprised of learning rate adjustment, data augmentation, and the addition of more layers to improve the performance of plant disease identification[36]. These aforementioned techniques are very essential in improving performance, especially in the case of plant leaf disease identification and classification in images[37]. Precise identification of plant diseases is much important in disease prevention, improving yields, and better management of plant health. In applying these advanced techniques, which contribute to more efficient and trustworthy ways of conducting plant disease management[38].

METHODOLOGY

This research will systematically evaluate and compare different transfer learning approaches using pragmatic methods and a quantitative research paradigm. Multiple testing, dataset standardization, statistical analysis (including t-tests and ANOVA), and performance metrics are required to verify the validity and reliability of the research. Figure 4 explains the complete process of methodology for this research.

Data collection and preprocessing

This research used a dataset that is available on Kaggle named "plant disease recognition dataset". It has 87000 images of plant leaves with 38 various disease categories. This dataset is taken due to its large size and the diverse nature of different classes. (https://www.kaggle.com/datasets/rashikrahmanpritom/plant-disease-recognition-dataset). This is quite a diverse and substantial dataset that can be useful for training and evaluating machine learning models in plant disease detection. All the images are supposed to be uniformly resized, having a dimension compatible with the pre-trained models selected. Perform basic image transformations of rotation, flipping, cropping, zooming, and color adjustment that increase the training set variance and hence will assist in improving model generalization. The implementation of data augmentation can be done using libraries like TensorFlow or PyTorch. The pixel values should be normalized to lie within the range of 0 to 1, or one can standardize them depending on the requirement of the pre-trained model. Encode disease categories into numerical labels if not done by using one-hot encoding. Also, check the correct encoding of multi-class labels.

Fine Tuning Process

Load Pre-trained Weights: The model can be initialized from weights pre-trained on ImageNet or other large datasets. Modify the output layer by replacing the last classification layer of the pre-trained model with a new dense layer that shall match the number of classes. Freezing of the initial few layers of the model preserves the learned features; only the later layers will be trained with the additional dense layer. One can also unlock some of the deeper layers and fine-tune them to adapt the model for plant-disease-specific features.

Tune Hyperparameters

Set an initial learning rate; for example, use 1e-4, and tune depending on needs. Use any optimizer, one can use Adam or SGD with momentum. Learning rate schedules and decaying can be implemented for better convergence.

Training the Model

The dataset is split into training 70%, validation 15%, and test sets 15%; classes to be balanced within each set. Choose an appropriate batch size, for instance 32 or 64, within reasonable GPU memory and train for tens of epochs, observing its performance. Use categorical cross-entropy loss for multi-class classification. It can track accuracy, precision, recall, F1-score, and confusion matrix to evaluate the model performance. The robustness of the model can be determined using k-fold cross-validation. Follow hyperparameter selection of the best set of hyperparameters using techniques including grid search or random search.

Performance Appraisal

General accuracy on the test set. Implement these measures for each class to get a view of the model performance in identifying each type of disease. Include a confusion matrix plot to show performance over various categories of diseases.

Visualization

The ROC curves are plotted for each class, enabling the analysis of the trade-off between the true positive rate and the false positive rate. Use class activation maps to highlight the portions of the leaf images that the model depends on for making a prediction.

Model Deployment and Usage

Convert the model to an appropriate, deployable format like TensorFlow Lite or ONNX, for mobile or edge devices. Design an easy-to-use interface via the web or mobile by which users can upload images of leaves and get real-time diagnoses of any disease contained within them. Incorporate the model into agricultural management systems or apps to provide real-time disease detection and management recommendations. Summarizing the effectiveness of the transfer learning approach for plant disease detection by its performance metrics. Then explain how it might affect agriculture and ways of crop management.

