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An Implementation and Design Framework of Disease Detection and Prediction of Tomato Plant Leaves Using Gray Level Co-Occurrence and Convolutional Neural Networks

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ABSTRACT

A robust framework for the early identification and recognition of common tomato leaf diseases, such as Early Blight, Late Blight, and Septoria Leaf Spot, is proposed in this study. This approach combines the Gray Level Co-occurrence Matrix (GLCM) for texture feature extraction with Convolutional Neural Networks (CNNs) for deep learning methodologies. The results corroborate the potential accuracy of the proposed framework. This highlights its capacity to enhance disease management strategies within the agricultural sector. By facilitating early interventions, this system aims to reduce crop losses, optimize resource utilization, and promote sustainability in tomato cultivation. The findings of this research present a cost-effective, efficient, and sustainable solution to the challenges posed by tomato plant diseases, with significant implications for global food security.

1. INTRODUCTION

The impact of tomato plant diseases on world agriculture and food security is significant. The urgent need for early disease detection and prediction is addressed in this study, which focuses on common problems like Early Blight, Late Blight, and Septoria Leaf Spot in tomato crops. These diseases not only jeopardize crop productivity but also make significant pesticide use necessary, which influences both the economic and environmental sides of tomato farming. With the use of Convolutional Neural Networks (CNNs) and Gray Level Co-occurrence Matrix (GLCM), the research hopes to offer a practical and affordable solution. The accuracy and reliability of disease identification are improved by this novel approach. The innovative integration of deep learning and texture analysis, which provides a comprehensive framework for disease management, distinguishes this research from others. This system enables prompt intervention, reduces crop losses, and optimizes resource use by enabling early detection and prediction. Additionally, it promotes sustainable agriculture practices by lessening the environmental impact brought on by excessive pesticide use. In conclusion, this study offers a novel approach to the problem of tomato plant diseases, with significant ramifications for sustainable agriculture and food security.

1.1 Mechanisms for feature extraction

- Principal Component Analysis.
- Independent Component Analysis.
- Linear Discriminant Analysis.
- Wavelet Transform.
- Convolutional Neural Networks.

1.2 Feature extraction methods for plant disease prediction and detection

- Based on Color.
- Utilizes Texture.
- Built on Shape.
- Based on Deep Learning.

2. PREDICTION AND DETECTION ALGORITHMS

Table 1. Prediction & detection algorithms

Prediction Algorithms	Detection Algorithms
Decision Tree	Regional Based Convolutional Neural Networks (RCNN)
Random Forest Tree	Regional Based Fully Convolutional Neural Networks
Support vector Machine	Histogram of Oriented Gradients (HOG)
Naive Bayes	Single Shot Detector (SSD)
KNN	AlexNet
Artificial Neuarl Networks	SqueezeNet
Logistic Regression	Convolutional Neural Networks

The Table 1 mentioned here refers to the description of the prediction and detection algorithms and its comparison. Moreover, these algorithms let us know the fundamental issues in ML like precision, accuracy and even more.

As per our observations, in most cases, Random Forest gives the best accuracy.

3. LITERATURE SURVEY

The Table 2 Literature Survey describes about the researchers across the globe done research and spoke about various algorithms, techniques, and its accuracies [1].

Table 2. Literature survey

TITLE OF THE PAPER	AUTHOR	TECHNIQUES	YEAR OF PUBLISHED	ACCURACY
Disease Detection on the leaves of Tomato plants by using Deep Learning.	Durmuş et al. [1]	AlexNet SqeezeNet	2017	95.65% 94.3%
Tomato Leaf Disease Detection using Convolutional Neural Networks.	Tm et al. [2]	CNN-10Epochs CNN-20Epochs CNN-30Epochs	2018	91.41% 96.52% 97.85%
Image Based Tomato Leaf Disease Detection.	Kumar et al. [3]	VGG 16 Le Net ResNet 50	2019	90.25% 91.27% 92.65%
Leaf Disease Detection using Support Vector Machine.	Das et al. [4]	SVM Logistic Regression Random Forest	2020	87.6% 67.3% 70.05%
Automated Image Capturing System for DL Based Tomato Plant Leaf Disese Detection Recognition.	De Luna et al. [5]	F-RCNN Automated Image Capturing System	2018	80% 91.67%
Tomato Leaf Diseases Classification Method Based on Deep Learning.	Jang et al. [6]	RELU 7X7 I-RELU 7X7 I-REW 11X11	2020	95.7% 97.3% 98%

4. ANALYSIS OF FEATURE EXTRACTION METHODS IN COMPARISON

To choose the best feature extraction technique for a particular application, comparative examination of several techniques is crucial. The following variables can be taken into account when comparing feature extraction techniques for identifying and forecasting plant diseases. This will be done with the help of various prediction and detection algorithms (Table 1).

