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Deep Learning based Robust Tomato Plant Leaf Disease Detection and Classification Model on Agricultural Sector

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Abstract: Tomato is an indispensable and edible crop across the globe. Tomatoes can be varied in quantity based on how it is fertilized. The main element affecting the quality and quantity of crop yield is Leaf disease. Initial detection of diseases would minimize the disease’s effect on tomato plants and have good crop yield. Various new methods of classifying and identifying some diseases were leveraged broadly. In recent times, many authors (universities, institutes, and labs) have examined and formulated several conventional deep learning (DL) and machine learning (ML) techniques for classification of plant diseases. Therefore, this article introduces a Deep Learning related Robust Tomato Plant Leaf Disease Detection and Classification (DL-TPLFDC) model. To detect tomato plant leaf diseases, the DL-TPLFDC technique initially executes U-Net segmentation technique to identify the leaf portions in the input image. Next, the fuzzy c-means (FCM) clustering with customized binary thresholding process takes place to detect the diseased leaf portions in the preprocessed image. Moreover, the DenseNet-169 model was employed to generate feature vectors from the segmented image. Furthermore, deep variational autoencoder (DVAE) model is applied to eliminate the noisy features exist from the DenseNet-169 model, and the resultant features are fed into the random forest (RF) model for classification process. The design of customized FCM with DVAE based noisy feature removal process demonstrates the novelty of the work. The performance analysis of the DL-TPLFDC technique can be performed on benchmark datasets and the outcomes were examined in various measures. The experimental values portrayed the improved outcomes of the DL-TPLFDC technique over other models.
Keywords: Tomato plant; Leaf disease; Computer vision; Image segmentation; Deep learning; Agriculture

1. Introduction

Plants are considered to be essential components of everyone’s life as they produce food and protect us from harmful radiation [1]. One cannot imagine life without plants; they support all terrestrial organisms and protect ozone layer that would filter ultraviolet radiation. Tomato was a food plant, an edible vegetable broadly cultivated. The annual consumption rate of tomatoes was 160 million tons (approx.) across the world. It is an important contributor to minimizing poverty and becomes a source of income for agricultural families [2]. It is one of the high nutritious crops on the earth, and their production and cultivation have an important effect on the rural economy. It is not just a nutritious crop and even has pharmacologic elements that protect from diseases like gingival bleeding, hypertension, and hepatitis [3]. The demand for tomatoes seems to be raising because of its widespread usage. The parasitic insects and diseases were the main elements which affect growth of tomatoes, thereby induces to make research on field crop disease identification.

The manual detection of pathogens and pests was expensive and inefficient [4]. Hence, it becomes essential to render automated AI image-related solutions to agriculturalists. Images were accepted and leveraged as a reliable way of finding disease in image-related computer vision (CV) applications because of the obtain ability of suitable software or tools [5]. Utilizing image processing, they process images, an intellectual image detection technology which improves recognition accuracy, rises image recognition reduces costs, and increases efficacy. Computer vision (CV) technology can be another type of potential non-destructive approach for plant identification, which includes merits of having a trivial effect on atmosphere and an affordable rate [6].

Furthermore, one most obvious indications of plant disease can be scars on leaves. The diseased ones can be easily identified by the spot with irregular texture or uneven leaf color. Also, the spot shape of diseased leaves will be diverse. Several imaging techniques and illumination atmosphere stability were learned in the lab [7].

Numerous authors have examined the numerous imaging approaches and disease feature extraction methods. They have utilized scientific approaches for capturing leaf images and accomplished classifier methods [8]. Today, deep learning (DL) approaches, particularly methods related to convolutional neural networks (CNNs), can be a subgroup of DL, and were broadly leveraged in plant disease classifier tasks. In previous research, spectral and image data reduction techniques are studied for multi-diseased leaves having same indications irrespective of the plant variety [9]. In this work, we pointed to do in-depth research on classifying unhealthy crop leaves. As the efficiency of ML methods changes with data and the issue to be solved, the purpose of this work was to identify the conventional DL or ML approaches with the highest classification precisions dependent upon the tomato disease classification problem and Plant Village data [10].

This article introduces a Deep Learning based Robust Tomato Plant Leaf Disease Detection and Classification (DL-TPLFDC) model. To detect tomato plant leaf diseases, the DL-TPLFDC technique initially executes U-Net segmentation technique to identify the leaf portions in the input image. Next, the fuzzy c-means cluttering with customized binary thresholding process take place to detect the diseased leaf portions in the preprocessed image. Moreover, DenseNet-169 model was leveraged to generate feature vectors from the segmented image. Furthermore, deep variational autoencoder (DVAE) model is applied to eliminate the noisy features exist from the DenseNet-169 model, and the resultant features are fed into the random forest (RF) model for classification process. The performance analysis of the DL-TPLFDC approach can be executed on benchmark database and the outcomes will be inspected under various measures.

2. Related Works

Gadekallu et al. [11] concentrate on enforcing ML method to classify tomato disease image data to proactively commence essential ways for combating agricultural crisis. This study collects the dataset from publicly accessible plant–village dataset. Utilizing the hybrid PCA–WOA, the extraction of features from the dataset can be made. Also, the data that is derived was given a DNN for classifying tomato diseases. In [12], devised the TL-related deep CNN approach for finding tomato leaf disease. Utilizing real-time images and stored tomato plant images, the method executes disease detection. Additionally, utilizing RMSprop optimizers, Adam, and SGD, the efficiency of the devised method can be assessed. Zhao et al. [13] modeled a deep CNN that compiles an attention system, which is better adapted to the analysis of various tomato leaf diseases. Attention extraction modules and residual blocks are the main network structure. The method can precisely derive complicated features of many diseases.

