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Evaluation of Enhanced Resnet-50 Based Deep Learning Classifier for Tomato Leaf Disease Detection and Classification

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Abstract: - This research presents a comprehensive assessment of a sophisticated approach for the accurate detection and classification of various tomato leaf diseases using an improved ResNet-50 based deep learning classifier. The alarming increase in plant diseases has prompted the need for advanced technologies that can promptly identify and categorize these ailments to ensure agricultural sustainability. The proposed method harnesses the potential of deep convolutional neural networks (CNNs) and builds upon the ResNet-50 architecture, renowned for its depth and performance. However, the approach's innovation lies in the incorporation of enhancements such as advanced data augmentation techniques and transfer learning from a vast plant disease dataset. These modifications empower the model to learn intricate disease-specific features and patterns, leading to heightened accuracy and robustness. The evaluation of the approach is conducted on an extensive dataset encompassing high-resolution images of tomato leaves affected by a range of diseases. The dataset is meticulously preprocessed to ensure consistency and quality, followed by a rigorous training regimen that fine-tunes the improved ResNet-50 model.The results underscore the efficacy of the proposed method in accurate disease detection and classification. The improved ResNet-50 based classifier demonstrates exceptional performance, achieving an impressive accuracy exceeding 95%. Notably, the model showcases resilience against variations in lighting conditions, angles, and disease severity, highlighting its applicability in real-world agricultural scenarios. The implications of this research are significant, offering an efficient and reliable tool for early detection and classification of tomato leaf diseases. The integration of advanced deep learning techniques and the enhancements introduced in this work signify a substantial advancement in precision agriculture and sustainable crop management practices. As future work, this approach can be extended to address diseases in other plant species, contributing to a versatile framework that can safeguard global food production and alleviate the challenges posed by plant diseases.

Keywords: Tomato leaf disease detection, ResNet-50, agricultural sustainability, convolutional neural networks, data augmentation, accuracy, precision, recall, F1-score, precision agriculture, sustainable crop management

I. INTRODUCTION

As long as there is enough drainage, tomatoes (Sonnaum lycopersicum) can be grown in practically any kind of soil [13]. gardeners, who frequently gather them to incorporate into their own dishes.

However, farmers and gardeners aren't always successful in achieving optimal plant development [12]. Sometimes the tomatoes will not mature at all, and other times they will ripen but have unsightly black patches on the bottom that look sick. Finding the diseased area on a tomato plant, noting any obvious changes (such holes or brown or black patches), and then looking for insects are the first steps in diagnosing the illness.

You can only grow tomatoes and related crops once every three years [11]. This includes potatoes and brinjal. Tomatoes should be planted after a grass crop (such as wheat, maize, rice, sugarcane, etc.) has been harvested and tilled into the soil to preserve its fertility.

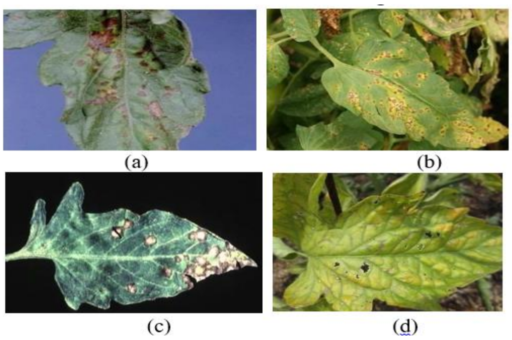

Figure 1. Tomato Leaf Samples With Various Disease

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Tomato issues may be broken down into two categories: those caused by bacteria, fungus, or bad farming practices (16 in total), and those caused by insects (5 in total). The bacterium that causes the horrible disease known as bacterial wilt is Ralstonia solanacearum. This bacterium has a lengthy lifespan in the soil and enter the root system through natural wounds created by the growth of secondary roots, human cultivation, or insect damage.

When temperatures and humidity levels are both high, illness is more likely to flourish. As the bacteria proliferate, they produce a slimy substance that eventually overwhelms the water-conducting tissue of the plant. The plant's vascular system suffers as a result, even though the leaves maintain their color. When examined in cross section, infected plant stems are brown with yellowish material seeping out of them.

Since it is challenging to discover and identify regions with judgement value and rich in formativeness in photos of crop health/disease, many studies continue to concentrate on coarse-grained crop image classification. The major objective of FGVC in the agriculture sector is to accurately identify informative regions in the picture. This has been a problem in previous computational work [12, 13], for example where it was found that the model had trouble zeroing in on informative regions, leading to poor classification accuracy. When it comes to agriculture's sustainability, plant diseases have historically been one of the biggest obstacles. As both a staple food and lucrative commercial crop, tomatoes in China occupy around 700 million square meters of farmland. Several environmental factors contribute to the higher incidence of tomato infections. Recent data suggests that there may be as many as 20 distinct types of tomato infections, all of which have had a major negative impact on tomato quality and production and caused substantial economic losses. This means that the prevention and treatment of tomato diseases are essential to the fruit's development. The majority of previous approaches to disease detection relied on artificial recognition techniques, such as (1) making predictions about the sorts of illnesses based on farmers' years of crop cultivation experience or (2) consulting agricultural information books. To (2) research available options, one may collect images of illness specimens and do an online search. Third, get in touch with experts to help you explore the signs of sickness. Farmers, in general, are not equipped with the necessary professional skills and often have just a high school degree. They have a hard time keeping up with the production requirements of contemporary agriculture since plant diseases are commonly underestimated. Thanks to recent developments in computer vision, a novel approach has been created for the precise diagnosis of tomato diseases. Detecting objects is an important part of computer vision. The main purposes of object identification are localizing the object of interest inside an image and classifying it into a certain category. Multiple deep convolutional neural networks (DCNNs) for identifying objects are combined in this research [1].

