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An Efficient Image Processing Technique To Increase Productivity In Agricultural Environment

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ABSTRACT

Tree physiology and condition are connected to climate effects in the immediate environment since it strongly associated with the environment. Line up for detecting and identifying plant diseases has proved to be a trustworthy source of information for making farm decisions. Artificial intelligence techniques such as Deep learning and Convolution Neural Network (CNN) are earning momentum from the area due to powerful tool for detecting leaf diseases. Previously, manual observation was used to identify pests is complicated and prone to errors. Several plant diseases are invisible to the naked eye. The incidents of early disease are insignificant. To improve the quality of plant output and yield, it's critical to identify and handle disease symptoms early on. Farmers in India are also worried about diagnosis. At the same time, fearing pest attacks, the farmer sprays pesticides throughout the entire farm, potentially causing soil and plant damage. The aim is to get farmers to spray a small amount of pesticide at a specific target area where a pest is present or where an attack will occur in the future. The use features extraction and classification algorithms to classify tree leaf diseases and suggest pests to provide an alarm system.

Keywords: Agricultural pests, Deep learning, Classification

1. INTRODUCTION

In India, seventy percent of the population mostly based on agriculture, so that India an agricultural country. To improve the productivity of crops is a key role at present. Many researchers are performing the consecutive analysis in the agricultural field. Utilizing the latest methodology and experimental execution are extremely simple pest infection of plants, on the other hand, currently one of the most pressing issues. The utilization of pesticides will cause damage to the air, water, and soil. Transferring the pesticides into the air will capture pollution in further regions. Thenmozhi and Reddy suggested that a CNN model is pre-owned to verify the pest databank; the top grouping of 96.75%, 97.47%, and 95.97% was reached on their advance CNN model [1]. By using GoogLeNet model, Li et al. allowed the composed databank and secure a better 6.22% differentiate to state-of-the- art technique exactly [2]. Tetila et al conferred a survey for the instinctive identification of soybean bud infection put in to pictures, grab directly from the unmanned aerial vehicle. Author estimated four DNN educated from various frameworks for perfect and convey knowledge. Author evaluated databank raised with the original gliding examination in edge-to-edge object identification outlook and outcome put forward that the author procedure greatly enhanced the recognition validity [16]. Liu et al. suggested PestNet, a zonal back-to-back method to extensive multiple class pest limitations found on deep learning that reached 75.46% mAP to sixteen species. Pest detection and prediction on extensive areas were extremely predominant. Citrus clips have never been hardly influenced before various surviving pathogens, but it now faces the risk of a massive epidemic recently appearing diseases around the world if no changes are made [5]. Despite the fact that these diseases persist for a long period, they result of a significant reduction in total citrus output as wellas unavoidable financial hardship. Many have used machine learning to study and analyze disease identification as a result of the widespread use of machine vision. The combination of radio spectral imaging and analytical chemistry was found to be an effective method for detecting the rice sheath curse disease [6]. For a variety of radio spectral images, Lee et al. created a cross-domain CNN. When three groups of tests were performed, the accuracy of the findings increased by one to three times when opposed to CNN's victimization strategy [17]. To spot and detect four cucumber diseases, Ma et al. projected the deep convolution neural network. This DCNN acquired sensible detection accuracy for powdery mildew, anthracnose, leaf spot and downy mildew from 14,208 images [8]. The method which is used in the artificial neural networks to compute the gradient, required to figure out the weights computed in the networks. In CNN [12] the error will be rectified only in the output whereas in BPNN the error will be rectified in the hidden layer and error free in the output. Hence, the proposed method uses the BPNN in the leaf disease detection by using image processing technique. It is a standard technique that is fast, straightforward, and easy to program.

