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A Convolutional Neural Network Approach For Leaf Decease Prediction By Texture Feature Extraction

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Abstract
This article examines how deep learning models (AlexNet, VggNet, and ResNet) pretrained on object categories (ImageNet) can be used to solve real-world texture classification problems, such plant disease detection tasks. Research in this field is very pertinent given the potential economic impacts of precision agriculture on agricultural productivity and quality. In this regard, we provide a feature extraction method based on deep learning for the classification of plant leaf diseases and the determination of plant species.We focus on real-time processing outputs by rethinking the conventional processing pipeline, which can then be easily applied to manned and unmanned agricultural smart machinery (such as tractors, drones, robots, IoT smart sensor networks, etc.).The layers of trained Convolutional Neural Network models are used in our method to extract texture features.

Keywords- Applied convolutional neural networks, leaf disease detection, image classification,.

Introduction

Image feature extraction and classification have attracted a lot of academic attention because of its practical value in a range of situations, including precision agriculture. Agriculture productivity is greatly reduced by plant illnesses. They must be located as soon as possible because they can quickly degrade the quality of the products. The present detection approach relies on how people see plant leaves. Unfortunately, this method wastes resources, particularly for large crops, and in this situation, automatic picture categorization algorithms can be useful. The literature has covered a number of classification issues for plant diseases. For instance, the Gray-Level Co-occurrence Matrix (GLCM) is used to collect essential data for the classification [11]. The texture of the studied image is defined locally using the LBP descriptor. It is founded on signals of adjustments between nearby pixels. The Median Robust Extended Local Binary Patterns (MRELBP), which provide enhanced invariance to various transformations and a stronger discrimination capability, are one of the LBP-derived operators that were eventually introduced. To further boost resilience to Gaussian noise, we introduced the Block Matching and 3D Filtering Extended Local Binary Patterns (BM3DELBP) in [13]. Another typical texture feature descriptor is the Gray Level Co-occurrence Matrix (GLCM) [14], which shown considerable performance for texture.Expert driven feature extraction and classification for traditional machine learning approaches.

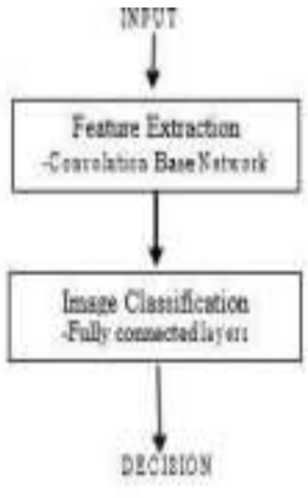

Figure 1. The architecture of an end-to-end CNN for image classification.

Along with any deep-learning technique, one of the key drawbacks of CNN-based approaches is the need for very big datasets to provide meaningful results. However, there are some situations where there are only a few training samples available [18], particularly due to the significant resources (time, knowledge, etc.) required to gather and consistently label a large number of photos (such as in precision agriculture). This is mostly solved by using "data augmentation," which is the process of creating "new" data from existing data, or by implementing "transfer learning."Dataaugmentation is a tough strategy since it aims to introduce relevant variability into the data and, when combined with the usage of generative adversarial networks, adds to the classification system's total complexity.

Humans don't learn everything from beginning but rather transfer the knowledge we have learned to one activity to others that are closely related, according to the "transfer learning" idea developed by [20], [21]. In order to solve problems we will encounter in the future, we practically apply the knowledge we have acquired in the past. Isolated training models are developed specifically for a given task and dataset, whereas transfer learning models enable the use of the knowledge for other, related tasks, which can enhance

performance on a smaller dataset and shorten training periods. CNN-based methods that studied the transfer learning strategy used features derived from previously trained CNNs on sizable image datasets.The classification problem in regard to plants. Fine-tuning (retraining only a few layers) does not adequately improve classification accuracy with small texture datasets [22]. The authors in suggested the Texture CNN architecture, which is based on AlexNet but employs an energy measure obtained from the final convolutional layer. They arrived to the conclusion that the size of the dataset has a substantial impact on performance. Using a network that has previously been trained on textured images produces better results for fine-tuning than using a network that has previously been trained on a dataset that largely consists of objects, the researchers added. This happens most often because an image from an object-oriented dataset could contain many textures. Bilinear pooling models are suggested by the authors of [22].