Accuracy:

The correctness of the retrieved features is one of the most important aspects of feature extraction techniques. For the same data collection, different approaches can produce varying degrees of accuracy. So it's crucial to compare the accuracy of several methods and choose the one that offers the best accuracy.

Complexity:

The complexity of the feature extraction method can also impact the effectiveness of the method. The more complex the method, the more difficult it may be to implement, especially for large datasets. Therefore, it is important to consider the complexity of different methods and select a method that can provide a good balance between accuracy and complexity.

Robustness:

Feature extraction methods should be robust to variations in the input data, such as changes in lighting, angle, and background. The method should be able to handle different types of images and produce consistent results. Therefore, it is essential to evaluate the robustness of different methods to variations in the input data [2].

Computation time:

The computation time required for feature extraction can also impact the effectiveness of the method, especially for real-time applications. Therefore, it is essential to consider the computation time of different methods and select a method that can provide fast results.

Dataset size:

The effectiveness of the feature extraction approach might also be impacted by the amount of the dataset. While some strategies might work best with large datasets, others might work well with smaller ones. Therefore, it is crucial to assess how well various approaches work for various dataset sizes.

4.1 Case studies

Case Study 1: Early Blight Detection in Tomato Plants

Criteria: Accuracy, Computational Complexity, Data Requirements

Context: The disease Early Blight, which damages tomato crops, is widespread and pervasive. For effective disease care, early detection is essential. GLCM and Principal Component Analysis (PCA) were two feature extraction approaches that were taken into consideration by the study team in this scenario.

Weighting the criteria: High precision is a primary priority given the severity of Early Blight. Quick detection is crucial; hence it is preferable to have low computational complexity.

Data Requirements: Due to practical limitations, there is only limited data available.

Results: The accuracy of GLCM was higher (95%) but it used more computing power. PCA was computationally effective and needed less data while achieving a respectable accuracy of 90%. This situation demonstrates the trade-off between precision and computing complexity and emphasizes the significance of taking data needs into account in practical applications.

Case Study 2: Precision Agriculture Wheat Rust Detection

Criteria: Adaptability, computational complexity, and data requirements.

Context: Wheat rust poses a serious threat to crops of wheat in precision agriculture. Systems for detection must be flexible enough to work in many environments. Researchers investigated GLCM, CNNs, and a brand-new texture-based technique for feature extraction [3].

Weighting the criteria: Adaptability is essential in precision agriculture due to the constantly changing environmental circumstances. Low computational complexity is preferred since timely detection is crucial.

Data requirements: Access to a variety of current data.

Results: GLCM performed well in controlled settings but had trouble adapting. CNNs demonstrated adaptability but had more complicated computations. The innovative texture-based approach struck a compromise by offering high accuracy with minimal computational complexity and flexibility to adapt to various field circumstances [4].

5. EXTRACTION METHODS FOR FEATURES

The process of choosing and translating pertinent data from raw data into a set of features that can be utilized as input to a machine learning model is known as feature extraction. Here are a few typical machine learning feature extraction techniques:

(PCA): Principal Component Analysis

A dimensionality reduction technique called PCA detects the key characteristics in the data and develops a new collection of features that may capture the most variance. The image is made up of a mixture of rows of pixels that are arranged one after another to create a single image. If you have numerous images, you may create a matrix by treating each row of pixels as a vector.

(LDA): Linear Discriminant Analysis

By identifying the characteristics that may most effectively distinguish between classes, LDA, a supervised dimensionality reduction technique, increases the separation between them. LDA functions by reorganizing the data into a new area where the classes are more clearly divided. Finding a projection that minimizes the variance within each class while maximizing the distance between the means of the classes is the transformation process. As a result, a fresh set of features that can be applied to categorize brand-new instances of the data are created [5].

