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DETECTION OF PLANT LEAF DISEASE USING IMAGE PROCESSING APPROACH

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ABSTRACT
A similar rise in food production is necessary due to the rapid growth of the human population. Diseases that spread quickly have the power to drastically reduce plant yields or even wipe out entire crops. Early disease detection and prevention are crucial for this reason. Conventional techniques depend on laboratory analysis and human knowledge, both of which are typically costly and unavailable in most of the developing world. In order to detect agricultural illnesses, experts have recently turned to automated picture analysis because cell phones are becoming more and more common, even in the most rural places. The most recent findings in this area are presented here, along with a comparison of the deep learning methodology and traditional machine learning techniques.

Keywords: Automated picture analysis, deep learning, machine learning.

I. INTRODUCTION
As the world's population continues to rise, so does the demand for food production. The UN projects [1] that there will be 9.7 billion people on Earth by 2050, which is 2 billion more than there are now. It is simple to deduce that reducing food waste in those countries is of utmost importance given that most of the population growth is expected to take place in the least developed countries (about 80% rise in the next 30 years), where food scarcity is the key issue. Global yield loss is thought to be between 20 and 40 percent [2], with many farms experiencing a complete loss. Conventional disease detection techniques necessitate the competent manual examination of plants. Continuous implementation of this procedure can be too expensive for large farms, or for many small farmers in rural locations, it may not be feasible at all. For this reason, throughout the past few decades, numerous attempts have been undertaken to automate the identification of disease. Hyperspectral imaging is one of the noteworthy methods. Typically, satellites or aerial imaging equipment capture hyperspectral images, which are then utilized for wide-area surveillance. This approach's drawbacks include a small number of samples, high dimensionality, and an exceptionally high equipment cost that precludes it from being used for machine learning (ML) analysis.

II. LITERATURE SURVEY
1) The global burden of pathogens and pests on major food crops
AUTHORS: Savary, Serge, et al.
Pests and crop diseases lower the quality and yield of agricultural output. They diminish food security at the household, national, and international levels, and result in significant economic losses. It is challenging to gather and compare quantitative, standardized data on agricultural losses across crops, agroecosystems, and geographical areas. Here, we present an expert-based evaluation of crop health and offer quantitative yield loss estimates for each of the five major crops grown worldwide and in hotspots for food security, broken down by pathogen and pest. Our findings list losses related to 137 pests and diseases that are linked to wheat, rice, maize, potatoes, and soybeans globally. Our estimates of yield loss (range) for wheat (21.5% (10.1–28.1%), rice (30.0% (24.6–40.9%)), maize (22.5% (19.5–

41.1%), potatoes (17.2% (8.1–21.0%), and soybeans (21.4% (11.0–32.4%)) at the global and hotspot levels indicate that the regions experiencing food shortages and rapidly expanding populations are often linked to the highest losses. Our analysis reveals variations in the effects of pests and crop pathogens as well as hotspots for food security. Agroecosystems can better sustainably provide benefits to society by prioritizing crop health management, thanks to the vital information this study provides.

2)Using deep learning for image-based plant disease detection

AUTHORS: Mohanty, Sharada P., David P. Hughes, and Marcel Salathe.

Food security is greatly threatened by crop diseases, but in many regions of the world, there is insufficient infrastructure to identify them quickly. The field of smartphone-assisted disease detection has gained momentum because to the growing worldwide smartphone penetration rate and the advancements in computer vision that deep learning has made feasible. By training a deep convolutional neural network using a public dataset of 54,306 photos of healthy and diseased plant leaves that were collected under controlled conditions, we are able to recognize 26 illnesses and 14 crop species (or lack thereof). The trained model shows that this strategy is feasible, achieving 99.35% accuracy on a held-out test set. All things considered, the method of using publicly accessible, progressively larger image datasets to train deep learning models offers a direct route to widespread, smartphone-assisted crop disease detection.

3)A practical plant diagnosis system for field leaf images and feature visualization

AUTHORS: Fujita.

