Multiple Leaf Disease Detection by Hybrid Machine and Deep Learning SVM-CNN Model

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ABSTRACT
Identity of the plant illnesses is the important thing toward stopping the losses within the yield and amount of the agricultural product. Because the plant life be afflicted by the disease, the production of crop decreases because of infections due to several sorts of illnesses on its leaf, crop, and branch. Leaf sicknesses are mainly as a result of bacteria, fungi, virus and so forth. Illnesses are frequently tough to manipulate. Analysis of the sickness should be done appropriately and proper movements must be taken at the correct time. A correct detection of leaf disorder is crucial for plant culture as well as the rural financial system. Even though many works were executed for identifying leaf disease, due to the inadequate strategies additionally the obligations about classifying leaf disorder are difficult to be expecting. Here, in our proposed paper, pre-processing is carried out to clear the image using Adaptive Adjustment Algorithm (AAA), and then threshold-based segmentation Otsu`s method is proposed to segment the based-on threshold values and then Resnet-50 based Convolutional Neural Network (CNN)transfer learning is proposed to extract the features and then Support Vector Machine (SVM) classification technique is used to classify the various leaf disease grade with plant crops. Finally, the performance of our proposed model gives the better accuracy 99.98% using our proposed model compared with other techniques.

Keywords: Soybean Leaf Disease, Pre-processing, Threshold based segmentation, Feature extraction and Classification.

1. INTRODUCTION

In recent years, studiesassociated with identification of sicknesses in crops have been an increasing number of pretentious a key position in enhancing the overall performance as well as competitiveness of trending agribusiness [1]. Plant sicknesses have a largeimpact on top of the rural efficiency. They are able to effortlessly corrupt the high-satisfactory of the merchandise [2]. Thus, it's far very vital to cure the plant sicknesses at early on otherwise better phases so that correct as well as appropriate achievement can be taken with the aid of using the farmers to keep away fromin addition loss [3]. The detection is historicallydonewith the aid of using human professionals. Human professionalsbecome aware ofsicknessesvisually however they face a fewproblemswhich candamage their efforts [4]. Due to this difficulty as well as toward the hugerange of cultivated flowers along with their presentphyto-pathological problems, even skilled agronomists and plant pathologists frequently fail to efficaciously diagnose precisesicknesses, and are thereforecausedflawed conclusions and treatments [5]. In the agriculture areaone of thevitalstudiessubjects is the popularity of plant disease. To keep away from the fatalities in the amount of agriculture merchandise and within side the yield, a vitalkey'sthe popularity of plant sicknesses [6].

There are distinctive kinds of sicknesses which subsist within the plants like fungal, bacterial, and viral and so forth. It’s been located 85% plant life are suffering from fungal like organisms. Following are the a few primary statistics on bacterial, viral, fungal illnesses. Bacterial sicknesses: bacterial diseases named as micro-organism reasons [7] distinctive varieties of signs that include overgrowths of plants, leaf spots, scabs and cankers. Bacterial infection signs are almost about comparable like fungal disorder. The most common form of signs found in bacterial sickness is leaf spot [8]. Viral illnesses: in the case of viral

sicknesses, it's far little difficult to become aware of and analyze. Symptoms of viral disease are Mosaic leaf sample, Plant stunting etc. A few of the primary viral disorder Cauliflower mosaic virus and so forth. Fungal sicknesses: those are the sicknesses that are normally observed on wide variety of vegetables.
Fungal diseases are liable for a substantial harm on plant. Some of principal fungal illnesses are Downy mildews, Powdery mildews, Rusts, etc [9, 10]. Newly, deep learning has gained super achievement in lots of fields, inclusive of specifically within the agriculture area, like pest identification weed detection, fruit detection, tomato sicknesses identity, cucumber sicknesses crop species and illnesses identity [11]. ResNet 50 (Residual Network) CNNs represent the maximum effective strategy for modeling complex strategies as well as performing image extraction in programs with large quantity of records, like the one in every of sample recognition in images [12]. Hence, the image of the infected leaves may be observed via image processing as well as extraction of the features of the infected spot [13]. In this paper, ResNet 50 (CNN) is utilized in our proposed version in particular advantages to the feature extraction system with minimum computational value [14, 15]. To begin with, pre-processing is executed after which threshold segmentation is carried out through the usage of locating the edge value of the photo [16]. Similarly, resnet-50 based totally CNN with deep learning is utilized to extract the feature extraction and eventually, SVM classifier is applied to classify the leaf disease [17].

