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Innovative Approach for Early Detection and Diagnosis of Tomato Leaf Diseases

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Abstract

Tomato plant disease detection has become a crucial research area during climate change and has increased concern for improving production quality and quantity. This paper proposes a hybrid DL-based approach to detect 9 classes of tomato leaf disease (TLD) images. To accomplish the mission, this study presents the combination of ResNet152V2 and Squeeze-and-Excitation (SE) blocks. The evaluation is done on the PlantVillage dataset between 10 classes of 11,000 images. A comparison by 4 pre-trained models such as Xception, ResNet152V2, InceptionV3, and VGG19 has been maintained. The results show that the proposed model achieves accurate extraction of the distinct features from tomato leaf images, with scores of 0.947, 0.948, 0.947, 0.946, and 0.970 for accuracy, precision, recall, F1 score, and area under the curve, respectively.

Keywords: Tomato Leaf Diseases; Artificial Intelligence; Deep Learning; Transfer Learning; Hybrid Model.

1 | Introduction

1.1 | Background

Tomatoes are considered the highest consumption rate among all other crops. With an annual yield of over 170 million tons, tomatoes are the most produced vegetable crop worldwide. Every year, several nations produce tomatoes worldwide, with the United States, Turkey, India, and Egypt being the top producers [1].

A study by the FAO found that the main cause of the tomato production rate slowdown is the existence of several illnesses, the majority of which originate from the leaves of the tomato plant and cause the annual production quantity to drop from 8 to 10% [1]. This is in sync with another FAO report that predicts an increase in the world's food demand by 2050 [2], and with crop yields decline because of climate change. All those factors can significantly lower the quantity and quality of food produced. As a result, it's critical to identify these irregularities in the plants at an early stage since they might lead to higher food prices and

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negatively affect farmers' profits. In its more destructive form, famine conditions can arise, particularly in developing nations [2].

Originally, the molecular biology and immunology domains provided techniques to the tomato leaf disease (TLD) inspection research community. These works suffer from significant processing complexity and a considerable deal of human knowledge. Since most crop growers are low-income people, they are unable to afford such expensive treatments. Therefore, classifying and identifying the many TLD is the main objective of this research. So, AI technologies can assist practitioners in more correct and early detection of TLD, saving farmers from suffering large losses [3].

1.2 |Tomato Plant Diseases

Plant diseases pose a significant problem for anyone engaged in gardening, farming, and other plant cultivation activities. Diseases in tomato plants can be caused by a wide range of pathogens, including bacterial, viral, fungal, and insect infections as well as nutritional problems. Table 1 lists the most tomato diseases [4].

Table 1. Tomato diseases categories.

Bacterial diseases	Bacterial Canker of Tomato
	Bacterial speck
	Bacterial spot
	Bacterial wilt
Fungal diseases	Alternaria stem canker
	Anthracnose
	Black mold rot
	Black root rot
	Powdery mildew
	Verticillium wilt
	Leaf mold
	Early blight
	Late blight
	Septoria leaf spot
	Fusarium wilt
	Target spot
Viral diseases	Tomato mosaic
	Yellow leaf curl
	Spider mite
	Cucumber mosaic
Nematodes	Root-knot
	Sting
	Stubby-root

Fungal disease can appear in the form of leaf spots, powdery mildew, lesions, and mold. Bacterial diseases can cause wilting, leaf spots, ulcers, and rot. Which leads to serious damage to the plant's leaves. Some examples of bacterial diseases are bacterial leaf spot, fire blight, and downy mildew.

Viral diseases are caused by plant viruses, which are transmitted through insects, contaminated tools, or infected plant materials. These diseases can lead to stunted growth, mottled leaves, yellowing, and misshapen plant parts. Tomato mosaic virus is a common example of a viral disease. Nematodes are little spherical parasites that can invade plant roots and inflict substantial harm. These organisms consume plant tissues, thereby interfering with the process of water and nutrient absorption. Nematode-infected plants may manifest symptoms such as inhibited growth, wilting, and chlorosis of the foliage [4].

In agriculture, early-stage diagnosis of plant diseases is critical, and leaf detection is frequently employed to distinguish between various illnesses. But diagnosing the illness necessitates a thorough understanding of its causes and signs. In isolated areas, manual assessments are still utilized, although they are unable to pinpoint the precise illness and its variations. Manual evaluation takes a lot of time and manpower on larger farms. Furthermore, crop health must be periodically monitored during the ongoing process of cultivation to identify illnesses. Since this other approach is more precise and efficient, it is required to automatically diagnose illnesses from leaf photos. Machine Vision and DL are techniques is recommended in plant disease recognition and identification especially in large fields and Demond for continuous monitoring [5].

1.3 |Aims and Scope of this Work

Generally, ML and DL techniques play an evolutionary role in agriculture. Automated agriculture systems can perform high-performance in different tasks such as monitoring, navigation, mapping, identifying plant diseases and pests. Plant disease detection is developed on captured images of pests or diseases. Classification is the most demanding phase in computer vision and ML. The completion of this stage depends on earlier ones like acquisition, preprocessing, as well as feature selection and extraction. This method uses a dataset that has been trained first to determine if the test image is Normal/diseased. Unfortunately, most plant images suffer from some complex problem that poses a challenge to this study [6]:

- Backgrounds that cannot be easily separated from the region of interest (usually leaf and stem).
- Boundaries of the symptoms often are not well defined, and uncontrolled capture conditions may present characteristics that make the image analysis more difficult.
- Certain diseases produce symptoms with a wide range of characteristics, the symptoms produced by different diseases may be very similar, and they may be present simultaneously.

