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Chili Crop Disease Prediction Using Machine Learning Algorithms

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ABSTRACT

Crop diseases are a major cause of reduced productivity in India, with farmers often struggling to identify and control them. Consequently, the development of advanced techniques for early disease detection is crucial for minimizing losses. This study investigates the performance of various Machine Learning (ML) algorithms, including Random Forest (RF), AdaBoost, Gradient Boosting (GB), and Multi-Layer Perceptron (MLP), for predicting diseases in chili crops based on images. The primary objective is to identify the most accurate model for chili crop disease prediction. A novel dataset, the Real Chili Crop Field Image Dataset, comprising approximately 1157 images across 5 distinct classes, is employed for this purpose. The experimental results demonstrate that the RF and GB algorithms achieve accuracies of 96% and 94%, respectively. Importantly, the study focuses on the Real Chili Crop Field Image Dataset, which offers significant advantages in terms of real-world applicability due to its development in natural, non-controlled environments. The methodology is further enhanced by employing popular and diverse feature extraction methods, such as Haralick and Hu moments, and improving the results using the Random Forest classification algorithm.

1. INTRODUCTION

Recent advancements in technologies such as object detection, image processing, Machine Learning (ML), and Deep Learning (DL) have led to the development of innovative solutions for quality assessment and early disease prediction in crops [1]. Machine learning has emerged as a highly accurate and reliable approach for diagnosing plant diseases, reducing the need for extensive monitoring in large agricultural farms and enabling early detection of disease symptoms on plant leaves. The integration of computer vision capabilities into the field of agriculture is becoming increasingly important with the progress of Artificial Intelligence. The rich libraries of Deep Learning, coupled with a user and developer-friendly environment, make it a preferred method for addressing this issue.

Chili crops are a significant commercial crop in India, with 32.76% of production originating from Andhra Pradesh and Telangana in 2017-18 [2]. Chili crops are particularly susceptible to disease, which can lead to reduced yields. Factors such as pests, environmental conditions, and natural diseases affect crop health; however, disease infection is the most severe issue in chili cultivation. Common diseases include die-back, anthracnose (fruit rot), Choeanephora blight/wet rot, mosaic complex, powdery mildew, bacterial leaf spot, leaf curl, Fusarium wilt, and pests [3]. This study presents an approach for detecting four types of real field chili crop leaf diseases using RF, GB, AdaBoost, and MLP algorithms. Disease detection in crops is a critical research area, as it can facilitate monitoring of large fields and early identification of disease symptoms on crop leaves. The proposed framework is a software solution that classifies crop diseases and evaluates the most suitable algorithm for this purpose. The experimental results indicate that the Random Forest (RF) and Gradient Boosting algorithms yield accuracies of 96% and 94%, respectively. The study focuses on a new dataset, the Real Chili Crop Field Image Dataset, which demonstrates promising results in terms of real-world applicability due to its development in natural, non-controlled environments.

The authors implemented a model [1] to detect corn diseases. They have acquired the data from Plant Village dataset consists of 3823images of 4 classes: Gray leaf spot, Common rust, Northern Leaf Blight and Healthy. The authors evaluated accuracies obtained from various feature extraction methods RGB, SIFT, SURF, ORB and HOG for identifying the diseases of corn crop using machine learning algorithms named RF, SVM, DT and NB. Best performance results evaluated for features with color information RGB with SVM.K-means and SVM were implemented to identify the diseases in the studies [4, 5] and results shown that the achieved accuracy is <95%. Ss. Poornima implemented an efficient method [6] to detect plant diseases using image processing techniques. The objectives of the proposed method were:1) Identification of diseases, 2) Quantify the affected region, 3) Find the boundaries of affected region, 4) Determine the shape and color of affected region, 5) Build the model to predict the disease. The authors used 800 images (7 classes of tomato and pepper) and methods are: K-Means clustering, Thresholding, Hough Transform and SVM. This research work also mentioned that ensemble hybrid approaches and deep learning have promising scope for improving the accuracy.

