An Efficient Tomato Leaf Disease Classification Framework by Background Removal using Fully Convolutional Network and Residual Transformer Network

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ABSTRACT

Tomato is a widely utilized vegetable that secured a superior place in enhancing the economic rate in agriculture. Production quantity of tomatoes secured seventh place worldwide. Still, leaf diseases attained in the tomato plant are considered a more challenging issue as they affect the normal growth of the plant badly. Here, different kinds of plant diseases have occurred in the plant leaves which generate more losses in crop yield. In the early phase, the accurate prediction of plant disease effectively minimizes the production loss and offered to enhance crop yield. Moreover, the conventional approaches faced more complexity as the existing system needs more computational time and they are costly. To overcome this problem, an effective tomato disease classification model is proposed using a transformer-based network. Initially, the raw tomato plant images are gathered through real-time data. Then, they have undergone a pre-processing stage to remove the unwanted image pixels. Further, the backgrounds of images are removed by using the Fully Convolutional Network (FCN). Finally, the disease classifications are accomplished by using Residual Transformer Network (RTN). The performance is validated with divergent measures and compared with traditional methods. Thus, the results declare that it achieves an impressive classification rate to avoid less crop productivity.
Keywords: Tomato Leaf Disease Classification; Background Removal; Fully Convolutional Network; Residual Transformer Network

INTRODUCTION

Tomato is a widely available vegetable variety available in globally. But, the yield of tomatoes is get affected by plants with multiple leaf infections [6]. The tomato leaf infection is determined as the contributor to the tomato crop yield reduction and generated more economic loss to the farmer. Thus, the detection of tomato plant leaf disease is highly related to the economical activity of agriculture. The yield of the tomato plant is enhanced when quick detection as well as several control measures are attained for the enhancement of the tomato plant [7]. Traditionally, manual tomato leaf disease identification is performed but, it needs more time to analyze the disease kind and is also inspired by several factors such as mood swings and fatigued. Most of the classical plant disease detection models required multiple analyses by individuals to analyze the disease-affected leaf by chemical or visual observation in the affected region which is considered a minimal identification rate and also a bad reliability rate related to human error [8]. Likewise, the farmers have minimal expert knowledge, and also the unavailability of professionals to detect the disease effectively affects the yield rate. Thus, carelessness leads to several threads in global food security and generate more loss to the stakeholder included in the tomato generation [9]. So, the researcher considered early disease detection and classification model is highly essential to support the farmer in resolving the issues [10].

In agriculture, real-time application contributes a lot to the enhancement of disease detection and classification rate [11]. These applications need minimal latency techniques in their devices along with reduced computational power and storage space [12]. Most professionals concentrate on designing lightweight models by utilizing a limited amount of disease-affected samples. Moreover, researchers have developed more plant disease detection models based on conventional machine learning models [13]. But, deep learning models generate great impact in the agriculture area by offering accurate outcomes to the users. In recent days, Convolutional Neural Network (CNN) is considered the essential tool to classify the required task, and also it effectively acquired the essential features from the image without any manual support [14]. The classical tomato plant leaf disease-based deep learning model faces multiple complexities, which badly affect the performance of the suggested system is detailed as follows. Initially, in the image noises are produced when an acquisition is performed and also the process of processing and transmission generates more complexity to acquire the features related to the disease. Then, the intra-class variability as well as the inter-class similarity produces more complexity in identifying the leaf disease [15]. Thus, to tackle the several limitations presented in the conventional tomato plant leaf disease classification technique, a novel tomato plant leaf disease classification framework is developed based on a network technique with a background removal process.

Multiple contributions involved with the recommended tomato plant leaf disease framework are explained as follows.

- To design a novel tomato leaf disease classification approach with deep learning models to classify the disease in the plant early for enhancing the yield production rate.
- To remove the image background with FCN for offering enhanced background removed image to offer accurate leaf disease classification rate.
- To classify the tomato leaf disease employ the RTN technique for providing an effective tomato leaf disease classification rate than the existing models.
- To validate the classification rate of the recommended tomato leaf disease classification model over the conventional classifiers is weighted up with multiple analyses.

