Transfer Learning for Tomato Leaf Disease Detection: A Comparative Study

Abstract—**For farmers, early detection and treatment of tomato leaf diseases are essential since they can severely reduce both production and quality. Researchers have recently employed transfer learning, a machine learning tool, to develop more accurate and efficient methods for recognizing and diagnosing tomato leaf diseases. This paper examines recent research on transfer learning for tomato leaf disease diagnosis and detection. It also explores the benefits and drawbacks of transfer learning in this situation and discusses several deep learning architectures that can be applied for this. For the purpose of identifying and diagnosing tomato leaf diseases, the study compares the efficacy of transfer learning models to conventional machine learning techniques. According to the findings, typical machine learning models are not as accurate or as effective as transfer learning models. The research also discusses the possible effects of these transfer learning approaches on tomato farming, such as crop yield improvement and a decrease in crop loss. The report concludes by addressing possible tomato farming impacts of these transfer learning techniques for the identification of tomato leaf disease.**

Index Terms—**Transfer Learning, Tomato Leaf Disease, Deep Learning, VGG16, VGG19, AlexNet, ResNet50, DenseNet201, DenseNet169.**

I. Introduction

Tomato is one of the most extensively grown crops worldwide and is an essential ingredient in many cuisines. However, a number of diseases that can seriously degrade the yield and quality of tomato plants are contagious. One such disease is the tomato leaf disease, caused by fungi and bacteria that can lead to severe leaf damage and reduce tomato production. Traditional methods of identifying and treating tomato leaf diseases are time-consuming and labor-intensive, making them impractical for large-scale farming.

To address this challenge, researchers have turned to machine learning techniques, specifically transfer learning, to develop more efficient and accurate methods for detecting and diagnosing tomato leaf diseases. In order to train a classifier to recognize and categorize new tomato leaf photos, transfer learning entails employing a pre-trained deep neural network to extract valuable characteristics from images of healthy and diseased tomato leaves. These studies looked into the advantages and drawbacks of transfer learning in this context and suggested several deep learning architectures.

In this review paper, we examine the recent research on the use of transfer learning for tomato leaf disease diagnosis and detection. We explore the advantages and limitations of transfer learning in this context and discuss the various deep learning architectures used for this purpose. Finally, we discuss the potential effects of these methods on tomato farming as well as the directions for future study in the area of transfer learning for the diagnosis of tomato leaf disease.

II. Background

Several studies demonstrated the use of transfer learning for tomato leaf disease diagnosis and detection. For example, Pattnaik et al. provide a framework based on transfer learning for classifying pests in tomato plants [1]. The authors created a database of 859 images of tomato plants online and divided them into 10 categories. Again, Peyal et al. conducted a comparative analysis of three convolutional neural network (CNN) models, namely VGG-16, VGG-19, and Inception-V3, for detecting tomato leaf diseases [2]. They compare the performance of three different models, VGG-16, VGG-19, and Inception-V3, on a dataset containing 11,000 images of tomato leaves with signs of nine different diseases.

Aversano et al. recommend using three previously trained convolutional neural networks (VGG-19, Xception, and ResNet-50) to analyze a picture of a tomato leaf in order to determine whether a tomato plant is ill and what kind of illness it has [3]. The authors use the openly accessible Plant Village dataset, which includes more than 50,000 images of 14 different crops, for the neural network's training, validation, and testing. In 2019, Hasan et al. employed a Convolutional Neural Network (CNN)-based precision farming system to identify high disease areas in tomato crops [4]. The suggested system is anticipated to boost crop yield, preserve crop quality, and give farmers access to real-time data so they can make wise decisions. A study by Khasawneh et al. classifies 9 tomato illnesses using deep transfer learning [5]. The method is based on transfer learning of well-established deep learning networks and uses leaf images as input. The findings indicate that it is possible to create smartphone-based applications that can help plant pathologists and farmers carry out disease diagnosis and management tasks swiftly and accurately.

