



Deep Learning-Based Plant Disease Detection Using Leaf Image Analysis

Sulaiman Alquwayfili¹, Rahaf Alsaiani¹, Mohamed Eassa¹

¹ College of Informatics, Midocean University, 98123, Moroni, Comoros

Email: [253000463 @st.midocean.edu.km](mailto:253000463@st.midocean.edu.km)

Abstract:

Plant disease identification is an important technique for food security in global food safety and enhancing agricultural yield. Automatic inspection by experienced person is an important tool for the plant disease diagnosis, but this traditional method is costly, labor-intensive, time-consuming and can lead to many errors due to visual subjectivity, especially in the context of large scale farms. Recent studies with advanced techniques in the fields of computer vision and deep learning has been conducted in automatic detection of plant diseases from images of plant leaves. In this research, a deep learning approach with integrated with convolutional neural network (CNN), Transfer Learning and FPN which helps in capturing the multi-scale features for better performance on both feature extraction and classification tasks. Image preprocessing and augmentation methods were applied on PlantVillage dataset, and the integrated model was then trained and validated. The experiment shows that the proposed model achieved the highest validation accuracy as 97.22% and the validation loss as 0.0951. In the classification report, the average precision, recall and F1-score of about 97% were also achieved. In addition, the confusion matrix proved that most of the chosen plant disease classes were correctly identified. This research demonstrates the accuracy and effectiveness of the proposed method for the automated detection of plant diseases and shows potential for smart agriculture.

Technique with this accuracy?

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

1. Introduction

Artificial intelligence and data mining technology is increasingly wide and rapidly developing to many intelligent systems which analyze data for supporting decisions-making, agriculture has already had a huge advancement in these years (Kamilaris & Prenafeta-Bold, 2018). Unfortunately, breakout of plant disease is one of the serious factors for crop yield, crop production and quality of all crops all around the world. Under the condition where the unfavorable environments can facilitate plant disease spreads causing a number of serious economic losses and threaten the global food security; rapid and accurate plant disease detection is very important for preventing crop damage and improving production of agriculture and for facilitating practice of agriculture to achieve sustainable development (Savary et al., 2019).

Diagnosis upon the observation of diseased symptom is the typical way and has been well accepted by people from agriculture field, but the diagnosis accuracy requires high degree of expertise; time consuming, expensive, slow, making it impractical to apply on big crop fields, Moreover, diagnosis can also be biased due to environmental conditions and even observer perceptions (Bock et al., 2010). Luckily, now there are plenty of labeled images are available, and we also achieve tremendous improvement in the various kind of deep learning models (CNN, Transfer learning, ResNet, EfficientNet, Vision Transformer) on benchmark data-set (PlantVillage), automatic plant disease detection based on leaf image is emerging as a very promising task (Mohanty et al., 2016; Too et al., 2019). Figure 1. Examples from the PlantVillage dataset of images with healthy, bacterial spot infected, and early blight infected leaves.



Figure 1. Representative examples of healthy and diseased plant leaves from the PlantVillage dataset used in this study.

1.1 Problem Statement

Even with such achievements, however, there are several issues associated with current plant disease detection methods. For example, many of the existing detection models necessitate massive computational cost, whereas some models achieve only poor generalization ability on datasets with different scales or in varied environmental conditions. Some other deep learning based models still possess inferior classification ability, in that it fails to correctly distinguish between two plant diseases with a similar appearance. Thus, such defects may limit their application in practice agricultural scenarios in which classification accuracy, cost and computational overhead are equally significant. In summary, the existing models present many constraints in terms of low detection accuracy and computational efficiency for real applications, resulting in the urgent demand for a more advanced and computationally less expensive but highly performant early plant disease diagnosis model.

1.2 Research Objectives

This research focuses on the design and implementation of a deep learning-based automatic plant disease detection model from plant leaf images. This research work focuses on the construction of the plant disease detection framework on the basis of the Xception architecture with the transfer learning method for better classification. It also validates the developed model by employing the benchmark PlantVillage dataset and compares it with other recent deep learning based model approaches available in literature to ensure efficiency. In addition to that, this work aspires to provide an intelligent and accurate system that enables the farmers to detect

the plant disease in the early stage to mitigate crop losses and contribute to the development of sustainable agriculture.

1.3 Research Contributions

In this paper, we develop a framework of deep learning to detect diseases automatically in plants using transfer learning in the Xception network architecture. Our proposed system uses well-established computer vision tools to identify diseases and categorize plants effectively. It allows accurate plant leaf picture review and helps make it available as an adaptive framework that can power future smart agriculture initiatives. In experimental tests conducted on the PlantVillage dataset, our proposed model yielded a 97.22% validation accuracy with about 97% recall, precision, and F1 score, establishing its reliability as an automated disease detection tool for plants.

