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# MACHINE LEARNING ALGORITHMS FOR PREDICTION OF TOMATO LEAF DISEASE DETECTION

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**Abstract**

The agricultural sector remains a key contributor to the Indian economy, representing about 20% of gross domestic product (GDP). Plant diseases are the major cause of low agricultural productivity and cause heavy losses in the country's economy. Mostly the farmers encounter difficulties in controlling and detecting the plant diseases. Therefore, early detection can mitigate the severity of diseases and protect crops. This paper focuses on supervised machine learning techniques such as linear discriminant analysis (LDA), Random Forest (RF), Extreme Gradient Boosting (XGB), Support Vector Machine (SVM) algorithms applied to tomato leaf disease detection was carried out with the help of the images of the tomato plant leafs. The aforementioned machine learning techniques are analyzed and compared in order to select the best suitable model with the highest accuracy for tomato leaf disease detection prediction. Comparative experiment results show that Support Vector Machine (SVM) algorithm results achieved with the highest accuracy of 81% as compared to the rest of the classification techniques. This work shows aforementioned model can be used by the farmers to encounter difficulties in controlling and detecting the tomato leaf disease as a preventive measure.

**Keywords:** Machine learning · Tomato leaf disease detection · Random Forest (RF), linear discriminant analysis (LDA), Extreme Gradient Boosting (XGB), Support Vector Machine (SVM)

## 1. Introduction

Tomatoes have become a staple of every household. It's a must for Indian curries, Maggi, Sandwich, and pastas. Recently prices of tomatoes, exceeded ₹150 per kg, triggering concerns among countless households. Due to a combination of tomato plants caused by pests, diseases, climatic conditions, and nutritional deficiencies and a virus causing a supply shortage [1]. As per the weather condition accurate and fast identification of tomato plant diseases and virus is significant to enhance the tomato productivity. Human experts in the field of agriculture all about identifying the diseases and virus through experiences and they are able to predict the problems with emotional equations hence it may causing a supply shortage. In order to produce greater prediction accuracy, automatic disease detections methods are required. In the literature survey automatic tomato leaf disease detections done with some conventional image processing methods and machine learning algorithms approaches are reported to overcome the supply shortage but which result are in less accuracy[2-4]. In this work introduced new approaches to produce more accurate prediction on tomato leaf disease detections by using comparative analysis of machine learning algorithms such as linear discriminate analysis (LDA), Random Forest (RF), Extreme Gradient Boosting (XGB), and Support Vector Machine (SVM) algorithms with the help of the images of the tomato plant leafs..The following sections of the paper systematically discussed the tomato leaf disease detections methodology, results and discussions followed by conclusion.