There has been a demand for an automated plant diagnosis system that is precise, quick, and inexpensive. Even though a number of research employing machine learning approaches have been carried out, there are still significant problems in the majority of cases when the dataset is not made up of field photographs and frequently contains a sizable number of incorrect labels. We present a workable automated plant diagnostic system in this paper. First, by growing plants under strict control, we create a very trustworthy dataset. Next, we create a strong classifier that can examine a broad range of field photos. In order to distinguish between Downy mildew, healthy plants, and seven common viral infections, we used 9,000 original photos of cucumber field leaves. We also depict the main foci of the diagnostic data. We confirm that our method catches key characteristics for the diagnosis of Downy mildew and achieve 93.6% average accuracy.

4)Textural features for image classification

AUTHORS: Robert M., Karthikeyan Shanmugam.

Whether an image is a photomicrograph, an aerial snapshot, or a satellite image, texture is one of the crucial factors utilized to identify items or areas of interest in an image. Using three different types of image data—photomicrographs of five different sandstone types, 1:20,000 panchromatic aerial photographs of eight land-use categories, and Earth Resources Technology Satellite (ERTS) multispeciality imagery—this paper describes some easily computed textural features based on gray-tone spatial dependencies and illustrates their use in category-identification tasks. To make decisions, we employ two different types of decision rules: a piecewise linear decision rule for convex polyhedra and a min-max decision rule for rectangular parallelepipeds. The data set for each experiment was split into a training set and a test set. The photomicrograph identification accuracy is 89 percent, the aerial photographic identification accuracy is 82 percent, and the satellite image identification accuracy is 83 percent. These findings suggest that a wide range of image-classification applications may benefit from the widespread applicability of the easily computed textural features.

5)Support-vector networks

AUTHORS: cortes,Corinna and Valdimir vapnik.

A new learning tool for two-group classification issues is the support-vector network. Conceptually, the machine implements the idea that input vectors are non-linearly mapped to a very large feature space. A linear decision surface is built in this feature space. High generalization ability of the learning machine is ensured by special qualities of the decision surface. The support-vector network's principle

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was previously put into practice for the constrained scenario where training data can be segregated without errors. Here, we extend this finding to training data that cannot be separated.Support-vector networks with polynomial input transformations are shown to have high generalizability. We contrast the performance of the support-vector network with a number of traditional learning methods that all participated in an Optical Character Recognition benchmark study.

III. BASIC STEPS FOR DISEASE DETECTION

In this section, the basic steps for plant disease detection and classification using image processing are shown (Fig. 1).

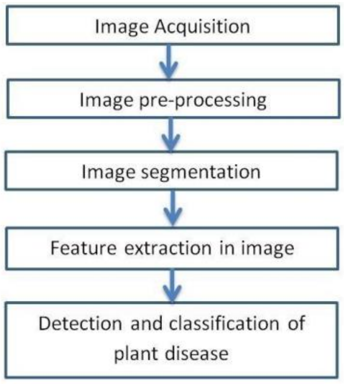

Fig. 1 Basic steps for plant disease detection and classification

A] Image Acquisition

The presence of an image is the primary requirement for performing image processing.An appropriate image with the required size and resolution must be provided. The image can be loaded from the root folder, or for real-time image processing,we can connect an external camera to our system. If necessary,we can use an online picture library to serve as an image source.Since the photos are kept in cloud storage,doing so allows us to load them directly otherwise,the system treats the input as a null matrix.

B] Image pre-processing

The incoming image is transformed into a two dimensional RGB matrix by the disease detection system. The dominant color of the input image can be identified as well as the classification of leaf image types based on the magnitude of the numbers inside the matrix. The input image is then transformed from conventional RGB format to LAB color space. preprocessing of the picture that was provided to enhance the image's quality and eliminate any unwanted distortion. To obtain the desired picture region, the leaf image is clipped. Next, the image is smoothed using the smoothing filter. To make the contrast stronger, Image enhancing is also carried out. Finally, every image has been shrunk to a uniform size.