2 Previous Studies

The early methods of plant disease identification was mainly based on classical machine learning such as SVM, decision tree, random forest, and KNN. Although these methods can obtain good accuracy, they depend on manual selection of features, color, texture, and shape. These methods cannot efficiently and effectively analyze large-scale, complex image datasets. With the development of AI technology, people focus on deep learning technology such as CNN to automatically extract the discriminative features from plant leaf images. Lately, transfer learning, attention mechanism, ViTs, and combined deep learning models are applied to enhance accuracy and robustness. Some representative researches are presented below:

Sharma et al. (2023) presented an attention-based Convolutional Neural Network (CNN) model that aims to improve plant disease classification and localization by paying attention to diseased regions of plant leaves. The attention mechanisms guide the CNN to focus on extracting informative features from infected areas while discarding irrelevant information from background objects. The proposed model, trained on the PlantVillage and real-field image datasets, achieved a classification accuracy of 98.7% and proved to increase localization and classification performance over traditional CNN methods, and increase model robustness under varying image conditions. However, attention modules also increase model complexity and computational costs.

Wang et al. (2025) developed an improved deep learning model using CNN and Transformer architectures for plant disease identification. The motivation behind the design of the model was to combine the ability of CNNs in capturing local features and the global reasoning capabilities of the vision transformers. The model was trained on a diverse plant disease database (e.g. PlantVillage) and resulted in classification accuracies above 97%. However, the hybrid model needed significant computing power and had scaling issues in real world agricultural scenario.

Sahu et al. (2025) A Hybrid Dilated Convolutional Neural Network architecture was introduced by to perform an accurate prediction of plant disease, where an optimal multiscale features extraction method was proposed along with an attempt to retain useful spatial information. This model was evaluated using a combination of PlantVillage and additional plant disease augmented datasets and showed an accuracy of about 98% overall for disease classification. However, the computational efficiency and training duration was increased as the architecture contained numerous dilated convolution layers for a better performance in identifying diseases.

Ibrahim et al. (2025) proposed an improved deep learning model for plant disease detection by combining several optimization strategies to boost the classification and generalization ability. They used both PlantVillage and real-field image data sets to train their model and obtained an accuracy of 97.5% for classifying plant disease. Even though their method was capable of generalizing well across several species of plants and diseases, they stated that they should further validate the model by including much more real field data before deployment.

Patel and Shah (2024) proposed a framework to perform plant disease classification using a Vision Transformer (ViT). The authors utilize the self-attention mechanism of ViTs to learn the global features of the image, thus overcoming the limitations of traditional CNNs in learning global features. The long-range dependency between image patches can be successfully captured, which helps to learn more representative features. The model trained on benchmark datasets, such as PlantVillage, achieved 99.1% classification accuracy, superior to many CNN-based approaches in both accuracy and features extraction. However, the ViT architecture requires a lot of computing power, large memory and vast training data, which makes it less practical in the low-resource agricultural regions.

Zhao et al. (2025) developed an object detection model based on Mask R-CNN and Faster R-CNN that could be utilized for the automated detection and localization of plant diseases. This framework differentiates itself from other image classification approaches because it identifies not only disease categories, but also the precise position of affected areas on plant leaves, based on their bounding boxes. This model was trained with a collection of plant disease datasets that had bounding-box labels for each affected region and achieved detection accuracies from 63% to 90% (depending on the data quality and labeling precision). Experimental analysis indicated that the two detection models were effective at pinpointing disease symptoms with accuracy, while also achieving dependable results in terms of classification. Yet, this research highlighted the fact that the performance of this model is strongly reliant on the completeness and precision of manual labels, which in turn makes dataset creation time-consuming and costly.

Ahmed et al. (2025) suggested a multi-scale Convolutional Neural Network (CNN) paired with a Feature Pyramid Network (FPN) in order to achieve better results for plant disease detection through different spatial resolutions of disease symptoms. The proposed framework leverages the combined features from various convolutional layers in order to assist the model in identifying smaller lesions as well as larger affected regions more accurately. This model was trained using numerous plant disease datasets which are publicly accessible, such as PlantVillage and real-field image datasets. The classification accuracy achieved was an overall score of 99.2%. When experimental tests were performed, it was determined that FPN had a positive effect on the feature representation, therefore enhancing classification outcomes over more traditional CNN models. Furthermore, the presented framework exhibited increased resilience in identifying early symptoms of disease. However, utilizing multi-scale feature extraction led to an increased memory usage and more intensive computational requirements during the training process.

Table 1 summarizes the selected previous studies by comparing **their** methodologies, datasets, reported accuracies, and major limitations.