Ramesh and Vydeki developed a system [7] to detect onsite rice blast images (451 images) using KNN and ANN classifiers. The Redmi Note 5 camera's high pixel intensity was used to capture the leaf for both its diseased and healthy regions. This system also used K -Means (K=3) algorithm for segmentation and extracted features like mean, standard deviation GLCM features, entropy and skewness. The authors used KNN where K=1,2,3 and the learning rates: 0.1, 0.2, 0.02 and 0.025. were tested for ANN. The experiment results had shown that ANN classifier given best results. Using the suggested strategy above, farmers can protect their crops against diseases. It is advised that Indian farmers use this strategy to prevent the spread of diseases among their crops and to determine whenever they want to increase crop production and obtain higher financial benefits. The authors developed a model [8] to detect tomato leaf diseases by using KNN and PNN. In this approach the authors used Sobel edge detection and morphological operations. And also used GLCM, Color and Gabor feature extraction methods. KNN classifier is applied on extracted features. If the disease is not detected then PNN classifier is applied on newly extracted features. Panigrahi et al. [9] compared the results obtained from machine learning algorithms: NB, K-NN, DT, SVM and RF to predict the maize diseases (3823 images and 4 classes). The images were segmented by the label edge detection method. The experiment results shown that the RF (79.23% of accuracy) classifier bagged best accuracy among all other classifiers. Table 1 represents the various acronyms used in the paper. Table 2 interprets the details of the various researches on crop leaf disease prediction and classification. The authors in the surveyed papers used various ML and DL methods to classify the multiple diseases of various crops and their experimental results shown that both the methods score better accuracies.

Table 1. Acronyms

ML	Machine Learning	**GB**	Gradient Boosting
DL	Deep Learning	**CNN**	Convolutional Neural Networks
PV	Plant Village	**RGB**	Red Green Blue
SVM	Support Vector Machine		
DT	Decision Trees	**SIFT**	Scale-Invariant Feature Transform
NB	Naïve Bayes	**SURF**	Speeded Up Robust Features
KNN	K-Nearest Neighbors	**ORB**	Oriented FAST and Rotated BRIEF
ANN	Artificial Neural Networks	**HOG**	Histogram Oriented Gradient
MLP	Multi-Layer Perceptron	**GLCM**	Gray-Level Co-occurrence Matrix
RF	Random Forest	**HSV**	Hue, Saturation, Value

Table 2. Details of the surveyed papers for the detection and classification of crop leaf diseases

Year	Reference No	Crop	Number of Images	Number of Classes	Algorithm	Accuracy
2019	[6]	Multiple	800	—	SVM-Multi class	65
2020	[9]	Maize	3423	4	Naïve Baye's	77.46
2018	[10]	Papaya	160	—	RF, SVM, LR, LDA, NAÏVE BAYES, KNN, CART	70
2018	[11]	Multiple	—	38	CNN	88.6
2019	[12]	Mulberry	—	3	CNN	82
2017	[13]	Cotton	900	7	SVM (regression)	83
2020	[14]	Papaya	10000	3	ResNet	85
2018	[15]	Tomato	1400	7	CNN	86.9
2018	[16]	Paddy	—	—	Alex Net	87
2019	[17]	Grape	130	4	Deep Siamese convolution network	90
2020	[18]	Tomato	4,671	3	MobileNet	90
2020	[19]	Multiple	148,775	38	Inception v3 transferred to target domain SVM	90.6
2020	[20]	Tomato	10000	10	CNN	91.2
2016	[21]	Cucumber	300	4	global-local SVD (single value decomposition) --SVM classifier	91.63
2019	[22]	Maize	100	4	CNN	92.85
2021	[23]	Multiple	87000	38	RF	93
2021	[24]	Mushroom and Soya bean	—	—	KNN, SVM, ANN, DT, RF	93.83
2016	[25]	Alfalfa	899	4	SVM	94.7

2. MATERIALS AND METHODS

The proposed system implemented by using Machine learning classifiers namely AdaBoost [26], Gradient Boosting [27], Multi-Layer Perceptron [28] and Random Forest [29] to do a comparative analysis to identify which among them is most efficient and identifies the disease of the crop by using the most efficient classifier. Initially we applied color conversion to convert the images to RGB and HSV and then applied Haralick et al. [30] and hu-moments [31] to extract the texture and color of the images of leaf of the crop that will be used for training and testing the models. We have exploited real time chili crop field images captured from Mi Note 7 Prime at Zaffergadh, Telangana, India. Every image in the data set is converted into 256×256. We have developed a model such that identifies 4 different crop diseases namely bacterial leaf spot, fusarium, and leaf curl and pests along with the healthy leaves. The details of the images are given in the Table 3.

