A REVIEW ON GRAPE LEAF DISEASE IDENTIFICATION USING E-GAN

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Abstract - In the country, planting is one of the important fields for farmers to grow crops and yield and crops. Plant disease is one of the major effects on production and the economy, affecting the quality and quantity of agricultural fields. Since most people depend only on these fields, through this, people can improve their economic situation. Prior to the earlier days, farmers should plant the crops that are to be monitored from an early stage; in doing so, they can easily prevent losses due to disease. One effective method of detection and treatment is through the use of image processing techniques, which allow for the immediate identification and cure of the disease without harming the surrounding plants. These techniques are used to detect the disease in the easiest way, and this paper reviews the potential of using various methods. In image processing, we have to use deep learning methods, such as CNN, to detect plant leaf diseases by analyzing images to extract features and to classify diseases. There are some popular CNN architectures, including AlexNet, Inception-V3 – V3, MobileNet, and InceptionResNet-V2, with models like MobileNet showing high accuracy. Through these methods, we can easily identify and detect the disease using some algorithms, which is one of the parts of deep learning concepts.

Keywords- CNN(Convolutional Neural Network), AlexNet, MobileNet, InceptionResNet – V2, Inception–V3

I. INTRODUCTION

In recent times, plant leaf disease identification and detection systems employ various techniques. Developing a combination of automated and semi-automated techniques is crucial for achieving faster, more cost-efficient, and more precise outcomes compared to traditional manual observations conducted by farmers. It will prompt farmers and researchers to use the most technologically advanced system for plant leaf disease identification, and it doesn't require human intervention

II. LITERATURE REVIEW

Bin Liu et al. (2020) explored the first, **Generating the Grape leaf disease dataset**: Data Acquisition, in which a total of 7,669 images of grape leaves were collected with a digital camera, and it belongs to seven categories, such as anthracnose, brown spot, mites, black rot, downy mildew, leaf blight, and healthy leaves. The second is a **Data Augmentation**: In this review paper, using this method, the over fitting problem in the training stage of CNN can be overcome using data augmentation. The brightness value of each image is adjusted by randomly increasing or decreasing the RGB values of pixels. **Identification model of** Grape **leaf disease**: The architectures of four classical CNN models namely, VGG16(Simonyan and Zisserman, 2014), GoogleNet(Szegedy et al, 2015), ResNet(He et al, 2016), and DenseNet(Huang et al, 2017), a novel CNN based model namely, DICNN is proposed for diagnosis of seven common grape leaf diseases. This model includes three parts: the first module, the 'pre-network module', and its deep separable convolutional layer, which is filtered with 64 kernels of size 3*3. The second model includes a cascade dense inception module, which is a four-inception structure with the use of dense connections. The third model includes composing of two max pooling layers, an inception layer, a global average pooling layer, and a 7–way softmax layer.

Prasad et al. (2024)highlight for the **Data preparation or a Dataset** is that the grape images in the dataset are all of 256*256 pixels in size, the collection is unbalanced and has a total of 9027 photos from four different classes of grape leaf disease and for **Data Augmentation**, it involves applying transformations to existing images is used to increase diversity and quantity of training data such as the random consists of rotations, flips, zooms and shifts are commonly used to simulate variations in disease patters, lighting conditions and camera angles and it improves model's generalization ability, and it can reduce overfit task, and enhances robustness and accuracy of grape leaf disease image classification. The following transformations are applied to grape leaf images to create an augmented image, such as zooming on the image, which is then resized to an interval [1-x,1+x], here the value of x is 0.1, a horizontal flip consists of all rows and columns of an image, where the pixels are reversed horizontally, further it creates a mirror image of the original image along a vertical line. While **splitting the data**. A total of 7222 images, or eighty percent of the data, were set aside for training, while 1805 images, or twenty percent, were set aside for testing. A further 20% of the training data, 1444 images, were used for validation. In **Methodology**, In this study, Convolutional neural network (CNN) models. We also designed a Deep Convolutional Neural Network (DCNN) classifier model employing the VGG16 architecture with three extra CNN layers and assessed its performance. In **CNN**, this study presents the development of a novel convolutional neural network (CNN) architecture that demonstrates the ability to automatically extract features through convolution and pooling. Convolutional layers are the essential components of a Convolutional Neural Network (CNN). Filters (or kernels) form these layers and move across the input picture. Each filter is optimized for identifying a particular class of visual characteristics, such as edges, corners, or textures. The CNN model incorporates three convolutional layers that utilize 3×3 filters. Pooling layers are commonly used after convolutional layers to decrease the spatial dimensions of the feature maps. A frequently employed pooling technique in the field is known as maxpooling. This technique involves down-sampling the feature maps by selecting the maximum value within each pooling region. This study employs three maxpooling layers.

