



RESEARCH ARTICLE

Grapevine leaf species and disease detection using DNN

Finney D. Shadrach*, Harsshini S, Darshini R

Abstract

The cultivation of grapes is one of India's most important produce industries. The grapes comprise 1.2% of the country's total produce production area. This accounts for 2.8% of the nation's total fruit production. Maharashtra produces approximately 80% of India's grapes, followed by Karnataka and Tamil Nadu. However, grape leaf maladies have impeded the growth of the grape industry and resulted in significant economic losses. Disease and pest control experts have, therefore, given considerable thought to identifying and analyzing grapevine leaf maladies. This article examines the image dataset of grapevine foliage. The dataset contains images of grapevine leaves infected with three distinct diseases: black, Esca (Black Measles), and leaf blight (Isariopsis Leaf Spot). This paper examines the efficacy of CNN-based algorithms for grapevine species identification and disease detection. The experimental findings demonstrate that the proposed model can accurately identify grape leaf varieties and their associated diseases.

Keywords: Grapevine, Leaf disease, Species identification, Image classification, Max pooling.

Introduction

It is crucial to contribute to the development of the nation and agricultural sectors. Agriculture is a unique source of prosperity that cultivates producers across the nation. For a powerful nation like India, the expansion of agriculture is inevitable and a market necessity. The world's population is expanding at an exponential rate, posing an imminent threat to vast food production. Information about various types of commodities and a variety of diseases that occur on them, as well as their study at an early stage, play a vital role in the agricultural industry. The incidence of numerous maladies on the farmer's yields is his primary concern. The classification and analysis of maladies are fundamental concerns for the highest-quality agricultural food production. Due to a lack of infrastructure and technology, food safety is a major concern, so crop disease classification and varieties of

crop identification will be crucial in the near future. This is necessary for yield estimation, product safety, and disease control. Detection of crop varieties and their diseases is a crucial area of study because it can be used to monitor a vast field of crops and detect disease symptoms as soon as they appear on plant foliage. Consequently, it is crucial to discover an efficient, inexpensive, and effective method for identifying crop disease instances (Bertsch *et al.*, (2013), FD Shadrach (2022)).

Artificial intelligence (AI) substantially assists agriculture, contributing significantly to a country's gross domestic product (GDP). Climate change, labor shortage, seasonal unpredictability, natural disasters, and numerous maladies on plant leaves are the most pressing issues in agriculture. Agricultural applications of edge intelligence plant leaf recognition and detection research. There are novel advances in various models of deep learning that surmount this difficulty.

The colossal crop loss resulted from the failure to predict disease in its earliest phases, which always leads to a decrease in crop production. Consequently, identifying and evaluating crop diseases is a crucial aspect of crop quality certification (Mondello *et al.*, (2018), FD Shadrach (2021b)).

However, the majority of published works have focused on plant taxon identification, whereas (within-species) species identification has been the subject of only a few studies. In one example of grapevine species identification, 13 features were computed from leaf red, green, and blue (RGB) images (Kamilaris & Prenafeta-Boldú (2018)). Using the above components, the artificial neural network (ANN) efficiently identified grapevine species (ur Rahman *et al.*, 2017).

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Similar research has been conducted with citrus plants (Ziwei Zhang *et al.*, 2020), Shadrach, F.D. & Kandasamy (2021a), (Alabandi, 2017).

Literature Review

In (Karen Simonyan & Andrew Zisserman (2014)) an automatic leaf disease analysis system employing a mechanical research method is described. The proposed system begins by using the grab-cut segmentation procedure to divide a leaf in half. Two distinct techniques are employed in specific regions of the leaf’s surface. In the unfavorable half, texture and color characteristics are extracted and trained using various separators, and the results are compared. (Pin Wang *et al.*, (2021) In this particular piece of research, the system distinguished between the various forms of grape leaf disease by employing convolutional neural network (CNN) fine-tuning, which is one of the transmission learning methodologies. CNN is a form of deep learning model that has several applications, including computer visualization, image classification, localization, and acquisition. These are only a few of its many uses. In this investigation, the experimental findings of the VGG16 adjustment for grapevine leaf disease between totally integrated layers, the SVM separator, and the global average PL (GAP) are compared to the final layer of the Soft Max separation. The system has obtained exceptionally precise results in disease categorization by utilizing optimized VGG16 in conjunction with the GAP layer.

