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Original Article

Plant Disease Detection and Classification Based on Rat Swarm Optimization using Deep Learning Approach

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Abstract *- Plant diseases and pests cause considerable agricultural and ecological damage. Earlier prevention and detection of plant diseases are the most important aspect of crop harvesting since they can efficiently decrease growth disorders, thereby minimalizing the pesticide application for pollution-free crop harvesting. In that regard, automatic recognition of plant ailment using diverse Deep Learning (DL) and Machine Learning (ML) models has become an effective approach for precision agriculture. This article introduces a Rat Swarm Optimization with DL-based Plant Disease Detection and Classification (RSODL-PDDC) approach. The presented RSODL-PDDC technique is focused on the recognition and categorizing of plant diseases by implementing Computer Vision (CV) and DL models. Initially, image preprocessing is performed for noise removal that occurs in the images. Moreover, the RSODL-PDDC algorithm uses an attention based RetinaNet model for image segmentation purposes. Besides, the Class Attention Learning (CAL) layer is exploited to capture the discriminatory class-specific features while class-wise attention based on the Inception v3 (I-v3) model is applied for fine-grained semantic feature maps. For adjusting the hyper-parameters of the I-v3 method, the RSO algorithm is employed. Finally, Adaptive Neuro-Fuzzy Inference System (ANFIS) technique can be exploited for plant disease categorization. In order to validate the performance of the RSODL-PDDC technique, a widespread experimental analysis is performed. The result analysis pointed out the enhancements of the RSODL-PDDC algorithm over other approaches.*

Keywords *- Plant disease detection, Precision agriculture, Rat swarm optimization, Attention layer, Deep learning.*

1. Introduction

Plant diseases and pests will cause considerable agricultural and ecological damage. Therefore, earlier prevention and identification of different plant ailments is a central approach in agriculture technology for orchards and commercial farms [1]. In general, manual visual inspection for disease diagnoses method was time-consuming and inefficient and considerably raised overhead costs [2]. Recently, with the advanced technologies of CV in precision farming, disease diagnosis technique has become an essential component of gathering data with respect to crop health monitoring that significantly enhances the output of crop production and efficacy of disease diagnosis [3]. Prior prevention and identification of plant ailment are the key aspects of crop production; meanwhile, they could efficiently decrease any growth disorder and thereby minimalize pesticide application for pollution-free crop harvesting [4]. Precision agriculture uses modern technology to improve the decision-making method. Due to the present digital technology, an enormous quantity of data is being gathered in real-time. Different ML techniques are utilized to provide optimum decisions that result in cost reduction [5]. But this part is still available for improvement, particularly in the decision-support system that helps to turn large amounts of information into helpful recommendations [6].

Accordingly, automatic plant disease recognition using distinct ML approaches becomes an effective precision agriculture technique [7]. ML algorithms like Support Vector Machine (SVM) and K-means cluster process are applied for disease and plant detection and categorization. But because of the complicated feature extraction and image preprocessing stages, this method has low speed and performance in real-time [8]. In addition, the major drawback of conventional ML techniques is that they will not be appropriate for real-time detection scenarios with non-uniform complex circumstances. Recently, DL has made considerable progress in the realm of CV with various applications. Also, it is applied in automatic agricultural technology involving image segmentation, crop detection, and fruit and crop classification [9]. Accordingly, Convolution Neural Network (CNN)-based model has received considerable attention by establishing high accuracy in object detection. With the advancement in hardware technology [10], the DL method is currently being used to resolve complicated challenges in a comparatively short duration.

This article introduces a Rat Swarm Optimization with DL-based Plant Disease Detection and Classification (RSODL-PDDC) approach. The presented RSODL-PDDC technique focuses on recognizing and categorizing plant ailments by implementing CV and DL models. Initially, image preprocessing is performed to get rid of the noise that exists in the images. Moreover, the RSODL-PDDC technique uses an attention-based RetinaNet model for image segmentation purposes. Besides, the Class Attention Learnings (CALs) layer is exploited to capture the discriminative classing of specific features, while class-wise attention based on the I-v3 model is applied for fine-grained semantic feature maps. The RSO algorithm is employed to adjust the hyperparameters of the I-v3 method. Finally, Adaptive Neuro-Fuzzy Inference System (ANFIS) technique can be exploited for plant disease categorization. In order to validate the performance of the RSODL-PDDC technique, a widespread experimental analysis is performed.

2. Literature Review

Jayaramu et al. [11] present an approach for disease diagnoses on the rice and cotton plant leaf image data. To express the presented technique, a Subtractive Pixel Adjacency Matrix (SPAM) algorithm is applied for feature extraction. At the same time, the Exponential Spider Monkey Optimization (ESMO) approach is presented for optimal feature selection from extracted features. In [12], the authors suggested a Deep Neural Networks (DNNs) approach to identify paddy leaf diseases by implementing a plant imaging dataset. Categorization error was minimalized by enhancing biases and weights in the DNN mechanism with the Crow Search Algorithm (CSA) at the time of fine-tuning and pretraining models. Uma and Meenakshi [13] developed an optimum DNN for efficiently recognizing the disease of apple trees. This study applies a CNN for capturing the feature of Apple leaves. The extracted feature was enhanced by means of optimization techniques. The optimized feature was applied in the leaf ailment detection method. The conventional DNN method is now adapted through the weight-optimizing process with Adaptive Monarch Butterfly Optimization (AMBO) technique.

