Applied Computer Science, vol. 20, no. 4, pp. 14–38
doi: https://doi.org/10.35784/acs-2024-38

Submitted: 2024-08-11 | Revised: 2024-10-23 | Accepted: 2024-11-03

Keywords: leaf disease, feature fusion, Deep Learning, Machine Learning, ensemble classifier

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ENHANCING TOMATO LEAF DISEASE DETECTION THROUGH MULTIMODAL FEATURE FUSION

Abstract

The need for an ensemble classifier is driven by better accuracy; reduced overfitting, increased robustness that copes with noisy data and reduced variance of individual models, combining the advantages and overcoming the drawbacks of the individual classifier. A comparison of different classifiers like Support Vector Machine (SVM), XGBoost, Random Forest (RF), Naive Bayes (NB), Convolutional Neural Network (CNN) and proposed Ensemble method used in the classification task was conducted. Among all the classifiers evaluated, CNN was found to be the most accurate having an accuracy rate of 93.7%. This indicates that CNN can identify complex data patterns that are also important for photo recognition and classification tasks. Nonetheless, NB and SVM only achieved medium results with accuracy rates of 82.66% and 85.6% respectively. These could have been due to either the complexity of data being handled or underlying assumptions made. RF and XGBoost demonstrated remarkable performances by employing ensemble learning methods as well as gradient-boosting approaches with accuracies of 83.33% and 90.7% respectively. The Ensemble method presented in this paper outperformed all individual models at an accuracy level of 95.5%, indicating that more than one technique is better when classifying correctly based on various resource allocations across techniques employed thereby improving such outcomes altogether by combining them. These results display the pros and cons of every classifier on the Plant Village dataset, giving vital data to improve plant disease classification and guide further research into precision farming and agricultural diagnostics.

1. INTRODUCTION

For the last decade there has been an increased emphasis on sustainable agricultural practices due to climate change threat, severe weather patterns, population growth as well as rising demand for food security and finite resources. Tomato plants are especially susceptible to an extensive range of maladies. Therefore, for maintenance of the quality preservation in Tomato crops, it is important that diagnosis be made promptly and accurately. Recent advances in neural network research (Ashqar & Abu-Naser, 2018;

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Kokate et al., 2023), image processing, feature extraction techniques (Basavaiah & Arlene Anthony, 2020), and computer power can greatly improve plant growth and protection approaches. This implies that understanding automatic plant disease diagnosis and detection becomes necessary as this will assist in monitoring large agricultural areas or automatically identifying diseases through symptoms visible on plant leaves. For the purpose of identification and classification of plant diseases artificial intelligence (AI) approaches are used.

Support vector machines (SVM), logistic regression, neural networks, decision trees, and k-Nearest Neighbors (k-NN) are popular AI methods. In particular, neural network technology (CNN) has shown outstanding performance in many fields, such as classification of Tomato plant diseases. These areas include machine learning and deep learning. This study uses the Plant Village dataset to compare and evaluate the performance of different classifiers, including XGBoost, Random Forest (RF), Support Vector Machine (SVM), CNN, Naive Bayes (NB), and Ensemble techniques.

Here, the authors developed a custom deep learning method specifically designed for the task of detection of diseases caused by a village dataset. The proposed architecture maximizes the model’s ability to extract and integrate relevant information from datasets using state-of-the-art integration techniques. The authors also provide Ensemble classifications using XGBoost, Naive Bayes, Convolutional Neural Network, Support Vector, and Random Forest methods. This Ensemble method utilizes the potential of each category and combines their results to provide a more efficient classification system. The efforts aim to solve the problems and challenges associated with plant disease classification and provide a robust framework to improve the efficiency of assessing and understanding the current status of agriculture. Combining state-of-the-art deep learning methods with new ensemble techniques, the proposed Ensemble method not only advances the field but also provides practical insights to improve agricultural evaluation and holistic farming practices. This article also aims to determine the potential of these classes in solving problems related to plant community datasets and provide practical guidance for researchers and practitioners looking to use machine learning in agriculture.

The following are the manuscript's major contributions:

– Multi-model plan leaf disease detection system based on majority voting classification and obtained satisfactory plan leaf disease detection utilizing SVM, RF, CNN NB, XGBoost and Proposed Ensemble Model.
– Serial fusion feature extraction methodologies such as color and shape feature extraction using the features like color histogram, color moment and image texture can be quantified using diverse parameters, including entropy, contrast, skewness, variance and homogeneity.
– Performance comparison of existing approaches with proposed work and other comparable techniques, it was discovered that the proposed approach outperforms other approaches in disease detection accuracy.
– The remainder of this paper is organized as follows. Section 2 discusses related work on Plant leaf disease detection. Section 3 discusses the materials and methods used in plant leaf disease detection. Section 4 describes the experimental results, the performance of the proposed model, and its comparison to existing models. Finally, in Section 5 the conclusions are presented.

2. LITERATURE REVIEW

Following are some key researches in the area of plant/leaf disease detection using different feature extraction techniques which are related to the proposed work.

Ghazouani et al. explores and compares different techniques, including ordered classification, sampling based clustering and reweighting-based approaches, to address the challenge of class imbalance in leaf disease detection and improve the accuracy and reliability of machine learning models in the context of precision agriculture, with the hierarchical approach achieving the highest accuracy of 97.17%. The ordered approach can be further enhanced by trying ensemble learning and/or using different CNN models for different plant species. - Limited attention has been given to addressing class imbalance in multi-class image datasets, compared to two-class problems. There is a need to develop techniques that can achieve high accuracy (over 93%) while dealing with high-class imbalance in multi-class image datasets (Ghazouani et al., 2023).

Kokate et al. presents a convolutional neural network (CNN) model for diagnosing Tomato leaf diseases, which achieved an average accuracy of 95.53% on a dataset of 14,240 images representing 9 disease classes. The need for a larger dataset of Tomato leaf disease images. The challenge of accurately classifying fine-grained Tomato leaf disease images (Afroz, 2023).

Chen et al. describes the development of an Android-based mobile application that uses a modified AlexNet convolutional neural network (CNN) architecture to detect and classify 10 different types of Tomato leaf diseases, achieving high accuracy, precision, recall, and F-measure values in classifying the Tomato leaf diseases. The modified AlexNet-based CNN model developed in the study can accurately classify Tomato leaf diseases, with an average accuracy of 96%, precision of 98%, recall of 95%, and F-measure of 97%. The model was designed to be embedded in a mobile-based Android application, allowing Tomato farmers to quickly identify the type of disease affecting their plants by uploading leaf photos, enabling early disease management. The mobile application is appropriate for Android devices due to the limited memory capacity of such platforms (Chen et al., 2022).

Chowdhury et al. proposes using deep learning, specifically the EfficientNet CNN model, to classify Tomato leaf diseases into binary (healthy vs. unhealthy), 6-class, and 10-class categories, and evaluates the performance of two segmentation models, U-Net and Modified U-Net, to segment the leaf from the background. The EfficientNet-B7 model outperformed other models in binary (healthy vs. unhealthy) and 6-class classification of Tomato leaf diseases, achieving over 99% accuracy. The EfficientNet-B4 model achieved 99.89% accuracy in the more challenging 10-class classification of different Tomato leaf diseases. The results of this study are comparable to the state-of-the-art in this domain (Chowdhury et al., 2021). The dataset is limited to a specific region and breed of Tomatoes, so the model may not generalize well to other regions and breeds. The current models may be too computationally heavy for real-world portable solutions, and investigating lighter CNN architectures could be useful.