The rest of the portions linked with the recommended tomato leaf disease classification approach are elaborated below. The respective works linked with the conventional tomato leaf disease classification technique are explained in Section II. The image background removal model with FCN is discussed in section III. An effective tomato leaf disease classification technique is offered in Section IV. Finally, the outcome and discussion are presented in Section V and the conclusion part is provided in Section VI.

LITERATURE SURVEY

A. Related Works

In 2021, Zhou *et al.* [1] have suggested a modified Residual Dense Network (RDN) identify tomato leaf disease. The combined deep learning model holds the advancement presented in the Deep Residual Network (DRN) that can minimize the parameters presented in the training for enhancing the accuracy rate. Existing RDN was utilized to provide an enhanced image resolution rate to modify the network structure. Finally, the recommended RDN secured an enhanced plant leaf disease classification rate than the existing techniques.

In 2022, Ahmed *et al.* [2] have developed a lightweight learning model to detect the disease in the tomato leaf. The suggested technique utilized an efficient pre-processing technique for improving the illumination correction in the leaf image. The initiated techniques acquired the features by the fused methods that hold a pre-trained mobile net structure as well as the classifier for efficient prediction. Here, data leakages were minimized by utilizing runtime augmentation. Experimental analysis displayed that the recommended leaf disease classification technique secured a higher accuracy rate than the conventional techniques.

In 2022, Anandhakrishnan and Jaisakthi [3] have initiated a Deep CNN (DCNN) to improve the accuracy rate and also to minimize the response time in tomato leaf disease detection. In the developed model, huge amounts of data were utilized for the analysis. To attain an effective outcome, both training data, as well as testing data, were utilized. Thus, the recommended DCNN technique for the tomato plant leaf disease classification model secured an effectively higher performance rate than the conventional models.

In 2023, Zhang *et al.* [4] have recommended an asymptotic technique for minimizing the noise interference attained in the image and also to eliminate the complexity presented in acquiring the deep feature for better detection. Further, Multi-channel Automatic Orientation Recurrent Attention Network (M−AORANet) was developed to attain more disease-related features. Thus, the recommended techniques effectively resolved the inter-class similarity issues and provided a better leaf disease classification rate than the conventional technique.

In 2022, Kaushik *et al.* [5] have introduced a tomato plant disease detection technique named TomFusioNet. In the feature extraction phase, the late-fusion approach was utilized to offer an effective outcome rate. The developed model was the fused combination of DeepPred and DeepRec for detecting the disease in the crop. A gate mapping model was utilized to minimize unwanted wastage in the mobile validation. The DeepPred hyperparameters were optimized by genetic approach. Further, to enhance effective performance rate Hue, Saturation, and Value (HSV)-based background noise removal approach was designed. Hence, the suggested model offered enhanced classification performance than the conventional techniques in terms of accuracy.

B. Problem statement

In recent days, food security in tomato plants gained more attention worldwide. But, several diseases attained in tomato plants effectively reduce the production rate. A lot of tomato leaf disease classification models are developed, but this kind of system should be more accurate, faster, and computationally inexpensive to help the farmers. In Table 1, several complexities and features presented in the traditional tomato leaf disease classification models are presented. RDN [1] performs classification effectively with minimal parameters and also it effectively resolves the gradient disappearing issue. Still, it needs to resolve time complexity issues to speed up the process. MobileNet V2 [2] attained better leaf disease classification in terms of accuracy and it efficiently minimizes data leakage as well as class imbalance problems. Yet, it wasn't able to classify more diseases from the single leaf. DCNN [3] successfully minimizes the response time and improves the accuracy of leaf disease classification. Moreover, it suffered a lot when an image with more noise is offered for the execution. M−AORANet [4] minimizes the noise interference presented in the image and also reduces the complexity of acquiring the leaf disease features. However, it needs to enhance the classification rate accuracy. TomFusioNet [5] automatically detects the disease type and classifies their classes and it detects the leaf disease more accurately in the initial phases. However, it utilized only limited data for the analysis and suffered in some cases also, it doesn't utilized deep learning models for background removal that reduces accuracy rate in the classification performance. So, we are in need to design a novel framework for tackling the limitations attained in the existing tomato leaf disease classification model with different background removal techniques.

