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Precision-Agriculture: An Image Net – Based Multilayer Convolution Neural Network for Leaf Disease Detection in Coffee Plant in Early-Stage System

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I. INTRODUCTION

Secured Plants often are affected by various fungal infections and leaf diseases that hinders the growth of healthy crop and eventually reducing yield in plants, lead, buds, flowers and fruits, Plant diseases are the leading source of agricultural production losses in terms of quantity and quality. These reductions have a severe influence on agricultural production. Farmers and plant pathologist have always relied on their eyes to diagnose diseases and make decisions based on experiences, which necessitates a significant amount of time and human work., It is sometimes inaccurate and sometimes prejudiced because many diseases appear to be much like the early stages, proper results may not be recorded, and accuracy may be low at times [1-4]. This technique leads to the usage of pesticides that aren't necessary, resulting in greater production costs. According for that knowledge, a precise disease detector linked to a trustworthy database to assist farmers is required, particularly in the presence of naive and inexperienced farmers [5-6]. Rapid development of computer vision open the way for this using province Deep learning (DL) and machine learning (ML) techniques. An early disease detector is also required to protect your crop in a timely manner. There have been numerous previous studies undertaken for this aim [7]. With CNN's most popular model, we used the "Plant Village" dataset, a well-known database that really is available on the internet. The CNNs, on the other hand, require a big amount of information for training. In this paper, we offer the following strategy: CNN models have been improved with ImageNet algorithm learning, which employs an Artificial Neural Network (ANN) with Feature Selection (FS) to address multi-class classification problems for four types of diseases, namely Cercospora, Miner, Phoma, and Rust The proposed frame work aim at increasing the models' accuracy when the data is limited [8-12].

II. MODULES

The flowchart of our suggested project is shown in Figure 1. In this study, a Multilayer Convolutional Neural Network relying on the Alex Net structure is proposed for the identification of coffee leaves afflicted by the fungal diseases Cercospora, Miner, Phoma, and Rust [13-18].

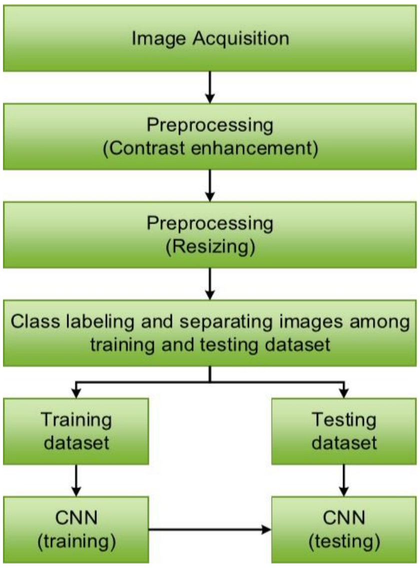

FIG 1: Work Flow of the Proposed MCNN

Algorithm

1. Acquire the real-time images of the coffee plant containing both diseased and non-diseased leaves and also, images from PlantVillage dataset.
2. Preprocess all the images for contrast enhancement using histogram equalization method and rescaling using central square crop method.
3. Assign the class labels to the image.
4. Categorize the images among training and testing dataset selecting from all the class labels.
5. Train the CNN with the help of training images.
6. Test the CNN with the help of testing images.
7. Validate the performance of the proposed model and compare the results with the other state-of-the-art approaches.

The procedure of proposed method is revealed by the algorithm given in Table 1.

