Engineering and Technology Journal e-ISSN: 2456-3358
Volume 09 Issue 01 January-2024, Page No. 3266-3270
DOI: 10.47191/etj/v9i01.02, I.F. – 7.136

Plant Disease Detection by Using Mobilentv2 and Xception on Filtered and Enhanced Images

Volkan Yamaçli[1], Muhammet Kürşat Yildirim[2]
[1]Mersin University, Computer Engineering Department, Mersin, Turkey
[2]Mersin University, Computer Engineering Programme MSc Student, Mersin, Turkey

ABSTRACT: The gathering, sorting, and processing of plant leaf images serves as the foundation for this study. These are crucial first steps in the plant health monitoring process that guarantee reliable findings. The work classifies and detects plant leaf photos, extracting data on plant health using state-of-the-art deep learning models like Xception and MobileNetV2. In order to assess the effectiveness of the system, additional filters are applied to the photos of plant leaves in order to adjust characteristics like brightness, contrast, sharpness, and blur. The study's results show that the deep learning models employed could accurately determine the health of plant leaves, offering important new information for related future research.

KEYWORDS: Deep Learning, MobilenetV2, Xception, Tensorflow, Plant, Agriculture

I. INTRODUCTION

Agriculture is key to humanity's survival since dark ages. In addition to feeding the world population, food production forms the basis of economic and social development. Agriculture is not only a food supplier but also a source of employment and income. In addition, agricultural raw materials are also used in the production of many industrial products [1]. But agriculture faces a number of challenges, such as climate change, limited natural resources, population growth and plant diseases make agriculture even more complex [2].

Plants are organisms that form the basis of agriculture. Plants are the basic food sources for the nutrition of humans and other living creatures. Additionally, plants play a critical role in maintaining the balance of ecosystems. In addition to providing food security, healthy plants are also vital for the sustainability of the natural environment. Therefore, plant health and plant protection are a critical element for the sustainability of the agricultural sector.

In agriculture, plant diseases can cause great damage. Plant diseases can cause crop losses and yield reductions. Additionally, these diseases can threaten food security and compromise the economic sustainability of agriculture. Especially due to climate change and increased international trade, plant diseases have become an even greater threat. To meet these challenges, scientists and researchers around the world are developing new methods to monitor plant health and diagnose diseases. Traditional diagnostic methods are often time-consuming and susceptible to human error. Therefore, automation and artificial intelligence technologies have significant potential for diagnosing and monitoring plant diseases [3-5].

Deep learning is a significant development in the field of artificial intelligence. This technique is known for its ability to process large data sets. Deep learning is used effectively in many application areas and has great potential in monitoring plant health and diagnosing diseases [6].

Image processing refers to the process of capturing, processing and analysing digital images, generally. This process involves extracting, transforming and interpreting information in the image. It offers a wide range of applications in image processing, medicine, automation, security, entertainment, agriculture and more. In the medical field, diagnoses are made by examining x-ray and MRI images. Automation uses image processing techniques to detect errors on the production line and ensure quality control. Security systems adopt facial recognition and object detection technologies with image processing. While the entertainment industry creates special effects with image processing, there are applications in agriculture such as diagnosing plant diseases. In this way, image processing is used as a powerful tool that forms the basis of data analysis and decision support systems in different industries [7].

Convolutional Neural Network (CNN) is a deep learning model widely used in computer vision and image processing. CNNs are specifically designed to process and analyse visual data. These networks are used in image classification, object recognition, face recognition and many other tasks. The main purpose of CNNs is to recognize features in data and learn these features in a hierarchical way [5].

The dataset used in this study was obtained from Kaggle website [8] which contains total 70.295 images belonging to 38 different classes. The selected 38 classes are important for early diagnosis of plant diseases and represent various plant species such as apple, blueberry, cherry, corn, grape, orange, peach, potato, raspberry, soybean, squash, strawberry and tomato. The dataset has healthy images of species as well as one or more plant disease and also the images are not equal in number so classifying these images are a challenge which would affect the life quality of humans and animals. In this study all the images and classes are used in order to train the deep learning methods namely CNNs.

