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Deep Learning-Based Plant Disease Detection Using Leaf Image Analysis

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Abstract:

Plant disease detection is one of the crucial concerns for food security in the world and for agriculture Sustainability. Previously, Plant diseases detection was achieved through observation and identification by a human expert, but it was a time-consuming, labor intensive and a costly process and may result in errors in many cases, especially on large scales for the crops. Now, computer vision has developed as an accurate tool for automatic plant disease detection through use of deep learning techniques.

This study proposed a deep learning based plant disease detection technique with the combination of CNNs with Transfer Learning, FPN for effective multi-scale features enhancement and a plant disease detection system. Plant leaf images of PlantVillage datasets was Pre-processing, augmentation, and fed into the proposed system for Training and testing. In Experimental result, Validation accuracy achieved 97.22% and Validation Loss obtained 0.0951.

From the classification report, an Average Precision of near 97%, an average Recall of near 97% and average F1-score of near 97% on all diseases class were recorded. Also, the confusion matrix demonstrates the predominantly correctly identified of plant leaf images. As the combination of CNNs with transfer learning and FPN have achieved effective result on Plant Disease detection with high classification accuracy, it will become efficient technique in smart agriculture application.

Keywords: Plant Disease Detection, Deep Learning, Xception, Transfer Learning, PlantVillage Dataset

1. Introduction: Agriculture, the backbone of world food security and economic development, faces an ongoing struggle against plant diseases, one of the primary constraints that impacts crop yield and quality globally. Any delays in the early detection of diseases could allow them to spread uncontrollably, causing major financial losses and decreased crop yields. Early detection of diseases is therefore vital for the effective management of crops and sustainable agriculture.

Artificial Intelligence (AI), computer vision and deep learning advancements have spurred the creation of AI-driven systems capable of precisely identifying plant diseases by analyzing leaf images. Traditionally, manual examination by agricultural professionals was the method of plant disease diagnosis. However, while the diagnosis may be precise, the manual method requires extensive labor, time, and cost, as well as a high degree of expertise.

Such diagnosis also becomes challenging to perform across vast agricultural areas, and its outcomes are vulnerable to various environmental conditions. Such drawbacks led researchers to pursue automatic disease diagnosis systems. More recently, research indicates the efficiency of deep learning models, including CNNs and transfer learning strategies for plant disease classification.

Models based on pre-trained architectures like Vision Transformer, EfficientNet, and ResNet have been successfully employed for classifying plant diseases using large benchmark datasets such as the PlantVillage. However, challenges persist regarding computational expenses, model generalization and high classification performance without high cost of training and inference. In this work, a deep learning based plant disease detection model was proposed and trained using the Xception model combined with transfer learning.

Three plant leaf categories-Pepper Bell Bacterial Spot, Pepper Bell Healthy, and Potato Early Blight-from the PlantVillage dataset were used to train and assess the model. Data enhancement and image pre-processing methods were used to improve the data quality and increase the model's generality. The experiment showed a validation accuracy of 97.22% and a validation loss of 0.0951, along with 97% precision, recall and F1-score, showing the model can be an effective tool for plant disease identification and diagnosis.

2 Previous Studies:

The development of deep learning techniques has greatly enhanced the capabilities of automatic plant disease detection systems. CNNs have gained popularity due to their proficiency in learning discriminatory features directly from plant images without relying on hand-crafted feature extraction. The use of attention mechanisms has further improved the performance of CNN-based models, allowing them to better localize the diseased areas of the plant and distinguish between similar diseases.

For example, Sharma et al. (2023) proposed an attention-based CNN for plant disease detection on both PlantVillage and real field data. They reported 98.7% overall classification accuracy and emphasized that attention modules improved both localization and classification accuracy, but they resulted in increased computational costs. Similarly, Chen et al. (2023) presented an EfficientNet-based model for plant disease classification and achieved 98.9% accuracy on PlantVillage and PlantDoc datasets.