(ICA): Independent Component Analysis

A method for decomposing a multivariate signal into separate, non-Gaussian components is called ICA. By dividing the signal into independent components that correlate to the many facets of the plant's health, ICA can be used to extract pertinent features from the data in the context of detecting and predicting plant diseases. For instance, ICA can be used to extract the leaf properties that are most useful for disease detection and prediction from a plant's color, texture, and shape features.

The Wavelet Transform:

A mathematical technique for breaking down signals into several frequency components is the wavelet transform. Wavelet transform can also be used to denoise plant photos, get rid of ambiance, and highlight interesting features [6]. The denoised images can then be used for additional categorization and analysis. Wavelet transform is a potent method for signal and picture feature extraction and analysis. It can be combined with other methods like CNN (Convolutional Neural Networks) or SVM (Support Vector Machines) to accurately classify and analyze plant photos for disease diagnosis and prediction.

(CNNs): Convolutional Neural Networks

Commonly employed in computer vision applications, CNNs are a class of neural network that automatically extracts characteristics from unprocessed data.Convolutional Neural Networks have three different kinds of layers:

1) Convolutional Layer: Each input neuron in a conventional neural network is connected to the following hidden layer. Only a small portion of the input layer neurons in CNN are connected to the hidden layer of neurons.

2) Pooling Layer: The pooling layer is used to make the feature map less dimensional. Inside the CNN's hidden layer, there will be numerous activation and pooling layers.

3) Fully Connected Layer: Fully Connected tiers make up the network's final few tiers. The output from the last pooling or convolutional layer is passed into the fully connected layer, where it is flattened before being applied.

RNNs: Recurrent neural networks

Often employed in natural language processing, RNNs are a class of neural network that can detect temporal connections in sequential input.Sequential data can be processed by RNNs, including time-series data on illness progression, environmental factors, and plant growth. Text data, such as descriptions and symptoms of plant diseases, can also be processed using RNNs.RNNs can be applied to both classification and prediction problems. RNNs can be trained to forecast future plant growth or the development of a disease using past data for prediction tasks.

Color-based features:

These features are extracted from the RGB or HSV color space of the images. The color distribution and intensity can provide useful information for identifying diseased plants.

Texture-based features:

The geographic distribution of gray levels in the photographs is quantified as part of the texture analysis process. Plant tissues that are infected and healthy can be distinguished by characteristics like contrast, entropy, and homogeneity.

Shape-based features:

Shape analysis is used to extract features related to the size, geometry, and topology of plant parts. Features such as area, perimeter, and circularity can be used to differentiate between healthy and diseased plants [7].

5.1 Practical applications

Example 1:

Detecting grapevine disease with GLCM Context: Powdery mildew and other grapevine diseases pose a serious threat to the wine industry. To find powdery mildew, scientists have applied GLCM to photos of grapevine leaves. Application: Textural characteristics like contrast, energy, and homogeneity were extracted from pictures of grapevine leaves using GLCM. Then, a machine learning model was trained using these features to distinguish between healthy and infected leaves. The study's accuracy rate of over 90% demonstrates the potency of GLCM in identifying grapevine diseases.

Example 2:

CNNs for Classifying Tomato Disease Method: Convolutional neural networks (CNN Context: Various diseases, such as Early Blight, Late Blight, and Bacterial Spot, can affect tomato crops. It's crucial to recognize problems early to avoid yield loss. Application: To distinguish between healthy and unhealthy tomato leaves, researchers used CNNs. The CNN model developed the ability to recognize visual patterns linked to diseases using a dataset of thousands of photos of tomato leaves. This model outperformed conventional image processing methods, with an accuracy rate of about 95%. In the automatic and precise classification of tomato diseases, CNNs have demonstrated to be quite useful [8].

