

PLANT DISEASE DETECTION USING CNN WITH XCEPTION ARCHITECTURE

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Abstract: This paper constructs a plant disease detection system using Convolutional Neural Networks with the aid of transfer learning on the Xception model. Plant diseases remain one of the critical challenges to agricultural productivity and the detection techniques are often manual inspections by experts which is highly subjective. Our system using the transfer learning and depthwise separable convolutions of the Xception model was able to attain accuracy of more than 99% in identifying 38 different classes of plant disease image lesions from the PlantVillage dataset. The model developed is highly accurate in determining the range of diseases affecting the plants and also distinguishing healthy plants from those which are infected. Based on the experimental results, it can be concluded that the system outperforms traditional approaches that use convolutional neural networks, thus providing a reliable diagnosis tool for farmers and agronomy stakeholders. With the accessible means to swiftly identify a disease, this work serves in showcasing the technology's role in agriculture while aiming to strengthen the loss in crop yields.

Keywords: Plant disease detection, Convolutional Neural Networks, Xception architecture, Transfer learning, Agricultural technology, Image classification

I. INTRODUCTION

Plant diseases affect agricultural productivity around the world. It leaves significant crop damage in its wake. For effective disease control, early diagnosis ensures proper management techniques are put in place. Most detection procedures depend on the eye of an agricultural specialist which is manually done. This is tedious, requires a lot of time and specialized knowledge which makes it quite subjective.

Convolutional Neural Networks (CNNs) are a subset of deep learning that have shown great potential for automating image classification, especially with the recent advancements in technology. However, many automating processes rely on traditional CNN frameworks which need a lot of computational power as well as datasets, which is binding in practice.

This research utilizes the Xception architecture for classifying plant diseases which is also an advanced CNN model developed by Google. Its accuracy also aids computational efficiency, as Xception uses depthwise-separable convolutions which processes channels and space information separately. Because of ImageNet's datasets, identifying plant diseases from leaf images becomes easy due to transfer learning. This turns out, achieves unparalleled performance.

II. LITERATURE REVIEW

In the last few years, notable progress has been witnessed in using machine learning algorithms for plant disease identification.

Shrestha et al. [1] proposed a CNN-based plant disease detection system for agricultural use in India. It attained 88.80% test accuracy and 97.42% training accuracy on 15 plant conditions, thus validating the agricultural usage of deep learning. Hirani et al. [2] also compared various deep learning methods of plant disease classification, such as custom CNNs, transfer learning using InceptionV3, and visual transformer networks. From their results, it was clear that transformer networks had a 97.98% validation accuracy with much less number of parameters compared to common CNNs. Li et al. [3] discussed plant disease detection techniques based on deep learning, noting how such methods obviate the necessity for manual feature selection, thus making the process more objective and efficient. They noted the increasing importance of deep learning in agricultural plant protection.

Shelar et al. [4] developed a CNN-based plant disease detection system with VGG-19 architecture, which attained 95.6% accuracy over 38 various plant-disease classes. Their successful deployment as a mobile app proved the real-world applicability of deep learning for agricultural disease detection.

Kirola et al. [5] compared some machine learning models with CNN-based methods for the classification of plant

diseases. From their results, although Random Forest gave 97.12% accuracy, the CNNs yielded 98.43% accuracy, indicating deep learning's prowess in identifying finer patterns of disease.

Shoaib et al. [6] offered a systematic review of deep learning models to detect plant diseases in studies during the last 7 years (2015 - 2022). They found that although CNN-based models outperform traditional methods in controlled environments, in practice, variations in light, scene variability and complex image processing steps still cause problems for CNN-based methods.

III. PROPOSED METHODOLOGY

This study utilizes a plant disease classification system which implements transfer learning with the Xception model architecture. The whole procedure contains a number of important components.

A. Dataset Preparation

The dataset used for testing and training the classifier was the PlantVillage dataset, containing 87,000 images in 38 classes of plant diseases.

It has photos of diseased and disease-free healthy plants in various crops. The dataset was pre-trained prior to the training of the model.