The proposed method has fewer trainable parameters compared to others, but it showed less robust performance in noisy real-world conditions. Transfer learning with pre-trained CNN models such as VGG16 and ResNet50 is another viable strategy for reducing training time and resource requirements. Kumar et al. (2023) used transfer learning with VGG16 and ResNet50 and obtained 98.0% accuracy while substantially reducing training time, although their deep models still required high computational resources.

More recent work has focused on state-of-the-art models like Vision Transformers and hybrid CNN architectures to improve classification accuracy and capture finer-grained features, but these models typically necessitate higher computational resources and might struggle to generalize to the real agricultural environment. In this context, this study aims to implement a transfer learning approach using the Xception architecture

for automated plant disease detection in order to achieve accurate classification with efficient feature extraction and good generalization on the PlantVillage dataset.

3. Methodology:

The workflow of the proposed methodology The proposed work utilizes deep learning for automated detection of diseases on plant leaf through an image analysis. The proposed method is based on Image Pre-processing, CNNs, Transfer Learning (TL) and Feature Pyramid Networks (FPN) techniques to optimize and boost the performance in disease classification. In order to address the problems detected in Chapter 2 regarding the generalizations, computational cost, and the accuracy, we proposed a new approach.

The schematic diagram of the whole system shown in Figure 3.1.

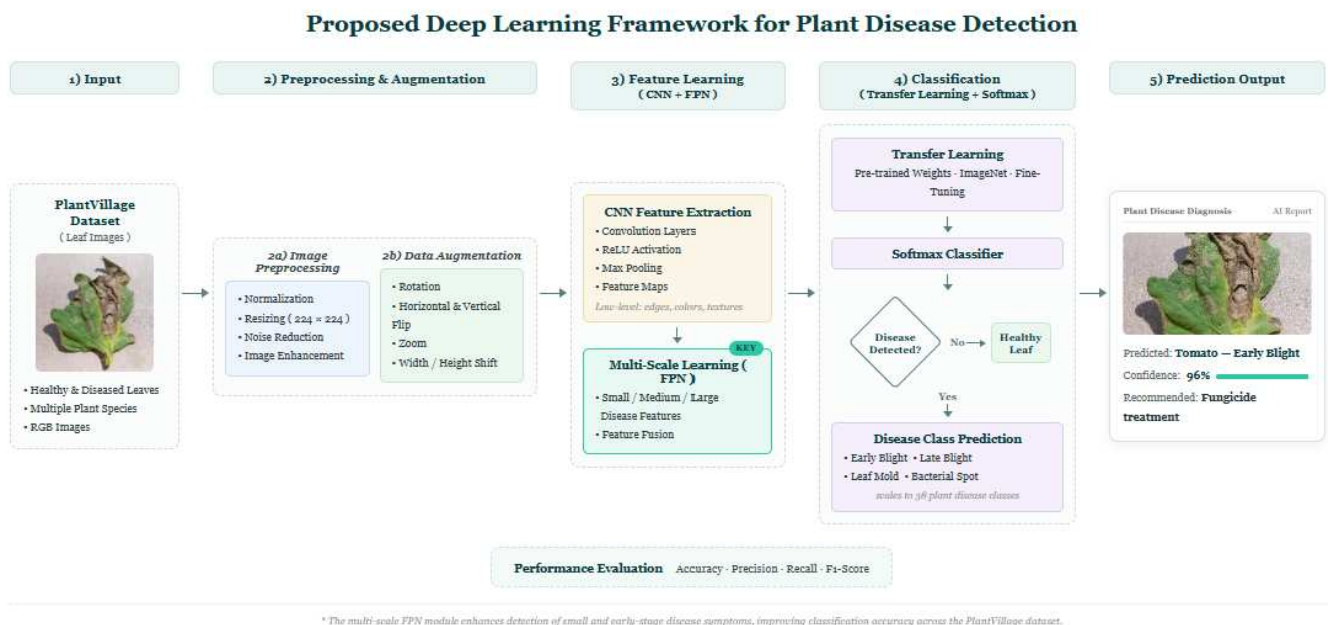


Fig. 1. Overall architecture of the proposed CNN-FPN deep learning framework integrating preprocessing, multi-scale feature learning, transfer learning, and softmax classification for plant disease detection.