TABLE1: Algorithm for the proposed work

1. **Use case diagram of Proposed System**

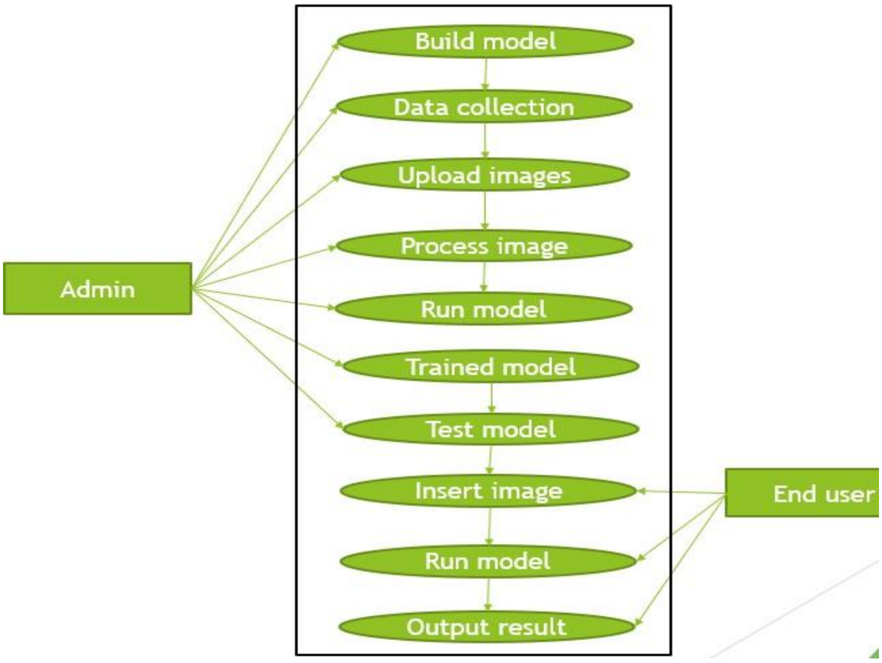

FIG 2: Use case for the proposed work

The two participants are user and system.
User: Trains the machine and inputs the images of leaves.
System: processes the images and runs it into the model and generates the output.
The data set is sent to image processing.
The image that is processed is next put up for data image.
Generates the data set and will be given to model.
Model compares the data set with the image fed if matched then generates the output otherwise [19]**.**

III. PROPOSED SYSTEM

The data Architecture of Proposed System.

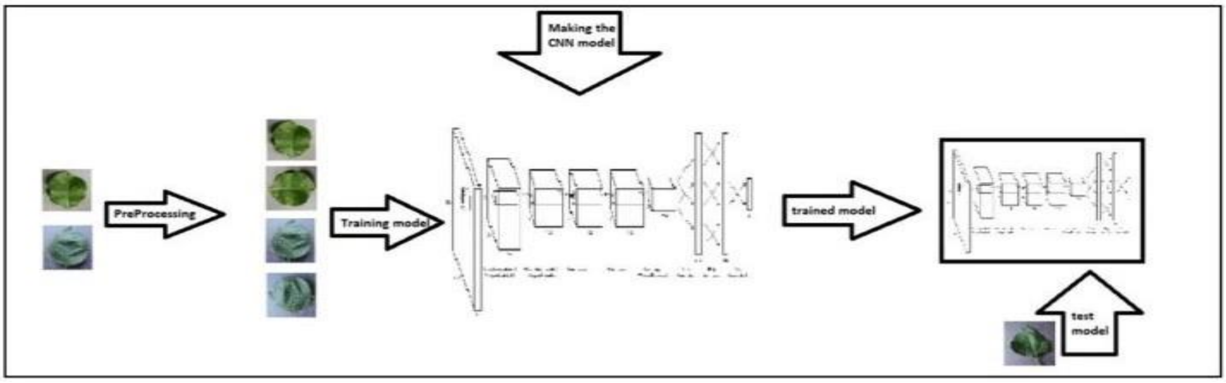

FIG 3: Architecture for the Proposed Work

The input to a CNN is a vector with both the shape (number of images) x (height) x (width) x (images). The picture is then abstracted to an input image with both the shape (number of images) x (feature map height) x (width) x (channels). The following attributes should be present in a convolutional neural network:

Convolution layers kernels have a width and thickness that define them (hyper-parameters).

The total number of inlet and outlet channels (hyper-parameter).

The depths of a Convolutional layer should be equivalent to a amount of operations (depth) of the input sequence (input channels).