Vadivel and Suguna demonstrated a CNN-based system to automatically recognize and classify different Tomato leaf diseases, achieving an accuracy of 99.4%. The proposed CNN-based architecture achieved a classification accuracy of 99.4%, outperforming other existing methods. The model was able to correctly classify crop disease from 10 possible classes in 497 out of 500 test images, without any feature engineering. The model needs to be improved to handle lower quality leaf images for detecting Tomato pests and diseases. The model should be further improved on the same dataset to increase the testing accuracy (Vadivel & Suguna, 2021).

Gonzalez et al. explored a comparison and evaluation of four popular deep learning models (MobileNetV2, NasNetMobile, Xception, and MobileNetV3) for disease detection in Tomato leaves. The models were implemented on a low-cost Raspberry Pi 4 microcomputer to demonstrate their potential for field deployment. The main contributions of the paper include extensive transfer learning and training of the selected models, quantitative and qualitative evaluation of the models, quantification of the models for implementation on Raspberry Pi 4, and development of a graphical user interface (GUI) for using the trained models on PCs, Raspberry Pi 4, and mobile devices. - Improving precision, especially for early disease detection. Exploring model optimization for different tasks (e.g. binary healthy vs. diseased classification vs. multi-class disease classification). The accuracy values obtained for the four models were MobileNetV2: 87.1%, NasNetMobile: 88.1%, Xception: 92.3% and MobileNetV3: 90.2% (Wagle & R, 2021).

Chen et al. described a Deep Convolutional Generative Adversarial Network to generate realistic Tomato leaf disease images in order to address the problem of insufficient training data and improve the generalization ability of the recognition model. Using image-to-image GANs instead of noise-to-image GANs to address data imbalance, designing a multi-scale convolutional neural network to better capture the varying characteristics of disease stages and classes. Addressing the challenge of few-shot learning due to difficulty in collecting leaf samples. The accuracy values obtained 94.33% (Wu et al., 2020).

Kaushik et al. explained a deep learning model using convolutional neural networks was developed to detect and classify diseases in Tomato leaves, achieving 97% accuracy after fine-tuning the ResNet-50 model. Using deep learning methods such as convolutional neural networks (CNNs), data augmentation and transfer learning, scientists have developed a model to detect Tomato leaf spot. After processing the ResNet-50 model, the proposed model achieved 97%, this is a useful tool for farmers to accurately diagnose Tomato leaf spot disease. Reduces training time by using model modification, use this model to detect diseases in different plant species such as brinjal, apple, potato and scallop (Nithish Kannan et al., 2020).

Ashok et al. established a reliable and accurate system and prevent losses in the agricultural sector, this research shows how to make early detection of Tomato leaf diseases using image processing and in-depth algorithms. Using deep learning techniques, the proposed method to detect Tomato leaf spot reached a high rate of 98.12%. The proposed method outperforms other methods such as Artificial Neural Networks and Deep Neural Networks (AlexNet) in terms of accuracy. The feature extraction technique, which maps and evaluates pixel values based on training statistics, is responsible for high accuracy (Ashok, et al., 2020).

Kumar et al. presented a deep learning-based method to detect and classify Tomato leaf spot diseases with a well-established VGGNet architecture that achieves a test accuracy of 99.25% on the PlantVillage dataset. A disadvantage of the proposed system is that it requires high-end hardware and a long training time. The authors plan to adapt the architecture to work with smaller datasets and shorten the training time. The authors plan to apply the study on Tomato leaf disease toother samples such as potato, apple, and sugar cane (Kumar & Vani, 2019).

3. MATERIALS AND METHODS

In this section, the authors describe the development of a comprehensive Tomato identification model using a combination of machine learning and deep learning approaches. The model includes both traditional machine learning classifiers such as Support Vector Machine (SVM), Naive Bayes (NB) and Random Forest (RF), as well as more advanced deep learning architectures such as Convolutional Neural Networks (CNN). Furthermore, a proposed ensemble model is introduced to improve the classification accuracy by exploiting the strengths of multiple algorithms. The process also involves using feature extraction techniques to identify key patterns in leaf images, which are essential for distinguishing different diseases. This combination of techniques was designed to create a robust and scalable system for the automatic detection of diseases in Tomato leaves. The general methodology is depicted in Figure 1.