In literature, there are various important studies of detection and classification of plant diseases by using deep learning methods in recent years. In particular, convolutional neural networks (CNN), which exhibit advanced performance in image processing and pattern recognition, attract intense attention in this field. MobilenetV2 [9] and Xception [10] are one of the most used and popular algorithms due to their high precision and fast computation abilities. Many studies have been carried out using MobileNet in the literature. Focusing on a leaf disease classification model that performs effectively on mobile devices, this study offers an innovative approach for disease diagnosis in agriculture. This lightweight and effective MobileNet model, which can be widely used on mobile devices, aims to accurately and quickly classify plant leaf diseases. Experimental studies and performance evaluations have shown that the MobileNet-based classification model provides time and cost savings in disease diagnosis processes in the agricultural sector [11]. In another study in the literature, various experiments were carried out for the detection of maize diseases using Xception [12]. In addition, many plant health detection and classification studies have been carried out with MobilenetV2 and Xception.

In this study, all classes in the Kaggle Plant Diseases dataset were trained and classified with MobilenetV2 and Xception CNNs. In addition, the effects of image quality blur, brightness, contrast and sharpness parameters on the test success of the trained network were examined and presented. It can be seen from the results that both MobilenetV2 and Xception CNNs can perform very successful classification and detection.

II. MATERIAL AND METHODS

In this study, a plant disease dataset, CNNs and modified test dataset including images with image quality parameters such as blur, brightness, contrast and sharpness are used to train and test the methods aforementioned in Section I.

A. Convolutional Neural Networks

In this work, plant disease and wellness are classified from the photos using MobilenetV2 and Xception CNNs. Among CNNs used for computer vision and detection, the MobilenetV2 and Xception architectures are among the most widely used. One of the most reliable models is MobilenetV2, which has Rectified Linear Units (ReLU) that improve non-linearity performance. In addition, a recently suggested CNN called Xception is an enhanced version of Inception-v3. Depth-wise separable convolutions in Xception facilitate more effective and efficient model training. The network's foundation for feature extraction is made up of 36 convolutional layers in the Xception model. The dimensions of the input data for MobilenetV2 and Xception are 224×224 and 299×299 pixels, respectively.

In this work, Tensorflow 2.10.1 [13] is used in this study with Python 3.10.1 [14] as given in Fig 1, on a Windows® 10 PC equipped with a GeForce RTX 3080 GPU, 16.0 GB of RAM, and an Intel® Core (TM) i7-10700F processor running at 2.90 GHz.

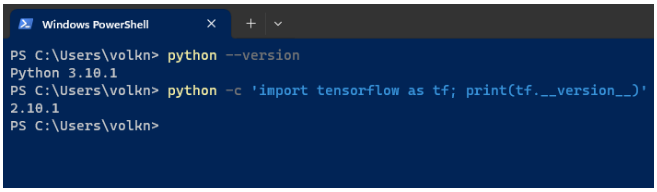


Fig 1: Python and Tensorflow version screen.

For deep learning training, initial learning rate, maximum epoch, and mini batch size are set at 1×10^{-4}, 16, and 10, respectively. Additionally, the parameters *horizontal_flip: True*, *vertical_flip: True*, and *zoom_range: 0.2* are used to apply augmentation to the images.

B. Plant Disease Dataset

The photos utilized in this investigation were taken from the Kaggle New Plant Disease Dataset [8]. In 38 classes, this dataset includes almost 90.000 unique or augmented photos. Many plant species, including apple, blueberry, cherry, maize, grape, orange, peach, potato, raspberry, soybean, squash, strawberry, and tomato, are included in the dataset. The dataset consists of three directories: *training*, *validation*, and *test*, containing 70.295, 17.572, and 33 files respectively. There are only 33 pictures for 38 classes in the test folder. Therefore, *training* folder is used for deep learning training and validation processes while *validation* folder is used for deep learning model testing; *test* folder is discarded.