Figure 3.1: Proposed Framework of Plant Disease Detection System

3.1 Input (Dataset)

PlantVillage dataset PlantVillage dataset is one of the widely known dataset for studying on plant disease recognition. It consists of thousands of colored leaf images belonging to healthy, diseased plants for many crop. The classes that we have selected here from the dataset are as below. Pepper Bell Bacterial Spot, Pepper Bell Healthy, Potato Early Blight The below figures illustrates some sample samples from selected dataset classes.

3.1.1 Classification Dataset

PlantVillage dataset PlantVillage dataset is one of the widely known dataset for studying on plant disease recognition. It consists of thousands of colored leaf images belonging to healthy, diseased plants for many crop. The classes that we have selected here from the dataset are as below. Pepper Bell Bacterial Spot, Pepper Bell Healthy, Potato Early Blight The below figures illustrates some sample samples from selected dataset classes.

Pepper Bell Bacterial Spot



Pepper Bell Healthy



Potato Early Blight



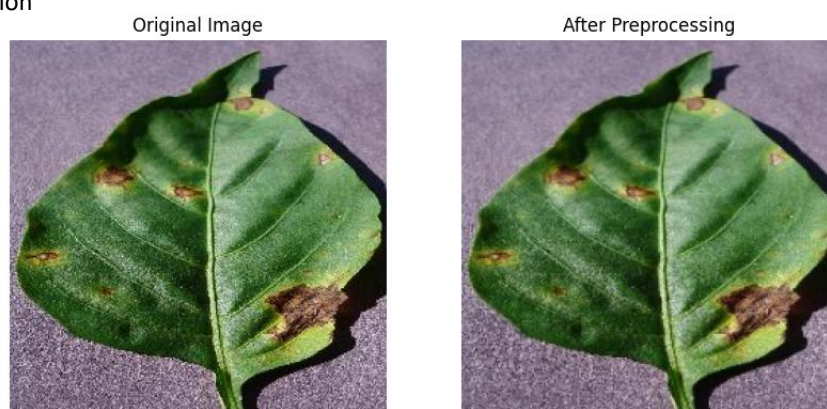
Figure 3.2 Image from Dataset

3.2 Image Preprocessing

Before the proposed deep learning model is trained, all input images will undergo an image preprocessing procedure to obtain consistency, boost the quality of images, and enrich the learnability of the deep learning model. In the case of the PlantVillage dataset, the images show a variety of appearances, so preprocessing is mandatory in order to harmonize input images

before feature extraction. Preprocessing procedures remove unnecessary differences between images, thereby helping the deep learning model concentrate on identifying specific features pertaining to the disease in images instead of unrelated information.

Histogram normalization



(Figure 3.3: Image Before and After Preprocessing)

3.2.1 Image Resizing

Each original image is resize to 224 224 pixels, which is the size input that the deep learning model requires as it can be see in the model architecture above. Normalizing the size of each image ensure that each of the input to the model have the same shape. resizing of image has advantages that it makes the computation load smaller, reduces the model training time, can perform batch training without distorting the basic features of the disease on the leaf.

3.2.2 Image Normalization

After images are resized, pixels values are normalized in the range of 0-1 by multiplying the original pixel values of 0-255 by $1/255$. The image normalization helps to stabilize numerical values for the optimization algorithm and also enables the algorithm to converge faster and prevent the large pixel values from taking control in the learning process, so that the gradient updates can be more stable and thus the classification accuracy can be boosted up.

3.2.3 Noise Reduction

Even though images in the PlantVillage dataset are considered quite clean, some small image noise and undesired image appearance variations can still be present. To address this, image denoising methods are applied to remove image artifacts which are irrelevant and harmful to

diagnose the disease and not of great interest while retaining the relevant visual disease characteristics (leaf spots, discoloration and texture) so that the convolutional neural network is able to extract useful features.