Study	Year	Methodology	Dataset	Accuracy	Limitations
Sharma et al.	2023	CNN + Attention	PlantVillage + Field Images	98.7%	High computational complexity
Wang et al.	2025	CNN + Transformer	Multi datasets	>97%	Scalability issues
Sahu et al.	2025	Hybrid Dilated CNN	Plant leaf datasets	~98%	High complexity
Ibrahim et al.	2025	Optimized Deep Learning Model	Combined datasets	97.5%	Needs real-world validation
Patel & Shah.	2024	Vision Transformer (ViT)	Benchmark datasets	99.1%	High computational cost
Zhao et al.	2025	Mask R-CNN, Faster R-CNN	Annotated datasets	63%–90%	Depends on data quality
Ahmed et al.	2025	Multi-scale CNN (FPN)	Multi datasets	99.2%	High memory usage

2. Methodology: Low Accuracy of proposed Method

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.

Justify

The schematic diagram of the whole system is shown in Figure 2.

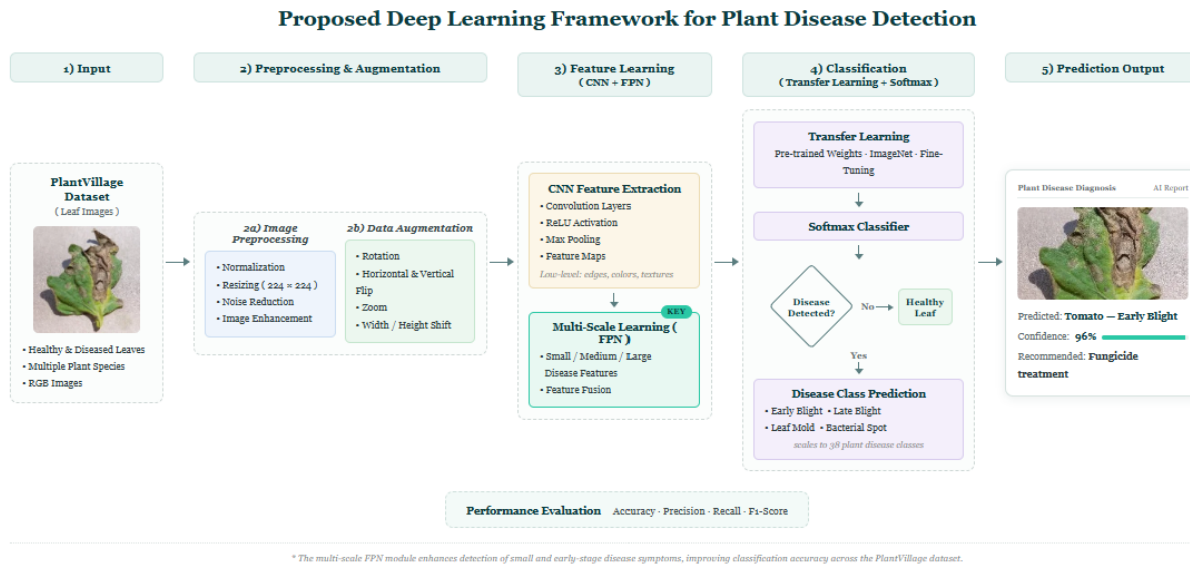


Figure 2: Proposed Framework of Plant Disease Detection System

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 coloured 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

The PlantVillage dataset has become one of the most famous publicly available benchmark dataset to classifying plant diseases. This dataset comprises a total of 54,306 high-quality RGB pictures, captured from multiple crop species under well-controlled settings and contains more than a hundred varieties of plant diseases, healthy or sick. With their highly quality of image and balanced number of entries for different diseases, the dataset was used widely to research a deep learning based approach for recognizing diseases on the plants. For this experiment, three categories of PlantVillage Dataset was extracted to be used which are: Pepper Bell Bacterial Spot, Pepper Bell Healthy, Potato Early Blight, due to contain some examples of both diseases as healthy one that allow to build a system that differentiate diseased samples from the healthy one, and due to the presence of the mentioned plant types and variety of disease that could greatly affects to the yield of plants. Figure 3 shows sample pictures of plant with some plant diseases which selected in the PlantVillage dataset such as: Pepper Bell Bacterial Spot, Pepper Bell Healthy and Potato Early Blight.

Pepper Bell Bacterial Spot



Pepper Bell Healthy



Potato Early Blight



Figure 3 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. Figure 4. Image Before and After Preprocessing

Original Image



After Preprocessing



Figure 4: 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

Justify

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

3.3

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**3.3.1**

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**3.3.2**

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. From Fig.5 the leaf image feed to CNN that consists of convolutional, activation, pooling, flattening, and fully connected layers extract important features and classifies the input leaf into predefined plant classes which are selected in the study.

