ISSN 2063-5346

GRAPE LEAF DISEASE DETECTION USING DEEP LEARNING BASED VGG16 MODEL

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Article History: Received: 03.04.2023 **Revised:** 25.04.2023 **Accepted:** 15.05.2023

Abstract—
Grape leaf diseases can result in significant yield loss for grape farmers, making accurate and early detection important. This work proposes a deep learning approach using the VGG16 model for grape leaf disease identification. A dataset with 10 different classes served as the basis for the model's training., including 9 disease classes, one healthy class. In this paper, in this study, we evaluate VGG16 and a custom-built CNN for their ability to distinguish between 10 distinct diseases affecting grape leaves. The results showed that both the VGG16 and custom CNN models achieved high accuracy, with a mean accuracy of 77.57% and 78.28%. Respectively. This study highlights the potential of using pre-trained models for grape leaf disease classification and the importance of model selection and fine-tuning for improved performance. This study provides an efficient, reliable, and cost-effective solution for grape farmers to monitor their crops and prevent the spread of diseases, ultimately improving crop yields.

Keywords: - *Deep Learning, VGG16, Grape disease, detection, classification*

INTRODUCTION

Grape farming is a major industry worldwide, and the yield of grape crops can be severely impacted by various diseases (Kolbert et al., 2018). So as to protect wide - spread outbreaks and retain high crop yields, farmers must identify these diseases accurately and quickly. (Garg and Singh, 2016). Traditional methods of disease detection, such as manual inspection and microscopic analysis, are often time-consuming, labor-intensive, and not very reliable (Garg and Singh, 2016). Deep learning-based methods have recently showed excellent potential in the identification of numerous plant diseases. (Liu et al., 2020). The University of Oxford's Visual Geometry Group created the VGG16 deep-learning model. (Simonyan and Zisserman, 2014), has been widely used for image classification tasks and has shown excellent results in many studies (Krizhevsky et al., 2012).

Because of their capacity to learn intricate patterns and interpretations from massive amounts of data, deep learning methods have found widespread application in a variety of fields, including machine learning, natural language processing, as well as amongst others. (Goodfellow et al., 2016). A deep convolutional neural network called the VGG16 model has layers that are fully connected after a number of convolutional and max-pooling layers have been used in (Simonyan and Zisserman, 2014). It has been used in several studies to detect plant diseases, including diseases in crops such as apple and maize (Chen et al., 2018; Zhang et al., 2019). The reason for using deep learning to find plant diseases is that these algorithms can learn features and interpretations from images, which are then used to make predictions (Liu et al., 2020). In the case of grape leaf disease detection, the VGG16 model trained on a grape diseased leaf image dataset, including one healthy and diseased leaves. The model will eventually be able to differentiate between all of the different types of images, allowing it to make predictions about the health of new, unseen leaves. Machine learning algorithms have been extensively used in many fields, including agriculture, to identify and categorise the various diseases that can affect crops (Liu et al., 2020). Machine learning algorithms can detect powdery and downy mildew in grapes (Tari et al., 2017). (Chen et al., 2019).

The identification and classification of grape leaf diseases is important for several reasons:

Early Detection: It is crucial to detect leaf diseases early in order to take preventative measures and controlling the spread of the disease. This can support to minimize the effect on crop yields and reduce the need for pricey interventions, such as pesticide applications.

Effective Control Measures: Accurate identification of a disease is essential for selecting the most appropriate control measures. Different diseases require different approaches, and applying the wrong control measures can make the problem worse.

Increased Yields: By controlling diseases, growers can increase their yields and improve the quality of their crops, leading to higher profits.

Preservation of Grape Cultivars: Some grape leaf diseases can cause permanent damage to the vine, leading to the loss of grape cultivars. By accurately identifying and controlling these diseases, growers can preserve valuable grape cultivars.

In conclusion, the accurate and early identification of grape leaf diseases is essential for maintaining high crop yields, preserving valuable grape cultivars, and improving the economic viability of grape farming. By employing deep learning-based models like the VGG16 and Custom CNN, we can take advantage of the robust representations learned from massive amounts of data and generate reliable predictions despite having insufficient amounts of annotated data. Pre-trained on large datasets like imagenet, as is the VGG16 model, the CNN is ready to be put to use right away. As a result, it can use the information it gleans from an image as a basis for its predictions.