Using ML models requires that all attributes, including pixel values, textures, orientations, shapes, and other characteristics, be identified by an expert before being manually created by a data analyst and a domain expert. The accuracy with which features are found or extracted determines how well the ML algorithm performs. DL algorithm, on the other hand, attempts to extract high-level characteristics from the data. DL is capable of automatically extracting features without the need for explicit feature engineering. By utilizing large amounts of labeled data, DL models can learn intricate features and capture complex relationships, leading to highly expressive representations that enable accurate pattern recognition and prediction [7].

CNN is a type of DL architecture that shows significant results in Plant disease detection. CNN uses deep neural networks (DNN) to analyze multidimensional data by utilizing several layers for classified diseases and extracted features. Many convolution layers, nonlinear pooling layers, and activation functions are used in feature extraction. Using fully connected layers as a classifier lowers the processing complexity of the images without any loss of features that are crucial for the classification process. Through a stack of convolution and pooling processes, CNN learns spatial properties from input images of plant leaves. The fully connected layers receive this vector, which is essentially a reduction of these features into probabilities for a subset of classes [4]. Release of CNN leads to various futuristic DL architectures like AlexNet, VGG, ZFNet, GoogLeNet, ResNet, SegNet, YOLO, U-Net, Fast R-CNN, and Mask R-CNN [8].

A bunch of studies have been done over the last few years by utilizing diverse image-processing techniques with different DL-based models in intelligent agriculture tasks. Which lead to [9]:

- Better leaf classification is caused by similarities between different types of tree leaves.
- Improved financial and environmental effects by effective by identifying the significant number of pesticides required which results in improved financial and environmental effects.

- Detect and discriminate weeds in a cost-effective manner and with no environmental side effects or issues.
- More effective, quick, accurate results by analyzing lead vein morphology which provides more information about leaf properties.

By leveraging the power of DL in the agriculture industry, Egypt can become more sustainable and profitable, ultimately contributing to the realization of the goals outlined Egypt Vision 2030 [10].

On top of all that, our goal is to focus on detecting TLD using hybrid DL techniques. Also, transfer learning (TL) has exploited the knowledge gained from a previous task to improve generalization about another.TL is developed for hybrid DL ResNet152V2 and Squeeze-and-Excitation (SE) block for classifying between 9 classes of TLD.

1.4 | Main Contributions

- The primary objective of this study is to investigate the effectiveness of transfer learning algorithms such as (Xception , ResNet152V2 , InceptionV3 , VGG19) in properly classifying nine unique classes to Tomato disease.
- Create a proposed model capable of diagnosis with high accuracy. It is a hybrid model that combines Architecture ResNet125V2 with Squeeze-and-Excitation (SE) block.
- The validity of the models was assessed using a range of metrics, such as accuracy, precision, recall, F1-score and AUC. In exploratory data analysis using ROC Curve and TSNE.
- The proposed model achieved satisfactory results of 0.947, 0.948, 0.947, 0.946, and 0.970 for accuracy, precision, recall, F1 score, and area under the curve, respectively.

The rest of this article is organized as follows **Section 3** reviews some ML and DL models for tomato plant disease detection; **Section 4** presents materials and methods; **Section 5** presents results and discussion; **Section 6** Implication of Egyptian Vision 2030; and **Section 7** presents conclusion and future work**.**

2 | Literature Review

In this part we discuss some implementation of ML and DL approach for TLD detection. Before the transformation of DL models, ML algorithms produced numerous research results for various agricultural operations. Support Vector Machines (SVM), KNN, Random Forest (RF) classifier, and DT are the most notable models in these algorithms.

In most cases, tomato diseases appear and identify on crop leaves first. Which resulting in using leaf picture datasets for tomato disease identification and recognition. Numerous studies have been put forth to determine the TLD, and each one documented a range of models, techniques, and characteristics. Consequently, a review of the literature was done to bring the prior research in this field to a close.

A ML proposed has been developed to identify TLD using Otsu's segmentation algorithm with a decision tree (DT) method. This study used hand-crafted features for learning the TLD characteristics. The classification accuracy was 97.30% [11]. Another study proposed a statistical-based model to identify six types of TLD. To minimize SIFT feature vector dimensions, the generalized extreme value (GEV) distribution was adopted which reduces algorithm computational time and attained an accuracy value of 84.7% [12].

Further contribution based on the Moth-Flame Optimization (MFO) and Moth-Flame Optimization Rough Set (MFORSFS) approach to identify a two of Fungal TLD. Comparison with the genetic algorithms (GA) and particle swarm optimization (PSO) with rough sets algorithms has been maintained. The proposed approach achieve accuracy 86% [13]. Another study based on optimization algorithms, Gangadevi et al. proposed a multi-objective hybrid fruit fly optimization algorithm using simulated annealing optimized SVM to identify tomato plant diseases earlier, avoiding global optimization problems. The method achieved 91.1% accuracy and reliability, outperforming current algorithms. Its operational efficiency was measured on statistical parameters and compared to existing algorithms, indicating a high methodological approach for crop disease diagnosis [14].

Gadade et al. proposed a ML method for identifying and classifying TLD based on PlantVillage dataset which have high, medium, low, and normal severity grading. The system extracts handcrafted feature to perform various classification techniques such as Support vector machine (SVM), KNN, Naive Bayes, DT, and LDA[15]. On the other hand, Ahmad et al. developed a new feature descriptor called the local triangular-ternary pattern (LTriTP) for TLD detection. It extracts feature vectors from leaf images using a triangular shape descriptor. The method uses an absolute mean value-based dynamic threshold and triangular histogram of gradient (T-HOG) to identify infected regions. The fusion of T-HOG and LTriTP features improves disease detection performance. The method outperforms renowned methods like Local Binary Pattern and Local Ternary Pattern [16].