## 2. Related Work

A plant disease as per plant nutrition textbook is defined as “anything that prevents a plant from performing to its maximum potential”. Diseases are anomalous conditions that adversely damage to a plant, animal, or human organism. Bacterial Canker, Leaf Mold, Late Blight, Alternaria Canker, Spotted Wilt, Early blight, Bacterial leaf spot, Bacterial wilt are common tomato leaf diseases. It can affect leaves, fruit, or even the whole plant depending on the severity of the infection and it may cause of low agricultural productivity and heavy losses to formers economy. Some researchers used information technology to diagnose and identify plant diseases as early as the 1990s [5]. In 1999, some of the authors employed genetic algorithms to identify the condition by establishing identification factors based on some characteristics such as spectrum reflection [6]. In 2007, the authors suggested some machine learning models after the use of neural network models and suggest some parameters for support vector machines and genetic algorithms [7]. In 2011, researchers diagnosed the tomato leaf features based on color and spots which are then combined and discriminated with original images using divergence approaches [8]. In 2017 the authors suggested different feature approaches such as “CYMK color feature”, “GA feature”, and “color and texture”, and then used a hybrid model for the classification task using the inception V3 network [9]. In 2017, the authors identified two insect pests and three cassava lesions using a neural network. “Brown leaf spot”, “red mite”, “green mite”, “cassava brown streak disease”, and “cassava mosaic disease” were all recognized at a rate of 38%, 42%, 53%, and 59%, respectively [10]. Some researchers provided a classification of symptoms identified in the leaves, with an accuracy rate of more than 90%. In 2018 authors suggested different CNN-based categorization models for the recognition and identification of a disease by using smart phone photographs, statistical inference, and segmented images are combined for the detection of disease with an accuracy rate of 79.4% [11]. In 2019, authors suggested different deep learning models for the recognition and identification of a disease with an accuracy rate of 93.4% and 96.64% using the 9-layer model [11]. In 2021, suggested a Deep Convolution Neural Network (DCNN) and this model are utilized to create the VGG16 and VGG19 architectures to categorization of leaf disease. The “Stochastic Gradient Descent” and “RMS Prop optimization algorithm” were used to increase the network’s performance [12]. In 2022 some machine learning models like SVM, Decision Tree, etc. are used with deep learning models such as CNN for the recognition of the disease in plant leaves. For better results, some deep learning models (VGG16 and VGG19) work with machine learning feature extractors such as K-NN to get an accuracy of 90.9%. The main challenging task in the area of agriculture is disease detection which can’t be identified accurately with naked eyes. For the diagnosis and categorization of leaf disease, many machine learning (ML) and Deep Learning (DL) approaches have been defined in the field of image processing. Observing a review of the above literature, the authors were more focused on the single disease, single class, and multi-class dataset. But a lesser amount of work has been done on multi diseases dataset. Also, the discussion related to segmentation and classification has been done. All focus is done on the complete leaf area, not on a diseased area. There is also a need to develop and implement a more generalized plant segmentation method that can be used in both controlled and outdoor environments. In this work introduced new approaches to produce more accurate prediction on tomato leaf disease detections by using comparative analysis of machine learning algorithms such as linear discriminate analysis (LDA), Random Forest (RF), Extreme Gradient Boosting (XGB), and Support Vector Machine (SVM) algorithms with the help of the images of the tomato plant leafs.

## 3. Tomato Leaf Disease Detection Methodology

In this work data gathering, data pre-processing (i.e., data preparation that includes feature extraction), and machine learning (ML) classification models (LDA, RF, XGB, and SVM) are used to detect tomato leaf diseases and the detection methodology are shown in Figure 1. The following sections presents tomato leaf disease detection methodology approaches in three stages. By observing Figure 1, the initial step is the data acquisition process in which gathering of data from various sources systems. Images retrieved from drone camera can be used, with additional care to be taken as to define the path of the device to coordinate the drone position with the camera for image acquisition in order to construct a larger tomato image data set of the whole cultivation field. Larger tomato image data set used for tomato leaf disease classification. Specifically it contains 16,000 images representing leaves affected by bacterial Spot, Early Bright, Late Bright, Leaf Mold, Septoria Leaf Spot, Spider mites Two Spotted Spider mites, Target Spot, Yellow Leaf Curl Virus, Mosaic Virus and it also includes images of healthy leaves. The few samples of larger tomato leaf image data set are shown in Figure 2.

