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An efficient segmentation using adaptive radial basis function neural network for tomato and mango plant leaf images

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ABSTRACT

Agriculture has become simply to feed ever-growing populations. The tomato is arguably the most well-known vegetable in agricultural areas and plays a significant role in the growth of vegetables in our daily lives. However, because this tomato has multiple diseases, image segmentation of the diseased leaf shows a key role in classifying the disease by the leaf's symptoms. Therefore, in this paper, an efficient plant disease segmentation using an adaptive radial basis function neural network (ARBFNN) classifier. The proposed radial basis function (RBF) neural network is enhanced by using the flower pollination algorithm (FPA). Firstly, the noise is detached by an adaptive median filter and histogram equalization. Then, from every leaf image, different kind of color features is extracted. After the extraction of features, those are fed to the segmentation phase to section the disease serving from the input image. The efficiency of the suggested method is analyzed based on various metrics and our technique attained a better accuracy of 97.58%.

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1. INTRODUCTION

About 70% of the country's economic output comes from agriculture [1]. The majority of the time, diseases affecting different crops has an impact on the quantity and quality of agricultural goods [2]. Vital crop processes like photosynthesis, pollination, transpiration, germination, and fertilization are altered by these diseases [3]. Some of these illnesses are brought on by pathogens like bacteria, fungi, and viruses [4]. Continuous inspections from farmers or agricultural professionals were required for traditional methods of disease detection [5]; though, these methods are frequently inefficient, exclusive, and require significant labor [6]. By creating techniques for plant disease diagnosis and mitigation, crop productivity can be increased while using fewer pesticides [7]. Therefore, ensuring food security requires disease detection [8]. The traditional technique of identification of illness has been a physical investigation by producers, although this could be time-consuming and costly [9], [10]. Crop yield can be boosted while using fewer pesticides by developing methods for the identification and mitigation of plant diseases [11]. As a result, guaranteeing food security necessitates both the detection of diseases and the creation of improved crop varieties [12]. The traditional technique of disease detection has been manual assessment by farmers [13], but this may be time-consuming and expensive [14]. The majority of farmers now use cell phones thanks to revolutionary changes in information innovation [15]. The application of technical advancement in the agricultural sector aids in reducing yield loss [16]. Following image receipt, techniques like contrast stretching and noise filtering are undertaken to improve the image [17]. In recent years, several methods were executed in segmenting plant illnesses in leaves. For identifying the characteristics, segmenting, and diagnosing crop disease, some of the efforts utilize the Gabor filter, homogeneous pixel counting, fuzzy C-means (FCM), and artificial neural networks (ANN). The proposed work develops an adaptive radial basis function neural network (ARBFNN) approach for the segmentation process.

Here, some recent literature that focused research on tomato leaf disease, as well as some other leaf disease detection is reviewed. Residual network (ResNet) and long short-term memory-deep neural network (LSTM–DNN) based plant leaf multi-disease classification. FCM clustering algorithm was used for image segmentation [18]. The segmented image was used for multi-disease classification process. The ResNet150 was used for classification process. Plant leaf disease classification and damage detection approach initially, they identified which type of disease affected in the input image using DenseNet. This model was trained using photos that were divided into categories based on their nature, such as healthy and different types of sickness [19]. Then, new leaf images were tested using this model [20]. An image of plant illness division typical depending on an improved pulse-coupled neural network (PCNN) using a shuffled frog-leaping algorithm (SFLA) [21]. It can successfully extract lesion pictures through the surrounding area, laying the groundwork for later disease identification. Dry bean leaf disease segmentation using U-Net mechanism initially, the found the disease name from the segmented part. Then, again, they classify the diseases present in the raw input images [22]. Utilizing computer vision techniques with a super pixel cluster and hybrid neural network, a diagnostic method may be automated. Different algorithms are used to evaluate feature evaluations for color, shape, and texture [23]. Finally, the photos were divided into three groups using seven different machine learning approaches. A leaf disease that can be identified from photos of the plant, and then the system's accuracy can be increased using machine learning or deep learning methods [24]. The convolutional neural networks (CNNs) algorithm [25]-[27] is applied with cameras on independent robotic platforms to distinguish crop and weed types.

2. PROPOSED MECHANISM

The suggested methodology's primary goal is to separate the infected area from the captured plant leaf. Most diseases of the tomato plant can be detected at an early stage by attacking the leaves first. The inevitable damage can be prevented by spotting illnesses in the plants as soon as possible. For the image classification process, the segmentation stage is significantly unique. Throughout the segmentation procedure, the illness portions are segmented. For the segmentation process, an ARBFNN classifier is utilized. The suggested method involves three stages: pre-processing, feature extraction, and segmentation.

