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Tomato plant disease prediction system with a new framework SSMAN using advanced deep learning techniques

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ABSTRACT

Agriculture plays a pivotal role in India's economy, and the timely detection of plant infections is essential to safeguard crops and prevent further spread of diseases. The conventional approach involves manual inspection of plant leaves to identify the specific type of disease, a task typically carried out by farmers or plant pathologists. In previous studies, you only look once (YOLO) and faster region-based convolutional neural network (R-CNN), machine learning algorithms were applied to datasets for detecting objects on tomato leaves which includes a total of images 2403 and got accuracies of 86 and 82 percent. In this paper, a deep convolutional neural network (DCNN) model proposed with a new framework separate, shift, and merge based AlexNet50 algorithm (SSMAN) is used to predict the disease at an earlier stage with higher accuracy. Among various pre-trained deep models, AlexNet emerges as the top performer, achieving the highest accuracy in disease classification. SSMAN can address anomalies in images by employing a class decomposition approach to scrutinize class boundaries. AlexNet exhibits a notable accuracy of 98.30% in successfully identifying tomato leaf diseases from images, with pre-trained new framework, superior to the original AlexNet architecture as well as traditional classification methods with other algorithms.

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1. INTRODUCTION

Identifying plant diseases is paramount to guarantee the cultivation of healthy agricultural production. Mitigating the detrimental effects of such diseases is essential, especially considering the wide array of food from popular plants such as tomato and onion. Farmers encounter challenges in accurately recognizing symptoms of plant diseases, particularly when dealing with subtle manifestations. Tomatoes not only fulfill daily nutritional requirements but also have a high economic value and play a significant role in many local and national economies. Deep learning has applications in various fields of artificial intelligence, particularly computer vision, where it has achieved success in plant leaves region of interest detection [1]. The deep learning models used the convolutional neural network (CNN) model to shape the data including you only look once (YOLO) and faster region-based convolutional neural network (R-CNN), for detecting tomatoes and improving detection accuracy [2]. Deep learning models in Tomato detection and compare the strengths and limitations of different architectures. However, the labor-intensive and inefficient nature of manual harvesting presents a significant challenge to the tomato farming industry [3]. The harvesting procedure is costly, raising the final cost to the consumer, and slow, delaying the product's delivery to the market and lowering its nutritional and aesthetic value. Tomatoes are now frequently cultivated in successive crops. Some important related studies indicate that tomatoes are afflicted by about 30 different types of fungal infections. In China, tomato infections have become a major problem, resulting in a 10% decrease in output. Complete crop failure has been reported in regions where these diseases have had a significant influence [4]. Due to the vague signs of tomato infections in their early stages, farmers sometimes fail to diagnose and treat these illnesses. Often, this error means that the best time to prevent and control disease is missed. The spraying of enormous amounts of fungicides proved to be ineffectual as tomato illnesses worsened. Another set of farmers finds it difficult to determine whether their tomatoes are contaminated and is unable to determine the extent of the illnesses [5]. As a result, they heavily rely on the use of fungicides to prevent and control disease. Regrettably, continued use of these methods results in an overuse of fungicides, endangering both human health and the environment [6]. There has been a rise in interest in tomato disease research in recent years due to the growing need for prompt and efficient tomato disease identification, detection, and therapy applications. Accurately differentiating the unique traits of various diseases is difficult when using existing learning models directly on tomato disease detection tasks. This restriction frequently results in a sizable number of errors or omissions.