In order to manage pests and avoid crop loss, Rubanga et al. conducted a research which suggests a deep learning-based method for early measurement of the effects of the *Tuta absoluta* pest on tomato plants [6]. Convolutional Neural Network (CNN) models were used in the study, and they were trained using a dataset of healthy and diseased tomato leaves that was acquired from actual field tests. In another study, Bouni et al. use transfer learning for identifying tomato leaf diseases using the deep learning CNN approach [7]. The CNN has used AlexNet, GoogleNet, and ResNet as its foundation in this case. When comparing the pre-formed models ResNet, DenseNet, Alexnet, and VGG, the authors of this paper attempt to classify 9 tomato leaf diseases discovered in the PlantVillage Dataset. Moreover, Abbas et al. developed a deep learning-based method to recognize tomato diseases by looking at tomato leaf photos [8]. In there research, tomato plant leaves are simulated using the Conditional Generative Adversarial Network (C-GAN), and the DenseNet121 model is trained using transfer learning on simulated and real-life photographs to categorize the tomato leaves images into ten categories of disease.

A deep learning model is employed in a study to identify the *T. absoluta* pest on tomato plants. In order to identify three cassava diseases and two pests using an image dataset made up of 11,670 photos taken in a Tanzanian field, Ramcharan et al. [9] used a predetermined InceptionV3. A deep learning model was put out by Liu et al. [10] to classify four diseases from a dataset of apple leaves that had 1053 photos of ill and healthy leaves with an overall accuracy of 97.62%. For instance, Zhang et al. identified eight tomato diseases using CNN architectures that were trained on 5550 images: early blight, yellow leaf curl, corynespora leaf spot, leaf mold, virus, late blight, septoria leaf spot, and two-spotted spider mite [11]. In order to identify nine tomato diseases, Brahimi et al. tested the effectiveness of shallow models versus pretrained deep models (AlexNet and GoogleNet). He claims to have great accuracy for AlexNet and GoogleNet of 98.66% and 98.53% [12]. Besides, Six tomato illnesses were classified by Rangarajan et al. using two pretrained deep learning models, VGG16 and AlexNet [13]. They made use of pictures of both healthy and diseased tomato leaves from the PlantVillage collection.

Furthermore, Saeed et al. conducted a study to diagnose tomato leaf disease by classifying healthy and unhealthy tomato leaf images using two pre-trained convolutional neural networks (CNN) model which are Inception V3 and Inception ResNet V2 [14]. K. Zhang et al. [15] looked at the efficacy of SGD and adaptive moment estimation (Adam) in the diagnosis of tomato leaf disease using three pretrained networks (AlexNet, Google Net, and ResNet). On another research, Bouni et al. categorized and divided several tomato plant leaf diseases into different categories using a deep neural network model [16].

III. Methodology

To conduct our literature review on transfer learning for tomato leaf disease classification, we searched various academic databases including IEEE Xplore, ScienceDirect, and Google Scholar. ”Transfer learning”, ”Tomato plant dieseases”, ”classification”, and ”deep learning” were the search phrases we used. Along with the identified papers, we also included relevant papers found through manual reference searching. After skimming the titles and abstracts, we chose 18 studies that fit our inclusion criteria. These papers, which addressed the use of transfer learning for classification of tomato leaf diseases, were published between 2017 and 2023. The common methodology involved training pre-trained convolutional neural networks on a dataset of tomato leaf images to detect various diseases, such as bacterial spot, early blight, and late blight. The majority of research here acquired their own images for training and testing or used publically accessible datasets. On the target dataset, transfer learning was frequently used to improve the classification accuracy of pre-trained models. Also, In certain research, the training dataset's diversity was increased by using synthetic images generated by generative adversarial networks.

A. Transfer Learning Methods

Researchers have used transfer learning to develop rapid and accurate methods for spotting and identifying tomato leaf diseases. This has been accomplished using a number of deep learning architectures, such as VGG-16, VGG-19, Inception-V3, DenseNet169, Xception, and ResNet-50. These architectures have obtained excellent classification accuracies in identifying various diseases and pests in tomato plants after being trained on large datasets of images of healthy and diseased tomato leaves. The experimental findings demonstrate that the suggested models have the potential to identify and classify numerous tomato leaf diseases and pests in the field with high classification accuracy rates, ranging from 88.83% to 99%.

1) VGG16: The VGG model, commonly known as VGGNet, is referred to as VGG16. It is a convolution neural network (CNN) model with 16 layers. VGG16 was created to categorize images into 1,000 different groups, including common items like cats, dogs, and cars. In VGG16, a max-pooling layer comes after each of the 13 convolutional layers and the three fully connected layers. The convolutional layers use tiny 3x3 filters to process the input image, while the max-pooling layers condense the output of the convolutional layers' spatial dimensions. The fully connected layers at the network's end use the output from the final max-pooling layer to generate a probability distribution across the 1,000 classes. With 138 million parameters overall, VGG16 is a relatively large network.

