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A NOVEL APPROACH FOR DETECTION OF GRAPE LEAF DISEASE USING CNN AND ALEXNET

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Abstract

Agriculture plays a key role in India's economic sector. More than 75% of the world's population is dependent on agriculture, with most of its GDP coming from agriculture. Climatic and other environmental changes have become a major threat to agriculture. Grapes are a well-known fruit crop in India and are considered very important from a commercial point of view. However, there is a loss of 10-30% in grapes due to diseases. Grape diseases can cause significant losses to farmers and their grape production if not detected and treated early. Downy mildew, powdery mildew, leaf blight, Esca and black rot are the major grape diseases. Machine learning is a very effective solution to solve this problem. According to our research, convolutional neural network (CNN) is the most popular deep learning algorithm widely used in plant disease detection. In this paper, we did comparative analysis between CNN and AlexNet architecture to detect the diseases in grape plant and compared the accuracy and efficiency between these architectures. We used CNN algorithm and achieved an accuracy of 95.84% and AlexNet is a kind of CNN architecture used and achieved an excellent accuracy of 98.03%. The final result shows that the AlexNet architecture obtained higher accuracy than the CNN algorithm. In this work, an Android application has been designed to detect grape disease. When a farmer captures or uploads a photo of a diseased grape leaf, the mobile app predicts the disease and offers solutions to reduce the risk of the disease.

Keywords:

Image Preprocessing, AlexNet, Convolutional Neural Network, Deep Learning, Tflite

1. INTRODUCTION

. Grapes are one of India's most commercially viable crops used for wine and raisin production. In India, grape productivity is highest and can be further increased. Grapes are a famous fruit crop in India and are considered very important from a commercial point of view as they can be exported to different countries. However, there is a loss of 10-30% in grapes due to diseases. Agriculture is our main source of livelihood. Agriculture is now seriously threatened by changes in the climate and other environmental factors. Due to unpredictable weather changes like uncertain rain, high temperatures or humidity, etc., grape plants are impacted and suffer from different diseases. It is now crucial to conduct relevant research for sustainable agricultural development because of advancements in agricultural technology and the application of artificial intelligence in the diagnosis of plant diseases [12], [14]. The existing modern irrigation system without the help of technology is unable to accurately estimate the actual quantity of water needed for grape farming. This can cause Under Irrigation or over Irrigation. Under Irrigation will affect soil moisture and crops may be destroyed. Excessive irrigation leads to crop diseases. It will affect the production of grapes. Grape diseases affect their quality and make an enormous difference in the production rate, causing significant losses to farmers and adversely affecting the economy and health.

Controlling the spread of disease and maintaining the healthy development of the grape industry depend heavily on the prompt diagnosis and precise identification of grape leaf diseases [15]. Downy mildew, powdery mildew, leaf blight, Esca and black rot are major grape diseases that can cause significant losses to farmers and reduce grape productivity. Grape diseases can be recognized by the shape and color of the affected area. However, some diseases can have similar colors and also the shape of the affected area, making it very difficult to classify different grape diseases. It is very important to identify diseases at an early stage and provide appropriate solutions to prevent these diseases. Many farmers use manual methods to detect diseases, but the results can be inaccurate. The farmer may not always be able to spot the disease early on, causing heavy losses to the farmers. A farmer usually needs experts to detect diseases, which requires a lot of time for large farms. The main task in the field of agriculture is to detect diseases at an early stage. It is essential to identify the diseases early on and provide the right solutions to avoid maximum problems and increase the profit.

According to recent research, the most popular deep learning algorithm for detecting plant diseases is the Convolutional Neural Network (CNN) [7], [8]. There are several uses for digital image processing technologies in a variety of sectors, including industry, agriculture, and medical. The most well-known use of digital image processing in agriculture is the identification of plant diseases. There are many pre-trained CNN architectures that are frequently used in image classification, including VGGNet, AlexNet, ResNet, GoogleNet, etc. One of the deep learning algorithms, the convolutional neural network algorithm (CNN), has been effectively utilized for solving computer vision problems such as image segmentation, image analysis, and image classification [9].