A potential DL modified Mask Region CNN (Mask R-CNN) was modeled for autonomous detection and segmentation of tomato leaf disease in [14]. Aiming to preserve computational expense and memory space, the recommended method includes a light head “Region CNN (R-CNN)”. The detection accuracy and calculating metric performance can be enhanced by changing anchor proportions in RPN network along with varying the feature extraction topologies. In [15], the authors using the Conditional GAN (C-GAN), devised a DL-related technique for tomato disease detection to make synthetic images of tomato leaves. Then, a DenseNet121 method can be on real and synthetic images using TL for categorizing the tomato leaves images into 10 categories of diseases.

In [16], the authors based on the detection accuracy of plant diseases detection evaluated the impact of dissimilar depth of CNNs. Numerous CNN architectures having distinct depths were examined. They are VGGNet (with 13 convolution layers), simple CNN baseline (with 2 convolution layers), and AlexNet (with 5 convolution layers). The authors even assessed GoogleNet architectures. Dissimilar to formerly mentioned architectures, GoogleNet will leverage convolution layers with different resolutions that have to be concatenated with one another, highlighting the effect on not merely deep architecture but also wide one. Altalak e al. [17] modelled a hybrid DL method to classify and detect tomato leaf diseases at the earlier stage. This hybrid mechanism was an amalgamation of a CNN, SVM, and convolutional attention module (CBAM). Firstly, projected method can identify 9 distinct tomato diseases but was not limited to this. Utilizing database comprising images of tomato leaves, the modeled method was tested.

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3. The Proposed Model

In this article, we have developed a new DL-TPLFDC method for the identification and classification of tomato plant leaf diseases. In the presented DL-TPLFDC technique, a series of processes were involved namely U-Net preprocessing, customized FCM segmentation, DenseNet169 feature extraction, DVAE based noisy feature removal, and RF classification. Fig. 1 represents the work flow of DL-TPLFDC approach.

3.1. Image Preprocessing

Firstly, the DL-TPLFDC model executes the U-Net model to identify the leaf areas from the input image. U-Net comprises Up Sampling, Convolutional Operation, Max Pooling, ReLU Activation, and Concatenation Layers and three sections: expansion, contraction, and bottleneck section [18]. The expansion section comprises many expansion blocks with every block passing input to a 2X2 upsampling layer and two 3X3 Conv layers that splits the number of feature channels. The contraction section has four contraction blocks. All the contraction blocks get an input, using a 2X2 max pooling and two 3X3 convolutional ReLu layers. The count of feature maps gets double at every pooling layer. The bottleneck layer employed 2X2 up convolution layer and 2 3X3 Conv layers. Also, it involves a concatenation with correspondingly cropped feature maps from contracting path. Eventually, 1X1 Conv layer was utilized for making feature maps similar to the number of segments that are desirable in the output. U-net exploits a loss function for all the pixels of an image. This assists in easier detection of individual cells within segmentation maps. Softmax was employed for every pixel ensued by a loss function. This transforms the segmentation problems into classification problems where we should categorize all the pixels to one of the classes.

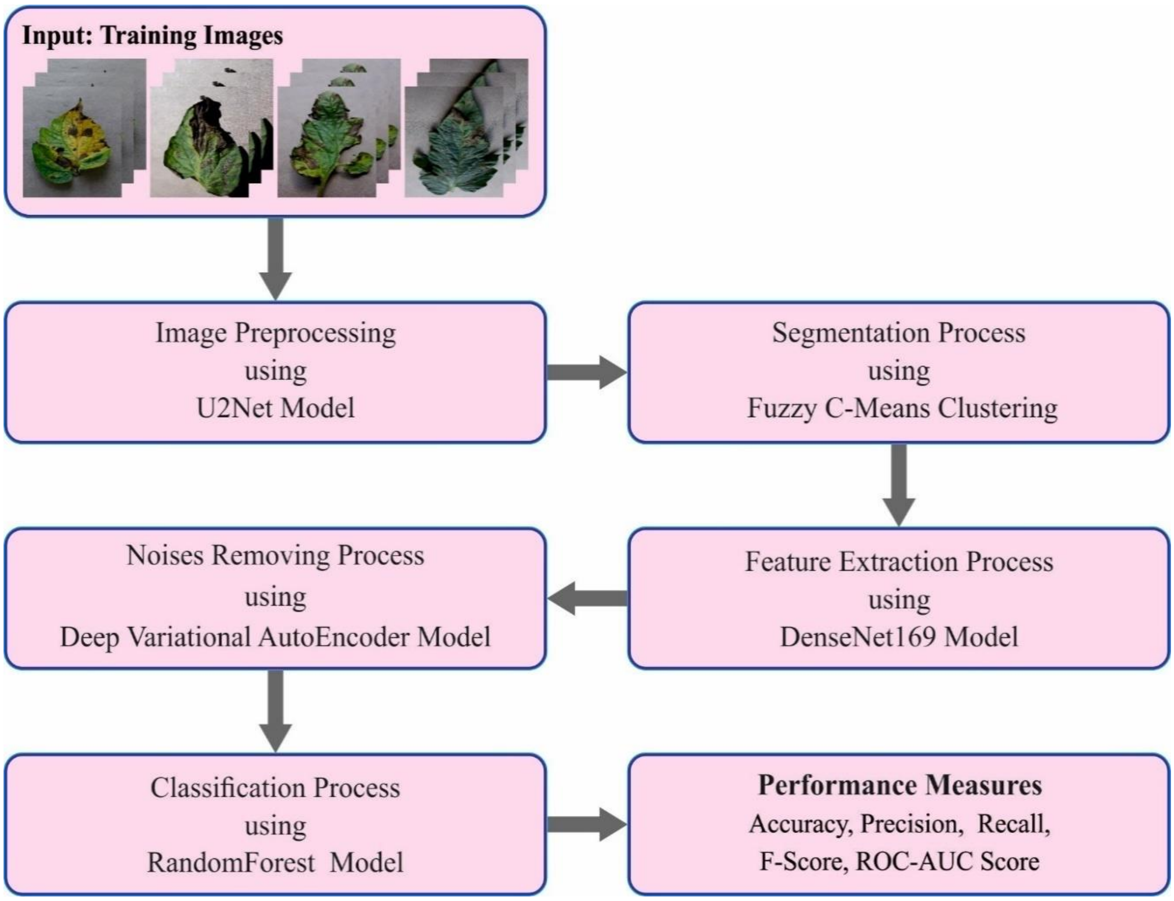


Fig. 1. Workflow of DL-TPLFDC system

3.2. Image Segmentation

For identifying the diseased portions from the leaf image, the customized FCM method was used. The localize leaf parts were cropped by means of the computed(x, y, w, h) coordinates, to define the precise boundary of diseased area [19]. To evaluate the boundary of diseased regions from healthy skin is determined FCM clustering for grouping pixels into diseased and healthy areas.