2.1. Pre-processing

For the segmentation phase, pre-processing is a crucial step. Since there will be significant distortion in the collected photos, the segmentation outcomes will be impacted. So, before being sent to the adaptive radial basis function (RBF) neural network, distorted data are pre-processed. For pre-processing, we use an adaptive median filter and histogram equalization. Initially, we apply an adaptive median filter followed that histogram equalization. The adaptive median filter is employed to eliminate the distortion from the vision. The pixel intensities frequency is changed to the median pixel value in a certain neighborhood while this filter keeps the image's essential characteristics. Avoiding distorting the image's boundaries, this filter reduces distortion in a picture. The average is determined by arranging each of the neighboring window's pixel elements in an arithmetic sequence and substituting the pixel under consideration using the center (median) pixel value. Figure 1 explains a graphical representation of the median filter and sample red, green, and blue (RGB) value is given in Figure 2. In (1) represents the mathematical expression of the median filtered image J(x,y) of the picture K(u,v) given in (1).

$$J(x,y) = \underset{(i,j)\in R_{xy}}{median}\{C(i,j)\} \quad (1)$$

Utilizing histogram equalization, the picture is improved after the distortion filtration. Changing the intensity distribution is a strategy for boosting contrast. Considering that J(x,y) is an image that has been delivered and is represented as an mr by mc matrix with integer image intensity that varies from 0 to L-1. L stands for the number of intensity values, which is often in the range of 256. Using a bin for each conceivable intensity as in (2) let the normalized histogram of J(x,y) be denoted by having a bin for every possible intensity.

$$P_n = \frac{Pixelcounthaving\ int\ ensityn}{totalpixelcount} n = 0,1,\ldots,L-1 \qquad (2)$$

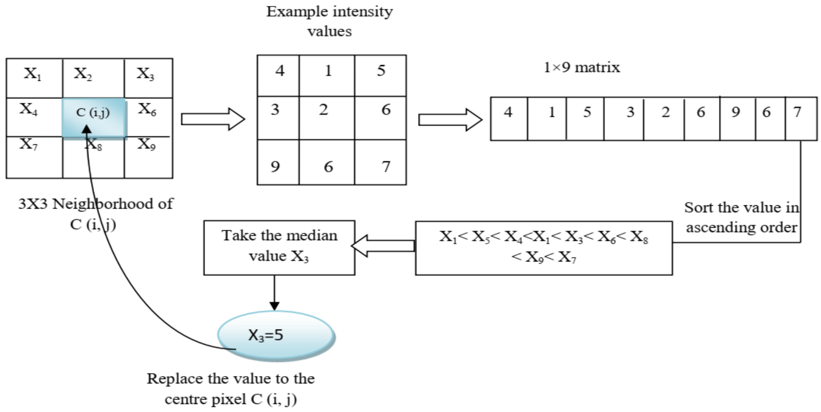

Figure 1. Graphical representation of the median filter

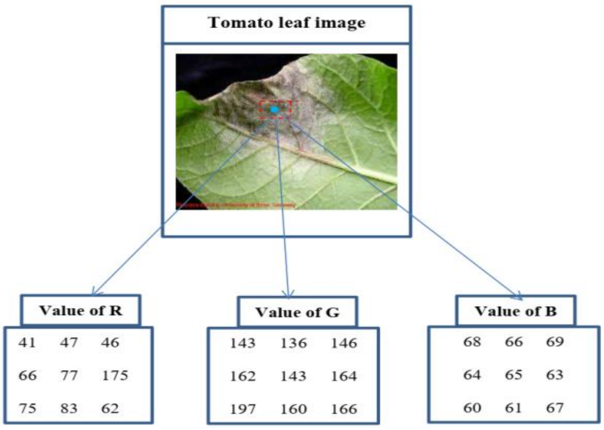

Figure 2. Color information attained through the RGB color model

2.2. Feature extraction

Here, four types of color models are expressed from every image. RGB color model consist of red (R), green (G), and blue (B). On the input image, we randomly choose twenty parameters for feature extraction. Ten of the twenty points are chosen from the healthy leaf section, and ten points are chosen through the sick area. We make the mask on each point after choosing it. Eight neighboring pixels surround the one central pixel that makes up the mask (3×3 masks). Then we record the standards R, G, and B for each point, yielding a total of 27 values [15]. Every point in Figure 2 has 27 results. As a result, 270 data (27 values multiplied by 10 photos) are collected through the ill area as well as 270 pieces of information through the normal area for every training sample. The R, G, and B components are then extracted for every image. Lighting variables have an impact on RGB photographs [16]. The following explains how to calculate ratios.

