

Tuned weighted feature fusion with hybridized DNN-RNN framework for plant disease detection and classification

K P Chaitanya & A. Mary Posonia

To cite this article: K P Chaitanya & A. Mary Posonia (2024) Tuned weighted feature fusion with hybridized DNN-RNN framework for plant disease detection and classification, International Journal of Remote Sensing, 45:5, 1608-1639, DOI: [10.1080/01431161.2024.2313995](https://doi.org/10.1080/01431161.2024.2313995)

To link to this article: <https://doi.org/10.1080/01431161.2024.2313995>



Published online: 16 Feb 2024.



Submit your article to this journal [↗](#)



View related articles [↗](#)



View Crossmark data [↗](#)



Tuned weighted feature fusion with hybridized DNN-RNN framework for plant disease detection and classification

K P Chaitanya^a and A. Mary Posonia^b

^aResearch Scholar, Sathyabama Institute of Science and Technology (Deemed to be University), Semmancheri, Chennai, TamilNadu, India; ^bComputer science and Engineering, Sathyabama Institute of Science and Technology (Deemed to be University), Semmancheri, Chennai, TamilNadu, India

ABSTRACT

In the world economy, agriculture is an essential part among individuals to earn money. But, the farmers face more obstacles because more diseases naturally affect the health of the plant. Hence, to overcome this limitation, automatic plant disease identification techniques are essential to monitor the growth as well as disease-affected plants and leaves. In most plants, symptoms related to plant disease can be identified by considering the leaves. Moreover, plant disease identification became more essential with deep learning architecture. Hence, it is important to enhance the solution for resource-constrained portable devices like smartphones, but it become a complicated issue as the deeply structured methods utilize extensive resources for the analysis. Hence, this paper aims to develop an automated plant disease detection framework with an advanced set of plant features. The plant images are taken from online sources. The acquired plant images undergo image enhancement using the contrast enhancement process. The enhanced images are fed in the feature retrieval phase 1, where the segmentation takes place using the Centre Optimized K-means clustering (CO-KMC) with the Modified Random Variable-based Black Widow Optimization (MRV-BWO). Later, the segmented images obtain the colour, shape, and texture features and they are considered as the first set of features. The second set of features is retrieved from the enhanced images using Multi-scale Dilated Attention CNN (MSDA-CNN). These two features are fused by the weighted feature fusion process using the developed MRV-BWO. Then, the plant diseases are detected using the Hybridized Deep Neural Network with Recurrent Neural Network (HDNN-RNN), which comprises RNN and DNN models. The parameter optimization takes place in the hybrid HDNN-RNN for improving the detection efficiency using MRV-BWO. From the verification of the findings, the recommended model obtains a 96.47 precision and accuracy rate. Therefore, the simulation results of the offered model reveal that it achieves enriched efficacy when comparing other baseline approaches.

ARTICLE HISTORY

Received 10 August 2023
Accepted 23 January 2024

KEYWORDS

Plant disease detection and classification; modified random variable-based black widow optimization; hybridized deep neural network with recurrent neural network; centre optimized K-means clustering; contrast enhancement

1. Introduction

The presence of different diseases in plants generates more impact on the quality and quantity of agricultural commodities. If plant diseases are not identified in the initial phases, then it efficiently enhances the food insecurity rate (Dwivedi et al. 2021). So, the initial warning stage and plant disease recognition are essential to control plants from diseases and make better decisions in agricultural production (Sunil, Jaidhar, and Patil 2022). The classical plant disease detection techniques are designed according to manual visual observations by field professionals. This process consumes more time and minimizes the prediction rate, but it does not execute in wide ranges and is a difficult procedure. Moreover, it is complicated to execute in real-world scenarios to effectively identify the plant disease (Zeng et al. 2020). The quick enhancement of image processing technology offered a new plant disease detection scheme with pattern identification and image processing models (Kumar, Kumar, and Palaparthi 2021). They offered a better disease detection rate in plant diseases using plant leaf images (Dwivedi, Dutta, and Hu 2022).

Classical visual investigations are done by professionals to recognize plant diseases (Barburiceanu et al. 2021). Moreover, they generate more errors according to biased perceptions. Here, different imaging and spectroscopic methods are developed to identify plant diseases (Zhou et al. 2019). But, they need highly accurate tools and numerous sensors, whose price ranges are high and offer minimal efficacy rates. Generally, professionals recognize plant disease with the naked eye, but it cannot be applied in remote sensing regions (Udutalapally et al. 2021). Moreover, the farmers utilized conventional techniques that are cost-effective, subject to errors, and consume more time (W.-L. Chen et al. 2020). Presently, the enhancements in digital cameras as well as electronic devices are widely utilized with machine learning techniques, and they offer better performance rates (Singh et al. 2019). In different cases, conventional machine learning techniques like KMC, Support Vector Machine (SVM), and decision trees are widely utilized in pre-processing and feature retrieval steps, but they provide a minimal disease diagnosis rate (Vigier, Pattey, and Strachan 2004). Generally, various parts of the plants are collected from benchmark resources to implement an innovative plant disease recognition model (Khan et al. 2019). Here, the plant leaves are the essential element in identifying the disease present in the plant (Sun et al. 2020).

Image processing techniques have become more efficient in identifying plant diseases, but they generate disparities in images according to texture, shape, image noise, and colour (Ai et al. 2020). Moreover, these images are employed to process using deep learning and machine learning models. Recently, more deep learning architectures have been used in the agricultural domain to resolve various analyses like fruit detection, leaf disease classification, pest recognition, plant leaf categorization, and fruit disease identification (Azimi, Wadhawan, and Gandhi 2021). Better detection of disease by the conventional machine learning model is complicated in real-world applications. Then, deep learning architectures are utilized to resolve the complications of generating a highly efficient structure in the agricultural sector. Numerous approaches are utilized to recognize and detect plant infection. Imaging observation executed in the plant leaves remains complicated because the symptoms of the plant disease look similar (Khattak et al. 2021). According to the

psychopathological issues and different crop varieties, professionals find more problems in identifying plant diseases (Huang et al. 2014). Computer vision and deep learning techniques offer the best performance rates to agriculture professionals and farmers in the effective identification of plant disease using plant images as input. So, we developed a plant disease classification and detection approach using plant images to overcome the challenges in the baseline systems.

Multiple objectives related to the implemented plant disease identification and classification method are listed here.

- To design a new plant leaf disease identification and classification technique by deep learning approaches for classifying the diseases to improve the yield rate in the agricultural domain.
- To secure good segmented outcomes, the effective CO-KMC model is developed to improve the system classification rate and enhance the variance and correlation coefficient by the proposed MRV-BWO.
- To select the optimal weighted features from the fused features by tuning the weights and maximizing the correlation using the proposed MRV-BWO.
- To offer good accuracy in the classification and detection of plant disease, the HDNN-RNN-based plant disease classification model is developed by optimizing the variables like epochs and number of suitable hidden neurons in DNN and RNN using the implemented MRV-BWO for minimizing the FPR.
- To implement an innovative heuristic technique named MRV-BWO to select the optimal weighted fused features and also to optimize the cluster centres in KMC, weights, hidden neurons, and epochs in DNN and RNN to increase the accuracy and FPR in classifying and detecting of the plant disease.
- To calculate the effectiveness of the proposed framework over conventional plant disease classification techniques with different performance measures.

The workflow of the identification of plant disease approach is reviewed as follows. Various plant disease identification models utilized in the existing research work are offered in [Section 2](#). Weighted feature selection by deep structured models for effectively identifying plant disease is elaborated in [section 3](#). Improved plant disease classification and identification and methods by segmentation and feature retrieval processes are provided in [Section 4](#). Weighted optimal feature fusion-aided plant disease and classification methods are given in [Section 5](#). Various validation analyses executed over the implemented framework are displayed in [Section 6](#). The given designed work is concluded in [Section 7](#).

2. Literature survey

2.1. Related works

In 2020, (J. Chen, Yin, and Zhang 2020) implemented an innovative mechanism for effectively detecting and classifying plant diseases. Here, the image processing techniques were used to carry out feature extraction and also developed an index system to perform effective prediction. Next, the obtained features were provided to the logistic

framework. Moreover, the suggested technique improved plant disease identification and classification rate in multiple experimental examinations.

In 2020, (P. Sharma, Berwal, and Ghai 2020) implemented a new model using neural networks and segmented image data as input. Here, the neural networks were employed to train the entire images with an enhanced efficacy rate. Here, the recommended plant disease detection framework effectively provided a higher efficacy than the classical methods in multiple analyses with minimal time.

In 2019, (Singh et al. 2019) proposed a multilayer CNN (MCNN) for performing effective classification in the mango leaves to identify the Anthracnose fungal disease in plants in its initial stages. Here, the developed model utilized the dataset containing infected and healthy leaf images. Finally, experimental verification was conducted and the recommended method gained a better efficacy rate than the existing models.

In 2020, (Yang et al. 2020) suggested a novel framework with three networks such as location, feedback, and classification. Here, the self-supervision approaches were usually used to detect the informative regions of tomato images without manual supervision. The location network was utilized for identifying the essential regions and optimizing the iteration using a feedback network. Moreover, the classification network used the instructive regions presented in the entire image for effective tomato plant disease classification. Thus, the proposed technique effectively achieved a better performance rate than the baseline technique and also provided a better control rate in identifying the infection in tomato plants.

In 2019, (Jiang et al. 2019) introduced an innovative CNN technique with real-world identification of apple leaf infections. The apple leaf dataset was employed to analyze the images in real-world conditions. Here, image annotation techniques were used to perform effective analysis. The suggested framework achieved an enhanced efficacy than the traditional models.

In 2021, (Ahmad et al. 2021) developed a stepwise transfer learning technique to overcome the overfitting and convergence issues. The proposed method used two standard databases for the observation. The suggested model attained an enhanced effectiveness than the existing methods in complicated images. Moreover, the suggested method effectively classified the plant disease in the initial stage with minimal time consumption.

In 2021, (Tiwari, Joshi, and Dutta 2021) suggested an innovative plant disease identification model using plant leaves collected at different datasets. Here, the CNN structure was trained with the huge plant leave image dataset. The images were presented with intra and inter-class modifications as well as complicated conditions. Here, a five-fold analysis was executed in the implemented technique with different parameters. In the experimental observation, the developed technique gained better performance than existing methods in a complicated background.

In 2021, (Umamageswari, Bharathiraja, and Irene 2021) suggested a new plant leaf disease detection model. Initially, overfitting and unwanted noise were eliminated from the images and the contrast enhancement rate was improved in the developed model. Next, the fuzzy technique was utilized to execute successful segmentation, and also the Gray Level Co-occurrence Matrices (GLCM) attributes were used to execute the extraction of the feature. Finally, neural network architecture was employed to provide better plant leaf disease identification. Hence, the developed method achieved comparatively higher performance than other models.

2.2. Problem statement

Plant disease detection is a complicated task as it has various struggles in identifying the leaves of the same and different plants based on the image noise, texture, size, colour, shape, and so on. Therefore, various models are suggested for identifying and classifying plant infections, and they are given in Table 1. GMDH-Logistic algorithm (J. Chen, Yin, and Zhang 2020) automatically selects essential features, and the estimated variables are greatly interpretable. However, it affects the classification rate that is most appropriate for classifying the plant disease images. CNN (P. Sharma, Berwal, and Ghai 2020) is an automated method for non-experts in the medical field for the early detection of diseases. On the other hand, it does not consider the task of image pre-processing, which reduces real-world applications. MCNN (Singh et al. 2019) is a simple and effective model in computation and

Table 1. Advancements and complications of baseline plant disease detection and categorization mechanism.