The data is combined using convolution, and the output is then sent to the subsequent layer. A neuron's reaction to a single stimulus in the visual system is comparable to this. Each convolutional neuron processes the data solely for the receptive area to which it has been given [20-22]. Although fully connected neural networks can identify faces and categorize information, they are not practical for mimicking. Even in a deeper (reverse of deep) architecture, a huge number of sensor nodes would have been necessary because to the enormous combinations associated with pictures, where each pixels is an essential parameter. For just a (small) picture of size 100 by 100 pixels, each neuron in the second layer of a fully linked layer contains 10,000 weights. The fourier method solves this problem by reducing the amount of independent variable in the system, making it stronger even with limited datasets [23-26].

For example, tiling 5 × 5 regions with the same pooling layers requires only 25 learnable parameters, regardless of image size. The vanishing gradients and inflating gradient difficulties encountered in classic neural networks are overcome by utilising regularised weights across fewer parameters [27-29].

A.1 Activation Function

The activation function calculates a weighted total and then adds bias to it to determine whether a cell must be engaged or otherwise. The activation function's objective is to propose non-linearity into the a neuron's response.

A.2 ReLU

The rectified linear neural network is a tested results that returns whatever value passed in as input, or 0.0 if the input is 0.0 or less.

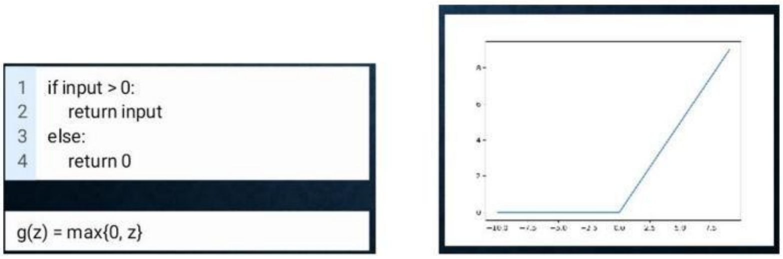

FIG 4:ReLU in MCNN

A.3 Max Pooling

Convolutional layers may include local or global switching states to speed up the basic computation. Max pooling reduce the dimensionality of data by combining the outputs of a neuronal cluster at one stage into a single atom at the next level [30-33]. There is usually a two-way agreement, which is integrated in local sharing. Global pooling, in instance, impacts how all of the neurons in the convolutional layer estimate a maximum or average value. In max pooling, the largest value in each clump of cells from the preceding layer is utilised. In the pooling layer [34], the average value out of each clump of cells out from preceding layer is utilised.

A.4 Flatten

We should now have a pooled feature map after completing the previous two processes. As the name suggests, we'll literally flattening our pooling feature vector into a column, as shown in the picture

below.

FIG 5: Flatten in the Proposed Work

As you see in the image above, we have multiple pooled feature maps from the previous step.

A.5 Full Connection

Adding a Completely layer is a (typically) low-cost approach of learning non-linear combinations of elevated information represented either by convolutional underlay output. In such area, the Fully Connected layer was learning a possibly non-linear parameter [35].

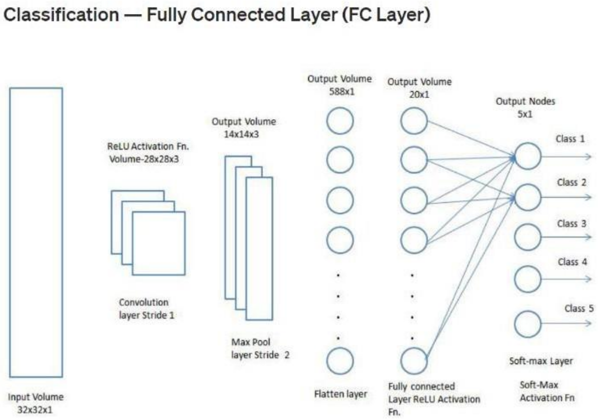

FIG 6: FC in the proposed work

A.6 LeNet Architecture

Second set of convolution, activating, and pooling levels are succeeded by a fully-connected unit, activation, additional fully-connected layer, and ultimately a SoftMax classification in the LeNet design.