Proposed Methodology

Grapevine Species Identification

This section presents the architectures of two classical CNN models, namely VGG16 and Inception V3.

Due to the fact that Deep Convolutional Networks (DCN) only contain 33 convolutional layers of varied depths, this network is regarded as being relatively easy to understand. If we successfully maximize our pooling use, we will observe a decrease in volume. Figure 1 demonstrates that our network consists of two connected layers, each with 4,096 nodes for a total of 8,192, followed by a SoftMax classifier.

Although 16- and 19-layer deep networks were considered in 2014, the ResNet design has made it possible to train at depths of 50–200 for ImageNet and over 1,000 for CIFAR-10 with reasonable efficiency. These levels of

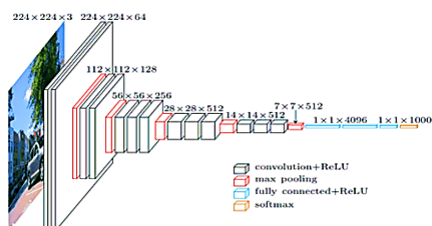


Figure 1: VGG architecture

network depth were thought to be unprecedented in 2014. In the business world, this phase is known as “pre-training.” The combined networks used the smaller ones as starting points for the larger, more comprehensive ones. Pre-training a network to initialize a deeper network is a very time-consuming and challenging process. The whole network needs to undergo this training.

VGGNet has two main disadvantages:

- Training is excruciatingly sluggish.
- The weights of the network design are significant (both in terms of disc space and bandwidth), and these weights include:

VGG exceeds 533MB for VGG16 and 574MB for VGG19 due to the depth of the graph and the amount of fully connected nodes it contains. Because of this, deploying VGG is a difficult and time-consuming endeavor. Figure 2 depicts the micro-architecture (Szegedy *et al.* (2015))

The inception module acts as a “multi-level feature extractor,” doing 11/33 and 55/55 convolution calculations all inside the same module of the network. The information produced by these filters is subsequently stratified in a subsequent network layer according to the channel dimension. GoogLeNet was the name given to this framework when it was originally implemented, but subsequent iterations are now known as Inception vN, where N is Google’s version number.

Rethinking the Inception design for Computer Vision, a following paper by Szegedy *et al.* (2015), serves as inspiration for the Inception V3 design. In order to enhance the precision of ImageNet classification, this paper proposes modifying the inception module. The changes were included into the main branch of Keras. When compared to the other VGG models, the Inception V3’s reduced weight is immediately apparent.

Grapevine Disease Classification with PLs

The CNN use an image as their input, and then use their architecture’s “convolutional layers” to generate feature maps depending on the information in the picture. The feature maps produced in this method solely consist of abstract symbols meant to represent the real-world aspects of the image. Due to the stacking of convolutional layers, the layers closer to the input of a deep model may learn low-level features (such as lines), while the layers further from

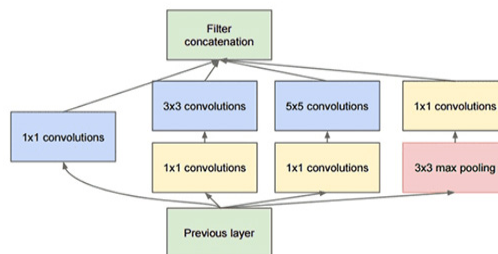


Figure 2: The original Inception module used in GoogleNet

the input may learn higher-order or more abstract features (such as contours and objects). In order to accomplish this task, neural networks are utilized.

The specific location of input features is recorded in the feature maps that are produced by convolutional layers, which is a shortcoming of the method. This suggests that making even minute alterations to the location of the feature inside the input image will result in a feature map that is completely unique. This may occur, for example, if the input image is rotated, moved, or re-cropped in addition to undergoing other relatively small alterations.

