Effectiveness of Deep Learning Model for Plant Disease Detection

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Abstract. In recent years, agriculture has become more and more important since global warming became a serious problem human beings must face. In this case, plant health needs to be noticed. It is very important to avoid food shortages as much as possible, given the fact that food is still scarce in today's society. If plants have any disease, the earlier people find it, the easier for the farmers to carry out the action to stop the disease and protect plants. Compared to the traditional machine learning Convolutional Neural Network (CNN) , deep learning has become very efficient dealing with the data. In this paper, two deep learning, specifically two convolutional neural network models, are compared to two machine learning models, on a plant disease diagnosis dataset. The author finds out the deep-learning-based model performs superior than traditional machine learning models. Moreover, designing domain specific techniques for the plant disease detection would help the accuracy of a model.

Keywords: Plant Disease; Deep Learning; Convolutional Neural Network; Machine Learning.

1. Introduction

In today's society where food is still scarce, it is very important to avoid food shortages as much as possible. New agricultural techniques continue to transform the conventional agricultural method. Labor is moving into a new frontier of finer precision, such that farmers are able to improve agricultural techniques in terms of the information they gather and how precisely they control the processes that can enhance production effectiveness. Fine agriculture is a refined technique that provides advanced techniques to increase agricultural productivity. Using these advanced agricultural technologies, economic growth can be achieved. Precision farming technology has a significant impact on plant pest detection and crop yield production. Farmers use pesticides to control pests, prevent diseases, and improve crop yields. Suffering from diseases like insects, plants, and weeds, the crop yields of this year are significantly weakened. Therefore, the diseases destroying the crop must be identified and carefully dealt with. It is common and vital to prevent diseases. False negatives cause losses for crop farmers and the agricultural industry of the country. Since artificial intelligence became more and more popular, this has already been used in agriculture. It can help the farmers to prevent disease in their agriculture. The deep learning models can analyze the agriculture pictures and provide very important suggestions to Agronomists. These models are used to identify sick plants by analyzing the uploaded photos. Thus, this also shows that in the future farmers can have the opportunity to get the help of AI more easily from their mobile to reduce unnecessary losses. In the following, the author introduces several models and compares them by their accuracy. In the last section, the author also writes about the future expectations in this area.

2. Deep Learning and Representative Works

2.1 Introduction of Deep Learning

Deep learning is a subset of machine learning that uses knowledge about the brain's neurons and neural pathways in an artificial agent or object. This attracts the attention of cognitive scientists and information technology. It has an efficient ability to process information compared to traditional machine learning algorithms.

For deep learning, research involving improving plant disease detection and classification seems to have the most potential. A few deep learning algorithms involving multiple imaging techniques have been used to deal with this task. Various performance metrics are also used to evaluate these studies.

Artificial Neural networks will be trained to simulate the functions of the brain. Their brain-like intelligence will help in the solution of problems around us. Included in this capacity, there is no other machine learning program that performs as well as ANN with respect to pattern recognition. The program is traditionally trained by showing samples of a 3D object that is recognized to train it to recognize similar objects. There are many applications; google explosion, face recognition, and even voice recognition.

Convolutional neural networks are cognitive systems inspired by the form of the human brain. Unlike traditional artificial neural networks, they are mainly focused on applications that model repetitive patterns in different areas of the space, such as image recognition. For the application of image matching, several levels of convolutional neural network methods have been developed, and they have been successfully used to effectively apply complex tasks in applying image re-identification by the feed-forward neural network.