$$Re_i = \frac{Re_i}{Re_i + Gr_i + Bl_i} \qquad (3)$$

$$Gr_i = \frac{Gr_i}{Re_i + Gr_i + Bl_i} \qquad (4)$$

$$Bl_i = \frac{Re_i}{Re_i + Gr_i + Bl_i} \qquad (5)$$

This tomato leaf has a minor amount of the color blue. We, therefore, disregard the blue characteristics. Additionally, we have included additional color models for features such as HSV, YCbCr, and YIQ. HSV color model: the HSV model views for hue (H), saturation (S), and value (V). Due to illumination situations, the S and V are affecting the segmentation accuracy. So, we eliminate the features value S and V from the feature vector and we only consider the hue feature from the HSV model. In this feature model, we get nine values. YC^bC^r color model: In the YC^bC^r classical, Y opinions for luminance that is disconnected since the two chrominance mechanisms (C^b, C^r) in this color space. The leaf images in this color sample have a weak blue value in the leaf range, making them suitable for leaf segmentation. The conversion of the RGB color space to the YC^bC^r color space is approved and available utilizing in (6).

$$\begin{bmatrix} Y \\ C^b \\ C^r \end{bmatrix} = \begin{bmatrix} 0.2990.5870.114 \\ 0.596 - 0.275 - 0.321 \\ 0.212 - 0.523 - 0.311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{6}$$

The "Y" element is affected by the lighting condition [15]. Therefore, we consider both "C^b" and "C^r" as ultimate characteristics vectors, eliminating the "Y" essentials. YIQ color model: similar YCbCr, luminance and chrominance are separated in YIQ, where "Y" is luminance and "I" and "Q" is chrominance mechanisms. For instance, the "Q" channel is particularly successful for boosting leaves, while channel "I" is quite for leaf differentiation. In (7) is applied to convert the RGB color interplanetary to the YIQ color space.

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.2990.5870.114 \\ 0.596 - 0.274 - 0.322 \\ 0.211 - 0.5230.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{7}$$

The Y element is impacted by the levels of light once the YIQ detaches the luminous elements "Y" from the "I" and "Q" chromins, hence the ultimate characteristic must be eliminated from the vector. To support to ultimate characteristics vector indicating the healthy leaf/diseased leaf, elements "I" and "Q" are taken. Nowadays, this characteristics vector consists of R, G, H, C^b, C^r, I, and Q. Individually components have nine values, so the feature vector size is 63.

2.3. Segmentation using ARBFNN

Subsequently feature extraction process; the extracted attributes are fed to the input of the segmentation process. For segmentation, in this paper, ARBNN is presented. ARBNN is a combination of a flower pollination algorithm (FPA) and an RBF neural network. Here, the weight values present in the RBF neural network are optimally designated by utilizing the AFP algorithm. The segmentation process contains two phases namely, training and testing. For training, 80% of images are used and 20% of images are used for the testing process. Initially, the training process is done. Throughout the training development, the extracted features are trained in ARBNN and the final trained RBF structure is deposited. Then, throughout the testing development, based on the trained construction the segmentation is carried out. Training process: for the training process, ARBF neural network is utilized. Let us assume $A_1, A_2, \ldots, A_a$ denotes as a vector of input nodes $B_1, B_2, \ldots, B_b$ represents a vector of hidden layer nodes and $C_1, C_2, \ldots, C_c$ represents a vector of output layer nodes. Additionally, the weight among the hidden and input is represented as W_{ij}^h and the weight between the hidden and output layers W_{jk}^o. The following describes the training procedure.