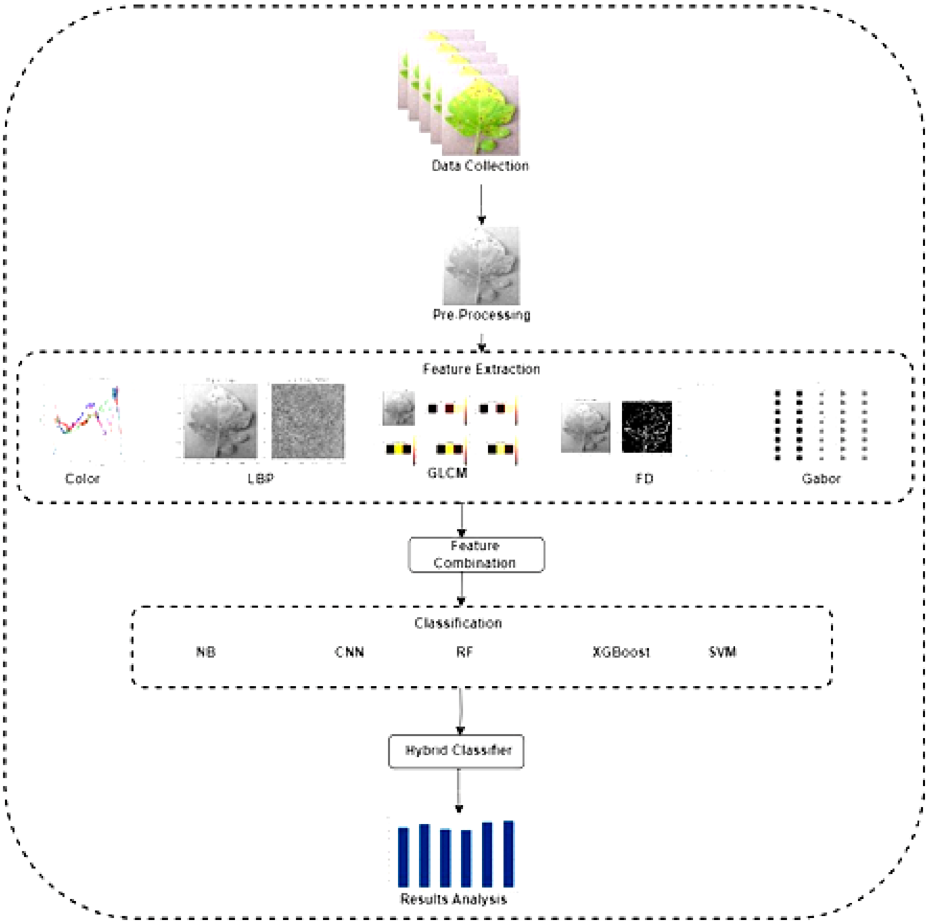


Fig. 1. General system flow

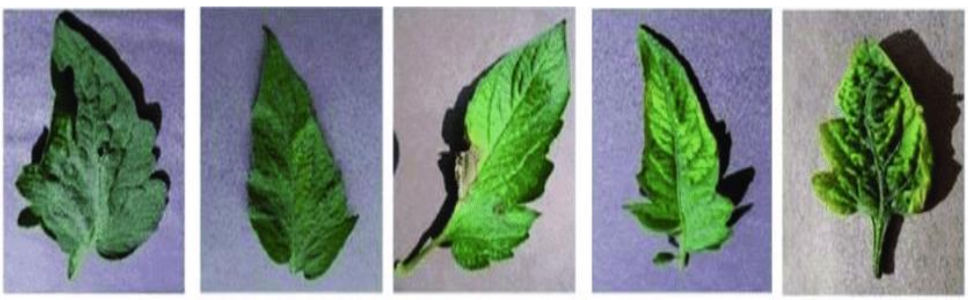
3.1. Dataset

The data used for this research was obtained from PlantVillage (Too et al., 2019). The dataset consists of 16,060 images of Tomato leaves with ten classes: Tomato_bacterial_spot, Tomato_early_damage,Tomato_small_spot,Tomato_leaf_mould,tomato_septoria_leaf_spot,tomato_spider_mit_two_spotted_spider_mit,Tomato_target_spot,Tomato_Tomato_yellowleaf__curl_virus, Tomato__Tomato_mosaic_virus and Tomato_healthy. The images were captured in different locations, seasons and in different lighting conditions. From the available dataset the authors used 80% for Training and 20% for Testing. Table 1. Shows the class distribution of the data set. The following are images of different Tomato classes (Fig. 2).

Tab. 1. Distribution of Tomato leaves samples per class

S. N.	Type of Tomato leaf diseases	Number of images
1	Tomato_Bacterial_spot	2127
2	Tomato_Early_blight	1000
3	Tomato_Late_blight	1909
4	Tomato_Leaf_Mold	1000
5	Tomato_Septoria_leaf_spot	1771
6	Tomato_Spider_mites_Two_spotted_spider_mite	1676
7	Tomato__Target_Spot	1404
8	Tomato__Tomato_YellowLeaf__Curl_Virus	3209
9	Tomato__Tomato_mosaic_virus	373
10	Tomato_healthy	1591

a) Healthy b) Bacterial Spot c) Early Blight d) Leaf Mold e) Septorial Leaf Spot



f) Target Spot g) Two Spotted Milte h) Late Blight Mold i) Mosaic Virus j) Yellow Leaf Curl Virus

Fig. 2. Plant village tomato leaves disease dataset (Islam et al., 2022)

3.2. Pre-processing

In the context of Tomato disease detection, image denoising is an essential preprocessing step to improve image quality and classification model accuracy. Denoising helps reduce unwanted noise and distortions in the image that can occur due to changes in lighting, environmental conditions or camera quality. To simplify the image and focus on the essential features, RGB images are first converted to grayscale using equation 1 which represents the red, green and blue channels of the original image. This grayscale conversion reduces computational complexity while preserving essential information about leaf structure and disease symptoms. Then, denoising techniques, such as Gaussian filtering or median filtering, can be applied to smooth the grayscale images, further reducing the noise without obscuring the important features of the diseases.

An RGB image I of size $H \times W$. Output: A feature vector F of size K.

Pre-process Image

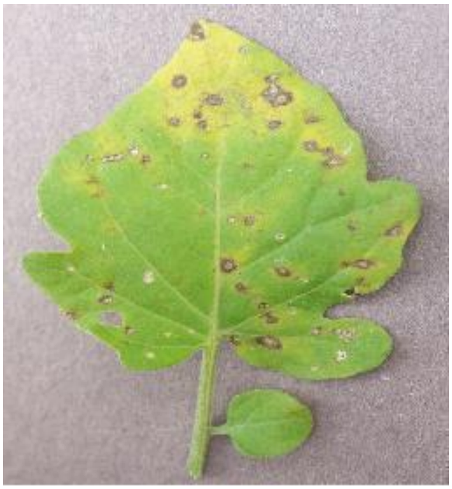


Fig. 3. Tomato image before denoising

Fig. 4. Tomato image after denoising

Convert the image to grayscale:

$$I_{\text{gray}} = 0.299 \times I_R + 0.587 \times I_G + 0.114 \times I_B \tag{1}$$

where I_R, I_G, I_B are the red, green, and blue channels of the image, respectively.

Fig. 5. Tomato disease leaf color image

Fig. 6. Tomato disease leaf gray scale image

3.3. Feature extraction

This study uses a multi-pronged strategy for feature extraction, including sophisticated descriptors, color, form, and texture to capture the inherent qualities of our dataset. To be more precise, relevant features were extracted using color histograms, shape indices, Gabor filters, and co-occurrence matrices. Fourier Descriptors and Gabor features are then used to capture spatial frequency and textural information. By integrating these techniques, the authors provide a solid and thorough representation of their data that makes analysis and categorization efficient.

3.3.1. Color features extraction

Compute color histograms to capture color distribution: $\mathrm{Hist}(I)=[h_1, h_2, \ldots, h_N)$, where h_i represents the count of pixels with intensity i.

It convey both the physical and graphic characteristics of colors, representing the responses of sensors to different wavelengths. These features demonstrate robustness against complex backgrounds, remaining invariant to orientation and scale variations. They encompass photometric insights like Lighting, shadow, shadiness and optical density of the color channels. Color moments offer significant statistical information about color channels, whereas color histograms skillfully depict the distribution of color inside pictures. Alternatively, color descriptors extract attributes through color gradients or textures present in the images (Mohameth et al., 2020; Chouhan et al., 2018).

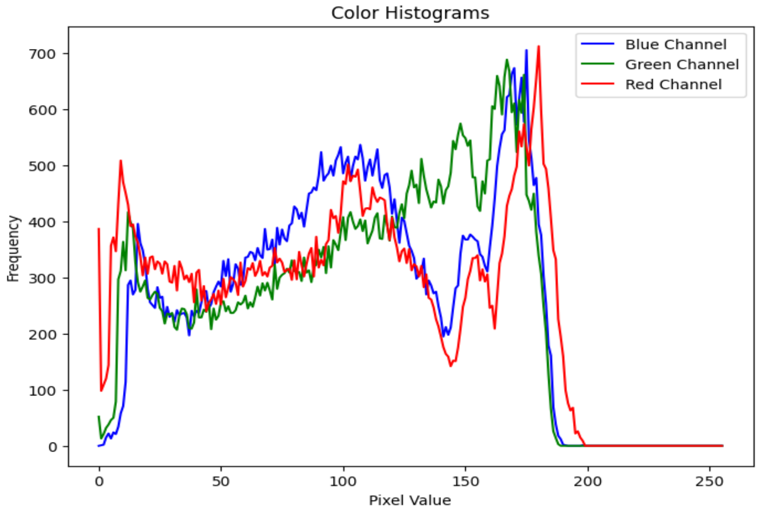


Fig. 7. Color histograms sample 1

Compute color moments to capture color characteristics: $\mu_i = \frac{1}{N}\sum_{j=1}^{N} I^{i}_{j}$, where μ_i is the i-th color moment and N is the total number of pixels.