C] Image segmentation

The input image contains all of the data needed to complete the processing. The fundamental challenge, though, is that the affected region could be anywhere on the picture. The K-means technique, which divides the image into tiny pieces and performs image processing on each one, is used to identify the damaged area. If any unaffected areas are found, they are not taken into account. If it finds the affected locations, it stores them for later investigation. The K-means algorithm divides the dataset into K pre-defined discrete non-overlapping subgroups using an iterative process.

k-Nearest Neighbor’s:

A very basic technique that is frequently used for classification problems is k-NN [7]. It lacks a training phase and is non-parametric, meaning it doesn't have a set amount of parameters. The underlying assumption of k-NN is that most samples within a class are located near to one another in the feature space. When classifying a sample, k-NN uses the simple majority rule to determine which class it belongs to by examining its k closest neighbors. Although they will be more susceptible to outliers, small values of k will permit greater non-linearity. While they accomplish good generalization, high values of k are unable to suit complex boundaries. Through experimentation, the ideal value for parameter k is found. In this dataset, low values of k were displayed.

Fully Connected Neural Network :-

The most basic kind of artificial neural network is FCNN. This approach for supervised learning can simulate highly nonlinear functions. It does not converge to the global optimum like SVM and k-NN do, but when set correctly, it typically produces results that are adequate.An FCNN with four hidden layers—two hundred, two hundred, one hundred, and fifty neurons in each layer—was employed by us. Reversed linear units (ReLUs), with softboxes in the output layer, serve as the activation function in hidden layers [8]. With a regularization parameter of 0.3, we employed L2 regularization. Adam optimizer was utilized with the default settings. We obtained an accuracy of 91.46% on the test set with this arrangement.

D] Feature Extraction

A key component of object identification is feature extraction. Feature extraction is employed in many image processing applications. Plant diseases can be detected using a variety of traits, such as color, texture, morphology, edges, etc. Color, texture, and morphology are taken into consideration by Monica Jhuria et al. in their study [3] as features for illness detection. They have discovered that morphological results outperform other features. The distribution of color, the image's hardness, and its roughness are all considered aspects of texture. Additionally, it can be applied to identify sections of plants that are sick.

i] Color co-occurrence Method :

Using this technique, the image's unique properties are obtained by considering both texture and color. In order to do that, the RGB image is translated into HSI.

$$H = \begin{cases} Theta & if\ B < G \\ 360 - Theta, & B > G \end{cases} \quad \text{.......(2)}$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R, G, B)] \quad \text{.......(3)}$$

$$I = \frac{1}{3}(R+G+B) \quad \text{...........(4)}$$

The SGDM matrix is created for the computation of texture statistics, and the feature is computed using the GLCM function.

ii) Leaf color extraction using H and B components:

Before separating the color from the background, the input image is improved by preserving the information of the impacted pixels using the anisotropic diffusion approach [8]. In order to differentiate the grape leaf from the non-grape leaf portion, the H and B components from the HIS and LAB color space are taken into account. To identify disease leaf hues, a backpropagation neural network-equipped SOFM is used.

E] Classification

i) **Using ANN**

Following feature extraction, a neural network is used to classify the images from the learning database. In an ANN, these feature vectors are regarded as neurons [3]. The function of the weighted sum of the inputs determines the neuron's output. It is possible to employ the multiclass support vector machines, modified SOM, and backpropagation technique.

ii) Back propagation:

In a recurrent network, the BPNN algorithm is employed. The neural network weights can be used to calculate output values for new query images that are not in the learning database once they have been trained and are fixed**.**

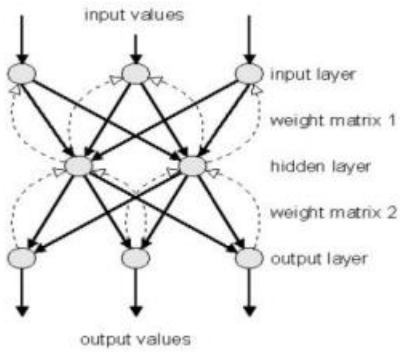

Fig. 2) Back propagation Network

Testing of query images :

The query image is tested once the learning database's weight has been determined. The flowchart for testing the query image using neural network techniques is displayed in Figure 3.

