ISSN 2347 - 3983
Volume 11. No.7, July 2023
International Journal of Emerging Trends in Engineering Research
Available Online at http://www.warse.org/IJETER/static/pdf/file/ijeter021172023.pdf
https://doi.org/10.30534/ijeter/2023/021172023

Computer Vision based Plant Disease Detection using Machine Learning Technique

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Received Date: May 25, 2023 Accepted Date: June 23, 2023 Published Date : July 07, 2023

ABSTRACT

Our lives would be incomplete without agriculture. As a result, disease identification is crucial in agriculture since untreated diseases cause many plants to go extinct. Since it is always visible and available, the leaf picture was chosen for detecting purposes. In addition to helping plants develop quickly, leaves also help plants produce more food. The suggested system may identify plant leaf disease by using an image of the leaf as the source data. In order to train computers and produce accurate predictions, AI systems also require a large amount of data. The diagnosis and detection of plant leaf disease is a crucial component of an AI-based system model for the agricultural sector. In this paper, performance-improving machine learning algorithms are presented for image-based plant leaf disease diagnosis. Python version 3.7 is used to run the simulation. The total accuracy for identifying various plant leaf diseases is 98%.

Key words: Agriculture, Leaf Detection, Disease Identification, Accuracy, Disease Name, Support Vector Machine.

1. INTRODUCTION

An important field of research in the use of agriculture is a self-management system based on artificial intelligence for the management of plants. The model that can correctly identify educational elements in tomato images without the need for manual explanation, such as bouncing boxes or pieces. The model's Area organization first locates educational districts in the tomato image and then streamlines emphasises with the help of the Input organization. Then, for order, the Arrangement network makes use of the complete image of the tomato and the enlightening districts suggested by the Area organization. Our model can be seen as a coordinated multi-network effort that allows organizations to advance together. The orientation for crop care administration travels immediately from the time of gathering as the endpoint to the planting of seeds as the starting point. The intricately arranged data gathered from IoT sensors in the field is explored along with the data gathered from sources of data locations and domain master inputs wherever it is needed using artificial intelligence techniques. The general restorative action is deduced from the (Proportional Integral and Derivative) PID regulator instrument following the analysis of all available information. In a similar way, the farmer is informed of the remedial procedures on their PDA to concentrate on the activity dependant on seriousness and desperation.

Figure 1: Sample of diseased image

Plant infection, especially in agricultural plants, poses a serious threat to global food security because many diseases directly affect the nature of organic products, grains, etc., decreasing farming productivity. Ranchers must determine if a leaf was infected by unaided sight and take appropriate action. This interaction is dubious, contradictory, and mistake prone. There have been a few proposals for using deep learning techniques to discriminate between leaf diseases. The majority of them used convolutional neural networks (CNNs) to create their models based on specific target images. The yield of tomatoes is actually affected by tomato leaf infection. Agriculture economics genuinely needs to differentiate between farming maladies. The traditional information expansion techniques, such as pivot, flip, and interpretation, are severely constrained and unable to produce excellent speculation results.

2. BACKGROUND

A rebuilt leftover thick organization was proposed by C. Zhou et al. [1] for the identification of tomato leaf infections. This hybrid deep learning model combines the advantages of deep lingering organizations and thick organizations, which can reduce the number of preparation process boundaries to increase estimation precision as well as improve the progression of data and angles. A deep learning-based component extraction technique is put out by S. Barburiceanu et al. [2] for the identification of plant species and the classification of plant leaf diseases. By reexamining the typical handling pipeline, we focus on outcomes applicable to ongoing handling scenarios that may be conveniently transferred to monitored/automated horticultural brilliant apparatus (such as farm transporters, drones, robots, IoT brilliant sensor organizations, and so forth).

According to M. Ahmad et al.,[3] convolutional neural nets have demonstrated cutting-edge performance in picture characterization and various other PC vision tasks. Discovering plant infections is a crucial field of deep learning that has been addressed by various novel techniques. However, there is a critical need to streamline these solutions for resource-constrained small devices, such cell phones. L. Falaschetti and others,[4] The overburdened CNN organization has been produced on a specific dataset and executed in a low-power, low-cost Python programmable machine vision camera for continuing arrangement. The results of a thorough trial and error process demonstrate that the LR-Net predominates the best networks in terms of both induction time and performance.

A fine-grained-GAN based grape leaf spot distinguishing proof technique was presented by C.Zhou et al.,[5] for the creation of neighborhood spot region pictures that were added and cared for them into deep-learning models for preparing to additionally strengthen the speculation capacity of the characterization models, which can successfully work on the accuracy and vigor of the expectation. Citrus natural product infections are cited by A.Khattak et al. [6] as the main cause of excessive citrus natural product yield declines. Therefore, it is important to plan a robotized identification framework for diseases of citrus plants. Recently, deep learning algorithms have shown promise in a number of artificial consciousness problems, which has motivated us to put them to the test when it comes to the perception of citrus meals developed from ground illness.