3.3.2. Texture features extraction

It is a defining feature of a particular visual region, especially when a small patch inside has significant tone fluctuations. It basically depicts the color schemes and spatial patterns seen in the picture. Factors such as illumination, contrast, separation and orientation play a role in influencing how texture is perceived. Image texture can be quantified using diverse parameters, including entropy, contrast, skewness, variance and homogeneity. The Gray Level Co-occurrence Matrix (GLCM) is a valuable technique for depicting relationships among pixel intensities in images, especially effective for texture analysis. Local Binary Patterns (LBP) (Salve et al., 2019) excel in capturing local texture patterns, while Gabor Filters have the capability to extract texture details across multiple scales and orientations (Towfek & Khodadadi, 2023). Figures 8, 9 and 10 illustrate the GLCM, LBP and Gabor Feature Extraction (Salve et al., 2021; 2022).

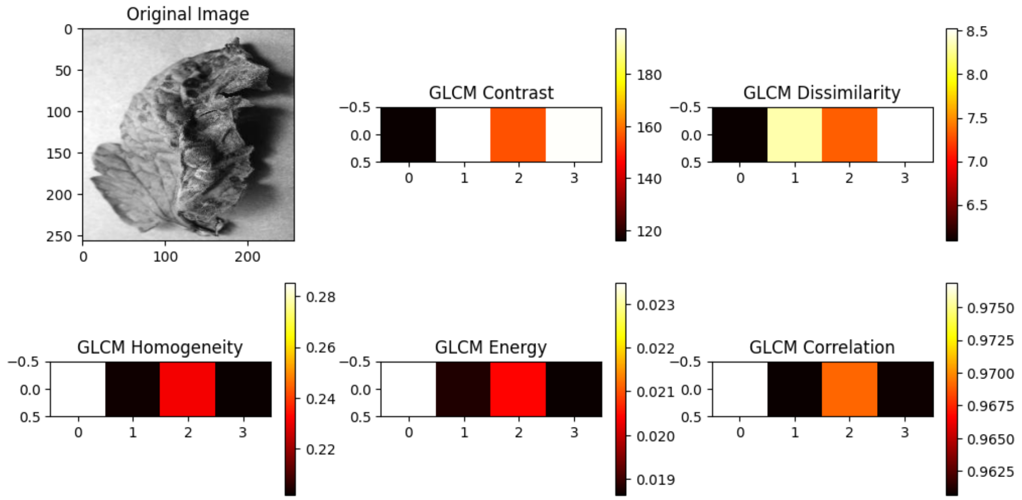


Fig. 8. GLCM feature extraction

Normalize the Color Histogram 4.1 Normalize the color histogram to ensure consistent scale across different images: $\text{Hist}_{\text{norm}}(I) = \dfrac{\text{Hist}(I)}{\|\text{Hist}(I)\|}$.

3.3.3. Local binary patterns features

Convert the Image to Binary. Apply the chosen threshold to convert the image to binary:

$$I_{\text{binary}}(x, y) = \begin{cases} 1, & \text{if } I(x, y) > T \\ 0, & \text{otherwise} \end{cases}$$

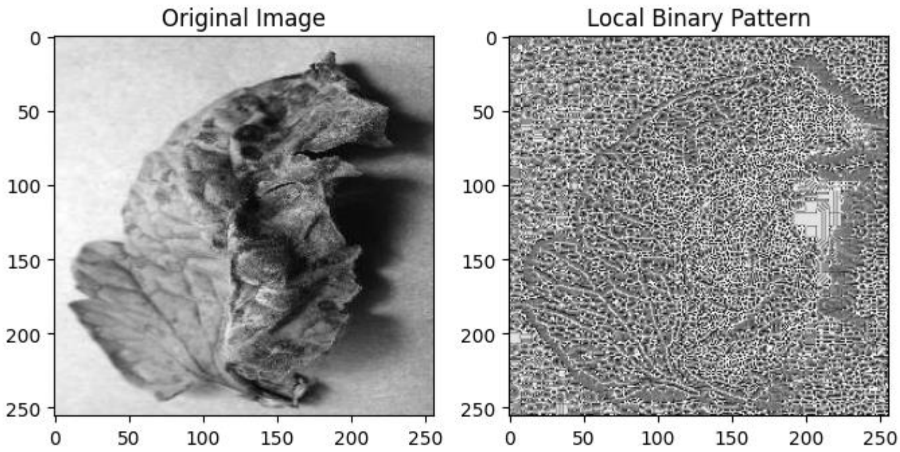


Fig. 9. LBP feature extraction

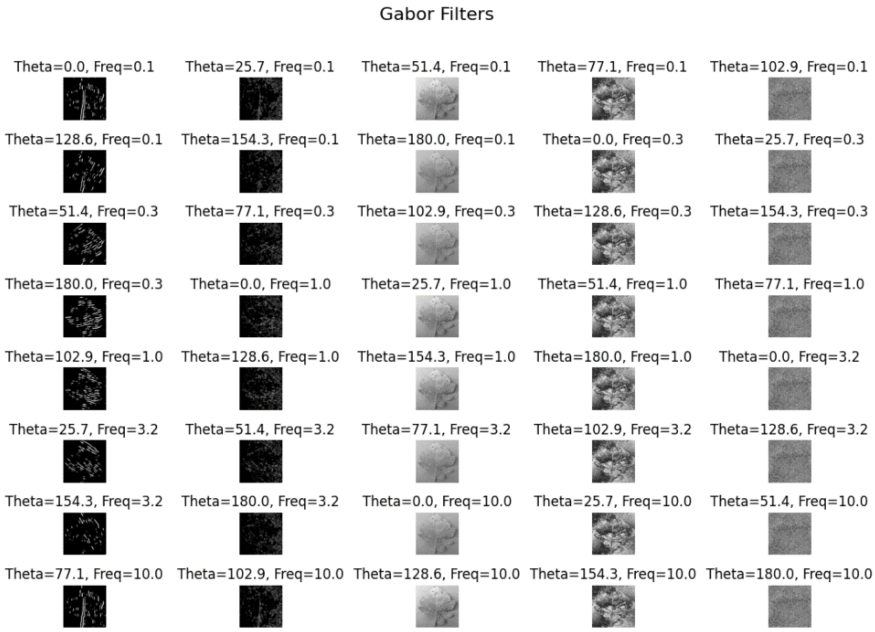


Fig. 10. Gabor feature extraction illustration

Extract Fourier Descriptor Fig. 11. Compute the Fourier descriptor from the binary image to capture shape information: $\mathrm{FD}\left(I_{\text{binary}}\right)$.