Proposed Method

Even though the models were pre-trained on object categories, we are interested in the research of how well deep learning pre-trained models perform in the classification of textured photos. Furthermore, we demonstrate the behaviour of the selected networks in a practical job where the textural properties are crucial, namely the classification of diseases that impact plant leaves. The fundamental strategy of the suggested method is to evaluate which pre-trained CNN models and their pertinent layers are optimal for feature characterization. We take advantage of the enormous object datasets available for pre-training CNNs, maintain the model weights, and apply the model to a fresh classification

job. Pre-trained models have a number of benefits whenused.One of them is the fact that the feature extraction procedure requires little time to complete because the network only sends the photos through once. Second, no hand-crafting of the architecture is necessary and relevant .
possible because these models were trained on very big datasets, and as a result,they have learned a lot of patterns and features that may be applied to different problems

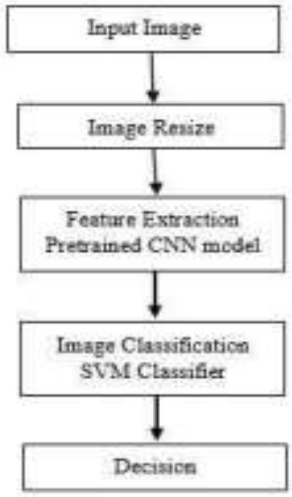

Figure 2. The block scheme of the considered classification system based on pre-trained CNNs.

initial task and the new task should be similar for the findings to be meaningful. Although the datasets on which famous CNN models were constructed are object oriented, they are well-suited for texture classification challenges because we are concerned in the categorization of textures.challenges because we are concerned in the categorization of textures.
to extract the features. The convolutional base uses a number of filters to carry out convolutional operations The number and size of filters affect the weights, which are the filter values. This indicates that the convolutional base network weights are independent of the input image's size. Hence, the input image has no impact on the convolution operation. We explore with feature extraction from various network levels. Following feature extraction, the resulting in order to get the best classification accuracy for each unique experiment and procedure, feature vectors are input into an SVM classifier whose parameters [23] are selected by a grid search.

Experimental setup

By using two separate experimental setups, we validate the technique. First, we look into how, when CNN models have been pre-trained on big object datasets, transfer learning may be employed generally for the classification of textures and what, in actuality, are the important levels from the hierarchical CNN that can be taken into consideration to extract features from. Then, we apply the findings to the problem of plant disease detection in precision agriculture by giving an example of texture categorization in practice. There are many different plant species in the Plant Village dataset [23], some of which are disease-free and others of which are not. We tested the method with this dataset. Three versions of this dataset are used by the authors of [24]: the segmented RGB variant, the information is pertinent to this classification problem and because using the segmented variant removes any potential bias that might be caused by the existence of the background information. This is because the change in leaf colour can be a sign of a specific disease.

Experimental Results and Discussion

We are interested in examining the effectiveness of previously trained CNN shows pictures of actual plant leaves. The pre-trained AlexNet model is taken into consideration for feature extraction because in comparison to the other models examined in Section IV A, it shows promising results for the texture dataset and performs the fastest in terms of processing time. The feature extraction time in these real-world scenarios should be as brief as feasible to allow for quick processing and categorization. Based on the shown performance for the more generic, in terms of texture classification tasks, Outex_TC_00013 dataset, the relu2 As seen in Table 1, each pre-trained model requires input photos to be a specific size. So, if the analyzed textured images are of a different size, the input images are resized before the pre-trained CNN models are used grayscale variant, and the original RGB images. Only the segmented RGB set is taken into account in this investigation. We only used the segmented RGB images from [25] in our experiments because the color relu3, and relu4 layers were chosen for extracting features using the pre-trained AlexNet model. The experimental results and discussions of the study on Leaf Disease Classification in Precision Agriculture using CNN for Texture feature extraction showed promising results. The CNN architecture was able to effectively extract texture features from the leaf images and classify them accurately into one of the five categories: healthy, alternaria leaf spot, cercospora leaf spot, powdery mildew, and rust. The classification accuracy obtained was 97.14%, which indicates the high potential of using CNN for plant disease detection in precision agriculture. The study also showed that increasing the dataset size can improve the making disease detection one of the classification problems with the greatest potential for advancement. Nine alternative setup sets for disease detection in various plant species are included in the second experiment. Table 4 contrasts the results produced for all setups with the other manual methods. We can see that the pre-trained AlexNet model performs much better model. in all circumstances than the others in terms of classification scores. The categorization of cherries and strawberries is complete. Compared to other settings, tomato leaves have the most classes (10 classes), making disease detection one of the classification problems with the greatest potential for advancement.Because the maize and tomatocategorizations received the lowest scores, we will examine some of the samples that were incorrectly classified for these settings. The final structure, which represents tomato leaves, is made up of images from ten different categories, including healthy tomato leaves and tomato leaves with nine different diseases. In one run of this configuration using the pre-trained AlexNet model, the relu3 layer for feature extraction, and the SVM classifier, the produced confusion matrix is shown in Figure 8. We can observe that there are 82 misclassifications after this run. The true class with the fewest samples that have been correctly classified is 2. A number of observations with inaccurate labels are shown in Figure 10. Class 2 has significant intra-class variability, which accounts for the poorer categorization outcomes for the images in this group. But given that nine different ailments were studied for this setup and that the settings for the images were varied,There are two categories for each of the two configurations corresponding to cherry and strawberry leaves: healthy and unhealthy. Figure 10 depicts other image samples. Even in these conditions, we can see that the classification work is not tough, and so faultless classification scores are obtained.