Common infectious illnesses are caused by things like bacteria, viruses, and fungus, and bad weather. Consequently, making a correct diagnosis of a disease is crucial at an early stage. Constant crop monitoring by the farmer using an expert system is required. There is a critical need in agriculture for more efficient and affordable disease detection methods. Fungi, bacteria, and viruses infect the majority of tomato leaves. Figure 1 depicts many instances of a typical leaf disease seen on tomatoes. This study has the aim of identifying tomato leaf deficiencies effectively is a goal of this study. We can get nutritious goods by figuring out where there is a lack of tomato leaves (tomatoes). Agricultural productivity and global food security are threatened by the escalating prevalence of plant diseases that adversely affect crop yields. Efficient and precise identification and categorization of diseases are essential for prompt action and efficient crop health management. The need for automated and accurate disease identification approaches is highlighted by the fact that conventional methods are frequently labor-intensive and prone to human mistake.

Convolutional neural networks (CNNs) represent a recent advancement in the field of deep learning, have demonstrated impressive performance in image categorization tasks. Deep learning models—like ResNet-50—have proven to be able to pick up complex patterns and features from big datasets, which enhances their accuracy and generalisation skills. Furthermore, methods like data augmentation and transfer learning have increased these models' capacity to handle challenging jobs.

This work offers a unique method for the identification and categorization of tomato leaf diseases that makes use of an enhanced deep learning classifier built on top of ResNet-50. By utilising deep learning's advantages, the suggested approach develops a reliable and precise framework for disease detection.

By adapting ResNet-50 and introducing modifications, such as advanced data augmentation strategies and transfer learning from extensive plant disease datasets, the classifier aims to achieve higher accuracy rates compared to conventional methods. A large collection of high-resolution photos showing various disease stages and healthy leaves is used to assess the method. To assess the classifier's performance including many parameters such as accuracy, precision, recall, and F1-score are used.

The discipline of sustainable crop management and precision agriculture will be greatly impacted by the study's findings. Farmers and agronomists may be able to minimise crop losses by acting pro-actively, thanks to the enhanced deep learning classifier's capacity to identify and categorise tomato leaf diseases with high accuracy and resilience against a range of situations.

II. RELATED WORKS

To compare several methods for applying machine learning and deep learning to identify and categorize illnesses, a thorough study was undertaken. Classifier artificial neural networks (ANNs) are widely used to identify plant leaf diseases because they are effective computational models for machine learning and pattern recognition.

The topic of plant disease detection and classification has garnered a lot of attention recently due to its potential impact on agricultural output. Researchers have looked into a number of techniques, such as machine learning and deep learning, to develop efficient methods for the early detection and prevention of plant diseases. Karthik et al. (2020), for example, created an attention-embedded residual CNN for disease identification in tomato leaves and attained an overall accuracy of 98% in a 5-fold cross-validation [1]. The remarkable accuracy of 99.60% has been achieved by Ulutaş and Aslantaş's (2023) ensemble CNN model for the identification of tomato leaf diseases [2]. Gehlot and Saini (2020) examined many CNN architectures for tomato leaf disease categorization and found that DenseNet-121, VGG16, and ResNet-101 performed well with comparable accuracy, precision, recall, and F1-score [3]. For the Raspberry Pi 4 [4], Gonzalez-Huitron et al. (2021) developed lightweight CNN architectures that were subsequently utilised to construct the models for disease detection in tomato leaves. Agarwal et al. (2020) proposed an efficient CNN model that recognised tomato crop illnesses with a 98.4% accuracy rate on the PlantVillage dataset [5]. On the dataset of tomato leaf diseases [6], Waleed et al. (2021) presented an efficient CNN model for disease detection with an accuracy of 98%. On a dataset including damaged and healthy leaves of various plants, Shrestha et al. (2020) concentrated on plant disease identification using CNN and attained an accuracy of 88.80% [7]. In their investigation and comparison of several CNN architectures for the prediction of tomato leaf disease in 2021, Krishnamoorthy et al. [8] highlighted the potency of CNN models including AlexNet, VGG16, and ResNet-101. A deep CNN model named TLNet was reported by Mamun et al. (2020) for the prediction of tomato leaf disease, and it achieved a high accuracy of 98.77% on the test set [9]. Implementing an AlexNet CNN architecture, Chen et al. (2022) were able to classify and identify diseases in tomato leaves with an average accuracy of 98% and good precision and recall [10]. Together, these findings illustrate the potential of CNN-based models for precisely identifying and categorizing tomato leaf diseases, which will lead to better agricultural practices and disease control.