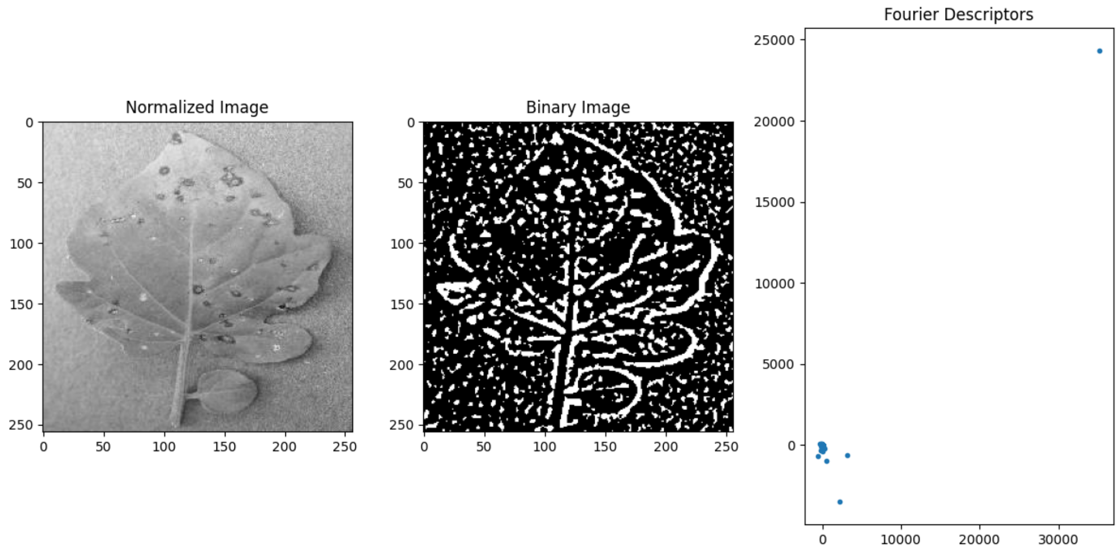


Fig. 11. Extract shape fourier features

3.3.4. Features concatenation

The authors used serial feature fusion to integrate multiple types of features into a unified representation to improve classification accuracy. In particular, Equation 1 represents the relationship of the features of the normalized histogram, the fractal dimension (FD) of the binary image, and the shape descriptors derived from the binary image. This approach exploits the strengths of each feature type: the normalized histogram captures texture and color information, the fractal dimension quantifies complexity. Image textures and shape descriptors provide geometric detail. By concatenating these features in series, the method creates a complete feature vector that improves the classifier's ability to distinguish between different types of leaf diseases, leading to more accurate and robust classification results.

$$F = [Hist_{norm}(I), FD\left(I_{binary}\right), Shape(I_{binary})] \tag{2}$$

3.4. Classifiers used for tomato leaf disease detection

Five Machine Learning algorithms were used for the training and testing. We have performed the experiments using Support Vector Machine (SVM), Random Forest, Convolutional Neural Network (CNN), Naive Bayes, eXtreme Gradient Boosting (XGBoost) and Proposed Ensemble Model. Most popular machine learning classifier for plant leaf disease detection were selected.

3.4.1. SVM classifier

Support Vector Machine (SVM) is a popular algorithm used in image classification tasks like Tomato leaf disease detection, aiming to find a hyperplane that maximally separates classes in the feature space. Mathematically, SVM minimizes the objective function subject to constraints. In tomato leaves disease detection, SVM is used to classify images into different disease categories based on extracted features like color, texture, shape, and spatial relationships, represented as feature vectors, with the goal of finding the optimal decision boundary that maximizes the margin between classes.

$$L(w,b) = \frac{1}{2}\left|\left|w\right|\right|^{2} + C * \Sigma i = 1 \; to \; n \; (\xi i + \zeta i) \tag{3}$$

Where, w is the weight vector, b is the bias term, C is the regularization parameter, and ξi and ζi are slack variables.

3.4.2. Random forest

For classification problems such as Tomato leaves disease detection, Random Forest is an ensemble learning technique that combines numerous decision trees to increase robustness and accuracy. The method is to build a collection of decision trees, train them on a randomized subset of characteristics and data samples, and then output the class label, which is the average of the classes that each tree predicted. Mathematically, Random Forest is represented as a set of decision trees (x, θ_i), where h_i is the prediction of the i -th tree, θ_i is the parameter, and x is the feature vector. The final prediction is generated by averaging or voting the projections from each individual tree. Random Forest is used to classify images of Tomato leaves illnesses into distinct disease groups based on extracted features including color, texture, shape, and spatial correlations. This process takes use of the benefits of many decision trees. Classification accuracy is improved by this.

For classification problems like Tomato leaves spot, Random Forest is a learning technique that combines multiple decision trees to increase power and accuracy. The method consists of creating a collection of decision trees, training them on expected features and sample data, and outputting a class label that is the average of the classes predicted by each tree. In mathematics, Normal Forest is represented as a list of decision trees (x, θ_i); where $h_i$is the prediction of the tree, $\theta_i$is a parameter, and x is the feature vector. The final prediction is made by comparing or voting the predictions for each tree. Conventional forest is used to classify images of Tomato leaves diseases into different disease groups based on the extracted features including color, shape, texture, and relatedness. More than one decision tree is used in this process. This will improve accurate classification.

$$H(x) = \frac{1}{N}\sum_{i=1}^{N} h_i(x) \tag{4}$$

3.4.3. CNN classifier

To detect Tomato leaves spot disease, the concept of Convolutional Neural Network (CNN) architecture has been developed to efficiently extract and classify features in input images. It consists of three verification units with 32, 64 and 128 filters to reduce spatial parameters and preserve important features. The MaxPooling section comes after each verification stage. The verification part uses 3x3 filter and ReLU to extract critical images from the image. Recordings from the attached sections were sent to the 128-neuron full Density method, which analyzed the extracted features. Input images are classified into one of ten categories of the final output using softmax activation. With a total of 14,840,266 trainable parameters, this architecture uses deep learning to diagnose different Tomato leaves diseases from picture data with good accuracy.

– Convolution Operation.

The convolution operation can be represented as:

$$(I * K)(i,j) = \sum_m \sum_n I(i+m, j+n) \cdot K(m,n) \tag{5}$$

Where $I$is the input image, $K$is the kernel (filter), and (i,j) are the coordinates of the output feature map.

– ReLU Activation.

The Rectified Linear Unit (ReLU) activation function is defined as:

$$f(x) = \max(0, x) \tag{6}$$

This function applies element-wise, setting all negative values to zero.

– Max Pooling.

The max pooling operation is defined as:

$$P_{max}(i,j) = \max_{(m,n)\,\in\,\text{window}} I(i+m, j+n) \tag{7}$$

Where the window is typically a 2x2 region of the input feature map.

– Flatten Layer.

The flattening operation converts the multidimensional output from the convolutional layers into a single vector:

$$\text{Flatten}(I) = [I_1, I_2, \ldots, I_n] \tag{8}$$

Where $I_1, I_2, I_3, \ldots \ldots I_n$ are the elements of the input feature map arranged in a single vector.

– Dense Layer (Fully Connected Layer).

The dense layer computes:

$$z_j = \sum_i x_i w_{ij} + b_j \tag{9}$$

$$a_j = f(z_j) \tag{10}$$

Where, x_i are the input features, w_{ij} are the weights, b_j are the biases, and $f(z_j)$ is the activation function applied element-wise (ReLU in the penultimate layer and softmax in the output layer).

– Softmax Activation.

The softmax function for a vector *z* is defined as:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{11}$$

Where z_i is the i-th element of the input vector *z*, and *K* is the number of classes.

– Cross-Entropy Loss

The categorical cross-entropy loss used for multi-class classification is defined as:

$$L = -\sum_{i=1}^{K} y_i \log(\hat{y}_i) \tag{12}$$

Where y_i is the true label (one-hot encoded) and $\hat{y}_i$ is the predicted probability for class i.

3.4.4. Naive Bayes classifier

Based on the Bayes Theorem, the Naive Bayes classifier is a probabilistic machine learning algorithm that is especially useful for the efficient and straightforward classification of Tomato leaves diseases. It works by assuming that features (like pixel values in images) are conditionally independent given the class label, which makes it easier to compute the posterior probabilities. To determine which illness group is most likely, the Naive Bayes classifier computes the likelihood of the input characteristics for each class and mixes this with the class's prior probability. In many real-world applications, such as image classification, Naive Bayes performs very well, even though it makes the assumption of feature independence, which may not hold true in real data. The ability to use high-quality data and accurate calculations makes it the best choice for rapid and accurate detection of various Tomato leaves diseases and facilitates timely and effective control of plant diseases.