Ruth et al. [14] present an architecture by using Optimum DNN (ODNN) to identify plant leaf diseases through the leaf image of diseased and healthy plants. The study makes use of work that uses CNN for feature extraction. In this work, a two-stage weight optimization is applied to boost conventional DNN accuracy. A two-stage weight optimization can be performed by Butterfly Optimization Algorithm. Now, the conventional BOA is enhanced by means of GA; this doubles weight updating optimizes the convergence speed to a substantial number. Pavithra and Kalpana [27] proposed a plant disease detection with DL-based EfficientNet using the KELM technique. In addition, the proposed technique comprises an EfficientNet B0-based feature-extracting process for deriving optimum feature vectors that are later categorized by the KELM technique.

Umamageswari et al. [16] developed a novel architecture for plant leaf disease recognition. The presented method comprises four stages involving classification, preprocessing, segmentation, and feature extraction. Initially, the image contrast level is improved, and overfitting and unwanted noise is eliminated. The feature extraction can be done by a faster GLCM feature extraction model, and in [17] proposed an automatic architecture with DL and feature selecting for cucumber leaf disease detection at the initial stage, fine-tuned 4 pre-trained methods. Following, fuse the feature of those tuned approaches and employ the Entropy-ELM method, and lastly merge with stage 1 chosen features.

3. The Proposed Model

In this research, a novel RSODL-PDDC approach for accurate plant disease recognition and categorization model by employing CV and DL models is designed. Initially, image preprocessing is accomplished to eradicate the noise existing in the image. Following, the RSODL-PDDC technique exploited the attention-based RetinaNet model for image segmentation purposes. Moreover, a class-wise attention-based I-v3 model with an RSO algorithm is employed for feature extraction. Finally, the ANFIS model can be utilized for plant disease categorization. Fig. 1 illustrates the comprehensive block diagram of the RSODL-PDDC algorithm.

3.1. Image Preprocessing and Segmentation

First, the median filter is implemented for noise removal, and attention-based RetinaNet is enforced for image segmentation. RetinaNet exploits ResNet as a backbone network for the feature extraction of the target in the image [18]. These layers realize the recognition of targets through the regression and recognition networks generated by the Fully Convolution Network (FCN). In Resnet50, the residual blocks are exploited to directly combine the output of shallow and deep layers to solve the difficulties of network degradation and gradient distribution difficulties. Fig. 2 depicts the infrastructure of RetinaNet. The small-scale target has fewer pixel data, so it could be easier to lose during the down-sampling process.

Hence, to manage the challenges of target detection with apparent scale difference, conventional approaches make use of image pyramids to extract multiscale features that include significant computation. FPN incorporates low-resolution feature mappings with high-resolution feature maps and strong semantic data with weak semantic datasets; however, rich spatial data to accomplish multiscale feature datasets of the target and resolves the problems.