In this paper, we designed a system by using deep learning techniques for the identification and classification of grape leaf diseases. The novelty of the proposed system is to guide farmers to maximize grape productivity. CNN [13] and AlexNet [10], [11] architecture are used to detect diseases in grape plant and Compare these architecture's accuracy and efficiency. The image dataset used in this work was obtained from the Kaggle website, and some images are downloaded from Google via the Internet. The dataset contains 10,216 images. We used the CNN algorithm which is most widely used deep learning algorithm and achieved an accuracy of 95.84% and AlexNet is a kind of CNN architecture used for identifying the diseases and obtained an excellent accuracy of 98.03%. In this work, an Android application for grape disease detection is designed. The mobile application allows farmers to take a photo or upload from the device. When a farmer captures or uploads a photo of a diseased grape leaf, the mobile application predicts the disease and offers solutions to reduce the risk of the disease.

2. LITERATURE REVIEW

This section includes a review of previous studies that have been done to identify plant diseases. Based on the requirements of our project. We studied the following recently published research papers.

Using a convolutional neural network, Hasan, M.A., Riana, D., Swasono, S., Priyatna, A., Pudjiarti, E., and Prahartiwi, L.I. developed a method for identifying grape leaf disease in 2020. In order to boost grape yield, this study aims to make it simpler for farmers to treat grape leaf diseases. The dataset utilized in this study was compiled from Kaggle and comprised three classes for sick grape leaves, including Black rot, Esca, and Leaf Blight, and one class for healthy leaves. Four different types of grape leaves were found in this investigation. Convolutional neural network model executes deep learning with 91.37% accuracy using Keras frameworks. The outcomes showed that accuracy can be increased by both utilizing a lower learning rate and more epochs. Future study is advised to make use of new varieties of grape leaf disease, algorithms, and deep learning structures [1].

In 2022 S. Rangeetha and B. Sruthi reviewed economic losses and significant agricultural damage are caused by plant diseases. The production and quality of the crop is significantly improved by early identification of plant diseases. Incorrect use of pesticides results from misdiagnosis of the illness and its consequences. The suggested work uses the GLCM, MultiSVM, and K-Means Clustering algorithms to detect different diseases that damage grape leaves. To enable the implementation of preventive actions, the impacted area is also computed. The motor attached to the insecticide is automatically activated upon diagnosis of the illness [2].

Using neural networks, Sannakki, S.S., Rajpurohit, V.S., Nargund, V.B., and Kulkarni (2013) constructed a model for the detection and classification of grape leaf disease. The image of a grape leaf with a convoluted background serves as the study's input. Green pixels are hidden using threshold while noise in the image is removed using anisotropic diffusion. Grape leaf disease is divided into various categories using K-means clustering. The segmented images are used to find the sick area. When a Feed Forward Back Propagation neural network was trained for classification, the best results were seen. The research took into account the two kinds of grape leaf diseases, downy mildew and powdery mildew. The use of algorithms based on feature extraction, classification, and image processing techniques. Utilizing the texture of an image to produce distinctive features that represent that image, the feature extraction technique used a color co-occurrence methodology. Future research in this area may examine the applicability of these approaches to samples of both healthy grapes and those with additional illnesses like anthracnose. Other segmentation methods can be employed in place of K-means to extract lesions with greater accuracy [3].

In 2015, Kumar, S., and Kaur, R. reviewed the application of image processing to identify plant diseases. More than 70% of people in our country are dependent on agriculture and related businesses. According to a recent survey, 33.33 percent of the nation's income comes from agriculture and allied sectors. Farmers are losing money on a daily basis due to environmental changes, excessive rain, numerous crop diseases, and a lack of water. We all know that a farmer's revenue is closely correlated with the calibre of his or her harvest. In this investigation, crop diseases and other issues are the main focus of the researchers. Early detection and control of crop diseases can help prevent crop loss and fertilizer waste because they have a detrimental impact on crop quality. In the past, crop diseases might be found using techniques like image processing. For detection and classification in this work, the machine learning method and image processing technologies are both used. Aspects of the image processing method include feature categorization, feature extraction, and other processes [4].