Fake recognition of tomato sicknesses is frequently tiresome, insistent, and emotional, according to G. Yang et al.'s [7] presentation. It can be challenging to arrange tomato leaf-based images in a fine-grained manner because it is difficult to identify subtle discriminative highlights between different tomato illnesses in tomato infection photographs. T. N. Pham et al.'s [8] presentation In this study, we use a fake neural organization (ANN) strategy to target identifying early infection on plant leaves with little disease masses that must be diagnosed with higher objective photos. Each of the permeating masses is divided for the entire dataset after a pre-handling phase using a difference improvement method.

The proposed Leaf GAN model by B. Liu, C. Tan, S. et al. [9] produces enough images of grape leaf disease with obvious lesions, offering a workable option for the data augmentation of images of grape leaf disease. The identification performance based on CNNs demonstrated higher accuracies for the eight dominant classification models with the expanded dataset, and all of the accuracies were higher than those of the initial dataset with alternative data augmentation techniques. The proposed novel method of data augmentation using generative adversarial networks (GANs) is proposed for leaf disease recognition in order to enhance Q. Wu, Y. Chen., [10] the recognition accuracy of tomato leaf illnesses. This model can achieve a top-1 average identification accuracy of 94.33% using generated images supplemented by deep convolutional generative adversarial networks (DCGAN) and original images as the input of GoogLeNet. The authors Q. Dai and X. Cheng [11] suggest DATFGAN, a generative adversarial network with topology-fusion and dual-attention methods, to solve this issue. This network is capable of converting hazy images into sharp, high-resolution ones. Additionally, our suggested network's weight sharing technique can substantially lower the number of parameters. The author advised a transmission module is created to link the detection module with the fine-tuning network, according to J. Sun and Y. Yang [12]. In order to increase the detection precision of small target diseases, the transmission module on the one hand combines the properties of the low-level and high-level. The feature sharing between the detection module and the fine-tuning network, on the other hand, is realized by the transmission module, which transforms the feature map linked to the fine-tuning network to the detection module. The detection module uses the optimized anchor as input in the third stage and concentrates on finding the unhealthy leaves. The time-consuming technique of using candidate regions layer by layer to identify is removed by sharing the properties of the transmission module. As a result, the overall model's efficiency is now equal to that of the one-stage model. Generalized intersection over union (GIoU) is used in place of the loss function to further enhance the model's detection capabilities.

The suggested methodology entails segmenting the plant leaves in the top-view photos captured during the flight using the SLIC [13] E. C. Tetila et al. method. We used an end-to-end computer vision approach to verify our data set that was derived from actual flight inspections. Author proposes a deep learning approach [14] P. Jiang that is based on improved convolutional neural networks (CNNs) for the real-time detection of apple leaf diseases. In this paper, the apple leaf disease dataset (ALDD), which is composed of laboratory images and complex images under real field conditions, is first constructed via ., data augmentation and image annotation technologies.

3. METHODOLOGY

The proposed methodology is built on the following sub modules:

- Data Collection
- Data Preprocessing
- Feature Extraction & Feature Optimization
- Classification
- Prediction
- Result Generation

Data Collection

The process of choosing data in the form of an image for identifying plant spices is known as data selection. In this study, the plant disease is identified using a random dataset.

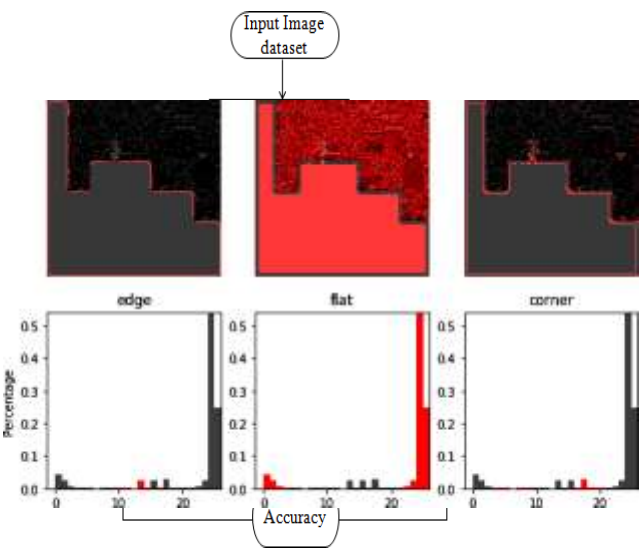

Figure 2: Architecture of the proposed methodology

Data Preprocessing

Missing data removal: In this step, zero is substituted for null values such as missing values and Nan values.

Feature Extraction and Feature Optimization

A global optimization technique called Spider Monkey Optimization (SMO) was inspired by the fission-fusion social structure of spider monkeys during foraging behavior. SMO, a swarm intelligence-based algorithm, has grown in prominence in recent years and is now being used to solve numerous engineering optimization issues. SMO is a collaborative iterative process based on trial and error, just like the other population-based algorithms. Six parts make up the SMO process: Local Leader, Global Leader, Local Leader Learning, Global Leader Learning, Local Leader Decision, and Global Leader Decision.