2.2 Representative Works for Plant Disease Diagnosis

Model 1 [1] uses a dataset of 87,848 images including 58 different types of plants, it has 99.53% accuracy. They use CNN as the main technique. They first selected 12 for both laboratory and field conditions from the 58 classes; they thought it best to have roughly equal numbers of images from each type. They tested five CNN structures including (i) AlexNet [2], (ii) AlexNetOWTBn [3], (iii) GoogLeNet [4], (iv) Overfeat [5], and (v) VGG [6]. They developed two models, one training with only laboratory images (null model) and testing with only field images (field model), and then having those 12 classes tested with laboratory images (reverse null model) and field images (field model) in the other train/test configuration. However, the accuracy was both low. They then used 5 models to train, and finally found out the VGG one had the highest accuracy which is 99.48%. They conclude that convolutional neural networks are a very suitable method for the building of automated disease computer programs. They are able to classify disease images very accurately.

Model 2 [7] Although deep learning is a popular classification technique, the difficulty in creating training data makes it difficult in many circumstances for it to identify plant diseases. Toward the goal of improving AI's ability to automatically identify plant diseases, data augmentation may be relatively effective. However, those do not help overcome the challenges arising from the range of peculiarity in plant diseases observed in practical situations. This deep learning model uses a different way to detect the disease. Instead of considering the entire leaf, they choose to find the individual lesions and spots for the task. Their new way has a 12% higher accuracy compared to the traditional way. The only shortcoming of this study is that it needs people to divide the types which might cause errors. The limitation of pixels might also lose some accuracy. They use GoogLeNet CNN because of its superior performance. Overall, the accuracy varies a lot, on some specific plants like Grapevines and cotton, the accuracy is perfect. They conclude the reason is that they don’t have enough data to train the model.

3. Machine Learning and Representative Works

3.1 Introduction of Machine Learning

Machine learning, generally, is a technique employed by computers to analyze data. This computer application enables them to learn from data and improve over time. It not only detects patterns, but also learns from being trained over time, in order to make its own predictions. These predictions make it possible to produce actions on our behalf or handle repetitive tasks.

In the agricultural area, machine learning has already a lot of studies including random forest, artificial neural network, support vector machine (SVM), fuzzy logic, K-means method, Convolutional neural networks etc.

3.2 Representative Works for Plant Disease Diagnosis

Model 3 [8] This algorithm was developed to identify plants in greenhouses, which have fungal, bacterial, and viral problems, in natural environments. The algorithm was trained using 160 images of papaya leaves and could correctly identify the plant organisms with 70 percent accuracy. The way they are doing it is first turning the image from RGB color to grey scale because the algorithm can only analyze on a single channel. Then, they use random forests classifier algorithm to analyze the Hu moments, the Haralick texture and the color histogram. The Hu moment can be used to compute the shape of objects based on their edges. Color histograms are used to generate a frequency distribution of Hue. Hue moments are used to correct for leaf texture.

In Model 4 [9], they do a specific detection on Cassava which is an important economic plant in west Africa. They analyze the whole leaf and classify the disease by analyzing the features on the leaves. Four leaf diseases have different features on the leaves. The dataset they use is over 7000 images. They used three classifiers (LinearSVC, KNN, Extra trees) to get the ORB features, and all three shows a highly efficient. They conclude their work is not complete because of insufficient data.

In [10], this paper writes about machine learning on agriculture. It talks about many different sections of a farm including crop management, livestock management and soil management and many subclasses under these main management. It shows that machine learning can be a very efficient way for the farm to know more about their farm not only based on the observations by themselves. Human beings are not able to analyze so many variables, however the computer can. The author reviewed 40 articles and found that eight machine learning models have been realized. The authors conclude that Machine learning models have been applied to quite a few crop management applications, such as yield predictions or disease detection. This reflects the data-intensive nature of these applications as well as the high usage of imagery (spectral, hyperspectral, reconnaissance, etc.). Data analysis is already mature in many of these fields, which makes machine learning models easier to apply in terms of data collection and handling (compression and fusion, calibration, etc.).