One of the most common solutions to this problem is using a downsampling technique in signal processing. The act of creating a signal with a reduced resolution by preserving the larger or more fundamental structural parts while removing the finer features that may not be as relevant for the purpose for which the signal was created is referred to as signal downsampling. Convolutional layers can be used to achieve downsampling by adjusting the step size of the convolution across the image. The utilization of a PL is a method that is more typical and dependable.

Following the processing of the convolutional layer comes the PL, which is the next layer in the algorithm to be processed. After the feature maps created by the convolutional layer have been treated to a nonlinearity, the layers of a model may look like this: input image, Convolutional Layer, Nonlinearity, and PL. This is the case after the nonlinearity has been applied to the feature maps. It is possible to combine the characteristics of several different convolutional layers into a single map by making use of PLs. It is highly unusual for a single CNN model to contain multiple instances of the layer ordering pattern in which a PL is positioned after the layer that is accountable for the convolutional operation.

Each individual feature map will result in the generation of the same number of pooled feature maps. In the same way as, applying a filter on feature maps requires the selection of a filtering operation. For instance, a PL applied to a 66 (36 pixel) feature map will produce a 33 (9 pixel) output pooled feature map.

Observation and Results

The dataset consists of 500 images of grape leaves representing five prevalent grapevine leaf types (100 Ak, 100 Nazli, 100 Dimnit, 100 Buzgulu, and 100 Ala_Idnis). These images comprise only a solitary image of a leaf. All image files were saved with the .jpg extension and a 256-by-256-pixel resolution. All photographs were captured with a uniform background and adequate illumination. Figure 3 depicts a sampling of the dataset. 8 GB of RAM is used for CNN model training. The proposed system was developed as a web application using the Flask framework for Python. Using Jupyter notebook, the CNN model is constructed. HTML and CSS are used to design the web page and make

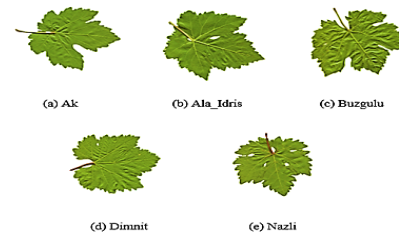


Figure 3: Samples from the dataset representing the five classes

the system compatible for consumers. In order to implement the AlexNet architecture, the Python library 'Keras' is utilised. Other Python libraries such as Numpy, h5py, and sciPy are utilised as well. The resulting feature matrix is saved locally in hdf5 format following model training.

This paper proposes two CNN models that have been pre-trained to detect the unique characteristics of each grape leaf image. The Inception v3 model achieved an ultimate accuracy of 77.99% in its final diagnosis. Using the VGG-16 model resulted in a final diagnosis accuracy of 51.99%, as shown in Figures 4 and 5.

Based on the results presented above, it has been established that the Inception-v3 model provides the most accurate results among these algorithms. The VGG16 and Inception-v3 models utilized twenty epochs. The aggregate result is calculated using 351 images for testing and 3212 images for training.

In model development, an epoch signifies that the model is trained with all of the training data for one cycle. The proposed algorithm has been implemented using 10, 15, and 20 epochs. Figure 6 depicts the comparative accuracy results provided by training and testing data for the Inception V3 model. Clearly, when the epoch is 10, the model performs well with test data. Comparing training data from epochs 15 and 20 reveals that its performance is marginally higher than the test data.

Figure 7 illustrates negligible performance difference between the VGG11 and the inception Vmodelsel. Consequently, it is evident that the proposed model inception V3 outperformed the VGG16 model.

Grapevine Disease Classification

The dataset consists of 2789 images of diseased and 433 images of healthy grape leaves. The images comprised only a solitary image of a leaf. All image files were saved with the .jpg extension and a 256-by-256-pixel resolution. All photographs were captured with a uniform background and adequate illumination. Figure 8 depicts a sampling of the dataset.