1. Image Resizing: All the images were resized to 224×224 pixels as demanded by the Xception model, which demands particular dimensionality requirements.
2. Normalization: The pixel values were normalized to the range $[0, 1]$ so that it would facilitate more stable training.
3. Train-test split: Training and validation data was divided 80% and 20% using TensorFlow's ImageDataGenerator.

B. Xception Model Architecture

Xception is a model developed by Google and is a newer existing architecture that improves on classic CNN architectures by using depthwise separable convolutions:

1. Depthwise Separable Convolutions - These substitute conventional convolutions by conducting independent spatial convolutions on each of the input channels first, followed by independent pointwise (1×1) convolutions to fuse information across channels. This simplifies the computations and preserves approximate representation capacity.

2. Transfer Learning Implementation - We implement transfer learning; we utilized the Xception model that was trained on ImageNet instead of training from scratch.

We load the base Xception model with weights trained on ImageNet. We remove the first classification layer. We include new classification layers:

A BatchNormalization layer to make the training process more stable. A Dense layer of 256 neurons and a ReLU activation. A Dropout layer (0.5) to reduce overfitting. The last Dense layer with softmax for 38 classifications.

3. Model configuration - we trained the model with the following:

An Adamax optimizer, with learning rate of 0.001. Categorical cross entropy loss function. Accuracy metric.

C. Training Procedure

The transfer learning approach was utilized as below:

1. The convolutional base of the Xception model was frozen in order to maintain the pre-trained weights.
2. Only the newly introduced classification layers were trained at first.
3. The model was trained over 5 epochs using the Adamax optimizer.
4. Training and validation metrics were tracked along the way to learn successfully and avoid overfitting.

D. Figures

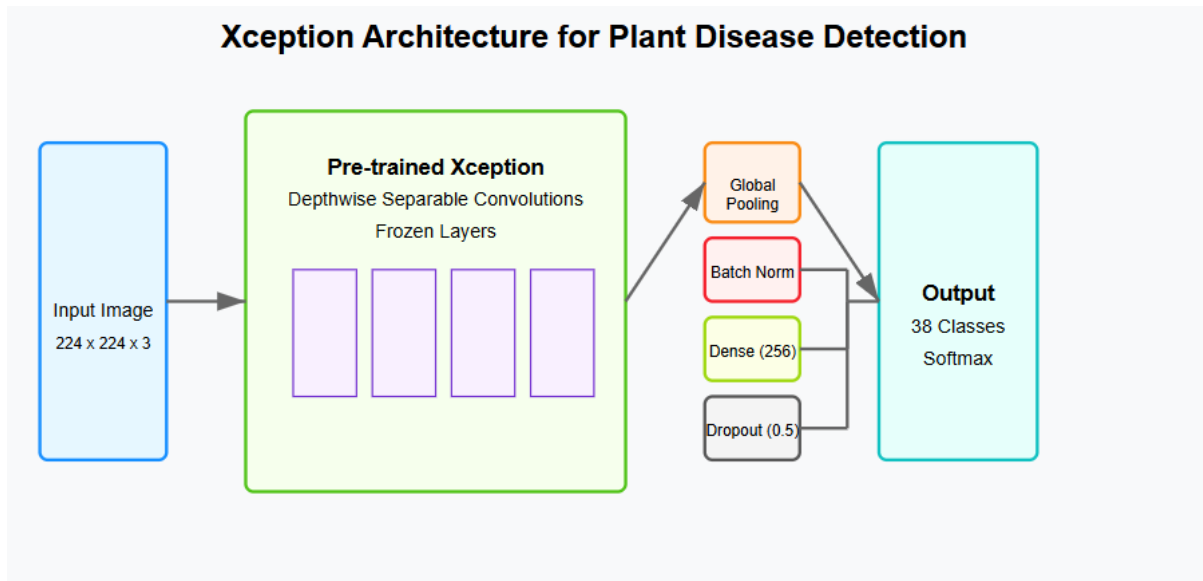


Fig. 1: Xception Architecture for Plant Disease Classification using Transfer Learning