As a result, both the academic and agricultural communities now confront similar issues in integrating with some existing learning methods with available old knowledge base and predict at early stage with higher performance like accuracy through joint "data model knowledge" approaches [7]. This research intends to combine deep learning models with disease related tomato leaves information to overcome the unbalanced distribution of disease samples and the lack of clear articulation. Taking into account the complexity of tomato disease data and making use of existing information, the study focuses on tomato diseases that arise in complex backdrops [8]. There are 504 articles in Google Scholar and 100 articles on IEEE from 2018 to 2024. The research unveils a novel deep-learning framework engineered to categorize a wide spectrum of plant diseases. Departing from conventional machine learning paradigms that mandate manual feature extraction and data feeding, the proposed model capitalizes on convolutional neural networks to significantly augment its performance. Within the domain of deep learning models, two fundamental operations are conducted. Initially, an artificial neural network is deployed to identify patterns within an input image. Subsequently, the model autonomously renders decisions. As a result, deep learning models demonstrate enhanced efficacy in image classification tasks compared to traditional learning algorithms. Utilizing a deep-learning neural network for image classification yields notable effectiveness. This innovative approach outperforms traditional methods, such as manual inspection of individual plant leaves, by delivering faster and more accurate results.

Farmers have the opportunity to utilizing the smartphone cameras to detect different plant diseases and take proactive measures to curb their spread by integrating with other interface applications. Many experts strive to bolster tomato leaves, by unique feature selection of plant diseases through the combined use of conventional methods and neural network-based techniques. Figure 1 shows the process of deep learning models for image classification. This framework serves as the foundation for the proposed model, which leverages the separate, shift, and merge pre-trained learning model.

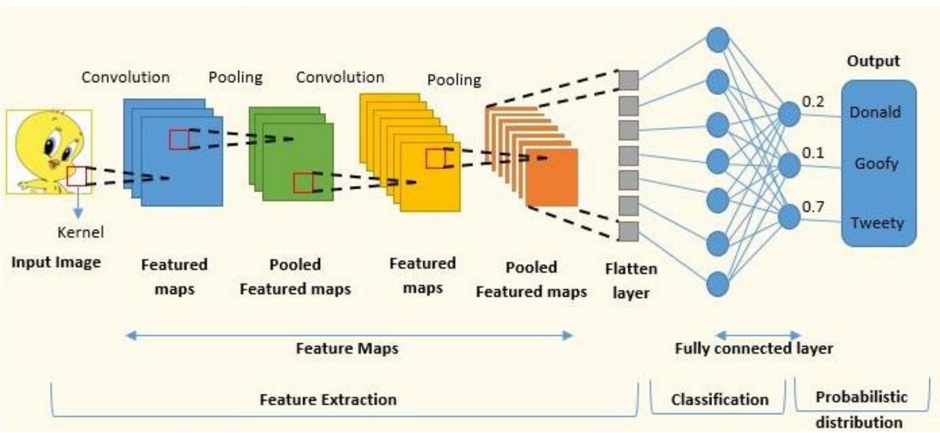


Figure 1. General process of "deep learning model for image classification"

Figure 1 taken as base for proposed framework separate, shift, and merge based AlexNet50 (SSMAN) to combine with AlexNet50, a deep learning model or algorithm. Section 2 delineates the methodology of the tomato dataset, offering insights into its structure and acquisition. In section 3, the proposed algorithm is expounded upon, providing a detailed account of its implementation, the intricacies of the SSM model, and an exhaustive analysis of the dataset. Moving to section 4, a thorough examination of the results with performance parameters were discussed for plant disease detections are presented. Concluding the study, section 5 encapsulates our findings and offers conclusive remarks.

2. RESEARCH METHOD

In the existing system, manual inspection methods and a few classification methods investigating individual plant leaves or clusters, not delivering faster and more accurate results. Therefore, this paper follows the deep learning technique as a base to solve the early prediction of tomato plant disease. For this CNN model used. In Figure 1 it shows the basic structure of CNN model. In this CNNs start with convolutional layers that apply filters or kernels to the input image. Filters traverse the input, either by sliding or convolving, to identify features like edges, textures, or patterns. Each convolution process produces a feature map that accentuates specific details of the input. Pooling layers follow "convolutional layers" for dimensionality reduction of the input. The traditional methods used for CNN include max pooling, which selects the highest value in a specified region, and average pooling calculates the average value in that region. Pooling decreases computational load and enhances the network's ability to handle input variations. The outputs from the convolutional and pooling layers are flattened into a one-dimensional vector, which is then input into the fully connected layers. In fully connected layers, each neuron is linked to every neuron in the next layer. These layers learn high-level features and generate predictions by combining these features. CNNs undergo training using labeled datasets. Throughout this process, the network iteratively adjusts its internal parameters, which include weights and biases, to minimize the discrepancy between predicted outputs and the provided labels.

