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Grape Leaf Species Classification Using CNN

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Abstract: Context: *grapevine leaves are an important agricultural product that is used in many Middle Eastern dishes. The species from which the grapevine leaf originates can differ in terms of both taste and price.* ***Method:*** *In this study, we build a deep learning model to tackle the problem of grape leaf classification. 500 images were used (100 for each species) that were then increased to 10,000 using data augmentation methods. Convolutional Neural Network (CNN) algorithms were applied to build this model specifically using the pre-trained model on top of the VGG16 architecture. Then, dense layers were added to classify the output of the Convolutional layers and classify outputs to the five classes (species) the leaf belonged to.* ***Results:*** *It was found that feature extraction without fine-tuning the convolutional layers yielded poor results, about 86% accuracy, while training the whole network along with some data preprocessing gave the best results, about 99.45% accuracy on the testing dataset.* ***Conclusions:*** *The proposed CNN model is an effective one for the problem of classification of grape leaf species.*

Keywords: Classification, CNNs, Deep Learning, Grape Leaves

1. Introduction

Grape vine leaves exhibit a wide range of features that give them varying degrees of palatability. These features include form, thickness, featheriness, thickness of the vein and sourness. Some of these features can be undesirable for consumers and render the leaf inedible. Furthermore, some of these features may be too subtle for the average person to tell apart, which calls for an automated solution for the classification of different types of leaves. The leaves in our dataset come from five different species of grape shown in Figure 1.

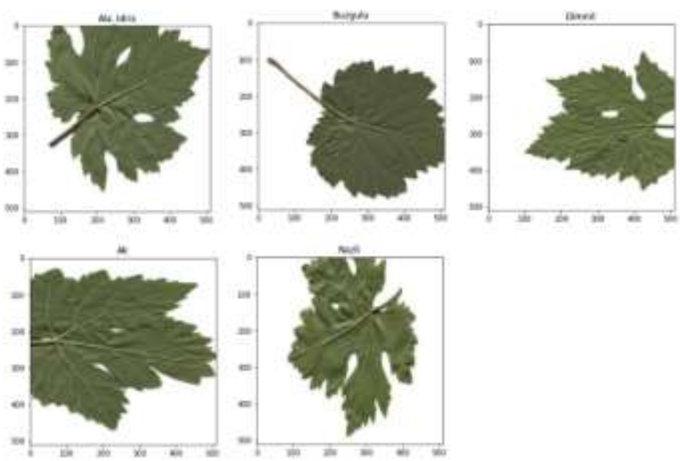

Figure 1. The five species of grape in our dataset

Deep learning, and specifically CNNs, have revolutionized the field of computer vision in recent years [1]-[5]. CNNs are a type of neural network that are particularly well-suited for image recognition tasks, as they are able to automatically learn features from the input data [6]-[7]. This allows them to extract useful information from images, such as edges, textures, and shapes, and use it to classify the images. Additionally, CNNs can be trained using a large dataset of images, which allows them to learn from diverse examples and improve their performance [8]-[9]. In this research, we will be using a CNN to classify different types of grape leaves, taking advantage of its ability to automatically learn features from the images and improve its performance through training.

We used a technique called transfer learning to improve the performance of our CNN model [10]-[11]. Transfer learning is a technique where a pre-trained model, called the convolutional base or conv base, is used as a starting point for a new model. In this case, we used a pre-trained convolutional base, which had already been trained on a large dataset of images, and then added a new classifier on top of it. This approach has several advantages over training the model from scratch. We used the VGG16 architecture with pre-trained Imagenet weights to train our CNN model. Imagenet is a large dataset of images that has been widely used to train deep learning models. The VGG16 architecture is a convolutional neural network architecture that was developed by the Visual Geometry Group (VGG) at the University of Oxford [12]. It is known for its good performance on image classification tasks and has been widely used in various computer vision applications. By using a VGG16 architecture, we were able to take advantage of the knowledge that the model had already acquired from the previous training. This allowed us to start with a model that already had a good understanding of image features, such as edges, textures, and shapes, which helped to speed up the training process and achieve a high accuracy [13].