Classification: Support Vector Machine

These data points are sent into a support vector machine, which produces the hyperplane—which is just a line in two dimensions—that best separates the tags. The decision boundary is represented by this line; everything falling on one side of it will be classified as blue, and anything falling on the other as red. Support Vector Machine (SVM) is a supervised algorithm that may categorize cases by employing a separator to separate an informational index into at least two classes. When information is not otherwise linearly separable, SVM works by: Mapping information to a high-dimensional component space so that information points can be sorted (kernelling).

4. EXPERIMENTAL ANALYSIS & RESULTS

For an experiment, the input data for the plant leaf image is shown in Figure 3. 32 photos in total, including tomato, banana, mango, and paper mulberry, were taken with seven distinct diseases

Figure 3: Sample of dataset

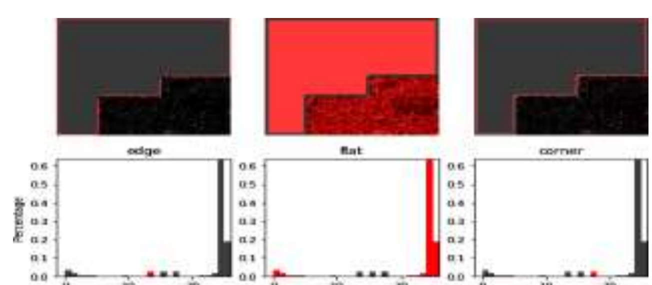

Figure 4: Training of image data

Due to training, this image data learned about various edges, flats, and corners at varied textures by employing the image features in terms of edge, flat, and corner.

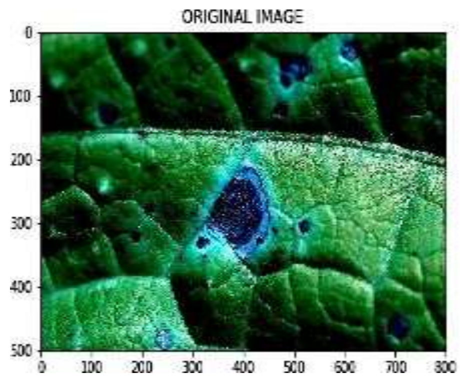

Figure 5: Tomato Leaf input original image

The input leaf image for identifying the plant disease is shown in Figure 5.

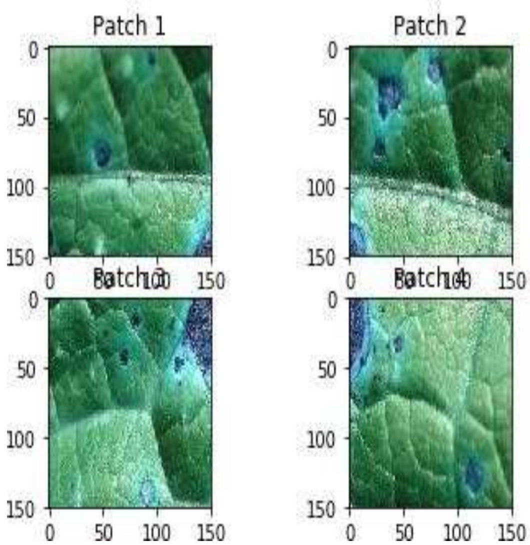

Figure 6: Patch Segmentation Sub plot

The segmentation or subplot of the processing plant leaf image is shown in Figure 6. Various edges and corners are taken into accounts here that are affected.

Table 1: Simulation Result

S. No.	Parameters	Values (%)
1	Accuracy	98
2	Precision	100
3	Recall	96
4	F-measure	97

The simulation parameters value shown in Table 1 was derived using the formula shown below:

Table 2: shows predictive conditions

Metric	Formula and Description
True Positive Rates (TPR)	*TPR = TP / (TP + FN)*
False Positive Rates (FPR)	*FPR = FP / (FP + TN)*
Precision	*Precision = TP / (TP + FP)*
Recall	*Recall = TP / (TP + FN)*
F-Measure	*F-Measure = 2TP / (2TP + FP + FN)*
Accuracy	*Accuracy = (TP + TN) / (TP + TN + FP + FN)*

Table 3: shows predictive

S.No.	Parameters	Previous Work [1]	ProposedWork
1	Method	Restructured residual dense network model	SVM andSMO
2	Accuracy (%)	95	98
3	Error Rate (%)	5	2

The findings parameters comparison between the prior work and the proposed work is shown in Table 3. The accuracy obtained using the suggested approach is 98%, compared to the previous 95%.

5. CONCLUSION

In this paper, to get the accurate result, put out a performance-improving adaptive machine learning strategy for identifying plant leaf diseases using images. The plant disease prediction is optimized and detected using the spider monkey optimization (SMO) and support vector machine (SVM). The accuracy obtained using the suggested approach is 98%, compared to the previous 95%. The proposed work has a 2% error rate while the existing work has a 5% error rate. As a result, the proposed methodology produced superior outcomes than the ones already obtained.

ACKNOWLEDGEMENT
The authors wish to acknowledge the Management and Staff of Kongunadu Arts and Science College, Coimbatore, Tamil Nadu, India, for supporting all the facility to complete this study.

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