Author [citation]	Approaches	Advancements	Complications
(J. Chen, Yin, and Zhang 2020)	GMDH-Logistic algorithm	<ul style="list-style-type: none">• It automatically selects essential features, and the estimated variables are greatly interpretable.	<ul style="list-style-type: none">• It affects the classification rate that is most appropriate for categorizing the disease-affected images.
(P. Sharma, Berwal, and Ghai 2020)	CNN	<ul style="list-style-type: none">• It is an automated method for non-experts in the medical platform for the early detection of diseases.	<ul style="list-style-type: none">• It has not considered the task of image pre-processing that reduces real-time applications.
(Singh et al. 2019)	MCNN	<ul style="list-style-type: none">• It is a simple and effective model in computation and generates accurate classification.	<ul style="list-style-type: none">• It lacks in working with real-time datasets.• It is unsuitable for several plant-related diseases and the severity of such diseases in other parts of plants.• It shows a minimal variation in the classification performance on categorizing multiple diseases.
(Yang et al. 2020)	LFC-Net	<ul style="list-style-type: none">• It learns the high-informative regions over the tomato images and also requires less number of iterations in the network.	<ul style="list-style-type: none">• It is involved with fewer classes of tomato diseases.• It is not easy to detect the different stages of tomato disease.• It wants to enhance accuracy, particularly in practical scenarios.
(Jiang et al. 2019)	GoogLeNet Inception	<ul style="list-style-type: none">• It is highly capable of applying to real-world disease identification applications with an improved accuracy rate.	<ul style="list-style-type: none">• It generates less accuracy when two characteristics of leaf diseases seem to be similar.
(Ahmad et al. 2021)	A stepwise transfer learning approach	<ul style="list-style-type: none">• It helps to reduce negative validation and also ensures a faster convergence rate.	<ul style="list-style-type: none">• It is not easy to develop with high-end hardware.
(Tiwari, Joshi, and Dutta 2021)	DenseNet-201	<ul style="list-style-type: none">• It provides superior training and testing accuracy with real-time performance.	<ul style="list-style-type: none">• It does not consider the plant leaf dataset with high diversity, which reduces the efficacy of trained methods in a challenging context.
(Umamageswari, Bharathiraja, and Irene 2021)	FCM-CSA	<ul style="list-style-type: none">• It requires less time to process the images.	<ul style="list-style-type: none">• It does not provide practical solutions for supporting the industry and consumers.

generates accurate classification. However, it lacks in working with real-time datasets, is not suitable for several plant-related diseases and the severity of such diseases in other parts of plants, and also shows a minimal variation in the classification performance on categorizing multiple diseases. Location Feedback Classification Network (LFC-Net) (Yang et al. 2020) learns the high-informative regions over the tomato images and also requires less number of iterations in the network. However, it is involved with fewer classes of tomato diseases, it cannot identify the multiple stages of tomato infections, and also it needs to improve its accuracy, particularly in practical scenarios. GoogLeNet Inception (Jiang et al. 2019) is highly capable of applying it to real-world leaf disease identification applications with high accuracy. On the other hand, it generates less accuracy when two characteristics of leaf diseases appear to be similar. The stepwise transfer learning approach (Ahmad et al. 2021) helps to reduce negative learning and also ensures a faster convergence rate. Still, it is not developed with high-end hardware. DenseNet-201 (Tiwari, Joshi, and Dutta 2021) provides superior training and testing accuracy with real-time performance. Yet, it does not consider the high diversity dataset, which deduces the efficacy of the trained approach in a challenging context. The fuzzy C-Means-based Chameleon Swarm Algorithm (FCM-CSA) (Umamageswari, Bharathiraja, and Irene 2021) requires less time to process the images. But, it does not provide practical solutions for supporting the industry and consumers.

Plant disease generates more complications in farm production. In case, the plant diseases are not identified in the beginning stage, it affects the food insecurity rate. So, initial observation for plant disease is highly essential to control the pest and also to improve crop yield. Here, the disease-affected plants have different signs in fruits, stems, leaves, and flowers. Every pest or disease present in the plant has different visible patterns to uniquely analyze the abnormalities. Generally, plant leaves (Sreedevi 2022) are commonly utilized to identify plant diseases in the initial stages. In maximal cases, forestry and agricultural experts easily identify pests and diseases according to their experience. These processes are biased, consume more time, and are inefficient and laborious. Inexperienced individuals perform misclassification and utilize the incorrect treatment during the identification stage. So, it is important to improve the efficacy of production by performing effective identification and diagnosis for plant disease. Presently, deep learning mechanisms are utilized to offer better results. They provide effective high-level and minimal-level features along with complications. The convolutional network model offers a better solution for image classification, disease identification, and pest classification. Yet, processing a huge dataset using the CNN technique requires high validation resources. Therefore, an improved plant disease identification and classification mechanism must be developed for better outcomes. So, we developed a detection and classification of plant disease model using plant images to overcome the challenges in the baseline systems.

3. Efficient heuristically modified weighted feature fusion with hybridized deep learning approach for detection and classification of plant disease model

3.1. Proposed detection and classification of plant disease model

The pictorial presentation of the offered detection and classification technique is presented in Figure 1.

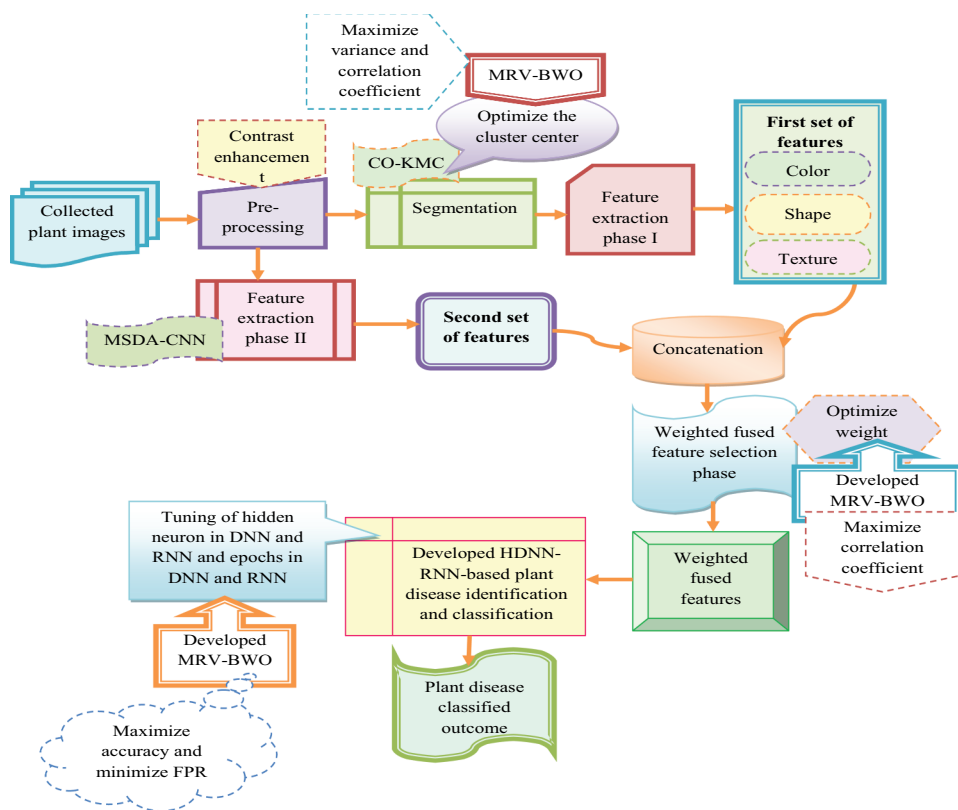


Figure 1. Architectural illustration of the implemented detection and classification of plant disease approach.

An innovative detection and classification of plant disease method is implemented using deep learning architecture to recognize the plant disease in the beginning stages and also it provides a better crop yield rate to the farmers. Initially, the images of plant leaves are garnered from standard resources. The collected sample plant images are fed into the pre-processing phase. Here, the pre-processing is done using the contrast enhancement approach. The enhanced images are further subjected to the segmentation region, where segmentation is carried out using the CO-KMC approach. The cluster centres of the CO-KMC approach are tuned by the offered MRV-BWO algorithm which helps to increase the correlation coefficient and variance rate of the given developed model. There are two feature extraction phases such as feature extraction stage I and feature extraction stage II. Here, the segmented images are forwarded to the extraction of feature stage I. In this phase, the first group of features like shape, texture, and colour attributes from the segmented images is obtained. In the features extraction stage II, the images are pre-processed and which is taken to the extraction of feature stage which is done by the MSDA-CNN technique. The acquired first and the second set of features are subjected to a concatenation phase. Later, the first and the second set of concatenated features are subjected to a tuned weighted feature fusion phase and the developed MRV-BWO is used to attain the tuned weighted features to improve the correlation coefficient rate. Finally,

the tuned weighted attributes are used as the input into the developed HDNN-RNN-based classification of plant disease approach to offer a better plant disease classification rate. The variables such as epoch count and number of suitable hidden neurons in DNN and RNN are effectively tuned in the developed HDNN-RNN model by the implemented MRV-BWO to enlarge the accuracy and decrease the FPR. Thus, the suggested plant disease identification model has finally secured better plant disease identification and classification outcomes.

3.2. Plant disease dataset

Here, the sample plant disease images are collected from PlantifyDr Dataset and the link '<https://www.kaggle.com/datasets/lavaman151/plantifydr-dataset>: Access Date: 30 May 2023'. The dataset contains the disease-affected leaf image of tomato, apple, strawberry, bell pepper, potato, cherry, peach, citrus, grape, and corn. In this dataset, 37 plant disease images are available with 125,000 jpg sample images. Here, the augmentation process is already performed in the sample images. Different images collected from the dataset are indicated by IM_k^{inp} , where, $k = 1, 2, \dots, K$ and the total plant disease images are given as K . Sample images utilized in the developed model are presented in Figure 2. Different kinds of plant diseases and the number of images for the designed model are given in Table 2.

3.3. Image pre-processing: contrast enhancement

The collected images IM_k^{inp} are offered as the input into the pre-processing phase. It is made by the contrast enhancement techniques. Generally, contrast enhancement (Trang et al. 2019) mechanisms are utilized to effectively enhance the quality of the images. The key use of this approach is to enhance the low-contrasting images to provide a good improvement according to contrast quality. Mainly, this process is used to continue better mean brightness in the input image when contrast alliterations are executed in the restricted area of the leaf image. In the primary phases, the coloured Red, Green, and Blue (RGB) input image channels are modified as Hue-Saturation-Intensity (HSI) colour channels. Moreover, the recommended model provides more attention to the contrasting constraint and follows better saturation and hue standards. Further, the intensity values are split into high and low groups using the golden section technique in Eq. (1).

$$\begin{aligned} \gamma_{qa} &= \{\gamma(Z) | c > \gamma_b\}, \\ \gamma_{ws} &= \{\gamma(Z) | v \leq \gamma_b\} \end{aligned} \quad (1)$$

The intensity value of a lower group is given by γ_{qa} , the intensity value of a higher group is indicated by γ_{ws} , and the trial threshold is represented by γ_b , which is used to split the input image into two various sub-images (Trang et al. 2019). Once, the image concentration examination values of two sub-parameters are received, and then a fusion is performed between them to maintain the enhanced intensity rate, which is given in Eq. (2).

$$\gamma_{Enhc}(Z) = \gamma_{ws} + (\gamma_{qa} - \gamma_{ws}) \times \varsigma(Z) \quad (2)$$

