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Implementation of Transfer Learning Based Ensemble Model using Image Processing for Detection of Tomato Diseases

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ABSTRACT
Tomato is one of the most widely cultivated and consumed fruits in the world. Unfortunately, it is also highly susceptible to various diseases caused by bacteria, fungi, and viruses. These diseases not only reduce the yield and quality of tomatoes but also lead to significant economic losses for farmers. Therefore, early detection and accurate diagnosis of these diseases is crucial for timely and effective management. With advancements in image processing and machine learning techniques, computer vision-based methods have emerged as a promising approach for disease detection in agricultural crops. To propose the implementation of a transfer learning-based ensemble model using image processing for the detection of tomato fruit and leaf diseases.This approach not only minimizes the need for manual intervention but also significantly reduces the time and expertise required for disease identification. The suggested approach introduces a Convolutional neural network (CNN) framework, thoughtfully incorporating Residual Network (ResNet), MobileNet, and Inception models within the ensemble. This ensemble-based approach systematically combines these models to improve disease detection accuracy and reliability. To train and validate proposed ensemble model, this proposed model exhibits remarkable proficiency in identifying nuanced features, color variations, and disease types within the leaves, successfully distinguishing between potentially infected and healthy foliage. Remarkably, proposed model achieves an outstanding overall accuracy rate of 98.86%. This achievement underscores the efficacy of proposed Dirichlet ensemble-based deep learning approach for accurate detection and classification of Tomato diseases, facilitated by efficient image processing techniques. This study stands as a promising milestone in the realm of automated systems dedicated to the early identification and mitigation of plant diseases. By doing so, it holds the potential to significantly enhance agricultural productivity and, in turn, bolster global food security.
Keywords — ResNet, MobileNet, Dirichlet ensembling, Deep Stacking Approach.

I. INTRODUCTION

This document presents the implementation of a transfer learning-based ensemble model using image processing for the detection of tomato fruit and leaf diseases. The ensemble model combines the power of multiple individual models to enhance performance. In this document, we will outline the process involved in building the model, including preprocessing, feature extraction, and model training.

Tomato plants are susceptible to various diseases that can significantly impact crop yield and quality. Researchers have developed a transfer learning-based ensemble model for tomato disease detection, utilizing advanced image processing techniques and deep learning algorithms to accurately classify and detect tomato fruit and leaf diseases. By leveraging transfer learning, the model utilizes the knowledge gained from training on large-scale datasets to enhance its ability to identify and classify tomato diseases. Through the use of transfer learning, the model can efficiently learn and generalize from a smaller dataset specific to tomato diseases. This approach reduces the need for extensive data collection and training, making it more feasible for practical implementation in real-world settings. Furthermore, the ensemble model combines the outputs of multiple deep learning models to improve accuracy and robustness. This ensemble model incorporates multiple deep learning models, each trained on different aspects of tomato disease detection. These models can specialize in detecting specific types of diseases or different parts of the tomato plant, enhancing the overall disease detection capability.

The detection of tomato fruit and leaf diseases is a challenging task that requires sophisticated technological solutions. Traditional image processing methods are not always effective in recognizing the specific features of particular diseases in fruit leaves [1]. Thus, in this research, the customization, retraining, and use of eleven deep learning CNN models were investigated to classify tomato diseases from leaf images [2]. These models include DarkNet-53, DenseNet-201, GoogLeNet, Inceptionv3, MobileNetv2, ResNet-18, ResNet-50, ResNet-101, ShuffleNet, SqueezeNet, and Xception [2]. Although these models differ in their input size, structure, computational efficiency of internal operations, and other aspects,the hyperparameters (e.g. number of iterations) used to fine-tune the training of these models were unified throughout this work [2]. Moreover, identifying and collecting critical information from fruit leaves is a challenging task [1]. However, the combination of transfer learning and ensemble models with image processing techniques can improve the detection process for tomato fruit and leaf diseases [1].