Also, training and validation split is chosen as 0.3 which results of 49.223 images for training; 21.072 images for validation and 17.572 images for test. Some example images of the used training dataset are given in Fig 2 below.

Fig 2: Example imagery obtained from the dataset.

In addition, in order to test the accuracy of the Xception and MobilenetV2 for different image quality characteristics, degradation including blur, brightness, contrast and sharpness quality of the images are applied. In this study, image filters are applied to images by using *PIL ImageFilter* [15] and *ImageEnhance* [16] modules in Python as given in Fig 3. The image filtering and enhancing parameters are given in Table I. Example imagery set is given in Fig 4.

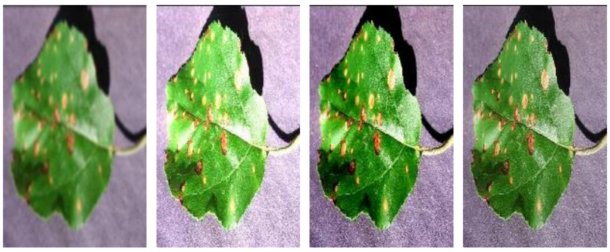
```
from PIL import Image, ImageEnhance
import os
import time

def contrast_en(image_path, output_folder, contrast_const):
    image = Image.open(image_path)
    enhancer = ImageEnhance.Sharpness(image)
    new_image = enhancer.enhance(contrast_const)

    if not os.path.exists(output_folder):
        os.makedirs(output_folder)

    new_image.save(os.path.join(output_folder, os.path.basename(image_path)))
```

Fig 3: Contrast Enhancement Example Code Block.

Table 1: Image Filtering Parameters.

Parameter	**Value**
Blur Radius	1.5
Brightness Constant	1.5
Contrast Constant	1.5
Sharpness Constant	1.5

a) Original Image of Apple Black Rot Example



b) Blur c) Brightness d) Contrast e) Sharpness

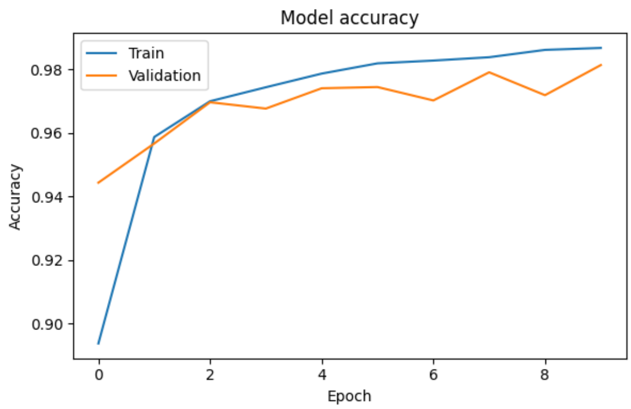
Fig 4: Image Filtering and Enhancement.

III.RESULTS AND DISCUSSION

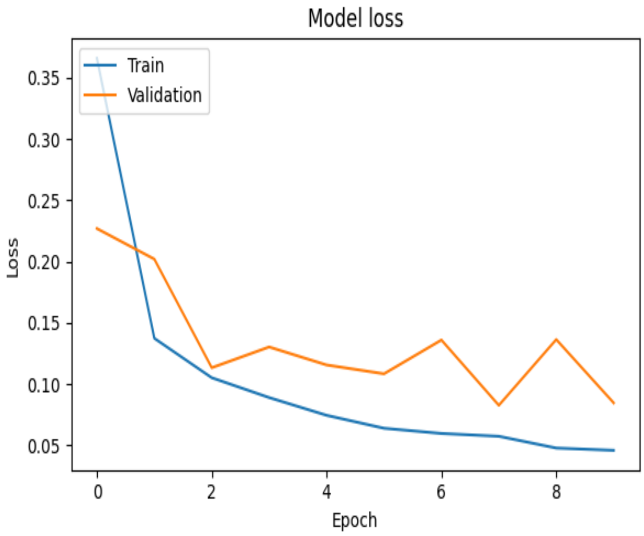
In this section, the results of the MobilenetV2 and Xception CNNs training and test processes are presented in detail.