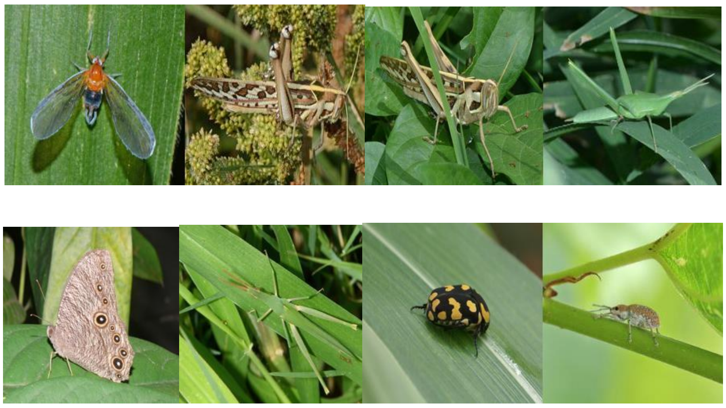

Figure 1. Sample images for pest dataset

2. RELATED WORKS

According to number of analyses, many of the leaf diseases were identified using the application of deep learning. J.Waldchen and P.Mader used the rich development and unreliability of applicable details such as phone photography and handheld devices to follow the plan near to the truth. The benefit of this work is easily identification of plants with minimum consumption of time. The traditional identification of plants are multiplex due to golden mastery of the botanist [9]. A.Joly developed the exact mastery to describe the geographic arrangement and utilize of plant species is mandatory for sustainable development of cultivation in addition for biodiversity conversation. The work is mostly focusing on photo plant recognition as a way to recruit additional funds and make horticultural information more available. The basic details are not essential to have the topmost plant diversity. Trigger the cluster and set apart of exposed botanical examination of details regarding the sustainable development of cultivation [10]. k.Thenmozhi and U. Srinivasulu Reddy suggested an efficient CNN[17][18] model with deep architecture is requested as it executes instinctive feature extraction in image classification approach. The benefit of this works are the discharge of hyper parameters such as learning rate, number of epochs and mini-batch size were look over. The discharge of advance training of CNN [14][16] model utilizing transfer learning were differentiated with the suggested method [1]. The author developed the GAN of Penta, persistent and thick diffusion pathways to process reduced pest pictures. The test conclusion displayed that after rebuilding with previous GAN [15], the remembrance rate expanded and classification accuracy additionally increased massively. For up scaling, other than the GAN haveused a novel picture amazingly tool.

The images are updated using the super-resolution process, accuracy rate and differentiation retrieval frequency improves. By GAN, only able to produce the low- resolution images [11]. According to the former analysis, the pest images taken directly from the agricultural field are commonly low-resolution and extremely minor in pixels, it has the poor footprint on the enhancement of pest picture recognition systems, low-resolution pictures are necessarily up scaled. Some of the works do not suggest the pesticide to the leaf diseases. So, image processing techniques are used along with the grey scale conversion for the identification of the accurate affected area in our leaf databank.

[11] PSRGAN comprises of a discriminator and generator. PSRGAN's generator is depicted in reduced images that have been positioned in the activation function then split into different branches. Just after key fully connected layer throughout the turbine organization, one has been inserted further into CARAFE upgrade unit, but this section passed into the personality subsystem. Another layer passed via the convolution layer after that, and the PReLU[13] initiation line entered the scaled down pictures and borders with both the projected information until passing through the convolutional layers and build an awesome pictures. We intend to use a discriminator network to distinguish legitimate elevated images with produced amazingly images. Author's used LeakyReLU[19] initiation and evade max-pooling all through the node. The output image is ready till take on the problem of augmentation. It consists of multiple convolution layers via a growing percentage for channel components, increasing by a factor of two from 64 to 512 bits. When the amount for indicators is increased, strangled converts can be used to reduce the image objective

3. PROBLEM STATEMENT

In previous works, authors have used the GAN technologies for the low-resolutionimages and CNN. CNN has more number of layers and the training period takes plenty of time if the software system doesn't have a proper Graphics Processing Unit (GPU) and it requires a large amount of databank to proceed and evaluate the neural networks. In CNN the error will be rectified only in the output whereas in BPNN the error will be rectified in the hidden layer and produces error free output.