Ji, M., Zhang, L., & Wu. (2020) United Model was used to implement an autonomous system for identifying grapevine leaf diseases based on multiple convolutional neural networks. The primary causes of severe grape decrease are grape diseases. The creation of a system for the automatic detection of illnesses affecting grape leaves is important. We will use deep learning techniques to identify grape diseases because they have lately demonstrated significant effectiveness in a variety of computer vision challenges. This research proposes integrated method-based unified convolutional neural network (CNN) architecture. Black rot, esca, and isariopsis are three prevalent grape diseases that can be distinguished from healthy leaves using the proposed CNN architecture, or United Model. According to experimental findings, the United Model performs well across a range of evaluation parameters. The United Model, which may be used as a decision support tool to assist farmers in identifying grape diseases, obtains an average validation accuracy of 99.17% and test accuracy of 98.57% [5].

R. J. Bharathi used the AlexNet architecture to create a system for detecting diseases in rice plants. In this study, sample photographs were taken using a digital camera, the features were extracted, and the features were then placed in the ImageNet dataset. In this study, researchers used deep learning techniques to create an intelligent system for spotting problems in rice plants. The classification of numerous rice pests, illnesses, and weeds is the major goal of this effort. The dataset used for this study includes 16 kinds of pests, weeds, and illnesses that affect rice. With an accuracy of 96.50%, the created intelligence system can identify and classify rice diseases. The development of a mobile application that enables farmers to use their smart phones to detect infections in rice fields and provides advice on how to lower disease risk is one outgrowth of this research. It is the most recent addition for farmers who use cutting-edge technology [6].

3. MATERIALS AND METHODS

The implementation is broken down into several phases. There are many steps utilised to create a disease detection model that detects diseases in grape leaves are covered in this section. We started by importing the necessary libraries, processed the dataset with image preprocessing and data augmentation, divided it into training and test sets, built the model, and then trained the model to see which one best fits the data and can predict the precise result.

3.1 IMAGE ACQUISITION

The Kaggle website provided the image dataset for this study, while some of the photographs were downloaded from Google's website. We used a variety of data augmentation approaches to boost the dataset's size due to its small nature. There are 10216 images in the collection, divided into 6 classifications. The dataset includes five disease categories: leaf blight, black rot, downy mildew, powdery mildew, and healthy category. The data set was split 80:20 between training and testing. For each class label, there are 2043 photos in the test set and 8172 images in the training set. Each image that is downloaded by default is saved in the JPG file format and uses the RGB colour space.

Table.1. Dataset details

Sl. no.	Class Name	Sample Size
1.	Black Rot	1701
2.	Downy Mildew	1706
3.	Esca	1705
4.	Healthy	1692
5.	Leaf Blight	1702
6.	Powdery Mildew	1710
Total		10,216

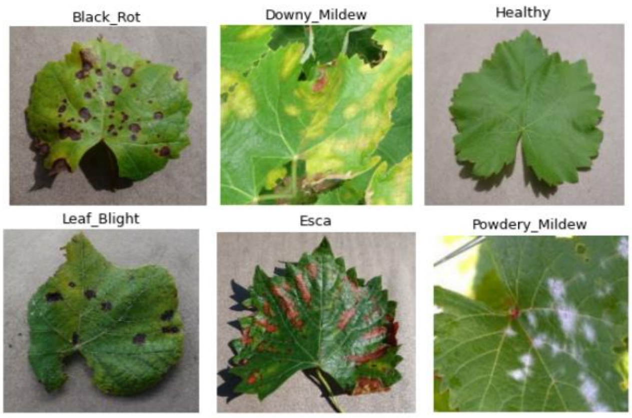

Fig.1. Different Images from Dataset

3.2 IMAGE PREPROCESSING AND DATA AUGMENTATION

To prepare raw data and make it acceptable for creating and training deep learning models, image pre-processing is a vital effort. This enhances the effectiveness and accuracy of the model. It enables you to enhance the quality of your data and derive important insights from it. All of the photos in our dataset have an RGB coefficient that ranges from 0 to 255. So, we changed the images' sizes and scales. The dataset has many formats with various resolutions and quality because some photographs were downloaded from Google and others from Kaggle. Therefore, in order to enhance feature extraction, save training time, and achieve consistency, we resize the images to 256 × 256 for CNN architecture and 227 x 227 for Alexnet architecture. The pre-processing stage resizes all of the photos in accordance with the model's specifications and rescales each image's pixel values to lie between 0 and 1. Numerous image augmentation techniques were utilised to increase the dataset's size because it was so little. Some picture augmentation techniques include rotation, vertical and horizontal image flipping, shearing, and random zooming.