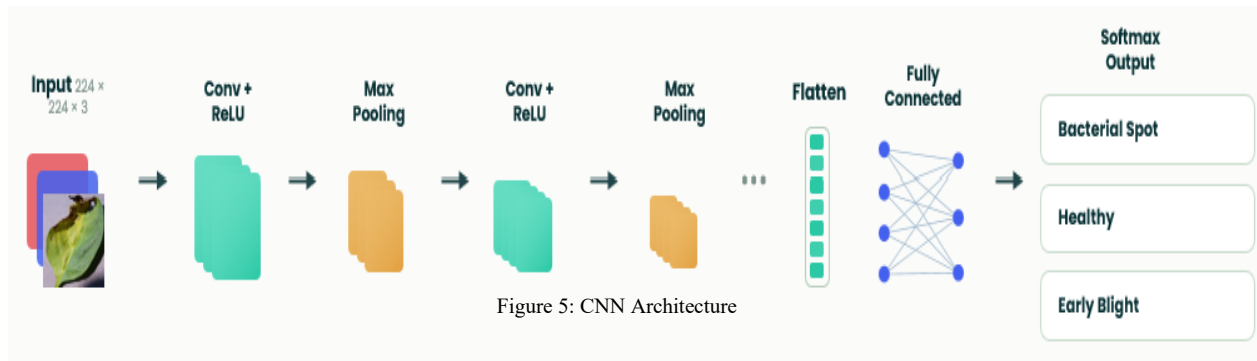


Figure 5: CNN Architecture

3.3.2 Feature Pyramid Network (FPN)

Figure 5

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 6. Feature Pyramid Network (FPN) Architecture.

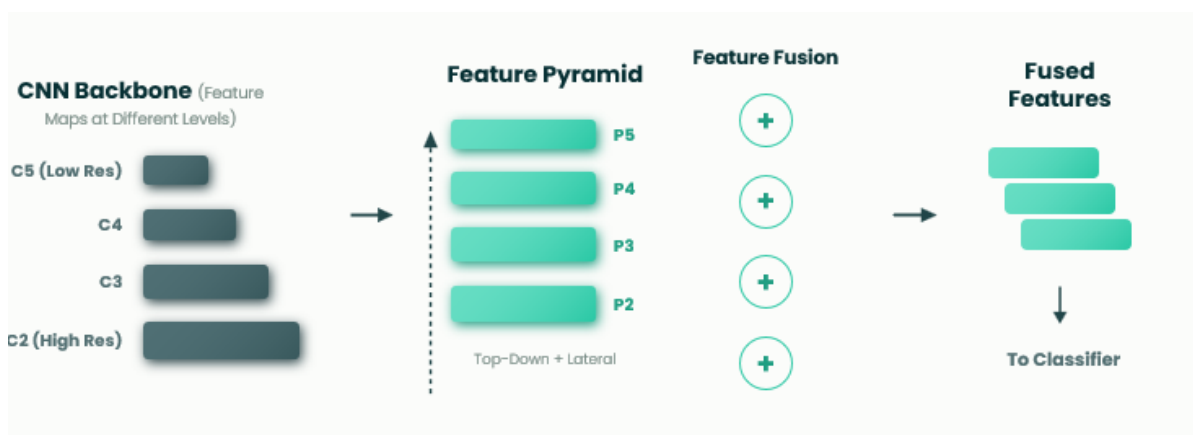


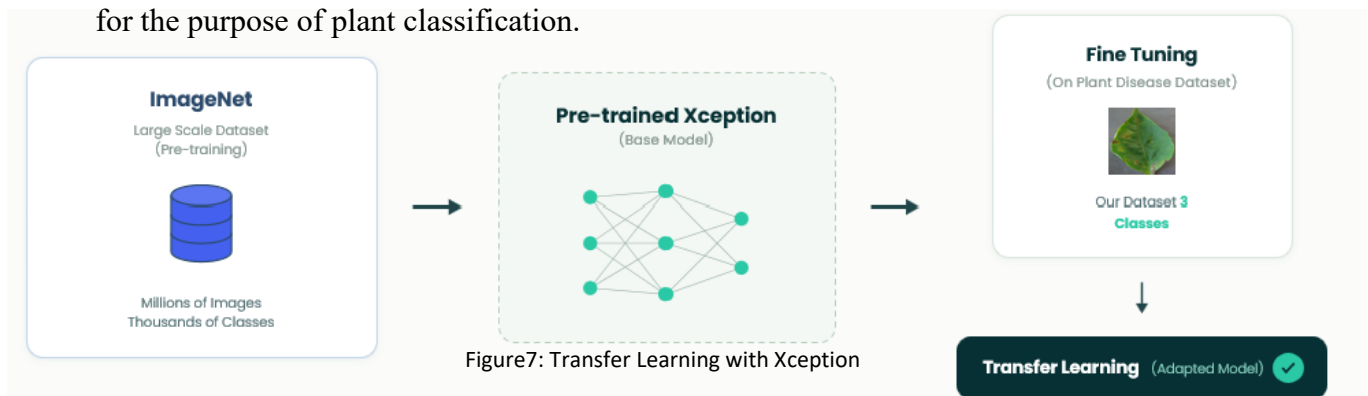
Figure 6: Feature Pyramid Network (FPN)

3.4 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.