Table 3. Details of the number of images

Real Chili Crop Field Image Dataset (1157)				
Bacterial_leaf_ spot (C_01)	**Fusarium (C_02)**	**Curl (C_03)**	**Pests (C_04)**	**Healthy _leaf (C_05)**
230	284	318	142	183

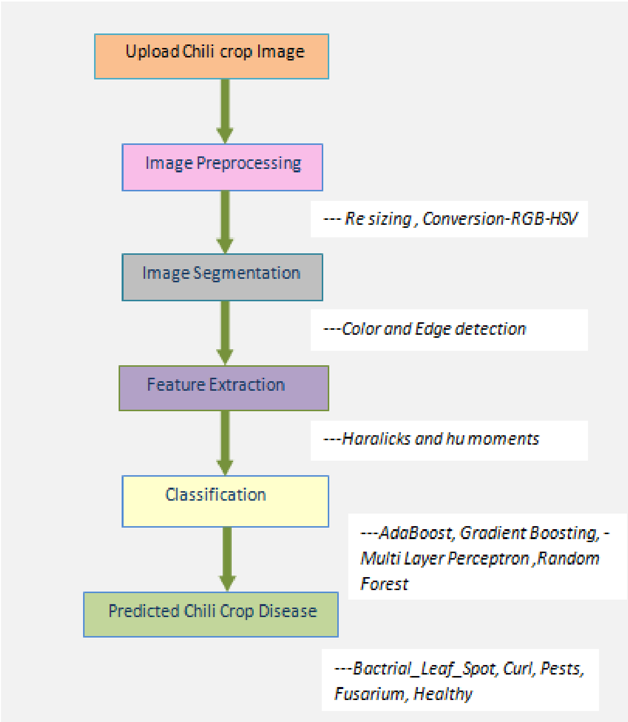


Figure 1. Architecture of the proposed model

The architecture design (Figure 1) shows the working of proposed application initially the dataset is uploaded. Then the images of the dataset are preprocessed and converted to HSV and RGB formats after which they are segmented and the features are extracted using Hu moments and Haralick and then the classifiers are trained with the dataset images. The GUI of the proposed application includes upload the image button and after submitting to the model it gives F1 score of the different classifiers exercised in each case ADA Boost, MLP, RF and Gradient Boosting and label of the disease.

2.1 AdaBoost

One of the ensembles boosting classifiers is AdaBoost, which stands for Adaptive Boosting [26]. It combines many classifiers to improve classifier accuracy. Ensembles are created iteratively using AdaBoost. The robust classifier is attained by AdaBoost through merging multiple classifiers which are performing low and resulting in best. To assure exact predictions for unknown observations AdaBoost establishes weights for classifiers and each iteration is done after training the sample. Any machine learning technique that accepts weights on the training data set can be used as a base classifier. Two conditions should be met by AdaBoost: Classifier must be interactively trained on multiple weighed training examples and it must attempt to produce an excellent match for these occurrences by minimizing training error in each iteration. AdaBoost works by weighing the observations, giving more weight to cases that are difficult to identify and less to those that are already well-classified. New weak learners are introduced one at a time, with the goal of concentrating their training on the increasingly challenging patterns. This means that difficult-to-classify samples are given increasingly greater weights until the computer finds a model that correctly classifies them.

2.2 Gradient boosting

The statistical framework views boosting as a numerical optimization issue in which the goal is to reduce the model's loss by employing a gradient descent-like approach to add weak learners. A stage-wise additive model [27] was employed to characterize this class of methods. This is because the model only adds one new weak learner at a time, while existing weak learners are frozen and unchanged. Gradient boosting is made up of three parts: A loss function that has to be optimized, a weak learner to make predictions, adding weak learners to an additive model to reduce the loss function.

