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Leaf Disease Detection using Deep Learning

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ABSTRACT

Plant diseases pose a significant threat to food security, but rapid detection remains difficult in many parts of the world due to a lack of infrastructure. The combination of rising technology penetration worldwide and recent advances in computer vision enabled by deep learning has paved the way for camera-assisted disease diagnosis. We train a deep CNN convolutional neural network to identify 14 crop species and 26 diseases using a public dataset of 50,000 images of diseased and healthy plant leaves collected under controlled conditions (or absence thereof). On a held-out test set, the trained model achieves a good accuracy, demonstrating the feasibility of this approach. The objective of this project is to create a new plant disease recognition model based on leaf image classification using CNN. The novel training method and methodology employed rapid and simple system implementation in practice. The model we are developing will be able to distinguish various types of plant diseases from leaves, as well as types of plant leaves from our surroundings.

KEYWORDS: *CNN*

1. INTRODUCTION

A variety of strategies have been developed to prevent crop loss due to disease. Disease diagnosis based on automatic image recognition is now possible due to the widespread use of high-definition cameras, deep learning models and high-performance computers. In this project, we will show the technical feasibility of a deep learning approach using images of crop species with diseases (or healthy) that are freely available through the Plant Village data set. The use of computer vision *CV* and machine learning (ML) could improve disease detection and treatment. Computer vision is a type of artificial intelligence *AI* in which computers is used to understand and identify objects. It is primarily used in driver testing, parking, and driving self-driving vehicles, and is now being used in medical processes to detect and analyze objects. Computer vision improves the accuracy of disease protection in plants, making food security a breeze. In this changing environment, disease identification and prevention, including early detection, has never been more important. Plant pathologies can be detected in a variety of ways. Some diseases have no visible symptoms, or the effect becomes apparent too late to act, in which case a sophisticated analysis is required. However, because most diseases manifest in the visible spectrum, a trained professional's naked eye examination is the most important.

2. Dataset Collection

A. Understanding the Data

For this topic, there are various dataset available, such as PlantVillage Dataset, Cassava Leaf Dataset, Plant Pathology 2020, and so on. But, for the purpose of our paper we have used PlantVillage Dataset. The PlantVillage dataset contains 54,303 healthy and unhealthy leaf images classified into 38 species and disease categories. Additionally, training a model with a huge number of photos may be impossible on a device that is not a high-end PC or laptop as we have around 50k images.

B. Dataset description

The diseases described in the PlantVillage datasets are bacterial spot, early blight, late blight, leaf mold, septoria leaf spot, target spot, yellow leaf curl virus, mosaic virus, two spotted spider mites etc. which were taken from the leaves samples of pepper, potato, tomato, etc.

3. Work Related To Leaf Disease Detection

Fungi typically cause plant diseases, and they typically attack the leaves. Many others are caused by viral and bacterial pathogens. With the increased use of ML and its related features, agricultural precision has improved. Agriculture's reduced production quantity harms many people and animals, and its solution requires modern technology. Because of its high accuracy and reduced complications and data duplication, image-based detection systems make disease extraction and detection easier. In some plants, such as tomatoes, using images to determine the diseases that affect them and the extent of the damage is impossible unless the accuracy rate is high. According to the plant disease survey, many different factors influence how technology-based image detection is used. In other words, diseases that cause visible dents and changes on the plants can be detected using this technology, as opposed to diseases that cause damage that cannot be detected through images of the plants.

According to the findings of this study, plant diseases are typically detected when they begin to affect the physical appearance of the plants. Further research [1] by reveals an insufficient database that could be used to provide context for comparing the images taken. Another challenge is that the symptoms and characteristics of the diseases vary and may be similar to some extent [2]. Many diseases, for example, can cause leaf wilting. The problem has yet to be solved because experts are constantly uploading new images.

4. Motivation

Plant diseases not only threaten global food security, but they can also be disastrous for smallholder farmers whose livelihoods rely on healthy crops. Over the last decade, integrated pest management (IPM) approaches have increasingly supplemented traditional pesticide application methods. As a result, the primary motivation for this project was to develop an efficient deep learning model capable of detecting specific plant leaf features, such as plant type and disease, via structure anomaly. Plants' importance in the world has grown over time. Plant discoveries about critical roles in medicine, energy production, and recent concerns about reducing global warming have long been a significant part of science and technology [2]. A reduction in global plant cover increases the risk of increased global warming and the associated challenges. The need to develop a cutting-edge convolutional system that supports image detection technology and plant disease classification has resulted in numerous research programmes to provide scientists with the necessary knowledge [3]. When necessary, image detection could be used to distinguish between healthy and unhealthy leaves. Convolutional neural networks (CNNs) provide differences between plant images that aid in determining abnormalities that may exist in plants in their natural environment. According to the background research, scanning images of healthy and unhealthy plants serves as a basis for comparison by scientists in this field.