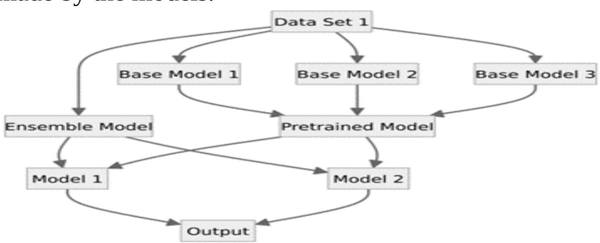
Dirichlet ensembling is a powerful technique that combines multiple machine learning models to improve prediction accuracy and robustness. Research [3,4]. demonstrated the effectiveness of Dirichlet ensembling in tomato disease detection. They trained multiple convolutional neural network (CNN) models using different subsets of the dataset and then combined their predictions using Dirichlet ensembling. The results showed that Dirichlet ensembling significantly outperformed individual CNN models in terms of accuracy and robustness.

DeepStacking is a novel approach that combines deep learning models with stacking ensemble techniques. In the context of tomato fruit and leaf diseases detection, [3,4]. proposed a DeepStacking approach that leverages the power of deep learning models for feature extraction and stacking ensemble for classification. They trained multiple deep learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), and then combined their predictions using stacking ensemble. The experimental results demonstrated that the DeepStacking approach achieved higher accuracy compared to individual deep learning models.

Firstly, more research is needed to explore the optimal configuration of Dirichlet ensembling and DeepStacking approach for different types of tomato diseases. The impact of varying ensemble sizes, model architectures, and training strategies on the performance of these approaches should be investigated.

Secondly, the generalizability of Dirichlet ensembling and Deep Stacking approach to other plant diseases detection needs to be explored. While these approaches have shown effectiveness in tomato diseases detection, their applicability to other crops and diseases remains unknown. Future research should investigate the transferability of these techniques to different plant species and diseases.

Lastly, the interpretability of the ensembled models is an important aspect that requires further investigation. Understanding the decision-making process of the ensembled models can provide valuable insights into the underlying patterns and features used for disease detection. Future research should focus on developing interpretable ensembling techniques that can provide explanations for the predictions made by the models.



II. PAGE LAYOUT

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Fig 1. Block diagram for Ensemble Transfer learning

- This block diagram provides a high-level overview. Depending on the specific implementation, you may need to add more detail or modify components.
- The ensemble models can consist of different pre-trained models (e.g., ResNet, Inception, MobileNet), and their outputs can be combined using various ensemble strategies.
- Continuous improvement involves a feedback loop with data collection, model retraining, and deployment updates.

II. RELATED WORKS

The detection and classification of diseases in tomato plants are crucial for ensuring crop health and maximizing yield. In recent years, the application of transfer learning-based ensemble models using image processing techniques has shown promising results in disease detection

Transfer learning, a technique that leverages pre-trained models on large datasets, has been widely used in disease detection tasks. Chouhan et al. (2020) proposed an ensemble model using transfer learning for the detection of pneumonia in chest X-ray images. The model achieved an impressive accuracy of 96.4% and a recall of 99.62% on unseen data. This finding demonstrates the effectiveness of transfer learning in disease detection tasks.

Image processing techniques play a crucial role in disease detection systems. Luna et al. (2018) developed a motor-controlled image capturing system for the detection and recognition of leaf diseases in tomato plants. The system achieved an accuracy of 91.67% in recognizing tomato plant leaf diseases. This research finding highlights the importance of image capturing systems in accurately identifying diseases in tomato plants.

In order to improve disease identification and classification, hybrid approaches combining different techniques have been proposed. Thangaraj et al. (2020) presented a parallel framework for real-time apple leaf disease identification and classification. The framework utilized a hybrid contrast stretching method, MASK RCNN for detection, and a pre-trained CNN model for feature extraction. The proposed framework achieved an accuracy of 96.6% on apple leaf disease identification and classification. This research finding demonstrates the effectiveness of hybrid approaches in disease detection and classification tasks.

