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APPLYING A DEEP LEARNING ALGORITHM TO THE PROBLEM OF CROP LEAF DISEASE

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Abstract

Agriculture requires plant disease detection to boost productivity. Recent image processing breakthroughs make visual plant disease analysis novel. Few papers, much alone in-depth studies, discuss this issue. Research explores the challenge of visual plant disease detection. Plant disease photos sometimes include several symptoms, irregularly distributed lesions, and different backgrounds, making them hard to recognize. We created a plant disease collection with 220,592 images and 271 categories for identification research. Reweighting visual regions and loss uncovers plant illnesses in this dataset. We use cluster distribution to calculate the weights of all split patches from each image to determine each patch's discriminative level.

To improve discriminative sickness component learning in weakly-supervised training, we weight each loss per pair of patches. We encode the weighted patch feature sequence into a complete feature representation using the LSTM network after extracting patch features from the loss reweighted network. Significant testing on this and other public datasets shows the recommended technique is superior. Our results should help image processing detect plant diseases.

Keywords: Deep learning, Active Contour Method, Convolutional Neural Network.

I. INTRODUCTION

Because plant diseases lower agricultural output worldwide, they represent a major threat to global food security. Statistics show that between 20 and 40 percent of crop losses globally are caused by plant diseases. Therefore, identifying plant diseases is essential to stopping their spread and lowering financial losses in agriculture.

A molecular test or the observation of a plant protector are the mainstays of most plant disease diagnostic techniques. But although the latter is complex and restricted to centralized laboratories, the former is laborious and prone to mistakes. However, the latter takes a lot of time and is prone to mistakes. These days, image-based technologies are extensively employed in a broad range of multidisciplinary activities, including cellular image analysis, culinary computing, and medical imaging, to comprehend visual content. Thanks to recent advances in machine learning, especially deep learning, we think that plant image analysis and identification may provide a new method for diagnosing plant diseases. Meanwhile, the development of image processing technology is aided by applications in visual plant disease diagnosis.

Two instances of plant image analysis research and investigation in this field are aerial phenotyping and leaf fingerprinting. However, these processes are challenging to mainstream since they generally depend on either expensive equipment or complex chemical technologies. Deep learning techniques have been used in some recent research to identify plant diseases. Nevertheless, most of them do not consider task criteria while extracting deep features from images of plant diseases. These projects are also restricted to tiny datasets with simple visual backdrops and fewer categories.

1. Deep Learning

You must create a network of neurons by combining many algorithms to create a deep learning model. The computational cost of deep learning is high. Deep learning models are made possible by a variety of deep learning platforms, including TensorFlow, Py-Torch, Chainer, Keras, and others. We have tried to replicate the human brain network using an artificial neural network in deep learning; the human neuron is called a perceptron in the deep learning model. By joining these perceptron units, we create a neural network, which is divided into three sections:

- Layers that are hidden
- The input layer
- The output layer

A perceptron is composed of input nodes output nodes, and an actuation function for making a tiny choice. Before assembling them into a deep learning model, we will examine the operation of a single perceptron. A certain amount of weight is applied to the input data that are sent to the actuation function. After making a decision, the actuation function sends a signal. Other neurons will receive this perceptron's output. Following batch processing, backpropagation error is calculated at each neuron using a cost function/cross-entropy. Consequently, input weights are re-allocated, and the procedure is repeated until cross-entropy satisfies the condition. RNN, CNN, and other prominent architectures are used to develop the Deep Learning model.

2. Convolutional Neural Network

The deep learning method known as a convolutional neural network (CNN) was developed mainly for image processing. In image processing and recognition, complex neural networks are used. Neural networks of a CNN are arranged similarly to the human brain's frontal lobe, which processes visual information. The following elements comprise the convolutional neural network: Examples of fully connected layers include a convolutional layer, a pooling layer, a fully connected input layer, a fully connected layer, and a fully connected output layer. Because of scaling issues, convolution neural networks have historically had limited applications. These neural networks only worked with low-resolution pictures and needed a lot of training data to be efficient. AlexNet, on the other hand, has made it possible to develop complicated convolutional neural networks by reintroducing multi-layered neural networks and using massive data sets from the ImageNet data set since 2012.