Non-linear activation functions, such as the Rectified Linear Unit (ReLU), are frequently employed after each convolutional and fully connected layer. The Rectified Linear Unit (ReLU) activation function is designed to transform the input values in a neural network. It operates by replacing all negative input values with zero while leaving positive input values unchanged. The utilization of softmax activation is implemented in the ultimate layer to classify four distinct diseases affecting grape leaves. Fully connected layers are commonly located at the terminal stage of a convolutional neural network (CNN) architecture. In the context of multiclass classification, it is common to employ a softmax activation function in the output layer. Transfer learning has emerged as a viable approach to achieving precise classification with a reduced number of training samples. The"VGG16", which consists of 16 learnable parameter layers, each of which possesses associated weights. The robust model accepts a 224×224 pixel image as its input and generates a vector of dimensions 1000, which signifies the probabilities associated with each class. The VGG16 architecture consists of a total of 13 convolutional layers, 3 fully connected layers, and 5 pooling layers, which sum up to 21 layers, but it has only sixteen weight layers. The pooling layers are implemented by employing 2×2 filters with a stride of 2, resulting in a reduction of spatial dimensions.

Osama Elsherbiny et al explored that in the **Image Database**. To overcome the limitations of the plant village database for real-life applications, the disease detection platform (PDD) datasets were created to support the plant. These datasets are accessible at pdd.jinr.ru, accessed on 10 December 2023. The PDD database differs from Plant Village as it encompasses diverse conditions, angles, and backgrounds. This study utilized a dataset of PDD images to discover diseases in grapevines, specifically including real-life images of grape leaves affected by diseases. These images were captured directly from grape-growing regions. The database comprises a total of 295 images, which are separated into five distinct categories of grape leaves. These classes consist of 31 images depicting black rot, 49 with chlorosis, 73 affected by esca, 121 healthy samples, and 22 showing powdery mildew. All images included in the database contain relevant information with a standardized size of 256 × 256 pixels. **Image Pre-processing Techniques.** To ensure effective model training and to minimize any defects that may arise during the imaging process, it is necessary to perform RGB image preprocessing before proceeding with data analysis. The preprocessing phase entails various stages, including segmentation to eliminate any background elements, data augmentation to increase the size of the training dataset, and feature transformation to normalize and standardize the characteristics of the images. First, performing background separation is essential to isolate the grapevine plant and eliminate any extraneous elements from the images. A segmentation process called the threshold technique, which involves converting the image to grayscale and producing a binary image. The image has two possible pixel values: a value equal to 1, representing grapevine pixels, and a value equal to 0, signifying non-grapevine pixels that may be excluded. The image is binary, with each pixel represented by a single bit. Once the grapevine pixels were separated from the background objects, a set of potential color features was obtained for further analysis. In this work, several augmentation techniques were performed to increase confidence in the categorization process. These included using the original image, applying a zoom range of 0.3, rotating the image up to 90 degrees, flipping it horizontally, and shifting its width by a range of 0.1 and its height by a range of 0.2. Normalization is applied to each feature individually. The normalization calculation is derived by dividing the range between the maximum and minimum feature values by the minimum image data value.