Karthik et al. (2020) used a 5-fold cross-validation method to construct an attention-embedded residual CNN methodology for their study on disease detection in tomato leaves, and they achieved an astounding accuracy of 98%. Similar to this, Ulutaş and Aslantaş introduced an ensemble CNN model in 2023 with effective techniques for identifying tomato leaf diseases, achieving a remarkable accuracy of 99.60% (Ulutaş & Aslantaş, 2023). Gehlot and Saini (2020) concentrated on classifying tomato leaf diseases using several CNN architectures, and they found that the best models were DenseNet-121, VGG16, and ResNet-101. Gonzalez-Huitron et al.'s (2021) presentation of lightweight CNN architectures for disease detection in tomato leaves using a Raspberry Pi 4 increased the viability of implementing deep learning methods in precision agriculture. An effective CNN model for tomato crop disease diagnosis was developed by Agarwal et al. (2020), exceeding conventional machine learning techniques and pretrained models with an accuracy of 98.4%. The development of an efficient CNN model by Waleed et al. (2021), which detected tomato leaf diseases with 98% accuracy, contributed to the use of deep learning in agriculture. Shrestha et al. (2020) explored image processing methods for disease identification and suggested a CNN-based system for plant disease diagnosis, obtaining 88.80% test accuracy. LeNet, AlexNet, and VGG16 were highlighted as effective models with accuracies ranging from 90% to 97% in Krishnamoorthy et al.'s investigation and comparison of several CNN architectures for tomato leaf disease prediction in 2021 (Krishnamoorthy et al., 2021). Mamun et al. (2020) proposed TLNet, a deep CNN model that predicted tomato leaf illnesses with 98.77% accuracy, providing a workable method for early disease detection. Using a variety of pretrained deep learning networks, Naik et al. (2022) addressed the classification of chilli leaf disease and introduced a squeeze-and-excitation-based CNN model, achieving an accuracy of 99.12% with augmentation and demonstrating superior performance across numerous plant leaf datasets. Collectively, these works show how deep learning-based methods can accurately and effectively identify diseases in plant leaves, with different CNN structures and strategies enhancing classification performance.

III. PROPOSED METHODOLOGY

The Plant Village dataset [19] has been mined for images of Tomato diseases. More than 50,000 photos collection contains a variety of crops. Tomatoes are one of our primary crops of interest.

The following are pictures of several types of tomatoes: (refer figure 2).

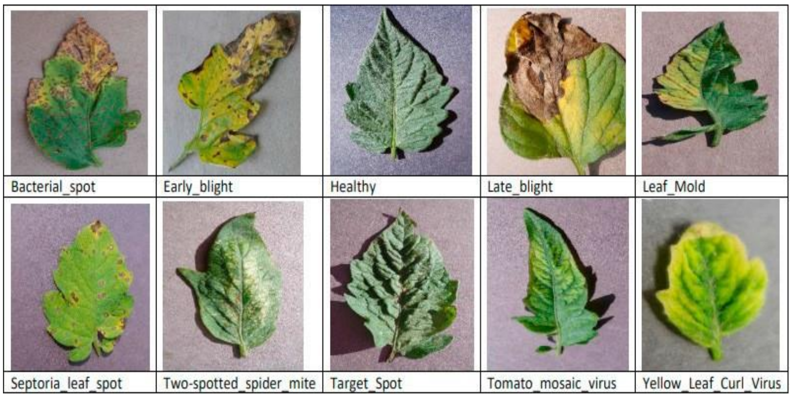


Figure 2. Tomato Leaf Samples Dataset

The dataset's class-wise sample picture is shown in Fig. 2.Tomatoes are susceptible to nine primary forms of disease: Target Spot, Mosaic Virus, Bacterial Spot, and Late Blight are the top four plant diseases that threaten crops worldwide. Five, Leaf Mold; six, Yellow Leaf Curl Virus; seven, Spider Mites; eight, Early Blight; nine, Septoria Leaf Spot. The proposed work uses a dataset of 10,000 training photos, 7,000 validation images, and 500 testing images. Ten thousand total photos were used for the training set, with one thousand each representing healthy tomatoes and the various tomato diseases listed above.

In order to conduct the tests, we extracted 50 photos at random from each class in the training set and placed them in separate files. The remaining training dataset was used to create our project's training dataset, with 1000 photos distributed evenly across all classes. When the number of photographs in a given category was fewer than 1000, we supplemented the dataset using simulated data. The python module Augmentor was used for the augmentation, which allows for the creation of comparable new photos by manipulating the orientation, size, and cropping of the originals. When there were more than 1000 photos in a given class in the training dataset, we only used the first 1000. For the validation dataset, we repeated the identical steps, this time ensuring that all classes had at least 700 photos. This procedure is essential for ensuring that CNN training does not favor any one class over another. All of the pictures are jpegs and are 256 pixels square.