3.4.5. XGBoost classifier

XGBoost (eXtreme Gradient Boosting) is a reliable and efficient machine learning technique that is particularly suitable for classification of Tomato leaves diseases due to its outstanding performance and ability to use rich data. Cascade boosting is a technique that XGBoost uses to build a group of decision trees sequentially, with each tree correcting the mistakes of the previous one. This process culminates in a real model that can recognize complex patterns in numbers. XGBoost also uses normalization techniques (L1 and L2) to ensure the model fits new data correctly and prevent overfitting. Its ability to handle missing values, analyze data in parallel, and use cross-sectional structures make it a useful tool in diagnosing various Tomato diseases from photographs. It provides speed and accuracy during sorting operations. A metaphor describes a purpose.

$$\mathrm{Obj}(\Theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{13}$$

Where l is the loss function, Θ is the regularization term, f_k are the trees, and Ω represents the parameters of the trees.

Model update is defined by:

$$\widehat{y}_i^{(t+1)} = \widehat{y}_i^{(t)} + \eta \cdot f_t(x_i) \tag{14}$$

Where η is the learning rate, f_t is the tree built at iteration t, and $\hat{y}_i$ is the predicted value.

3.4.6. Proposed ensemble classifier

An Ensemble classifier has been proposed that combines the results of different machine learning methods: Support Vector Machine (SVM), eXtreme Gradient Boosting (XGBoost), Random Forest (RF), Naive Bayes (NB) and Convolutional Neural Network (CNN). As an improvement method, the same dataset is used to train these different models and the sum of each model is estimated. The Ensemble classifier uses a majority voting technique in which the class with the most votes from the ensemble of models determines the final predicted class label for each input instance. The robust feature extraction of CNN, the potent ensemble techniques of RF and XGBoost, the probabilistic reasoning of NB, and the margin optimization of SVM are just a few of the classifiers whose capabilities are combined in this methodology. The Ensemble classifier seeks to enhance overall classification performance and resilience against individual model shortcomings by merging these several approaches, offering a more trustworthy diagnosis of Tomato leaves diseases.

The predicted class label y by the Ensemble classifier based on majority voting can be defined as:

$$\widehat{y}_i^{(t+1)} = \widehat{y}_i^{(t)} + \eta \cdot f_t(x_i) \tag{15}$$

$$y = \arg \max_{k \in \{1,2,\ldots,K\}} \sum_{i=1}^{M} \mathbb{I}(C_i(x) = k) \tag{16}$$

Where, M different classifiers: C1,C2,C3,…,CM (SVM, XGBoost, RF, NB, CNN), K possible class labels: {1,2,3,…,K}, x as the input sample to be classified.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Evaluation metrics

1. Confusion matrix

A confusion matrix is a performance measurement tool used to evaluate the effectiveness of a classification model. Summarize the results of the prediction in a table, which shows the number of true positives, false positives, true negatives and false negatives. For a Tomato blight classification model, the confusion matrix helps to understand how well the model discriminates between different disease classes.

True Positive (TP): The model correctly predicts a disease class (for example, correctly identifying a Tomato leaves as having a specific disease).

True Negative (TN): The model correctly predicts that a leaf does not belong to a disease class.

False positive (FP): the model incorrectly predicts that a leaf belongs to a disease class when it does not (type I error).

False negative (FN): the model incorrectly predicts that a leaf does not belong to a disease class when it does (type II error).

Tab. 2. Example of confusion matrix representation for a 3-class classification (e.g. healthy, Disease A, Disease B)

	Predicted: Healthy	**Predicted: Disease A**	**Predicted: Disease B**
Actual: Healthy	TN	FP	FP
Actual: Disease A	FN	TP	FP
Actual: Disease B	FN	FN	TP

2. Accuracy

Accuracy is a widely used metric to evaluate the performance of classification models. It measures the proportion of correct predictions (both true positives and true negatives) compared to the total predictions made. For your Tomato disease classification model, accuracy indicates how often the model correctly classifies the leaves disease or health condition.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (17)$$

4.2. Performance evaluation of Support Vector Machine (SVM)

The confusion matrix (Fig. 12.) details the performance of an disease detection task conducted using a Support Vector Machine (SVM) classifier. The numbers in the matrix represent the number of examples categorized for each class label, and each row and column corresponds to a particular class label. While off-diagonal elements indicate incorrect classifications, diagonal elements provide precise predictions. All things considered, the confusion matrix provides an all-encompassing perspective on the SVM classifier's performance, illustrating its ability to accurately identify different classes and regions where misclassifications transpire, so supporting the evaluation and improvement of the classification model.

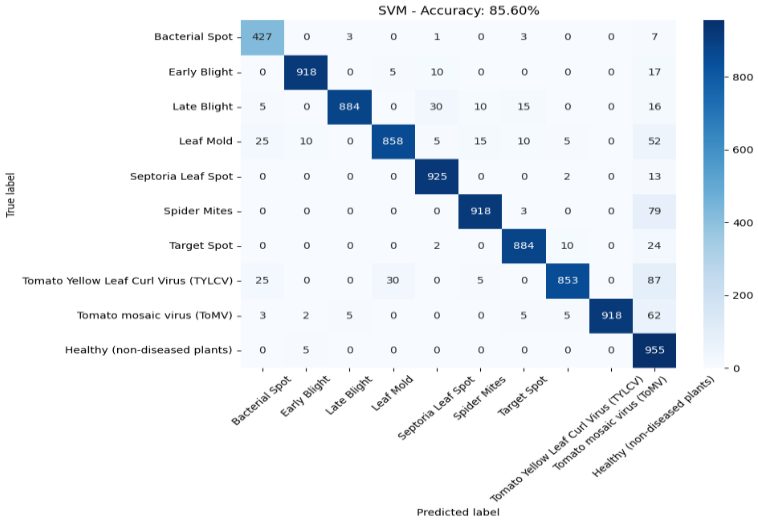


Fig. 12. Confusion Matrix for SVM

4.3. XGBoost

The performance of an image classification challenge employing an XGBoost classifier is demonstrated by the confusion matrix (Fig. 13).

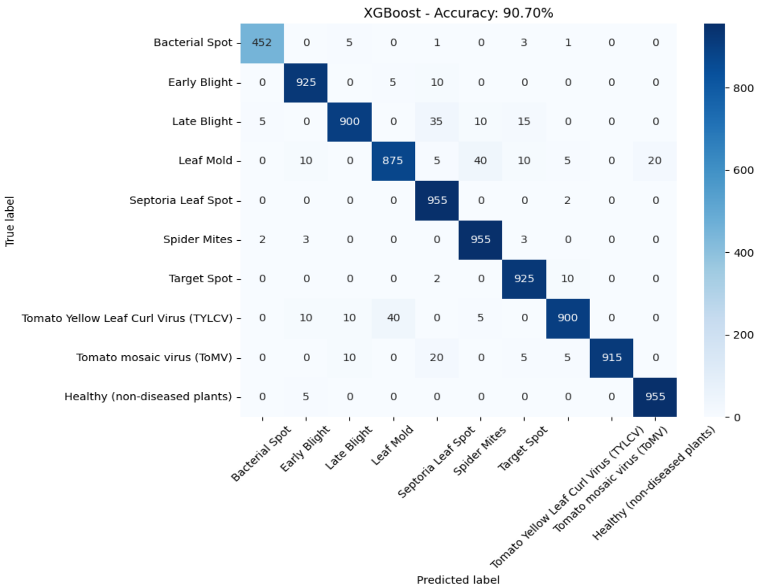


Fig. 13. Confusion Matrix for XGBoost

4.4. Performance evaluation of Random Forest

The confusion matrix (Fig.14) shows how well Random Forest (RF) performs in processing images. Non-diagonal elements represent misclassifications, while diagonal elements provide correct predictions. All items were evaluated. The confusion matrix provides understandable information about the performance of the RF classifier and verifies that it is correct and work correctly.