The BPNN algorithm is being used to solve this problem. It is a springy and secure method as it does not require any initial mastery of the networks compared to the CNN model. Here we are using the grayscale conversion as it converts the RGB images to grayscale images and it gives a clear outlook of the leaf images.

4. PROPOSED SYSTEM

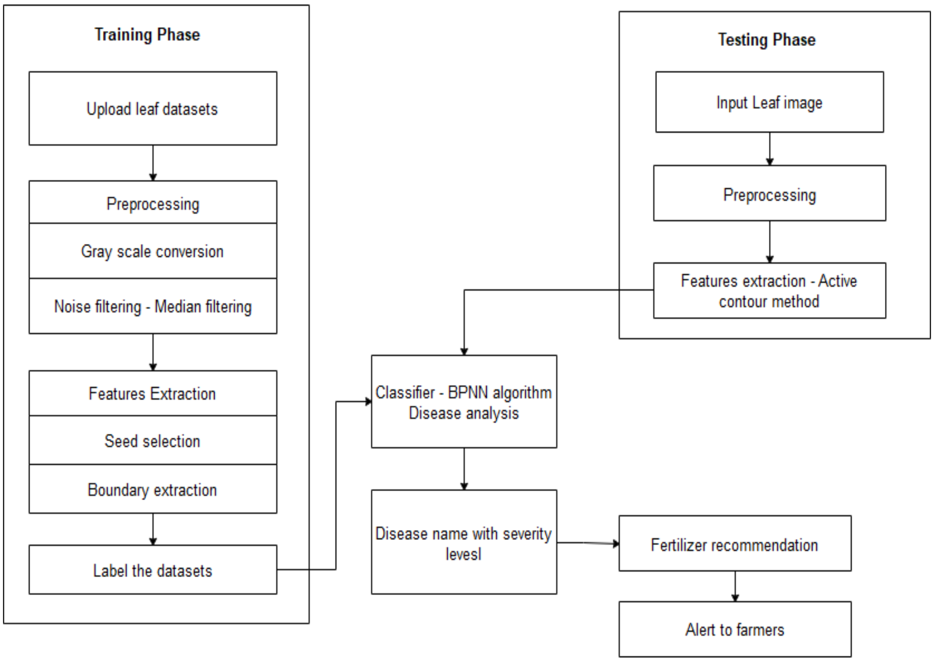

Figure 2. Block diagram of the Proposed System

The median filtering procedure is for eliminating salt and pepper noise. A wavelet transform slides all images and the average image intensity of the pixels inside the window controls the output intensity including its image. Feature extraction in machine learning, pattern recognition, and image processing starts with an overarching arrangement of approximate knowledge and constructs determined features that are useful and non-repetitive, facilitating the learning and speculation measures and often prompting better human performance. In this method, segmentation can be done easily to split the leaf and its disease. It also classifies the affected parts in tree leaves and provide improved accuracy rate and also gives alert to farmers. Generally, the proposed system consists of three phases.

- Training,
- Testing,
- BPNN algorithm.

4.1. Training phase

In training phase, upload the leaf datasets from the online source Kaggle dataset. There are more than 2500 images for training the dataset. Then, median filtering is used in preprocessing process to remove the noise in the images. Gray scale conversion converts color pictures into image pixels, converting RGB values of 24 bits into grayscale values of 8 bits using the equation (1).

$$G=(r+g+w)/3 \qquad \text{-------------} (1)$$

The median filter removes distortion from a data point through pixels, returning through value as the mean point including its nearest pixels. Feature extraction is a method for reducing and extracting the number of numerical features in a databank by generating new ones from the old ones. Seed selections are used for grouping the main components from the testing cells. Boundary extraction process is used to detect the boundary of the image. Training phase steps are listed below:

Step 1: Input I from "Kaggle" dataset.
Step 2: Resizing of I [256 x 256].
Step 3: RGB conversion of I from Step 2
Step 4: Median filtering(I), when I from Step 3.
Step 5: Extract features, affected area.