3.4.1. Xception

The Xception deep learning architecture is the main model incorporated into the proposed plant disease detection method. Xception is a convolution-based architecture that operates mainly on depth wise separable convolution, which spatially convolves the input and separate channel-wise feature extraction. This design allows the network to process more intricate visual characteristics while maintaining computational efficiency compared to its normal convolution operation. In this work, the Xception model is used with a transfer learning strategy, where the pre-trained weights on ImageNet are utilized. In addition to removing the original classification layer, the convolution base is used as a feature extractor to the plant leaf image. The output features from this convolution base is fed into the new classification layers of the proposed method to classify input images into the three target classes which are Pepper Bell Bacterial Spot, Pepper Bell Healthy, and Potato Early Blight. Through applying the pre-trained transfer learning technique, the proposed network could leverage on visual knowledge obtained from trained models. Xception being chosen because of depthwise convolution that efficiently extracts image features, and it effectively addresses the detection of intricate visual features, like leaf colour and texture, spotting, disease symptoms, so that the model can acquire relevant features from the existing trained models, and re-train on the PlantVillage selected for the study. As is evident from Figure 7, the present method uses transfer-learning through pre-trained Xception model, to transfer the knowledge from image net on our classes selected for the purpose of plant classification.



3.4.2 Disease Classification

Once the features are extracted, they go into the final classification layer. In the proposed work, the output layer of the proposed model has three neurons for the three classes: Pepper Bell Bacterial Spot, Pepper Bell Healthy and Potato Early Blight. It passes through the Softmax activation function. This function converts three neuron output scores into values with a range of 0 and 1, which is probability and the sum of values = 1, to perform multi-class classification. The class with maximum probability is chosen as output.

3.5 Prediction Output

In Result Section

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 8

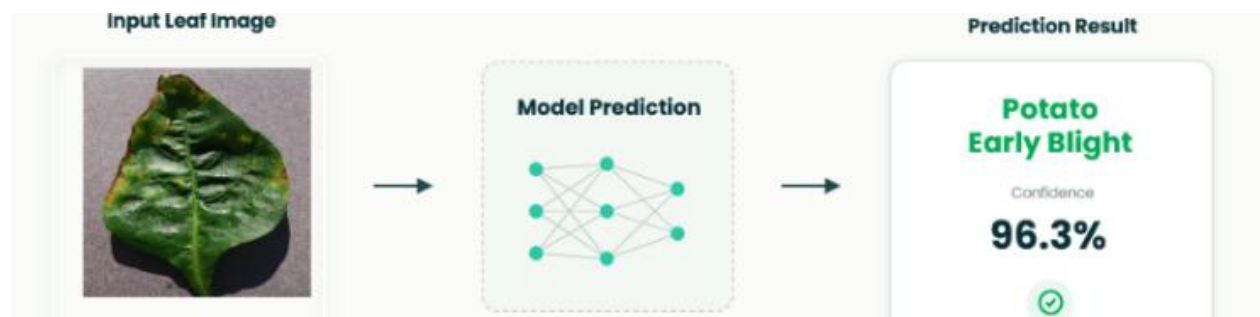


Figure 8: Prediction Output

3.5

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

4.Results and Discussion:

4.1 Preprocessing and Visual Standardizations

Deep Learning Model training included an image preprocessing stage, used to homogenize data consistency and facilitate features learning. All the training data was reshaped into a 224 224 dimension, according to Xception architecture input. Then, the pixel intensity values were normalized for a more stable training and a faster convergence of the training procedure. The preprocessing process decreased noise in the dataset, minimizing differences related to images size and intensity, while maintaining features relevant to the pathologies under consideration. In this way, the model had the ability to attend the salient pathologies features instead of the background noise, thus improving its ability to learn and identify these symptoms. Some examples of images before and after the processing steps can be seen in Figure 9.



Figure 9: Prediction Output

4.2 Performance Evaluation of the Proposed Model

4.2.1 Exception

4.2.1 Overall Performance of the Proposed Model

A.

The proposed Xception model was assessed overall on the validation set and determined by calculating validation accuracy, validation loss, precision, recall, and F1-score. Table 4.1 below illustrates the accuracy, loss, precision, recall and F1-score of the proposed Xception model on the plant leaf classes selected in this research. Table 4.1: Proposed Xception model average results Validation accuracy, validation loss and average precision, recall and F1-score of the proposed model are estimated as 97.22%, 0.0951 and 97% respectively. Table 4.1 Overall Performance of the Proposed Model

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

These results suggested that the developed method had high classification accuracy with balanced results across all metrics.