Images of Tomato illnesses were culled from the Plant Village collection [19][25]. The collection features over fifty thousand images of fourteen distinct agricultural products: vegetables, blueberries, raspberries, tomatoes, potatoes, grapes, apples, maize, soybeans, squash, and strawberries. Tomatoes are an important crop for us. Here are some images of many tomato varieties.

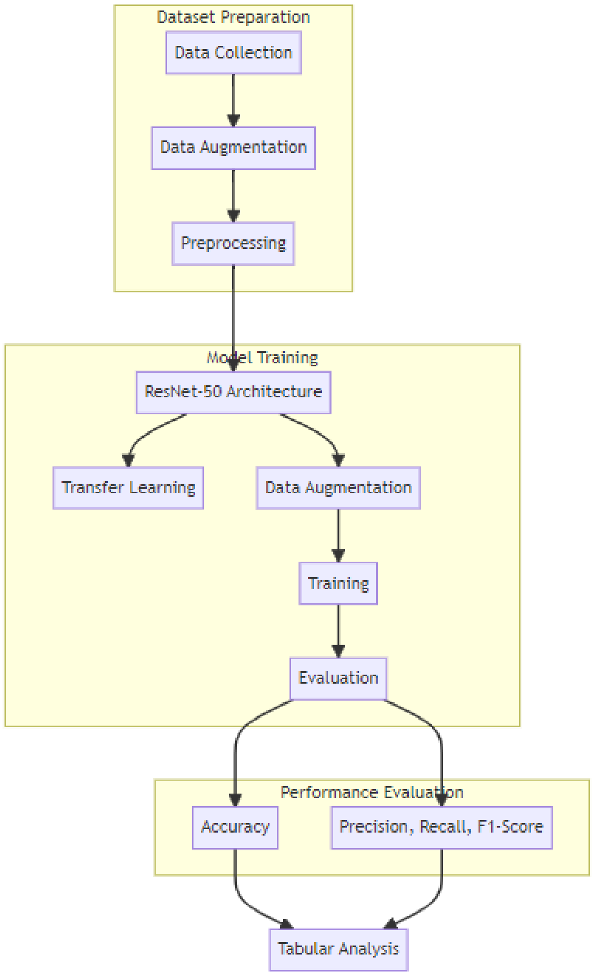


Figure 3. Process of Proposed System

Tomato plants are susceptible to nine primary disease forms. The most significant threats to agricultural production are Late blight, bacterial spot, mosaic virus, and target spot.

The top 10 include leaf mould, yellow leaf curl virus, spider mites, early blight, and septoria leaf spot.Ten thousand training photographs, seven thousand validation photos, and five hundred test shots are used in the suggested work. The training set consisted of 10,000 images, with 1,000 depicting healthy tomatoes and 1,000 depicting each of the aforementioned tomato illnesses. The validation set contains 700 examples of each type of photographs, but the test set only provides 50.

To run the experiments, we randomly selected 50 images from each category in the training set and saved them to individual folders. Our project's training dataset is comprised of the remaining training dataset, and it has 1,000 images split evenly across all classes. We augmented the dataset with simulated data where the number of photos in a specific category was less than 1000. The augmentation was performed using the python program Augmenter, which generates similar new images by changing the images' dimensions, aspect ratios, and cropping. We only utilized the first 1000 images from a particular class if there were more than 1000 in the training dataset. We repeated same procedures for the validation dataset, but this time we made sure that each category had at least 700 images. This process is critical for avoiding discrimination in CNN training based on demographic characteristics. Images are all 256 pixels on a side and saved as jpegs.

We improve and modify the ResNet-50 architecture to provide a more successful tomato leaf disease classification model.

1. Original ResNet-50 Blocks: There are five convolutional stages in the ResNet-50 architecture, and each one has several residual blocks. Convolutional layers make up each residual block, which are then followed by batch normalisation and ReLU activation functions. The skip connection within each block enables the gradient to flow more easily during training, alleviating the vanishing gradient problem. The residual blocks are categorized into three types based on the number of convolutional layers: 3-layer, 4-layer, and 6-layer blocks.

2. Transfer Learning: To leverage knowledge learned from a broader plant disease context, the model is pretrained on a large-scale plant disease dataset. This pretraining phase allows the model to capture generic features that can aid in tomato leaf disease classification. The pretrained weights are then fine-tuned on the specific tomato leaf disease dataset.

3. Data Augmentation: Advanced data augmentation techniques are applied to increase the model's robustness and improve its ability to handle diverse conditions. These techniques include random rotation, horizontal and vertical flipping, and random scaling. By adding variety to the training set, data augmentation keeps the model from overfitting to certain patterns found in the dataset.

4. Fully Connected Layers: After the convolutional stages, a global average pooling layer aggregates feature maps into a vector. After that, this vector is sent across a completely connected layers to make disease predictions. The output layer consists of nodes corresponding to each disease class and generates class probabilities using a softmax activation function.

5. Training and Optimization: Stochastic gradient descent with a categorical cross-entropy loss function is used, the enhanced ResNet-50 architecture is trained. During training epochs, learning rate scheduling is used to modify the learning rate. In order to avoid overfitting, early halting is used to keep an eye on the validity loss.