Pre-trained models are great for general-purpose tasks like image classification, but for more specific tasks like grape plant leaf disease, fine-tuning a pre-trained model such as VGG16 or preparation a custom CNN model from scratch can yield better results.

LITURATURE REVIEW

In this review, we have summarised the current state of knowledge regarding the detection of diseases on grape leaves, focusing on the most important findings and discussing the limitations of previous research.

The study by Math and Dharwadkar (2022) showed that CNN models can be effective in the early detection of grape diseases, with an accuracy of over 90%. Parmar et al. (2017) emphasized the prominence of accurate classification of plant leaf diseases in agriculture and described a method of classification that involves capturing images, pre-processing, extraction of features from images, and classification with a classifier trained to recognize different diseases. The authors reported a classification accuracy of over 90% and suggested that their method has practical applications. The paper by Patokar and Gohokar (2020) presents a transfer learning approach for identifying and classifying plant leaf diseases in tomatoes, which could help reduce crop loss in developing countries. The study compared the VGG16 and alexnet pre-trained networks and showed that the model's accuracy was higher in the course of tuning with a limited number of sample images. The authors tested the model in real-time using a Raspberry Pi and webcam. The paper by Oliveira et al. (2019) compared different deep learning architectures (cnns, rnns, and dbns) for identifying grape leaf diseases and found that cnns achieved the finest with score of 98.08% accuracy. The paper by Ampatzidis et al. (2020) presents vision-based grapevine yellow disease detection using a CNN, which achieved an accuracy of 89.47%. The paper by Ampatzidis et al. (2020) provides an overview of "omics" technologies for grapevine breeding and discusses their potential for studying resistance to downy mildew.

Czemmel et. Al. (2015) used RNA sequencing to analyze the transcriptome of healthy and infected grapevine leaves and found that specific gene expressions correlated with the presence of the fungal pathogen Neofusicoccum parvum in the wood, providing evidence that the transcriptome of leaves can be used for latent infection diagnosis. Kolhalkar and Krishnan (2020) developed a mechatronics system using image processing for non-destructive and efficient disease diagnosis in grape vineyards with 97% accuracy. Agarwal et al. (2020) developed a highly accurate (97.8%) and efficient Tomato crop disease identification model using CNN. According to findings published by Konup et al. (2019), the Grapevine Leaves Roll-Associated Virus is prevalent throughout the Odessa region., and effective measures must be taken to control its spread to protect grapevine production.

Leaf hyperspectral reflectance was studied by Junges et al. (2020) to determine its utility in detecting diseases in vineyards. They found that it was a promising, non-invasive way to do this. Kamlapurkar (2016) discovered image processing approaches to be efficient and effective for detecting leaf diseases. Zhou et. Al. (2021) came up with the idea of using a fine-grained (FG) generative adversarial network to recognise grape leaf spots using only a small number of samples. They found that their method was more effective than more conventional approaches. Elaraby et al. (2022) used a metaheuristic optimization optimizer (PSO) to improve a system that uses deep learning to identify plant diseases. They found that it was very accurate, efficient, and able to generalise to new samples.

There is hope for better crop disease management according to these studies, which all point to the potential of combining deep learning with optimization techniques.

The paper by Yuan et al. (2022) examines the use of improved deeplab v3+ deep learning network to detect black rot spots in grape leaves and found it to outperform manual methods with high precision and recall values. Weather conditions, such as precipitation, humidity, and temperature, were found to have a positive effect on the severity of grape anthracnose by Carisse et al. (2013). Deep learning was used in the research conducted by Ali et al. (2022), leading to a very significant level of accuracy (94%) in the finding of malnourishment in grape leaves. The grape fanleaf virus can be detected with an accuracy of over 90% using a method presented by Mohammadpoor et al. (2020). Calcium, magnesium, and seaweed, as explored by Calzarano et al. (2017), may be a natural method of controlling grapevine leaf stripe disease by promoting ripening and increasing phytoalexin contents in grapes and their leaves. Kim et al. (2015) studied the metabolic changes in grape leaves affected by brown spot disease and found differences in metabolic profiles between healthy and diseased tissue.