B. 4.2.2 Per-Class Classification Performance

In addition to overall performance evaluation, precision, recall, and F1-score are computed for each class in the context of three plant leaf classes as shown in Table 4.2. Potato Early Blight gets the best classification performances

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

C. 4.2.3 Confusion Matrix Analysis

Additionally, a Confusion Matrix was built to gauge the performance of classification of Xception model by finding number of correct and incorrect classifications within each category. suggests that the values across the diagonal represent the cases classified accurately while the ones off the diagonal represents cases misclassified. The Xception model successfully predicted 286 images of Pepper Bell Bacterial Spot, 413 images of Pepper Bell Healthy, and 297 images of Potato Early Blight. While 10 of Pepper Bell Bacterial Spot images are wrongly predicted as Pepper Bell Healthy and 3 as Potato Early Blight, among Pepper Bell Healthy images, 30 are wrongly classified as Pepper Bell Bacterial Spot and none as Potato Early Blight. The model misclassifies only 3 out of 300 images as Pepper Bell Bacterial Spot while correctly classifies the rest of 297 images of Potato Early Blight. Most misclassification happened in between Pepper Bell Bacterial Spot and Pepper Bell Healthy implying both categories possess strong resemblances. However, majority elements lie on the diagonal, indicating effectiveness in the prediction based on proposed model to different categories of plants leaves. As Shown in Figure 10.

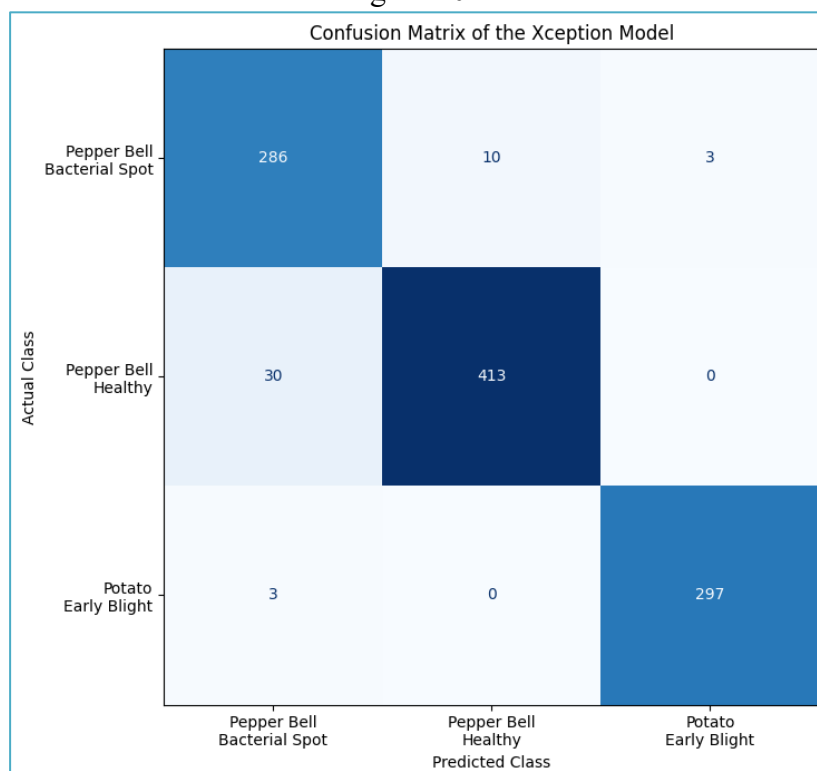


Figure 10. Confusion Matrix of the Xception Model for the Three Plant Disease Classes.

D.

4.2.4 ROC Curve Analysis

Receiver Operating Characteristic (ROC) curve analysis was also performed to further assess the classification performance of the Xception model for the 3 classes of plant leaves. The ROC curve describes the correlation between True Positive Rate (TPR) and False Positive Rate (FPR) for varying thresholds in the classifier and the Area Under the Curve (AUC) reflects the model's efficiency in distinguishing between the different classes. Figure 11 provides the ROC curves obtained for each class of leaf.

