PLANT DISEASE RECOGNITION USING VGG-16

MR. ASWIN, MR. SHISHAND, MR. DHANUPRASATH, MR. SABARIGIREESON

Department of Artificial Intelligence and Machine Learning

Sri Shakthi Institute of Engineering and Technology Coimbatore, India

MS. NIVEDHA

Department of Artificial Intelligence and Machine Learning

Sri Shakthi Institute of Engineering and Technology Coimbatore, India

ABSTRACT :

Agriculture and modern farming is one of the fields where IoT and automation can have a great impact. Maintaining healthy plants and monitoring their environment in order to identify or detect diseases is essential in order to maintain a maximum crop yield. The implementation of current high rocketing technologies including artificial intelligence (AI), machine learning, and deep learning has proved to be extremely important in modern agriculture as a method of advanced image analysis domain. Artificial intelligence adds time efficiency and the possibility of identifying plant diseases, in addition to monitoring and controlling the environmental conditions in farms. Several studies showed that machine learning and deep learning technologies can detect plant diseases upon analyzing plant leaves with great accuracy and sensitivity. In this study, considering the worth of machine learning for disease detection, we present a convolutional neural network VGG-16 model to detect plant diseases, to allow farmers to make timely actions with respect to treatment without further delay. To carry this out, 19 different classes of plants diseases were chosen, where 15,915 plant leaf images (both diseased and healthy leaves) were acquired from the Plant Village dataset for training and testing. Based on the experimental results, the proposed model is able to achieve an accuracy of about 95.2% with the testing loss being only 0.4418. The proposed model provides a clear direction toward a deep learning-based plant disease detection to apply on a large scale in future.
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INTRODUCTION :

Agriculture has always been a basic human need ever since humans' existence as plants were a primary source of food. Even nowadays, agriculture is still considered an essential food resource and is the center of several aspects in humans' lives. As a matter of fact, agriculture serves as the pillar of economy in many countries regardless of their developmental stages. The various domains that show the importance of agriculture include the fact that agriculture is a main source of livelihood where approximately 70% of the population depends on plants and their cultivation for livelihood. This great percentage reflects on agriculture being the most important resource that can actually stand a chance in the face of the rapidly increasing population.

Typically, the commonly used approach for farmers, scientists, and even breeders, to detect and identify plant disease was the manual inspection of plants. Of course, this process requires expertise and knowledge for the proper detection. With time, manual inspection became tiresome and time consuming and not as quite efficient especially when large amounts of plants needed to be inspected. Another factor that proves the inefficiency of manual inspection is the similar conditions that might be caused by different pathogens that might look alike in their effect on the plant for this reason, humans needed a better suited technique that can deliver effective plant detection results in less time.

Artificial intelligence, computer vision and machine learning utilizations can greatly enhance the process of plant disease detection, and is already applied in multiple research papers. Such technologies are capable of not only detecting the presence of a disease, but it is also possible to determine its severity, and to classify exactly which kind of disease is present in a given plant sample.

Based on their depth, the plant disease detection methods can be divided into shallow architectures and deep architectures. Basic machine learning methods like Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes (NB), and K-Nearest Neighbor (KNN) rely on specific design intended for features such that good features and patterns must be recognized. These specific features include hue saturation value (HSV), Histogram of Oriented gradient (HOG), linear binary pattern (LBP), and red-green-blue RGB color features. In machine learning, according to the complexity of the classifier, the more data is required for its training in order to achieve satisfactory results. The Fig. 2 illustrates the general flow of the implementation of machine learning techniques in detecting plant diseases. Initially, the data is acquired and labeled according to disease classes or healthy class. A specific dataset is then created for the model, where the input images can be pre-processed before feature extraction can take place. Machine learning algorithms are capable of recognizing the changes in features upon comparison, and thus determining the output as diseased or healthy.

On the other hand, deep architectures like CNN (Convolutional Neural Networks) have also been heavily used in studies that are concerned with plant disease detection. These deep architectures differ from the shallow ones by not requiring hand-designed features since deep learning algorithms are able to learn the features themselves. Thus, deep learning approaches undergo three basic stages in detecting plant diseases.

After SVM machine learning approach was the most commonly used one for so long, approximately after the year 2015 CNN replaced SVM as the most popular ML technique for detection of diseases. CNN is considered state-of-the-art model that has been used in plant disease detection nowadays, especially since this task requires dealing with image data applications. CNN can execute tasks such as classification of images, segmentation, object detection, and recognition. In their structure, CNNs are made up of artificial neural networks where tens and even hundreds of layers are used. CNNs is made up of an input layer, several convolutional layers, along with pooling layers in between them, and finally full connection layer in addition to activation function layers, and output layer. There exist several forms of CNN architectures like VGG-16, Inception-V3, ResNet50, and AlexNet. However, CNN architectures need large data numbers which is often considered as a challenge.

Since agriculture is essential there's a need to provide methods that enhance the agricultural methods in terms of planting, monitoring crop environment, detecting plant disease, and even harvesting. These important details led to significant research to be conducted and several papers to be published with the purpose of providing solutions to these agricultural challenges. This study proposes a model based on CNN, namely VGG-16 architecture in order to detect and classify a total of 19 plant conditions (several crop types and diseases) with the best accuracy possible.

IMPLEMENTATION OF THE MODEL :

In this project, we implement several deep learning technologies in order to classify the diseases in crops. Among machine learning techniques, deep learning is an interesting area since it can easily recognize patterns and perform complicated procedures, which makes it suitable for the disease classification task. In deep learning, deep neural networks are created, among which is the CNN, short for Convolutional Neural Networks, that can easily analyze images upon training. In our project, VGG-16 was selected to be the CNN classifier of different plant diseases.

