Plant Disease Detection

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Abstract — Currently, disease detection is important for better crop yield and quality. Deterioration in the quality of agricultural products, plant diseases can lead to huge economic losses for individual farmers. Plants are the food source of the earth. Plant diseases therefore pose a great threat that can cause many infections, while the usual diagnosis is mainly made by examining the plant body for the presence of visual symptoms. In this research, we proposed a deep convolutional neural network to detect plant diseases from leaf images. To detect a disease, we have a dataset that consists of different open datasets and contains images of different plants. All of the steps required to implement this disease detection are fully described in the paper, starting with collecting images to create a database for the data. With the help of this research work, we can find out the disease and reduce the economic losses. Methods based on machine learning can be used to identify diseases since they are mainly applied to data superiority results for specific tasks. In this approach, a comprehensive review of the different techniques used in plant disease detection using artificial intelligence (AI) based machine learning and deep learning techniques was conducted.

Keywords: Convolutional Neural Networks, Machine Learning, Agriculture, Leaf, Disease, Artificial Intelligence

I. INTRODUCTION

Plant disease detection is a very important research content in the field of machine learning. It is a technology that uses image processing equipment to obtain images to check whether there are diseases in the plant images or not. In today's world, technologies have enabled people to provide the necessary nutrition and sustenance needed to meet the needs of the growing world population. There are several ways to detect plant pathologies. With some diseases there are no clear or definite symptoms, or the effect makes itself felt too late, and in these situations a first-class analysis is mandatory.

In order to achieve accurate disease diagnosis, a plant pathologist should have good observational skills so that one can recognize symptoms occurring in a plant. At present, the conventional technique of human visual inspection by visual inspection makes it impossible to characterize plant diseases. Advances in computer vision models provide fast, normalized, and accurate answers to these problems. Classifiers can also be sent as an attachment during preparation.

All you need is an internet connection and a cell phone with a camera. Self-learning and trained rather than explicitly programmed, these systems excel in areas where response or recognition of features is difficult to express during a traditional computer virus. However, determining the health of a plant from a picture is a very difficult task. Plants are indeed rich and complex environments.

The focus is on increasing productivity without considering the environmental impacts that have led to environmental degradation. Since plant diseases are inevitable, disease detection plays a major role in agriculture. Plant pathogens consist of fungi, organisms, bacteria, viruses, phytoplasma, viriods, etc. Three components are absolutely necessary for diseases to occur in any plant system and infect all types of plant tissues including leaves, shoots, stems, crowns, roots, tubers, fruits, seeds and vascular tissue.

Therefore, disease detection and classification is an important and urgent task. Expert neck-eye observation is the main approach used in practice to detect and identify plant diseases. However, this requires constant monitoring by experts, which can be prohibitively expensive in large operations. We can analyze the image of disease sheets using computer image processing technology and extract the characteristics of disease spots by color, texture and other characteristics from a quantitative point of view.

II. LITERATURE REVIEW

Prasanna Mohanty et al., has proposed an approach to detect diseases in plants by training a convolutional neural network. The CNN model is trained to identify healthy and diseased plants from various species. The model achieved approx. 98% accuracy on test data. Using the model on images obtained from trusted online sources, the model achieves about 31% accuracy, although this is better and a simple random selection model, a more diverse set of training data can help increase accuracy of the model. Also, some other variations of model or neural network training can achieve higher accuracy, thus paving the way to making plant disease detection easily available to everyone.

Malvika Ranjan et al. proposed an approach to detect diseases in plants using the acquired image of the diseased leaf in the publication Detection and Classification of leaf disease using Artificial Neural Network. Artificial neural networks (ANN) are trained by properly selecting feature values to distinguish diseased plants from healthy samples. The ANN model achieves an accuracy of about 80%.

S.Arivazhagan et al. The disease identification process includes the following four main steps: First, a color transformation structure is taken for the input RGB image, and then by means of a specific threshold, the green pixels are detected and uninvolved, followed by a segmentation process, and to obtain advantageous segments, texture statistics are calculated. Finally, the classifier is used for the features that are extracted to classify the disease.

