PLANT DISEASE DIAGNOSIS USING TRANSFER LEARNING BASED MODELS

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***Abstract*— Plant disease diagnosis is the process of identifying and characterizing diseases that affect plants. The primary goal of plant disease diagnosis is to determine the cause of the disease, and to develop appropriate control and management strategies to minimize its impact on crop yields and quality. In this research, four transfer learning models such as AlexNet, VGG16, MobileNetV2, and InceptionV3 has been used for the classification of plant disease into different categories. Out of all the four transfer learning models, the best performing model is InceptionV3 with the value of accuracy as 0.92 and precision as 0.84.**

Keywords—Crop diseases, Convolutional neural networks, Plant disease detection, Diagnosis

I. INTRODUCTION (*HEADING 1*)

Plants diseases can cause significant reductions in crop yields and quality, and can also have a major impact on wild plant populations and the environment. Plant disease diagnosis can be accomplished using a variety of methods, including visual observation, laboratory tests, and machine learning algorithms. Visual observation involves examining the plants and their symptoms to identify the disease, while laboratory tests use samples of the affected plant tissue to determine the cause of the disease [1-2]. Plant disease diagnosis can be done using machine and deep learning by the following ways

Data Collection, Image Pre-processing, Feature Extraction, Model Training, Model Deployment. Machine learning-based approaches for plant disease diagnosis use algorithms to analyze images of the affected plants and to classify them based on their symptoms [3-4]. These algorithms have been shown to be highly effective in accurately diagnosing plant diseases and have been widely adopted in agriculture and horticulture applications. Plant disease diagnosis is important for a number of reasons:

- Food security: Plant diseases can cause significant reductions in crop yields and quality, which can have a major impact on food supplies and the livelihoods of farmers.
- Environmental protection: Plant diseases can also spread to wild plant populations, which can lead to declines in biodiversity and changes in ecosystem functioning.
- Economic benefits: Early and accurate diagnosis of plant diseases can help farmers make informed decisions about crop management, including the use of pesticides and other treatments. This can help to minimize the economic impact of plant diseases and increase overall agricultural profitability.
- Scientific understanding: Accurate plant disease diagnosis also contributes to a better understanding of plant diseases, their causes, and the mechanisms by which they spread. This information can be used to develop new methods for controlling and preventing plant diseases, as well as for improving crop breeding and management practices.

Despite the advances in plant disease diagnosis using machine and deep learning, there are still several research gaps that need to be addressed:

- Lack of large and diverse dataset: A significant challenge in plant disease diagnosis using machine learning is the availability of large and diverse datasets that are representative of different plant species and diseases [5-6]. This limits the generalizability of the models and affects their accuracy in diagnosing new and previously unseen diseases.
- Interpretability and explainability of the models: Deep learning models, while highly accurate, are often considered to be black boxes and their internal workings are not easily understood. This makes it difficult to explain their predictions and to identify the underlying factors that contribute to a particular diagnosis. Research is needed to improve the interpretability and explainability of deep learning models for plant disease diagnosis.
- Scalability and real-time implementation: Plant disease diagnosis in large-scale agricultural systems requires fast and efficient algorithms that can be implemented in real-time. Research is needed to develop scalable and efficient machine learning

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models that can handle large amounts of data and provide real-time predictions.

Overall, plant disease diagnosis is a critical component of sustainable agriculture and food security, and it has far-reaching implications for both the environment and the global economy.

The remaining of the research is as follows: machine and deep learning based papers are shown in section 2, followed by description of dataset in section 3, section 4 shows the description of different transfer learning models. Section 5 shows the results followed by conclusion in section 6.

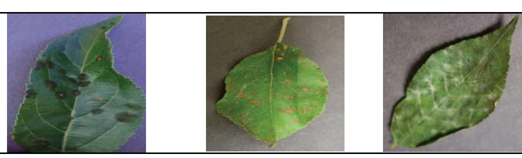
II. Literature Review

This collection of papers discusses the current state of the art in plant disease diagnostics using machine learning algorithms and methodologies, as well as the challenges that these methods face. They provide a foundation for more investigation into the topic.

In 2017, Prashanthi et al. [7-8] employed CNNs to diagnose plant illnesses in photographs of plant leaves. Decision trees, deep neural networks are just some of the machine learning techniques that have been employed for plant disease recognition, as reviewed by Ale et al. [9-11] in 2019. Earlier study Sharma et al. [12] had provided a thorough overview of machine learning algorithms for plant disease identification. These methods included decision trees, ANNs, SVMs, and deep learning. The following publications offer a comprehensive review of the state of the art in plant disease diagnostics using deep learning algorithms and methodologies, as well as a discussion of their advantages and disadvantages. CNNs and RNNs, and GANs are only some of the deep learning methods that Patil et al. [13] reviewed in detail for their application to plant disease diagnosis (GANs). For the purpose of identifying plant diseases from leaf photos, Islam et al. [14] introduced a CNN based technique. Using a (CNN and Transfer Learning, Das et al. had presented a deep learning-based method for disease identification in plant leaves. Sahoo et al. [15, 16] had previously described a (DCNN based method for disease identification in plants using photographs of their leaves.

