Plant Health Monitoring with Photos based on Deep Learning

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***Abstract*—The quality and output of agricultural products can be affected by plant diseases. To safeguard the well-being of everyone on the planet, it is crucial to identify plant diseases as soon as possible. One of the most active research areas is autonomous plant disease detection. Large agricultural fields may be monitored with its help, and it aids in spotting disease signs when they appear on leaves. Finding plant diseases that cause reduced crop loss and, as a result, increase production efficiency is the major objective of this study. With the use of a Deep Learning (DL) approach, our suggested study can identify the first signs of plant diseases and classify them based on those signs. We hope to at most attain a 97percent accuracy in the disease detection with a deep CNN technique in this approach. The model's performance as a warm-up or early advisory tool will be validated by this accuracy rate. (abstract will be updated after the conclusion of the paper)**

***Index Terms*—Plant health monitoring, plant diseases, crop, crop products, deep learning, CNN**

I. Introduction

Finding plant diseases is one of the biggest issues the agriculture business has to deal with. In the past, knowledgeable individuals would identify diseases. It is exceedingly challenging for farmers to get in touch with professionals in remote towns. One of the main causes of plant diseases is climate change. In big farms, there is a significant loss in agricultural output if the illness is not identified at the appropriate time. Because they can't precisely view the farmer's issue at the service center, they occasionally advise farmers on plant diseases in the wrong way. The crop can be destroyed as a result of this.

Artificial intelligence (AI), deep learning (DL), and digital image processing (DIP) methods have all advanced significantly in recent years. It's critical to spot various plant diseases in their early stages in order to assist farmers. Therefore, it is essential to include these latest technology into contemporary approaches. The proliferation of plant diseases will result in a decrease in agricultural productivity. These diseases can harm plants, modify their structure, have an impact on the color and texture of the leaves, and even have an impact on the fruits, among other things. The characteristics of the diseases are quite similar. Therefore, it is very difficult for farmers to detect diseases in plants with their naked sight and they are unable to fully comprehend the severity of the condition, which might occasionally result in incorrect disease detection. Plant infections may be difficult to manage because of the less skilled or inexperienced farmers. Therefore, it is essential to create contemporary techniques that can help farmers spot ailments at an early stage and offer treatments for such diseases. For the recognition of diseases and various classifications of such diseases in plants, several researches [1], [2] have presented several machine learning methods, and image processing approaches. Machine learning algorithms are created for pattern extraction and image processing, which might lower the accuracy of a classification task. Deep learning algorithms are now mainly employed for pattern recognition since they have successfully identified various outlines. DL makes feature extraction automated. The DL delivers a high accuracy rate in the classification job and decreases error rate and computational time compared to other conventional machine learning methods. With the use of the CNN model, the primary goal of our work is to identify plant diseases and offer treatments for them.

The rest of the paper is followed by, Related work, then we introduce the deep learning algorithms, and then introduce the image processing for health monitoring, then the methodology with deep learning, then the implementation, result and discussion, then finally the conclusion.

II. Related Work

Finding plant diseases has mostly been done in the early stages using various machine learning approaches. The following stages are generally followed by all systems. Digital cameras are first used to capture the photographs. The photos are then preprocessed using several preprocessing methods. Then, the experts take the crucial elements out of those photos, and the classifier uses those features as inputs. Here, the method of image processing and feature extraction is what determines the classification accuracy. It takes a long time and is really difficult. Deep Convolutional neural networks (CNN) have recently demonstrated a considerable increase in picture segmentation and classification to improve classification accuracy in several domains, such as the categorization of digits and natural language. Because DL can utilize the picture directly, the computer vision community [16] accepted DL. The characteristics of the photos may be automatically learned by CNN using the datasets. It can be extracted and categorised more quickly with the same architecture.

This section discusses the most current developments in the use of CNN and deep learning architectures in agricultural applications. CNN uses photos of the leaves in [8] to identify diseases in cucumber leaves. Using CNN, they conducted their study and learned that two severe viral viruses are damaging the leaves: Melon Yellow Spot Virus (MYSV) and Zucchini Yellow Mosaic Virus (ZYMV). Their method has a 94.9% accuracy rate when using the Four-Fold Cross-Validation Strategy.

