Plant Disease Detection using SVM based Machine Learning Technique

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***Abstract*— Artificial Intelligence (AI) based model is using for various application. The technology advancement is applying in on the large area that is agriculture Sector. AI systems also need a lot of data to train machines and to make precise predictions. Plant leaf disease detection and identification is important part of AI based system model for agriculture field. This research presents machine learning techniques for image based plant leaf disease identification with performance improvement. The Simulation is performed using Python sypder 3.7 version. The overall accuracy is achieved 98% in different plant leaf disease identification.**

***Keywords*— Sypder, Python, Accuraccy, AL, Plant, Disease, Machine Learning.**

I. Introduction

A self-management system based on the artificial intelligence for the plants management is key research area in the application of agriculture. The model, which can adequately recognized instructive areas of tomato picture without the requirement for manual explanation, for example, bouncing boxes/parts. The Area organization of the model initially identifies instructive districts in the tomato picture, and streamlines emphasess under the direction of the Input organization. Then, at that point, the Arrangement network utilizes enlightening districts proposed by the Area organization and the full picture of the tomato for order. Our model can be viewed as a multi-network coordinated effort, and organizations can advance together.

The crop care administration direction traverses directly from the planting of seeds as start point till the hour of gathering as endpoint. The complex organized information examined from IoT sensors from the fields are investigated alongside the information gathered from wellsprings of data locales alongside domain master inputs any place required through Artificial Intelligence methods. After the investigation of complete information, the general restorative thing to do is inferred out of PID regulator

instrument. In like manner, the restorative measures are made aware of the farmer on their PDA to focus on the activity dependent on seriousness and desperation.

Figure 1: Sample of diseased image

Plant infection, particularly crop plants, is a significant danger to worldwide food security since numerous illnesses straightforwardly influence the nature of the organic products, grains, etc, prompting a diminishing in farming efficiency. Ranchers need to notice and decide if a leaf was contaminated by unaided eyes. This interaction is questionable, conflicting, and blunder inclined. A few deals with deep learning methods for distinguishing leaf infections had been proposed. The vast majority of them fabricated their models dependent on restricted goal pictures utilizing convolutional neural organizations (CNNs). Tomato leaf infection truly influences the yield of tomato. Agricultural economy actually should distinguish farming sicknesses. The conventional information expansion strategies, like pivot, flip and interpretation, are seriously restricted, which can't accomplish great speculation results. To further develop the acknowledgment precision of tomato leaf sicknesses, another strategy for information expansion by generative antagonistic organizations (GANs).

II. BACKGROUND

C. Zhou et al.,[1] presents, a rebuilt leftover thick organization was proposed for tomato leaf infection ID; this half and half deep learning model consolidates the upsides of deep lingering organizations and thick organizations, which can diminish the quantity of preparing process boundaries to further develop estimation precision just as upgrade the progression of data and angles.

S. Barburiceanu et al.,[2] propose a deep learning-based component extraction strategy for the recognizable proof of plant species and the grouping of plant leaf illnesses. We center around results applicable to ongoing handling situations that can be handily moved to monitored/automated horticultural brilliant machinery (for example farm haulers, drones, robots, IoT brilliant sensor organizations, and so forth) by reexamining the normal handling pipeline.

M. Ahmad et al.,[3] presents, convolutional neural organizations have shown cutting edge execution in picture characterization and different other PC vision undertakings. Plant infection discovery is a significant area of deep learning which has been tended to by numerous new strategies. Notwithstanding, there is a desperate need to streamline these answers for asset obliged compact gadgets, for example, cell phones.

L. Falaschetti et al.,[4] The packed CNN organization so got has been prepared on a particular dataset and carried out in a low-power, minimal expense Python programmable machine vision camera for ongoing arrangement. A broad trial and error has been led and the outcomes accomplished show the prevalence of LR-Net with deference over the best in class networks both as far as induction time and memory inhabitance.

C. Zhou et al.,[5] presents a fine grained-GAN based grape leaf spot distinguishing proof technique was proposed for nearby spot region picture information increase to the created neighborhood spot region pictures which were added and taken care of them into deep learning models for preparing to additionally reinforce the speculation capacity of the characterization models, which can viably work on the precision and vigor of the expectation. .

A. Khattak et al.,[6] presents citrus natural product illnesses are the significant reason for outrageous citrus natural product yield decreases. Therefore, planning a robotized identification framework for citrus plant illnesses is significant. Deep learning strategies have as of late acquired promising outcomes in various man-made consciousness issues, driving us to apply them to the test of perceiving citrus foods grown from the ground illnesses.

G. Yang et al.,[7] presents fake acknowledgment of tomato illnesses is regularly tedious, relentless and emotional. For tomato infection pictures, it is hard to track down little discriminative highlights between various tomato illnesses, which can carry difficulties to fine-grained visual arrangement of tomato leaf-based pictures. T. N.

Pham et al.,[8] presents In this examination, we target recognizing early infection on plant leaves with little illness masses, which must be identified with higher goal pictures, by a counterfeit neural organization (ANN) approach. After a pre-handling step utilizing a difference improvement strategy, every one of the pervaded masses is divided for the entire dataset.