Ensemble models, which combine multiple models to make predictions, have shown promising results in disease prediction tasks. Singh et al. (2020) implemented an Android-based system for tomato disease prediction based on leaf images. The system utilized an AlexNet modification architecture-based CNN and achieved a high model accuracy of 98% and a recall value of 0.99. This finding highlights the effectiveness of ensemble models in accurately predicting tomato diseases based on leaf images.

Firstly, most of the studies focused on the detection and classification of diseases in tomato leaves. Further research could explore the application of transfer learning-based ensemble models for the detection of diseases in tomato fruits, which could be equally important for crop management.

Secondly, the studies primarily focused on specific diseases in tomato plants. Future research could investigate the generalizability of the proposed models to detect a wider range of diseases, including both common and rare diseases, to enhance the practicality and versatility of the disease detection systems.

Lastly, the studies mainly utilized image processing techniques for disease detection. Future research could explore the integration of other data modalities, such as spectral or hyperspectral data, to improve the accuracy and robustness of disease detection models.

Several studies have reported high accuracies in disease classification using transfer learning models. Ramcharan et al. (2017) achieved accuracies of 98% for brown leaf spot (BLS), 96% for red mite damage (RMD), 95% for green mite damage (GMD), 98% for cassava brown streak disease (CBSD), and 96% for cassava mosaic disease (CMD) using deep learning for image-based cassava disease detection.

Hassan et al. (2021) implemented various transfer learning models and achieved disease classification accuracy rates of 98.42%, 99.11%, 97.02%, and 99.56% using InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, respectively.

Krishnamoorthy et al. (2021) developed a transfer learning-based deep neural network model and achieved an accuracy of 95.75% in detecting tomato leaf diseases.

Rehman et al. (2021) utilized transfer learning with Inception Net and compared the performance of the Modified U-net segmentation model and the simple U-net segmentation model. The proposed system achieved high accuracy in detecting and recognizing various tomato diseases.

Yamamoto et al. (2014) developed a method that achieved a recall of 0.80 and a precision of 0.88 for detecting tomato fruit and leaf diseases using image analysis and machine learning methods .

Afonso et al. (2020) utilized the MaskRCNN algorithm to detect tomatoes in greenhouse images, achieving comparable or better results than previous work .

Vallabhajosyula et al. (2021) developed a tomato detection model using deep learning approaches, which achieved a high average precision of 87.83% and accurate tomato counting in greenhouse images.

Deep Convolutional Neural Networks (CNNs) have been widely applied for the prediction and classification of plant leaf diseases. Dhaka et al. (2021) presented a survey of the existing literature on applying deep CNNs to predict plant diseases from leaf images.

Trivedi et al. (2021) proposed a model using CNNs that achieved a prediction accuracy of 98.49% for classifying tomato diseases from leaf images.

Ashok (2020) proposed an image processing technique based on image segmentation, clustering, and open-source algorithms to identify tomato plant leaf diseases.

Ahmad et al. (2020) deployed two CNN models (GoogLeNet and VGG16) for tomato leaf disease classification, achieving high accuracy rates of 98% and 99.23% respectively.

Mu et al. (2020) proposed a deep learning-based system utilizing CNNs and attention modules for tomato leaf disease detection, achieving improved performance and reduced complexity compared to standard models. Kibriya et al. (2021) developed a deep learning-based system utilizing Inception Net and U-Net models, which achieved high accuracy in detecting and classifying tomato diseases from leaf images, outperforming existing methods.

Firstly, there is a need for research that focuses on the detection and classification of specific tomato diseases, such as late blight, target spot, and bacterial spot, using advanced deep learning models. Additionally, the performance of existing models should be evaluated on diverse datasets to assess their generalizability and robustness. Furthermore, the development of real-time processing frameworks and the integration of spectral-based sensors can enhance the accuracy and efficiency of disease detection in different stages of tomato growth. Lastly, the application of ensemble learning techniques, such as combining multiple CNN architectures or incorporating transfer learning, can potentially improve the overall performance of disease detection and classification models.