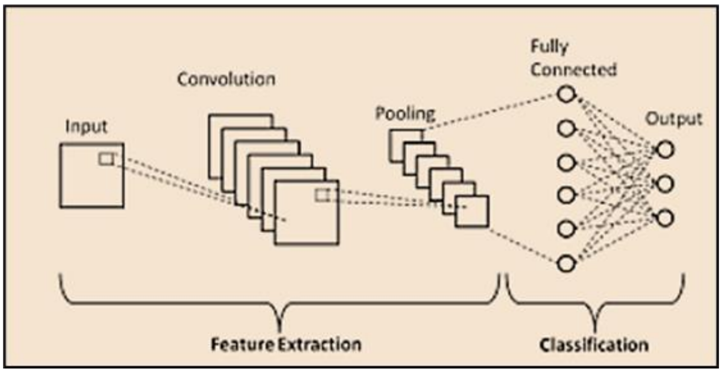

Fig. 1.2.a. Convolutional Neural Network process flow

3. Active Contour Method

The segmentation technique known as "active contour" separates the pixels of interest from the rest of the picture for further processing and analysis by applying energy forces and constraints. A model that is used in the segmentation process is referred to as a "active contour" model. The lines in an image that outline the area of interest are called contours. A collection of interpolated points is called a contour. The image's curve is described by the interpolation process, which might be polynomial, splines, or linear. Various active contour models are used in the segmentation process of image processing. Active contours are most often used in image processing to establish a closed contour for an area and form a smooth shape in an image. Active contour models include snake models, balloon models, gradient vector flow snake models, and geometric or geodesic contours.

II. LITRATURE REVIEW

A overview of the many categorization techniques for plant leaf diseases is provided by Ghaiwat et al. The k-nearest-neighbor approach seems to be the most suitable and uncomplicated class prediction technique for the present test scenario. One of SVM's apparent drawbacks is that it is hard to choose optimal parameters if the training data is not linearly separable.

A system for categorizing and diagnosing plant diseases is described by Mrunalini. The Indian economy will greatly benefit from machine learning-based recognition systems as they save time, money, and effort. This article extracts feature sets using the color co-occurrence approach. Automatic disease detection in leaves is accomplished via the use of neural networks. With minimal computational effort, the suggested approach may significantly aid in precise leaf recognition and seems to be a helpful strategy in the case of root and steam infections.

According to the study, there are a number of steps involved in the illness detection process, but the four most crucial ones are as follows: The input RGB picture is first given a color transformation structure, after which the green pixels are masked and removed using a threshold value. Next, a segmentation process is carried out, and lastly, texture statistics are calculated to provide segments that may be used.

Lastly, a classifier receives the characteristics that were gathered in order to categorize the illness. The robustness of the proposed technique is shown using experimental results from around 500 plant leaves in a database.

Kulkarni et al. provide a strategy that uses an artificial neural network (ANN) together with other image processing methods to correctly and early identify plant diseases. With a recognition rate of up to 91%, the proposed technique yields superior results since it utilizes a Gabor filter for feature extraction and an ANN classifier for classification. An ANN-based classifier uses a combination of textures, colors, and features to identify and categorize different plant diseases.

III. PROPOSED SYSTEM

Because it can assist in monitoring vast fields of crops, automatic leaf disease diagnosis is a crucial area of study in agriculture. High-level characteristics like color, shape, and texture are extracted using image processing methods. Utilizing the Graph Cut technique, divide the tree leaves according to the green component's pixel intensity. Convolutional neural networks are used to categorize illnesses and propose fertilizer. A variety of image classification applications have made extensive use of CNN, a highly potent technique. It has generated interest in a number of professions, including as computer vision, object identification, picture recognition, and image analysis. The CNN's hierarchical structure allows it to process pictures in real time and quickly extract information from them. A fresh "convolved" picture including the features from the previous stage is created at each convolution stage. The benefits of this suggested method include automatic segmentation, the extraction of pertinent information, and the discovery of many leaf illnesses. It has a very high accuracy rate.

IV. DATA-SEIT CONSTRUCTION

The complexity, variety, and unpredictability of plant diseases make it challenging to compile a large-scale, high-quality dataset. First, a range of specialists from different fields should annotate agricultural datasets. For instance, noting diseases on juglans and apple fruit trees requires distinct knowledge, which is time-consuming and dependent on demand. Second, the collection of images of plant diseases is limited by time and place.