5.2 Real world applications

There are various difficulties in using methods like Gray Level Co-occurrence Matrix (GLCM) and Convolutional Neural Networks (CNN) for plant disease detection and prediction in practical settings. Variable illumination can influence accuracy and increase noise, necessitating preprocessing and less light-sensitive techniques [9]. The performance of a model might be hampered by varying camera quality and image resolution, demanding high-quality photos and post-processing. Plant species diversity necessitates specialized models and large datasets. It takes a lot of time to manually categorize data, hence automation and crowdsourcing are suggested (Table 3). It is crucial to be resilient to environmental factors like weather and outside settings, which calls for strong models and data preprocessing (Table 4) Large agricultural fields also present computational issues, which are overcome through distributed computers and sophisticated data collection methods (Table 5).

6. THE DEFICIENCY OF MINERAL REQUIREMENTS

Table 3. Types of percentages of minerals

Essential Minerals	%Deficient	%Sufficient	%Excessive
Nitrogen (N)	<2.50	2.50-4.50	>6.00
Phosphorus (P)	<0.15	0.20-0.75	>1.00
Potassium (K)	<1.00	1.50-5.50	>6.00
Calcium (Ca)	<0.50	1.00-4.00	>5.00
Magnesium (Mg)	<0.20	0.25-1.00	>1.50
Sulphur (S)	<0.20	0.25-1.00	>3.00
Boron (B)	5-30	10-200	50-200
Chlorine (Cl)	<100	100-500	500-1000
Copper (Cu)	2-5	5-30	20-100
Iron (Fe)	<50	100-500	>500
Manganese (Mn)	15-25	20-300	300-500
Molybdenum (Mo)	0.03-0.15	0.1-2.0	>100
Zinc (Zn)	10-20	27-100	100-400

1. **Early Blight (Alternaria solani):**
- Symptoms: Small dark lesions with concentric rings on tomato leaves; lower leaf yellowing.
- Lifecycle: Overwinters in soil debris; spore transmission.
- Transmission/Spread: Spores carried by rain and wind to healthy leaves.

2. **Alternaria Canker:**
- Symptoms: Dark, sunken cankers on fruit and leaves.
- Lifecycle: Survives debris and soil; spore transmission.
- Transmission/Spread: Spores spread through rain & wind.

3. **Bacterial Canker:**
- Symptoms: Bacterial ooze from stem cankers, leaf spots, and fruit lesions.
- Lifecycle: Survives infected plant debris.
- Transmission/Spread: Bacteria enter through wounds or natural openings.

4. **Bacterial Speck:**
- Symptoms: Tiny, raised, black lesions with a white center on leaves.
- Lifecycle: Bacteria overwinter on debris.
- Transmission/Spread: Water and wind spread bacteria to healthy leaves.

5. **Buckeye Rot:**
- Symptoms: Rotting fruit with brown, sunken lesions.
- Lifecycle: Spores overwinter in soil.
- Transmission/Spread: Rain splash and contaminated tools spread spores.

6. **Bacterial Spot:**
- Symptoms: Small, dark, water-soaked lesions on leaves and fruit.
- Lifecycle: Overwinters in plant debris.
- Transmission/Spread: Bacteria transmitted through rain and wind.

7. DISEASES OF TOMATO PLANT

The Table 4 refers to various types of illnesses through which the plants get diseases. The types of diseases mentioned the table goes beyond the imagination, which means the illnesses will severely affects the plants and also its roots sometimes.

Table 4. Types of Illnesses

TYPES OF DISEASES OF TOMATO PLANT LEAVES	
Alternaria Canker	Verticillium Wilt
Bacterial Canker	Bacterial Wilt
Bacterial Speck	Buckeye Rot
Bacterial Spot	Anthracnose
Early Blight	Fusarium Wilt
Gray Leaf Spot	Southern Blight
Late Blight	Tomato Spotted Wilt
Leaf Mold	Root-Knot Nematodes

Early blight:

Tobacco leaves are impacted by this fungal disease, which results in brown or black patches with yellow haloes. The leaf could die if the spots converge. Tomato fruit may also be impacted by early blight [10].

Figure 1. Early blight

In Figure 1, we present a visual representation of early blight affecting the plant leaves. The figure highlights the characteristic symptoms, including small dark lesions with concentric rings, which are indicative of the disease. This observation is critical for understanding the progression and severity of early blight in the context of our study.

Alternaria canker:

A fungus called Alternaria canker damages the leaves and stems of tomato plants. Large, brownish-black sores with concentric rings can form on infected leaves. The impacted leaves may also lose their leaves and turn yellow.