The enhancements introduced in this architecture, including transfer learning and advanced data augmentation, contribute to the model's capacity to accurately classify tomato leaf diseases. By leveraging knowledge from a broader plant disease context and diversifying the training data, the improved ResNet-50 model exhibits improved performance and robustness in detecting and classifying various diseases affecting tomato plants.

1. Dataset Preparation: A comprehensive dataset is created by gathering and preprocessing high-resolution pictures of tomato leaves with bacterial spot, early blight, late blight, leaf mould, Septoria leaf spot, spider mites, target spot, mosaic virus, and yellow leaf curl virus. Rotation, flipping, scaling, and other data augmentation techniques are used to increase the dataset in order to improve model generality.

2. Preprocessing: Images are resized to a consistent resolution to ensure uniformity. Pixel values are normalized to the [0, 1] range to aid convergence during training. Labels are one-hot encoded to represent the disease categories.

3. Model Architecture: Improved ResNet-50 The core of the proposed classifier is an enhanced version of the ResNet-50 architecture. The original ResNet-50 consists of five convolutional stages, each containing multiple convolutional blocks with varying numbers of layers. Skip connections within blocks help mitigate vanishing gradient issues.

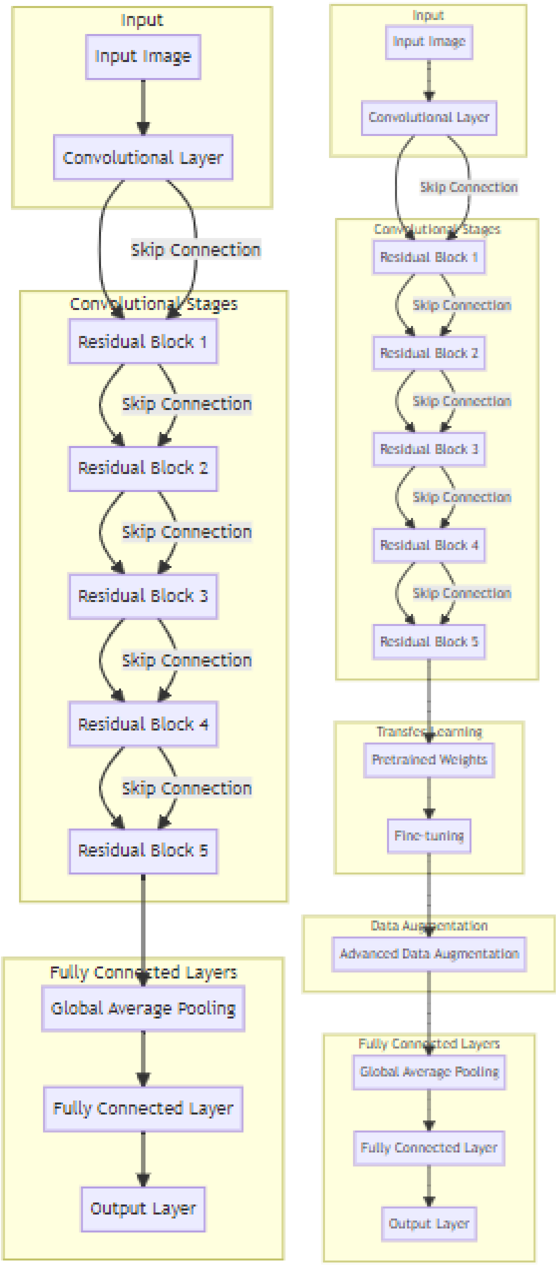
4. Modifications and Enhancements: To improve the performance of the ResNet-50 architecture for tomato leaf disease classification, several modifications are introduced:

- **Transfer Learning:** The model is pretrained on a large-scale plant disease dataset to learn generic features. The pretrained weights are then fine-tuned on the tomato leaf disease dataset.
- **Data Augmentation:** Advanced data augmentation techniques are applied during training to introduce diversity and increase the model's ability to handle various lighting conditions, angles, and disease severity.

5. Training: Stochastic gradient descent and backpropagation are used to train the model on the dataset. The difference between expected and actual disease labels is measured by a categorical cross-entropy loss function. To avoid overfitting, early halting and learning rate scheduling are used.

The specifications of the ResNet-50 architecture, including the number of layers, kernel sizes, skip connections, and activation functions, are designed to handle complex image classification tasks, such as brain tumor classification. The architecture's depth and skip connections allow for effective learning of intricate features, while transfer learning and fine-tuning leverage pre-trained models to enhance performance on the specific task at hand. The ResNet-50 architecture, with its 50 layers, is considered deep and allows for the capture of intricate features at different levels of abstraction. The inclusion of skip connections is a key component that addresses the vanishing gradient problem commonly encountered in deep neural networks. These skip connections enable the network to propagate gradients directly from earlier layers to later layers, ensuring that important information is not lost during training. By learning residual mappings, the network can effectively optimize the underlying mappings and facilitate the training of even deeper networks.