Das et al. proposed an approach based on SVM, logistic regression (LR), and Random Forest (RF) to classify seven classes of TLD. The hand-crafted feature is extracted using the Haralick algorithm. These features are the input to the classifier. The results confirms that SVM outperforms with an accuracy of 87.60% followed by RF 70.05% and LR 67.30% [17]. Another study proposed an approach to identify TLD based on multiple features fusion for four classes. The features are extracted and input to RF and DT algorithms for classification process. RF Shows the highest detection accuracy of 94% whereas the DT is 90% [18].

A study by Gupta et al., shows the effect of weather parameters on early blight disease in tomato plants. Using a real-time dataset, three resampling techniques, and five classifiers, 20 models were evaluated. The proposed model, KELM-KM, outperformed all others with a mean accuracy of 85.82%. This model can be used to warn farmers about fungicide spray on diseased plants in conducive environments [19].

Some Studies used HOG for feature extraction based on Streamlight application for image classification. The features are input to Classifiers such as SVM, LR, RF. The proposed aims to develop an end-to-end system for detecting TLD [20].

Over the last ten years, there has been a surge of interest in the field of DL. Artificial neural networks (ANN) have multiple layers to extract high-level features from raw data. The parallel processing capability of DL models makes them suitable for solving a wide range of problems and reducing error rates. These techniques have become popular in the realm of smart farming, as they can handle complex issues and improve farming methods. Image recognition is a key application of DL that has overcome numerous obstacles in the agriculture industry. Automated image identification and classification methods are being used in various aspects of farming such as detecting crop diseases, determining maturity, counting plants, and identifying weeds [21].

Convolution neural networks (CNNs) specifically designed to process image data. CNNs uses convolutional layers that apply filters to the input data, capturing local patterns and features. These layers extract important features, such as edges and textures. Through the process of iterative training on a substantial dataset. CNNs acquire the ability to autonomously extract hierarchical features from the input data. Every layer within the network modifies the inputs, constructing progressively more intricate and sophisticated representations. The process of hierarchical representation learning allows Convolutional Neural Networks (CNNs) to efficiently capture intricate patterns and perform exceptionally well in tasks like image recognition. Once the model has finished training, it is ready and can be used to make predictions on new data by passing it through the network and leveraging the learned weights to create accurate predictions. There is what is known as transfer learning, which is algorithms that are trained on a huge dataset of ImageNet [21].

Transfer learning is a powerful technique in the field of DL that involves fine-tuning pre-trained networks to create new models. The fundamental idea behind transfer learning is to leverage the knowledge gained from solving one problem and apply it to solve a related but different problem. By transferring learned representations from one domain to another, transfer learning can effectively address various tasks and domains with established knowledge. One of the significant advantages of transfer learning is its ability to save training time and resources while improving performance [22].

Many research papers aim to find efficient results in plant diseases identification and classification specially in TLD using CNNs. Vini and Rathika proposed TrioConvTomatoNet, which is based on deep convolutional neural network (DCNN) architecture for tomato leaf image classification. It uses a 3-series convolution layer and a stochastic gradient descent optimizer for efficient learning. The method achieves an accuracy of 99.39% in disease classification [23]. Another contribution based on CNN evaluated on PlantVillage dataset. The proposed TomConv model aims to classify between different classes of TLD. The improved CNN achieves an accuracy of 98.19% and is compared to existing models under various parameters [24].

Priyadharshini and dolly proposed work involves data collection, pre-processing, training, feature extraction, testing, and classification utilizing the Visual Geometry Group (VGG 16) to identify damaged or healthy leaves. VGG 16 is incorporated to categorize the leaves as healthy or diseased based on the data and Regression's boundary box method is adopted. Therefore, using Faster RCNN, a model is created to identify and categorize diseases from every image of a tomato leaf that is used as an input, providing a forecast with a considerably greater degree of accuracy. We obtain an accuracy of approximately 98% after fitting the collected features into the neural network over 20 iterations [25].

A Novel contribution in pests and disease detection based on lightweight network. The proposed maintain Squeeze and SE Net (SSNet), a new CNN-based on SqueezeNet and SENet. The proposed study achieves model accuracies of 98.80% and 98.39% for tomato pests and diseases, respectively, with only 0.398 M parameters [26].

A novel framework known as PCA DeepNet was created by Roy et al. that combined Principal Component Analysis (PCA) with a customized Deep Neural Network. To obtain a good mixing of datasets, the hybridized framework also includes a Generative Adversarial Network (GAN). Faster Region-Based Convolutional Neural Network (F-RCNN) is used for the detection. With an average precision of 98.55% and a classification accuracy of 99.60% overall, the work produced a promising Intersection over Union (IOU) score of 0.95 in detection [27].

Some studies use Residual Neural Network (ResNet) in TLD. Hajraoui et al. proposed DL model for TLD RGB images classification. The proposed integrated both VGG16 and ResNet152v2 models with transfer learning. The evaluation is done over 5500 images of tomato leaves in 5 different classes, 4 diseases (Tomato_Bacterial_spot, Tomato_Early_blight, Tomato_Late_blight, Tomato_Leaf_Mold) and one healthy class (Tomato_healthy). The proposed achieves 99.08% accuracy in training, 97.66% in validation, and 99.02% in testing [28].

A contribution based on Xception architecture is Proposed by Bakır by examines the use of pre-trained CNN architectures in a DL model for TLD identification. The researcher suggests using these architectures as feature extraction and tuning them alongside the classification phase. They use hyperparameters to optimize the model, and a random search algorithm is used to refine the model. The Xception-CNN model outperforms the Scratch-CNN model in all evaluation metrics, with a classification accuracy of 99.40%. The study emphasizes the importance of meticulous deep-learning model refinement and pre-trained models [29]. Patokar and Gohokar proposed DL architecture for TLD detection. The study compares between three optimizers in ResNet50 and Xception architectures Xception Architecture with Adam optimizer and learning rate of 0.0001 achieved higher accuracy, recall, precision, and F-score values of 99% compared to Nadam and RMSProp [30].