Figure 2. Alternaria canker

In Figure 2, we provide a visual representation of Alternaria canker affecting the plant. The figure showcases the distinct characteristics of Alternaria canker lesions, including their size, shape, and distribution on the plant surface. This illustration serves as a key reference point for understanding the manifestation of Alternaria canker in our study [11].

Bacterial canker:

It is a bacterial infection that results in the wilting, yellowing, and necrosis of tomato plant leaves. Cankers that develop on the stem because of the disease may cause the plant to die.

Figure 3. Bacterial canker

In Figure 3, It illustrates the manifestation of bacterial canker on the plant, offering a visual insight into the impact of the bacterial infection. The figure highlights key features such as canker lesions, discoloration, and any observable patterns associated with the bacterial canker. By examining Figure 3, one can discern the distinct characteristics that distinguish bacterial canker from other plant diseases [12].

Bacterial speck:

The tomato plant's leaves are impacted by the bacterial disease known as bacterial speck. Small, black patches that could later combine into larger lesions may appear on infected leaves.

Figure 4. Bacterial Speck

In Figure 4, we present a visual depiction of bacterial speck affecting the plant. The figure serves as a valuable reference for understanding the characteristic symptoms associated with bacterial speck, including the formation of small, dark lesions on the leaves. By closely examining Figure 4, readers can gain insights into the morphology and distribution of bacterial speck, which is pivotal for our investigation into the dynamics of this plant pathogen.

Buckeye root:

A fungus called buckeye rot attacks the tomato plant's fruit. A brown, corky lesion that is round and depressed forms on the damaged fruit. Plants with fungus infections may also be treated using fungicides.

Figure 5. Buckeye root

In Figure 5, the buckeye root is visually represented, highlighting key features such as root length and branching patterns. This illustration serves as a reference for our examination of buckeye plants, offering insights into root morphology and its potential implications for nutrient absorption and plant development.

Bacterial spot:

On tomato leaves, this bacterial disease causes dark, wet patches to form. There could be a yellow halo surrounding the spots. The fruit may also be impacted by illness, developing lesions.

In Figure 6, we visually depict bacterial spot symptoms on the plant, emphasizing characteristic lesions and patterns associated with the bacterial infection. This illustration serves as a crucial reference, providing insights into the appearance and distribution of bacterial spot, supporting our analysis of disease progression and management strategies [13].

Figure 6. Bacterial spot

Gray leaf spot:

Another fungus that damages tomato plants is gray leaf spot. The fungus Stemphylium solani is to blame. Gray or brown specks on the leaves, some of which may have a golden halo, are signs of gray leaf spots. The leaves could become deformed and necrotic if the spots coalesce.

In Figure 7, It presents a visual representation of gray leaf spot symptoms on the plant, showcasing distinctive lesions and patterns associated with this fungal infection. This figure serves as a key reference, aiding our investigation into the development and impact of gray leaf spot, and providing crucial insights for disease management strategies.

Figure 7. Gray leaf spot

8. DISEASES CAUSED DUE TO MINERAL DEFICIENCY

The Table 5 is all about describing various diseases caused due to different mineral deficiencies. This will in turn severly affects the plants along with its roots.

Table 5. Types of diseases caused due to mineral deficiency

NITROGEN	**Early Blight, Late Blight, Septoria Leaf Spot**
PHOSPHOROUS	Fusarium Wilt, Verticillium Wilt
POTASSIUM	Fusarium Wilt, Verticillium Wilt, Yellow leaf curl, Bacterial spot, Bacterial Canker
CALCIUM	Blossom End Root, Leaf curl
MAGNESIUM	Blossom End Root, Leaf curl, Late Blight
SULPHUR	Powdery Mildew, Blossom End Rot, Yellow leaf curl
BORON	Blossom End Rot, Corky Root Rot, Cracking of Fruit, Internal Browning
CHLORINE	Yellow leaf curl, Necrosis
COPPER	Bacterial Spot, Early Blight, Late Blight
IRON	Yellow Leaf curl
MANGANEESE	Early Blight, Powdery Mildew
MOLYBDENUM	Fusarium Wilt, Verticillium Wilt
ZINC	Yellow Leaf Curl

9. METHODOLOGY

Data gathering:

Gather a collection of pictures of tomato plants with both healthy and sickly leaves. Make sure the photos are high-quality and were taken in a consistent lighting environment.