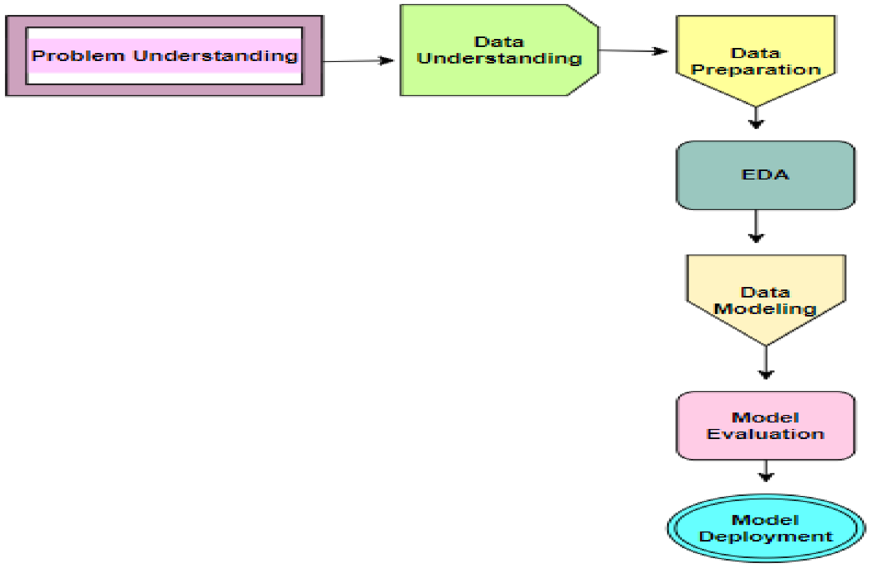


Figure 3: Methodology process

i. Problem Understanding

The general objective of this paper is to achieve a comprehensive insight into the diseases that attack plants, their variety, and the kind of loss this causes to the yield. It goes on to explain the aspect of diseases, the impacts on plant health, and hence various economic losses and agricultural losses. Understand the problem of plant disease along with its various species, and their damage towards crop yields.

ii. Data Understanding

The dataset used for plant disease detection is large; hence, transfer learning will most need to be performed. Check the authenticity of the dataset by way of citations and references in existing literature about their credibility and relevance.

iii. Data Preparation

The data must be described in as much detail as possible, including the type of images current in the dataset and any possible data quality problems. The comments concern whether it is clean or if some preprocessing steps should be taken to deal with missing values, inconsistencies, or irrelevant information.

iv. Exploratory Data Analysis

The distributional characteristics of the dataset will be analyzed, and it will be checked whether the dataset is balanced or needs some adjustments in terms of either oversampling or under sampling. Apply statistical analysis to the distribution across the data. If the distribution is not normal for the data across each attribute, apply any normalization procedures.

v. Data Modeling

The goal is to develop the predictive model by extracting relevant features, fine-tuning the pre-trained models, leveraging transfer learning, and training the model on the labeled datasets. In this stage, the model configuration should be developed to accurately identify and classify plant diseases.

vi. Model Evaluation

Assess the performance of the trained model through various evaluation metrics, which will include confusion matrix analysis to get insight into the performance by classification, performing cross-validation that makes sure the model results are reliable, and checking the generalization on other datasets.

vii. Model Deployment

Evaluate the efficiency of the model in practical applicability and how well it predicts plant diseases for new, unseen images. This includes the model's effectiveness and functionality in the real world, ensuring that the performance of the model is good enough in practical scenarios. Each step plays a vital role in making the methodology sound, the data well-represented, and the final model effective in detecting and classifying plant diseases.

RESULTS AND DISCUSSION

The generalization across the dataset of each model is discussed, along with robustness in plant disease detection. The detailed comparison of five transfer learning models outlines the strengths and limitations of each, such as the deep residual connections in ResNet, structured convolutional layers in VGG16 and VGG19, pre-trained baseline of ImageNet, and multi-scale feature extraction in Inception. All are evaluated against their adaptability to the plant disease dataset. The results are contextualized to assess the applicability and relevance of those results in real-world agricultural scenarios; this provides insight into the efficiency, accuracy, and practicality of deployment in resource-constrained environments. Key observations pertain to the trade-off between accuracy and computational cost for each model. It then concludes the chapter by synthesizing findings and zeroes in on the model that exhibits an optimal balance between performance and computational efficiency for plant disease detection. This structured approach helps develop a deep understanding of the results and implications of such, yet keeps clarity and repeatability in check in the research process. The discussion ties results into the broader objective: the development of an effective, practical solution for agricultural disease detection by transfer learning techniques.