Paul et al. developed a lightweight CNN model using transfer learning models VGG-16 and VGG-19 to classify TLD. The model, with eleven classes and optimal parameters, achieved 95.00% accuracy and recall. The model was used to create an end-to-end system for tomato cultivators [31]. Another study maintains a mobile app-based system for intelligent TLD identification using CNNs. The system, fine-tuned using transfer learning, achieves over 95% accuracy, with DenseNet-121 leading the pack with a 99.85% accuracy [32]. Table 2 presents the literature review on tomato leaf disease detection using ML/DL.

Table 2. Literature review in tomato leaf disease detection using ML/DL.

Ref.	Year	ML/DL	Model	Results
[11]	2016	ML approaches	DT	97.30%
[12]	2017		Statistics based model	84.7%
[13]	2017		MFORSFS	86%
[14]	2024		Fruit fly optimization, simulated annealing, SVM	91.1%
[15]	2021		SVM KNN, Naive Bayes, DT, and LDA	-
[16]	2023		LTriTP	-
[17]	2020		SVM,LR,RF	87.60% for SVM
[18]	2020		RF and DT	94% for RF
[19]	2024		KELM-KM	85.82%
[20]	2022		SVM, LR, RF	-
[23]	2024	DL approaches	TrioConvTomatoNet	99.39%
[24]	2023		TomConv	98.19%
[25]	2023		Based on VGG 16, Faster RCNN	98%
[26]	2024		SSNet	98.80% and 98.39%
[28]	2023		Based on VGG16 and ResNet152v2	99.02%
[27]	2023		Based on PCA F-RCNN, GAN	99.60%
[29]	2023		Xception-CNN	99.40%
[30]	2023		Different optimizer under ResNet50 and Xception	Acc=99% for Xception
[31]	2023		VGG-16 and VGG-19	95%
[32]	2023		AlexNet, ResNet-50, SqueezeNet-1.1, VGG19, and DenseNet-121	99.85% for DenseNet-121

3 | Materials and Methods

3.1 | Dataset Description

This study utilizes a publicly accessible dataset called PlantVillage [17,18], obtained from several sources, primarily from plant village records. The dataset has a total of 10 distinct classifications. Among the 10 classes, one was healthy and the remaining 9 represented different diseases of tomato leaf such as (Tomato___Tomato_mosaic_virus, Tomato___Early_blight, Tomato___Septoria_leaf_spot , Tomato___Bacterial_spot, Tomato___Target_Spot, Tomato___Spider_mites , Tomato___Tomato_Yellow_Leaf_Curl_Virus, Tomato___Late_blight and Tomato___Leaf_Mold) , The Dataset distribution as shown in Table 3 where the dataset consisted of a total of 11,000 images acquired from a plant village dataset and some collected images distributed into two separate folders: training and validation sets. This study utilizes the whole validation set for testing, consisting of 1000 images divided into 100 images for each class. The training data set is divided into two parts: 70% for training and 30% for validation. The training data set consists of 7000 images. Each class is allocated a total of 700 images for training purposes, whereas the test set consists of 3000 images, leading to each class having 300 images allocated for testing. The dataset has a well-balanced distribution, making it appropriate for developing a deep learning model capable of predicting a specific disease in tomato leaves and then classifying them accordingly. Figure 1 presents the depiction of infected and healthy images in this dataset.

Table 3. Description of used tomato dataset.

Classes		Mosaic Virus	Early blight	Septoria Leaf spot	Bacterial Spot	Target Spot	Spider mites	Yellow Leaf Curl Virus	Late blight	Leaf Mold	Healthy
Training	Count	700	700	700	700	700	700	700	700	700	700
	Total	7000									
Testing	Count	300	300	300	300	300	300	300	300	300	300
	Total	3000									
Validation	Count	100	100	100	100	100	100	100	100	100	100
	Total	1000									

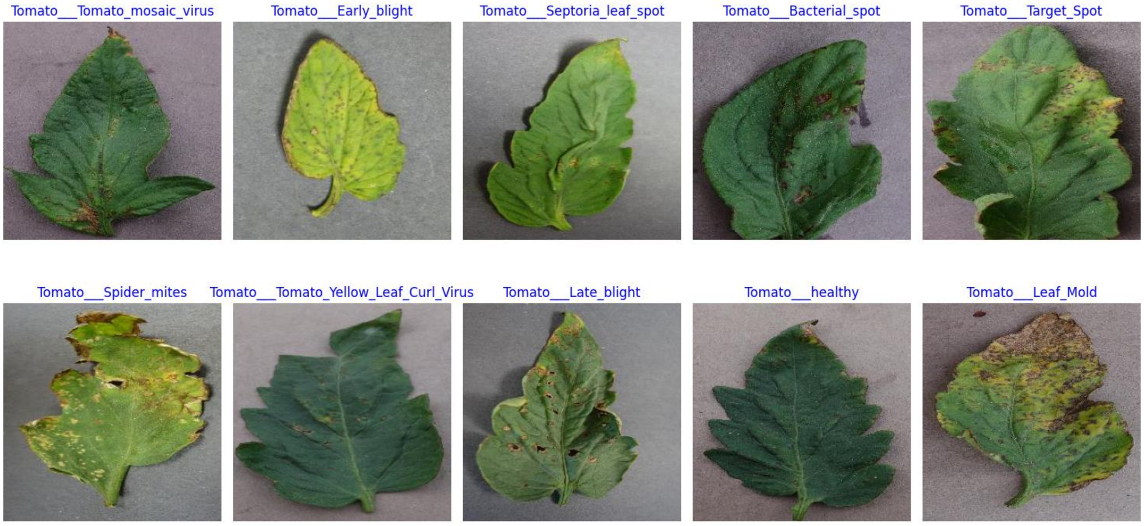


Figure 1. Depiction of infected and healthy images in this dataset.