2) VGG19: A further extension of the VGG16 architecture, VGG19 is a deep convolutional neural network architecture. The network has 19 layers, including 3 fully connected layers and 16 convolutional layers. VGG19 is intended to identify things in images and classify them into one of 1000 item categories, much as VGG16. The extra layers in VGG19 help the model be better at identifying more intricate elements in images. VGG19 contains more parameters than VGG16 and requires more processing resources to train. It is a common option for picture classification tasks in computer vision research because of its increased accuracy in object recognition tasks.

3) Inception V3: Inception-v3 is a convolutional neural network that is deep with 48 layers and designed by Google. By lowering the number of parameters while preserving accuracy, it was intended to increase the network's efficiency. To extract features from the input image, Inception-V3 employs a combination of various convolutional filter types (1x1, 3x3, and 5x5). Inception-v3 is renowned for its great accuracy, efficiency, and speed when compared to other well-known deep learning models. It is faster and more memory-efficient than VGG-16 and VGG-19 while yet reaching comparable levels of accuracy because it has fewer parameters. On some tasks, such as finding small objects or identifying minute details in images, it might not perform as well as some other models.

4) Xception: Another convolutional neural network design that Google introduced is called Xception. Similarly to Inception-V3, Xception uses depthwise separable convolutions for traditional convolutions. This keeps the accuracy while requiring fewer computational resources.

5) DenseNet: In a similar manner to a convolutional neural network, a DenseNet uses Dense Blocks to directly connect all layers (with matching feature-map sizes) with one another, utilizing dense connections between the layers. The design is built around the concept of "Dense connectivity" in which every layer of the network is connected to every other layer in a feed-forward method. DenseNet-121, DenseNet-169, DenseNet-201, and DenseNet-264 are the different variants of DenseNet that contain additional layers. These versions differ in the number of layers and the number of filters in each layer. DenseNet's larger iterations typically do better at classifying images but use much more computational resources. Also, When DenseNet is trained using RMSprop, the dense connection ensures that information is successfully conveyed across the network, and the adaptive learning rate of RMSprop helps in effectively optimizing the weights.

6) RseNet50: A 50-layer convolutional neural network called ResNet-50 consists of 48 convolutional layers, one MaxPool layer, and one average pool layer. In order for ResNet-50 to learn the residual input–output mapping, residual connections are used. In doing so, the network is able to learn deeper representations with fewer parameters.

In terms of accuracy, DenseNet-169 and ResNet-50 are considered to be the most accurate models. VGG-16 and VGG-19 have good accuracy but require high computational resources. Inception-V3 and Xception are designed to be efficient and have good accuracy.

IV. Discussion

In our review of the existing literature on transfer learning for tomato leaf disease detection, we found several key themes and patterns. We found transfer learning is really effective in improving the accuracy of tomato leaf disease detection. Many studies reported significant improvements in detection accuracy when using transfer learning compared to conventional machine learning methods.

In their research, Pattnaik et al. performed transfer learning to classify tomato plants into ealthy tomato leaves and plants with various pests and diseases, such as early blight, late blight, leaf mold, septoria leaf spot, spider mites, target spot, mosaic virus, yellow leaf curl virus, and bacterial spot [1]. The authors present a system based on transfer learning for classifying pests in tomato plants using the DenseNet169 model. In addition to describing the hyperparameters utilized in the training process, such as learning rate and batch size, they also describe the process of fine-tuning the pre-trained model. Additionally, to expand the training dataset, they employ data augmentation approaches. According to the findings, among the 15 models, the DenseNet169 model had the best classification accuracy, at 88.83%. Additionally, the authors evaluated how well their method classified tomato plant diseases in comparison to other cutting-edge methods. This framework provides a promising approach for the early detection and classification of tomato plant diseases and pests using deep learning models. However, the study has limitations, such as a limited dataset size and the need for further research to evaluate its generalizability to other plant diseases and crops.

Fig. 1. Example of images in Plantvillage dataset

Similarly, the experimental results of the research conducted by Peyal et al. show that the Inception-V3 model outperformed the other two models with an accuracy of 90% [2]. The authors suggested that their proposed approach can be used for the early detection and classification of tomato leaf diseases in the field. In the research of Aversano et al., the proposed three pre-trained CNN models have acceptable precision and accuracy coefficients, demonstrating the applicability of convolutional neural networks to this type of problem. One could argue that in this research, the VGG-19 model performs significantly better than ResNet-50 and only slightly better than Xception with accuracy at 97% [3].