During training, a loss function is applied to measure the disparity between predicted outputs and true labels, and an optimization algorithm, such as stochastic gradient descent, is employed to iteratively update the network's parameters. This iterative adjustment of parameters enables CNNs to autonomously extract hierarchical features from input images. This inherent capability positions them as powerful tools for various image-related tasks, including object detection, image classification, and segmentation. Simultaneously, a CNN model was trained for a tomato plant images dataset collected from the Andhra Pradesh region, totaling 2,403 images, in this 80% were allocated for training data, while the remaining 20% were selected for testing data. This experimental configuration was implemented at the Machine Learning Laboratory within the Artificial Intelligence Department at Saveetha School of Engineering, part of Saveetha Institute of Medical and Technical Sciences, located in Chennai, Tamil Nadu. The subsequent section outlines the proposed SSM model.

3. PROPOSED SSMAN MODEL WITH DEEP LEARNING

The proposed methodology employs the separate, SSMAN model of deep CNN for classifying plant diseases with higher accuracy. Figure 2 presents a detailed depiction of the AlexNet deep learning model, showing how the various layers are integrated before and after the knowledge transformation process. This figure highlights the strategic placement and utilization of these components to increase the order of performance in overall efficiency and functionality of the model. In this model, we utilized an AlexNet model pre-trained on ImageNet dataset. The class decomposition layer divides a set of images in different n subclasses, with each subclass being processed independently. The class composition component subsequently recombines these subclasses to form the final set of results with classified system for original image dataset [8]–[10].

In the AlexNet architecture, it is noted that eight layers contain trainable parameters. It is observed that among these layers, five utilize a combination of convolutional operations and max pooling, while the remaining three consist of fully connected layers. It is also mentioned that rectified linear unit (ReLU) activation is applied to all layers except the output layer. Notably, due to the depth of the AlexNet50 architecture, the authors introduced padding to mitigate the significant reduction in the size of the feature maps. It Is stated that the input to this model comprises images sized at 227×227×3. The architecture of AlexNet50 reportedly includes convolutional layers along with max-pooling layers. If you are unfamiliar with calculating the output size of a convolutional layer of the AlexNet50 architecture, the first convolutional layer applies 96 filters sized at 11×11 with a stride of 4. The activation function employed in this layer is ReLU. Subsequently, the resulting feature map is sized at 55×55×96.