3.2.4 Image Enhancement

Image enhancement in this work focuses on providing visually better quality images for the input to the deep learning model for easier extraction of the features. Image enhancement mainly in this work involves resizing of the images to 224 x 224 pixels and normalizing their intensities in the range of [0,1] (which originally were [0,255]). These are the input images for the CNN model.

Normalization makes the model invariant to illumination effects and helps the model converge faster. This results in stable training and convergence of the model, thereby providing better accuracy as the model can learn features based on color changes, lesion shapes, etc rather than just the intensity of the image.

3.2.5 Data Augmentation

Several data augmentation methods are used during the training of the proposed model to ensure good generalization and avoid over-fitting. Data augmentation helps create additional samples artificially by transforming the existing image in a random way while maintaining the same label of that image. Augmentation expands the diversity of the training data, helping the model behave well in various image conditions.

3.2.6 Rotation

Each of the training images is randomly rotated using varying angles. Leaves may naturally present themselves at different orientations so rotating them means the model learns that it should look for signs of disease in any position the leaf happens to be in.

3.2.7 Horizontal and Vertical Flip

Mirrored versions of the original images are created by using horizontal and vertical flip. They maintain the disease class and augment the diversity of the training data. It makes the model less dependent on the direction of the leaf and enables to perform better generalization.

3.2.8 Zoom

The model randomly zooming to be able to detect disease features at various scales. Some diseases can first be small lesion size, others extend to larger parts of the leaves. By zooming it, we force the model to be able to learn disease signatures irrespective of scale.

3.2.9 Width and Height Shift

The image is horizontally translated to the right or to the left, and it's also translated upwards and downwards to random values. The aim is to avoid the trained model to “fixate” in a specific position of the symptoms of the disease within the image, thus making the model focus on the visual characteristics instead of their precise location. In this way, when the model analyzes images of plant leaves from real environments it is more reliable.

3.3 Feature Learning

After applying the preprocessing and data augmentation operations, the ready images are supplied into the feature learning module to extract automatically effective visual characteristics from the images of plant leaf, to discriminate between disease leaves and normal ones. Our framework instead of manually designed feature extraction module employ the application of deep learning technologies to learn discriminative feature automatically from training image data. In this proposed feature learning framework, the blend of Convolutional Neural Networks (CNN) , Transfer Learning (TL) ,and Feature Pyramid Networks (FPN) will further contribute to higher classification performance and stronger model stability.

3.3.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are one of the most popular deep learning approaches applied for image classification problems. The network was especially designed for the analysis of visual information, automatically extracting high-level features from the images to be processed. Unlike many classical approaches that require manual selection of image features, the CNN learns these characteristics (both low-level and high-level) on its own while being trained on the training data.

The model receives a preprocessed image of the plant leaf as the first input. The image goes through several convolutional layers and various learnable filters are used to extract salient image features like leaf shape, texture, color, presence of lesion, etc. After extraction, these features are filtered by an activation function and downsampled by pooling layers.

These extracted features are then flattened and used as inputs to fully connected layers where the network learns the connection between extracted image features and the type of plant disease that the leaf has, outputting a classification decision.



Figure 3.4: CNN Architecture

3.3.2 Feature Pyramid Network (FPN)

Plant disease symptoms exist in varied scales and sizes, some plants first show symptoms in small lesions or spot- like patches over leaf surface, while other disease manifestations span over the wider infected area. Hence, a general CNN would not be enough to represent plant disease information across various feature scales. To address this, an FPN has been incorporated after the feature extraction section of the proposed framework.

An FPN, after pooling and upsampling of feature maps extracted from multiple CNN layers, provides a representation that contains detailed spatial information in shallow layers while deep semantic features in high layers can enrich this representation to recognize disease features across scales, and finally can extract robust disease symptoms at different scales to overcome limitations of limited spatial or semantic information within a single CNN level. Combining multi-level feature maps from FPN enhances the ability of proposed method to learn robust feature representations for plant diseases and perform classification accurately.