III. METHODOLOGY

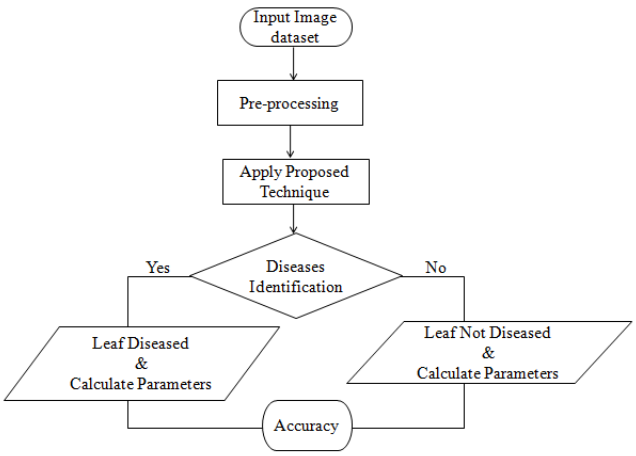

Figure 2: Flow Chart

The proposed methodology is based on the following sub modules-

- Data Selection and Loading
- Data Preprocessing
- Feature Extraction & Feature Optimization
- Splitting Dataset into Train and Test Data
- Classification

- Prediction
- Result Generation

Data Selection and Loading

- The data selection is the process of selecting the data in form of image for detecting the plant spices.
- In this research, the random dataset is used for detecting the plant disease.

Data Preprocessing

- Missing data removal: In this process, the null values such as missing values and Nan values are replaced by 0.

Feature Extraction & Feature Optimization

Spider Monkey Optimization (SMO) is a global optimization algorithm inspired by Fission-Fusion social (FFS) structure of spider monkeys during their foraging behavior. SMO has gained popularity in recent years as swarm intelligence based algorithm and is being applied to many engineering optimization problems. Similar to the other population-based algorithms, SMO is a trial and error based collaborative iterative process. The SMO process consists of six phases: Local Leader phase, Global Leader phase, Local Leader Learning phase, Global Leader Learning phase, Local Leader Decision phase and Global Leader Decision phase.

Classification: Support Vector Machine

A support vector machine takes these data points and outputs the hyperplane (which in two dimensions it's simply a line) that best separates the tags. This line is the decision boundary: anything that falls to one side of it we will classify as blue, and anything that falls to the other as red.

Support Vector Machine (SVM) is a supervised calculation that can classify cases by isolating an informational index into at least two classes using a separator. SVM works by: Mapping information to a high-dimensional component space so that information points can be sorted (kernelling), in any event, when the information are not otherwise linearly separable.

IV. Simulation and Result Discussion

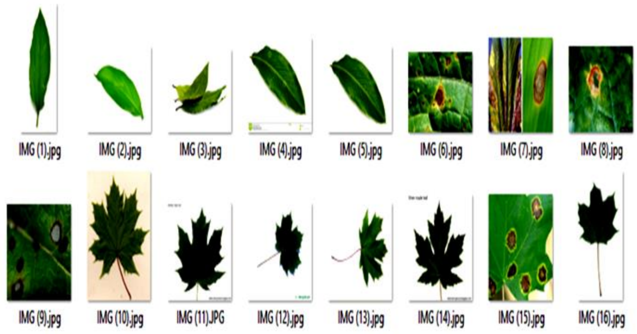

Figure 3: Sample of dataset

Figure 3 is showing the plant leaf image input data. Total 32 images taken with 7 different disease, which includes tomato, banana, ginger, mango, norway maple, onion and paper mulberry.

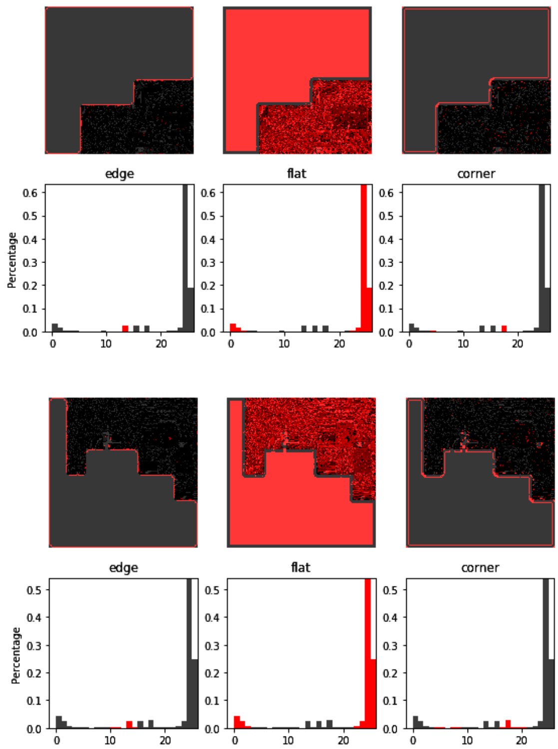

Figure 4: Training of image data

This image data trained by using the image features in terms of edge, flat corner, due to training its learn about various edges, flats and corners at different texture.