$$Output = ((Input - filter\ size)/\ stride) + 1 \tag{1}$$

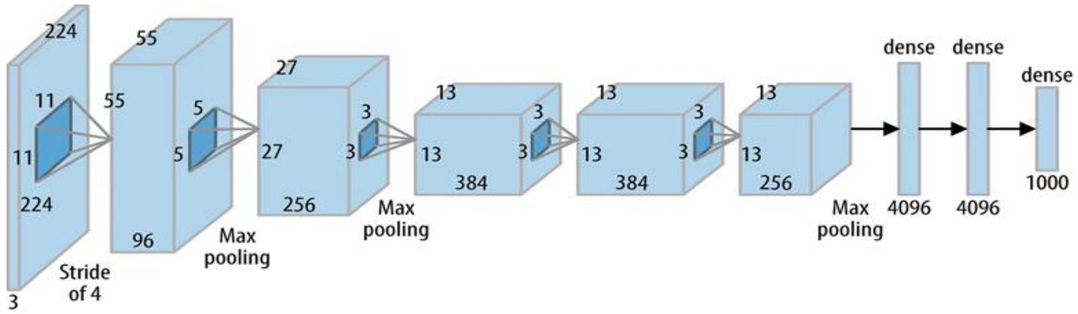


Figure 2. AlexNet, deep learning process model

It is mentioned that in the subsequent step, the number of filters determines the channels in the output feature map. Following this, the first maxpooling layer is introduced, sized at 3×3 size of 2. Consequently, the resulting feature map is obtained with dimensions of 27×27×96. Following that, the second convolution operation is applied, with a reduction in filter size to 5×5, consisting of 256 filters. The stride is set to 1, with a padding of 2. Following the application of the second convolution operation, ReLU activation function is once again utilized. Consequently, the output size obtained is 27×27×256. Subsequently, a max-pooling layer of size 3×3 with a stride of 2 is applied, resulting in a feature map with dimensions of 13×13×256. Next, the third convolution operation is conducted, employing 384 filters sized at 3×3 with a stride of 1 and padding of 1. The ReLU activation function is applied once more, yielding an output feature map with dimensions of 13×13×384. Following the third convolution operation, the fourth convolution operation is executed, utilizing 384 filters sized at 3×3, with a stride of 1 and padding also set to 1. Additionally, the activation function is applied such as ReLU, is applied. Subsequently, the output size remains unaltered at 13×13×384. Following this, the final convolution layer, comprising 256 filters sized at 3×3, is introduced. Both the stride and padding are set to one, and the ReLU activation function is applied. Consequently, the resulting feature map maintains a shape of 13×13×256. Observing the architecture thus far, it is evident that the number of filters increases as we delve deeper. This progressive increase facilitates the extraction of more intricate features as we advance through architecture.

Furthermore, it is worth noting that the filter size is decreasing progressively. This implies that the initial filters were larger, and as we progress, the filter size reduces, consequently leading to a reduction in the shape of the feature maps. Following this observation, the third max-pooling layer, sized at 3×3 with a stride of 2, is applied. This operation yields a feature map with dimensions of 6×6×256. Subsequently, the first dropout layer is introduced with a rate of 0.5, continuation of this fully connected layer is implemented, utilizing the ReLU activation function. The output size is set at 4096 images. Subsequently, another dropout layer is applied with a rate of 0.5. This is succeeded by a second fully "connected layer" comprising 4,096 neurons, with ReLU activation fucntion. Concluding the architecture, the final layer consists of 1,000 neurons, corresponding to the 1,000 classes in the dataset. This last fully connected layer utilizes the SoftMax activation function. The architecture of the AlexNet model comprises a total of 62.3 million learnable parameters distributed across 8 layers. The input to the model consists of RGB images. It features 5 convolution layers accompanied by a combination of max-pooling layers. This architecture comprises "3-fully connected layers", each utilizing the ReLU activation function. Additionally, it integrates two Dropout layers. The output layer utilizes the SoftMax activation function. The total parameter counts for this configuration amounts to 62.3 million.

AlexNet stands as a groundbreaking CNN renowned for its prowess in image recognition and classification. Its triumph in the 2012 ImageNet large scale visual recognition challenge marked a pivotal moment in the advancement of deep learning [11]. The architecture of AlexNet, characterized by its pioneering implementation of convolutional layers and ReLU, established a cornerstone for contemporary deep learning models. Its impact has been instrumental in propelling advancements in computer vision and pattern recognition applications. The adoption of ReLU as an activation function notably expedited the training process, enhancing its speed by nearly sixfold [12]. Additionally, integration of dropout layers effectively mitigated overfitting concerns, bolstering the model's generalization capabilities. Moreover, the model undergoes training using the ImageNet dataset, which comprises nearly 14 million images distributed across one thousand classes. The leaf image dataset was utilized to fine-tune a pre-trained CNN model originally trained on ImageNet, employing shallow tuning [13]. Additionally, we can denote the class category L as a vector of length n, where each element corresponds to the class label of the respective image. Here, k represents the number of classes [14].