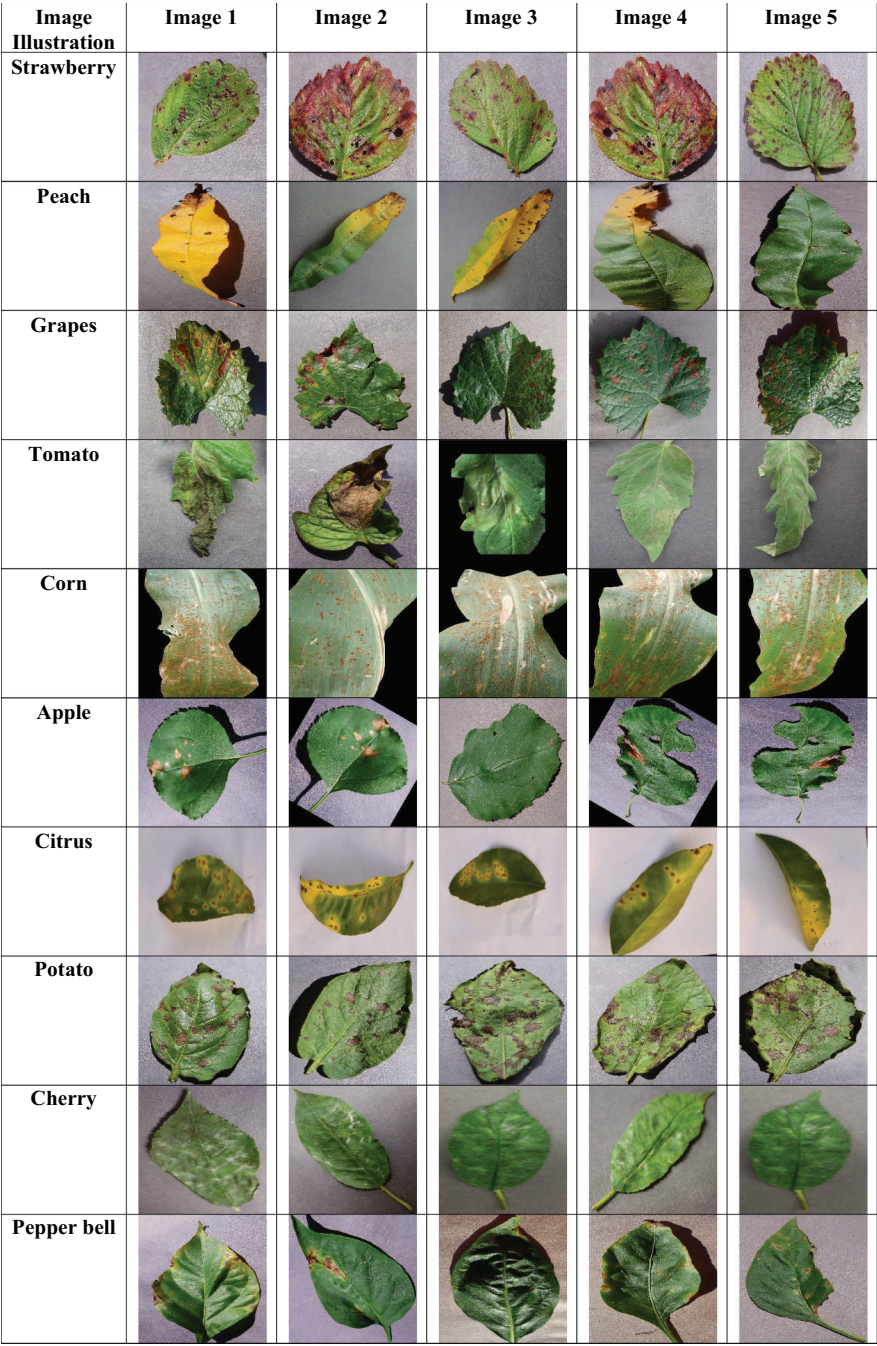


Figure 2. Sample plant disease images collected from the dataset.

The intensity of cumulative in Z^{th} the pixel is termed as $\zeta(Z)$. Further, the enhanced intensity level and the basic hue and saturation values are fused and distorted as RGB channels to offer the final image outcome. The obtained contrast enhancement-based pre-processed images are presented by IM_u^{pre} .

Table 2. Different categories of plant diseases and the number of images.

Categories of crops	Plant diseases	Number of images
Citrus	Citrus canker	163
	Citrus greening	204
	Citrus healthy	58
	Citrus Melanose	13
	Citrus Black spot	171
Apple	Apple Cedar apple rust	440
	Apple scab	504
	Apple healthy	502
	Apple Black rot	497
Corn	Corn (maize) Northern Leaf Blight	477
	Corn (maize) Common rust	477
	Corn (maize) Cercospora leaf spot Gray leaf spot	410
	Corn (maize) healthy	465
Cherry	Cherry (including sour) healthy	456
	Cherry Powdery mildew	412
Peach	Peach healthy	432
Strawberry	Peach Bacterial spot	459
	Strawberry Leaf scorch	444
Grape	Strawberry healthy	456
	Grape Esca (Black Measles)	480
	Grape Leaf blight (Isariopsis Leaf Spot)	430
	Grape healthy	423
Tomato	Grape Black rot	472
	Tomato healthy	481
	Tomato Late blight	463
	Tomato Leaf Mold	470
	Tomato Bacterial spot	425
	Tomato Septoria leaf spot	436
	Tomato Spider mites Two-spotted spider mite	435
	Tomato Early blight	480
	Tomato Yellow Leaf Curl Virus	490
	Tomato Target Spot	457
	Tomato mosaic virus	448
Pepper	Pepper, bell Bacterial spot	478
	Pepper, bell healthy	497
Potato	Potato healthy	456
	Potato Early blight	485
	Potato Late blight	485

4. Enhanced plant disease detection and classification with the support of segmentation and dual feature extraction phase

4.1. K-Means clustering

KMC (Geng et al. 2020) is a widely used clustering technique to select the groups according to their neighbouring validation for finding the Euclidean distance among the points. Here, the clusters $CL = \{CL_1, CL_2, \dots, CL_h\}$ and sample datasets $Da = \{l_1, l_2, \dots, l_r\}$ are chosen randomly as partitions. Further, $r \geq h$ they are split into the nearest cluster, and revalidation is executed in the cluster centre point. Then, terminate the iteration until it reaches the convergence condition. The convergence function is offered in Eq. (3).

$$SS(CL) = \sum_{h=1}^H \sum_{l_u \in CL_h} l_u - cl_h^2 \quad (3)$$

Here, the term SS denotes the least square error of cluster division based on the algorithmic sample clustering, the cluster centre point is represented by cl_h and the arithmetical expression of the centre point is verified and minimized. Moreover, the mean value of every point is termed as the best cluster centre, and it is validated using Eq. (4).

$$cl_h = \frac{\sum_{l_u \in CL_h} l_u}{|CL_h|} \quad (4)$$

Hence, the KMC technique effectively minimizes the clustering outcome and also tackles the optimization problems. Moreover, the clustering techniques offer a better scalability rate, centre point, and speed.

4.2. Improved image segmentation with CO-KMC

Here, the pre-processed images IM_u^{pre} are utilized to effectively segment the developed classification and identification of the plant disease model. KMC-based approaches are easy to implement and offer a better efficacy rate. Moreover, they are highly proficient in large dataset collection with good measurable rates. However, selecting the optimal clusters is complex and also limits the count of the fixed data. Thus, to resolve this complication in the classical KMC technique, an innovative CO-KMC technique is developed by tuning the cluster centres. Here, the cluster centres of KMC are optimized by the proposed MRV-BWO in the range of $[0, 255]$ to maximize the correlation and variance. Here, the correlations between the features from the same class were maximized. The fitness function of the CO-KMC-aided segmentation process is presented in Eq. (5).

$$ft_1 = \arg \min_{\{CC_i^{kmc}\}} \left(\frac{1}{\text{var} + cco} \right) \quad (5)$$

Here, the term CC_i^{kmc} indicates the cluster centres, var represents the variance, and cco denotes the correlation coefficient. The expected value of squared variation in the random variable from their mean variable is known as variance and it is given in Eq. (6).

$$\text{var} = \frac{\sum (g_r - \bar{g})^2}{y - 1} \quad (6)$$

Here, the first observation value is presented by g_r , a mean value of the whole observation is given as \bar{g} , and the observation count is denoted by y . A statistical measure used to reinforce the linear connection between the two variables is termed as correlation coefficient and it is offered in Eq. (7).

$$cco = \frac{\sum (w_e - \bar{w})(r_u - \bar{r})}{\sqrt{\sum (w_e - \bar{w})^2 \sum (r_u - \bar{r})^2}} \quad (7)$$

Here, the term w_e indicates the values of w^{th} the variable in the sample, \bar{w} represents the w variable mean value, r_u presents the values r in the sample, and \bar{r} denotes the mean value of the constraint w . The attained CO-KMC-based segmented outcome is denoted by IM_j^{Seg} . The architectural view of the CO-KMC-based segmentation model is offered in Figure 3.

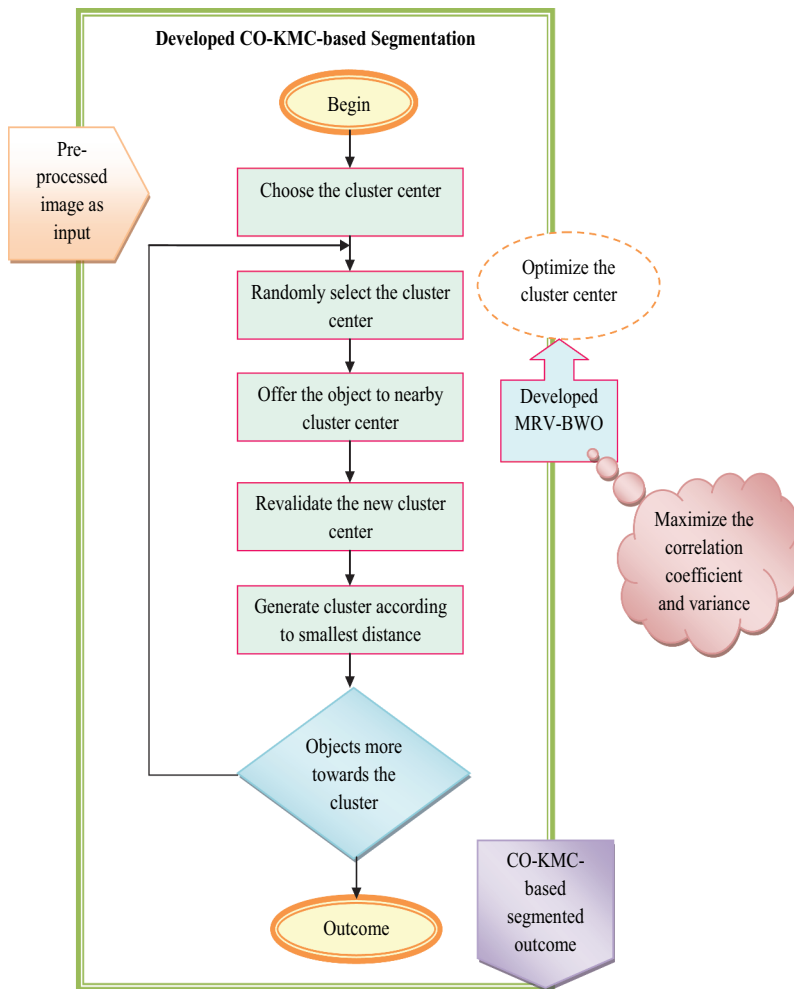


Figure 3. Structural representation of CO-KMC-based segmentation.

4.3. Feature extraction phase I: color, shape, and texture features

The obtained segmented images IM_j^{Seg} from CO-KMC are inputted into the feature extraction phase-1 to extract the first set of features like shape, texture, and colour (Latif et al. 2019).

4.3.1. Colour feature

In the colour feature extraction, the colours are represented as an intensity value. Using the colour space technique, creation, specification, and visualization are performed. Different colour feature extraction techniques are listed below.

4.3.2. Histogram Intersection (HI)

This technique determines the global colour features. In the HI technique, the bins count produces more impact on their efficacy rate. The huge bin number makes the image more complex and enhances the validation complexity rate.

4.3.3. *Zernike chromaticity distribution moments*

It extracts the colour feature from the chromaticity region. This technique offers a fixed validation and reduces the length of the image that contains different colour content within the image. But, their sizes are getting changed in flipping and rotation conditions.