- Step 1: initially, the extracted features $(A_1, A_2, \ldots, A_{63})$ are fed to the input layer of RBFNN. The extracted features and input layer neurons are idle. Following input, the weight quantity correlating to the input and hidden neuron is compounded by the feature values. The hidden layer's input, as specified in (8), receives the produced output is given below. Where α_j represent the bias value of the hidden layer.

$$B_j = \alpha_j + \sum_{i=1}^{a} A_i W_{ij}^h \tag{8}$$

- Step 2: then, the obtained B_j is fed to the gaussian RBF activation function. This function monotonous reduces the detachment through the center. It is described by its center $O_j: j = 1,2, \ldots, m$ and covariance matrices $M_j = \omega_j^2 P$. The input vector A_i with j^{th} a hidden unit is given in (9). Where, D represent the maximum distance and λ is an empirical scale factor that is used to regulate the smoothness of the mapping function. The (10) is substituted to (9) and the output layer is given below.

$$\Psi_j(B_j) = exp\left(\frac{-\|B_j - O_m\|^2}{2\omega_j^2}\right) \tag{9}$$

$$\omega^2 = \frac{\lambda D^2}{2} \tag{10}$$

$$\Psi_j(B_j) = exp\left(\frac{-\|B_j - O_m\|^2}{\lambda D^2}\right) \quad (11)$$

– Step 3: following the activation computation, we determine the RBFNN's outcome. The output layer is provided the activation function's result in this case. The (12) describes the output function. Where O_k denotes the output layers. The (13) to determine the network's learning error. Where, n represents the training information, represent the target and the output value. Adjusting the weight values is necessary to lower the error value. In this paper, we employed the FP algorithm to do this.

$$O_k = \alpha_k + \sum_{k=1}^{c} W_{jk}^{o}\, \Psi_j(B_j), j = 1,2,\dots,b \quad (12)$$

$$Error = \frac{1}{2n}\sum_{k=0}^{n-1}\sqrt{(T_k - O_k)} \quad (13)$$

2.3.1. Optimal weight selection using FP algorithm

To regulate the standards of the RBF neural network, the FP algorithm is utilized. Depending on how flowers pollinate one another, an algorithm for flower pollination was created. Generally, flower pollination involves the movement of pollen, which is commonly associated with pollinators like birds. Since some flowers may recruit and rely on specific kinds of insects or birds for successful pollination, some flowers and insects have a very skilled flower-pollinator cooperation. The majority of plant species rely on biotic pollination, in which pollinators spread pollen. The rest of pollination observes an abiotic phase that does not demand any pollinators, like grass; such flowering plants' pollination work is supported by wind and diffusion. On the other hand, self-pollination or cross-pollination can be used for pollination. Self-pollination is when one flower is pollinated by the pollen of another flower on the same plant or another flower. Cross-pollination is the process of pollinating a bloom from a different plant. The FPA can easily solve low-dimensional uni-modal optimization issues and fall on local optimum. When taking care of the high dimensional and multi-modular enhancement issues, we can find that the solution got by FPA are sufficiently bad. To enhance the global searching and local searching abilities, the firefly algorithm operation is included in the local pollination.
Stage 1: solution encoding: this algorithm's primary goal is to determine the ideal weight ratio among the hidden input and hidden output layers. A fundamental component of optimization is creating an early solution. Only after the solution has been determined can the algorithm be advanced. Initially, the solutions or flowers (S_i) are arbitrarily initialized. The initial solution is given in (14). The solution is consisting of weight values.

$$S_i = \{F_1, F_2, \dots, F_n\} \quad (14)$$

Step 2: fitness calculation: utilizing fitness value, the solution's usefulness is evaluated. We assess the fitness of each proposal following initiation. The fitness function is used to define segmentation results. The ideal approach is regarded as having the highest fitness value. In (15) contains the fitness function.

$$Fitness = Max(Accuracy) \quad (15)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (16)$$

Step 3: updation using EFPA: after the fitness calculation, each flower is updated with the help of EFPA. In FPA, two types of pollination are available namely, global pollination and local pollination. To enhance the performance of FPA, local pollination is replaced with the help of the firefly algorithm. Global pollination can be represented mathematically as (17).

$$F_i^{t+1} = F_i^t + \gamma L(\lambda)(G_* - F_i^t) \quad (17)$$

Where, F_i^t is the pollen i or resolution vector F_i at emphasis t, and is the present best solution found among all solutions at the present age/cycle. The progression size is constrained by a scaling operator γ. Here, $L(\lambda)$ means the Levy flight-based advance size that relates to the capacity of pollination. The local pollination and flower consistency can be demonstrated to as below. In that overhead equation, F_i^{t+1} demonstrates the fresh updated solution, F_i^t illustrates the present i^{th} solution and F_j^t performs the j^{th} solution. Moreover, σ_t shows the arbitrary factor and μ_i^k is a random number and $\gamma$is the constant value.

$$F_i^{t+1} = F_i^t - \beta_0^{at} e^{-\gamma \ddot{D}_{ij}^2}\left(F_j^t - F_i^t\right) + \sigma_t \mu_i^k \tag{18}$$

2.3.2. Segmentation

Images can be segmented using a method known as classification. The image's pixels each represent a pattern that can be classed. We employ fresh, untrained photos for testing purposes. We used every pixel in the tested image as well as its surrounding pixels, just like during training. The testing procedure makes use of the generated RBF neural network. A trained ERBF classifier uses the attributes to identify the class to which the samples correspond to characterize the image. It will be categorized as a damaged class if the value is larger than 0.5; else, it will be categorized as a background class.