III. Input Dataset

The original dataset was used to build this new dataset using offline augmentation. About 87,000 rgb photos representing both healthy and diseased plant leaves are included in this collection, which is divided into 38 distinct categories [17]. The full dataset splitting ratio is 80:20, out of which 80% is used for training and 20% is used for testing. Afterwards, 33 test photos are compiled into a new directory specifically for use in the prediction process.



(a) (b) (c)

Fig. 1 Dataset samples (a) Apple Scab, (b) Apple Rust, (c) Cherry

IV. Different Transfer Learning Models

In this study, many different transfer learning models are applied, including AlexNet, VGG16, MobileNetV2, and InceptionV3, to the problem of plant disease identification.

A. AlexNet Model

AlexNet is a deep learning model that was introduced in 2012 by Alex Krizhevsky [18]. It is one of the most influential models in the history of deep learning and has played a significant role in advancing the field of computer vision. AlexNet is a CNN that was designed for image classification tasks. This model was trained on over 1 million images and was able to achieve a top-5 accuracy of 85.3%, which was a significant improvement over previous models. Since its introduction, AlexNet has inspired a large number of follow-up studies and has been used as a basis for many subsequent deep learning models.

B. VGG16

VGG16 is a deep learning model that was introduced in 2014 [19]. It is a convolutional neural network CNN designed for image classification tasks, and it is widely used in computer vision and image processing. VGG16 is composed of multiple convolutional layers and fully connected layers, which are used to extract features from the input images and to classify them into different categories. The model is called VGG16 because it has 16 weight layers, which makes it a relatively deep model compared to other models at the time. One of the key innovations of VGG16 was its use of very small convolutional filters, with a size of 3x3, which allowed the model to learn finer-grained features from the input images. VGG16 has been widely used as a basis for many subsequent deep learning models.

C. MobileNetV2

MobileNetV2 is a deep learning model that was introduced in 2018 by Google. It is a CNN designed for image classification tasks, with a focus on being efficient and fast. MobileNetV2 is a lighter and faster version of the original MobileNet model, and it has been optimized for both accuracy and speed. One of the key innovations of MobileNetV2 is its use of the inverted residual structure, which allows the model to capture both fine-grained and coarse-grained features from the input images. MobileNetV2 has been widely adopted for deployment on mobile devices. The model has also been widely used as a basis for many subsequent deep learning models and has played a significant role in advancing the field of computer vision.

D. InceptionV3

InceptionV3 is a deep learning model that was introduced in 2015 by Google [20]. InceptionV3 is named after its Inception module, which is a building block that allows the model to learn both local and global features from the input images. The model is composed of multiple Inception modules, along with other types of layers. One of the key innovations of InceptionV3 is its use of factorized convolutions, which reduce the number of parameters and computation required, while still maintaining good performance. InceptionV3 has been widely used as a basis for many subsequent deep learning models

V. Results On Different Transfer Learning Models

In this study, the different transfer learning models such as AlexNet, VGG16, MobileNetV2, and InceptionV3 models are used for the plant disease diagnosis. Out of which InceptionV3 model is considered to be one of the best-performing deep learning models for image classification tasks due to several factors:

1. Inception Module: The Inception module is the building block of the model and allows it to learn both local and global features from the input images. This makes the model capable of recognizing different features at different scales, which is essential for image classification.
2. Factorized Convolutions: The use of factorized convolutions in the InceptionV3 model helps to decrease the number of parameters and computation required, though still preserving good performance. This makes the model faster and more efficient, which is important for deployment on resource-constrained platforms.

InceptionV3 is a relatively deep model, with multiple Inception modules and other types of layers. In summary, the combination of these factors makes InceptionV3 best in performance and its performance is still competitive even compared to more recent models.

A. *Results on AlexNet Pre-trained Model*

Adam optimizer simulations on 80 epochs with 32-batch sizes produce these findings. Figure 2 demonstrates that as epoch grows larger, accuracy improves and loss decreases. The loss value is 1 on the 75th epoch, whereas the accuracy value is just 10%. As a result, the data is fed into a different model that has already been pre-trained.