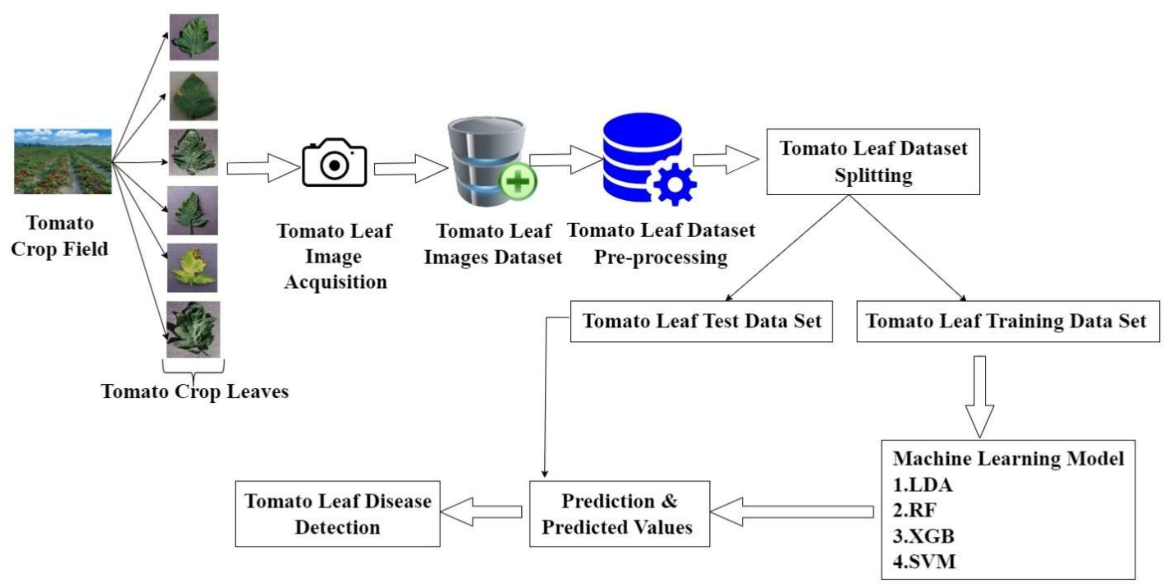


**Figure.1 Tomato Leaf Disease Detection Methodology**

**Figure.2 Healthy and Unhealthy leaf sample images for the large tomato leaf image dataset**

After collection of large data set of tomato leaf images then go for the second step as pre-processing technique as shown in Figure 1. Pre-processing a collected large data before feeding it to the model is common in most ML-based applications. Pre-processing technique is used to improve the tomato leaf image quality.A grayscale image having a value of each pixel. It's a single sample that represents the amount of light only, which means it contains only intensity information. The grayscale image is like a black and white or gray monochrome which is composed of shades of gray colors. The RGB images are converted into gray images using flattening technique[13]. Then go for the image feature extraction process refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. Such that accuracy improvements, over fitting risk reduction, speed up in training model, and improved data visualization can be done. After data is processed and features are extracted, ML models (LDA, RF, XGB, and SVM) can be used for classification, and regression, purpose as shown in Figure 1. In classification, a new data sample is assigned a label according to the relations retrieved during the training process. In regression, a continuous output value is estimated from the input variables. It is observed that the highest accuracy recorded in the SVM classifier among the rest of the classification models for disease detection in testing image data. The following sub-sections contain a brief description about machine learning algorithms such as linear discriminate analysis (LDA), Random Forest (RF), Extreme Gradient Boosting (XGB), and Support Vector Machine (SVM) algorithms which are used for comparative analysis of prediction on tomato leaf disease detections.

### 3.1 Linear Discriminate Analysis (LDA):

Linear Discriminant Analysis (LDA) is a supervised learning algorithm used for classification tasks in machine learning. Whenever there is a requirement to separate two or more classes having multiple features efficiently, the Linear Discriminant Analysis model is considered[14]. It is a most common technique to solve such classification problems.

### 3.2 Random Forest (RF):

It is an ensemble of randomized decision tree classifiers learning methods. It is operated by constructing multiple decision trees at the training time. The class labels of the testing dataset are measured based on the voting of each classification tree. The outcome of the classifier depends on the class labels that have the maximum voting by the classification trees[15]. This algorithm uses bagging and randomness of features during building of each individual tree and tries to create an uncorrelated forest of trees that will predict the performance more accurately than that of the individual tree[16].

### 3.3 Extreme Gradient Boosting (XGB):

Extreme gradient boosting refers to a class of ensemble machine learning algorithms that can be used for classification or regression predictive modeling problems. Ensembles are constructed from decision tree models. Trees are added one at a time to the ensemble and fit to correct the prediction errors made by prior models[17]. This is a type of ensemble machine learning model referred to as boosting. Models are fit using any arbitrary differentiable loss function and gradient descent optimization algorithm. This gives the technique its name, *"Extreme gradient boosting,"* as the loss gradient is minimized as the model is fit, much like a neural network[18].

### 3.4 Support Vector Machine (SVM):

SVM is a supervised machine learning classifier model that creates a hyper-plane that separates two classes. By maximizing the distance, or margin, between the nearest data points (support vectors) of each class to the hyper-plane, SVM chooses the optimum hyper-plane to segregate the data. SVM can also perform well in non-linear data by using the so called kernel trick technique[19]. The SVM kernel is a function that transforms a low dimensional input space into a higher dimensional space that is linearly separable and it could transform the features into the higher proportions by computing the dot products without transforming the feature set [20]. For this reason, SVM can be very effective in high dimensional spaces.