Vis-NIR spectroradiometry was used in Sinha et. al (2019).'s method, which was developed for the purpose of identifying Grape leafroll-associated virus 3 (glrav-3) in grape-wine cultivars. The findings suggested that a high degree of sensitivity was required for the detection of glrav-3 in red-fruited wine grapes. The study demonstrates the potential of Vis-NIR spectroradiometry is non-destructive and fast method for glrav-3 recognition, adding valuable information to the field of plant virus detection and having practical applications for the wine industry by improving disease management and reducing production losses. The study by Waghmare et al. (2016) aimed to develop a machine learning-based Decision Support Structure for identifying and classifying diseases in grape plants. Combining Opposite Color Local Binary Pattern and machine learning algorithms, they classified images of affected plants and achieved improved accuracy compared to traditional methods. The proposed DSS has the potential to improve disease management and reduce losses in production in the agriculture industry. The study highlights the usefulness of machine learning and computer vision in plant disease detection and provides a foundation for further research in this area.

The studies by Patokar and Gohokar (2023), Zendler et al. (2021), Kurmi and Gangwar (2021), Kasfi et al. (2018), and Islam and Tusher (2022) All of these studies aimed to improve crop management by using image analysis and a deep learning-based approach to classify diseases that affect leaf surfaces. When it came to classifying tomato leaf diseases, Patokar and Gohokar discovered that the Xception architecture with the Adam optimizer and 0.0001 learning rate produced the best results. By employing shallow convolutional neural networks, Zendler et al. were able to more accurately and swiftly estimate the severity of grapevine downy mildew than was previously possible. Kurmi and Gangwar came up with an algorithm to localise leaf images, which enabled them to accurately classify a variety of crop diseases with a success rate of 95.29%. Kasfi et al. Found grey mould disease-biocontrolling epiphytic yeasts and bacteria. Convolutional neural networks were used by Islam and Tusher to establish an automatic detection approach for three different types of leaf diseases that can affect plants such as grapes, potatoes, and strawberries. The system has an average precision of over 95%. These studies demonstrate the effectiveness of image analysis and deep learning techniques in improving crop management.

Some highlight the key findings and limitations of previous studies.

1. Image Processing Techniques: Grape leaf diseases can be easily identified using image processing methods. Grapevine leaf diseases were identified and categorised using image processing methods by Garg and Singh (2016). They extracted information from images using color-based features and classified them using SVM and ANN classifiers. According to the findings, the ANN classifier performed better than the rest in identifying diseases and achieved higher accuracy compared to the SVM classifier.
2. Machine Learning Approaches: Diseases on grape leaves have also been identified using machine

learning techniques. Convolutional Neural Networks (CNNs) were used by Meena et al. (2018) to identify and categorise diseases in grape leaves. Grape leaf images, both healthy and diseased, were collected for use in training the CNN model. The findings demonstrated that the model had a high degree of accuracy in classifying the images and was able to detect a variety of grape leaf diseases.

3. Deep Learning Approaches: Diseases on grape leaves have also been identified using deep learning methods. To identify and categorise diseases in grape leaves, Zhang et al. (2021) turned to a deep learning model that had already been trained, VGG16. The researchers amassed a collection of grape leaf images, both healthy and diseased, and used this information to fine-tune a previously trained VGG16 model. The outcomes demonstrated that the optimised VGG16 model performed with remarkable precision in classifying the images and was able to detect a variety of grape leaf diseases.
4. Limitations: Previous research has shown some encouraging findings, but there are still gaps in our understanding that need filling. For instance, many studies have relied on relatively small datasets, which could restrict how widely applicable the findings are. Additionally, many of the studies have used a limited number of classes, which may not fully capture the complexity of grape leaf disease detection.