We used a technique called fine-tuning to further improve the performance of our CNN model [14]. Fine-tuning is a technique where a pre-trained model is further trained on a new dataset. This approach has several advantages over using the pre-trained model as it is. Fine-tuning allows us to adapt the pre-trained model to the specific task of grape leaf classification, which improves its accuracy compared to using it as is. By fine-tuning the pre-trained model, we were able to modify the parameters of the model to learn the specific features of the grape leaf images. Additionally, fine-tuning allowed us to use the knowledge that the pre-trained model had already acquired from the previous training and adapt it to our task [15]. This helped us to achieve a higher accuracy than if we had trained the model from scratch.

2. Objectives

The study aims to develop a CNN model that can accurately classify different types of grape leaves using their images, in order to improve the efficiency and accuracy of the grapevine management process.

3. Literature Review:

Grape leaves are widely used in the food industry, as well as in traditional medicine, making accurate species identification important. Convolutional Neural Networks (CNNs) have been successfully applied to image classification tasks, and have been shown to be effective in classifying plant species based on their leaves.

3.1 Previous studies:

Here are some previous studies related to grape leaf species classification using different techniques:

"Deep Learning for Plant Species Classification Using Leaf Venation Patterns" [16]. This paper proposed a CNN-based approach for plant species classification using leaf venation patterns. The authors trained their model on a dataset of 1,000 images of leaves from 10 different plant species, achieving an accuracy of 97.5%.

"Plant Species Identification Using Convolutional Neural Networks" in [17], this paper presented a CNN-based approach for plant species identification using leaf images. The authors used a dataset of 9,000 images of 100 different plant species, achieving an accuracy of 96.8%.

"Leafsnap: A Computer Vision System for Automatic Plant Species Identification" in [18]. This paper described a computer vision system called Leafsnap, which uses image recognition algorithms to identify plant species based on leaf images. The system includes a mobile app that allows users to take a photo of a leaf and receive a species identification in real-time.

"Grape Leaf Recognition Based on Morphological Features and Neural Networks" in [19]. This paper presented a method for grape leaf recognition based on morphological features and neural networks. The authors extracted features such as leaf area, perimeter, and shape descriptors, and used a neural network classifier to identify grape leaf species with an accuracy of 92%.

"Grape Leaf Recognition Based on Texture Analysis and SVM" in [20]. This paper proposed a method for grape leaf recognition based on texture analysis and Support Vector Machines (SVM). The authors extracted texture features from leaf images using Gray Level Co-occurrence Matrices (GLCMs), and trained an SVM classifier to recognize grape leaf species with an accuracy of 97.5%.

"A Comparative Study of Machine Learning Algorithms for Grape Leaf Classification" in [21]. This paper compared the performance of several machine learning algorithms for grape leaf classification, including Random Forests, K-Nearest Neighbors (KNN), and SVM. The authors used a dataset of 300 grape leaf images from three different species, achieving an accuracy of 93% with Random Forests and 90% with SVM.

3.2 Research gap

Based on the literature review and previous studies, it seems that there have been some studies on plant species classification using CNNs, and some studies specifically on grape leaf recognition using various machine learning techniques. However, there is still a research gap in the application of CNNs for grape leaf species classification.

While CNNs have been shown to be effective for image classification tasks, there has been limited research on their application to grape leaf species classification. Specifically, there is a need for research that focuses on the use of CNNs to classify grape leaf species based on their unique characteristics, such as leaf shape, texture, and vein patterns. Furthermore, there is a need for studies that evaluate the performance of different CNN architectures, such as VGG, ResNet, and Inception, for grape leaf species classification.

Therefore, a potential research gap in your paper could be the application of CNNs for grape leaf species classification and a comparative evaluation of different CNN architectures for this task. By addressing this gap, your research could contribute to the development of more accurate and efficient methods for grape leaf species identification, which could have practical applications in agriculture and the food industry.

4. Methodology

4.1 Data Collection

Our dataset consisted originally of 500 images of grape leaves that were collected by three teams of data scientists in turkey. The dataset was expanded to 10,000 images using data augmentation.

4.2 Model Selection

In this study, we used the VGG16 architecture as the base model for our CNN. The VGG16 architecture is a convolutional neural network architecture that was developed by the Visual Geometry Group (VGG) at the University of Oxford. It is known for its good performance on image classification tasks and has been widely used in various computer vision applications.