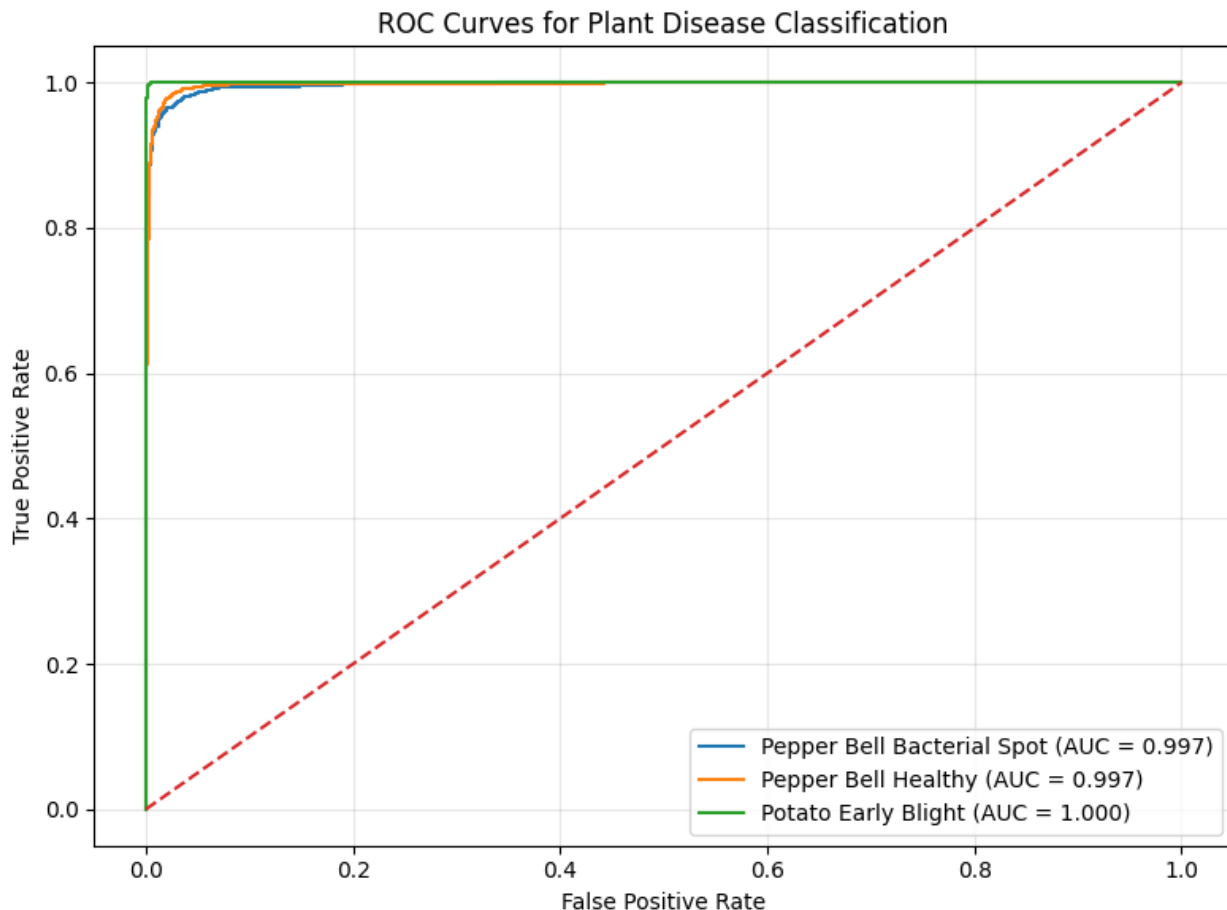


Figure 11. ROC Curves of the Xception Model for Plant Disease Classification

The ROC curve in Figure 11 shows an AUC value of 0.997 for Pepper Bell Bacterial Spot and 0.997 for Pepper Bell Healthy with AUC value of 1.000 for Potato Early Blight. The ROC curves are concentrated close to the upper left of the graph which shows the True Positive Rate is higher with a low False Positive Rate. The discriminative power of Potato Early Blight is shown by the AUC value of 1.000. The AUC value of 0.997 for Pepper Bell Bacterial Spot and Pepper Bell Healthy show the class can be easily distinguished from the rest of the classes.

4.2.3 4.2.5 Other Techniques Results

4.2.2 ResNet 50

Another few deep learning based methods have also been utilized beside the Xception model that has been planned in order to assess these methods effectiveness for the mentioned plant disease

classification task. CNN and ResNet are chosen as alternative classification methods. They have been taught on the chosen plant leaf classes so that to observe and analyse the performance of distinct deep learning based methods, for this purpose Table 4.3 represents the acquired experiment outcomes of these techniques.

Technique	Epochs	Final Validation Accuracy	Best Validation Accuracy
CNN	10	95.82%	97.26%
ResNet	10	99.42%	99.71%
Xception	10	97.22%	98.31%

4.2.6 Comparison with Related Work

In order to give an evaluation of our proposed method, Table 4.4 represents a comparison between our proposed model (Xception model) and a selected number of related papers regarding the used model, database and stated accuracies of plant diseases classification. Table 4.4. Comparison of the Proposed Model with Related Work.