2. LITERATURE REVIEW

SaberiAnari, M., A 2022 [18] have proposed a noticeably powerful shape that may be implemented to classifying more than one leaf illnesses of plants and fruits throughout the characteristic extraction step. It makes use of a deep transferlearning model that has been changed to serve this cause. SupportVector Machine (SVM) are hired toward enhance function discrimination and processing pace. Kernel parameters of the Radial Basis Function (RBF) are determined based totally on the chosen version inside the training step. The effects show the capability of an effective version in type operations, in an effort to be useful for a spread of future leaf disease diagnostic applications for the agricultural industry.
Zhang, K et al., 2021 [19] developed a manufactured soybean leaf sickness picture dataset to handle the issue of inadequate dataset from the start. Further, distinguishing soybean leaf sickness in complex form require the identification model toward have the option to unequivocally separate different features, like healthy leaf features as well as unhealthy leaves, highlights of leaves with various illnesses, etc. We acquire the ideal mean typical accuracy with 83.34% in genuine test dataset.
Rice leaf sicknesses prediction the use of deep neural networks with transfer gaining knowledge of was confirmed by using (Krishnamoorthy, N et al., 2021) [20]. The development of technical help in agriculture greatly assists for automatic identification of infectious organisms within the rice plants leaves. The Convolutional Neural Network set of rules (CNN) is one of the algorithms in deep learning has been successfully appeal intended for solving computer imaginative and prescient problems like image type, item segmentation, picture analysis, etc. here, InceptionResNetV2 is a type of CNN model utilized with switch mastering approach for spotting sicknesses in rice leaf pictures. The proposed model parameters are optimized for the type assignment and acquired a very good accuracy of 95.67%.
Leaf Illness Location as well as Characterization Framework for Soybean Culture was exhibited by (AhilaPriyadharshini, R., et al., 2019) [21]. The plan is toward recognized whether the leaf is healthy otherwise disease and assuming it is impacted, figuring out the illness as well as distinguish the level of disease. The segmentation stage is finished with the assistance of grouping calculation and followsviaclassification utilizing unsupervised learning calculation. Utilizing our idea recognizing the soybean illness with 91% precision in average we have obtained.
Dandawate, Y et al., 2015 [22] created on the methodology in view of image processing intended for recognition of sicknesses of soybean plants. Our proposed work orders the pictures of soybean leaves as healthy as well as unhealthy utilizing Support Vector Machine (SVM). The pre-preprocessing step incorporates transformation from RGB to HSV (Hue Saturation Value) color space. For removing the ROI (Region of Interest) from the first picture, multi thresholding is utilized. The color based as well asgroup-based strategies are utilized for division. The algorithm utilizes Scale Invariant FeatureTransform (SIFT) strategy which consequently perceives the plant species in view of the leaf shape. Exploratory outcomes that this approach can arrange the leaves with a typical precision of 93.79% obtained.
A Multiplant Leaf Disease Detection (MLDD) representation is proposed with the aid of (Islam, M.T 2022) [23] the use of deep transfer getting to know technique for training as well as identity of multi-plant leaf ailment dataset with 3 pre-trained fashions MobileNet-V2, Inception-V3 and ResNet-50 to find on and pick out diverse leaf diseases of potato, tomato and pepper. Powerful deep features were leveraged by great-tuning the pre-educated models. We as compared and examine the performance of the switch gaining knowledge of approach to become aware of and categorize crop leaf sicknesses. The accuracy in identifying leaf illnesses turned into on common 97.54% in MobileNetV2, 94.01% in Inception-V3 and

ninety-nine.01% in ResNet50. Precision, remember, f1-score, and accuracy have been calculated and tracked as standards for assessing performance.
A streamlined wide Convolutional Neural Network (CNN) model for sickness acknowledgment and characterization in corn leaf was made sense of by (Waheed, A et al., 2020) [24]. Side effects of these leaf sicknesses are not differentiable in their early stages. Thus, the recent flow research presents an answer through DL realizing so that health of crop can be checked and, it will prompt an expansion in the amount as well as the nature of harvest creation. The proposed improved DenseNet model has accomplished an exactness of 98.06%. This study shows that the presentation of the advanced DenseNet model is near that of the laid-out CNN structures with far less factors with calculation time.
Kumari, A et al., 2018 [25] have depicted how to recognize leaf infections consequently. This paper is imagined to aid the identifying and grouping leaf illnesses utilizing Multiclass SVM classification method. To start with, the impacted place is found utilizing division by Fuzzy C-Means (FCM) grouping, then, at that point, highlights (color and texture) are removed. Ultimately, classification strategy is applied in identifying the sort of leaf illness. The proposed framework successfully distinguishes and furthermore groups the infection with precision of 92%.

