Introduction

Pear production is an essential agricultural activity, widely practiced in various regions around the world, particularly in countries with temperate climates such as China, Italy, and the United States. According to the Food and Agriculture Organization (FAO), global pear production reached approximately 24 million metric tons in 2022 [1]. China leads as the top producer, contributing more than 70% of the world's total pear output, followed by Italy and the United States [1]. The cultivation of pears significantly supports the economies of these countries, providing employment and sustaining local agricultural industries. Pears are primarily consumed fresh, but they are also used in processed forms such as canned pears, juices, and jams [1]. The diverse varieties of pears, such as Bartlett, Bosc, and Anjou, cater to different consumer preferences and market demands, enhancing their global trade and consumption [1].

Despite the economic significance of pear cultivation, pear trees are vulnerable to various diseases that can severely impact yield and quality. Common pear diseases include fire blight, scab, rust, and various fungal infections, which can lead to substantial economic losses for farmers. Fire blight, caused by the bacterium Erwinia Amylovora, is particularly devastating, as it can rapidly kill young trees and severely damage older ones [2]. Pear scab, resulting from the fungus Venturia Pirina, leads to blemished fruits and defoliated trees, reducing both marketability and photosynthetic efficiency [3]. Pear rust, caused by different species of Gymnosporangium, affects leaves and fruits, causing deformations and premature drop [4]. Effective management of these diseases is crucial for maintaining healthy pear orchards and ensuring consistent production levels. However, traditional disease detection methods, relying on visual inspections, are often time-consuming, labor-intensive, and subject to human error [5].

To address these challenges, automated disease detection systems utilizing advanced machine learning and deep learning techniques have been developed. These systems offer a promising solution for timely and accurate identification of pear leaf diseases, facilitating early intervention and reducing crop losses. The DiaMOS Plant dataset, specifically designed for the diagnosis and monitoring of plant diseases, provides a robust foundation for developing such systems [6]. This dataset includes high-quality images of pear leaves affected by various diseases, enabling the training of deep learning models to recognize and classify disease symptoms with high accuracy [7]. The use of Convolutional Neural Networks (CNNs), particularly enhanced with attention mechanisms and other advanced features, has shown significant potential in improving the precision and reliability of disease detection in complex agricultural environments [8].

In this research, we propose an automatic disease detection system for pear leaves using a customized deep learning network. The proposed network leverages the DiaMOS Plant dataset to train a model capable of accurately identifying and classifying multiple pear leaf diseases [9]. Our approach integrates several advanced modules, including Explainable AI (XAI) methods to provide insights into model decisions, fostering trust and adoption among users, to enhance the network's performance in capturing intricate disease features. With this system, we aim to provide farmers with a practical tool for remote and real-time monitoring of their orchards [10]. This system aims to enhance disease management practices, support sustainable agriculture by reducing unnecessary pesticide use, and optimize resource allocation. By providing scalable and reliable tools for monitoring plant health and efficiently mitigating disease impacts, the system contributes to precision agriculture, ultimately improving crop yield and quality.