Other studies have also shown promising results using transfer learning for tomato leaf disease detection. Khasawneh et al. used eleven deep convolutional neural network models to categorize ten classes and found that DenseNet-201 had the highest mean F1 score, at 98.5%, whereas SqueezeNet had an F1 score of 90.9% [5]. The SqueezeNet model trained the quickest and had the shortest inference time, while the DenseNet-201 model provided the greatest results with 99.2%. Confusion matrices revealed a pattern of incorrectly categorizing diseased leaves. This study used photos of sick leaves to diagnose nine tomato illnesses using deep transfer learning and tried-and-true models. Using images of sick leaves, deep transfer learning was used to identify and categorize tomato disease. With three data split strategies, the performance evaluation of deep transfer learning models was repeated ten times.

Furthermore, Hasan et al. took images of tomato leaves using an infrared camera mounted on a drone [4]. These photos are then processed and categorised using deep learning algorithms to distinguish good, average, and unhealthy leaves. The model employed in this work is Google's pretrained CNN model, also known as Inception-v3, which was retrained using a dataset of 2100 photos of tomato leaves that were found online and 500 images that were taken at nearby farms. In order to reduce the usage of pesticides and diseases while still targeting the necessary amount, the system is built to spray precise pesticides on afflicted areas based on their level of infection. Due to the utilization of transfer learning on Inception-v3, 99% accuracy and quick system execution were achieved in this investigation.

In the research of Rubanga et al., Inception-V3 performed the best, with an average accuracy of 87.2% in determining the severity status of *Tuta absoluta* in tomato plants [6]. Four pretrained CNN architectures (VGG16, VGG19, ResNet, and Inception-V3) were used to accomplish this. The pretrained models could distinguish between the High Tuta severity condition more quickly than the Low Tuta and No Tuta severity states. The study adds to the sparse literature on estimating tomato plant pest severity and suggests a method for assessing *T. absoluta* effects early in tomato plant development. This method will aid farmers and extension experts in making decisions that will increase tomato productivity and reduce losses.

In another study by Bouni et al. big data methodology was applied, which is important in the agriculture sector [7]. With the help of field video cameras, sensors, and micrometeorological data, precision farming aspires to turn agriculture into data-driven practices that monitor and offer real-time crop information. After analyzing all of the observations, they found that DenseNet with Rmspro optimizer obtained the greatest result and was the most appropriate and efficient model for their data with the highest level of accuracy of 99.99%. Besides, Abbas et al. developed a deep learning-based method to recognize tomato diseases by looking at tomato leaf photos where they used the PlantVillage dataset [17] and achieved classification accuracy for tomato leaf images into 5 classes, 7 classes, and 10 classes of 99.51%, 98.65%, and 97.11%, respectively [8]. Moreover, In order to identify three cassava diseases and two pests using an image dataset made up of 11,670 photos taken in a Tanzanian field, Ramcharan et al. used a pretrained InceptionV3 which could accurately identify the diseases and pest damages where the results were 96% red mite damage, 95% green mite damage, 98% cassava brown streak disease, and 96% cassava mosaic disease [9].

In his research by Zhang et al., they were able to clearly and accurately classify the tomato diseases using CNN architectures where AlexNet scored 95.63%, GoogleNet scored 95.66%, and ResNet50 scored 96.51% [11]. On the other hand, Rangarajan et al. used two deep learning models, VGG16 and AlexNet, where the models achieved classification accuracy rates of 99.24% and 96.51% respectively [13]. They employed