Hulya Yalcin et al. [9] employed a CNN model to identify and categorize the phonological phases of the various plants. He trained and tested the model using photos of leaves. Several plants were classified according to their phonological stage using a pre-trained AlexNet architecture. The accuracy of this model was 87%. This model provides great accuracy when compared to other conventional machine learning algorithms.

The author of study [10] utilized the LeNet architecture to identify diseases in soybean plants. Three various kinds of pictures, including segmented, colorful, and grayscale images, were employed by the author. The colorful picture provides an accuracy of 99.32% after categorization. In contrast to segmented and grayscale pictures, it is quite easy to extract characteristics from colorful images. In study [12], the author employed AlexNet and VGG-16, two common architectures, to recognize the diseases affecting tomato leaves. To make the dataset larger, the author also used data augmentation. In his writing, the author applied transfer learning. The accuracy of these two models was 96% and 97.49%, respectively. The author of this research came to the conclusion that adding more photos directly affects how well the network model performs.

III. Deep Learning

A neural network with three or more layers is essentially what deep learning, a subset of machine learning and AI, is all about. These neural networks attempt to emulate the functioning of the human brain, but they are unable to match the brain's capacity for learning from a massive quantity of data. The accuracy of predictions made by a single-layer neural network may be improved and refined with the help of additional hidden layers. AI has a topic called machine learning that enables a system to learn from concepts and information without having to be explicitly programmed. To prepare for data aspects and patterns and enhance upcoming outcomes and judgements, it starts with observations, such as in-person encounters. In order to represent high-level abstractions in data, a variety of machine learning methods are combined to create deep learning [3]. Deep learning has several benefits, one of which is feature learning, or the automated extraction of characteristics from raw data. A key benefit of deep learning is feature learning, or the automated extraction of features from raw data. The composition of lower-level components results in the production of features from higher hierarchy levels [4]. Two common deep learning networks used in agriculture are the recurrent neural network (RNN) and the convolutional neural network (CNN).

A. Convolutional Neural Network(CNN)

Multiple convolutional layers, pooling layers, and fully linked layers make up a CNN, a deep learning method [5]. The animal visual cortex serves as the foundation for this multi-layer neural network [6]. CNNs are mostly utilized for handwritten character recognition and picture processing. CNNs have been utilized in various computer vision research for a variety of tasks, including image classification, object identification, picture segmentation, speech recognition, text and video processing, and medical image analysis. Convolutional, pooling, and fully linked layers are the traditional building blocks of a CNN architecture [7]. The architecture of CNNs is shown in Figure 1, and the layers are briefly described:

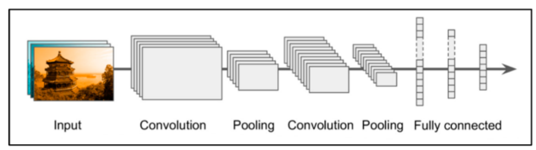

Fig. 1. A CNN Architecture [7]

1) Convolutional Layer: The most fundamental layer in a CNN is the convolutional layer. To create an activation map for the given image, the resulting pixel matrix for the supplied image or object is rotated or multiplied. The fundamental benefit of the activation map is that it stores all the distinctive features of a picture while reducing the quantity of data that has to be processed at once. Different picture variations are produced by using varying feature detector levels once the data is merged in a feature detector matrix. In order to obtain the least amount of error feasible in each layer, the complex model is additionally trained via backpropagation. The error set with the fewest mistakes determines the depth and padding [7]. The extraction of visual characteristics is done by the convolutional layer. Figure 2 shows the process of the convolution operation.