3. RESULTS AND DISCUSSIONS

The suggested leaf disease segmentation model is simulated in the platform of Python with the system having an Intel Core i5 processor, and on a computer with 6 GB of memory using the Windows 10 OS. In this work, two types of plant leaves are used for experimentation namely, tomato and mango. The images are collected from the plant village dataset. This dataset includes several kinds of diseases in tomato and plant leaves. In the training dataset, 1,000 images are included for each disease. As well, 100 images are included for each disease in the testing dataset. Figure 3 shows segmentation output of tomato leaf. This figure contains 4 components such as: original image, noise removed image, contrast enhancement image, segmented output. Finally, the proposed model decides the healthy or specified disease name. This figure shows the five different leaves samples. The original leaves image noise is removed then go to contrast enhancement image. Next, provide the segment output and this output decides bacterial spot, Early_blight, Late_blight.

Figure 4 shows the segmentation output of mango leaf. This figure contains 5 components such as: original image, noise removed image, contrast enhancement image, segmented output. Finally, the proposed model decides the disease name or healthy. Anthracnose. This figure shows the five different leaves samples. The original leaves image noise is removed then go to contrast enhancement image. Next, provide the segment output and this output decides Anthracnose disease.

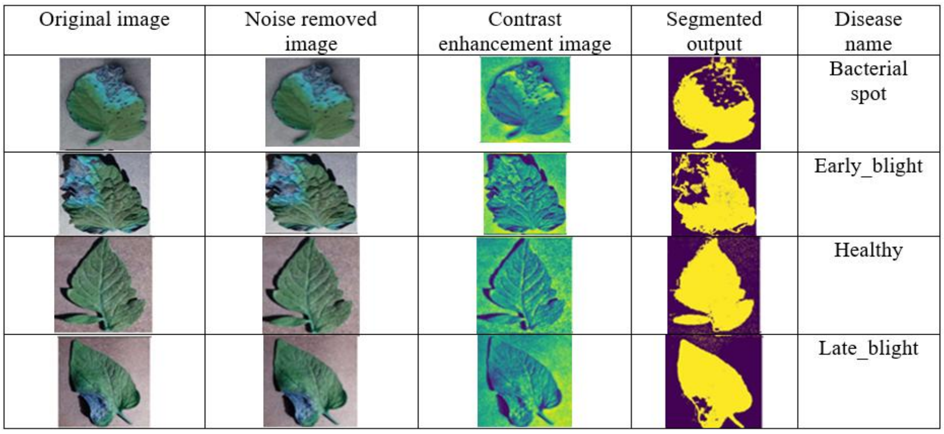

Figure 3. Segmentation output of tomato leaf

3.1. Performance analysis of tomato leaf segmentation

This section explains the suggested approach is measured against the currently used segmentation methods, such as traditional RBF, FCM, and region expanding (RG). We concluded from this investigation that the segmentation system depending on the suggested methodology yields more accurate outcomes than the RBF, FCM, and RG. The comparison of precision, recall, F-measure, accuracy, Jaccard coefficient (JC), and Dice coefficient (DC) of different segmentation models such as RBF, FCM and RG is illustrated in Figures 5 to 10.

Based on the aforementioned explanations: (i) the FCM approach degrades when initializing the cluster center and calculating the number of clusters; (ii) the RG approach suffers from over-segmentation and takes a long time; and (iii) the standard RBF applies the same weight to each attribute, which may have an impact on segmentation accuracy. As illustrated in the figure, RBF, FCM, and RG attained 95.08%, 93.97%, and 91.73% of precision correspondingly. But the suggested method attained the maximum precision i.e., 96.78%. The relative investigation of the recall of dissimilar segmentation simulations is depicted in Figure 6. The proposed method-based segmentation model attained 96.93% of the recall. The F-measure of different segmentation methods is depicted in Figure 6. Compared to RBF, FCM, and RG, the F-measure of the proposed method is increased to 97.06%. Figure 7 demonstrates the assessment of the accuracy of various segmentation approaches. Because of the proposed method-based segmentation, the accuracy is increased to 97.58% while the existing models RBF, FCM, and RG attain 94.91%, 93.08%, and 90.72% correspondingly. Figure 8 illustrates an assessment of the JC of various segmentation approaches. As illustrated in the figure, compared to FCM and RG-based segmentation models, the conventional RBF model attained the highest JC i.e., 92.05%. Thus, the proposed method attained 94.83% of the JC. The comparative analysis of the DC is depicted in Figure 9. As portrayed in the Figure 10, the proposed method-based segmentation attained 92.84% of the DC.