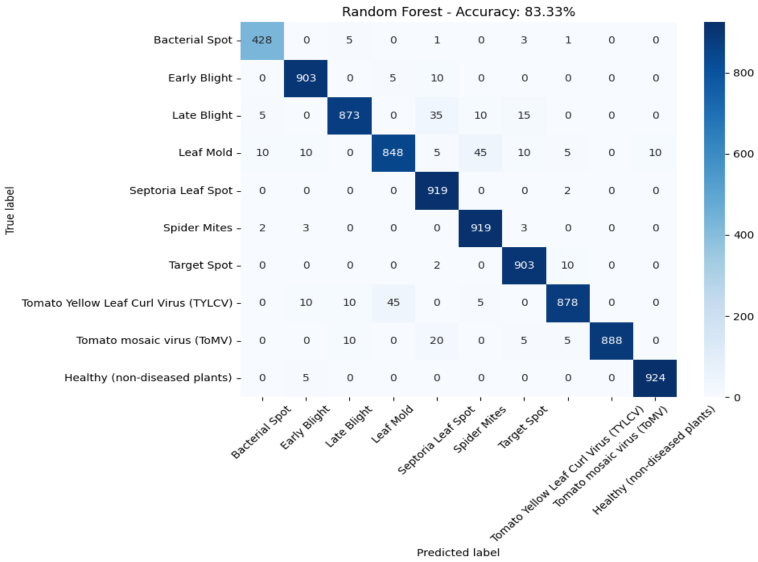


Fig. 14. Confusion Matrix for Random Forest

4.5. Performance evaluation of Naive Bayes

The confusion matrix of the Convolutional Neural Network (CNN) is shown in Fig. 15.

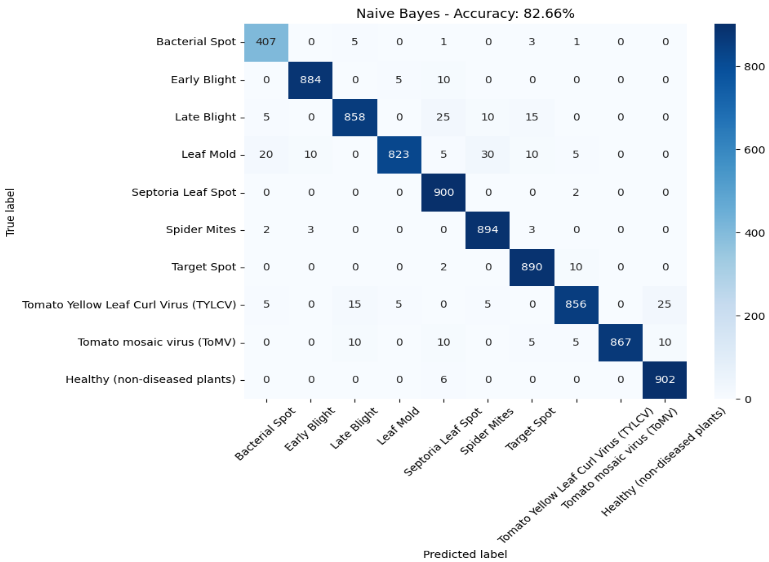


Fig. 15. Confusion Matrix for Naive Bayes

4.6. Performance evaluation of Convolutional Neural Network

The confusion matrix of the Convolutional Neural Network (CNN) is shown in Fig. 16.

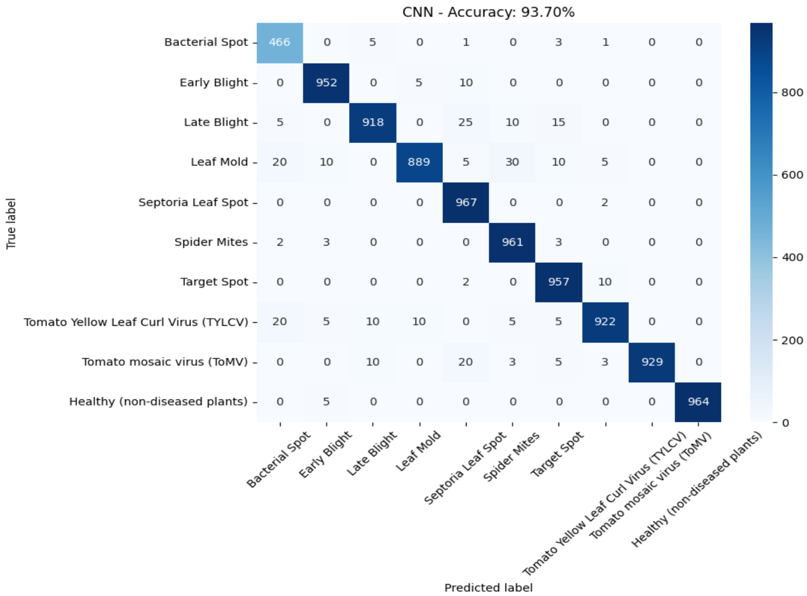


Fig. 16. Confusion Matrix for CNN

4.7. Performance evaluation of Proposed Ensemble Classifier

The classification outcomes produced by a voting classifier are shown in the confusion matrix. Based on average probabilities or the majority vote, this classifier aggregates the results of several separate classifiers to forecast the class label. Like the earlier confusion matrices, this matrix has values that represent the number of examples categorized according to a certain class label for each row and column. The Proposed Ensemble classifier's overall performance is comprehensively outlined in the confusion matrix, which also highlights regions of misclassification and the classifier's areas of strength in accurately categorizing particular classes. This data can be useful for assessing and enhancing the classifier's performance in correctly classifying incoming data.

An ensemble approach, Support Vector Machine (SVM), XGBoost, Random Forest (RF), Naive Bayes (NB), and Convolutional Neural Network (CNN) are among the classifiers whose performance is compared in Fig. 18. CNN, with an accuracy of 93.7%, was found to be the most effective classifier, demonstrating its ability to identify complex patterns in image data, making it particularly suitable for tasks involving recognition and image classification.