Kulkarni et al. In the work Applying image processing technique to detect plant diseases, a methodology for early and accurate detection of plant diseases using artificial neural networks (ANN) and various image processing techniques. Since the proposed approach is based on the ANN classifier for classification and the Gabor filter for feature extraction, it provides better results with a detection rate of up to 91%.

Emaneul Cortes et al.. An approach to plant disease detection using Generative Adversarial Networks has been proposed. Background segmentation is used to ensure proper feature extraction and output mapping accuracy.

Jyotsna Bankar et al have proposed the use of the Inception v3 model, which classifies plants into different species. Inception v3 can be used to classify objects and categorize them. This capability of Inception v3 makes it a tool for various image classifiers.

P.Revathi, M.Hemalatha& et al.. This proposed work is based on segmentation techniques for image edge detection, where the captured images are first processed for enrichment. Then, R, G, B color feature image segmentation is performed to obtain target regions. Later, image features such as border, shape, color, and texture are extracted for the disease spots to detect diseases and control pest recommendation. This research consists of three parts: leaf spot, leaf color segmentation, edge detection-based image segmentation, analysis and disease classification.

Amandeep Singh, Maninder Lal Singh& et al.. The main challenge during the work was to capture high-quality images with maximum detail of the leaf color. It is a very typical task to get the image with all the details in a workable memory. Such images are generated by high resolution and are therefore 5-10 MB in size. This was accomplished with a camera manufactured by Nikon, which did the job very well. The second challenge was to eliminate the lighting conditions, since the lighting varies greatly from the beginning to the end of the rice field harvest, even when the imaging time is fixed. However, the solution to this is a variable custom threshold and making necessary adjustments to the shades of LCC

III. MATERIAL AND METHODS

Plants are prone to various disease-related disorders and seizures. There are various causes that can be characterized by their effect on plants, disturbances from environmental conditions such as temperature, humidity, over- or undernutrition, light and the most common diseases such as bacterial, viral and fungal diseases. A diseased plant will show symptoms such as a change in color, shape, size, growth retardation, etc. These symptoms vary at different stages of a disease.

In the transition period, disease-causing factors begin to affect a healthy plant, and disease symptoms gradually appear. At this stage it is difficult to distinguish a healthy plant from a diseased plant. In addition, there is a good chance that one disease will weaken the immune system and several diseases will attack the plant.

Thus, two or more diseases have similar symptoms. In addition, environmental factors such as temperature, wind, humidity, solar radiation and other meteorological phenomena can alter the symptoms of a disease. These factors result in variations in the shape, color, and size of the region affected by the disease.

In such cases, it becomes challenging to identify a disease by merely examining a plant or plant part with naked eyes. On the other hand, the advanced techniques of Artificial Intelligence (AI), such as Convolutional Neural Networks (CNN) and can minimize human intervention.

A. *Datasets*

The amount of information and the variety of images varies between studies. The Plant Village dataset consists of images of healthy and unhealthy leaves, divided into different categories by species and disease.

We analyzed different images of plant leaves with distributed class labels and tried to predict the class of diseases.

Fig. 3.1.1: Apple Rot

Fig. 3.1.2: Apple Healthy

Fig. 3.1.3: Grape Rot

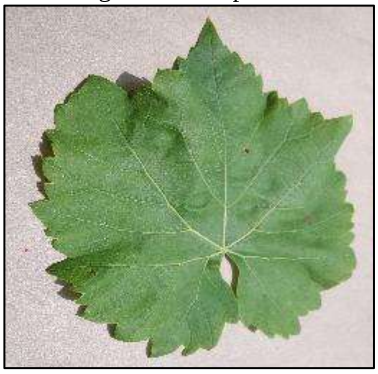

Fig. 3.1.4: Grape Healthy

B. *Data Processing and Augmentation*

Image enhancement plays a key role in building an effective image classifier. Although datasets can contain anywhere from hundreds to a few thousand training samples, the variety may still not be enough to create an exact model. Some of the many image enlargement options are flipping the image vertically/horizontally, rotating it at different angles and scaling the image. These extensions help increase the relevant data in a data set. Compared with other image recognition methods, deep learning-based image recognition technology does not go beyond extracting specific features, and can only find appropriate features through iterative learning, which can be global and contextual characteristics of images, and has strong robustness and higher recognition accuracy.