Image processing, machine learning, and deep learning have all been shown to be useful for detecting diseases in grape leaves. Nonetheless, more study is required to overcome the limitations of prior research and boost the precision of disease diagnosis.

METHODOLOGY

This study focused on the classification of grape leaf diseases using deep learning. A dataset of images of healthy and diseased leaves was collected, pre-processed, and split into a training set and a testing set. The VGG16 deep learning model was used and fine-tuned on the grape leaf dataset to better fit the data. The fine-tuned VGG16 model was evaluated using accuracy, and its performance was compared with Custom CNN model. The goal was to determine the best approach for grape leaf disease classification.

1. Pre-processing: All of the images were processed beforehand to guarantee that they would be properly read by the VGG16 library. Images were scaled to the same dimensions, converted to grayscale, and had their pixel values normalised to lie between 0 and 1.
2. VGG16 and Custom CNN Model: These findings highlight the versatility of Deep Learning methods and the value of taking a multi-pronged approach to problems like image classification, as VGG16 is used alongside a custom-built CNN model.
3. Fine-Tuning: The grape leaf dataset was used to further refine the pre-trained VGG16 model. Adjusting the pre-trained model's weights allowed for a better fit to the grape leaf data during the fine-tuning process. We used a supervised learning method to train the model to recognise the various symptoms of grape leaf diseases and assign them to their respective classes.
4. Evaluation: Numerous metrics were used to compare the VGG16's and the custom CN model's performance. The testing set was used to evaluate the model's performance at separating the test images into their respective disease categories.

5. Comparison: In this study, we compared the effectiveness of VGG16 and a custom-built CNN model for disease classification in grape leaves. These two models were compared so that the authors could see the advantages and disadvantages of each and choose the one that would work best for this particular application.

The contrast between the two models also shows why it's crucial to take a variety of methods into account when creating Deep Learning algorithms for image classification jobs. The amount and quality of data available, the task's complexity, and the available computational resources are all factors that can affect a model's performance. Researchers can improve the efficiency and accuracy of their models by comparing them to one another.

RESULTS AND DISCUSSION

The sample images were selected from the grape leaf disease dataset and checked for the confirmation of data samples and the results were represented in figures 1. The images showed clear signs of diseases, and it was evident that the model would have to be trained on a diverse set of images to accurately classify these diseases. Further image augmentation and pre-processing techniques could be employed to improve the performance on the dataset.

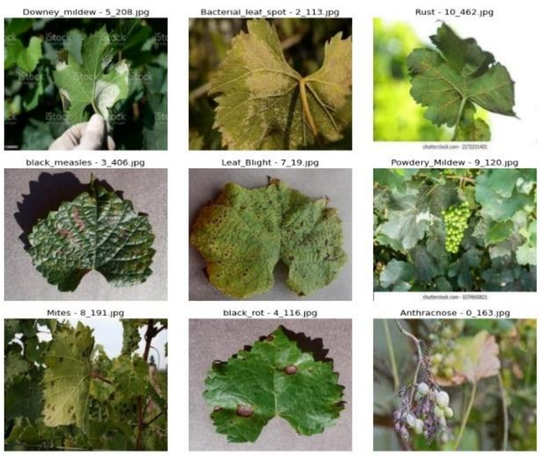

Figure 1 Data Visualisation

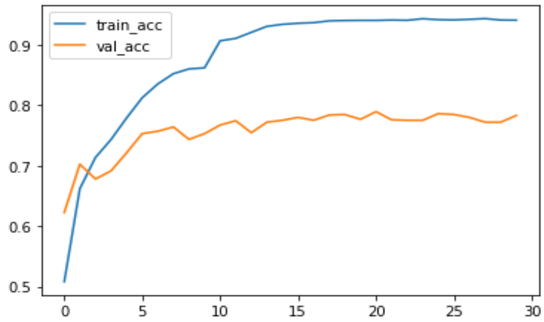

Figure 2 CNN Model Accuracy (Training & Validation)