A. MobilenetV2

In this subsection, MobilenetV2 training and confusion charts are given in Fig 5 and Fig 6, respectively. Also, accuracy values for test cases of normal, blur, brightness, contrast and sharpness enhanced images are also given in Table 2. The MobilenetV2 reaches up to 98.67% accuracy for training and 98.13% accuracy for validation in 10 epochs.



a) Model Accuracy



b) Model Loss

Fig 5: MobilenetV2 Training and Validation Performance.

Table 2: MobilenetV2 Test Accuracy for Different Cases.

Test Case	**Test Accuracy**
Normal	96.45%
Blur	78.32%
Brightness	90.97%
Contrast	92.78%
Sharpness	95.86%

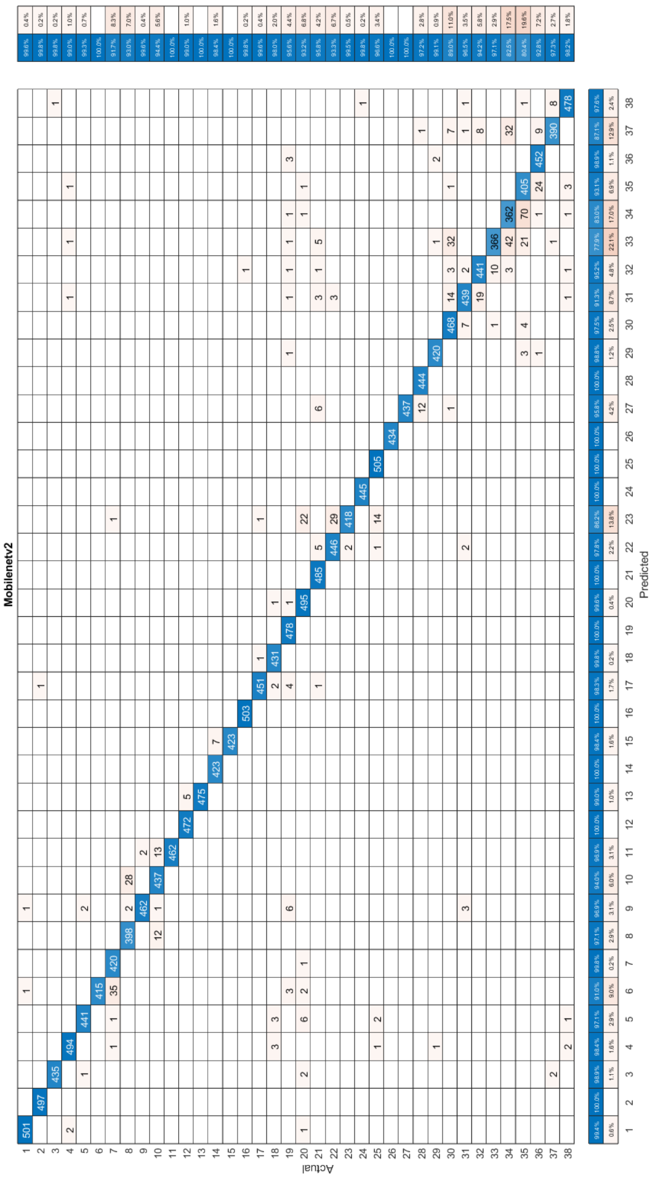
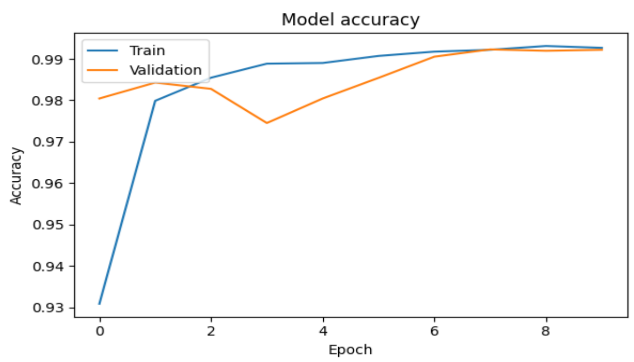