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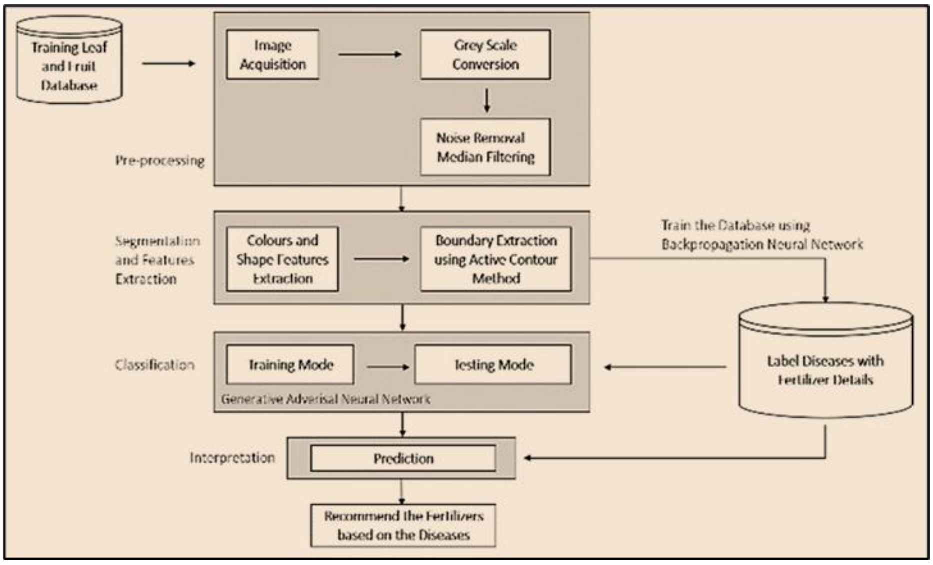

Fig. 3. System Architecture for leaf disease detection

The three elements listed below make up the data building process.

1. Creation of a taxonomy framework

We develop a four-layer hierarchical taxonomic framework for the PDD271 dataset. We bring together a group of agricultural experts to discuss the most common plant diseases that individuals face every day. The plant that is affected determines the upper-level categorization for each disease. Additionally, each plant is allocated to an upper-level class based on its morphology and planting conditions. The apple brown spot, for instance, destroys the fruit tree's apple. Lastly, we use the dataset root, macro-classes, plant categories, and plant diseases to construct a structure of 1, 3, 43, and 271 nodes in the first, second, third, and fourth levels, respectively. Fig. 4 displays the results of the visualization of the plant disease hierarchy.

2. Dataset gathering.

To get a large number of photographs of illnesses, we create 10 teams. Eight university students studying agriculture and four experts in relevant fields make up each team. Thirty distinct illnesses are gathered by each team, and each disease comprises more than five hundred photographs from different plants. Ensuring the quality of disease photographs and annotations is the responsibility of experts.

Maintaining a same visual scope by keeping the distance between the camera and the plant between [20, 30 cm] is a common method for taking pictures. Each category contains more than 200 species and at least 500 photographs of plant diseases. A single plant may also be shot from a variety of angles.

3. Dataset expansion and processing.

To guarantee label correctness, each picture is double-checked by three experts after collection. Professionals then remove noisy photographs and fuzzy shots to maintain a clean dataset. To make sure that each category's picture requirement is fulfilled, we gather additional photos for categories with less images. A reliable dataset is necessary to develop image processing technologies in a particular field. For instance, ATRW is essential for animal conservation, whereas HiEve is essential for human-centric studies. Likewise, a broad variety of plant diseases are included in the proposed dataset PDD271. It will expand the use of image processing technologies in the agricultural industry and further the goal of identifying plant diseases.

Fig. 4. Taxonomy of the PDD271 dataset

V. MODULE DESCRIPTION

- Leaf image acquisition.
- Preprocessing.
- Leaf segmentation.
- Disease prediction.
- Recommendation of solution.

1. Leaf Image Acquisition

Specialized structures for photosynthesis, leaves are positioned on the tree to maximize light exposure while preventing shading. This module allows us to upload the leaf pictures from the datasets. Shape and textural characteristics extracted from digital photos of leaf specimens from various plant species comprise this collection.

Using edge detection, filtering, and thresholding techniques, the leaf portion of the picture was separated from the background. The relative error rate of the software's estimations was less than 7% when the leaf area was measured using an electronic planimeter; the digital camera had the lowest relative error rate and the scanner the highest. Pearson's correlation values were more than 95% regardless of the equipment used to take the images, demonstrating that the algorithm could provide accurate estimates of leaf area.