## 4. Results and Discussions

In machine learning, classification is the process of categorizing a given set of data into different categories. To measure the performance of Linear Discriminant Analysis (LDA), Random Forest (RF), Extreme Gradient Boosting (XGB), and Support Vector Machine (SVM), machine learning algorithms we use the confusion matrix.

A confusion matrix is a square table in which columns represent true classes of tomato leaf diseases, while rows represent the classifier's tomato leaf disease predictions with all correct classifications along the upper-left to lower-right diagonal. After all the training processes finally our model is tested by 16000 data, the confusion matrix was generated and then F1 score, precision, recall and accuracy and overall accuracy as metrics to evaluate the effectiveness of LDA, RF, XGB, SVM models. The mathematical expressions are shown below.

$$\text{F1 Score} = 2\left(\frac{\text{Precision X Recall}}{\text{Precision} + \text{Recall}}\right) \qquad (1)$$

Where Precision is the ratio between the number of correctly identified disease images and the number of correctly predicted disease images; Recall is the ratio between the numbers of correctly identified disease images and the number of all correct disease images in that category.TP is true positive, TN is true negative, FP is false positive, FN is false negative.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad (3)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \qquad (4)$$

Figure 3,4,5,and 6 shows the confusion matrix of LDA, RF, XGB, SVM and their performance are tabulated in Table.1, 2,3,and 4 respectively.

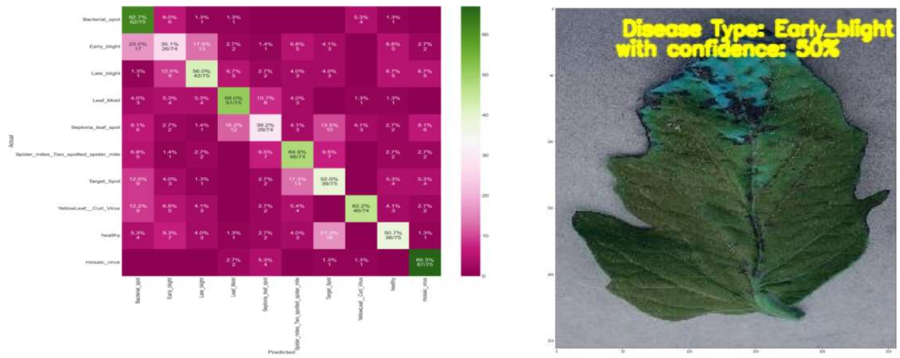


**Figure.3 Confusion matrix of LDA**

**Table.1 Performance Analysis of LDA**

| Class | Accuracy | Precision | Recall | F1 Score | Detected Disease | Overall Accuracy | Confidence Probability |
|---|---|---|---|---|---|---|---|
| Bacterial Spot | 91.02% | 0.83 | 0.53 | 0.65 | Early blight | 60.05% | 50% |
| Early Bright | 88. 61% | 0.35 | 0.41 | 0.38 | | | |
| Late Bright | 91.82% | 0.56 | 0.60 | 0.58 | | | |
| Leaf Mold | 93.7% | 0.68 | 0.69 | 0.68 | | | |
| Septoria Leaf Spot | 90.21% | 0.39 | 0.51 | 0.44 | | | |
| Spider mites Two Spotted Spider mites | 91.96% | 0.65 | 0.59 | 0.62 | | | |
| Target Spot | 89.81% | 0. 52 | 0.49 | 0. 51 | | | |
| Yellow Leaf Curl Virus | 95.04% | 0.62 | 0.84 | 0.71 | | | |
| Healthy | 91.96% | 0. 51 | 0. 62 | 0.56 | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Mosaic Virus | 95.98% | 0.89 | 0.75 | 0.82 | | | |