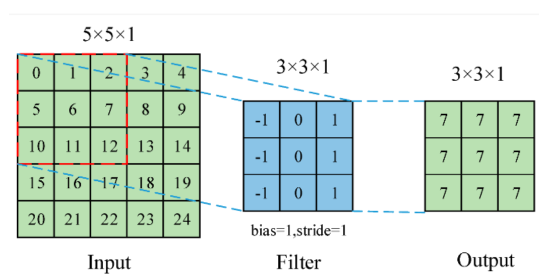

Fig. 2. A Convolution Operation Process [19]

2) Pooling Layer: It is a critical step that seeks to further reduce the size of the activation map while simultaneously retaining just the fundamental characteristics and decreasing the remarkable invariance. The model's learnable feature count is subsequently decreased, which helps to alleviate the overfitting problem. In order to recognize the provided item, a CNN must pool all the distinct dimensions of the image. This is possible even if the object's shape is distorted or at an odd angle. There are several methods for doing pooling, including maximum pooling, average pooling, stochastic pooling, and spatial pyramid. Max pooling is the approach most frequently employed [7]. Figure 3 shows the process of the pooling operation

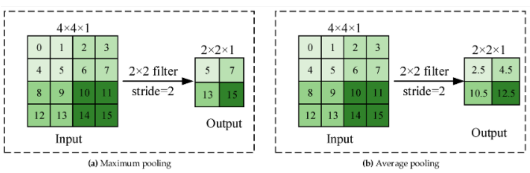

Fig. 3. A Pooling Operation Process [19]

3) Fully Connected Layer: The neural network is fed in this last layer. The matrix is typically flattened before being sent to the neurons. After this, data are challenging to follow because of several hidden layers with variable weights for each neuron's output. Here, all data computation and reasoning take place [7].

B. Recurrent Neural Network (RNN)

The neural sequence model known as an RNN excels at critical tasks including language modeling, speech recognition, and machine translation [17]. RNNs, as opposed to conventional neural networks, utilize the sequential information of the network; this feature is crucial in many applications where the underlying structure of the data sequence provides significant information. For instance, you need to comprehend the context before you can grasp a word in a phrase. The input layer x, hidden (state) layer s, and output layer y make up an RNN, which may be thought of as a short-term memory unit [6]. An RNN's general construction is shown in Figure 4. A RNN architecture called long short-term memory (LSTM) was developed to model temporal sequences and their long-term associations with more accuracy than standard RNNs [18]. The LSTM architecture is shown in Figure 5.

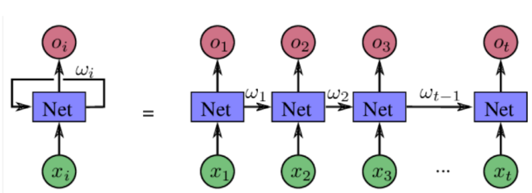

Fig. 4. A Generic Structure of RNN [6]

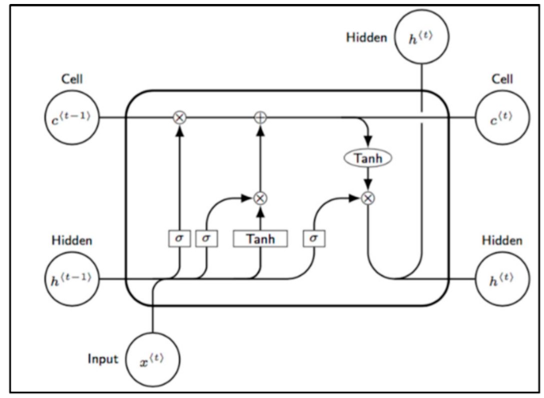

Fig. 5. A LSTM Architecture [18]

IV. Plant Health Monitoring With Photo Based

Techniques for image processing can be used to find plant diseases. Disease signs are often visible on the fruit, stem, and leaves. The plant leaf is taken into consideration for disease identification as it exhibits disease signs. This study provides an introduction to the image processing method used to find plant diseases. The fundamental procedures for plant disease classifications and detection utilizing image processing are displayed in figure 6.

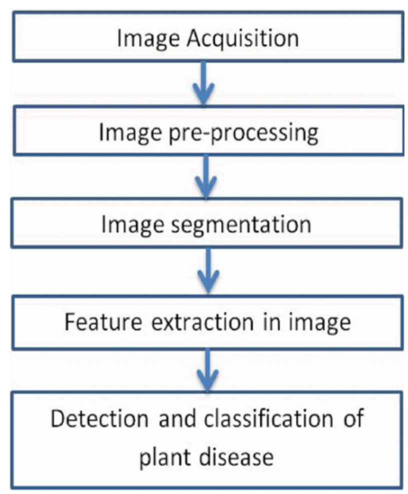

Fig. 6. Plant Disease Detection and Classification using photos/image processing [2]

A. Image Acquisition

The camera is used to take pictures of the plant leaf. Red, Green, and Blue, or RGB, is the format for this picture. A device-independent colour space transformation is then performed to the colour transformation structure, which was first generated for the RGB leaf picture [2].