Table 1. Features and challenges of conventional Tomato leaf disease classification models

Author [citation]	**Methodology**	**Features**	**Challenges**
Zhou *et al.* [1]	RDN	• It performs classification effectively with minimal parameters. • It effectively resolves the gradient disappearing issue.	• It needs to resolve time complexity issues to speed up the process.
Ahmed *et al.* [2]	MobileNet V2	• It attained better leaf disease classification in terms of accuracy. • It efficiently minimizes data leakage as well as class imbalance problems.	• It wasn't able to classify more diseases from the single leaf.
Anandhakrishnan and Jaisakthi [3]	DCNN	• It successfully minimizes the response time and improves the accuracy of leaf disease classification.	• It suffered a lot when an image with more noise is offered for the execution.
Zhang *et al.* [4]	M−AORANet	• It minimizes the noise interference presented in the image and also reduces the complexity of acquiring the leaf disease features.	• It needs to enhance the classification rate accuracy.
Kaushik *et al.* [5]	TomFusioNet	• It automatically detects the disease type and classifies their classes.	• It utilized only limited data for the analysis and suffered in some cases.

		• It detects the leaf disease more accurately in the initial phases.	

BACKGROUND REMOVAL-BASED TOMATO LEAF DISEASE CLASSIFICATION USING DEEP LEARNING

A. Image Datasets

Initially, tomato leaf images are utilized for the analysis and are acquired from the real-world scenario to validate the efficacy of the suggested tomato plant leaf classification framework. In the real-world dataset, the images are acquired from the Kuntloor village, hayath nager, Hyderabad. The dataset holds nearly 2000 sample images with different classes such as Tuta absoluta, fungal-leaf Early blight, healthy leaf, leaf serpentine miner, fungal-leaf Gray mold, and tobacco caterpillar leaf damage.

The acquired input real-world tomato leaf images are offered as IMG_p^{sp} , where $p = 1,2,3\ldots,P$. The term P denotes the entire quantity of images needed to be acquired.

B. Developed Model

Plant leaf diseases generated more complexity in food security. Agricultural production gets minimized when sudden rain, fog, wind, and mist are attained in the agricultural region. The sudden production losses effectively minimize the country's economic growth. The plant tomato is associated with the Solanaceae group which is commonly utilized all over the world. They are easily grown in greenhouses and agricultural land. But, tomato plants are affected by several leaf diseases such as bacterial wilt, leaf spot, leaf curl, and so on. These kinds of diseases are attained in the several phases of plant growth based on climatic factors. The leaf disease attained in the plant generated more impact on the productivity and the production of tomato yield. Once, the leaf disease is detected in the initial phase, several safety measures are taken to enhance the tomato cultivation rate for reducing the loss. Tomato plant monitoring in acres needs immense individual manual intervention and they are considered to consume more time and be cost-effective. The leaf diseases of tomatoes detected by the farmers are subjected to more errors. Thus, to tackle the above-mentioned limitations, a novel tomato plant leaf disease classification framework is designed based on deep learning techniques. The structural presentation of the recommended tomato plant leaf disease classification is offered in Fig 1.

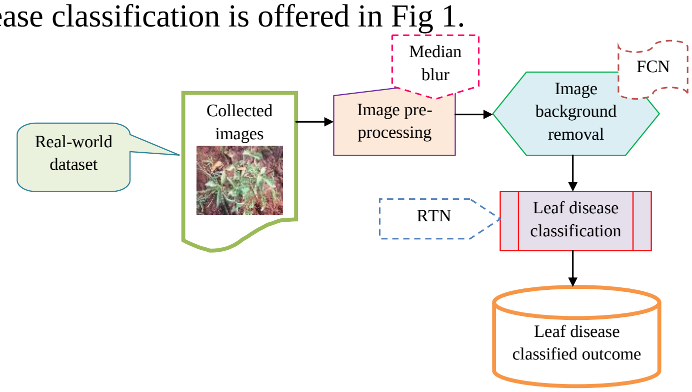


Figure 1. Diagrammatic representation of Recommended Tomato Plant Leaf Disease Classification Framework with background removal techniques

A brand new tomato plant leaf disease classification technique is recommended related to heuristic models and deep learning methods for classifying the disease variant presented in the crop in the early phase. In this beginning phase, images related to the tomato leaf disease are acquired from the real-time scenarios and offered to the image pre-processing region. Here, images are pre-processed by utilizing the median blur technique and the pre-processed image is fed to the image background removal phase. In this phase, the image backgrounds are removed by employing the FCN method. Further, the attained background removed images are provided to the leaf disease classification region. Finally, tomato plant leaf diseases are classified by RTN schemes. Thus, the recommended tomato leaf disease classification framework secured a better leaf disease classification rate than the classical schemes.