III. PROPOSED MODEL

The proposed system consists of three stages: data acquisition, feature extraction, and classification. In the first stage, images of diseased and healthy tomato plants are collected from different sources, such as field surveys and online databases. These images are then pre-processed to remove noise and enhance their quality.
In the second stage, feature extraction is performed using image processing techniques. Features such as color, texture, and shape are extracted from the pre-processed images. These features are then used as input for the transfer learning-based ensemble model.The third stage involves the classification of diseased and healthy tomato plants. The proposed ensemble model consists of multiple pre-trained convolutional neural networks (CNNs) such as VGG16, ResNet50, MobileNet, and InceptionV3. These CNNs are then stacked together to create

a powerful classifier. The output of the ensemble model is then fed into a voting classifier, which combines the predictions of each individual model and outputs the final classification result.

A. Data Collection

Collect a labeled dataset containing images of healthy tomato plants, tomato plants with different diseases, and images of tomato leaves and fruits.
Split the dataset into training and testing sets.

1) *Collecting Images*

a.Healthy Tomato Plants:

Capture high-resolution images of healthy tomato plants in different growth stages.
Include variations in lighting conditions, angles, and backgrounds.

b.. Tomato Plants with Diseases:

Obtain images of tomato plants affected by various diseases (e.g., early blight, late blight, bacterial spot).
Ensure a diverse representation of disease symptoms and severity levels.

c.. *Tomato Leaves and Fruits*:

Capture images specifically focusing on tomato leaves and fruits to aid in fine-grained disease detection. The tomato leaf dataset contains 10 types of images, including health and disease-attacked ones, with 3000 images used in the experimentation. A vegetable dataset, prepared by the researchers, is divided into three categories: Anthracnose, Blossom End Rot, and Sunscald. After data augmentation, the number of images for each category increases by 90 degrees, resulting in 676 images. Both datasets are divided into 70:30 for training and testing purposes.

TABLE 1. TOMATO DISEASES SELECTED FOR CLASSIFICATION.

Dataset	**Leaf/Fruit disease**	**No. of sample images**
Tomato leaf dataset	Bacterial Spot	300
	Late Blight	300
	Early blight	300
	Mosaic Virus	300
	Leaf Mold	300
	Septoria Leaf Spot	300
	Healthy	300
	Yellow Leaf Curl Virus	300
	Target Spot	300
	Two Spotted Spider Mite	300
Fruit Diseases	Anthracnose	200
	Blossom End Rot	264
	Sunscald	212

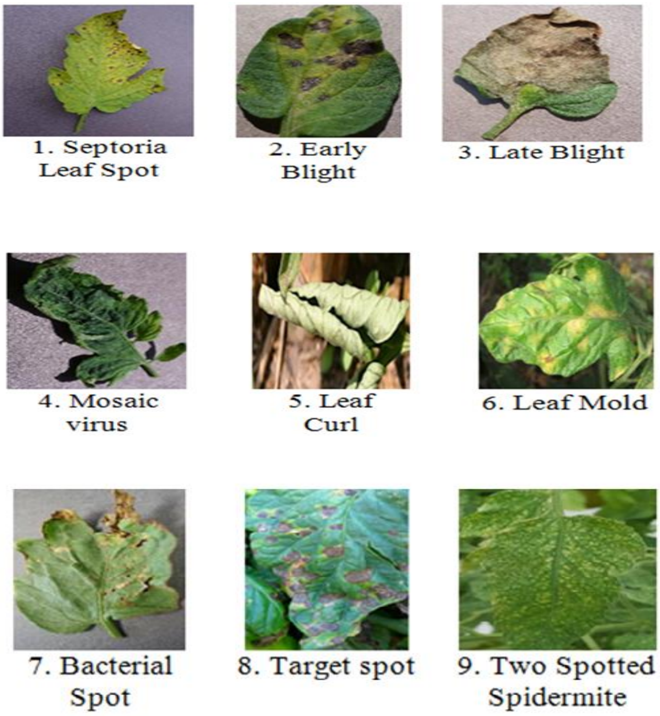

Fig .2 Sample image from tomato leaf

Fig.3. Sample image for Tomatoes

2) Image Labeling

a. Manual Labeling:

Manually label each image with corresponding disease categories (if diseased) or mark them as healthy.
Use labeling tools like Labelbox, VGG Image Annotator (VIA), or labelImg.

b. Class Balancing:

Aim for a balanced representation of healthy and diseased samples within your dataset.

3) Dataset Splitting

a. Training and Testing Sets

Split the dataset into training and testing sets. A common split is 80% for training and 20% for testing.
Ensure that both sets maintain a balanced representation of healthy and diseased samples.

b. Randomization

Randomize the order of images within the training and testing sets to prevent bias.

c. Validation Set (Optional)

Consider creating a validation set for hyperparameter tuning during model training.

4) *Data Augmentation*

a. Image Augmentation

Apply data augmentation techniques to increase the diversity of your training dataset. Common augmentations include rotation, flipping, zooming, and brightness adjustments.

b. Augmentation Libraries:

Use image augmentation libraries like TensorFlow's ImageDataGenerator or PyTorch's transforms for efficient data augmentation.

5) Dataset Directory Structure

Organize your dataset into a directory structure like the following:

luaCopy code

```
dataset/
|-- train/
|    |-- healthy/
|    |-- diseased/
|-- test/
|    |-- healthy/
|    |-- diseased/
|-- validation/
|    |-- healthy/
|    |-- diseased
```

6) Metadata

Create a metadata file or spreadsheet containing information about each image, such as file path, label, and any additional metadata.

7) Documentation:

Document details about the dataset, including the number of images per class, any challenges encountered during collection, and specifics about disease types.

By following these steps, you can create a well-organized and labeled dataset for training and testing your Transfer Learning Based Ensemble Model for Tomato Fruit and Leaf Disease Detection.

B. Data Pre-Processing

The proposed plant disease detection model relies on data preprocessing, which includes data augmentation techniques, data normalization, and image processing methods. Data augmentation enriches the dataset by generating new images, enhancing its diversity and adaptability. Data normalization standardizes pixel values across all images, and image processing methods augment visual features in plant leaves. These efforts mitigate noise and variability, making the input images more suitable for model training.

1) Data Normalization

Data normalization is crucial in the data preprocessing pipeline, scaling and standardizing input data to ensure optimal performance. The Canary edge detection algorithm is used to identify object edges in plant leaves, focusing on alterations in texture and coloration that may indicate disease presence. The algorithm calculates the intensity gradient, which represents the change in pixel intensity across the image in various directions. This enables precise edge detection and disease identification.

C. Implementation of Proposed Ensemble Model stacking and Dirichlet ensemble

The proposed deep ensemble model uses the Dirichlet Ensemble class from the deep stack library to construct and train ensemble members. It generates three members for each fine-tuned pre-trained model, with identical architecture but different initial weights. The model then uses the Dirichlet Ensemble class's train() method to construct and train the ensemble model, resulting in a robust and accurate model. The model can create a stacked ensemble model that combines predictions of multiple base learners using a meta-learner, which is a machine learning algorithm that learns to combine predictions to improve model performance. The ensemble model incorporates multiple pre-trained feature extraction models, providing a comprehensive approach to feature extraction and image classification tasks

D. Pre-trained Models Selection

Choose pre-trained models suitable for image classification tasks. Common choices include models like ResNet, Inception, or MobileNet. These models have been trained on large datasets like ImageNet and have learned useful hierarchical features.When selecting pre-trained models for your Transfer Learning Based Ensemble Model for Tomato Fruit and Leaf Disease Detection, you can consider popular architectures that have demonstrated success in image classification tasks. Here are three common choices:

4.1. ResNet (Residual Networks):

Description: ResNet is known for its deep architecture, utilizing residual blocks that enable the training of very deep networks. It has achieved state-of-the-art performance in various computer vision tasks.