TANH optimization algorithms were employed instead of RELU in the initial LeNet design. Since of a number of pleasant, desirable qualities, we choose RELU here as it tends to yield considerably greater classification accuracy [36-40].

The layers that make up the LeNet architecture are as follows:

INPUT => CONV => RELU => POOL => CONV => RELU => POOL => FC => RELU => FC

Figure 2: LeNet Architecture

In the first set of CONV => RELU => POOL layer sets.

This Convolution layer will learn a total of 20 convolution filters, each measuring 5 x 5 pixels. This evaluation intake parameters are the same as our input images' size, height, and thickness, and with a weighted linear channels, we'll get 28 x 28 data (grayscale).

Afterwards, the ReLU function generator will be used, followed by 2 x 2 max-pooling both in the x and y angles including a stride 2 (imagine a 2 x 2 sliding door that "slides" from across thicker users, going to take the maximum procedure of each neighbourhood while beginning to move 2 pixel values both longitudinally and transversely).

In our second set of CONV => RELU => POOL layers

> We'll train 50 convolutional filters rather than the 20 convolutional we learnt in the input layer set. It's common to see the amount of Convolution filters taught rise as you go further into the system.

As in the previous batch, the identical ReLU activation function and 2 x 2 max pooling will be utilised. The LeNet design and convolutional layer (sometimes called as "dense" layers) will be discussed subsequently.

We combine the information from the previous MaxPooling2D layer into a descriptor number, allowing us to implement dense/fully connected layers. In a network, a dense/fully interconnected healthcare layer is indeed a "standard" type of layer where every nodes in the preceding layer links to each and every node in the following layer (thus the label "fully interconnected"). Our completely linked layer will have 500 units where we will transit through.

Finally, a list with likelihood for each of the different classifiers is generated using an Adequate surfaces (regression analysis extrapolation). The final classification of the system would be determined upon on classification problem that has the highest likelihood [41-43].

The Adam optimizer is used with this LeNet Framework. The Adam may be seen of as a hybrid of RMSprop and Stochastic Gradient Descent, with both the addition of velocity. It scales the training set using squared gradients, similar to RMSprop, and it takes full advantage of velocity by utilising a weighted average of a gradient rather than the gradients itself, similar to SGD with velocity.

IV. RESULTS

The program's information were disposed of by the implementation, which comprises 3000 generic agricultural data points such as crop, disease, quality, and so on. Machine learning models need two types of data to use the prophetic paradigm. Data that has been trained and data that has been tested. Training data are data collected over the course of a year, whereas test data is indeed the datacollected right now.

1. Classification Technique

The categorization technique is the most crucial part of the procedure since it is here that the method is used. The random forest method is used in the process to provide them with the results of the information. Because as size supplied to the architecture, the system starts through 20% of the examination data (random information). and the train data is gathered in 80 percent of the time. Data values in the matrix form, such as true positives, true negatives, and so forth) The matrix itself can be used to determine the expected data. The parameters of the matrices are gradually used to forecast the land which will be used to grow the appealing produce, which is provided the season's highlights.

V. CONCLUSION

It's crucial to know if a leaf is normal or sick. The illness must be recognised after it has been discovered. In this investigation, four distinct coffee illness classifications were discovered, i.e., Cercospora, Phoma, Miner and Rust. This paper has proposed a leaf disease detection approach that is based on Convolutional Neural Networks. The deep learning-based approach can automatically extract the discriminative features of the diseased leaf images and detect the diseases with high accuracy. Finally, a CNN model, LeNet is developed for classification stage using the extracted features. In future, we want to target multiple plants with multiple disease. This will enable them to make the option to increase production by implementing the appropriate safeguards, preventative measures, and corrective actions to improve citrus orchard health. With additional training examples, we can enhance the accuracy of our findings. With the help of domain specialists, we can apply our design protocol to the identification of illnesses in other plants. We want to create a mobile application obtained by the proposed method for the farmer's obvious benefit. Standard publically available data are still required to improve the overall performance of such programs and to broaden the scope of computer aided diagnosis systems that are capable of reliably identifying and quantifying various diseases.

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