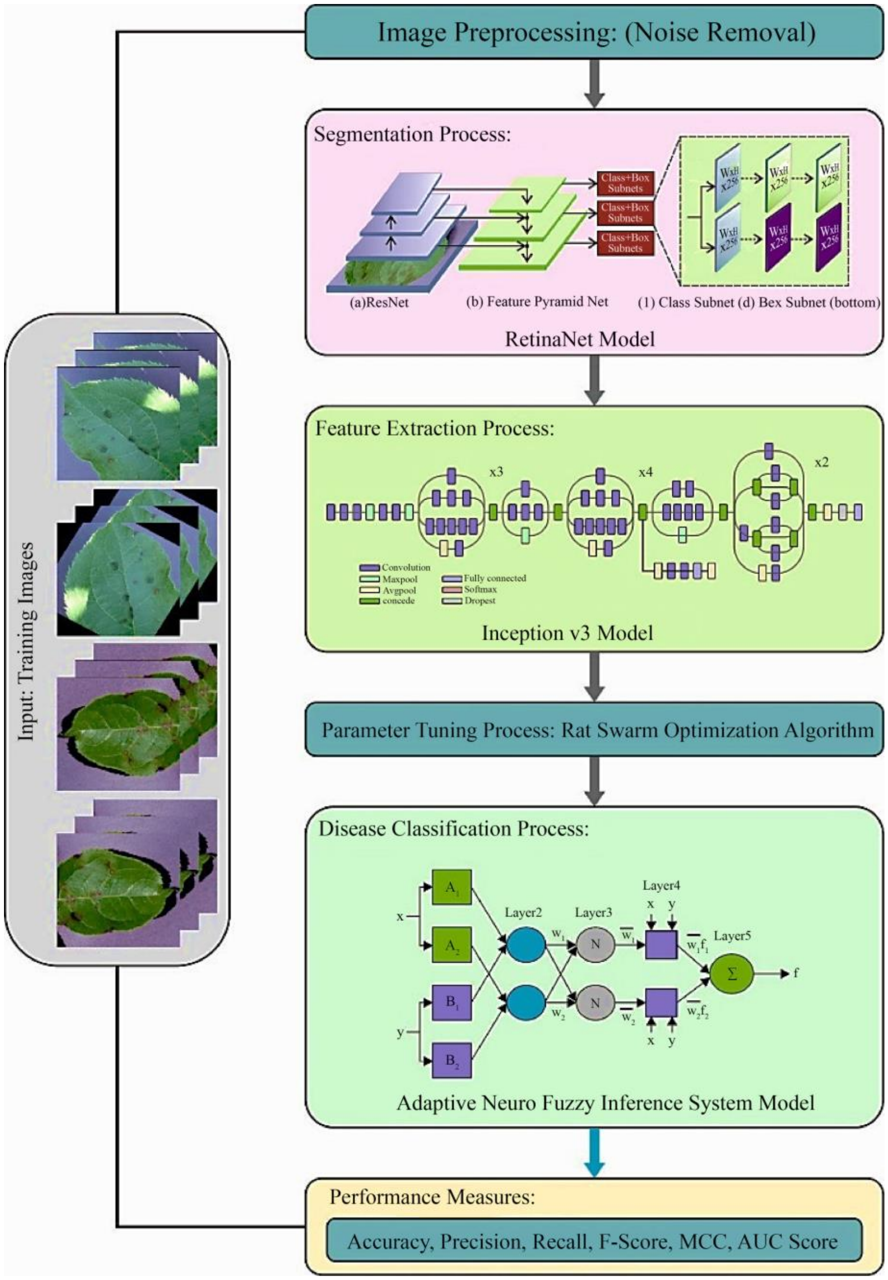

Fig. 1 Overall block diagram of RSODL-PDDC system

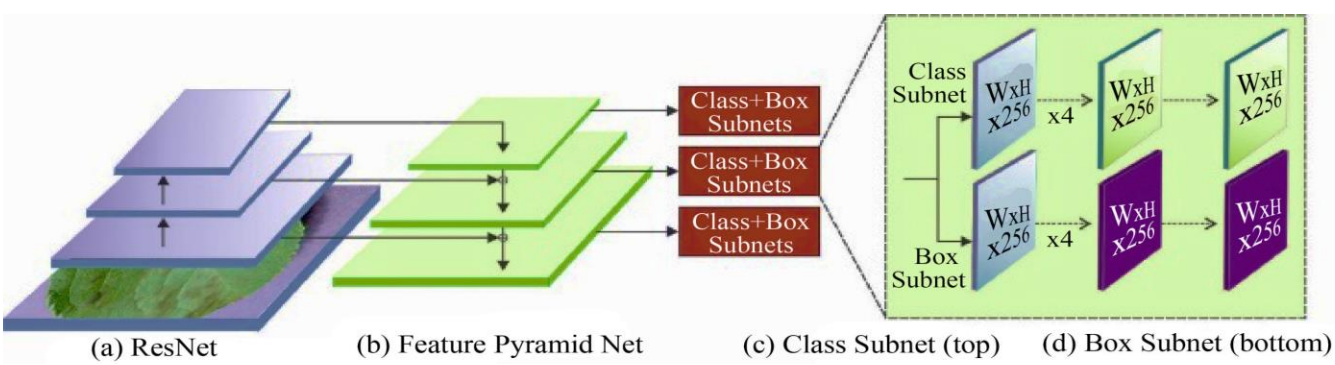

Fig. 2 Structure of RetinaNet

Though RetinaNet obtained enhanced performance when compared to the other classical networks, it has a complication in correctly recognizing and classifying the tea leaf disease in the image as a result of the complex background sand largescale change in the image of contaminated tea leaf. The X model integrates the multi-scale features extracted by the Resnet50 to obtain feature layers with rich semantic data that resolves the problems of gradient vanishing. Thus, the efficient feature layer is attained by multiscale feature fusion, thus decreasing the misdetection.

3.2. Feature Extraction

For producing feature vectors, the CAL with the I-v3 model is used. This model is a pretrained CNN mechanism comprising connections of 350 and layers of 316 [19]. The amount of complex layers is 94 of dissimilar filtering size, whereby the initial input layer size is 299x299x3. Activation can be implemented on the initial complex layer and attain a weight matrix of dimensional value 149x149x32, whereby 32 represents the amount of filters. Next, add ReLu activation and batch normalization layers. The ReLu layer can be mathematically formulated as follows:

$$\mathrm{Re}_i^{(l)} = \max\left(hv, hv_i^{(l-1)}\right) \tag{1}$$

Among the complex layering, add a pooling layer for attaining active neurons. In the initial max pooling layer, the filtering size is 2x2. The max pooling can be mathematically expressed as follows:

$$mx_1^{(q)} = mx_1^{(q-1)} \tag{2}$$

$$mx_2^{(q)} = \frac{mx_2^{(q-1)} - F(q)}{Sq} + 1 \tag{3}$$

$$mx_3^{(q)} = \frac{mx_3^{(q-1)} - F(q)}{Sq} + 1 \tag{4}$$

Whereas, S^M represents the stride, x_1^M , mx_2^M, and mx_3^M represent the filter for feature set maps as 2x2 and 3x3. Furthermore, other layers are added, namely concatenation and addition layers. Eventually, an average pooling layer is included. The activating process can be implemented, and in the result, the resulting weight matrices are attained by the feature maps of 1x1x2048 dimension. The final layer is FC; its learned weight matrices are 1000x2048, and the resultant feature matrices are 1x1x1000. The layering of FC is mathematically represented by:

$$Fc_i^{(l)} = f\left(z_i^{(l)}\right) with\ z_i^{(l)} = \sum_{j=1}^{n_1^{(l-1)}} \sum_{r=1}^{n_2^{(l-1)}} \sum_{s=1}^{n_3^{(l-1)}} w_{i,j,r,s}^{(l)} \, (Fc_i^{(l-1)})_{r,s} \tag{5}$$

Extracting discriminatory class-wise features has played a crucial role in effectively bridging CNN and RNN and determining class dependencies for multi-label classification tasks [20]. Now, a class attention learning layer is proposed for exploring features for all the categories, and the presented layer comprises the subsequent two phases: (1) vectorizing all the class attention maps to accomplish class-specific features and (2) generating class attention maps through the 1x1 convolution layer with stride 1:

$$M_l = X * w_l \tag{6}$$

In Eq. (6), l will range from 1 to the class numbers and denotes the convolution function.