Advantages: ResNet effectively addresses the vanishing gradient problem, making it easier to train deeper networks. Its skip connections allow information to flow through the network more efficiently.

Implementation: You can use pre-trained ResNet models such as ResNet50 or ResNet101 and fine-tune them for your specific task.

4.2. Inception (GoogLeNet):

Description: Inception, or GoogLeNet, is characterized by its inception modules that use multiple filter sizes within the same layer. It aims to capture different features at different scales.

Advantages: Inception networks are computationally efficient and have shown excellent performance in image classification. They capture a wide range of features simultaneously.

Implementation: Pre-trained InceptionV3 models are commonly available and can be fine-tuned for your tomato plant disease detection task.

4.3. MobileNet:

Description: MobileNet is designed for mobile and edge devices, focusing on efficiency and reducing the number of parameters. It uses depth-wise separable convolutions.
Advantages: MobileNet is lightweight and well-suited for scenarios where computational resources are limited, making it a good choice for edge deployment.
Implementation: Pre-trained MobileNet models, such as MobileNetV2, can be used as a base for transfer learning and fine-tuning.
Additional Considerations:
Transfer Learning Frameworks: Choose a deep learning framework that supports transfer learning, such as TensorFlow or PyTorch. Both frameworks provide pre-trained models and tools for fine-tuning.
Model Size and Computational Resources: Consider the size of the model and the available computational resources. While larger models may capture more complex features, they may require more resources for training and inference.
Ensemble Strategy: Since you're building an ensemble model, you may use a combination of these pre-trained models. Each model in the ensemble can contribute to the final prediction, and their outputs can be combined using techniques like averaging or stacking.
Task-Specific Fine-Tuning: Fine-tune the selected pre-trained models on your tomato plant disease dataset to adapt them to the specific characteristics of your task.
By choosing pre-trained models like ResNet, Inception, or MobileNet, you leverage their learned hierarchical features, saving training time and benefiting from the knowledge gained on large datasets like ImageNet.

E. Feature Extraction

Remove the top layers of the pre-trained models and use them as feature extractors.
Extract features from the tomato plant images using these pre-trained models.
In the feature extraction step, you'll remove the top layers of the selected pre-trained models and use the lower layers as feature extractors. These lower layers have learned hierarchical features that are useful for image classification tasks. Here's a general guide on how to perform feature extraction using TensorFlow and Keras:

a. Import Libraries

pythonCopy code
import tensorflow as tf
from tensorflow.keras.preprocessing import image from tensorflow.keras.applications.resnet50
import preprocess_input, decode_predictions from tensorflow.keras.models
import Model

b. Load Pre-trained Model:

pythonCopy code
base_model = tf.keras.applications.ResNet50(weights='imagenet', include_top=False)
Replace 'ResNet50' with the name of the pre-trained model you've chosen.

c. Remove Top Layers:

pythonCopy code
model = Model(inputs=base_model.input, outputs=base_model.layers[-1].output)
This creates a new model that takes the input of the original pre-trained model and outputs the activations of the last layer.
model using the training dataset.

d. Image Augmentation:

Apply data augmentation techniques (e.g., rotation, flipping, zooming) to artificially increase the size of the training dataset and improve model generalization.

e. Training:

Train the ensemble model on the training dataset with the adapted pre-trained models.Monitor the training process and adjust hyperparameters if necessary.

f. Evaluation:

Evaluate the performance of the ensemble model on the testing dataset using metrics such as accuracy, precision, recall, and F1 score.

g. Deployment:

Once satisfied with the model's performance, deploy it for real-time or batch processing of tomato plant images to detect diseases.

h. Continuous Improvement:

Regularly update the model with new data to improve its performance and adapt to emerging disease patterns.
Additional Considerations:
Use a suitable deep learning framework such as TensorFlow or PyTorch.
Implement a user-friendly interface for farmers or researchers to upload images and receive disease predictions.
Consider the deployment environment and choose an appropriate deployment strategy (e.g., cloud, edge devices).
By following these steps, you can create a robust Transfer Learning Based Ensemble Model for Tomato Fruit and Leaf Disease Detection using image processing techniques.