C. Median Blur-based Image Pre-processing

At first, gathered plant leaf images IMG_p^{sp} from the dataset are offered as the input to pre-processing region. Here, the median blur technique is utilized to pre-process the plant leaf disease image. Median blur is the widely used non-linear digital filtering technique, which is mainly utilized to remove the unwanted noise presented in the image. Normally presented noise in the image are Gaussian noise, impulse noise, and salt and pepper noise. Median blur is worked by choosing the intensity of the median presented in the window. It operates in the form of pixel-by-pixel format and also it substitutes the neighbor pixel value with the median value. Here, the neighbor pattern is referred to as the window which is transferred in a pixel-by-pixel format in the entire image. This kind of noise minimization is considered the basic pre-processing phase for enhancing the pre-processing outcome. Median blur is normally utilized in digital image pre-processing due to its special feature like securing the edges during noise elimination and also they are generally utilized in several image processing applications. The attained median blur-based pre-processed images are presented IMG_q^{MD} and further they are provided for the background removal phase.

BACKGROUND REMOVAL CONCEPT WITH DEEP LEARNING-BASED TOMATO LEAF DISEASE CLASSIFICATION

A. Background Removal using FCN

The attained pre-processed images IMG_q^{MD} are utilized as the input to the background removal phase. Here, the background removal process is performed in the image by employing the FCN technique.

FCN [16] is considered the pixel-to-pixel convolution framework to perform effective background removal in images. Mostly, FCN is referred to as enlarged CNN which prediction rates are transferred the class number to a background removal image that is widely utilized to perform dense leaf image disease prediction. Here, the entire DNN is presented with different phases such as up-sampling and down-sampling. In the down-sampling phase, it holds several layers such as a dropout layer, pooling layer, and convolutional layer. Similarly, the up-sampling layer consists of a deconvolutional layer.

The down-sampling layer in FCN utilized nearly 19 layers for the analysis. The down-sampling techniques are utilized for the analysis because it has an enhanced effectiveness rate and also effectively minimize the training period. Then, the phase up-sampling is considered an essential part of the FCN, because it effectually inverses the down-sampling process that is subjected to dense prediction. In the up-sampling region, the local information, as well as the global information, is fused by adding the special layers from the deconvolutional and convolutional layers and gaining the background removal noise as the outcome. Further, the acquired background removed image is termed as IMG_w^{BR} and they are offered as the input to the leaf disease classification phase. The diagrammatic representation of the FCN-based background removal model is offered in Fig. 2.