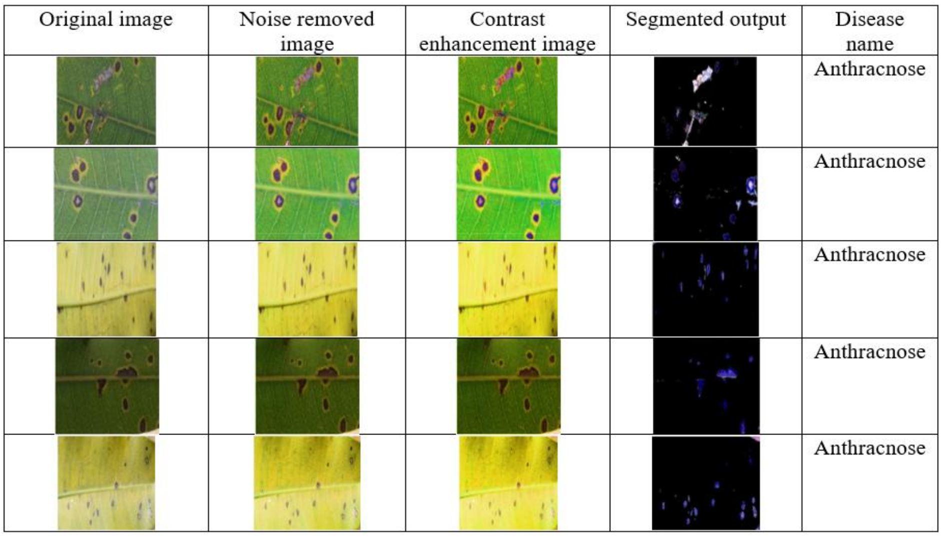

Figure 4. Anthracnose disease segmentation output

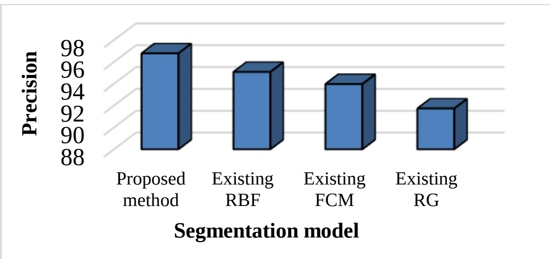

Figure 5. Precision of different segmentation

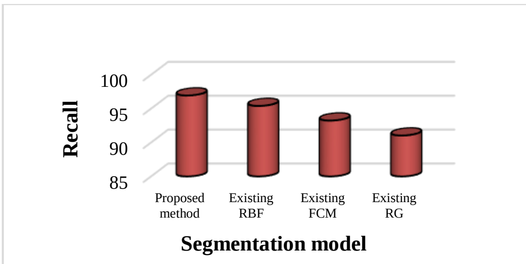

Figure 6. Recall of different segmentation

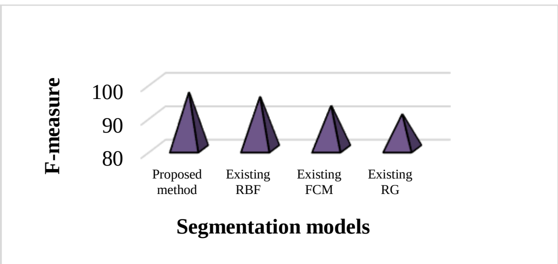

Figure 7. F-measure of different segmentation

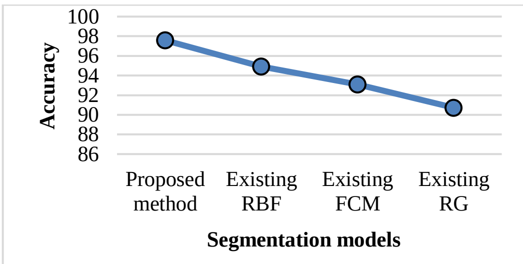

Figure 8. Accuracy of different segmentation

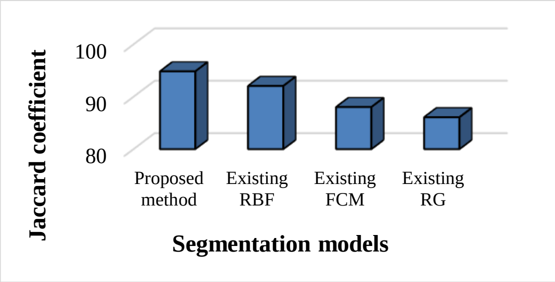

Figure 9. JC of different segmentation

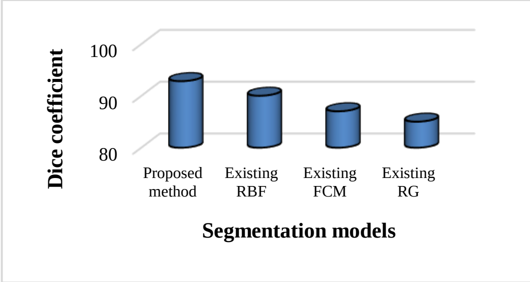

Figure 10. DC of different segmentation

3.2. Performance analysis of mango leaf segmentation

Figure 11 represents the comparison of precision with different segmentation models such as RBF, FCM, and RG. As illustrated in the figure, RBF, FCM, and RG attained 94.08%, 92.97%, and 90.86% of precision correspondingly. But the anticipated method attained the maximum precision i.e., 95.97%. The qualified investigation of the recall of various segmentation approaches is depicted in Figure 12.

As depicted in the figure, the proposed method-based segmentation model attained 95.93% of the recall. The F-measure of various segmentation representations is depicted in Figure 13. Compared to RBF, FCM, and RG, the F-measure of the proposed method is increased to 96.06%. Figure 14 demonstrates the assessment of the accuracy of various segmentation simulations. Because of the proposed method-based segmentation model, the accuracy is improved to 96.58% though the existing simulations RBF, FCM, and RG attain 93.91%, 92.08%, and 89.72% correspondingly. Figure 15 illustrates an assessment of the JC of various segmentation approaches. As illustrated in the figure, compared to FCM and RG-based segmentation models, the conventional RBF model attained the highest JC i.e., 90.05%. Thus, the proposed method attained 93.83% of the JC. The comparative analysis of the DC of different segmentation models is depicted in Figure 16. As depicted in the figure, the proposed method-based segmentation model attained 91.84% of the DC.