3.3 MODEL BUILDING

In model building phase, we used two deep learning architectures for the purpose of detecting grape leaf diseases: Convolutional Neural Network (CNN) and AlexNet Architecture.

3.3.1 Convolutional Neural Network (CNN):

The convolutional neural network is a well-known deep learning approach that successfully trains many layers. There are nine layers in our CNN architecture, including three convolution layers, three max pooling levels, one dropout layer, and one output layer. The supplied image is scaled down to 256 × 256 x 3. Most calculations are done in the convolutional layer, which is the first layer of the CNN architecture.

The first convolutional layer utilises 32 filters with a kernel size of 3 x 3 and a 256 × 256 input image with a relu activation function as its input. The size of the feature map is then decreased by applying this pooling layer with a filter size of 2 x 2. The second convolutional layer, which employs 64 filters of size 3 x 3, uses the output of the first convolutional layer as its input and employs the relu activation function. The feature map is then reduced by applying a pooling layer with a 2 x 2 filter size a second time. The third convolution layer, which has a kernel size of 3 x 3, 64 filters, a relu activation function, and is fed the output of the second convolution layer. The lower dimension feature map is after that made smaller using a pooling layer with a 2 x 2 filter size. Before transmitting the resulting array to the fully connected layer, the flatten layer will convert the input from the multidimensional array into a single-dimensional array. Two fully connected layers, each containing 64 and 6 neurons, were used. The dropout layer is used to exclude the neurons that were selected at random with 0.2 probabilities in order to avoid the issue of overfitting. The output layer's softmax activation function separates the image into six different categories and delivers the candidate that fits the target class the best. The Fig 2 shows the architecture of convolutional neural network.

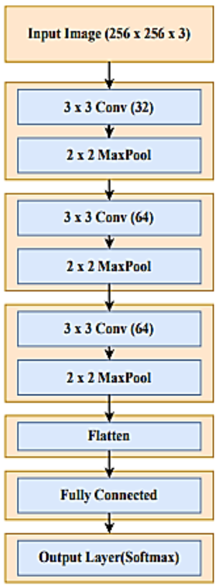

Fig.2. CNN Architecture

3.3.2 AlexNet Architecture:

AlexNet is one of the CNN architectures that is most frequently utilised. The AlexNet architecture was developed by Alex Krishevesky. It features five convolutional layers and three fully connected layers. Each convolutional layer in AlexNet is followed by relu, max pooling, and normalising. By convolving a picture with a collection of filters in a convolution layer, a feature map is produced. Convolutional layers are combined with the ReLU layer to execute non-linear operations and make all negative values equal to zero. The feature map obtained from the previous layer must be reduced by the pooling layer.

The first convolutional layer utilises 96 filters with a kernel size of 11 x 11 and a stride of 4 pixels on an input image with a resolution of 227 × 227 and relu as the activation function. The feature map's dimension is subsequently decreased by the pooling layer using 2 x 2 filters. The second convolutional layer, which employs 256 filters with a stride of 1 pixel and a size of 5 x 5, filters the output of the first convolutional layer. With a 3 x 3 kernel size, the third and fourth convolutional layers employ 384 filters, and the fifth convolutional layer employs 256 filters. There are 1024 neurons, 1024 neurons, and 6 neurons spread across three fully connected layers. These fully linked layers are combined with a dropout layer to reduce the overfitting issue with a probability of 0.5. After classifying the image into six unique categories, the output layer, which makes use of the softmax activation function, gives the result of the target class with the highest probability. The Fig 3 shows the architecture of AlexNet.

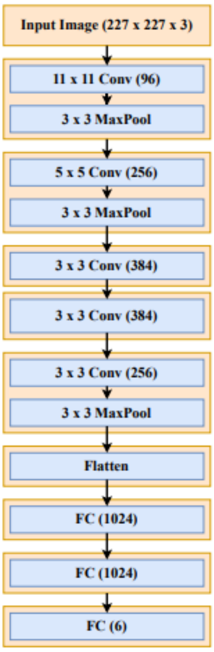

Fig.3. AlexNet Architecture

4. RESULTS AND DISCUSSION

For training and validation, we used 2043 images, while for testing, we used 8172 images. According to Fig. 4 and Fig. 5, the training accuracy of CNN is 95.84%, while that of AlexNet is 98.03%. The model's classification efficiency is evaluated using a confusion matrix (Fig. 6 and Fig.7). True positive, true negative, false positive, and false negative values can be found in the confusion matrix. In the confusion matrix, higher diagonal values represent the model's more accurate predictions. The accuracy, precision, and recall figures from the confusion matrix produced from the CNN and AlexNet architectures are provided in Fig. 6 and Fig.7. When compared to CNN's (95.84 percent) accuracy, the outcome demonstrates that AlexNet architecture achieves the highest accuracy (98.03 percent).