2.3 Multi-layer perceptron

The most frequent neural network model used in deep learning is the multi-layered perceptron (MLP) [28]. MLP is often referred to as a "vanilla" neural network because it is simpler than the complicated models of the earlier. The interconnected neurons in a multi-layered perceptron transfer information to each other in the same way that neurons in the human brain do [12]. A value is assigned to each neuron. There are three layers to the network namely Input, Hidden and Output layers. MLP is a feed forward neural network, which implies that data is sent from the input layer to the output layer in the forward direction shown in the Figure 2. Weights are assigned to the links between the layers. The importance of a relationship is determined by its weight. While the inputs get their values from the backgrounds, the values of all the other neurons are calculated using the weights and values from the layer preceding it. For example, the value of the H_3 node is $H_3=I_1*W_{13}+I_2*W_{23}$.

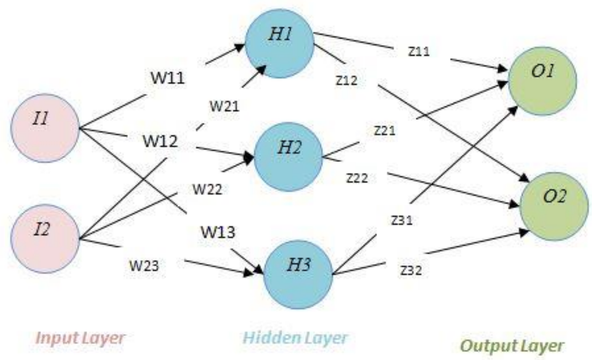


Figure 2. Illustration of MLP

2.4 Random forest algorithm

A Random Forest [29] is a supervised learning technique. It produces a "forest" out of an ensemble of decision trees that are often trained using the "bagging" method. The main idea of the bagging approach is that combining several learning models enhances the final outcome. Random forest has the advantage of being able to solve classification and regression problems.

3. RESULTS AND DISCUSSIONS

The implementation of proposed model is made by using python3.9.11 and GoogleCOlab. The images are preprocessed and segmented by Color and edge detection. Table 4 represents the diseased image after segmentation. Then features were extracted by Haralick and Hu moments methods later classification takes place. The performance of the ML techniques is represented in the Table 5. Models were trained with 926 images; got accuracy around 95% later decreased it to 868 images and got an accuracy of 97% with RF and 93% with Gradient Boosting, got an accuracy of 97% with RF and 93% with MLP and below 70% accuracy with AdaBoost. Table 5 illustrates the Accuracies of various classifiers vs. ratio of the training and testing images.

Table 4. Original image vs. segmented image

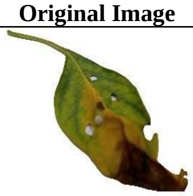
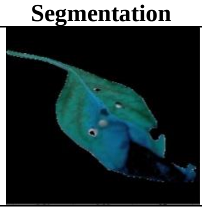
Bacterial_Leaf_Spot Original Image	Bacterial_Leaf_Spot after Segmentation
	

Table 5. Accuracies of various classifiers

Training: Testing (No. of Images)	MLP	AdaBoost	Gradient Boosting	RF
80:20	89	51	94	95
75:25	88	58	93	**97**
70:30	87	66	93	95

The proposed model also calculated the performance measures such as precision, Recall, F1-score and Support for all classifiers. The obtained results were represented in Table 6 for RF Classifier. Figure 3 represents the analysis of average accuracies of 4 classifiers. Figure 4 represents the accuracies recorded for training and testing images on 3 cases i.e. 80:20, 75:25 and 70:30.

Table 6 represents the Performance of RF for predicting chili crop disease detection for 80:20 ratios of training and testing images.