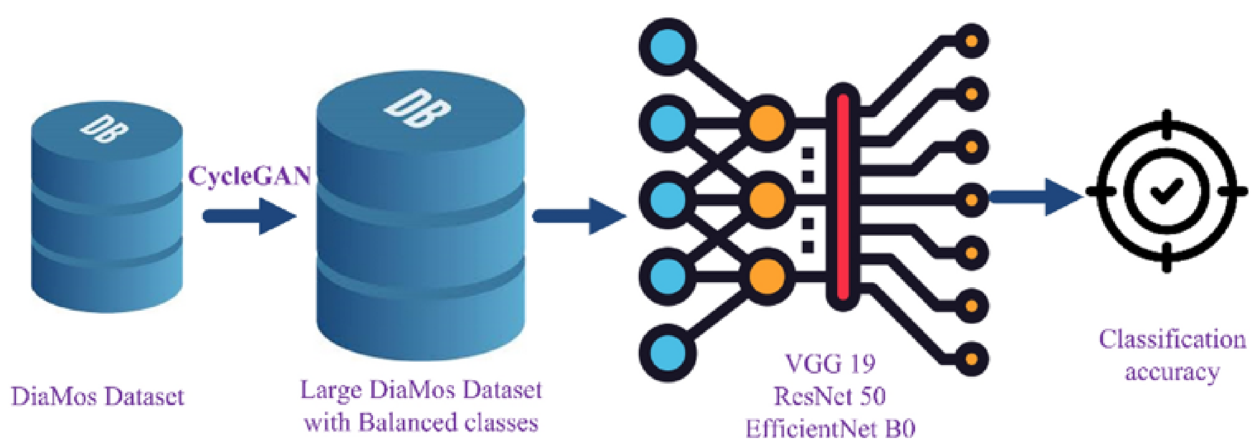
Data Augmentation

The training process of deep learning models requires a large number of records of paired examples. However, in most cases, preparing large datasets are not valid, as with the employed DiaMOS dataset. The **CycleGAN** is a method that involves an autonomous training of image-to-image translation models without paired examples using the GAN architecture, where these models are trained in an unsupervised approach, using a collection of images from the source and target domain that do not require to be related in any way.

In general, the CycleGAN architecture consists of two models: the generator model and a discriminator model. The generator receives a point from a latent space as an input and produces new plausible images from the domain, whereas the discriminator takes an image as an input and predicts whether the taken image is a real one (from the DiaMOS dataset) or fake (from the generated dataset).

Our approach involves generating new labelled images through training the CycleGAN, for two main reasons: balancing the classes in the DiaMOS dataset, and increase the size of the DiaMOS dataset in order to obtain better classification accuracy, where the new generated images will be added to the original image dataset in order to enhance the initial dataset, through incorporating more images. Next, the designed CNN model is employed to train using the new generated dataset.

DiaMOS dataset contains a small number of records, in addition, DiaMOS includes imbalanced data classes, and hence this leads to poor plant disease classification performance. Therefore, one of our main goals was to increase the size of the DiaMOS dataset and balance the records in each class.



Preprocessing

1. **Image Normalization**:

   Normalizing image pixel values helps in faster convergence of the neural network training process. It ensures that the input data has a consistent scale and prevents issues related to varying magnitudes of pixel values.

   Technique: Common normalization techniques involve scaling pixel values to a specific range, such as [0, 1] or [-1, 1]. For example, normalizing to [-1, 1] can be done using the formula: normalized_pixel=(pixel−127.5)/127.5\text{normalized_pixel} = (\text{pixel} - 127.5) / 127.5normalized_pixel=(pixel−127.5)/127.5.

2. **Resizing and Cropping**:

   Standardizing the size of images is crucial because neural networks typically require fixed-size inputs. Resizing ensures uniformity, while random cropping can increase the model's robustness by introducing slight variations in the input data.

   Technique: Resize images to the target dimensions (e.g., 256x256 pixels). Random cropping involves selecting random regions of the resized images to use as input during training.

3. **Histogram Equalization**:

   Histogram equalization improves the contrast of an image by spreading out the most frequent intensity values. This technique can be particularly useful in images with poor lighting or low contrast.

   Technique: Convert the image to grayscale, compute the histogram, and redistribute pixel values to achieve a uniform histogram.

4. **Noise Reduction**:

   Reducing noise in images can help the model focus on the relevant features rather than the noise. This is especially important in real-world images where noise can be prevalent.

   Technique: Apply denoising filters like Gaussian blur, median filtering, or more advanced methods like Non-Local Means Denoising.

5. **Color Space Conversion**:

   Different color spaces can highlight different features. For instance, converting to the Lab color space separates lightness (L) from color information (a and b), which can be useful for certain image processing tasks.

Technique: Convert images from RGB to another color space (e.g., YUV, HSV, Lab) using appropriate transformation functions.

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