3. PROPOSED METHODOLOGY

Plant disease is a substantially refined plant toward present protein as well as lubricate utilized intended for citizens. Moreover, by means of the increase of people, the call for is using crops is rising day-to-day. Even though, multi leaf disease will origin significant yield losses as well as create a chance toward food protection simultaneously. In our proposed methodology, we have classified the various soybean leaf diseases by taking various leaf images. Initially, pre-processing is done by removing the non-illuminated image using AAA, then segmenting the given image as cluster that contains the disease part of the leaf by otsu's threshold segmentation and then the features are extracted by using ResNet-50 based CNN with transfer learning wasexplained. Finally, the leaf disease is classified using SVM is proposed to identified the leaf disease with various crops explained in fig 1.

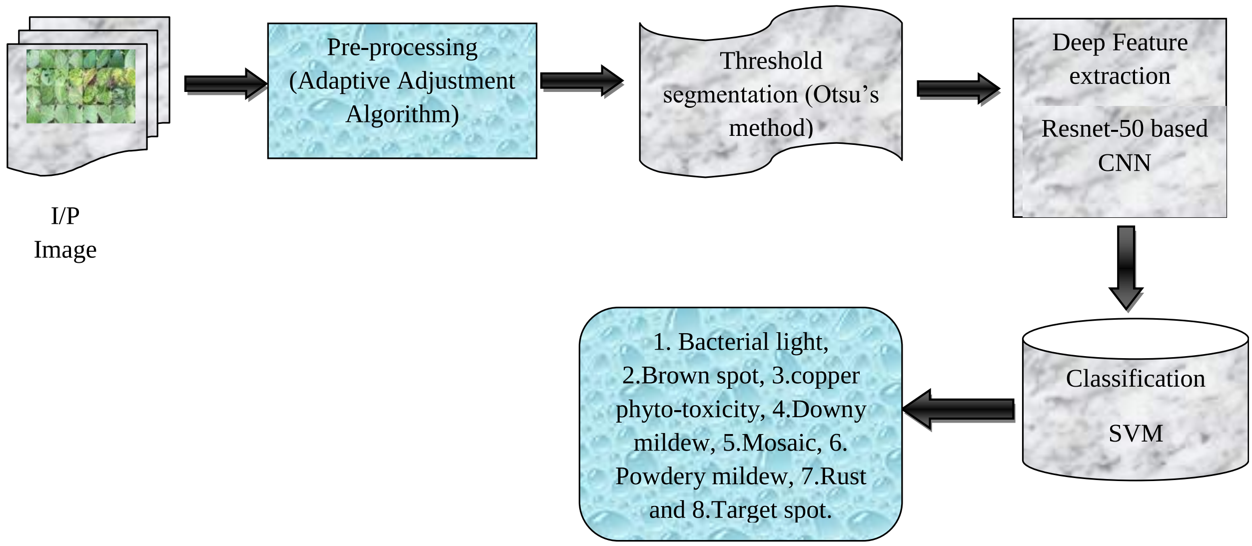

Fig 1: Proposed diagram

3.1 Data augmentation

This process is utilized to increase the number of images in the training dataset. It helps to preclude the overfitting problem in the training process. Where, overfitting is the problem, when the network learns the data rather than the general pattern of the dataset. Image augmentations were performed by introducing particular variations in the images such as rotation, width shift, height shift, shear range, horizontal flip.

3.2 Pre-processing Model

Preprocessing is a crucial step in improving the performance due to non-uniform illumination of the input leaf pictures. Gamma correction may be used to manipulate the general brightness of a picture. It can be used with image that is observed to be either faded out or too darkish. Expansion and compression of pixel intensity values are favored for darker and faded pix.

3.3 Segmentation

After pre-processing, the un-noised image given to the segmentation, in that, the disease of the leaf area is segmented based on the threshold values.

Otsu's method: In image processing method, otsu's approach is applied toward carry out clustering based totally threshold of image. The concept in the back of otsu's approach is that the approach exams the pixel values along with guess the first-rate spot in which the two classes can be divided into two with the aid of minimizing the variance over the histogram of it. In Otsu's thresholding we intensely pick out the threshold value that minimizes the intra-class variance or variance inside the class. That is defined as weighted sum of variances of two classes.

$$\delta_v{}^2(t) = v_0(t)\delta_0{}^2(t) + v_1(t)\delta_1{}^2(t) \quad (1)$$

Where $v_0 and v_1$ are the probabilities of the two classes divided through a threshold t, $\delta_0{}^2 and \delta_1{}^2$ are the variance of these two classes. The Otsu's method lessen intra-class variance, which is similar since reducing the inter-class variance is explained by

$$\delta_a{}^2(t) = \delta - \delta_v{}^2(t)$$

$$= v_0(t)v_1(t)[\eta_0(t) - \eta_1(t)]^2 \quad (2)$$

Where η_0, η_1 are class variance.