3.3. Hyperparameter Tuning

At this level, the RSO technique is utilized for the parameter tuning the I-v3 approach. The RSO technique is dependent on the attacking and chasing actions of rats [21].

They have medium-sized and long-tailed rodents, are socially intelligent, and are territorial animals that live in groups of two females and males; they participate in different actions like tumbling, jumping, boxing and running. On the other hand, they are extremely aggressive in most cases leading to death.

These behaviours during fighting and hunting with prey. Those behaviours of the rats can be mathematically modelled for designing the RSO and accomplishing the optimization. Due to their agonistic social behaviour, they hunt prey in groups. Consider that the finest researchers know the prey position. Another search agent could upgrade the position against the better search agent and formulated as follows:

$$X = A \times X_i + C \times (X_{Best} - X_i) \tag{7}$$

In Eq. (7), $\vec{X}$ characterizes the position of rats, and X indicates the better solution. A and C are evaluated by:

$$A = R - x\left(\frac{R}{Max_{Iteration}}\right), 1 \leq R \leq 5 \tag{8}$$

Where x in $[0,12 \ldots \mathrm{Max} - \mathrm{iteration}]$. Consequently, R and C are randomly generated numbers within [1,5] and [0,2]. A and C parameters are accountable for the best exploitation and exploration in the iteration process. The fighting activity of rats with prey is mathematically expressed by:

$$X_{i+1} = |X_{Best} - X_i| \tag{9}$$

Algorithm 1: Pseudocode of RSO
Start
Initialization of the rat population Pi whereas $i = 1,2 \ldots n$.
Select the initial parameter of RSO: A, C, and R.
Compute the value of fitness for all the search agents.
The improved search agent is explored in the provided search range.
Update the position of the searching agent based on Eq. (7).
Check if any searching agent goes beyond the boundary limits of the searching range and then adjust it.
Then, compute the upgraded fitness value of the searching agents and upgrade the vector Xbest when there exists a best solution than the prior optimum solution.
End the procedure if the ending standards are reached.
Or else, go to Step 5.
Return to the better solution obtained so far.
End

In Eq. (9), X_{i+1} determines the recently upgraded location of the rat. It stores the better solution and updates the position of other searching agents against the better searching agent. By altering the parameter, as demonstrated in Eq. (8), the number of locations can be obtained around the present location. The adjusted value of A and C parameters assurance better exploitation and exploration. The RSO technique records the ideal solution with the smallest operator.

3.4. Image Classification

In this work, the ANFIS technique is exploited for the classification process. ANFIS is the NN learning capacity that can enhance the efficacy of intellectual methods by implementing a priori data [28]. Generally, it is based on the theory of (T-S)-Type FIS. This technique constructs a Fuzzy model and alters the Membership Function (MF) by implementing particular inputted and outputted data. ANFIS is a networking-type architecture similar to NN and applies fuzzy MF for mapping the inputted and outputted data. The Takagi-Sugeno 2-rule method depended on the ANFIS approach with a single outputting value (Y) and various inputting values (M and N). Now, the fuzzy MF to M and N inputs are a_1, a_2, and b_1, b_2 correspondingly. The Takagi-Sugeno ANFIS includes the succeeding 2 rules:

$$if\ M\ is\ a_1\ and\ N\ is\ b_1, then\ f_1 = r_1 M + s_1 N + t_1 \quad (10)$$

$$if\ M\ is\ a_2\ and\ N\ is\ b_2, then\ f_2 = r_2 M + s_2 N + t_2 \quad (11)$$

Where r_j, s_j, and t_j indicates the consequence parameter. Generally, the ANFIS model encompasses five layers.

In layer 1, the amount of nodes relies on the inputted value MF. Every individual is an adaptive node, and its outcome is given by:

$$O_{1,j} = \mu a_j(M)\ for\ j = 1,2 \quad (12)$$

$$O_{1,j} = \mu b_{j-2}(N) for\ j = 3,4 \quad (13)$$

Where μ, and $O_{1,j}$ shows the MF and their value to the M and N inputs correspondingly.

Layer 2 nodes have static nodes, proceed the outputting value (the value of membership) in the preceding layer, and its outcome is mentioned as follows:

$$O_{2,j} = z_j = \mu a_j(M)\mu b_j(N) for\ j = 1,2 \quad (14)$$

In layer 3, every node is regarded as a set layer node that was applied for scaling the firing strength is represented as follows:

$$O_{3,j} = \overline{z}_j = \frac{z_j}{z_j + z_j} \quad (15)$$

In layer 4, the rule consequent is applied to compute and adapt all the nodes by employing the succeeding relation:

$$O_{4,j} = \overline{z}_j f_j = \overline{z}_j\left(r_j M + s_j N + t_j\right) \quad (16)$$

Finally, to obtain the concluding output, each input signal is added together, as given below:

$$O_{5,j} = \sum \overline{z}_j\, f_j = \frac{\sum_j z_j\, f_j}{\sum_j z_j} \quad (17)$$

In Eq. (17), z_j indicates the minimal quantity of MFs and f characterize the resulting MF centre value. The ANFIS technique-trained function was reliant on the iteration count. Layer 4 describes the resulting nodes from each iterating; however, layer 5 defines the consequent parameter. The ANFIS method was trained through a fusion mechanism incorporating Backpropagation (BP) with Least Square Estimations (LSEs) to enhance the premise and the related co-efficient.