Texture Characteristics derived from the Gray Level Co-Occurrence Matrix. The use of the gray-level co-occurrence matrix (GLCM) for detecting and diagnosing plant diseases has been extensively studied in various research works. Yogeshwari and Thailambal employed a GLCM as a feature extraction method in their framework for detecting plant leaf diseases, successfully capturing texture details from the images. The co-occurrence matrix is a statistical technique employed for the analysis of texture in a grayscale image. By examining the grayscale correlation between two pixels in the image space separated by a specific distance. This study involved six different versions of the GLCM, namely, contrast, dissimilarity, homogeneity, angular second moment (ASM), energy, and correlation, as feature extraction techniques. The depth and texture of an image are indicated by its contrast, whereas dissimilarity calculates the separation between pairs of pixels within a specified area. Homogeneity evaluates how close the distribution of elements in the GLCM is, while ASM detects the roughness of the distribution and texture of the image. Energy is a measurement of the uniformity of texture, and correlation determines the degree of correlation present in the local grayscale image. This work utilizes the GLCM methodology to extract texture information from segmented grape leaves. The GLCM algorithm computes texture characteristics for each pixel region that plays a crucial role in subsequent analyses.

Karim et al. (2024)explored **Image Acquisition.** The dataset for this research was obtained from the “Grapevine Disease Dataset (Original)”, which contains four classes with a total of 7222 images for the training part and 1805 images for the test part. Each class contains approximately 1600–1900 training images with 400–450 test images. The images were originally unbalanced RGB images of 256×256 each in size. The dataset for grape disease obtained from Kaggle consisted of a small amount of data, which is not suitable for proper model building. When a model is equipped with a large number of parameters but is given only a limited amount of data, its ability to effectively learn the underlying patterns is compromised, leading to vulnerability to overfitting. **Preprocessing of Image Data:** One of the most important steps in obtaining data ready for CNN model training is data preprocessing. There were duplicate/redundant images in every class, which resulted in increased training time and memory consumption. The images were subjected to a conversion process that transformed them into RGB color mode, thereby guaranteeing a comprehensive representation of colors. Dataset balancing was implemented using image augmentation techniques in which new augmented images were created from each image using width shift, height shift, rotation, flip, and zoom augmentation techniques. This approach contributed to improving the model’s performance in three primary ways: increasing the size of the dataset without requiring the collection of additional data, improving model generalization by exposing the dataset to a diverse range of data variations, and enhancing model robustness to real-world variations such as lighting and orientation. Finally, for each class of the training dataset, 6000 images were obtained after removing duplicate images. A similar method was also applied to increase the size of the test dataset. It was ensured that under no circumstances would the training and test data have similar images.

Ismail Kunduracioglu et al. (2024) investigated the Grapevine Dataset. In this study, a publicly available dataset called the Grapevine dataset is used to more effectively detect the type of grapes from grape leaves. The Grapevine dataset consists of 500 leaf images, with 100 images for each of the five grape types in separate groups (Koklu et al. 2022). In our research, we used this dataset to examine the use of grape leaves for type diagnosis. In Deep Learning architecture, these applications utilize deep learning techniques, which are a branch of machine learning methods used in "deep" network architectures. Deep learning enables the learning of data using computational models and algorithms consisting of one or more layers. It can detect complex structures in large datasets using the backpropagation algorithm. These methods have propelled technologies developed in different fields, such as speech recognition, image recognition, and object detection, to the highest levels.

Deep convolutional networks play a significant role in tasks like image, video, speech, and audio processing, while recurrent networks enable the discovery of sequential data like text and speech (LeCun et al. 2015). Although the concept of deep learning emerged in 2006 (Hinton 2006), it gained widespread popularity, particularly through the ImageNet competition. The ImageNet competition provided a platform for showcasing algorithms for image recognition, where deep learning architectures stood out. Deep learning architectures have achieved remarkable results in the field of object recognition. Additionally, they are used in pattern recognition, detection, classification, and future prediction. Studies have shown that deep learning structures yield significantly better results compared to other known methods (Pacal 2024b).