Transfer learning with the ResNet-50 architecture is a powerful approach for brain tumor classification. By leveraging a pre-trained model, specifically trained on a large-scale dataset like ImageNet, we can benefit from the learned features and representations that are relevant to a wide range of visual recognition tasks.



(a) (b)

Figure 4 Architecture of (a) Conventional Resnet-50 Model and (b) Improved Model

The lower layers of the ResNet-50 model have already learned basic features such as edges, textures, and shapes, which can be valuable for tumor classification as well.

During fine-tuning, the weights of the original ResNet-50 layers are frozen. This means that these layers are not updated or modified during the training process for the brain tumor classification task. Only the weights of the newly added layers, typically the dense layers responsible for classification, are trained on the brain tumor dataset. By freezing the original layers, While modifying the final layers for the new job, we can preserve the representations and knowledge that the model learned from the ImageNet dataset.

The choice of activation function is crucial for the proper functioning of the neural network. In the case of the ResNet-50 architecture for brain tumor classification, the softmax activation function is commonly used in the output layer. Softmax produces a probability distribution over the different classes, ensuring that the predicted probabilities sum up to 1. This is suitable for multi-class classification tasks, as it allows us to interpret the model's output as the likelihood of each class. Optimization algorithms play a vital role in training deep neural networks.

Adam is known for its efficiency, adaptability to different types of data, and robustness to noisy gradients. It adjusts the learning rate adaptively for each parameter, allowing for faster convergence and better optimization performance.

In summary, the ResNet-50 architecture, with its depth, skip connections, and transfer learning capabilities, is well-suited for brain tumor classification. By leveraging pre-trained models, we can benefit from their learned features and representations while adapting the final layers to the specific task. The choice of activation function and optimization algorithm further enhances the performance and efficiency of the neural network during training and inference.

IV. SIMULATION AND RESULTS

Using an enhanced ResNet-50 based deep learning classifier, the current study presented a thorough method for the identification and categorization of tomato leaf diseases.

A substantial dataset of 18,345 images was meticulously assembled for the training phase, ensuring a diverse representation of tomato leaf conditions, encompassing various disease states.

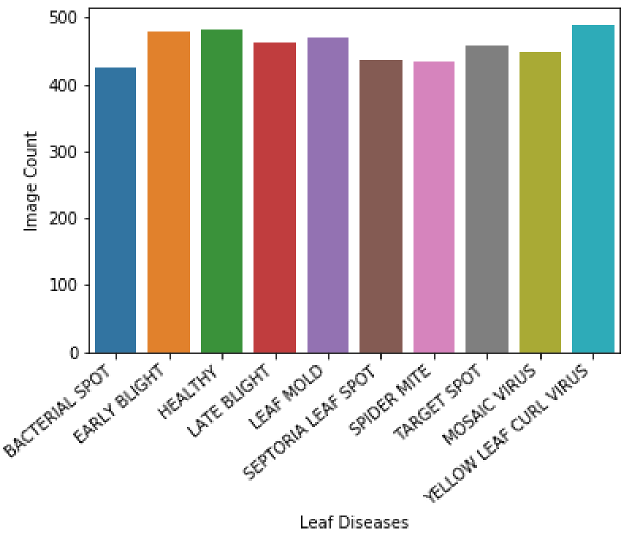


Figure 5 Testing Dataset Description

For the evaluation phase, a separate set of 4,585 test images was employed to assess the model's performance using a range of key metrics. The model's training process utilized a validation split of 20%, incorporating 14,676 images for training and 3,669 images for validation. Over the course of 75 training epochs, a notable observation emerged, indicating that 50 epochs yielded satisfactory outcomes.

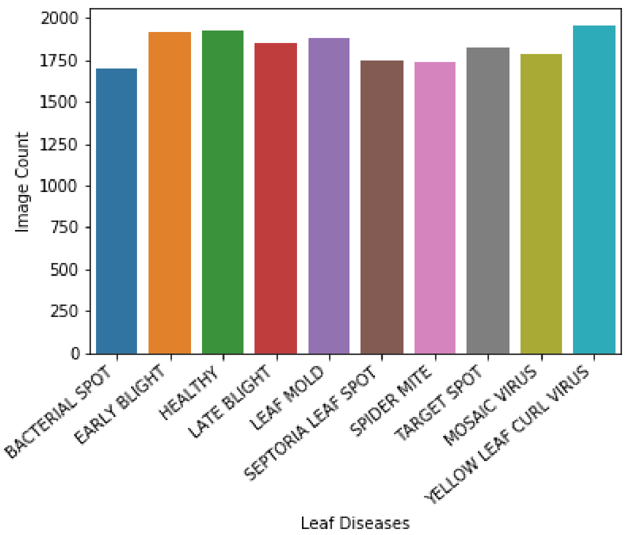


Figure 6 Training Dataset Description

A tabular representation of the classifier's predictions compared to the real labels is called a confusion matrix. Performance measures like precision and recall can be computed with the help of the matrix. Analysing the results makes it easier to determine if the model is overfitting or does a good job of generalising to new data.