Key Components of CNN Architecture:
Input Layer: The input layer consists of $N\times k$ neurons, where k represents the number of input variates in a time series and N denotes the length of each univariate series. In this layer, raw input data are prepared for further convolutional operations.

Convolutional Layer: This layer performs convolution operations on the input data from the preceding layer using predefined filters. The number of filters defines how many different features the layer can learn and stride defines the step size of the convolution. There is a nonlinear activation function applied to the output that enables the network to learn complex patterns.

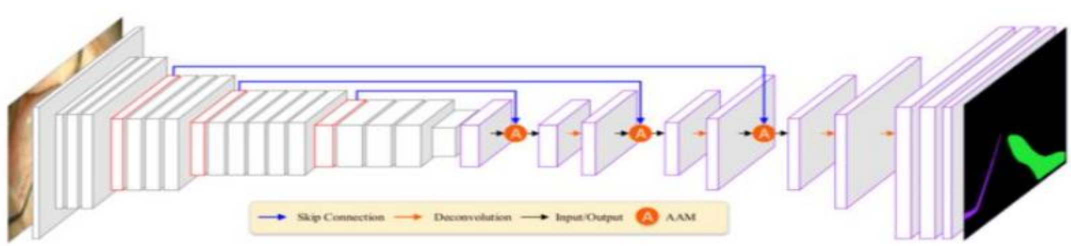
Pooling Layer: The pooling layer reduces the spatial dimensions of the feature map while retaining the most important features. A pooling layer improves the mathematical calculation process by reducing variance and preventing overfitting.

Fully Connected Layer: This layer combines the extracted features and feeds them into a classifier or regression model that makes the final prediction. It allows the CNN to extract hierarchical features effectively from input data, which is why these are so powerful in images and time-series data; however, the computational demands hint toward optimized parameter selection either based on domain knowledge or through empirical experimentation.

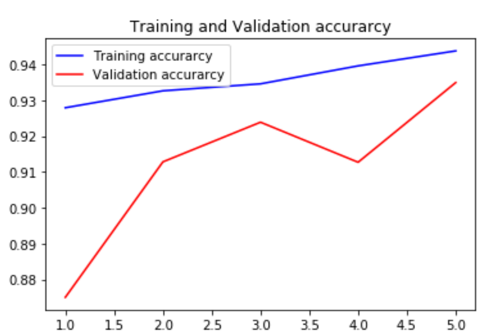
ResNet	Deep (50-152 layers)	High	93.5	Avoids vanishing gradients, hierarchical features	Complex datasets
VGG16	16 layers	Moderate	93.1	Simplicity and structured features extraction	Medium complex datasets
VGG19	19 layers	Very high	93.9	Deeper patterns than VGG16	Fine-grained tasks need deep extraction
CNN	Variable (5 layers)	High	89.7	Broad knowledge transfer from large datasets	Tasks with limited labeled data
InceptionV3	Modular, scalable	Moderate	91	Multi-scale feature extraction	Diverse datasets with various features

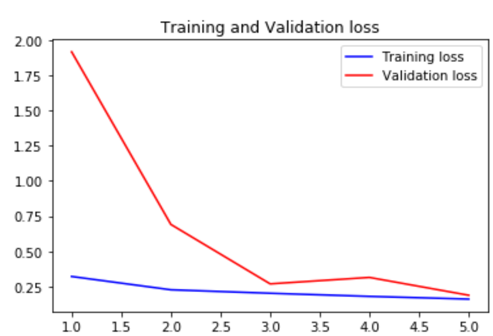
According to the table presented, five different models of transfer learning ResNet, VGG16, VGG19, CNN, and InceptionV3 were found to vary in depth, efficiency, accuracy, and other aspects for which each may have strengths.