3.2 | Dataset Preprocessing

Before building and training a DL model, the tomato disease dataset is preprocessed in order to improve the performance of the DL models. In this study, image normalization is solely relied upon to expedite the convergence speed. This is achieved by transforming the input images into a range of values between 0 and 1, as determined by the following formula:

$$image' = image/255 \tag{1}$$

Where $image'$ is a normalized image and $image$ is the input image. The input image is divided by 255 to convert the image from RGB to Gray scale so that the image becomes composed of range 0 and 1.

3.3 | Building Deep Learning Models

In this study, we depend on some of the TL Models, such as Xception, ResNet152V2, InceptionV3, VGG19, in addition to the Proposed Model.

- Xception is a DL architecture based on the Inception modules. It substitutes standard convolutional layers with depth-wise separable convolutions for more efficient learning. This architecture seeks a compromise between model complexity and efficiency, providing innovative results.
- ResNet152V2 is a form of ResNet architecture that includes 152 layers. It uses residual connections, also known as skip connections, and bottleneck blocks to avoid the vanishing gradient problem and accurately train DNNs.
- The InceptionV3 module uses parallel convolutional algorithms across various sizes. The current architecture improves feature extraction by successfully gathering both local and global information.
- VGG19 is made up of 19 layers, a mix of convolutional and fully connected layers. Where it can be acknowledged for its ease of use and efficacy in feature extraction and classification.
- Proposed Model as shown in Figure 2 the proposed model is a hybrid combination between ResNet152 V2 and Squeeze and Excitation (SE) block, which is lightweight and has the ability to classify tomato plant diseases with high accuracy and efficiency. By leveraging the derived ResNet152 V2 architecture, with its 152 layers including pooling layers, activation functions, batch normalization, convolutional layers, and residual blocks. Since skip connections are introduced to alleviate the problem of vanishing gradient, this architecture has the potential to effectively train deep neural networks. The Squeeze and Excitation (SE) block is added to ResNet152 V2 to improve its feature representation and discrimination ability. The global average pooling and the two fully connected layers form the SE cluster. First, by reducing the spatial dimensions of feature maps, global average pooling captures the global context of the input. Next, fully connected layers capture channel dependencies, enabling the network to adaptively recalibrate feature responses according to their importance.

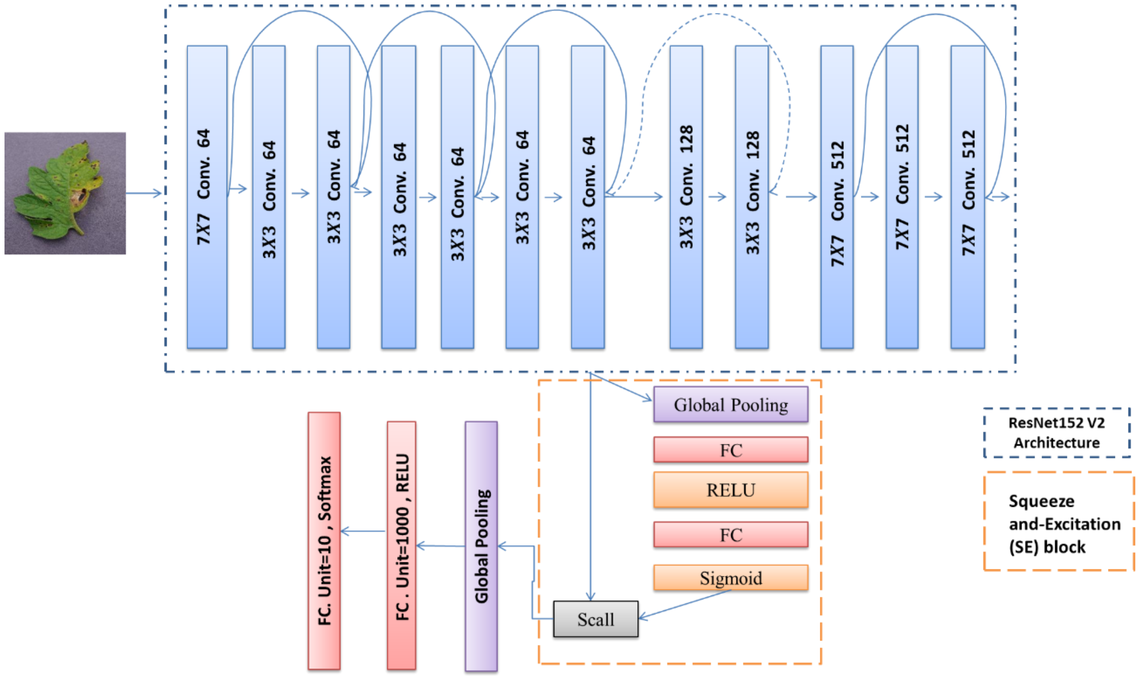


Figure 2. The proposed model.

The investigated Transfer Learning Models are built using the default hyperparameters. The all models are then compiled to determine the loss function, sgd optimizer, and metrics for evaluating performance. The Categorical cross entropy loss function is used to optimize the initial weights of certain DL models to increase classification accuracy. The loss function is mathematically defined as follows:

$$\text{Minimize: } \mathrm{loss} = -\sum_{i=1}^{M} y_i \cdot \log \breve{y}_i \tag{2}$$

Where y_i represent real values and $\breve{y}_i$ represent predicted values.