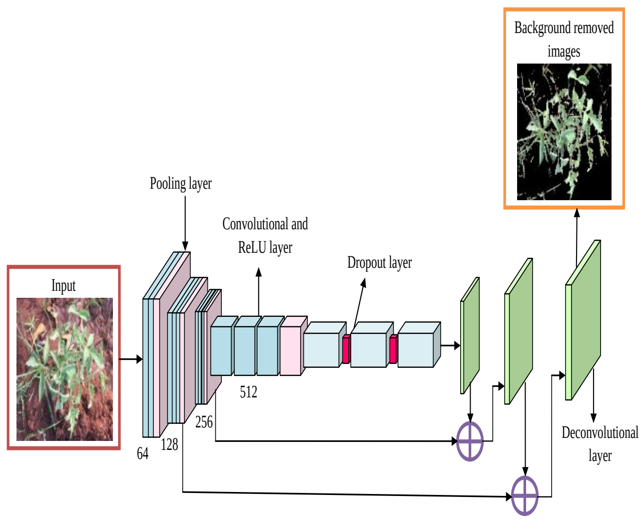


Figure 2. Diagrammatic representation of the FCN-based background removal model

B. Residual Transformer Network-based Disease Classification

The FCN-based background image IMG_w^{BR} is offered as the input to the leaf image classification phase. In this leaf disease classification phase, the RTN technique is utilized to perform effective leaf disease classification. The RTN is developed based on the combination of Resnet and transformer. The Resnet network easily trained the layer without enhancing the error percentage. It effectively reduces the gradient vanishing issues. But, it is too weak to select the correlation because it didn't offer missing variable-related data. Further, a transformer is utilized as it has high efficiency for superior frequency range, the implementation, as well as the principle of working is considered as more simple, and also they are linked in reverse format. They need more space and also it is heavy and bulky in size. Thus, to overcome the several complexities presented in both Resnet and the transformer a new combination named RTN is designed. The developed RTN model holds two essential layers the transformer layer and the shortcut connection. Here, the transformer plays a major role due to it can able to attain the temporal dependency among the inflow data. The transformer is presented with linear layers and it effectively processes the inflow presented in the multi-traffic modes and also attains the correlation over various traffic nodes.

Thus, the developed RTN offered effectively classified leaf disease as the outcome. The pictorial representation of the RTN-based leaf disease classification technique is displayed in Fig. 3.

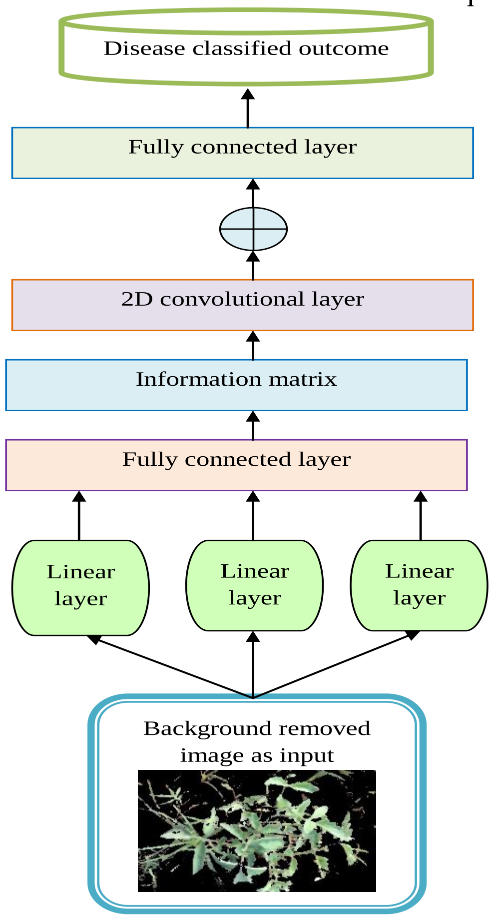


Figure 3. The pictorial view of the RTN-based leaf disease classification method

RESULT AND DISCUSSION

A. Experimental Setup

A novel tomato leaf disease classification framework was executed in Python software and also different analyses were performed to assure the efficacy of the recommended tomato leaf disease classification method. The performance rate of the suggested tomato leaf disease classification technique was validated by contrasting the conventional tomato leaf disease classification schemes. The developed tomato leaf disease classification approach was contrasted over different traditional classification models such as CNN [17], Resnet [18], and RNN [19] to attain accurate classification outcomes.

B. Performance Metrics

The suggested tomato plant leaf classification framework is over multiple qualitative metrics listed as follows.

(a) Accuracy AY is the computation of metrics linked with a specific gain presented in Eq. (1).

$$AY = \frac{(k+j)}{(k+j+h+g)} \tag{1}$$

Here, the term j indicates the true negative, h denote the false positive, k presents the true positive, and g denote the false negative values in this phase.

(b) Specificity Ik is the preposition of negatives that are founded correctly as given in Eq. (2).

$$Ik = \frac{j}{j+h} \tag{2}$$

(c) F1-score Rf is the computation of accuracy in the entire analysis that is presented in Eq. (3).

$$Rf = 2 \times \frac{2k}{2k+h+g} \tag{3}$$

(d) MCC Qa is the computation of binary quality types of the observation and it is presented in Eq. (4).

$$Qa = \frac{k \times j - h \times g}{\sqrt{(k+h)(k+g)(j+k)(j+g)}} \tag{4}$$

(e) FNR Ef is the fraction of positive which attained negative observation outcomes in the different analyses offered in Eq. (5).