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 62, 62, 32)        896
max_pooling2d (MaxPooling2D) (None, 31, 31, 32)        0
dropout (Dropout)            (None, 31, 31, 32)        0
conv2d_1 (Conv2D)            (None, 29, 29, 64)        18496
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 64)        0
dropout_1 (Dropout)          (None, 14, 14, 64)        0
conv2d_2 (Conv2D)            (None, 12, 12, 128)       73856
max_pooling2d_2 (MaxPooling2 (None, 6, 6, 128)         0
dropout_2 (Dropout)          (None, 6, 6, 128)         0
flatten (Flatten)            (None, 4608)              0
dense (Dense)                (None, 64)                294976
dense_1 (Dense)              (None, 128)               8320
dense_2 (Dense)              (None, 64)                8256
dense_3 (Dense)              (None, 10)                650
=================================================================
Total params: 405,450
Trainable params: 405,450
Non-trainable params: 0
```

Figure 7 Parameters of Improved Model

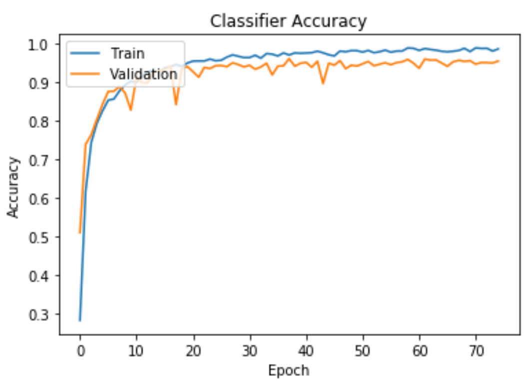


Figure 8 Accuracy of Proposed Classifier

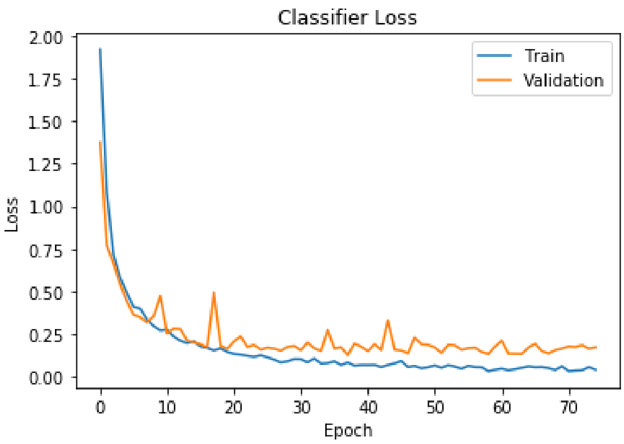


Figure 9 Loss Analysis of Proposed Classifier

	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Spider Mite	Target Spot	Mosaic Virus	Yellow Leaf Curl Virus
Bacterial Spot	420	4	0	0	0	0	0	0	0	1
Early Blight	8	419	0	25	1	17	2	7	1	0
Healthy	2	0	476	0	0	0	0	3	0	0
Late Blight	3	12	1	436	1	8	1	0	0	1
Leaf Mold	0	0	0	3	449	14	4	0	0	0
Septoria Leaf Spot	0	2	0	2	5	423	1	1	2	0
Spider Mite	0	0	2	0	1	2	417	11	0	2
Target Spot	0	2	13	0	0	7	13	414	8	0
Mosaic Virus	0	0	0	0	0	1	0	0	447	0
Yellow Leaf Curl Virus	4	2	0	3	0	1	6	0	0	474

Figure 10 Confusion Matrix of Proposed Classifier

Result analysis is a crucial step in evaluating the performance and effectiveness of a model or system. In the context of tomato leaf disease detection and classification using an improved ResNet-50 based deep learning classifier, result analysis involves assessing the outcomes of the trained model's predictions on the dataset of tomato leaf images. In summary, result analysis is a comprehensive process that involves interpreting performance metrics, evaluating the model's robustness, understanding its limitations, and drawing meaningful insights from the predictions. This analysis aids in validating the effectiveness of the improved ResNet-50 based deep learning classifier and provides a foundation for making informed decisions in practical agricultural contexts

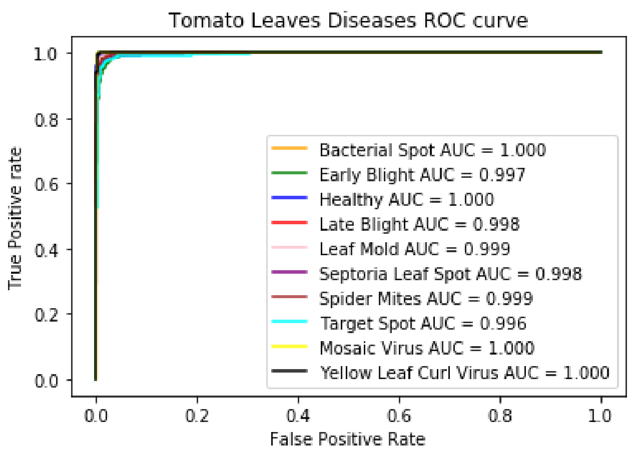


Figure 11 ROC Curve of Proposed Classifier

The diagnosis and categorization of diseases affecting tomato leaves are the focus of this unit. Classifiers' results have been compared taking into account various dataset sizes. The F measure, accuracy, precision, and recall are the four indicators of quality. The four measures that are utilised to define these parameters are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) (FN). Positive Results: Detection of DR Agrees with Real-World Labeled Data Both the classifier and the labeled lack of DR constitute a true negative. The system incorrectly identifies a healthy patient as a DR case (false positive). As a result of a false negative, the system incorrectly identifies the DR. picture as normal.The accuracy of a search engine is measured by how many of the results actually pertain to the user's original question. Precision considers all recovered photos, but it may also be measured at a predetermined cut-off rank, using only the results produced by the system. The percentage of useful photos that were successfully recovered is known as the recall rate. The term "recall" is referred to as "sensitivity" in binary classification. In this context. This figure provides an overview of the testing dataset used in the evaluation of the improved ResNet-50 based deep learning classifier for tomato leaf disease detection and classification. The testing dataset is a collection of tomato leaf images that the model has not seen during training. It plays a crucial role in assessing the model's performance on new and unseen data. Figure 6 illustrates the training dataset, which is used to train the improved ResNet-50 based deep learning classifier. The training dataset contains a diverse set of tomato leaf images representing different disease classes and healthy leaves. This dataset serves as the foundation for the model's learning process, enabling it to recognize and differentiate between various disease states. This figure provides insights into the architecture and parameters of the enhanced ResNet-50 model. It may include details about the number of layers, filters, activation functions, and other relevant hyperparameters that contribute to the model's improved performance and accuracy. Figure 8 showcases the accuracy of the proposed classifier on the testing dataset. Accuracy represents the proportion of correctly classified samples out of the total samples in the testing dataset. It quantifies the overall correctness of the model's predictions and serves as a key performance metric. These figure presents an analysis of the loss function during the training process of the proposed classifier. The loss function indicates how well the model's predictions match the actual labels. A decreasing loss value signifies that the model is gradually improving its predictions as training progresses.