The preceding section of this article discussed maximum pooling, also known as max pooling, which was applied on the presented data set. It's a process that takes in a lot of information and spits out whatever part of the map has the most significance.



Figure 4: Performance of Inception V3 Model

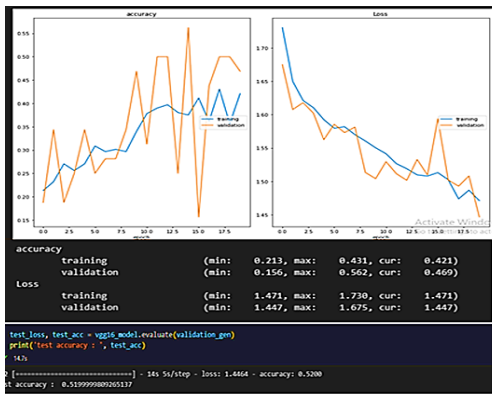


Figure 5: Performance of VGG16 Model

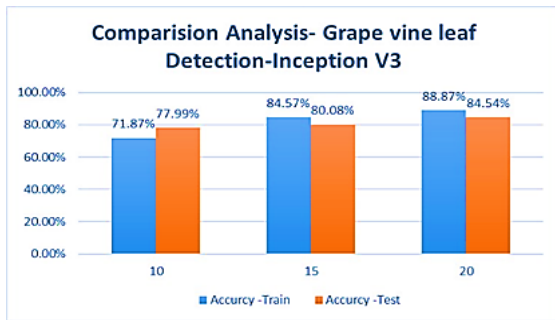


Figure 6: Comparative Analysis according to epoch for Inception V3

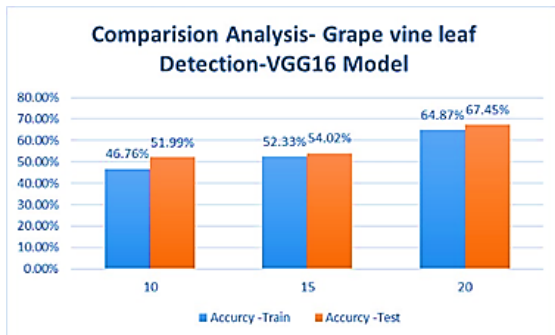


Figure 7: Comparative analysis according to epoch for VGG16

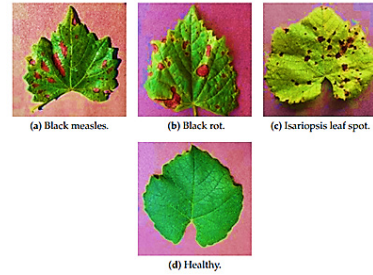


Figure 8: Instances from the dataset representing the four classes

A downsampled version of the feature map is the final outcome, emphasizing the most striking characteristic of the damaged area. This method has been shown to be more effective than the common technique of pooling when dealing with digitalized tasks like image categorization. According to the model description provided in Figure 9, a single feature map of the specified shape will be fed into the PL, while a single feature map of varying dimensions will be generated from the maximum PL. Both of these results follow from the fact that the maximum PL will only generate a single feature map.

Figure 10 depicts the outcomes of building a neural network model with convolution, max pooling, and dense layers. The resultant model has been calibrated with 15% randomized validation data. The model identified the leaf disease in the given dataset with an accuracy of 98.34%, demonstrating exceptionally high performance. The performance of the proposed algorithm for disease classification is significantly enhanced when compared to test data, as shown in Figure 11. The accuracy of the training data is very high, and the model becomes overfit to the training data. Consequently, test performance is inferior to training precision.

```
Model: "sequential"
-----
```

| Layer (type) | Output Shape | Param # |
|--------------------------------|----------------------|---------|
| conv2d (Conv2D) | (None, 256, 256, 32) | 896 |
| conv2d_1 (Conv2D) | (None, 254, 254, 32) | 9248 |
| max_pooling2d (MaxPooling2D) | (None, 31, 31, 32) | 0 |
| conv2d_2 (Conv2D) | (None, 31, 31, 32) | 9248 |
| conv2d_3 (Conv2D) | (None, 29, 29, 32) | 9248 |
| max_pooling2d_1 (MaxPooling2D) | (None, 3, 3, 32) | 0 |
| activation (Activation) | (None, 3, 3, 32) | 0 |
| flatten (Flatten) | (None, 288) | 0 |
| dense (Dense) | (None, 256) | 73984 |
| dense_1 (Dense) | (None, 4) | 1028 |

```
-----
Total params: 103,652
Trainable params: 103,652
Non-trainable params: 0
```