4.3.4. *Color histogram*

It offers the image from various perceptions. The images presented in the colour bins with frequency allocation are indicated as the colour histogram, and also it stores the image with the same pixel count. Colour histogram observation confirms the entire statistical colour frequency present in the image. Here, modifications are obtained in rotation, translation, and angle view, and these issues are effectively tackled using the colour histogram model. Moreover, validating the local colour histogram process is simple to attain the retrieval image database.

4.3.5. *Shape features*

Shape is a significant content widely utilized to perform object identification. Here, the objects are accurately detected without shape visual information. Moreover, images are incomplete without identifying the accurate shape. Generally, two objects don't have any accurate shapes, but different techniques can be used to identify the same shapes. Multiple shape feature extraction models are given below.

4.3.6. *Binary image algorithm*

This algorithm modifies the image into two colours, white and black. Next, it traces the region of the external boundary and applies the shape factor within the image. Images are offered as the inputs into the shape identification techniques to effectively improve the quality, and modified as black-and-white images for observation. Next, boundaries are traced, and the images are transformed in binary format. Moreover, the shape is validated by shape factors as offered in Eq. (8).

$$SF = \frac{area}{(diameter)^2} \quad (8)$$

4.3.7. *Horizontal and vertical segmentation*

Here, the images are split as horizontally and effectively trace the coordinate points to determine the object shape to resolve the sitting location issue. Similarly, in the vertical image segmentation model, the images are split vertically and trace vertical coordinate axis points based on the coordinate axis to accurately recognize the objects.

4.3.8. *Texture features*

The textural features are generally obtained from grey-scale images to reduce unsuitable colours. Moreover, the textural features contain information about leaves, clouds, bricks, and so on. Moreover, they efficiently elaborate the surface with environmental relationships. The textural features represent the surface's physical composition. Different techniques employed to attain the texture features are given below.

4.3.9. Grey Level Co-occurrence Matrix (GLCM)

It is a statistical technique utilized for validating the texture features derived from statistical distribution. This technique is commonly utilized to collect essential statistical textural features. Here, the elements are presented in matrix format to show the relative frequency and describe the texture by generating the statistics of dispersal intensity value and location of similar pixels. The arithmetical presentation of GLCM is provided in Equation (9).

$$glcm = \sum_{f=1}^u \sum_{g=1}^p \begin{cases} 1 & \text{if } J(f, g) = t; J(f + q_f, g + q_g) \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

4.3.10. Edge detection

It is used to determine the textural complication based on edge pixels in the specific location, and the edgeless per unit area is validated by Equation (10).

$$E_{edg} = \frac{|\{kMag(k) > N\}|}{X} \quad (10)$$

Here, the pixel regions are indicated by X , and the gradient magnitude is given as $Mag(k)$.

4.3.11. Laws texture energy metrics

It is commonly used to identify the textures utilized in local masks. Furthermore, convolution masks are employed to confirm the energy in the texture in every pixel.

Different extracted features attained from the first set are referred to as FE_1^{cts} , and they are further employed in the weighted feature fusion step.

4.4. Feature extraction phase II: deep features

The pre-processed images IM_u^{pre} are given as the input to the MSDA-CNN-based extraction of the feature stage. MSDA-CNN (Xia et al. 2020) mechanism is commonly used to overcome segmentation and classification challenges and also it effectively obtains the most important features. It contains three different dilated rates such as 1, 3, and 5. The MSDA-CNN model employs 3x3 convolutional kernels with three dilation rates to attain the feature map from the max pooling layer. Further, the feature maps are fused using 1x1 convolutions to create a new feature map that efficiently minimizes the parameters of the network. Later, in the encoder phase, various multi-scale dilated methods are connected to achieve a higher dilation rate. Moreover, the dilated convolution approaches perform a better recognition rate in disease identifications and classifications. The dilated convolutions successfully gain the temporal-spatial characteristics with massive context data. The dilation operation performed in the CNN model is depicted in Equation (11).

$$(A *_i r)(Y) = \sum_{u+io=Y} A(u)r(o) \quad (11)$$

Here, the dilated convolution is represented by $*$; performing a simple one-dilated convolution. The overfitting problem is overcome by minimizing the count of variables. Further, the attention layer is linked to the CNN and input feature weights. Essential features presented in the input images are acquired without the need to evaluate the entire data.

The attention network reveals the essential features required for accurate plant disease detection and classification. The acquired second set of features from MSDA-CNN is given as FE_2^{mdc} , and they are subjected to the weighted feature fusion phase. The pictorial representation of the MSDA-CNN-based extraction of the feature model is shown in Figure 4.

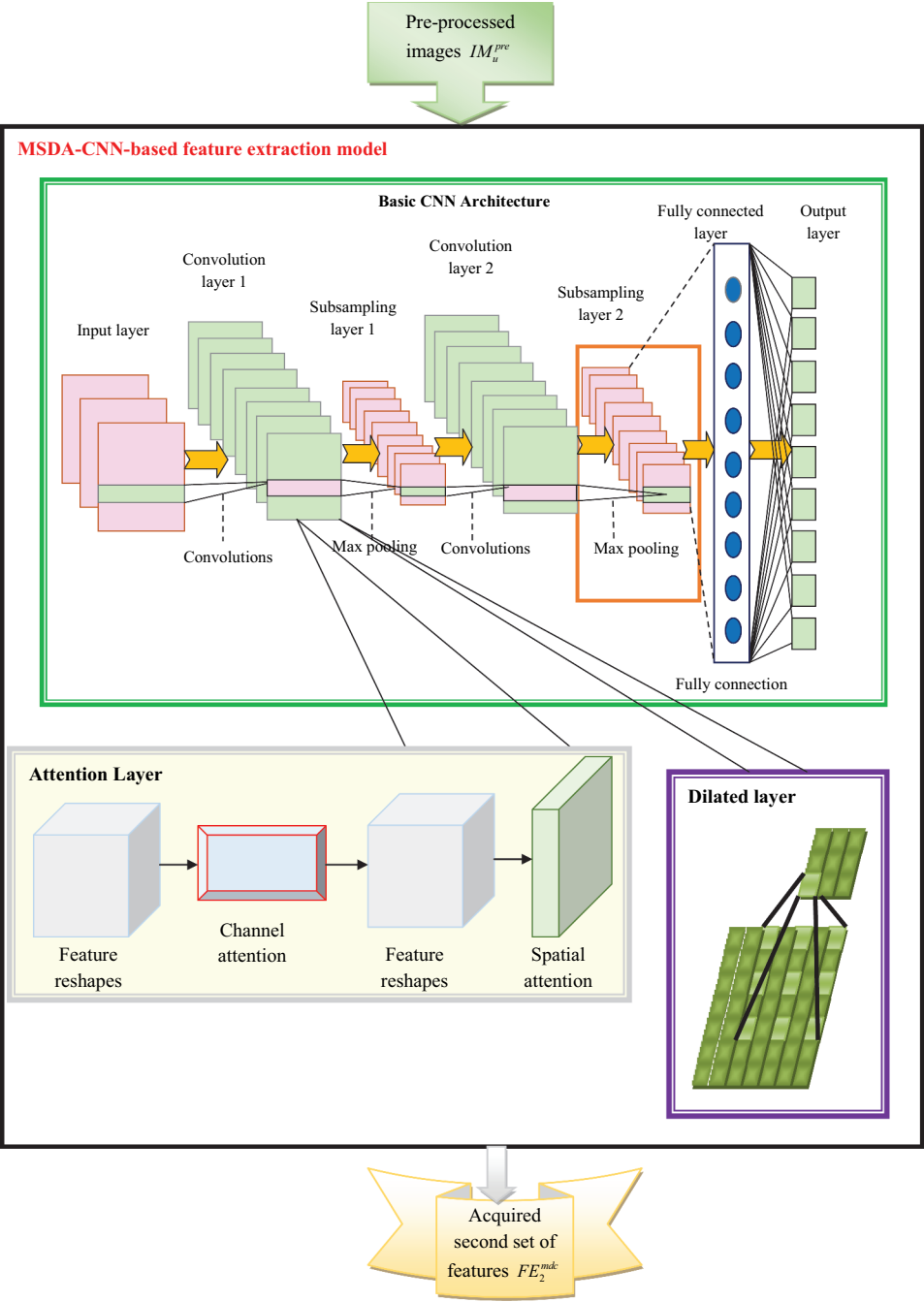


Figure 4. Pictorial representation of MSDA-CNN-based extraction of feature model.

4.5. Developed MRV-BWO

A newly implemented optimization model named MRV-BWO is used to increase the efficacy of plant disease identification and classification rate by tuning the parameters such as hidden neurons in DNN and RNN, epochs count in DNN and RNN, and weights in the suggested model. BWO (Peña-Delgado et al. 2020) successfully provides a higher convergence rate, and efficiently eliminates the local optima concerns. Nonetheless, it offers a low precision rate in resolving optimization issues according to real-world settings. To address these issues, different modifications are performed in the existing technique, and developed a new optimization model named as MRV-BWO. Here, the random float number β produced in the bound $[-1.0, 1.0]$ is enhanced by the newly developed theory presented in Equation (12).

$$\beta = -1 - V * \left(\frac{(-2)}{MXitr} \right) \quad (12)$$

Here, the variable V presents the search agent, and the parameter $MXitr$ indicates the maximum iteration count.

4.5.1. Introduction

BWO (Peña-Delgado et al. 2020) is the most recent biologically inspired optimization technique and also it is utilized to resolve the Selective harmonics elimination (SHE) set of formulations. It guarantees the exploration and exploitation of the search space. The optimization of outcomes visualizes the dependability of the BWO algorithm and gives more competitive findings when tested with other baseline heuristic algorithms. It can be used for an online optimization computation in low-requirement hardware. Initially, this algorithm provided the diverse propagation schemes of spiders and then the algorithm was developed.

BWO (Peña-Delgado et al. 2020) is a heuristic technique used to overcome issues caused by numerical problems, and it is determined as an evolutionary strategy using various operations. Here, the spider movement is mathematically expressed in the following phases.

4.5.2. Phase 1-movement

The moving techniques used by the spider in the web are termed spiral and linear, equated in Equation (13).

$$\vec{C}_t(V+1) = \begin{cases} \vec{C} * (V) - n\vec{C}_{p_1}(V) & \text{if } \text{Rand}(\leq 0.3) \\ \vec{C} * (V) - \cos(2\pi\beta)\vec{C}_t(V) & \text{othercase} \end{cases} \quad (13)$$

Here, the search agent's latest location is presented by $\vec{C}_t(V+1)$ that indicates the spider movement, and the constraint $\vec{C} * (V)$ denotes the optimal search agent identified from the existing iteration. The floating number obtained randomly in the range of $[0.4, 0.9]$ is given as n , a random integer number produced in the different limit of the search agent is represented by p_1 , and it selects the search agent $\vec{C}_{p_1}(V)$. The current search agent is referred to $\vec{C}_t(V)$, and the random float number β is renewed by the newly implemented idea provided in Equation (12).

4.5.3. Phase 2-Pheromones

It plays an important role in the counter-ship mating process. The relationship between the spider diet, as well as the pheromone changes in the signal, influences the quantity and quality of the silk. The pheromone rate of the black widow spider is offered in Equation (14).

$$Pheromone(t) = \frac{ft_{mx} - ft(t)}{ft_{mx} - ft_{mn}} \quad (14)$$

Here, the current generation's worst fitness is termed by ft_{mx} , the best fitness is noted by ft_{mn} , and the current fitness value in t^{th} the search agent is represented by $ft(t)$. Here, the pheromone value is lower, so, the hungry cannibal spider can be applied using Equation (15).

$$\vec{C}_t(V) = \vec{C} * (V) + \frac{1}{2} \left[\vec{C}_{p_1}(V) - (-1)^\sigma * \vec{C}_{p_2}(V) \right] \quad (15)$$

Here, the search agent with a lower pheromone rate is updated as $\vec{C}_t(V)$, a random integer number produced in the limit of maximal size the search agent is denoted by p_1 and p_2 , the binary number generated randomly is represented as σ and the good search agent identified from existing iteration is indicated as $\vec{C} * (V)$. Here, the pseudo-code of the MRV-BWO is given in Algorithm 1.