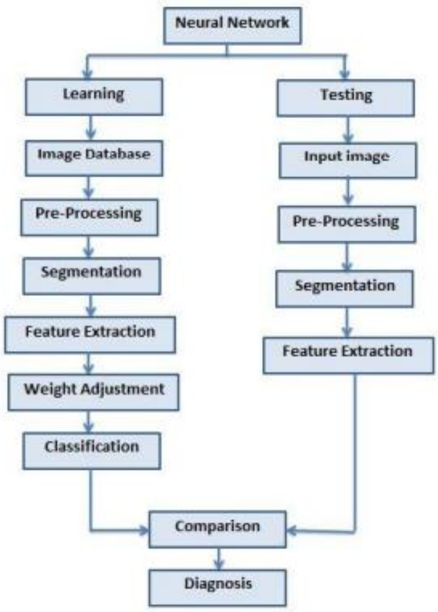

Fig. 3) Working principle of ANN

IV. CONCLUSION

For crop cultivation to be effective, precise plant disease identification and classification are essential, and image processing can help with this. This paper covered a number of methods for dividing the plant's diseased portion.

In addition, certain feature extraction and classification methods for identifying plant illnesses and obtaining information from infected leaf characteristics were covered. The achieved accuracy and ease of use of the method validate that the DL is the best choice for picture classification tasks involving huge datasets.

REFERENCES

[1] Wenjiang Huang, Qingsong Guan, Juhua Luo, Jingcheng Zhang, Jinling Zhao, Dong Liang, Linsheng Huang, and Dongyan Zhang, "New Optimized Spectral Indices for Identifying and Monitoring Winter Wheat Diseases", IEEE journal of selected topics in applied earth observation and remote sensing,Vol. 7, No. 6, June 2014

[2] Dr.K.Thangadurai, K.Padmavathi, "Computer Vision Image Enhancement For Plant Leaves Disease Detection", 2014 World Congress on Computing and Communication Technologies.

[3] Monica Jhuria, Ashwani Kumar, and Rushikesh Borse, “Image Processing For Smart Farming: Detection Of Disease And Fruit Grading”, Proceedings of the 2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013
[4] Zulkifli Bin Husin, Abdul Hallis Bin Abdul Aziz, Ali Yeon Bin Md Shakaff Rohani Binti S Mohamed Farook, “Feasibility Study on Plant Chili Disease Detection Using Image Processing Techniques”, 2012 Third International Conference on Intelligent Systems Modelling and Simulation.
[5] Mrunalini R. Badnakhe, Prashant R. Deshmukh, “Infected Leaf Analysis and Comparison by Otsu Threshold and k-Means Clustering”, International Journal of Advanced Research in Computer Science and Software Engineering, Volume 2, Issue 3, March 2012.
[6] H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik and Z. ALRahamneh, “Fast and Accurate Detection and Classification of Plant Diseases”, International Journal of Computer Applications (0975 – 8887)Volume 17– No.1, March 2011
[7] Chunxia Zhang, Xiuqing Wang, Xudong Li, “Design of Monitoring and Control Plant Disease System Based on DSP FPGA”, 2010 Second International Conference on Networks Security, Wireless Communications and Trusted Computing.
[8] A. Meunkaewjinda, P. Kumsawat, K. Attakitmongcol and A. Srikaew, “Grape leaf disease detection from color imagery using hybrid intelligent systems”, Proceedings of ECTI-CON 2008.
[9] Santanu Phadikar and Jaya Sil, “Rice Disease Identification using Pattern Recognition”, Proceedings of 11th International Conference on Computer and Information Technology (ICCIT 2008) 25-27 December, 2008, Khulna, Bangladesh.