FCM clustering is dependent upon optimized of main function J_d, for refining the segmentation of cluster $c_a \epsilon (1,2)$, under primary conditions. Where d represents the overall amount of pixels of $R(x, y, w, h)$ in RGB color space, S_{sa} represent degree of pixel membership in the cluster a, and c_a indicates center of cluster. The fuzzy clustering partition $R(x, y, w, h)$ in optimized iteration manner, for reducing the distance by upgrading the membership S_{sa} of $R(x, y, w, h)$ with related clusters c_a.

$$S_{sa} = \frac{1}{\sum_{k=1}^{24} \frac{\|R-c_a\|^{\frac{2}{d-1}}}{\|R-c_k\|}} \tag{1}$$

$$c_a = \frac{\sum_{s=1}^{N} S_{sa} R}{\sum_{s=1}^{N} S_{sa}^{d}} \tag{2}$$

$$J_d = \sum_{s=1}^{d} \sum_{a=1}^{2} S_{sa}^{d} |R - c_a|^2 \tag{3}$$

Initial termination condition y was determined amongst 0 and 1. For terminating the iteration y a threshold was chosen higher than $\max_a 1 S_{sa}^{k+1} - S_{sa}^{k} 1 < \gamma$, whereby k refers to iteration count for updating the cluster center c_a to reevaluate the calculated probability of association within c_a. In such cases, FCM needs $k = 24$ as maximal iteration count for segmenting the infection region. Lastly, on convergence of cluster centroid stops the process, and led to clusters of affected and non-affected areas.

In this work, the traditional FCM model is customized by replacing the kernel size (5*5) with the binary thresholding mechanism, which helps in appropriate recognition of diseased portions.

3.3. Feature Extraction

For feature extraction purposes, the DL-TPLFDC model uses DenseNet169 model, which derives only the convolution features. Huang et al. developed the architecture of dense convolution neural networks encompassing pooling and convolution layers, transition layer, dense block, and classification layer [20]. The convolution layer holds the filter to be employed on the feature map, while the pooling layer assists in minimizing the dimension of feature map. The dense block is applied for connecting each layer in such a way that every layer receives input from each earlier layer.

The present layer concatenates the feature and passes its own feature map to every succeeding layer. The extension of dense block raises the number of channels resulting in a complicated model. Thus, the transition layer assists in controlling the DenseNet difficulty. Also, the idea of skip connection same as residual networks is exploited for enhancing the network performance without raising its depth. The vanishing-gradient problem is circumvented successfully in DenseNet by using skip connection.

In CNN, two layers l and $l - 1$ are interconnected by means of the F composite function that comprises ReLU, convolution layer, pooling layer, and BN. The outcome of prior layer X_{l-1} is taken into account as input to the following layer X_l as follows:

$$X_l = F(X_{l-1}). \tag{4}$$

But the layer $0,1,2, \dots, l - 1$ are interconnected in the dense blocks so that the concatenation of the output $[X_0, X_1, X_2, \dots, X_{l-1}]$ of each layer is passed as input to the succeeding layer as signified in Eq. (5). Thus, a layer obtains aggregate data of each prior layer. Therefore, called dense convolution network because of these dense connectivity's amongst the layers in the network:

$$X_l = F([X_0, X_1, X_2, \dots, X_{l-1}]). \tag{5}$$

3.4. Noisy Feature Removal

Once the features are derived, they are fed into the DVAE model for removing the noisy features. DVAE is an integration of Bayesian inference and neural networks. As a type of directed-graph model (DGM), DVAE has an architecture that is same as AE [21]. The generative module (decoder) can be utilized for generating data, whereas the detection module (encoder) compresses dataset to lower dimension space.

Generally, DVAE is utilized for generating data by arbitrary procedure. Assume a dataset X $=\{x_i\}_{i=1}^{N}$ comprising of N i.i.d instance of continual parameter x, generative method comprises two stages: (1) observation x can be produced based on the conditional distribution $p_\theta(x|z)$. Generally, $p(z)$ is selected as a uniform distribution (O, I); (2) a continuous arbitrary parameter $z$was sampled from the previous distribution $p(z)$. This is defined in the following expression:

$$p_\theta(x,z)=p_\theta(x|z)p(z) \tag{6}$$

In Eq. (6), $p_\theta(xz)$ refers to Gaussian distribution $N(\mu(x;\theta), di(lg(\sigma^2(x;\theta$ the diagonal matrix $(\sigma^2(x;\theta))$ and the mean vector $\mu(x;\theta)$ are calculated using the generative network.

The recognition module $q_\varphi(Zx)$was the variational approximation to the intractable posterior distribution $p_\theta(z|x)$. The outcome was Gaussian distribution $N(\mu(z;\varphi), diag(\sigma^2(z;\varphi)))$ where diagonal matrix $di(lg(\sigma^2(z;\varphi))$ and the vector $\mu(z;\varphi)$ are calculated using recognition network.

To ensure the distribution, produced by arbitrary parameter z, is as reliable as feasible with the true dispersal of observation x:

$$L(\theta,\varphi;x_i)= \log p_\theta(x_i)-D_{KL}[q_\varphi(z|x_i)\|p_\theta(z|x_i)] \tag{7}$$

Where $D_{KL}(p\|q)$ represents the KL divergence that could measure the variance among 2 distributions. As the KL-divergence is often non-negative, function $L(\theta,\varphi;x_i)$was determined by the Variational lower bound on marginal likelihood $\log p_\theta(x_i)$.