A. Dataset:

The chosen dataset for our study is the Plant Village dataset which contains numerous images of plant diseases totaling for 15,915 images. From these images, the dataset is divided into nineteen different classes, each class resembles a disease, and these classes do not overlap, meaning that a single image only belongs to one class and cannot simultaneously belong to two or more classes.

B. Proposed Model:

VGG-16 is one of the most commonly used CNN architecture, especially since it works well with the ImageNet, which is large project utilized for visual object recognition procedures and it is considered one of the best models to be proposed so far due to its extreme usefulness in the image classification's field in the deep learning domain. Initially, this model was created by Karen Simonyan and Andrew Zisserman in 2014, where they developed in during their work in Oxford University titled "Very Deep Convolutional Networks for Large-Scale Image Recognition". In fact, "V" means Visual," G" Geometry while "G" stands for research group who contributed in the development of this Convolutional Neural Network model, whereas the number 16 refers to the neural network layer's number.

ImageNet is so large that it contains more than fourteen million images distributed over thousand classes. This architecture is one of the top 5 models in terms of performance achievement in the ImageNet dataset, where its accuracy reached 92.7%. As an approach for the AlexNet enhancement, this architecture was submitted to ImageNet.

C. VGG-16 Architecture and Training Procedure:

The training Procedure is made up of three consecutive steps:

- Preparing the images.
- Classifying the photos.
- Printing the decision.

Image Processing: The input of the convents is 224 × 224 RGB image with a fixed size where the value of each pixel is subtracted from the RGB mean value of the training image.

Classifying the data: The proposed model is made up of thirteen convolution layers, two batch normalization layers, along with five max-pooling layers and three full connection layers.

The processed image passes through several convolutional layers that contains filters that are characterized by a receptive field of size 3 × 3 for capturing the notions of left and right, up and down along with the center. Despite its small size of the mentioned filter, this filter is accompanied by the same efficiency as that of a receptive field of size 7 × 7 due to its deep

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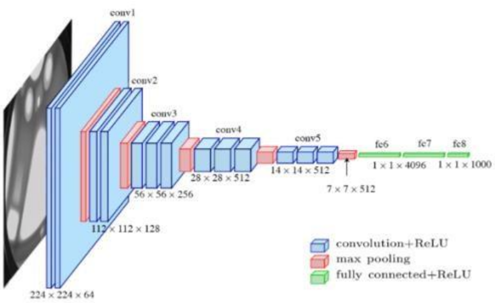
characteristics such as including more nonlinearities and lesser parameters. In addition to that, a 1x1 convolution filter was used as an input channel's linear transformation in a certain configuration. On the other hand, both spatial padding and the convolution stride are fixed to 1 pixel for 3 × 3 convolutional layers, in which the spatial resolution's preservation becomes easy to occur. Also, spatial pooling is easier in case of a five max-pooling layers' addition after some of the convolutional layers and the Max- pooling layer takes place over a 2×2- pixel window, with stride 2.

In addition to that, a total of three varying FC (Fully Connected) layers in depths are fixed behind a group of convolutional layers, where the first two FC layers is made up of 4096 channels per FC layer, and the third performs 1000 way ILSVRC classification and is made up of 1000 channels for each class. Finally, the final layer is the soft-max layer, it's important to say the Fully Connected Layer's configuration does not vary among different networks.

The architecture of the VGG-16 model is portrayed.



RESULTS :

The performance of our proposed model was assessed in terms of Loss Function and Accuracy, which was measured during the training/validation step as well as during the testing step.

In the testing phase, the proposed VGG-16 model achieves the 93.5% accuracy, taking into consideration that the model performs classification on 19 different classes. The performance of our model is excellent for detecting diseases automatically from plant images. On the test set, which is excellent accuracy for classifying 19 items of plant images where the Test loss has reached 0.44 while the Test accuracy has reached 0.95.

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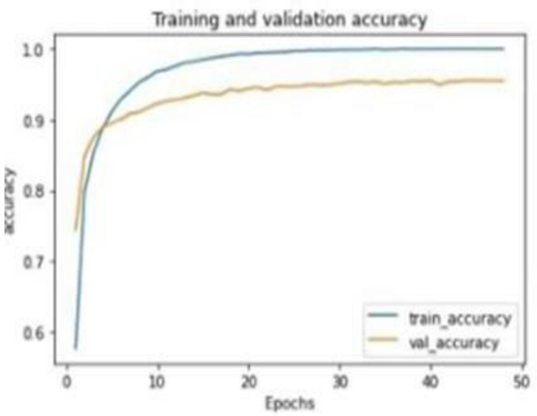

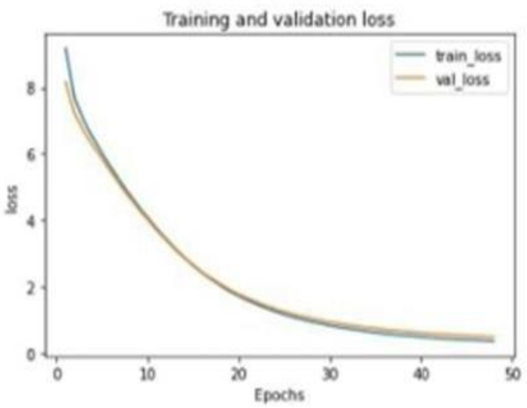

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