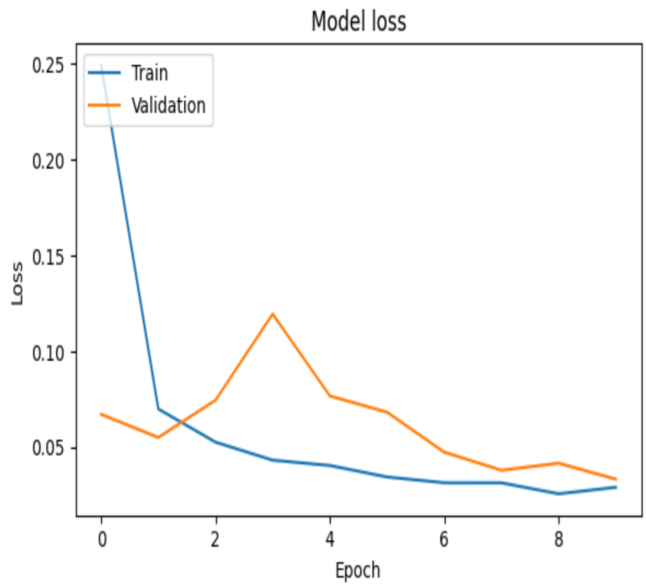
Fig 6: MobilenetV2 Test Performance.

B. Xception

In this subsection, Xception training and confusion charts are given in Fig 7 and Fig 8, respectively. Also, accuracy values for test cases of normal, blur, brightness, contrast and sharpness enhanced images are also given in Table 3. The Xception reaches up to 99.30% accuracy for training and 98.90% accuracy for validation in 10 epochs.



a) Model Accuracy



b) Model Loss

Fig 7: Xception Training and Validation Performance.

Table 3: Xception Test Accuracy for Different Cases.

Test Case	Test Accuracy
Normal	98.01%
Blur	90.37%
Brightness	96.24%
Contrast	96.21%
Sharpness	97.67%

CONCLUSIONS

In this work, deep learning models are used to plant leaf images to identify and categorize the state as healthy or unhealthy. Plant status is successfully detected and classified using MobilenetV2 and Xception, two deep learning models. The findings show that both models perform well in terms of categorization. The following conclusions can be made:

1. Both MobilenetV2 and Xception attain satisfactory outcomes for the test cases.
2. Xception can classify blurry photos with 90.37% accuracy, compared to MobilenetV2's 78.32% output.
3. Both models have above 90% classification accuracy for normal and enhanced pictures with sharpness, contrast, and brightness.