The concluding form of $L(\theta,\varphi;x_i)$ is expressed by:

$$L(\theta,\varphi;x_i)=E_{q_\varphi(z|x_i)}[\log p_\theta(x_i|z)]-D_{KL}[q_\varphi(z|x_i)\|p(z)] \tag{8}$$

Where the initial term in RHS was 0the expectation of log $p_\theta(X_i|z)$ with respect to $q_\varphi(z|x_i)$, signifies the reconstructed error, and the next term in RHS can be the KL-divergence amongst the posterior and prior distributions. Lastly, the DVAE architecture will be trained using mini-batch SGD.

3.5. Image Classification

Finally, the useful set of features is passed into the RF method to carry out the classification process. The RF classifier was an ensemble method that continuously uses bagging, bootstrapping, and averaging for training several DTs. By using different subsets of accessible features, several independent DTs are built concurrently on various segments of training instances. Bootstrapping ensures that any DTs inside RF was different, lessening the RF variance. RF classification compiles several DTs for the final judgment; hence, RF method contains a strong generalization. The RF method intends to reliably outperform almost other classifier methods with regard to accuracy without problems of overfitting and imbalanced data. A MSE for an RF is described as Eq. (9).

$$MSE=\frac{1}{N}\sum_{k=0}^{n}\binom{n}{k}(Fi-Yi)b^2 \tag{9}$$

Here Fi displays the result returned by model Yi, Nsignifies the number of different data points; and i is the precise value for point value.

4. Experimental Validation

In this section, the plant leaf disease detection performance of the DL-TPLFDC method is investigated using a PlantDoc dataset [23] comprising 5452 images as shown in Table 1. The dataset holds four class labels. The distribution of the samples under each class is depicted in Fig. 2.

Table 1 Details on Dataset

Classes	**No. of Images**
Early_Blight	1000
Late_Blight	1909
Leaf_Mold	952
Healthy	1591
Total Images	**5452**

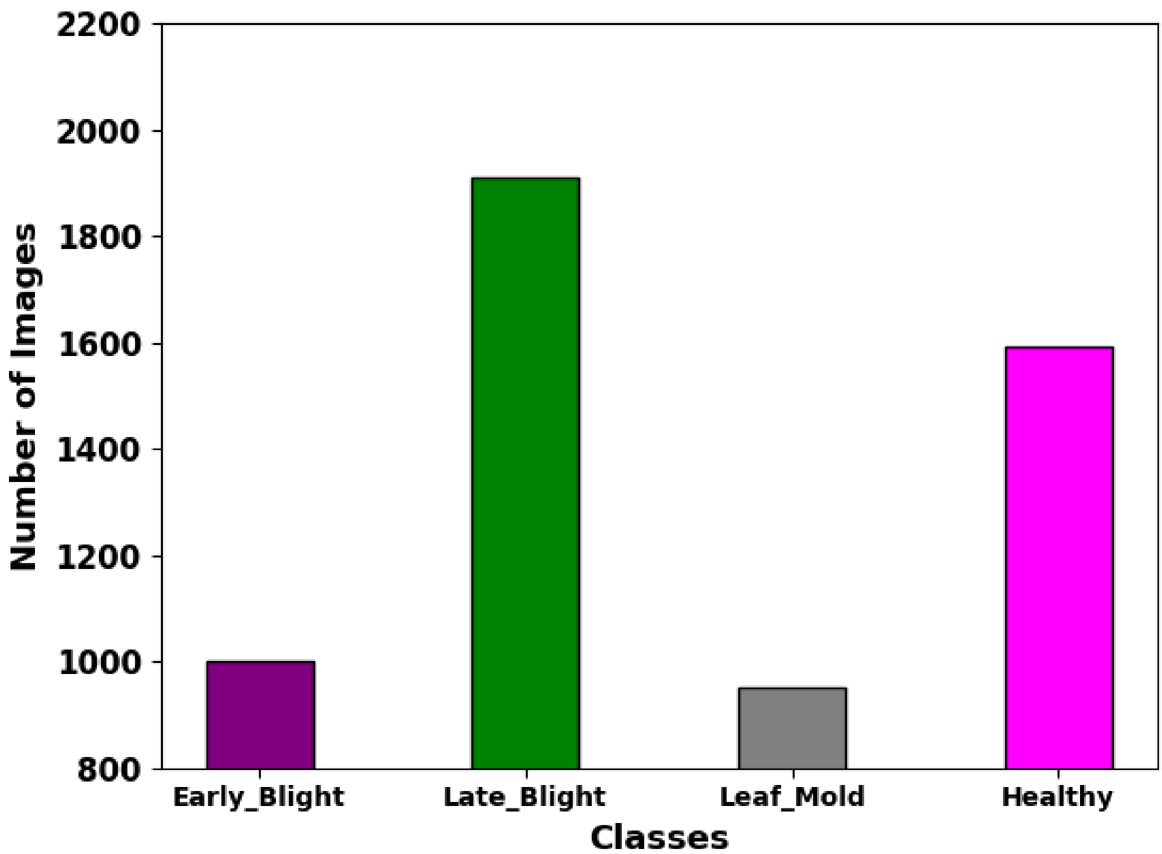


Fig. 2. Sample images on Dataset classes

Fig. 3. a) Original Images b) Pre-processed Images c) Segmented Images

In Fig. 3, a sample results analysis of the DL-TPLFDC model is investigated. Fig. 3a represents the sample original images and its pre-processed versions are provided in Fig. 3b. Then, the segmented images are illustrated in Fig. 3c.