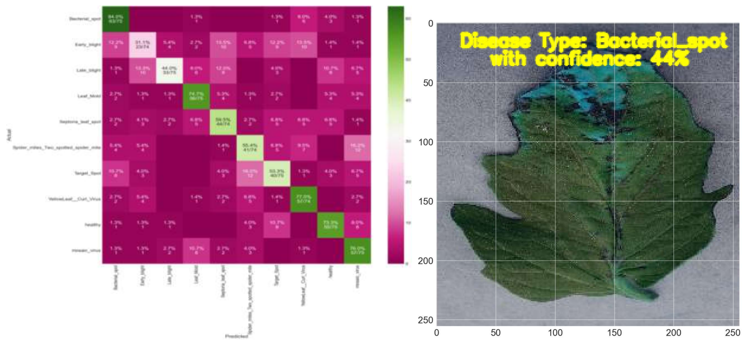


**Figure.4 Confusion matrix of RF**

**Table.2 Performance Analysis of RF**

| Class | Accuracy | Precision | Recall | F1 Score | Detected Disease | Overall Accuracy | Confidence Probability |
|---|---|---|---|---|---|---|---|
| Bacterial Spot | 94.37% | 0.84 | 0.68 | 0.75 | | | |
| Early Bright | 89.54% | 0.31 | 0.46 | 0.37 | | | |
| Late Bright | 93.03% | 0.44 | 0.77 | 0.56 | | | |
| Leaf Mold | 94.37% | 0.75 | 0.71 | 0.73 | | | |
| Septoria Leaf Spot | 91.82% | 0.59 | 0.59 | 0.59 | Bacterial spot | 62.87% | 44% |
| Spider mites Two Spotted Spider mites | 91.42% | 0.55 | 0.57 | 0.56 | | | |
| Target Spot | 90.75% | 0.53 | 0.54 | 0.54 | | | |
| Yellow Leaf | 93.7% | 0.77 | 0.66 | 0.71 | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Curl Virus | | | | | | | |
| Healthy | 94.1% | 0.73 | 0.70 | 0.71 | | | |
| Mosaic Virus | 92.63% | 0.76 | 0.61 | 0.67 | | | |

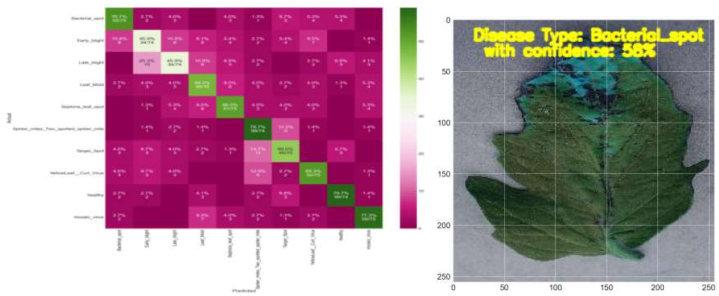


**Figure.5 Confusion matrix of XGB**

**Table.3 Performance Analysis of XGB**

| Class | Accuracy | Precision | Recall | F1 Score | Detected Disease | Overall Accuracy | Confidence Probability |
|---|---|---|---|---|---|---|---|
| Bacterial Spot | 94.37% | 0.71 | 0.73 | 0.72 | Bacterial spot | 66.08% | 58% |
| Early Bright | 90.08% | 0.46 | 0. 50 | 0.48 | | | |
| Late Bright | 91.15% | 0.46 | 0.57 | 0. 51 | | | |
| Leaf Mold | 91.96% | 0.64 | 0.59 | 0.62 | | | |
| Septoria Leaf Spot | 93.83% | 0. 68 | 0.70 | 0.69 | | | |
| Spider mites Two Spotted | 93.3% | 0.80 | 0.63 | 0.70 | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Spider mites | | | | | | | |
| Target Spot | 91.82% | 0. 60 | 0.59 | 0. 60 | | | |
| Yellow Leaf Curl Virus | 93.97% | 0. 69 | 0.70 | 0.70 | | | |
| Healthy | 95.98% | 0.80 | 0.80 | 0.80 | | | |
| Mosaic Virus | 95.71% | 0.77 | 0.79 | 0.78 | | | |