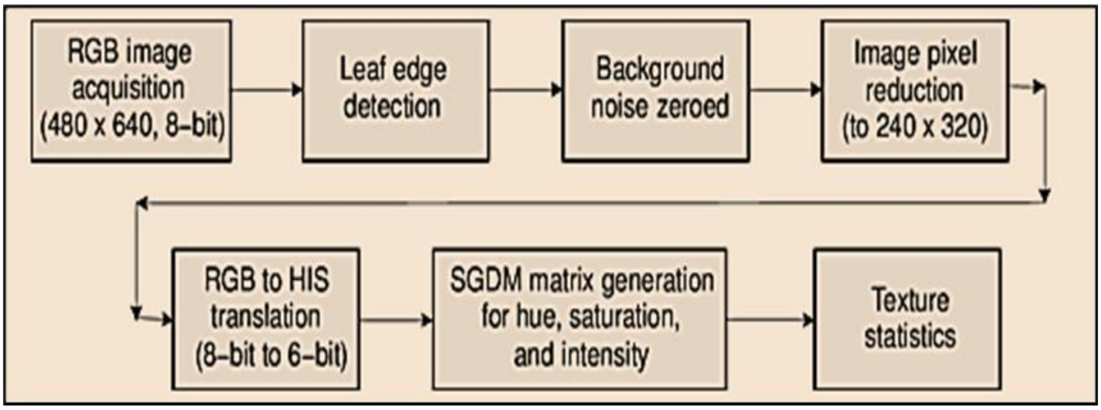

Fig. 5.1.a. Leaf Image Acquisition flowchart

2. Preprocessing

Steps that are required to do pre-processing are as follows:

Data Cleaning/Cleansing.

Data that has been deemed "dirty" must be cleaned. Data in the real world is frequently incomplete, noisy, and inconsistent.

Data Integration.

Data from several sources is combined.

Data Transformation.

Creating a data cube.

Data reduction.

Reducing the size of the data set's representation.

This module converts the RGB picture used in our study to grayscale. The color characteristic of leaves is unpredictable due to the range of environmental changes, even if they are always green. In order to identify different plants by their leaves, the RGB leaf image that was received will be converted to greyscale prior to pre-processing. Next, eliminate the noise from the images using filtering algorithms. The picture has been affected by noise, which the filter is meant to eliminate. It uses a statistical method. Generally speaking, filters are designed to have a certain frequency response.

3. Leaf Segmentation

We can use the graph cut method with automatic descriptors in this module. Unconstrained borders applied to the intricate natural imagery we're working with would result in disappointing contours that tried to squeeze through every crevice and aw in the leaf's border. The method we propose is to use the polygonal model created in the first phase not only as an initial leaf contour, but also as a shape prior that will steer the evolution of the model toward the true leaf boundary.

4. Disease Prediction

Bacteria, fungus, viruses, and other insects all harm the leaves. Use a convolutional neural network technique to categorise the leaf picture as normal or impacted in this module. Leaf properties such as colour, shape, and texture are used to create vectors.

Then, using conditions, layers can be built to categorise the pre-processed leaves. Also, by using a multiclass classifier, we can more accurately forecast illnesses in leaf photos.

VI. CONCLUSION

Identification of plant diseases is an interesting and practical subject. However, this topic hasn't been thoroughly examined since there hasn't been a systematic investigation or a large-scale dataset. Establishing a sensible structure from an agricultural and image processing perspective is the most challenging aspect of developing such a dataset.

In this work, we explore the field of plant disease detection within the image processing community. With the help of agricultural experts, we produced the first extensive collection of plant diseases, which included 220,592 images and 271 categories. Additionally, we provide a framework focused on plant diseases that identifies them by their distinctive characteristics. In order to guide model improvement, we develop a method for calculating patch weights based on the patch feature cluster distribution. We then reweight both patch features and the loss using learned weights. Evaluations on the PDD271 and Plant Village datasets, both qualitative and quantitative, show the effectiveness of the suggested approach.

The many segmentation and classification techniques and algorithms that have been put forward to enhance segmentation quality will be examined in this study. Nevertheless, the findings indicate that segmentation techniques are challenging to use and perform poorly in big datasets when compared to the recommended graph cut model. Based on the optimization of a polygonal leaf model used as a shape prior for an accurate grab cut segmentation, we have put forward a technique for segmenting a leaf in a natural scene. Additionally, it offers a collection of global geometric descriptors that may be used to classify tree species in conjunction with local curvature-based traits that were retrieved from the final contour.

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