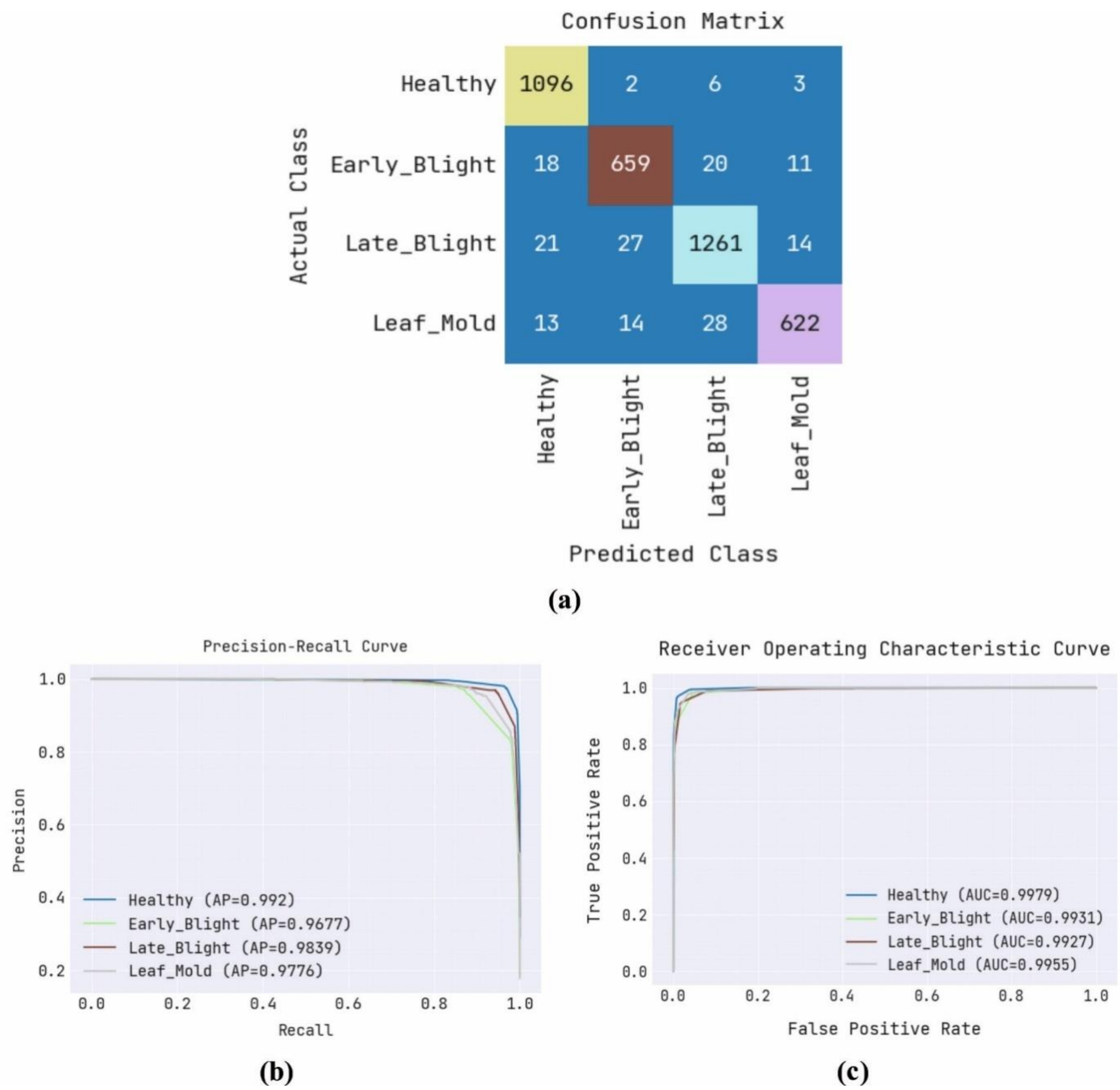
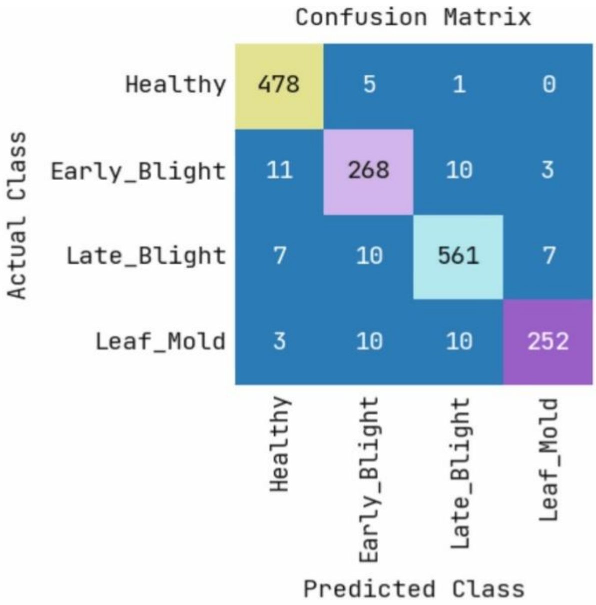
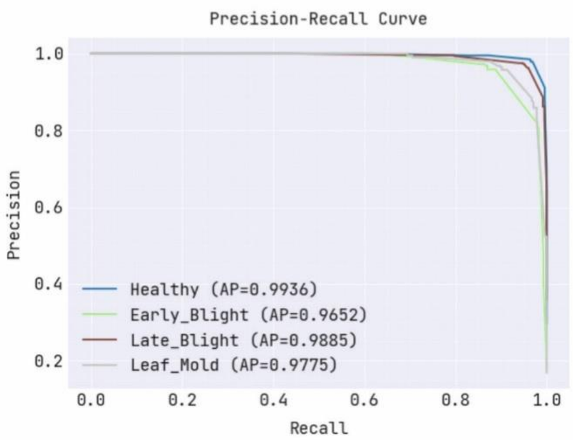