Algorithm 1: Developed MRV-BWO

```

Assign the initial inhabitants
Validate the fitness
Choose the best solution
Renew random float number  $\beta$  using new idea offered in Eq. (12)
While  $itr < MXitr$ 
  Initiate the random parameter  $\beta$  and  $n$ 
  If  $Rand < 0.3$ 
    Update the solution by  $\vec{C} * (V) - n\vec{C}_{p_1}(V)$ 
  Else
    Update the solution using  $\vec{C} * (V) - \cos(2\pi\beta)\vec{C}_t(V)$ 
  End If
  Validate the pheromone for every search agent
  Renew the search agent with minimal pheromone value
  Validate fitness for a new search agent
End While
Show the optimal solution

```

The flowchart for the implemented MRV-BWO model is presented in [Figure 5](#).

5. Weighted optimal feature fusion-based enhanced plant disease detection and classification with heuristic description

5.1. Weighted optimal feature fusion

Here, the two set features of extracted features such as FE_1^{cts} and FE_2^{mdc} are used to acquire the weighted optimal features. At first, feature fusion is performed using the extracted features, and the fused features are termed as $FF_{hi}^{tw} = \{FE_1^{cts} + FE_2^{mdc}\}$. Then, using the

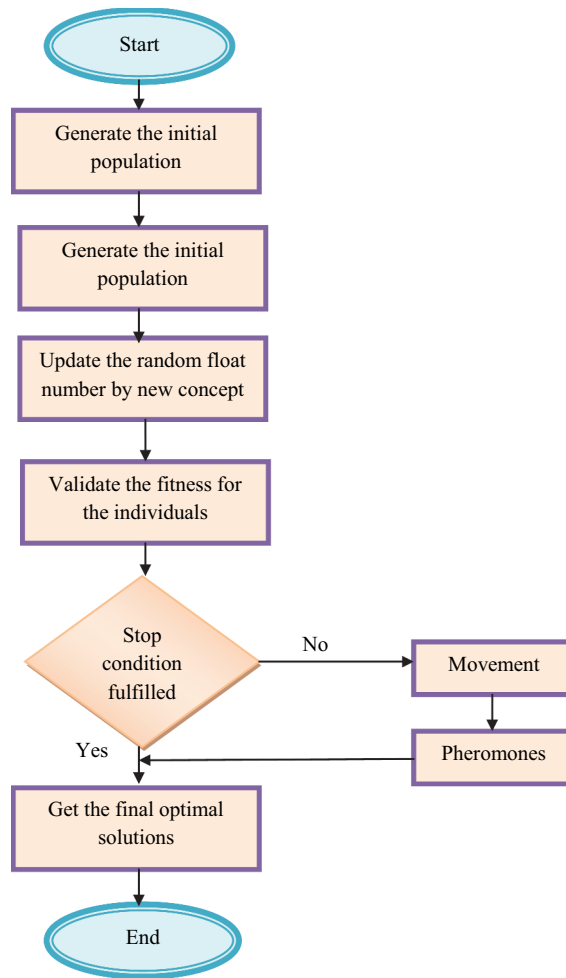


Figure 5. Flowchart for initiated MRV-BWO.

fused features optimal features are selected and represented using the term Ff_{jk}^{opt} . Next, the weighted optimal features are selected by the developed MRV-BWO offered in Equation (16).

$$Ff_{lp}^{wof} = Ff_{jk}^{opt} * W_y^{sd} \quad (16)$$

In Eq. (16), the weighted optimal features are termed as Ff_{lp}^{wof} , weights are provided as W_y^{sd} , and the optimal features are denoted by Ff_{jk}^{opt} . Here, the weights are arbitrarily chosen by the MRV-BWO algorithm in the limit of $[0.01, 0.99]$ to maximize the correlation coefficient rate of the suggested identification and classification of plant disease models. The fitness function of the suggested model is presented in Equation (17).

$$ft_2 = Arg \min_{\{W_y^{sd}\}} \left(\frac{1}{cco} \right) \quad (17)$$

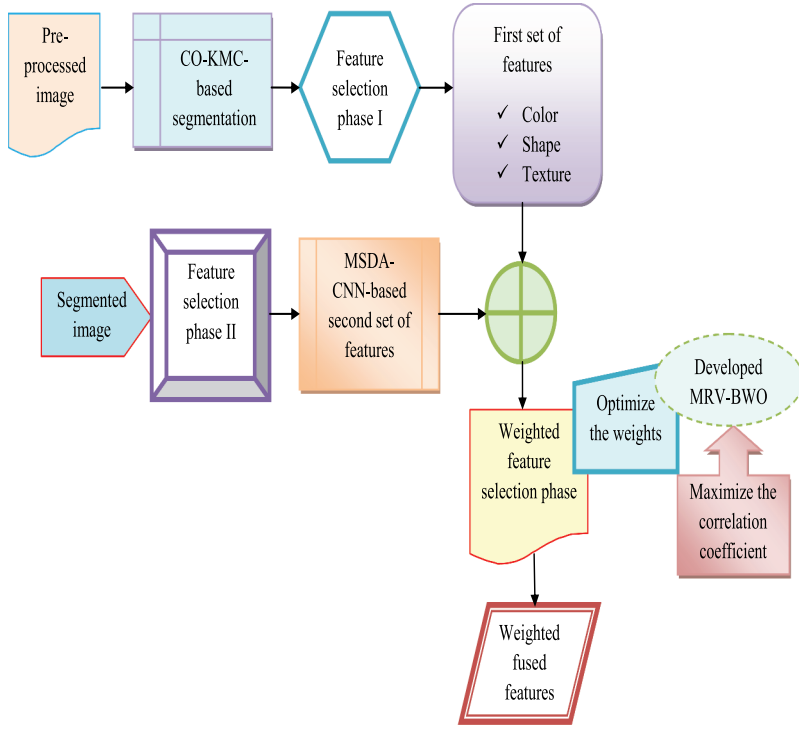


Figure 6. Diagrammatic illustration of weighted optimal feature fusion.

Here, the variable c conotes the correlation coefficient, and it is given in Equation (7). The architectural presentation of the weighted optimal feature fusion model is presented in Figure 6.

5.2. Deep neural network

DNN (Rao, Rao, and Prasad Reddy 2021) is utilized to classify various diseases found in plants. The DNN model is the hybrid of Multi-Layer Perceptron (MLP) and Feed Forward Neural Network (FFN). Here, the entire layer has few neurons, which are linked towards the forward path by neurons. The arithmetical representation of the DNN network is given as $WR : \mathbb{R}^{ft} \times \mathbb{R}^{hi}$. Here, the input vector is indicated by $ky = ky_1, ky_2, ky_3, \dots, ky_{ft}$, the input vector size is presented as ft , the size is represented as hi , and the input is termed as Ff_{jk}^{opt} . The examination of hidden neurons is displayed in Equation (18) and Equation (19).

$$NB_{qc}(e_{qc}^{ls+1}) = up(W_{fqc} + dj_{qc}^{(ls+1)}) \quad (18)$$

$$W_{fqc} = Ac_i^{ls} V_{hd}^{(ls, ls+1)} \quad (19)$$

In the DNN network, neurons from the last layer are combined with a neuron qc , and the neurons existing in the activation function are offered as Ac_i^{ls} in the ls^{th} layer. Moreover, the neurons presented in the contribution are given as Ac_i^{ls} for the neurons present in the

activation region of $ls + 1$ the layer. Then, the non-linear activation function is indicated by up , the neuron bias is denoted by $d_{qc}^{(ls+1)}$, and the weight function is termed as $V_{hd}^{(ls,ls+1)}$. The huge number of hidden layers gathered from MLP is determined as DNN. The mathematical expansions of DNN with hidden neurons are presented in Equation (20).

$$Jy_d(nf) = Jy_d(Jy_{d-1}(Jy_{d-2}(\dots(Jy_d(nf)))))) \quad (20)$$

The basic DNN structure contains more hidden layers, with the ReLu layer serving as the activation function of non-linearity. The ReLU layers are utilized to reduce the vanishing gradient and error issues. The efficacy of the ReLu layer is fast, and it rapidly trains more hidden layers. The attained DNN-based predicted score is used in the averaging phase.

5.3. Recurrent neural network

RNN (Xiong et al. 2021) is a deep learning structure that analyzes the sequence data. The memory functions are used to retrieve data from the past time steps in the network. Then, the result of the baseline steps is given as input for the subsequent time steps. Hence this cyclic procedure is termed a cyclic neural network. Furthermore, the neurons in the hidden layers are linked, and the output of neurons is gathered in the early time steps of the output and the input layer of neurons. The arithmetic representation of the RNN model is offered in Equation (28).

$$C_r^h = \sum_{p=1}^D k_{tp} sh_p^l + \sum_{j^*}^J k_j * hw_{j^*}^{l-1} \quad (21)$$

$$w_{j^*}^l = S_j(vy_j^l) \quad (22)$$

$$h_m^l = \sum_{j=1}^J k_{jm} w_j^l \quad (23)$$

Here, the neurons present in the hidden layers are given as sh_p^l for p^{th} layer and $w_{j^*}^{l-1}$ for i^{th} layer, and the input in the time ranges is given as a . Time instant initial phase is indicated by C_r^h , the weights linked into the hidden layer is indicated by the term h_m^l , the weight obtained among the hidden layers is presented as k_{j^*j} , weight obtained between the hidden layer and the resultant layer is referred to as k_{jm} , and the activation function of nonlinear is represented as $S_j()$. At last, the obtained RNN-based predicted score is given to the averaging phase.

5.4. Developed HDNN-RNN-based detection and classification of plant disease

A unique disease identification and classification model named HDNN-RNN is designed to efficiently identify the plant disease in a short period, and also, the parameters of RNN and DNN-like epochs and hidden neurons are tuned by developed MRV-BWO. DNNs are used to learn complex data effectively, and their implementation procedure is straightforward. However, it required effective analysis, which takes more time. Hence, to resolve the complications in traditional DNN, a new combination of HDNN-RNN is implemented. In this case, the RNN technique has a greater flexibility speed,

and also it successfully minimizes the vanishing gradient issues. In the developed HDNN-RNN-based plant disease detection and classification approach, a better performance rate is obtained by averaging the predicted score from DNN and RNN. Here, the hidden neurons of DNN and RNN are present in the limit of [5, 255], and also, the epochs are present in the range of [5, 50] are tuned by the developed MRV-BWO algorithm. Hence, the major objective of the offered HDNN-RN techniques is to enhance the accuracy and reduce the FPR rate using MRV-BWO. The objective of the implemented detection and classification of plant disease approach is offered in Equation (24).

$$ft_3 = \arg \min_{\{Hd_i^{dnn}, Ep_t^{dnn}, Hd_u^{rnn}, Ep_o^{rnn}\}} \left(\frac{1}{acy} + fpr \right) \quad (24)$$

Here, Hd_i^{dnn} denotes the DNN hidden neuron count, Ep_t^{dnn} indicates the epoch's count of DNN, Hd_u^{rnn} represents the RNN hidden neuron, and Ep_o^{rnn} represents the epochs of RNN. The closeness validation among the measurements of a specific value is termed accuracy, as shown in Equation (25).

$$acy = \frac{(Tp + Tn)}{(Tp + Tn + Fp + Fn)} \quad (25)$$

The preposition among the negative values is incorrectly identified as positive in the entirety of the negative values is determined as FPR, given in Equation (26).

$$fpr = \frac{Fp}{Fp + Tn} \quad (26)$$

Here, the term Fp denotes the false positive, Tn represents the true negative, Fn indicates the false negative, and Tp offers the true positive values. The diagrammatic presentation of the HDNN-RNN-based plant disease identification and classification mechanism is given in Figure 7.