5. DISCUSSION

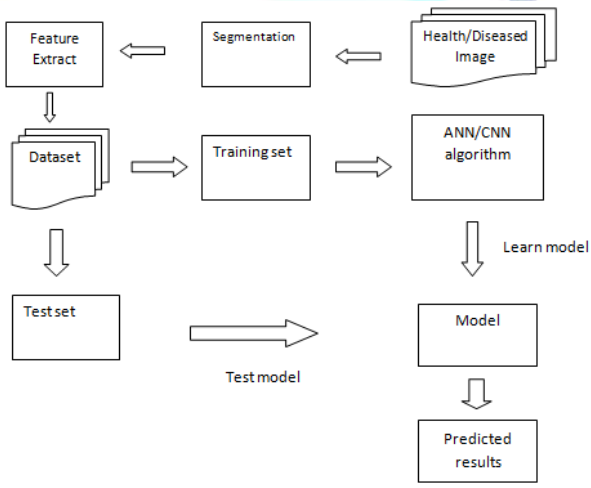
The performance of convolutional neural networks in object recognition and image classification has improved dramatically in recent years. Previously, hand-engineered features such as SIFT (Lowe, 2004), HoG (Dalal and Triggs, 2005), SURF (Bay et al., 2008), and others were used for image classification tasks, followed by some type of learning algorithm in these feature spaces. Feature engineering is a time-consuming and complex process that must be repeated whenever the problem or the associated dataset changes significantly. This problem arises in all traditional computer vision attempts to detect plant diseases because they rely heavily on hand-engineered features, image enhancement techniques, and a slew of other complex and time-consuming methodologies.

However, there are several limitations that must be addressed in future work at this time. First, when tested on images taken in conditions other than those used for training, the model's accuracy drops dramatically, to just above. It should be noted that this accuracy is much higher than the one based on random class selection, but improving the accuracy requires a more diverse set of training data. Our current findings indicate that simply collecting more (and more variable) data will be sufficient to significantly improve accuracy, and data collection efforts are currently underway.

6. ARCHITECTURE

The AlexNet architecture follows the same design pattern as the 1990s LeNet-5 architecture (LeCun et al., 1989). Typical LeNet-5 architecture variants consist of stacked convolution layers followed by one or more fully connected layers. The convolution layers may optionally be followed by a normalisation layer and a pooling layer, and all layers in the network are usually associated with ReLu non-linear activation units. AlexNet is made up of five convolution layers, three fully connected layers, and a softMax layer. The first two convolution layers (conv1, 2) are followed by a normalisation and a pooling layer, respectively, and the final convolution layer (conv5) is followed by a single pooling layer. In our adapted version of AlexNet, the final fully connected layer (fc8) has 38 outputs (equaling the total number of classes in our dataset), which feeds the softMax layer. Finally, the softMax layer exponentially normalises the input from (fc8), resulting in a distribution of values across the 38 classes that add up to 1. These values represent the network's confidence that a given input image is represented by the corresponding classes. All of AlexNet's first seven layers are associated with a ReLu non-linearity activation unit, and the first two fully connected layers (fc6, 7) are associated with a dropout layer with a dropout ratio of 0.5.

The GoogleNet architecture, on the other hand, is much deeper and wider, with 22 layers, but with a much lower number of parameters (5 million parameters) in the network than AlexNet (60 million parameters). A key feature of the GoogleNet architecture is the use of the "network in network" architecture (Lin et al., 2013) in the form of inception modules. The inception module uses parallel 1 1, 3 3, and 5 5 convolutions, as well as a max-pooling layer, to capture a variety of features in parallel. In terms of implementation practicality, the amount of associated computation must be kept in check, which is why 1 1 convolutions are added before the previously mentioned 3 3, 5 5 convolutions (and also after the max-pooling layer) for dimensionality reduction. Finally, a filter concatenation layer simply concatenates all of these parallel layers' outputs. While this constitutes a single inception module, the version of the GoogLeNet architecture that we use in our experiments employs a total of nine inception modules. For reference, a more detailed overview of this architecture can be found in (Szegedy et al., 2015).



7. GOAL

Plant disease symptoms are visible in various parts of a plant, such as leaves, stems, and roots. Plants Pathology detection by hand is time-consuming to use leaf images. As a result, new computational methods must be

developed which will automate the detection and classification of diseases using leaf images by applying Deep Learning techniques.

The scope of the paper is Application in Precision Agriculture, Modern Farming and A boon for botanists (plant life researcher).

8. Approach

We assess the suitability of deep convolutional neural networks for the aforementioned classification problem. We focus on two popular architectures, AlexNet (Krizhevsky et al., 2012) and GoogLeNet (Szegedy et al., 2015), which were designed for the ImageNet dataset as part of the "Large Scale Visual Recognition Challenge" (ILSVRC) (Russakovsky et al., 2015). (Deng et al., 2009).

We compare the performance of these architectures on the PlantVillage dataset by training the model from scratch in one case and then using transfer learning to adapt previously trained models (trained on the ImageNet dataset) in the other. In the case of transfer learning, the weights of layer fc8 in AlexNet and the loss 1,2,3/classifier layers in GoogleNet are re-initialized. Then, when training the model, we don't restrict the learning of any of the layers, as is sometimes done with transfer learning. In other words, the key distinction between these two learning approaches (transfer vs. training from scratch) is in the initial state of a few layers' weights, which allows the transfer learning approach to exploit the large amount of visual knowledge already learned by the pre-trained AlexNet and GoogleNet models extracted from ImageNet (Russakovsky et al., 2015).

9. Conclusion

In this paper, a novel approach to using deep learning methods to automatically classify and detect plant diseases from leaf images was investigated. The developed model was able to detect the presence of leaves and distinguish between healthy leaves and 13 different diseases that can be diagnosed visually. The entire procedure was described, starting with collecting the images used for training and validation, moving on to image preprocessing and augmentation, and finally training and fine-tuning the deep CNN. Several tests were run to evaluate the performance of the newly created model.

Future work will also involve expanding the model's application by training it for plant disease recognition on larger land areas, combining aerial photos of orchards and vineyards captured by drones, and convolution neural networks for object detection. The authors hope that by expanding this research, they will have a significant impact on sustainable development, affecting crop quality for future generations.

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Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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