TABLE I
COMPARISON OF DIFFERENT MODEL'S ACCURACY

Author	Dataset	Model	Accuracy	Comment
Pattnaik et al. (2020) [1]	PlantVillage	DenseNet169	88.83%	DenseNet169 performs better
		VGG-16	Data not available	
Peyal et al. (2021) [2]	PlantVillage	Inception-V3	90%	Inception-V3 performs better
		VGG-16	87%	
		VGG-19	87%	
Aversano et al. (2020) [3]	PlantVillage	VGG-19	97%	VGG-19 performs better
		Xception	95%	
		ResNet-50	60%	
Hasan et al. (2019) [4]	PlantVillage	inception-v3	99%	
Khasawneh et al. (2022) [5]	PlantVillage	DenseNet201	99.20%	DenseNet201 performs better
		SqueezeNet	97.20%	
Rubanga et al. (2020) [6]	In house dataset	Inception v3	87.20%	Inception-V3 performs better
		ResNet-50	83.70%	
		VGG-19	78.30%	
		VGG-16	87.10%	
Bouni et al. (2022) [7]	PlantVillage	DenseNet (Rmsprop optimizer)	99.99%	DenseNet (Rmsprop optimizer) performs better
		ResNet	99.90%	
		AlexNet	92.30%	
		VGG-16	98.10%	
Mkonyi et al. (2020) [9]	In house dataset	VGG-16	91.90%	VGG-16 performs better
		VGG-19	83.10%	
		ResNet-50	86.80%	
Saeed et al. (2023) [14]	PlantVillage	Inception ResNet V2	99.22%	Inception ResNetV2 performs better
		Inception V3	97.80%	
Bouni et al. (2023) [16]	PlantVillage	DenseNet (Adam optimizer)	99.90%	DenseNet and Inception ResNet V2 (Adam) performs better
		AlexNet	88.50%	
		VGG-16	98.90%	
		ResNet	99.90%	

The ImageNet database's ResNet50 convolutional neural network was trained on more than a million photos. Using a 224 x 224 image as input, this network generates an output with a probability of a particular class. The model that performed best in this study was VGG16, which classified 66 previously undiscovered photos from the test set with an overall accuracy of 91.9%.

In addition to these studies, transfer learning was used in the research conducted by Saeed et al. to retrain the two models, which had previously been trained using open-source databases and field recorder photos [14]. Image pre-processing and data augmentation were performed in this study. The two models' performances differ slightly as a result, with Inception ResNet V2 performing best with a 99.22% accuracy rate. On another research, Bouni et al. achieved 99.9% accuracy rate when utilizing Adam optimizer as its optimizer, and it's DenseNet with transfer learning surpassed all the others [16]. For this study, certain authors gave their perspectives in detail picture preprocessing, picture capture, and image investment corrections were done for input preparation in an effort by S. Adhikari et al [18] to automatically classify and diagnose plant illnesses with an emphasis on tomatoes.

Overall, our review suggests that transfer learning has great potential for improving the accuracy of tomato leaf disease detection. However, further research is necessary to address gaps and limitations in the existing research.

V. Analysis

According to the table I, the DenseNet model using the Rmsprop optimizer on the PlantVillage dataset produced the maximum accuracy, which was 99.99%. The DenseNet model using the Adam optimizer on the same dataset came in second place, with an accuracy of 99.90%. With a 99.22% accuracy rate on the PlantVillage dataset, the Inception ResNet V2 model comes in third. Other models with high accuracy levels between 90% and 97% include VGG-19 and Inception-V3. On the PlantVillage dataset, some models, like ResNet-50, however, only managed to achieve low accuracies of between 60% and 86.80%.

In general, we found that each of the models the authors presented has advantages and disadvantages of its own. For instance, VGG-16 and VGG-19 have a reputation for being straightforward and effective at image identification tasks. Inception-V3 can adjust to variations in image size and shape due to its unique architecture. On the other hand, DenseNet169 may effectively use information from feature maps of varying depths. The efficient architecture of Xception reduces the number of training parameters needed. ResNet-50 employs remaining connections to address the vanishing gradient problem. It is challenging to decide which model works better for a particular task of tomato leaf disease classification. Each model's performance, nevertheless, can be affected by a number of variables, including the dataset's size and quality, the preprocessing methods employed, and the hyperparameters chosen during training. We may conclude that DenseNet and Inception-ResNetV2 appear to perform well on the PlantVillage and In-house datasets based on the results of the literature review. However, a performance comparison of these models can assist practitioners and researchers in the field of plant disease detection in selecting the best model for their particular use case.

VI. Conclusion

In conclusion, utilizing deep learning models, transfer learning has become a promising method for the early identification and categorization of illnesses affecting tomato leaves. In comparison to conventional methods of disease detection and diagnosis, the use of transfer learning has a number of benefits, including shorter training times and increased precision. The requirement for huge datasets and more study to assess the generalizability of models to different plant diseases and crops are drawbacks of this strategy, too. Through increased crop yields and decreased disease-related losses, future research in transfer learning for tomato leaf disease diagnosis and detection may have a significant impact on tomato farming.

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