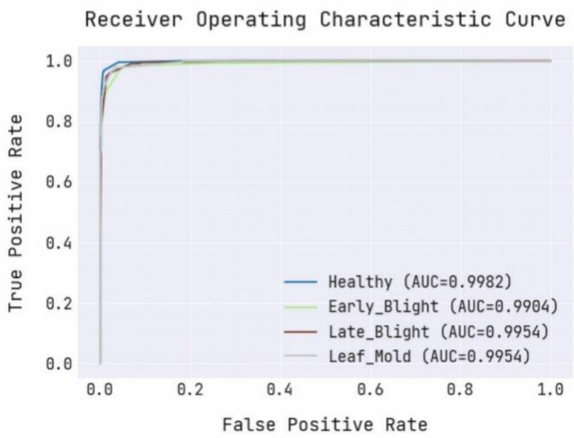
Fig. 4. Result Analysis of Training Set a) Confusion Matrix b) PR-Curve c) ROC

Fig. 4 depicts the classifier outcome of the DL-TPLFDC algorithm under training set. Fig. 4a showcases the confusion matrix offered by the DL-TPLFDC method. The outcome stated that the DL-TPLFDC approach has identified 1096 instances under HY, 659 instances under EB, 1261 instances under LB, and 622 instances under LM. Also, Fig. 4b exhibits the PR investigation of the DL-TPLFDC approach. The figures revealed that the DL-TPLFDC algorithm has attained higher PR performance in several class labels. Lastly, Fig. 4c represents the ROC study of the DL-TPLFDC algorithm. The figure exhibited that the DL-TPLFDC system has capable outcomes with superior ROC values in several class labels.



(a)





(b) **(c)**

Fig. 5. Result Analysis of Testing Set a) Confusion Matrix b) PR-Curve c) ROC

Fig. 5 reports the classification outcomes of the DL-TPLFDC methodology under testing set. Fig. 5a defines the confusion matrix offered by the DL-TPLFDC system. The figure referred that the DL-TPLFDC approach has identified 478 instances under HY, 268 instances under EB, 561 instances under LB, and 252 instances under LM. Followed by, Fig. 5b demonstrates the PR analysis of the DL-TPLFDC method. The figures pointed out that the DL-TPLFDC methodology has attained higher PR performance in distinct classes. Eventually, Fig. 5c illustrates the ROC examination of the DL-TPLFDC system. The figure represented that the DL-TPLFDC algorithm has resulted in capable outcomes with superior ROC values under various classes.

In Table 2, the overall tomato plant leaf disease detection and classification results of the DL-TPLFDC model are provided briefly.

In Fig. 6, the classification outcomes of the DL-TPLFDC method on tomato leaf disease diagnosis on TR set are given. The results stated that the DL-TPLFDC model has properly identified the leaf diseases under various classes. It is observed that the DL-TPLFDC model has obtained $accu_y$ of 95.36%, $prec_n$ of 95.23%, $reca_l$ of 94.82%, $F1_{score}$ of 95.01%, and AUC_{score} of 99.48%.

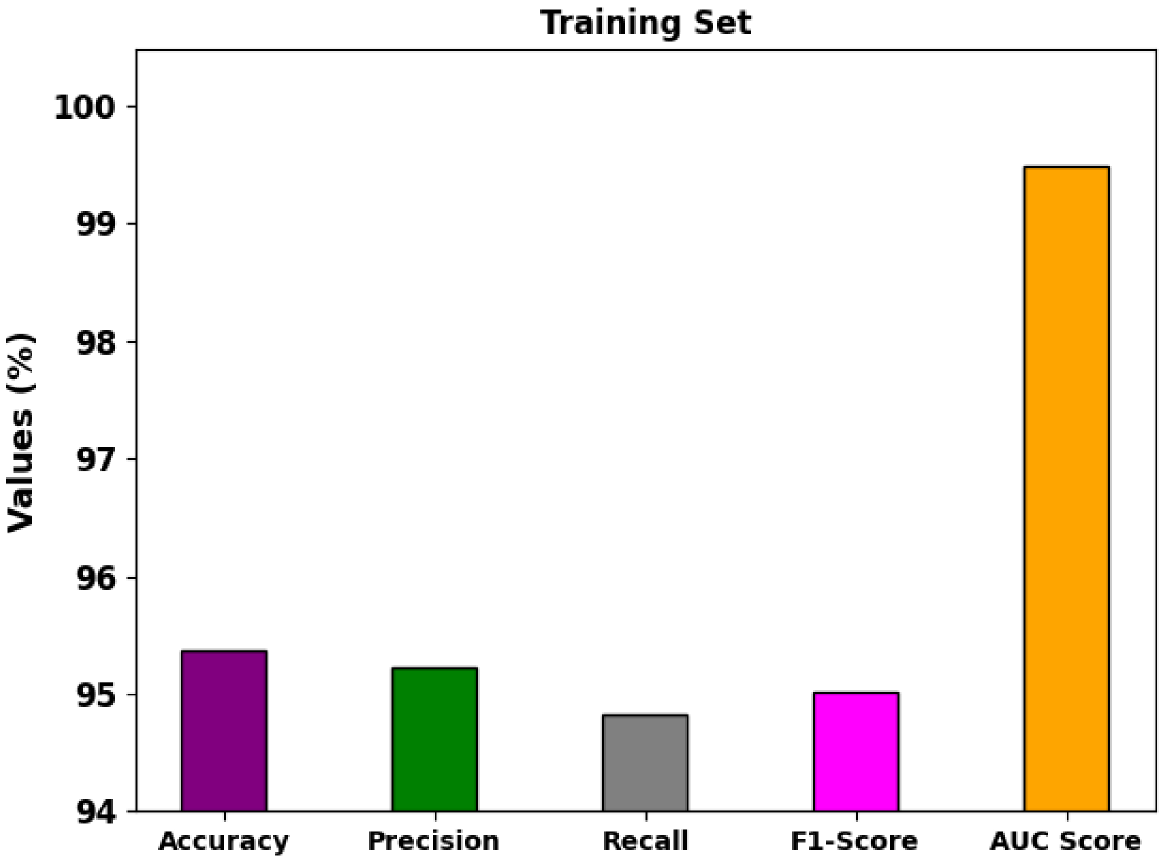


Fig. 6. Overall analysis of DL-TPLFDC system under training set

In Fig. 7, the classification outcomes of the DL-TPLFDC approach on tomato leaf disease diagnosis on TS set are given. The outcomes denoted that the DL-TPLFDC algorithm has properly identified the leaf diseases in several classes. The DL-TPLFDC system has achieved $accu_y$ of 95.29%, $prec_n$ of 94.96%, $reca_l$ of 94.52%, $F1_{score}$ of 94.72%, and AUC_{score} of 99.48%.