All want to do is simply run via the total range of t values [1, 256] as well as select the cost that reduce $\delta_v{}^2(t)$. The overall variance for any given threshold will be the total of the inside class (intra-magnificence) variances and the among magnificence (inter-elegance) variances. Inter-class variance is the total of weighted squared space among the class mean as well as the grand mean. Then the entire variance can be expressed as:

$$\delta^2 = \delta_v{}^2(t) + \delta_0(t)[1-\delta_0(t)][\eta_0(t) - \eta_1(t)]^2 \quad (3)$$

This means that the whole is steady and impartial of t, the impact of changing the threshold is just toward move about the assistance of each intra-class variance along inter-class variance backward and forward. So, minimizing the intra-class variance is similar to reducing the inter-class variance.

3.4 Transfer learning

Transfer learning is a machine learning technique that allows for adapting networks and models developed for certain specific applications to other applications.It is utilized toward reduce the redundancy for creating a new model each time for different purposes There are two different ways of implementing transfer learning on CNN. Fine-tuning a CNN or by using CNN as a fixed feature extractor. Here, feature extraction is carried out (Jiang, Z., Dong et al, 2021) [28].

3.4.1 Feature extraction

The gain of capabilities extracted the usage of deep learning algorithms is that the community learns imagecapabilitiesmechanically layer-by-layer. Generally, the ultimate layer of any deep learningcommunitywhich includes ResNet50 produces an output class predication the usage ofsoftmax classification. However, high-degreecapabilitiesmay be extracted earlier than the FC layers. Here, deep (high-degree) capabilities are extracted the usage of TL-ResNet50 version after the 5th residual block (Conv5_x, Fig 2) at the `avg-pool` layer. This output serves as a deep imagefeature extractor. The size of the deep feature vector is of length 2048. These capabilities are acquiredas soon aseducation of the TL-ResNet50 is completed.

3.4.2 ResNet 50

Here, we have taken a pretrained model which has already been trained over thousands of images. Since the concept of image classification, the ResNet model also known as the base network would have already extracted some features of images such as corners, edges, and shapes. It makes it viable to teach loads of layers that go deeper and deeper and nonetheless gain good performance ((Mukti, I.Z. et al., 2019) [26]. In the last, features are extracted from the new updated weight whichthe dimensions of extracted functions are less. The original ResNet50 was trained for 1000 classes and having the last 3 layers of ResNet50, namely, 'FC 1000', 'FC1000 Softmax', and 'FC Classification. In the current study, ResNet50 is modified by replacing the mentioned layers with the new layers of 'FC 8', 'FC8 Softmax', and 'Class output' for our classes 8 diseases. The 'avg-pool' layer of the TL-ResNet50 has 2048 neurons connected with succeeding layers of 3 neurons, each representing a crop class.