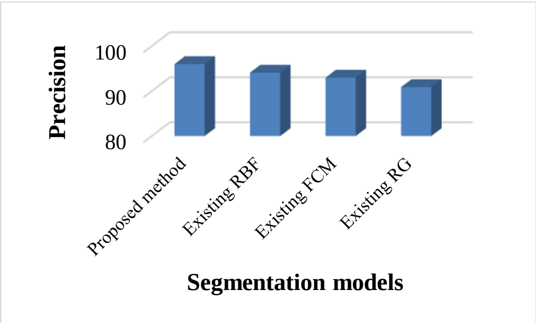

Figure 11. Precision of different segmentation

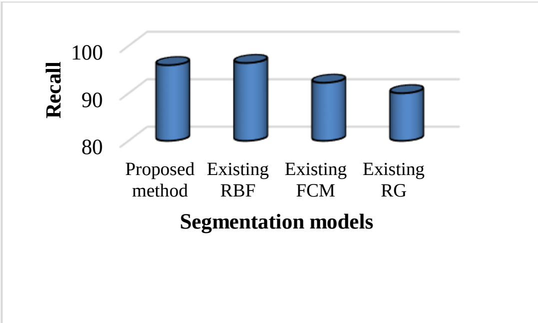

Figure 12. Recall of different segmentation

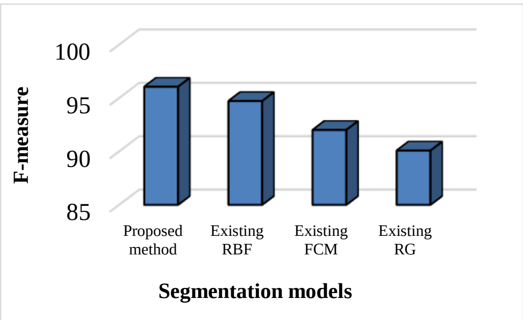

Figure 13. F-measure of different segmentation

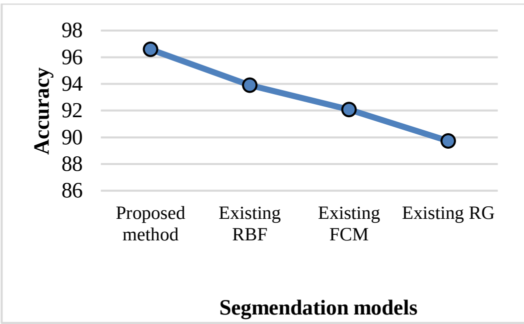

Figure 14. Accuracy of different segmentation

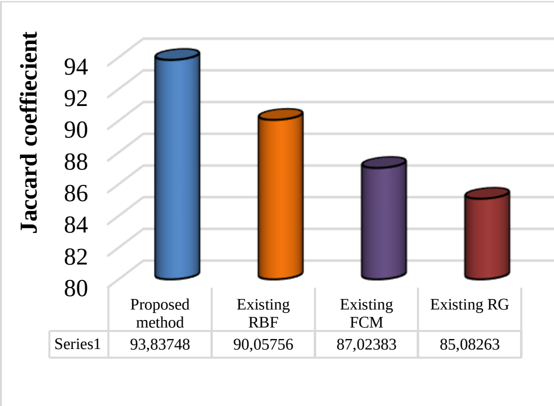

Figure 15. JC of different segmentation

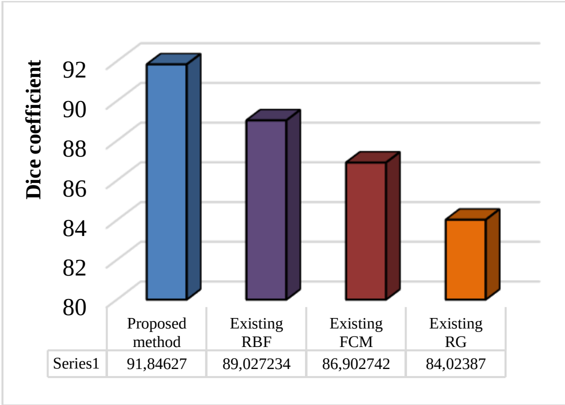

Figure 16. DC of different segmentation

3.3. Comparative analysis of previous works

This section depicts the comparative investigation of the suggested work with the previous work like precision, recall, F-measure, accuracy, JC, and DC. Agarwal *et al.* [9] had obtainable a deep learning CNN algorithm for tomato leaf segmentation. As a result of this algorithm's increased usage of computations to determine the validity index, the accuracy of the work is lower than that of the planned work by 2.71%. Nevertheless, the accuracy of the work was increased to 0.97%. An enhanced RBFNN is used for plant leaf segmentation. The JC of the work was decreased to 15 % more than that of the proposed work. Chouhan *et al*. [23] had presented a segmentation method using Superpixel cluster and hybrid neural network. Namely, compared to the proposed work, the accuracy of the work decreased to 4.6% and the specificity is 95.34%. A min-max hue histogram and K-mean clustering is used for tomato leaf segmentation. The JC of the work is decreased to 17% more than the proposed work.

4. CONCLUSION