B. Image Pre-Processing

Various pre-processing approaches are taken into consideration in order to reduce noise from images or other objects.

Picture clipping, or cropping, is the process of selecting the desired area of a leaf image. The smoothing filter is used for image smoothing. The purpose of image enhancement is to boost contrast, the RGB photos into the grey images utilizing equation(1) to convert colours.

$$\mathrm{f(x)} = 0.2989^{*}\mathrm{R} + 0.5870^{*}\mathrm{G} + 0.114^{*}\mathrm{B} - - - - - - - \quad (1)$$

Then, histogram equalization, which distributes image intensities, is applied to improve the pictures of plant diseases. Intensity values are distributed using the cumulative distribution function [20].

C. Image Segmentation

Segmentation is the division of a picture into different parts with the same properties or similarities. Several techniques can be used for segmentation, including the otsu method, k-means clustering, and transforming the RGB picture into the HIS model.

D. Feature Extraction in Image

The identification of an item depends heavily on feature extraction. The use of feature extraction in image processing is widespread. The characteristics that may be employed in the identification of plant diseases include colour, texture, morphology, edges, and others. In their study [21], Monica Jhuria et al. take into account morphology, colour, and texture as features for illness identification. They discovered that morphological results outperform other characteristics. The term ”texture” refers to the image’s hardness, roughness, and colour distribution. Infected plant regions can be found using it as well.

1) Color Co-Occurrence Method: This technique uses both colour and texture to give a picture its own distinctive traits. To do so, the RGB picture is translated into the HSI format.

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

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

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

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

2) Leaf Color Extraction Using H and B Components: Before separating the colour from the background, the input picture is improved using the anisotropic diffusion approach to retain the information of the impacted pixels [22]. H and B components from the HIS and LAB colour spaces are taken into account to differentiate between the grape leaf and the non-grape leaf section. The use of a SOFM with a back propagation neural network enables the identification of disease leaf hues.

E. Detection and Classification

1) Using ANN: Following feature extraction, neural networks are used to classify the learning database photos. In an ANN, these feature vectors are regarded as neurons [21]. The neuron’s output is a function of the inputs’ weighted total. The back propagation method, Multiclass Support Vector Machines, and Modified SOM may all be employed.

2) Back Propagation: A recurrent network employs the BPNN algorithm. The neural network weights are fixed after they have been learned and may be used to compute output values for new query photos that are not already in the learning database.

V. Plant Health Monitoring With Photo Based on Deep Learning

This section describes the suggested methods for identifying plant diseases. Different image processing techniques using deep learning algorithms are applied to the picture of a leaf to categorize it as having a disease or not by taking into account that image.

A. Resnet50

VI. Implementation

The whole procedure, including data collection, preprocessing, feature extraction, and model creation, is described in length in this section. Utilizing metrics for performance evaluation, the model will be verified.

A. Dataset Collection

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B. Dataset Preprocessing

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C. Model Building

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D. Feature Extraction

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E. Classification

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VII. Result and Discussion

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VIII. Conclusion

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REFERENCES

[1] A Akhtar, A Khanum, SA Khan and A Shaukat, "Automated Plant Disease Analysis (APDA): Performance Comparison of Machine Learning Techniques", 11th International Conference on Frontiers of Information Technology IEEE Computer Society, pp. 60-65, 2013.

[2] Al Hiary H, Bani Ahmad S, Reyalat M, Braik M and ALRahamneh Z, "Fast and Accurate Detection and Classification of Plant Diseases", International Journal of Computer Applications, vol. 17, no. 1, pp. 31-38, 2011.