4. Results and Discussion

In this segment, the RSODL-PDDC approach's plant ailment identification outputs are investigated by implementing two datasets [23]: Grape Plant Disease (GPD) dataset and Apple Plant Disease (APD). Table 1 details the description of the dataset. Fig. 3 exhibits the sample apple and grape plant disease images.

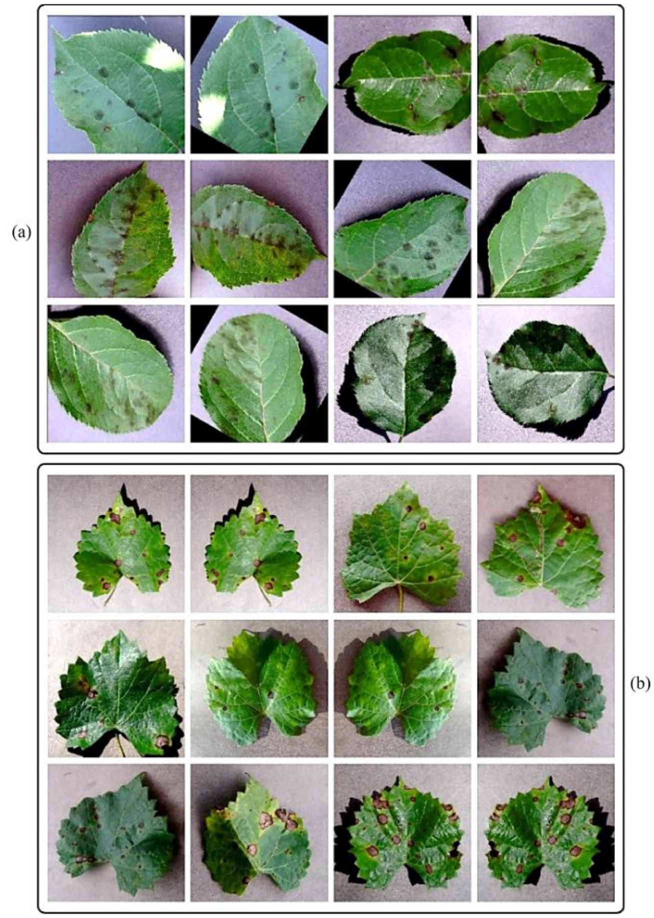

Fig. 3 Images a) APD b) GPD

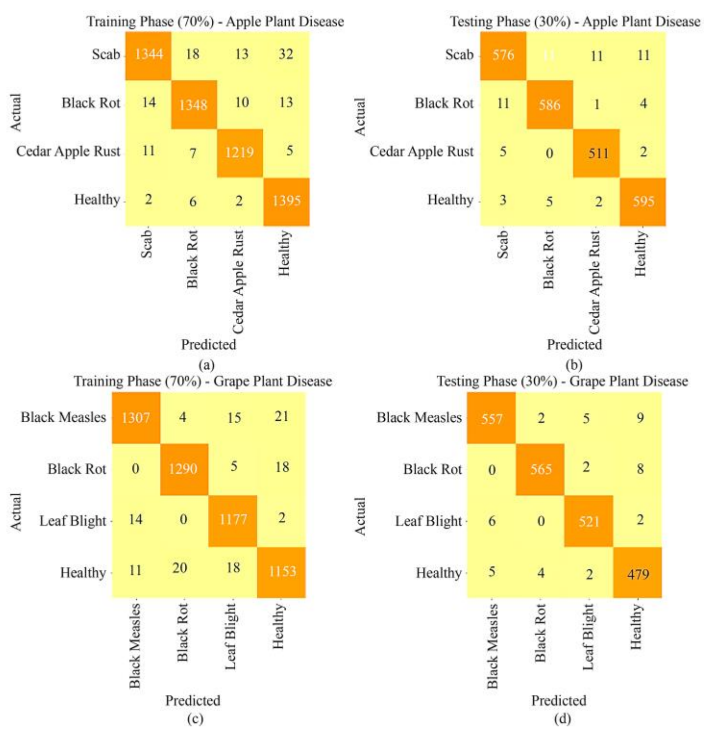

Fig. 4 Confusion matrices of RSODL-PDDC model of 70 and 30 percent TR/TS data on (a-b) APD and (c-d) GPD

Table 1. Details of dataset

APD Dataset		GPD Dataset	
Disease	**Image Nos**	**Disease**	**Image Nos**
Scab	2016	Black Measles (BM)	1920
Black Rot (BR)	1987	BR	1888
Cedar Apple Rust (CAR)	1760	Leaf Blight (LB)	1722
Healthy	2008	Healthy	1692
Overall Imageries	**7771**	**Overall Imageries**	**7222**

The confusion matrices of the RSODL-PDDC approach have illustrated in Fig. 4. The outcomes denoted that the RSODL-PDDC approach has categorized different kinds of plant diseases on both datasets.