Plants are a significant origin of food for the world population. Plant diseases lead to production loss that can be tackled with uninterrupted observing. This research presents an adaptive RBF neural network classifier-based segmentation algorithm to enhance the segmentation accuracy of diseased tomato leaves and mango leaves. Using an adaptive median filter and histogram equalization, noise that was present in the training and testing photos was eliminated during pre-processing. The suggested segmentation design adaptable RBF neural network's weight values were then enhanced utilizing the FPA, employing the obtained color features of each pixel as input. In terms of accuracy, JC, and DC, the performance of the suggested segmentation model has been examined. As depicted in the results, the proposed segmentation model has attained 97.58% of accuracy. The proposed mechanism offers suitable insights, treatments, disease avoidance, and leading in enhanced crop yields. In future, we use an artificial intelligence with machine learning algorithm to improve the accuracy in tomato and mango plant leaf images.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Jolakula Asoka Smitha	✓	✓	✓		✓	✓		✓	✓	✓			✓	
Bichagal Shadaksharappa	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
Sheela Parvathy	✓	✓	✓	✓	✓	✓			✓	✓	✓		✓	
Kilingar Veena	✓	✓		✓	✓	✓		✓	✓	✓		✓		
Albert Jenifer	✓	✓	✓		✓	✓	✓		✓	✓		✓	✓	✓
Baddala Vijaya Nirmala	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓		

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding acquisition
Fo	: **Fo**rmal analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest relevant to this paper.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [J.A.S]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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