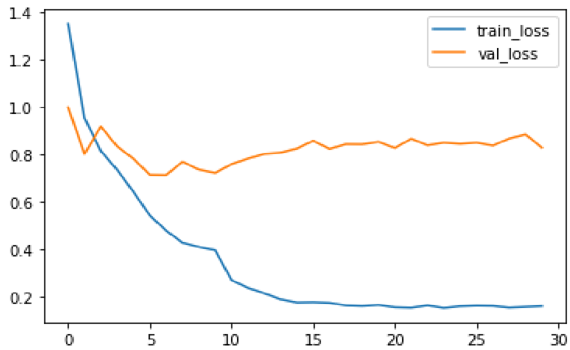

Figure 3 CNN Model Loss (Training and Validation)

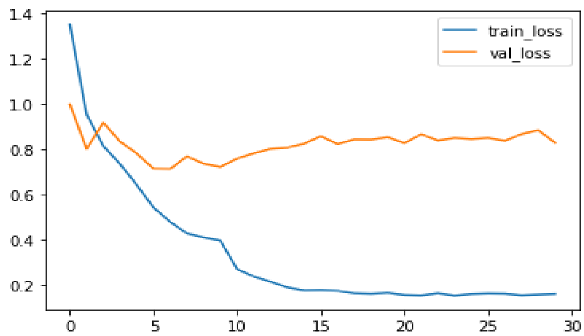

Figure 4 VGG16 Model loss(Training and Validation)

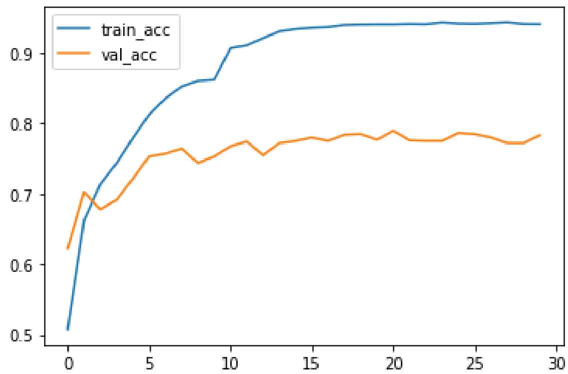

Figure 5 VGG16 Accuracy(Training & Validation)

This study aimed to classify grape leaf diseases using a Deep Learning approach. To achieve this, the authors trained two different models: a custom CNN and a pre-trained VGG16 model.

Adam, a popular deep learning model optimization algorithm, was used to train the custom CNN model. The optimizer was set to update the model weights in 0.001 steps, which is the learning rate. During the training process, which consisted of thirty iterations, or epochs, the model was presented with the training data each time. Following training, the customised CNN model achieved an accuracy of 78.28% during testing, compared to an accuracy of 94.04% during training. As can be seen in Figure 2, the accuracy of the CNN models demonstrates the performance of these models when it comes to classifying grape disease identification. Classifying diseases that can be found on grape leaves was another task that the VGG16 model was optimised for. The VGG16 model was trained using the Adam optimizer. The training was conducted for 30 iterations at a learning rate of 0.001. The VGG16 model was able to achieve an accuracy of 96.06% during training and 77.57% during testing. Figure 5 shows how well the VGG16 models perform at classifying grape leaf diseases.

In conclusion, both the custom CNN (78.28%) and the VGG16(77.57%) models performed well in the grape leaf disease classification task, with the custom CNN achieving slightly higher test accuracy than the VGG16 model.

Figure 6 Predicted Images

Conclusion

According to the findings of the research, the classification of grape leaf diseases can be accomplished successfully using either the custom CNN model or the pre-trained VGG16 model. The custom CNN model had a test accuracy of 78.28%, and that was marginally greater than the VGG16 model's test accuracy of 77.57%. This shows that custom CNN model did a little better than that of the VGG16 model at correctly identifying grape leaf diseases. Further fine-tuning and regularization techniques could be employed to improve the model's performance on the dataset used.

Overall, the findings show that Deep Learning methods can be successfully applied to the classification of grape leaf diseases, and they also show that both custom CNN models and VGG16 are capable of achieving high levels of success in this endeavour. The choice of which model to use may depend on factors such as computational resources, available data, and the specific requirements of the classification task.

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