3.4 | Training Deep Learning Model

The DL models were trained with 50 epochs. In addition, the early stopping with a patience of 5 was used in our experiments and applying mini-batch gradient descent technique to decrease the error calculated from the loss function (Categorical Cross Entropy). In each epoch, the data is divided into 219 batches so that the weights in each batch are updated. This number is calculated by dividing the length of the training data, which is 7000, by the batch size, which is 32, yielding 219, which means that in every epoch, the weights change 219 times, corresponding to the number of batches. Figure 3 presents the deep learning pipeline for Tomato diseases data classification.

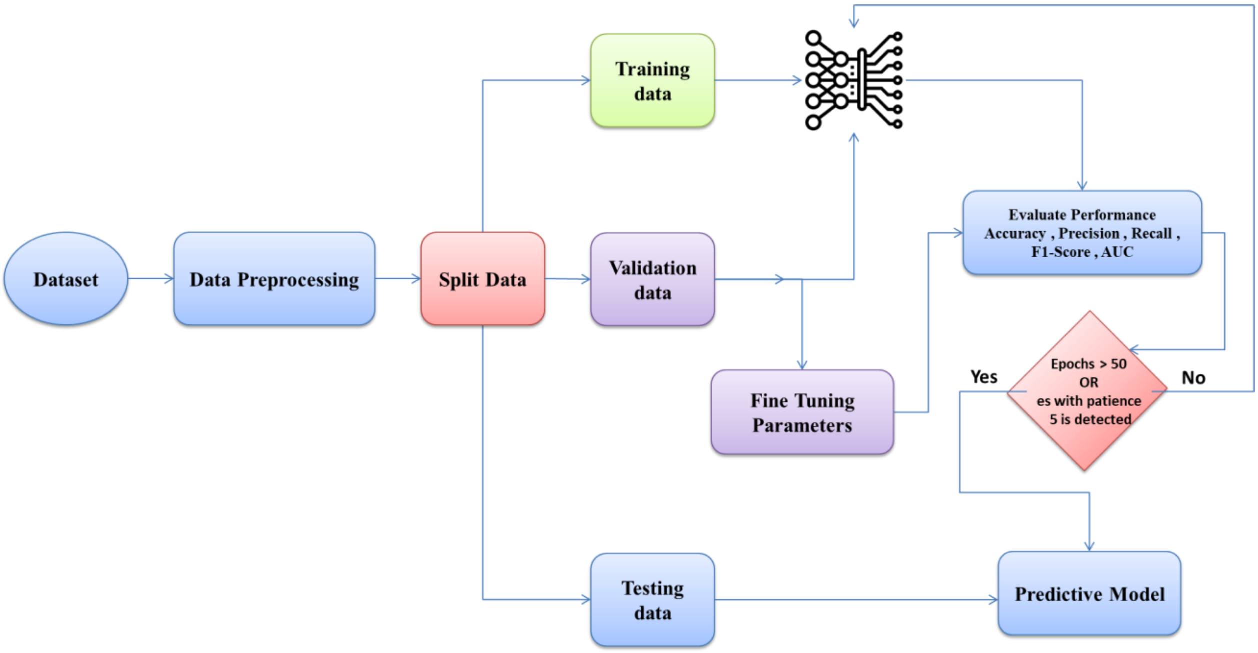


Figure 3. Deep learning pipeline for Tomato diseases data classification.

Initially, The extract important features from a preprocessed dataset of tomato diseases. Next, the dataset is partitioned into several sets for training, validation, and testing purposes. The utilization of a training dataset is employed for the purpose of training deep learning models then evaluate performance and check epochs and early stopping, if a defect occurs in any of them, the model stops because it has been finished the training process or is unable to learn, so it stops to prevent the overfitting, otherwise it completes the learning and development process. The validation dataset is utilized to evaluate the performance of the model and adjust its parameters. Lastly, the testing dataset is employed to analyze the final performance and generalization ability of the trained model on unknown data.

4 | Result and Discussion

This section investigates the performance of the proposed model using a widely used dataset, PlantVillage[33], [34]. In addition, it has been compared to several DL models, such as Xception, ResNet152V2, InceptionV3, VGG19. Those models are implemented in Python using the Kaggle platform and Keras API. The SGD optimizer was used to train the weights of those models for 50 epochs. In addition, the early stopping with a patience of 5 was used in our experiments. The performance indicators used to evaluate the performance of those models are described as follows:

- Accuracy: The definition of this metric is the proportion of correctly predicted samples to all samples in a particular dataset. To compute this metric, use the equation that follows:

  $$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FP}+\text{TN}+\text{FN}}. \tag{3}$$

  where TP, FN, TN, and FP represent true positive, false negative, true negative, and false positive, respectively.

- Precision: Precision is a metric that quantifies how accurate positive predictions produced by a certain model are. The percentage of correctly detected positive instances to all anticipated positive instances is quantified by the statistic. This metric can be computed using the following equation:

  $$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}}. \tag{4}$$

- Recall: This metric, which is also known as true positive rate or sensitivity, assesses how well the model can identify positive samples out of all the real positive samples. This metric can be computed using the following equation:

  $$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}}. \tag{5}$$

- F1-score: The F1 score offers a fair evaluation of model performance by integrating recall and precision into a single metric. This metric can be computed using the following equation:

  $$\text{F1} - \text{score} = 2 * \frac{Precision \cdot Recall}{Precision + Recal}. \tag{6}$$

- AUC: It shows how well the model can discriminate between positive and negative examples; a greater AUC denotes superior performance. This metric can be computed using the following equation:

  $$\text{AUC} = \frac{1+\frac{\text{TP}}{\text{TP}+\text{TN}}-\frac{\text{FP}}{\text{FP}+\text{TN}}}{2} \tag{7}$$

- Confusion Matrix: A confusion matrix is a visual aid that offers a brief summary of a machine learning and deep learning model's performance on a particular dataset. It is a way of displaying the number of accurate and inaccurate occurrences based on the model's predictions. It is common practice to assess the effectiveness of classification models using the previously mentioned matrices, such as F1Score, Accuracy, Permission, and Recall. When all of the true values are as enormous as they can be, the model performs at its peak.