$$Rf = \frac{g}{g+k} \tag{5}$$

(f) NPV Rd is the sum of whole plants without disease during the analysis and presented in Eq. (6).

$$Rd = \frac{j}{j+g} \tag{6}$$

(g) FPR Ws is the ratio of a negative event which is categorized wrongly as positive in the whole negative event and equated in Eq. (7).

$$Ws = \frac{h}{h+j} \tag{7}$$

(h) Sensitivity pl is the fraction of positives that are classified accurately and it is elaborated in Eq. (8).

$$pl = \frac{k}{k+g} \tag{8}$$

(i) Precision PRS is considered as the preposition of a specific item over the classified item and it is provided in eq. (9).

$$PRS = \frac{k}{k+h} \tag{9}$$

C. Resultant Background Removed Images

The FCN-based background removed images are presented in the tomato leaf disease classification model offered in Fig. 4.

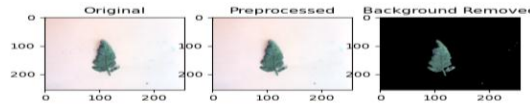
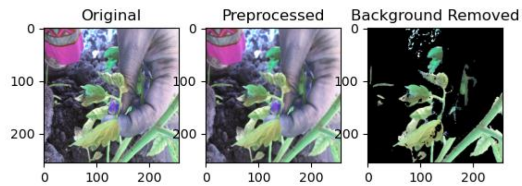
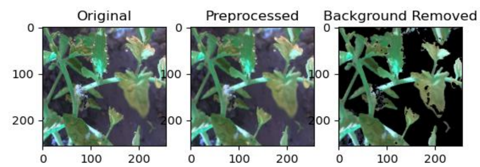
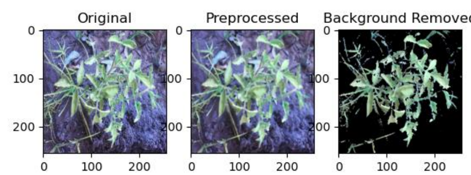
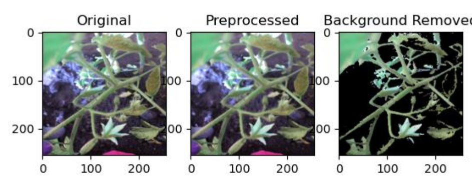
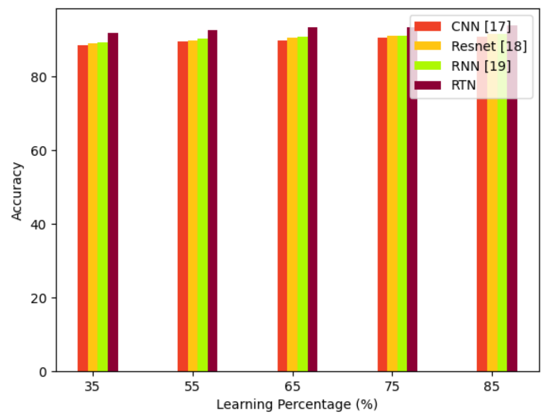
Image Description-Disease name	Background removed image
Healthy leaf	
Leaf early blight	
Tuta absolute	
Leaf serpentine miner	
Tobacco caterpillar leaf damage	

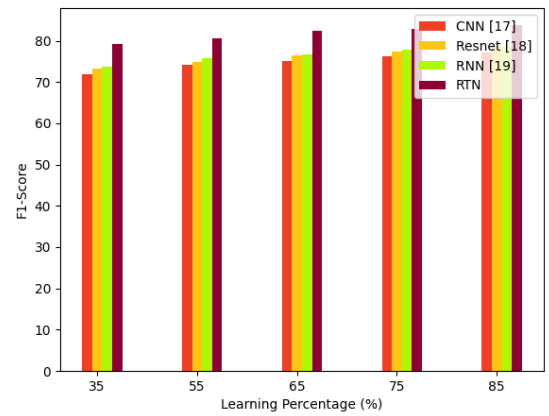
Figure 4. Background removed image outcome for tomato leaf disease classification framework