Ahmed et al;

Technique

Study	Model	Year	Accuracy	Vs. Ours
HOWSVD-MDA	Ouamane et al.	2024	98.36%	+1.14%
Mob-Res	Pal et al.	2025	99.47%	+2.25%
EfficientNet	Recent Plant Disease Detection Study	2025	98.27%	+1.14%
CNN	Plant Disease Identification Study	2025	93.82%	-3.40%
DAA-MDeNet	Sahu et al.	2025	94.58%	-2.64%
Proposed Study	Xception	2026	97.22%	-

4.3 Discussion

Our findings show that **Xception** based approach works well for plant disease classification. High performance of the model is attributable to the use of transfer learning and the capacity of the Xception architecture to discriminate visual features from the plant leaf images. Low validation loss along with high validation accuracy demonstrates that learned features were proficient to classify the chosen healthy and diseased leaf classes. Further, the analysis of the class specific performance brings further insights into the behavior of the implemented model. Although the model showed great performance over the three classes the classification errors were not evenly distributed. The confusion matrix reveals most of the misclassification was among Pepper Bell Bacterial Spot and Pepper Bell Healthy, implying the two classes were comparatively difficult to classify. Some leaf properties of the two diseases were similar to each other which led to classification errors, whilst Potato Early Blight showed more discrimination with far fewer erroneous misclassifications. Thus, classification confusion mainly arises due to the discrimination of visually identical diseased and healthy leaves, rather than a fundamental flaw in the ability of the model to classify plant disease. In line with the conclusions from the confusion matrix, the ROC curves show that Xception has a great capacity to discriminate between each of the chosen leaf varieties' curves provide AU C scores 0.997 for Pepper Bell Bacterial Spot, 0.997 for Pepper Bell Healthy and 1.000 for Potato Early Blight, suggesting strong discriminability. Perfect AUC for Potato Early Blight may be a correlate to its excellent performance in the confusion matrix. lower AUC for the two Pepper Bell varieties may be correlated to the confusion between their respective diseases. Therefore ROC and confusion matrix offer complimentary insight. Comparing the proposed methods against the other deep learning methods investigated, Xception performed favorably. While the three deep learning techniques achieved different classification rates, the differences are attributed to differences in architectural capacity to extract relevant plant leaf image features. The comparison also shows the importance of model architecture in terms of classification accuracy for plant disease. However, due to the ability of Xception depth wise separable convolution to extract features effectively and to implement transfer learning, it stands as a good choice for the proposed frame work. Comparison against other methods In compared with the above mentioned previous works on plant disease classification with deep learning approaches, our proposed work gives competitive accuracy compared with previously reported works. Some works has given the reported classifier accuracy is higher than our work, while some previous models give a lower classifier accuracy than our model, but this is not sufficient to confirm superiority. This study compares their efficacy and demonstrates that Xception can serve as a powerful classifier for the specific classes of Plant Village dataset and still holds the good discriminability. IN sum, transfer learning via Xception appears to be a suitable technique for the automatic classification of plant diseases. However, confusion between visually similar classes of Pepper Bell disease and normal plant remains an important issue for future research. Increasing the dataset diversity and also evaluating the developed framework under real world conditions would present more informative evaluation result about the generalizability.

5. Conclusion

This paper presented a deep learning-based automatic plant disease classification framework based on the **Xception** architecture with transfer learning. The proposed framework automatically learns discriminative features from the plant leaf images thus avoiding manual feature engineering and selection. A validation accuracy of 97.22% with values close to 0.97 for precision, recall, and F1-score were achieved after training on the PlantVillage dataset. The proposed approach achieved remarkable classification performance across all the selected plant leaf categories according to the presented results. The confusion matrix shows that the model performed quite accurately; however,

a few errors were found between Pepper Bell Bacterial Spot and Pepper Bell Healthy. The ROC curve generated AUC values of 0.997, 0.997 and 1.000 for Pepper Bell Bacterial Spot, Pepper Bell Healthy, and Potato Early Blight respectively, indicating that the chosen features are discriminative. A comparison made against other deep learning approaches along with recent similar contributions in the field indicated that the Xception-based approach we have proposed has competitive accuracy for the classification of plant diseases. Based on the results, transfer learning with the Xception architecture proves to be successful for plant leaf image-based classification that is very beneficial for intelligent agriculture system to identify the plant diseases at the early stage. Nevertheless, the model was tested under controlled environment which captured by the PlantVillage dataset. It needs to be tested on images captured from real agricultural scenarios, which include diverse lighting conditions, varied backgrounds, leaf orientations, and other environmental factors. The application of lightweight network architecture and model compression techniques needs to be investigated for the deployment of the designed system on the mobile devices and edge computing platforms..

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