5.5. Experimental setup

The experimentation of the recommended plant infection identification and classification approach was implemented in Python. Then, the performance of the implemented framework was analysed over classical methods. Here, the chromosome length was 4, the population count was 10, and the maximum iteration count. Multiple existing heuristic techniques utilized for the experiments are Eurasian Oystercatcher Optimization (EOO) (Salim et al. 2022), Chameleon Swarm Optimization (CSO) (Braik 2021), Mine Blast Optimization (MBO) (Sadollah et al. 2013), and BWO and also multiple classifiers utilized were LSTM (Montaha et al. 2022), DNN (Rao, Rao, and Prasad Reddy 2021), RNN (Xiong et al. 2021) and FDNN-RNN. The entire data are split into two stages such as testing and training. Here, 75% of the data is subjected to the training phase and also 25% of the data is fed to the testing stage.

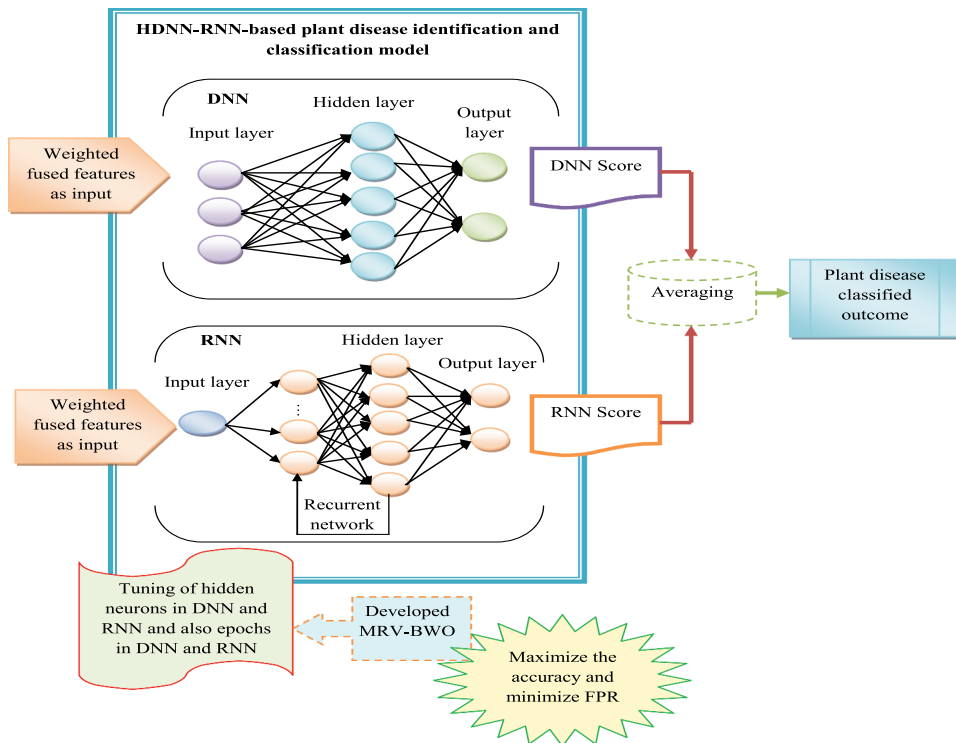


Figure 7. Systematic view of HDNN-RNN-aided identification and classification of plant disease approach.

6. Results and discussions

6.1. Performance measures

The offered plant disease identification and classification model utilized different performance measures, and they are listed as follows.

(a) The percentage of correctly detected positive values is said to be Sensitivity, given in Equation (27).

$$\text{Sensitivity} = \frac{Tp}{Tp + Fn} \quad (27)$$

(b) The F1-Score is employed to validate examination accuracy, given in Equation (28).

$$F1 - \text{Score} = 2 \times \frac{2Tp}{2Tp + Fp + Fn} \quad (28)$$

(c) The preposition of respective samples between the obtained results is called precision, presented in Equation (29).

$$\text{Precision} = \frac{Tp}{Tp + Fp} \quad (29)$$

(d) The quality computed in the binary classification on analysis is termed as MCC, provided in Equation (30).

$$MCC = \frac{Tp \times Tn - Fp \times Fn}{\sqrt{(Tp + Fp)(Tp + Fn)(Fn + Tp)(Tn + Fn)}} \quad (30)$$

(e) The ratio of positives that obtained negative examination outcomes is determined as FNR, presented in Equation (31).

$$Fnr = \frac{Fn}{Fn + Tp} \quad (31)$$

(f) The fraction of negatives detected correctly is referred to as Specificity, given in Equation (32).

$$Specificity = \frac{Tn}{Tn + Fp} \quad (32)$$

(g) The total number of plants affected by the disease in the analysis is NPV, presented in Equation (33).

$$NPV = \frac{Tn}{Tn + Fn} \quad (33)$$

6.2. Segmented image outcome from implemented framework

The CO-KMC-based segmented outcome obtained from the developed model is offered in [Figure 8](#).

6.3. ROC curve analysis on the suggested method

ROC curve analyses accomplished in the implemented MRV-BWO-HDNN-RNN-aided plant disease identification and categorization model are presented in [Figure 9](#). The Receiver Operating Characteristic (ROC) curve is generated to visualize the efficacy of the classification model. Here, the ROC curve observation is carried out over false positive and true positive rates which enlarge the TPR and FPR rates effectively. Here, it evaluates the logistic regression approach many times with diverse categorization thresholds. Here, LSTM, DNN, RNN, and HDNN-RNN techniques are utilized to analyse developed MRV-BWO-HDNN-RNN and the implemented technique obtained a good plant disease classification rate.

6.4. Efficacy analysis of the proposed plant infection identification and categorization technique

Efficacy analysis executed in the developed mechanism over classical baseline model and classification techniques is shown in [Figures 10 and 11](#). Precision observation employed in the suggested MRV-BWO-HDNN-RNN-based approach resulted in a higher efficacy rate of 9.4% higher than EOO-HDNN-RNN, 14.08% effectual than MBO-HDNN-RNN, 9.45% improved than CSO-HDNN-RNN and 5.19% enhanced than BWO-HDNN-RNN, in corn plants. Similarly, the recommended framework achieved greater efficacy than the conventional strategies.

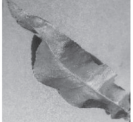








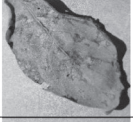
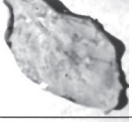







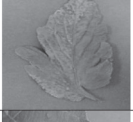






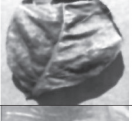

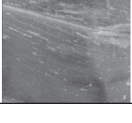
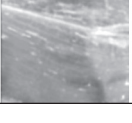

Image Description	Original image	Pre-processed image	Segmented image
Peach			
Grapes			
Cherry			
Potato			
Strawberry			
Citrus			
Tomato			
Apple			
Pepper bell			
Corn			

Figure 8. CO-KMC-based segmented outcome obtained from the proposed plant disease detection and categorization model.

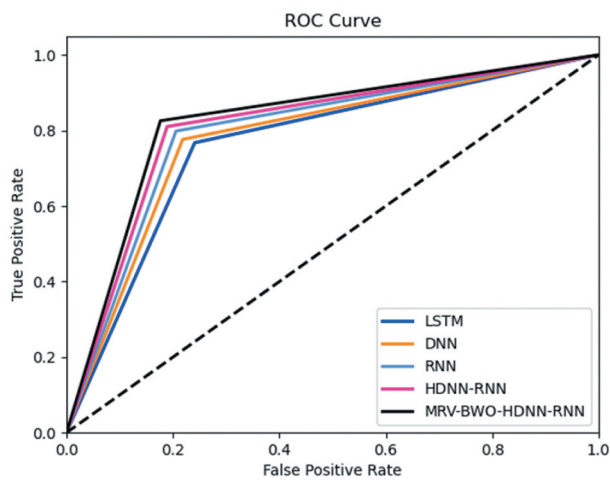


Figure 9. ROC Curve Analysis on the Initiated Plant disease Identification and categorization framework.

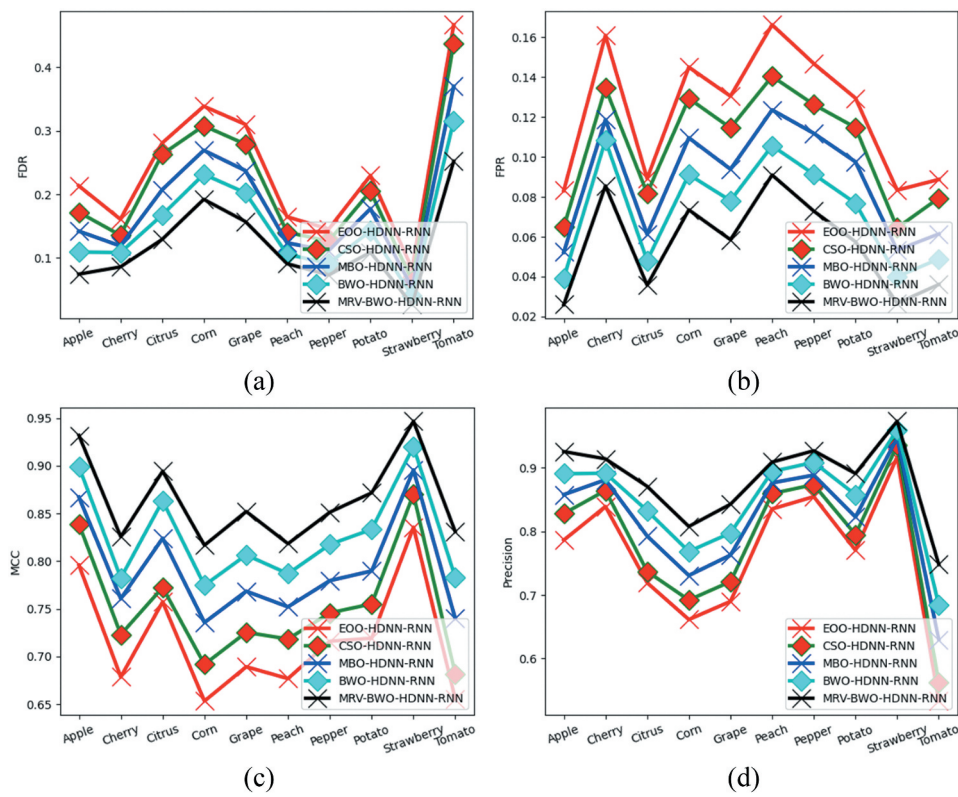


Figure 10. Efficacy of the developed plant disease detection and classification model over classical heuristic models based on“(a) FDR, (b) FPR, (c) MCC, and (d) precision”.