Table 2 and Fig. 5 demonstrate a comprehensive classifier output of the RSODL-PDDC approach on the APD dataset. The investigational values signified that the RSODL-PDDC system has demonstrated all classes. As a sample, on 70 percent TR data, the RSODL-PDDC technique has obtained average $accu_y$ of 98.78%, $prec_n$ of 97.58%, $reca_l$ of 97.57%, F_{score} of 97.57%, AUC_{score} of 98.38%, and MCC of 96.76%. Simultaneously, on 30% of the TS dataset, the RSODL-PDDC technique has obtained average $accu_y$ of 98.58%, $prec_n$ of 97.17%, $reca_l$ of 97.23%, F_{score} of 97.20%, AUC_{score} of 98.14%, and MCC of 96.25%.

The TACC value and VACC value of the RSODL-PDDC method under APD dataset achievement in Fig. 6. The figure illustrates that the RSODL-PDDC model has demonstrated greater achievement with enhanced TACC value and VACC value. It is evident that the RSODL-PDDC model has attained greater TACC results.

Table 2. Overall classifier result of RSODL-PDDC technique under APD dataset

Apple Plant Disease Dataset						
Class	**$Accu_y$**	**$Prec_n$**	**$Reca_l$**	**F_{Score}**	**AUC_{Score}**	**MCC**
Training (70%)						
Scab	98.35	98.03	95.52	96.76	97.43	95.66
BR	98.75	97.75	97.33	97.54	98.28	96.70
CAR	99.12	97.99	98.15	98.07	98.78	97.50
Healthy	98.90	96.54	99.29	97.89	99.02	97.17
Average	**98.78**	**97.58**	**97.57**	**97.57**	**98.38**	**96.76**
Testing (30%)						
Scab	97.77	96.81	94.58	95.68	96.74	94.19
BR	98.63	97.34	97.34	97.34	98.21	96.42
CAR	99.10	97.33	98.65	97.99	98.94	97.41
Healthy	98.84	97.21	98.34	97.77	98.68	96.99
Average	**98.58**	**97.17**	**97.23**	**97.20**	**98.14**	**96.25**

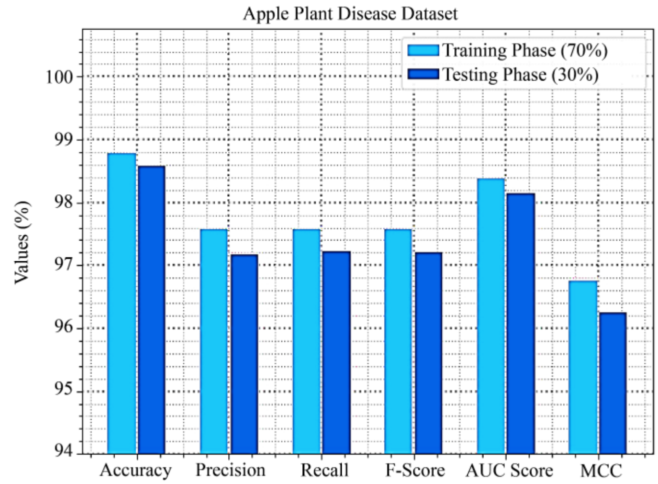

Fig. 5 Overall classifier outcome of RSODL-PDDC approach under APD dataset

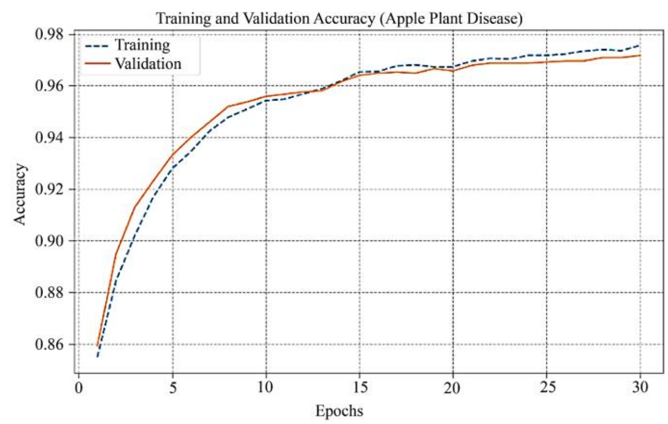

Fig. 6 TACC and VACC output of RSODL-PDDC approach under APD dataset

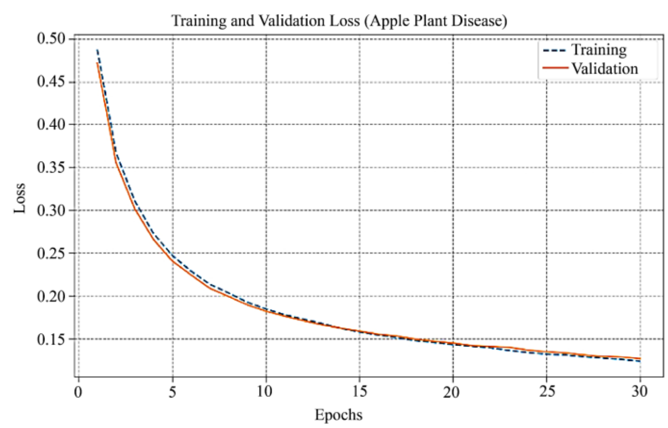

Fig. 7 TLS and VLS output of RSODL-PDDC approach under APD dataset

The TLS value and VLS value of the RSODL-PDDC model are examined under APD dataset achievement in Fig. 7. The figure concluded that the RSODL-PDDC methodology exhibited advanced achievement with lesser TLS value and VLS value. It is noticeable that the RSODL-PDDC methodology has given an outcome in mitigated VLS results.