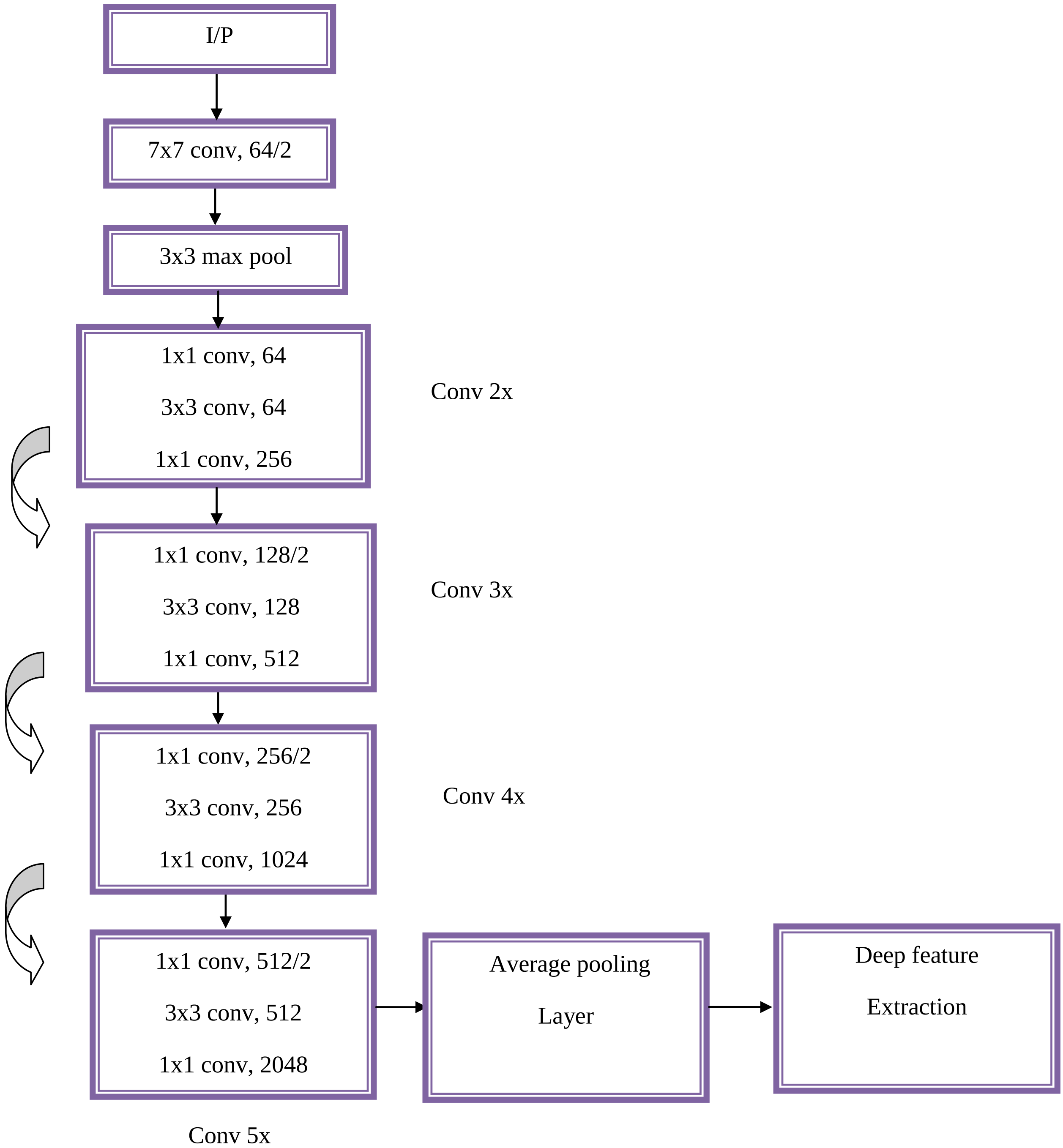

Fig 2: Transfer learning based Deep feature extraction

Convolutional Layer
The convolutional layer is the vital element as well as the core building block of the Deep Learning (DL) CNN. It's far answerable meant for feature extraction technique, as its yield sets of 2nd matrices were known as feature maps (Kaushik, M., Prakashet al, 2021) [30]. The dimensions of the filters were chosen in resnet50 (7 × 7), (1 × 1), as well as (3 × 3). In the course of the training process, every filter out attains the capability toward stumble on the analyzed images low-degree features, such as colorations, boundaries, blobs, as well ascorners.

$$N_j^i = h(\sum_{i \in Mj} N_i^{i-1} \times w_j^l + b_j^l$$

where $h(\sum_{i \in Mj} N_i^{i-1} \times w_j^l + b_j^l$ represents an activation function. M_j denotes the number of filters. $M_j^{\;l-1}$ denotes feature map. $w_j^{\;i}$ denotes weight matrix, and $b_j^{\;i}$ denotes bias term.

Pooling layer: Pooling layersareavailablenexttoward convolutionallayers and in that layer, the subsampling part is liable designed for reducing the dimensions of the feature maps to create the convolutional layers. The max-pooling process is based at the separation of the image into units of two × 2 un-overlap regions and two × 2 pooling layer reduces the dimensions of the characteristic map through four instances. Adding together, it reduces the computational fee through decreasing the range of parameters. Moreover, the average pooling layer is some other form of pooling. This layer acts as max pooling, but it calculates 2 × 2 rectangles' averages to create a subsampled images in place of considering the limit value.

Fully Connected Layer: The fully connecting layer is the last layer in the resnet50 architecture. It actslike a classifier, plusits characteristic is toward connecting the layers within the network along it deliver the very last end result of the classification

SoftMax layer: Normally, it is observed via using the final layer through a normalized exponential function (SoftMax). This layer has been changed to fine-track the resnet50 and it is given by following equation

4. Classification

The classification is done by using the SVM machine learning techniques. In this, we have classified the disease based on thelinear kernel function.

4.1 Support Vector Machine (SVM)

SVM is utilized for both classifications as well as regression problems and it is a discriminative supervised machine learning algorithm. The main aim of SVM is toward map them toward superior space dimension, with given set of training data as well as then it builds the hyperplane good otherwise set of hyperplane toward divide the data points toward their possible classes (Padol, P.Bet al., 2016) [29].The input data can be shift toward the necessary form via utilizing kernel functions. Here, we have utilized linear kernel and it gives best classification performance and it has only few parameters toward improve. The linear kernel can be written as follows

$$K(a_i, b_i) = a_i * b_i$$

where a_i and b_i, indicate input vectors δ^2. Via reducing the margin from the support vectors toward the hyperplane, the good division among information points can be attained. Toward guess the margin maximum, SVM plan toward deal with the underneath optimization problem

$$z_i\left(w^u \theta(a_i + b\right) \geq 1 - \delta_i$$

where δ denotes the distance toward margin correct designed for $\delta \geq 0, i = 1,2...n$, $\theta(a_i)$ indicate the shifting input vector, where b indicate a bias parameter, where z_i indicate the i_{th} target value.