Figure 9: Model summary for disease classification

```
Epoch 1/10
86/86 [-----] - 308s 4s/step - loss: 1.9539 - accuracy: 0.5406 - val_loss: 0.7808 - val_accuracy: 0.6608
Epoch 2/10
86/86 [-----] - 308s 4s/step - loss: 0.4882 - accuracy: 0.7928 - val_loss: 0.3355 - val_accuracy: 0.8734
Epoch 3/10
86/86 [-----] - 312s 4s/step - loss: 0.2366 - accuracy: 0.9295 - val_loss: 0.5419 - val_accuracy: 0.8382
Epoch 4/10
86/86 [-----] - 308s 4s/step - loss: 0.1635 - accuracy: 0.9465 - val_loss: 0.4828 - val_accuracy: 0.8299
Epoch 5/10
86/86 [-----] - 308s 4s/step - loss: 0.1376 - accuracy: 0.9545 - val_loss: 0.2396 - val_accuracy: 0.9176
Epoch 6/10
86/86 [-----] - 315s 4s/step - loss: 0.1217 - accuracy: 0.9696 - val_loss: 0.1253 - val_accuracy: 0.9627
Epoch 7/10
86/86 [-----] - 308s 4s/step - loss: 0.0848 - accuracy: 0.9793 - val_loss: 0.0748 - val_accuracy: 0.9793
Epoch 8/10
86/86 [-----] - 308s 4s/step - loss: 0.1878 - accuracy: 0.9718 - val_loss: 0.8912 - val_accuracy: 0.9689
Epoch 9/10
86/86 [-----] - 308s 4s/step - loss: 0.0548 - accuracy: 0.9885 - val_loss: 0.8758 - val_accuracy: 0.9689
Epoch 10/10
86/86 [-----] - 308s 4s/step - loss: 0.8921 - accuracy: 0.9882 - val_loss: 0.8717 - val_accuracy: 0.9834
```

Figure 10: Model summary for disease classification

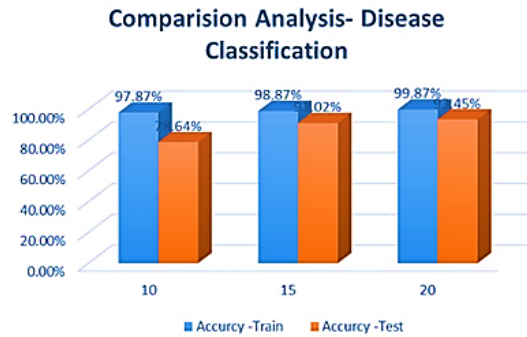


Figure 11: Comparison Analysis for Disease classification

Conclusion

This paper proposes an automatic leaf recognition system that recognizes the leaf type and identifies maladies in grape leaves using different CNN algorithm implementations. The proposed CNN-based identification method for grape leaf and disease detection was implemented using the TensorFlow and Keras frameworks. Based on 2789 images of grape leaf, an enhanced CNN model for the identification of grape leaf maladies is proposed. The maximum pooling convolution was applied to the model instead of the average pooling convolution to prevent overfitting. According to experimental findings, the proposed algorithm achieves a recognition accuracy of 98.34%, which is superior to other well-known transfer learning methods. In terms of species identification, the Inception v3 model achieves an accuracy of 77.99%, while the VGG-16 model achieves an accuracy of 51.9%. Therefore, it has been demonstrated that the Inception v3 functions well for grape leaf identification.

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