ResNet achieved a great accuracy of 93.5%, while its deep architecture (50-152 layers) and residual connections helped avoid vanishing gradient problems. ResNet is good at learning hierarchical features and hence has been quite suitable for complex datasets where detailed feature representation and classification are required. The efficiency of this model, given its depth, outlines its robustness and practicality for large-scale tasks.

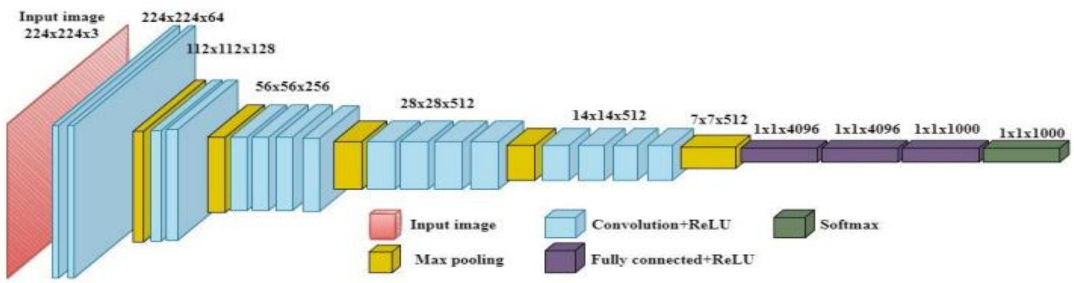


Architecture of ResNet

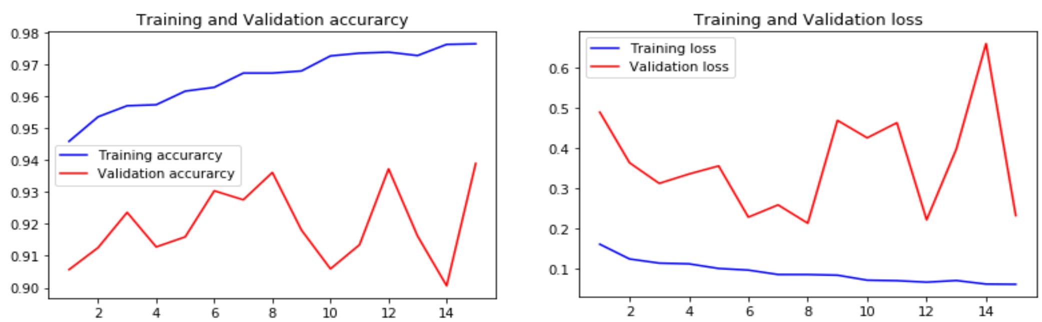




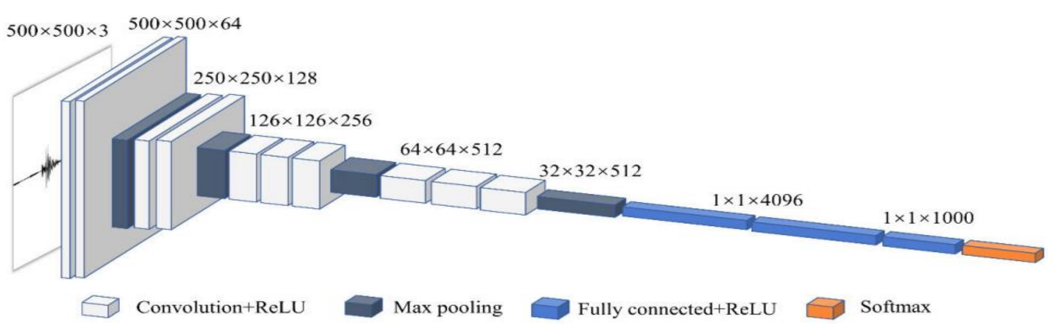
VGG19 has a deeper architecture compared to VGG16, and it gave an accuracy of 93.9%, slightly higher than the results provided by other models. Because of this nature, it becomes very efficient in learning deeper patterns for finer details, hence suitable for tasks that require intricate feature extraction. This model is very efficient and excellent in scenarios where high accuracy and speed are both crucial.