Table 3. Overall classifier result of RSODL-PDDC technique under GPD dataset

Grape Plant Disease Dataset						
Class	**$Accu_y$**	**$Prec_n$**	**$Reca_l$**	**F_{Score}**	**AUC_{Score}**	**MCC**
Training (70%)						
BM	98.71	98.12	97.03	97.57	98.18	96.70
BR	99.07	98.17	98.25	98.21	98.80	97.58
LB	98.93	96.87	98.66	97.76	98.84	97.06
Healthy	98.22	96.57	95.92	96.24	97.43	95.08
Average	**98.73**	**97.43**	**97.47**	**97.45**	**98.31**	**96.61**
Testing (30%)						
BM	98.75	98.06	97.21	97.63	98.26	96.79
BR	99.26	98.95	98.26	98.60	98.94	98.10
LB	99.22	98.30	98.49	98.39	98.97	97.88
Healthy	98.62	96.18	97.76	96.96	98.31	96.07
Average	**98.96**	**97.87**	**97.93**	**97.90**	**98.62**	**97.21**

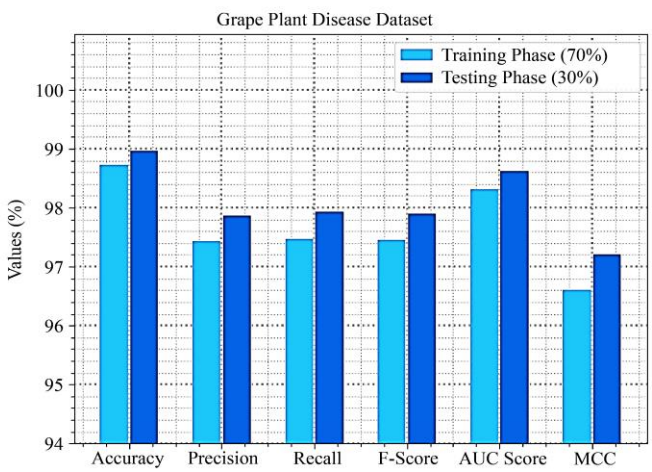

Fig. 8 Overall classifier outcome of RSODL-PDDC approach under the GPD dataset

Table 3 and Fig. 8 signify a comprehensive classifier output of the RSODL-PDDC approach on the GPD dataset. The investigational values specified that the RSODL-PDDC approach has demonstrated all classes. As a sample, on 70 percent TR data, the RSODL-PDDC approach has obtained average $accu_y$ of 98.73%, $prec_n$ of 97.43%, $reca_l$ of 97.47%, F_{score} of 97.45%, AUC_{score} of 98.31%, and MCC of 96.61%. Simultaneously, on 30% of TS data, the RSODL-PDDC model has accomplished average $accu_y$ of 98.96%, $prec_n$ of 97.87%, $reca_l$ of 97.93%, F_{score} of 97.90%, AUC_{score} of 98.62%, and MCC of 97.21%.

The TACC value and VACC value of the RSODL-PDDC method under GPD dataset achievement in Fig. 9. The figure depicted that the RSODL-PDDC approach has illustrated enhanced achievement with enhanced TACC value and VACC value. It is evident that the RSODL-PDDC approach has attained extreme TACC results.

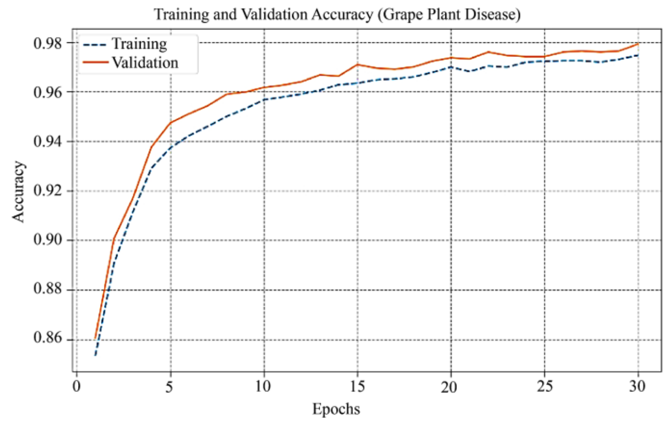

Fig. 9 TACC and VACC outcome of RSODL-PDDC model under GPD dataset

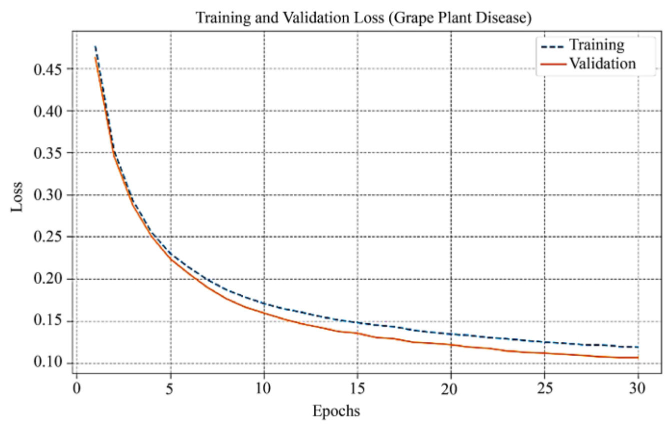

Fig. 10 TLS and VLS outcome of RSODL-PDDC technique under GPD dataset

The TLS value and VLS value of the RSODL-PDDC model are examined under GPD dataset achievement in Fig. 10. The figure illustrates that the RSODL-PDDC model has shown an improved achievement with lesser TLS value and VLS values. It is noticeable that the RSODL-PDDC method has given an outcome in decreased VLS results.