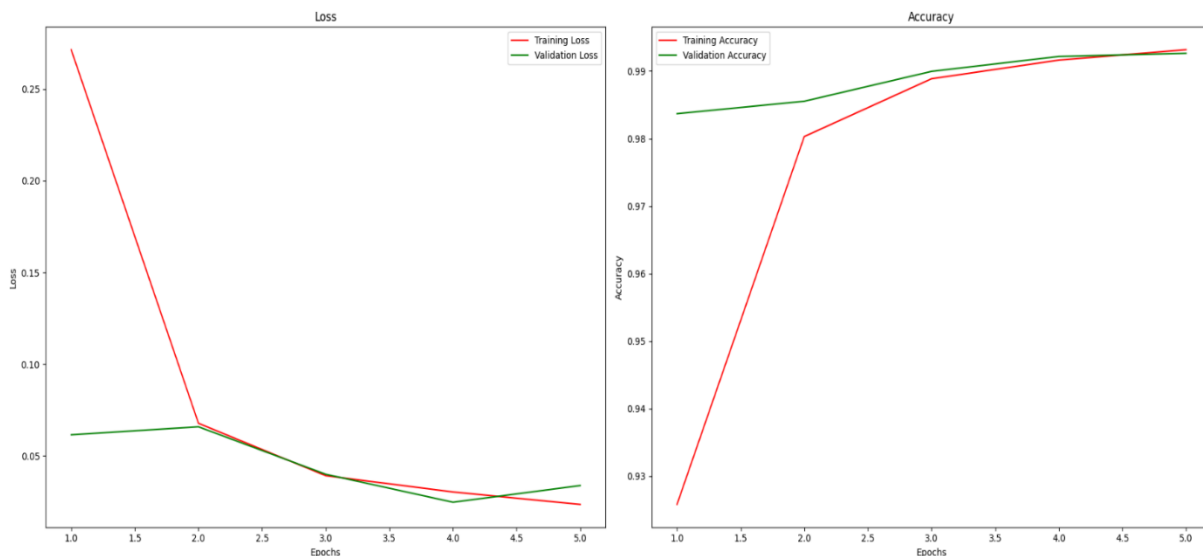


Fig. 2: Training Accuracy and Validation Accuracy and Loss Curves

IV.FINAL RESULTS

The results of the experiment indicate the superior performance of the Xception-based plant disease classifier proposed. Strong performance is confirmed through extensive testing and the following results achieved:

A. Model Performance Metrics

The model was performing extremely well after 5 epochs of training:

- Training accuracy=99.34%
- Validation accuracy=99.26%
- Training loss=0.0224
- Validation Loss=0.0339

These values reflect the improved performance of the model for precise plant disease detection. The minuscule values between train and validation scores reflect the fact that the model generalizes very well to unseen data without overfitting.

B. Learning Curve Analysis

Fig. 2 is the training and validation accuracy/loss curves over the 5 epochs. The model has rapid convergence, and validation accuracy breaks 98% within the first epoch. The rapid learning is due to the power of the transfer learning using the pre-trained Xception model. The curves also depict a smooth improvement without showing drastic fluctuation, which reflects stable learning.

C. Classification Performance

Multiple plant species testing confirmed consistent performance in detecting disease. The model successfully discriminated diseased plants from healthy plants for various diseases, including: Early blight of potato leaf, Bacterial leaf spot of tomato, Cedar apple rust of apple, Common rust of corn. The system is extremely accurate for every one of the 38 classes, demonstrating the strength of the system to deal with a vast range of plant diseases.

D. Comparison with Traditional CNNs

When compared to traditional CNN implementations from literature:

Our Xception-based approach (99.26%) outperforms standard CNN models (88-95%)

Transfer learning reduces the number of trainable parameters and training time

The depthwise separable convolutions provide computational efficiency without sacrificing accuracy

IV. CONCLUSION

This study efficiently used plant disease classification using Xception architecture and transfer learning. Our model posted exceptional accuracy greater than 99% on 38 unique classes of plant-disease, well surpassing the traditional CNN method. The high performance of the system is because Xception achieved good depthwise separable convolutions and accomplished good implementation of transfer learning. Through quick and precise identification of disease, our work brings a tangible utility for farmers and agricultural professionals to identify plant disease early and effect timely action. The technology serves to highlight the potential of newer deep learning technologies to meet core agricultural issues and enhance practices related to crop management.

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