Characteristics of SVM are as follows

- SVM can be summed up in high-dimensional spaces with just a little measure of training tests.
- The ideal outcome can be given by SVM through changing the issue into a quadratic programming issue.
- SVM can recreate nonlinear functional relationships.

5. RESULT AND DISCUSSION

In this part, the dataset taken from https://www.digipathos-rep.cnptia.embrapa.br/ and it consists of various leaf images with variety of crops. Here, totally 270 images considered from the given data set. The system is trained 70% and 30% for testing. The compared CNN are MobileNet-V2, Inception-V3, DenseNet with our proposed model ResNet-50. The Performance analysis of Sensitivity, F1 score, Accuracy and Precision values were calculated.

5.1 Performance evaluation

Precision, Recall, Accuracy and F1 score are performance evaluation metrics used to identify the overall accuracy of training models for some datasets and it is defined by FP (False Positive), FN (False Negative), TP (True positive), TN (True Negative).

Accuracy: the percentage of the number of records classified correctly versus the total records shown in the equation below:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Sensitivity or recall: It measures the number of positive cases that a model is able to predict correctly among all positive cases in dataset.

$$Sensitivity \frac{TP}{TP + FN}$$

Precision: It measures the number of positive predictions that are detected correctly.

$$\Pr ecision = \frac{TP}{TP + FP}$$

F1 score: F1 score tells us the harmonic mean on precision and recall.

$$F1score = \frac{2xprecisionxrecall}{\Pr ecision + recall}$$

Table 1. classification results using SVM

Classification Report:

	precision	recall	f1-score	support
Bacterial_blight	1.00	1.00	1.00	11
Brown_Spot	1.00	1.00	1.00	11
Copper_Phytotoxicity	1.00	1.00	1.00	11
Downy_mildew	1.00	1.00	1.00	11
Mosaic	1.00	1.00	1.00	11
Powdery_mildew	1.00	1.00	1.00	11
Rust	1.00	1.00	1.00	11
Target_spot	1.00	1.00	1.00	11
accuracy			1.00	88
macro avg	1.00	1.00	1.00	88
weighted avg	1.00	1.00	1.00	88

Table 1 explains the classification using SVM for predicting various diseases.Here, 8 types of leaf diseases predicted with our proposed SVM liner kernel technique. Also, we have achieved precision 1.00 for bacterial blight disease likewise we have obtained better classification performance measures for diseases with our proposed SVM technique.

Fig: 3(a)