4. Result

4.1 Dataset

The plant village dataset they are using are widely separated from the types of plants. The Model 1 used were a combination of 25 types of plants and total 58 classes which included the healthy plants and sick plants. They used 80% of the dataset to be the training set and 20% to be the testing set. 80/20 is the most common dividing way of the dataset in machine learning, the other paper uses this way too. The Model 2 uses a dataset of 46,409 images including 12 different plants and about 100 classes. They also use people to divide their dataset roughly to 5 subclasses by the different symptoms on the leaves (scattered small, scattered large, isolated, widespread and powdery). Compared to deep learning, the dataset Model 3 uses is very small. They use only 160 images to analyze the disease on papaya leaves. They use HOG to prepare the dataset before analyzing. It's a preprocessing process of the images, which would reduce all the images' sizes to a uniform one. The Model 4 has 7386 images which include 1476 healthy cases and four types of disease (CMD:3012 cases, CBSD:1751 cases, CBB:425 cases, CGM:722 cases).

4.2 Result Comparison

On the test set of 17,548 images, the Model 1, a CNN model, achieved a classification accuracy of 99.53%. This would correspond to 17,466 images and 99.53% accuracy, exactly as presented above. Among the classifications that were "wrong," some cases show that the plant leaves are not present at all in the green-yellow, and they were classified to be healthy maize. Here the model considered it a misclassification. In order to evaluate the effectiveness of the model, the final results are interpreted with images that are falsely classified as belonging to a certain class. Since these examples of misclassified images contain no leaves, they do not belong to any of the target classes. By contrast, healthy maize plants should be considered as the correct target designations. Therefore, if these examples are removed, the model's actual accuracy would be even better than 99.53%. Model 2 uses data augmentation. In most cases, the inclusion of healthy samples had only little effect on the accuracy of the model; only those same 3 crops were affected instead—and to a lesser extent. The changes to maize showed the largest margin of error, of a 2% increase. Image interpretation is dependent on the activity level of the lesion. If greater than 25 percent of the images contain disease tissue, then the chances of a successful detection are high. That as much as 90% of the time most errors are due to the presence of extraneous elements, including dust, debris, water droplets, and open spaces. The classified images had an average accuracy of less than the 10% to 12% registered using manually cropped images.

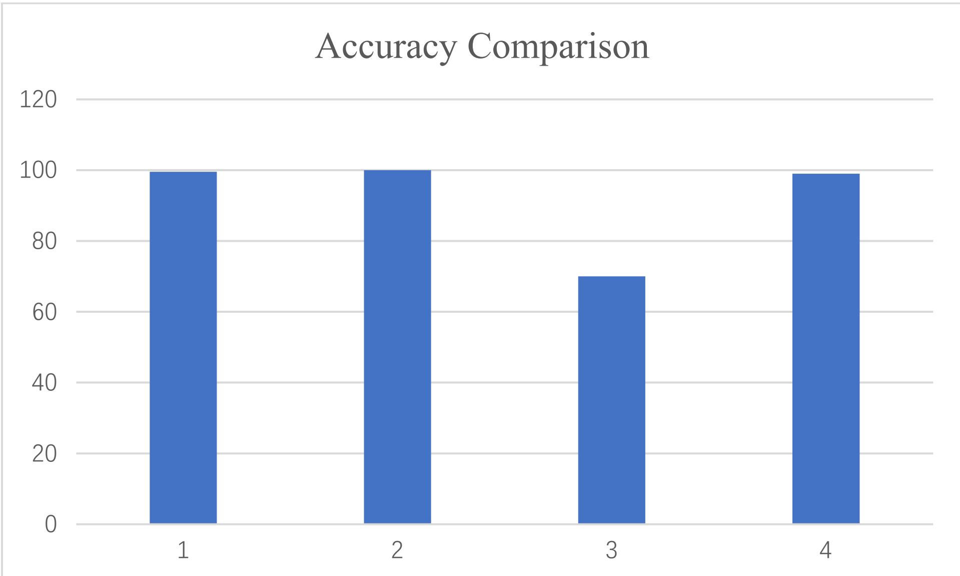

Fig 1. Result comparison of the deep learning and machine learning models.