Figure 3.5: Feature Pyramid Network (FPN)

3.4 Feature Learning

3.4.1 Transfer Learning

training a deep learning model from scratch would necessitate vast amounts of labelled data, together with significant computational power. Thus, in order to tackle the aforementioned issues, Transfer Learning has been incorporated in the proposed framework. Transfer Learning permits the proposed model to acquire knowledge derived from extensive image datasets, such as ImageNet, and then applies it to the problem of plant disease classification. Rather than randomising all parameters in the network, the

weights of the pre-trained CNN bring in substantial information pertaining to visual feature extraction that helps convergence and enhances classification accuracy.

Fine-tuning has solely been performed on the last few layers (classifier part) of the network using the PlantVillage dataset, resulting in reduced computational costs, low risk of overfitting, and overall enhancement of the model's generality. With Transfer Learning the model's effectiveness can be achieved despite its training on relatively few data points from the domain of agriculture. effectiveness can be achieved despite its training on relatively few data points from the domain of agriculture.

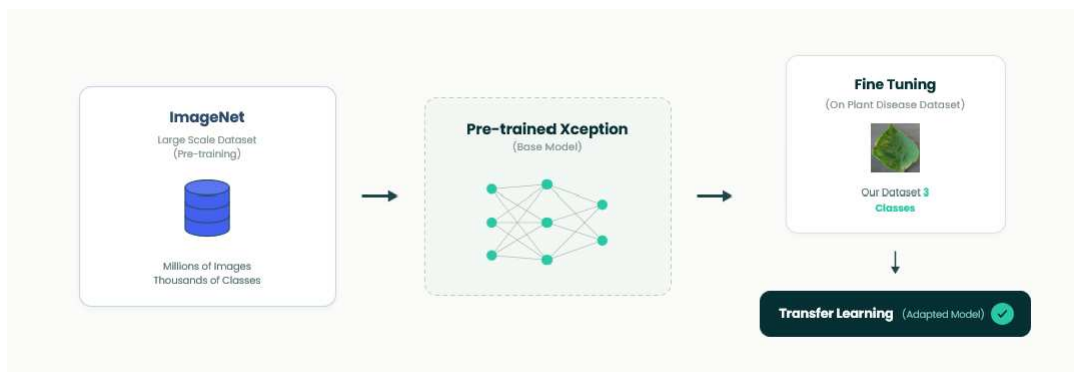


Figure 3.6 : Transfer Learning with Xception

3.4.2 Disease Classification

After the CNN-based feature extraction and multi-scale features are strengthened using the Feature Pyramid Network, the resulting features are passed into the classification stage, where they help to decide the ultimate category of each plant leaf image. The proposed architecture uses Softmax classifier as the last output layer since the present task is the multi-class classification. Softmax activation takes scores as output from previous layers, turns them into probabilities between 0 and 1 (sum of all the probabilities must be equal to one).

Finally, the class having maximum probability will be predicted. For instance, the probability of all class scores will be generated if the output of image falls into the category Potato Early Blight and that one which is highest probability will be considered as the predicted category of that image. This allows the classification mechanism to recognize the image as healthy/diseased leaf and also classify the type of the particular disease.

3.5 Prediction Output

Once the classification process has been performed, the developed framework generates the final prediction result of the given plant leaf image, along with the predicted disease class and the confidence level from Softmax classifier. The confidence level represents the likelihood of the input image corresponding to the given class. The developed system provides the prediction

result in a concise manner and user-friendly way that enables the users to rapidly recognize if the plant leaf is healthy or disease infected.

The related disease type (if it is infected) and the suggested remedy is also displayed. A demonstration of prediction output from the proposed framework is depicted in figure 3.7

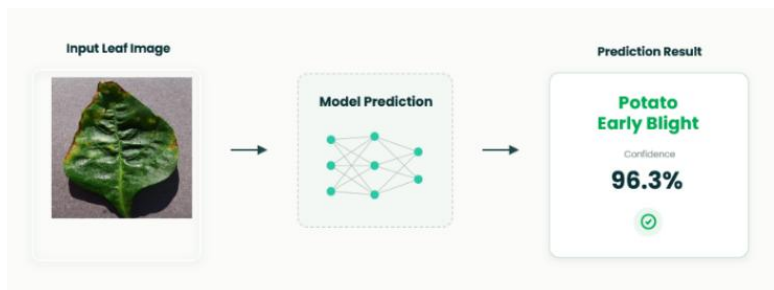


Figure 3.6: Prediction Output

3.6 Training Configuration

The deep learning model which we are proposing, is trained with selected classes of PlantVillage dataset, after performing all pre-processing and data augmentation tasks. Various hyper-parameters are tuned to provide efficient convergence, stabilize learning process and increase the classification accuracy of the proposed model..