To break down the dataset, this study employed k-means clustering. Each pattern within the new class category L received a class label based on the nearest centroid, determined by the squared Euclidean distance (SED) [15]. Centroids are labeled as cj. Because of the restricted availability of training datasets, the stochastic gradient descent (SGD) method may display substantial fluctuations in the learning function. Convolutional neural networks are employed in this study for the categorization of different plant diseases [16]. At the onset, the convolutional layer of the model extracts information from the input images. The convolution layer applies multiple filters to an image, generating a feature map to extract unique features. After the convolution layers, pooling layers are used. These layers reduce the number of parameters and downscale the image. Commonly used pooling techniques include max pooling, average pooling, and sum pooling [17]–[19].

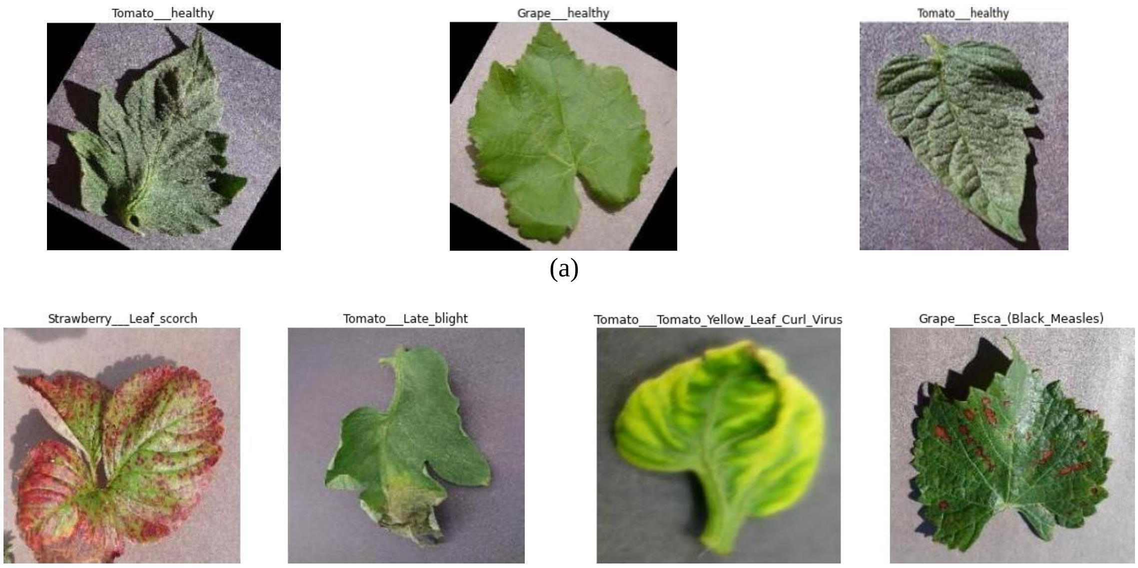
$$m(x) = maximum[0, x] \tag{2}$$

These models exhibit high predictive performance due to their extensive training on visual data. In this study, the YOLO and R-CNN models adapted with “transfer learning” training technique [20].

2.1. About dataset

This research study used 2,403 tomato plant photos and these images were classified into four categories: ‘leaf blight’, ‘black rot’, ‘esca (black measles)’, and ‘healthy (isariopsis leaf spot)’. The dataset consists of 423 images showing healthy leaves, 1,180 images of leaves infected with black rot, 1,383 images of leaves affected by esca, and 1,076 images of leaves affected by leaf blight [21]–[23]. The data employed in this study is sourced from rural farm fields and is accessible at “https://www.kaggle.com/datasets/emmarex/plantdisease”, known as the Plant Village collection, this dataset comprises over 55,000 images categorized into 38 classes, covering 14 distinct plant species.