The expansion options used for training are as follows: Rotation - Used to randomly rotate a training image through different angles. Brightness - Helps the model adapt to variations in lighting as images of different brightness are fed during training. Shear - Adjust the shear angle.

C. CNN Performance

When it comes to image classification, CNNs outperforms various traditional images to processing various methods in several applications. This general trend is also reflected in the automatic detection of plant diseases. Some of the selected studies compared the performance achieved with CNN compared to other methods. The figure below shows the groups with the best results obtained for a CNN and for an alternative method in comparative studies. Adopting a CNN-based classification network has become the most widely used pattern in classifying plant diseases and pests. In general, the feature extraction part of the CNN classification network consists of a cascaded convolutional layer, followed by a structure of the full connection layer (or average pooling layer) for classification.

The main purpose of this methodology is to classify the images with the given perspective. It is quite different from other neural network methods. In general, CNNs use a small pre-processing contrast with calculations of other image arrangements. This implies that the classification learns the channel, which is created by hand in the usual calculation. The parameter level consists of a group of channels (or pieces) that are learnable and have a small open field, on the other hand reach the full complexity of the information volume. Therefore, the system learns channels that are initiated as soon as it classifies some kind of specific highlight in some spatial positional information.

The experimenter has presented several factory splint complaint discovery styles grounded on CNNs in the last five times. Remarkably, nearly all of the publications were released and published, demonstrating how new and ultramodern this system is in husbandry. CNN is simply a mound of several layers pooling and completely connected layers, beginning with a complication subcaste and progressing through the following layers pooling, Relu correction, and ending with a completely- connected subcaste.

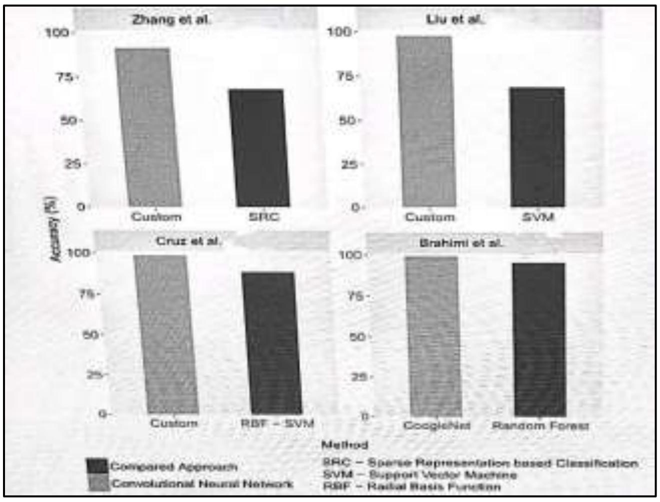

Fig. 3.3.1:

D. Open-source tools for deep learning

The commonly used third party open-source deep learning tools are Tensorflow, Torch/PyTorch, Caffe, Theano. The four commonly used third-party deep learning open-source tools all support cross-platform operation, and the platforms that can run include Linux, Windows, iOS, Android, etc.

In order to have good scalability and a large number to support third party -party libraries we use PyTorch, Tensorflow and deep network structures, and it is the fastest training speed when training large conventional neural networks on GPU.