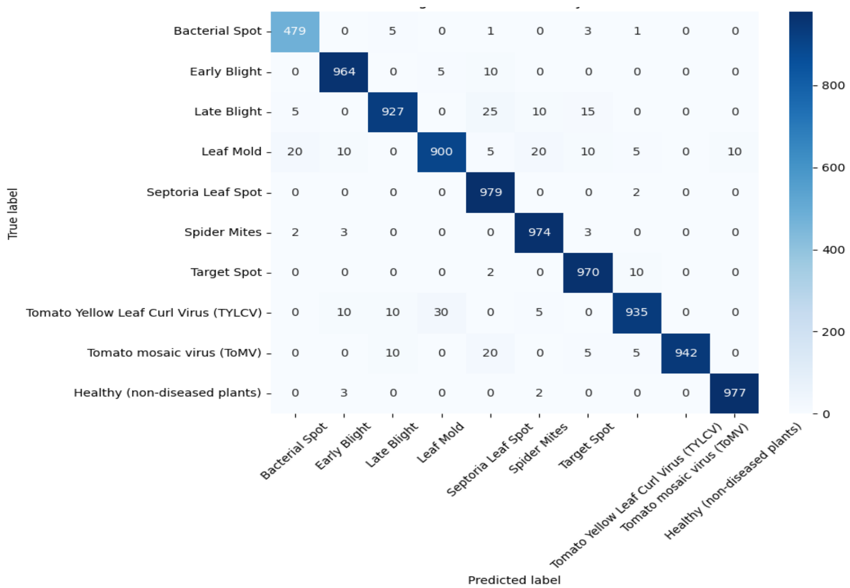


Fig. 17. Confusion Matrix for Proposed Ensemble Classifier

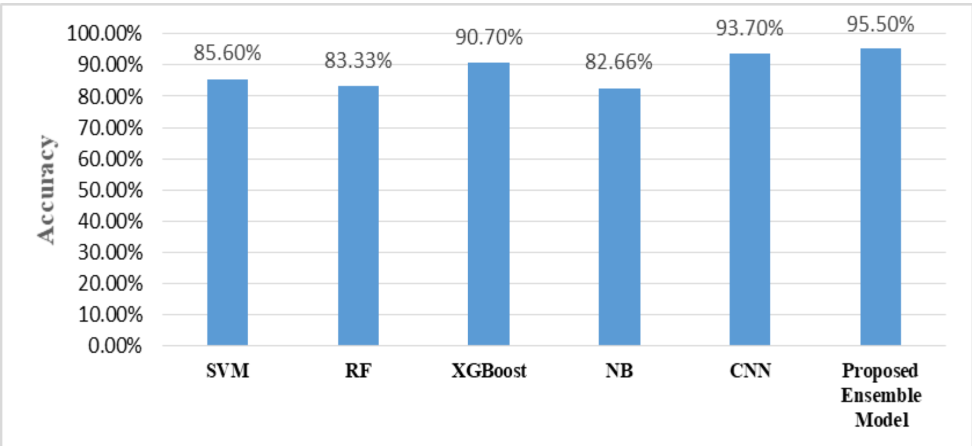


Fig. 18. Comparative Performance evaluation of Proposed Ensemble Model in terms of Accuracy with existing approaches

On the contrary, Naive Bayes and SVM did not perform well, achieve 82.66% and 85.6%, respectively, probably due to their inability to handle complex relationships in high-dimensional image data. Both Random Forest and XGBoost have shown robustness, benefiting from ensemble and gradient learning techniques, with accuracy of 83.33% and 90.7%, respectively.

5. DISCUSSION

Table 2. shows the Comparative performance evaluation of our Proposed Ensemble approach using Majority Voting classifier with the existing classifiers . It is found that our approach outperforms the other approaches in the detection accuracy of 95.50% on the Tomato Leaf Diseases.

Table 2. Comparative performance evaluation of our proposed ensemble approach using majority voting classifier with the existing classifier's accuracy (%)

Approach	Method	Accuracy(%)
Atasever et al. (2023)	VGG-19, VGG-16, and ResNet	60% to 90%
Shahoveisi et al. (2023)	ResNet	97.28%
Wu, Q et al. (2020)	combination of DCGAN and GoogLeNet	94.33%
Kokate et al. (2023)	CNN	95.53%
Peyal et al. (2023)	CNN	98.4%
Noon et al. (2020)	VGG16 and VGG19	98.7%
Ansah et al. (2023)	Gabor Wavelet and SVM	99.5%
Proposed Ensemble Model	SVM,CNN,XGBoost,RF and NB	95.5%

However, the Ensemble technique outperformed all individual models, achieving an accuracy of 95.5%, demonstrating the potential of combining different classifiers to improve overall classification performance. When comparing the results with other studies, a similar trend is observed. For example, Shahoveisi, et al. (2023) reported a high accuracy of 97.28% with ResNet for the detection of Tomato blight, which slightly outperforms our CNN model but does not outperform our Ensemble model. In another study, Wu et al. (2020) achieved 94.33% using a combination of DCGAN and GoogLeNet on the PlantVillage dataset, which is comparable to our CNN performance, but still lower than the accuracy of our Ensemble. Studies such as Kokate et al. (2023), which used a CNN on a dataset of 14,240 images to detect multiple diseases achieved an accuracy of 95.53%, which corresponds closely to the 95.5% of our Ensemble classifier. In contrast, studies such as Atasever et al. (2023) that used VGG-19, VGG-16, and ResNet for the detection of Tomato blight in the laboratory and in the field reported accuracies ranging from 60% to 90%, highlighting the limitations of these models in different environments. More advanced models, such as those in Peyal et al. (2023) that used lightweight CNNs on the PlantVillage dataset, achieved an impressive accuracy of 98.4%, while Noon et al. (2020) used a set of VGG16 and VGG19 to achieve 98.7 %. These results are consistent with our finding that ensemble methods tend to outperform individual classifiers. Finally, Ansah et al. (2023) achieved an even higher score of 99.5% using Gabor wavelet transform and SVM for powdery mildew and early type classification, highlighting the effectiveness of extraction techniques of custom features on disease-specific features. The presented study contributes to this growing body of work by showing that while individual models such as CNN perform well, the ensemble technique, which combines the strengths of multiple classifiers, provides a higher level of accuracy and robustness, especially for complex jobs with many classes like Tomato. Classification of foliar diseases. This highlights the potential for future work to explore more hybrid models and advanced feature extraction methods to push the limits of classification accuracy.

6. CONCLUSION

The authors developed a method for serial fusion feature extraction and leaves disease detection of Tomato based on majority voting using plantvillage Tomato leaves dataset. The dataset is widely used in similar studies, providing a strong benchmark for comparison. The presented approach included a diverse range of machine learning and deep learning classifiers, including SVM, XGBoost, Random Forest, Naive Bayes, and CNN, as well as a new ensemble model. In comparison, studies like Too et al. (2019) reported 86% accuracy for SVM and 91% for CNN, while Banerjee et al. (2023) achieved 92% with Random Forest. In contrast, our testing accuracies results show that SVM achieved 85.66%, XGBoost 90.7% and CNN 93.7%, which shows better performance than most models used in previous research. The Naive Bayes classifier performed with an accuracy of 82.6%, which is consistent with its typical limitations in image-based tasks. However, the most significant improvement was observed with the proposed ensemble model, which achieved a detection accuracy of 95.5%, outperforming existing models in the literature. This demonstrates the effectiveness of combining several classifiers, exploiting the strengths of each classifier to improve the classification accuracy of Tomato leaves dataset. While some studies have reported higher accuracies, such as 98.40% and 97.82%, which indicate near-perfect classification, our model's performance is still commendable and surpasses several other approaches. The slight variance in accuracy could be attributed to differences in dataset size, disease selection, feature selection or model architecture.

Acknowledgement

The authors would like to thank R. C. Patel Institute of Technology, Shirpur for the support.

Funding sources

The authors declare that no funds, grants, or other support were received during this work.

Conflict of Interest

The authors report there are no competing interests to declare.

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