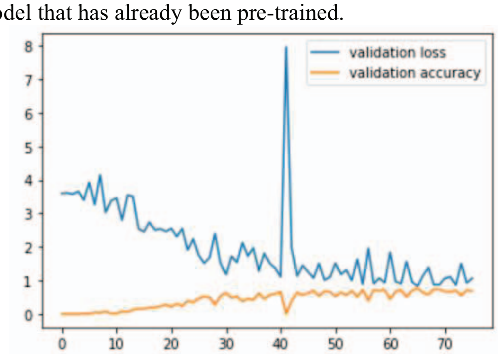


Fig. 2 Accuracy and Loss curve on AlexNet Model

B. *Results on VGG16 Pre-trained Model*

In this section, the VGG16 pre-trained algorithm is used to generate the results. The model is run through 50 iterations of the simulation with a 32-batch size. Figure 3 shows that the accuracy improves with increasing epoch values. The accuracy value is roughly 0.8%.

C. *Results on MobileNetV2 Pre-Trained Model*

The MobileNetV2 pre-trained model is used to generate the findings presented here. Figure 4 shows that MobileNetV2's model has improved accuracy and a higher loss value (0.5). So, in the following section, we redo the calculations with a new model and show the results.

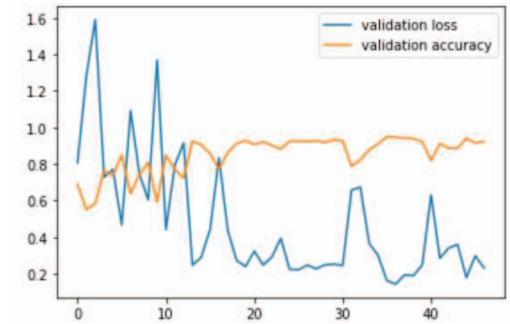


Fig. 3 Accuracy and Loss curve on VGG16 Model

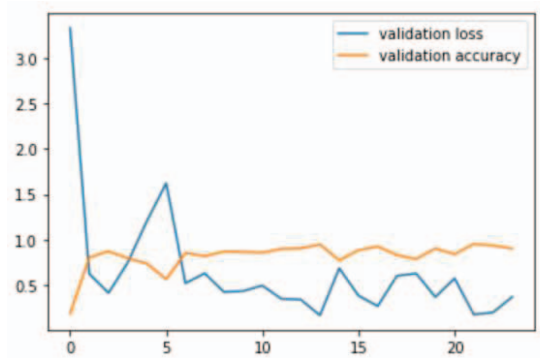


Fig. 4 Accuracy and Loss curve on MobileNetV2 Model

D. *Results on Inception Pre-Trained Model*

Here, we apply the Inception pre-trained algorithm to the calculations. When the number of epochs increases, so does the value of accuracy. Figure 5 displays that on the 25th epoch, the accuracy is 0.92 and the loss is 0.1.

Fig. 5 Accuracy and Loss curve on Inception Model

E. *Comparison of all the transfer learning models on the basis of epochs*

Table 1 displays a comparison of models based on a selection of epoch values. According to the data, the InceptionV3 model has an accuracy of 0.92. In order to replicate the InceptionV3 model, various parameters like the Adam optimizer, block size 32, and epoch values of varying lengths are used in the simulations. Values of accuracy and loss tend to rise and fall in tandem with the number of epochs.

TABLE I. COMPARISON OF TRANSFER LEARNING MODELS USING DIFFERENT EPOCH VALUES

Model	Epochs	Loss	Accuracy	Val_Loss	Val_Accuracy
AlexNet	15	2.5864	0.2651	2.5419	0.1581
	30	1.4508	0.5497	1.5164	0.5312
	45	1.1794	0.6209	1.4401	0.5597
	60	0.9925	0.6886	0.9345	0.7169
VGG16	10	0.5799	0.8123	1.3690	0.5919
	20	0.4723	0.8489	0.2398	0.9283
	30	0.4147	0.8633	0.2530	0.9320
	40	0.3637	0.8880	0.2483	0.9228
MobileNetV2	5	0.6546	0.8150	1.2062	0.7362
	10	0.5218	0.8517	0.4337	0.8649
	15	0.4767	0.8599	0.6846	0.7721
	20	0.3936	0.8859	0.3686	0.9035
Inception V3	5	0.4651	0.8558	0.4064	0.8906
	10	0.3855	0.8866	0.1902	0.9403
	15	0.3563	0.8969	0.2866	0.9237
	20	0.3023	0.9147	0.2329	0.9329

VI. CONCLUSION

The diagnosis of plant diseases entails locating and describing the pathogens responsible for plant illness. Diagnosing plant diseases is important because it allows for the creation of effective control and management strategies that lessen the negative effects of the disease on crop yields and quality. AlexNet, VGG16, MobileNetV2, and InceptionV3 are the four pre-trained models utilized to categorize plant diseases in this study. With an accuracy of 0.92 and a precision of 0.84, InceptionV3 is the top performer among the four transfer learning models.

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