- ROC Curve: The receiver operating characteristic (ROC) curve shows how well a model performs in classification. At various classification thresholds, it plots the specificity (1 - false positive rate) against the sensitivity (true positive rate). A greater ROC curve denotes better performance, and it is used to assess the model's ability to distinguish between positive and negative cases.

- TSNE: A dimensionality reduction method called t-SNE (t-Distributed Stochastic Neighbor Embedding) is frequently used to display high-dimensional data in a low-dimensional space. For exploratory data analysis, it is helpful. Its goal is to map data points so that related points are positioned near one another. By grouping comparable classes after the prediction process, we may determine the model's effectiveness based on the increased distance between related classes [35].

As shown by the data shown in Table 4, The proposed model demonstrates the highest accuracy among the compared deep learning models, achieving an accuracy score of 94.7% after being trained for 15 epochs. despite its substantial parameter count of 60,917,122, It is closely followed by ResNet152 V2, with an accuracy of 88.3%, displaying its strong performance. Next is Xception, achieving an accuracy of 82.5%. InceptionV3 and VGG19 show lower accuracy scores of 74.3% and 65.0%, respectively, and relatively poorer performance compared to the proposed model and ResNet152 V2. This confirms the superiority of the proposed model in terms of accuracy, followed by ResNet152 V2, among the evaluated architectures. In Table 5 illustrate Confusion Matrix which displays the number of cases in which the actual class matches the estimated class. In addition, it displays the recall ratio for each class and the precision ratio for the overall model performance. In Figure 4 Illustrate the performance evaluation of the proposed model is examined under the accuracy curve, loss curve, ROC curve and TSNE histograms.

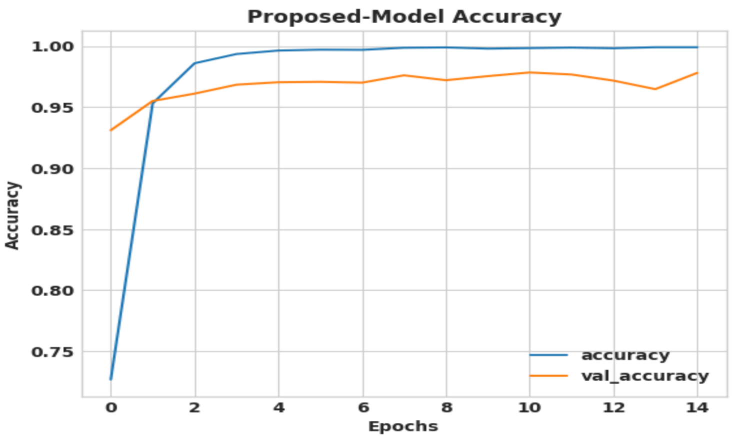
According to the accuracy curve (a), the learning process stopped after the 15th epoch, and the model continued to learn in each subsequent epoch. The stability of the learning process can be inferred. The initial accuracy starts at 0.7269%, and with each subsequent attempt the results show significant improvement until reaching the highest point of 99% training and 97% verification. According to the loss curve (b), it is an inverse process for accuracy, and our goal was to reach the smallest possible value, and this was achieved after 15 epochs, where loss: 0.0039, loss value: 0.0734 , The receiver operating characteristic (ROC) curve (c) for a 10-class classification model shows an overall mean area under the curve (AUC) of 97%, with the majority of classes having AUC values greater than 95%. However, it should be noted that Categories 1 and 6 which scored 94% and 92%. According to the TSNE plot (d), similar predicted values are grouped close to each other.

Table 4. Comparison between the proposed model and others in terms of various performance indicators.

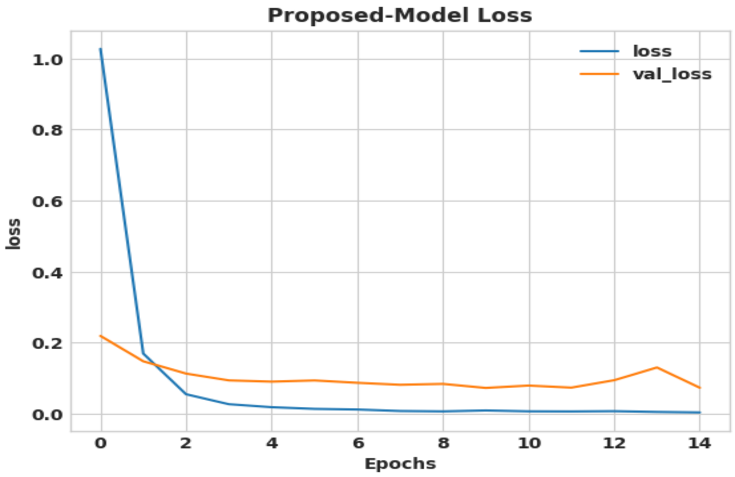
Model Name	# Epochs trained	# Parameters	Accuracy	Precision	Recall	F1-Score	AUC
Proposed Model	15	60,917,122	0.947	0.948	0.947	0.946	0.970
ResNet152V2	27	60,390,658	0.883	0.889	0.883	0.882	0.934
Xception	50	22,920,490	0.825	0.840	0.825	0.823	0.902
InceptionV3	14	23,861,794	0.743	0.794	0.743	0.740	0.857
VGG19	40	20,547,394	0.650	0.689	0.650	0.613	0.805

Table 5. Confusion matrix of the proposed model.