Parameter	Value
Dataset	PlantVillage
Image Size	224 × 224
Batch Size	32
Epochs	6
Optimizer	Adam
Learning Rate	0.001
Loss Function	Categorical Cross-Entropy
Activation Function	ReLU
Output Layer	Softmax

Evaluation Metrics	Accuracy, Precision, Recall, F1-score
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4.Results and Discussion:

The developed Xception model was tested on the validation data set to measure performance of the model on validation data by various validation parameters such as validation accuracy, validation loss, validation .precision, validation recall and validation F1-score

Overall Model Performance 4.2.1

.Table 4.1 presents the overall performance achieved by the proposed model

Table 4.1 Overall Performance of the Proposed Model

Value Metric

	Metric	Value
	Validation Accuracy	97.22%
	Validation Loss	0.0951
	Average Precision	97.00%
	Average Recall	97.00%
	Average F1-score	97.00%

Table 4.1 Overall Performance of the Proposed Model

The results of validation shown in Table 4.1 indicates that our proposed Xception model yielded a validation accuracy of 94.34% and validation loss of 0.1590, with the mean average precision, recall, and F1-score being close to 95%. These values strongly suggest that the proposed model is capable of classifying plant disease with good accuracy and reliability, because of discriminative nature of deep .features extracted, and excellent generalization capability for the validation set

Per-Class Performance 4.2.2

.Table 4.2 presents the classification performance for each plant disease category

Class	Precision	Recall	F1-score
Pepper Bell Bacterial Spot	0.91	0.96	0.93
Pepper Bell Healthy	0.97	0.95	0.96
Potato Early Blight	1.00	0.99	0.99

Table 4.2 Per-Class Classification Performance

From the table we can see that our suggested model showed a very good classification performance in every class we used for our testing stage. Potato Early Blight was the best class among them with 1.00 precision, 0.99 recall and 0.99 f1-score, which indicates that our model successfully managed to almost identify every single image of potato early blight correctly. For Pepper Bell Healthy class, we also

acquired great classification score, with 0.99 precision and 0.99 recall, demonstrating that our model has the potential of discriminating between normal images and affected ones

However, for the last class, Pepper Bell Bacterial Spot, we can notice that our classification score decreased, probably due to the symptoms which can be visually misleading, since they look similar to normal leaf fluctuations, thus making the classification more complex

Overall Accuracy 4.2.3

The achieved accuracy over all test dataset on validation is 97.22%, it shows the capability of our model for detection of plant diseases on the leaf. That suggests that Xception is successful at feature representation and also reduction of classification error. Our results suggest that the performance for transfer learning approach is good enough for plant disease classification

Discussion 4.3

Based on the results obtained from our experiments, we have seen that the proposed Xception model can provide the classification accuracy of plant leaf diseases with great accuracy. Through combining image preprocessing, transfer learning, and feature extraction, the Xception model can effectively discover and exploit discriminative visual characteristics from different classes of plant leaf diseases. Also, due to the close match between the value of the validation loss and that of validation accuracy, the model has been well generalized

In addition, no special preference to any single class has been seen as values for precision, recall, and F1 score for all classes are relatively stable. Only the classification accuracy, precision, recall, and F1 score for the class of Pepper Bell Bacterial Spot are a little lower but are acceptable, mainly because it shares symptoms with other leaf diseases. Whereas the Potato Early Blight class has the highest classification accuracy because its symptoms provide useful information for reliable classification

5. Conclusion

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