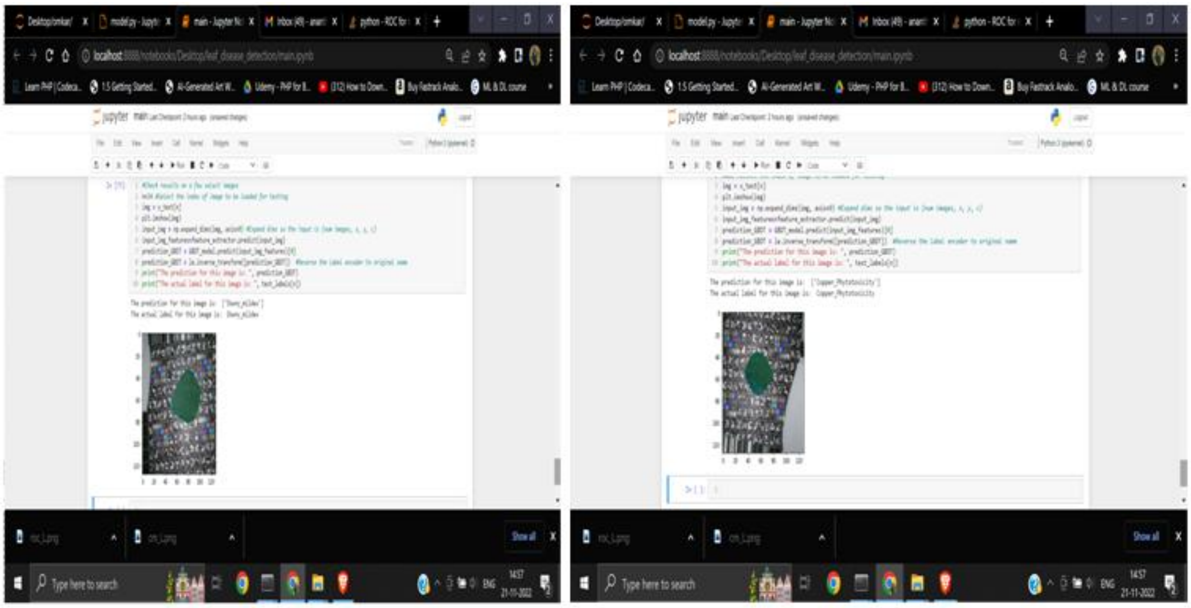

Fig: 3(b)

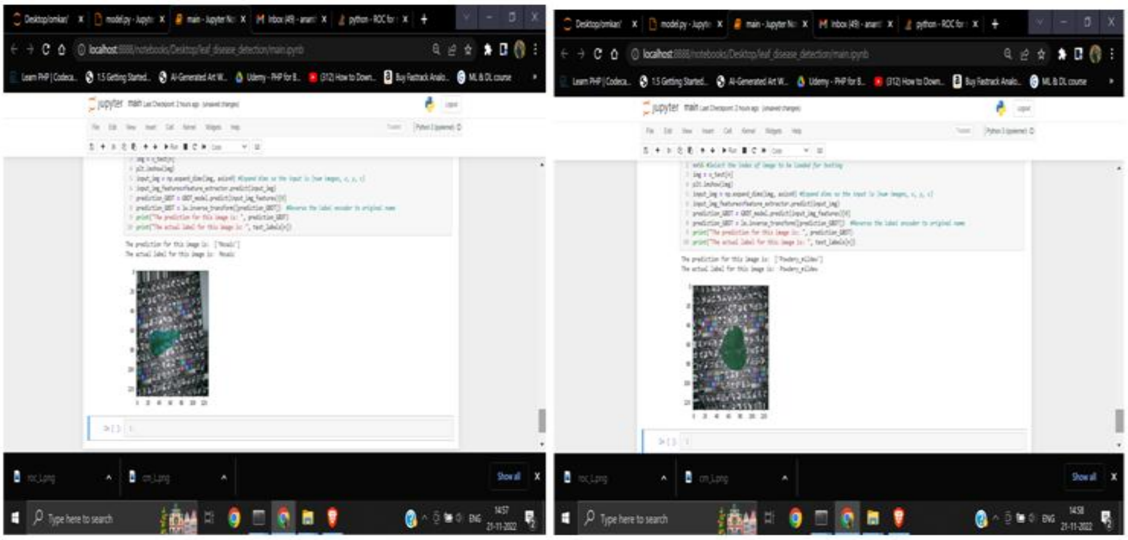

Fig: 3 (c)

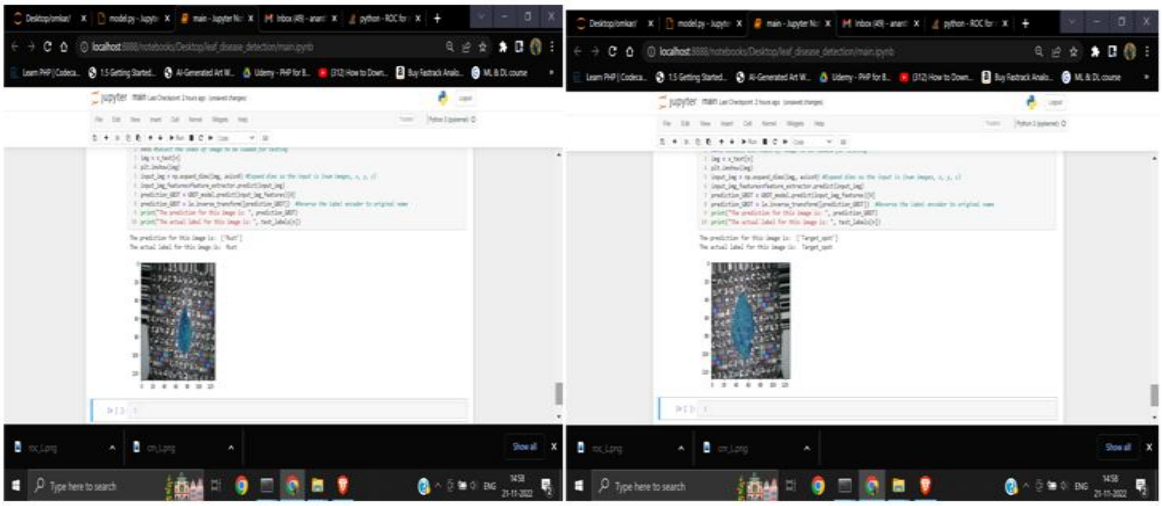

Fig: 3 (d)

In fig 3 (a) to (d) various leaf disease have been classified according to their features.By using SVM and feature extraction method we have predicted diseases with multi input crops.