Figures 3(a) and 3(b) illustrates sample data from various classes [24], in this Figure 3(a) has “Sample images of healthy tomato”, “grape”, and “strawberry leaves” and Figure 3(b) has sample images of diseased leaves. Deep learning models require extensive datasets to function effectively. Before implementing enhancements like rotation, zooming, and shifting, the images are resized to 224×224 pixels using Keras' Image data generator [25]. The augmentation technique serves two primary purposes: expanding the dataset and addressing overfitting during training. The dataset is divided into training and validation sets in an 80:20 ratio for experimentation. Specifically, the validation set contains 481 images, while the training set comprises 1,922 images.



(a)

(b)

Figure 3. Sample data from various classes (a) “sample images of healthy tomato”, “grape”, and “strawberry leaves” and (b) sample images of diseased leaves

Table 1. Tomato plant disease dataset summery

Category	Class	Training samples	Testing samples
Tomato (Healthy)	1	646	162
Tomato (Late Blight)	2	631	158
Tomato (Yellow_Leaf_Curl_Virus)	3	645	161

2.2. Proposed pre-trained SSMAN framework for leaf disease classification

The AlexNet architecture, despite being a straightforward and efficient model for scene classification, has limitations. It struggles with the "non-transparency of intermediate layers" and faces challenges in handling multi-scale thematic scenes in classification tasks [26]. This process entails employing the pre-trained AlexNet architecture, which originates from training AlexNet on extensive natural image datasets [27]. Benefiting from analogous semantic scene information, the uses AlexNet architecture achieves swift and satisfactory results for scene images [28]. To accommodate the multi-scale complexity of particular semantic scenes, the AlexNet architecture incorporates the semantic scene module (SSM), a potent multi-scale pooling operation. Improving the representation of intermediate layer information within the pre-trained AlexNet architecture not only boosts classification performance by strengthening the robustness of network weights but also enhances transparency throughout intermediate layers. Utilizing the benefits of the SSM strategy and with the objective of enhancing region of interest classification performance through the AlexNet architecture, the following framework SSMAN model proposed and presented in Figure 4.