Convolutional Neural Network. In the field of deep learning, the convolutional neural network (CNN) is a key model that is utilized in many applications. Especially used in image processing and recognition domains, CNN has a specialized structure and operates by employing convolutional, pooling, and fully connected layers on input data. The convolutional layers utilize filters to identify and extract features from the data as output. The pooling layers reduce the output size while scaling the features, and the fully connected layers are used for classification or prediction tasks. **Vision Transformer.** Unlike traditional CNNs, the vision transformer processes input images through a transformer architecture, demonstrating its effectiveness in image recognition and object detection. The transformer architecture was created for natural language processing (NLP) tasks, and ViT is based on it (Pacal and Kılıcarslan 2023). The key component of ViT is the self-attention mechanism, which models the interaction between different parts of the input image and focuses on important features. The input image is divided into patches of a certain size, and these patches interact with each other through attention heads and fully connected layers within transformer blocks. As a result, the output layer produces results for classification or another task. One of the main advantages of a vision transformer is its ability to handle images of different sizes and effectively process data. However, it can be computationally expensive and demand a lot of memory and processing power. There are differences in image dimension processing, computational complexity, transfer learning, and performance compared to CNN architectures. By pretraining with large-scale datasets and using transfer learning, vision transformers can achieve successful results in various computer vision tasks. Additionally, it allows for the processing of large images and can be more efficient in terms of computational cost due to the absence of convolution operations.

The process of detecting and identifying plant diseases generally consists of 4 main stages, as shown in Figure 1.

- **Stage 1: Image Acquisition—Leaf** images are collected using tools like digital cameras, smartphones, or internet-based sources.
- **Stage 2: Image Preprocessing** — The collected images undergo preparation steps such as resizing, normalization, augmenting data, and reducing noise to improve the quality for analysis.
- **Stage 3: Segmentation—This** stage involves isolating the diseased parts of the leaf, allowing the system to accurately pinpoint affected areas rather than simply categorizing the whole image.
- **Stage 4: Feature Extraction—Critical** features from the leaf images are extracted, which helps to increase the precision of disease classification and diagnosis.