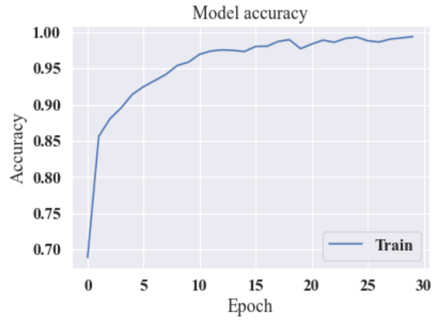

Fig.4. CNN graph

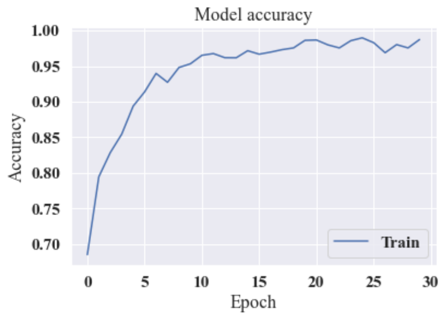

Fig.5. AlexNet graph

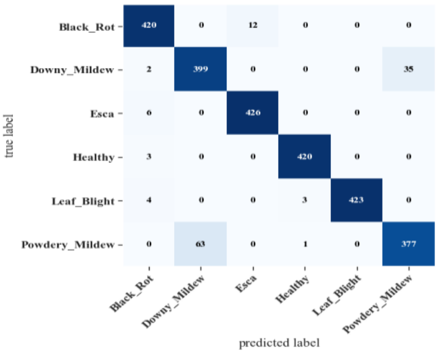

Fig.6. Confusion Matrix of CNN

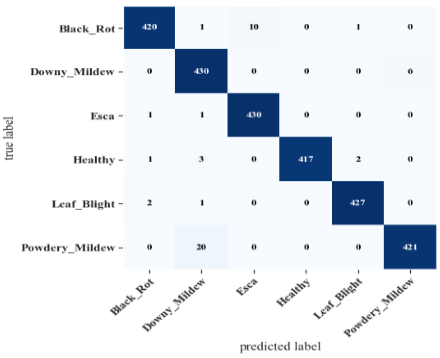

Fig.7. Confusion Matrix of AlexNet

After categorizing and contrasting the deep learning-based work, Fig. 4 and Fig. 5 clearly demonstrate that accuracy may be increased by utilizing AlexNet architecture. When compared to CNN, it has been observed that AlexNet architecture takes longer to train because it has more layers. Both models are able to identify the disease and classify it after training. In our experiment, we found that the model can be executed on the CPU without the need for any additional hardware. This is so because the filter sizes used by the CNN and AlexNet architectures are smaller, and there are fewer training parameters. As a result, the model offers a straightforward and effective solution to the problem of grape disease identification with comparable outcomes.

In this paper, the android application has been designed for the detection of Grape Disease. For importing the deep learning model into the android application, we converted the model into TensorFlow Lite file. The mobile app allows farmers to capture a photo or upload from the device. When farmer captures a picture of diseased grape leaf, mobile application predicts disease and offers solutions to reduce the risk of disease. Fig. 8 shows the system architecture of proposed system.