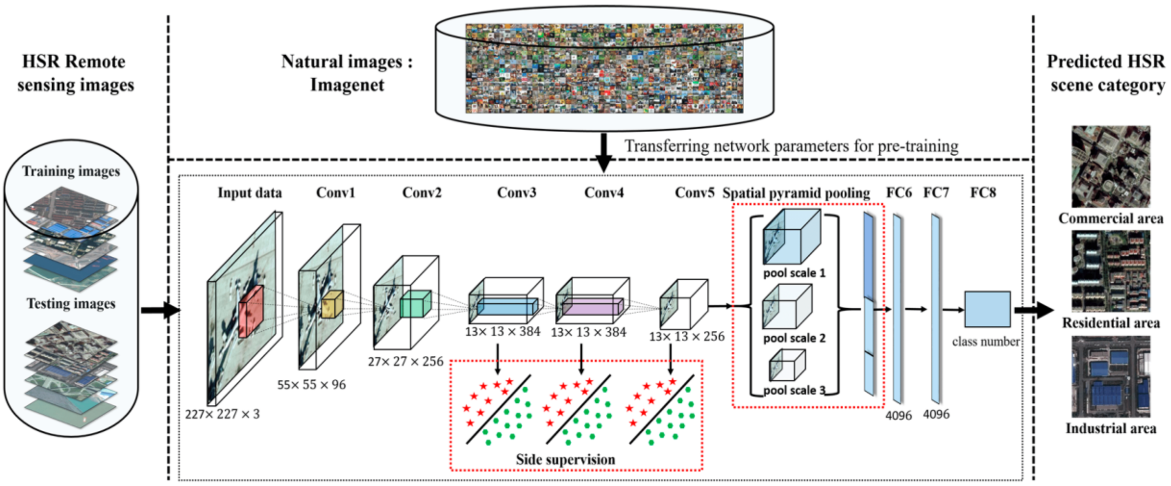


Figure 4. Proposed SSMAN model architecture

This model integrates the SSM strategy into the deep learning AlexNet architecture as a means to achieve improved performance. It is explained that the supervision layers are integrated as intermediate layers within deep learning AlexNet architecture [29]. Furthermore, they stated that the SSM model is combined with the AlexNet architecture, granting the pre-trained AlexNet architecture the ability to handle multi-scale information effectively. In a comprehensive assessment, it was noted that the SSMAN model, depicted in Figure 4, enables improved scene classification performance even with limited sample imagery.

4. RESULTS AND DISCUSSION

Tomato plant leaves dataset is utilized to train the proposed SSMAN framework, and its results are contrasted with those of prominent pre-trained models like YOLO and R-CNN [30]. The employed AlexNet model consists of pairs of convolution and pooling layers. Convolution layers are responsible for filtering and extracting features from the input image, while pooling layers reduce the network's computation and decrease the input image size. The AlexNet model is trained over 10 epochs, utilizing the Adam optimizer and categorical cross-entropy as the chosen loss function. Sensitivity indicates the accuracy with which the model identifies plants with a disease, while specificity reflects its ability to predict plants without the disease accurately. These results show that a multi-classification occurs while using tomato leave dataset. To evaluate their model, they utilized a multi-class confusion matrix. Before error correction, each input image could be classified into one of the ‘non-overlapping classes’. Therefore, the ‘confusion matrix’ for a specific class i is as shown in Table 2. The performance parameters for multiclass classification are given in Table 3.

Table 2. Tomato plant disease classification and related confusion matrix results

S.No.	Performance metrics	Formula
1	Accuracy	(True Positive+True Negative) / (True Positive+True Negative+False Positive+False Negative)
2	Sensitivity	(True Positive) / (True Positive+False Negative)
3	Specificity	(True Negative) / (True Negative+False Positive)
4	F1 score	2 * [(Sensitivity * Specificity) / (Sensitivity+Specificity)]

True Positive (TP): Correctly classifying a plant as diseased when it actually has a disease.
True Negative (TN): Correctly classifying a plant as healthy when it is indeed healthy.
False Positive (FP): Incorrectly classifying a healthy plant as diseased.
False Negative (FN): Incorrectly classifying a diseased plant as healthy.

Table 3. Plant disease classification performance parameters for multiclass classification

Sl. No	Performance metrics
1.	$TP_i=\sum_{i=1}^{n} Xii$
2.	$TN_i=\sum_{i=1}^{n}\sum_{i=1}^{n} xjk, j=i$
3.	$TP_i=\sum_{i=j}^{n} Xji;\ \ j \neq 1$
4.	$TN_i=\sum_{j=1}^{c} Xij,\ j \neq 1$

Furthermore, Figure 4 provides detailed information on the training and testing accuracy, as well as the loss obtained by the AlexNet algorithm. To illustrate the robustness of SSMAN, the researchers utilized a variety of ImageNet with machine learning based CNN models, such as YOLO and R-CNN, during the transfer learning phase in AlexNet. The outcomes are presented in Table 4. Figure 5 has the graphical representation for performance comparative study between proposed SSMAN and existing machine learning algorithms. In this we can see that SSMAN performs better in accuracy, sensitivity, specificity and F1-score parameters than other machine learning algorithms. According to Figure 6, the SSMAN framework, which incorporates the AlexNet algorithm, achieved the high accuracy of 98.30%, with a sensitivity of 97.56% and a specificity of 96.71%.