Table 2 Overall analysis of DL-TPLFDC system with various measures

Measures	**Training Set**	**Testing Set**
Accuracy	95.36	95.29
Precision	95.23	94.96
Recall	94.82	94.52
F1-Score	95.01	94.72
AUC Score	99.48	99.48

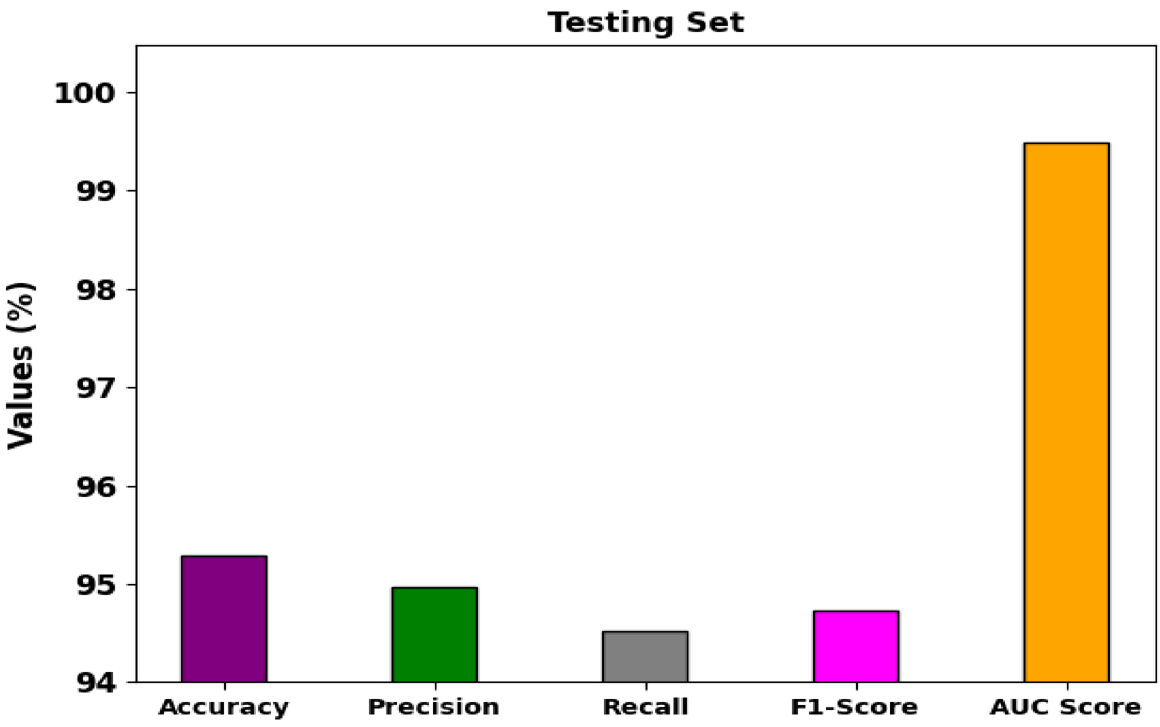


Fig. 7. Overall analysis of DL-TPLFDC system under testing set

The TLS and VLS of the DL-TPLFDC approach are tested on tomato leaf disease performance in Fig. 8. The figure referred that the DL-TPLFDC algorithm has exposed superior performance with minimal values of TLS and VLS. It is observable that the DL-TPLFDC algorithm has resulted to decrease VLS outcomes.