The different characteristics of each open-source tools are shown in below:

– Tensorflow
– Torch/pytorch
– Caffe
– Theano

Tools/ Requirements	Publisher	Hardware	Interface to applicable	Usable
Tensorflow	Google	CPU	C, Python	Flexibility, portability, excellent performance, can performed on distributed applications
Torch or Pytorch	Facebook	CPU, GPU	C, Python,	Easy to debug, easy to develop, applicable on dynamic neural network, expandable, and low cost
Caffe	BAIR	CPU, GPU	Python, Matlab	High readability, expandable, speed is fast, very large number of users and vast community
Theano	MILA	CPU, GPU	Python	Flexibility and excellent performance

E. Flow Chart

The input test image is developed and pre-processed in the following stage, and then converted into an array form for difference. The selected database is separated and pre-processed accordingly and then renamed into appropriate folders. The model is well trained with CNN, and then the classification takes a stand. The evaluation of the test image and the trained model is tracked by displaying the result.

The task of discovery network is to break the position problem of factory conditions and pests. Still, the exploration significance and demand of early opinion are lesser, which is further conducive to the forestallment and control of factory conditions and pests and help their spread and development.

If the plant has a bug or infection, the packaging will indicate the disease along with the remedy.

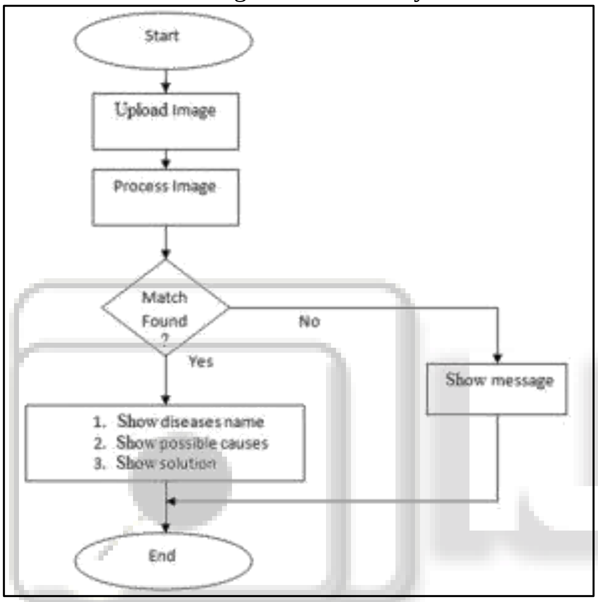

Fig. 3.5.1:

IV. RESULT

Compared to traditional methods, deep learning algorithms achieve better results, but their computational complexity is also higher. When the recognition accuracy is guaranteed, the model needs to fully learn the characteristics of the image and increase the computational load, which inevitably leads to slow recognition speed and cannot meet the real-time requirements.

In order to ensure the recognition speed, it is usually necessary to reduce the amount of computation. However, this leads to undertraining and false or missed detection. Therefore, it is important to design an efficient algorithm with both recognition accuracy and recognition speed.

V. CONCLUSION AND FUTURE WORK

In this article, we have highlighted some of the key problems and shortcomings of work that has used CNNs to automatically report plant diseases. We have also provided guidelines and procedures to be followed in order to maximize the potential of CNNs used in real-world application. In this review, deep learning approaches to plant disease detection have been discussed. In addition, many visualizations techniques/mapping have been combined to identify disease symptoms. A more efficient method for visualizing disease spots in plants should be introduced as it saves costs by avoiding the unnecessary use of pesticides. Plant disease severity changes over time, so deep learning models should be improved to enable them to detect and classify diseases throughout their cycle of occurrence. The deep learning model should be efficient for many lighting conditions, so the data sets should not only reflect the real environment but also include images taken in different field scenarios.

The agriculture department wants to automate the collection of yield crops from the eligibility process. To automate this process, view the prediction end in the web application or desktop application. Optimizing work to implement in an AI environment. The proposed system is based on python and offers an accuracy of about 86%. Accuracy, and therefore speed, is often increased by using GPU for processing. The system is often installed on drones for frequent aerial surveillance of crop fields. A comprehensive study is required to understand the factors that influence plant disease detection such as like. In most of the investigations, the dataset was used to assess the accuracy and performance of the respective deep learning architectures to rate. Although this dataset contains many images of multiple plant species with their diseases, it has a simple, unadorned background. However, for a practical scenario, the real environment should be considered.

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