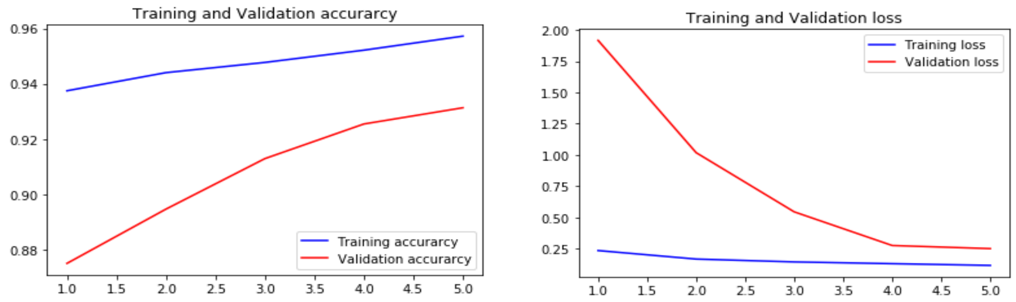
Architecture of VGG19



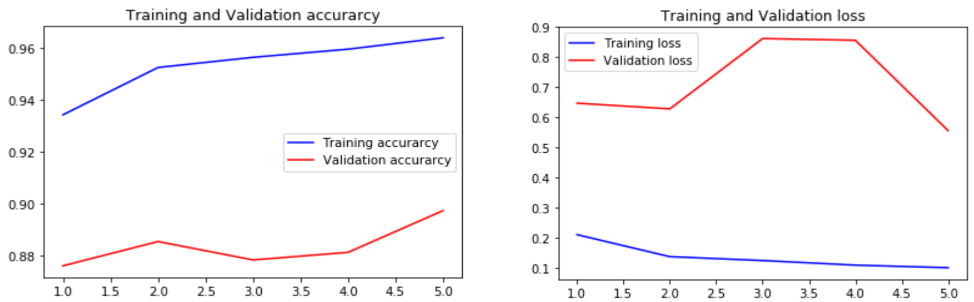
VGG16 had 93.1% accuracy, with the advantages of simplicity and straightforward feature learning. The performance-computational complexity tradeoff is very adequate in a 16-layer network, hence excellent performance can be achieved at medium-complexity datasets. However, giving up a bit of accuracy compared to VGG19 may be more practical in certain environments due to its lower computational cost.