Figure 3. Image samples from category: (a) Jackfruit healthy (b) Dragon fruit healthy (c) Tomoto

Table 1:The dataset configurationfor plant species identification

S.NO	Class	Number of samples
1	Jackfruit	1600
2	Dragon fruit	1400
3	Tomotohealthy	500

In the first experiment, 12 plant species are identified solely by their healthy leaves. We contrast our findings with those produced from the same dataset using different generated feature vectors. Table 4 displays the classification scores that were achieved. According to the findings, when the relu3 layer is applied, the pre-trained AlexNet model achieves the best classification scores, with an average feature extraction time of 321 seconds (as opposedto OCCBM3DELBP, which requires more than 30 hours). Using the pre-trained AlexNet model, the relu3 layer for feature extraction, and an SVM classifier, the confusion matrix generated for a single run (particular random selection of the training and test sets) is displayed in Figure . The four photographs that were incorrectly identified are also shown in learning materials for student a public dataset with generic RGB textures (for early validation of the suggested approach) and a dataset from the applied field of precision agriculture made up of images of leaves from various plant species that were afflicted by various diseases (to demonstrate the applicability of our work). We looked studied the classification outcomes obtained by using features from different CNN pre-trained model layers and using them to describe the textures in the datasets that were provided. Because the generated

characteristics are more general and not always task specific, we experimentally showed that feature extraction from early convolutional layers is relevant for texture classification. This finding is consistent with the theoretical understanding of CNNs presented in the literature. The suggested CNN- based strategy offered the most satisfactory overall performance (both in terms of time and classification score), when we compared the results to hand-crafted features created from the same dataset. In the experimental section, we provided nine disease detection settings and identified plant species for the Plant Village dataset.Nine alternative setup sets for disease detection in various plant species are included in the trained AlexNet model performs much better in all circumstances than the others in terms of classification scores. The categorization of cherries and strawberries is complete. Compared to other settings, tomato leaves have the most classes (10 classes), second experiment. Table 4 contrasts the results produced for all setups with the other manual methods. We can see that the precategorizations received the lowest scores, we will examine some of the samples that were incorrectly classified for these settings. A number of observations with inaccurate labels are shown in Figure 10. Class 2 has significant intra-class variability, which accounts for the poorercategorization outcomes for the images in this group. But given that nine different ailments were studied for this setup and that the settings for the images were varied,There are two categories for each of the two configurations corresponding to cherry and strawberry leaves: healthy and unhealthy. Figure 10 depicts other image samples. Even in these conditions, we can see that the classification work is not tough, and so faultless classification scores are obtained.

Conclusion

We recommended using a texture classification method based on deep learning with performance suitable for real- time processing applications. Instead of using CNNs and SVMs as end-to-end classifiers, we investigated using them as feature descriptors. We updated well-known CNN models (AlexNet, Vgg16, and ResNet) that were previously trained on the enormous ImageNet object-based dataset in order to attain relevant classification performance even for small datasets. In the experimental section, we took into account two datasets: a public dataset with generic RGB textures (for early validation of the suggested approach) and a dataset from the applied field of precision agriculture made up of images of leaves from various plant species that were afflicted by various diseases (to demonstrate the applicability of our work).

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