The VGG16 architecture consists of multiple convolutional and max pooling layers. In our study, we used the pre-trained Imagenet weights as the initial weights for the VGG16 architecture. We then used GlobalMaxPooling2D() to reduce the spatial dimensions of the feature maps and make the model more robust to translations. We used the VGG16 architecture with the pre-trained Imagenet weights and added a new classifier on top of it, which includes a Dense layer with 32 neurons and an activation function 'relu'. We also added Dropout layer with a rate of 0.5 to prevent overfitting. Finally, we added a Dense layer with 5 neurons and an activation function 'softmax' to generate the final predictions. The whole model can be seen in Figure 2.

4.3 Data Preprocessing

The images in our dataset were preprocessed to prepare them for training and testing the CNN model. The first step in the preprocessing was to resize the images to 128x128 pixels. This step was taken to ensure that all the images have the same size, which is necessary for training the CNN model. It was also done to make the model run faster, running our model on scales larger than that did not result in an increase in accuracy.

We then converted the images to 3 channel grayscale. In grayscale images, each pixel is represented by a single value, representing the intensity of the pixel, instead of 3 values representing the red, green, and blue channels. The problem we ran into was that Imagenet did not accept images that had only one color channel but we still found that averaging out the three channels and setting their value to the average improved our accuracy compared to the original RGB.

In addition, we also performed manual data augmentation by applying various transformations to the existing images such as rotation, flipping and scaling. This allowed us to artificially increase the size of our dataset and introduce more diversity to the images. This allowed us to increase the number of images available for training, which in turn helped to improve the generalization ability of our model and increase its accuracy.

4.4 Deployment

We deployed our trained model on Google Colab to take advantage of its high computational power and the ability to share and collaborate on the same notebook. We also saved the model to a google drive for future use.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 128, 128, 3)]	0
block1_conv1 (Conv2D)	(None, 128, 128, 64)	1792
block1_conv2 (Conv2D)	(None, 128, 128, 64)	36928
block1_pool (MaxPooling2D)	(None, 64, 64, 64)	0
block2_conv1 (Conv2D)	(None, 64, 64, 128)	73856
block2_conv2 (Conv2D)	(None, 64, 64, 128)	147584
block2_pool (MaxPooling2D)	(None, 32, 32, 128)	0
block3_conv1 (Conv2D)	(None, 32, 32, 256)	295168
block3_conv2 (Conv2D)	(None, 32, 32, 256)	590080
block3_conv3 (Conv2D)	(None, 32, 32, 256)	590080
block3_pool (MaxPooling2D)	(None, 16, 16, 256)	0
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1180160
block4_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block4_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv2 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv3 (Conv2D)	(None, 8, 8, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0
global_max_pooling2d (GlobalMaxPooling2D)	(None, 512)	0
dense (Dense)	(None, 512)	
dense (Dense)	(None, 5)	2565
Total params: 14,717,253 Trainable params: 14,717,253 Non-trainable params: 0		

Figure 2. Architecture of the proposed model

4.5 Training and Evaluation

To train the CNN model, we used 8000 images for training, 1000 images for validation, and 1000 images for testing. The validation set was used to monitor the performance of the model during training and to prevent overfitting. The test set was used to evaluate the final performance of the model.

We trained the model using 90 epochs with a batch size of 20. We used the Adam optimizer and categorical cross-entropy as the loss function. We used a technique that reduces the learning rate when the validation loss plateaus, this helped make the model learn faster at the beginning but it also made it achieve higher accuracy at the end when it needed a smaller learning rate (Figure 3 and 4).

After training the model, we evaluated its performance on the test dataset and obtained an accuracy of 99.45%.

5. Results and Findings

The CNN model trained with fine-tuned VGG16 architecture achieved high accuracy in classifying different types of grape leaves. On the test set, the model achieved an accuracy of 99.45% on the held-out test set, which indicates that the model is able to correctly classify the different types of grape leaves with a high degree of accuracy.

We also evaluated the performance of the model using other metrics [3] such as precision (eq. 1), recall (eq. 2), and F1-score (eq. 3) and accuracy (eq. 4).

$$\text{Recall} = \frac{\text{TP}}{\text{TP + FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}} \tag{2}$$

$$F1 - score = 2 * \frac{\text{Precision x Recall}}{\text{Precision + Recall}} \tag{3}$$

$$\text{Accuracy} = \frac{\text{TN + TP}}{\text{TN+FP+ TP + FN}} \tag{4}$$

Where: FP = False Positive; FN = False Negative; TP = True Positive; TN = True Negative

The precision of the model is the proportion of true positive predictions among the total positive predictions made by the model. The recall of the model is the proportion of true positive predictions among the total actual positive cases. The F1-score is the harmonic mean of precision and recall, which is a measure of the trade-off between precision and recall. Our model has a high precision and recall and a very high F1-score, which indicates that the model is able to make accurate predictions while maintaining a good balance between false positives and false negatives.