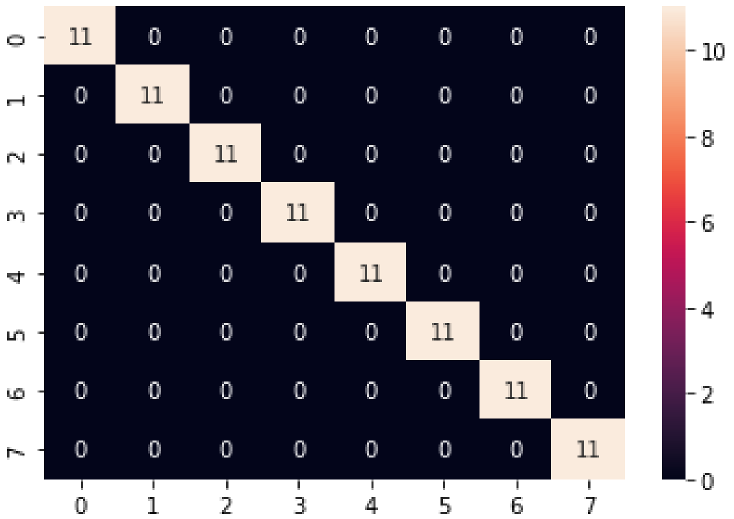

Fig 4. Confusion matrix based on SVM

In fig 4 explains the confusion matrix obtained utilizing the division of training and testing images. Here, x-axis represents the predicted class and y-axis represents the actual class. The identified leaf diseases are bacterial blight, brown spot, and copper-phytotoxicity, Downy-mildew, Mosaic, Powdery-Mildew, Rust and Target-spot. Also, we have achieved maximum accuracy using our proposed model.

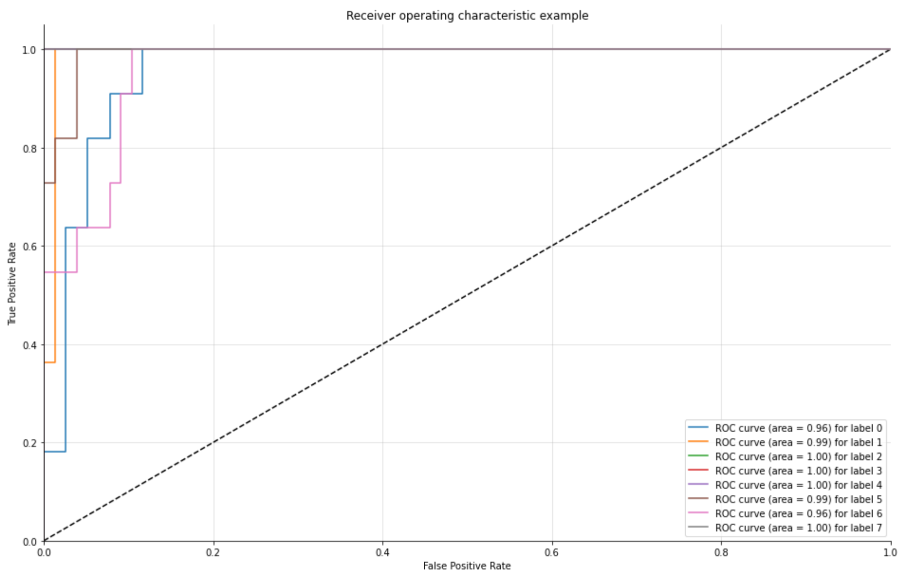

Fig 5. ROC curve for SVM

In fig 5 explains ROC curve for 8 disease classification. X-axis represents the FPR (False Positive Rate) and TPR (True Positive Rate).Copper-phytotoxicity, Downy-mildew, Mosaic gives maximum results as well as target spot disease also.

6. CONCLUSION

In conclusion part, increasing rate of disease is caused mainly due to many losses in the field. A deep learning technique with transform and augmentation was used to overcome the overfitting problem and also improved the model's performance.Here,pre-processing, segmentation, feature extraction and classification are performed. Feature extraction is done by using ResNet-50 based CNN is proposed to extract features and classification. The proposed model achieves 99.99% accuracy, precision, F1 Score and Recall performance measures by using SVM kernel linear functions with good performance measures. In future work, we will use hybrid approach with other CNN model architecture.

Conflict of Interest
The Author declare that they have no conflict of interest.

Data Availability Statement
Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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