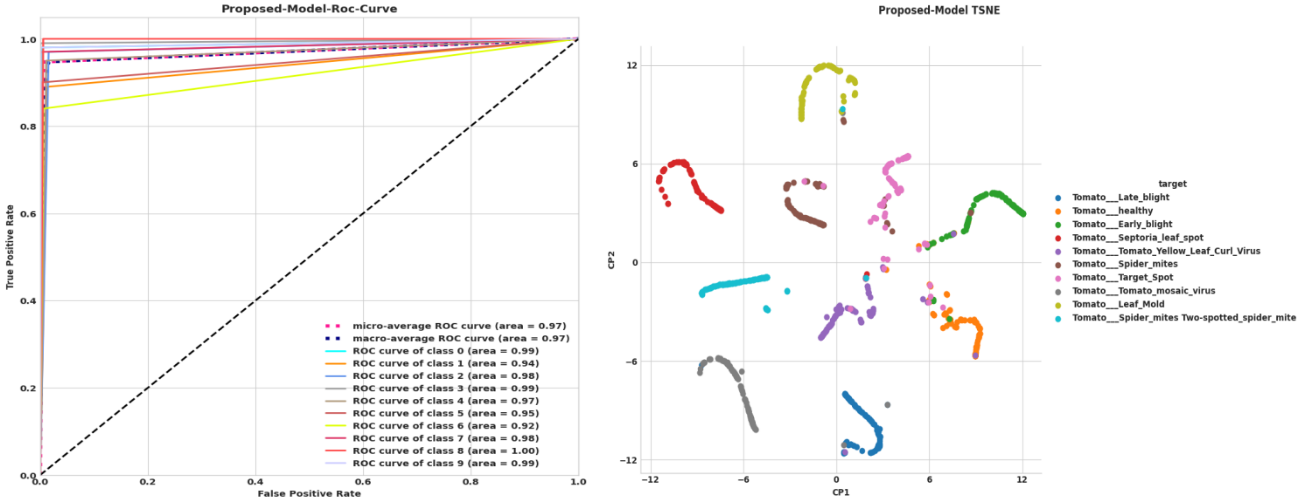
		Estimated classes										
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Recall (%)
Actual classes	C1	98	0	0	0	1	0	0	1	0	0	0.98 %
	C2	0	89	8	0	3	0	0	0	0	0	0.89 %
	C3	0	3	97	0	0	0	0	0	0	0	0.97 %
	C4	0	0	0	99	1	0	0	0	0	0	0.99 %
	C5	1	3	1	0	95	0	0	0	0	0	0.95 %
	C6	0	0	2	0	0	90	5	0	3	0	0.90 %
	C7	0	6	3	0	4	2	84	0	0	1	0.84 %
	C8	2	0	0	0	0	0	0	97	1	0	0.84 %
	C9	0	0	0	0	0	0	0	0	100	0	1.00 %
	C10	0	0	0	0	1	0	0	0	1	98	0.98 %
Precision (%)		0.97 %	0.88 %	0.87 %	1.00 %	0.90 %	0.98 %	0.94 %	0.99 %	0.95 %	0.99 %	



4-1) Accuracy curve



4-2) Loss curve.



4-3) ROC curve

4-4) TSNE

Figure 4. Performance evaluation of the proposed model under accuracy curve, loss curve, ROC curve, and TSNE events.

5 | Implication of Egyptian Vision 2030

Egypt Vision 2030 seeks to establish a contemporary, globally competitive economy. DL algorithms are for identifying tomato leaf disease since they have the potential to completely transform disease detection procedures. DL algorithms have the potential to improve farming operations by encouraging data-driven decision-making and giving farmers the ability to make well-informed choices. Implementing DL algorithms in agriculture requires specific understanding in data science, machine learning, and agricultural sciences; capacity building and skill development are therefore essential. Through the reduction of crop losses, the elimination of chemical inputs, and the facilitation of early disease identification, DL algorithms can support sustainable agriculture. Achieving these goals requires cooperation between governmental organizations, academic institutions, businesses, and foreign partners.

6 | Conclusion and Future Work

Early diagnosis of tomato plant diseases is a complex task that requires great experience from the plant treatment specialist and is crucial to increasing crop productivity and improving production quality. Due to its importance, we do not have to depend on only on traditional diagnosis where Traditional diagnosis include performing periodic visual inspections on tomato plant this approach is subjective and prone to errors due to the presence of various tomato diseases and possible human oversight. According to sustainability, this paper aims to leverage advanced artificial intelligence and deep learning algorithms to create Proposed Model hybrid DL. The Proposed Model was trained on PlantVillage Dataset. The Proposed model that accurately detects and classifies 9 different tomato plant diseases such as MosaicVirus, Earlyblight,Septoria Leaf spot , Bacterial Spot , Target Spot .Spider mites,Yellow Leaf Curl Virus , Late blight and LeafMold through leaf images. The model architecture was designed by combination between ResNet125V2 Architecture and Squeeze-and-Excitation (SE) block, by comine these two models can improve its feature representation and discrimination ability can classify tomato plant diseases with high accuracy and efficiency. The proposed Model was compared by 4 pre-trained models such as Xception, ResNet152V2, InceptionV3, VGG19. The results achieved demonstrate the efficacy of the proposed model in accurately extracting the distinct features from tomato leaf images, with scores of 0.947, 0.948, 0.947, 0.946, and 0.970 for accuracy, precision, recall, F1 score, and area under the curve, respectively.

Additionally, we outlined some of the crucial DL problems related to the identification and classification of plant diseases that could have a big influence on the model's functionality. Deep learning faces several challenges, including the need for large datasets, limitations in performing beyond the expressiveness of the dataset, time-consuming data pre-processing, and limited open datasets in computer vision and agriculture. Techniques like data augmentation can augment the dataset, but real-life problems require hundreds of images to improve classification accuracy. Additionally, developing your own datasets for applications in these domains is time-consuming and requires significant effort.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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