D. Analysis of Initiated Model with Conventional Classifiers

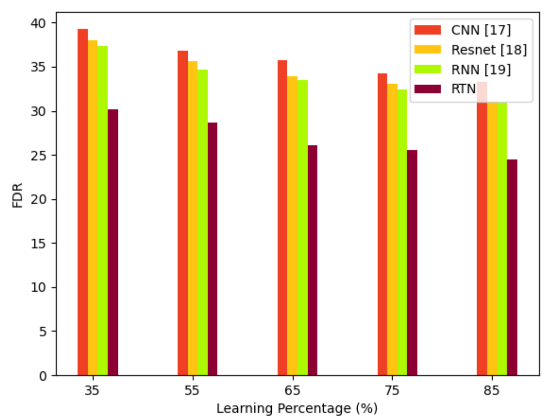
Different analyses performed in the developed tomato leaf disease classification framework over traditional techniques are displayed in Fig. 5. Accuracy analysis performed in the recommended tomato leaf classification model RTN secured 8.04% enhanced than CNN, 6.81% better than Resnet and 4.445 superior to RNN. Thus, the recommended tomato leaf disease classification framework with background removal secured a more highly accurate leaf disease classification model than the classical techniques.


CNN [17]
Resnet [18]
RNN [19]
RTN
Accuracy
35 55 65 75 85
Learning Percentage (%)

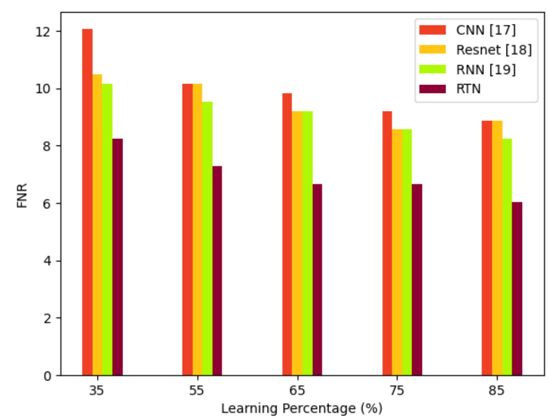
(a)


CNN [17]
Resnet [18]
RNN [19]
RTN
F1-Score
35 55 65 75 85
Learning Percentage (%)

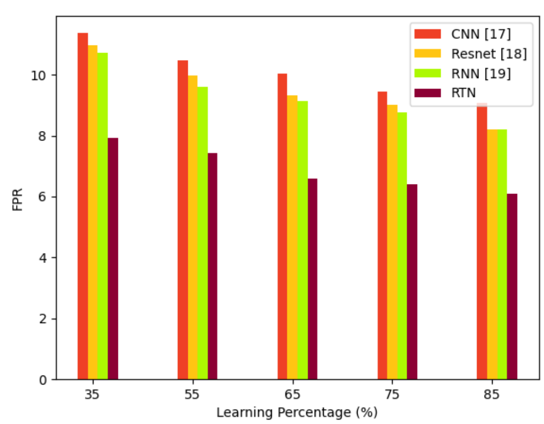
(b)


CNN [17]
Resnet [18]
RNN [19]
RTN
FDR
35 55 65 75 85
Learning Percentage (%)

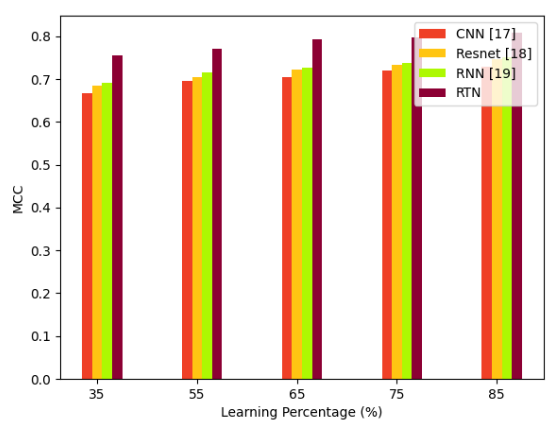
(c)


CNN [17]
Resnet [18]
RNN [19]
RTN
FNR
35 55 65 75 85
Learning Percentage (%)