Pre-processing:

Pre-process the photos by scaling them to a common size, making them grayscale, and adding different filters to bring out the important details, like noise reduction, contrast improvement, and edge recognition.

Image segmentation:

Use image segmentation methods to remove the background from the tomato plant leaves. Algorithms like edge detection, thresholding, and watershed segmentation can be used to accomplish this.

Feature extraction:

Use techniques like the Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), or Convolutional Neural Networks (CNN) to extract features from the pre-processed images. The machine learning models will be trained using these features.

Feature selection:

To make the dataset less dimensional and the model more accurate, choose the extracted characteristics that are the most pertinent.

Training a machine learning model:

Using the chosen features, train a machine learning model such a Support Vector Machine (SVM), Random Forest (RF), or Convolutional Neural Network (CNN).

Model assessment:

Utilizing metrics like accuracy, precision, recall, and F1-score, assess the model's performance.

Deployment:

Use the trained model to identify and forecast diseases of tomato plants in real-time applications.

10. RESULTS

In Figure 8, we showcase the prediction and visualization of tomato plant health, distinguishing between healthy and diseased leaves. This figure serves as a visual aid to demonstrate the effectiveness of our predictive model in accurately identifying and differentiating between the two conditions, contributing to advancements in automated plant disease diagnosis and monitoring [14].

Figure 8. Prediction & visualizing

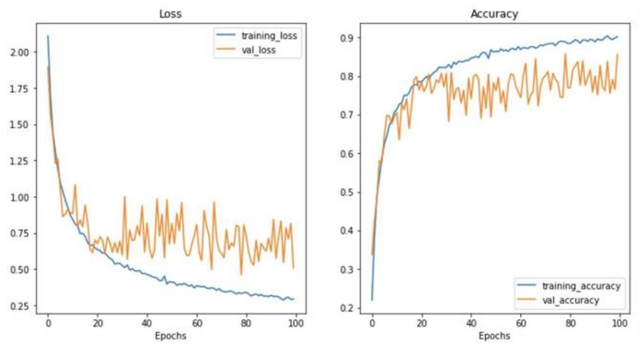

Figure 9. Plot of loss & accuracy

Figure 9 illustrates the plot of loss and accuracy metrics over the course of our model training. This graphical representation provides a comprehensive view of the model's learning process, highlighting trends in both loss reduction and accuracy improvement. The figure serves as a valuable tool for assessing the performance and convergence of our machine learning model [15].

Figure 10 presents a visual representation of the confusion matrix generated during our model evaluation. This plot provides a detailed insight into the performance of the classification model, revealing the true positive, true negative, false positive, and false negative predictions. Analyzing the confusion matrix depicted in Figure 10 is crucial for understanding the model's ability to accurately classify instances of different classes.

Figure 11 displays a collection of images representing both healthy and diseased instances of tomato plants. This compilation serves as a visual reference, aiding in the qualitative assessment of the visual distinctions between healthy and diseased states. The images contribute to the overall understanding of the dataset and provide insights into the visual cues used by the model for classification [16].