4.2. Testing phase

The same process takes place which are done in the training phase. Here we are using the Local visual primitives (LVP) algorithm. Then we are using the active contour algorithm to find the range of the border and so on. After calculating the infection region we are calculating the percentage level of infection area in the leaf. Testing phase steps are listed below:

Step 1: Input I "Acrida-exaltata1.jpg".
Step 2: Resizing of "Acrida-exaltata1.jpg" [256 x256].
Step 3: RGB conversion of "Acrida-exaltata1.jpg" from Step 2.
Step 4: Calculate infected area by active contour algorithm.

4.3. BPNN Algorithm

The core of neural net training is back-propagation. It's a technique of great the strengths of the computer vision algorithms using the current error rate. You will reduce failure rates or boost that model's generalization by great the parameters, making it more accurate. The term "backward propagation of errors" is abbreviated as "back-propagation." It's a popular way to train artificial neural networks. This approach is useful for calculating the gradient of a loss function with respect to all of the network's weights. The formula for the BPNN algorithms are which is how to find the error in the output layer is expressed in equation (2). BPNN algorithm steps are listed below:

$$\partial_k^i = \frac{\partial_x}{\partial_k^i} \tau y_k^i \qquad \text{------------- (2)}$$

Step 1: Input I come across prefect footpath.
Step 2: Using real weights the input is modeled.
Step 3: For every neuron in the cell the output are calculated.
Step 4: Calculate error from output.
Step 5: From output layer travel to hidden layer to decrease the error by adjusting the weights.

5. RESULTS AND DISCUSSION

The "python" software has been used for implementation. In that, the additionally using libraries such as tensor flow, keras, numpy, seaborn, pickle, and pandas. By using this method, easily find the type of disease in a particular leaf. Figure 3 shows the original image, grayscale image, noise removal and the invert image of the leaf. Some of the leaf names and disease names were listed in Table. 1. Table 2 shows the Accuracy and loss function of Training phase. From the measurement of accuracy rate, it is an efficient way to identify the disease type in the leaf.

Table 1. Identification of Leaf disease and accuracy rate of different Input Leaves

Leaf name	**Disease name**	**Leaf name**	**Disease name**
Corn(maize)	Northern leaf blight	Orange	Haunglongbing
Tomato	Bacterial spot	Potato	Early blight
Apple	Cedar apple rust	Tomato	Septoria mites
Cherry	Powdery mildew	Clinteria	Klugi

Grape	Black rot	Squash	Powdery mildew

Table 2. Accuracy and loss function of Training phase

Epoch	Accuracy	Loss function	Epoch	Accuracy	Loss function
1	0	1.04	11	0.051	0.95
2	0.007	1.04	12	0.052	0.94
3	0.015	1.03	13	0.053	0.93
4	0.025	1.02	14	0.054	0.93
5	0.032	1.00	15	0.055	0.92
6	0.036	0.99	16	0.055	0.92
7	0.041	0.98	17	0.056	0.91
8	0.044	0.97	18	0.057	0.91
9	0.047	0.96	19	0.057	0.90
10	0.049	0.96	20	0.057	0.90

Figure 3. Output images

6. CONCLUSION

Experts and academics have undertaken comprehensive studies into image processing technologies as computing technology and artificial vision technology progress. In recent years, deep learning-based leaf disease recognition has been growing adoption in the field of agriculture. In order to improve the accuracy and efficiency of image recognition for leaf disease, this research proposes an approach based on image processing algorithm like BPNN to classify leaf diseases. This approach shows the ability to recognize and discriminate between healthy and diseased leaves. The proposed approach is error-free in producing the output, as shown by the experimental findings. As a result, it's thought to be well-suited to producing quick and easy results for identifying leaf disease photographs. It will be further developed by early detection of pests in the leaves and its corresponding alert message will be sent to the farmers via Internet of Things.

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