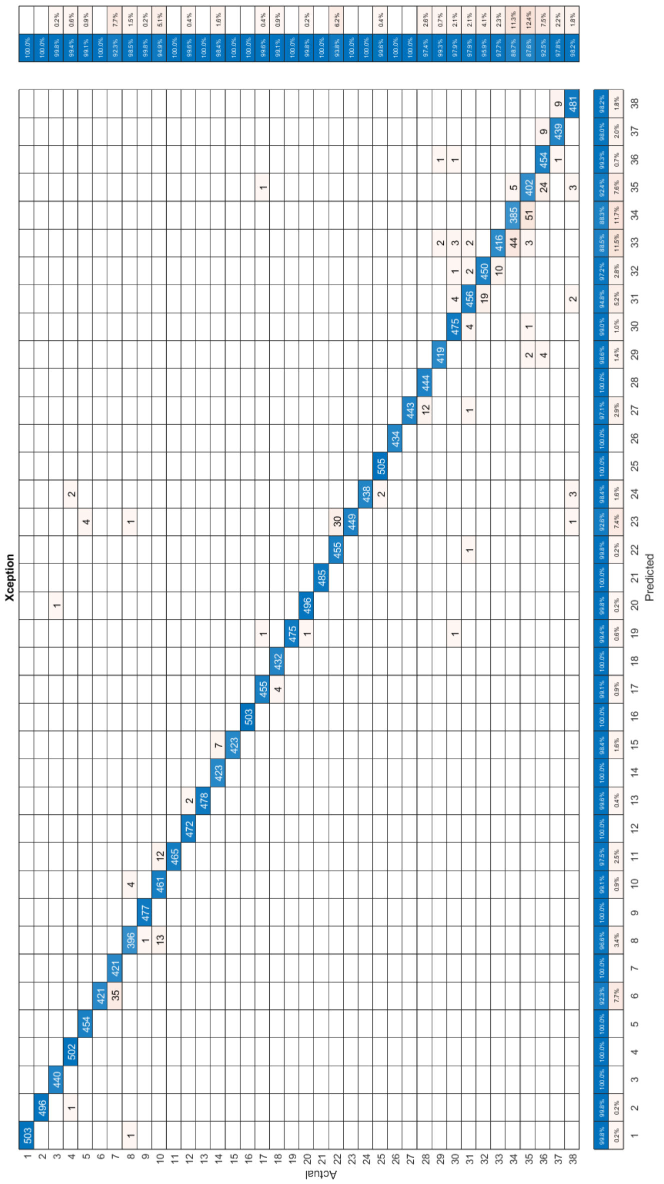


Fig 8: Xception Test Performance.

REFERENCES

1. Kopittke, P., Menzies, N., Wang, P., McKenna, B., and Lombi, E., "Soil and The Intensification of Agriculture for Global Food Security", Environment International, 132, 2019.
2. Yamacli, V., Yildirim, K. M. 2023. Health Classification for Plants by Using Computer-Aided Deep Learning Methods in Proceedings of the International Conference on Advances and Innovations in Engineering.
3. Alharbi, A., Khan, M. U. G., and Tayyaba, B., "Wheat Disease Classification Using Continual Learning", IEEE Access, 2023.
4. Vallabhajosyula, S., Sistla, V., and Kolli, V. K. K., "Transfer learning-based deep ensemble neural network for plant leaf disease detection", Journal of Plant Diseases and Protection, 129, 545–558, 2022.
5. Hassan, S. M., and Maji, A. K., "Deep Feature-Based Plant Disease Identification Using Machine Learning Classifier", Innovations in Systems and Software Engineering, 2023.
6. Hosny, K. M., El-Hady, W. M., Samy, F. M., Vrochidou, E., and Papakostas, G. A., "Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern", IEEE Access, 2023.
7. Kaur, P., Harnal, S., Gautam, V., Singh, M. P., and Singh, S. P., "A Novel Transfer Deep Learning Method for Detection and Classification of Plant Leaf Disease", Journal of Ambient Intelligence and Humanized Computing, 2022.
8. https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset [Accessed on December 2023].
9. Sandler, M., Howard, A., Zhu, M., Zhmoginov A., and Chen, L.C. "MobileNetV2: Inverted Residuals and Linear Bottlenecks", Computer Vision and Pattern Recognition, arXiv:1801.04381, 2019.
10. Chollet, F., "Xception: Deep Learning with Depthwise Separable Convolutions", Computer Vision and Pattern Recognition, arXiv:1610.02357, 2017.
11. Patil, M. A., and Manur, M., "Sensitive Crop Leaf Disease Prediction Based on Computer Vision Techniques with Handcrafted Feature", International Journal of System Assurance Engineering and Management, 2023.
12. Ahmad, A., Gamal, A. E., and Saraswat, D., "Toward Generalization of Deep Learning-Based Plant Disease Identification Under Controlled and Field Conditions", IEEE Access, 2023.
13. https://www.tensorflow.org/install/pip [Accessed on December 2023].
14. https://www.python.org/downloads/ [Accessed on December 2023].
15. https://pillow.readthedocs.io/en/stable/reference/ImageFilter.html/ [Accessed on December 2023].
16. https://pillow.readthedocs.io/en/stable/reference/ImageEnhance.html/ [Accessed on December 2023].