In Table 4 and Fig. 11, a short relative study of the RSODL-PDDC approach with other methods on the Apple dataset is given [24-26].

Table 4. Accuracy analysis of the RSODL-PDDC method with other algorithms under the APD dataset

Apple Dataset	
Method	**Accuracy (%)**
RSODL-PDDC	98.78
SVM	68.73
BP	54.63
AlexNet	91.19
CNN-MN	73.50
I-v3	75.59
ResNet152	77.65

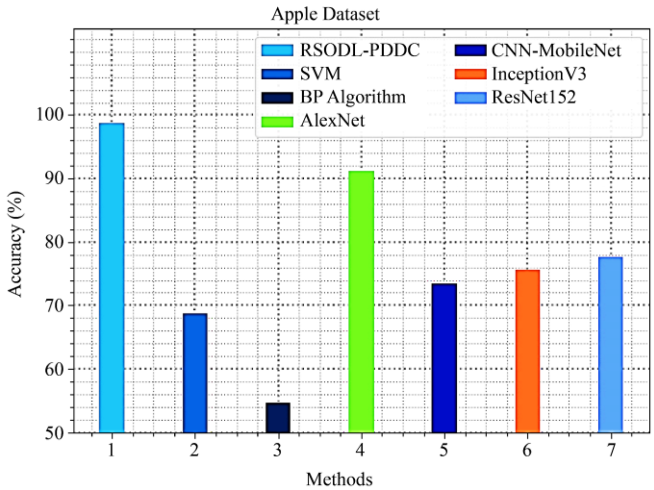

Fig. 11 $Accu_y$ analysis of the RSODL-PDDC approach under the APD dataset

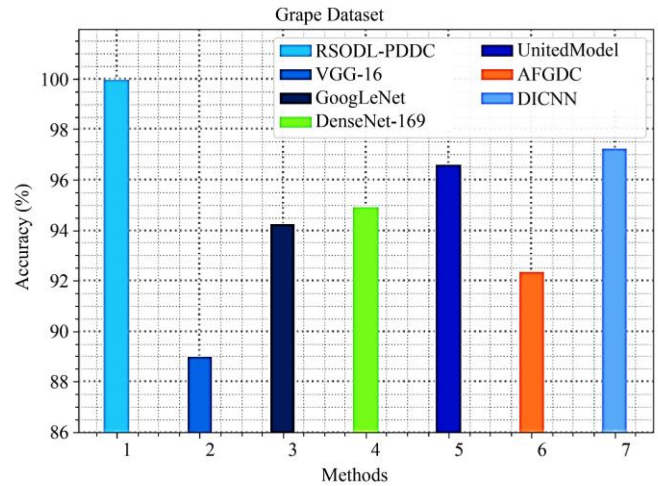

Fig. 12 $Accu_y$ analysis of the RSODL-PDDC approach under the GPD dataset

The investigational values inferred that the BP and SVM systems had reported lesser performance with $accu_y$ of 54.63% and 68.73% correspondingly.

Next, the SVM, CNN-MobileNet (CNN-MN), I-v3, and ResNet152 models have accomplished closer $accu_y$ of 68.73%, 73.50%, 75.59%, and 77.65% correspondingly. But the RSODL-PDDC model has reached maximum $accu_y$ of 98.78%.

The result confirmed the enhanced achievement of the RSODL-PDDC model compared to other approaches to plant disease classification.

Table 5. Accuracy analysis of the RSODL-PDDC method with other algorithms under the GPD dataset

Grape Dataset	
Methods	**Accuracy (%)**
RSODL-PDDC	99.96
VGG-16	88.96
GoogLeNet	94.25
DenseNet-169	94.89
UnitedModel	96.58
AFGDC	92.33
DICNN	97.22

Table 5 and Fig. 12 show a short relative study of the RSODL-PDDC method with other approaches on the Grape dataset. The experimental value shows that the VGG-16 and AFGDC methods have reported lower performance with $accu_y$ of 88.96% and 92.33% correspondingly. Next, GoogLeNet, DenseNet-169, United and DICNN models have accomplished closer $accu_y$ of 94.25%, 94.89%, 96.58% and 97.22% correspondingly. But the RSODL-PDDC model has reached maximum $accu_y$ of 99.96%.

5. Conclusion

In this research, a novel RSODL-PDDC technique for accurate plant disease recognition and categorization technique by employing CV and DL models is designed. Initially, image preprocessing is accomplished to eliminate the noise existing in the imageries. Following, the RSODL-PDDC technique exploited the attention-based RetinaNet model for image segmentation purposes. Moreover, a class-wise attention-based I-v3 model with an RSO algorithm is employed for feature extraction. Finally, the ANFIS model can be utilized for plant disease classification. In order to validate the performance of the RSODL-PDDC technique, a widespread experimental analysis is accomplished. The result analysis reported the enhancements of the RSODL-PDDC method over other approaches. In the future, the accomplishment of the RSODL-PDDC approach can be enhanced by contrast enhancement and feature fusion approaches.

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