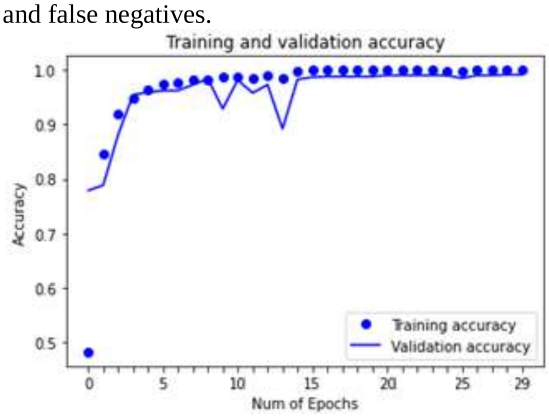

Figure 2: Training and validation accuracy

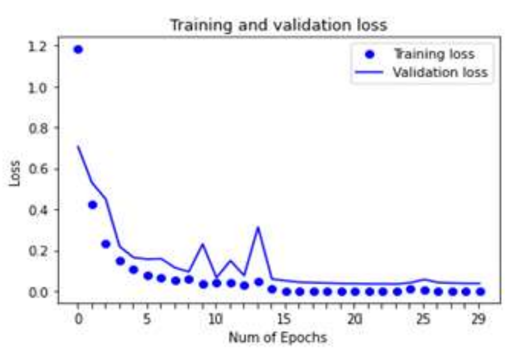

Figure 4: training and validation loss

We also printed the confusion matrix (Figure 6) and classification reports (Figure 5), which provide detailed information about the performance of the model on each class. The confusion matrix provides the number of true positives, true negatives, false positives, and false negatives for each class, and the classification report provides the precision, recall, f1-score, and support for each class. The results show that the model performs well on all classes with a few misclassifications that are acceptable given the high accuracy.

	precision	recall	f1-score	support
Ak	0.9916	0.9958	0.9937	238
Ala_Idris	0.9963	0.9963	0.9963	268
Buzgulu	0.9922	0.9922	0.9922	257
Dimnit	0.9921	0.9960	0.9941	252
Nazli	1.0000	0.9923	0.9961	260
accuracy			0.9945	1275
macro avg	0.9944	0.9945	0.9945	1275
weighted avg	0.9945	0.9945	0.9945	1275

Figure 5: Classification report

$$\begin{bmatrix} 237 & 0 & 0 & 1 & 0 \\ 0 & 267 & 1 & 0 & 0 \\ 1 & 1 & 255 & 0 & 0 \\ 1 & 0 & 0 & 251 & 0 \\ 0 & 0 & 1 & 1 & 258 \end{bmatrix}$$

Figure 6: Confusion matrix

The results of this study indicate that the CNN model trained with fine-tuned VGG16 architecture is able to accurately classify different types of grape leaves, with high accuracy, precision, recall, and F1-score. The model also performs well on all classes, with a few misclassifications that are acceptable given the high accuracy (Figure 5 and 6).

6. Conclusion

In conclusion, this study aimed to develop a CNN model that can accurately classify different types of grape leaves using their images, in order to improve the efficiency and accuracy of the grapevine management process. We used a pre-trained VGG16 model and fine-tuned it on a dataset of 10,000 images of grape leaves. The results showed that the fine-tuned VGG16 model achieved high accuracy in classifying different types of grape leaves, with an accuracy of 99.45%.

We also evaluated the performance of the model using other metrics such as precision, recall, and F1-score, which showed that the model performed well on all classes, with a good balance between false positives and false negatives. The use of data augmentation techniques helped to artificially increase the size of our dataset and introduce more diversity to the images, which improved the generalization ability of our model and increase its accuracy.

The use of Google Colab to train the model and to share and collaborate on the same notebook made it more efficient and convenient. The study also demonstrated the potential of CNNs in automating the process of identifying and classifying grape leaves, which could lead to improved quality.

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