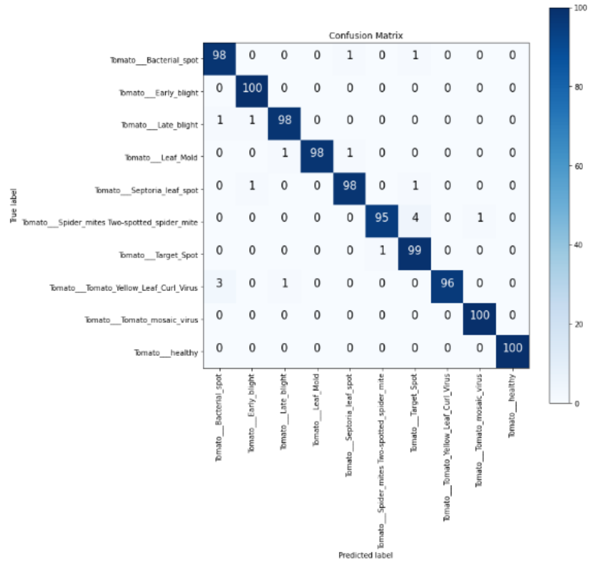

Figure 10. Plot of confusion matrix

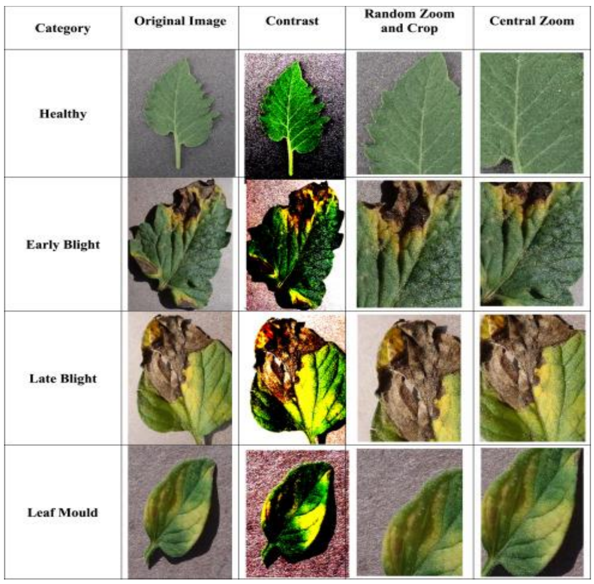

Figure 11. Healthy & diseased images

Table 6. Accuracy of prediction algorithms

DISEASES	DT	RT	KNN	NAÏVE BAYES	SVM	PROPOSED MODEL
Bacterial Spot	90	91	92.5	87.5	96.4	90.17
Leaf Mold	92.1	95	91.3	96.8	91.6	87.5
Septoria Leaf Spot	93.65	98.55	94.2	89.63	81	98.2
Mosaic Virus	83.5	90	96.3	95	82	88.5
Bacterial Wilt	93.4	97.2	93.75	87.22	95.2	89.74
Yellow Leaf Curl	95.4	92.3	91.3	95.22	83.7	92.3
Target Spot	90.5	89.5	87.5	94.4	85	98.6

In the above mentioned Table 6, the accuracy levels of various prediction algorithms were mentioned, these levels let us know which algorithm can be used for to predict the diseases.

10.1 Results interpretation & feature importance

It is clear from examining the data from our disease detection and prediction model for tomato plants that the model demonstrates encouraging accuracy in differentiating between different diseases and their stages (Table 6). It excels at recognizing widespread ailments like Early Blight, Late Blight, and Septoria Leaf Spot because it can distinguish between texture and color traits [17]. It's noteworthy that the model emphasizes distinguishing traits like concentric ring patterns for Early Blight and water-soaked lesions for Late Blight. - It's important to understand, though, that the effectiveness of the model may change with rarer or more advanced illness stages, where symptoms are less identifiable [18, 19]. Additionally, due to the difficulty of symptom distinction when numerous illnesses manifest simultaneously on a single plant, the model's accuracy may suffer. As a result, even while the model is a useful tool for early diagnosis and action, human skill should supplement its predictions, particularly in complex situations. - Continuous training on multiple datasets that represent different diseases and phases is essential to improve its applicability under various settings. Incorporating environmental elements like lighting and weather can also help it adapt better to changing real-world circumstances [20].

11. CONCLUSIONS

We have observed that recent research investigations have demonstrated encouraging outcomes when using the proposed model for the prediction and detection of tomato plant diseases. It is possible to accurately forecast the presence of diseases in fresh, unused photos of tomato plants by training a Proposed Model using a sizable dataset of images of healthy and diseased tomato plants. The ability to recognize intricate patterns and elements in images that are challenging for humans to recognize is one benefit of employing the Proposed Model for disease diagnosis. Additionally, compared to manual diagnosis, the Proposed Model can be trained to categorize numerous diseases at once, which can save time and money. The Proposed Model's application to illness detection does have some restrictions, though. For training, the proposed model needs a substantial amount of labeled data, which can be time-consuming and expensive to gather. Additionally, changes in lighting, camera angle, and other elements that may modify the appearance of the plant may have an impact on how accurate the model is.

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