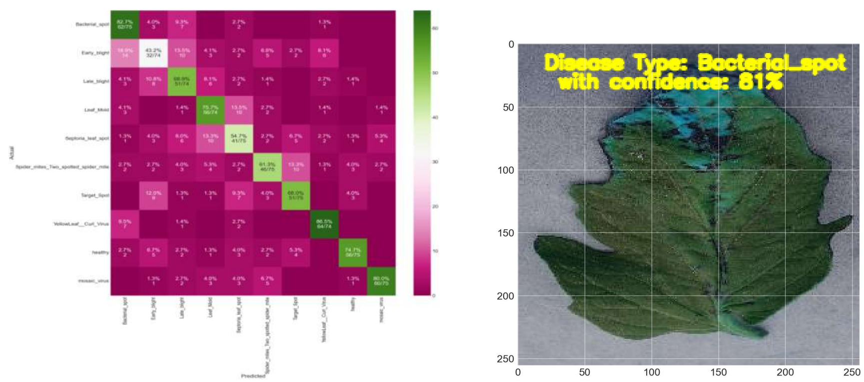


**Figure.6 Confusion matrix of SVM**

**Table.4 Performance Analysis of SVM**

| Class | Accuracy | Precision | Recall | F1 Score | Detected Disease | Overall Accuracy | Confidence Probability |
|---|---|---|---|---|---|---|---|
| Bacterial Spot | 93.97% | 0.83 | 0.66 | 0.73 | Bacterial spot | 69.57% | 81% |
| Early Bright | 90.21% | 0.43 | 0.51 | 0.47 | | | |
| Late Bright | 92.49% | 0.69 | 0.61 | 0.65 | | | |
| Leaf Mold | 93.83% | 0.76 | 0.67 | 0.71 | | | |
| Septoria Leaf Spot | 91.02% | 0.55 | 0.55 | 0.55 | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Spider mites Two Spotted Spider mites | 93.43% | 0.61 | 0.70 | 0.65 | | | |
| Target Spot | 93.97% | 0.68 | 0.71 | 0.69 | | | |
| Yellow Leaf Curl Virus | 96.92% | 0.86 | 0.83 | 0.85 | | | |
| Healthy | 96.25% | 0.75 | 0.86 | 0.80 | | | |
| Mosaic Virus | 97.05% | 0.80 | 0.90 | 0.85 | | | |

The improve performance on the test set, as can be seen in Figure 7 and their comparative analysis of all the 4 models are summarized in Table.5.

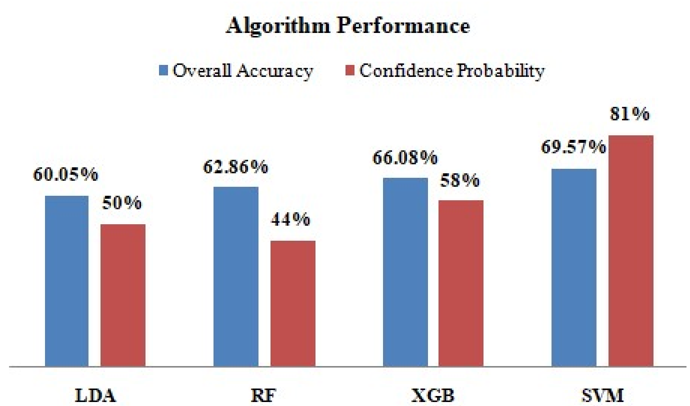


**Figure.7 Algorithm Performance**

**Table .5: Summarization of tomato leaf diseases detection performance**

| **Machine Learning Module** | **Overall Accuracy** | **Confidence Probability** |
|---|---|---|
| LDA | 60.05% | 50% |
| RF | 62.86% | 44% |
| XGB | 66.08% | 58% |

| | | |
|---|---|---|
| SVM | 69.57% | 81% |

It is observed that the highest overall accuracy of 69.57% and 81% of confidence probability is recorded in the SVM classifier among the rest of the classification models. Hence the farmers can take necessary actions based on detected diseases at the earliest to avoid various tomato leaf diseases as well as supply shortage.

## 5. Conclusion

In this work, the supervised machine learning techniques namely linear discriminate analysis (LDA), Random Forest (RF), Extreme Gradient Boosting (XGB), and Support Vector Machine (SVM) algorithms are used for the prediction of tomato leaf diseases. This work considered 16000 image data sets out of which 10 classes of diseases along with the healthy images are taken and from the comparative analysis it is observed that the highest overall accuracy of 69.57% and 81% of confidence probability is recorded in the SVM classifier among the rest of the classification models. Our proposed solution will help farmers to grow more crops by detecting and identifying diseases easily that will ensure sustainable economic growth through increased quality and quantity of crops. In the future, these models can be implemented by using several high-dimensional data sets with several other classification methods.

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