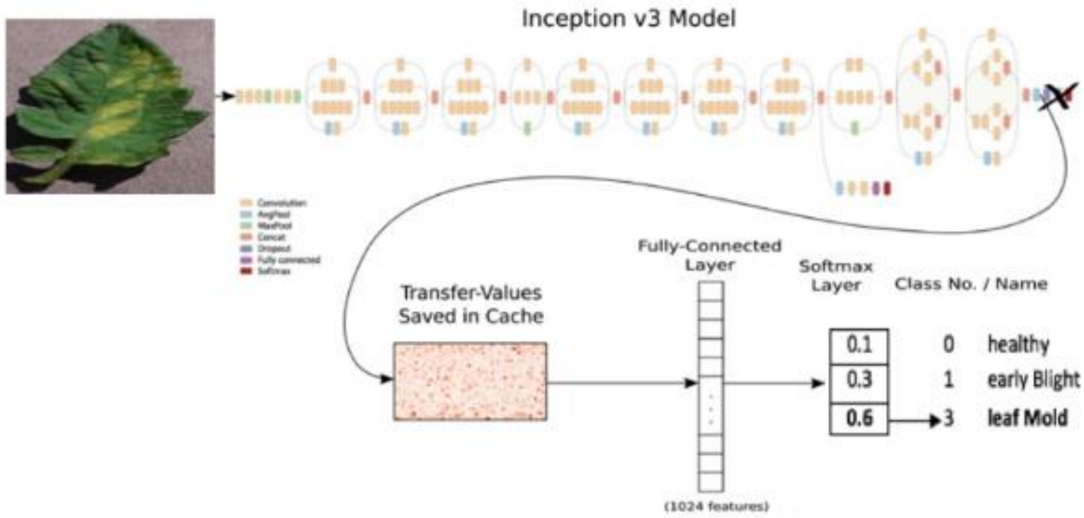
Architecture of VGG16



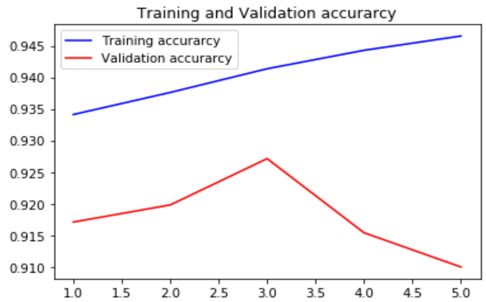
Our best performance for the custom CNN architecture is 89.7%, while the best overall results came from pre-trained models, the fact that this network is only five layers and performs well really speaks to its generalization ability. The performance of this model benefits a lot from its broad knowledge gained from big data, so it would be especially effective for tasks where there is only a little labeled data.

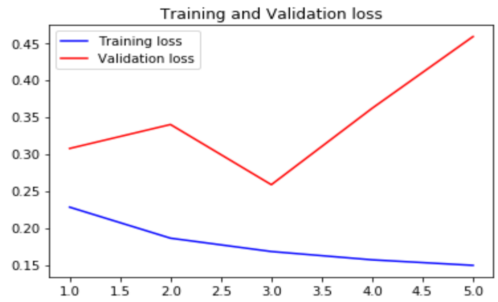


Finally, InceptionV3 reached an accuracy of 91%, while it was very effective for multi-scale feature capture due to its modular and scalable design. The capability to process a wide range of diverse datasets with varying features has made the model versatile. Its accuracy is somewhat lower compared with ResNet and VGG models, but there is a unique advantage in balancing the efficiency of feature extraction with the computational cost in this architecture.



Architecture of Inception V3





In summary, the result showed that ResNet and VGG19 are the most accurate models, dealing with highly complex datasets and extracting deep hierarchical features. InceptionV3 strikes a good balance for different tasks while VGG16 is an efficient alternative for medium-complex datasets. The custom CNN is less accurate but still useful in scenarios where limited labeled data is available. This demonstrates the flexibility and robustness of transfer learning techniques.

CONCLUSION

Transfer learning has already become a cornerstone in deep learning, which can achieve competitive results even with a much smaller amount of data. The work is based on the idea of deploying pre-trained models, previously trained over large, well-established benchmark datasets, to solve particular problems similar to the original. The process of transfer learning extracts knowledge from previously learned models to avoid training a completely new model, saving much in regards to computational resources and time.

During the transfer learning process, the last layers of any pre-trained network are replaced with new layers that are conjoined for the particular classification task. It generally consists of a fully connected layer along with a SoftMax classification layer. It is altered by changing the number of target classes. Other added layers would improve the performance of the model: an activation layer followed by a batch-normalization layer and a dropout layer. These changes have been done to improve generalization and avoid overfitting.

In the following models that were used in this research, a range of hyperparameters is explored systematically, such as dropout rates, learning rates, and batch size, for optimal performance. Most of the fine-tuning was performed with pre-trained CNN architectures like VGG16, VGG19, ImageNet, Inception, and ResNet on the plant disease classification task. This consisted of selective unfreezing of some layers within the network to allow it to learn from the task at hand, while still retaining much of the robustness in feature representations of the original model.

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