Table 4. Comparison between proposed SSMAN and existing YOLO and R-CNN models and related results

Deep learning model	Learning accuracy	Learning sensitivity	Learning specificity	Learning F1-score
YOLO	97.33	96.33	95.33	96.07
R-CNN	96.22	96.11	95.01	95.55
SSMAN	98.30	97.56	96.71	97.13

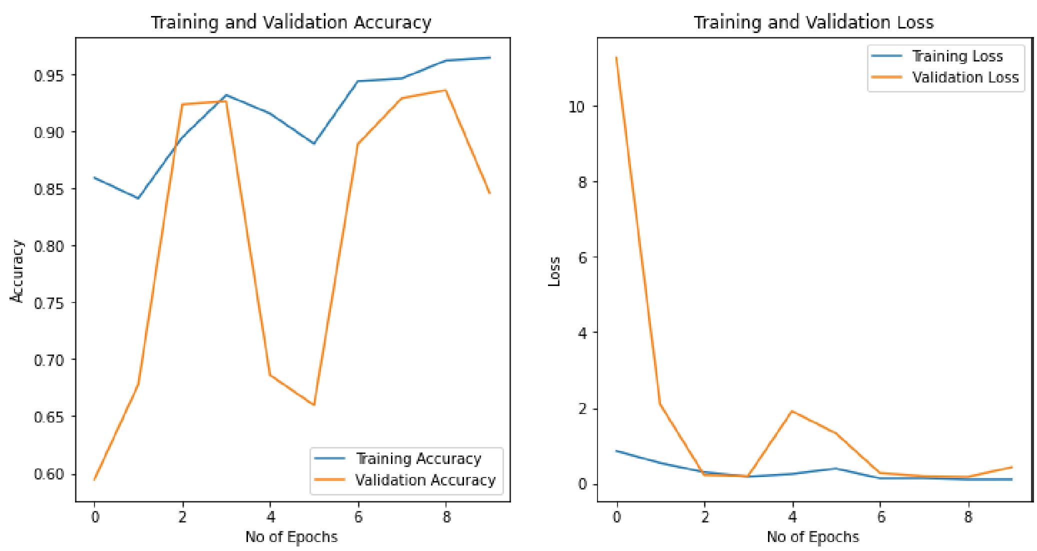


Figure 5. Results of accuracy and loss for training and testing data

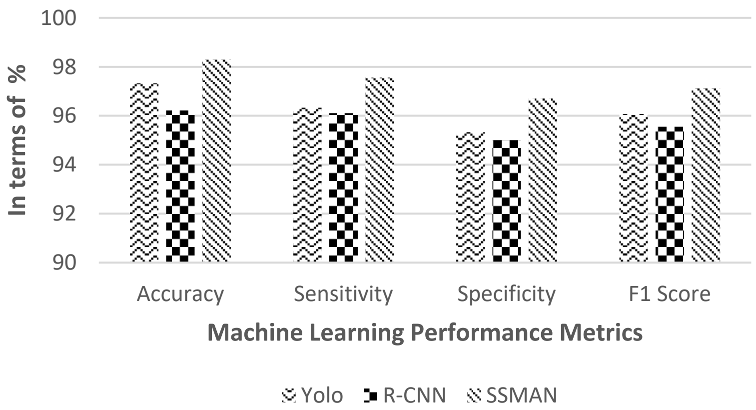


Figure 6. Comparison of performance of "proposed SSMAN Model" with existing (YOLO and R-CNN model)

5. CONCLUSION

The study introduces SSMAN, a deep learning architecture that utilizes a layer-based class decomposition technique to classify the for tomato leave dataset. To validate the SSMAN model, we employed various pre-trained CNN models such as YOLO and R-CNN. SSMAN utilizing AlexNet attained the highest accuracy of 98.30%. During testing, performance estimation metrics including "accuracy", "precision", "recall", and "F1-score" were employed for the model evaluation. This discovery facilitates early detection of plant diseases, thereby reducing crop loss and the spread of diseases. Ultimately, the model's deployment on portable devices aims to enhance efficiency further.

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