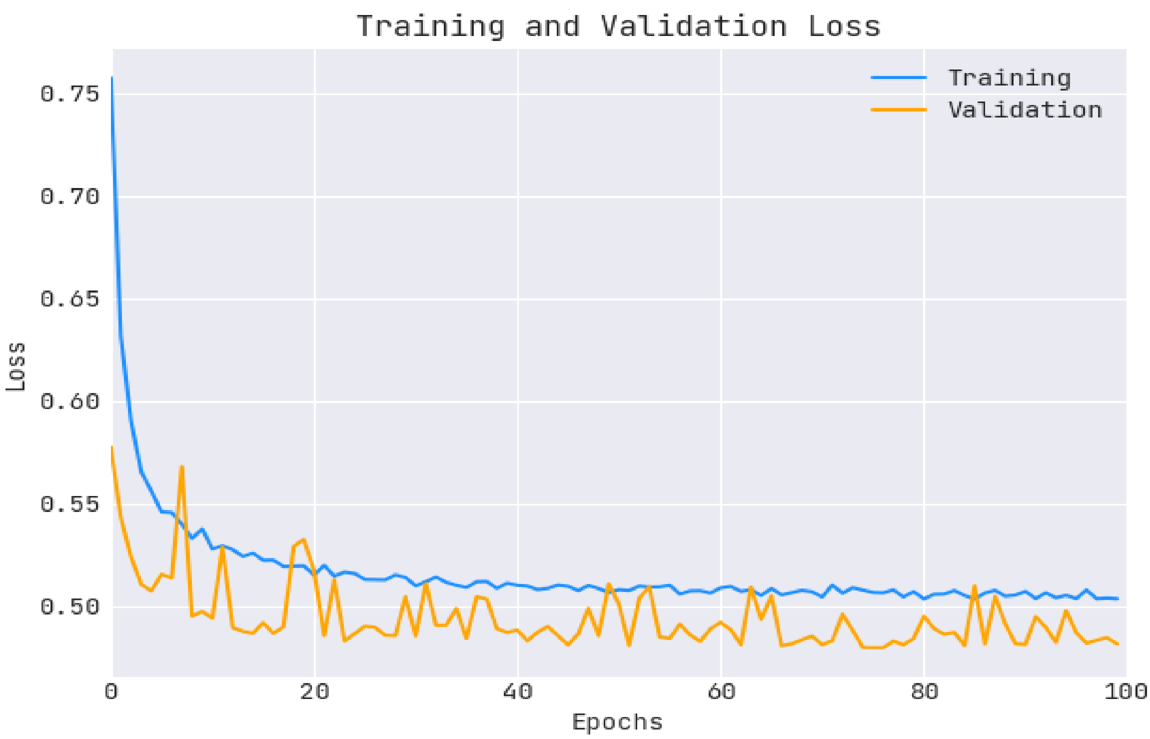


Fig. 8. TLS and VLS analysis of DL-TPLFDC approach

In Table 3 and Fig. 9, a comprehensive comparative study of the DL-TPLFDC model is investigated in detail [6, 24]. Among the available models, the Inception v3 model has demonstrated poor performance with minimal $accu_y$ of 63.40%.

Table 3 Accuracy analysis of DL-TPLFDC technique with other recent algorithms

Methods	Accuracy (%)
Proposed DL-TPLFDC	95.36
HCF-QSVM	83.50
ACNN	76.00
CNN-LVQ	86.00
HCF-SVM	88.89
VGG-16 CNN	77.20
INCEPTION V3	63.40

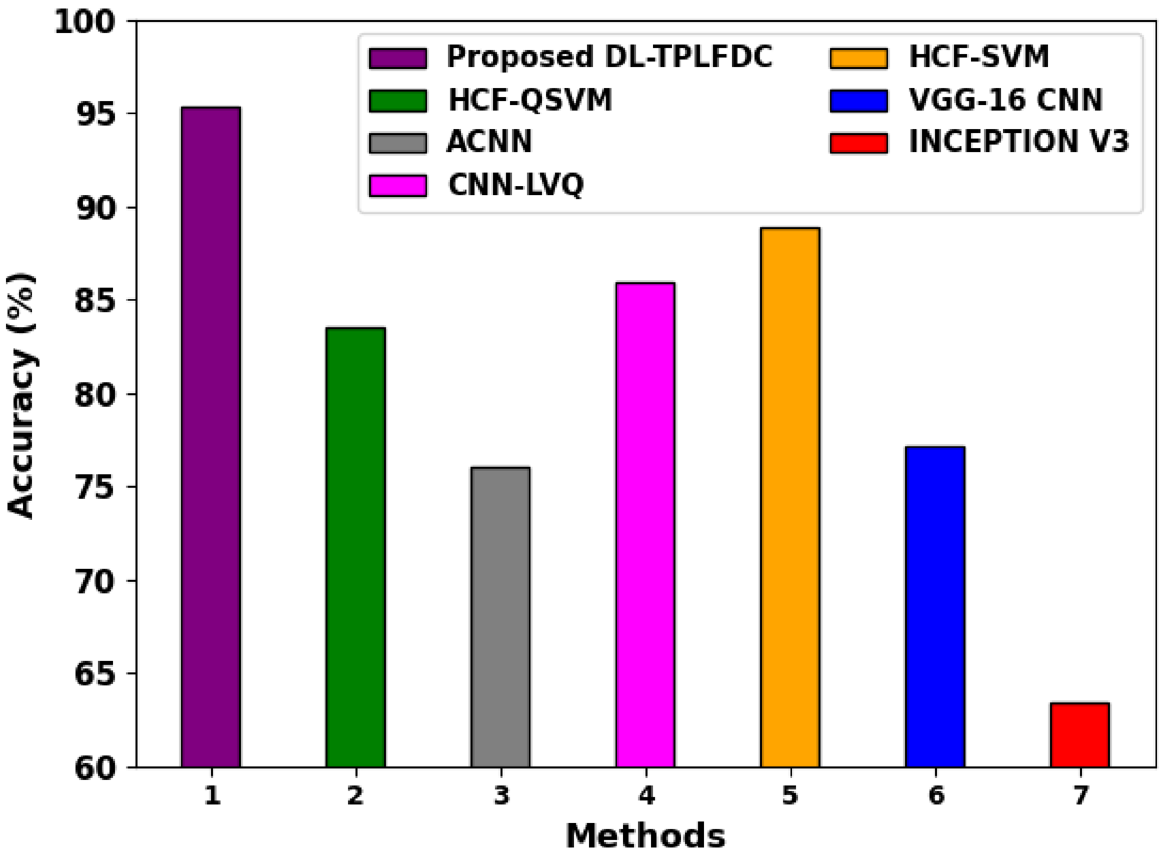


Fig. 9. $Accu_y$ analysis of DL-TPLFDC approach with other recent algorithms

In addition, the experimental values implied that the ACNN and VGG-16CNN systems have reported certainly enhanced $accu_y$values of 76% and 77.20% correspondingly. Meanwhile, the HCF-QSVM, CNN-LVQ, and HCF-SVM models have exhibited moderately closer $accu_y$ values of 83.50%, 86%, and 88.89% respectively. But the DL-TPLFDC model has shown its superior performance to other models with maximum $accu_y$ of 95.36%. These results assured that the DL-TPLFDC model has shown enhanced tomato leaf disease classification performance over other recent models.

5. Conclusion

In this article, we have formulated a new DL-TPLFDC model for the identification and classification of tomato plant leaf diseases. In the presented DL-TPLFDC technique, the U-Net segmentation is applied for leaf portion identification and FCM with customized binary thresholding process for the recognition of diseased leaf portions. Moreover, DenseNet-169 model was employed to generate feature vectors from the segmented image. Furthermore, the DVAE model is applied to eliminate the noisy features that exist from the DenseNet-169 model, and the resultant features are fed into the RF method for classification process. The performance analysis of the DL-TPLFDC approach can be executed on benchmark dataset and the outcomes were examined under various measures. The experimental values portrayed the improved outcomes of the DL-TPLFDC technique over other models. In future, the performance of the DL-TPLFDC method will be improvised by hyperparameter optimizers.

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