Table 6. Performance of RF on 5 classes of chili images

Class Name	Precision	Recall	F1-Score	Support
C_01	0.98	1	0.99	47
C_02	0.93	0.95	0.94	74
C_03	1	1	1	56
C_04	0.84	0.93	0.88	28
C_05	1	0.81	0.9	27

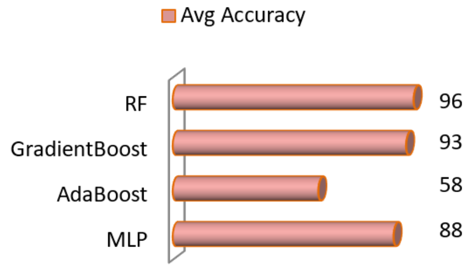


Figure 3. Accuracies of classifiers

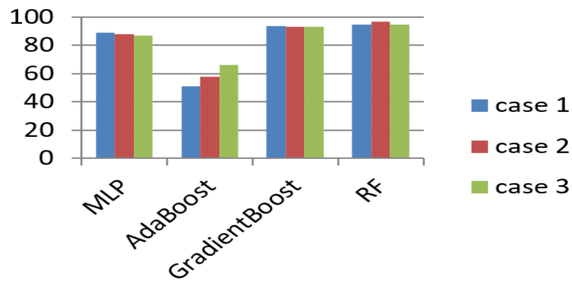


Figure 4. Accuracies of classifiers taken at 3 cases

The comparisons between past studies and proposed method are represented in Table 7. The proposed work implemented not under controlled conditions and specialized equipment with prominent accuracies. This approach easily deployable in smart computing devices as it requires limited resources.

Table 7. Comparison of proposed work with the past works

Reference No.	Year	Crop Type-Dataset	Number of Images	Number of Classes	Image Processing Methods	Classifier	Accuracy	Specialized Hardware Requirements Needed	Dataset Built under Controlled Conditions
[32]	2017	Tomato-Private	5000 (43000)	10	Image annotation and data augmentation	DL Meta architectures-Faster RCNN, F-RCNN, SSD combined with VGGNet and ResNet	85	Yes	No
[13]	2017	Cotton-Private USA	900	7	Color transform and thresholding: for feature extraction-color moment: colorfeature; gaborfilter: texture feature	Support Vector Machine based regression system	83.26	No	No
[33]	2018	—	—	2	Color, HarlickLBP, moments	KNN, SVM, Random Forest, Logistic regression, Naïve bayes	58	—	—

[6]	2019	—	—	—	Sobel edge detection, Medianfilter, Segmentation - K-means, circular Hough transform, canny edge detector	Multi-class Support Vector Machine	65	—	—
[34]	2019	Leaf dataset	61486	39	—	CNN	96	Yes	Yes
[35]	2020	Plant Village	2598	13	—	MobileNet, RCNN	70.5	Yes	Yes
[36]	2020	Grape-Private	62286	5	Brightness, contrast, and sharpness rotation (including 90, 180, and 270◦) and symmetry (vertical and horizontal), Gaussian noise removal	Faster R-CNN	81.1	Yes	No
[18]	2020	Plant Village	4,671	3	—	MobileNet V2	94.3	Yes	Yes
[23]	2021	Plant Village	87000	25	Gaussian filter, Otsu'sthresholding, GLCM	RF	93	No	Yes
Proposed work		Chili-Private	1157	5	Image Smoothening, Brightness, Backgroundremoval, Imageaugmentation, Haralick feature extraction, Hu moments	**RF**, AdaBoost, GradientBoost and MLP	**97**	**No**	**No**

4. CONCLUSIONS

The proposed method uses Color and Edge detection, Haralick et al. [30] moments feature extraction methods and four state of the art machine learning algorithms in order to detect the real field chili crop images captured with Red Mi Note 7 mobile phone namely AdaBoost, Gradient Boosting, Multi-Layer Perceptron and Random Forest. The experiment recorded in 3 cases i.e., 80:20, 75:25 and 70:30 of training and testing images. The experiment results shown that Random Forest and Gradient Boosting scored top i.e. nearer to 95% of accuracy with 75:25 ratio of training and testing. The Curl class has predicted very accurately among all classes. The dataset used in this study contains four diseases, although the chili crop contains many more. Farmers can protect their crops from diseases using the method described above. Our future works may be adding more diseases to the dataset and detection of the disease module can be converted into an application for the mobiles so that it can be exploited in the field by the farmers for immediate detection of the disease.

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