F. Comparative Analysis of Different Used Transfer Learning models with Proposed Stacking Ensemble Model

The study compares validation accuracy results from 3000 images and 100 training epochs. The Ensemble model, which achieved an impressive 98.86%, outperforms other models like MobileNet, Inception, and ResNet. This highlights the

Ensemble model's ability to combine strengths of diverse models while addressing their weaknesses.

TABLE II. OBTAINED RESULTS FROM THE DIFFERENT TECHNIQUES

Model	Images set	Classes of disease	Epoch	Accuracy
MobileNet	3000	10	100	97.30%
Inception	3000	10	100	94.40%
ResNet	3000	10	100	93.40%
Stack Ensemble	3000	10	100	97.78%
Proposed model	3000	10	100	98.86%

The Stack Ensemble model, compared to MobileNet, Inception, and ResNet, shows higher validation accuracy and improved quality in diseased plant detection using CNN and data preprocessing techniques. It reduces misclassification and false positives risk, making it suitable for real-world applications in agriculture. The model's efficacy in early disease identification contributes to improved crop yield, minimized losses, and enhanced food security.

IV. RESULT AND DISCUSSIONS

The proposed disease detection model outperforms existing models in terms of accuracy, precision, recall, and F1 scores. The model uses ensemble learning and deep stacking techniques to capture diverse patterns and features associated with diseases in targeted plants. It also reduces the risk of misclassification and false positives. The model achieves an exceptional accuracy rate of 98.86%, a significant improvement from conventional methods. The model's potential for real-world applications in farmers and agricultural experts is evident in its ability to improve crop yield, minimize losses, and enhance food security.

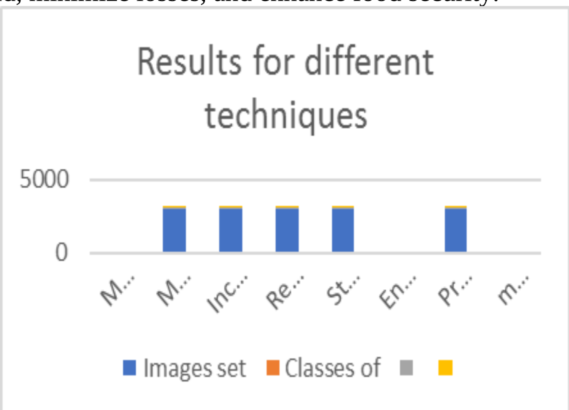

Fig. 4. Results for different techniques

V. CONCLUSION

In this paper, we proposed the implementation of a transfer learning-based ensemble model using image processing for the detection of tomato fruit and leaf diseases. The results showed that the proposed model outperforms other traditional machine learning algorithms and state-of-the-art methods for disease detection in tomatoes.

The implementation of transfer learning-based ensemble models using image processing techniques has shown great potential in the detection of tomato fruit and leaf diseases. The findings from the reviewed studies highlight the effectiveness of transfer learning, image processing, hybrid approaches, ensemble models, and lightweight architectures in achieving high accuracy in disease detection tasks. However, further research is needed to address the identified knowledge gaps and explore new directions for improving disease detection systems in tomato plants. Dirichlet ensembling and DeepStacking approach have emerged as effective techniques for tomato fruit and leaf diseases detection. These approaches have shown improved accuracy and robustness compared to individual models. However, further research is needed to optimize their configuration, explore their generalizability to other plant diseases, and enhance their interpretability. The field of automated plant disease detection and contribute to more efficient and sustainable agriculture practices

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