The results of the four models are shown in Figure 1. Model 2 has the highest accuracy even though it doesn't work for some plants. The accuracy varies from 60%-100%. The Model 4 works very well, it has high accuracy on analyzing cassava. No.3 has the lowest accuracy which is only 70%. This model has an obvious shortage that is its insufficient dataset. It has only 160 pieces of data while another similar model has over 50,000 pieces of data. Insufficient data will limit the efficiency and accuracy of the training model because it doesn't have many things to learn about. CNN (Convolutional Neural Networks) require a big dataset to train. In Model 2, the authors mention that in their dataset, no plant has more than ten diseases, yet in reality, a plant could have more than a hundred diseases, which is the sample they are missing. This also forced the authors to wonder if, in all models, if a plant has multiple diseases but is detected with only one or less than all of its diseases, it will be judged to be detected correctly and whether it will bring an error in the accuracy of the model

5. Discussion

The models struggle with insufficient data. They all need more data pieces to perfect and higher the accuracy of the model. All four models write that the image would be hard to analyze, and many of the images in their dataset come from laboratories which are very clean compared to the real ones taken from the field. In Model 2, they need people to roughly classify the images for better results. Model 4 also shows that the severities of leaves' disease would affect the accuracy. It is a new method of detection. There are five levels depending on the severity of the plant's illness. For farmers, knowing the severity of plant disease determines how they treat the plant, such as the extent of pesticide spraying and the amount of pesticide spraying. Their 99% accuracy only works for these particular ORB feature representations in the region. After comparing four different models, the authors found two approaches to universal image processing, analyzing the whole leaf and analyzing the points on the leaf. Both methods have their own advantages, starting from the whole will be faster, without any manual operation and with high correct rate, starting from analyzing the spots, which requires some manual operation and with high correct rate, but its part that requires manual work still needs to be improved. CNN training may require a large number of images to produce reliable results. More images provide more opportunities for neural networks to understand the actual characteristics of symptoms. But having a larger, more homogeneous dataset comes with a significant risk that the large amount of data may contain incorrect data, i.e., it will reduce the correctness of the model, and this incorrect data needs to be manually screened, as also mentioned in Model 1, where their model automatically identifies images that do not contain leaves as carrying the disease. The author also found references to issues regarding the size of the data set in all four pieces. This problem of dataset size, the authors thought that if the model was successfully recommended to the farmers, the photos taken by the farmers and uploaded to the server would also become part of the dataset, which would become a virtuous circle. Therefore, it is necessary to push the lab product into practice. As stated in Model 4, they designed the Android platform to securely and perfectly upload the photos taken by users with their smartphones to their server through the python framework and perform analysis. They can expand their dataset and improve the accuracy of their model by using photos of farmers.

6. Conclusion

Disease prevention for crops will become important because they are not only an economic source for farmers but also a source of food for society, and if food faces shortages, it will be a world-class disaster. In Model 4, they made software on Android phones to help farmers analyze crop diseases, which will be a major development in the future, transplanting artificial intelligence to mobile to facilitate farmers to prevent crop diseases. Driven by the need to increase crop production to satisfy the ever-rising demand for edible foods and feed, the global agricultural industry is up-scaling towards more advanced technological methods. This entails considering the use of artificial intelligence models to make better production recommendations and insights for subsequent decisions and actions. In the future, we expect the adoption of machine learning models will be more widespread. This provides the capacity to adapt and apply tools allowing a broader range of possibilities involving process improvement. Generally, all existing approaches are only considering individual manual actions but are not fully connected to the decision-making process like in other application areas, thus making it difficult to improve production levels and product quality. This integration of automation, big data and machine learning techniques, intelligent decision making, and support tools will provide decision making in automated web management and provide practical charges to enhance agricultural production capability.

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