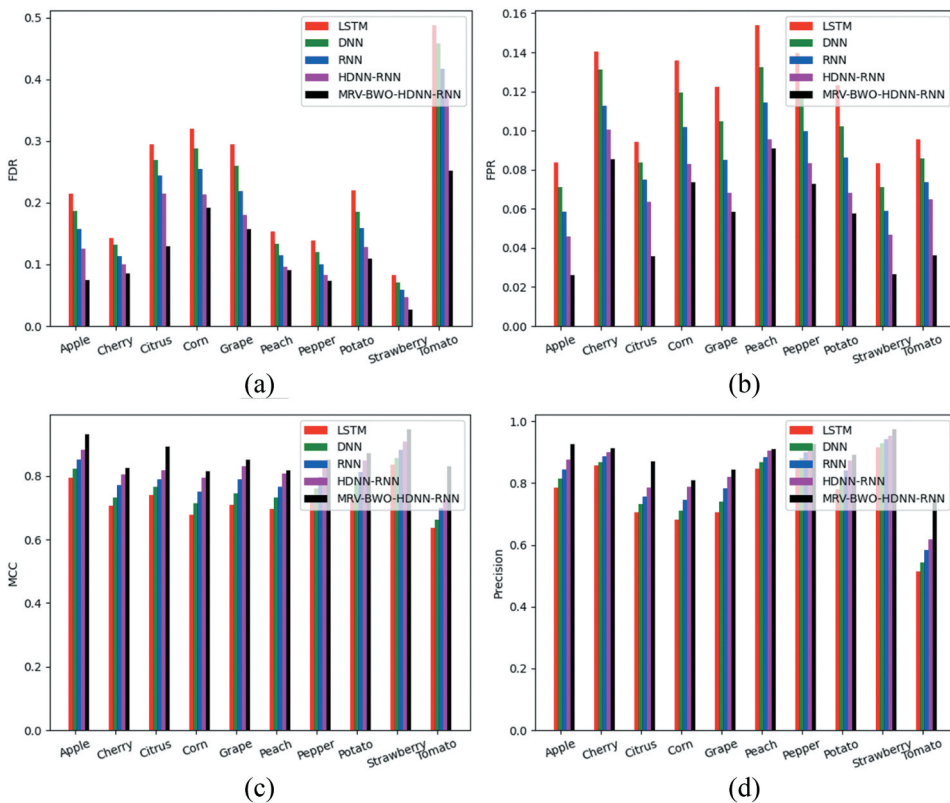


Figure 11. Validation of the recommended model over classical classification models based on “(a) FDR, (b)FPR, (c) MCC, and (d) precision”.

In Figure 10(a,b), the figure depicts the FDR and FPR rate of the designed model where the EOO algorithm scores a higher error rate which can affect the efficacy of the system. Simultaneously, the BWO algorithm achieves a second better performance. While considering Figure 10 (c,d), the proposed method displays the MCC and the precision rate. The EOO algorithm achieves the lowest performance because it lacks the ability to resolve the optimization issues which can increase the computation complexity.

6.5. Computation of the implemented framework

Calculation of the recommended plant disease detection and classification method over classical heuristic methods and classification techniques is presented in Tables 3 and 4. Accuracy observation performed in the suggested MRV-BWO-HDNN-RNN-based plant disease identification and classification technique yielded enhanced efficacy rates of 6.69%, 5.2%, 4.32%, and 3.2%, respectively, when compared to conventional techniques such as LSTM, DNN, RNN, and HDNN-RNN. While taking Table 3, the LSTM model attains lower performance. Owing to its poor performance proves highly erroneous for the entire process and also the accuracy is

Table 3. Examination of developed MRV-BWO-HDNN-RNN-based model over classical heuristic models.

Performance Measures	EOO-HDNN-RNN (Salim et al. 2022)	MBO-HDNN-RNN (Sadollah et al. 2013)	CSO-HDNN-RNN (Braik 2021)	BWO-HDNN-RNN (Peña-Delgado et al. 2020)	MRV-BWO-HDNN-RNN
Accuracy	91.05	91.96	94.13	95.15	96.47
Sensitivity	90.99	91.90	94.18	95.32	96.47
Specificity	91.11	92.02	94.07	94.98	96.47
Precision	91.10	92.01	94.08	95.00	96.47
FPR	8.89	7.98	5.93	5.02	3.53
FNR	9.01	8.10	5.82	4.68	3.53
NPV	91.11	92.02	94.07	94.98	96.47
FDR	8.90	7.99	5.92	5.00	3.53
F1-Score	91.04	91.96	94.13	95.16	96.47
MCC	82.10	83.92	88.26	90.31	92.93

Table 4. Examination of developed MRV-BWO-HDNN-RNN-based model over traditional classification techniques.

Performance Measures	LSTM (Montaha et al. 2022)	DNN (Rao, Rao, and Prasad Reddy 2021)	RNN (Xiong et al. 2021)	HDNN-RNN (Luo, Zou, and Huang 2017)	MRV-BWO-HDNN-RNN
F1-Score	90.43	91.63	92.47	93.45	96.47
Sensitivity	90.54	91.79	92.47	93.50	96.47
FNR	9.46	8.21	7.53	6.50	3.53
FDR	9.67	8.52	7.53	6.61	3.53
Precision	90.33	91.48	92.47	93.39	96.47
FPR	9.69	8.55	7.53	6.61	3.53
Accuracy	90.42	91.62	92.47	93.44	96.47
NPV	90.31	91.45	92.47	93.39	96.47
Specificity	90.31	91.45	92.47	93.39	96.47
MCC	80.84	83.24	84.95	86.89	92.93

higher than other baseline approaches. Similarly, multiple observations are executed in the designed plant disease detection and classification model and the developed model outperformed the classical models when considering all the measures.

6.6. Convergence observation on the implemented heuristic model

Convergence observations executed over the classical optimization model are displayed in [Figure 12](#). The convergence analysis of the offered model is validated according to the number of parameters. The better convergence rate is attained at the 25th iteration. If the iteration increases then the convergence rate is also minimized. The CSO attains lower performance and also the BWO attains second better performance. Hence, the suggested plant disease detection and classification secured effectively better disease classification rate than existing models.

6.7. Statistical examinations of the recommended model

Statistical observations carried out in the proposed techniques are displayed in [Table 5](#). Here, the efficacy of the developed model is evaluated based on the best metrics. The best evaluation executed in the implemented model was 11% more effective than EOO-HDNN-

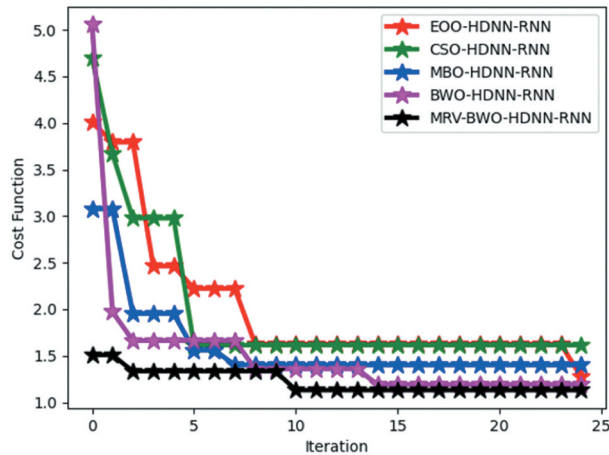


Figure 12. Convergence validation on the implemented plant disease detection and classification model.

Table 5. Statistical examination of the implemented plant disease detection and classification technique.

Measures	EOO-HDNN-RNN (Salim et al. 2022)	MBO-HDNN-RNN (Sadollah et al. 2013)	CSO-HDNN-RNN (Braik 2021)	BWO-HDNN-RNN (Peña-Delgado et al. 2020)	MRV-BWO-HDNN-RNN
BEST	1.270207	1.613629	1.401015	1.191266	1.130428
WORST	4.010639	4.69996	3.077387	5.054437	1.508114
MEAN	2.018431	1.982699	1.614145	1.530689	1.225854
MEDIAN	1.625262	1.613629	1.401015	1.359693	1.130428
STD	0.743481	0.797551	0.466923	0.752569	0.124879

RNN, 29.9% enhanced than MBO-HDNN-RNN, 19.3% higher than CSO-HDNN-RNN and 5.10% improved than BWO-HDNN-RNN. Hence, the recommended technique effectively attained a higher performance rate than the preceding strategies.

6.8. Accuracy-based evaluation of the developed model using image classification networks

Accuracy-based evaluation of the designed model using image classification networks is shown in Table 6. Therefore, the empirical outcomes show that the recommended MRV-BWO-HDNN-RNN-based model attains better performance than the other image classification networks.

7. Conclusion

A unique disease classification and detection mechanism was designed using deep learning approaches to effectively classify the plant disease in the early stages to provide a good crop production rate to the farmers. Initially, essential plant images were gathered from benchmark resources and pre-processed using a contrast enhancement technique. Next, the pre-processed images were provided to the

Table 6. Estimation of the developed MRV-BWO-HDNN-RNN-based plant disease detection model using image classification models.

Performance Measures	GAN (Lamba et al. 2023)	MIR-V2 (Kaur et al. 2023)	ResNet50V2 (Anwar et al. 2023)	DLMC-Net (V. Sharma, Tripathi, and Mittal 2023)	MRV-BWO-HDNN-RNN
Accuracy	91.05	91.96	94.13	95.15	96.47
Sensitivity	90.99	91.90	94.18	95.32	96.47
Specificity	91.11	92.02	94.07	94.98	96.47
Precision	91.10	92.01	94.08	95.00	96.47
FPR	8.89	7.98	5.93	5.02	3.53
FNR	9.01	8.10	5.82	4.68	3.53
NPV	91.11	92.02	94.07	94.98	96.47
FDR	8.90	7.99	5.92	5.00	3.53
F1-Score	91.04	91.96	94.13	95.16	96.47
MCC	82.10	83.92	88.26	90.31	92.93

segmentation stage using the proposed CO-KMC to increase the variance and correlation coefficient rate. Next, the segmented images were offered to feature retrieval stage 1 and obtained the first set of features like colour, texture, and shape. Next, in feature extraction phase II, the pre-processed images were used to acquire the deep features by MSDA-CNN. Then, these two sets of features were concatenated to secure the tuned weighted features by the developed MRV-BWO to enhance the correlation coefficient rate. Finally, the tuned weighted features were used in the HDNN-RNN-based plant disease classification phase and secured better plant disease identification and classification rate by tuning the constraints like the number of suitable hidden neurons in DNN and CNN, and epochs in DNN and CNN by the developed MRV-BWO algorithm to increase the accuracy and decrease the FPR. Precision analysis executed in the suggested MRV-BWO-HDNN-RNN-based plant disease detection and classification technique achieved a superior performance rate of 9.4% higher than EOO-HDNN-RNN, 14.08% enhanced than MBO-HDNN-RNN, 9.45% improved than CSO-HDNN-RNN and 5.19% enhanced than BWO-HDNN-RNN, in corn plants. Hence, the implemented plant disease identification and classification technique secured a higher effectiveness rate than the classical method in various observations with minimal validation time. However, the developed model cannot detect all possible diseases which will be addressed in future works. Also, we will extend our work with robotic arm-based solutions and real-time detection for plant disease identification and treatment.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Ahmad, M., M. Abdullah, H. Moon, and D. Han. 2021. "Plant Disease Detection in Imbalanced Datasets Using Efficient Convolutional Neural Networks with Stepwise Transfer Learning." *Institute of Electrical and Electronics Engineers Access* 9:140565–140580. <https://doi.org/10.1109/ACCESS.2021.3119655>.