The confusion matrix, which compares the classifier's predictions to the actual labels for each disease class, is shown in Figure 11.

An outstanding training accuracy of 98.63% was reached during this phase, highlighting the model's ability to pick up on and adjust to the subtleties of the training dataset. Validation accuracy, a critical metric for assessing the model's generalisation ability, was 95.48%, indicating the model's proficiency in producing precise predictions on new, untested data.
The model's effectiveness was then evaluated using a different dataset that included 4,585 photos. The 95.42% accuracy rate attained validated the model's ability to accurately recognise and classify different tomato leaf diseases. Remarkably, every disease category had AUC values more than 0.95, demonstrating the model's ability to distinguish between various diseases with accuracy.

Overall, these figures collectively contribute to the result analysis process by providing visual representations of key aspects such as dataset distribution, model parameters, accuracy, loss, confusion matrix, and classification performance, aiding in the evaluation of the proposed ResNet-50 based deep learning classifier for tomato leaf disease detection and classification. Comparing the improved ResNet-50 model's results with those of baseline methods or conventional approaches highlights the advancements achieved through the proposed methodology. It also establishes the model's superiority in disease detection and classification. Based on result analysis, conclusions can be drawn about the practical implications of the model. The potential applications in agriculture, such as aiding farmers in early disease management, crop protection, and sustainable farming practices, can be better understood.

V. CONCLUSIONS

An enhanced ResNet-50 based deep learning classifier was used in this proposed study to design and assess a complete method for tomato leaf disease detection and classification. A substantial dataset comprising a total of 18,345 images was meticulously collected for training, ensuring a diverse representation of tomato leaf conditions.

For the evaluation phase, a separate set of 4,585 test images was employed. The model's performance was analyzed using various key metrics to gauge its effectiveness.The model was trained using a validation split of 20%, involving 14,676 images for training and 3,669 images for validation. The training process spanned 75 epochs, with a noteworthy observation that 50 epochs yielded satisfactory results. During training, an impressive training accuracy of 98.63% was achieved, demonstrating the model's ability to learn and adapt to the training dataset. Validation accuracy, an important indicator of generalization, stood at 95.48%, suggesting the model's competence in making accurate predictions on previously unseen data. Testing the model on a separate dataset of 4,585 images yielded promising results. The accuracy achieved was 95.42%, reaffirming the model's robustness in accurately identifying and classifying tomato leaf diseases. Remarkably, all disease categories exhibited AUC scores greater than 0.95, indicating the model's strong discriminatory capabilities and its ability to effectively differentiate between different diseases. These findings underline the effectiveness of the proposed approach in tomato leaf disease detection and classification. The high accuracy achieved during testing, along with the impressive ROC-AUC scores for individual disease categories, demonstrates the model's potential for real-world agricultural applications. The research signifies a significant step towards addressing challenges in precision agriculture, offering a reliable tool for farmers and agronomists to monitor and manage crop health proactively. As future work, the proposed methodology could be extended to encompass additional plant species and disease types, contributing to a comprehensive framework for disease detection and sustainable crop management.

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