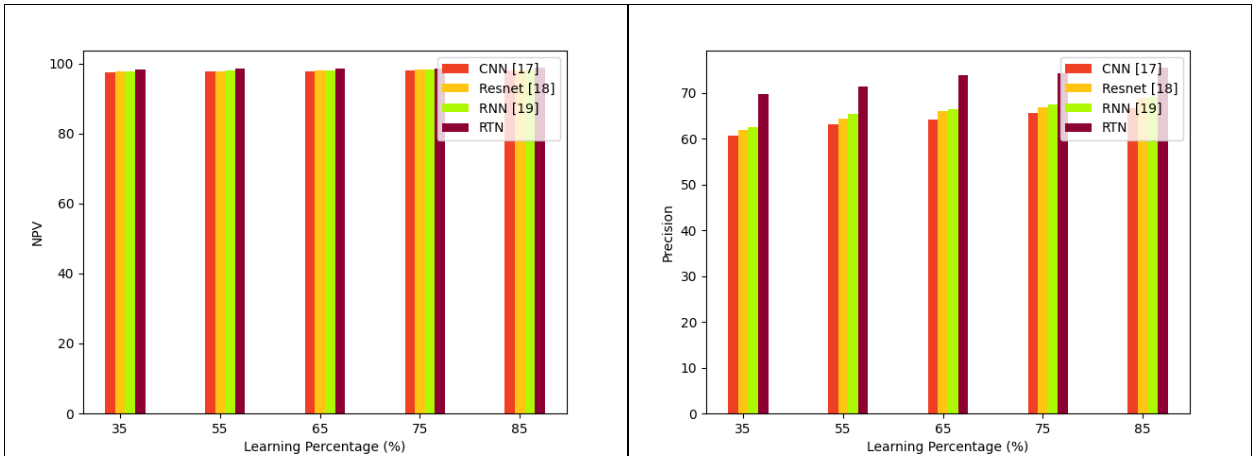
(d)


CNN [17]
Resnet [18]
RNN [19]
RTN
FPR
35 55 65 75 85
Learning Percentage (%)

(e)


CNN [17]
Resnet [18]
RNN [19]
RTN
MCC
35 55 65 75 85
Learning Percentage (%)

(f)



(g) (h)

Figure 5. Analysis of the developed tomato leaf disease classification model with background removal over existing classifiers with (a) Accuracy, (b) F1-score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NVP and (h) Precision

E. Performance Analysis on the Recommended Model

Performance analysis executed in the recommended tomato leaf disease classification model is tabulated in Table II. Multiple analyses performed in the developed tomato leaf disease classification model and the suggested RTN technique secured an enhanced performance rate than the existing technique. Sensitivity analysis carried out in the initiated tomato leaf classification secured 3.13%, 3.14%, and 2.42% enhanced leaf disease classification rate than the traditional models like CNN, Resnet, and RNN, respectively. Hence, the proposed RTN with an improved background removal rate secured an effective leaf disease classification rate than the classical approaches.

Table 2. Performance analysis on the Developed Tomato Plant Leaf Disease Classification Framework with background removal

Performance measures	CNN [21]	RESNET [22]	RNN [23]	RTN
Accuracy	90.95	91.69	91.80	93.92
Sensitivity	91.11	91.11	91.75	93.97
Specificity	90.92	91.81	91.81	93.90
Precision	66.74	68.99	69.14	75.51
FPR	9.08	8.19	8.19	6.10
FNR	8.89	8.89	8.25	6.03
NPV	98.08	98.10	98.23	98.73
FDR	33.26	31.01	30.86	24.49
F1-Score	77.05	78.52	78.85	83.73
MCC	72.92	74.59	75.03	80.77

CONCLUSION

A newly designed tomato leaf disease classification framework with deep learning approaches attained an enhanced leaf disease classification rate in the plants at the early phases. At first, gathered diseased leaf images were offered as the input to the image pre-processing region. Here, the pre-processed images were attained by utilizing the median blur technique and fed to the image background removal phase. In this phase, the background of the image was removed by employing the FCN technique. Then, the attained background removed images were provided to the tomato leaf disease classification region. Finally, effective tomato leaf disease classification was performed by the RTN model. Accuracy analysis performed in the recommended tomato leaf classification model RTN secured 8.04% enhanced than CNN, 6.81% better than Resnet, and 4.445 superior to RNN with improved background removal rate. Thus, the recommended tomato leaf disease classification framework with background removal secures an enhanced disease classification rate than the existing techniques.

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