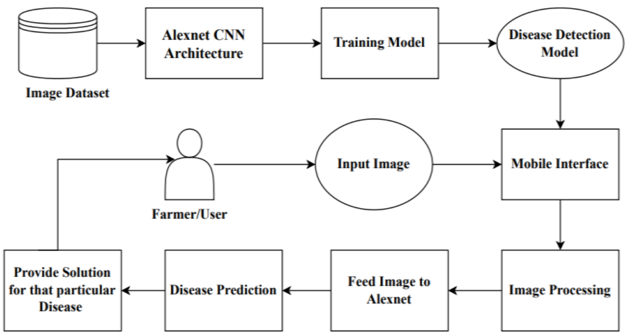

Fig.8. System Architecture

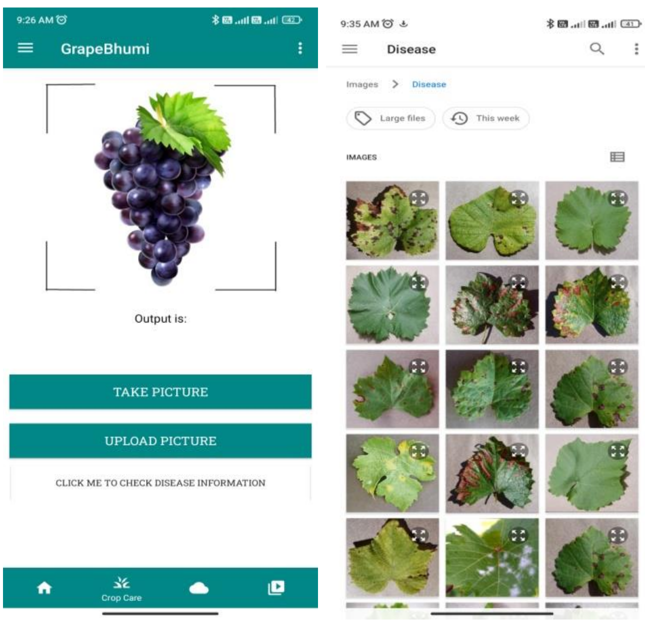

Fig.9. Screenshots Mobile app for Detecting Grape Disease

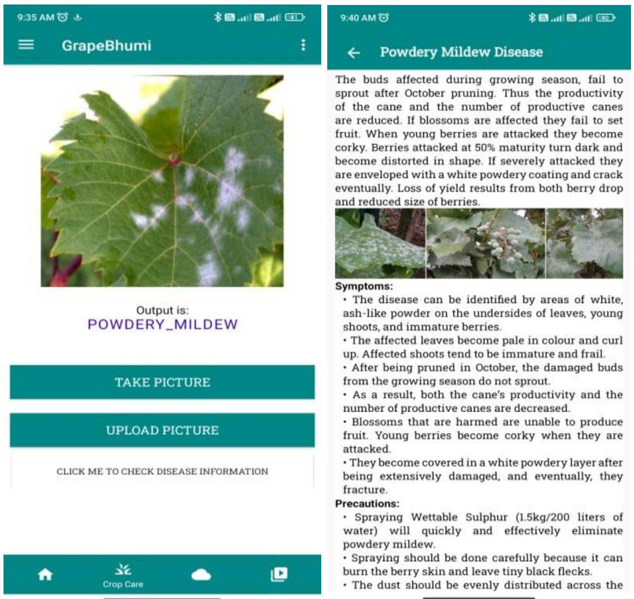

Fig.10. Screenshots Mobile app for Detecting Grape Disease

The Fig.9 and Fig.10 shows some screenshots of mobile application. The proposed system would allow farmers to take pictures of diseased plants or upload existing images from their phones. Once the correct image is taken, the app will preprocesses that image and feed that image to the AlexNet model that detects the disease class and displays a result of the AlexNet model on the mobile app.

5. CONCLUSION

In this paper, a comparative analysis of CNN and AlexNet architecture is performed for grape leaf disease detection. For this research, five main attacking grape diseases are considered: downy mildew, powdery mildew, leaf blight, black rot, Esca and healthy class. As a result, AlexNet design outperforms CNN architecture in terms of accuracy and precision. Compared to CNN architecture, AlexNet architecture requires a longer training period because to the higher number of layers. This work shows that deep learning architectures can distinguish between most important and less important features in images. After 30 epochs of fine-tuning with various hyper parameters, a straightforward CNN model achieved an accuracy of 95.84 percent. Using 30 epochs, AlexNet has achieved an optimized accuracy of 98.03 percent. In conclusion, the paper presents the model's comprehensive analysis and outcomes. Images of both healthy and diseased grape leaves were used in the experiments. It is concluded that the proposed approach successfully classifies and identifies five distinct grape diseases.

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