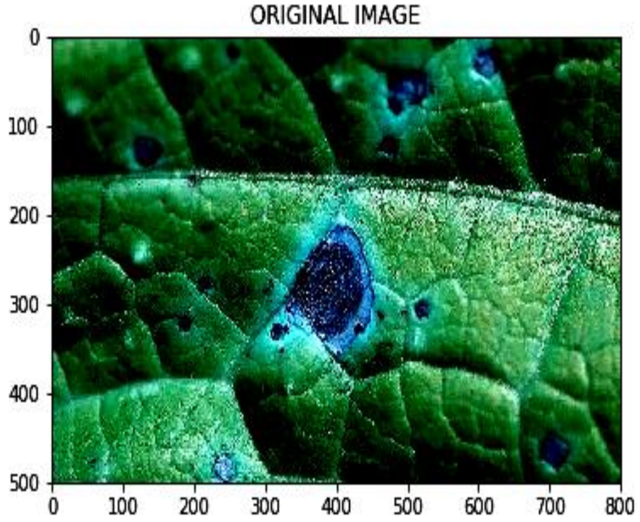

Figure 5: Tomato Leaf input original image

Figure 5 is presenting the input leaf image for the identification of the plant disease

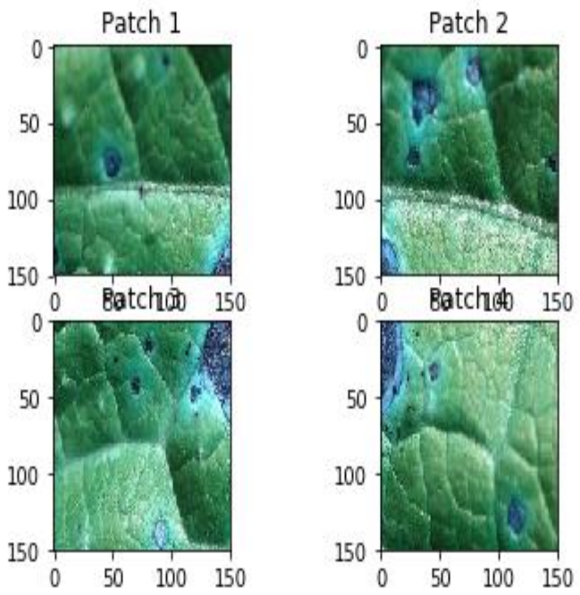

Figure 6: Patch Segmentation Sub plot

Figure 6 is presenting the segmentation or sub plot of the processing plant leaf image. Here various edge, corner is considered which is effeccted.

Table 1: Simulation Result

Sr. No.	Parameters	Values (%)
1	Accuracy	98
2	Classification Error	2
3	Precision	100
4	Recall	96
5	F-measure	97
6	Sensitivity	96
7	Specificity	100

Table 1 is presenting simulation parameters value, which is calculated by the following standard formula-

Precision = True Positive/(True Positive + False Positive)

Recall = True Positive/(True Positive + False Negative)

F1-Score = 2x (precision x recall)/(precision + recall)

Accuracy = (TP + TN)/(TP + TN + FP + FN)

Error Rate = 100 – Accuracy

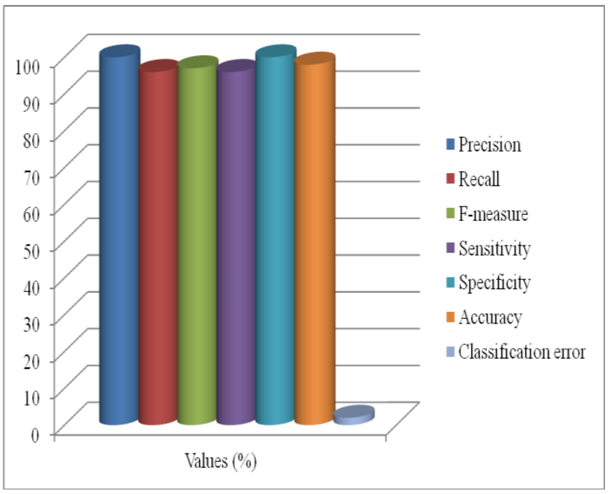

Figure 7: Comparison graph

Table 2: Result Comparison

Sr No.	Parameters	Previous Work [1]	Proposed Work
1	Method	Restructured residual dense network model	SVM and SMO
2	Accuracy (%)	95	98
3	Error Rate (%)	5	2

Table 2 is showing the results parameters comparison of the previous work and the proposed work. The accuracy achieved by the proposed approach is 98% while previous it is 95%.

IV. CONCLUSION

This research proposed an adaptive machine learning approach for image based plant leaf disease identification with performance improvement. The spider monkey optimization and support vector machine is used to optimize and identified the plant disease prediction. The accuracy achieved by the proposed approach is 98% while previous it is 95%. Error rate is 2% by the proposed work while 5% by the previous work. Therefore proposed methodology achieved better result than the existing results.

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