- Ai, Y., C. Sun, J. Tie, and X. Cai. 2020. "Research on Recognition Model of Crop Diseases and Insect Pests Based on Deep Learning in Harsh Environments." *Institute of Electrical and Electronics Engineers Access* 8:171686–171693. <https://doi.org/10.1109/ACCESS.2020.3025325>.
- Anwar, S., S. R. Soomro, S. K. Baloch, A. A. Patoli, and A. R. Kolachi. 2023. "Performance Analysis of Deep Transfer Learning Models for the Automated Detection of Cotton Plant Diseases." *Engineering, Technology & Applied Science Research* 13 (5): 11561–11567. <https://doi.org/10.48084/etasr.6187>.
- Azimi, S., R. Wadhawan, and T. K. Gandhi. 2021. "Intelligent Monitoring of Stress Induced by Water Deficiency in Plants Using Deep Learning." *IEEE Transactions on Instrumentation and Measurement* 70 (5017113): 1–13. <https://doi.org/10.1109/TIM.2021.3111994>.
- Barburiceanu, S., S. Meza, B. Orza, R. Malutan, and R. Terebes. 2021. "Convolutional Neural Networks for Texture Feature Extraction. Applications to Leaf Disease Classification in Precision Agriculture." *Institute of Electrical and Electronics Engineers Access* 9:160085–160103. <https://doi.org/10.1109/ACCESS.2021.3131002>.
- Braik, M. S. 2021. "Chameleon Swarm Algorithm: A Bio-Inspired Optimizer for Solving Engineering Design Problems." *Expert Systems with Applications* 174:114685. <https://doi.org/10.1016/j.eswa.2021.114685>.
- Chen, W.-L., Y.-B. Lin, F.-L. Ng, C.-Y. Liu, and Y.-W. Lin. 2020. "RiceTalk: Rice Blast Detection Using Internet of Things and Artificial Intelligence Technologies." *IEEE Internet of Things Journal* 7 (2): 1001–1010. <https://doi.org/10.1109/JIOT.2019.2947624>.
- Chen, J., H. Yin, and D. Zhang. 2020. "A Self-Adaptive Classification Method for Plant Disease Detection Using GMDH-Logistic Model." *Sustainable Computing: Informatics and Systems* 28 (100415): 100415. <https://doi.org/10.1016/j.suscom.2020.100415>.
- Dwivedi, R., S. Dey, C. Chakraborty, and S. Tiwari. 2021. "Notice of Violation of IEEE Publication Principles: Grape Disease Detection Network Based on Multi-Task Learning and Attention Features." *IEEE Sensors Journal* 21 (16): 17573–17580. <https://doi.org/10.1109/JSEN.2021.3064060>.
- Dwivedi, R., T. Dutta, and Y.-C. Hu. 2022. "A Leaf Disease Detection Mechanism Based on L1-Norm Minimization Extreme Learning Machine." *IEEE Geoscience & Remote Sensing Letters* 19 (8019905): 1–5. <https://doi.org/10.1109/LGRS.2021.3110287>.
- Geng, X., Y. Mu, S. Mao, J. Ye, and L. Zhu. 2020. "An Improved K-Means Algorithm Based on Fuzzy Metrics." *Institute of Electrical and Electronics Engineers Access* 8:217416–217424. <https://doi.org/10.1109/ACCESS.2020.3040745>.
- Huang, W., Q. Guan, J. Luo, J. Zhang, J. Zhao, D. Liang, L. Huang, et al. 2014. "New Optimized Spectral Indices for Identifying and Monitoring Winter Wheat Diseases." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 7 (6): 2516–2524. <https://doi.org/10.1109/JSTARS.2013.2294961>.
- Jiang, P., Y. Chen, B. Liu, D. He, and C. Liang. 2019. "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks." *Institute of Electrical and Electronics Engineers Access* 7:59069–59080. <https://doi.org/10.1109/ACCESS.2019.2914929>.
- Kaur, P., S. Harnal, V. Gautam, M. P. Singh, and S. P. Singh. 2023. "A Novel Transfer Deep Learning Method for Detection and Classification of Plant Leaf Disease." *Journal of Ambient Intelligence and Humanized Computing* 14 (9): 12407–12424. <https://doi.org/10.1007/s12652-022-04331-9>.
- Khan, M. A., M. I. U. Lali, M. Sharif, K. Javed, K. Aurangzeb, S. I. Haider, A. S. Altamrah, et al. 2019. "An Optimized Method for Segmentation and Classification of Apple Diseases Based on Strong Correlation and Genetic Algorithm Based Feature Selection." *Institute of Electrical and Electronics Engineers Access* 7:46261–46277. <https://doi.org/10.1109/ACCESS.2019.2908040>.
- Khattak, A., M. U. Asghar, U. Batool, M. Z. Asghar, H. Ullah, M. Al-Rakhami, A. Gumaei, et al. 2021. "Automatic Detection of Citrus Fruit and Leaves Diseases Using Deep Neural Network Model." *Institute of Electrical and Electronics Engineers Access* 9:112942–112954. <https://doi.org/10.1109/ACCESS.2021.3096895>.

- Kumar, M., A. Kumar, and V. S. Palaparthi. 2021. "Soil Sensors-Based Prediction System for Plant Diseases Using Exploratory Data Analysis and Machine Learning." *IEEE Sensors Journal* 21 (16): 17455–17468. <https://doi.org/10.1109/JSEN.2020.3046295>.
- Lamba, S., P. Saini, J. Kaur, and V. Kukreja. 2023. "Optimized Classification Model for Plant Diseases Using Generative Adversarial Networks." *Innovations in Systems and Software Engineering* 19 (1): 103–115. <https://doi.org/10.1007/s11334-022-00507-w>.
- Latif, A., A. Rasheed, U. Sajid, J. Ahmed, N. Ali, N. I. Ratyal, B. Zafar, S. H. Dar, M. Sajid, and T. Khalil. 2019. "Content-Based Image Retrieval and Feature Extraction: A Comprehensive Review." *Mathematical Problems in Engineering* 2019:1–21. <https://doi.org/10.1155/2019/9658350>.
- Luo, D., Y. Zou, and D. Huang. 2017. "Speech Emotion Recognition via Ensembling Neural Networks." 2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), Kuala Lumpur, Malaysia.
- Montaha, S., S. Azam, A. K. M. R. H. Rafid, M. Z. Hasan, A. Karim, and A. Islam. 2022. "TimeDistributed-CNN-LSTM: A Hybrid Approach Combining CNN and LSTM to Classify Brain Tumor on 3D MRI Scans Performing Ablation Study." *Institute of Electrical and Electronics Engineers Access* 10:60039–60059. <https://doi.org/10.1109/ACCESS.2022.3179577>.
- Peña-Delgado, A. F., H. Peraza-Vázquez, J. H. Almazán-Covarrubias, N. T. Cruz, P. M. García-Vite, A. B. Morales-Cepeda, J. M. Ramírez-Arredondo, and S. A. Edalatpanah. 2020. "A Novel Bio-Inspired Algorithm Applied to Selective Harmonic Elimination in a Three-Phase Eleven-Level Inverter, Advances in Numerical Optimisation: Theory, Models, and Applications." *Mathematical Problems in Engineering* 2020:1–10. <https://doi.org/10.1155/2020/8856040>.
- Rao, K. N., K. V. Rao, and P. V. G. D. Prasad Reddy. 2021. "A Hybrid Intrusion Detection System Based on Sparse Autoencoder and Deep Neural Network." *Computer Communications* 180:77–88. <https://doi.org/10.1016/j.comcom.2021.08.026>.
- Sadollah, A., A. Bahreininejad, H. Eskandar, and M. Hamdi. 2013. Mine Blast Algorithm: A New Population Based Algorithm for Solving Constrained Engineering Optimization Problems. *Applied Soft Computing* 13 (5): 2592–2612. <https://doi.org/10.1016/j.asoc.2012.11.026>.
- Salim, A., W. K. Jummar, F. M. Jasim, and M. Yousif. 2022. "Eurasian Oystercatcher Optimiser: New Meta-Heuristic algorithm." *Journal of Intelligent Systems* 31 (1): 332–344. <https://doi.org/10.1515/jisys-2022-0017>.
- Sharma, P., Y. P. S. Berwal, and W. Ghai. 2020. "Performance Analysis of Deep Learning CNN Models for Disease Detection in Plants Using Image Segmentation." *Information Processing in Agriculture* 7 (4): 566–574. <https://doi.org/10.1016/j.inpa.2019.11.001>.
- Sharma, V., A. K. Tripathi, and H. Mittal. 2023. "DLMC-Net: Deeper Lightweight Multi-Class Classification Model for Plant Leaf Disease Detection." *Ecological Informatics* 75:102025. <https://doi.org/10.1016/j.ecoinf.2023.102025>.
- Singh, U. P., S. S. Chouhan, S. Jain, and S. Jain. 2019. "Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease." *Institute of Electrical and Electronics Engineers Access* 7:43721–43729. <https://doi.org/10.1109/ACCESS.2019.2907383>.
- Sreedevi, A., Manike, C. 2022. "A Smart Solution for Tomato Leaf Disease Classification by Modified Recurrent Neural Network with Severity Computation." *Cybernetics and Systems* 55 (2): 1–41. <https://doi.org/10.1080/01969722.2022.2122004>.
- Sunil, C. K., C. D. Jaidhar, and N. Patil. 2022. "Cardamom Plant Disease Detection Approach Using EfficientNetv2." *Institute of Electrical and Electronics Engineers Access* 10:789–804. <https://doi.org/10.1109/ACCESS.2021.3138920>.
- Sun, J., Y. Yang, X. He, and X. Wu. 2020. "Northern Maize Leaf Blight Detection Under Complex Field Environment Based on Deep Learning." *Institute of Electrical and Electronics Engineers Access* 8:33679–33688. <https://doi.org/10.1109/ACCESS.2020.2973658>.
- Tiwari, V., R. C. Joshi, and M. K. Dutta. 2021. "Dense Convolutional Neural Networks Based Multiclass Plant Disease Detection and Classification Using Leaf Images." *Ecological Informatics* 63 (101289): 101289. <https://doi.org/10.1016/j.ecoinf.2021.101289>.
- Trang, K., L. T. That, N. G. M. Thao, and N. T. T. Thi. 2019. "Mango Diseases Identification by a Deep Residual Network with Contrast Enhancement and Transfer Learning." 2019 IEEE Conference on

- Sustainable Utilization and Development in Engineering and Technologies (CSUDET), Penang, Malaysia, 138–142.
- Udutalapally, V., S. P. Mohanty, V. Pallagani, and V. Khandelwal. 2021. "sCrop: A Novel Device for Sustainable Automatic Disease Prediction, Crop Selection, and Irrigation in Internet-Of-Agro-Things for Smart Agriculture." *IEEE Sensors Journal* 21 (16): 17525–17538. <https://doi.org/10.1109/JSEN.2020.3032438>.
- Umamageswari, A., N. Bharathiraja, and D. S. Irene. 2021. "A Novel Fuzzy C-Means Based Chameleon Swarm Algorithm for Segmentation and Progressive Neural Architecture Search for Plant Disease Classification." *ICT Express* 9 (2): 160–167.
- Vigier, B. J., E. Pattey, and I. B. Strachan. 2004. "Narrowband Vegetation Indexes and Detection of Disease Damage in Soybeans." *IEEE Geoscience and Remote Sensing Letters* 1 (4): 255–259. <https://doi.org/10.1109/LGRS.2004.833776>.
- Xia, H., W. Sun, S. Song, and X. Mou. 2020. "Md-Net: Multi-Scale Dilated Convolution Network for CT Images Segmentation." *Neural Processing Letters* 51 (3): 2915–2927. <https://doi.org/10.1007/s11063-020-10230-x>.
- Xiong, J., D. Yu, S. Liu, L. Shu, X. Wang, and Z. Liu. 2021. "A Review of Plant Phenotypic Image Recognition Technology Based on Deep Learning Electronics." *Electronics* 10 (1): 81. <https://doi.org/10.3390/electronics10010081>.
- Yang, G., G. Chen, Y. He, Z. Yan, Y. Guo, and J. Ding. 2020. "Self-Supervised Collaborative Multi-Network for Fine-Grained Visual Categorization of Tomato Diseases." *Institute of Electrical and Electronics Engineers Access* 8:211912–211923. <https://doi.org/10.1109/ACCESS.2020.3039345>.
- Zeng, Q., X. Ma, B. Cheng, E. Zhou, and W. Pang. 2020. "GANs-Based Data Augmentation for Citrus Disease Severity Detection Using Deep Learning." *Institute of Electrical and Electronics Engineers Access* 8:172882–172891. <https://doi.org/10.1109/ACCESS.2020.3025196>.
- Zhou, G., W. Zhang, A. Chen, M. He, and X. Ma. 2019. "Rapid Detection of Rice Disease Based on FCM-KM and Faster R-CNN Fusion." *Institute of Electrical and Electronics Engineers Access* 7:143190–143206. <https://doi.org/10.1109/ACCESS.2019.2943454>.