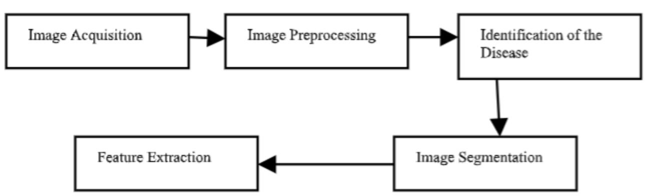

Figure 1: Steps involved in identifying plant diseases using the E-Gen Method

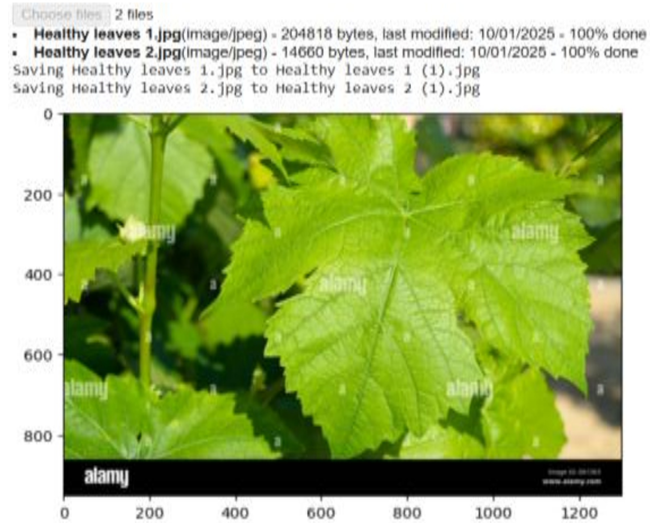

Figure 1: Healthy grape leaves are displayed using pre-processing methods

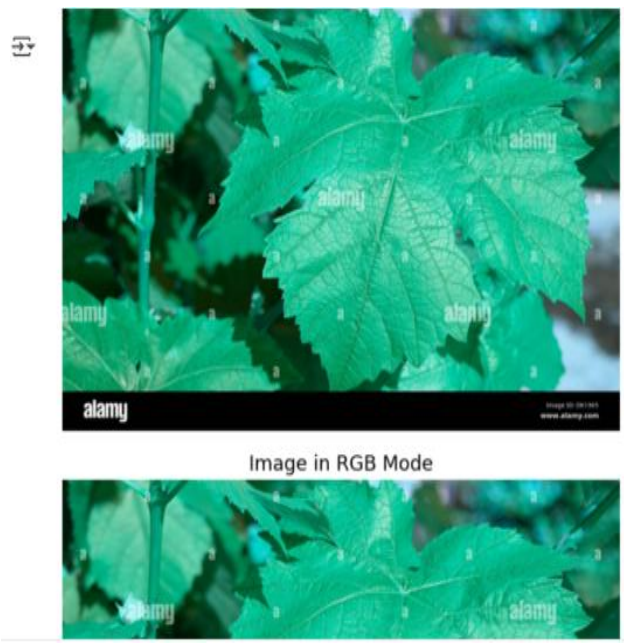

Figure 2: Grape leaf images are shown in BGR and RGB modes

Figure 3: The Original image is converted into RGB Color Channels

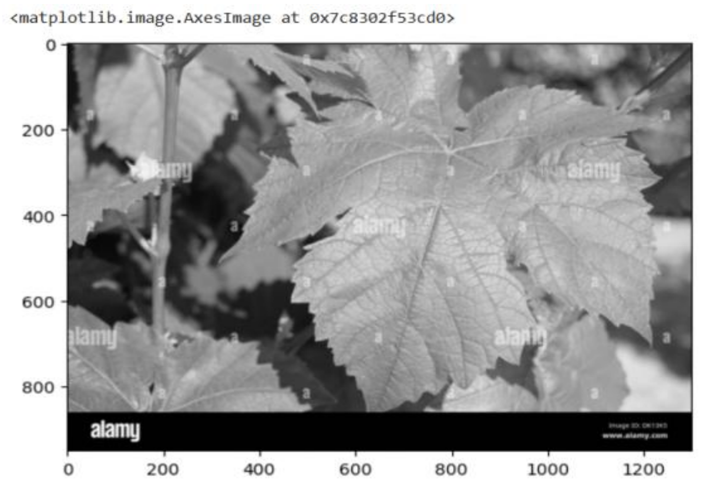

Figure 4: The Original image of grape leaves is converted to grayscale

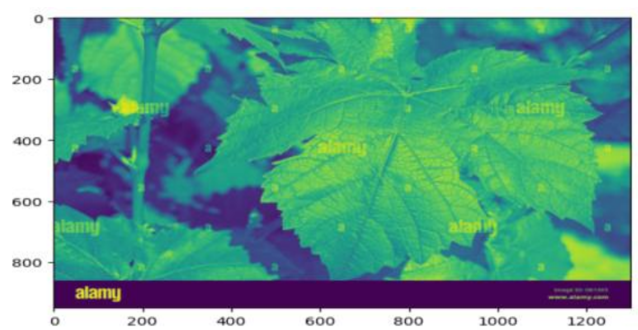

Figure 5: The Original image of grape leaves is converted to a normalized image

III. RESULTS AND DISCUSSION

In this review paper, various methods of image processing will be employed to detect plant diseases using Convolutional Neural Networks, Deep Convolutional Neural Networks, AlexNet, and VGG16, among others. It can easily identify and detect the diseases that can affect the grape leaves. In the stage of pre-processing methods, the original image is processed further and converted into different colors to identify the diseases correctly.

IV. CONCLUSION

This paper provides an overview of various image processing methods used in recent years for detecting plant diseases. Key approaches include CNN, DCNN, VGG16, AlexNet, and Xception. These models enable efficient identification of whether a plant leaf is healthy or infected. Although these systems can effectively diagnose leaf diseases, they still face certain limitations. As a result, there remains significant potential for future improvements and advancements in this area.

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