[3] Dargan, S.; Kumar, M.; Ayyagari, M.R.; Kumar, G. A survey of deep learning and its applications: A new paradigm to machine learning. Arch. Comput. Methods Eng. 2020, 27, 1071–1092.

[4] LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. Nature 2015, 521, 436–444.

[5] Zhu, N.; Liu, X.; Liu, Z.; Hu, K.; Wang, Y.; Tan, J.; Guo, Y. Deep learning for smart agriculture: Concepts, tools, applications, and opportunities. Int. J. Agric. Biol. Eng. 2018, 11, 32–44.

[6] Pouyanfar, S.; Sadiq, S.; Yan, Y.; Tian, H.; Tao, Y.; Reyes, M.P.; Shyu, M.-L.; Chen, S.C.; Iyengar, S.S. A survey on deep learning: Algorithms, techniques, and applications. ACM Comput. Surv. (CSUR) 2018, 51, 1–36.

[7] Ajit, A.; Acharya, K.; Samanta, A. A review of convolutional neural networks. In Proceedings of the 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), Vellore, India, 24–25 February 2020.

[8] Y Kawasaki, H Uga, S Kagiwada and H Iyatomi, "Basic Study of Automated Diagnosis of Viral Plant Diseases Using Convolutional Neural Networks", Advances in Visual Computing: 11th International Symposium ISVC 2015, pp. 638-645, December 14–16, 2015.

[9] Hulya Yalcin, Plant Phenology Recognition using Deep Learning: Deep-Pheno.

[10] "Soybean Plant Disease Identification Using Convolutional Neural Network Serawork Wallelign Jimma Institute of Technology" in Ethiopia LAB-STICC ENIB France wallelign@enib.fr Mihai Polceanu LAB-STICC ENIB France polceanu@enib.fr C' edric Buche LAB-STICC ENIBFrance buche@enib.fr Copyright(c), Association for the Advancement of Artificial Intelligence, 2018

[11] X. Wu and C.-N. Yang, "Partial reversible AMBTC-based secret image sharing with steganography," Digital Signal Processing, vol. (leaf annotation).

[12] Aravind Krishnaswamy Rangarajan, Raja urushothaman and Aniirudh Ramesh, "Tomato crop disease classification using pre-trained deep learning algorithm", ELSEVIER International Conference on Robotics and Smart Manufacturing, 2018. 93, pp. 22–33, Oct. 2019.

[13] A Krizhevsky, I Sutskever and GE Hinton, "ImageNet Classification with Deep Convolutional Neural Networks", Commun, vol. 60, no. 6, pp. 84-90, 2017

[14] N. Srivastava, G. Hinton, A Krizhevsky, I. Sutskever and R. Salakhutdinov, "Dropout: a simple way to prevent neural network from overfitting", Journal of Machine Learning Research, vol. 15, pp. 1929-1958, 2015.

[15] SP Mohanty, DP Hughes and M Salathe, "Using Deep Learning for Image- ' Based Plant Disease Detection", Frontiers in Plant Science, vol. 7, pp. 1-7, September 2016.

[16] Shakya Subarna, "Analysis of Artificial Intelligence based Image Classification Techniques", Journal of Innovative Image Processing (JIIP), vol. 2, no. 01, pp. 44-54, 2020.

[17] Zaremba, W.; Sutskever, I.; Vinyals, O. Recurrent neural network regularization. arXiv 2014, arXiv:1409.2329.

[18] Sak, H.; Senior, A.; Beaufays, F. Long short-term memory recurrent neural network architectures for large scale acoustic modeling. arXiv 2014, arXiv:1402.1128.

[19] Gu, J.; Wang, Z.; Kuen, J.; Ma, L.; Wang, G. Recent Advances in Convolutional Neural Networks. Pattern Recognit. 2015, 77, 354–377.

[20] K. Thangadurai and K. Padmavathi, "Computer Visionimage Enhancement For Plant Leaves Disease Detection", World Congress on Computing and Communication Technologies, 2014.

[21] 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.

[22] A. Meunkaewjinda, P. Kumsawat, K. Attakitmongcol and A. Srikaew, "Grape leaf disease detection from color imagery using hybrid intelligent system", Proceedings of ECTI-CON, 2008.